INTEGRATIVE FREIGHT DEMAND MANAGEMENT IN THE NEW YORK CITY METROPOLITAN AREA

Cooperative Agreement #DTOS59-07-H-0002

Final Report

Submitted to:

United States Department of Transportation

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September 30, 2010

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ACKNOWLEDGEMENTS

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1. EXECUTIVE SUMMARY

This project is one of the first in the world that has successfully integrated the use of remote sensing technology—in this case Global Positioning System (GPS) enabled cell phones—as part of a system that effectively reduces truck traffic in the congested hours of the day, through the use of incentives to receivers. In doing so, the project designed, developed, and pilot tested a concept that:

- Exploited the use of GPS technology and its estimates of travel times and delays, for compliance verification, data sharing among participating partners, and validation of the traffic models used to predict the effects of the proposed program on the traffic network.

- Developed state of the art analytical formulations and simulation systems to study and predict the behavior of carriers and receivers—together with the underlying behavioral theories—that were successfully verified during the pilot test conducted.

- Led to new policy paradigms that, by exploiting the nature of Large Traffic Generators and unassisted deliveries, greatly reduce the need for financial incentives to receivers.

- Garnered the enthusiastic support of large corporations involved in urban delivery activities, trade organizations, trade publications, and the industry at large, as they understood the concept's potential as a business-friendly and effective freight demand management tool they could embrace. It is worthy of notice that some of the companies involved in the pilot test are considering using off-hour deliveries on a permanent basis, or have already decided to commit to off-hour deliveries, and that the *Journal of Commerce* published two articles on the project (which is highly unusual as its main focus is not on research projects).

- Conducted institutional analyses to identify and preliminarily discuss potential inter-agency arrangements that could support the concept. These analyses—together with a vigorous outreach to relevant agencies, and representatives of the freight industry, shippers, and receivers—have provided the project an outstanding support base. This has engendered the support of the key transportation agencies involved in the project as they were able to appreciate the demand management potential of the concept.

- Has received considerable research acclaim. As of the publication of this report, the research supporting the project has received three awards, was selected to be presented as the Plenary Lecture at the International Transportation Economics Conference in Minneapolis in June 2009, has produced seven journal papers, was featured in two *Journal of Commerce* articles (Journal of Commerce, 2009; 2010), was written about in the *Wall Street Journal* (Wall Street Journal, 2010), and was recognized by the NYCDOT Commissioner Janette Sadik-Khan for its potential impact in New York City at a ceremony to publicly recognize the pilot test participants. This is a considerable achievement for a project of this nature, and one that provides testimony of the validity of its conceptual foundations.

In the opinion of the team, the project has opened new doors for the use of remote sensing technology as a central component of a freight demand management concept that is widely supported by both the freight industry and transportation agencies, which is solidly supported by cutting edge research. The team is optimistic that the project will prove to be a watershed in freight demand

management in urban areas. The following sections discuss the key findings in each of the key areas of work. Additional information can be found in the corresponding chapters in the final report.

1.1 Project Background

This project has enjoyed strong industry support since its inception. The foundation of this project is the work conducted for the New York State Department of Transportation (NYSDOT) by team members. The original NYSDOT project entitled "Potential for Off-Peak Freight Deliveries to Congested Urban Areas" was the result of a request made in early 2002 by the New York City Chapter of the then Council of Logistics Management (now Council of Supply Chain Management Professionals) to NYSDOT to find ways to encourage off-hour deliveries in New York City. The NYSDOT agreed that the proposed subject was worthy of study and issued a Request for Proposals on December 2002, which led to the selection of Rensselaer Polytechnic Institute as the lead contractor. The main focus of the original NYSDOT project was Manhattan, and its objectives were to:

- "Define the set of policies and programs that would induce a shift of deliveries to off-peak hours (referred to here as *off-peak delivery initiatives*)."
- "Quantify stakeholders' costs and benefits associated with off-peak deliveries initiatives."
- "Perform an economic analysis of the expansion of hours during which pick-ups and deliveries are made to commercial areas."
- "Quantify extra costs to stakeholders so that compensation schemes could be implemented, should off-peak deliveries be found to be economically beneficial to Society at large."

In May 2005 the Southwest Brooklyn Industrial Development Corporation (SWBIDC)—that heard about the project through informal channels—requested NYSDOT to include Brooklyn in the study. NYSDOT agreed and a second phase of the project with a Brooklyn focus was added. A final report for both phases was issued on December 8, 2006 (Holguín-Veras, 2006).

The current project titled "Integrative Freight Demand Management for the New York City Metropolitan Area" was funded by the United States Department of Transportation's Commercial Remote Sensing and Spatial Information Technology Applications Program in March 2007, in response to a proposal submitted to the BAA DTPH56-06-BAA-0002 by a consortium of Rensselaer Polytechnic Institute, Rutgers University, Rudin Center for Transportation Policy and Management at NYU-Wagner, and ALK Technologies Inc. The original scope of work, which included a pilot test of substantial size, was reduced to place more emphasis on the design of the system, and the large pilot was transformed into a "small scale deployment."

The main charge of the project could be summarized as follows:

"The project would design and develop a self-sustaining urban freight traffic management system for the New York City metro area that integrates state of the art remote sensing technology, cutting edge freight demand management, traffic simulation, and policy. The project

combines the revenue generation power of time-of-day pricing, with tax deductions to receivers willing to accept off-peak deliveries, and GPS based traffic monitoring, to induce a shift of truck traffic to the off-hours."

1.1.1 Funding

The work started on July 1, 2007. The total funding provided by the USDOT was about $1.2 million. The project partners provided $0.64 million in matching funds.

1.1.2 Goals and Objectives

In terms of goals and objectives:

"The proposed concept is expected to: (1) induce a significant shift of truck traffic to the off-peak hours (preliminary estimates suggest that, in some industry segments, the shift could reach 20% of local day truck traffic) (Holguín-Veras et al., 2006b); (2) bring about significant improvements in traffic congestion and environmental conditions; and (3) increase the competitiveness of NYC via tax deductions to local businesses, productivity increases from improved traffic conditions, and significant reductions in parking fines (that frequently exceed $1,000 per truck per month). Once the concept has been designed and developed, it will be demonstrated in a small scale field deployment test."

1.1.3 Project Focus

It is important to stress that the project focused on urban deliveries, i.e., the transportation of cargo to urban locations. The main reason being that they represent the bulk of the freight traffic in urban areas, most likely accounting for more than 80% of the entire freight traffic, and the natural target for freight demand management programs aimed at reducing the congestion they produce. Other segments, e.g., external-external flows that pass through the urban area, are not discussed.

The project focus must be kept in mind as urban deliveries are quite different than other segments of the freight industry. First, they are typically made in relatively long delivery tours—with an average of 5.5 delivery stops per tour in New York City—that start and end at the home base. Second, in cases where there is cordon pricing, the tours incur a toll at the entrance of the urban area in order to deliver to the customers inside (which translates into the toll surcharge being a fixed cost). Third, the shipment sizes tend to be relatively small as they are frequently delivered with relatively smaller vehicles. All these aspects, and others not listed here, make urban deliveries a rather unique operation with characteristics not found in other segments of the freight industry.

As a result, the conclusions and methodologies developed here should be assumed to be valid only for the urban delivery case. Further research must be conducted to assess how valid they are for application in other types of freight operations.

1.2   Methodology

1.2.1   Remote sensing and pilot test

The pilot test was organized around a set of four industrial partners, i.e., industry leaders with interest in exploring off-hour deliveries. The partners were: (1) Foot Locker and New Deal Logistics; (2) Sysco and a sample of its customers; and (3) Whole Foods Market and its vendors. It is important to mention that all partners are leaders in their respective field of business.

In all cases, these partners switched their distribution chains—particularly the transportation and the receiving end—to the off-hours for at least a month. In total, 25 receivers (30 receivers if partial participation is counted) and eight carriers/vendors participated in the test. Since there were no interactions among each of the industrial partner groupings, the pilot tests were run independently of each other, and started as soon as each group was ready to begin. It is important to mention that the industrial partners committed a significant amount of effort and expenses to participate in the test. High level executives and, in some cases, their entire logistic teams participated in dozens of conference calls discussing the preparations for the pilot test. Although the team decided to give the carriers designated as industrial partners a token payment of $3,000—as a show of appreciation for their efforts—the fact of the matter is that this amount does not cover even a fraction of their staff time. Their investment in this effort provides clear evidence of the industry support for the concept. The dates of participation are shown in parenthesis next to the company names. The partners were:

- **Group 1: Foot Locker and New Deal Logistics (October 2-November 14, 2009):** Eight Foot Locker stores and New Deal Logistics participated.

- **Group 2: Sysco and a sample of its customers (December 21-January 23, 2010):** Thirteen stores successfully completed the test, five participated partially and dropped out for reasons unrelated to the project, and another three agreed to participate but did not order products from the vendor during the pilot test (reasons unknown).

- **Group 3: Whole Foods Market and its vendors (December 28-January 31, 2010):** This group included the four Whole Foods Market locations not subject to night delivery restrictions plus six of their vendors. The other two Manhattan Whole Foods Market locations could not participate; one due to a lease restriction and the other due to neighborhood restrictions on overnight deliveries.

The participating receivers were provided a financial incentive of $2,000 for successful participation in the pilot test. This incentive was larger than the ones considered during the research work—which are associated with a long term commitment to off-hours—to compensate for the setup costs associated with switching to the off-hours at the beginning of the pilot, and then back to the regular hours upon completion. The participating carriers were given an incentive of $300 per truck participating in the pilot test to compensate for the corresponding setup costs. Obviously, since they stand to benefit from delivering during the off-hours, the incentive could be smaller than the one for receivers.

1.2.2 Approach to reducing peak deliveries

The analyses of the data collected from carriers as part of both the Evaluation Study of the Port Authority of New York and New Jersey's Time of Day Pricing Initiative (Holguin-Veras et al., 2005; Holguín-Veras, 2006), and the NYSDOT's "Potential for Off-Peak Freight Deliveries to Congested Urban Areas" project (Holguín-Veras, 2006), produced findings that challenge long-held assumptions. The data showed that: (1) the ability of carriers to unilaterally change delivery times is quite limited as it necessitates the concurrence of the receivers (which tend to prefer regular-hour deliveries as they can take advantage of the staff at hand, as opposed to off-hour deliveries that may require extra staff, security, lighting, and other costs); and, (2) cordon tolls are not likely to be effective in inducing a switch to the off-hours, as most segments of the urban freight industry cannot pass toll costs to their customers depriving them of the price signal needed to effect a change. It is very telling that: (1) only about 9% of carriers could pass the toll costs to their customers; and (2) when carriers were asked about why they did not change behavior in response to time-of-day tolls, about 70% of them cited "customer requirements" as the reason (Holguín-Veras et al., 2006c). In essence, the receiver is the key decision maker.

Further analyses (Holguín-Veras, 2008) concluded that the difficulties that carriers have in passing cordon time-of-day tolls to their customers reflect a highly competitive market with delivery rates equal to marginal costs. Since the cordon toll is a fixed cost—as it does not depend on the unit of output—it does not enter into the rates. The empirical data confirmed that only the market segments with market power (i.e., carriers of stone/concrete, wood/lumber, food, electronics, and beverages) could pass toll costs in a meaningful way (Holguín-Veras, 2008). The key insight is that, since the price signal only reaches the receivers in those cases where the carrier has market power (though in a diluted fashion because they allocate the toll costs among the multiple receivers in the tour), carrier centered pricing policies are not as effective as they should be because receivers have no incentive to change behavior. Since the consent of the receivers is needed for the carriers to change behavior, it follows that a new policy paradigm is needed. These new policies specifically target the receivers of the cargoes as they are the ones that determine whether or not the carriers can switch to the off-hours.

The fundamental tenet of this project is that the key to inducing a shift of truck traffic to the off-hours is to convince receivers to accept off-hour deliveries by either: (1) providing incentives in exchange for their commitment to off-hour deliveries; or (2) by fostering the use of concepts such as unassisted deliveries that do not require receivers to provide staff to handle deliveries during the off-hours. Since the carriers stand to benefit from doing off-hour work (delivering in the off-hours is between 20-30% cheaper than delivering during the regular hours), they would be glad to do off-hour deliveries as long as a sufficient number of receivers would be willing to accept off-hour deliveries. This means that, if the carrier is able to switch an entire distribution route to the off-hours, it will save money.

However, it is not likely that a carrier will find it beneficial to split a regular-hour route into two routes, one for regular-hour customers and another for the off-hours, because the cost of the extra route would offset the operational cost savings.

Inducing receivers to accept off-hour deliveries will lead to the following chain of events:

- The barrier that prevents many carriers from doing off-hour deliveries will be removed.

- A significant number of carriers will switch to the off-hours.

- Congestion will be reduced, and environmental conditions will improve.

- The competitiveness of the urban area will increase as business activities will be more productive and efficient.

1.2.3 Behavioral/economic research supporting the concept

The estimation of the potential participation in off-hour deliveries is of great importance as it determines the economic benefits attributable to the practice in terms of travel time reductions, improvement of environmental conditions, and sustainability. Estimating participation in off-hour deliveries necessitates the combined use of behavioral research—to estimate the likely response of the freight industry to various policies—and freight trip generation analyses to get an idea about the total number of deliveries that would switch to the off-hours. It is important to acknowledge that, though state of the art methodologies have been used throughout the project, there is an unknown amount of uncertainty in the estimates provided. To account for this, whenever possible, the estimates are presented in the form of ranges. This section summarizes the process followed and the key results.

The behavioral research produced by the project has significantly advanced freight transportation modeling, and freight behavior research, as well as enhanced the transportation community's ability to understand and predict the freight industry's response to various policies. The research conducted included: (1) the development of a Behavioral Micro-Simulation (BMS) (Silas and Holguín-Veras, 2009), and of an approximation model to estimate participation in off-hour deliveries (Holguín-Veras, 2010); (2) the formulation of an analytical model that explains the observed limitations of freight road pricing, and the need for comprehensive carrier-receiver policies (Holguín-Veras, 2008; 2009); and (3) the application of these novel developments to the New York City case.

The behavioral research conducted has led to insight of great practical and theoretical significance. More specifically, the research demonstrated on the basis of theory and empirical data that:

- Receiver participation in off-hour deliveries increases with the amount of the incentive provided (though there are industry segments that are more sensitive than others).

- Conducting off-hour deliveries is about 30% cheaper than delivering in the regular hours. The cost estimates produced by the team—and confirmed with the input of the industrial partners—clearly indicate that off-hour deliveries are about 30% cheaper than regular-hours'

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(even after premium wages are paid to the off-hour crews). In addition to the lower operational costs, making deliveries in the off-hours leads to highly reduced parking fines. This is a major issue as the parking fines incurred during the regular hours average between $500 and $1,000 per truck per month (Holguín-Veras, 2006). Moreover, since parking fines are not a valid business expense—they are a violation of traffic law—the businesses cannot deduct them from taxes.

- The carriers most inclined to participate are those that have delivery tours with fewer delivery stops. Carriers stand to benefit from off-hour deliveries if a substantial number of the customers in a tour accept off-hour deliveries (if the carrier would have to make two trips to deliver during both regular and off-hours, the operation may not be profitable). Since the smaller the number of customers, the easier it is to have all of them agreeing to do off-hour deliveries (Holguín-Veras, 2009), it follows that carriers with short delivery tours are likely to be the ones most inclined to do off-hour deliveries.

- Cordon time-of-day pricing is of limited usefulness for freight demand management. The reason is related to the inherent weakness of the urban delivery industry which has limited ability to pass the toll costs to the customers. (The explanation is rooted in economic theory as the cordon toll is a fixed cost that does not enter in the freight rates which are equal to marginal costs.) As a result, since the toll signals do not reach the customers, they have no incentive to switch to the off-hours. Equally important is that, even if the carriers can pass the toll costs to the customers, the practical range of the tolls is such that the ensuing increases would not induce the receivers to move to the off-hours (Holguín-Veras, 2009).

- Time-distance pricing is slightly more effective than cordon time-of-day tolls, though in order to produce a significant shift to the off-hours it would require massive tolls. The research revealed that time-distance tolls can be passed by carriers to receivers—as they enter in the marginal costs that determine the rates in a competitive market. However, in order for time-distance pricing to induce receivers to change to the off-hours, the cost increase to the receivers would have to be larger than their incremental cost of moving to the off-hours. This leads to time-distance tolls that, for the average tour of five receivers, are about five times larger than current operational costs which sounds politically unfeasible (Holguín-Veras, 2009).

1.2.4 Data collection scheme

The remote sensing component was undertaken with GPS enabled smartphones and the Copilot|Live turn-by-turn navigation software. The selected smartphone model was the MWg Zinc ii. It was selected because it contains a powerful 500 MHz processor, bright 2.8" touch screen, high quality built-in SiRf Star_iii GPS receiver, substantial memory, a pull-out QWERTY keyboard, and the Windows Mobile 6.0 operating systems. The smartphones were configured in such a way that the only action required by the driver was to turn the phone on at the beginning of the route; no further interaction between the driver and the smartphones was required while driving. Safety is of the upmost concern and the project team ensured that the smartphone would not be a distraction to the driver. Usage and safety information was personally provided by a representative of ALK Technologies when the smartphones were distributed to

the participating carriers for use during the pilot test. In cases where the carrier already had GPS equipment for fleet monitoring purposes, they were given the option of sharing the data with the team instead of using the phones. A noticeable number of participants elected to do that, and some even provided data for the entire metropolitan area, not just the routes involved in the pilot test. This enabled the team to obtain background performance data for a much larger fleet of trucks. In some cases, passive GPS data loggers were used as a backup. Upon receiving the GPS data, the team analyzed them to obtain estimates of travel speeds, delays, standard deviations, and other useful indicators of performance.

1.3   *Results from Base Case Data and Pilot Test*

This section discusses the results obtained during the pilot test, which are contrasted with the base case conditions, in terms of both productivity performance measures and the feedback received from the participating companies. The productivity analyses focus on the travel speeds, both from the depot to the first customer in Manhattan and from customer to customer, as well as the service times (time spent doing a delivery) at the stops. The team separated the travel to the first customer from the customer to customer trips, because they have radically different characteristics (the former is a relatively long trip with few stops in between, while the latter are typically short trips with many stops due to urban driving conditions, e.g., signals, pedestrians, etc). Furthermore, the focus on customer to customer travel speeds enables one to consider the collective impact of these traffic delays produced by the urban driving conditions. On the other hand, the analyses of service times provide very useful insight into the delays associated with making deliveries. As discussed later in the document, the team discussed the results with the industrial partners who verified the validity of the conclusions and findings obtained. Since the data from the different groups that participated in the pilot test were not enough to produce statistically representative results for the entire range of times of travel, the different data sets were pooled together to produce a more robust set of estimates.

An important technical note is that the speeds represent space mean estimates, which are defined as the distance traveled from a point of origin to a point of destination divided by the time it takes to make that trip. This obviously includes the interruptions to the traffic created by traffic signals, pedestrians, and other vehicles. Instantaneous speeds are not used in the analyses because they exhibit a great deal of variability and cannot capture the obstructions mentioned above. When interpreting the results, the reader should be aware that there are no data for the time between 10 PM and 4 AM (the 4 - 5 AM time period only contains a handful of observations). Similarly, although the entire data include about 4,000 individual trips, no assurances can be provided about how representative the data are of the overall truck traffic in the New York City metropolitan area. In spite of these caveats, the data do seem to provide a coherent picture of the potential impacts of off-hour deliveries.

The results are displayed in the form of a box and whisker plot that presents the 2nd, 25th, 50th (median), 75th, and 98th percentiles, and the outliers. (The percentile is the value below which a given percent of the observations fall under. For instance the 25th percentile is the value below which 25% of the observations fall under.) In the plot, the 2nd percentile is the tip of lower whisker, the 25th percentile is the lower tip of the box, the 50th percentile (median) is the line in between the boxes, the 75th is the top of the box, and the 98th percentile is the tip of the upper whisker. Values outside these percentiles are shown as crosshatches.

1.3.1   Customer to customer travel speeds

The customer to customer speeds and the corresponding percentiles are shown in Figure 1. The results indicate a clear pattern in which the speeds decrease in the day hours and increase in the off-hours. As illustrated in the figure, while the speeds in the 5 - 7 AM period reach almost 8 miles/hour (mph); they drop to below 3 mph during the day hours. The sparse data in the 4 - 5 AM hour (only four observations) suggest that in the early hours of the day, travel speeds could be much higher.

In terms of the overall productivity of the off-hour tours, these results indicate that a truck that travels for ten miles making deliveries could save 1.25 hours of travel time if the average speeds are assumed to be 8 mph (off-hours) and 4 mph (regular hours) respectively. Obviously, the longer the tours are, the larger the economic savings associated with a switch to the off-hours.
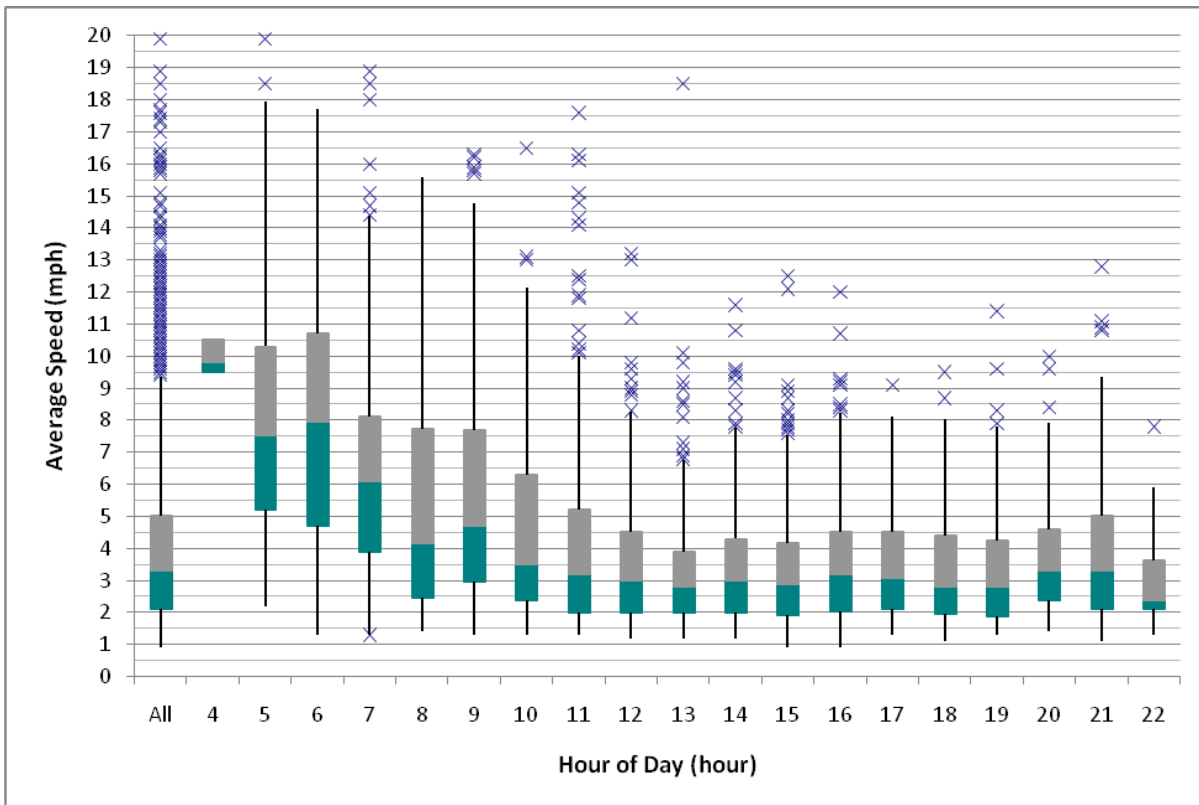
Figure 1: Customer to Customer Space Mean Speeds by Time of Day

1.3.2   Service times

The second performance measure used is the service time, which is defined as the total time spent by the driver at the customer location. This includes the amount of time that the driver spends: loading/unloading the cart used to transport the cargo, walking from/to the truck to/from the customer location, finding the person that would accept the delivery, waiting for the authorized individual to review the shipment made, waiting for proper signatures and/or payment, sorting out any problems that arise, and other related activities. Figure 2 shows the estimates produced by the team.

Figure 2 shows that service times increase in the day hours, and decrease during the off-hours. The differences in magnitude are significant. While in the morning hours—which is when the bulk of the deliveries are made—the service times consistently exceed an hour, reaching a maximum median value of 1.8 hours in the 10 - noon period. During the night hours, the service times drop to a median value of about half an hour. Although no one knows how representative these numbers are of industry-wide conditions, they do indicate that carriers could save up to 1.3 hours per delivery when they switch from the morning to the night hours.

It is important to mention that the team discussed these results with the industrial partners to make sure they conform to their experience. The industrial partners concluded that these results do represent the realities on the ground and that they are part of the "…cost of doing business…" in New York City. They indicated that in the day hours, drivers: typically are forced to park 2-3 blocks away from the customer location, have to wait for loading docks, experience delays in getting access to elevators (either because of other deliveries, or building visitors), have to move their trucks to other locations to avoid fines, and other challenges. In contrast, in the off-hours, they can park closer to the customers and almost all the remaining issues diminish or disappear altogether.

The team also asked about delivery sizes in both the regular and off-hours. The participants indicated that during the off-hours the shipment sizes tend to be larger than in the regular hours (because they take advantage of the larger productivity to transport more cargo). This eliminates any possibility that the larger service times in the regular hours are the result of larger shipments. The implication is that, once the larger shipment sizes in the off-hours are factored in, the productivity savings associated with reductions in service times will be larger than those suggested in Figure 2.
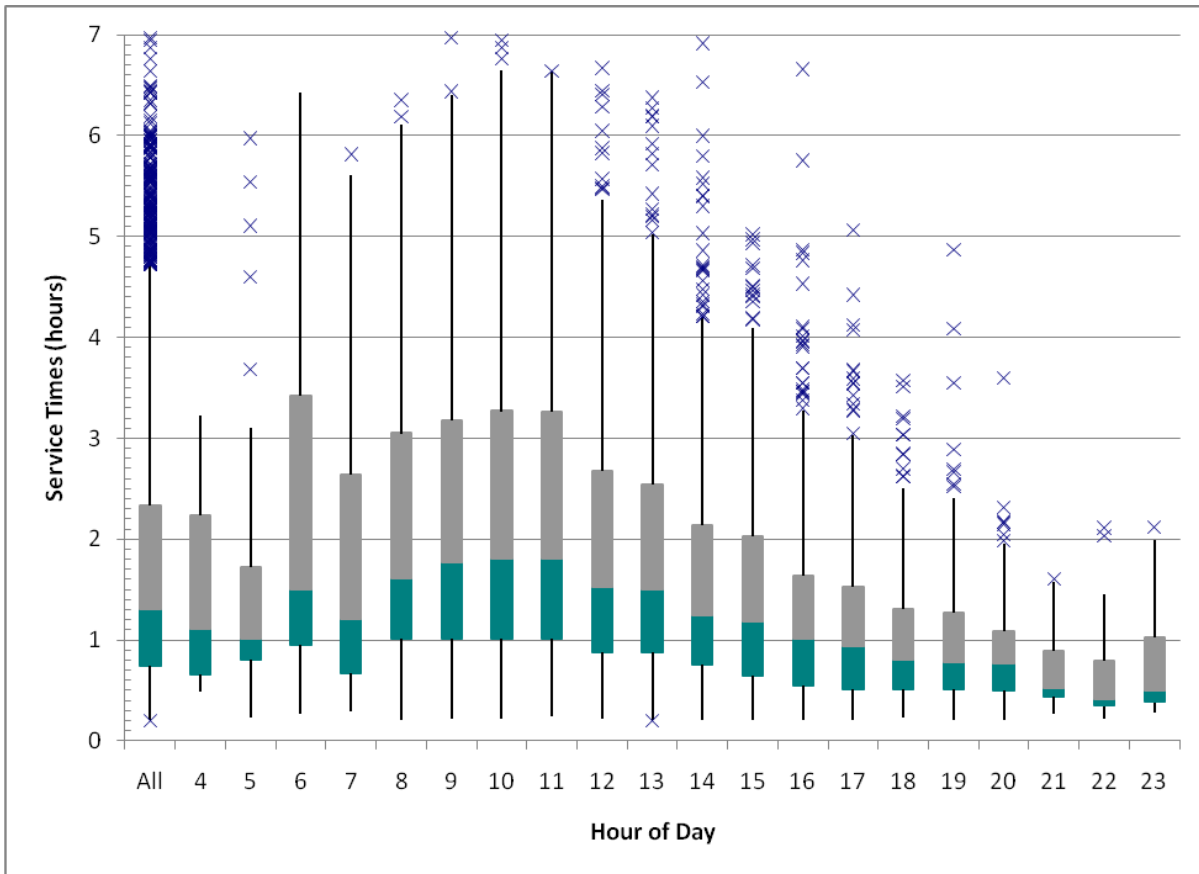
Figure 2: Service Times by Time of Day

These findings have major implications in terms of economic impacts. The most obvious one is that reducing service times will increase the profitability of delivery operations and, ultimately, lower the cost of the products consumed in New York City. A delivery truck that saves 15 minutes at each of the six deliveries, that on average carriers make, will save a total of 1.5 hours (which represents a reduction of $60 per tour). A carrier that saves an average of half an hour per delivery would save about three hours. Regardless of the assumption made, the economic savings are substantial.

Although significant, it is important to keep in mind that these estimates only reflect the benefits of off-hour deliveries to the participating carriers. The benefits associated with lesser truck traffic in the regular hours are discussed in the traffic simulation section.

1.3.3   Feedback from participants

1.3.3.1   Receivers

Mr. Paul Cox, Vice-President for Global Transportation and Supply Chain at Foot Locker, indicated in a call on November 11, 2009, that Foot Locker's experience with off-hour deliveries was quite positive, particularly in regard to the larger volume stores that had employees dedicated to backroom

operations. As of the project team's last communication with Mr. Paul Cox, Foot Locker was considering expanding off-hour deliveries to other stores in Manhattan.

The team also conducted satisfaction surveys. However, in the Foot Locker case, there were some communication problems that impacted the responses from the store managers. More specifically, at the time of conducting the survey, the store managers had not been informed that headquarters had received a financial incentive to compensate them for the additional costs (neither did the survey instruct them to assume that all additional costs would be covered by the financial incentive). Not surprisingly, many of the managers viewed the off-hour deliveries as unfavorable due to the additional costs. On a scale of one to five (with one being the most favorable, and five the least favorable), the average rating was 3.88. For these reasons, these survey results are representative of the attitude towards off-hour deliveries without incentives—which is not what was conducted in the project. In subsequent versions of the survey, the team addressed these issues.

Mr. Rob Twyman, Regional Vice President of Operations for Whole Foods Market - Northeast Region, indicated that he had received good feedback from the stores and that the shifting of delivery times for the participating vendors was "relatively seamless." The project team has also been informed that many of the vendors of Whole Foods Market that shifted delivery times as part of the pilot test continue to deliver to Whole Foods Market during the off-hours.

The project team received satisfaction surveys from twelve of the participating Sysco receivers. The average response concerning the overall impression of off-hour deliveries was 1.50 on a scale of one to five with "1" being "Very Favorable" and "2" being "Favorable." In regard to requesting off-hour deliveries in the future, of the twelve, nine were "Very Likely," one was "Likely," with the remaining customers responding "May or May Not." Six of the twelve utilized unassisted deliveries during the pilot test with five of the other six expressing interest in receiving unassisted deliveries during the off-hours in the future if all liability issues were addressed.

1.3.3.2   Carriers

Mr. Bobby Heim, Sysco Metro New York Vice-President of Operations, indicated that Sysco was extremely happy with the pilot test results. He added that Sysco had been trying to promote off-hour deliveries for years with limited success. The incentive provided to their receivers for participating in the pilot test helped them to go from one overnight route to five. Since the end of the pilot test and the elimination of the financial incentive, some receivers reverted back to regular-hour deliveries and the number of off-hour routes dropped to four. However, it is worthy of notice that the bulk of the receivers elected to continue to receive off-hour deliveries, which was not anticipated. This must be related to the fact that these receivers were using unassisted deliveries (they provided a key to access the establishment

to the Sysco drivers). The main reasons given for continuing with unassisted off-hour deliveries upon completion of the pilot test were related to the increased reliability associated with this practice.

Mr. Joe Killeen, Chief Operating Office of New Deal Logistics, has indicated that making off-hour deliveries reduced the cost of deliveries. He also indicated there were significant increases in travel speeds, availability of parking, and reductions in service times. On one of the routes, New Deal Logistics saw an increase in travel speed of nearly 75% from the depot to the first stop in Manhattan. During the pilot test, New Deal Logistics only made off-hour deliveries to the participating Foot Locker stores during the 7 - 9 PM which limited them to three off-hour deliveries per route. Mr. Killeen indicated that if receivers were to implement methods for unassisted deliveries during the off-hours, it would dramatically impact the number of off-hour deliveries they could make and would significantly reduce their overall costs.

The project team received six satisfaction surveys from participating vendors of Whole Foods Market. Of the six, one had a "Very Favorable" view of off-hour deliveries, three had a "Favorable" view, one was "Neutral," and the remaining vendor had a "Very Unfavorable" view. This vendor had encountered an issue with occasionally having to wait for an extended period of time for receiving and indicated that they would be "Unlikely" to perform off-hour deliveries in the future if requested by customers. The other five vendors indicated that they would be "Very Likely" or "Likely" to make deliveries during the off-hours if requested by the customer.

1.3.3.3 Drivers

The participating drivers for the various carriers in the pilot test overwhelmingly preferred delivering during the off-hours. The survey asked seven questions related to how delivering during the off-hour affected various aspects of the delivery process. The scale used "1" to indicate a very positive effect and "5" to indicate a very negative effect. The data show (see average ratings in parentheses) that drivers experienced much faster travel speeds (1.50), much lower congestion (1.17), a large increase in available parking (1.17), much lower levels of stress (1.17), a lower amount of time to deliver goods at each stop (1.58), a lower amount of time to complete the route (1.58), and an increase in the driver's feeling of safety (2.42). Of the twelve drivers surveyed ten "Strongly Prefer Off-Hour" deliveries, one "Somewhat Prefer Off-Hour" deliveries, and the remaining driver "Strongly Prefer Regular hour" deliveries for an overall impression of 1.42 on the five point scale. The dissatisfied driver worked for the previously mentioned vendor which occasionally had to wait an extended period of time to make a delivery.

1.4 Economic Impacts of a Full Implementation

The quantification of the economic impacts of a full implementation of an off-hour delivery program required: (1) the quantification of the total number of truck-trips that would switch to the off-hours in

response to a given financial incentive to compensate them for the additional costs; (2) the use of network models to simulate what would happen in the network for various scenarios involving a shift to the off-hours; and (3) the estimation of the economic value of the impacts produced, in terms of travel time savings, environmental benefits and the like. This chapter succinctly describes the process followed and the chief results obtained.

1.4.1 Quantification of the potential switch to the off-hours

The estimation of the potential participation in off-hour deliveries required a two step process involving estimating the market response to financial incentives and quantifying the number of deliveries generated by the various industry segments.

The estimation of the market response to the financial incentive to receivers was undertaken with the assistance of a BMS (Silas and Holguín-Veras, 2009), and an analytical model (Holguín-Veras, 2010) specifically designed for that purpose. Both models produced similar results. In essence, these models estimate the market response to the incentive (and other policies) by:

- Estimating how many receivers in the simulated delivery tours would switch to the off-hours. These estimates are produced on the basis of state of the art discrete choice models calibrated from the stated preference data collected by the team, that quantify what receivers would do if offered an incentive.

- Simulating the response of the corresponding carriers. The survey data collected by the team provide great detail on delivery tours, number of delivery stops, and other operational patterns. This allowed the team to estimate the financial impact on the carrier produced by receivers' decisions to switch to the off-hours, by computing the cost savings/increases associated with delivering to the receivers in their time of choice. Typically, if most of the receivers in the tour switch to the off-hours the carrier saves money and therefore would like to do off-hour deliveries; conversely, if only a handful of receivers do so, the delivery costs may increase and the carrier is likely to refuse to do so.

- Aggregating the results for the various industry segments. After simulating the results for randomly generated tours from the data, the team was able to estimate what number and percent of receivers and carriers were willing to do off-hour deliveries for the various industry segments (e.g., food, retail).

The next step was to quantify the total number of deliveries made by the various industry segments, to compute the impacts of off-hours deliveries on the transportation network. As part of this the team:

- Post processed the survey data collected to estimate freight trip generation models (the only models available for New York City conditions).

- Used the models to estimate the total number of deliveries by industry segment and ZIP code for the Manhattan area.

- Computed the number and percentage of deliveries that would switch to the off-hours for each ZIP code.

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- Used these estimates to modify the inputs to the Best Practice Model (BPM), and a mesoscopic traffic simulation model developed by the research team for Midtown and Downtown Manhattan.

The analyses revealed that:

- A staggering number of freight deliveries are made to Manhattan. The estimates—based on the freight generation data collected—show that about 113,000 freight deliveries per day are made to Manhattan, which corresponds to an average trip rate of 0.163 freight deliveries/employee, or 2.798 freight deliveries/establishment. Reflecting the consumer nature of the area, the industry segments with the largest share are: Consumer Goods with 54.48% (wholesale and retail), and the Food sector with another 24.28% (Eating / Drinking Places, and Food Stores).

- The best candidates for participation in off-hour deliveries are the Food and Consumer Goods sectors. On the basis of the total number of deliveries generated and the inclination of each industry segment to participate in off-hour deliveries, the team concluded that in terms of potential payoff, the industry segments that are the best candidates are the Food and Consumer Goods sectors. Although there are several sources of uncertainty, the team estimates that financial incentives of $5,000-$10,000/year would switch about 7-15% of the truck trips to the off-hours, which represents 7,000-16,000 truck trips/day.

- Large Traffic Generators (LTGs) generate about 4-8% of the total number of freight deliveries in Manhattan. This is a notable result. Although there are no hard data to accurately quantify the share of LTGs in the total freight traffic, the team estimated that the 88 buildings with their own ZIP code, e.g., Empire State Building, generate about 4% of the total freight traffic in Manhattan. Adding other buildings that do not have their own ZIP code such as Grand Central Terminal and the Javitts Center, plus large establishments that generate considerable truck traffic, it is entirely possible that LTGs in Manhattan generate 4-8% of the total truck traffic. More importantly, since the LTGs tend to have their own centralized delivery stations, it should be possible for the LTG to receive the off-hour deliveries, and then deliver them to the corresponding businesses during the regular hours.

- Unassisted deliveries provide a great alternative to the provision of financial incentives. "Unassisted deliveries" refers to a range of delivery systems that eliminate the need for human intervention at the receiving end. Examples include: (1) "key deliveries" in which the receiver gives a key to the delivery drivers, which enables them to deposit the goods inside the store; (2) double doors that enable the driver to deposit the deliveries in the secured area (between the doors) with a key provided by the customer; (3) delivery lockers in which a delivery is made to an electronically controlled cabinet at which the consignee could retrieve the goods during the regular hours; and (4) the implementation of two-stage delivery systems in which supplies are transported during the off-hours and stored at a container, or storage pod, at a convenient location, e.g., a secured parking lot, from where the carrier staff delivers the goods during the regular hours using small, and/or environmentally friendly, vehicles; among others. Regrettably, there are no behavioral data that could be used to assess how willing the various industry segments would be to participate in unassisted deliveries.

The process followed during network modeling and traffic simulation is described next.

1.4.2 Network modeling and traffic simulation

The team estimated the traffic impacts of alternative off-hour delivery scenarios with the assistance of both a macroscopic travel demand model, i.e., New York Metropolitan Transportation Council's Best Practice Model (BPM), and a mesoscopic traffic simulation model of an extracted network focusing on Manhattan. In doing this, the team undertook the following activities:

- Acquisition of the New York Best Practice Model and up-to-date hourly volume data from New York-area transportation agencies. The acquired data was used to calibrate the model to the most up-to-date truck traffic volumes available.

- Extraction of a sub-network focusing on Manhattan for more detailed mesoscopic simulation and analysis. The extracted network, calibrated with available data, enabled estimation of traffic impacts on both the regional level (using BPM) and at the local level.

- Studied several scenarios of potential traffic shifts in both traffic models. Using the data and models developed in the behavioral research, percentages of commercial traffic bound for Manhattan were shifted from the regular to the off-hours, simulating the changes to delivery times that would be brought upon by the proposed program.

- Compiled and analyzed the impacts to the traffic network predicted by both models. By comparing modeled scenarios to the base case, changes to travel times, link speeds, and other key measures were calculated. The team used a customized post-processor developed by Ozbay et al. (2008).

The extensive traffic simulation conducted produced a good estimate of the impacts to the Manhattan and the New York City regional traffic network. The most prominent results indicate that:

- The proposed program has a net positive impact on the traffic networks of Manhattan and the entire New York City region over the entire day. Negative impacts to off-hour traffic conditions caused by increased commercial vehicle traffic are eclipsed by benefits seen during regular hours due to a reduced amount of commercial vehicles.

- Impacts are observed at both the local level in Manhattan and at the regional level, i.e., the entire New York City Metropolitan area. While most delivery trips in Manhattan originate within Manhattan (as they are part of a delivery tour), a significant number of freight trips also originate outside of Manhattan (from major generators such as the ports located outside of the city and region). Therefore the modeling shows that benefits from reduced commercial traffic during the regular hours are observed, not only in Manhattan, but throughout the rest of the city and region.

- As an illustration of the results produced by the simulation, 10% carrier participation in off-hour deliveries in Manhattan is estimated to produce a reduction of more than 6% in travel times on Manhattan links during the regular hours. When averaged with the increase in travel times during the off-hours, this still leads to an overall reduction of 4% in Manhattan link travel times. Estimates for a number of other scenarios corresponding to receiver participation were produced.

The next section discusses the economic impacts of the various alternatives considered.

1.4.3   Economic impacts

The team used the results from both the regional network model (BPM), and the mesoscopic traffic simulation (MTS) to estimate the economic impacts in terms of travel time savings and air pollution reductions. The estimates are based on the use of a composite value of time and valuations of the criteria pollutants. However, due to the uncertainty associated with the exact composition of the traffic in the entire network, the results are presented for a range of values of the composite value of time. Assuming a traffic composition of 83% passenger cars, 13% small trucks, 3% large trucks, and 1% buses; and values of time of $24 (which assumes an average occupancy of 1.2 passengers/vehicle), $35, $55, and $750 (which includes the time value of all passengers plus driver and vehicle) per vehicle class, respectively, leads to a composite value of $33.62/vehicle-hour. Different assumptions lead to values as low as $25/vehicle-hour, and as high as $40/vehicle-hour. The analysis considers three different cases:

- Financial incentives to Food and Retail Sectors. This is the policy identified by the NYSDOT project as the most effective one. It provides a financial incentive for participation in off-hour deliveries.

- Targeted programs aimed at Large Traffic Generators (LTGs). These policies focus on the major generators of truck traffic, which include large buildings that house scores of individual establishments, and large establishments (in this case, those with more than 250 employees). Since there are no data about the incentives that may be required, and how many of these LTGs would accept the incentive, a question mark has been added to the cost column. Two cases are considered: (1) Large buildings, which only includes those buildings that have a unique ZIP code, which is a subset of the total; and (2) Large Buildings & Establishments with more than 250 employees.

- Unassisted deliveries. This group considers policies that encourage off-hour deliveries without the intervention of the staff from the receiving establishment. These concepts have great potential as they could lead to economic benefits comparable to those produced by the financial incentives, at a fraction of the cost. Together with policies targeting LTGs, unassisted deliveries must be the subject of further research.

The total benefits and costs for the various stakeholders are shown in Table 1 (Roadway Users), Table 2 (Carriers) and Table 3 (Receivers and Public Sector). Since there are no data about the incentive costs or the benefits in some of the alternatives, question marks have been added to the corresponding cells. As shown in these tables, the magnitude of the economic impacts depends on the value of times used in the analyses. For reference purposes, the values considered by the team as the most likely ones have been shaded. These values correspond to $30/hour for the composite VOT of roadway users, and $40/hour for the VOT for delivery trucks (large and small).

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Table 1: Summary of Economic Impacts: Roadway Users

		Annual Benefits (millions) [1]								Public Sector Incentives (millions)
		Composite Value of Time (passenger cars, buses, and trucks) [2]								
		$20/hr		$25/hr		$30/hr		$35/hr		
	Trips Shifted	BPM [3]	MTS [4]	BPM [3]	MTS [4]	BPM [3]	MTS [4]	BPM [3]	MTS [4]	
Financial incentives to Food and Retail Sectors										
$5,000	7,262	$38.61	$20.68	$47.89	$23.95	$57.10	$27.23	$66.34	$30.51	$0.00
$10,000	15,982	$57.58	$51.23	$70.96	$58.74	$84.42	$66.25	$97.84	$73.76	$0.00
$15,000	23,617	$68.24	$65.50	$84.24	$76.11	$100.24	$86.72	$116.23	$101.94	$0.00
$20,000	28,634	$99.27		$122.71		$146.15		$169.58		$0.00
Targeted programs aimed at Large Traffic Generators										
Large Buildings [5]	8,345	$24.36	$17.68	$30.23	$21.28	$36.10	$24.87	$41.97	$25.18	?
Large Bldgs. & 250+ [5]	17,878	$53.60	$26.86	$67.33	$32.84	$81.07	$38.82	$94.81	$41.87	?
Unassisted deliveries										
Security incentives	?	?	?	?	?	?	?	?	?	?
Bonded deliveries	?	?	?	?	?	?	?	?	?	?
Double doors	?	?	?	?	?	?	?	?	?	?

Notes: (1) Estimated based on changes to congestion, operating costs, noise, and air pollution assuming 250 days/year; (2) The benefits depend on the composite value of time estimate used; (3) BPM refers to Best Practice Model. Benefits are calculated for links covered by the 28-county NYMTC region; (4) MTS refers to Mesoscopic Traffic Simulation. Benefits are calculated based on links located only within Manhattan; and (5) Assume 100% participation in off-hour deliveries.

Table 2: Summary of Economic Impacts: Carriers

		Annual Benefits (millions)								Public Sector Incentives (millions)
		Average Value of Time Carriers that Shift to the Off-hours								
	Trips Shifted	$30	$35	$40	$45	$50	$55	$60	$65	
Financial incentives to Food and Retail Sectors										
$5,000	7,262	$21.54	$25.13	$28.72	$32.31	$35.90	$39.49	$43.08	$46.67	$0.00
$10,000	15,982	$47.40	$55.30	$63.20	$71.10	$79.00	$86.90	$94.80	$102.70	$0.00
$15,000	23,617	$70.05	$81.72	$93.39	$105.07	$116.74	$128.42	$140.09	$151.77	$0.00
$20,000	28,634	$84.93	$99.08	$113.23	$127.39	$141.54	$155.70	$169.85	$184.01	$0.00
$25,000	32,856	$97.45	$113.69	$129.93	$146.17	$162.41	$178.65	$194.90	$211.14	$0.00
Large Buildings [5]	8,345	$24.75	$28.88	$33.00	$37.13	$41.25	$45.38	$49.50	$53.63	?
Large Bldgs. & 250+ [5]	17,878	$53.02	$61.86	$70.70	$79.54	$88.37	$97.21	$106.05	$114.89	?
Unassisted deliveries										
Security incentives	?	?	?	?	?	?	?	?	?	?
Bonded deliveries	?	?	?	?	?	?	?	?	?	?
Double doors	?	?	?	?	?	?	?	?	?	?

Assumptions:

Travel time saved (hours/tour):	0.80	Days per year:	250.00
Service times savings (hours/delivery):	0.25	Delivery stops/tour:	5.50

Table 3: Summary of Economic Impacts: Receivers and Public Sector

	Trips Shifted	Annual Cost to Receivers (millions) [1]	Public Sector Incentives (millions)[2]
Financial incentives to Food and Retail Sectors			
$5,000	7,262	($16.20)	$16.20
$10,000	15,982	($76.07)	$76.07
$15,000	23,617	($172.91)	$172.91
$20,000	28,634	($284.13)	$284.13
$25,000	32,856	($413.72)	$413.72
$50,000	47,605	($1,244.39)	$1,244.39
Targeted programs aimed at Large Traffic Generators			
Large Buildings [3]	8,345	$24.75	?
Large Bldgs. & 250+ [3]	17,878	$53.02	?
Unassisted deliveries			
Security incentives	?	?	?
Bonded deliveries	?	?	?
Double doors	?	?	?

Notes: (1) Assumed to be equal to the incentive; (2) Calculated by multiplying the number of receivers expected to participate times the incentive; and (3) Assume 100% participation in off-hour deliveries.

Table 4 and Figure 3 show summaries of the economic impacts to stakeholders for the case in which the composite VOT of roadway users is $30/hour, and the average value of time of delivery trucks is $40/hour. As noted previously, the costs to receivers have been assumed to be equal to the incentive cost. As shown, the economic benefits to carriers and roadway users increase with receiver participation in off-hour deliveries. However, the rate at which these benefits grow decreases with the amount of off-hour deliveries and the incentive amount. The cost to receivers, and consequently the associated incentive costs, increases at an accelerating pace due to the effect of the incentive amount and the number of establishments that take the incentive.

Table 4: Economic Analysis Results

	Cost to receivers	Benefit to carriers	Benefit to road users	Total benefits	Total Incentive Costs	Net benefits	Marginal B/C ($\Delta B/\Delta C$)
Financial incentive to food and retail sectors							
$5,000	(16.20)	$28.72	$57.10	$85.81	($16.20)	$69.62	5.30
$10,000	(76.07)	$63.20	$84.42	$147.62	($76.07)	$71.55	1.03
$15,000	(172.91)	$93.39	$100.24	$193.63	($172.91)	$20.72	0.48
$20,000	(284.13)	$113.23	$146.15	$259.38	($284.13)	($24.75)	0.59
Targeted programs aimed at Large Traffic Generators							
Large Buildings [1]	?	$24.75	$24.36	$49.11	?	?	?
Large Bldgs. & 250+ [1]	?	$53.02	$53.60	$106.62	?	?	?
Unassisted deliveries							
Security incentives	?	?	?	?	?	?	?
Bonded deliveries	?	?	?	?	?	?	?

Notes: (1) Assume 100% participation in OHD.
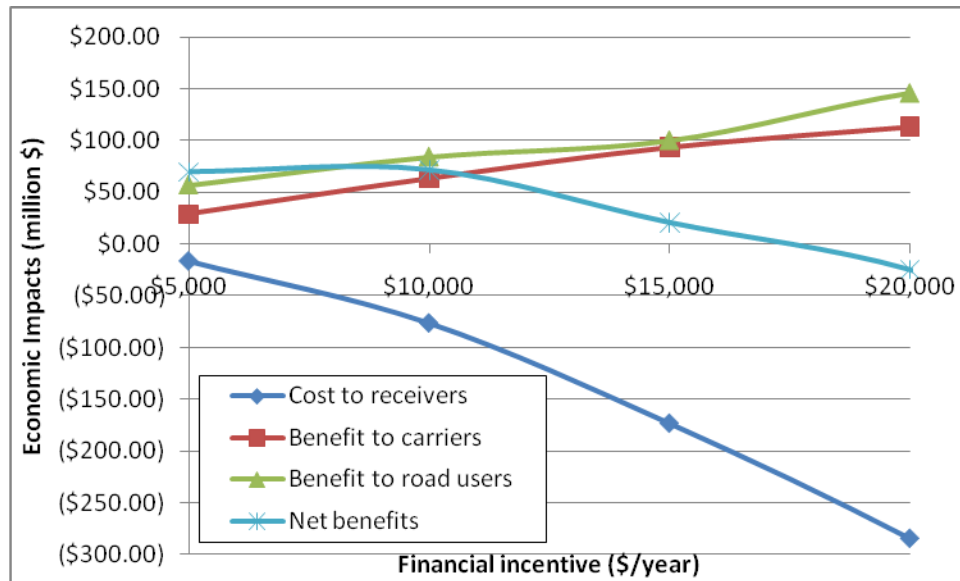
Figure 3: Cost and Benefits

These analyses show that beyond the $15,000/year incentive, the total costs outweigh the benefits brought about by off-hour deliveries. However, the optimal amount of incentive is about $10,000/year. The table shows the marginal benefit/cost ratio. This economic indicator measures the ratio of the increase in benefits brought about by a given alternative, with respect to the increase in costs. It is optimal when the marginal benefits equal marginal costs, for a $\Delta B/\Delta C = 1$. As shown in the table, increasing the financial incentive to $10,000/year leads to a marginal benefit of $61.81 million/year ($147.62 million/year - $85.81 million/year), at a marginal cost of $59.87 million/year ($76.07 million/year - $16.1 million/year). This translates into a $\Delta B/\Delta C$ of 1.03.

The results indicate that:

- Both the BPM and MTS produce consistent results, though they cover different areas and are built on different assumptions.

- In all cases, the economic benefits associated with increasing off-hour deliveries exhibit diminishing returns though the incentive costs continue to grow.

- The optimal financial incentive is about $10,000 per year, depending on the composite value of time. For certain combinations of financial incentive and composite value of time, the economic benefits exceed the total incentive cost.

- Policies aimed at increasing off-hour deliveries at large traffic generators have great potential. As shown, switching to the off-hours the truck traffic generated by the 88 large buildings that have their own ZIP code (which are only a fraction of all large buildings in Manhattan), produces economic benefits comparable to the ones for the $5,000/year incentive at only a small fraction of the cost.

- Policies that also target large establishments with more than 250 employees could produce significant economic benefits. As shown, shifting all truck-trips produced by these LTGs to the off-hours would lead to economic benefits comparable to the ones for the $10,000/year incentive at, yet again, a fraction of the cost.

- Unassisted deliveries represent a huge opportunity, though not much is known about their market potential. However, a small survey of the receivers that participated in the pilot test indicated that 80% would do unassisted deliveries if the liability issues are satisfactorily addressed. Should this finding be confirmed by future research, it could lead to a situation in which a small public investment could produce economic benefits similar to the ones brought about by the financial incentives.

- Future research must tackle the design of policies and quantification of market potential, and implementation costs for both LTGs and unassisted deliveries. Both concepts offer the potential to shift significant number of truck-trips to the off-hours at a fraction of the cost. This must be a high priority research area.

It should be noted that the economic impacts estimated here are the ones associated with reducing truck traffic in the regular hours. Since in the absence of complementary policies, passenger car traffic is likely to increase to take advantage of the road capacity made available by the trucks that switched to the off-hours (as part of a process of induced demand), congestion may again increase. This does not mean, however, that off-hour deliveries have not produced these economic benefits. Instead, the correct interpretation is that these economic losses (due to the increased congestion produced by the induced passenger car traffic) are the cost of not having appropriate passenger car demand management. The key implication is that coordinated demand management policies—targeting both passenger car traffic and freight deliveries—are a must.

1.5   *Conclusions and Suggested Next Steps*

This project has been lauded by the freight industry, agencies, and by the research community, as a path-breaking effort to be emulated and expanded. The most visible demonstrations of these were the highly successful meetings with the Industry Advisory Group (IAG) and the Technical Advisory Group (TAG) comprised of representatives of key transportation agencies held on December 9, 2009; and the publication of two highly complimentary articles by the prestigious and influential *Journal of Commerce* (Journal of Commerce, 2009; 2010). Also, the project was written about in the *Wall Street Journal* (Wall Street Journal, 2010), and was recognized by the NYCDOT Commissioner Janette Sadik-Khan for its potential impact in New York City at a ceremony to publicly recognize the pilot test participants. In essence, the work done has clearly and unambiguously established that the proposed concept: (1) is effective in inducing a shift of urban deliveries to the off-hours; (2) enjoys broad-based industry support; (3) would bring about substantial reductions in congestion and environmental pollution thus increasing quality of life; and (4) would increase the competitiveness of the urban economy. The fact that this is a

win-win concept that benefits all the participants in urban deliveries provides a unique opportunity for expansion and full implementation. The analyses conducted by the team indicate that:

- Financial incentives to receivers will be effective in inducing a shift of carriers to the off-hours. Once the receivers are compensated for the extra costs of off-hour deliveries they have an incentive to switch to the off-hours; while the carriers—that benefit from off-hour work because of the lower delivery costs and parking fines—happily follow suit. The analyses indicate that, depending on the industry segment and incentive provided, the shift could be between 10% and 20% of the truck traffic in these segments.

- The traffic simulations indicate that the switch of truck traffic to the off-hours brings about substantial economic benefits. The estimates produced by the team indicate that the optimal financial incentive is slightly higher than $10,000 a year. This incentive would be accepted by about 7,600 establishments at a total cost of $76 million. The economic benefits would range between $83 and $129 million, depending on the value of travel time used in the calculations. Beyond the $10,000 incentive, the marginal benefits get smaller while the incentive costs continue to increase.

- The GPS devices installed in the participant vehicles indicate that, on average, a truck traveling in the off-hours achieves speeds of about 8 miles per hour, while in the regular hours they typically fall below 3 miles per hour. A truck that travels 10 miles delivering from customer to customer would save 1.25 hours per tour shifted to the off-hours.

- There are substantial reductions in service times during the off-hours. In the regular hours, due to the effects of longer walks from parking to customer, elevator congestion, waiting for customers to check deliveries and the like, service times exceeding 1.5 hours per customer are common. In the off-hours, all these impediments to expedient deliveries all but disappear, leading to service times that average half an hour. Since delivery trucks serve the needs of multiple customers in the same tour, the total service time savings are bound to be substantial and likely larger than the travel time savings.

In spite of the concept's great promise and the encouraging results obtained in this project, there are a number of important questions that need to be answered before proceeding to a full implementation. These questions are related to: (1) noise impacts on surrounding communities; (2) statistical validity of the results obtained in the small pilot test conducted; (3) the potential role of targeted programs aimed at large traffic generators; (4) fostering of unassisted off-hour deliveries; and (5) inter-agency coordination and policy development. These are important questions to be addressed because:

- Noise impacts were not assessed during the project. Although no community complaints were received during the execution of the small pilot test, it is natural to expect that

community members would be concerned about noise impacts. In this context, it is important to both assess noise impacts, and define appropriate mitigation strategies should noise be deemed a potential obstacle for implementation. The goal here is to ensure that local communities are not negatively impacted.

- The small size of the pilot test conducted does not support the estimation of statistically representative results. Although a significant and important effort, the test conducted is minuscule when compared to the number of deliveries made in New York City. An increase in the size of the pilot will lead to greater insight into how best to integrate remote sensing into a workable prototype, and to assess the overall benefits attributable to off-hour deliveries. It is important to mention that the size of the pilot test has been recognized as an issue by both team members and USDOT. At the end of 2008, an expansion of the pilot test was considered though USDOT and the team ended up deciding against it because the economic climate prevailing at the time—in the midst of the collapse of the finance industry—was not conducive for business participation in such research efforts. However, the marked improvement in economic conditions, the stability of financial markets, and the success of the project provide a unique opportunity to conduct another path-breaking effort by expanding the pilot test.

- About 4-8% of all deliveries to New York City are generated by Large Traffic Generators. As a result, inducing LTGs to do off-hour deliveries could have a noticeable impact on traffic congestion. Equally important is that since the number of LTGs is small (between 90 and 500, depending on what definition of LTG is used), the coordination effort is insignificant when compared to the potential payoff. It is therefore possible that the City of New York could play a key role in convincing the owners of the LTGs to switch to the off-hours as part of the City's sustainability efforts.

- Unassisted deliveries could play a key role as part of a sustainability strategy involving off-hour deliveries. Unassisted off-hour deliveries provide a unique opportunity to achieve the benefits attributable to financial incentives, at a fraction of the cost. In this context, public sector programs that successfully address the liability issues that deter businesses from doing unassisted off-hour deliveries will increase off-hour activity. Over time, as the business sector gets accustomed to unassisted off-hour deliveries, more establishments will join the practice. As an illustration of the potential of the concept, it suffices to mention that 80% of the participating receivers indicated that they would do unassisted off-hour deliveries if the liability issues were resolved.

- Inter-agency coordination of efforts will facilitate implementation. As established in the project, off-hour deliveries have significant economic, environmental, and energy consumption impacts. For that reason, it is natural to involve all agencies whose primary mission is to promote economic development, environmental improvements, and energy conservation. Involving these agencies in the definition of a common off-hour delivery strategy is bound to lead to robust policies and a smooth implementation of the concept.

Fostering off-hour deliveries at large traffic generators and fully exploiting the use of unassisted deliveries are extremely important because they eliminate the need (and the cost) for the receiver to be

present when the off-hour deliveries are made. As a result, they are very cost-effective as they only require a fraction of the incentives required by the broad-based off-hour delivery program. However, in spite of their considerable potential, major questions remain concerning policies to foster off-hour deliveries at large traffic generators and the use of unassisted deliveries. These include: (1) how to integrate remote sensing elements to ensure compliance; (2) liability issues; (3) cost/benefits to participants; and (4) effectiveness of alternative policies, among others.

Both macroscopic and mesoscopic traffic models show beneficial impacts in terms of congestion reductions and improved environmental conditions. Both the regional and sub-regional models showed benefits though the estimates produced by each differed. The integration of two levels of models is essential in order to realistically assess different types of impacts such as dynamic traffic impacts at the facility level. Modeling has also focused mainly on short-term impacts of the proposed program, with long-term network-wide impacts requiring a more significant process of data collection and study. Moreover, an extended pilot test will allow the team to collect and have access to more data, and ensure a better calibration of the models. The use of these simulation models is crucial for a better understanding of the various scenarios, to quantify their impacts, and to garner support of the involved agencies. The research team is now in a unique position due to the extensive experience it has gained to expand these simulation studies beyond what has been done so far.

All of this suggests the steps outlined below:

- Research and design:
  - Conduct behavioral research to identify and select the most cost-effective incentive policies to foster unassisted off-hour deliveries, and off-hour deliveries at large traffic generators.
  - Expand and improve the traffic simulation models to ensure they provide a meaningful representation of the transportation network in New York City.
  - Engage the city and state agencies and stakeholder groups that could collaborate in the full implementation of such policies to define their potential roles as part of a comprehensive implementation. This could include: New York City Economic Development Corporation, New York State Energy Research and Development Agency, Real Estate Board of New York, among others.
  - Launch a publicity campaign to get industry support and sign up potential participants in an expanded pilot test.
  - Conduct research on noise impacts and potential mitigation strategies.
  - Design community feedback programs to ensure concerns are properly addressed.
  - Design and establish compliance verification mechanisms.

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- Expanded pilot test and Implementation:
  - Roll out a comprehensive set of incentive policies; recruit participants.
  - Design a monitoring plan involving: the use of GPS devices to assess performance of delivery operations before and after the pilot; the installation of noise measuring devices to assess noise impacts; the use of the GPS data currently being collected by NYCDOT to monitor network-wide impacts.
  - Launch and monitor the expanded pilot test.
  - Use behavioral models to predict participation in the implementation phase.
  - Use the traffic simulation models to assess the network impacts of both the expanded pilot test, and a full implementation.
  - Organize community hearings and gather stakeholder input.
  - Decide on implementation.

The team is of the opinion that an expansion of the pilot test, combined with the steps outlined above, could bring about an enhanced understanding of the potential benefits of integrating cutting edge remote sensing technology as part of a novel freight demand management concept. Furthermore, a revised focus on LTGs and unassisted deliveries could provide much needed empirical evidence on the practical challenges as well as the benefits and costs of what is likely to become a business-friendly way to do freight demand management in congested cities.

2. INTRODUCTION

Urban congestion is one of the most pervasive issues impacting large metropolitan areas and modern societies. It is also a problem that has defied easy solutions, that does not show any signs of abating, and that is likely to get worse as forecasts indicate that demand will continue to increase, leading to increases in the duration of the peak periods. A study conducted by the Texas Transportation Institute found that in the year 2007, congestion cost about $87.2 billion in the 437 urban areas of the United States, compared to $73.1 billion in 2004. This represents an average delay per peak traveler of 38 hours per year, with users from large metropolitan areas of 3 million residents or more experiencing almost 51 hours of delay (Texas Transportation Institute, 2009). The New York City region ranks second in the nation in terms of congestion delay with about 46 hours of delay, up 35% from the year 2000. This represents 379 million hours of delay, 239 million gallons of fuel, and $8 billion in delay costs (Texas Transportation Institute, 2009). In this context, transportation demand management could play a key role in reducing congestion by inducing a behavior change on the part of the users. Although there is a long tradition in passenger transportation demand management, the amount done in freight is minimal.

An important strand of transportation demand management is based on the use of road pricing to change user behavior. However, for reasons discussed later in this introduction, such concepts are of limited effectiveness in urban freight. The concept designed and developed in this project overcomes the limitations of pricing based approaches with the joint use of remote sensing, i.e., Global Positioning System (GPS) cell phones, to verify compliance and gather dynamic traffic information; and the provision of financial incentives to the receivers willing to participate in off-hour deliveries (OHD). These incentives remove a constraint imposed on the carriers—as most receivers prefer deliveries during the regular hours and cannot be forced by the carriers to switch to the off-hours—making it easier for them to switch to the off-hours, where delivery costs tend to be lower. In turn, this leads to lower congestion, improved environmental conditions, and enhanced competitiveness of the urban areas. The rationale of the proposed concept, together with the empirical evidence and research, is discussed in this chapter.

2.1 Freight Road Pricing and Comprehensive Carrier-Receiver Policies

The fundamental assumption of road pricing is that adjusting the private costs felt by drivers to match the social costs their driving produces would move the equilibrium solution to a situation in which deadweight losses are eliminated. In the case of automobile transportation, there is ample theoretical support and empirical evidence that, indeed, show that road pricing is an effective transportation demand management technique—that not only increases economic welfare but generates a significant amount of revenues that could support transportation investment (Sullivan, 2000). A particular feature of the passenger transportation case is that the unit of demand happens to be the decision maker. From the

behavioral point of view, this translates into a very clear situation in which the impact of the tolls is directly felt by the agent that makes the travel decision. The importance of this shall be obvious shortly.

The case of urban freight is very different. There is a significant body of evidence that calls into question the effectiveness of freight road pricing as a tool to move truck traffic to the off-hours (Holguín-Veras et al., 2006a). Although there are a multitude of reasons (e.g., market imperfections of various kinds, contractual constraints, interactions between agents that dampen the effectiveness of the price signals), the most important of these factors is the role played by the receivers in setting the delivery times. The data collected indicate that delivery times are determined by the receiver in 40% of the cases, jointly by the receiver and the carrier in 38% and by the carrier in the remaining 22% (Holguín-Veras et al., 2006b). This should not be a surprise because the receivers are the carriers' customers and, as such, they are expected to have something to say about the time at which deliveries are made. It shall be obvious that, in order for carriers to be able to switch to the off-hours, the receivers must be willing to extend their operations to the off-hours. Ultimately, the effectiveness of freight road pricing depends on the strength of the price signal sent by the carrier to the receiver; and the receiver's willingness to work during the off-hours.

At this point, it is important to examine the empirical evidence about the behavioral changes produced by pricing. The only data available on the impacts of pricing on the behavior of carriers correspond to the evaluation of the implementation of time-of-day pricing at the Port Authority of New York and New Jersey facilities in 2001 (Holguin-Veras et al., 2005). These data indicate that 20.2% of the sample changed behavior because of the time-of-day pricing initiative. However, the nature of their behavioral responses is not what may be expected. Carriers responded to time-of-day pricing by implementing complex multi-dimensional responses involving *Productivity increases, Cost transfers,* and *Change in facility usage,* implying a more nuanced response than simply changing facility usage. The data show that the three combinations of strategy groups represent almost 90% of the cases: *Productivity increases* (42.79%), followed by *Changes in facility usage* and *Cost transfers* (27.60%) and *Productivity increases* and *Changes in facility usage* and *Cost transfers* (19.32%). The fact that some of these responses impact only the carrier (i.e., *Productivity increases*), while others mostly impact the receivers (*Changes in facility usage* and *Cost transfers*), suggests that the nature of the response is determined by the balance of power between carriers and receivers. Equally important is that 69.8% of the carriers that did not change their behavior indicated they could not change due to "customer requirements."

Significantly, only 9.0% of the sample reacted by increasing shipping charges to receivers. This is obviously a sign of the weakness of the urban delivery carrier industry, which is a consequence of the competitiveness introduced by its low entry cost. Equally important, the increase in shipping cost was relatively small, about 15%, which is to be expected because the carriers usually allocate the toll increase

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among the multiple customers in a delivery route, about 5.6 deliveries per tour (Holguin-Veras et al., 2005). In summary, the price signals sent by carriers are small and only reach a tiny portion of receivers. All of this clearly indicates the need to broaden the scope of transportation policy so that it takes into account the key role played by the receivers that, as the customers, play a crucial role setting delivery times. In this context, it seems obvious that freight road pricing, by itself, is not likely to succeed in inducing a significant shift of truck traffic to the off-hours, for the simple reason that the price signals reaching receivers are not likely to be strong enough to force them to extend operations to off-hours.

In essence, the key lessons from the analyses of the behavioral data (Holguín-Veras et al., 2006c) are that: (1) the ability of carriers to unilaterally change delivery times is quite limited as it necessitates the concurrence of the receivers (which tend to prefer deliveries during the regular hours as they could take advantage of the staff at hand, as opposed to OHD that may require extra staff, security, lighting, and other costs); and, (2) cordon tolls are not likely to be effective in inducing a switch to the off-hours, as most segments of the urban freight industry cannot pass toll costs to their customers depriving them of the price signal needed to effect a change. Further analyses (Holguín-Veras, 2008) concluded that the difficulties that carriers have to pass cordon time-of-day tolls to their customers reflect a highly competitive market with delivery rates equal to marginal costs. Since the cordon toll is a fixed cost—as it does not depend on the unit of output—it does not enter in the rates. The empirical data confirmed that only the market segments with market power (i.e., carriers of stone/concrete, wood/lumber, food, electronics, and beverages) could pass toll costs in a meaningful way (Holguín-Veras, 2008). The key insight is that, since the price signal only reaches the receivers in those cases where the carrier has market power (and in a diluted fashion because the toll is allocated among the multiple receivers in the tour), carrier centered pricing policies are not as effective as they should be because receivers have no incentive to change behavior. Since the consent of the receivers is needed for the carriers to change behavior, it follows that a new policy paradigm is needed. These new policies specifically target the receivers of the cargoes as well as the carriers, and are referred to as "carrier-receiver" policies. The goal here is to combine elements of carrier centered policies, e.g., freight road pricing, with receiver centered policies.

A number of carrier-receiver policies were designed and evaluated in a series of papers that: discussed constraints to implementation of OHD (Holguín-Veras, 2006); analyzed the potential of the restaurant sector as a target for off-hour delivery programs (Holguín-Veras et al., 2006b); provided a framework for analyses of carrier-receiver interactions, and discussed the behavioral models estimated with stated preference data collected from receivers and carriers (Holguín-Veras et al., 2007; 2008). These behavioral models clearly showed that: (1) receivers would be willing to switch to the off-hours in exchange for financial incentives; (2) all carriers are sensitive to requests from receivers; and (3) only a handful of industry segments are sensitive to tolls (i.e., carriers of petroleum/coal, wood/lumber, food

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products, and textiles/clothing). The analyses clearly indicate that this type of policy will be supported by the carriers as delivering in the off-hours, in equality of conditions, is about 30% cheaper than delivering during the congested hours of the day (Holguín-Veras, 2006).

2.2   *Previous Experiences with Off-Hour Deliveries*

The idea of fostering OHD to combat congestion is far from new. The first initiative on record was reported in Julius Caesar's collection of laws called the "Lex Juliana Municipalis." It mandated that goods deliveries in Rome be done during the evening hours (Desau, 1892), with the specific intent of reducing congestion. It is interesting to note that Roman citizens complained about the increased noise during off-hours, as noise remains today an obstacle to OHD.

More recently, a number of studies have focused on OHD. The first one reported took place in London in 1968, and involved one hundred companies changing their shipping and receiving operations to the off-hours. The study found that OHD was effective in cases where fewer deliveries take place with large shipment sizes (Churchill, 1970). A study on OHD conducted by the Organization for Environmental Growth in 1979 summarized the findings from interviews with carriers, third-party carriers, receivers, and officials from public agencies. The study found that the impacts of OHD were not clear, and that pilot testing was needed to understand its implications (OFEGRO, 1979). Another study conducted in the late 1970s (Noel et al., 1980) found that: (1) delivery and commodity transportation companies that do OHD approve of this operation because of the cost and time savings derived from the higher productivity; (2) carriers are generally willing to make OHD to their requesting customers; (3) security issues present a big obstacle in the implementation of OHD; and (4) carriers who do OHD typically do so for convenience. The Urban Gridlock Study examined the impacts on congestion of OHD, and found that OHD would moderately impact traffic congestion because the capacity made available by the trucks that switch to the off-hours would be promptly occupied by passenger cars (Grenzeback et al.; Cambridge Systematics, 1988b; a). A study on OHD in Los Angeles investigated its legal implications. The proposal considered, i.e., banning trucks from the Los Angeles metropolitan area during the peak hours, was strongly opposed by the business community because of the additional operational costs that they would incur (Nelson et al., 1991). The Port Authority of New York and New Jersey's study on OHD analyzed how peak-hour traffic could be reduced on the New York City area interstates. Using a carrier survey, it was concluded that: commercial trucking firms already attempt to avoid peak periods for travel; trucking firms are highly concerned with meeting customer demands, while not violating district curfews and union-agreed working hours. It was also found that trucking companies have major doubts about the usefulness of peak-hour tolls to reduce congestion (Vilain and Wolfrom, 2000).

Recent pilot tests were conducted to understand how OHD would impact traffic and the environment in Athens, Barcelona, Dublin, and London. The Athens study examined land use, delivery requirements

per type of service, and traffic conditions (Yannis et al., 2006). This study used simulations and interview data to quantify the impacts of OHD upon congestion levels and environmental pollution. It was concluded that shifting truck traffic to non-traditional business hours would reduce traffic congestion and improve environmental conditions, by reducing nitrogen oxides, hydrocarbons, and sulphur dioxide emissions from trucks during regular business hours (Yannis et al., 2006). In Barcelona, OHD were piloted with 20 supermarkets. The original seven smaller daily deliveries were replaced with two larger night deliveries to these locations. Likewise, in Dublin off-hour delivery operations were pilot tested with supermarkets, and combined with external consolidation centers and delivery curfews. The Barcelona and Dublin studies concluded that these operations lead to: (1) reductions in logistical delays, traffic congestion, emissions, and energy consumption; (2) increases in road safety; and (3) economic benefits from lower shipping costs and higher profit margins (NICHES, 2008). In London's borough of Wadsworth, OHD were pilot tested using low noise equipment and larger trucks for Sainsburys' Garret Lane grocery store (London Noise Abatement Society, 2008). The pilot started in 2007, and suggested that OHD operations saved the companies about seven hundred working hours per year, or about $25,000 in savings. Other findings include increased efficiency of workers, increased sales, and positive customer feedback about service and product availability (London Noise Abatement Society, 2008). The review of these experiences indicates the widespread interest in OHD.

2.3   *Project Background*

This project has enjoyed strong industry support since its inception. The foundation of this project is the work conducted for the New York State Department of Transportation (NYSDOT) by team members. The original NYSDOT project entitled "Potential for Off-Peak Freight Deliveries to Congested Urban Areas" was the result of a request made in early 2002 by the New York City Chapter of the then Council of Logistics Management (now Council of Supply Chain Management Professionals) to NYSDOT to find ways to encourage OHD in New York City. NYSDOT agreed that the proposed subject was worthy of study and issued a Request for Proposals on December 2002, which led to the selection of Rensselaer Polytechnic Institute as the lead contractor. The main focus of the original NYSDOT project was Manhattan, and its objectives were to:

- "Define the set of policies and programs that would induce a shift on deliveries to off-peak hours (referred to here as *off-peak delivery initiatives*)."
- "Quantify stakeholders' costs and benefits associated with off-peak deliveries initiatives."
- "Perform an economic analysis of the expansion of hours during which pick-ups and deliveries are made to commercial areas."
- "Quantify extra costs to stakeholders so that compensation schemes could be implemented, should off-peak deliveries be found to be economically beneficial to Society at large."

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In May 2005 the Southwest Brooklyn Industrial Development Corporation (SWBIDC)—which heard about the project from informal channels—requested that NYSDOT include Brooklyn in the study. NYSDOT agreed and a second phase of the project with a Brooklyn focus was added. A final report for both phases was issued in December 8, 2006 (Holguín-Veras, 2006).

The current project titled "Integrative Freight Demand Management for the New York City Metropolitan Area" was funded by the United States Department of Transportation's Commercial Remote Sensing and Spatial Information Technology Applications Program in March 2007, in response to a proposal submitted to the BAA DTPH56-06-BAA-0002 by a consortium of Rensselaer Polytechnic Institute, Rutgers University, Rudin Center for Transportation Policy and Management at NYU-Wagner, and ALK Technologies Inc. The original scope of work, which included a pilot test of substantial size, was reduced to place more emphasis on the design of the system, and the large pilot was transformed into a "small scale deployment."

The main charge of the project could be summarized as follows:

"The project would design and develop a self-sustaining urban freight traffic management system for the New York City metro area that integrates state of the art remote sensing technology, cutting edge freight demand management, traffic simulation, and policy. The project combines the revenue generation power of time-of-day pricing, with tax deductions to receivers willing to accept off-peak deliveries, and GPS based traffic monitoring, to induce a shift of truck traffic to the off-hours."

2.4   Funding

The work started in July 1, 2007. The total funding provided by the USDOT was about $1.2 million. The project partners provided $0.64 million in matching funds.

2.5   Goals and Objectives

The main motivation of the project was to explore the use of remote sensing technologies—specifically of GPS enabled smartphones—combined with the use of financial incentives to receivers of urban deliveries, to create a holistic freight demand management system that overcomes the limitations of pricing-only approaches. In this context, the goal and objectives of the projects could be summarized as:

"The proposed concept is expected to: (1) induce a significant shift of truck traffic to the off-peak hours (preliminary estimates suggest that, in some industry segments, the shift could reach 20% of local day truck traffic) (Holguín-Veras et al., 2006b); (2) bring about significant improvements in traffic congestion and environmental conditions; and (3) increase the competitiveness of NYC via tax deductions to local businesses, productivity increases from improved traffic conditions, and significant reductions in parking fines (that frequently exceed

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$1,000 per truck per month). Once the concept has been designed and developed, it will be demonstrated in a small scale field deployment test."

The scope was centered on congested urban areas, using New York City as the case study, as these areas are the ones where OHD would be most beneficial. It is important to mention that the concepts and methodologies produced here are applicable to other large metropolitan areas.

2.5.1 Project focus

It is important to stress that the project focused on urban deliveries, i.e., the transportation of cargo to urban locations. The main reason being that they represent the bulk of the freight traffic in urban areas, most likely accounting for more than 80% of the entire freight traffic, and the natural target for freight demand management programs aimed at reducing the congestion they produce. Other segments, e.g., external-external flows that pass through the urban area, are not discussed.

The project focus must be kept in mind as urban deliveries are quite different than other segments of the freight industry. First, they are typically made in relatively long delivery tours—with an average of 5.5 delivery stops per tour in New York City—that start and end at the home base. Second, in cases where there is cordon pricing, the tours incur a toll at the entrance of the urban area in order to deliver to the customers inside (which translates into the toll surcharge being a fixed cost). Third, the shipment sizes tend to be relatively small as they are frequently delivered with relatively smaller vehicles. All these aspects, and others not listed here, make urban deliveries a rather unique operation with characteristics not found in other segments of the freight industry.

As a result, the conclusions and methodologies developed here should be assumed to be valid only for the urban delivery case. Further research must be conducted to assess how valid they are for application in other types of freight operations.

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3. INSTITUTIONAL ANALYSIS, COORDINATION, OUTREACH, AND ARRANGEMENTS

As part of the study, the project team conducted institutional analyses and coordination. The purpose of this task was to identify institutional and policy challenges and alternatives, and potential inter-agency arrangements that could support the concept of off-hour deliveries (OHD). In the following sections, incentives to receivers, potential barriers, and suggestions on institutional arrangements are discussed.

3.1 Description of Institutional Setting

The study region, the greater New York metropolitan area, is home to nearly 20 million residents including the residents of three states, dozens of counties, and hundreds of municipalities centered around the central business districts of the City of New York. Each year the regional freight system delivers approximately 47 million tons of food, 2.8 million tons of clothing, and 70 million tons of gasoline, which are all necessities for the daily activities of the region's residents and businesses (NYMTC, 2007). The complexity of moving goods through the region's severely congested traffic on aging physical infrastructure is compounded by the multiplicity of jurisdictions responsible for the planning and execution of the surface transportation program.

Many public agencies in this region govern some aspects of freight movement, and thus the region is not structured in a way to promote efficient planning and execution of transportation programs. At the regional level, the public agency with the broadest formal jurisdiction is the New York Metropolitan Transportation Council (NYMTC) that must create a Regional Transportation Plan (RTP) for many key sections of the region (essentially the downstate New York counties). However, NYMTC does not plan for the New Jersey or Connecticut parts of the common economic region. Further, the RTP only provides a regional vision; the adoption, funding, and execution of specific projects are the responsibility of many agencies involved. For example, the New York State Department of Transportation (NYSDOT) plays the primary role in building and maintaining federal and state highways, while New York City Department of Transportation (NYCDOT) is responsible for local systems in the city of New York, with counties and towns having comparable responsibility for their own systems. Further complicating the regional goods movement system is the fact that the primary operators of the infrastructure that moves people and goods between New Jersey and New York City, and between New York City boroughs and other New York State counties, are other special purpose agencies such as the Port Authority of New York and New Jersey (PANYNJ) and the Metropolitan Transportation Authority (MTA). PANYNJ owns and operates all of the ports, bridges, and tunnels connecting New York and New Jersey, all of which are important infrastructure elements in moving people and goods. The MTA manages bridge crossings throughout New York City's boroughs. Since the bulk of freight delivery trips are made between New Jersey and New York City, several New Jersey agencies such as the New Jersey Department of Transportation

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(whose regional planning entity is the North Jersey Transportation Planning Authority) are also involved in freight transportation plans. Private sector entities are responsible for the actual delivery of goods across the region, but they too are subject to numerous regulatory interventions by federal, state, and local governments in the three states. This extreme complexity of institutional arrangements forms the back-drop for the work of the project. While formal integration is unlikely, creating forums for inter-jurisdictional cooperation is essential for the execution of any effective regional strategies, hence the outreach that was a key part of this task.

3.2   *Public Outreach and Institutional Analysis*

3.2.1   **Public outreach**

To increase the likelihood of successful implementation of OHD, substantive input is needed from industry and public sector stakeholders. Thus, the project team developed a list of all potential industry and public agency contacts to form an Industrial Advisory Group (IAG) and a Technical Advisory Group (TAG). After communicating by phone calls, e-mails, and in-person meetings, six private sector representatives joined the IAG and seven public agency representatives agreed to participate in the TAG. In Task 2 (IC2), a series of interviews with IAG and TAG members were conducted and the project team followed up with the participants for their further advice. The IAG was asked to help the project team better understand the concerns related to shifting the time of day for deliveries, while the TAG provided advice on policy challenges and opportunities related to the proposed OHD. In addition, two public outreach meetings were convened at the Puck Building of New York University (June 16, 2009,and December 8, 2009) and a series of follow-up discussions were carried out. The purpose of the public outreach was to identify key issues and concerns specific to OHD, as well as to characterize the policy challenges and opportunities related to current truck traffic and potential shifts resulting from the project.

3.2.2   **Institutional analysis**

3.2.2.1   *The role of financial incentives*

As an earlier study by Holguin-Veras identified, the efficacy of the program would be different depending on who pays costs or receives incentives (Holguin-Veras et al., 2005). A pricing scheme such as a higher toll to carriers for day time deliveries would not have meaningful implications in shifting deliveries to off-peak hours or night time (Holguín-Veras, 2008). The reason is that, in general, receivers choose the delivery time windows. Off-hour deliveries may be beneficial to carriers in terms of travel time savings, reduction in the number of trucks used for deliveries, lower fuel costs, lower traffic violation costs, and as a result, overall logistics cost savings and increases in productivity of carriers (Browne et al., 2006). On the other hand, a shift to off-hours provides little benefit, if any, to receivers. Unless there are substantial benefits to receivers, they will not voluntarily shift to the off-hours. As such

an arrangement would necessitate extra employees to handle deliveries as their usual business practice, shifting to off-hours delivery is not financially advantageous. In this sense, the provision of financial incentives to receivers may encourage their participation in OHD.

3.2.2.2   Types of incentives

As one may expect, carriers, shippers, and receivers will not participate in OHD if the costs of participation exceed the benefits that they would obtain. Thus, the next step is to identify the types of incentives and how they would work. The project team looked at the financial incentives to receivers (broad-based, and targeted incentives), and a voluntary green certificate program.

First, as is discussed in more detail elsewhere in this report, the project team found that financial incentives to receivers would encourage a shift of a significant number of deliveries to the off-hours. At the incentive levels of $5,000 and $10,000, with an assumption of $25/hour value of time for congestion, the policy would yield more benefits than costs, shifting 3-7% of deliveries to the off-hours. However, the implementation of this broad-based program could be constrained by the complexity of coordination among the multiple receivers and carriers that would be involved. Thus, the actual costs of implementing this scenario could be considerably more expensive.

Given the complexity of receiver-carrier coordination with the broad-based program, incentives targeting Large Traffic Generators (LTGs) would be more attractive to many practitioners and decision makers. A program focusing on LTGs would yield a relatively large payoff in terms of truck traffic shifted to the off-hours. This finding is due to the sheer daily truck traffic volume to the LTGs, which are clusters of multiple businesses (e.g., malls) or large buildings with unique ZIP codes (e.g., Rockefeller Center). These facilities tend to generate significant amounts of truck traffic and handle incoming and outgoing deliveries with a central delivery station.

However, tailored information campaigns targeted at building owners would be necessary. An IAG member with 103 retail tenants in one building pointed out that OHD in the building are only allowed when a tenant has designated staff to receive the delivery. The IAG member suggested that the provision of unassisted deliveries would help promote off-hour delivery in LTGs.

The third type of incentive is not monetary, but image-enhancing: the "Green Certificate" model. The project team found that many companies want to be good corporate citizens. They are making positive changes on their own as a way to promote their image, which in the long run will lead to an increase in customer loyalty and sales. Public agencies could create a Green Certificate program to recognize companies that voluntarily take steps to increase sustainability. This could involve different levels of certification depending on their participation level. Such public recognition of a good deed could spur others. Furthermore, customers could pressure non-compliant businesses to implement changes. If a large and influential city such as New York decides to promote this program, it could be very impactful.

A purely voluntary program that provided no incentive does not have quantifiable benefits at this time. If receivers were willing to participate without an incentive, they already would be doing so (i.e., we would have the status quo). A program that provided some sort of publicity (i.e. "Green Apple" award) may have an impact, but there is no way to know what kind of participation it would generate. Benefits would be positive and costs would be minimal.

3.2.3 Foreseeable barriers that may incur costs and suggested solutions

3.2.3.1 *Extra employees for off-hours: roving crews and/or tax credits*

While the behavioral model for this study estimated a potential level of extra cost for the receiver, it is not clear whether this cost is appropriate until a program is put into practice. One of the major costs of implementing OHD is labor. Unless a retail store is open 24 hours, an extra employee for handling deliveries would need to be hired. Since the delivery time window for each store would be only an hour or two, it would not be easy to hire someone who works for a short time period during the off-hours. As one IAG member pointed out, "the labor costs, in particular, are not insignificant with cost differentials for those working overnight hours cited by one company as being near 10%."

Throughout the interviews with IAG members, two alternatives were identified. The first is "roving crews" that would be shared among multiple stores within certain commercial districts, a mall, or a building. By sharing the crews, the stores could share the labor costs associated with instituting OHD.

The second alternative is a tax credit for labor costs. Indeed, there is some initial support for this idea. Recently, U.S. Representative Anthony Weiner (New York's 9th District) proposed using city tax credits to compensate for staffing costs associated with off-peak deliveries. He proposed that businesses willing to move to off-peak deliveries should receive a city tax credit, matched by the federal government (Weiner, 2010).

3.2.3.2 *Unassisted delivery facilities*

A key dilemma facing retailers is ensuring that the necessary workers are in place to receive goods during the off-hours. Employing such workers entails additional costs in terms of wages as well as costs associated with heating, lighting, and insurance. A potential solution to this labor issue is unassisted delivery facilities like central drop box locations.

However, the implementation of a central drop box strategy would also entail some additional costs. In some cases, building codes would need to be modified to allow for installing a central drop box. Additionally, the public sector may need to provide subsidies to build such facilities. The project team's future study should include acceptance of unassisted delivery facilities and conduct performance simulation that takes the related building costs into account.

3.2.3.3 *Community resistance to noise*

As many European cases demonstrate, noise pollution is one of the major concerns that motivate neighborhoods to resist OHD. Yannis, in the case study of Athens, Greece, states that the most important negative social impact of OHD is the noise produced by unloading operations during the night (Yannis et al., 2006). This concern was also raised during the interview with IAG members. Noise as an issue is particularly challenging to address in areas of mixed land use, where businesses and residences are located in close proximity. In some cases, addressing this problem requires changing ordinances that prohibit certain levels of noise at certain times of the night (Ogden, 1992). In other cases, addressing noise concerns means using different abatement techniques—for example, using plastic roll cages instead of metal roll cages on storefronts to limit noise when they are rolled up and down for deliveries (Whitegift Centre, 2007). As Browne et al. pointed out, such abatement techniques can mean higher costs for receivers (and for carriers) (Browne et al., 2006).

3.2.4   Potential avenues for implementation

While this study found that a certain level of incentives would shift a substantial number of truck delivery trips to the off-hours, how to pay for an OHD program is another question that would be very difficult to answer. Given the assumption that both elected officials and the private sector do not want to increase taxes to finance an OHD program, the most feasible option is to utilize financial incentives (e.g. tax credits) to promote the program to participating receivers. Another option is the use of road pricing to pay for the program.

Indeed, Holguín-Veras et al. (2006), studied the role of the receivers in shifting deliveries to the off-hours, since, as mentioned above, an empirical study found that the delivery time is set by receivers, not by carriers or shippers. The project estimated that tax deductions, combined with time-of-day pricing, could induce a shift of up to 20% of the truck traffic in some market segments, e.g., restaurants.

3.3   *Institutional Arrangements Suggested*

3.3.1   Types of potential institutional arrangements

Despite several potential benefits of OHD such as reductions in logistics costs, travel time, traffic congestion, and air pollution (Huschebeck, 2004; NICHES, 2008), the effective implementation of this program would require a new institutional arrangement that must be based on inter-agency and public-private cooperation within the jurisdiction. According to a recent report for the National Cooperative Freight Research Program (NCFRP), an institutional arrangement on freight transportation systems is defined as "a structural foundation that enables relevant parties to advance the general interests of freight mobility—infrastructure, operations, services, and regulations—or particular programs and projects to increase freight mobility (Cambridge Systematics, 2009)." Institutional arrangements can be categorized

into three types depending on specific objectives of each arrangement. First, Type I organizations focus on the advocacy function by concentrating on education and consensus building (Cambridge Systematics, 2009). This study has played a role in fostering collaboration among public and private sector stakeholders by forming the IAG and TAG, and hosting public outreach meetings as a way to advocate and disseminate the idea of OHD. Second, Type II organizations function to "evaluate, prioritize, and fund freight projects in a particular region or of a particular type (e.g., city or state transportation agencies)" (Cambridge Systematics, 2009). Finally, "type III organizations are formed to implement a specific project, such as financing, environmental clearances, and negotiating contractual arrangement" (Cambridge Systematics, 2009).

In a sense, a spectrum from Type I to Type III organizations is a somewhat linear development process in which Type III organizations include all or most characteristics of the previous two institutional arrangements. Most projects generally begin with needs identification and consensus building among stakeholders (Type I); alternative analysis for prioritization within public agencies (Type II); and the formation of a large temporary or permanent institution to implement a large-scale project based on multi-jurisdictional collaboration and partnerships with the private sector (Type III). The Alameda Corridor project is a good example of freight transportation planning and policy that evolved from Type I to Type III. The project was a culmination of the collaboration of multiple agencies and multiple private sector stakeholders, including the Southern California Association of Governments (SCAG), the regional metropolitan organization; city and state governments; and private sector stakeholders (e.g., truckers and rail operators). This type of public-private partnership could be formed for the successful implementation of an OHD program in the New York metropolitan area.

The successful formation of a new institutional arrangement would need at least four conditions. First, it would need one or more champions with "vision, commitment, drive, and initiative (Roberts, 2010)." Often, this would need political will and support with which the public agency can educate the stakeholders and implement an OHD scheme. In some cases, this can be a top-down decision because of a legislative mandate, but other times can be a bottom-up approach initiated by technical staff. As this study has identified significant interest from the public agencies in the New York metropolitan area, the next step would be to establish a formal policy that provides guidance for OHD. Second, the identification of key stakeholders from the private sector is necessary (NICHES, 2008; Cambridge Systematics, 2009). Identifying incentive programs for attracting the private sector is vital. Interviews with the IAG members and a previous study by Holguin-Veras et al. reveals that many private sector stakeholders do not think that OHD can be successfully implemented without providing incentives for participants (Holguín-Veras, 2006). Third, the needs assessment workshop with stakeholders is useful to define the purpose of a new institutional arrangement (Cambridge Systematics, 2009). While the two public outreach meetings for the

current study have identified issues and challenges in terms of providing OHD policy, this region still needs a more comprehensive roundtable to identify stakeholders and the structure of a new institution. Fourth, once the exploratory group has reached a preliminary agreement on the need and purpose of an institutional arrangement, an action plan should be developed to detail short-term and long-term activities (Cambridge Systematics, 2009).

3.3.2 Institutional and structural challenges

The project team explored some of the potential reactions of various approaches with key community leaders and firms. While there was broad support for the notion of OHD, there is widespread wariness of heavy governmental intervention in the operations of private firms. Since the costs for the shift to OHD vary widely by type of firm, location, and other variables, setting a single incentive level risks substantial overpayment or underpayment that can result in either wasting resources or making the program ineffective. A program based on the specific costs for each firm would be difficult to administer and prone to abuse. Some further research is certainly warranted, but some broad conclusions can be drawn from the project team's interaction with key local entities.

First, strong public sector support is essential. Especially for any voluntary program, significant recognition from the city government would be important. Given the number of agencies involved in supporting OHD shifts, coordination among local government agencies—traffic, environmental, planning, transit, sanitation, among others—would be required by a leader with a stake in the program's success and the imprimatur of the Mayor and local officials.

Second, leadership from the public sector must be paired with private sector leadership. Whether the voluntary program or the targeted LTG program is chosen, significant private sector support is essential. The project team has had discussions with a wide array of private sector entities—including freight firms, receivers of goods, and landlords—but clearly more engagement is required as part of any implementation effort. It should be noted that indications thus far have been very positive, with some major firms already indicating their willingness to move to OHD, and a major real estate association indicating interest in the program on behalf of land-owners.

Third, in these strained financial times, it is very unlikely any program requiring on-going operating subsidies to large numbers of firms is viable. In general, government coffers are bare due to the sharply negative effects of the recent great recession, and public authorities are being forced into making significant service reductions as well as cuts to their capital programs. Tolls and fare increases are already pledged to the support of core operations at these entities and any incremental increases dedicated to this purpose are unlikely to be widely supported. Two conclusions can be drawn from the recognition of these circumstances. Any financial commitment from the public sector should be confined to one-time support

for physical improvements made by building owners and tenants, likely to accommodate unstaffed good receiving locations and additional security. Also, a strong and visible effort to implement an effective voluntary program should be considered before any large-scale or even targeted subsidy effort is planned. Effective implementation of such a program could demonstrate the potential for real change, build up demand for larger scale efforts, and help the public sector isolate the real financial costs of any shift to OHD by the receivers of goods.

3.4   References

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4. MARKET ANALYSES

4.1 Identification and Quantification of Potential Target Markets

Implementing off-hour delivery programs faces the challenge of identifying the most appropriate industry segments that would be the target of the programs. This is important because, as previous experiences indicate (Churchill, 1970), in order for off-hour deliveries (OHD) to be of benefit to the carrier, a minimum scale of operation is required. For that reason, focusing on specific industry segments will help ensure the corresponding carriers find the minimum scale needed to consider OHD.

This section describes the process used to determine the best market segments to target for participating in OHD in Manhattan. While previous works have focused on using commodities as an indicator of market segments (Holguín-Veras et al., 2007; 2008), it has been found that using the commodity type as a proxy for the industry segment has some limitations. The key limitation is that it is very difficult to relate the model results to specific business types, as the only information in the model is the type of commodity received or transported. For that reason, it is a challenge to link the behavioral models to economic databases that are classified and organized using the line of business, defined by coding systems such as Standard Industrial Classification (SIC). This is important because doing so enables one to use these databases for important analyses such as trip generation. Another complication with the use of commodity types is that, since most businesses receive deliveries of multiple commodities from one or more carriers, there is no clear way to determine the distribution of a commodity being transported by a given carrier among its receivers. Alternatively, the use of SIC codes enables one to relate previously obtained survey data with data obtained regarding business establishments in the New York City (NYC) metropolitan area.

Identifying the best market segments to target is crucial to any policy attempting to decrease congestion by encouraging OHD due to the nature of the interaction between the carriers and the receivers of the goods. Many carriers are interested in increasing the number of deliveries during the off-hours due to the potential for transportation cost savings. The key for increasing OHD depends on devising means to encourage receivers to request OHD since the carrier-receiver relationship regarding delivery times dictates that the carriers involved in delivering goods must be responsive to the needs of the receivers of the goods, as they are the customers and therefore have more control in the process of determining delivery times. While the potential savings for the carriers are obvious, the receivers typically would see an increase in costs since many are not normally open during the off-hours and thus are more reluctant to shift. Determining which receivers are most likely to be willing to shift to OHD is therefore the crucial step in selecting appropriate targets for the implementation of policies encouraging OHD.

The approach used utilizes the data previously obtained from a New York State Department of Transportation funded project, which includes descriptive characteristics of the businesses surveyed, such

as number of employees and number of deliveries among others, as well as their stated preferences pertaining to the feasibility and willingness to shift to OHD given various policy scenarios.

4.1.1 Behavioral modeling of off-hour delivery initiatives

In order to understand which types of industries are more likely to be willing to implement off-hours deliveries, behavioral modeling results were obtained by applying discrete choice models to scenarios discussed in detailed in Holguin-Veras et al. (Holguín-Veras et al., 2007; 2008). These scenarios were intended to assist in determining the types of policies that would have the greatest impact upon the willingness of carriers and receivers to participate in OHD.

The modeling results presented in this section are divided into two sub-sections, one concerning the scenarios considered for receivers and the other for carriers. The two scenarios analyzed for receivers are a tax deduction for doing OHD or a reduction in shipping costs during the off-hours. The scenarios for carriers consider the percentage of customers requesting OHD and the following incentives: designated street-side parking during the off-hours, pre-approved security clearances allowing trucks to bypass inspections at tunnels and bridges, toll savings, financial rewards per mile traveled during the off-hours, and permits to do OHD.

The best models of all scenarios take into account basic company characteristics as well as interaction terms and behavioral variables. The type of facility, number of employees, and primary line of business are among the basic company characteristics considered. In all cases, a positive coefficient indicates a positive relationship between the variable and the utility of implementing OHD, while a negative coefficient indicates the opposite. It is also important to note that given the nature of the data, a bootstrap process was conducted to deal with the repeated measurement problem.

4.1.1.1 Behavioral modeling of receivers

Two policy scenarios targeting receivers were considered: (1) a tax deduction, and (2) shipping cost discounts for receivers accepting OHD. As discussed before, the receiver policies considered here involve financial incentives to compensate receivers for the extra costs associated with off-hour operation.

The first scenario asked receivers how likely they would be to accept a certain percentage of their deliveries during the off-hours in return for a tax deduction. The amounts of the tax deduction considered in the stated preference survey were $3000, $6000, and $9000 annually. As the project team expected, the coefficient of the policy variable in the model is positive and significant implying that the likelihood of a receiver accepting OHD will increase as the amount of the tax deduction increases. Additionally, using interaction terms, the model indicated the impact of the type of business on the likelihood of accepting OHD in exchange for a tax deduction. It was determined that the likelihood increases for receivers

involved in building materials, home furnishings, retail baked goods, and eating establishments while the likelihood decreases for receivers of jewelry.

The second scenario asked receivers how likely they would be to accept a certain percentage of their deliveries during the off-hours in return for a reduction in shipping costs. The amount of the cost reductions in the stated preference survey were 20% and 40%. As expected, the coefficient of the policy variable is positive and significant implying that the likelihood of a receiver accepting OHD will increase as the amount of the shipping cost savings increases. It was also found that the likelihood of receiving OHD increases for receivers involved in home furnishings, professional and commercial equipment and supplies, piece goods, and liquor stores.

4.1.1.2 *Behavioral modeling of carriers*

This section discusses the results obtained for the policy scenarios targeting carriers. The carrier policies consider the percentage of customer requesting OHD and the following incentives: designated street-side parking, pre-approved security clearances allowing trucks to bypass inspections at tunnels and bridges, toll savings, financial rewards per mile traveled during the off-hours, and permits to do OHD. Although not a policy scenario, the use of a neutral company to do the last leg of deliveries to Manhattan is also considered.

The first carrier scenario took into consideration the impact on the likelihood of participation in OHD of three incentives: 1) a given percentage (which in all scenarios is 25%, 50%, or 75%) of customers requesting OHD, 2) designating street-side parking for OHD in addition to the given percentage of customers requesting OHD, and 3) giving carriers pre-approved security clearances allowing trucks to bypass inspections at tunnels and bridges as an incentive in addition to the given percentage of customers requesting off-hour delivers. The model indicated that all three incentives considered are significant, particularly the percent of customers requesting OHD. Designated street-side parking during the off-hours was shown to significantly increasing the likelihood of performing OHD. This agrees with the finding in the model that carriers who experienced average monthly fines less than $400 are less likely to implement OHD since parking is not as severe of an issue and therefore designated parking does not provide a significant benefit. Additionally carriers of wood/lumber and medical supplies were shown to have a larger likelihood to participate in OHD. Also of note is that long haul trucking firms were found to be more inclined to participate in OHD whereas local trucking firms were disinclined to participate.

The second carrier scenario was concerned with the likelihood of carriers to increase the number of OHD if a certain percentage of their customers requested it and toll savings were awarded for traversing bridges and tunnels during the off-hours. Toll savings were set at $3 per axle, $4 per axle, or $7 per axle. The model once again showed that the percent of customers requesting OHD was highly significant and had a positive effect on the likelihood of a carrier to participate. The toll savings policy variable itself was

not significant in the model. Considering interaction terms, it was seen that carriers who receive toll discounts and are involved in the grocery, furniture, or non-local trucking industries are more inclined to do OHD. Worth noting is that many of the variables that considered the line of business (e.g., Shipper, Warehouse, Mover) had significant and positive relationships between the lines of business and propensity to participate in OHD.

The third carrier scenario evaluated the likelihood of carriers making more OHD to Manhattan if a percentage of their customers request OHD and the carriers received a financial reward per mile traveled during the off-hours. The financial reward offered was either 5 cents/mile or 10 cents/mile. The model indicated that: (1) carrier companies who receive rewards for the transport of food are more likely to participate to in this scenario; (2) carriers that are not local are more willing to make OHD since they have to travel longer distances and therefore receive more benefits for traveling during the off-hours; and (3) carriers of furniture are less likely to participate in OHD. Once again the percentage of customers requesting OHD is highly significant as is the number of total trips to Manhattan.

The fourth carrier scenario considered the impact of customer requests for OHD and the option that the carrier could pay for a permit that let them double park for 20 minutes at each delivery stop. The cost of the permit was set at $3000, $6000, or $9000 per year for the permit. The policy variable coefficient was highly significant and negative. The model also indicated that carriers feel even less inclined to do OHD when they purchase parking permits and they are part of the industrial sectors of lumber, wood, brick and construction materials, food, and local trucking without storage, as are carriers who make more trips and are part of the industrial sector of plumbing, heating and air-conditioning equipment. Carriers who make more trips and are part of the industrial sector of motor vehicle supplies, electrical apparatus, electronic equipment, and construction materials are more likely to participate in this scenario.

The fifth carrier scenario considered the impact of a neutral company—which could well be owned by many different carriers—that will be in charge of doing the last leg of deliveries to Manhattan. With this company, carriers wishing to deliver to Manhattan would transfer their deliveries, and the consolidated cargo would then be delivered to the respective consignees. This alternative could significantly reduce truck trips (by increasing the truck utilization and reducing empty trips) to Manhattan and could bring about significant environmental savings, if alternative fuel trucks or environmentally friendly trucks are used. The data show that 17.40% of the participating companies expressed interest in using this neutral company to make the last leg of delivery to Manhattan. The model illustrated that this scenario is particularly appealing to carriers of food and paper goods.

The key result obtained from considering the five carrier scenarios is that the percent of customers requesting OHD is highly significant and positive. Once again it is seen that the receivers as the customers have a large impact on the ability to implement OHD.

4.1.2 Amounts of deliveries by industry segments

While the determination of which industry segments are more receptive to OHD is vital, equally important is determining which industry segments account for a significant portion of deliveries, in order for a shift to OHD to have an impact on congestion levels during the rest of the day. To determine this, data from various sources was utilized to estimate the number of daily deliveries performed by various industry segments, based on SIC codes of businesses, in the NYC metropolitan area.

The number of establishments per ZIP code in Manhattan was obtained from the 2005 ZIP Code Business Patterns data from the U.S. Census Bureau[1]. Rates for the number of daily deliveries generated per establishment in various industry segments were calculated by the authors from survey data. Using these values an estimation of the total number of deliveries was determined. Due to the limitations of the survey data, the industry segments, for the purpose of rate calculation, were aggregated at the 2-digit SIC level and only SIC codes 7-59 were considered. These SIC codes were determined by the project team to be "freight deliveries". The SIC codes above 60 are in the "Finance, Insurance, and Real Estate", "Services", and "Public Administration" divisions. Delivery estimates for 20 of the SIC codes in Manhattan and NYC can be seen in Table 5.

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[1] http://www.census.gov/epcd/cbp/download/05_data/zbp05totals.txt

Table 5: Delivery Estimates for 20 SIC Codes in Manhattan and NYC

SIC	SIC Description	Estimated number of deliveries in Manhattan	Estimated number of deliveries in NYC
Food Sector		**27,408 (24.24%)**	**65,854 (25.63%)**
58	Eating And Drinking Places	19,314	36,834
54	Food Stores	7,941	28,122
20	Food And Kindred Products	153	898
Consumer Goods		**65,751 (58.15%)**	**134,458 (52.33%)**
50	Wholesale Trade-durable Goods	28,984	58,809
51	Wholesale Trade-non-durable Goods	22,968	46,453
59	Miscellaneous Retail	5,689	9,479
23	Apparel And Other Finished Products Made From Fabrics	3,668	6,192
56	Apparel And Accessory Stores	1,489	2,506
57	Home Furniture, Furnishings, And Equipment Stores	1,047	2,099
55	Automotive Dealers And Gasoline Service Stations	820	4,476
53	General Merchandise Stores	554	3,076
36	Electronic And Other Electrical Equipment, Except Computer Equipment	392	713
25	Furniture And Fixtures	141	657
Industrial Goods			
27	Printing, Publishing, And Allied Industries	5,161	7,201
17	Construction Special Trade Contractors	2,747	20,054
15	Building Construction General Contractors And Operative Builders	2,202	5,187
34	Fabricated Metal Products, Except Machinery And Transportation Equip.	1,078	2,303
37	Transportation Equipment	1,077	1,739
39	Miscellaneous Manufacturing Industries	453	898
22	Textile Mill Products	415	763
Total for all SIC codes (including those not shown above)		**113,069**	**256,956**

The food related industry segments of Food Stores and Eating and Drinking Places as well as the Wholesale Trade industry segment all generate an estimated number of deliveries in excess of 20,000 per day. When considering these results, an aggregation of SIC groups 50 to 59, which are the SIC codes associated with trade, represents a high percentage of the number of deliveries in NYC and will receive special attention.

4.2   *Behavioral Analyses: Behavioral Micro-Simulation (BMS)*

Section 4.1 discussed the results of various models to determine the impact of various policies on the behavior of receivers and carriers. It also provided an estimate of the number of daily freight deliveries made to Manhattan. This section utilizes the results of the behavior models to create the Behavioral Micro-Simulation (BMS) model which determines the shift in deliveries to the off-hour in various industry segments for various incentive levels.

The fundamental purpose of this model is to gain a better understanding of how to increase the participation in OHD through the use of a BMS of carrier-receiver interactions, to study the effectiveness

of various policy incentives such as: time-of-day pricing and financial incentives to receivers in exchange for accepting OHD. The main components of this BMS are the simulation of receiver and carrier behaviors. The simulation of receiver behavior uses a discrete choice model as a function of the tax deduction incentive to estimate receivers' decision to accept or reject OHD. In turn, the carriers use the decisions of the receivers and the resulting impact on their delivery costs to make decisions about whether or not to make OHD.

The analyses reveal that tax deductions given to receivers in exchange for extending their hours of operations to the off-hours would provide a noticeable shift to OHD as noted in Section 4.1. It was also verified that certain industry segments were more receptive to OHD than others. These industry segments are: Food, Non-Alcoholic Beverages, Alcoholic Beverages, Wood/Lumber, Paper, Chemicals, Plastic, and Medical Supplies. The BMS was used to analyze the influence of the distance to the first delivery stop on off-hour delivery participation. The results indicate that carriers located close to their urban customers are more likely to participate in OHD. This is because it is easier for them to start accruing the benefits from off-hour delivery operations. Finally, the BMS showed that: (1) increased enforcement of parking fines for double parking during the regular hours could increase the number of carriers participating in OHD; and (2) tax deductions to receivers and financial rewards to carriers have more influence on OHD than toll surcharges imposed on carriers.

4.2.1   Scope of the behavioral analyses

The previous research done in terms of estimating off-hour delivery participation used discrete choice models to estimate market shares. This method has significant limitations in what they could consider as impacting the decisions to participate in OHD. First, discrete choice models cannot truly account for geographic factors such as: (1) delivery route distances in reference to the locations of their receivers; and (2) costs accumulated from accepting and making deliveries by time of the day. This is an issue because the geographic location of receivers and carriers dictates logistic operations and delivery routes for carriers, and ultimately delivery costs. This is important because the cost for participating in OHD is a driving factor in making a final decision about delivery scheduling.

Furthermore, the consideration of other real-world conditions should be added to the analyses, to assess their impact on OHD. These factors include the consideration of: (1) budget and working constraints imposed on receivers and carriers; (2) delivery routes selection; (3) productivity levels (e.g., travel time, and traveling speed estimations during regular and off-hour hours); and (4) other government regulations and policies that interact with and limit off-hour delivery activities. To understand the effectiveness of off-hour delivery operations, there is a need to simultaneously consider as many of these factors together with financial incentives (e.g., tax deductions, time-of-day tolls) as possible. The

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following sections describe the BMS developed by the authors to address these limitations, and to discuss preliminary findings achieved by applying it to a set of hypothetical test cases.

4.2.2   Methodology

The basic outline of the BMS is shown in Figure 4. As shown, it assumes a sequential decision making process leading to a decision regarding participation in OHD (Holguín-Veras et al., 2008). The main modules in this behavioral micro-simulation, which are the components inside of the dotted box in Figure 4, are the receiver behavioral simulation and carrier behavioral simulation. In this schematic, the decisions to participate in OHD is first influenced by the given policy incentives given to receivers and carriers, denoted Πr and Πc respectively. It should also be recognized that the carriers' decisions to do OHD is directly influenced by the receivers' decisions of whether or not to accept OHD, and the resulting delivery costs. The overall goal of the BMS is to understand how the use of economic incentives given to receivers and carriers could influence carrier participation in OHD and subsequently influence the amount of truck traffic in urban areas during the regular and off-hours of the day.
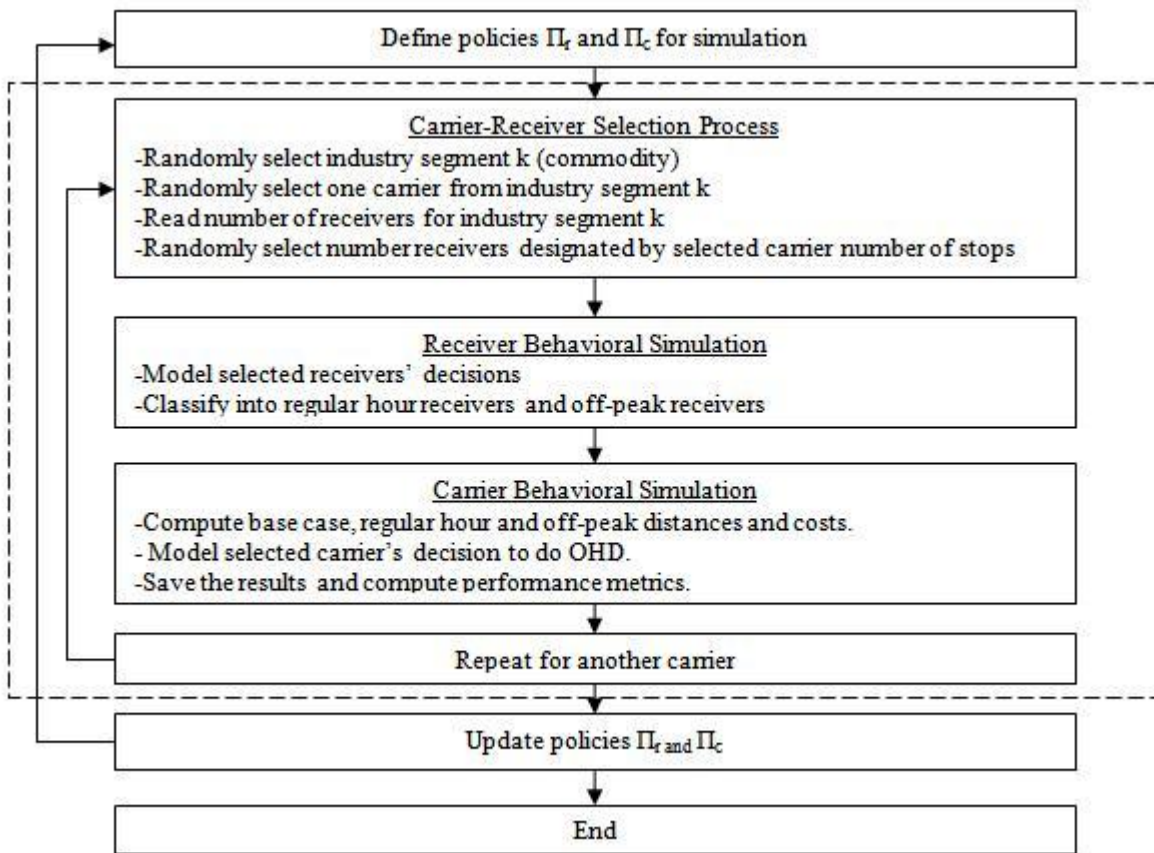
Figure 4: Behavioral Micro-Simulation (BMS) Framework

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The receivers are provided with a tax deduction given for one worker to accept deliveries during the off-hours, while carriers are assessed time-of-day tolls with a surcharge for regular-hour deliveries. These instruments were used for this micro-simulation formulation because they were previously found as the most efficient means of fostering OHD (Holguín-Veras et al., 2007; 2008). Both incentives were also used in this formulation to understand how the participation in OHD by carriers changes when receivers were encouraged to change their receiving schedules.

The carrier-receivers selection process is simple to follow. The objective here is to generate a synthetic population of carriers to understand how the delivery scheduling of commodities are influenced by the incentives. The following industry segments were considered: plastics, jewelry/art, chemicals, wood/lumber, medical supplies, non-alcoholic beverages, alcoholic beverages, petroleum/coal, stone/concrete, paper, printed material, computers/electronics, office supplies, textiles/clothing, metal, furniture, household goods, machinery, and food (Holguín-Veras et al., 2008). The process starts first by having a single industry segment randomly selected from list previously mentioned. Next, a carrier is randomly selected from the industry segment's population. Lastly, using the selected carrier's number of stops, that number of receivers is selected from the corresponding industry segment's population. This is the set of customers that the behavioral simulation of receivers will be used for. The carrier will then use the decisions of the receivers to estimate delivery costs during regular and off- hours, and make a decision on the participation of off-hour activities.

4.2.3 Receiver behavioral simulation

The micro-simulation of receiver behavior is driven by the behavioral model estimated in a previous phase of the research, displayed in Table 6, which specifically considers the role played by a tax deduction (Holguín-Veras et al., 2007; 2008). The data used for estimating this model came from the previously mentioned project funded by the New York State Department of Transportation's Potential for Off-Peak Freight Deliveries to Congested Urban Areas (Holguín-Veras et al., 2006b). Two hundred receivers located in Manhattan were interviewed in 2005; stakeholders gave information about their: (1) receiving and shipping patterns, (2) operations and flexibility, (3) receptiveness to OHD when given economic incentives, and (4) company characteristics. As shown, the model is a function of the tax deduction variable (TDEDUCT), reasons for not accepting OHD, and interaction terms between the policy variable and the commodity types: wood/lumber, alcohol, paper, medical supplies, food, printed material, and metal (Holguín-Veras et al., 2008).

Table 6: Binary Logit Model for Receiver Tax Deduction Scenario (Holguín-Veras et al., 2008)

Variable	Name	Coefficient	t-value
Utility of off-peak deliveries:	C1CHOICE		
A tax deduction for an employee assigned to OHD	TDEDUCT	8.392E-05	1.410
Reasons for not receiving OHD			
No access to building/freight entrance after hours	REASON1	-1.234	-1.571
Additional costs to the business if accepting more OHD	COST	-0.888	-3.232
Interferes with normal business	REASON2	-0.591	-1.208
Policy interaction terms			
Tax deduction for receivers of Wood/lumber	TDCOM8	6.968E-04	2.219
Tax deduction for receivers of Alcohol	TDCOM4	4.356E-04	2.209
Tax deduction for receivers of Paper	TDCOM9	2.627E-04	2.988
Tax deduction for receivers of Medical supplies	TDCOM22	2.598E-04	3.188
Tax deduction for receivers of Food	TDCOM2	1.875E-04	3.973
Tax deduction for receivers of Printed Material	TDCOM21	1.652E-04	1.802
Tax deduction for receivers of Metal	TDCOM13	1.415E-04	1.410
Other interaction terms			
Number of employees in a branch facility	BRANEMP	9.867E-03	1.612
Utility of no off-peak deliveries:			
Alternative specific constant	CONSTANT	1.599	4.151
R^2		0.172	
Adjusted R^2		0.140	

In the BMS, the response of the receivers to a given incentive is simulated. This is accomplished by computing that particular receiver's utility for accepting this incentive, $U(OHD)$, using the discrete choice models in Table 6. Once these calculations are made, a random number between 0 and 1 is generated, and if $P(OHD)$ is greater than the random number, then that particular receiver will accept OHD for that incentive. This process is continued for the entire set of selected receivers, for various levels of the incentive.

4.2.4   Carrier behavioral simulation

The third component of this simulation is the carrier behavioral simulation. After the receivers have made their decisions on accepting OHD when given an incentive, the carriers use that information to make their own decisions. It is assumed that the carriers' decisions depend on the profits generated. The first step consists of the selection of a set of receivers for each carrier based on that carrier's industry segment. The number of receivers in this set is designated by the selected carrier's number of stops. This set of receivers, together with their geographic locations, determines the base case conditions, which will be used in determining the base case delivery costs, as shown in Figure 5.

To estimate what would happen as a response to the incentives, the receivers' decisions are simulated. As a consequence of an incentive such as a tax deduction, some receivers may decide to switch to the off-hours while others may elect to receive deliveries during the regular hours. This would translate into a partition of the original base case network into the mixed case (i.e., two sub-networks associated with

regular-hour and off-hour deliveries respectively). This is exemplified in Figure 6 and Figure 7. For example, if the selected carrier makes five stops, then a set of five receivers is randomly selected; and if two receivers are accepting OHD and three receivers are not, then optimal routes for off-hour delivery routes and regular-hour deliveries should be estimated. Next, the transportation costs for regular-hour $(RHDCosts)$ and off-hour deliveries $(OHDCosts)$ are calculated by using cost functions that include the toll surcharges. Lastly, it is assumed that the individual carrier agrees to do OHD if the delivery costs for the mixed case $(RHDCosts + OHDCosts)$ are less than the "Base Condition Costs" (i.e., the delivery cost when all of the receivers in the network only accept regular-hour deliveries).

The simulation of the carrier decisions requires the identification of optimal routes taken for the base case, and the sub-networks of the regular hours and off-hours, since the locations of the receivers and carriers are known. This is needed to estimate travel costs for these conditions. Since the latitude and longitude are known for all receivers and carriers, the methodology used for the simulation of carrier behavior is driven by solving separate vehicle routing problems. The determination of optimal routes was done by using a Radial Sweep Heuristic (Holguín-Veras, 2006).

Using the framework just explained, various analyses were conducted to understand how participation in off-hours deliveries is influenced by: tax deductions given to receivers, time-of-day tolls, distances to the first stop in a delivery route for carriers, and parking fine enforcement on carriers.

Finally, the simulations are concluded for each incentive set once convergence is reached. After many experimental trials, it was found that estimates for participation in OHD converge after one-hundred thousand replications.
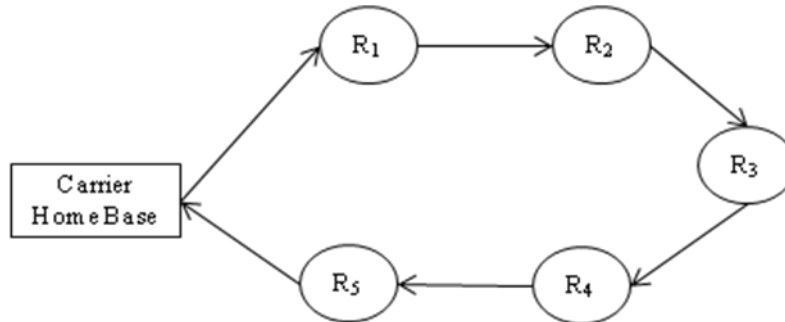
Figure 5: Base Condition (all receivers are accepting regular-hour deliveries)
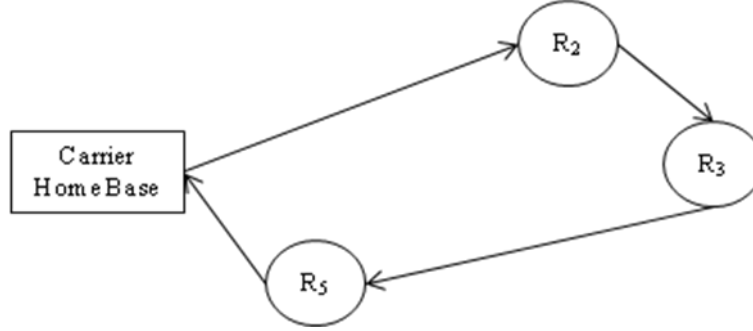
Figure 6: Sub-network of Receivers Accepting Regular-hour Deliveries
(note: assuming receivers 2, 3, and 5 elected to stay accepting regular-hour deliveries)
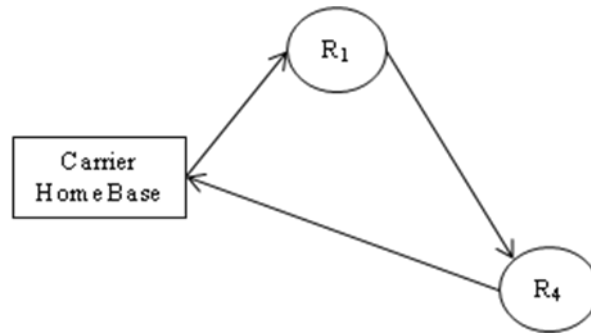
Figure 7: Sub-network of Receivers Accepting Off-hour Deliveries
(note: assuming receivers 1 and 4 elected to accept off-hour deliveries)

4.2.5   Numerical experiments

In order to understand the impacts of key variables, several numerical experiments were conducted, using carriers making urban deliveries to multiple receivers. These experiments analyze the impacts of: giving tax deductions to receivers, by industry segments, the distance to first delivery stop, parking fine enforcement, toll surcharges alone, and toll surcharges combined with tax deductions.

4.2.5.1   Tax deductions to receivers

Since it is known that receivers are important in determining the participation in OHD, it is essential to understand how economic incentives given to receivers will dictate the participation of carriers. For that reason, the overall participation of carriers was analyzed as a function of tax deductions being only given to receivers, by running the BMS for different levels. The results are shown in Figure 8. This figure shows how the participation in OHD by carriers increases as the tax deduction increases, and further confirms the usefulness of this economic incentive. For the sake of completeness, the results shown in Figure 8 consider tax deductions up to \$50,000, even though values that high are not likely to be considered in real life implementations. Finally, it should be noted that even a \$10,000 tax deduction to receivers for the acceptance of goods during the off-hours will provide about a 20% shift in carrier

delivery operations. This finding indicated that this policy could help in reducing some of the traffic congestion during the regular hours of the day. Furthermore, the estimates in this figure are what is called the "base case" market shares in the upcoming analyses (i.e., the situation when only tax deductions are given to receivers).
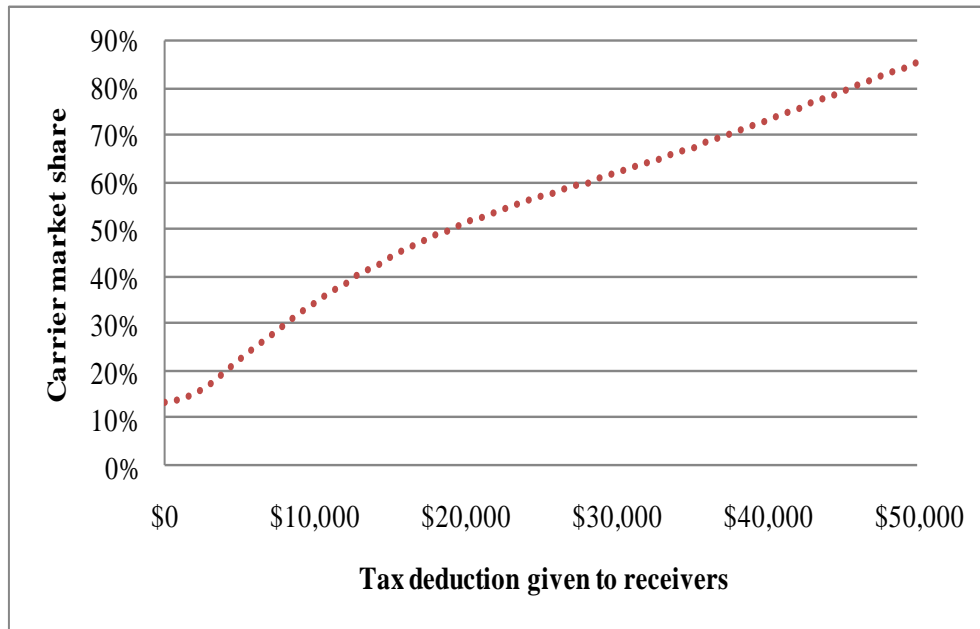
Figure 8: Carrier Market Shares as a Function of the Tax Deduction Given to Receivers

This BMS framework was then directly compared to behavioral models for carriers found by Holguín-Veras, et al. (Holguín-Veras et al., 2008). The comparison of the market share estimates of off-hour delivery participation from both approaches (displayed in Table 7) indicates that the BMS's estimates are higher than the ones provided by the discrete choice models. This may be a reflection of the fact that the BMS considers more dynamics than the behavioral models.

Table 7: Carrier Market Share Comparisons between the Behavioral Models and the BMS

Tax Deductions to receivers	Carrier Market Share from behavioral models (%)	Carrier Market Share from Behavioral Micro-Simulation (%)	% Difference
$0	11.71%	11.71%	0.00%
$2,000	13.25%	12.37%	-0.88%
$4,000	14.52%	14.00%	-0.52%
$6,000	15.92%	16.83%	0.91%
$8,000	17.19%	20.54%	3.35%
$10,000	18.11%	25.05%	6.94%

4.2.5.2 Impact of toll surcharges during regular hours

Additionally, an analysis was done to understand if tax deductions to receivers and time-of-day toll surcharges for regular-hour travel would foster more OHD. The outcomes from this analysis are shown in Table 8, where it is revealed that there are no significant changes in market shares when comparing the columns, which indicates that there are no major changes in off-hour delivery participation with respect to time-of-day pricing. However, when looking at the table vertically, it can be seen that off-hour participation increased with the amount of tax deduction incentive. These findings are consistent with the understanding that tax deductions are more significant in moving truck traffic to the off-hours than toll surcharges, which is consistent with the necessary conditions presented by Holguín-Veras.

Table 8: Carrier Market Share (Function of Toll Surcharges, Tax Deductions to Receivers)

Tax Deduction	Toll Surcharge Per Axle					
	$0	$1	$2	$3	$4	$5
$0	11.71%	11.62%	11.65%	11.71%	11.70%	11.71%
$5,000	15.30%	15.28%	15.24%	15.29%	15.30%	15.32%
$10,000	25.05%	24.96%	25.07%	24.75%	25.05%	25.07%
$15,000	34.80%	35.22%	34.75%	34.99%	34.88%	34.78%
$20,000	43.43%	43.81%	43.36%	43.88%	43.55%	43.51%
$25,000	51.53%	51.11%	51.30%	51.47%	51.16%	51.56%
$30,000	57.38%	57.18%	57.36%	57.07%	57.36%	57.47%
$35,000	62.30%	63.00%	62.51%	62.57%	62.62%	62.21%
$40,000	68.04%	68.15%	67.91%	68.19%	67.91%	68.06%
$45,000	73.88%	73.66%	74.04%	74.04%	74.02%	73.88%
$50,000	80.16%	80.22%	80.19%	79.96%	80.45%	80.24%

4.2.5.3 Impacts by industry segments

Figure 9 and Figure 10 show the carriers' participation as a function of the tax deduction and by industry segments. These figures show that in all cases the market shares increase as the tax deduction increases with some industry segments being more sensitive to these incentives than others. The industry segments displaying the most sensitivity (shown in Figure 9) are: Food, Non-Alcoholic Beverages, Alcoholic Beverages, Wood/Lumber, Paper, Chemicals, Plastic, and Medical Supplies. Alternatively, the industry segments least sensitive to tax deductions are shown in Figure 10. This analysis of the market shares of the individual industry segments might be helpful in identifying good targets for the implementation of an OHD program.
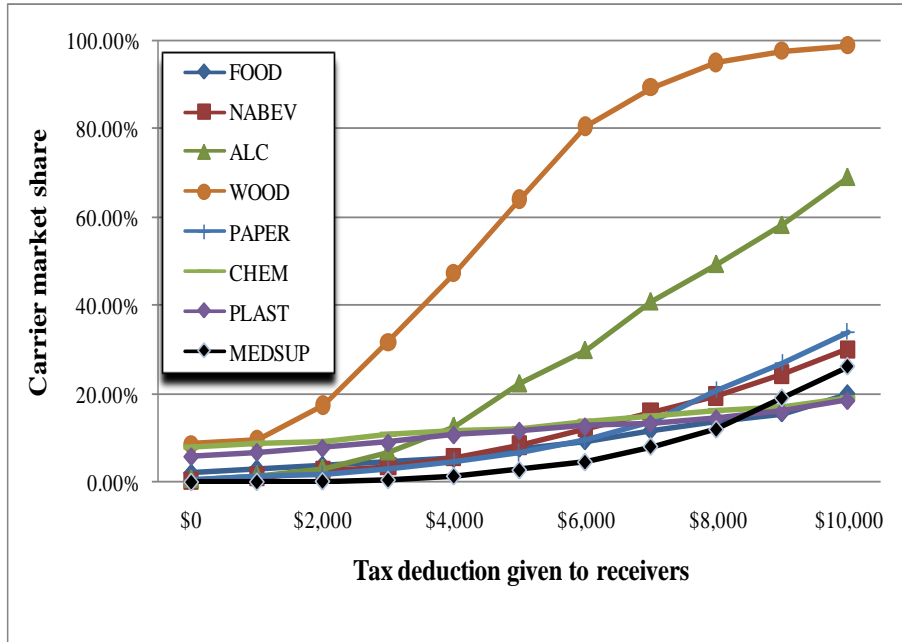
**Figure 9: Most Sensitive Industry Segments' Market Shares
(as a function of the tax deduction given to receivers)**
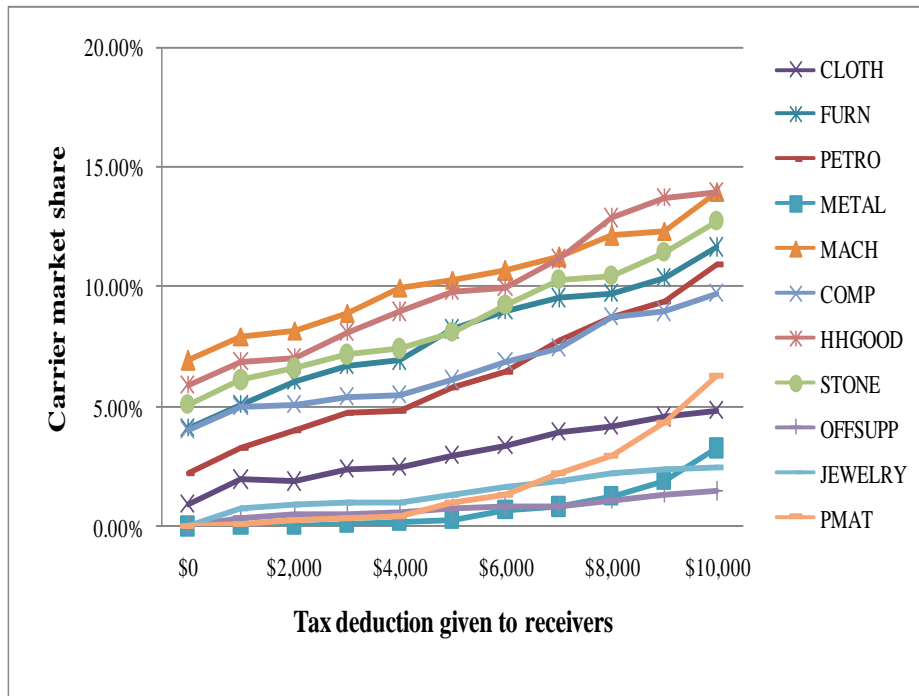
**Figure 10: Least Sensitive Industry Segments' Market Shares
(as a function of the tax deduction given to receivers)**

4.2.5.4 Impact of distance to the first delivery stop

Next, an analysis was done to understand how the decision to do off-hours deliveries would be influenced by carriers' traveling distance to their first delivery stop. This is important because traveling distances to first delivery stops were mathematically found to be influential on the carriers' decisions to make off-hours deliveries, which is due to the fixed amount imposed on delivery costs (Holguín-Veras et al., 2006b). The results are shown in Figure 11. The general shapes of these market share estimations tend to follow the logistic distributions of the underlying receiver behavioral models. Also the figure reveals that carriers are more likely to make deliveries during the off-hours when they are relatively close to their first delivery stop. This is due to reduced fixed transportation costs and higher productivity levels that carriers are able to take advantage of (Holguín-Veras et al., 2006b). Overall, this analysis is a justification of why carriers located close to congested urban areas should be targeted for this type of policies.
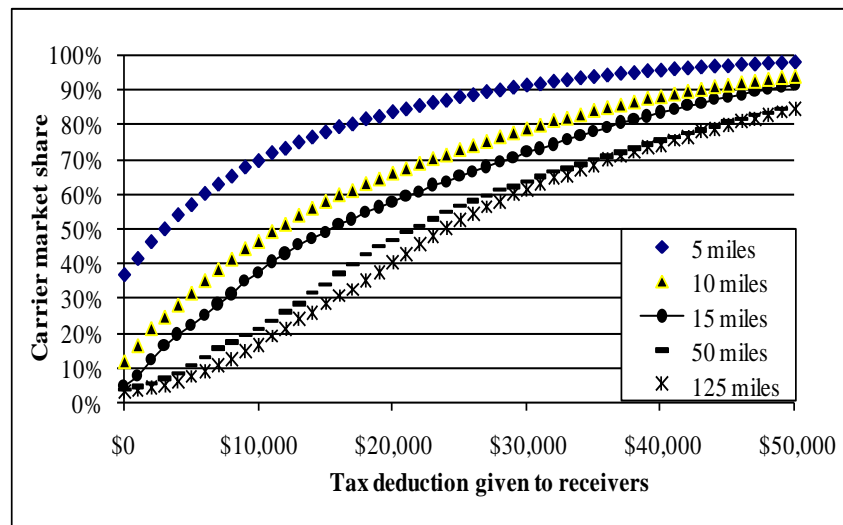
Figure 11: Carrier Market Shares (Tax Deduction to Receivers, Distance to First Stop)

4.2.5.5 Impact of parking fines

An analysis was done to understand how parking fine enforcement during the regular hours of the day could influence the decision to do OHD. It should be first noted that determining the probability that a carrier gets a parking fine is very complex in nature, because it is a function of: police enforcement, travel behavior, traffic congestion, and other factors. This challenge caused the authors to do a sensitivity analysis using the values shown in Table 9. Using these probability estimations and the tax deductions given to receivers, carrier market shares were again estimated, and the results are shown in Figure 12. The graph shows that there is an increase in the percentage of carriers participating in OHD operations as the probability of getting parking fines during the regular hours increases. This analysis, from a policy perspective, demonstrates how the enforcement of traffic ordinances could influence this transportation practice, since carriers are forced to absorb parking fines as an added transportation cost.

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Table 9: Probability Estimations for Parking Fines

Number of Stops Per Trip	One ticket per how many tours?	Trips Per Day	Probability for Parking Fine per stop
6	10	2	1/120
6	3	1	1/18
5	2	1	1/10
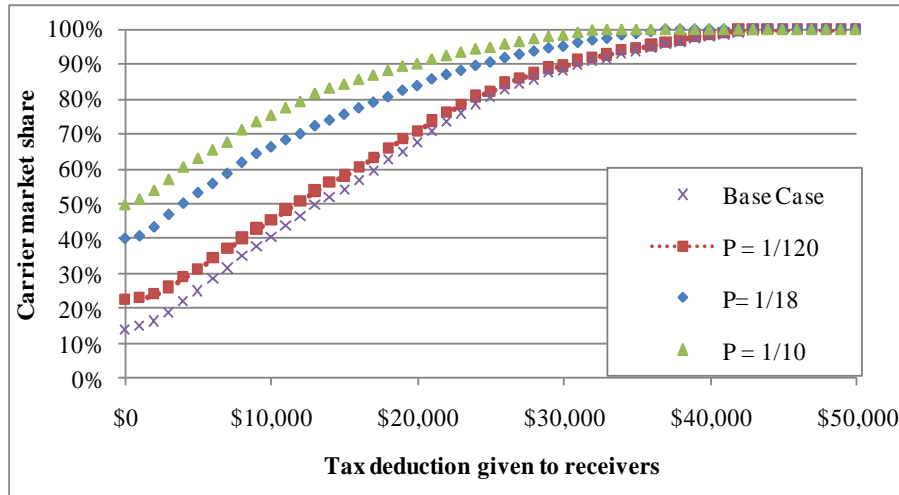
Figure 12: Carrier Market Shares (Tax Deduction to Receivers, Parking Fine Enforcement)

4.2.5.6 *Impact of financial rewards for off-hour travel*

A different analysis was conducted to understand how financial rewards for off-hour travel alone would also influence carriers to shift their operations. The results shown in Figure 13 reveal that carrier participation in OHD is noticeably influenced by this incentive alone, which may be due to the idea that carriers stand to make money for traveling during the off-hours.
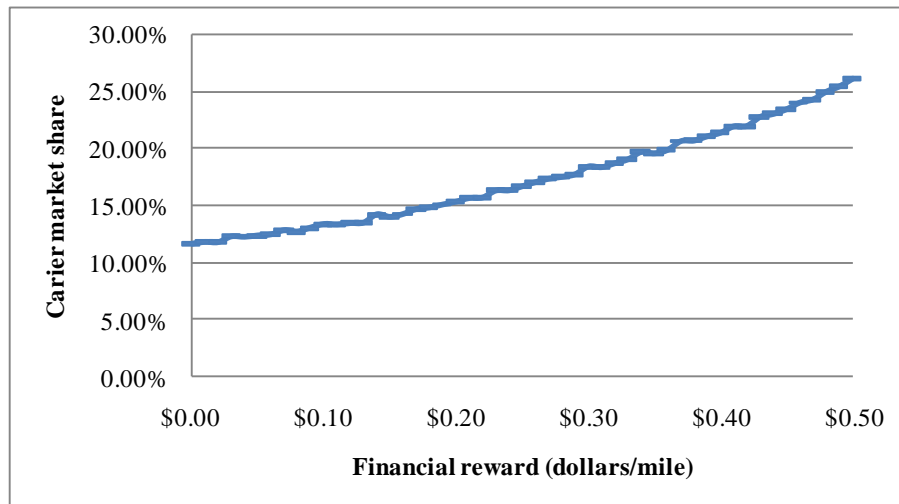
Figure 13: Off-hour Delivery Market Shares (Financial Rewards for OH Travel in $/mile)

Next, an analysis considering both a tax deduction to receivers and a financial reward to carriers was done. The results displayed in Figure 14, again revealed that participation in OHD can be influenced by both financial incentives jointly. This may be due to both stakeholders being able to make profits for participating in OHD.
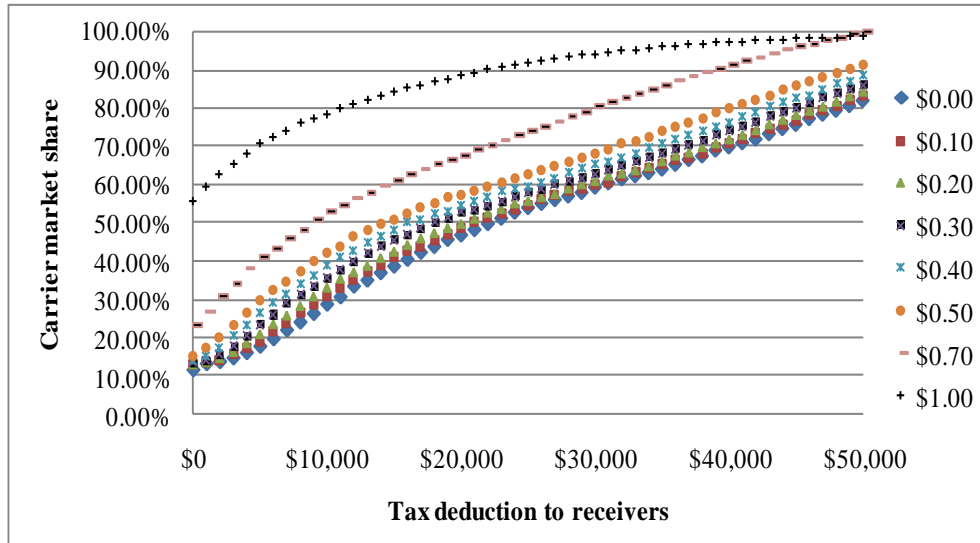
Figure 14: Off-hour Delivery Market Shares (Tax Deduction, Financial Rewards)

4.2.5.7   Policy implications

The analyses conducted using the BMS reveal several notable implications. First, it can be seen that with a $10,000 tax incentive given to receivers that there is a 20% shift to OHD by carriers. This reflects the power that receivers have on the delivery scheduling and practices, and says that tax incentives to receivers would have a definite impact on off-hour delivery participation. Secondly, the industry segments found to display the most receptiveness to OHD are: Food, Non-Alcoholic Beverages, Alcoholic Beverages, Wood/Lumber, Paper, Chemicals, Plastic, and Medical Supplies. This finding is helpful in targeting industry segments that may be used for the implementation of these policies. Thirdly, it is important to note that carriers located close to their first delivery stop are more likely to participate in OHD than carriers located further away. This suggests that carriers located in close proximity to their urban customers might be good targets for implementing these policies into practice. Fourth, when parking fine enforcement increases during the regular hours, the carriers are more likely to participate in OHD. This finding is due to the extra costs incurred for making deliveries during the regular hours, and suggests that increased parking fine enforcement during the regular hours will foster OHD. The analysis revealed that financial rewards for off-hour travel, on a per mile basis, could increase participation in OHD. Finally, the BMS revealed that toll surcharges do not really influence participation in OHD, which is consistent with the theoretical formulations developed by Holguin-Veras (Holguín-Veras et al., 2006b). This finding suggests that time-of-day toll surcharges are not strong enough in encouraging more OHD,

since carriers still have the demand of making deliveries during the regular hours, which may cause them to absorb these surcharges. Having said this, it is important to mention that toll surcharges could be used as a revenue generator for financing the tax deductions given to receivers for accepting OHD.

4.2.6 BMS conclusions

A behavioral micro-simulation for the analysis of off-hour delivery policies in urban areas has been presented. The main components of this BMS are the receiver behavioral simulation and the carrier behavioral simulation. The analyses reveal that tax deductions given to receivers would provide a noticeable shift to off-hour delivery activities. Then, using the BMS model, it was verified that certain industry segments were more receptive to OHD than others. These groups are: Food, Non-Alcoholic Beverages, Alcoholic Beverages, Wood/Lumber, Paper, Chemicals, Plastic, and Medical Supplies. The results show the BMS estimates market shares that are higher than previously reported, which were based on discrete choice models. This result is significant since the BMS considers more real life factors than the discrete choice models. The analysis conducted to assess the influence of the distance to the first delivery stop on the decision to do OHD reveals that carriers located close to their urban customers are more likely to participate in OHD, and, as a result, they would be a good group to focus on in terms of the implementation of this transportation policy. This is due to their lower fixed costs for making deliveries that these carriers have to account for. The BMS showed that increased enforcement of parking fines for double parking during the regular hours could increase the number of carriers participating in OHD. The analysis done also revealed that financial rewards for OHD could increase off-hour delivery participation. On the other hand, the BMS then demonstrated that toll surcharges for regular-hour deliveries are not influential enough on the participation in OHD.

On a conceptual basis, the BMS provides a framework for the estimation of the impacts of policies aimed at increasing OHD. The main benefit is that this framework can be as detailed as necessary, and can be tailored to understand how receptive any region is to OHD, while further extending the research done on understanding the interactions between receivers and carriers.

It is important to mention that the use of off-hours deliveries in urban areas has many requirements beyond the ones discussed here. In general, these overlapping requirements include the political, financial and social backing of major stakeholders affiliated with the transportation of goods within the target region. Specifically, other actions are required to gain a full picture for implementing OHD, including the gathering of more behavioral data from receivers and carriers, and pilot testing off-hour delivery policies on smaller scales to better understand the advantages and disadvantages of this practice.

4.3 Behavioral Analyses: Approximation model

The main objective of this section is to develop an approximation model to estimate the joint carrier-receiver response to OHD policies. The main intent here is to bypass the need for more complex approaches that require expensive data for model calibration. Having access to such models may make it easier for transportation agencies and metropolitan planning organizations to analyze and design OHD programs and policies.

4.3.1 Notation

To a great extent, the notation follows that of previous work (Holguín-Veras, 2008). Throughout the paper, the subscripts i, and j refer to receiver i, and carrier j, respectively. Superscripts BC, R and O refer to base case, regular, and off-hour operations, respectively.

G_j^{BC}, G_j^M = Gross revenues (base case, mixed operation) to carrier j

$\Delta G_j(\pi_C) = G_j^M - G_j^{BC}$ = Incremental gross revenues to carrier j associated to policy π_C

C_j^{BC} = Total cost of carrier j's base case operations (no off-hour deliveries)

$C_j^M = C_j^R + C_j^O$ = Total cost of carrier j's mixed operations (regular plus off-hour deliveries)

C_j^R = Total cost of carrier j associated with regular deliveries in a mixed operation

C_j^O = Total cost of carrier j associated with off-hour deliveries in a mixed operation

$\Delta C_j(\pi_C) = C_j^M - C_j^{BC}$ = Incremental total costs to carrier j in response to policy π_C

$\Delta G_i(\pi_R) = G_i^M - G_i^{BC}$ = Incremental gross revenues to receiver i associated to policy π_R

$\Delta C_i(\pi_R) = C_i^M - C_i^{BC}$ = Incremental total costs to receiver i associated with switch to off-hours in response to policy π_R

$\Delta C_{F,j}$ = Incremental fixed costs to carrier j

$\Delta C_{D,j}$ = Incremental distance costs to carrier j

$\Delta C_{T,j}$ = Incremental time costs to carrier j

$\Delta C_{S,j}$ = Incremental toll costs to carrier j

C_{FC}^{BC}, C_{FC}^R, C_{FC}^O = Cost of trip to first customer (base case, regular, and off-hour operations)

C_{HB}^{BC}, C_{HB}^R, C_{HB}^O = Cost of returning to home base (base case, regular, and off-hour operations)

c_D^{BC}, c_D^R, c_D^O = Unit cost per distance traveled (base case, regular, and off-hour operations)

c_T^{BC}, c_T^R, c_T^O = Unit cost per time traveled (base case, regular, and off-hour operations)

D^{BC}, D^{R}, D^{O} = Tour distance (base case, regular, and off-hour operations)

S^{R} = Toll surcharge to trucks traveling during regular hours as part of the cordon scheme

α_{D}^{R}, α_{D}^{O} = Distance based unit toll for distance traveled in tolled area (regular, and off-hours)

α_{T}^{R}, α_{T}^{O} = Time based unit toll for time spent in tolled area (regular, and off-hours)

τ_{i}^{O} = Length of time during which off-hour deliveries are accepted by receiver i

τ_{min}^{O} = Minimum amount of time required for off-hour deliveries

ϕ = Parameter of approximation model

A = service area, i.e., area of the minimum size rectangle that envelopes all customers

$A = L_{x}^{max} L_{y}^{max}$ = Size of the actual service area

L_{ox} = X dimension of the rectangular service area

L_{oy} = Y dimension of the rectangular service area

$A_{o} = L_{ox} L_{oy}$ = Total area considered

$N^{BC} = N^{R} + N^{O}$ = Total number of customers for base case conditions

N^{R}, N^{O} = Total number of customers during regular and off-hours (mixed operation)

u^{R}, u^{O} = Average travel speeds (regular and off-hours)

$\gamma = \dfrac{u^{R}}{u_{O}^{O}}$ = Ratio of average travel speeds

$\theta = \dfrac{c_{T}^{O}}{c_{T}^{R}}$ = Ratio of unit time costs

$\delta^{BC} = \dfrac{N^{BC}}{A^{BC}}$ = Customer density

$\Omega_{j}^{BC} = \Omega_{j}^{R} + \Omega_{j}^{O}$ = Original set of receivers during base case conditions, served by carrier j

Ω_{j}^{R} = Set of receivers, served by carrier j, that prefers regular-hour deliveries

Ω_{j}^{O} = Set of receivers, served by carrier j, that decides to accept off-hour deliveries

Γ^{O} = set of carriers that do off-hour deliveries

F = Financial incentive provided to receivers for committing to accept off-hour deliveries

$P(F)$ = Probability that a receiver would commit to off-hour deliveries

4.3.2 Carrier-receiver interactions, necessary conditions, and impacts of pricing

The formulation of the approximation model requires taking advantage of a number of analytical developments that provide support to the assumptions used. Foremost in this list are the necessary conditions for carrier and receivers to switch to the off-hours (Holguín-Veras, 2008), and the research conducted on the impacts of cordon time-of-day and time-distance pricing (Holguín-Veras, 2009). Because of their importance and relevance to this paper, these publications are discussed and used here.

The fundamental tenet of this research is that the interactions between carrier and receivers are what determine how they jointly respond to pricing. In this context, while carriers in equality of conditions prefer OHD because of the higher productivity and lower delivery costs; most receivers favor regular-hour deliveries because they could handle those with the staff at hand, and without incurring additional costs. This type of interaction is referred to as the Battle of the Sexes game (Rasmusen, 2001) and is known to have two Nash equilibria, with the final outcome being imposed by the player with the most clout. Since the data clearly show that the majority of deliveries are done in the regular hours (Holguín-Veras et al., 2007), the unavoidable conclusion is that the receivers play the dominant role.

The explicit consideration of carrier and receivers as separate economic agents that interact when deciding on delivery times, leads to a more realistic model of their joint response to pricing (Holguín-Veras, 2009) that, more importantly, is able to adequately explain the observed behavioral response to pricing. Among other aspects that are explained with the aid of this new paradigm, the consideration of carrier-receiver interactions sheds light into why the carriers interviewed after the Port Authority of New York and New Jersey's implementation of time-of-day pricing: attempted to deal with the toll increases by, primarily, means of productivity increases; could pass the toll costs to their customers in only 9% of the cases; and when asked why they could not change behavior said "…customer requirements…" in 70% of the cases (Holguín-Veras et al., 2006c). All these behaviors could only be explained once carrier-receiver interactions are accounted for in the context of a competitive market.

The consideration of carrier-receiver interactions leads to the realization that, in order for them to switch to the off-hours, both of them must be better off. In response to policies π_C and π_R targeting carrier and receivers respectively, this condition could be represented mathematically (Holguín-Veras, 2008) as:

$$\Delta G_i\,(\pi_R) \geq \Delta C_i\,(\pi_R) \quad \forall i \in \Omega_j^O \tag{1}$$

$$\Delta G_j\,(\pi_C) \geq \Delta C_j\,(\pi_C) \tag{2}$$

$$\tau_i^O \geq \tau_{min}^O \quad \forall i \in \Omega_j^O \tag{3}$$

Where: $\Delta G_i (\pi_R)$ and $\Delta C_i (\pi_R)$ are the incremental gross revenues and incremental costs to receiver i associated with the shift to the off-hours under policy π_R; $\Delta G_j (\pi_C)$ and $\Delta C_j (\pi_C)$ are the incremental gross revenues and incremental costs to carrier j associated with the shift to the off-hours under policy π_C; and τ_i^O is the delivery time for receiver i.

These equations provide the basis for the development of cost functions that capture the costs to the carriers associated with delivering to a set of N receivers that are divided among the regular and the off-hours. These cost functions, in turn, are used to estimate the delivery rates and consequently if, and how much of, the toll costs can be passed by the carrier to the receivers.

In a separate publication (Holguín-Veras, 2009) the author studied the joint behavior of carrier and receivers in response to pricing, and comprehensive carrier-receiver policies. The research revealed that in response to a financial incentive, some receivers may decide to switch to the off-hours which leads to a situation in which the carrier has a mixed operation with both regular-hour and off-hour deliveries. The paper identifies three cases in terms of the profitability of the resulting operation: an approximation to the best case (termed here "quasi-best"), the expected value, and the worst case. The optimal tour distances are estimated with an approximation model for the Probabilistic Traveling Salesman Problem (Beardwood et al., 1959). The analytical cost functions consider: a fixed cost associated with traveling to/from the home base to the study area, and time, distance, and toll costs; for both cordon time-of-day, and time-distance pricing. The results are shown in terms of the incremental costs to the carrier (negative if cost savings). The subscripts used are: F (fixed cost), D (distance costs), T (time costs), and S (toll costs under time-of-day pricing), and TDP (toll costs under time-distance pricing). The cost functions obtained for cordon time-of-day are shown in equations (4) through (11).

4.3.2.1 *Summary of results for cordon time-of-day pricing*

All cases (quasi-best, expected value, worst case):

$$\Delta C_{F,j} = \begin{cases} \left[(C_{FC}^R + C_{HB}^R) + (C_{FC}^O + C_{HB}^O) - (C_{FC}^{BC} + C_{HB}^{BC}) \right] \cong (C_{FC}^O + C_{HB}^O), \forall_{N^O < N^{BC}} \\ 0, \forall_{N^O = N^{BC}} \end{cases} \tag{4}$$

$$\Delta C_{S,j} = \begin{cases} 0, \forall_{N^O < N^{BC}} \\ -S^R, \forall_{N^O = N^{BC}} \end{cases} \tag{5}$$

Quasi-best case:

$$\Delta C_{D,j} = 0, \forall_{N^O,N^{BC}} \tag{6}$$

$$\Delta C_{T,j} = \frac{\phi}{u^R} \frac{N^O}{\sqrt{\delta^{BC}}} \left[\frac{\theta}{\gamma} - 1 \right] c_T^R, \forall_{N^O,N^{BC}} \tag{7}$$

Expected value case:

$$\Delta C_{D,j} = \begin{cases} \phi c_D \sqrt{L_{ox}L_{oy}}\left[\left(\dfrac{N^R-1}{N^R+1}\right)\sqrt{N^R} + \left(\dfrac{N^O-1}{N^O+1}\right)\sqrt{N^O} - \left(\dfrac{N^{BC}-1}{N^{BC}+1}\right)\sqrt{N^{BC}}\right], \forall_{N^O<N^{BC}} \\[4mm] 0, \forall_{N^O=N^{BC}} \end{cases} \tag{8}$$

$$\Delta C_{T,j} = \begin{cases} \phi \dfrac{c_T^R}{u^R}\sqrt{L_{ox}L_{oy}}\left[\left(\dfrac{N^R-1}{N^R+1}\right)\sqrt{N^R} + \dfrac{\theta}{\gamma}\left(\dfrac{N^O-1}{N^O+1}\right)\sqrt{N^O} - \left(\dfrac{N^{BC}-1}{N^{BC}+1}\right)\sqrt{N^{BC}}\right], \forall_{N^O<N^{BC}} \\[4mm] \phi \dfrac{c_T^R}{u^R}\sqrt{N^{BC}L_{ox}L_{oy}}\left[\dfrac{\theta}{\gamma}-1\right]\left(\dfrac{N^{BC}-1}{N^{BC}+1}\right), \forall_{N^O=N^{BC}} \end{cases} \tag{9}$$

Worst case:

$$\Delta C_{D,j} = \begin{cases} \phi c_D \sqrt{N^{BC}L_{ox}L_{oy}}\left[\dfrac{\sqrt{N^R}+\sqrt{N^O}}{\sqrt{N^{BC}}}-1\right] = c_D\left[f_D'-1\right]D^{BC}, iff\ N^O < N^{BC} \\[4mm] 0, iff\ N^O = N^{BC} \end{cases} \tag{10}$$

$$\Delta C_{T,j} = \begin{cases} \phi \dfrac{c_T^R}{u^R}\sqrt{AN^{BC}}\left[\dfrac{\sqrt{N^R}+\dfrac{\theta}{\gamma}\sqrt{N^O}}{\sqrt{N^R+N^O}}-1\right], iff\ N^O < N^{BC} \\[4mm] \phi \dfrac{c_T^R}{u^R}\sqrt{AN^{BC}}\left[\dfrac{\theta}{\gamma}-1\right]c_T^R, iff\ N^O = N^{BC} \end{cases} \tag{11}$$

As shown, the incremental fixed costs are the same regardless of the case in question, while the incremental distance, time, and toll costs are not. Worthy of mention is that, in most cases, the costs exhibit a discontinuity when all receivers switch to the off-hours. In the case of the fixed cost, equation (4) clearly shows that there would be a fixed cost (associated with the extra trip during the off-hours) unless all receivers are in the off-hours, when the fixed costs would become zero. The fundamental implication of this finding is that the farther the carrier is located from the delivery area, the larger the incremental fixed cost, and the more difficult for the mixed operation to be profitable.

Equation (5) has important policy implications as it shows that the toll surcharge only provides an incentive to the carrier when all receivers are in the off-hours. This is because the carrier could have only one tour in the off-hours, thus avoiding the toll surcharge for regular-hours travel. In all other conditions, the carrier has to travel during both regular and off-hours and has to pay the toll anyway. As a result, the incremental toll cost with respect to the base case is equal to zero, i.e., it does not incentivize the carrier to switch to the off-hours. This calls into question the use of cordon time-of-day pricing for freight demand management purposes.

The analytical derivations produced indicate that the incremental distance and time costs depend on the case considered. In the quasi-best case, there would be cost savings in time and distance even if only a small number of receivers switch to the off-hours. As shown, the incremental distance cost is equal to zero (though more likely, the carrier would be able to re-optimize the tours in the absence of congestion), and the incremental time cost is negative from the start as long as $\theta/\gamma < 1$, which represents the ratio of the wage increase to the ratio of the speeds between off-hours and regular hours. In the expected value case, the quadratic nature of the problem leads to cost increases up to a point where they start to diminish leading ultimately to cost savings when the number of receivers in the off-hours is large. In the worst case, there are distance and time cost increases almost always.

The analytical derivations for time-distance pricing indicate that the incremental fixed, distance, and time costs are exactly the same for cordon time-of-day pricing, which are shown in equations (4) to (11). For brevity sake, these are not repeated here. The key difference is on the incremental toll costs that are shown below.

4.3.2.2 *Summary of results for time-distance pricing*

Quasi-best case:

$$\Delta C_{TDP,j} = \phi \sqrt{\frac{A^{BC}}{N^{BC}}} \left[\left(\alpha_D^R + \frac{\alpha_T^R}{u^R} \right)\left(N^R - N^{BC} \right) + \left(\alpha_D^O + \frac{\alpha_T^O}{u^R} \right) N^O \right] \tag{12}$$

Expected value case:

$$\Delta C_{TDP,j} = \phi \sqrt{L_{ox} L_{oy}} \left[\begin{array}{c} \left(\alpha_D^R + \frac{\alpha_T^R}{u^R} \right)\left(\left(\frac{N^R - 1}{N^R + 1} \right)\sqrt{N^R} - \left(\frac{N^{BC} - 1}{N^{BC} + 1} \right)\sqrt{N^{BC}} \right) \\ + \left(\alpha_D^O + \frac{\alpha_T^O}{u^R} \right)\left(\frac{N^O - 1}{N^O + 1} \right)\sqrt{N^O} \end{array} \right] \tag{13}$$

Worst case:

$$\Delta C_{TDP,j} = \phi \sqrt{A^{BC} N^{BC}} \left[\left(\alpha_D^R + \frac{\alpha_T^R}{u^R} \right)\left(\sqrt{\frac{N^R}{N^{BC}}} - 1 \right) + \left(\alpha_D^O + \frac{\alpha_T^O}{u^R} \right)\sqrt{\frac{N^O}{N^{BC}}} \right] \tag{14}$$

The first and most obvious feature of these results is that, in all cases, time-distance pricing does provide an incentive for the carrier to switch to the off-hours as the unit distance tolls enter into the incremental toll costs. The results also indicate that a sound pricing policy, with $\alpha_D^R > \alpha_D^O$ and $\alpha_T^R > \alpha_T^O$ would also lead to cost savings to the carrier, regardless of how many receivers are in the off-hours. Equally important is that the larger the difference between the unit tolls for the regular and the off-hours,

the larger the incentive to the carrier. This stands in sharp contrast with the results for cordon time-of-day pricing where the toll surcharge would only come into play when all receivers switch to the off-hours.

4.3.3   Minimum number of receivers for a profitable mixed operation

The results obtained for cordon time-of-day and time-distance pricing suggests that OHD would cause increases in some components of the incremental costs, and reductions in others. This leads to a situation in which the profitability of the mixed operation (with both regular and off-hour deliveries) depends on the number of receivers in the off-hours. If the number of off-hour receivers is "small," it is likely that the carrier would face cost increases and refuse to do OHD. If, at the other end, the number of receivers in the off-hours is "large" there would be cost savings and the carrier would participate. Then, the fundamental challenge is how to ensure that a "large" number of receivers are in the off-hours. Three possibilities exist: using freight road pricing, regulation, and providing incentives to the receivers in exchange for their commitment to do off-hours. It is important to discuss them in some detail.

Although appealing, both empirical evidence and theory suggest that pricing truck traffic will not lead to substantial changes in the behavior of receivers. In the case of cordon time-of-day pricing under a competitive market, the carriers cannot pass the toll costs to their customers (Holguín-Veras, 2008) because the toll cost is part of the fixed cost. The theoretical findings are confirmed by the empirical evidence as only the carriers with market power were able to pass toll costs to receivers in a meaningful way (Holguín-Veras et al., 2006c; Holguín-Veras, 2008). In contrast, under time-distance pricing the carriers should be able to pass the toll costs to the receivers. However, the analyses made indicate that in order for the tolls to induce the receivers to change behavior, the unit tolls would have to be about six times larger than current operating costs. Such tolls are politically unacceptable (Holguín-Veras, 2009).

The second alternative entails the use of regulatory approaches, such as banning regular-hour deliveries as done in Beijing, China. However, this is likely to lead to massive protests from the business sector and widespread cost increases as all receivers would face increasing operating costs. The experience of Los Angeles in the 1980s clearly indicates that the business sector will vigorously fight such measures (Ogden, 1992).

The approach suggested in this paper consists of providing incentives to receivers for participation in OHD. This concept has a number of advantages as it: (1) is a voluntary program that leads to increases in the receivers' welfare because only those that stands to benefit from the incentive would join; (2) could lead to a substantial shift of delivery operations to the off-hours, e.g., 20% for a tax deduction to receivers of food; (3) would reduce congestion and pollution in urban areas thus improving quality of life; (4) would increase the productivity of urban delivery operations via the congestion reductions; (5) will enjoy the enthusiastic support of the carriers as delivering in the off-hours is 30% cheaper than in the regular

hours; and (6) would increase the competitiveness of the urban areas via the increases in productivity and quality of life.

The research conducted clearly supports giving incentives to receivers in exchange for their participation in OHD. However, a fundamental question remains concerning what is the minimum number of receivers required for the carrier operation to be profitable. To answer this question, the cost functions shown in equations (4) through (14) are used. The analyses are based on a toll surcharge of $20, which is about what is typically charged to delivery vans for access to congested urban areas, e.g., New York City (Port Authority of New York and New Jersey, 2009). To ensure a fair comparison, the cordon time-of-day surcharge and the unit distance and time tolls for time-distance pricing were selected so that both of them have approximately the same total impact in the costs. This was accomplished with $\alpha_D^R = $ $2/mile, $\alpha_D^O = $ $0.9/mile, $\alpha_T^R = $ $4/hour, and $\alpha_T^O = $ $2/hour, which were arbitrarily selected. The results correspond to: $L_{ox} = 2$ miles, $L_{oy} = 11.5$ miles, $u^R = 10$ miles per hour, $c_D = $ $2/mile, $c_T = $ $50/hour, and $\phi = 0.75$. These values are what may be expected for Manhattan. Typical results are shown in Figure 15 for a tour with 20 receivers (Holguín-Veras, 2009). Solid bullets are used to represent cordon time-of-day, and clear ones for time-distance pricing.

The results shown in the Figure 15 illustrate a number of key features. The impact of the fixed cost associated with the extra trip is obvious (marked by an up arrow at $N^O = 1$). There are cost increases if the number of receivers in the off-hours is "small" and cost savings if this number is "large." Obviously, this also depends on the pricing regime and the case (quasi-best, expected, worst) that arises in terms of the service areas. The results also show the superiority of time-distance pricing as it increases the profitability of the mixed delivery operation. As shown for the best case, while under cordon time-of-day pricing a minimum number of 19 receivers is required for a profitable operation, only 12 receivers are needed under time-of-day pricing. It should be said that in the other cases, the differences between the pricing regimes are smaller. The numerical experiments conducted produced similar results for other tour lengths.
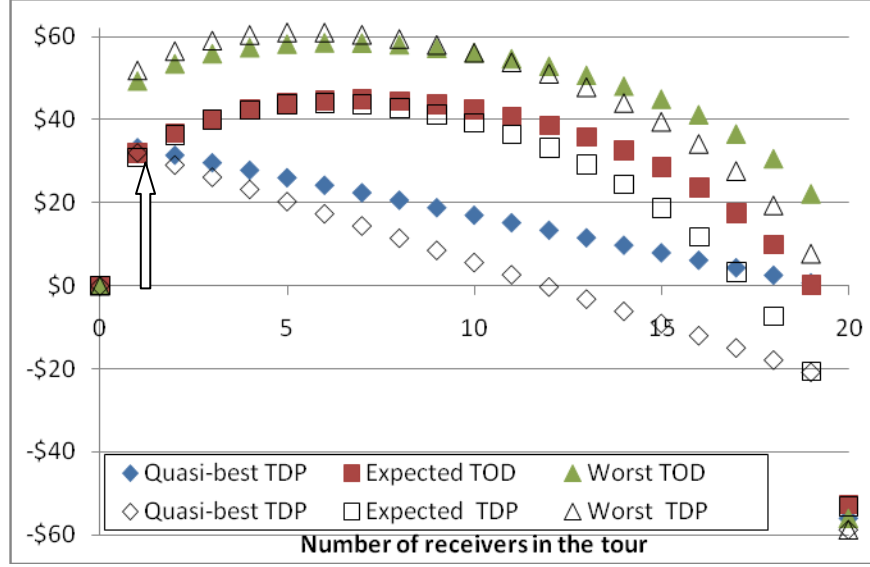
Figure 15: Incremental Costs for a Tour with Twenty Receivers

4.3.4 Approximation model

The results discussed in previous chapters indicate that: (1) delivering during the off-hours is cheaper than during the regular hours; and (2) if all receivers decide to accept OHD, the carrier is likely to follow suit as it will save money. These observations provide the basis for the development of a lower bound that enables the estimation of the joint market share for carrier-receiver participation in OHD. This lower bound assumes that: (1) the receivers are observationally identical, and independent; (2) the carrier will switch to the off-hours, if and only if, all receivers agree to the switch; and (3) there are no other policies, e.g., time-distance pricing, that provide an external stimulus to the carrier. The second assumption is not problematic as this is expected to hold in all congested areas where delivering in the off-hours is cheaper than in regular hours. The second and third assumptions imply that if the carrier decides to do OHD—even when not all receivers agree or if there are other external stimuli impacting the carrier—that the actual joint response may be larger than the one estimated by the model.

Consider now that carrier j has a number of customers R_i receiving regular-hour deliveries as part of the base case conditions, $R_i \in \Omega_j^{BC}$. Assume that, as a consequence of a given financial incentive F, the receivers have a probability $P(R_i \in \Omega_j^O) = P(F)$ of accepting OHD. Since the receivers in the delivery tour can be assumed to make independent decisions, the probability that all of them agree to OHD (and therefore belong to the set with off-hour customers Ω_j^O) is then:

$$P(R_1 \in \Omega_j^O \cap R_2 \in \Omega_j^O \cap R_3 \in \Omega_j^O \cap ... R_M \in \Omega_j^O / M^{'} = \left| \Omega_j^{BC} \right|) = \left[P(F) \right]^{M^{'}} \tag{15}$$

Where: M' is the cardinality of the set Ω_j^{BC}.

Defining Γ^O as the set of carriers that do OHD, the probability that carrier j would do OHD is equal to the joint probability that all its receivers agree, and that the resulting operation with m receivers is profitable, denoted by the probability $P(G_M > C_M / M)$:

$$P(j \in \Gamma^O) = [P(F)]^M P(G_M > C_M / M) \tag{16}$$

Letting: Q_M be the total number of tours with M delivery stops, the expected value of the number of tours that would be switched to the off-hours in response to an incentive F is:

$$E(Q) = \sum_{M=1}^{M^*} Q_M [P(F)]^M \tag{17}$$

Where: M^* is the upper bound of the number of delivery stops per tour expected in the area.

Defining $Q_* = \sum_{M=1}^{M^*} Q_M$, and $f_M = \dfrac{Q_M}{Q_*}$ as the relative frequency of a tour with M delivery stops, then the market share of off-hour tours is:

$$MS^O = \sum_{M=1}^{M^*} f_M [P(F)]^M \tag{18}$$

Equation (18) has some interesting implications related to what segments of the industry are likely to participate in OHD. Since the term $[P(F)]^M$ decreases geometrically with M (tour length), equation (18) implies that the bulk of the tours that would participate in OHD are the ones with short tour lengths, particularly those with one and two stops with proportions f_1, and f_2. In other words, cities with distribution patterns characterized by "large" proportions of "short" tours are likely to achieve a larger share of OHD than cities with predominantly "long" tours. Although it seems natural to think that the market share would be related to the average tour length, the reality is that it is not. To illustrate why, consider the case of the following two urban areas. In the first case, there are 50% of deliveries with one stop, and 50% with ten stops; while in the second, there are 50% of tours with four stops, and the other 50% with seven stops. In both cases the average stop number is the same (5.5 stops/tour) but the market shares are very different. Assuming a probability of receiver participation of 50%, the market share in the first case is 25.05% ($0.5 \times 0.5^1 + 0.5(0.5)^{10}$), and in the second only 3.5% ($0.5 \times 0.5^4 + 0.5(0.5)^7$).

In order to produce numerical estimates, the data for New York City were analyzed to estimate the frequency distribution of the number of stops. Figure 16 shows the values obtained. As shown, although the vast majority of tours have less than five stops, there is a wide range of values with some tours having more than 90 stops. The average number of stops is 6.8 stops/tour.

Information about $P(F)$ is available from the behavioral research conducted by Holguín-Veras and his colleagues and reported elsewhere (Holguín-Veras et al., 2007). Figure 17 shows the market shares estimated for food receivers as a function of a tax deduction in exchange for their commitment to accept OHD. As shown, a tax deduction of $10,000 per year would lead to 50% participation.
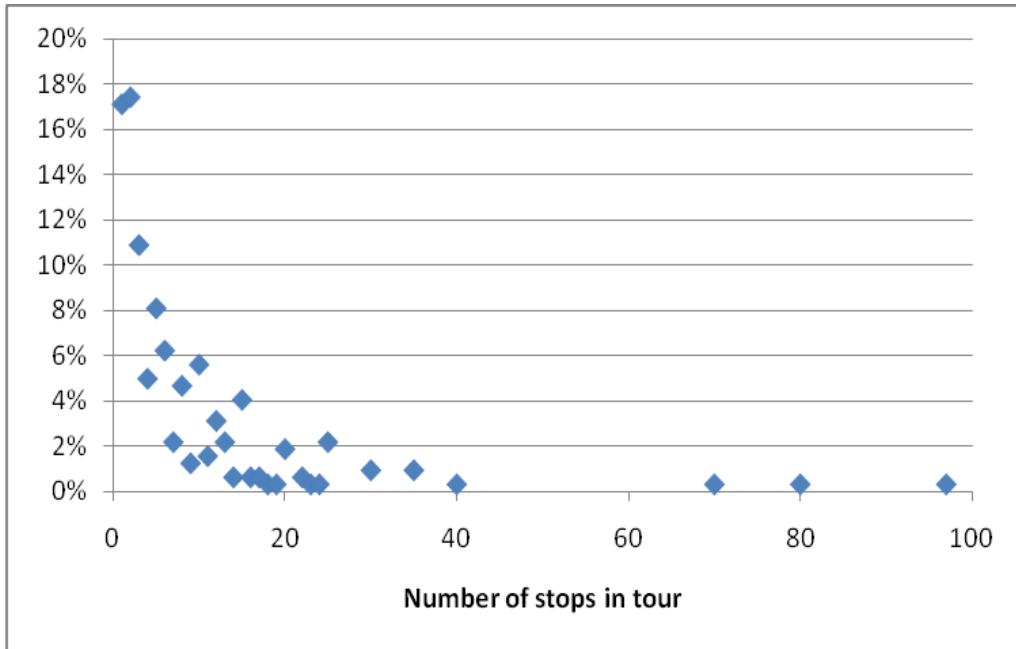
Figure 16: Frequency Distribution of Number of Delivery Stops per Tour
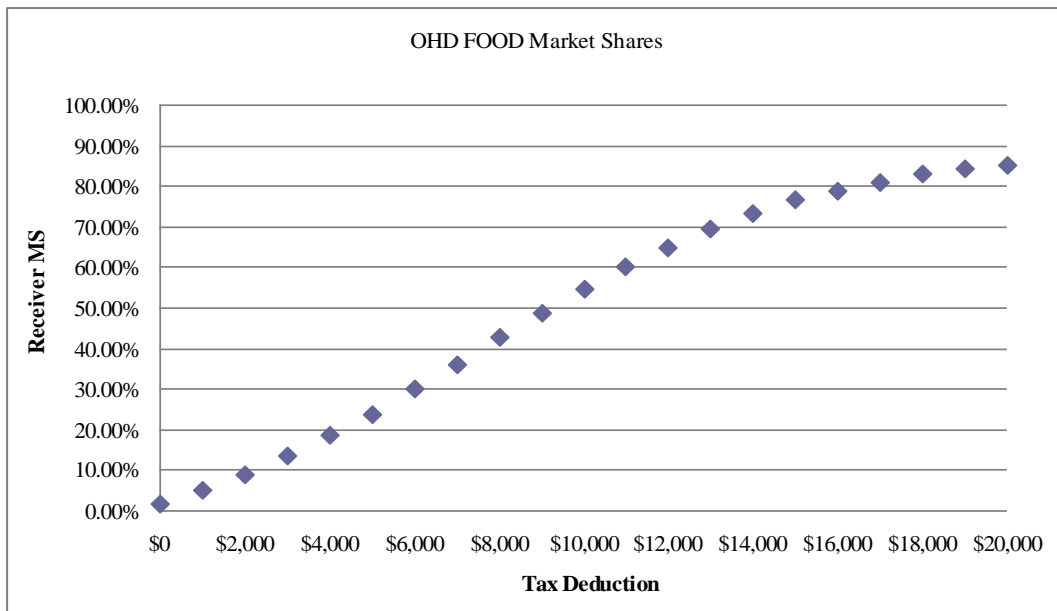
Figure 17: Food Receiver Participation in Off-hour Deliveries

In order to assess the performance of equation (18), the formulation developed was applied to the different industry segments studied using the BMS (Silas and Holguín-Veras, 2009). In general, the results exhibit similar patterns to that of Figure 18 that shows the estimates produced with the assistance of the BMS and the ones produced by the approximation model (Silas and Holguín-Veras, 2009). The results labeled "MS" correspond to the approximation model presented in this chapter, while the ones labeled "BMS" represent the ones produced by the Behavioral Micro-Simulation.

Figure 18 shows that the approximation model performs remarkably well as long as $P(F)$ is less than 80%. After this value, the magnitude of the underestimation is significant. This seems to be a consequence of assuming that the off-hour delivery tour is profitable if and only if all receivers agree to it. It is entirely possible that, for instance, a tour in which nine out ten receivers agree to OHD is profitable to the carrier, which is a possibility not considered by the lower bound. If $P(F)$ is small, the probability of finding such cases is negligible. However, as $P(F)$ increases, the number of cases in which almost all receivers agree, and the operation is profitable to the carrier, increases. Since the lower bound does not consider such cases it underestimates the actual market share for high values of $P(F)$.
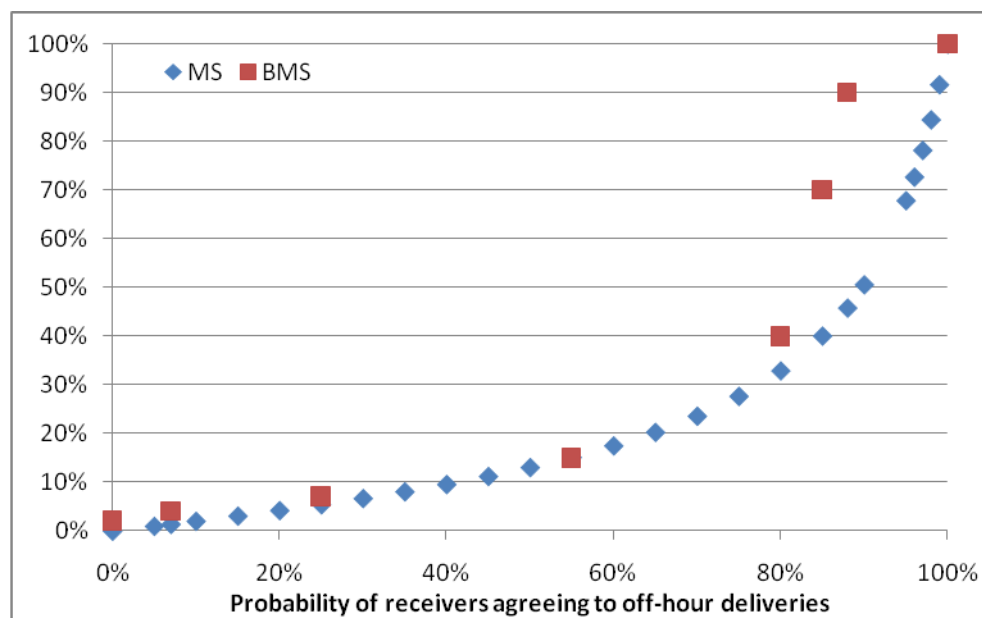
Figure 18: Expected Market Shares of Off-hour Deliveries

Equation (18) does provide a convenient way to produce quick estimates of the potential participation in OHD as it only requires an estimate of receiver participation in response to a given policy, and basic data about the number of stops in the delivery tours. These estimates could be readily obtained from consultations with industry representatives.

4.3.5 Approximation model conclusions

The research conducted on the impacts of pricing on urban deliveries has highlighted that delivery time decisions are jointly made between carriers and receivers. In this interaction the carriers prefer OHD, while the receivers favor regular-hour deliveries. Because of this mismatch the outcome that materializes is the one favored by the agent with the most clout. In the case of urban deliveries, where the vast majority of deliveries are made in the regular hours, it is obvious that receivers play the dominant role, and where without receivers' consent, OHD cannot take place.

The paper discusses different approaches to ensure participation of receivers: pricing, regulation, and financial incentives, and reaches the conclusion that the latter alternative is the only practical alternative. The analyses indicate that pricing the carriers is not likely to lead to changes in receivers' behavior because either the carriers have great difficulties passing the tolls to the receivers (the case of cordon time-of-day pricing), or the toll charges would have to be huge to have any effect (in time-distance pricing). Using regulation, e.g., banning regular-hour deliveries, would impose significant costs in the entire business sector as they would have to switch the entire operations to the off-hours. This is bound to generate massive opposition from the private sector, as the unsuccessful attempt to ban regular-hour deliveries at Los Angeles in the 1980s demonstrates (Ogden, 1992). In contrast, the proposed financial incentives would: (1) increase receivers' welfare because only those that stand to benefit from the incentive would join; (2) shift a significant number of deliveries to the off-hours; (3) reduce congestion and pollution; (4) increase the productivity of urban deliveries; (5) enjoy the enthusiastic support of the carriers as delivering in the off-hours is 30% cheaper than in the regular hours; and (6) increase the competitiveness of the urban areas.

The analyses in the paper also indicate that, from the carrier standpoint, a large number of receivers are needed for a profitable operation. These conclusions were reached with the use of analytical cost functions that capture the incremental costs to the carriers associated with a mixed operation and with OHD. In general, the mixed operation leads to increases in operational cost to the carriers if the number of receivers in the off-hours is small.

In its final section, the paper introduces a formulation to estimate the joint market share (receivers and carriers) of OHD. This formulation builds on the insight gained from the analyses with the cost functions and is based on the following assumptions: (1) the carrier would participate in OHD if and only if all the receivers in the tour are in the off-hours; (2) there are no external incentives that could impact the carrier's decisions; and (3) receivers are observationally random, make independent decisions, and have a known probability to participate in OHD. The model computes the joint probability that all receivers agree to accept OHD, and with the assistance of the tour length distribution, computes the market shares.

The approximation model clearly indicates that, for a given probability of receiver participation in OHD, the joint market share is going to be determined primarily by the proportion of "short" tours as the probability of all receivers agreeing to OHD geometrically decreases with tour length. This implies that policies aimed at increasing delivery payloads could play a role in fostering OHD as they would incentivize the carrier to convert "long" tours into "short" ones. Examples of such policies are the ones implemented in a number of European cities that require a minimum load factor (percent of truck capacity actually used) to enter the city center as done in Copenhagen (Kjaersgaard and Enslev Jensen, 2003).

The results provided by the model were compared with the results from a behavioral micro-simulation (Silas and Holguín-Veras, 2009). The analyses indicate that the approximation model is very accurate as long as the probability of receiver participation is less than 80%. Beyond this value, the approximation model underestimates the market share. The reason for this seems to be related to the assumption that the carrier operation would be profitable only if all receivers are in the off-hours.

In terms of practicality, the approximation model is clearly superior to any of the available techniques as it only requires: an estimate of the probability of receiver participation in OHD, and the tour length distribution. These pieces of information could be easily estimated from surveys or interviews with industry representatives.

The research conducted enhances the transportation community's understanding of the potential market shares that OHD could reach. More importantly, by providing easy to use mathematical models—that bypass the need for more complex approaches—this research is contributing to the implementation of off-hour delivery programs in the Nation's congested urban areas.

4.4   Assessment of Impacts

Upon completion of the estimates of freight deliveries for Manhattan and the resulting shift in market share of OHD for various incentive levels determined by the BMS, the results were used to determine the target markets for policies designed to foster OHD.

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5.   PILOT TEST PREPARATIONS

5.1   Process Followed to Assemble the Companies for the Pilot Test

The team experienced delays with the pilot test because the meltdown of the finance industry center in Wall Street coincided with its preparations. The financial collapse, that had New York City as its epicenter, severely impacted the local economy and led to a situation in which potential participants were primarily concerned with surviving the economic turmoil, making recruitment for the pilot test a challenging endeavor. This was a direct consequence of: (1) the importance of the financial system to the economy of the State of New York and New York City (20% of state tax revenues come from Wall Street); and (2) the dependence of restaurants on financial sector customers. Because of these linkages, the downturn in the financial industry had a significantly negative impact on the state's economy and, particularly, on the restaurant sector (the target of the pilot test) in New York City. As a consequence of the dramatic economic and financial backdrop, the team had to change course several times in its efforts to assemble the test. The key phases are discussed below.

Phase I: Recruitment through the Industry Advisory Group (February-April 2008)

The efforts to assemble the participants for the pilot test started in earnest in February 2008 as the period of June-December 2007 was spent putting together the Industry Advisory Group and Agency Advisory Group, gathering input from stakeholders, trying to gather the simulation networks, and reviewing relevant remote sensing technologies. It was decided to start contacting companies for participation in the pilot test at the end of January 2008, to allow them to get ready for the holiday sales period, and finish post-holiday season work.

The original plan was to use the Industry Advisory Group (IAG) to recruit the pilot test participants. New York University team members made numerous attempts to recruit participants through the New Jersey Motor Truck Association and the New York Motor Truck Association. These efforts proved unsuccessful. In retrospect, it seems obvious that the depression was gripping the economy. In this period, the financial system—so important to the economy of New York City—began to crumble with the collapse of Bear Stearns.

Phase II: Recruitment via the New York State Restaurants Association (May-July 2008)

Upon realizing the lack of progress in recruitment through the IAG, a change of strategy was implemented. As part of the new approach, the team approached the New York State Restaurants Association (NYSRA), which sent a request for participation to its members. Unfortunately, after spending considerable time and effort dealing with NYSRA in preparing the request for participation, a survey to restaurants, no expressions of interest came forward.

Phase III: Direct recruitment of restaurants (July-September 2008)

As it became evident that recruitment through NYSRA was not going to succeed, the team changed its approach and decided to directly contact restaurant owners. The team purchased a data set containing the contact information of a sample of about three hundred restaurants. A memo requesting participation was sent out, and complemented with phone calls from team members. No positive responses were received. These efforts coincided with the complete collapse of the financial system culminating in the largest one day drop in the Dow Jones.

Phase IV: No recruitment efforts (September-October 2008)

Following the financial meltdown of Wall Street, it became clear that the state of the economy had been at the root of the difficulties in assembling the participants for the pilot test. This realization led to the decision to delay recruitment efforts until the economic situation reached a minimum level of stability.

Phase V: Recruitment through "Project Champions" (November 2008-April 2009)

The infusion of a massive amount of federal aid into the financial system brought a measure of stability to Wall Street. Taking advantage of this welcomed change, the team decided to aggressively pursue another recruitment strategy. In this new approach, the team focused on identifying "project champions," i.e., industry leaders with interest in supporting off-hour deliveries (OHD) that could help convince others to participate in the pilot test. This approach, together with an improved economic environment, led to the identification of a number of candidates, which included:

> **Union Square Hospitality Group**: An influential restaurant group with twenty-five high end restaurants in New York City.

> **B. R. Guest Restaurants:** An important restaurant group with thirteen high end restaurants in New York City.

> **White Rose Food:** A food distributor that delivers to more than 100 supermarkets in Midtown and Downtown Manhattan.

> **Sysco:** One of the largest distributors of food products in the United States. It delivers food products to hundreds of food stores in New York City.

> **Whole Foods Market:** A large natural and organic grocery store chain with six stores in Manhattan.

> **Foot Locker / New Deal Logistics:** One of the most successful sportswear and footwear retail chains in the country. New Deal Logistics, a company with a long tradition of environmental initiatives and the logistics provider for Foot Locker in Manhattan, approached the team and requested participation in the project.

At the end, the team decided to focus on Sysco, Whole Foods Market, and Foot Locker / New Deal Logistics as they provided a nice combination of restaurants (Sysco's customers), food stores (Whole Foods Market), and representatives from the retail sector (Foot Locker). These companies became the

industrial partners of the project. The next step was to proceed to plan the implementation of the pilot test, which is discussed next.

Phase VI: Preparations for the Pilot Test (May-December 2009)

Having identified the industrial partners for the pilot test, the team had to undertake the necessary steps to coordinate OHD. These activities took two different forms, depending on whether or not the committed participant was a carrier or a receiver. In the cases where the industrial partner was a receiver of goods (i.e., Whole Foods Market, Foot Locker), the team had to contact the corresponding suppliers/vendors to encourage them to participate in the test. However, in the Foot Locker case, since New Deal Logistics was the only company delivering to the stores the coordination effort was minimal.

The project team then contacted all vendors serving the Whole Foods Market stores in Manhattan to gauge interest in the pilot test. Of the 94 vendors contacted, 20 expressed interest in participating in the pilot test. The top reasons given as to why vendors were not interested in participating were that they use a third party delivery service such as UPS or FedEx, they already make their deliveries in the off-hours, and participation would result in a split route since they did not have a Whole Foods Market only route. The team worked with the four participating individual Whole Foods Market stores, and their vendors to coordinate the necessary changes in delivery times.

In the case of Sysco, team members visited about 160 of its customers in midtown Manhattan. Out of the 160 establishments contacted, 41 expressing interest in participating in the pilot test of which 16 were very interested. Of the businesses not interested, some of the most commonly given reasons were: not being open or having employees available during the off-hours, building constraints making OHD unfeasible, and the size of the business and the amount of goods they received from Sysco would not justify changing their operations.

Once the initial contacts were made, the corresponding company had to set up the details with their business partners (vendors in the case of Whole Foods Market, and food stores and restaurants in the case of Sysco). The companies managed to complete this process by mid December 2009 which opened the door for the pilot test.

5.2   *Phases of the Pilot Test*

The pilot test had four major industrial partners. In all cases, their entire distribution chains—particularly the transportation and the receiving end—switched to the off-hours for at least a month. In total, 25 receivers (30 receivers if partial participation is counted) and eight vendors participated in the test. Since there were no interactions among each of the industrial partners, it was decided to run the pilot tests independently of each other as soon as each group was ready to begin. It is important to mention that the industrial partners committed a significant amount of effort and expenses to participate in the test. High level executives and, in some cases, their entire logistic teams participated in dozens of conference

calls discussing the preparations for the pilot test. Although the team decided to give the carriers designated as industrial partners a token payment of $3,000—as a show of appreciation for their efforts— the fact of the matter is that this amount does not cover even a fraction of their staff time. <u>Their investment in this effort provides clear evidence of the industry support for the concept.</u> The dates of participation are shown in parenthesis next to the company names. The partners were:

> **Group 1: Foot Locker and New Deal Logistics (October 2-November 14, 2009):** Foot Locker operates numerous stores in Manhattan. New Deal Logistics, Foot Locker's logistic provider, has long pioneered environmental initiatives. Eight Foot Locker stores and New Deal Logistics participated.

> **Group 2: Sysco and a Sample of Customers (December 21-January 23, 2010):** Sysco delivers food products to hundreds of food stores in New York City. Thirteen stores successfully completed the test, five participated partially and dropped out for reasons unrelated to the project, and another three agreed to participate but did not order products from the vendor during the pilot test (it may be that they changed vendors).

> **Group 3: Whole Foods Market and its Vendors (December 28-January 31, 2010):** A large natural and organic grocery store chain with six locations in Manhattan. This group included the four Whole Foods Market locations not subject to night delivery restrictions plus six of their vendors.

Locations of the participating receivers are shown in Figure 19.
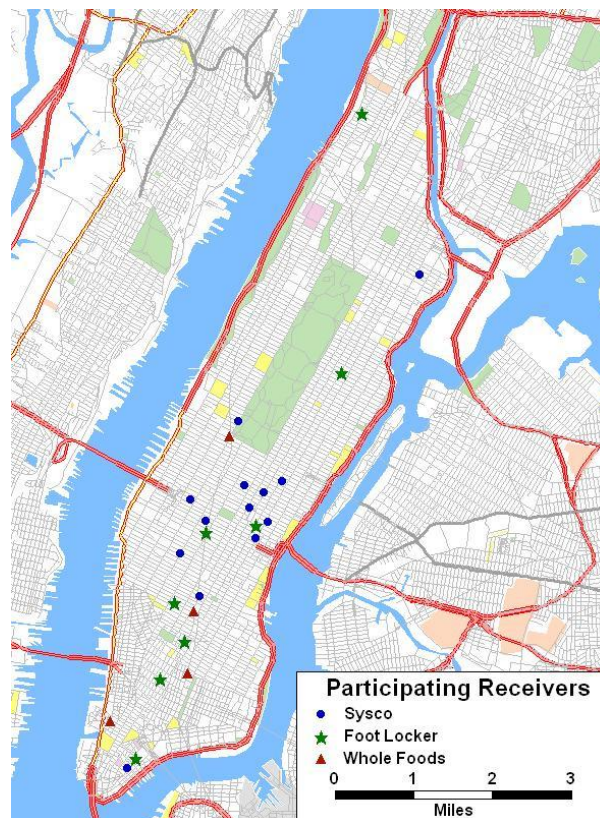
Figure 19: Pilot Test Locations

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5.3　　Additional Details of the Pilot Test

The participating receivers were provided a financial incentive of $2,000 for successful participation in the pilot test. This incentive was larger than the ones considered during the research work—which are associated with a longer term commitment—to compensate for the setup costs associated with switching from the regular hours to the off-hours at the beginning of the pilot test and then back to the regular hours at the end. The participating carriers were given an incentive of $300 per truck participating in the pilot test to compensate for the corresponding setup costs. Obviously, since the carriers stand to benefit from working in the off-hours, the amount of the incentive could be smaller than the ones for receivers.

The remote sensing component was undertaken with GPS enabled smartphones and the Copilot|Live turn-by-turn navigation software. The selected smartphone model was the MWg Zinc ii. It was selected because it contains a powerful processor (500 MHz, Samsung SC32442), bright 2.8" touch screen, high quality built-in SiRf Star_iii GPS receiver, substantial memory (64 MB RAM, 256MDROM and 140MD internal storage plus SD card slot for an additional 2GB of memory), a pull-out QWERTY keyboard, and the Windows Mobile 6.0 operating systems. Also, it was very reasonably priced at $250. Each phone was equipped with a T*Mobile cellular data SIM card allowing for real-time two-way data communications. Installed on each smartphone was CoPilot|Live version 8 (http://www.alk.com/copilot/). The smartphones were configured in such a way that the only action required by the driver was to turn the phone on at the beginning of the route; no further interaction between the driver and the smartphones was required while driving. Safety is of the upmost concern and the project team ensured that the smartphone would not be a distraction to the driver. By virtue of a single button launch, this software enabled the smartphone to log its GPS position, velocity, date and time every three seconds and transmit, via cellular data services these data to a privacy-protected website that displayed, with proper permissions, the real-time location and next stop of each of the participating smartphones. CoPilot|Live is a full-featured navigation system focused on the logistics industry. Most importantly, it contains commercial truck restrictions so that the routing instructions it computes in real time are legal for commercial trucks.

The cellular smartphones were distributed to the participating carriers for use during the pilot test. In cases where the companies already had GPS equipment, they were encouraged to use the provided GPS smartphones but were given the option of sharing the data with the team instead of using the phones. A noticeable number of participants elected to do that. While these systems did not provide as rich of a data stream (position and speed data frequency was, at best, once every minute, and the heading component of velocity was not available, nor was there any real-time availability of any of the data), some of them provided data for the entire metropolitan area, not just those involved in the pilot test. This enabled the team to obtain background performance data for a much larger fleet of trucks. In some cases, passive GPS data loggers were used as a backup.

6. PILOT TEST RESULTS: REMOTE SENSING AND OPINION SURVEYS

6.1 *Sysco Base Case Conditions*

In order to assist the team in determining the base case conditions, Sysco shared with the research team remotely sensed location-time waypoint data from the movement of all of its trucks assigned to its Jersey City, New Jersey (NJ), depot for the period December 1, 2009, through January 31, 2010, as well as six (6) weeks of data during the period September 1 through October 31, 2009. Figure 20 below shows all of the remotely sensed GPS waypoint data near Manhattan color-coded by instantaneous speed with pure blue being 35 mph and pure red being 5 mph. Waypoints with speeds under 5 mph are not drawn. Many waypoints are super positioned.
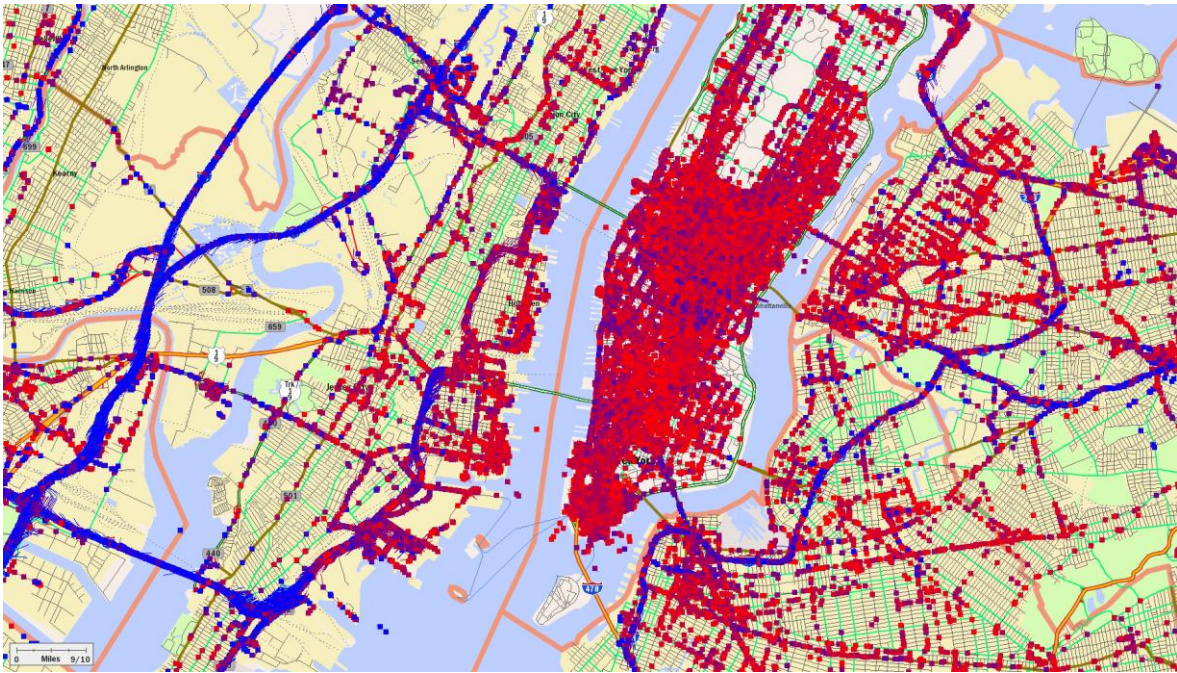
Figure 20: Geographic Display of Remotely Sensed Waypoint Data Near Manhattan

6.1.1 Overall characteristics of Sysco's base case conditions remotely-sensed GPS position-time waypoint data

The cumulative speed distribution of the 3,561 Manhattan customer-to-Manhattan customer (c2c) tour segments is shown in Figure 21, and Figure 22 displays the corresponding distribution for tour segments between non-Manhattan customers. The summarization of those distributions is presented in the box and whisker plot in Figure 23. In general, travel between customers in Manhattan is extremely slow. Only 1.85% of the route segments were made at an average space mean speed (AverageSpeed) of greater than 10 mph and the median AverageSpeed was only 3.7 mph, whereas the median c2c AverageSpeed between non-Manhattan customers served from the same Jersey City depot in the New York Metropolitan Area was more than 2.5 times greater at 10.7 mph.
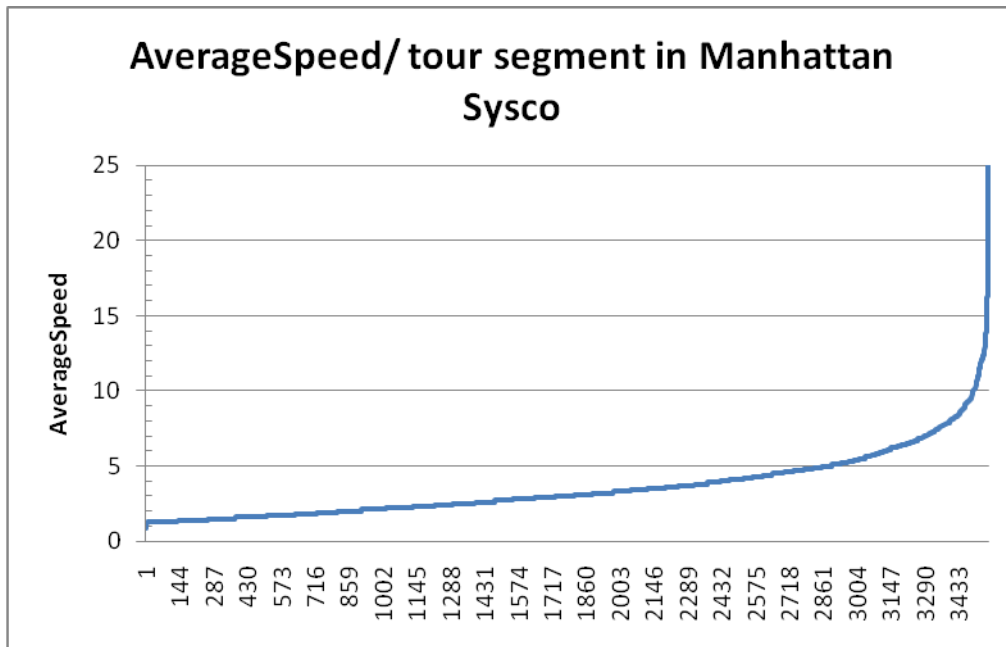
Figure 21: Cumulative Speed Distribution of the 3,561 Manhattan c2c Tour Segments
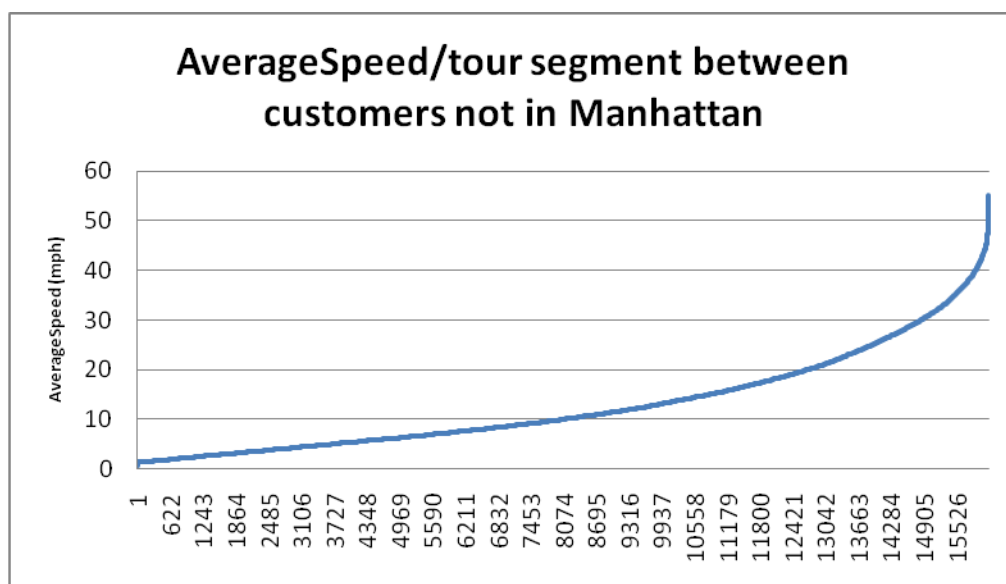
Figure 22: Cumulative Speed Distribution of the 32,272 Non-Manhattan c2c Tour Segments
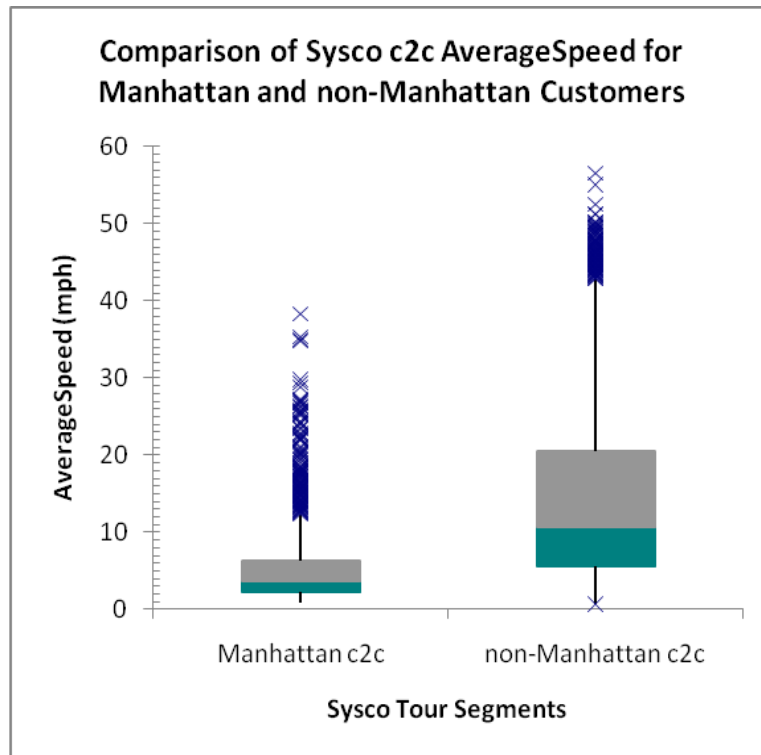
Figure 23: Comparison of c2c AverageSpeed for Manhattan and Non-Manhattan Customers

6.1.2   Tour segment speeds by time-of-day (ToD)

6.1.2.1   *Manhattan customer-to-Manhattan customer tour segment AverageSpeed by time of day (ToD), Sysco base case conditions*

Figure 24 displays the time varying nature of the congestion encountered by Sysco drivers in traveling from one customer to another in Manhattan. Displayed are box and whisker plots (see Figure 25 for a description) of the various AverageSpeeds experienced by the Sysco drivers in the various hours of the day. One can readily see that before 8 AM is substantially better than after 8 AM. Median values before 8 AM are twice those of after 8 AM. Unfortunately, Sysco had no operations in Manhattan in the very early morning hours (between 23:00 and 6:00). What is surprising about the time-of-day (ToD) distribution is that there is relatively little variation in median value from 8 AM through 10 PM. The highest median is 3.8 mph at 8 AM and the lowest is 2.4 mph at 10 PM, surprisingly. There is a steady reduction in the median value of AverageSpeed from 8 AM through 1 PM—from 3.8 mph to 2.8 mph, a 26% reduction—after which it remains essentially constant (stays within a 10% band) until the 10 PM hour when it dips 20% to 2.4 mph. The variance in the hourly data is rather tight within the low speed range. After 10 PM, less than 25% of the tour segment average speeds are made at AverageSpeeds of greater than 5 mph. While the graph shows what may seem to be many outliers at higher speeds, there are in fact relatively few considering that the graph is a summary 3,561 data points in which there are less than 100 outliers.
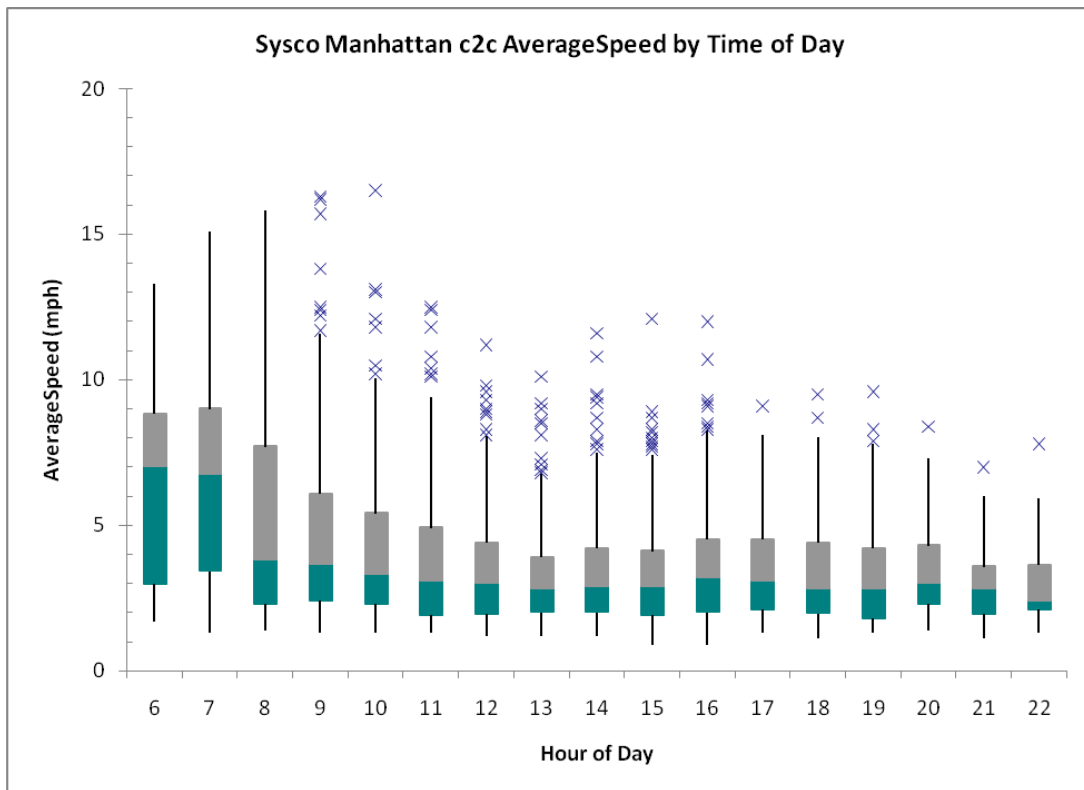
Figure 24: Manhattan c2c Tour Segment AverageSpeed by ToD for Sysco's Base Case
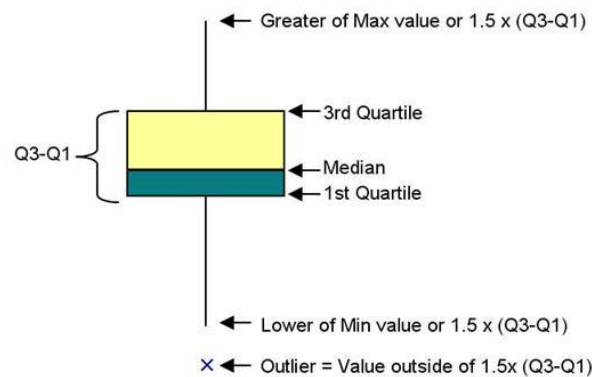
Figure 25: Diagram Defining Elements of Box and Whisker Chart
(from http://www.qimacros.com/qiwizard/Box-and-Whisker-analysis.jpg)

6.1.2.2   *First and last tour segment AverageSpeed by time of day, Sysco base case*

The first and last tour segments involve the crossing of the Hudson River. The first tour segment includes travel from Sysco's Jersey City, NJ, depot to the first customer in Manhattan, which involves the crossing of the Hudson River at the Lincoln Tunnel, and the congestion that may occur in the approach to that facility. The last segment, from the last customer in Manhattan to Sysco's Jersey City facility, involves the return crossing of the Hudson River. Again the Lincoln tunnel is used essentially exclusively.

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Here the Manhattan congestion leading to the Tunnel in and around Astonia comes into play. Figure 26 compares the hourly box and whisker charts of AverageSpeed for the first tour segment and Figure 27 that of the last tour segment. Each figure also includes the corresponding box and whisker chart for all of the data. As can be seen, AverageSpeeds into Manhattan (First Leg) are much faster than out of Manhattan (Last Leg); median values overall being 11.8 mph versus 8.3 mph, a 42% increase. By time-of-day, median values do not vary all that much. Inbound, they are a little higher in the very early morning hours of 3 AM and 4 AM where there is a higher variance and congestion may be caused by maintenance being done on the Lincoln Tunnel and its approaches. The substantially higher variance in the data indicates that higher speeds are achievable. Starting with 5 AM AverageSpeeds higher than 15 mph occur significantly less than 25% of the time, until 11 AM. At the noon hour, substantial congestion is indicated; however, one must note that this graph included only six data points and thus should be held as suspicious. No data was available for the afternoon, evening, or very early morning hours because Sysco did not dispatch any tours during those hours.

For the return to the depot, the Last Leg, median AverageSpeeds and their variances are within a very narrow band. A high value of 9.2 mph was achieved in the early afternoon in the 2 PM hour and a low value of 7.7 mph was achieved in the 8 PM hour. AverageSpeeds were above 11 mph less than 25% of the time. The nature of the operation was such that no truck returned to the depot during morning hours.

6.1.2.3   Customer service time by time of day, Sysco base case

An investigation of the amount of time spent at Manhattan customer location was conducted using the remotely sensed waypoint data. During the determination of base case conditions, Sysco made a total of 5,569 customer service stops in Manhattan. The median value of the duration of these stops was 1.31 hours with 75% of the service stops lasting less than 2.32 hours and fewer than 25% requiring less than 45 minutes. As such numerous deliveries are being made at each of these customer locations and the vehicles remain stationary for a substantial amount of time. Unfortunately, the data did not contain attributes that indicated service facility (off-street loading dock, curb parking, double parking) at each of these customers. As can be seen from the box and whisker chart, Figure 28, on average, stops served at mid-day took longer (1.6 to 1.8 hours) than those in the very early morning or very late evening hours (median values of around 1 hour). Unfortunately no attribute data were available to classify the customer stops by any measure of size. We believe that it is a reasonable assumption that there is little correlation of delivery size and time of day; thus, the absence of overall congestion of pedestrians and street traffic leads to this significant reduction of customer service time in the very late and early morning hours; a 40% decrease in customer service time in the late evening hours relative to the late morning hours.

Customer service times at specific locations in Manhattan were also investigated in four areas of Manhattan where a useable amount of data existed: Lower Manhattan, Rockefeller Center, Times Square,

Midtown. Box and whisker charts of customer service times are presented for each of these specific locations by time-of-day in Figure 29 through Figure 32. Figure 33 charts the data for Times Square and Midtown together because the data for each is a little sparse. What is consistent in the charts is that service times are much greater during the late morning hours and early afternoon than in the late evening and early morning hours at the individual locations. This is highlighted in Figure 34 where the data are aggregated into just three time blocks: overnight (18:00 - 8:00), late morning (8:00 - 13:00) and afternoon (13:00 - 18:00). The median service time in late morning is twice as long as (103% or 53 minutes longer) per stop than those in the overnight period. In the afternoon, the median service time is 34% longer or 17 minutes longer than during the overnight.
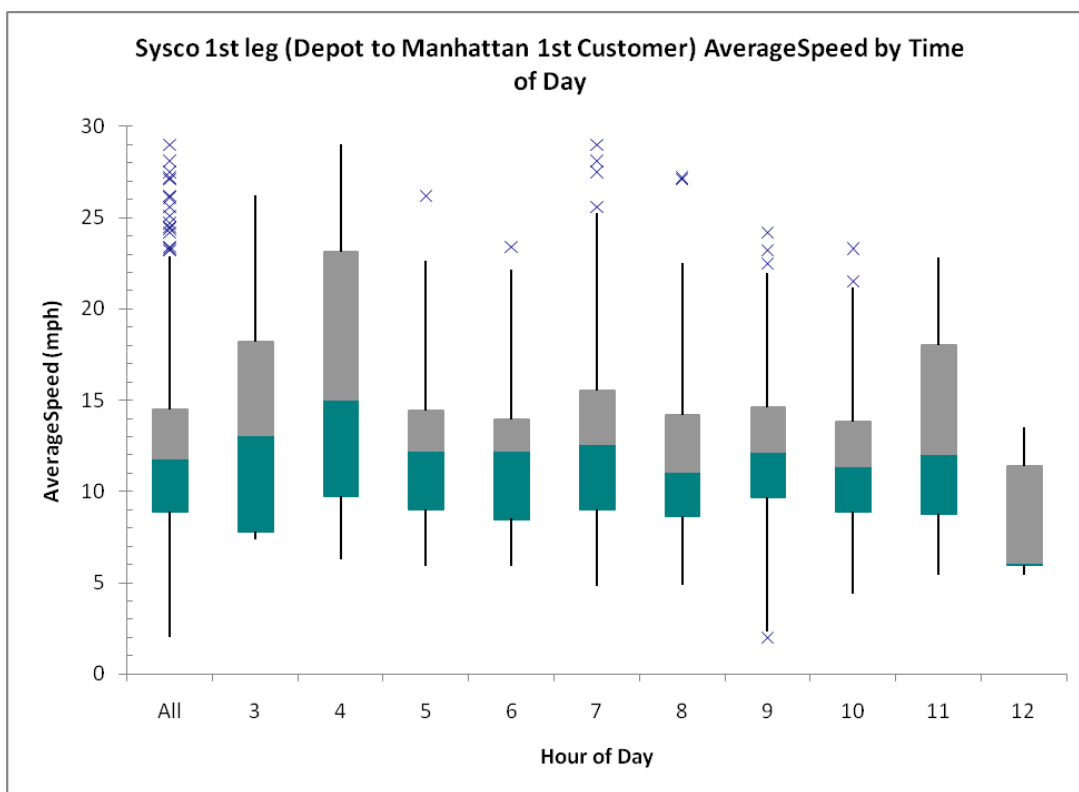
Figure 26: First Leg AverageSpeed by ToD for Sysco Base Case
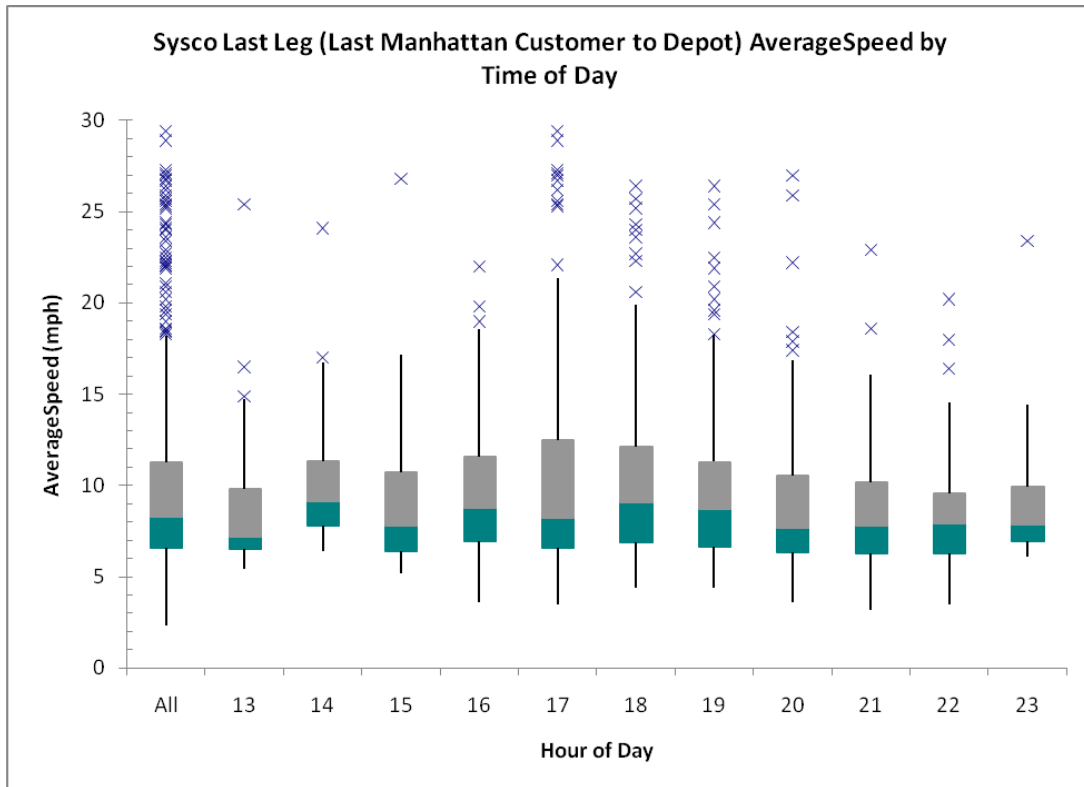
Figure 27: Last Leg AverageSpeed by ToD for Sysco Base Case
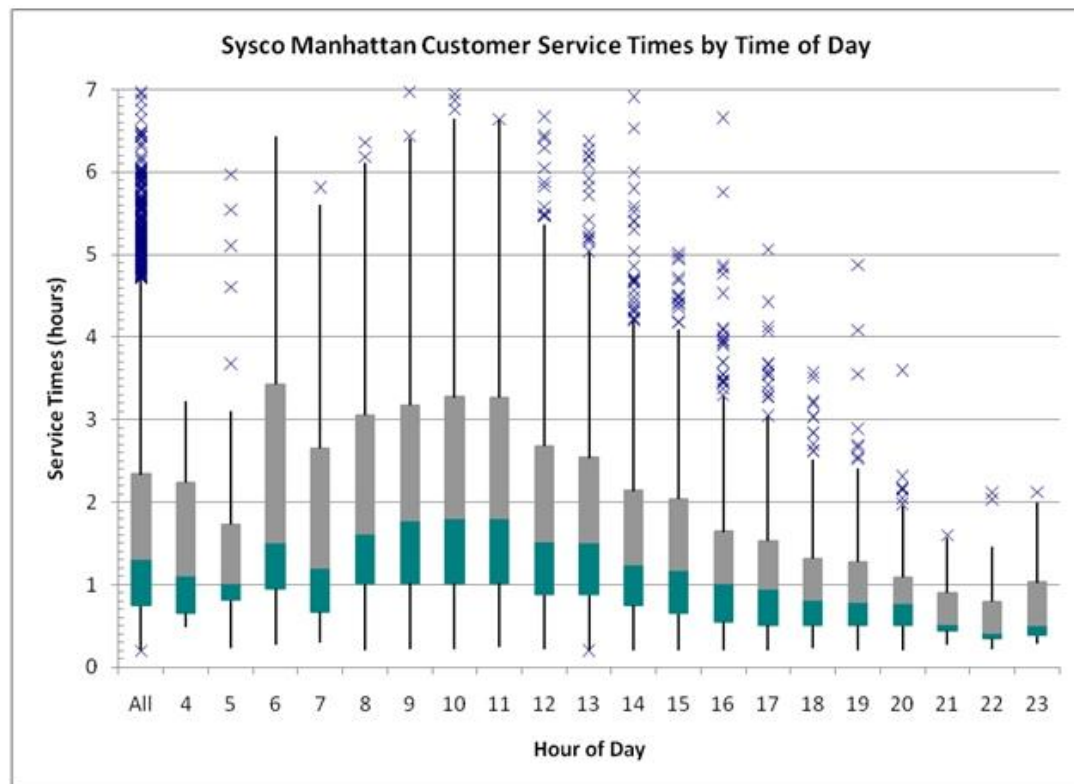
Figure 28: Manhattan Customer Service Times by ToD for Sysco Base Case

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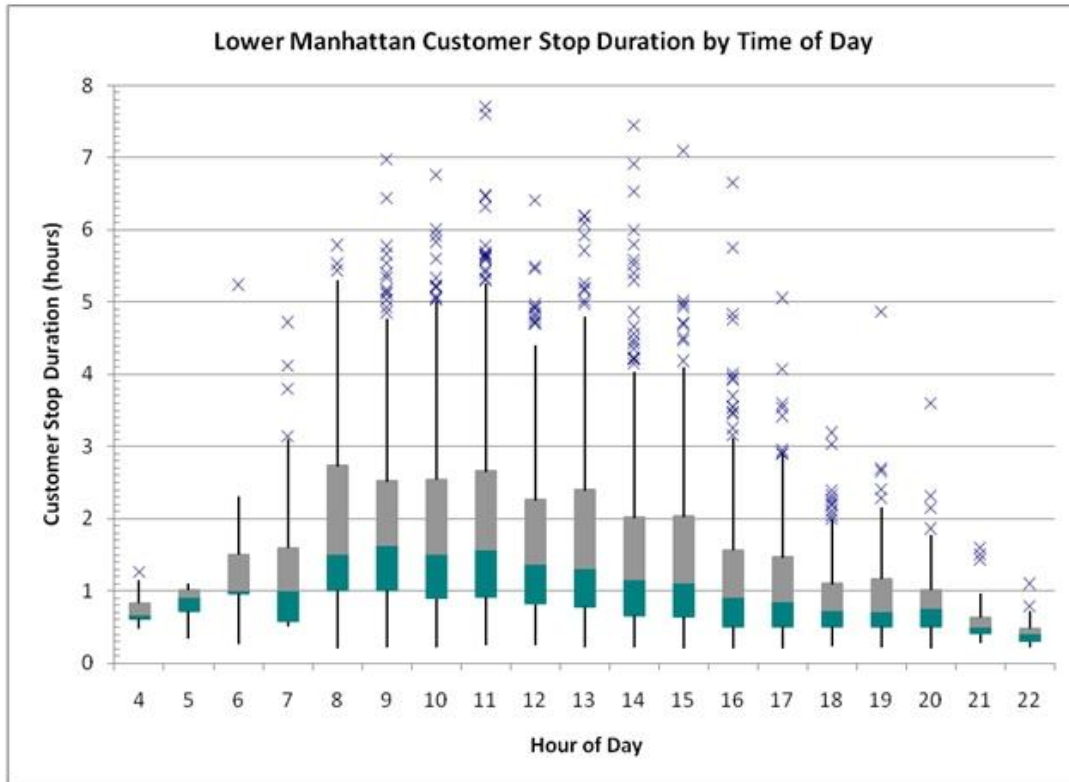
Figure 29: Lower Manhattan Customer Service Times by ToD for Sysco Base Case
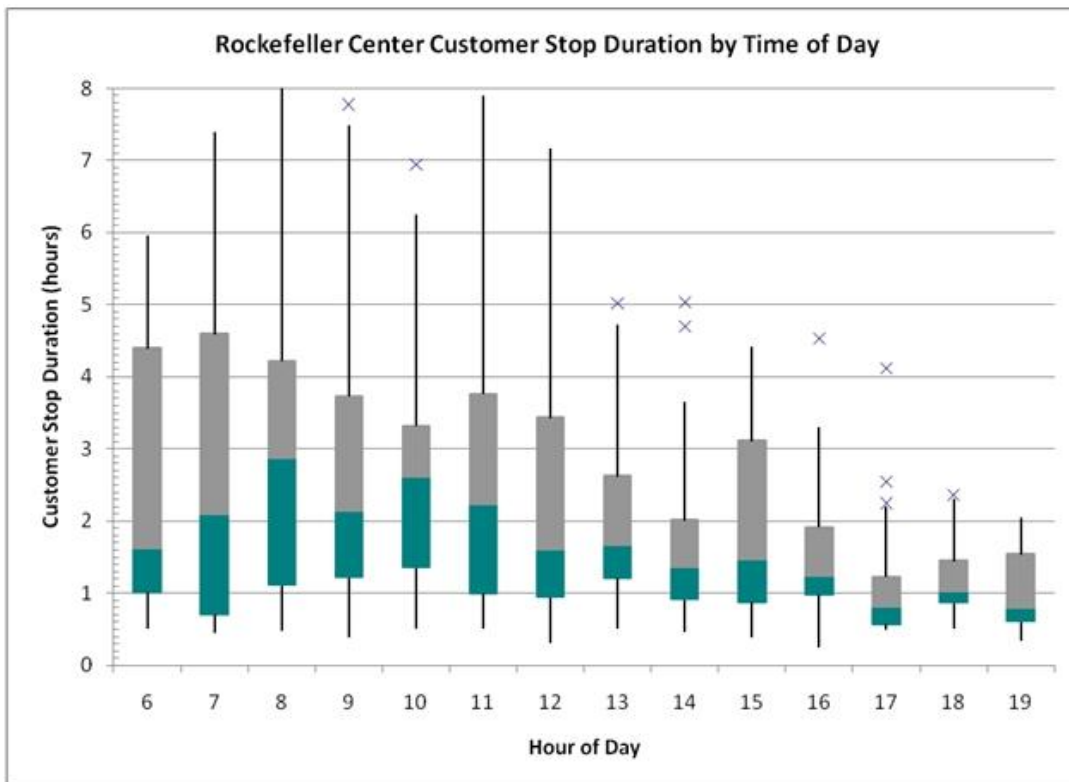
Figure 30: Rockefeller Center Customer Service Times by ToD for Sysco Base Case
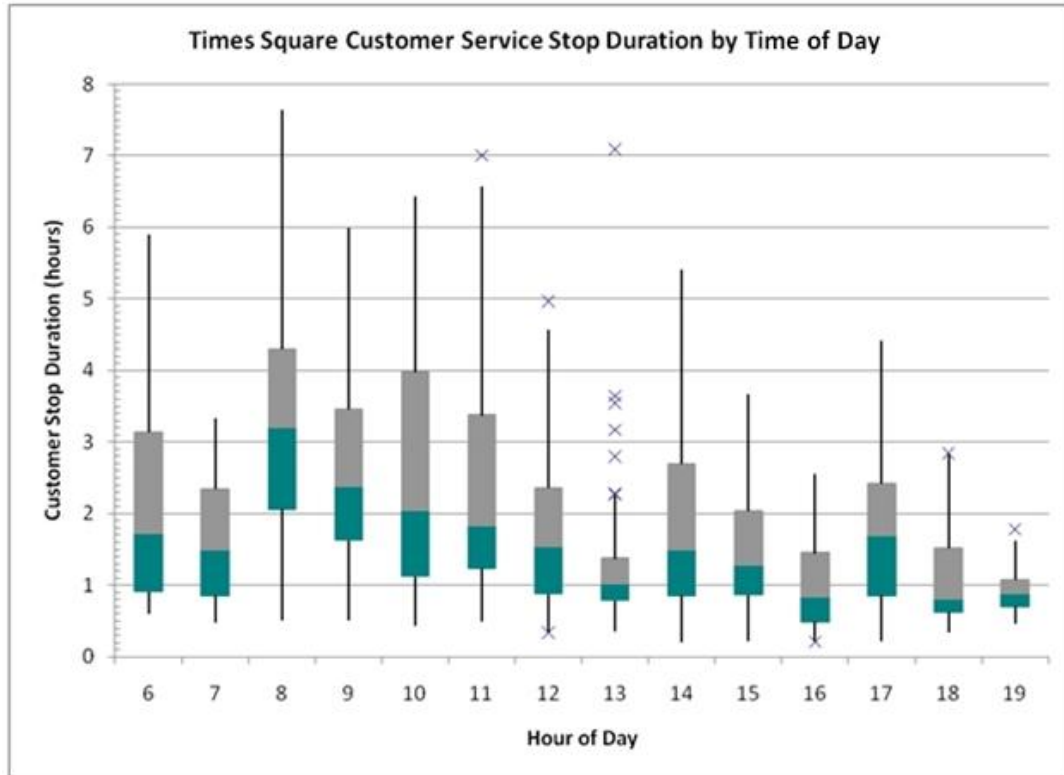
Figure 31: Times Square Customer Service Times by ToD for Sysco Base Case
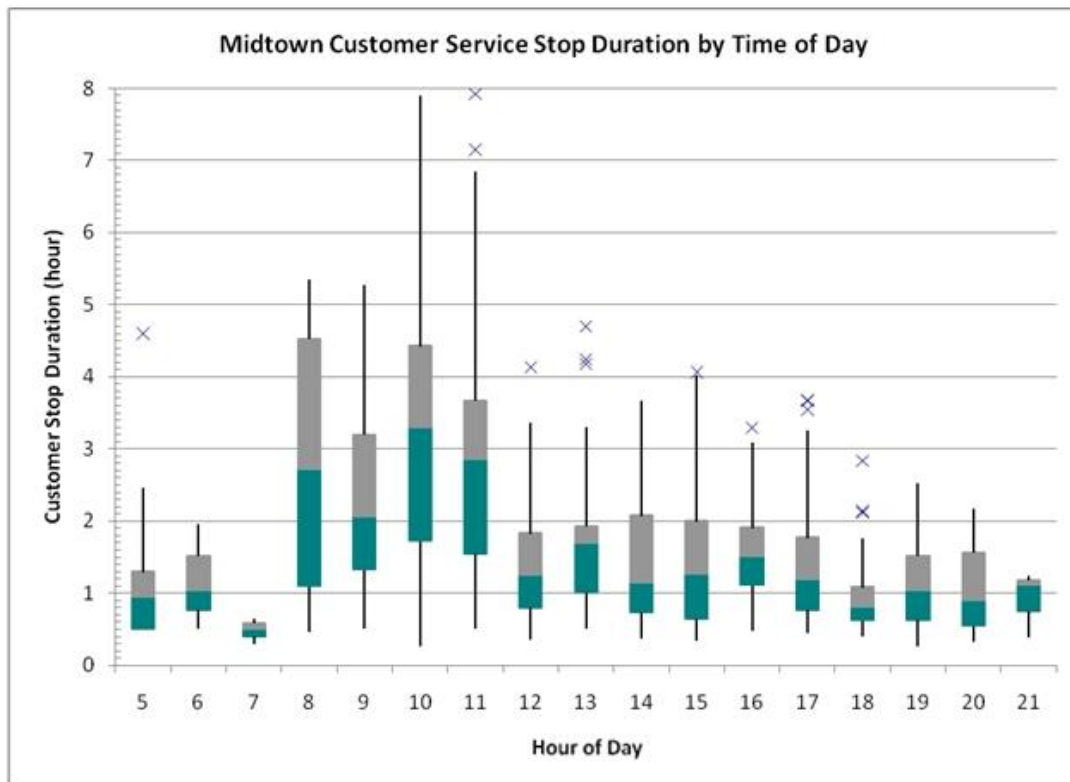
Figure 32: Midtown Customer Service Times by ToD for Sysco Base Case
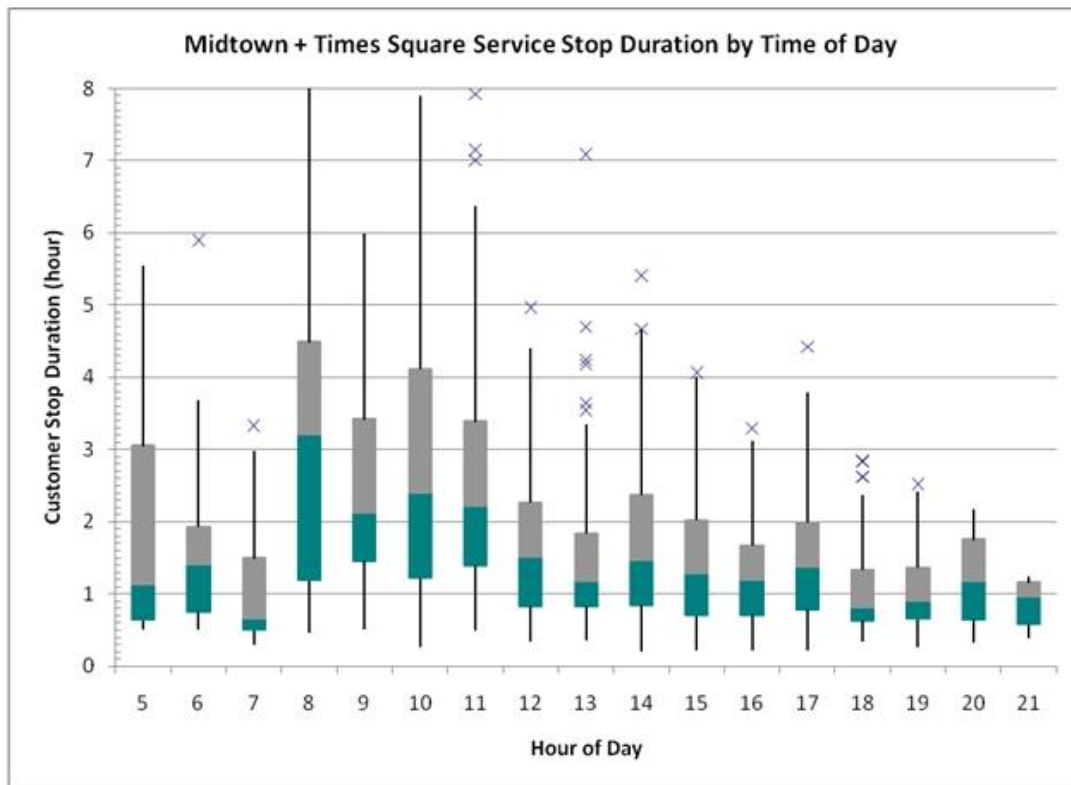
Figure 33: Midtown + Times Square Customer Service Times by ToD for Sysco Base Case
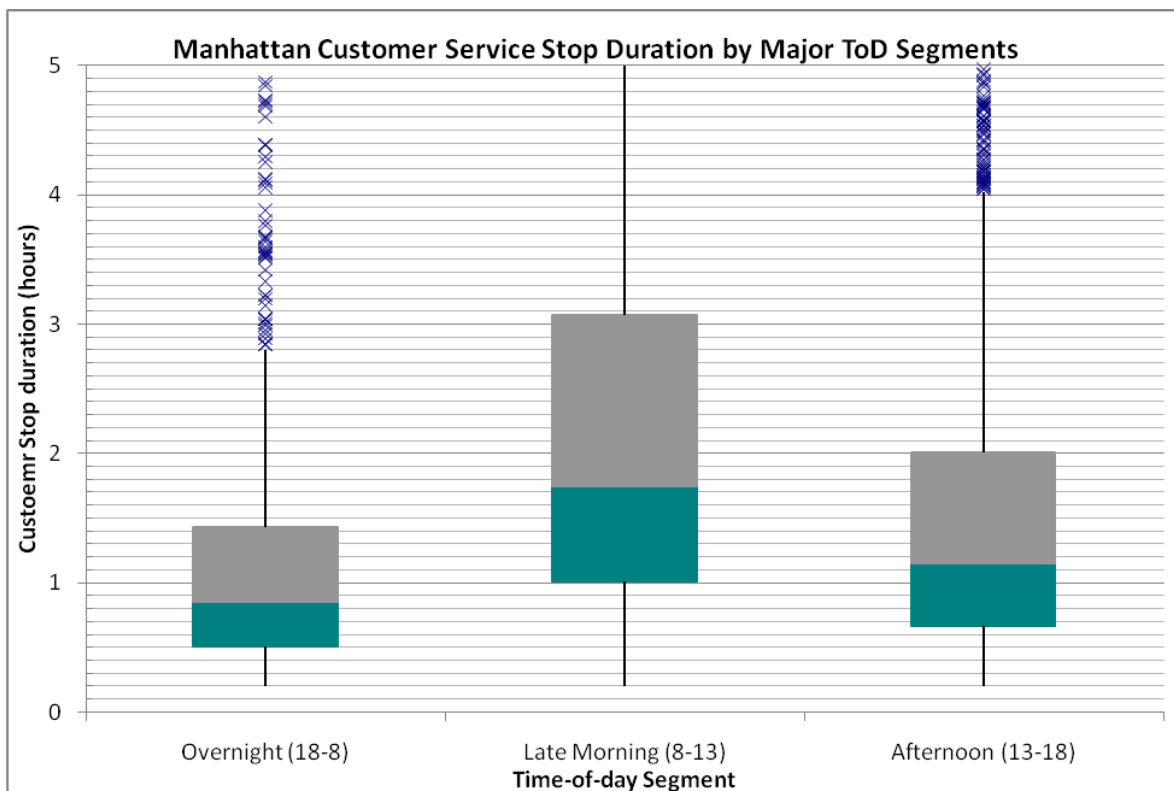
Figure 34: Manhattan Customer Service Times by Major ToD Segments for Sysco Base Case

The implications of these findings are considerable, unexpected, and deserve further scrutiny. Congestion, while substantial in getting from customer to customer in Manhattan and from and to the depot (travel speeds under 3 mph—less than walking speed—in Manhattan, but travel distances are short), may be dwarfed by the congestion effects in serving the customer where most of the tour time is spent. During the base case determination, Sysco made 2,380 or 42.8% of its customer service stops during the late morning. These service stops took a total of 5,265 hours to complete, or on average 2.21 hours. Had they all been done during the overnight time period at Sysco's average value of service time during that period (1.19 hours), they would have saved 2,439 hours or an average of 61 minutes per stop. This cuts customer service time almost in half which implies that tours which are approximately one-third travel time and two-thirds customer service time could serve 50% more customers per tour. This suggests an enormous productivity opportunity. In fact, if Sysco had done the 2,380 late morning customer deliveries at the overnight customer service duration rate it would have served all of its Manhattan customers in 16.5% less total truck tour time. While some of this difference in customer service time may be due to factors other than time-of-day congestion, the improved efficiency in serving the customer may well deliver the largest value derived from moving to overnight good delivery in Manhattan.

6.2   Foot Locker/New Deal Logistics Pilot Test

New Deal Logistics (NDL) provides a broad array of goods movement services in the northeast region. Included are less-than-truckload (LTL) trucking services out of its Kearney, New Jersey (NJ), depot from which it delivers products to various retailers in Manhattan and throughout the region. Some of its customers include Foot Locker stores in Manhattan that participated in the pilot test by requiring NDL to make its deliveries in the off-hours. As a participant in the pilot test, NDL used four of the GPS smartphones to remotely sense the operational characteristics of four of its trucks that served Manhattan customers. NDL also provided the research team with some of its remotely-sensed GPS location time data that it collects as part of its normal fleet management activities.

6.2.1   The remotely-sensed GPS position-time data

6.2.1.1   NDL remotely-sensed GPS fleet management position-time data

NDL provided the research team with its fleet management position-time data for seven trucks that provided service to Manhattan customers for the one week period of November 4 through November 11, 2009. Table 10 contains a sample of this NDL fleet management data. Included is a unique identifier of a truck (NDL tends to assign the same truck as well as the same driver to the same service area), date, time (local EST), Ignition Status, NDL Location reference, GPS derived Speed, and GPS derived Latitude and Longitude. When the truck is moving, data are recorded every two minutes as well as at the time of

arrival ("stop"), departure ("start") and ignition on/off. When stopped at the depot or at a customer location, data are recorded much less frequently, typically every 45 minutes.

While Ignition Status is provided it was not found to be a reliable indicator of the arrival or departure of a truck at any location. There is no guarantee that an ignition off message is received by the fleet management system. Consequently, an ignition off message could be sent by the truck, but because of communications dead zones such messages may not be received. Thus a customer stop is necessary in the neighborhood of any ignition-off message but it is not sufficient. What was determined to be more sufficient was to compute and inspect the distance and the average speed between neighboring time sequenced locations. If distance traveled and speed was small between any two points, a stop was feasible between these locations-times. An actual stop was declared if sufficient neighboring pairs assembled to span at least 6 minutes and have no neighboring points greater than 0.1 miles apart or speed between neighboring points to be less than 3 mph. This algorithm proved to be very robust in identifying stops except is sever congestion situations when traveling through the Lincoln or Holland tunnels. In those situations, it may well take more than 6 minutes to cross the Hudson River and the computed speed from the last GPS location prior to entering the tunnel to the first GPS location once emerging from the other side of the tunnel can often yield a computed speed of less than 3 mph. However, because of the location of these two points they are readily identified as being near each end of the tunnel and are discarded by the algorithm. No other similar situation was discovered where because of the loss of GPS due to urban canyon effects and/or communication dead zones was of such duration that a false positive was suspected.

Table 10: Sample of NDL Remotely-sensed GPS Position-time Data

NDL Remotely Sensed GPS Vehicle Location Data							
Driver_ID	date-Time	Ignition Status	NDL Location Reference		Speed (mph)	Longitude	latitude
500 Torres M	11/4/2009 21:42	On	8 E 58th St	NY	27	40.76324	-73.973191
500 Torres M	11/4/2009 21:44	On	63 W 57th St	NY	24	40.76416	-73.976462
500 Torres M	11/4/2009 21:46	On	971 8th Ave	NY	6	40.76686	-73.982933
500 Torres M	11/4/2009 21:48	On	485 W 56th St	NY	2	40.76857	-73.988338
500 Torres M	11/4/2009 21:50	On	523 W 57th St	NY	2	40.76949	-73.989262
500 Torres M	11/4/2009 21:52	On	569 W 57th St	NY	4	40.7702	-73.990258
500 Torres M	11/4/2009 21:54	On	756 11th Ave	NY	34	40.768	-73.993031
500 Torres M	11/4/2009 21:56	On	624 11th Ave	NY	19	40.76316	-73.996516
500 Torres M	11/4/2009 21:58	On	N/A	NY	20	40.7589	-73.998436
500 Torres M	11/5/2009 7:15	On	N/A	NJ	N/A	40.74012	-74.101404
500 Torres M	11/5/2009 7:16	On	202 Pennsylvania Ave	NJ	N/A	40.73906	-74.101404
500 Torres M	11/5/2009 7:18	On	N/A	NJ	11	40.74012	-74.103538
500 Torres M	11/5/2009 7:19	Off	N/A	NJ	N/A	40.74027	-74.103538
500 Torres M	11/5/2009 7:21	On	N/A	NJ	N/A	40.74027	-74.103538
500 Torres M	11/5/2009 7:23	On	N/A	NJ	N/A	40.74034	-74.103609

Figure 35 presents a cartographic display of the 40 tours operated by NDL in the Manhattan area during the week of November 4, 2009. The operation of these tours was recorded by the remotely-sensed GPS position time data captured by NDL's fleet management system. Each tour segment is individually colored. NDL's Kearney, NJ, depot is labeled and one can see that access to Manhattan is primarily via the Lincoln Tunnel. During the pilot test, commercial vehicles operated by NDL were prohibited from using the Holland Tunnel.

Close visual inspection of the geographic display of the position data, a representative example of which is contained in Figure 36, showed that the GPS derived position data was of high quality and contained no indication of adverse urban canyon effects. Points between stops aligned along feasible routes and exhibited no signs of substantial scatter. Points intervening the arrival and departure from customer locations tended to be tightly clustered in the neighborhood of the arrival and departure locations with deviations of order of tens of meters. These deviations were deemed to be minor; thus, the conclusion that the GPS location data was of very high quality and more than commensurate with subsequent computations of travel distance and ultimately average speeds that were accurate to 0.1 mph.
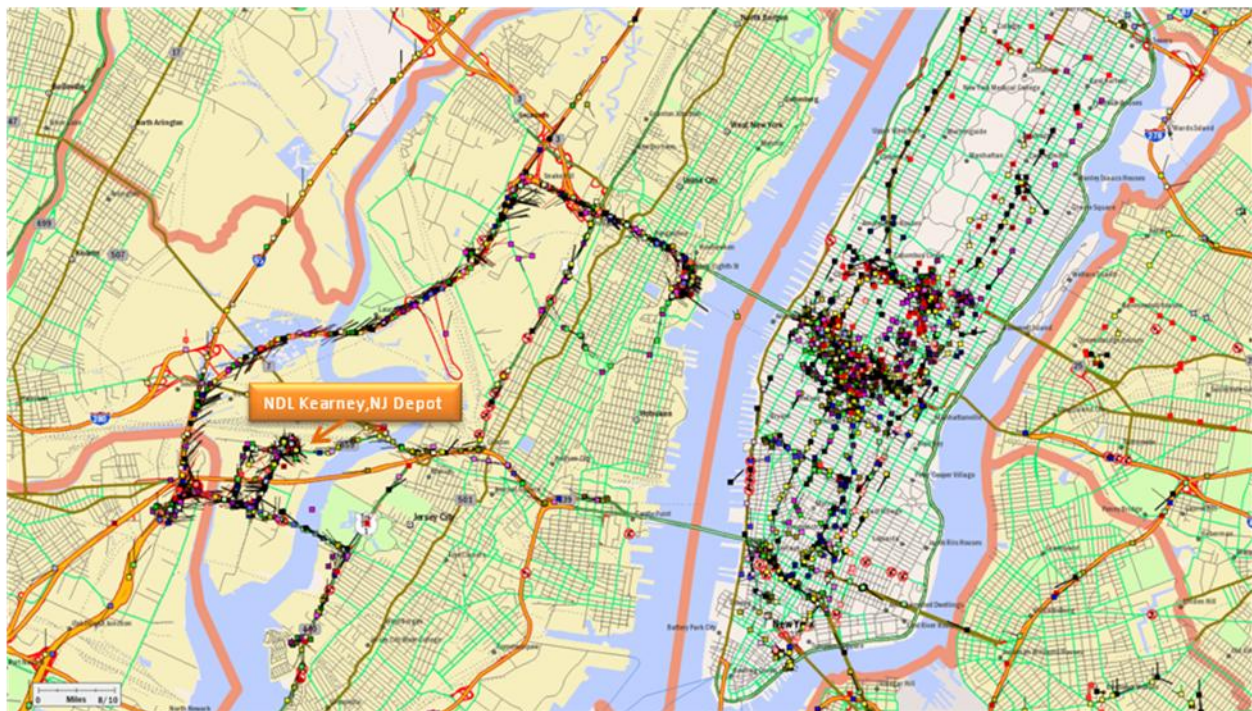
Figure 35: Cartographic Display of All of the NDL Position-Time Data
(7 trucks during the week of Nov. 4, 2009)

Figure 36: Cartographic Display of NDL Remotely Sensed GPS Vehicle Position-Time Data (showing urban canyon scattering that occurs around midtown Manhattan)

While a value of speed is provided in the data, it was not used in the analysis. Instantaneous speed varies greatly during any trip. Not only does each tour segment start and stop from rest, but it generally has many intermediate stops of varying duration caused by traffic control, and congestion. An accurate characterization of the average of such a wildly varying function would require a large number of observations. A data rate of every two minutes does not provide enough observations to properly characterize the average speed of urban tour segments that are typically less than a few miles in length.

Fortunately, the data do contain an accurate and reliable location and time for the start and end of each tour segment. An "average" customer-to-customer (c2c) speed is computed for each tour segment as the ratio of computed distance traveled between the departure location from the previous customer to the arrival location at the current customer divided by measured travel time. The distance is computed as the sum of the "great circle" distance between each of the time-sequenced intermediate locations available for that tour segment. The measured travel time is simply the difference in the date/time of the arrival record and the departure record for the previous customer. The slight underestimation of actual travel distance that can occur on trips that may actually zigzag between recorded locations was deemed to be of insufficient significance to require that distance be computed by the substantially more computationally intensive "sum of over the street network path distances" between the intermediate locations. Differences in computed path distance from sum of great circle distances was found to be consistently less than 3% for a random sample of route segments. An average speed was also computed for each tour's first and last segments, from the depot to the first customer, and from the last customer back to the depot.

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6.2.2 Tour specific data

The raw NDL data (Table 10) were processed to produce 40 individual tour and trip segment summaries and to prepare the data for graphical display. An example of the data produced is Table 11. Each of the 40 tours begins and ends at NDL's depot in Kearney, NJ. In rare cases the location data for a vehicle ended prior to the vehicle returning to the depot. An example can be seen in Table 11 where the last recorded position for the vehicle was at the entrance to the Lincoln Tunnel on its return to the depot. Between the initial depot departure segment and the last depot return segment, there are individual customer-to-customer segments. The name of a nearby landmark is assigned to each customer location to provide cognitive relevance to the locations while maintaining the privacy of the individual customer. Attributes contained in Table 11 for each segment include: drive time (hours), drive distance (miles) and average speed (mph, the ratio of miles to hours). Also listed for each segment is the time to next trip (T2NxtTrp). For all but the last segment it is the time spent serving a customer. For the last segment, it is the time spent in the depot until the beginning of that vehicle's next trip. For a vehicle's last trip, the entry is meaningless because it is simply the difference in the depot time of arrival of this vehicle and the time of departure from the depot of the next vehicle on the list. Usually this is a large negative number that needs to be disregarded.

Individual tours are summarized and characterized by the following attributes: trip departure date and time, number of customer stops, tour length (sum of the trip segment lengths), tour duration (difference between the depot departure time and the depot arrival time), drive duration (sum of the tour segment drive time), stop duration (sum of the T2NxtStp without the last one) and average drive speed (tour length/drive duration). Cartographic display of a sample of typical tour segments from the set of 40 NDL Manhattan pilot test tours are presented in Figure 37 through Figure 39. Figure 37 shows the tours for vehicle_ID # 500 for the week of Nov. 4, 2009. Each tour segment is individually color-coded. Figure 38 shows only one of those tour segments, the depot-to-Manhattan first segment on Nov. 11, 2009. Note the circuitous access to the mouth of the Lincoln Tunnel to avoid severe congestion on the NJ 495 viaduct. A little less than 1 mile (almost 10%) was added to the segment trip length. The 13.6 mile trip took 0.93 hours to complete yielding an average speed of 14.5 mph. Unfortunately no data exists that would document how much time was saved, or lost, by the circuitous route.

Table 11: Sample NDL Tour Data

Veh_ID	Trip_ID	Obs	Origin		Destination		Origin		Destination	
			City	State	City	State	Lon	Lat	Lon	Lat
500	1	14	Kearney	NJ	Union City	NJ	-74104889	40739200	-74023182	40764800
500	2	12	Union City	NJ	New York	NY	-74025031	40763020	-73991964	40735080
500	3	2	New York	NY	New York	NY	-73992249	40734860	-73996231	40736140
500	4	11	New York	NY	Triborough	NY	-73996089	40737000	-73955271	40779660
500	5	12	Triborough	NY	Ansonia	NY	-73956338	40779240	-73998436	40758900
500	8	21	Kearney	NJ	Midtown	NY	-74103964	40739200	-73993244	40753920
500	9	2	Midtown	NY	Midtown	NY	-73990187	40751150	-73991893	40749870
500	10	4	Midtown	NY	Midtown	NY	-73990258	40748590	-73990116	40750010
500	11	9	Midtown	NY	Franklin D R	NY	-73989902	40749940	-73985138	40749160
500	12	10	Midtown	NY	Midtown	NY	-73986276	40750580	-73989333	40750510
500	13	6	Midtown	NY	Times Square	NY	-73987911	40749940	-73991680	40755700
500	14	3	Times Square	NY	Times Square	NY	-73991538	40755130	-73987911	40753420
500	15	2	Midtown	NY	Midtown	NY	-73987129	40749580	-73988267	40751220
500	16	23	Midtown	NY	Kearney	NJ	-73990542	40751000	-74101618	40740480

Veh_ID	Trip_ID	Obs	Origin		Destination		Hours	Miles	MPH	T2NxtTrp
			Date	Time	Date	Time				
500	1	14	20091104	184500	20091104	191200	0.45	8.42	18.70	0.23
500	2	12	20091104	192600	20091104	194800	0.37	3.48	9.50	0.53
500	3	2	20091104	202000	20091104	202200	0.03	0.23	6.80	0.50
500	4	11	20091104	205200	20091104	211000	0.30	4.12	13.70	0.43
500	5	12	20091104	213600	20091104	215800	0.37	3.38	9.20	9.30
500	8	21	20091105	73300	20091105	82300	0.83	10.45	12.50	0.15
500	9	2	20091105	83200	20091105	83400	0.03	0.13	3.80	0.13
500	10	4	20091105	84200	20091105	84700	0.08	0.45	5.40	1.53
500	11	9	20091105	101900	20091105	103500	0.27	1.14	4.30	0.55
500	12	10	20091105	110800	20091105	112700	0.32	0.96	3.00	0.17
500	13	6	20091105	113700	20091105	114700	0.17	0.80	4.80	0.60
500	14	3	20091105	122300	20091105	122600	0.05	0.23	4.50	0.90
500	15	2	20091105	132000	20091105	132200	0.03	0.13	3.80	1.93
500	16	23	20091105	151800	20091105	160300	0.75	11.44	15.20	97.63

Figure 39 shows another creative route between NDL's Kearney depot and the Lincoln Tunnel. Here the driver of vehicle_ID #509 used exit 15x of the NJ Turnpike and Secaucus Road to avoid heavy congestion in the vicinity of exit 16 and the beginnings of the NJ 495 viaduct. This truck departed the depot at 8:15 AM and exited the Lincoln Tunnel 45 minutes later. It ultimately arrived at its first customer at 9:28 AM for an average speed of 17.0 mph.

There was a commonality among the 40 tours in that they served at least one customer in Manhattan. Consequently each traveled the streets and avenues of Manhattan for some portion of its tour and each involved two water crossings, usually using the Lincoln Tunnel; a few tours used the George Washington Bridge, while others crossed the East River by using the back door route via the Verrazano Narrows Bridge and Staten Island in the process of serving customers in Brooklyn and Long Island.
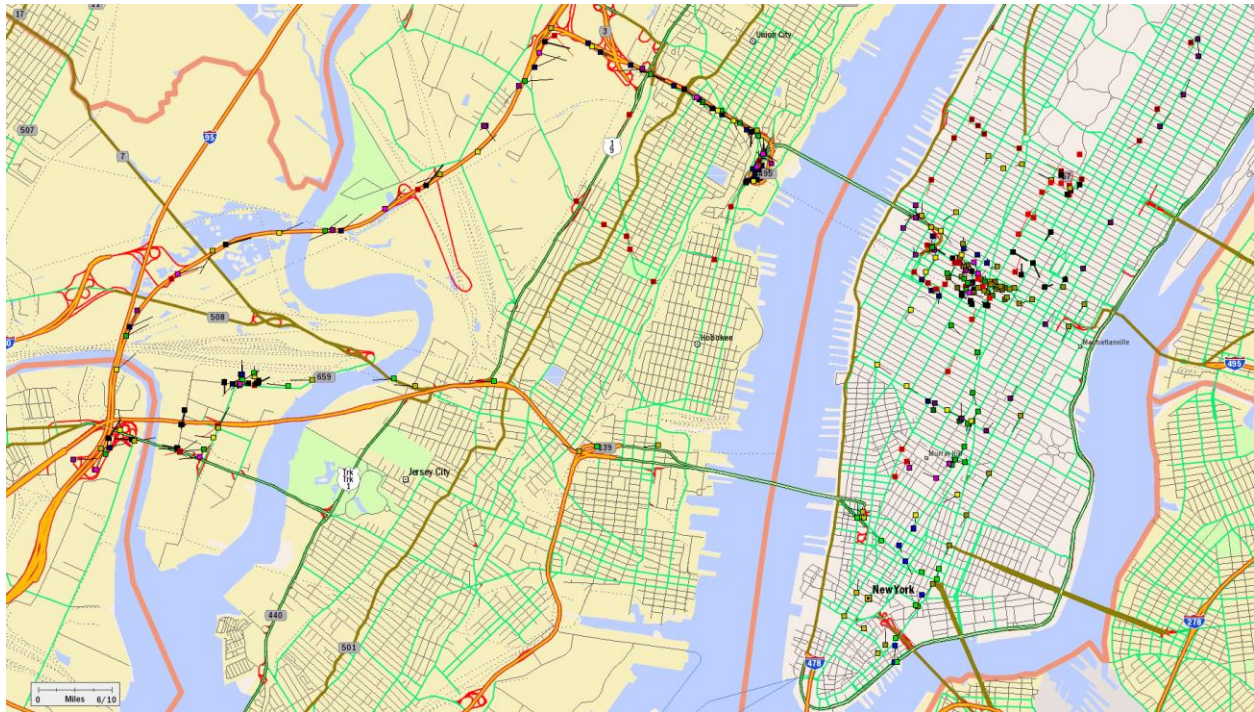
Figure 37: NDL Manhattan Tours of Vehicle_ID #500 for the Week of Nov. 4, 2009
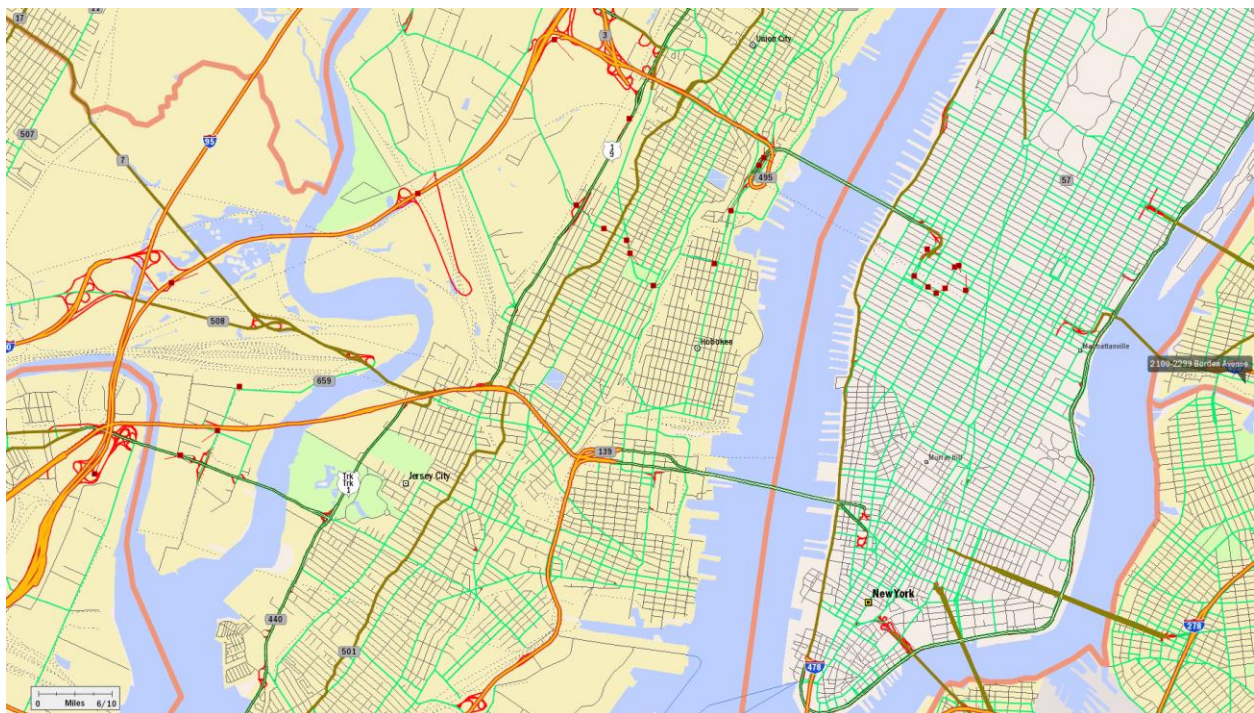
Figure 38: NDL Depot-to-Manhattan Tour Segment for Vehicle #500 on Nov. 11, 2009

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Figure 39: NDL Depot-to-Manhattan Tour Segment for Vehicle #509 on Nov. 10, 2009
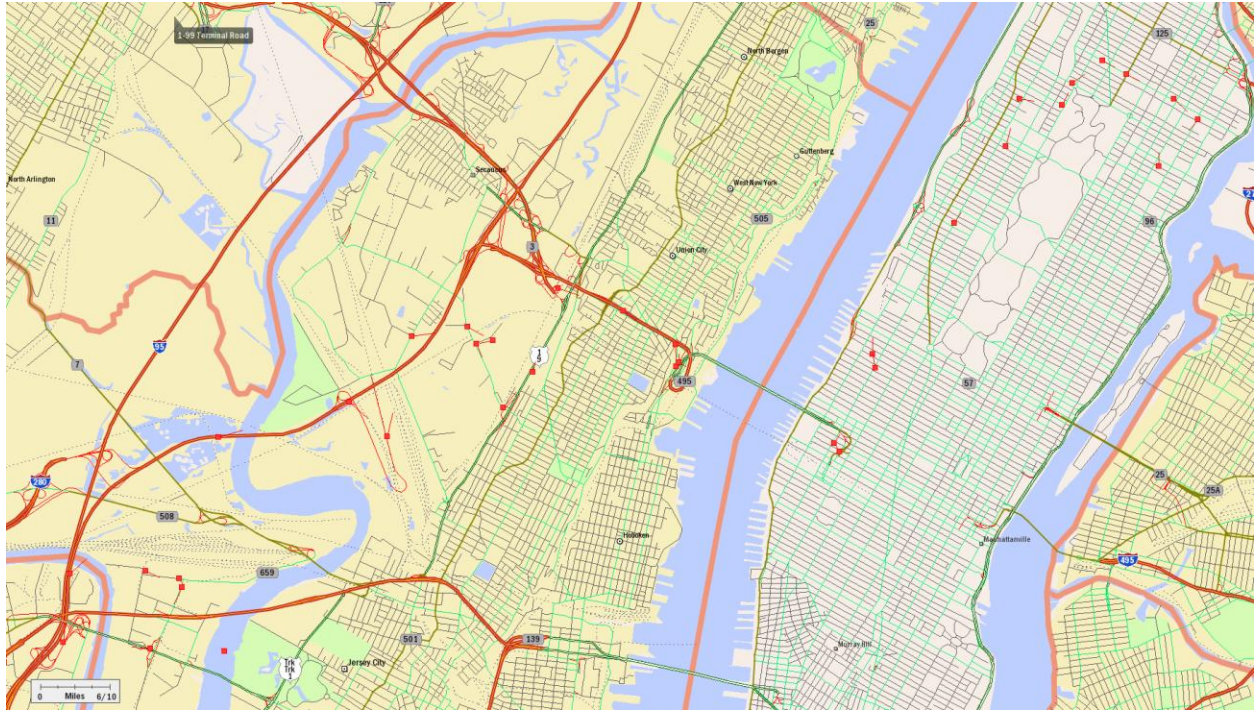
Otherwise the tours tended to be quite different. They served different numbers of customers, in different sequences. Figure 40 contains a box and whisker graph describing the variation in number of customers served per tour. Accompanying each graph is a table containing values of the statistics inherent in the graphical box and whisker representation. A median of 5 customers are served on these 40 tours, but a wide range exists with as many as 15 customers being served on one of the tours.

6.2.2.1   *How time is spent on NDL tours by type of activity*

For the most part tours represent a day's work for a driver. They are at the depot before and after the goods delivery tour, but the remotely-sensed data only provides information about the whereabouts of the driver from the time he/she leaves the depot, until their return. This time is spent driving from the depot to the first customer, servicing that customer, driving to the next customer, servicing that customer and so on until a return to the depot. In analyzing these tours, the drive from the depot to the first customer tends to be similar across tours, as long as the customer is in Manhattan, and similarly for the last tour segment. Also, travel between customer locations in Manhattan tends to have more similarities than differences, especially when compared with trips between customers in Manhattan and anywhere else in the region or in comparison with trips between non-Manhattan locations. Consequently, the analysis focuses on three types of tour segments: (1) those from the depot to a customer in Manhattan; (2) between Manhattan customers; and (3) from a Manhattan customer to the depot. Only tours serving Manhattan customers have been included in the tour analysis. These tours tend to involve only Manhattan customers; however,

some do include the making of a few stops in New Jersey and a few in Brooklyn, and are included in the overall tour data. In the subsequent analyses, the focus is on only the Manhattan c2c segments and the from/to depot segments. Consequently, New Jersey and Brooklyn internal segments are excluded so that only depot-Manhattan and Manhattan-Manhattan segments are examined.
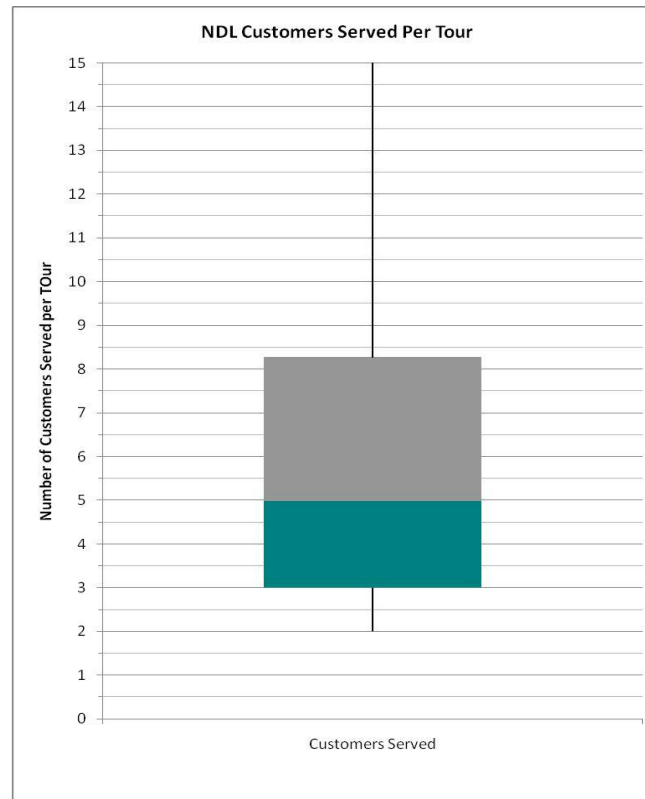
Figure 40: Distribution of NDL Customers Served Per Tour during Field Test

Figure 41 presents the tour duration characteristics of the NDL tours serving Manhattan customers. The median tour duration is slightly less than 8 hours with a wider variation for shorter tours than for longer ones. Time required to serve the customers was fairly uniformly distributed around the median value of 4 hours with the first quartile value of 2 hours and the third quartile value of just under 6 hours. The Hudson River crossing legs of the tour required a considerable amount of time. On average almost 1.5 hours was required for these two segments even though the distance travelled for both amounted to only about 25 miles. The median value of c2c drive time was rather low because Manhattan customers were well-clustered and for tours serving few customers the c2c drive time was very small, with median value of less than a half hour.

Figure 42 depicts the time of departure for the 40 tours. The tours are sequenced in increasing order of departure time. The graph readily shows that 60% of the tours depart between 7:30 AM and 9 AM. Essentially none depart during the midday hours. Departures resume at 6 PM and extend until 10 PM. It is these evening departures that were to Foot Locker and part of the off-hour pilot test.

Manhattan is a small island and c2c tour segments tend to be short. Figure 43 shows the distribution of Manhattan c2c drive distances. Median value is less than 1 mile with fewer than 10% of the segments being longer than 4 miles. These distances are path distance though each of the waypoints is contained in the remotely-sensed data. Figure 44 shows the distribution of average speed achieved for those tours. As can be seen, average speeds are very low with 25% being under 5 mph, a median value of essentially 7 mph and less than 15% in double digits.
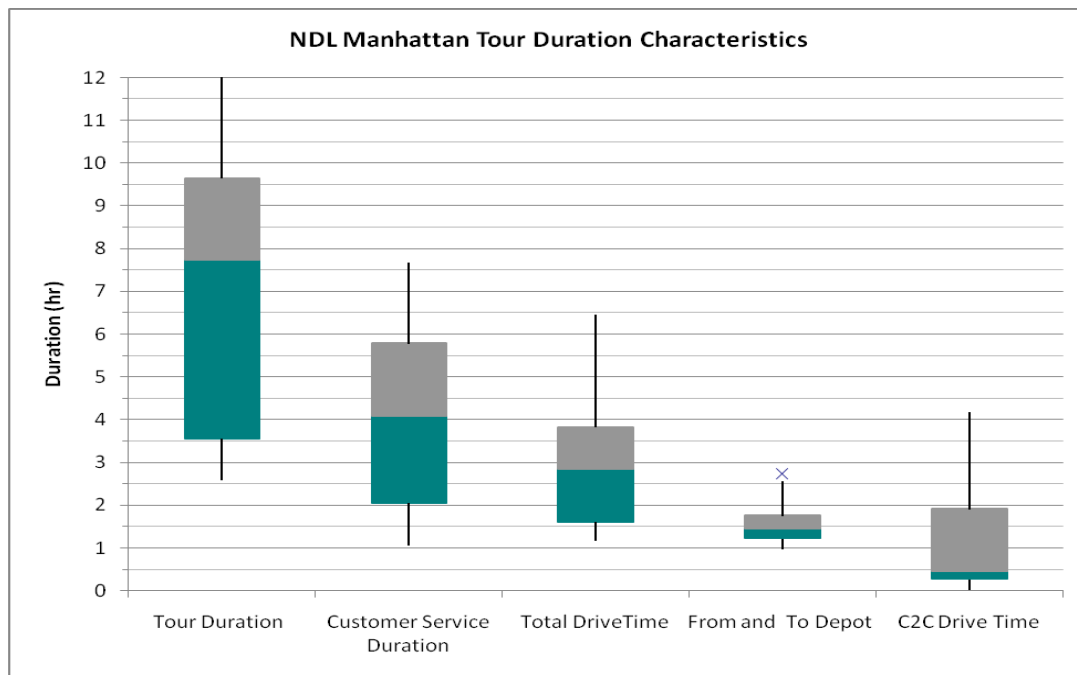
Figure 41: Manhattan Tour Duration Characteristics
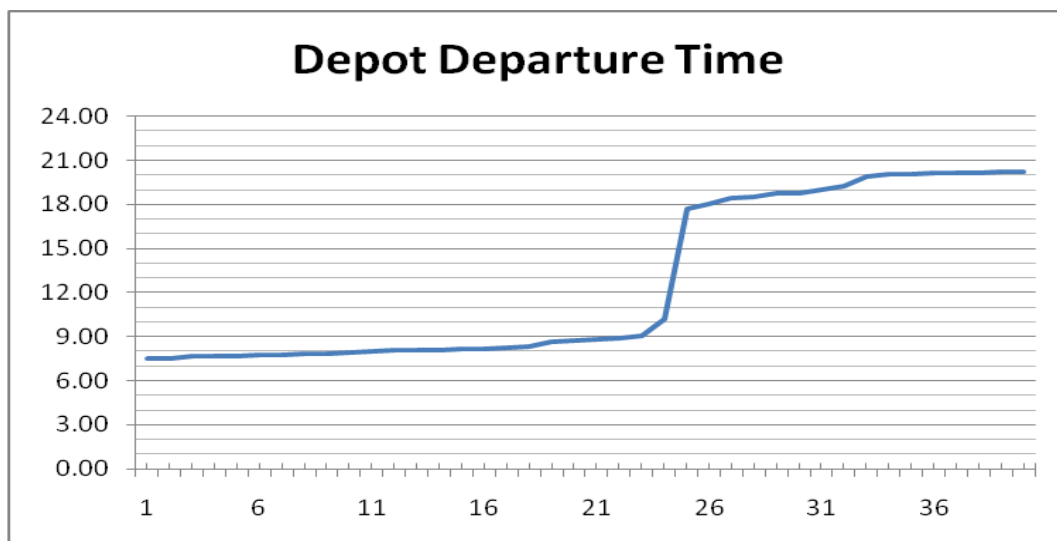
Figure 42: Depot Departure Time for the 40 NDL Tours
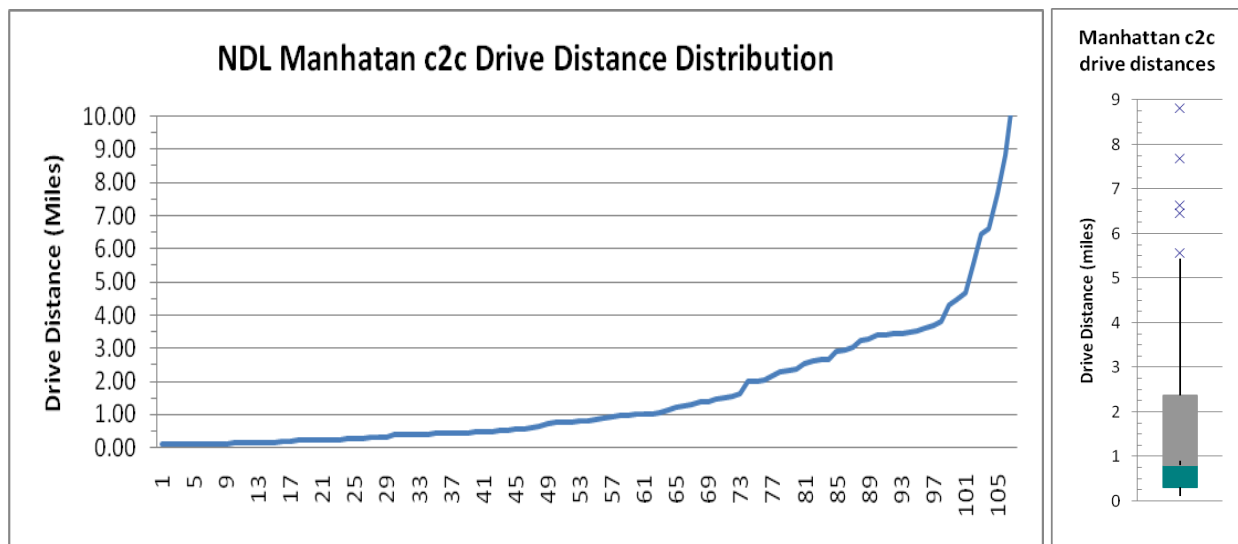
Figure 43: NDL Manhattan c2c Drive Distance Distribution
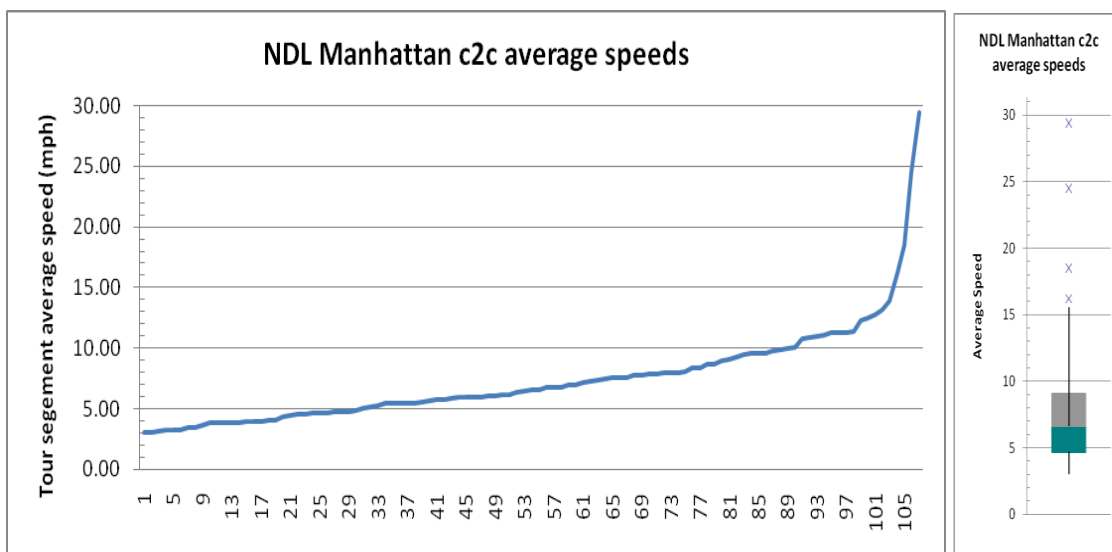
Figure 44: NDL Manhattan c2c Average Speeds

6.2.2.2   *NDL time-of-day tour performance analysis*

The most important analysis of the NDL data is the time-of-day (ToD) tour performance analysis. The objective is to quantify consistent performance variations, if any, for tours serving customers at different times of the day. A "perfect" experiment would have had NDL replicate the exact same tour each day but departing at different times throughout a day and repeating this experiment on many days. Unfortunately, NDL has a business to run and such an experiment is out of the realm of possibilities. Also, every day is different in its details; however, one is looking for recurring variations. A slightly less perfect experiment would have had NDL replicating the exact same tour sequences departing at different times on different days. This experiment is closer to operational feasibility; however, while there are

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many similarities in day-to-day operations to serve customer demands, there are some differences that preclude each operation from being perfectly repeatable. More importantly, tours are an ensemble of segments that vary day-to-day, and one is really interested in the expected relative ToD performance of each of the segments. The performance of the segments at different times can then be assembled to assess the performance of the entire tour. Finally, segments are specific location pairs of which there are many; however, the Manhattan customer pairs are of similar length (shorter) and between traffic-similar locations as are the first and last segments between customers in Manhattan and NDL's depot in Kearney, NJ. Thus, segments were clustered into two groups: (1) the from/to Depot (f/tD) segments; and (2) the customer-to-customer (c2c) segments. The NDL data was used to characterize the variation in the performance of each of these two types of segments by time of day.
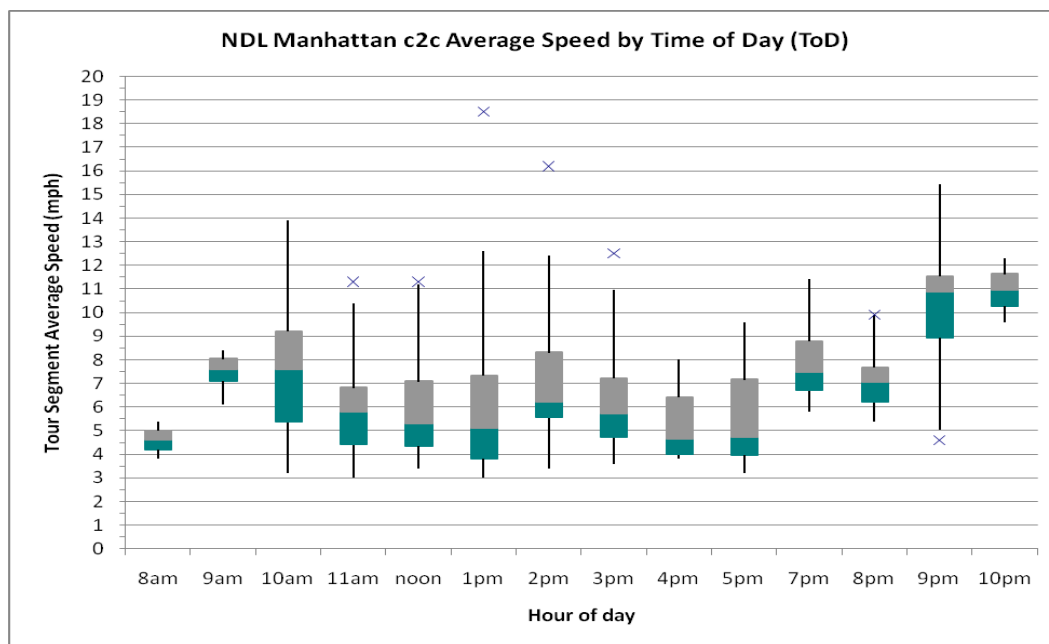
Figure 45: NDL Manhattan c2c Average Speed by ToD

Figure 45 displays the time-of-day travel performance characteristics of tour segments serving Manhattan customers. This graph is essentially the bottom line implications on goods-movement companies trying to serve customers in Manhattan. It quantifies the fundamental implications of the variation in congestion by time of day in Manhattan. The congestion situation, as experienced by NDL in its service of its Manhattan customers, was most severe in the 8 AM hour, around noon (11 AM - 1 PM), and in the late afternoon (4 - 5 PM). A sizeable improvement existed in mid-morning (9 - 10 AM), early afternoon (2 PM), and early evening (7 - 8 PM). The best times were in the evening (9 - 10 PM), when average speeds almost doubled from what was achieved in the worse times.

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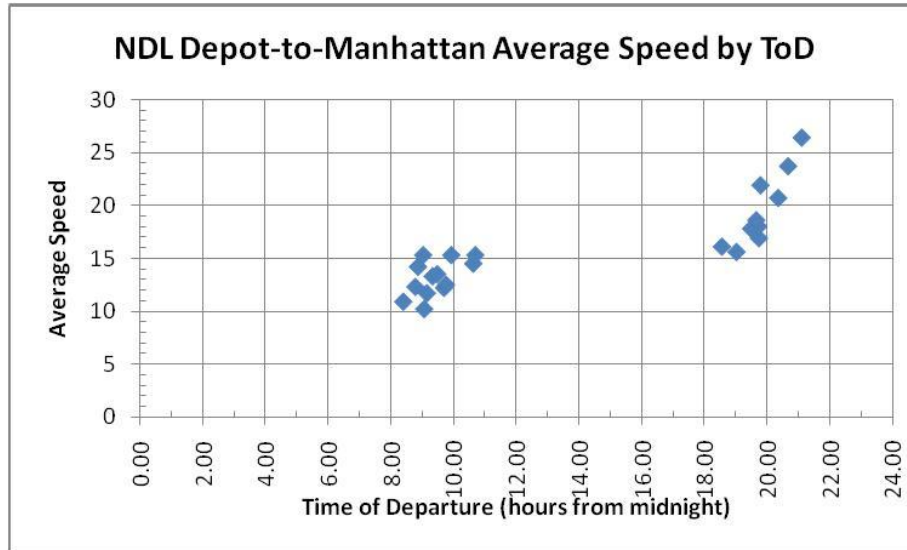
Figure 46: NDL Depot-to-Manhattan Average Speed by Time of Day
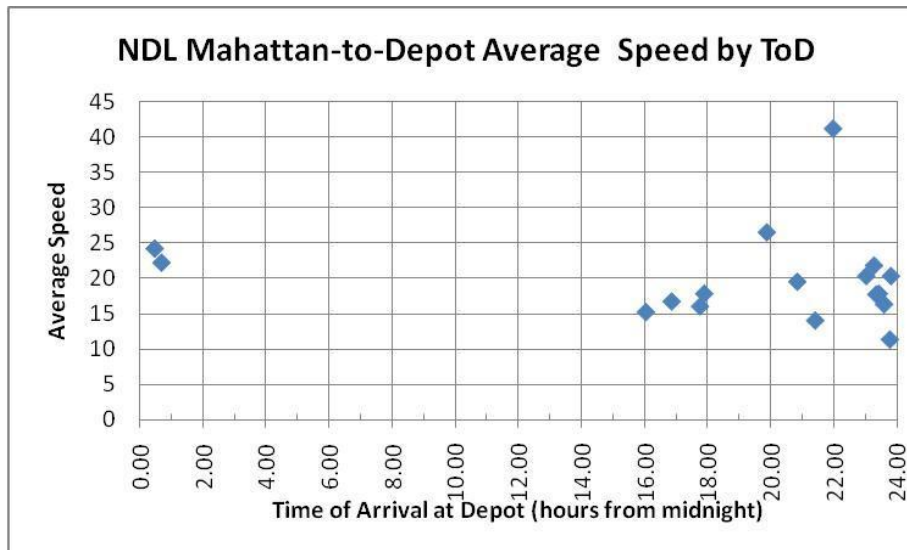
Figure 47: NDL Manhattan-to-Depot Average Speed by Time of Day

Figure 46 and Figure 47 are displays of the average speed experienced by NDL on the first and last segment of the tours serving Manhattan customers. As can be seen from Figure 46, the NDL tours departed the depot in only two time periods, between 8 AM and 11 AM and after 6 PM but before 10 PM. The late group served customers participating in the pilot test. One can readily see the substantially higher average speed achieved by the tours participating in the pilot test. They experienced a 50% increase in average speed on these first long tour segments. For the return segment, the variation in average speed is not as apparent and they are mostly in the off-hours.

6.3   Sysco Pilot Test

Sysco is a global leader in selling, marketing, and distributing food products to a wide variety of customers who prepare meals away from home. It has numerous distribution centers throughout North America. The depot that services customers in the New York metropolitan area, Sysco Metro New York, LLC, is located in Jersey City, NJ. Much of its operation utilizes class 6 box and combination trucks serving a sequence of geographically clustered clients in daily tours originating from and terminating at the Jersey City facility. Essentially all of its tours take place during normal business hours as that is when the customers have constrained their deliveries. Sysco has been operating one off-hour Manhattan tour, and is keen to expand its off-hour operations. The company agreed to collect and share remotely-sourced GPS position-time data for its fleet that serves the New York metropolitan area as part of the pre-pilot test from July 6, 2009, through August 6, 2009. Sysco also took part in a slightly expanded off-hour delivery service during the pilot test from December 1, 2009, through January 31, 2010.

6.3.1   Sysco's remotely-sensed GPS position-time data

Each of Sysco's trucks is equipped with a precision GPS unit as part of its XataNet asset tracking and fleet management system. This system captures, transmits, and archives truck locations every one or two minutes while the vehicle is in motion and every half hour while it is stationary. Time stamped locations are also captured when a vehicle arrives and departs locations. A sample of the raw archived data that was shared with the research team is presented in Table 12.

Table 12: A Snippet of the Sysco Remotely-sensed Position-time Data

Message #	VehicleID	Longitude	Latitude	Date-Time	Status	Speed	Heading
3074886	91228	40.751006	-73.986816	7/10/2009 8:39	1	27	45
3076738	91228	40.756005	-73.984396	7/10/2009 8:40	1	NULL	NULL
3076739	91228	40.757203	-73.988068	7/10/2009 8:42	1	NULL	NULL
3091550	91228	40.757203	-73.988068	7/10/2009 9:10	0	0	225
3110051	91228	40.757341	-73.987774	7/10/2009 9:40	0	0	225
3123174	91228	40.757315	-73.989073	7/10/2009 9:57	0	0	225
3123380	91228	40.758208	-73.990208	7/10/2009 9:58	0	NULL	NULL
3128275	91228	40.764518	-73.984838	7/10/2009 9:59	1	NULL	NULL
3128276	91228	40.767356	-73.979782	7/10/2009 10:01	1	NULL	NULL
3125435	91228	40.763621	-73.971772	7/10/2009 10:02	1	0	135
3147713	91228	40.763621	-73.971772	7/10/2009 10:33	0	0	135

The location data, longitude and latitude, were found to have a precision that was significantly better than 100 meters. In using any GPS data from Manhattan it must be recognized that Manhattan has an extremely harsh "urban canyon" environment. Substantial scatter can occur essentially anywhere, especially at the tunnel portals and on the streets where there is little set-back of the buildings, such as Wall Street, Madison Avenue in midtown, and cross streets such as 56th. Even with this adverse urban canyon environment, there is no indication through inspection of the geographical display of the data, as

are depicted in Figure 49 through Figure 52, which suggests that there are any significant location outliers with precision worse than 30 meters (100 feet).

6.3.1.1 *Computation of tour segment average speed*

Date-time was provided to a precision of seconds (seconds are contained in the actual data, though not displayed in Table 12). Instantaneous speed proved to be unreliable and was not used. Instead, a measure of "average speed" (distance divided by travel time) between "stops" (the depot or customer location) was computed and used as the measure of operational performance for each tour segment, where distance is the sum of the path distance between each pair of location points along the sequence of location data for any segment. The travel time is simply the difference in time between the data point designated as the "start" point and the one designated as the "stop" point for the route segment. The path distance was found using the CoPilot software to compute the most likely route actually taken between data points. Since the data points are so closely spaced it is unlikely that the driver traveled another path. There is high confidence that the computed distance is highly accurate, as is the travel time, and thus the computed "average speed" is deserving of its presentation in tenths of miles per hour.

What becomes most critical in the computation of the performance measure average speed is the proper identification of a vehicle's departure from and arrival to a customer/depot location. Since position data are recorded both when a vehicle is moving and when it is stopped, one needs to determine which point represents the transition and to not miss-identify being stopped in extreme congestion, as occurs at the approaches to the Hudson River crossings, as a customer location. Unfortunately, the vehicle "status" Boolean was not sufficiently reliable to be used exclusively as the determinant of the departure/arrival data points. It does provide the first indication; however, an algorithm was developed to check both previous and subsequent data points to determine if the transition occurred earlier or later. An arrival at a stop was shifted to the previous data point if the distance travel from that data point was less than 0.1 miles. Similarly, the arrival at a customer/depot could be moved forward in time if the subsequent data point was 2 minutes or less into the future and the distance between points was greater than 0.1 miles. The reverse was used to modify the departure from a customer/depot.

New stops were also triggered by a transition in the rate of the GPS position-time data. Due to the substantially different data rate moving versus stopped, order of 1 minute versus 10 minutes, transitions between these data rates were also used in the algorithm to identify departures and arrivals. To be added, the cluster of points contained between the new arrival and departure had to all be within a 0.1 mile radius and the time duration for the stop had to be greater than 0.1 hour (6 minutes). As can be seen from Figure 48, the median stop length is just under 1 hour and only outliers have customer stops of greater than 3 hours. It is suspected that some, if not all, of these outliers did involve undetected customer stops. Their absence does not negatively affect the assessment of the congestion experienced by the vehicles, except

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that, had they been observed, they would have contributed additional observations to the customer-to-customer average speed data set. Unfortunately, this logic has trouble discerning the difference between a stop and severe congestion as can exist at the mouth of the Hudson River crossings. Fortunately, Sysco has no customers near these locations so stops near those locations were collapsed. This method was used to break down the Sysco pre-pilot test data into 1,766 tours making 14,929 service stops at customer locations resulting in 16,695 tour segments.
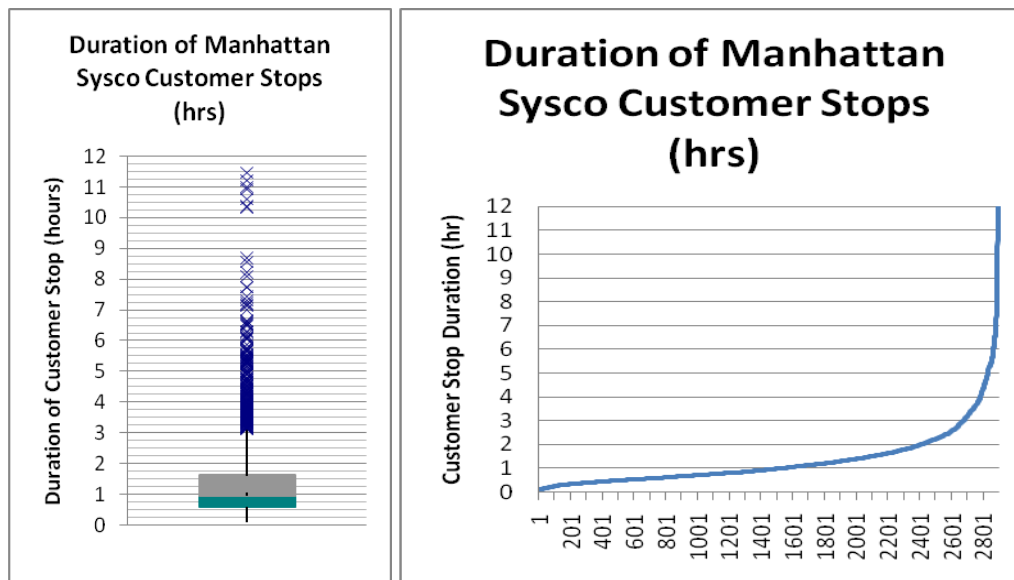
Figure 48: Box and Whisker and Sorted Order Graphs of Duration of Customer Stops

6.3.1.2   *Cartographic display of Sysco GPS remotely-sensed position data*

Figure 49 is a cartographic display of the remotely-sensed pre-pilot test GPS position data shared by Sysco with the research team. The data are color-coded by tour segment. As can be seen there is a lot of activity recorded in Manhattan as well as the surrounding area. Out of the 1,766 tours centered at Sysco's Jersey City depot, 471 serve Sysco customers in Manhattan. These tours consist of 2,613 customer-to-customer (c2c), depot-to-customer (d2c) and customer-to-depot (d2c) tour segments. The average speed attained by each of these tour segments comprise to characterize and quantify the congestion experienced by the goods movement industry in traveling to, through, and from Manhattan by time of day. One of those tour segments, from Sysco's depot in Jersey City to a customer location on the upper West Side, is shown in Figure 50. One can readily see that the physical location of the location data aligns well with what is the likely path of travel between the Sysco depot and the customer location. Also note the cluster of points near the entrance and exit of the Lincoln Tunnel. These could have been discerned as customer locations which were appropriately rejected by the stop insertion algorithm. Figure 51 is the display of data that is typical of shorter c2c segments in Manhattan. Once again, one can see that substantial scatter does not exist in this location. Figure 52 is the display of a long tour segment from Sysco's depot in

Jersey City to a customer location in Brooklyn. While these two points are very close in "as the crow flies" distance, the actual path taken by the driver is really the best way to get there. At the time of this trip, inbound commercial traffic was forbidden to use the Holland Tunnel. This restriction was recently rescinded for light duty commercial traffic but remains in force for combination (truck-tractor) class 6 and class 8 commercial vehicles which represent about half of Sysco's fleet.
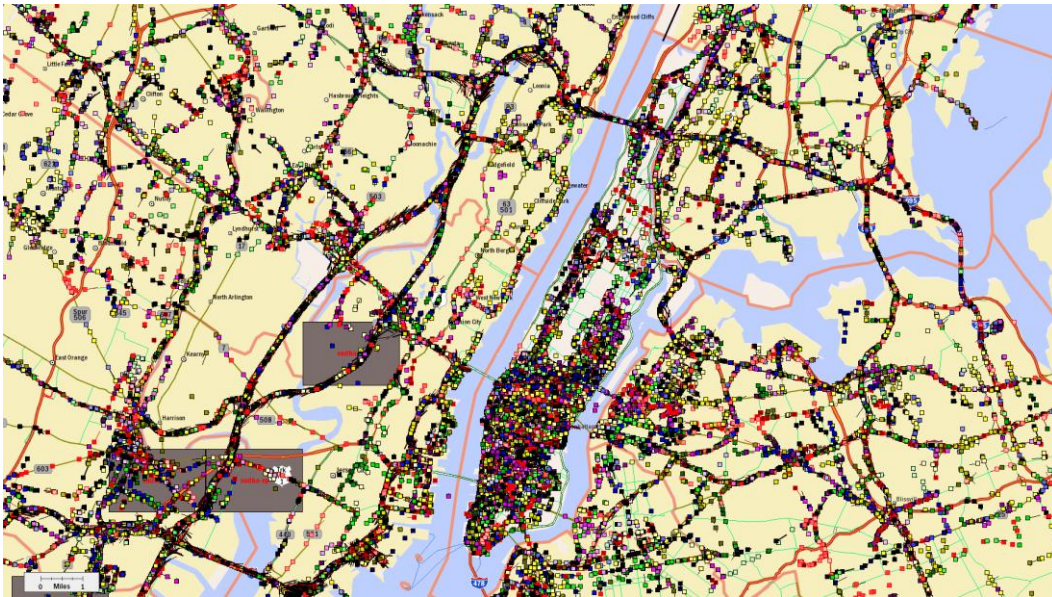
Figure 49: Sysco Tour Segments Contained in the Pre-Field Test Dataset
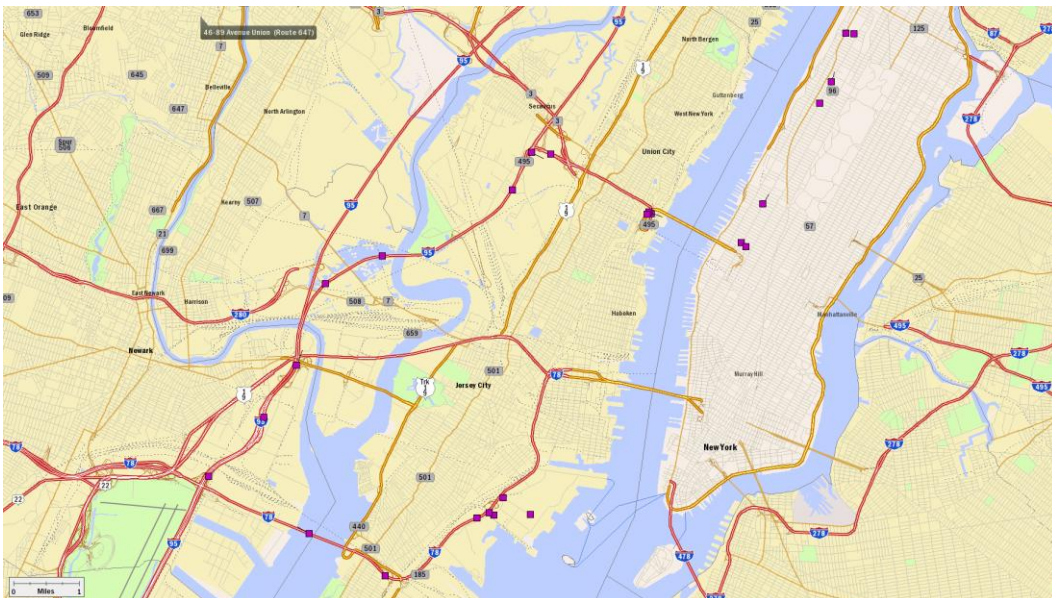
Figure 50: Sysco Tour Segment from Depot to an Upper West Side Customer
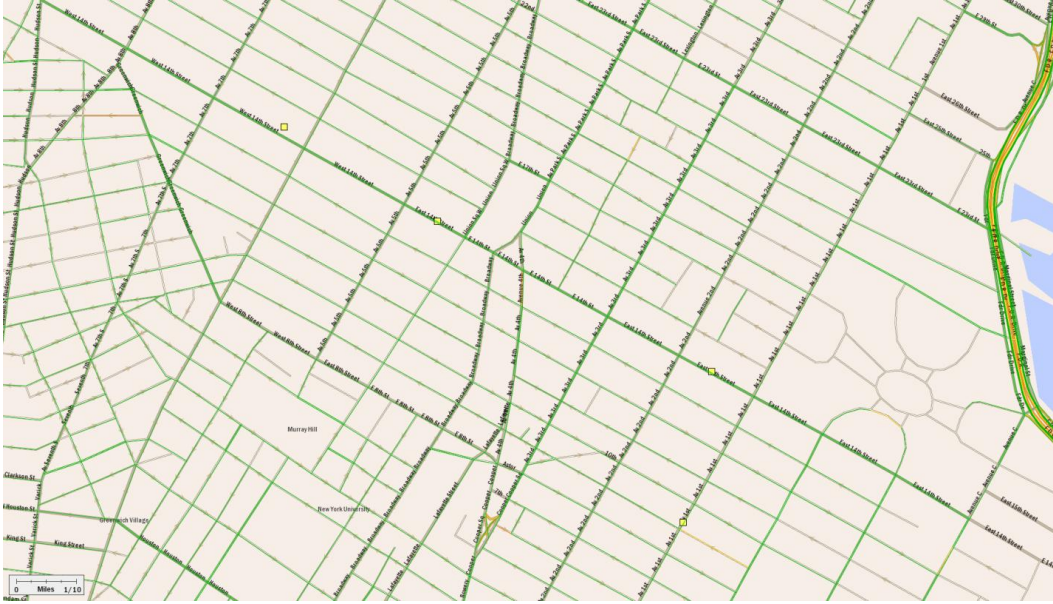
Figure 51: Sysco Manhattan Customer-to-Customer Route Segment
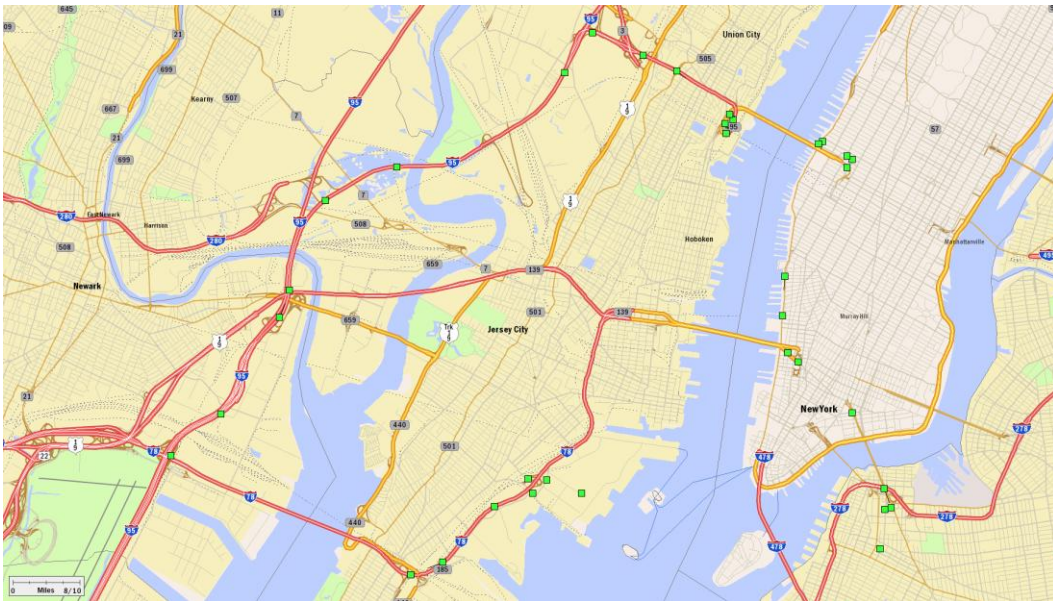
Figure 52: Sysco Depot to Brooklyn Customer Segment

6.3.2 Tour-specific data

The raw Sysco data (Table 12) were processed to produce individual tour and trip segment summaries as was discussed above. An example of the data produced is shown in Table 13. Each tour begins and ends at Sysco's depot in Jersey City, and consists of the individual tour segment between customer stops. Each customer stop is assigned a name of a nearby point to provide cognitive relevance to the locations while maintaining the privacy of the individual customer. Provided is the date and time of the ends of each segment. Summary data are assembled for each trip segment. These include: drive time, segment length, segment average speed (length/time in miles/hour), and the time spent serving the customer

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(T2NxTr). The T2NxTr for the last tour segment is actually the time the vehicle spends at the depot until it is placed into service again. (The value for the last tour for a particular truck should be disregarded because it is the meaningless time between the end of this tour and the first tour in the database for the next truck_ID.)

Table 13: Sample of Sysco Pre-field Test Tour Summary Data.

Veh_ID	Trip_ID	Observ	Origin City	State	Destination City	State	Origin Lon	Lat	Destination Lon	Lat	Origin Date	Time
69835	229	18	Jersey C	NJ	Rockefel	NY	-74064410	40703710	-73979741	40763266	90706	54000
69835	230	4	Rockefel	NY	Rockefel	NY	-73979969	40763146	-73976437	40763245	90706	91600
69835	231	4	Columb	NY	Columb	NY	-73981349	40766215	-73985681	40763655	90706	94500
69835	232	2	Rockefel	NY	Rockefel	NY	-73980539	40761175	-73980406	40762351	90706	102740
69835	233	9	Rockefel	NY	Times S	NY	-73981462	40763276	-73985469	40762065	90706	110739
69835	234	3	Times S	NY	Times S	NY	-73987886	40762286	-73991464	40762168	90706	120214
69835	235	16	Union C	NJ	Jersey C	NJ	-74024006	40765148	-74056000	40698813	90706	130400
69835	236	17	Jersey C	NJ	Rockefel	NY	-74063138	40703338	-73980294	40763495	90707	54200
69835	237	7	Times S	NY	Rockefel	NY	-73986148	40762401	-73980037	40762331	90707	111500
69835	238	24	Rockefel	NY	Jersey C	NJ	-73979766	40760143	-74056255	40698546	90707	131600
69835	239	19	Jersey C	NJ	Columb	NY	-74059465	40701468	-73985421	40763425	90708	54800
69835	240	2	Rockefel	NY	Rockefel	NY	-73975521	40760721	-73980396	40762873	90708	93100
69835	241	3	Rockefel	NY	Rockefel	NY	-73983639	40760988	-73982446	40761315	90708	123339
69835	242	20	Columb	NY	Jersey C	NJ	-73984624	40769941	-74056268	40698529	90708	135221

Trip_ID	Destination Date	Time	Hours	Miles	MPH	T2NxTr	FrMan	FrNJ	ToMan	toNJ	ToD
229	90706	60500	0.417	8.65	20.7	3.18	FALSE	1	TRUE	0	5
230	90706	92236	0.11	0.23	2.1	0.37	TRUE	0	TRUE	0	9
231	90706	95041	0.094	0.89	9.5	0.62	TRUE	0	TRUE	0	9
232	90706	102900	0.022	0.43	19.5	0.64	TRUE	0	TRUE	0	10
233	90706	112638	0.317	1.40	4.4	0.59	TRUE	0	TRUE	0	11
234	90706	123500	0.546	0.32	0.6	0.48	TRUE	0	TRUE	0	12
235	90706	133200	0.467	7.61	16.3	16.17	FALSE	1	FALSE	1	13
236	90707	60604	0.401	8.78	21.9	5.15	FALSE	1	TRUE	0	5
237	90707	112525	0.173	0.39	2.3	1.84	TRUE	0	TRUE	0	11
238	90707	135400	0.633	8.90	14.1	15.90	TRUE	0	FALSE	1	13
239	90708	61318	0.422	8.44	20	3.30	FALSE	1	TRUE	0	5
240	90708	93339	0.044	0.58	13.3	3.00	TRUE	0	TRUE	0	9
241	90708	123600	0.039	0.32	8.1	1.27	TRUE	0	TRUE	0	12
242	90708	142000	0.461	8.63	18.7	39.15	TRUE	0	FALSE	1	13

Traditionally, Manhattan customers have preferred to be served during normal business hours. This preference is reflected in Sysco's operational data. Figure 53 shows the depot departure time for each of the 438 tours serving a Manhattan customer in the pre-field trial remotely-sensed GPS location-time data set. These departures are sorted in time order showing the earliest departures on the left and moving across to the latest departures. As can be seen, only 50 departures occurred before 7 AM and most of this occurred prior to 6 AM, probably avoiding the major recurring congestion that exists in the approach to

the Lincoln Tunnel around 7 AM. Departure rates remain relatively constant from 7 AM through 9 AM when 70% of the departures occur. Less than 50 departures occur between 10 PM and 4 AM.
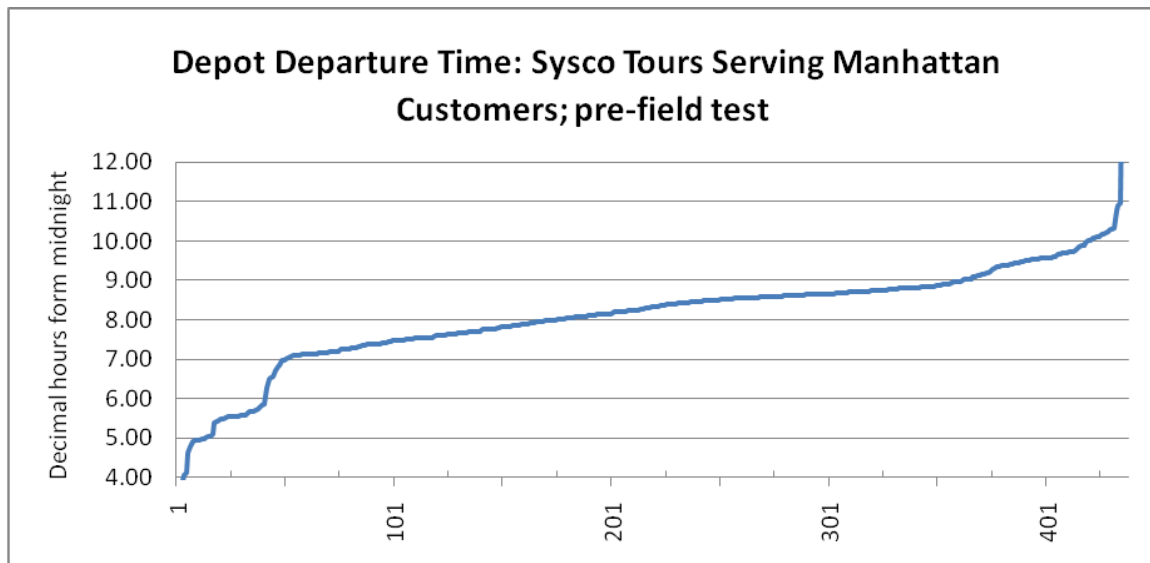
Figure 53: Depot Departure Time: Sysco Tours Serving Manhattan Customers

The return to the depot is more spread out over time as can be seen from Figure 54. Very few return before 1 PM and the highest rate of return occurs between 5 PM and 9 PM. Less than 20% of the tours return after 10 PM.
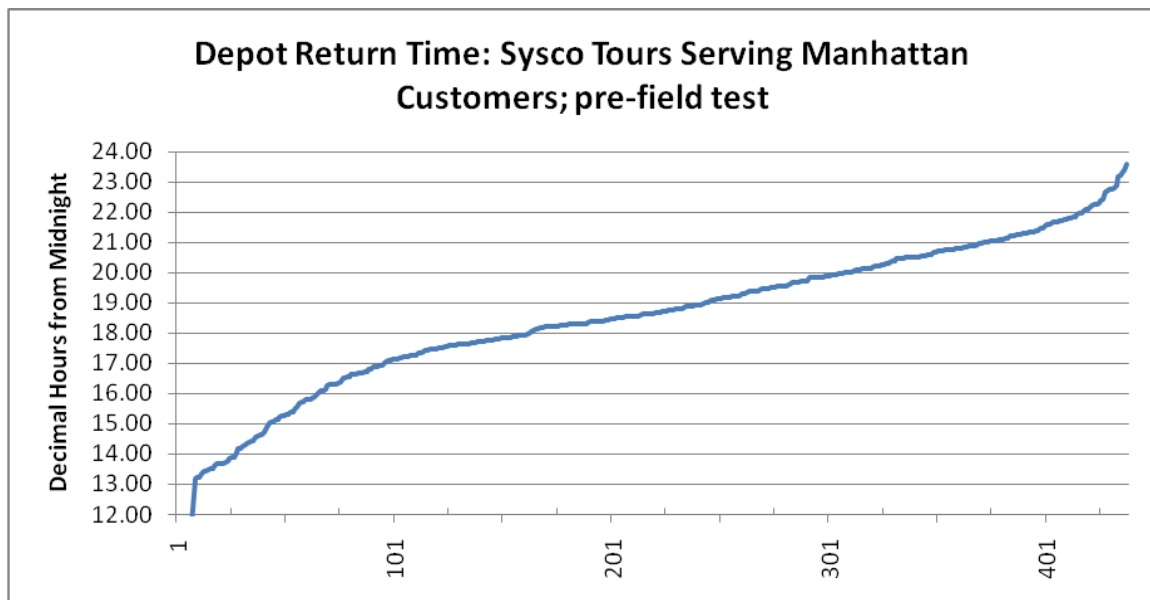
Figure 54: Depot Return Time: Sysco Tours Serving Manhattan Customers

6.3.2.1   Customers served per tour

Figure 55 characterizes the distribution of number of customers served per tour out of Sysco's Jersey City depot. The median value for the 1,766 tours is essentially 9 customers per tour, ranging from low outlier values of 1 and 2 customers to high outlier values of 15, 16, and 17. Seven to 10 customers are served by 50% of the tours. Baldor (a Whole Foods Market vendor to be discussed later) tours exhibited a very similar characteristic.
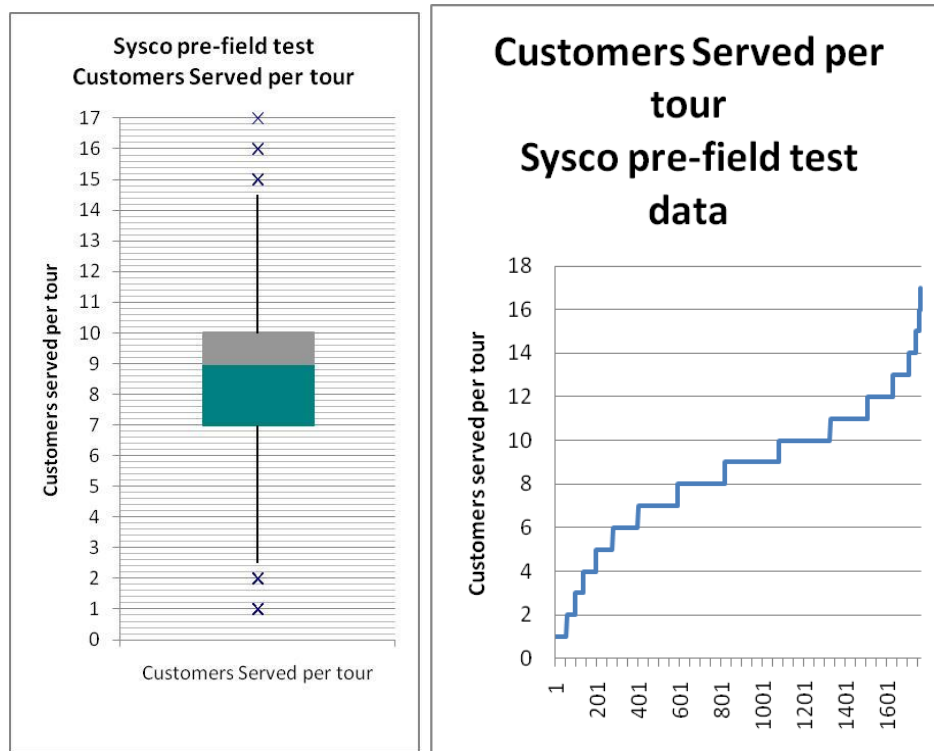
Figure 55: Distribution of Customers Served Per Tour in Sysco's GPS Data

6.3.2.2   Manhattan tour segment length characteristics

Sysco tours that serve Manhattan customers cluster into two distinct types: (1) those that are between customers that are both in Manhattan; and (2) those that are required to cross the Hudson River because one customer end or the depot is on the New Jersey side and the other end is in Manhattan. Each exhibits its own congestion-related performance characteristics that vary by time of day. Figure 56 characterizes the distribution of tour segment lengths by the type of segment, intra Manhattan or across the Hudson. As can be readily seen, intra Manhattan tour segments are very short with a median of only 0.5 miles while the segments that cross the Hudson are an order of magnitude longer. Those coming from the depot tend to have their first customer location in Manhattan while those that return to New Jersey tend to serve one or more customers in New Jersey as they finish their tours.

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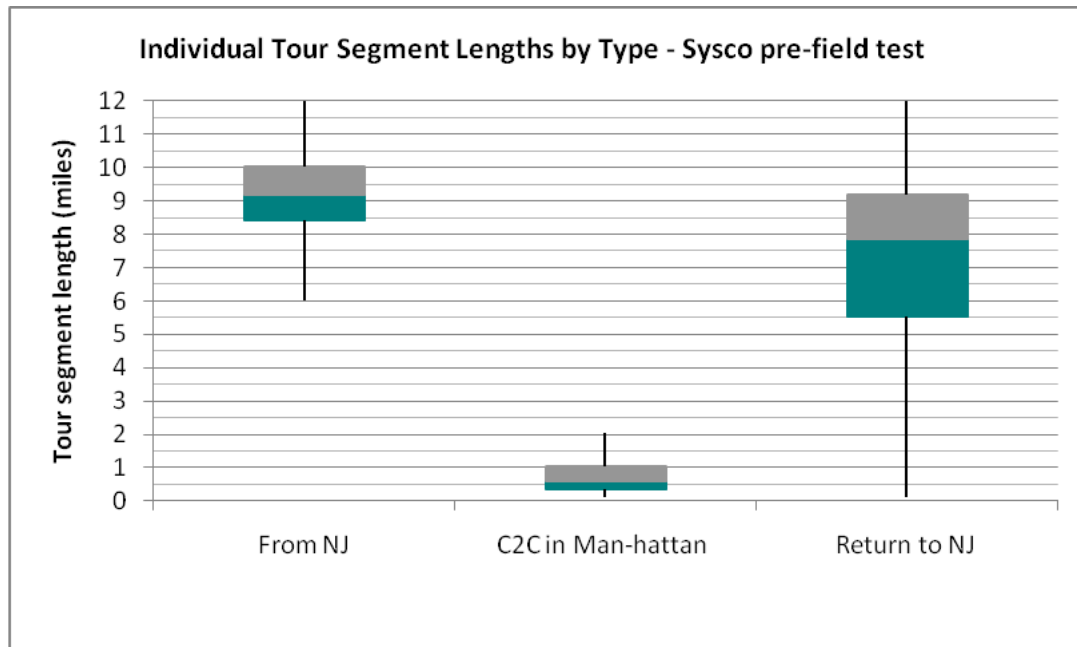
Figure 56: Distribution of Tour Segment Lengths by Segment Type

6.3.2.3 *Manhattan tour distance characteristics*

Figure 57 displays the characteristics of the length of the segments of Sysco pre-pilot test tours that serve customers in Manhattan. Sysco's operation, like that of Baldor and NDL, is such that Manhattan customers are served by tours that usually include only Manhattan customers. Rarely is a Manhattan customer served on a tour that also includes customers in New Jersey, the outer boroughs, Long Island, suburban New York counties or Connecticut. Thus these tours tend to be rather short, involving segments that go from and back to the home depot and between the 7 to 10 or so Manhattan customers that tend to be served during each tour. More than 75% of the tours are less than 30 miles in total length with a 3rd quartile tour length value of 26.55 miles. The median tour is less than 23 miles in total length (22.71 miles). The shortest is 11.56 miles and involves the service of only two customers in Mid-town. The total length distribution is very tight with the bulk of the tours being between 20 and 25 miles in length. Interestingly, the total tour length is roughly one-third derived from the first tour segment (depot-to-1st customer), one-third from the last tour segment (last customer-to-depot) and one-third from the travel between each customer. The distribution of these individual distances is also very tight. The long upper tail to the distribution is essentially always due to the "tacking on" of service to a non-Manhattan customer onto a tour serving Manhattan customers. Since Sysco does not have customers that are along the direct path from its Jersey City depot to the mouth of the Lincoln Tunnel, the addition of even a single non-Manhattan customer to a Manhattan route can considerably increase the tour length. Essentially each outlier can be attributed to the addition of a non-Manhattan customer to a Manhattan tour. Sometimes that customer is served first, thus, the larger outliers in first segment distances. Sometimes they are the last

served, thus the larger outliers in the last segment distances. Some of the outliers in the Manhattan c2c total distances are from those tours which have the outlier values of customers served; a very few may be from "urban canyon" bad GPS data.
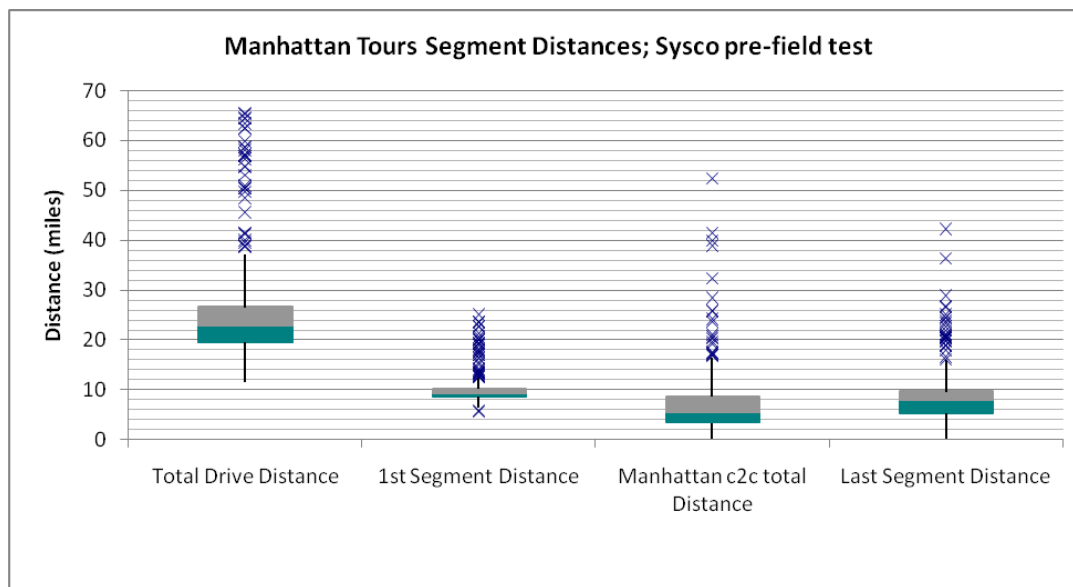
Figure 57: Manhattan Tour Distance Characteristics

6.3.2.4 *Manhattan tour duration characteristics*

Figure 58 displays the characteristics of the duration of Sysco pre-pilot test tours that serve customers in Manhattan. At the median, tours take 10.56 hours to complete with 25% of the tours requiring an additional 1.33 hours to complete. This is a full day's work for these drivers fully utilizing their government regulated daily hours of service. The duration of the tours is such that the drivers tend to work a 4-day 10+ hours per day work week rather than the traditional 5 day work week. Only 25% of the tours are shorter than 5.23 hours.

Since Sysco's depot is so close to Manhattan, with direct drive distances from the depot to the first Manhattan customer being typically under 10 miles, and the small geographic area of Manhattan, drive distances for an entire tour are typically total well under 30 miles. If it were not for congestion, drive time would be well under one hour; however, congestion typically adds at least another hour to the tour travel time. Median drive time experienced by Sysco trucks serving Manhattan during the pre-test was 2.06 hours. 25% of the tours experienced drive times greater than 2.5 hours of which more than two-thirds was wasted due to congestion accessing, egressing and moving from customer to customer in Manhattan. Of that excess time, typically half was encountered accessing and egressing and half was encountered travelling between customers.

With respect to total tour time, whose median duration was 10.56 hours, typically 80% was spent serving customers and 20% traveling to and from customers. As will be discussed later, the time required

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to serve Manhattan customers is much smaller during off-hour times suggesting that patron, pedestrian and curbside parking congestion substantially increases the time required for Sysco drivers to make their deliveries. Thus moving deliveries to uncongested off-hours can considerably improve driver productivity by not only decreasing the time required to get to and from customers but also the time to service those customers. Sysco's pre-pilot test remotely sensed tour duration data suggests that a tour that would require 10 hours to complete during normal business hours could be accomplished in as little as 8 hours if done in the overnight hours. Alternatively two additional customers could be served during a 10 hour overnight tour if physical truck capacities allowed for the additional volume of food products that would be required to serve the additional customers.

Manhattan Tour Duration Characteristics; Sysco pre-pilot test					
	Low Whisker	1st Quartile (1Q)	Median (M)	3rd Quartile (3Q)	High Whisker
Tour Duration	5.23	9.23	10.56	11.90	14.71
Customer Service	3.87	7.33	8.50	9.63	12.17
Total Drive Time	0.87	1.59	2.06	2.49	3.84
From Depot Drive Time	0.28	0.47	0.53	0.61	0.82
C2C Drive Time	0.00	0.60	0.98	1.39	2.56
To depot Drive Time	0.04	0.32	0.49	0.66	1.14

Figure 58: Manhattan Tour Duration Characteristics

6.3.2.5   *Manhattan tour average speed characteristics*

Tour average speed was computed as the ratio of total tour distance divided by total tour drive time. It is a single scalar that averages over what is typically a widely varying measure that can reach instantaneous values of over 50 mph on stretches of limited access highways, typically part of the first and last legs of the tour, but can be reduced to low single digits at the river crossings and on the streets of Manhattan. Also each tour involves many stops at traffic lights, stops signs, toll plazas, and while mired in severe traffic congestion. The tour average speed smoothes all that variation into a single scalar. The box and whisker graph in Figure 59 summarizes the distribution of this measure across all Sysco tours serving Manhattan. The average speed of the median tour is less than 11.5 mph. Only a few outliers achieve average speeds of greater than 19 mph and fully 25% of the tours average in the single digits. When viewed in sorted order, as is depicted in Figure 60, one sees how few of these tours were able to achieve average speeds in excess of 20 mph.

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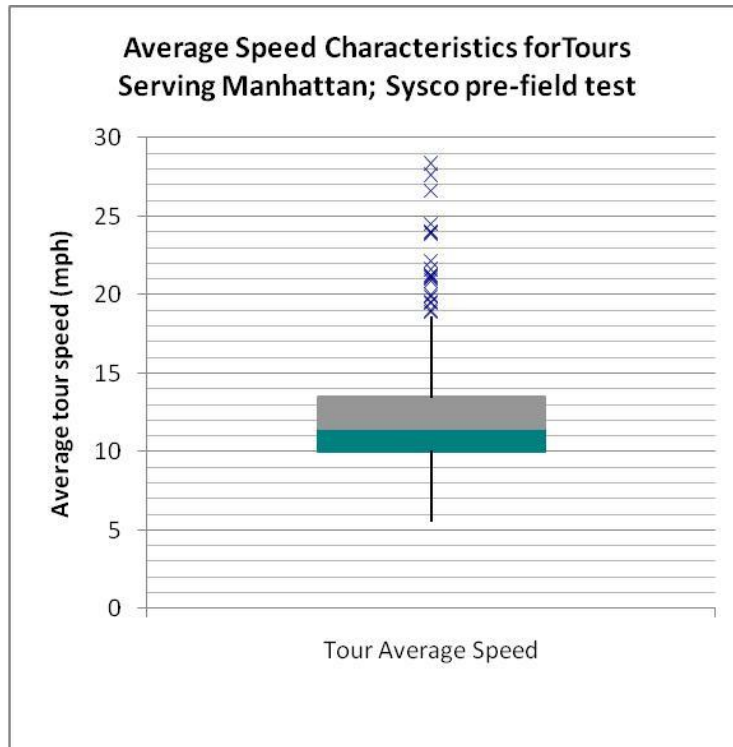
Figure 59: Average Speed Characteristics for Tours Serving Manhattan
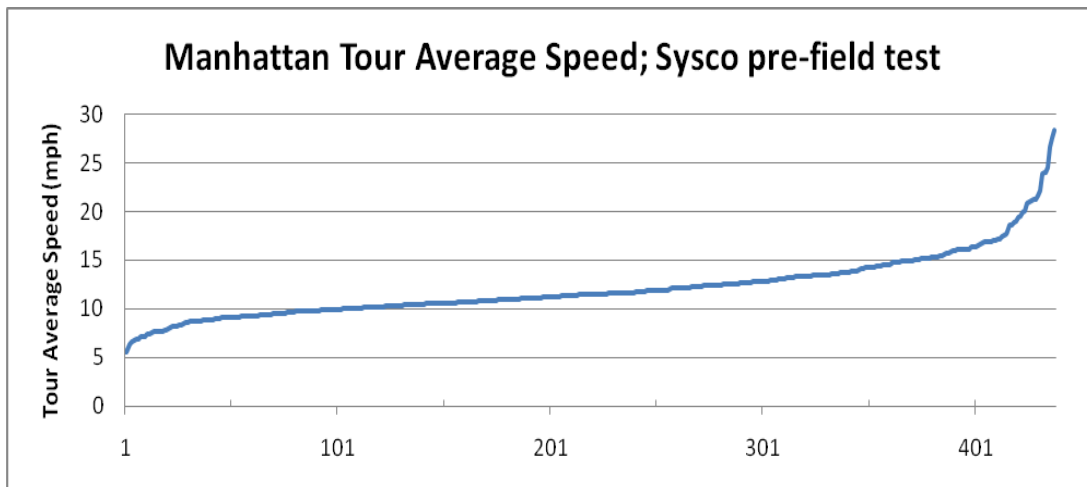
Figure 60: Manhattan Tour Average Speeds

6.3.3 Time-of-day (ToD) performance

The Sysco pre-pilot test has verified that, on average, tour average speeds are very low. This section focuses on quantifying time-of-day (ToD) correlations with not only the travel speed performance of the entire tour, but also the principle components of those tours: the first and last segments of those tours crossing the Hudson River and the customer-to-customer tour segments in Manhattan. For tours as a whole Sysco's pre-pilot test average speed data shows little variation with ToD as can be seen from Figure 61. Each point is a tour that served at least one Manhattan customer. Since most tour departures

occurred after 7 AM and before 10 AM, most tours operated in the same time period. They left the depot at about the same time, traveled over Manhattan streets at about the same time, and returned to the depot at about the same time. One can see that those tours that departed early tended to have lower tour average speeds. The few that departed very late had very low tour average speeds; however, those low speeds may be caused by other tour variations, such as specific customer locations or characteristics. In any event, they are so few in number that they cannot be relied upon to indicate a fundamental characteristic. What is noticeable from the graph is that few trips depart between 6 AM and 7 AM. This may be due to an operational consideration to avoid as much as possible known recurring congestion at the Lincoln Tunnel. Depending on Manhattan customer time window service requirements, some tours depart early to beat the congestion while others wait as long as possible for it to subside.
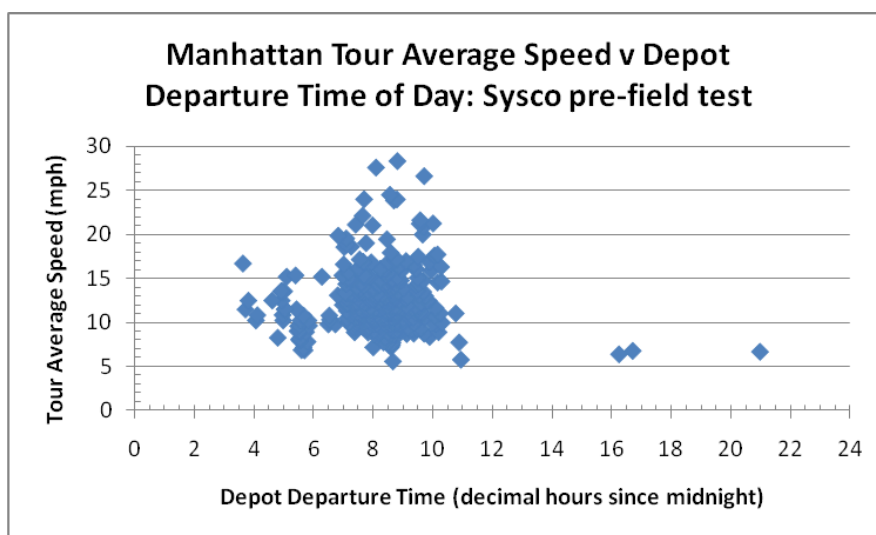
Figure 61: Manhattan Tour Average Speed versus Depot Departure ToD

Figure 62 presents the average speed achieved by Sysco drivers in going from c2c locations in Manhattan at different times of the day. Summarized in the box and whisker chart is data from 2,397 c2c tour segments in Manhattan. A multiplicity of specific c2c pair is represented. What they have in common is that they are all located in Manhattan. Each box and whisker summarizes the average speed of all segments starting in that hourly block. As can be seen, the distribution of average speeds in the early morning hours are substantially different than through the body of the day. Speeds decrease steadily through the morning hours and remain uniformly poor (median value less than 5 mph) through the afternoon and early evening hours. They remain poor and even further decay through 9 PM in the evening (median value less than 4 mph). Unfortunately, insufficient data exists in the Sysco pre-pilot test data set to characterize average speed between 10 PM and 5 AM.

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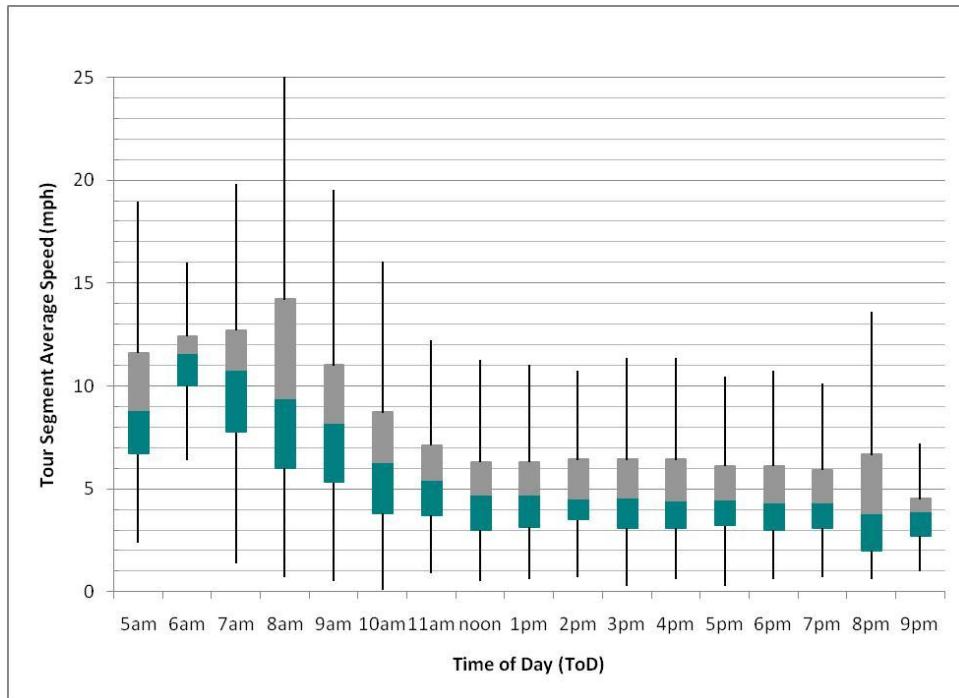
Figure 62: Intra-Manhattan Tour Segment Average Speed by Time of Day

Figure 63 presents the average speed achieved by Sysco in traveling from its Jersey City depot to its first customer in Manhattan. Summarized in the box and whisker chart is data from 458 eastbound crossings of the Hudson River, essentially all via the Lincoln Tunnel. The distributions are surprisingly similar across the morning hours.
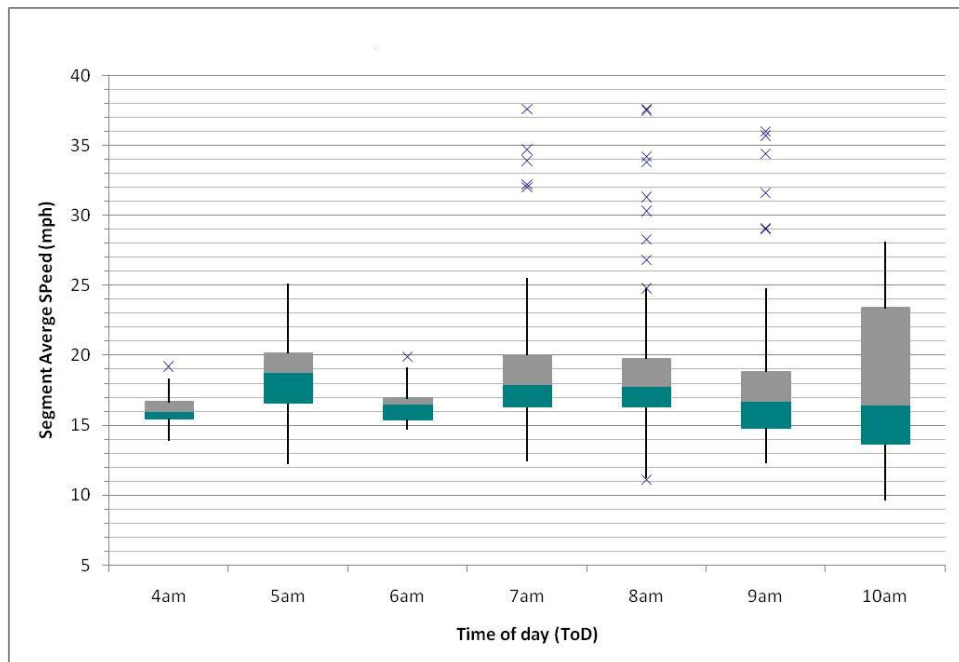
Figure 63: Segment Average Speed by ToD for Eastbound Crossings of the Hudson River

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Figure 64 presents the average speed achieved by Sysco in returning to its Jersey City depot from its last customer in Manhattan. Summarized in the box and whisker chart is data from 467 westbound crossings of the Hudson River, mostly via the Lincoln Tunnel, although a few did use the Holland Tunnel, which was permitted for some Sysco trucks at the time of the pre-pilot test.
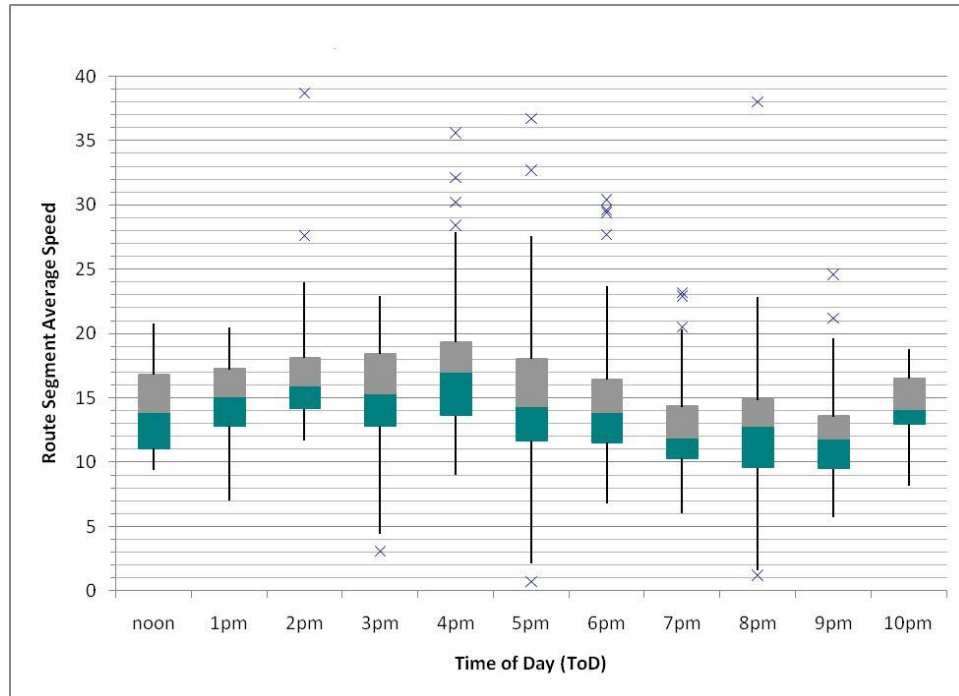
Figure 64: Segment Average Speed by ToD for Westbound Crossings of the Hudson River

6.4   *Whole Foods Market/Baldor Specialty Foods Pilot Test*

Baldor Specialty Foods is a food service company that specializes in the sourcing and distribution of specialty food items. Based in the Hunts Point Market, Bronx, NY, it distributes food products with 150 refrigerated box trucks to establishments between Boston and Philadelphia with a focus in the New York metropolitan area. As part of the pilot test it made off-hour early morning deliveries to Whole Foods Market stores in Manhattan. These deliveries were made as part of standard operational delivery tours involving other customers. These tours, encompassing deliveries to multiple establishments, depart and return to Baldor's depot at Hunts Point. They tend to be configured to fill a driver's work day rather than being constrained by the size of the truck, thus drive time is an active constraint on the productivity of the driver and the delivery fleet.

To quantify the effectiveness of off-hour deliveries Baldor made available to the research team remotely-sensed GPS position-time data for Baldor's truck making the early morning Whole Foods Market deliveries in Manhattan, as well as several other trucks serving other customers in the New York metropolitan area. Data were provided for the test which ran for two months from December 1, 2009, through January 30, 2010, for which data were available for 51 days. The nature of the business is such

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that, while there are many similarities—tours depart and return to Hunts Point, and the customers are all Manhattan—each day involves differences in the actual list of customers served, volumes to be delivered, and the ordered sequence of deliveries. However, what does emerge is that there are substantial quantifiable differences in performance at different times of the day.

6.4.1   The remotely-sensed GPS position-time data

Table 14 contains a snippet of the Baldor remotely-sensed GPS position-time data. Included is a unique identifier of a truck (Baldor tends to assign the same truck as well as the same driver to the same service area), date, time (local EST), GPS derived Latitude and Longitude, GPS derived Speed, and an attribute identifying the arrival and departure of the truck at a customer location. When the truck is moving, data are recorded every two minutes as well as at the time of arrival ("stop"), departure ("start") and ignition on/off. It was verified that the capture of the position-time data at customer arrival and departure was done reliably and consistently. When stopped at the depot or at a customer location, data are recorded much less frequently, typically every 45 minutes. Visual inspection of the geographic display of the position data, a representative example of which is contained in Figure 65, showed that the GPS derived position data was of high quality and contained no indication of adverse urban canyon effects. Points between stops aligned along feasible routes and exhibited no signs of significant scatter. Points intervening the arrival and departure from customer locations tended to be tightly clustered in the neighborhood of the arrival and departure locations with deviations of order of tens of meters. These deviations were deemed to be minor; thus, the conclusion that the GPS location data was of very high quality and more than commensurate with subsequent computations of travel distance and ultimately average speeds that were accurate to of order 0.1 mph.

While a value of speed is provided in the data, it was not used in the analysis. Instantaneous speed varies greatly during any trip. Not only does each start and stop from rest, but generally has many intermediate stops of varying duration for traffic control, and congestion. An accurate characterization of the average of such a wildly varying function would require a high data rate. A data rate of every two minutes is simply not sufficient to properly characterize the average speed of urban tour segments that are typically less than a few miles in length.

Table 14: Sample of Baldor Remotely-sense GPS Position-time Data

TruckID	Date	Local Time	Baldor Location Reference	City	St	Speed (mph)	Longitude	Latitude	Vehicle Status
1120	1/2/2010	4:14:19	BALDOR FCD	Bronx	NY	0	40.8097224	-73.8734841	Ign on
1120	1/2/2010	4:14:55	BALDOR FCD	Bronx	NY	2	40.8097224	-73.8734841	Start
1120	1/2/2010	4:16:55	TEAMSTERS LOCAL 202	Bronx	NY	0	40.8127932	-73.8811312	Moving
1120	1/2/2010	4:18:55	SNOW FRESH	Bronx	NY	42	40.8118407	-73.8886139	Moving
1120	1/2/2010	4:20:55	1056 Leggett Ave	Bronx	NY	0	40.8129731	-73.8977703	Moving
1120	1/2/2010	4:22:55	407 Bruckner Blvd	Bronx	NY	40	40.8080417	-73.9054737	Moving
1120	1/2/2010	4:24:55	134 Bruckner Blvd	Bronx	NY	31	40.8040029	-73.9206641	Moving
1120	1/2/2010	4:26:55	232 E 128th St	New York	NY	34	40.8053903	-73.933657	Moving
1120	1/2/2010	4:28:55	142 E 125th St	New York	NY	9	40.8043631	-73.9373676	Moving
1120	1/2/2010	4:30:55	1783 Lexington Ave	New York	NY	20	40.7951774	-73.9441796	Moving
1120	1/2/2010	4:32:55	1439 Lexington Ave	New York	NY	27	40.7844038	-73.9520606	Moving
1120	1/2/2010	4:34:55	1073 Lexington Ave	New York	NY	27	40.7729431	-73.9604192	Moving
1120	1/2/2010	4:36:55	727 Lexington Ave	New York	NY	27	40.7617576	-73.9685822	Moving
1120	1/2/2010	4:38:55	279 Lexington Ave	New York	NY	31	40.7478951	-73.9786505	Moving
1120	1/2/2010	4:40:55	146 E 33rd St	New York	NY	13	40.7456937	-73.9800413	Moving
1120	1/2/2010	4:42:55	166 E 23rd St	New York	NY	0	40.7391655	-73.9839234	Moving
1120	1/2/2010	4:44:55	168 E 17th St	New York	NY	11	40.7355154	-73.9864261	Moving
1120	1/2/2010	4:46:55	20 Union Sq E	New York	NY	2	40.7361058	-73.9894047	Moving
1120	1/2/2010	4:48:55	WHOLE FOODS UNION SQ	New York	NY	0	40.7346378	-73.9919725	Moving
1120	1/2/2010	4:50:43	WHOLE FOODS UNION SQ	New York	NY	0	40.7346378	-73.9919725	Stopped
1120	1/2/2010	4:51:13	WHOLE FOODS UNION SQ	New York	NY	0	40.7346378	-73.9919725	Idling
1120	1/2/2010	5:00:25	WHOLE FOODS UNION SQ	New York	NY	0	40.7346378	-73.9919725	Start
1120	1/2/2010	5:02:25	240 E 14th St	New York	NY	11	40.7330651	-73.9862161	Moving
1120	1/2/2010	5:04:17	307 E 12th St	New York	NY	0	40.7309281	-73.9857793	Ign off
1120	1/2/2010	5:04:18	307 E 12th St	New York	NY	0	40.7309281	-73.9857793	Stopped
1120	1/2/2010	5:24:37	307 E 12th St	New York	NY	0	40.7309281	-73.9857793	Ign on
1120	1/2/2010	5:25:39	307 E 12th St	New York	NY	0	40.7309281	-73.9857793	Start
1120	1/2/2010	5:26:11	222 1st Ave	New York	NY	0	40.7309259	-73.9829567	Ign off
1120	1/2/2010	5:26:12	222 1st Ave	New York	NY	0	40.7309259	-73.9829567	Stopped
1120	1/2/2010	5:38:23	222 1st Ave	New York	NY	0	40.7309259	-73.9829567	Ign on
1120	1/2/2010	5:39:46	222 1st Ave	New York	NY	13	40.7309259	-73.9829567	Start

Fortunately, the data do contain an accurate and reliable location and time for the start and end of each tour segment. Drivers are trained to reliably signify the departure from and arrival at each customer location by a simple tap for which the vehicle information system logs a GPS location and time message to the data stream. As a backup, the system automatically logs a GPS position and time message when the ignition is turned on and off. As a final check, the distance between each time sequenced data point is computed algorithmically. Ultimately, customer arrival and departure locations and times are selected

from the cluster of time sequenced points for which: (1) the distance between sequenced points is less 0.1 miles; (2) one point has a vehicle status of "Start" and one with "Stopped"; and/or (3) one point has a vehicle status of "Ignition off" and one with "Ignition on". The earliest member of this cluster is deemed the arrival location and time to the target customer. The latest is deemed the departure location and time.

An "average" c2c speed is computed for each tour segment as the ratio of computed distance traveled between the departure location of the previous customer to the arrival location at the current customer divided by measured travel time. The distance is computed as the sum of the "great circle" distance between each of the time-sequenced intermediate locations available for that tour segment. The measured travel time is simply the difference in the date/time of the arrival record and the departure record for the previous customer. The slight underestimation of actual travel distance that can occur on trips that may actually zigzag between recorded locations was deemed to be of insufficient significance to require that distance be computed by the substantially more computationally intensive "sum of over the street network path distances" between the intermediate locations. Differences in computed path distance from sum of great circle distances was found to be consistently less than 3% for a random sample of route segments. An average speed was also computed for each tour's first and last segments, from the depot to the first customer and from the last customer back to the depot.

Figure 65: Cartographic Display of Baldor Vehicle Position Data

6.4.2 Tour specific data

The raw Baldor data (Table 14) were processed to produce individual tour and trip segment summaries and to prepare the data for graphical display. An example of the data produced is Table 15. Each tour begins and ends at the depot, Hunts Point, and consists of the individual tour segment between customer stops. Each customer stop is assigned a name of a nearby point to provide cognitive relevance to the locations while maintaining the privacy of the individual customer. Provided is the date and time of the ends of each segment. Summary data are assembled for each trip segment. These include drive time, segment length, segment average speed (length/time in miles/hour), and the time spent serving the customer (Time2NxtTrp).

Table 15: Sample Baldor Tour Data

Veh ID	Trip ID	Note	Tour	Int Obs	Orig Dest ---- ---- City State City State	Orig Dest ---- ---- Lon Lat Lon Lat
931	1	Start	1	12	HUNTS POINT NY Floral Park NY	-73875446 40809374 -73756081 40749209
931	2		1	19	Horace Harding NY Brentwood NY	-73754278 40749730 -73265081 40806290
931	3		1	11	Brentwood NY Centereach NY	-73265081 40806290 -73132603 40863912
931	4		1	14	Centereach NY Commack NY	-73132603 40863912 -73308586 40841647
931	5		1	14	Commack NY Holbrook NY	-73308586 40841647 -73092795 40788489
931	6		1	2	Holbrook NY Holbrook NY	-73092795 40788489 -73096081 40789880
931	7		1	12	Holbrook NY Central Islip NY	-73096081 40789880 -73185015 40811048
931	8		1	18	Central Islip NY Huntington Station NY	-73184042 40811036 -73417551 40886568
931	9		1	5	Huntington Station NY Huntington NY	-73417551 40886568 -73426203 40870260
931	10		1	9	Huntington NY Northport NY	-73426203 40870260 -73360908 40900766
931	11		1	13	Northport NY Huntington Station NY	-73360908 40900766 -73411978 40827874
931	12	End	1	35	Huntington Station NY HUNTS POINT NY	-73411978 40827874 -73873580 40809790

Veh ID	Trip ID	Note	Tour	Int Obs	Orig ---- Date	Orig Time	Dest Date	Dest ---- Time	Hours	Miles	MPH	Time2 NxtTrp	Seg
931	1	Start	1	12	20091201	60741	20091201	62752	0.34	11.85	35.2	0.128	1
931	2		1	19	20091201	63533	20091201	70944	0.57	26.96	47.3	0.556	2
931	3		1	11	20091201	74306	20091201	80218	0.32	8.48	26.5	0.787	3
931	4		1	14	20091201	84930	20091201	91442	0.42	9.46	22.5	0.405	4
931	5		1	14	20091201	93901	20091201	100329	0.41	12.58	30.9	0.242	5
931	6		1	2	20091201	101801	20091201	101918	0.02	0.20	9.1	0.135	6
931	7		1	12	20091201	102724	20091201	104740	0.34	5.86	17.3	0.473	7
931	8		1	18	20091201	111603	20091201	114811	0.54	14.72	27.5	0.472	8
931	9		1	5	20091201	121629	20091201	122313	0.11	1.23	10.9	0.407	9
931	10		1	9	20091201	124739	20091201	130303	0.26	4.49	17.5	0.424	10
931	11		1	13	20091201	132829	20091201	135202	0.39	7.15	18.2	0.241	11
931	12	End	1	35	20091201	140629	20091201	151341	1.12	34.40	30.7	0.343	12

A graphic display of the data for 51 daily Baldor tours serving lower Manhattan customers is presented in Figure 66. The data covers December 1, 2009, through January 31, 2010. Each color in the figure is a tour. One can see from the display that indeed there is relatively little urban canyon scatter in the data and that the avenues are used to get from the home depot in Hunts Point to the customer locations and then return. The customer locations are scattered throughout Manhattan south of Central Park.

Individual tours are summarized and characterized by the following attributes: trip departure date and time, number of customer stops, tour length (sum of the trip segment lengths), tour duration, drive duration, stop duration, and average drive speed (tour length/drive duration). Cartographic display of a sample of typical tours from the set of 51 Baldor Manhattan pilot test tours are presented in Figure 67 through Figure 70.

Figure 67 is a Baldor Manhattan tour on December 16, 2009, departing at 4:33:26, returning 8.05 hours later after serving 10 customers requiring 6.14 hours. Drive time to the first customer required 0.637 hours at an average speed of 15.0 mph, and c2c speeds averaged 5 mph. Figure 68 is a Baldor Manhattan tour on December 18, 2009, departing at 4:32:07, returning 9.45 hours later after serving seven customers requiring 6.96 hours. Drive time to the first customer required 0.635 hours at an average speed of 15.2 mph, and c2c speeds averaged 5.9 mph. Figure 69 is a Baldor Manhattan tour on January 13, 2010, departing at 4:44:16, returning 7.59 hours later after serving 10 customers requiring 4.43 hours. Drive time to the first customer required 0.577 hours at an average speed of 16.0 mph, and c2c speeds averaged 4.5 mph. Figure 70 is a Baldor Manhattan tour on January 26, 2010, departing at 4:38:25, returning 7.98 hours later after serving 9 customers requiring 5.24 hours. Drive time to the first customer required 0.626 hours at an average speed of 15.2 mph, and c2c speeds averaged 7.72 mph.

While the tours are very similar in that they all serve a cluster of customers located primarily south of 42nd Street in Manhattan, and all but two departed the Hunts Point depot in the 4 AM hour of the morning (those two departed early in the 5 AM hour), they differ in their details, number of customers served, exact sequence of customers served—although the Whole Foods Market stores were served first—and the congestion experienced by each of the tour segments as represented by each segments average speed. Figure 71 through Figure 75, along with their corresponding tables, present the statistics of these variations in the form of standard box and whisker graphs.

Figure 66: Display of Location Data of 51 Daily Baldor Tours

Figure 67: Baldor Manhattan Tour on December 16, 2009

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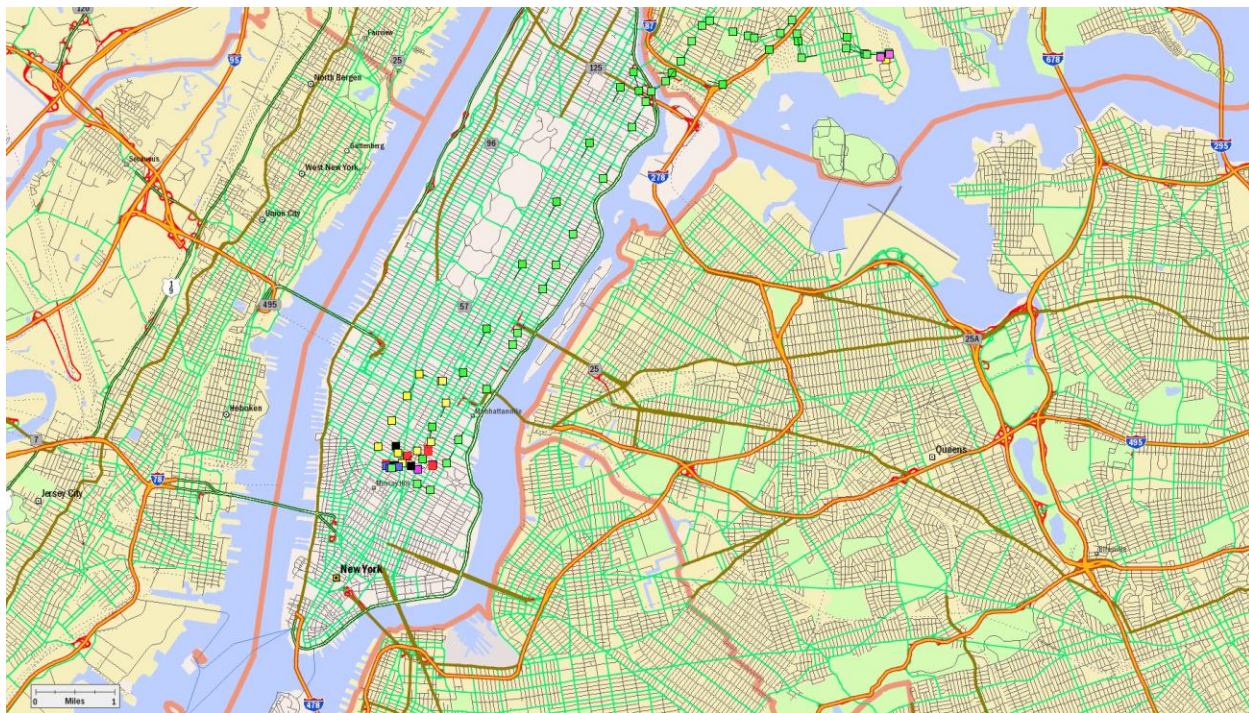
Figure 68: Baldor Manhattan Tour on December 18, 2009
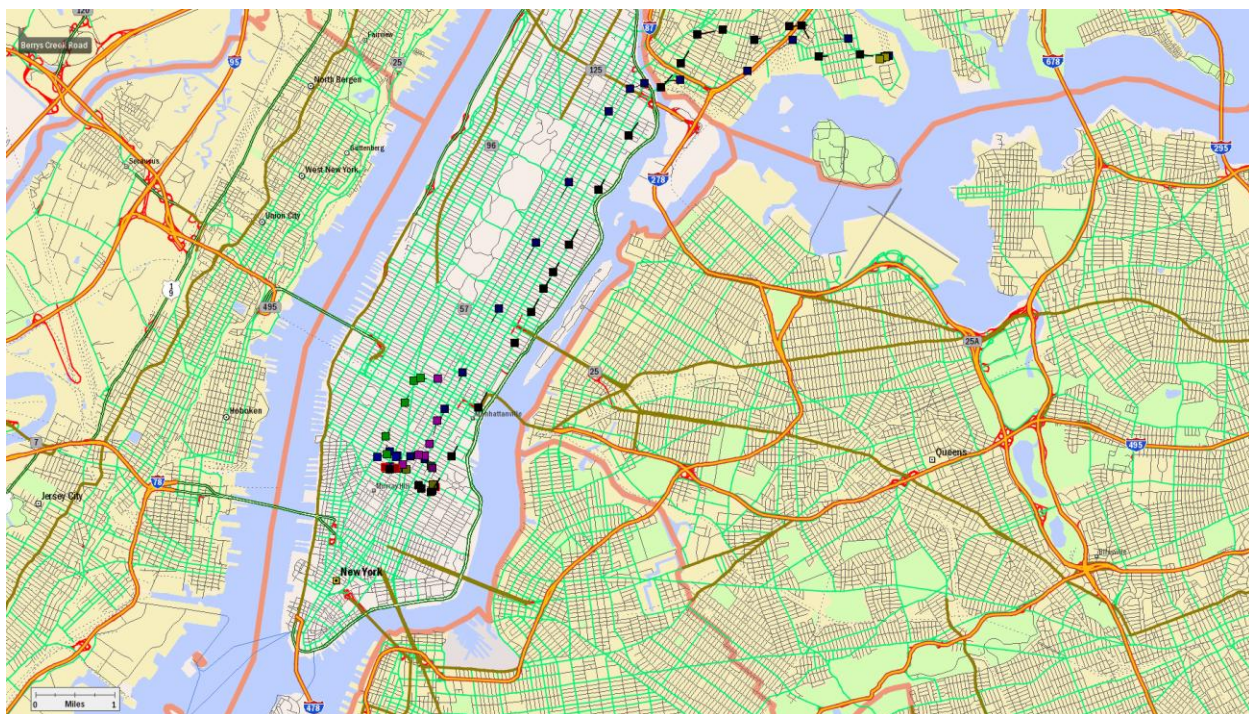
Figure 69: Baldor Manhattan Tour on January 13, 2010

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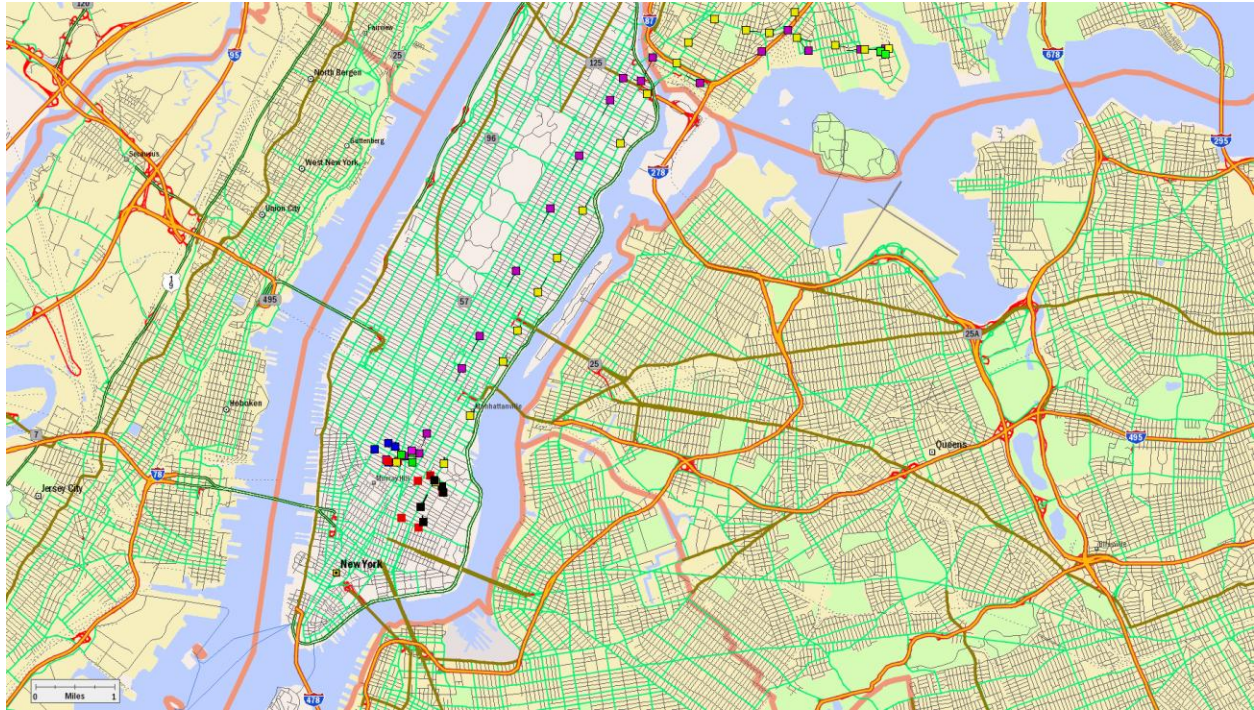
Figure 70: Baldor Manhattan Tour on January 26, 2010
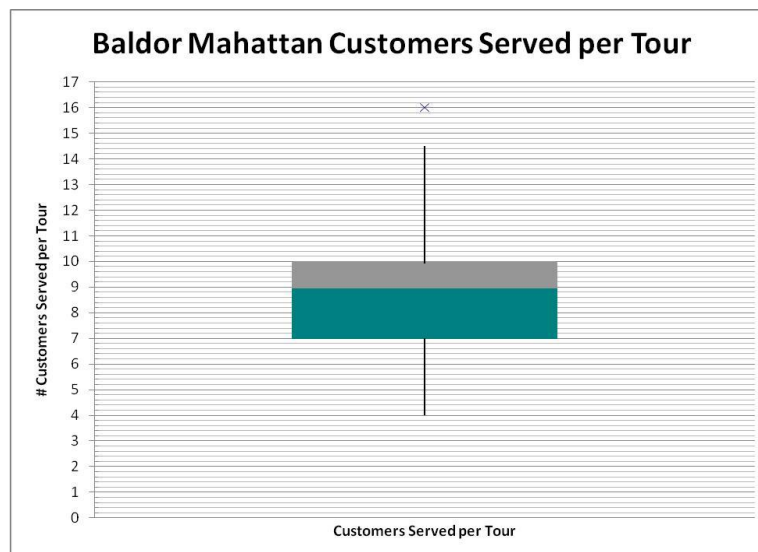
Figure 71: Baldor Manhattan Customers Served Per Tour

Variations exist in each of the individual trip segments that comprise the tours. Individual trips are classified in two types: (1) the trip segments between stops; and (2) the two trip segments involving the home depot, the initial and final trip segments. The latter tend to be substantially longer than segments between stops, and they tend to be traversed over major roadways while much of the between customer segments tend to be on more local roads.

6.4.2.1 *Manhattan tour segment length characteristics*

Figure 72 highlights the disparity in segment tour lengths between the first and last segments going from and returning to the depot in the Bronx and the segments going between customer locations in Manhattan. The Manhattan customers are all well-clustered and tend to be less than a half a mile apart, while the distance traveled is almost 20 times greater when going to and from the cluster of customers. Median values are almost 10 miles (9.3 for the first segment and 9.2 miles for the last segment).
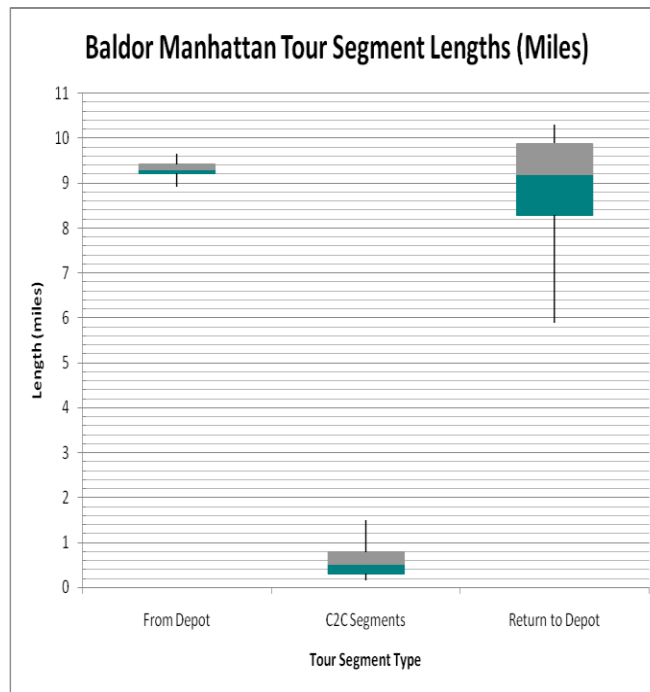
Figure 72: Baldor Manhattan Individual Tour Segment Lengths

Baldor Manhattan tours tend to be a full day's work for the drivers. Figure 73 presents the statistics on how that day's work is distributed among the primary elements of each tour. The left most box and whisker summarizes the duration of the entire tour. As can be seen the median tour is almost exactly 8 hours (8.053 hours) and most tours are within a very narrow band of 8 hours in duration. No tour is shorter than 7 hours and the high whisker extends only to 9.5 hours. Typically about two-thirds of this time is spent serving the individual customers and one-third is spent traveling between tour stops. Of that travel about half is spent getting to the first customer and from the last customer, and half is spent travelling between customers. Combining the information contained in Figure 73 with that contained in Figure 71 describing the distribution in the number of customers served per tour, the average customer requires approximately a half hour to be served.

6.4.3 Time-of-day tour performance analysis

The most important analysis of the Baldor data is the ToD tour performance analysis. The objective was to quantify consistent performance variations, if any, for tours serving customers at different times of

the day. A "perfect" experiment would have had Baldor replicated the exact same tour each day but departing at different times throughout a day and repeating this experiment on many days. Unfortunately, Baldor has a business to run and such an experiment is out of the realm of possibilities. A slightly less perfect experiment would have had Baldor replicating the exact same tour departing at different times on different days. This experiment is closer to operational feasibility; however, while there are many similarities in day-to-day operations to serve customer demands, there are some differences that preclude each operation from being repeatable. More importantly, tours are an ensemble of segments that vary day-to-day, and one is really interested in the expected relative ToD performance of each of the segments. The performance of the segments at different times could then be assembled to assess the performance of the entire tour. Finally, segments are specific location pairs of which there are many; however, the customer pairs are of similar length (shorter) and between traffic-similar locations in Manhattan. The first and last segments, from the Hunts Point depot to the first customer location and the from the last customer location back to the depot, are also of similar length (longer) and involve a location whose traffic characteristics differ from those in Manhattan. Thus, segments were clustered into two groups: (1) the from/to Depot (f/tD) segments; and (2) the customer-to-customer (c2c) segments. The Baldor data was used to characterize the variation in the performance of each of these two types of segments by ToD.
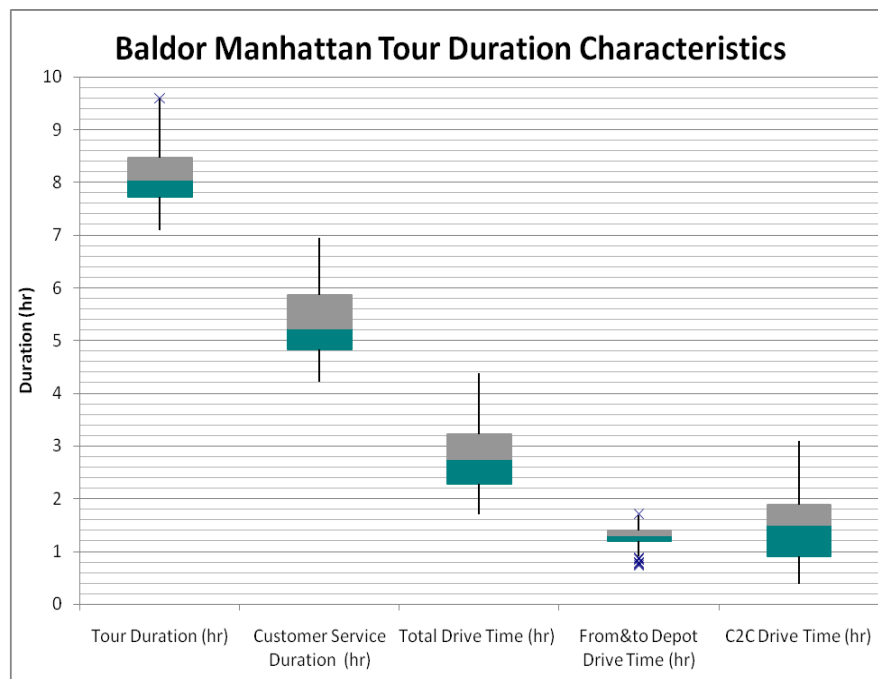
Figure 73: Baldor Manhattan Tour Duration Characteristics

6.4.3.1   *From/to depot (f/tD) time-of-day (ToD) performance*

The from and to depot tour segments are characterized by relatively long north-south segments as shown in Figure 66. Much of the length of these segments takes place on Manhattan's one-way avenues

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on which traffic tends to move faster than on cross-town streets. Their length distribution is shown in Figure 72 and is about 20 times the length of c2c segments. The speed by which these are travelled varies by time of day as can be seen in Figure 74. Attained average speeds in the very early morning departures prior to 6 AM are substantially faster than those attained during the morning or early afternoon.
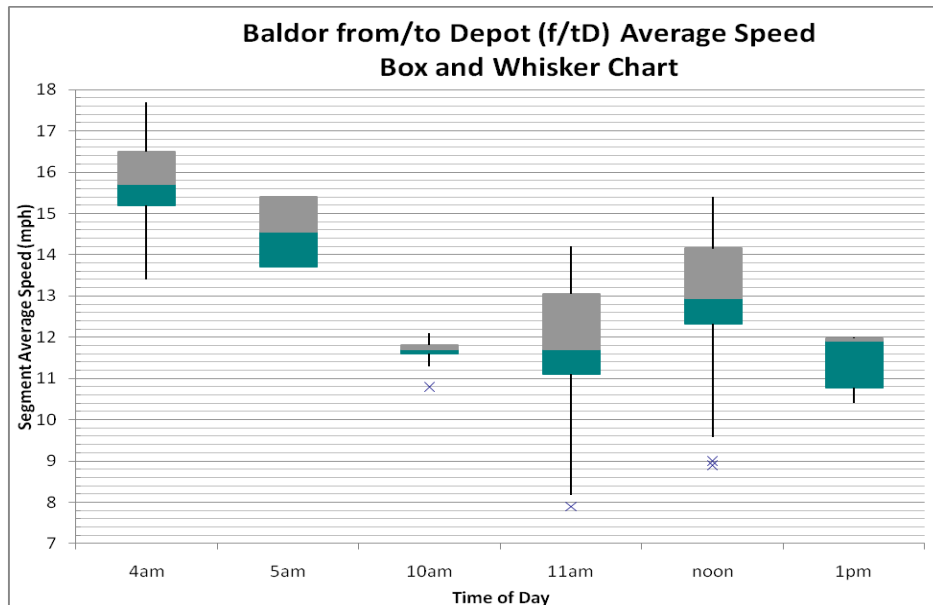
Figure 74: Baldor from/to Depot Average Speed by Time of Day

6.4.3.2   *Manhattan customer-to-customer, time-of-day performance*

Figure 75 presents the statistics for average speed attained in travelling between Manhattan customers. The data indicates that even in the early morning hours average speeds are very low averaging about 6 to 7 miles per hour and were not substantially faster in the early morning hours. The 4 AM data point is significantly higher, but unfortunately not a lot of data points underpin that value.
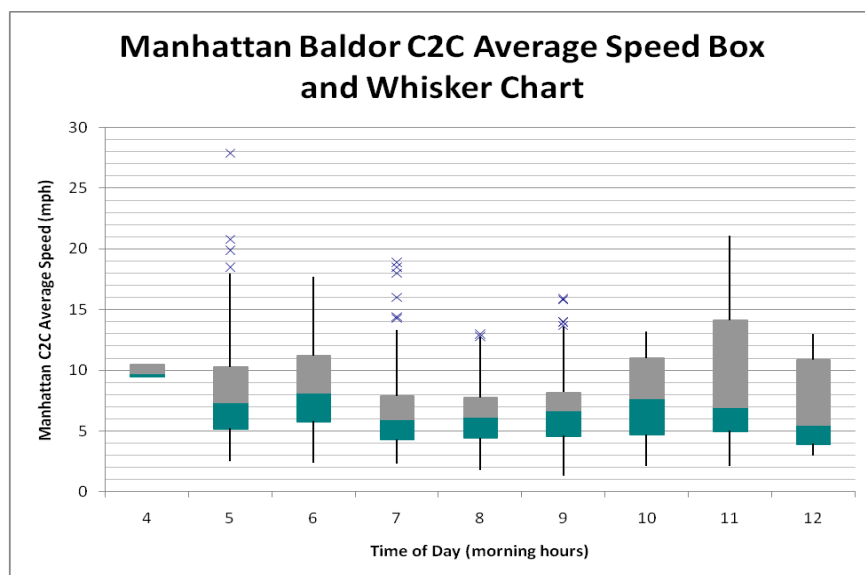
Figure 75: Baldor Manhattan C2C Average Speed by Time of Day

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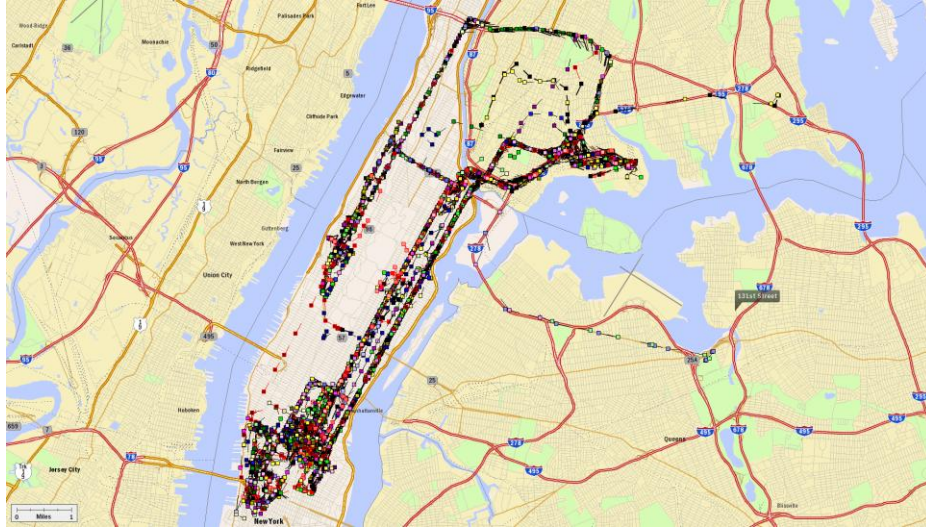
Figure 76: Pre-Field Test Baldor Vehicle Location-Time Data

6.5   *Overall Results: Analysis of Pooled Data*

The data for each group of the pilot test were initially analyzed individually. It was found that the individual data files were not large enough to provide a comprehensive look at the time of day variations. For that reason, the data were pooled for the purposes of the final analyses which are discussed here.

Figure 77 below presents the distributions of travel speeds between Manhattan customers during different hours of the day. AverageSpeed is simply the ratio of actual travel distance and actual travel time between consecutive Manhattan customers (i,j) during any service tour during the pilot test. The value achieved was assigned to the hour of departure from customer i. The overall Median AverageSpeed for all was 3.30 mph with 25% of the AverageSpeeds being less than 2.10 mph and 25% being over 5.0 mph. Figure 78 and Figure 79 are the distributions of AverageSpeed during each hour of the day from 4:00 to 23:00. (No Manhattan customers were served between the hours of 23:00 and 4:00). Each of these distributions tends to have a heavy tail with a few instances of AverageSpeeds above 15 mph. This causes average values of AverageSpeed to be somewhat higher than the median value. The standard deviation values are modest.

The box and whisker chart in Figure 80 readily shows that that AverageSpeeds achieved in the early morning hours are substantially larger than those later in the morning, which are greater than those in the afternoon and early evening. Median AverageSpeeds during the early morning hours in Manhattan are essentially twice the median values during the late morning. In the afternoon and early evening attained AverageSpeeds are essentially walking speeds of 3.0 mph or less. These low values persist through the evening. Unfortunately, no tours were conducted during the very early morning hours prior to 4 AM so the pilot test was not able to determine the extent to which congestion is relieved prior to 4 AM.

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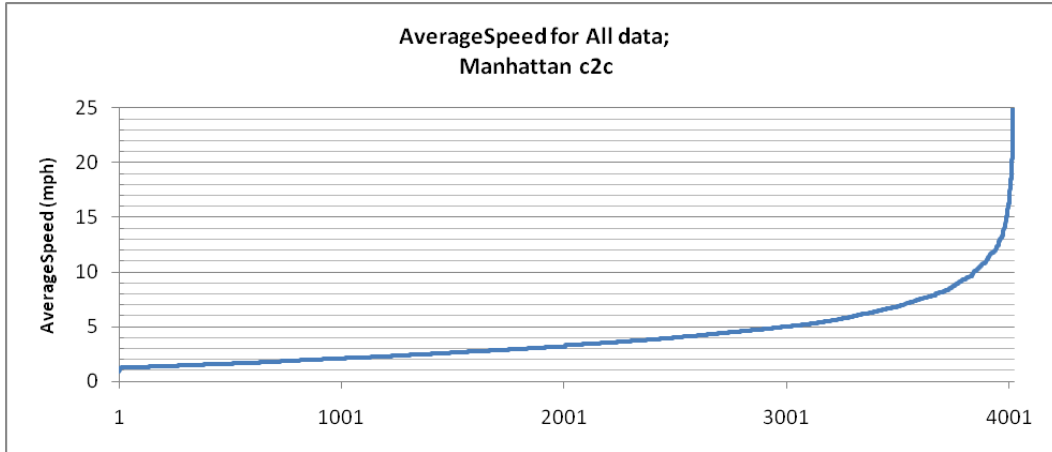
Figure 77: Distribution of AverageSpeed for 4,020 Individual Manhattan c2c Tour Segments
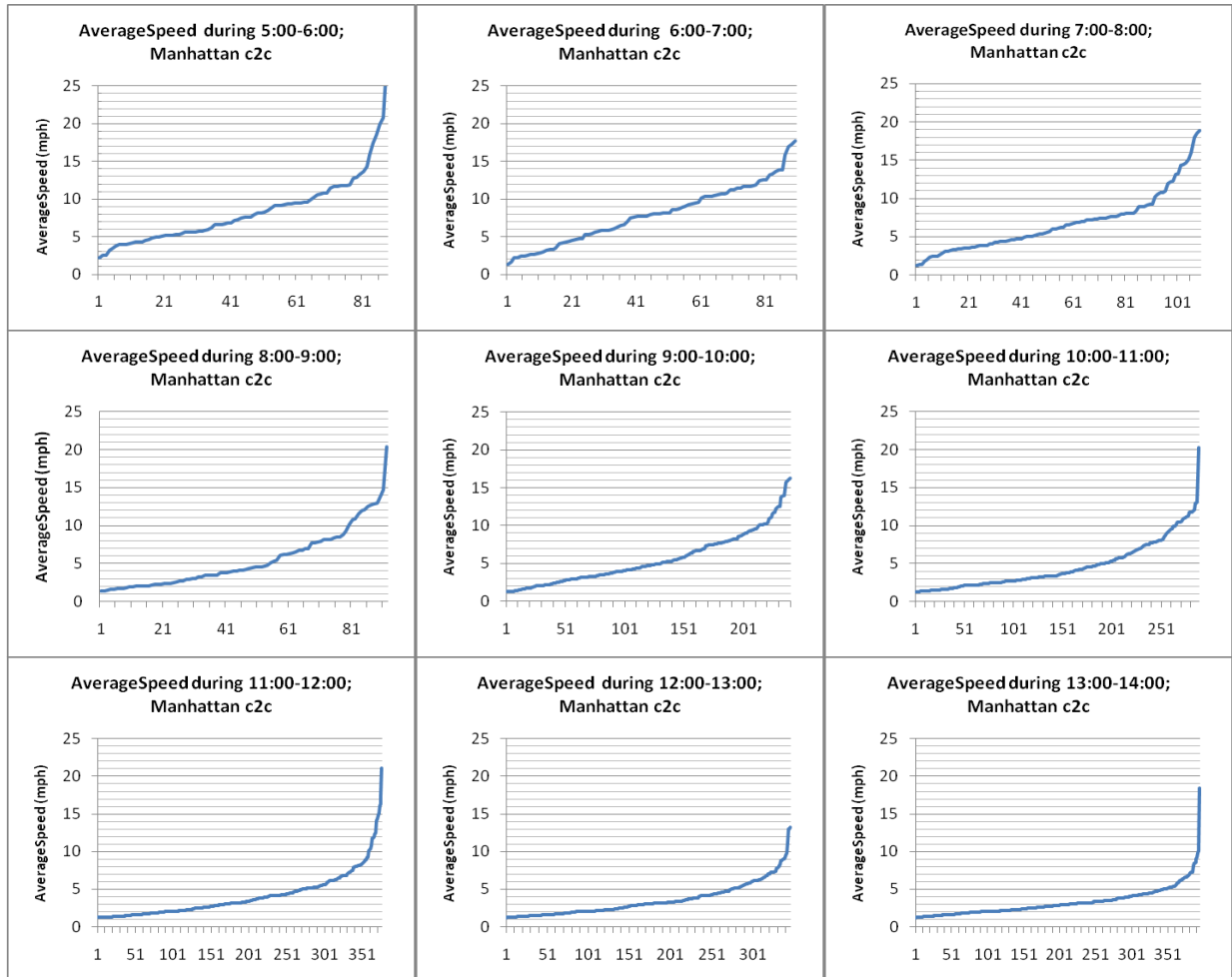
Figure 78: AverageSpeed Distributions for 5 AM to 2 PM - Manhattan c2c Tour Segments

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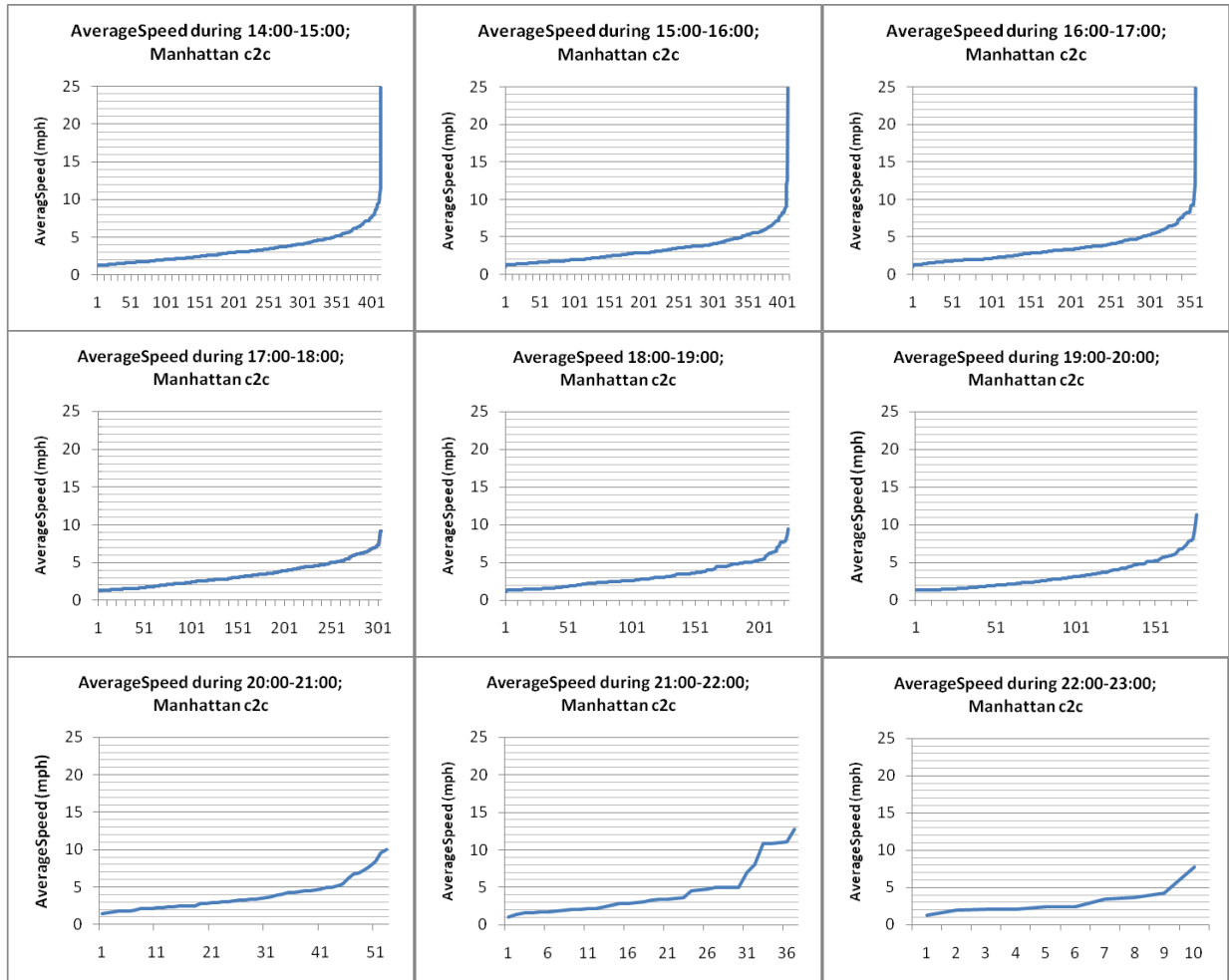
Figure 79: AverageSpeed Distributions for 2 PM to 11 PM - Manhattan c2c Tour Segments
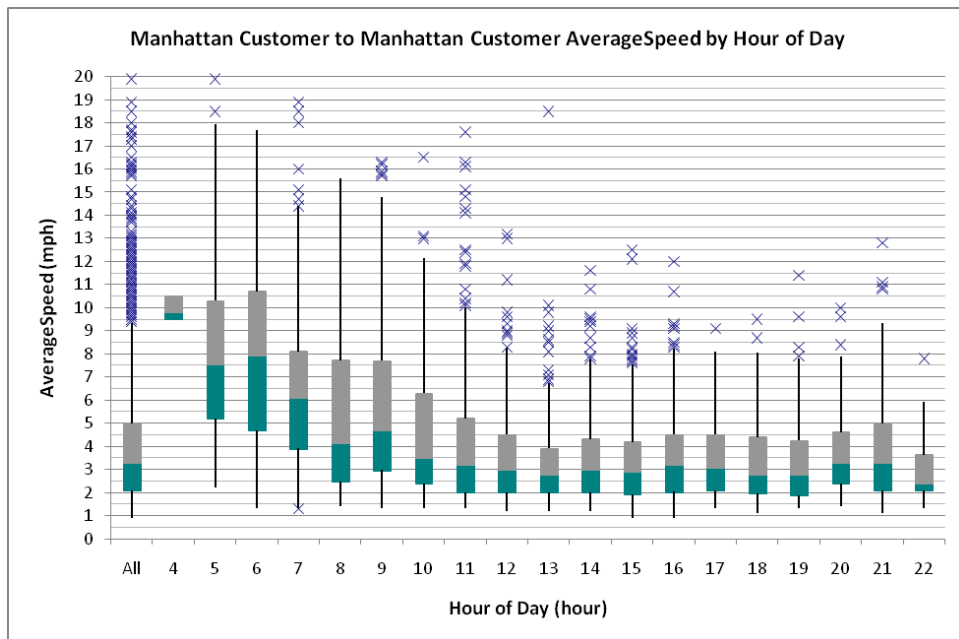
Figure 80: Manhattan c2c AverageSpeed by Hour of Day - Field Test (Sysco, Baldor, NDL)

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During the analysis of the data, it was noted that the peak traffic periods for Manhattan did not correspond to the peak traffic periods for the rest of New York City. The Manhattan time of day traffic periods lag those for the rest of the city. The traditional groupings show a higher mean AverageSpeed during the AM Peak and MidDay as compared to the proposed Manhattan time of day groupings (21.8% and 7.5% respectively) but, during the Off-Hours, the Manhattan groupings show a 57.4% increase in the mean AverageSpeed over the traditional groupings. These results indicate that the definition of off-hours for Manhattan may need to be redefined in future off-hour delivery research. Figure 81 presents a box and whisker plot of the Manhattan c2c AverageSpeed for traditional time of day traffic groupings while Figure 82 presents the c2c AverageSpeeds grouped according to what the data indicates are the time of day traffic groupings for Manhattan.
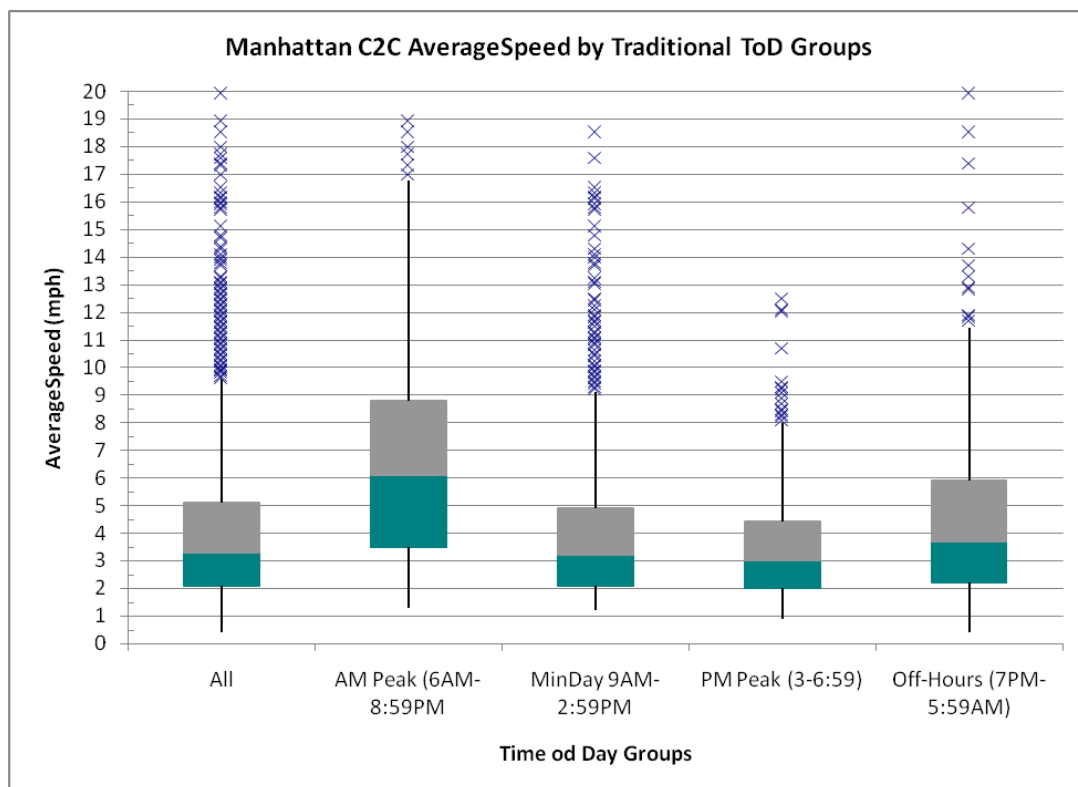
Figure 81: AverageSpeed by Traditional ToD Grouping
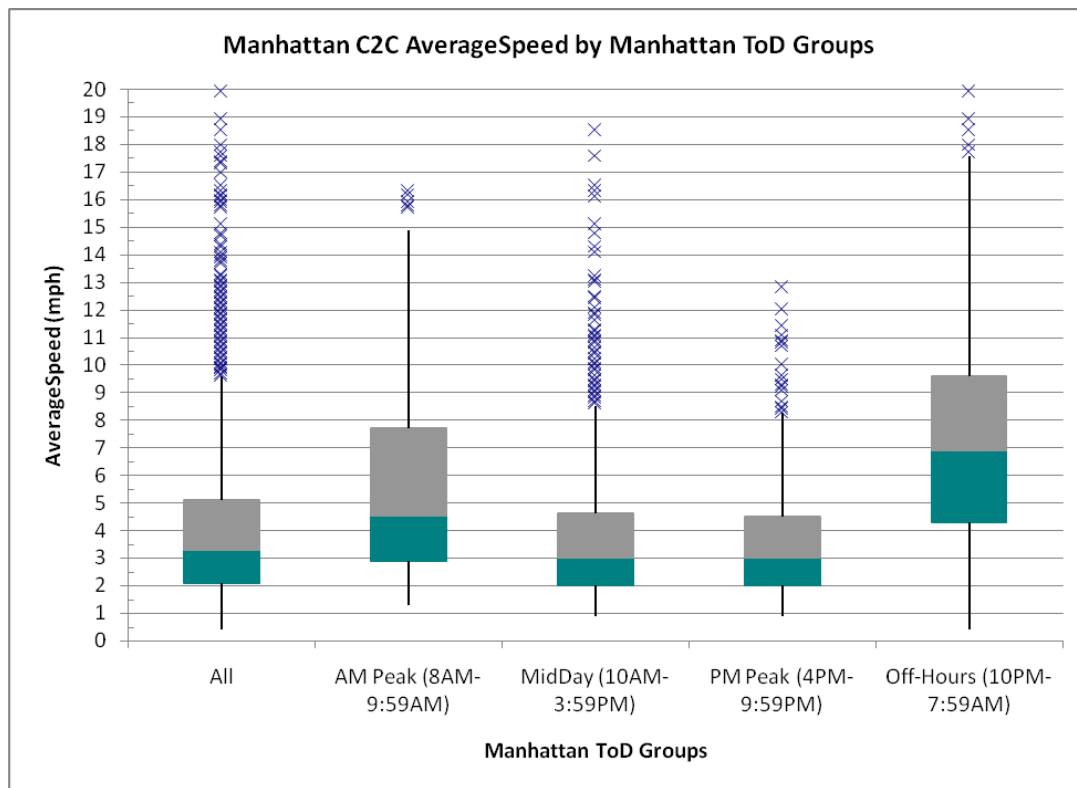
Figure 82: c2c AverageSpeed by Manhattan ToD Grouping

6.6 Results from the Opinion Surveys from Carriers and Receivers

Upon successful completion of the pilot test, all participants were asked to complete a short survey about their experiences (see Appendix). The following sections provide the results of the returned satisfaction surveys.

6.6.1 Receivers

6.6.1.1 Foot Locker stores

Paul Cox, VP, Global Transportation & Supply Chain at Foot Locker, indicated in a call on November 11, 2009, that Foot Locker's experience with OHD was quite positive, particularly in regard to larger volume stores that had employees dedicated to backroom operations. As of the project team's last communication with Paul Cox, Foot Locker was considering expanding OHD to other Manhattan stores.

The survey given to the individual store managers did not explicitly indicate that when responding the manager should assume all additional costs would be covered by the financial incentive. Consequently, many of the managers viewed the OHD as unfavorable due to the fact that they incurred additional costs. The responses of the eight participating Foot Locker stores are summarized below.

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What was your impression of off-hour deliveries?

Very Favorable	Average Response	**Very Unfavorable**
1	3.88	**5**

How much did receiving off-hour deliveries affect your operations?

	Average Response	**Drastic Changes**
No Changes		
1	2.75	**5**

How were your operations affected?

- "The store's shipment arrived during store closing. The shipment remained on floor until the next morning causing the store to be cluttered at start of next business day."
- "Reschedule of associates to come in for shipment delivery. If the delivery truck was running late, the store incurred overtime. Store had to add an extra associate to process shipment at late delivery time."
- "Store had to adjust work schedule to receive product."
- "Change of associate's schedules – Store had to work receiver all day to accommodate both parcel and pool deliveries. Due to the hours accumulated that day, the associate was scheduled an extra day off during the week. All other associates then also had to be rescheduled to accommodate the day off of the receiving associate."
- "Receiving off-hours slowed processing and start for the next business day. Shipment boxes were in the way of store opening."
- "Not as many associates were available to work at the start of business day. It was difficult to schedule associates to receive shipments."
- "Pool agent arriving after store closure. Store paid overtime to keep personnel late."

If it were up to you, how likely are you in the future to request deliveries from your vendors in the off-hours?

Very Likely	Average Response	**Very Unlikely**
1	3.63	**5**

What did you like about receiving deliveries in the off-hours?

- "Store could process freight faster in off-hours."
- "Nothing."
- "Receiving shipment did not compete with customers. Boxes from shipment were not on the sales floor. Store was clean for early morning shoppers."
- "Nothing."
- "Less traffic in store – Very few customers were interrupted due to the receiving of shipment."
- "Receiving shipment did not compete with business. Customers were not interrupted by receiving shipment."
- "Nothing."
- "Store manager did not like off-hours deliveries."

What did you dislike about receiving deliveries in the off-hours?
- "Nothing."
- "Store could not get new product out on sales floor until the next business day causing a loss of sales."
- "Late hours – Clean up of store in evening plus late receiving of freight necessitated store personnel to work late adding extra overtime."
- "Store parcel freight is delivered early in the morning. Manager had to schedule stock person late in the evening to get pool freight received. If the pool agent was late, store personnel also had to stay late resulting in payment of overtime to associate to receive shipment."
- "Changing of schedules for all personnel to accommodate late pool deliveries."
- "Do not like receiving shipment so close to store closing time."
- "Missed sales opportunities – Large shipments could not be processed until the next morning. Parcel shipments also received in the morning got mixed with pool shipments."
- "Manager had to stay late after regular store hours to receive freight. Store had to pay overtime to associates to receive shipment."

It can be seen by the responses to the questions regarding their impression of OHD and how likely they are to request OHD in the future that the receivers did not like receiving OHD. Nearly all of the receivers listed reasons why receiving OHD affected their operations. These responses could be separated into two groups: issues related to (1) the hassle or cost of having to schedule or reschedule someone to receive the off-hour delivery; or (2) the inconvenience and delay at the start of the next business day after an off-hour delivery because the shipments were in the way and had to be handled. Although nearly half of the receivers indicated that they did not like any part of receiving deliveries in the off-hours, the other half listed that the store could process freight faster, and that processing the freight did not interrupt business, i.e. the customer. As far as what the receivers disliked about receiving deliveries in the off-hours, many receivers cited how it was hard or expensive to schedule associates to receive the off-hour delivery, and some said that receiving OHD led to missed sales because the shipments could not be processed before business the next morning. Upon review of the many dislikes listed by the receivers about OHD, it can be seen that nearly all of the negative implications of the OHD for receivers were only a byproduct of the pilot test and would not reflect the actual program. For example, many of the difficulties with scheduling and rescheduling employees are only a short-term problem and in the long-term schedules would only be altered once. Also, all concerns over the extra costs associated with off-hours deliveries would be taken care of with the previously mentioned financial incentive provided for receiving deliveries in the off-hours. Overall it seems that receivers should receive a few efficiency benefits from OHD, and all negative effects should be taken care of in the long-term project. The only difficulty may be in convincing the receivers to go along with the idea because of their initial hesitation towards having to go through rescheduling.

6.6.1.2 Sysco's customers

The project team received satisfaction surveys from twelve of the participating Sysco receivers. The average response concerning the overall impression of OHD was 1.50 on a scale of one to five with "1" being "Very Favorable" and "2" being "Favorable." In regard to requesting OHD in the future, of the twelve, nine were "Very Likely," one was "Likely," with the remaining customers responding "May or May Not." Six of the twelve utilized unassisted deliveries during the pilot test with five of the other six expressing interest in receiving unassisted deliveries during the off-hours in the future if all liability issues were addressed.

Receiving the OHD seemed to cause significant changes to their operations but almost always for the positive. Aside from some extra costs in rescheduling or in returns/exchanges, the receivers said that the deliveries were easier, more reliable, always on time, and that the OHD saved them money by having the order in before the start of business and not having to put the deliveries in the walk-in themselves. With that in mind, nearly all of the receivers said that they were very likely to request deliveries in the off-hours in the future. In general, the receivers felt that the reliability, labor savings, convenience, and little to no disturbance to business or customer were clear and overwhelming benefits of OHD, whereas, the additional costs of rescheduling, lack of immediate verification, problematic returns, and possible security issues were the only draw-backs. Below is a summary of the surveys received from the participating customers of Sysco.

What was your impression of off-hour deliveries?

Very Favorable	Average Response	**Very Unfavorable**
1	1.50	**5**

How much did receiving off-hour deliveries affect your operations?

No Changes	Average Response	**Drastic Changes**
1	3.60	**5**

How were your operations affected?

- "Changes in operations dealing with delivery."

- "Very helpful to have order in prior to start of business. As luck would have it we would often get delivery in during a rush period. Having it put away before opening was great. Also can change the way I order/stock inventory."
- "Required additional employee scheduling and costs, required additional time for returns/exchanges of items."
- "They were always on time and we save by not having to put everything in the walk-in ourselves."
- "Never missing products."

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- "Makes delivery more easy."
- "More reliable."
- "We prep a lot of food for stores and delays in delivery time will cost us real labor dollars."
- "Better delivery times."
- "It was much better than having to interrupt our customer space with boxes and mess."
- "Re-scheduling of labor."

If it were up to you, how likely are you in the future to request deliveries from your vendors in the off-hours?

Very Likely	Average Response	**Very Unlikely**
1	1.42	**5**

What did you like about receiving deliveries in the off-hours?
- "Receiving deliveries in the off-hours will not interrupt the operation during the busy hours."
- "Very helpful to have order in prior to start of business. As luck would have it we would often get delivery in during a rush period. Having it put away before opening was great. Also can change the way I order/stock inventory."
- "Receiving deliveries during the off-hours is more convenient and plus I receive my order earlier in the day."
- "There was no/little disruption of customers overlook experience due to deliveries, quick check in and rotation into stock, did not affect the kitchen cooking process."
- "They were never late for delivery!!"
- "No issues with delivery."
- "Reliability!"
- "Reliability and they put stuff away."
- "Labor savings."
- "Better delivery times."
- "It was much better than having to interrupt our customer space with boxes and mess."
- "The advance receipt of goods."

What did you dislike about receiving deliveries in the off-hours?
- "The additional cost of assigning a staff to receive the orders in the off-hours."
- "We arranged to provide access to the driver ... so that product could be kept safely before staff gets in. While we didn't have a problem…on a larger scale of this could lead to issues that we would deal with."
- "Nothing."
- "Additional cost for employee dedicated to handle delivery, return/exchange process is made more difficult."
- "If you are shorted or get wrong item, you cannot give to the driver the next day. Sales guy has to come and get it."
- "No real issues."
- "All Good."
- "No immediate verification."

- "It is problematic to return items."
- "Nothing."
- "Can't check quality or wrong items."
- "No dislikes."

If all liability issues were addressed, would you be interested in receiving unassisted deliveries (e.g. driver places goods in a secure location at your establishment)?

Very Interested	Average Response	**Very Uninterested**
1	2.17	**5**

6.6.1.3   Whole Foods Market stores

The project team received satisfaction surveys from all four participating Whole Foods Market stores. The average response concerning the overall impression of OHD was 2.50 on a scale of one to five with "2" being "Favorable" and "3" being "Neutral." The participating Whole Foods Market stores all received deliveries during the off-hours before the pilot test. Consequently, the operations were minimally affected and there was very little interest in the idea of unassisted deliveries. Below is a summary of the surveys received from the participating Whole Foods Market stores.

What was your impression of off-hour deliveries?

Very Favorable	Average Response	**Very Unfavorable**
1	2.50	**5**

How much did receiving off-hour deliveries affect your operations?

No Changes	Average Response	**Drastic Changes**
1	2.00	**5**

How were your operations affected?

- "Most of our deliveries were already overnight."
- "Scheduling."
- "Scheduling of deliveries, more timely deliveries due to less traffic at night."

If it were up to you, how likely are you in the future to request deliveries from your vendors in the off-hours?

Very Likely	Average Response	**Very Unlikely**
1	2.00	**5**

What did you like about receiving deliveries in the off-hours?
- "Less traffic on the street."
- "Avoiding traffic from rest of building."
- "Less congestion outside receiving. Less late deliveries."
- "Less traffic congestion and pedestrians."

What did you dislike about receiving deliveries in the off-hours?
- "Requires more overnight."

If all liability issues were addressed, would you be interested in receiving unassisted deliveries (e.g. driver places goods in a secure location at your establishment)?

Very Interested	Average Response	**Very Uninterested**
1	3.50	**5**

6.6.2 Carriers

The project team received satisfaction surveys from eight participating carriers. Of the eight, two had a "Very Favorable" view of OHD, four had a "Favorable" view, one was "Neutral," with the remaining vendor having a "Very Unfavorable" view. This vendor had an issue with occasionally having to wait for an extended period of time for receiving and indicated that they would be "Unlikely" to perform OHD in the future if requested by customers. The other seven vendors indicated that if requested by the customer that they would be "Very Likely" or "Likely" to make deliveries during the off-hours.

6.6.2.1 Management

The managers cited that OHD reduced parking violations and increased availability of parking, but they also had concerns over the safety of the drivers and said that they disliked having to wait for customers to open; a problem that should be could be taken care of by an implementation of unattended deliveries. Below is a summary of the surveys received from the managers of the participating carriers.

What was your impression of off-hour deliveries?

Very Favorable	Average Response	**Very Unfavorable**
1	2.13	**5**

How much did receiving off-hour deliveries affect your operations?

No Changes	Average Response	**Drastic Changes**
1	2.38	**5**

How did making off-hour deliveries affect your costs?

Moderate Decrease	Average Response	**Moderate Increase**
1	2.88	**5**

If it were up to you, how likely are you to make deliveries the off-hours if requested from your customers?

Very Likely	Average Response	**Very Unlikely**
1	1.88	**5**

What did you like about receiving deliveries in the off-hours?
- "Reduced parking violations, available parking for our vehicles, fewer traffic delays."
- "Increased the revenue potential of hard assets - the truck. Decreased the delays and cost of traffic congestion. Allowed the potential for increased revenue and decreased cost by expanding the hours each day for producing revenue."
- "Helped with time spent at Whole Foods loading docks. Less wait time."
- "Timing."
- "Less stressful, more room to park."
- "Less congestion and much quicker deliveries."
- "We don't like it."

What did you dislike about receiving deliveries in the off-hours?
- "Safety of our delivery associates at night."
- "Nothing I cannot take care of. Security in the hours 3am – 6am may require some change. Nothing unexpected."
- "Waiting for customers to open."
- "Nothing."
- "Longer days, but more productive."
- "Getting up earlier."
- "We need to wait for their receiving for about 2 hours."

6.6.2.2 Drivers

The twelve participating drivers from the various carriers in the pilot test overwhelmingly preferred delivering during the off-hours. The survey asked seven question related to how delivering during the off-hours affected various aspects of the delivery process. The scale used "1" to indicate a very positive effect and "5" to indicate a very negative effect. Drivers experienced much faster travel speeds (1.50), much lower levels of congestion (1.17), a large increase in available parking (1.17), much lower levels of stress (1.17), a lower amount of time to deliver goods at each stop (1.75), a lower amount of time to complete the route (1.58), and an increase in the driver's feeling of safety (2.42). Ten of the twelve drivers stated that they "Strongly Preferred" OHD with the main exception being a driver that encountered the issue of having to wait for extended periods of time for receiving to be able to accept his delivery. Drivers also stated that they appreciated the reduced congestion, not having to deal with the customer (in the case of unassisted deliveries), reduced stress, and no tickets. Below is a summary of the surveys received from the drivers.

The drivers were asked how the following seven aspects were affected by making deliveries in the off-hours:

1) **Availability of Parking**

Large Increase	Average Response	**Large Decrease**
1	1.17	**5**

2) **Average Travel Speed**

Much Higher	Average Response	**Much Lower**
1	1.50	**5**

3) **Level of Congestion**

Much Less Congested	Average Response	**Much More Congested**
1	1.17	**5**

4) **Level of Stress from Driving**

Much Lower	Average Response	**Much Higher**
1	1.17	**5**

5) **Amount of Time Needed to Complete the Delivery Route**

Much Lower	Average Response	**Much Higher**
1	1.75	**5**

6) **Length of Time Needed at Each Stop to Deliver Goods**

Much Lower	Average Response	**Much Higher**
1	1.73	**5**

7) **How Safe Do You Feel Making Off-Hour Deliveries**

Much More Safe	Average Response	**Much Less Safe**
1	2.42	**5**

What is your personal preference of delivery time?

Strongly Prefer Off-Hour	Average Response	**Strongly Prefer Regular hour**
1	1.42	**5**

What did you like about making deliveries in the off-hours?
- "Easier to maneuver through the city, easier to park, and less foot traffic to hold me up."
- "Not having to deal w/customer."
- "My stores were in midtown. 7PM-9PM window has less traffic."
- "No stress."
- "The reasons addressed in the seven questions above."
- "No tickets."
- "Streets are easier to manage and better parking."
- "Less congestion and much quicker deliveries."
- "I don't like it."
- "Less traffic, less stress."
- "My stores were in midtown. 7PM-9PM window has less traffic."

What did you dislike about making deliveries in the off-hours?
- "I have no dislikes, as long as I have a job to do."
- "Nothing."
- "Nothing."
- "None."
- "Waiting for customers to open."
- "Longer day, but less stressful."
- "Getting up earlier."
- "I need to wake up very early and I need to wait for the store's receiving for a long time."
- "Nothing I could think of."
- "7PM-9PM my stores in midtown still had theatre district traffic."

7. TRAFFIC SIMULATION

7.1 Introduction

An off-hour delivery (OHD) program is expected to provide benefits to the highway network, since fewer trucks and commercial vehicles (CMV) during congested hours would improve highway speeds and decrease travel times. However the precise effects are unknown and their estimation is difficult. Freight planning models or highway networks can be developed and run in simulation software but these processes are both time-consuming and require extensive data procurement. Instead many city transportation agencies or metropolitan planning organizations already have developed traffic planning and simulation models. The usage of the Best Practice Model (BPM), a regional planning model developed by New York Metropolitan Transportation Council (NYMTC), and an extracted mesoscopic sub-simulation model, to model and observes the impact of an off-hour delivery program to the traffic network of Manhattan and the New York metropolitan area is described in detail. A research methodology is developed to manipulate and distribute freight trip tables based on the percentage of freight vehicles participating in the off-hour delivery program, and calibration is conducted to make appropriate changes to the models used.

Once the models' results are obtained, analysis is conducted to determine the effectiveness and impacts of the scenarios modeled. These analyses focus on the changes predicted by the models to the traffic networks, mostly focusing on travel times and speeds. Additional evaluation is conducted looking at economic impacts in terms of savings from congestion decreases and other external benefits. The results from both models are compared and analyzed and a discussion on the usage of these models is presented. Finally analysis is conducted combining the OHD program with congestion pricing and dynamic pricing programs.

7.2 Traffic Modeling Tools Evaluated

In order to formulate a methodology to estimate traffic impacts of freight congestion control measures, literature in the field of freight planning was reviewed. The review focused on freight planning modeling and using available traffic planning and simulation tools to estimate the impacts of a policy measure. The following sub-sections provide a brief summary of these subjects.

7.2.1 Applicable transportation models

Much work has been done regarding the quantification of the traffic impacts of congestion mitigation programs but less has been done concerning programs targeted specifically at trucks or commercial vehicles. Programs addressing highway freight transportation problems are new and experimental, with only a handful of cities implementing congestion control measures (Crainic et al., 2004). The effects of truck and commercial vehicles on highway networks are known to be negative, specifically causing

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congestion due to their nature as large vehicles which generally travel at a slower speed than automobile traffic. Studies have shown that truck traffic negatively affects the flow rate of highways and local roads, thereby causing congestion on roadways with high traffic volumes (Ioannou et al., 2001).

Holguin-Veras et al. (2006) determined that freight traffic generated by delivery vehicles to city businesses not only contributed to congestion but caused added problems due to double-parking and blockages as a result of the lack of parking spaces during the day-time, peak delivery hours (Holguín-Veras et al., 2006a). These claims are supported by research into the effects of illegal parking on traffic congestion which show that illegal parking (primary conducted by CMVs) causes significant capacity losses to roadways, which produce more severe effects during peak hours than during off-peak hours (Han et al., 2005). As a result, policy makers have sought to control truck and commercial vehicle traffic, particularly within cities' central business districts, either with value pricing measures or by introducing off-peak delivery programs. Both ideas are gaining popularity in the United States, but the degree of their success is yet unknown.

The focus of interest for this study is to find the effects of the OHD shift program described by employing commonly used transportation modeling and simulation packages. While transportation planning and simulation software are widely used for modeling and evaluation of passenger travel by agencies, consultants, and researchers, not as much attention has been paid to utilizing these for truck and freight studies.

There are several traffic simulation tools available but selection of the right software is contingent upon the needs and budget of the study. The Federal Highway Administration has produced guidelines on the selection of the appropriate tools for traffic modeling purposes: the Traffic Analysis Toolbox, a series of reports begun in 2004, detailing the types of available tools and their applications (FHWA, 2004). Holguin-Veras et al. (2001) conducted a thorough investigation of freight modeling strategies and their applicability to the New York region (Holguin-Veras et al., 2001). Similarly Boile and Ozbay (2005) compiled a synopsis of several available transportation modeling tools and strategies used in practice in the New Jersey area (Boile, 2005). A brief review of freight modeling techniques and their uses is presented here.

7.2.1.1 *Freight planning models*

Some states and regions have developed statewide freight planning models, commonly in the form of discrete event simulation models for freight planning. Freight modeling is generally considered to be more complex than passenger modeling primarily because freight transport is influenced by a number of different agents, which are continuously changing (Cambridge Systematics, 1997). Freight models can be produced in different forms, such as input-output, trip-based, or commodity-based models. A trip-based model is more similar to a traditional transportation planning model, in that it models an individual

vehicle's travel. Similar to passenger car models, they predict trip generation rates and their distribution. Meanwhile commodity-based models follow the exchange of goods in the market, which better accounts for the complex interactions involved in freight transportation (Holguin-Veras et al., 2001).

Several agencies have developed different types of freight models, generally at the statewide level. The literature includes descriptions of models built for Florida, Kentucky, Iowa, Massachusetts, Oregon, Virginia, Indiana, Wisconsin, Minnesota, Oklahoma, Kansas, and Texas (Boile et al., 2004; Giuliano et al., 2007). New Jersey, a major portion of New York City's metropolitan area, did not initially develop a statewide freight model; rather it included freight operations as a sub-section of its statewide travel demand model. Later on, a multi-commodity model was developed for the state using GIS tools (Boile et al., 2004). While having freight planning models would be useful for a freight demand management study, full estimation of impacts to all traffic is not possible without a model that includes all of the vehicle classes.

7.2.1.2   *Travel demand models*

Travel demand models are typically used by transportation planners to predict travel patterns within a given city, state, or region. They are generally based on large networks and perform modeling tasks on an aggregate basis. Travel demand models are often developed for metropolitan planning organizations to assess the impact of an improvement, forecast future travel, or air-quality analysis. The theoretical framework for most travel demand models is built around the four-step planning process: trip generation, trip distribution, mode choice, and traffic assignment. Commercial software tools have been developed to automate the process, which is particularly useful for large networks. Some tools that government agencies and transportation consultants use include TransCAD, CUBE/TP+/TRANPLAN, EMME/2, TRANSIMS, and VISUM (FHWA, 2004).

The modeled networks generally contain all major roads and highways, and in some cases rail and bus lines. Travel demand is based on population and employment as well as other features of various sub-zones throughout the modeled area. Traffic assignments are run for different segments of the day, and are generally used to forecast future traffic conditions; however, large-scale regional models generally perform static traffic assignment. That is, assigned volumes as link flows are not time dependent; they are aggregated over the full period, and thus, every vehicle simultaneously exists on every link that it uses in the period (Boile, 2005).

Regional travel demand models seek to incorporate all travel throughout a region, or as deemed necessary by the developers. This can include models that only consider passenger cars, freight-only planning models, or a combination of both. Historically freight planning has garnered much less attention than passenger car models, and thus far fewer freight planning models have been developed. Boile and Ozbay (2005) report that:

"Currently, there are no transportation modeling approaches which account for both passenger and freight considerations. Some of the transportation planning packages that were reviewed … [have] the flexibility to account for freight flows. Typically, however, for these types of applications, major modifications of the existing models are required and caution should be exercised to develop meaningful models." (Boile, 2005)

7.2.1.3 *Passenger and freight planning models*

In order to assess the impact of a freight targeted policy program, it is important to consider the effects to all classes of vehicles and the entire transportation system. While some domestic freight is moved by rail, a significant percentage of goods are transported by trucks and delivery vans, which use the same highway infrastructure as all other vehicles. This study focuses solely on trucks and delivery vans (CMVs), and thus any changes to their travel patterns will affect the entire highway network and in turn passenger travel. To fully assess traffic impacts throughout the region, a model is required that considers both passenger and freight travel.

In recent years, NYMTC developed the BPM, while collaborating with other neighboring Metropolitan Planning Organizations investigating a regional freight planning model for the New York metropolitan region. BPM is a comprehensive regional travel demand model that incorporates all aspects of vehicular travel, including highway freight travel (Holguin-Veras et al., 2001; Boile et al., 2004). Regional travel analysis can be efficiently conducted with integrated passenger car and freight components. Simulations can be run to evaluate the effects of policies like toll increases, congestion pricing, or time-of-day shifts in freight activity.

Using travel demand models to estimate the impacts of similar OHD programs has been attempted before in the city of Athens. Yannis, et al. (2006) presented a methodology to model modified commercial vehicle OD demands on a highway network when delivery operations within the city of Athens were restricted (Yannis et al., 2006). The researchers simulated the city's roadways under observed and modified commercial vehicle demands using a road network simulation model. They first observed existing traffic conditions to collect sufficient data to build a comprehensive roadway network, and then calibrated the collected data against actual conditions. Using the traffic simulation program SATURN, they were able to conduct traffic assignment based on actual (base) traffic demands and again with modified demands, which were caused by restricting delivery vehicles from entering the study area within certain times of day. It is important to note that SATURN is strictly a traffic assignment model, not a large-scale travel demand model (FHWA, 2004).

Yannis et al. created a network that consisted of 285 production and attraction zones, with demand matrices for six separate time periods throughout the day. Additionally land uses and average stop times were also studied to represent the effect that actual delivery activities have on roadways, which manifest themselves in the forms of double parking or lane blockages. The researchers were able to code these

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activities into the network and thus modify the capacity of certain roads where deliveries were taking place. The simulations showed that by barring delivery vehicles from the study area from 7 AM - 10:30 AM, simulated average roadway speeds increased by 4.7%, and a similar restriction from 2 PM - 4:30 PM increased simulated average speeds by 1%. Conversely, the average speed for the 10:30 AM - 2:00 PM period decreased by 5.8% as the displaced delivery vehicles were assumed to use this period to enter the study area. However the researchers noted that the increase in speeds during the morning and afternoon periods had a greater benefit than the loss in the midday periods, due to higher traffic volumes in the morning and afternoon (Yannis et al., 2006).

For New York the availability of BPM eliminates the need to create a new network model for this study. However, it should be emphasized that BPM was not designed specifically for or with an emphasis on freight modeling. NYMTC is currently studying alternative ways to study freight transportation and plan for future changes (NYMTC, 2005). Using BPM the same changes tested in the Athens study can be simulated and measured. Furthermore, a shift of commercial activity from daytime peak hours to off-peak night hours can be simulated by similarly modifying OD demands of CMVs. Finally, some of the shortcomings of a large-scale travel demand model can be overcome by extracting a localized sub-model to be analyzed with mesoscopic simulation. A methodology is developed to study the effects of the proposed OHD program in a similar manner to the study by Yannis et al. (2006), by employing the BPM (covering the full New York metropolitan region) and an extracted sub-network of Manhattan as the modeling and analysis tools. The following sub-sections describe the two models used in this study.

7.2.2   Regional travel demand model (BPM)

In order to measure the effects of any type of shift in vehicular travel patterns, such as the proposed OHD program, the changes in traffic conditions throughout the entire regional highway network are considered. If commercial vehicle traffic are shifted from one time period of day to another—from peak periods to off-peak periods—it is critical to observe whether there is a measurable improvement to traffic conditions during the peak periods, and conversely whether off-peak conditions are significantly disrupted. The Best Practice Model, a regional travel demand model, will be used to estimate these impacts and the differences between current conditions and what would happen were the proposed program to be implemented.

The research team identified several macroscopic planning models, as well as microscopic simulation models, of the study region that were previously constructed, and could be used to estimate changes due to the behavioral changes in different capacities respectively. Micro-simulation models cover relatively small portions of the overall study area (the New York metropolitan region), but the regional planning model, BPM, covers 28 counties in the New York area. BPM allows for studying the full effects of the program under study to the complete highway network of New York City and its surrounding areas.
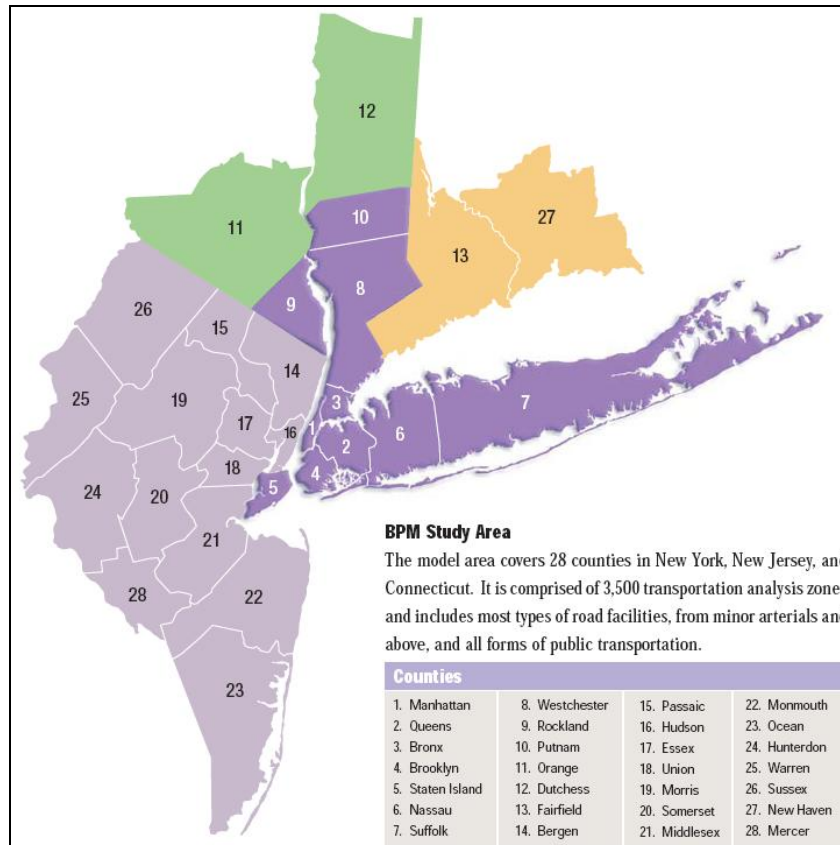
Figure 83: BPM Coverage Area[2]

BPM is a well known and used model for forecasting travel patterns and behavior for all vehicle types in the New York region. It is a comprehensive macroscopic travel demand model developed for the TransCAD software tool, containing nearly all major transportation facilities within the Lower New York/Western Connecticut/Northern New Jersey region. The full coverage of BPM is shown in Figure 83. The model contains networks for four time periods, composed of about 4,000 transportation analysis zones, ten motorized modes of travel, and six trip purposes. The highway network itself contains over 50,000 links (classified into 21 link types) and is modeled for six vehicle class types. The full highway network can be seen in Figure 84. The advantages of the BPM are that it transcends a typical four-step highway modeling procedure by utilizing specifically developed approaches to address the complexities of the New York metro-area transportation network. These include using micro-simulation-based travel behavior, a new procedure for trip generation, a mode-destination stop choice model that is based on household characteristics and land use to predict the locations of intermediate stops, modeling entire journeys rather than trips, and a pre-assignment processor that generates time-of-day distributions for origins and destinations in the different time periods (Parsons Brinckerhoff, 2005).

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[2] Image taken from http://nymtc.org/project/BPM/background/BPMnewsltr.pdf
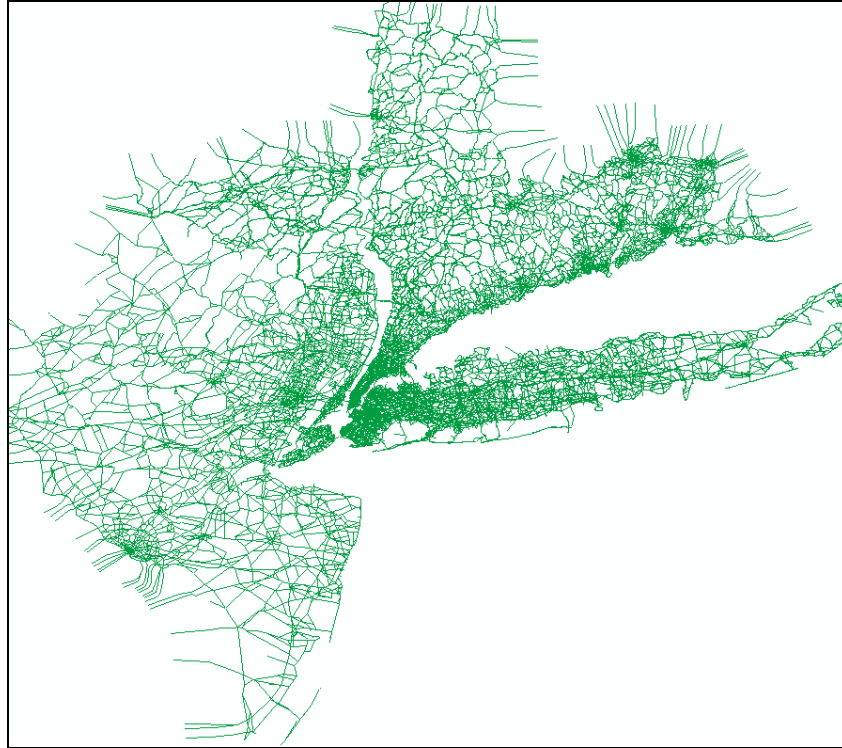
Figure 84: BPM Highway Network

BPM is particularly useful for analysis of the changes and redistributions of truck travel patterns, since it utilizes TransCAD's multi-modal, multi-class, assignment feature. The input origin-destination (OD) matrices for highway assignment are six-fold, one each for SOV, HOV2, HOV3+, truck, and other commercial. In the multi-class assignment, each trip class is treated separately and utilizes its own cost or volume-delay function, and classes prohibited on certain links are accounted for. Cars and trucks are assigned separately, but still allowed to find the best route to minimize their cost. The actual OD matrix for trucks was estimated from three separate components: gravity model, origin-destination surveys, and estimates from state models. Trip tables were then made for a specific truck network created containing 294 truck zones and then this matrix was merged with the full BPM matrix (List et al., 2001).

The assignment portion of the model is a collection of four models for four periods of the day. The four periods, each with their own networks and origin-destination (OD) matrices, are AM Peak Period (6 - 10 AM), Midday Period (10 AM - 3 PM), PM Peak Period (3 - 7 PM), and Overnight Period (7 PM - 6 AM). The defined network periods and separate OD matrices allow for modeling to be based on shifting demand from the daytime periods to the overnight period, as described by the OHD program. The methodology developed for traffic simulation in the BPM is shaped around the model's construction, described in the next section.

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7.2.3 Mesoscopic simulation

The Best Practice Model, running in TransCAD, also allows for transfer of the highway network to TransModeler, both software tools developed by Caliper[3]. After initial testing, the TransModeler simulation has been identified as a sufficient addition to BPM, as a traffic simulation tool capable of achieving the goals of this study. While TransCAD is a static traffic assignment tool, TransModeler is a traffic simulator that is capable of performing simulations at a microscopic and mesoscopic level. The difference between microscopic and mesoscopic simulation lies in the level of detail in the network (geometry and network parameters), and the signal data.

At the mesoscopic level TransModeler can individually track each vehicle. However, the vehicle movements are based on aggregate speed-density relationships. The speed and density of a traffic platoon (called traffic cells in TransModeler) determine the movements of individual vehicles. To perform a simulation at a mesoscopic level two main inputs are required: the network and OD matrix. The network is a link-node layer which can be imported from the BPM regional network developed for TransCAD. The same applies for the BPM OD matrices. However, BPM's OD matrices have to be converted into time-dependent OD matrices with departure time choices, calibrated according to dynamic data. Some calibration is required for the network as well.

Since the simulation procedure is computationally intensive and the mesoscopic simulation is desired for detailed analysis, the research team focused the mesoscopic simulation on a sub-network of Manhattan, which is the most densely populated and congested borough of New York City. It contains the bulk of commercial activity in the region and is the focus of the Behavioral Micro-Simulation (BMS), pilot test, and other tasks of this study. Running both the Best Practice Model and the Manhattan sub-network meso-simulation allows for analyses at both the regional level and on a more detailed localized scale. The methodology for these analyses is presented in the following section.

7.3 Research Methodology

A methodology is developed to translate the findings of the BMS into scenarios of potential OHD shifts to study the traffic effects of the OHD program. The relevant behavioral findings are summarized, followed by a description of a research methodology for the traffic models. Scenarios of potential demand shifts are constructed, and finally model-specific issues are discussed for both models employed.

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[3] http://www.caliper.com

7.3.1 Summary of relevant behavioral findings

The BMS studies provide the foundation for the analytical effort of this study. Some of the elements that the BMS focuses on are: the receptivity of food and retail industry receivers and their carriers to participate in OHD; and estimates of truck traffic in the New York City region, with the main focus on the borough of Manhattan. The data from the BMS used by the traffic simulation research team can be briefly summarized as the percentage of receivers within Manhattan willing to accept a certain tax incentive to shift their delivery operations to the off-hours (7 PM - 6 AM). This program, representing a broad-based incentive program, provides data based on businesses in the food and retail industries located in Manhattan. Additionally, the behavioral estimates are for every ZIP code in Manhattan, which for simplicity are grouped into community board groupings. There are four main community board groupings in Manhattan, shown in Figure 85.
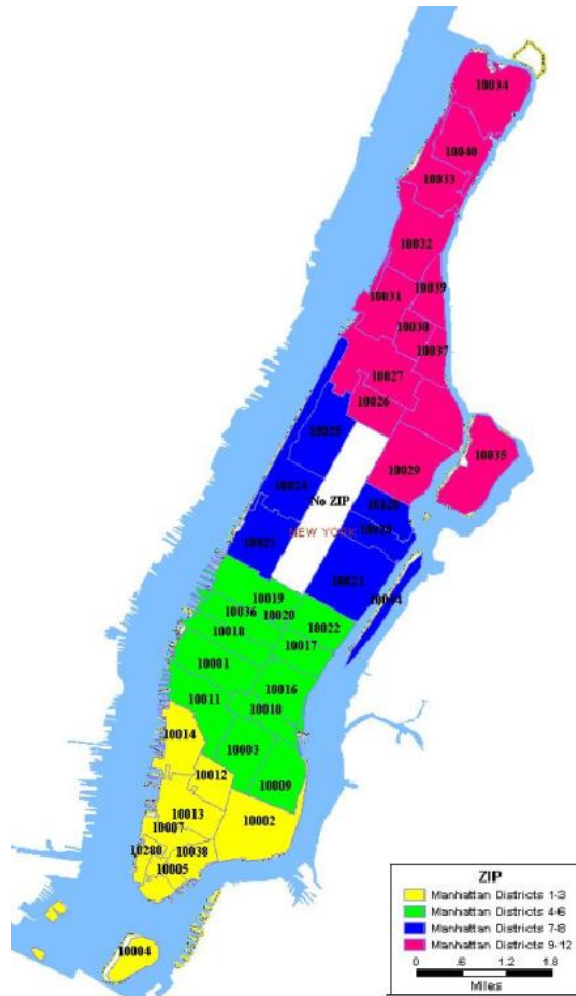
Figure 85: Community Board Districts in Manhattan

For traffic simulation purposes, the research team must know what proportion of commercial traffic in the study area falls under the broad-based program, or corresponds to food and retail deliveries. While impacts to the food and retail industries are studied, commercial traffic serving other industries is not. Various industries respond differently to the incentive, and their percentages of total truck traffic varies. Since, as a result, only food or retail related commercial traffic would be expected to change behavior, the team needs to estimate the probability that a CMV in the traffic stream would be making food or retail deliveries. This is accomplished using the trip generation models developed by the BMS research team. Table 16 shows the total and percentage breakdown of deliveries by each Manhattan community board district grouping. Table 17 shows the breakdown of deliveries within the groupings by industry (food and retail), and as a percentage of total deliveries.

Table 16: Delivery Percentages for Community Board District Groupings

Area	Daily Deliveries	%
Community Districts 1-3	12,202	26.46%
Community Districts 4-6	20,169	43.74%
Community Districts 7-8	7,778	16.87%
Community Districts 9-12	5,964	12.93%
Total Food Deliveries for Manhattan	46,113	100.00%

Table 17: Proportion of Truck Traffic by Industry

Area	Food Deliveries	Retail Deliveries	Total Deliveries	Food Percentage	Retail Percentage	Food and Retail Percentage
Community Boards 1-3	12,202	17,244	92,163	13.24%	18.71%	31.95%
Community Boards 4-6	20,169	63,458	271,407	7.43%	23.38%	30.81%
Community Boards 7-8	7,778	10,217	71,277	10.91%	14.33%	25.25%
Community Boards 9-12	5,964	5,292	30,788	19.37%	17.19%	36.56%
Total	**46,113**	**96,211**	**465,635**	**9.90%**	**20.66%**	**30.57%**

Using the data from Table 17 the total percentage of CMV traffic responding to the proposed incentive of this program can be calculated. This calculation assumes that all CMV trips destined for Manhattan are deliveries. The results of the behavioral studies estimate what percentage of truck traffic will shift from day time operations to overnight hours. A shift model is developed to model the OHD program in the traffic models selected, and to integrate the findings of the BMS.

7.3.2 Commercial vehicle (CMV) demand shift model

While the BPM and associated sub-simulation model offer some advantages over other four-step demand forecasting models with feedback, an iterative planning process, and micro-simulation components, they still do not exactly accommodate all the needs of this study. For example, they do not automatically re-assign and redistribute traffic based on predicted changes. Therefore, the research

methodology must be modified to account for the intricacies of the models. In BPM, the traffic assignment module is run without user control, with vehicles choosing the best routes between their origin and destination at their onset (Parsons Brinckerhoff, 2005). Therefore, changes to truck behavior and routing will be represented by manipulating the number of commercial vehicle trips between each OD pair for each time period. For both models, these CMV trips between origin and destination zones are stored in an OD matrix, with each cell containing the number of trips between zones per period. Once the existing commercial vehicle OD matrices are altered, the traffic assignment module of BPM (and the mesoscopic simulation network) will be re-run, and the results of the assignment based on the altered OD demands can be compared against the results of the base assignment. Alterations to the CMV OD matrices are accomplished with shift factors calculated from the behavioral data.

7.3.2.1 *Destination zones*

Most of the commercial activity in New York City is located in the borough of Manhattan, which was the focus of the BMS. Manhattan also has the highest population density and traffic in the city, and is the focus of other proposed traffic control programs such as congestion pricing. Manhattan can be further subdivided into districts, based on geography or commercial density. Being an island with very limited entry points, Manhattan is additionally easy to isolate from a transportation modeling perspective.

The level of detail and size of zones are subject to two input constraints: (1) the zone system of the traffic simulation model; and (2) the zone system used by the behavior modules. BPM employs a zone system loosely based on census tracts, resulting in 3,586 transportation analysis zones for the entire New York region. Out of these, 2,374 are located within New York City and 318 inside Manhattan (Parsons Brinckerhoff, 2005). The number of deliveries is known for market segments for all unique ZIP codes in Manhattan. These ZIP code areas can be grouped by their community boards, and into four general zones in Manhattan, as seen in Figure 85. The zones used by each traffic model can be similarly grouped to roughly approximate the four community board groupings.

Shift factors calculated from the behavioral data are applied to CMV OD demands between all originating zones outside of Manhattan and destination zones within Manhattan. In addition to these simulation runs, additional runs are conducted when the shift factors are only applied to OD demands with destination zone in Downtown or Midtown Manhattan. Defined here as "Lower Manhattan", these zones comprise community board groupings 1-6, and cover the two central business districts of Manhattan. These areas also contain the bulk of the commercial establishments in Manhattan and over 75% of the deliveries that take place within Manhattan occur in these areas.

7.3.2.2 Time periods

The shift factors, α_J, developed from the behavioral data are used to factor the commercial vehicle origin-destination demand, x_{ij}, as shown in Equation 19:

$$x_{ij(new)}^p = x_{ij(old)}^p \times \alpha_j \tag{19}$$

where x_{ij} = *CMV trip demand between origin 'i' and destination 'j'*

            α_J = *shift factor for trips with destination in zone J*

$$p = \begin{cases} 1 \text{ for AM Peak Period} \\ 2 \text{ for Midday Period} \\ 3 \text{ for PM Peak Period} \\ 4 \text{ for Overnight Period} \end{cases}$$

The results of the BMS are not time period specific, and they apply to all daytime hours. Thus the same α_J factor is used for the demands of the three daytime periods.

Since the purpose of this study is to model and assess the impact of time-of-day shifts in freight traffic, particularly shifting daytime traffic to the off-hours, it will be assumed that all freight traffic reduced from the three daytime periods will be shifted to the overnight off-hour period. Therefore the total daily commercial vehicle demand between an OD pair, X_{ij}, remains constant for the entire 24-hour day for the base (existing) and shifted scenarios, regardless of the values of α_J.

$$X_{ij} = \sum_{p=1}^{4} x_{ij}^p \text{ is constant for all } ij \text{ pairs} \tag{20}$$

As a result, no α_J factor is applied to period 4 (overnight). Instead, the demand for the overnight period will be equal to the existing demand combined with the shifted demands from the three other times periods. So for each OD pair, the new overnight off-hour demand is calculated by Equation 21:

$$x_{ij(new)}^4 = x_{ij(old)}^4 + \alpha_J \left(x_{ij(old)}^1 + x_{ij(old)}^2 + x_{ij(old)}^3 \right) \tag{21}$$

7.3.2.3 *Assignment of shift factors*

A destination zone refers to the end point of trips in the model, with trips being contained in an origin-destination matrix before assignment to the network. Thus, to apply a shift factor to a certain group of zones, all OD pairs with destination in the group of *J* zones being considered will receive the factor. This implies that for freight traffic from all origins bound for Manhattan (or a particular area of Manhattan), a certain percentage will shift to the off-hours. Computationally all OD trip shifts are done exogenously in a MATLAB script which required modification to update the zones of the model having trip shifts.

To apply the shift percentages, the following scheme was used: in BPM, zones in the network number from 1 to 4000, with zones 1 to 318 located inside Manhattan. The OD pairs qualifying for a shift were those with the origin as all zones in the network (1-4000), and the destination within Manhattan (1-318, or *(i,j) = (1:4000,1:318)*. This signifies that even trips originating within Manhattan are shifted. This was done purposely to account for chained trips, and to maintain the link between 'deliveries' and 'trips.' For simplicity, shift factors are used corresponding to the community board groupings described to account for the more than 1,200,000 OD pairs receiving a shift factor. For this purpose, the percentage of commercial vehicle traffic shifting to OHD is represented as a shift factor, α_J, calculated by Equation 22:

$$\alpha_J = \sum_e \rho_J^e \omega_J^e \tag{22}$$

where,   *J = destination zone where receivers are located*

e = industry segment {retail, food}

ρ = percentage of deliveries from industry 'e' shifting to off-hour

ω = proportion of total deliveries associated with industry 'e'

For the scenarios simulated in BPM the shift factors shown in Table 18 are used. The shift factors are calculated for four community board groupings in Manhattan, and by accounting for both the number of food & retail receivers located in these groupings, and the participation levels predicted by the BMS. This represents the shifting induced by the broad-based OHD program.

Table 18: Broad-Based Program Shift Factors by Scenario

Scenario	Tax Incentive	Community Boards, J	Retail Proportion, ρ^R	Food Proportion, ρ^F	Retail Percent, ω^R	Food Percent, ω^F	Shift Factor, α_J
1	$5,000	1, 2, 3	16.47%	12.83%	4.59%	22.21%	3.60%
		4, 5, 6	21.45%	7.15%			2.57%
		7, 8	11.82%	10.11%			2.79%
		9, 10, 11, 12	14.34%	17.13%			4.46%
2	$10,000	1, 2, 3	16.47%	12.83%	10.44%	52.92%	8.51%
		4, 5, 6	21.45%	7.15%			6.02%
		7, 8	11.82%	10.11%			6.58%
		9, 10, 11, 12	14.34%	17.13%			10.56%
3	$15,000	1, 2, 3	16.47%	12.83%	18.39%	74.75%	12.62%
		4, 5, 6	21.45%	7.15%			9.29%
		7, 8	11.82%	10.11%			9.73%
		9, 10, 11, 12	14.34%	17.13%			15.44%
4	$20,000	1, 2, 3	16.47%	12.83%	26.71%	83.55%	15.12%
		4, 5, 6	21.45%	7.15%			11.70%
		7, 8	11.82%	10.11%			11.60%
		9, 10, 11, 12	14.34%	17.13%			18.14%
5	$25,000	1, 2, 3	16.47%	12.83%	36.39%	86.17%	17.05%
		4, 5, 6	21.45%	7.15%			13.97%
		7, 8	11.82%	10.11%			13.01%
		9, 10, 11, 12	14.34%	17.13%			19.98%
6	$50,000	1, 2, 3	16.47%	12.83%	74.80%	87.12%	23.49%
		4, 5, 6	21.45%	7.15%			22.28%
		7, 8	11.82%	10.11%			17.65%
		9, 10, 11, 12	14.34%	17.13%			25.65%

7.3.3 Scenario selection

Among the results of the BMS are predicted receiver participation levels based on the amount of tax incentive offered. The traffic simulation team used this output to convert to demand shifts for simulation modeling. Six scenarios are chosen for the broad-based program modeling, representing the results of when receivers accept tax incentives of $5,000, $10,000, $15,000, $20,000, $25,000, or $50,000. These six scenarios are modeled in BPM while only the first three scenarios used for BPM modeling are selected for the mesoscopic simulation, given that the simulation involves more complex computational tasks. Additionally six further scenarios are run in BPM for when the incentive was only extended to Lower Manhattan receivers.

These scenarios are only chosen for simplicity: to study the traffic impacts of a certain percentage shift in deliveries, rather than the impacts associated with a tax incentive level offered. Results are presented in terms of the average shift factor of each scenario, which is the average of the shift factors for each community board grouping shown in Table 18, weighted by the proportion of deliveries to each community board grouping. These weighted averages are shown in Table 19 and plotted in Figure 86.

Figure 86 shows that as tax incentive amount increases, the marginal increase in average shift factor decreases, due to a limit in receiver participation predicted by the BMS.

Table 19: Average of Shift Factors for Broad-Based Program Scenarios

Scenario	Tax Incentive	Average Shift Factor
Base	$0	0.00%
1	$5,000	2.93%
2	$10,000	6.90%
3	$15,000	10.42%
4	$20,000	12.79%
5	$25,000	14.83%
6	$50,000	22.03%
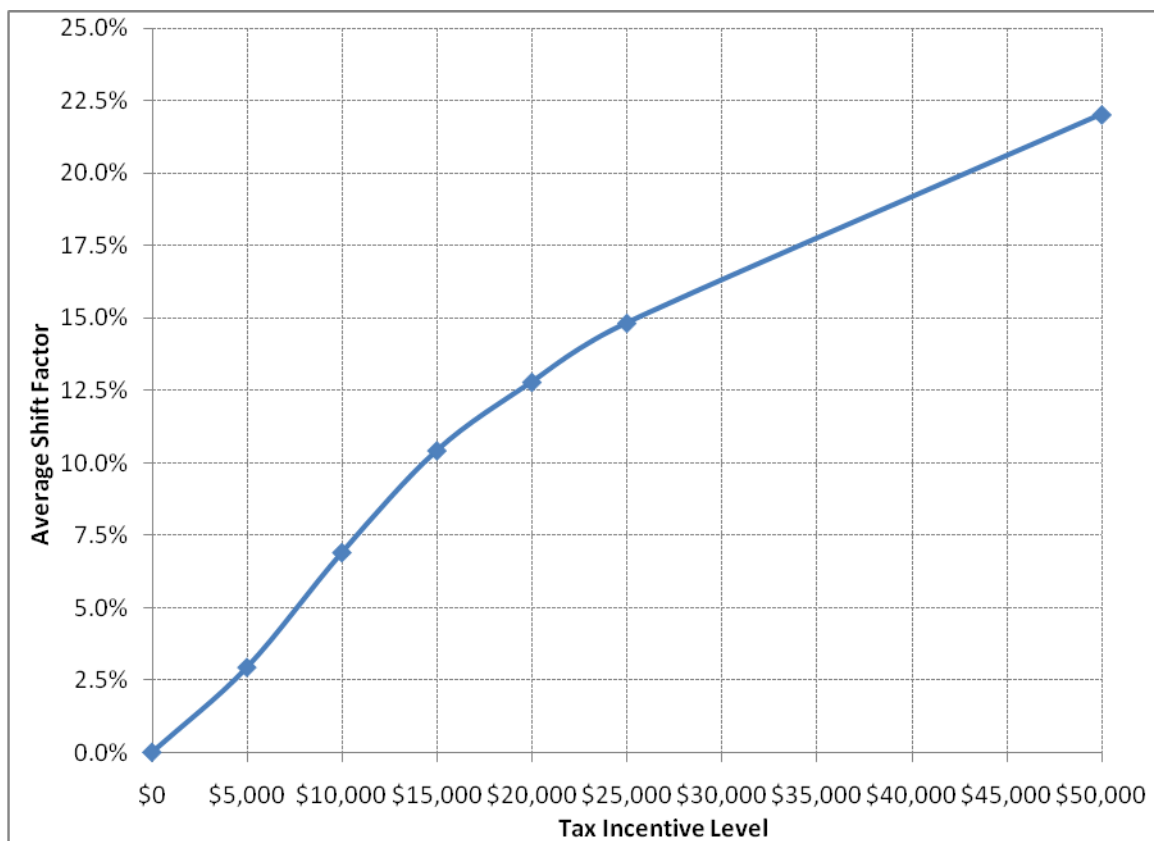
Figure 86: Average Shift Factor by Tax Incentive Level

7.3.4   Model-specific methodologies

7.3.4.1   *Best practice model research methodology*

As described, the model is split into four time period models, each running traffic assignment independently. They are the AM Peak Period (AM) from 6 - 10 AM, Midday Period (MD) from 10 AM - 3 PM, PM Peak Period (PM) from 3 - 7 PM, and the Overnight Period (NT) from 7 PM - 6 AM. The shift model moves CMV trips from three daytime periods—AM, MD, and PM—to the NT period. In BPM, the

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traffic assignment module is run without user control, with vehicles choosing the best routes between their origin and destination at their onset (Parsons Brinckerhoff, 2005). Changes to commercial vehicle (trucks and other commercials) behavior and routing are represented by manipulating the number of CMV trips between each origin-destination pair for each time period. Prior to this, the OD matrices undergo an extensive calibration process described in the following section. Once the existing truck and other commercial OD matrices within BPM are altered, the models' outputs are compared to the base case. The BPM modeling methodology is illustrated in Figure 87.
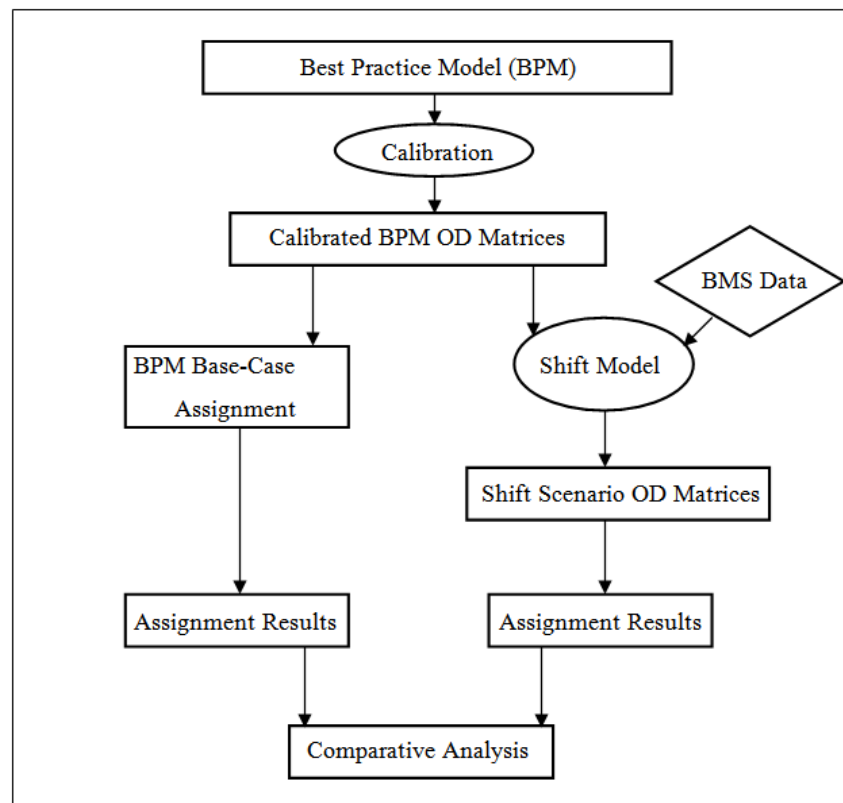
Figure 87: BPM Research Methodology

7.3.4.2 *Methodology for mesoscopic simulation*

The methodology adopted is to perform a mesoscopic simulation of an extracted sub-area (Manhattan) of the BPM network. A simulation of the whole BPM network is extremely complex and computationally expensive. The large-scale nature of the network (route choice, number of links, etc.) and the running time of the model would be computationally prohibitive due to the number of operations required. Therefore, the simulation is performed on a sub-network of Manhattan and its access facilities (bridges and tunnels) only, while adapting the sub-network to TransModeler requirements.

The methodology for mesoscopic simulation consists of two simultaneous procedures (see Figure 88). The sub-network is extracted from the BPM to study the effects of the OHD program in Manhattan in a

more detailed way using a dynamic, mesoscopic simulation. Figure 88 shows that the first task is related to developing a model for the base case and the second to scenario generation. Since BPM has been designed for modeling macro-scale static behavior it cannot be directly used as an input for meso-simulation, since only major intersections in the local network have intersection geometry details. However, it is still appropriate for mesoscopic simulation provided that the BPM has the necessary road class information, free flow speeds, capacities, number of lanes, etc. Hence, the network can be imported directly to TransModeler for the main features of the network. Once imported, the network is calibrated to assure a minimum exit-flow and avoid queues and spillovers.
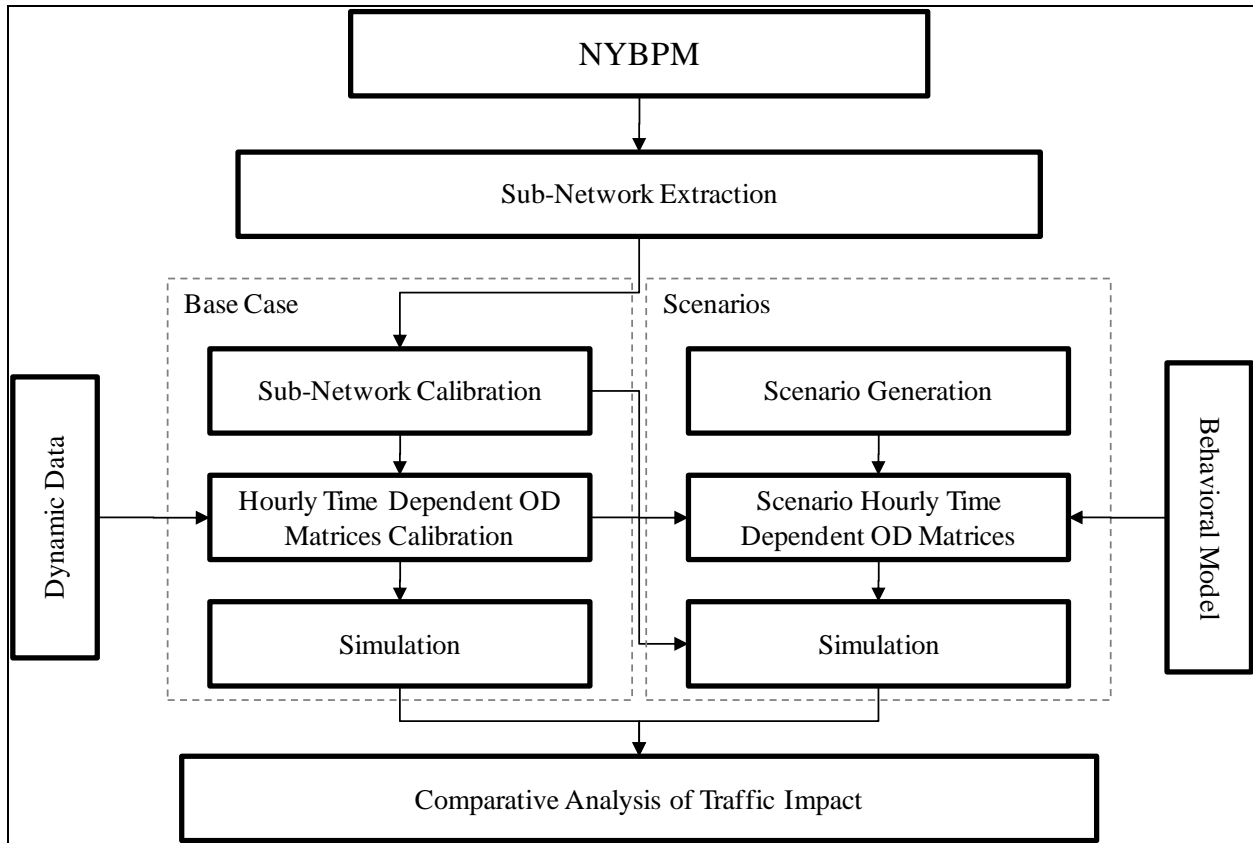
Figure 88: Sub-network Simulation Research Methodology

Unlike BPM, the sub-simulation uses hourly OD matrices, with three classes being simulated: PC = passenger cars, SU = trucks, and PU = other commercial vehicles (pickups, vans). These OD matrices are constructed based on the BPM OD matrices and further calibrated with the dynamic data. These hourly time-dependent OD matrices are used in the simulation of the base case and they are adapted according to the scenarios generated for study. The truck and other commercial vehicle demands shifted away from the daytime periods are distributed uniformly across the overnight (NT) period. TransModeler uses the same zone system as BPM while associating these zones with centroids in the sub-network, thus the shifting is performed using the codes of the zones. For the hourly OD matrices in NT period, the demand extracted

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from AM, MD, and PM periods is uniformly distributed among the 11 hours of the NT period (defined by the superscript *TT*) using Equation 23:

$$Truck_J^{TT} = Truck_J^{TT} + \frac{\sum\limits_{T=6am-7pm}^{6pm-7pm} \alpha_J.Truck_J^T}{11}(1-\alpha_J).Truck_J^{6am-7am} \qquad (23)$$

After using the shifting percentages in Table 18, the truck and other commercial flows are transferred from the daytime periods to the overnight period exogenously, and inputted for simulation. Finally, since the mesoscopic simulation requires a good estimate of travel times, historical travel times are obtained for the base case condition using a sample of runs (five in total) and aggregating the travel times following an averaging procedure akin to the method of successive averages (MSA). These travel times, referred to as historical travel times, are used for all mesoscopic simulations. There is an alternative method for running the mesoscopic model; instead of using historical travel times for each demand scenario, the updated travel times from the previous scenario can be used as base travel times. The research team experimented with this approach and reported results based on this alternative scenario as part its deliverables. However, after deliberations among team members, the first approach of using historical travel times as the base case for all the scenarios has been deemed to produce more realistic and reliable results and thus it is adopted. A summary of the efforts in calibrating both models to the methodology and the needs of this study is presented in the following section.

7.4 Network Calibration

This section summarizes the initial investigation and calibration of the two traffic models used. The calibrations conducted result in finalizing all of the inputs to the two simulation models used for simulating the proposed programs of this study. The first sub-section focuses on investigating the behavior of BPM and implementing the developed research methodology. Secondly, calibration of the commercial vehicle OD matrices used by the model is conducted. Finally, the third sub-section focuses on extraction and calibration of the Manhattan sub-network simulation used to run in the mesoscopic simulation tool TransModeler. After initial testing was conducted to check the validity of the models' results, a thorough calibration procedure involving the most up-to-date data available was necessary to ensure their fidelity. Completion of these tasks allows for final implementation of the research methodology and fulfillment of the study's objectives.

7.4.1 BPM initial testing

Initial testing of BPM showed that it performed well at a macroscopic level, and coupled with its widespread use as an evaluation tool for many studies in the New York metropolitan area, it was accepted by the research team as a credible model. Development and calibration by NYMTC are still ongoing,

including producing newer versions of the model, and much work has been put into making it a reliable model (Parsons Brinckerhoff, 2005). The research team then focused on testing the model to incorporate the developed methodology. Since the behavior model was not yet complete, shift factors were not available to the traffic simulation team. Arbitrary shift values were chosen and the OD demands manipulated. Then, the results were compared against existing, base case results. These tests were run to observe how the model reacted to the changes, and as baseline scenarios for future tests and changes.

7.4.1.1 *Predicted link flow and travel time changes*

The results obtained from running the full BPM model were inconsistent with expected trends, with the expectation being that lower commercial vehicle demands during a period should result in decreased congestion. The network assignments produced link flow, speed, and travel time changes that were unexpected, including daytime period travel times and congestion increasing when commercial traffic was shifted away from the period. It was found that as a result of lower CMV demands, the model increased auto and other vehicles' trip generation rates. Because the network is already near saturation, the large increase in the number of auto trips made up for the decrease in CMV traffic, and increased congestion on the network. The increased auto trip generation caused a net decrease in average travel times throughout the network. This result forced the research team to conduct a more detailed study on the generation and assignment processes of BPM.

7.4.1.2 *Predicted trip generation changes*

Even before the assignment results are compared, the results of trip generation can be analyzed to observe whether the expected effects of CMV OD demand modifications occur. Due to the iterative nature of BPM, trip generation rates for non-commercial vehicles (grouped together as "autos") are affected by changes and shifts in commercial vehicle traffic. Figure 89 shows the change in auto trip generation based on the percentage shift in commercial vehicle demand (trends based on data points at 10%, 20%, 50%, and 100% shift of CMV demand throughout the region). As expected, auto trip generation increased for the AM Peak, Midday, and PM Peak periods as a larger percentage of CMVs were shifted away from these periods. An unexpected result was that similar trends were observed even for the Night period. This was a counter-intuitive result, since if shifting commercial vehicles away from a time period is thought to encourage more auto activity, shifting more CMVs to the other time period was expected to reduce the number of auto trips generated. The explanation was found to be that the BPM's pre-assignment processor, which distributes the generated trips throughout the day, maintains a similar distribution of trips throughout the day, regardless of actual traffic conditions. Or more simply, BPM generates more auto trips as a result of decreased truck activity, but distributes them throughout the day the same way every time (Parsons Brinckerhoff, 2005). This represents a weakness in the model's suitability to this study, and necessitated a revision to the proposed methodology.
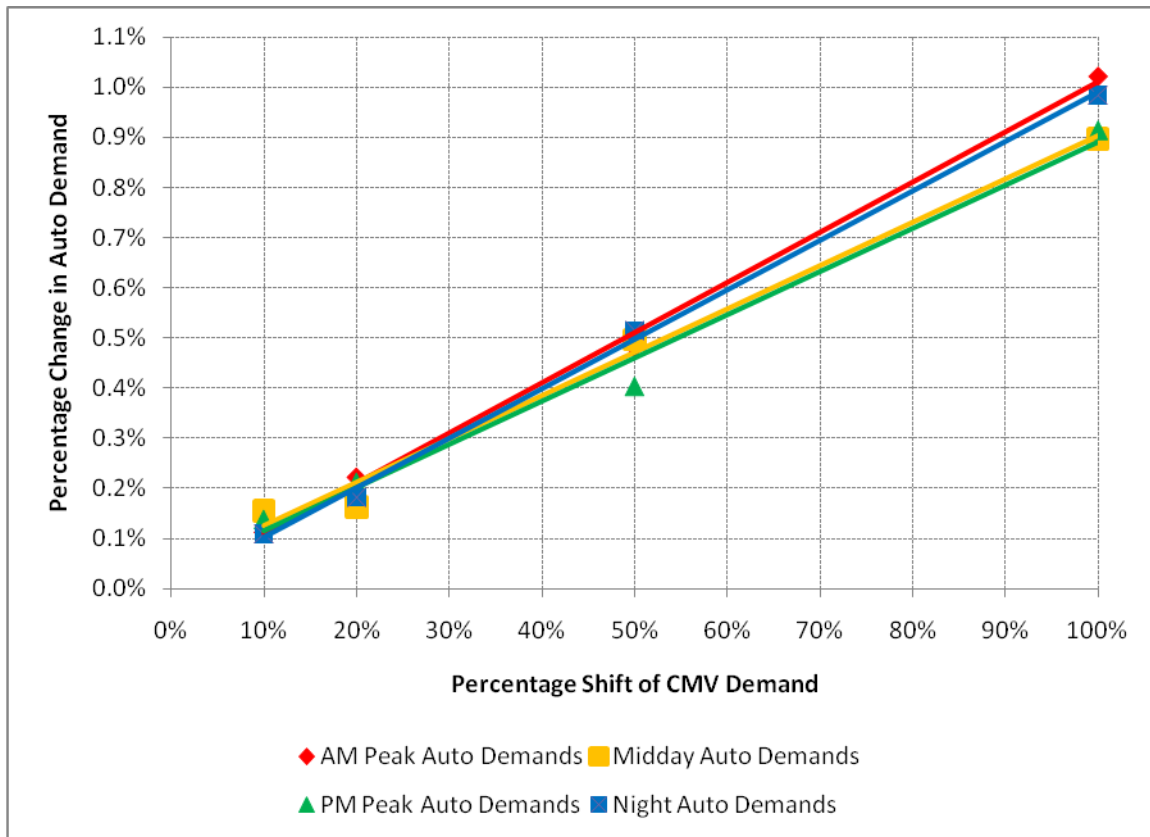
Figure 89: Change in Auto Trip Generation due to CMV Shift

7.4.1.3 *Adapting research methodology to BPM*

Information was gathered from the Final Report Documentation supplied with the Best Practice Model from the New York Metropolitan Transportation Council (Parsons Brinckerhoff, 2005). In the model, the trip generation component produces "journeys" based on destinations, stops, and modes. These are produced aggregately for the entire day. After journey generation is complete, a time-of day processor converts all journeys into individual "trips" between zones (so that they may be read as an OD matrix by TransCAD). Journeys are converted to trips based on a cumulative arrival time distribution and a cumulative activity duration distribution for each journey purpose.

The aggregated trips for each journey type, with their assigned arrival times, are split into trips within 48, ½-hour time periods, weighted using constant factors given in a 76 (journey types) x 48 (time periods) matrix. The trips for each ½-hour time period and 76 classes are then re-aggregated into OD matrices for four model time periods (AM Peak, Midday, PM Peak, Night), each split into six highway vehicle classes and four transit classes. Trips are also assumed to be exclusive to those time periods (no overlap). The implication is that identical ToD factors are used (based on factors in the 76 x 48 matrix) regardless of what happens during trip generation and mode split. Increase or decrease in trip generation leads to corresponding increases or decreases (based on factors) for all time periods.

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Due to lower travel times for three out of the four time periods, due to fewer truck trips, the model generated an overall increase in trips for the day (more activity). However, since constant ToD shifts were used to split trips during the day, constant percentage increases in demand were then seen for all four time periods. The developers of BPM mention in their final report that:

> *...it would be desirable to incorporate more flexible timing considerations. This would allow for better replication of individual travel patterns (in terms of journey sequencing and scheduling) as well as make the modeling system more sensitive to policy measures aimed at congestion relief (Parsons Brinckerhoff, 2005).*

In response to the inability of the BPM time-of-day splits to correctly model truck ToD shifts a number of strategies were considered to fix the problem while still utilizing the power of BPM.

7.4.1.3.1 *Assume non-commercial trips to be constant*

One potential solution is to not allow trip generation and mode splits to re-run after an α percentage of commercial vehicle traffic is shifted. Instead, shifts to CMV traffic would be performed exogenously from the model and only the highway assignment module of the model is re-run for each scenario. The trip generation, distribution, and mode split modules are thus ignored, but assignments differ since the OD matrices will be manually manipulated before the assignment. This result is realistic for short-term analysis since shifts in truck traffic would not immediately result in changes to travel patterns or trip generation; such changes would only develop over time. The drawback is that the model is not allowed to fully run, thus only the network and TransCAD's highway assignment features are used. In terms of long-term trends, changed network conditions should affect trip generation, which would not be modeled using this solution. If it is desired to only study the immediate traffic impacts of a commercial vehicle shift in the network, it produces accurate estimates.

7.4.1.3.2 *Manipulate time-of-day factors*

The time-of-day factors splits inherent to BPM are held in a pre-defined matrix. These can be manually edited and used for a run of BPM. Instead of manually shifting an α percentage of commercial vehicle traffic, increases can be made to the ToD factors for freight travel taking place in the night periods. Correspondingly, decreases can be made to daytime values such that the total splits over the day remain constant. The advantage of this method is that it will eliminate the need to manually shift trips from daytime OD matrices to the night OD matrices, and will ensure that trips throughout the day for all vehicle classes remain constant. The challenges are deciding exactly how much to alter the ToD factors. Little documentation is offered on how these factors were chosen and thus deciding how to manipulate them becomes challenging.

7.4.1.3.3 *Manually redistribute newly generated night auto trips to other periods*

Another strategy is to allow the model to maintain its existing trip generation and time-of-day processing procedures but to then manually redistribute the newly generated night auto trips back to the existing daytime periods. This can be done by stopping the BPM model run between the ToD processor and the highway assignment. The base level origin-destination matrix for the night period is then subtracted from the newly generated OD matrix. This difference (for each OD pair) is then added to the newly generated AM Peak, Midday, and PM Peak matrices, by way of proportion. The proportions are given by the ToD splits, but are also roughly equal to the percentage of daily total OD demand for that time period. The extra night demand is then redistributed to the daytime periods. The advantage of this method is that it allows the model to properly generate the new demand levels caused by increased trucks, while preserving the existing auto level for the night period. The disadvantages include its complexity and the lack of clarity in terms of how much demand to distribute to which time period.

Owing to the complexity and lack of explicit methodologies to conduct model manipulation, the research team decided that the first solution, maintaining constant auto trip generation, would be used for the BPM run results in the near term. The results shown in the following section employ this technique. It also greatly reduces the time spent running the model, and makes it convenient to analyze many different scenarios. Instead of running the model over several days, it now only requires several hours to conduct traffic assignment. The benefits of TransCAD's highway assignment procedures are still used; however, it should be noted that only the assignment portion of the BPM is employed.

7.4.2 Truck origin-destination matrix calibration

This sub-section describes the calibration of the OD matrices used to assign truck trips onto the regional highway network in the BPM. The OD matrices used in the model were first developed and calibrated in the 1990s, thus the research team wanted to check them and ensure their validity. Link volume data was acquired for highway links throughout the New York metropolitan area and compared against the assigned volumes of BPM. This check found that the existing model, even when inflated to the current year, under-assigns trucks throughout all zones in the network. Several procedures were developed and tested to adjust the existing BPM truck OD matrices without necessitating the collection of any new data. The OD matrices were adjusted so that the output of the model's assignment closely matched the up-to-date field data, and finalized for usage as a base case scenario of the model. The following sub-sections describe the data acquired and the procedures used.

7.4.2.1 *Origin-destination matrix adjustment methodology*

Much information exists in the literature regarding origin-destination matrix estimation and calibration. A very brief summary is presented followed by strategies to efficiently implement an effective solution. Strategies utilized to calibrate OD matrices based on field data are of particular

interest. Since BPM is the focus, the problem is further narrowed to only static cases. OD estimation techniques can be broadly classified into three categories: (1) trip generation adjustments using extensive data surveys; (2) trip distribution models; (3) and non-assignment based adjustment using volume data (Cho et al., 2009). The third strategy is simplest and most easily implementable given the current data sources and study limitations. One disadvantage of this method is that since the proportion of links with data to total network links is so low (321 to 55,000+), the problem is severely underspecified. Thus a number of potential OD matrices can be estimated based on the link flows (List and Turnquist, 1994).

BPM's truck OD matrices were originally developed through a trip generation approach with support for input of link counts (List et al., 2001). Beginning with a target trip matrix, all OD estimation problems seek satisfy the following general condition (Crainic et al., 2001):

$$Minimize \ \frac{1}{2}\left(\sum (g - g^*)^2 + \sum (v - v^*)^2\right)$$

(24)

where, g = demand matrix,

   g* = adjusted demand matrix,

   v = link flows (vehicles per hour),

   v* = adjusted link flows (vehicles per hour)

This can be simply described as minimizing the total differences between the initial and target trip matrices, as well as the given and assigned link flows. While BPM is further advanced in freight modeling than typical travel demand models—with inclusion of class-stratified origin-destination matrices, class-stratified generalized costs, and Multi-Class Assignment—it still was not the main focus of the model. The creators of BPM explain that:

> ...while addressing commercial traffic as part of the overall BPM regional models was considered essential, the emphasis for the initial BPM was clearly on developing an advance set of private passenger travel models. The resources for development of the commercial travel element were significantly more limited. Consequently, rather than grounding these models in the overall framework of freight or goods movement analysis, the methodology aimed directly at an empirically oriented modeling of truck and other commercial traffic that would make maximum use vehicle class traffic count and origin-destination data in the region (Parsons Brinckerhoff, 2005).

BPM originally estimated commercial vehicle OD matrices based on a combination of surveys and link volumes. Additionally, the process was begun in 1988, and final estimation was made only for the base BPM year of 2002. All model runs for subsequent years are based on inflated versions of the 2002 base year matrices. With the availability of more recent data, it is beneficial to evaluate and update the BPM commercial trip matrices to match current commercial vehicle volume levels. The research team acquired comprehensive link volume data from area transportation agencies and checked the results of

BPM's assignment. A full litany of techniques for OD matrix calibration was tested using the acquired data described in the following sub-section.

7.4.2.2 Data acquired for calibration

The research team was active in aggressively pursuing actual data on truck volumes throughout the New York metropolitan area for the purpose of validating and calibrating the output of the BPM, as well as for input into the mesoscopic simulations of TransModeler. The following sources of data were identified for acquisition:

- New York City Bridge and Tunnel Counts (From New York City Department of Transportation (NYCDOT), Metropolitan Transportation Authority (MTA), and Port Authority of New York & New Jersey (PANYNJ)
- New York & New Jersey State Departments of Transportation Weight-In-Motion (WIM)/Volume Data
- New Jersey Turnpike Truck EZ-Pass Volumes at All Interchanges
- Other available reports and studies

The following sub-sections describe the available volume data and its comparison with the BPM output.

7.4.2.2.1 Weigh-In-Motion (WIM) data

Weight-In-Motion stations are located on highways throughout the region, where class-wise volume data is collected by time of day. Aggregation and filtration of this data enables the researchers to determine the average volume for a given link by vehicle class. In addition to this data, weigh stations where trucks must stop to be weighed also count the number of trucks stopping and the times of their stops, which are then stored in a database. Access to these databases enables the research team to aggregate truck volumes by hour or period, which can then be taken as the truck volume for the link that the station is located. Then the counted volume on that link can be compared to the assignment output of BPM for the same or similar link on the highway network. New York State and New Jersey Departments of Transportation were contacted to obtain data from year 2007 (the most recent available year at the time). The collected data was aggregated and post-processed to obtain average link volumes for the links in network, for all the hours of the day.

7.4.2.2.2 New York City DOT Bridge and Tunnel volume counts

For the purposes of this study, New York City Department of Transportation's Bridge and Tunnel Volume datasets (NYCDOT, 2007) are most useful since the focus area is Manhattan. Since Manhattan is an island, counts are available at all entry points into Manhattan. However, the collected data does not perfectly hold suit for comparison to BPM output; several agencies own and operate the crossings into Manhattan and collect and provide data differently. For example, NYCDOT counts are only available hourly from 7 AM - 7 PM, whereas BPM assignments are for periods covering 6 - 10 AM, 10 AM - 3

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PM, 3 - 7 PM, and 7 PM - 6 AM. In order to use the collected data, the research team had to aggregate certain classes of vehicles into two large categories: trucks and other commercials. To account for lack of data and for simplification only the trucks category was used in calibration. Additionally, some links could not be used for calibration since data was not collected, especially during overnight hours.

7.4.2.2.3 New Jersey Turnpike volumes

Data was already available to the research team for the New Jersey Turnpike, a major carrier of truck traffic in the New York metropolitan area. The New Jersey Highway Authority collects EZ-Pass data, the electronic toll collection system used, for vehicles entering and exiting the system at every interchange. By extrapolating this data, vehicular flows can be estimated for every link of the system, and separated by class. Data for the New Jersey Turnpike is available for all hours of the day, thus it can aggregated and directly compared to the output of BPM.

7.4.2.3 Comparison of BPM output with acquired data

The goal of this process is to ultimately determine whether the BPM OD matrices are up-to-date and suitable for this study. However, analysis of only individual links or points on the highway network can provide misleading results since differences might be due to variances within the assignment and not problems with the OD matrices. A complete aggregation of all collected data was made for full comparison. All combined the research team collected average hourly truck volume counts for 321 links in the regional network, mostly concentrated in and immediately around New York City. The links with available truck counts are highlighted in the BPM network in Figure 90.

Figure 90: New York City Area Links with Truck Volume Counts

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For the sake of evaluating BPM output, the 2007 volumes were compared with the assignment output of a 2007 BPM scenario. Since BPM is really a collection of four separate models, representing the four separate time periods, analysis is conducted separately for each. Figure 91 shows BPM predicted truck flows plotted against the actual truck volume counts for all the links where data is available. It can be seen that the majority of the data points are to the right or below the 1:1 ratio line, indicating that the actual truck volume counts are higher than the BPM predicted volumes. The discrepancy is most noticeable during the PM Peak period, where nearly all link truck volumes are underestimated.
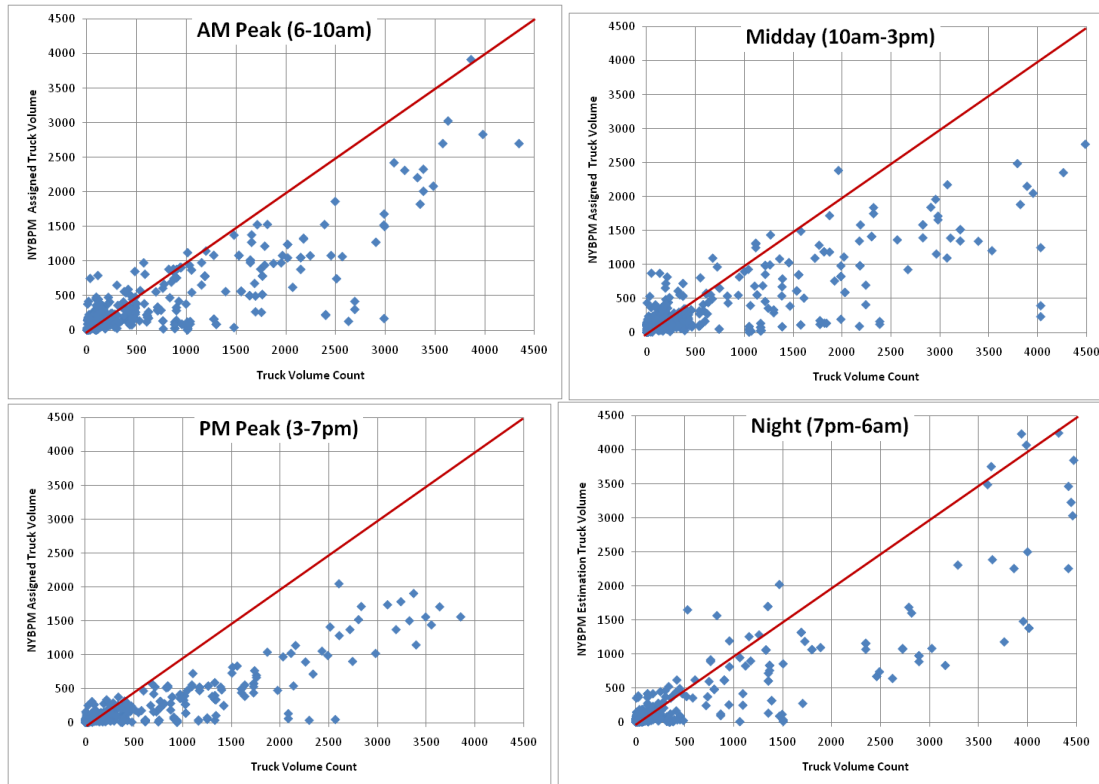
Figure 91: 2007 Truck Volumes vs. BPM Assigned Flows

Table 20 shows a further breakdown of BPM underestimation by geography. The percentages listed are the differences between 2007 BPM assigned truck link flows and 2007 truck volume counts from the acquired data. The underestimation is fairly constant throughout the network for all time periods.

Table 20: Underestimation of 2007 Truck Volumes by BPM by Region

Truck Link Volumes	Manhattan Crossings	Other New York	New Jersey
AM Peak	-25%	-43%	-34%
Midday	-31%	-44%	-43%
PM Peak	-53%	-69%	-54%
Night	-56%	-42%	-32%

From the data comparison, it is clear that the old BPM truck OD matrices, even when projected for a 2007 model run, are resulting in significantly fewer truck trips throughout the network than what is observed from 2007 data counts. The following summarizes the actions taken to calibrate the truck OD matrices to suit the needs of the study, described fully in the task deliverables.

7.4.2.4 Calibration trials

Three main strategies were tested to calibrate the 2007 truck OD matrices of BPM: (1) re-estimation of the OD matrices using TransCAD; (2) manual inflation of the matrices; and (3) an iterative inflation of the matrices. After usage of the OD estimator, the subsequent techniques were only employed due to the ineffectiveness of the estimator to produce reasonable estimates within the time constraints of the study. TransCAD software suite has a built-in OD estimation procedure that conveniently used the existing BPM OD matrices, and BPM assignment output, as inputs. Since BPM already functions within the TransCAD environment, it facilitates an easy transfer to estimate and calibrate new OD matrices. As four separate OD matrices exist in BPM, and each OD estimation routine requires approximately three hours each—combined with BPM assignment and pre- and post-processing—each scenario took approximately three days to run.

The scenarios themselves were designed to integrate the available link counts from data sources to produce OD matrices that could themselves closely match the link counts once they were assigned in BPM. Since the results of BPM assignment were not expected to completely replicate existing conditions, links were aggregated for analysis purposes. The links for which data were available were grouped into three categories: Manhattan crossings, Other New York links, and New Jersey links. Performance of the newly estimated OD matrices was gauged based on how closely the combined truck link flows for each group matched the data from the observed truck link volumes. The experience with re-estimating new OD matrices proved to be ineffective in conforming to observed link volumes. Due to its ineffectiveness, as well as its long running time, the research team decided to stop this process and pursue other ways of updating the truck matrices of BPM.

As a precursor to running the OD estimation procedure within TransCAD, the effects of a direct scaling of the OD matrices was tested. In this process, the average difference between BPM assigned volumes and actual volume counts on the link data were available for were calculated. This single average percentage difference was used as a multiplier to scale, or inflate, the period OD demands. The scaling of the OD matrices produced disparities of lower magnitude than the base 2007 assignment link flows. While tempered, the volume discrepancies were still not fixed. Simply scaling the matrices did not adequately eliminate the problem due to regional differences.

In order to fine-tune the matrices created from the manually scaling procedure, an iterative approach was used. Starting with the final matrices produced from the manual inflation approach, they were further

scaled to reach a target conformity level, or having each sub-regional average difference within 10% conformity to observed data. The process consisted of repeating the manual scale sub-procedure with the average difference values, except by updating the difference level—before each iteration—with the new difference level produced from the assignment of the previous iteration. The procedure was repeated until all average measures were within 10% conformity. This was completed within five iterations, producing matrices for all four periods that are now up-to-date with current observed truck volumes. Figure 92 shows a comparison of estimated truck link flows to observed volumes ratios for uncalibrated and calibrated matrices. The diagonal line represents a 1:1 ratio between assigned and observed volumes. For the uncalibrated case, nearly all points are to the right of the line, meaning observed volumes are greater than assigned. The calibrated points are more evenly distributed around the equal line.

To assess the impact of this sub-task, the sums of the origin-destination matrices for all OD pairs are compared. Table 21 compares the overall size of matrix, compared to the base matrix size, with the average difference between assigned flow and observed truck volumes, for each of the calibrated scenarios described. The final calibrated matrices are considerably larger than the uncalibrated matrices, particularly for the PM Peak case, where the sum of the new matrix is more than two times larger than the previous truck OD demand matrix. It is, however, important to emphasize the fact that these OD matrices are not unique. They are one of the many possible OD matrices that can generate similar conformity results based on the initial matrices and the scaling approaches employed. On the other hand, this issue of the non-uniqueness of OD matrices is true for any OD matrix estimation method presented in the literature. Since all of these matrices reach the conformity criteria set by the research team, they are accepted for usage in the other modeling tasks of this study.

Table 21: Matrix Change to Flow Difference Change Comparison

Scenario		AM Peak		Midday		PM Peak		Night	
		Matrix	Flows	Matrix	Flows	Matrix	Flows	Matrix	Flows
Base	*Uncalibrated*	*0%*	*-37%*	*0%*	*-43%*	*0%*	*-61%*	*0%*	*-37%*
TransCad OD Estimator	Regional Average	123%	64%	100%	38%	44%	-33%	146%	85%
	County Average	387%	154%	203%	114%	55%	-28%	139%	112%
	Highways & Arterials	36%	63%	37%	39%	12%	-37%	43%	69%
	Highways Only	8%	32%	7%	17%	2%	-41%	28%	52%
Manual Scaling	Full Network Average	46%	-9%	53%	-13%	86%	-27%	48%	-3%
	NJ O-Ds Only	19%	-30%	27%	-34%	41%	-52%	14%	-30%
	NJ & Manhattan O-Ds	23%	-27%	34%	-31%	56%	-47%	38%	-22%
	All Pairs	59%	0%	70%	-3%	161%	0%	63%	6%
Iterative Approach	2nd Iteration	60%	-1%	75%	0%	171%	0%	60%	4%
	3rd Iteration	62%	0%	75%	2%	176%	0%	57%	2%
	4th Iteration	62%	1%	70%	0%	177%	0%	55%	1%
	5th Iteration	**63%**	**1%**	**71%**	**0%**	**180%**	**1%**	**53%**	**1%**
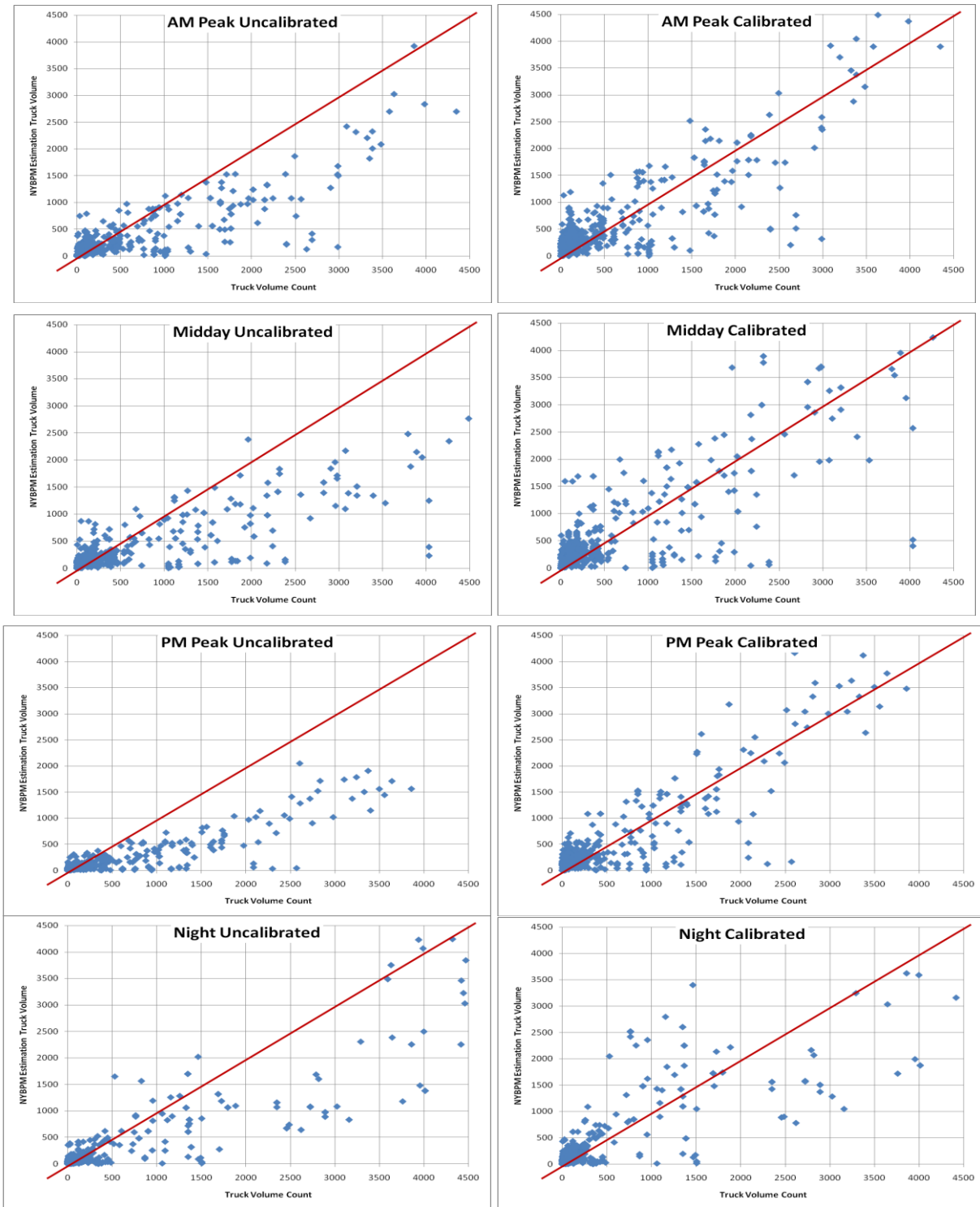
Figure 92: Comparison of Calibrated and Uncalibrated Matrices

7.4.3 Calibration of mesoscopic model

This sub-section focuses on extraction and calibration of the sub-network used for detailed mesocopic simulation of the Manhattan road network. As mentioned, the sub-network and OD matrices resulting from the network extraction of the BPM cannot be directly used in the mesoscopic simulation. A calibration of both the network and time-dependent OD matrices is required.

7.4.3.1 *Acquisition of data for calibration*

Planning models such as the BPM focus on regional impacts. Under this context, the data and network have been calibrated to run a multi-mode multi-class static traffic assignment. On the other hand, simulations for transportation focus more on analysis of corridors or facilities. These models require detailed information such as traffic volumes (e.g., number of cars per hour using a road), turn percentages (e.g., percentages of turning left, right, etc), lane geometries, intersection control information, speeds, etc. These inputs are important for a detailed calibration of the simulation because unlike static models, where high congestion in a link is captured with an increase in the generalized cost, simulations are very sensitive and can show unreasonable gridlocks, spillovers, and other problems related with the dynamic nature of the model. During this study the research team has been active in pursuing the required data to calibrate a simulation model; specifically, dynamic data to calibrate not only hourly matrices but also traffic signal information, hourly speeds, and occupancy studies for speed-density relationships, which are parameters for the simulation.

The lack of detailed studies for the whole Manhattan traffic network has been a limitation that the team had to deal with. After contacting several institutions only partial data to calibrate the hourly matrices has been made available, mostly from the 2002-2007 NYCDOT Bridge and Tunnel counts previously described (NYCDOT, 2007). The data includes hourly information for different vehicle classes; however, the classification is not the same for all facilities, and for most of overnight period (7 PM - 6 AM) only total counts (which include the summation across all classes) are available, making calibration more difficult. In addition, this partial availability of data provides a limitation because only bridges and tunnels can be calibrated in detail. It affects the size of the simulation because, given that only access facilities' counts are available, external stations have to be chosen at the end of the bridges and tunnels that serve as access to Manhattan. Therefore, the calibration can only be done for the inflow/outflow to/from Manhattan. Another limitation is the lack of speed and density data to calibrate speed-density functions, important parameters for the simulation. Some studies and manuals (Cambridge Systematics, 1988a; FHWA, 2004; Singh et al., 2009) were reviewed and used as references to verify the appropriateness of the speeds in the BPM.

In summation, given the limited data available, the mesoscopic simulation has focused on: (1) using the BPM model as the main source for data, and trying to maintain most of the parameters of the BPM

while using the limited data to calibrate and verify the hourly matrices and simulation results; (2) using some of the GPS data from the pilot test of this study as a source for validation of the simulation, e.g., speeds; and (3) changing some parameters of the BPM network in order to avoid unreasonable congestion effects that block the simulation, all while producing a simulation pattern that resembles reality. Since the mesoscopic simulation requires both dynamic OD matrices and a calibrated network, the calibration has been restricted to the calibration of hourly OD matrices using the BPM OD matrices as initial inputs as the inflow and outflow data to Manhattan, as well as a calibration of the parameters of the network behavioral model.

7.4.3.2 *Mesoscopic hourly matrix calibration*

As a static network, the BPM uses one OD matrix for each period of study: AM Peak (AM), Midday (MD), PM Peak (PM) and Overnight (NT). Each of these period OD matrices are loaded in BPM without giving consideration to the internal distribution of flow inside a period.

Initial tests using the OD matrices resulting from TransCAD's sub-area analysis using the departure profiles presented without further calibration showed inconsistency in the distribution of truck flow among the bridges and tunnels used (Table 22). In aggregated terms, the differences are reasonable: 15.86% (6 - 7 AM), 13.55% (7 - 8 AM), 7.88% (8 - 9 AM) and -1.51% (9 - 10 AM). However, the disaggregate results (Figure 93) show a significant variation between the hourly simulation results and the actual bridge counts. This highlights the need to construct a time-dependent OD matrix to handle the differences at the disaggregate level.

Table 22: Facilities Used for Comparison

Facility	ID
Brooklyn Battery Tunnel	BBT
Manhattan Bridge	MB
Queens Midtown Tunnel EB	QMT-EB
Queens Midtown Tunnel WB	QMT-WB
Queensboro Bridge	QB
Willis Ave Bridge	WAB
3rd Ave Bridge	3rd
E 145th Bridge	E145
Macombs Dam Bridge	MDB
Washington Bridge	WB
Broadway (from Bronx)	B
G. Washington Bridge	GWB
Lincoln Tunnel	LT
Holland Tunnel	HT
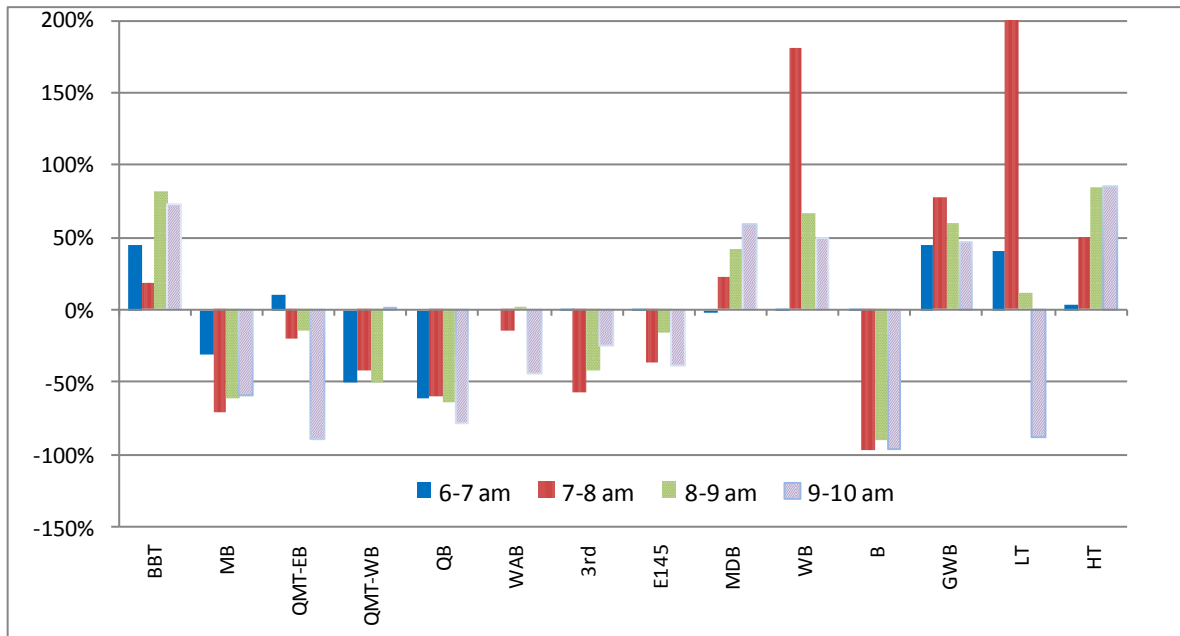
Figure 93: Percent Difference between Hourly Counts and Simulation Volumes by Crossing

In order to correct the variations in the truck counts between the simulation and the truck counts available at bridges and tunnels, a procedure has been developed to obtain accurate hourly OD matrices. The procedure uses the volume data that provides hourly counts for trucks for most of the crossings to Manhattan. Even when the data does not provide hourly counts for all 24 hours (in particular, the report provides very few bridge and tunnel counts for the overnight period), data for the bridges and tunnels that provide access to Manhattan were used in the calibration procedure.
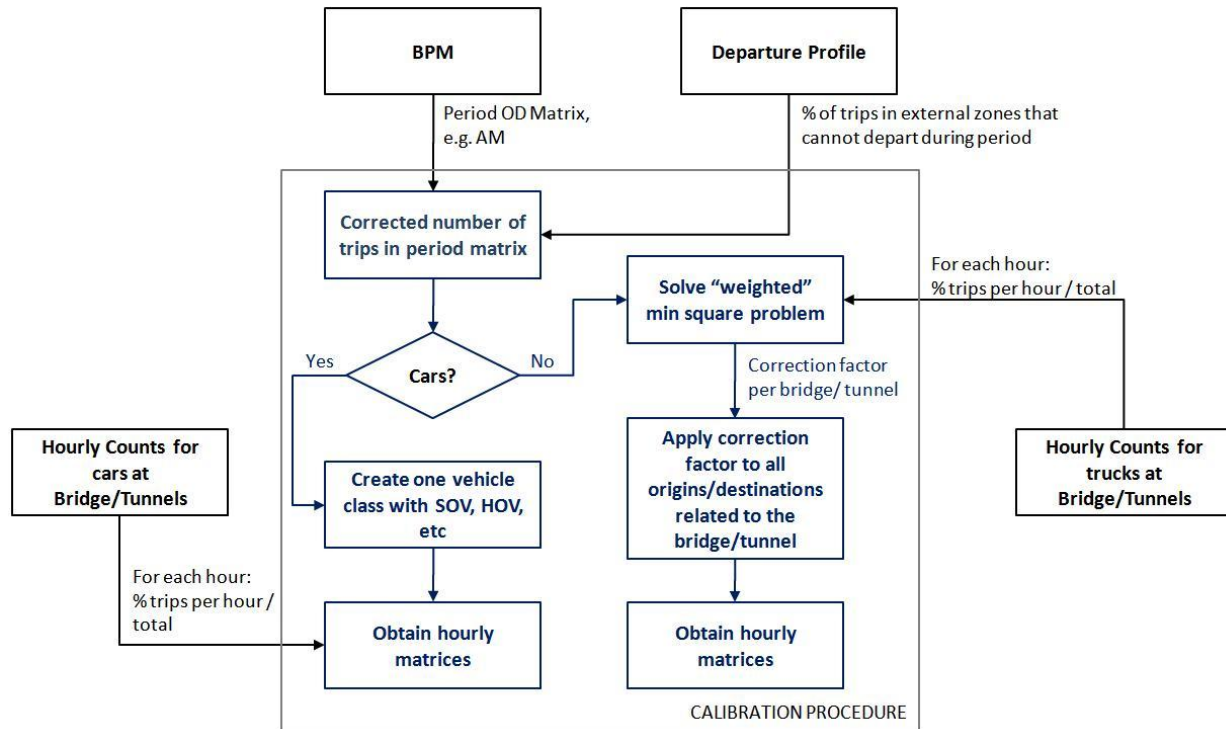
Figure 94: Hourly Matrix Calibration Procedure

The calibration procedure is different for each vehicle class with more effort put in the re-assignment of truck flow to match the hourly volume counts. The general framework can be observed in Figure 94 and is explained as follows:

- First, the amount of trips is corrected using the departure profile obtained. Since the BPM network is reduced into a sub-area network, some of the flow departing in the BPM network during a period, e.g. AM, arrive in the next period (MD) to the external station that is now the new origin of these aggregated flows. The procedure to correct the period OD matrices using the departure profile input consists of the following:
  - The flow departing in 15 minutes intervals is known for each partition.
  - Then, using free flow travel times, the arrival time to the external zone associated with each partition is obtained.
  - If the arrival time is later than the end of the period, the trips are shifted to the following period.
- The process is repeated for all periods (AM, MD, PM, NT) such that there is a net shift of vehicles. The amount of flow that has to be moved from one period to the following period is shown in Table 23. These changes in flow affect only the external zones because they aggregate flow as a result of the simplification of the network.

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Table 23: Correction Factors for Calibrated OD Matrices

	AM Peak (6-10 AM)	Midday (10 AM-3 PM)	PM Peak (3-7 PM)	Night (7 PM-6 AM)
Trips not arriving during period	53,389.11	45,540.11	41,133.37	20,404.53
Trips arriving from previous period	20,404.53	53,389.11	45,540.11	41,133.37
Net change	(32,984.58)	7,849.00	4,406.74	20,728.84
Correction factor	0.905	1.024	1.010	1.056

For cars (classes SOV, HOV +2, HOV +3, Externals), two adjustments were performed. The first one is a correction in the period flow using the data of the pattern from the bridge/tunnels counts. The amount of cars loaded to the period maintains the proportion of the flow of the bridge/tunnel's counts. Then all car-related class matrices are aggregated into one matrix[4] and the period flow is split proportionally to the hourly amount of flow obtained from the volume counts (Table 24).

Table 24: Hourly Flow Distribution

% of Flow	AM (6-10 AM)	MD (10 AM-3 PM)	PM (3-7 PM)	NT (7 PM-6 AM)
Hour 1	22.50%	20.00%	24.31%	15.88%
Hour 2	34.81%	18.87$%	25.24%	13.89%
Hour 3	21.99%	19.61%	25.74%	12.66%
Hour 4	19.97%	20.30%	24.74%	11.92%
Hour 5	N/A	21.18%	N/A	9.50%
Hour 6	N/A	N/A	N/A	6.17%
Hour 7	N/A	N/A	N/A	3.98%
Hour 8	N/A	N/A	N/A	3.24%
Hour 9	N/A	N/A	N/A	3.55%
Hour 10	N/A	N/A	N/A	5.73%
Hour 11	N/A	N/A	N/A	13.44%

For trucks a more sophisticated procedure is followed, where aside from using the hourly distribution for the total per hour, correction factors are obtained in order to distribute the flow according to the bridge count distribution. The correction factors seek to maintain the total amount of trucks as in the corrected BPM matrix, by solving the following minimization problem in Equation 25:

$$\min \quad \frac{(x_{ij} - z_{ij})^2}{z_{ij}} \text{ s.t. } w_{ij}y_{ij} = x_{ij}, \quad \forall i,j \ \sum_i x_{ij} = \sum_i z_{ij}, \quad \forall j \qquad (25)$$

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[4] By simplifying different classes into a single class, computational time is gained in the route choice procedures of the simulation.

where y_{ij} is the count at bridge/tunnel i in hour j for an hourly OD matrix obtained from the calibration of the BPM OD matrix[5], and z_{ij} is the real truck count at bridge/tunnel i in hour j. The variable of the problem is w_{ij}, which is the correction factor for bridge i at hour j, and will be applied to all origin/destination nodes/centroids associated with bridge i. Note that the objective function seeks to minimize the normalized least squares difference between the final value of the bridge count x_{ij} once it has been corrected by is w_{ij}. Results of this optimization procedure have demonstrated to be effective, as can be observed in Table 25.

Table 25: Normalized Min Square Results for Sub-Network Truck Volume Calibration

Period	Before Optimization	After Optimization
AM	7,478.54	65.84
MD	21,148.23	1,311.06
PM	35,025.10	3,498.63

In addition, a validation has been carried out to verify the consistency of the hourly calibration. Virtual sensors were placed in selected bridges in the network for which the truck volume counts were available. The sensors were set to identify the truck vehicle class (ST) and the outputs were aggregated by hour. The results of the hourly counts in all crossings analyzed are presented in Figure 95, as a comparison between real volume data (BTR07) and simulation counts. The calibration has shown to be efficient during periods AM, MD, and PM, in which the procedure is more detailed and efficient (maximum difference was estimated around 30%). For the NT period (7 PM - 6 AM), the procedure was roughly applied given the lack of detailed hourly counts.

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[5] This referential hourly OD matrix was obtained by dividing the period OD matrix by the number of hours in the period.
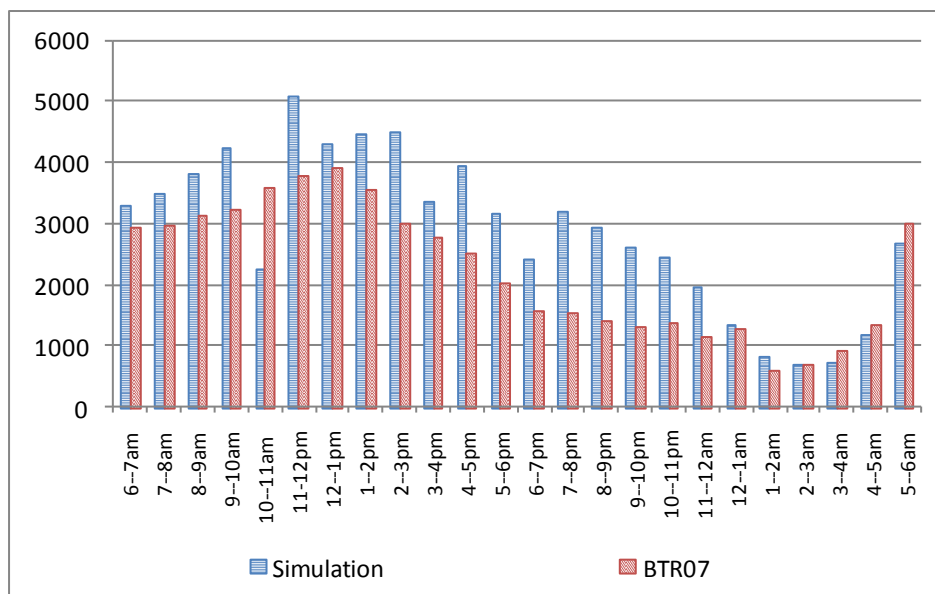
Figure 95: Sub-Network Truck Counts per hour Comparison

The aggregated results per period for the AM, MD, and PM periods show to be accurate to the calibration. Figure 96, Figure 97, and Figure 98 show a comparison for each period for a sample of crossings to Manhattan. In general, considering all bridges, AM shows an absolute difference of 6.1%, MD an absolute difference of 5.7%, and PM 24% with respect to the real counts.
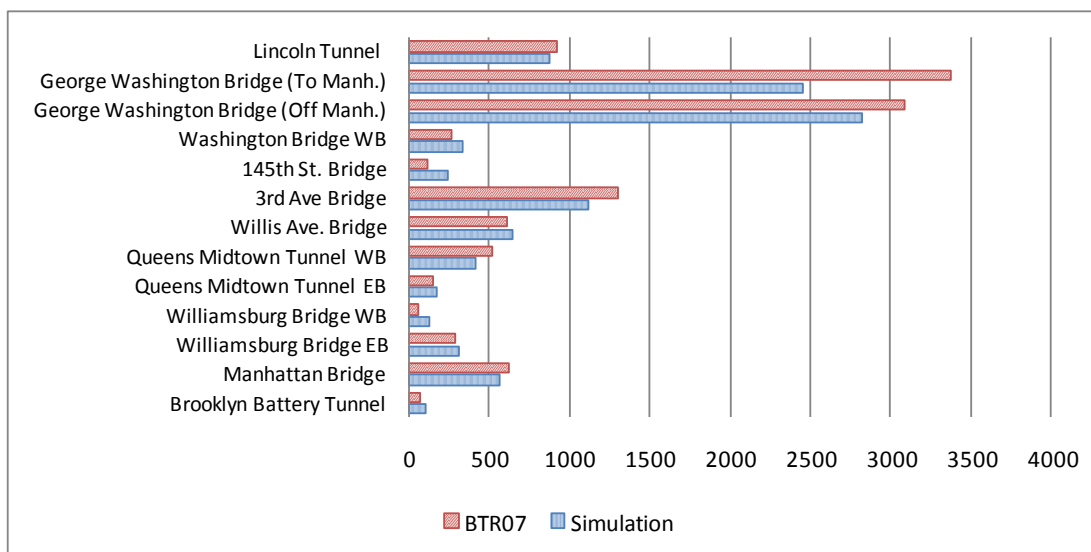
Figure 96: Sub-Network Truck Counts Comparison (AM Peak Period)
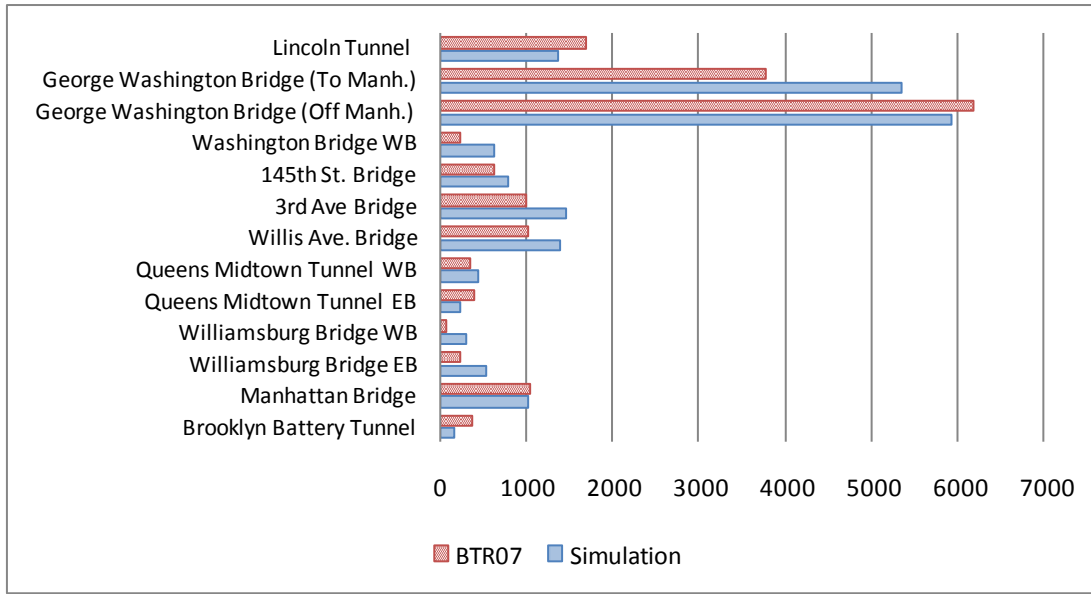
Figure 97: Sub-Network Truck Counts Comparison (Midday Period)
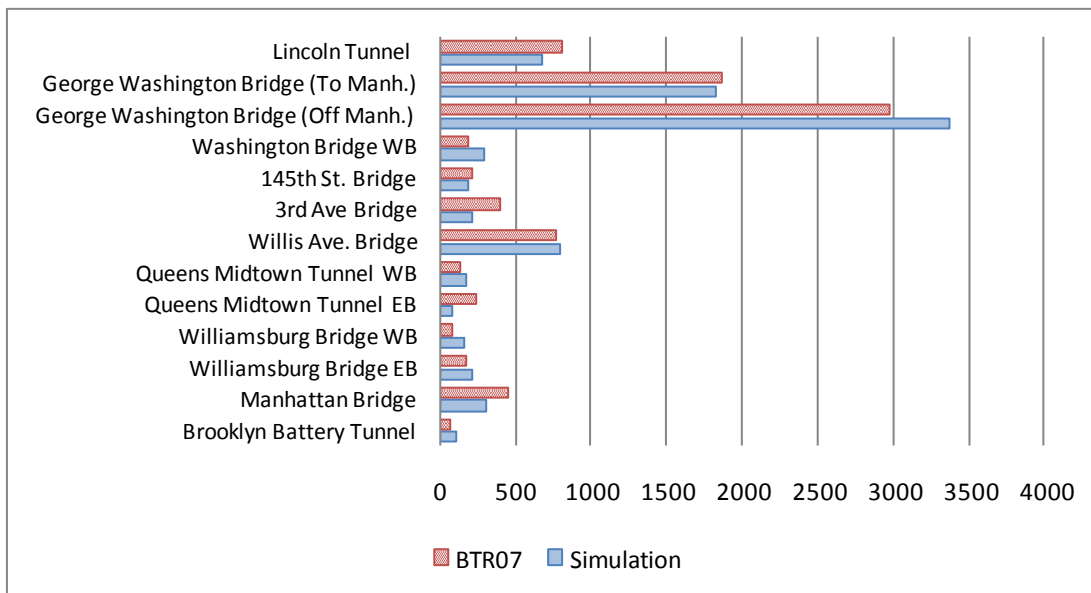
Figure 98: Sub-Network Truck Counts Comparison (PM Peak Period)

7.4.3.3   *Calibration of the mesoscopic network*

The calibration of the mesoscopic network has been a challenging task, which included the adaptation of a static network (a sub-network of the BPM) to a more dynamic environment (TransModeler). This required manual correction and inclusion of movements, lane connectors, and changes in geometry.

For intersections, the lack of signal data for all intersections in Manhattan was another limitation to calibrate the model. The intersections were kept as unsignalized, and the delays computed using a deterministic formula based on the methodology described in the FHWA Highway Capacity Manual.

Besides these changes, improvements on the behavioral model through the correction of speeds per road class have been the main task in this calibration.

Free flow speed on a transportation link is used to describe the average speed that a vehicle would travel if there were no congestion or any other adverse conditions. It is usually slightly higher than the posted speed limit depending on different factors, for instance, safety. The current best practice in regional travel modeling is to determine the free-flow speed (FFS) for a link based on the physical attributes of the link and the nature of the surrounding area. In BPM the free-flow speed model is a look-up table that varies depending on the road class and area type. The values have been determined based on surveys and adjusted according to the consulting team's knowledge of NY region. These values "although not reflective of free-flow conditions, provided usable guidance (Parsons Brinckerhoff, 2005)."

In static models, such as the BPM, these speed values work correctly; however, in a dynamic model (i.e., mesoscopic simulation) these values produce spillovers that were observed when testing the applicability of using these speeds in the simulation model. This happens because the mesoscopic model is based on speed-density functions defined for each road class; thus, if the FFS is too low, significant high values of density per mile—which seems to be the case of high demand and congested networks as Manhattan—can reduce the speed to minimum values producing blockages at links and intersections. Moreover, the meso-scale simulation in TransModeler is very sensitive to this parameter; each road class has to have a calibrated function in order to avoid problems in the simulation. Without a reasonable calibration of these speed-density relationships, some different results can be expected and different problems can arise in the simulation. For instance, a speed-density parameter might be appropriate for one segment but would be different for a segment in another part of the network, even when they belong to the same class.

However, the data to calibrate the network is more extensive than the data required to calibrate an OD matrix. In particular, detailed data for speeds is required (at least at mesoscopic level): different speed values for different density values for each road class in each zone are needed. Finding this data requires studies of occupancy which are not available for this study, in particular because of the great effort required. Two alternatives were considered when seeking to calibrate the speed-density relationships. One included changing capacities of links while maintaining the speeds from the original BPM network. The second was to design an iterative process to change the FFS in links with extremely low values that produced spillovers in the network. The addition of a capacity alternative was discarded because it implied a change in the fidelity of the network in terms of link capacities, allowed lane movements, and other network parameters.

Since the alternative of changing speeds did not compromise most of the remaining parameters, it was selected for calibration. An initial comparison of the design speeds defined by the same road classes using

the default values from TransModeler have shown to be significantly higher than the BPM (see Table 26). Moreover, a recent study by Singh et al. (2009) uses higher speeds than the BPM (see Table 27) in particular for the Urban Minor and Residential Areas which have values of 20-25 mph and 15 mph as minimum speeds (Singh et al., 2009). This was used as a reference because the study has focused on the most congested part of Manhattan (Lower Manhattan) and has used a minimum speed of 15 mph, which is considerably higher than the free-flow speeds used for Major Arterials in BPM (see Table 26).

Tests were performed with piecewise combinations of density and speeds for each road class until congested links became acceptable, and by increasing the minimum free flow speed until the gridlocks and spillovers are removed while maintaining congestion with a degree of realism. As explained earlier, increasing the speeds guarantees a minimum link outflow, which helps to avoid gridlocks.

Table 26: Free Flow Speed Values for Road Classes Used in the SubNetwork

	TransModeler Default Values	BPM		
		Average	Min	Max
CLASS 11; Freeway	65	48.49	24	57
CLASS 12: Expressway	60	39.28	19	48
CLASS 14: Major Arterial	50	13.04	9	19
CLASS 16; Minor Arterial	45	7.13	6	9
CLASS 17: Collector	45	10.09	6	21
CLASS 19: Street	30	13.88	7	19
CLASS 20: Ramp	45	28.21	12	46

Table 27: Speed Values by Road Classes used in (Singh et al., 2009)

Description	Category Numbers	Speed (mph)	Type	Lane Width
Through -FDR	10-19	45	Highway Major	12
Through -BB	20-29	30	Highway Major	12
Through -West	30-39	35	Urban Major	12
Through -Other	40-49	30	Urban Major	12
Access	50-59	30	Urban Major	11
Activity	60-69	30	Urban Major	11
Support	70-79	25	Urban Minor	11
Support Narrow Sts.	90-89	20	Urban Minor	10
Residential & Alleys	90-99	15	Urban Minor	10

Finally, to improve the path construction used by the route behavioral model in TransModeler, the number of paths was increased through: (1) changes in perception of the travel times (40% of error for each road class); and (2) changes in the allowed difference with the respect to the shortest path (50% of deviation from the shortest paths). This has improved to increase the number of path choices. However, the TransModeler path construction model proved to be less robust than expected. Tests showed that all the possible paths are not covered. The improvement of the path construction requires the design of better algorithms, which is beyond the scope of this study.

7.4.4 Evaluation of the mesoscopic network calibration

The calibration of the mesoscopic model is evaluated by first comparing the results with the BPM assignment (flow and speed), and second the speed data acquired from the ongoing pilot test.

7.4.4.1 *Comparison with BPM model*

BPM provides average speeds that can be used for comparison and validation of the results. The same set of links selected for constructing the sub-network (Figure 99) are selected, and using their IDs, the average speed is computed using Equation 26:

$$S_{BPM} = \frac{\sum_i f_i s_i}{\sum_i f_i} \tag{26}$$

where, i   is the set of links in Manhattan sub-network

f_i   is the resulting flow on link i (veh)

s_i   is the resulting average speed on link i (mph)
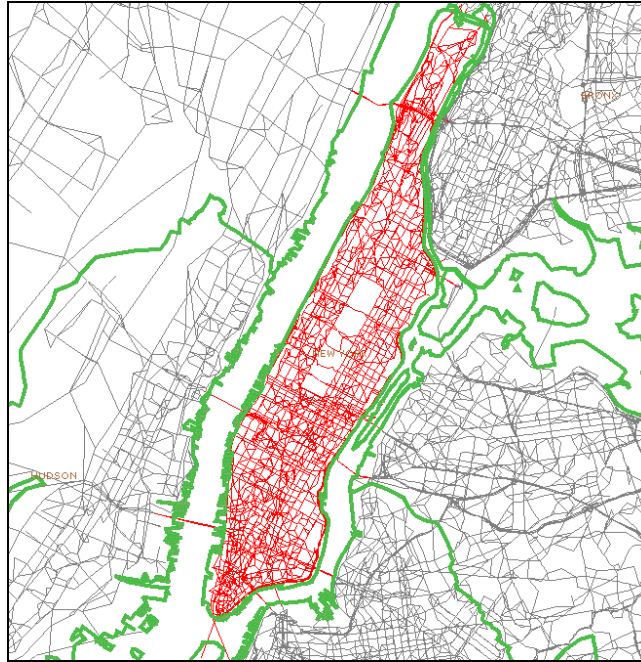
Figure 99: BPM Selected Area for Comparison with Sub-network

Results are gathered after running the base case scenario simulation. For comparison purposes, speeds of segments are obtained for the whole simulation network. Segment speeds account for the average speed of all vehicles crossing a certain link, giving a better estimate of the speed under congested conditions. The simulations show an average speed slightly lower than the overall BPM average speed (maximum difference of 3.64%). The results are found to also be within an acceptable range for the Peak Hour (see Table 28).

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Table 28: Average Speed in BPM and Sub-Network

Period	NYBPM			MESOSCOPIC SIM.			
	Speed AB direction	Speed BA direction	MEAN	MEAN - Manhattan	MEAN - L. Manhattan	MEAN - Manhattan (Peak Hour)	MEAN L.Manhattan (Peak Hour)
AM	11.5	17.08	13.63	13.134	12.244	12.965	12.071
MD	11.48	16.52	13.39	12.248	12.308	13.213	12.285
PM	11.02	15.95	12.87	12.634	11.889	11.730	11.451
NT	15.68	22.65	18.34	17.750	16.568	17.570	16.354

7.4.4.2 *Results comparison with pilot test GPS data*

GPS data from two different periods is used to validate the calibrated mesoscopic sub-network. The first provides speed data for trips starting in New Jersey (NJ) with their first stop in Manhattan. It shows an average speed of 11.8 mph at the AM period, 11.50 mph at the PM period and 20.20 mph in the NT period. The data obtained from the pilot test shows similar results in only one direction of the flow for BPM data in the peak periods. In the overnight period the difference is about 33.33% higher.

Since the speeds vary depending on the location of the destinations (not provided in the GPS data), in order to compare the results from the simulation, random centroids are selected after dividing Manhattan into four zones: Lower Manhattan, East Manhattan, West Manhattan and Upper Manhattan (Figure 100). Given that the GPS data provided does not specify the origins of the trucks, two origins are selected: Lincoln Tunnel and George Washington Bridge (Holland Tunnel has not been included due to a restriction that banned commercial vehicles). The aggregated results are shown in Table 29. These results are similar to the values for the peak times provided by the pilot test data for trips originating at the Lincoln Tunnel. The results are slightly higher for trips originating at the George Washington Bridge. This can be explained by the fact that these trips are able to use freeways which have higher speeds than the rest of the network.
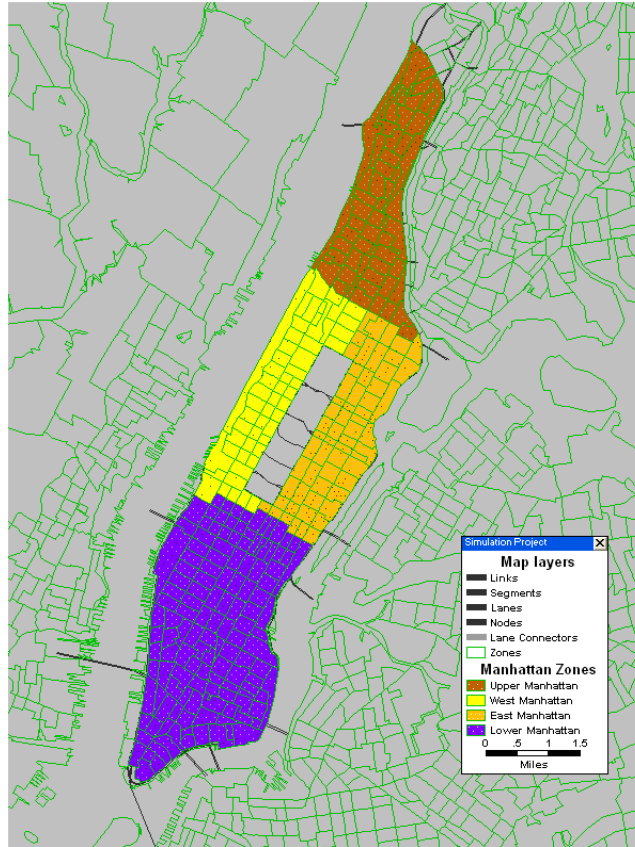
Figure 100: Zones Used for Sub-Network Validation with GPS Data

Table 29: Simulation Speeds from NJ to Manhattan

Origin	Destination	AM			PM		
		Average Speed	Speed at Peak Hour	Sample Size	Average Speed	Speed at Peak Hour	Sample Size
Lincoln Tunnel	Lower Manhattan	12.701	9.034	9192	16.110	14.438	2149
	East Manhattan	12.696	9.683	705	15.152	12.815	339
	West Manhattan	13.707	10.141	1036	15.556	9.043	459
	Upper Manhattan	16.982	13.713	15	21.768	17.495	36
George Washington Bridge	Lower Manhattan	21.898	20.340	2667	24.991	19.824	312
	East Manhattan	22.317	20.083	1672	26.397	20.093	449
	West Manhattan	22.869	21.739	1318	26.974	20.924	382
	Upper Manhattan	23.300	21.803	2418	24.300	22.154	1305

A second comparison uses the Baldor Foods Data provided by the pilot test during November 1, 2009, through December 2, 2009. The rough estimates (Figure 101) shows an average speed of 13.8 mph, which matches with the values in Table 29. The map in Figure 101 also shows a pattern of speeds that matches with the patterns shown in Figure 102, where it is possible to observe that the areas with lower speed are basically south of Central Park in Midtown and Lower Manhattan.

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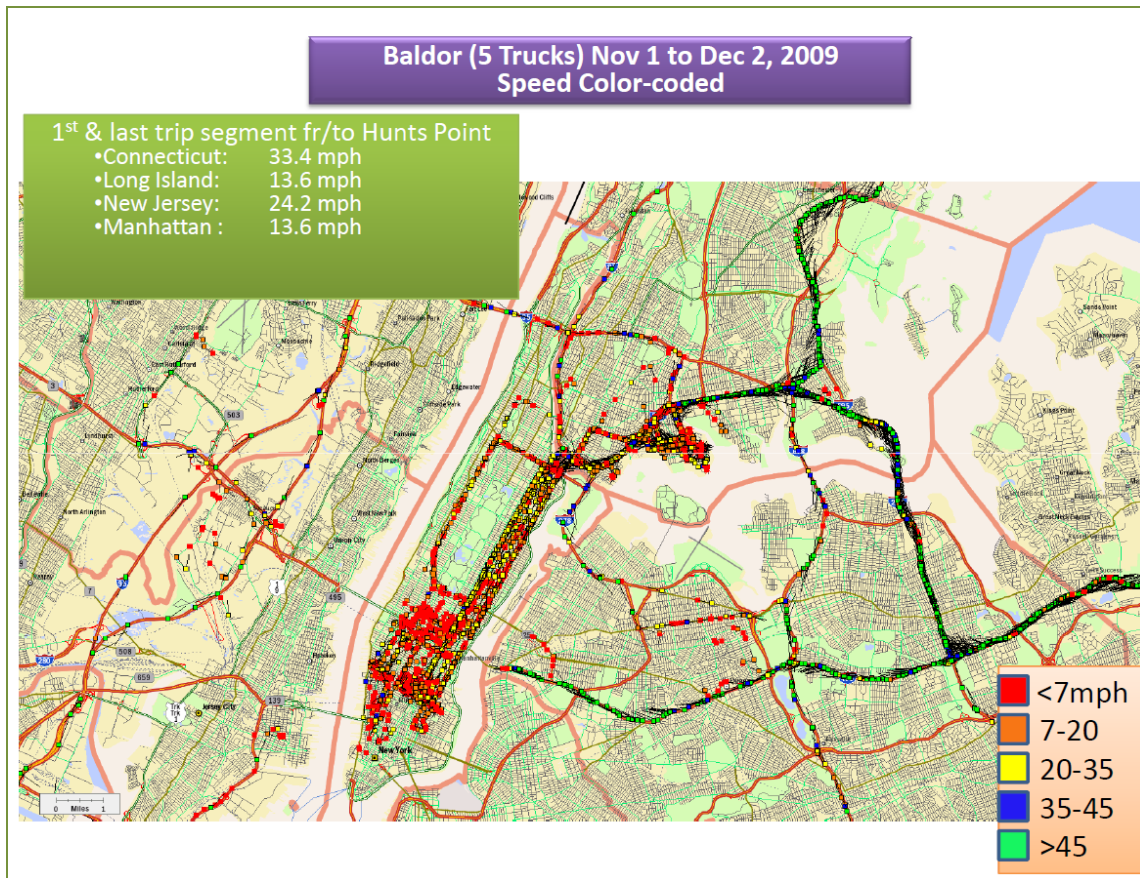
Figure 101: Baldor Foods Pilot Test Data
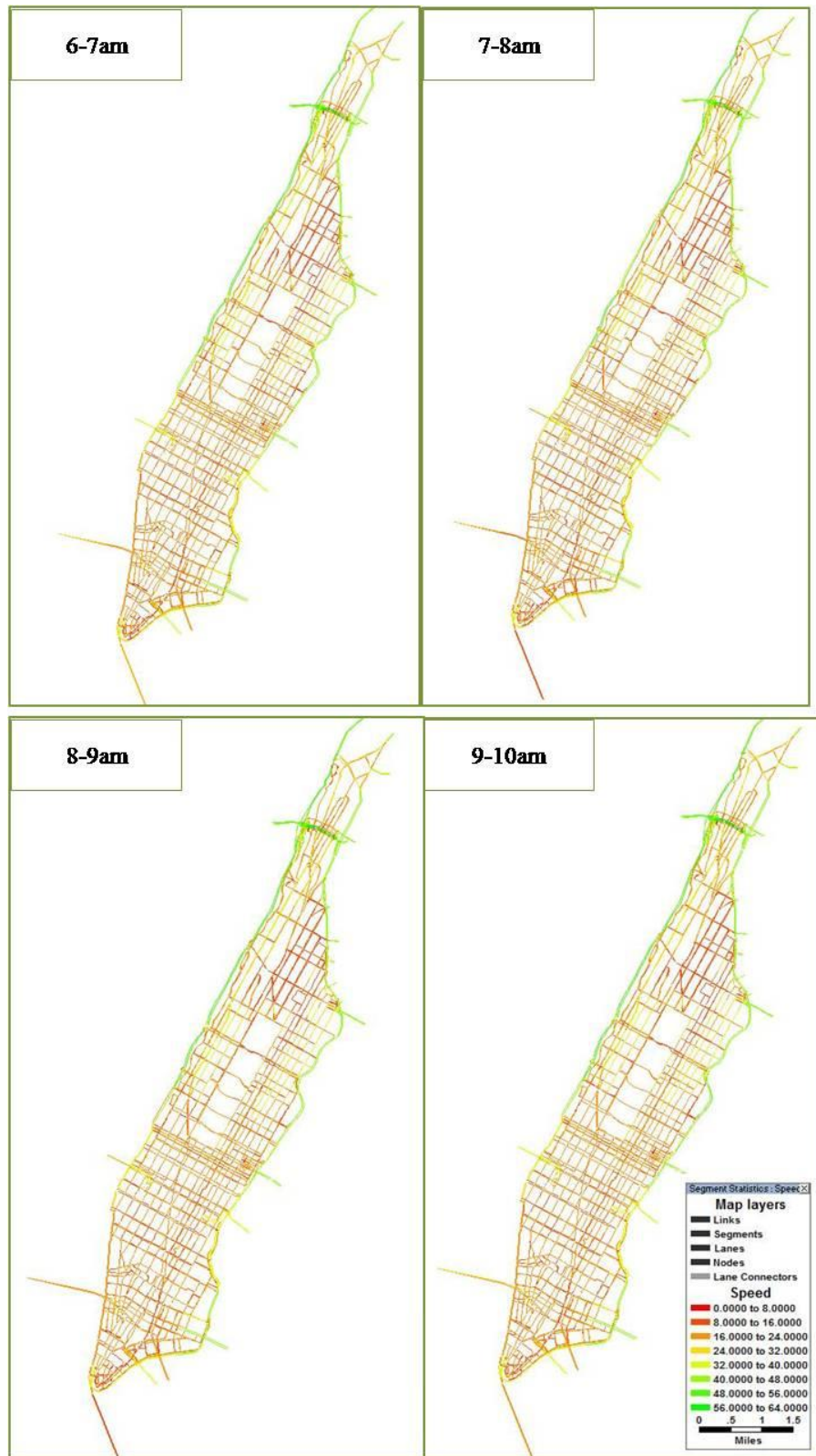
Figure 102: Simulation Speed Map (AM Period)

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This section focused on finalizing all of the inputs to the two simulation models to be used for modeling the proposed study program. These tasks included adjusting the research methodology to suit the BPM, calibration of the OD matrices used by the BPM, for which real truck volumes were used to firstly validate the available BPM matrices and correct them if necessary, and finally the gathering of data and calibration of the inputs required by the mesoscopic sub-model in TransModeler and its validation with data from the pilot test task of this study. The completion of these tasks allow for full modeling to estimate the traffic impacts of the OHD program.

7.5   *Simulation Results for Broad-Based Incentive Policy*

A methodology was developed to model an off-hour delivery program to food and retail industry businesses in Manhattan in the BPM and an extracted mesoscopic simulation sub-network. This was done by shifting the truck and commercial van OD trips bound for Manhattan from the three daytime periods (AM Peak, Midday, PM Peak), covering 6 AM - 7 PM, to the Night period (7 PM - 6 AM) of the models. Twelve scenarios of the broad-based incentive program (food and retail industries) were modeled in BPM (with three simulated in the Manhattan sub-model). The following are results aggregated from the BPM highway assignment and mesoscopic simulation.

7.5.1   Commercial Vehicle shift model results

The CMV shift model described was applied to shift the OD demands from the three daytime periods to the overnight period. The OD demands that were shifted were commercial vehicles (trucks and commercial vans) from all originating zones and with a destination in Manhattan. This includes trips originating in Manhattan, and accounts for chained trips for delivery vehicles originating outside Manhattan and making multiple stops within Manhattan. A breakdown of the geographic location of where CMV trips bound for Manhattan originate (excluding those originating in Manhattan) can be seen in Figure 103. The majority of commercial trips headed to Manhattan originate in the other four boroughs of New York City. The next highest number of trips comes from New Jersey and points west. Trips originating north of the city make up slightly less than 10% of total trips bound for Manhattan, and the fewest trips come from Long Island to the east.
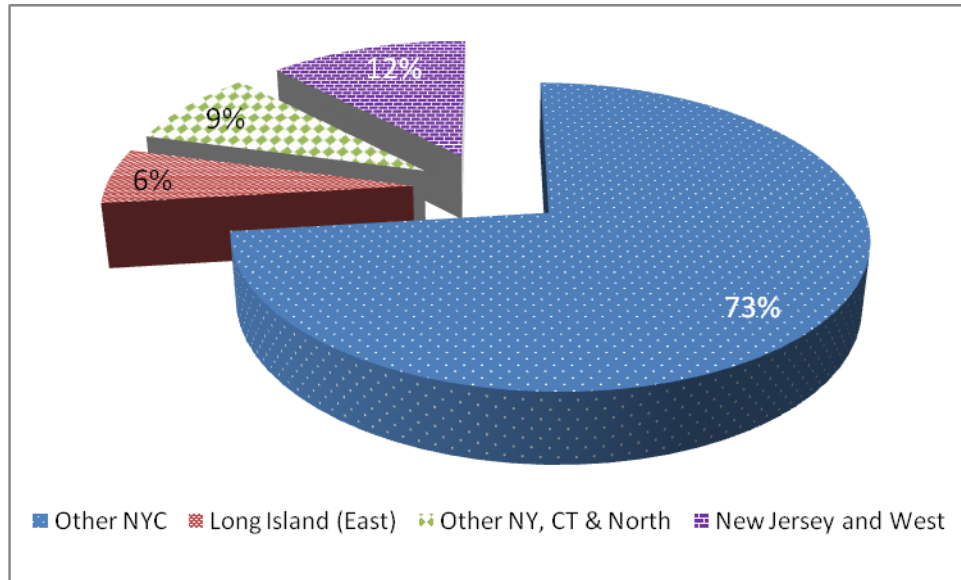
Figure 103: Origin of CMV Trips Destined for Manhattan

The shift factors developed in Table 18 were applied equally to all CMV trips regardless of zone of origin or time of day (6 AM - 7 PM). The final number of trips shifted and the percentage among all CMV trips in the entire New York region can be seen in Table 30 for the BPM all-Manhattan scenarios. The relationship between scenario and number of trips shifted follows that of Figure 86.

Table 30: CMV Trips Shifted – All-Manhattan Scenarios

Scenario	CMV Trips Shifted	% of all CMV Trips
1	7,262	0.31%
2	15,982	0.68%
3	23,617	1.00%
4	28,634	1.21%
5	32,856	1.39%
6	47,605	2.02%

The resultant matrices from the shift model were input to BPM highway assignment and the mesoscopic simulation. The network results are shown in the following sub-sections.

7.5.2   BPM assignment results

The macroscopic network model's (BPM) assignment output contains information for all 55,000+ links in the highway network, including vehicle flows by class, travel time, and average speed. Two of the important parameters for measuring traffic effects can be calculated from this output: (1) Vehicle Miles Traveled (VMT), and (2) Vehicle Hours Traveled (VHT). VMT gives an idea of the total distance traveled by all vehicles in the region on a typical day, while VHT is a convenient method of measuring travel times, and by extension, congestion. While changes to VMT do not clearly indicate whether the network is more or less congested, this conclusion can be reached from observing changes to VHT. For

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example, vehicles may take longer paths to avoid congested links, and in turn reduce their overall travel time, thus saving time and reducing VHT while increasing VMT.

The results show the net differences between output parameters from the calibrated year 2007 base model and the shift scenario model, and percentage changes of the output parameters. First, Figure 104 and Figure 105 show the change in VMT by a shifting scenario's assignment on the network, for scenarios where all Manhattan-destined demands where shifted or only Lower Manhattan (Midtown and Downtown) destined demands, respectively. Then, Figure 106 and Figure 107 are the changes to VHT for the two cases of scenarios.
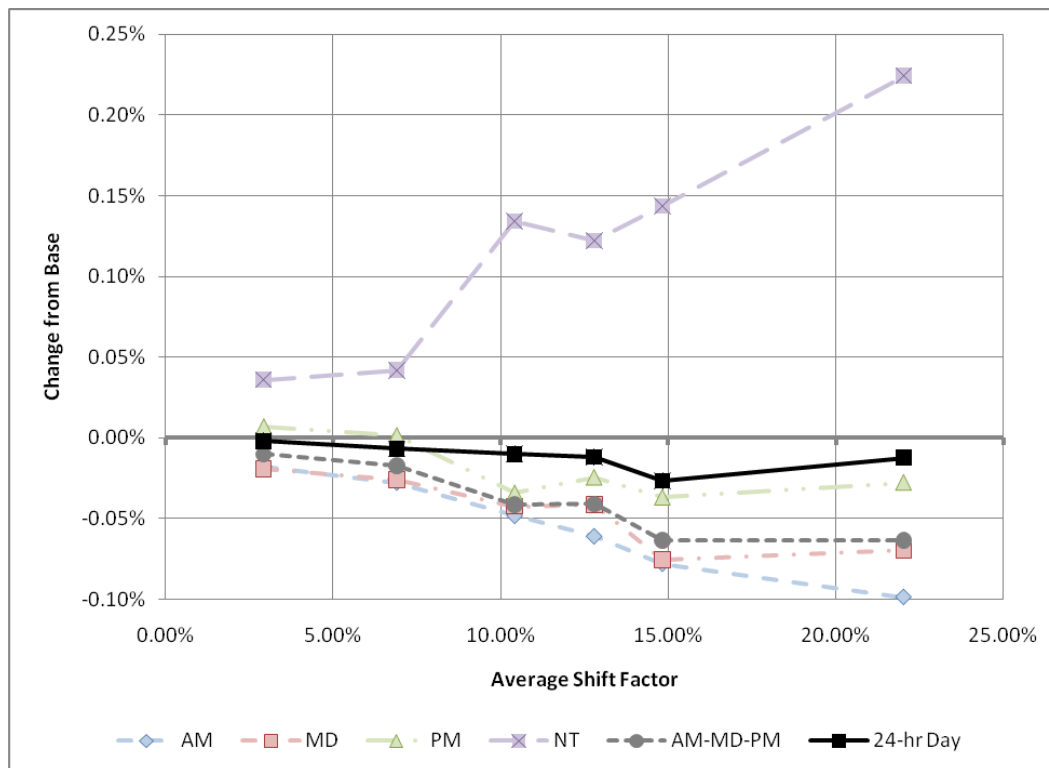
Figure 104: Change in VMT – All Manhattan Destinations Shifted
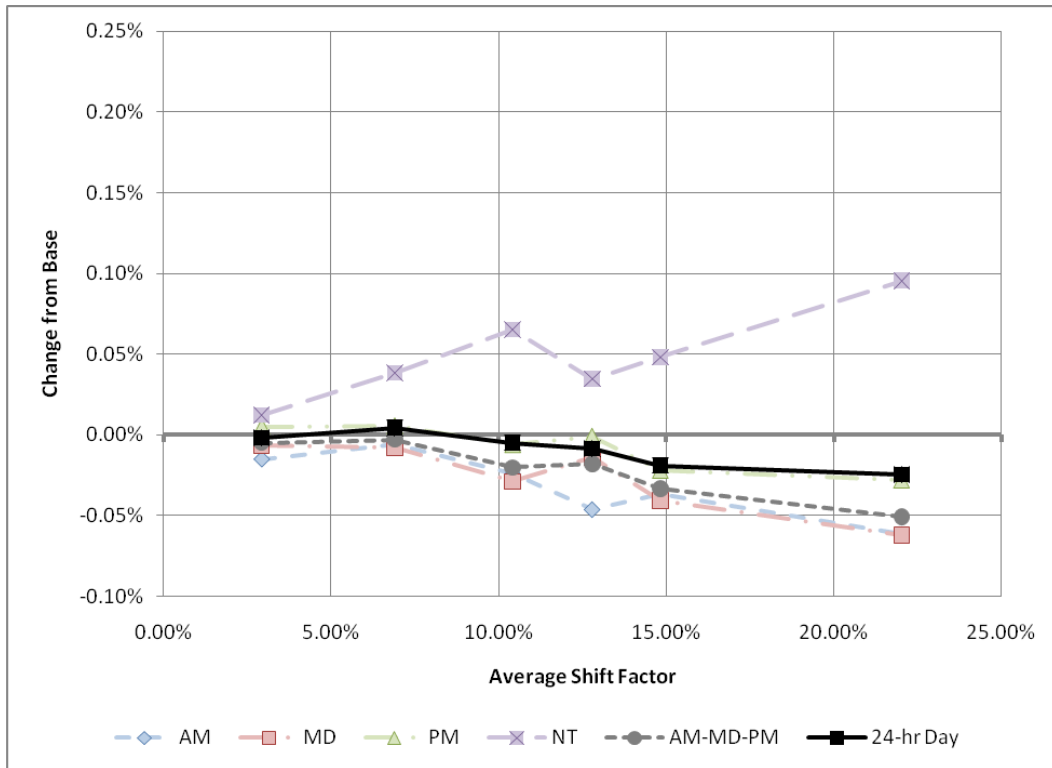
Figure 105: Change in VMT – Lower Manhattan Destinations Shifted
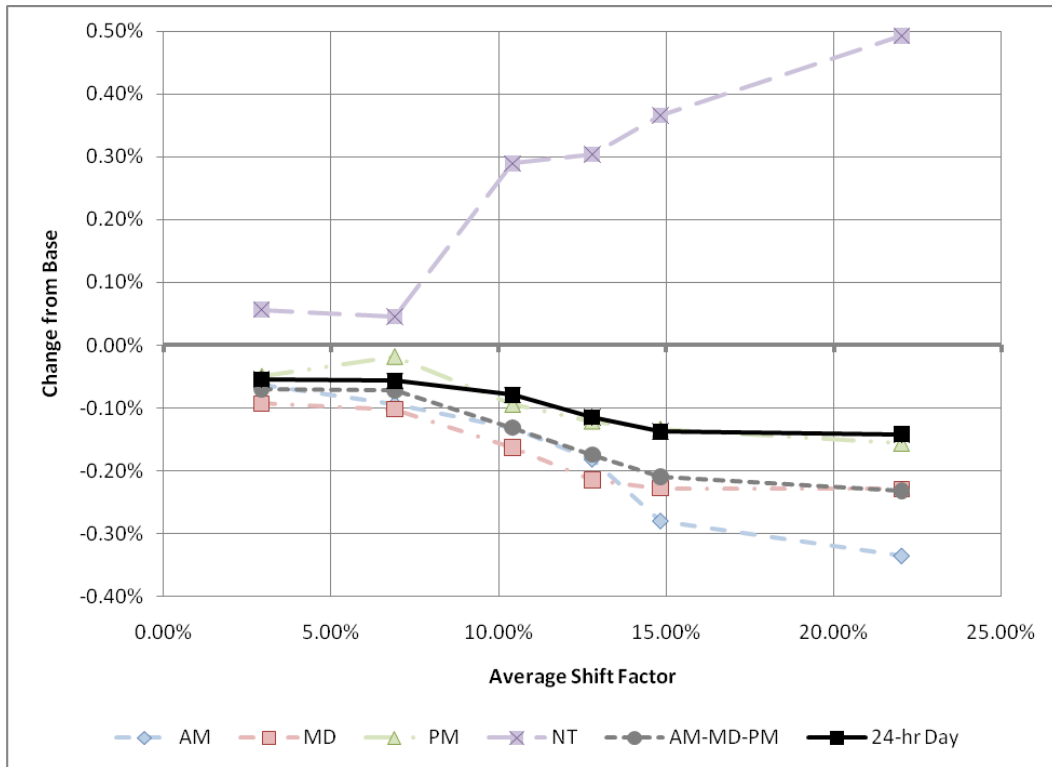
Figure 106: Change in VHT – All Manhattan Destinations Shifted

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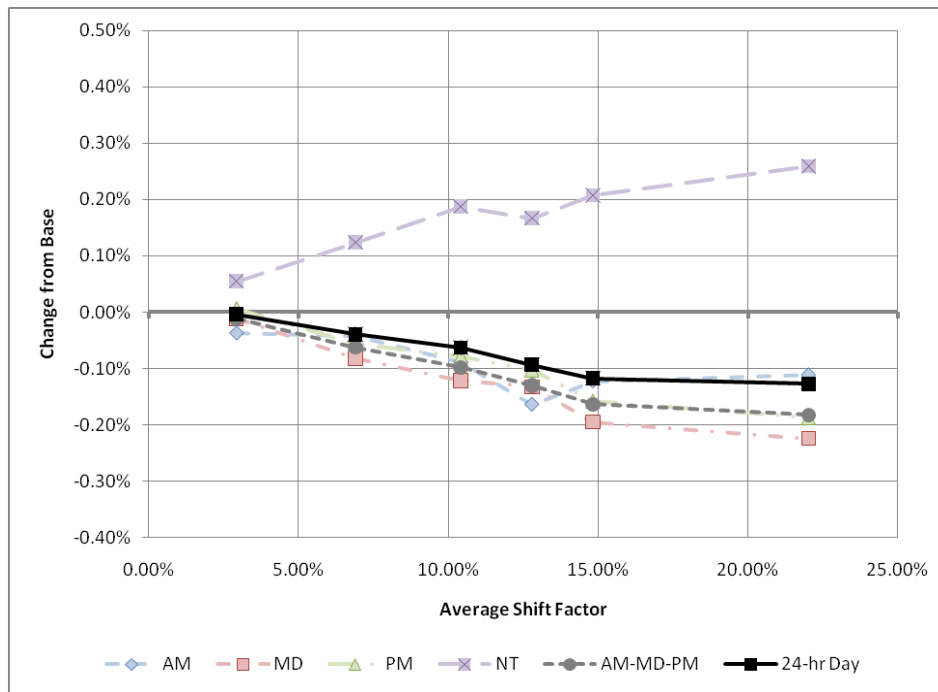
Figure 107: Change in VHT – Lower Manhattan Destinations Shifted

Figure 104 through Figure 107 show the resulting output from the entire New York City metropolitan area network of all links in the BPM. In Figure 104 and Figure 105 the total changes in VMT as a result of a specific scenario's assignment. The entire 24-hour day (sum of all four periods) is represented by the "24-hr Day" line, while the "AM-MD-PM" line represents only the three daytime periods from when truck traffic is subtracted. Similarly, Figure 106 and Figure 107 are the changes to VHT for the two cases of scenarios, respectively.

The composite full-day trends show that as the average shift levels increase, vehicle miles traveled and vehicle hours traveled for all vehicles in the network both decrease. However, they also show that as the proportion of deliveries shifted increases, the marginal benefits decrease. For example, beyond a 15% average shift the net benefits are only minimally increased. The 24-hour day net changes in VMT and VHT for the scenarios where all Manhattan-destined truck OD demands and only lower Manhattan-destined truck OD demands were shifted are aggregated, and the net changes from the base case scenario can be seen in Figure 108 for all network links and in Figure 109 for only Manhattan links. Manhattan, being the target of the program, covers a large proportion of the total network effects. In many scenarios, half of the reduction in VHT is experienced in Manhattan. Figure 110 also shows the change in volume to capacity ratio (v/c), a measure of congestion, for Manhattan roads based on the scenarios of demand shift. Daytime congestion (volume/capacity ratio) in Manhattan is estimated to reduce in excess of 1.5% for significant demand shifts.

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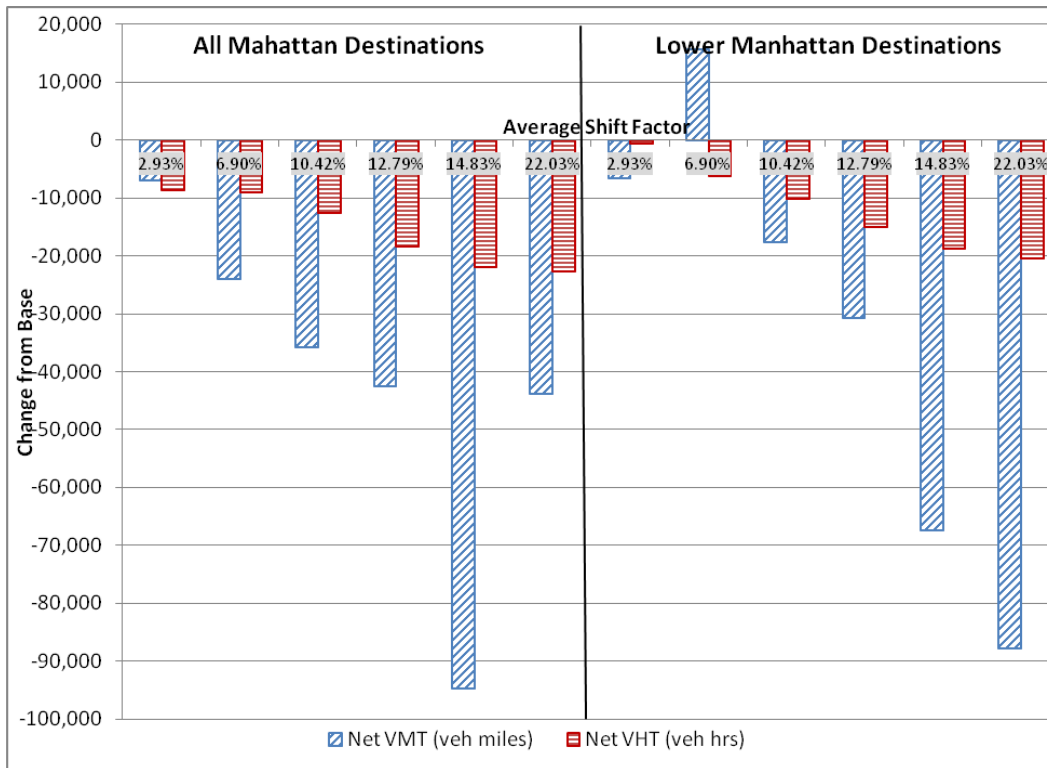
Figure 108: Scenario Net Benefits – All Network Links
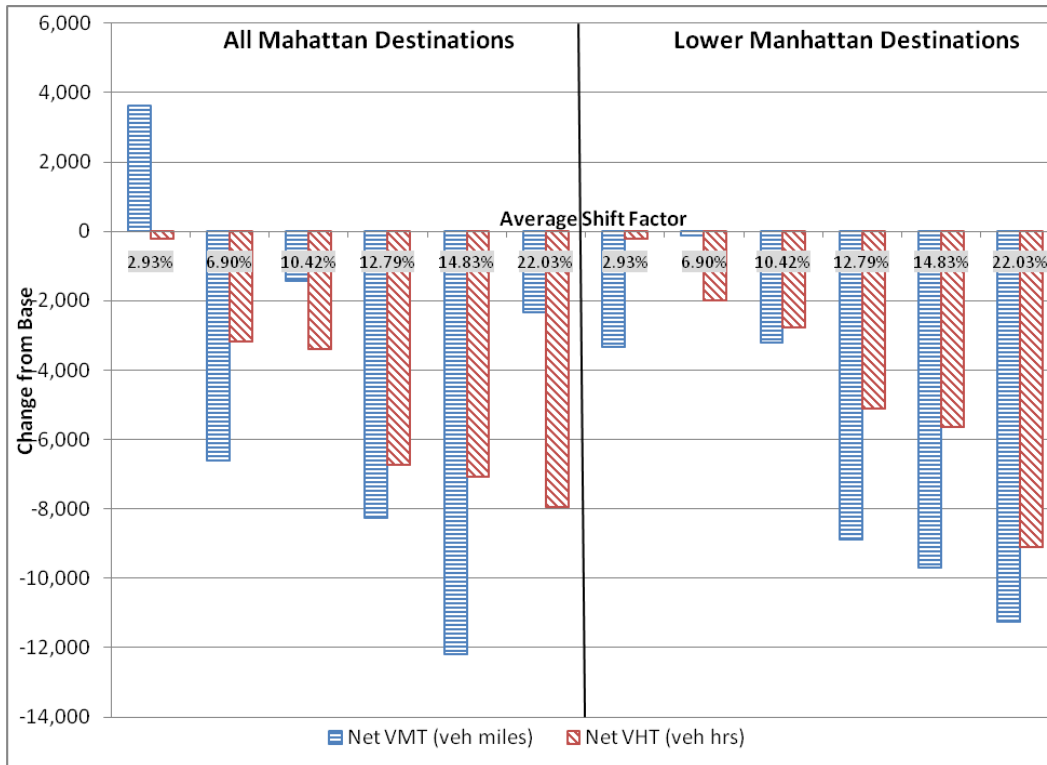
Figure 109: Scenario Net Benefits – Manhattan Links

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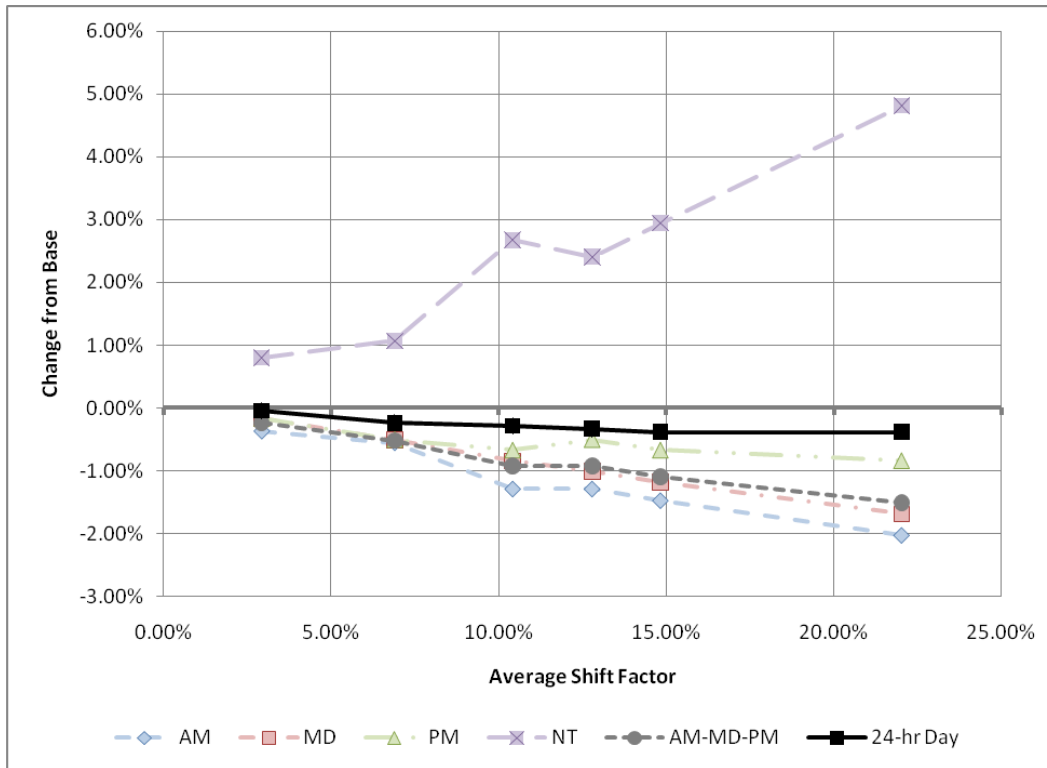
Figure 110: Change in Manhattan Links' Volume/Capacity Ratios

While the expected benefits from network assignment were expected to resemble the general relationship between tax incentive and percentage of freight traffic shifted shown in Figure 86, the exact relationship cannot be followed due to network assignment affects. Particularly, vehicle miles traveled do not always decrease with decreased levels of traffic. Specifically, this can be explained as vehicles taking longer paths that are less congested which might still save them time, as they seek to minimize their total trip costs. Vehicle hours traveled, however, do incrementally decrease with increasing tax incentives and therefore decreased freight traffic in most cases. It should be noted that these results are for changes to links within the network, and not all roads in the region are represented by links modeled in the BPM network. For some scenario-to-scenario comparisons, reducing the amount of CMV using the network does not always result in a decrease to VHT. Since BPM employs user-equilibrium assignment instead of system optimal assignment, the effect to the entire system is not always desirable.

7.5.3 Mesoscopic simulation results

Different from the BPM, the statistics obtained through the mesoscopic simulation are calculated at the path level. In other words, the statistics of travel times and speeds are computed from the beginning of each vehicle trip until they reach their respective destinations. The results have also been aggregated to find the overall effect per day and per period of time (AM, MD, PM, NT), which is a better measure to account for network effects in a more consistent fashion. As expected, the results show an inverse

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relationship between percentage shifts and the travel times (Figure 111), as well as speeds (Figure 112). The daytime periods account for the aggregated results in the three periods (AM, MD, and PM) in which the truck and other commercial vehicle demands are reduced. These periods under all scenarios show a decrease in total travel time, with the AM period showing the highest decrease in total travel time. The results also show a monotonic increase in travel times for all scenarios, up to 4.2% in Scenario 3 (which represents an average shift of 10.42% of the daytime CMV) in the NT period. However, this increase in travel time is in all cases outweighed by the reductions in the other daytime periods. This is expected given that the NT period has much less volume than the daytime periods, and the increase is not as significant because the vehicles can move at slightly decreased speed.

In particular, the effects are largest during the AM and MD periods, as compared with the reduction in the PM peak, which has a more compact distribution of trips. Figure 113 shows the congestion pattern for the 24 hours of the simulation, and it can be observed that the scenario with the lowest average shift (2.93%) has a similar pattern as the base case (no shift). However, once the shifts are larger (6.90% or 10.42%) the congestion reduces significantly between 7 AM and 10 AM and between 12 PM and 3 PM. During the NT hours (7 PM - 6 AM) congestion is increased slightly due to the new traffic added during these hours. The shifts have significant effects during the peak hours of each period, when the traffic is reduced. The overall reduction in total travel times over a 24-hour period are 0.93% for Scenario 1 (2.93% average shift), 2.93% for Scenario 2 (6.90% average shift), and 4.2% for Scenario 3 (10.42% average shift).
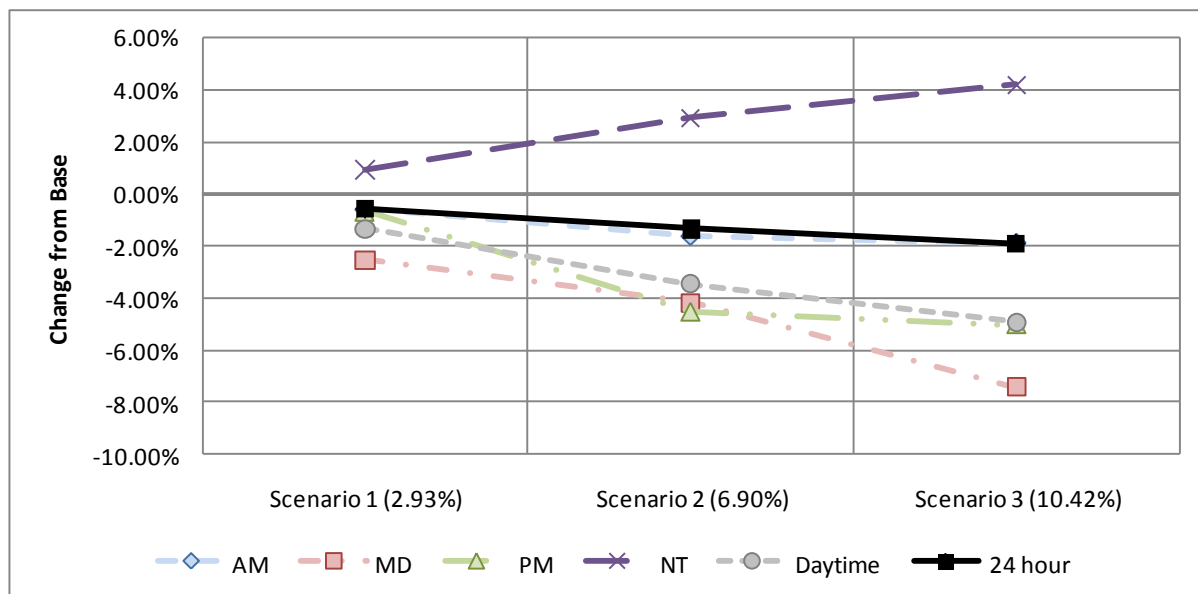
Figure 111: Change in Total Travel Time by Period
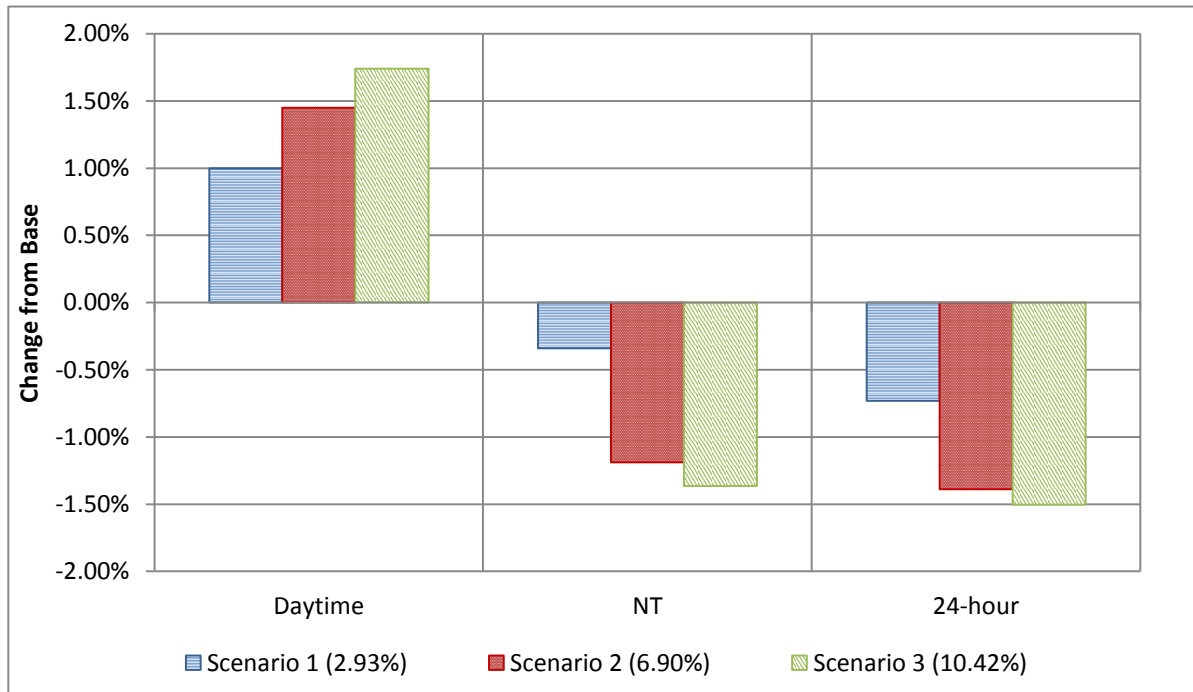
Figure 112: Change in Average Speed per Vehicle for Trips Completed
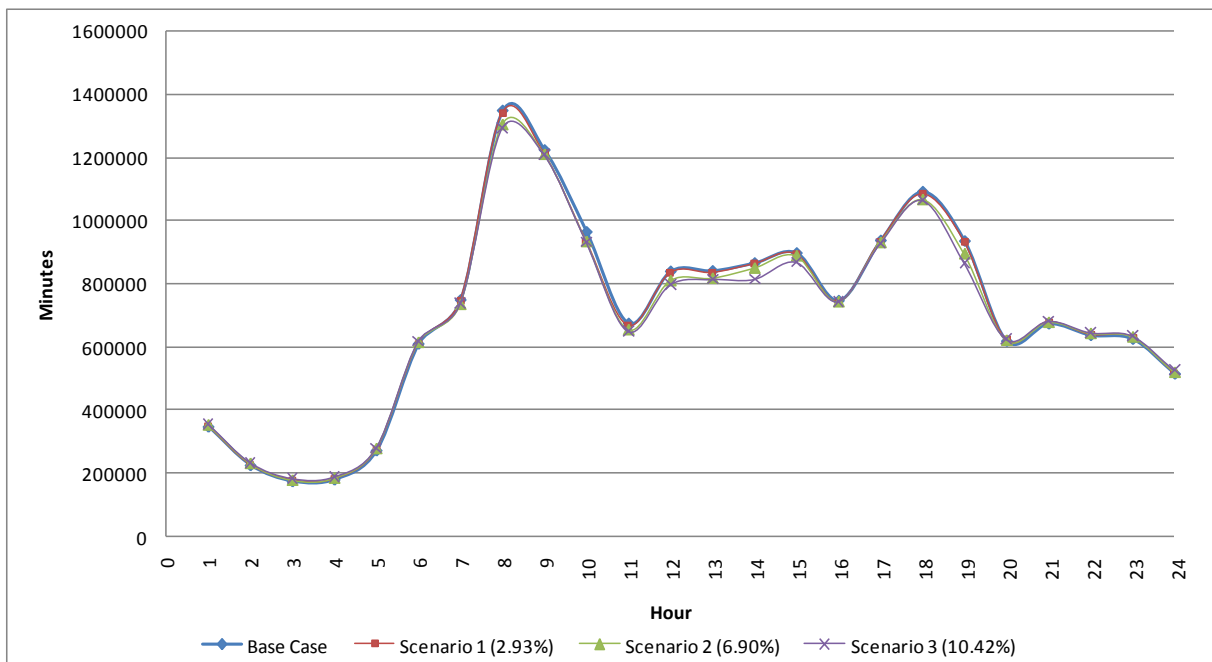
Figure 113: Travel Time Pattern by Shifting Scenario

7.5.4 Regional trip impacts

Further analysis of network impacts to the entire metropolitan region was conducted by isolating specific paths taken by vehicles serving a destination in Manhattan. Using a post-processing tool (ASSIST-ME) developed to take BPM output and calculate shortest paths between OD pairs (RITSL, 2009) changes to these paths from one scenario's network assignment to another can be analyzed. A sampling of 50 random OD pairs (Figure 114) was selected where the origin node is anywhere in the network and the destination node is in Manhattan. The shortest paths for these same 50 OD pairs were calculated for each scenario for all four network periods, and the average results calculated. The average change to travel times between these 50 nodes was calculated for each period in each scenario, and the differences between the average for a scenario and the base case are summarized in Figure 115.

Figure 115 shows the decrease in average travel times for the AM and MD periods for the six scenarios outlined in Table 19. As the incentive amount was increased, the average of the travel times for the shortest paths between sampled OD pairs decreased. For the PM case, the differences were very minor, and in some cases even increased. For the NT cases, travel times rose as more CMVs were added.
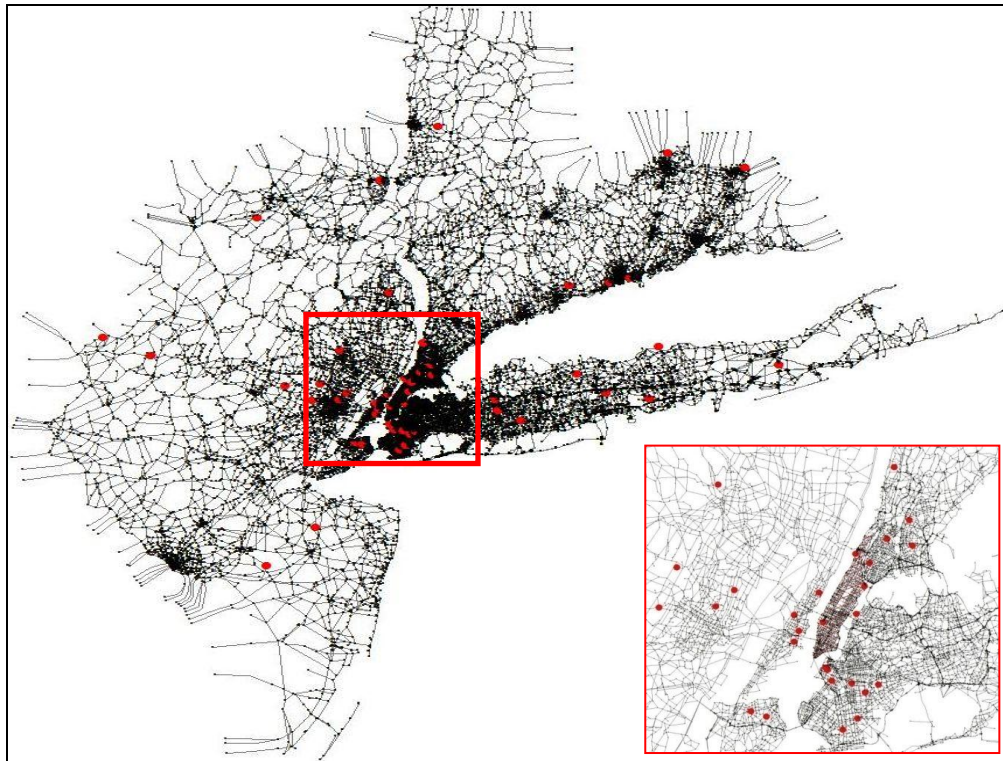
Figure 114: Sampled OD Pairs for Path Analysis
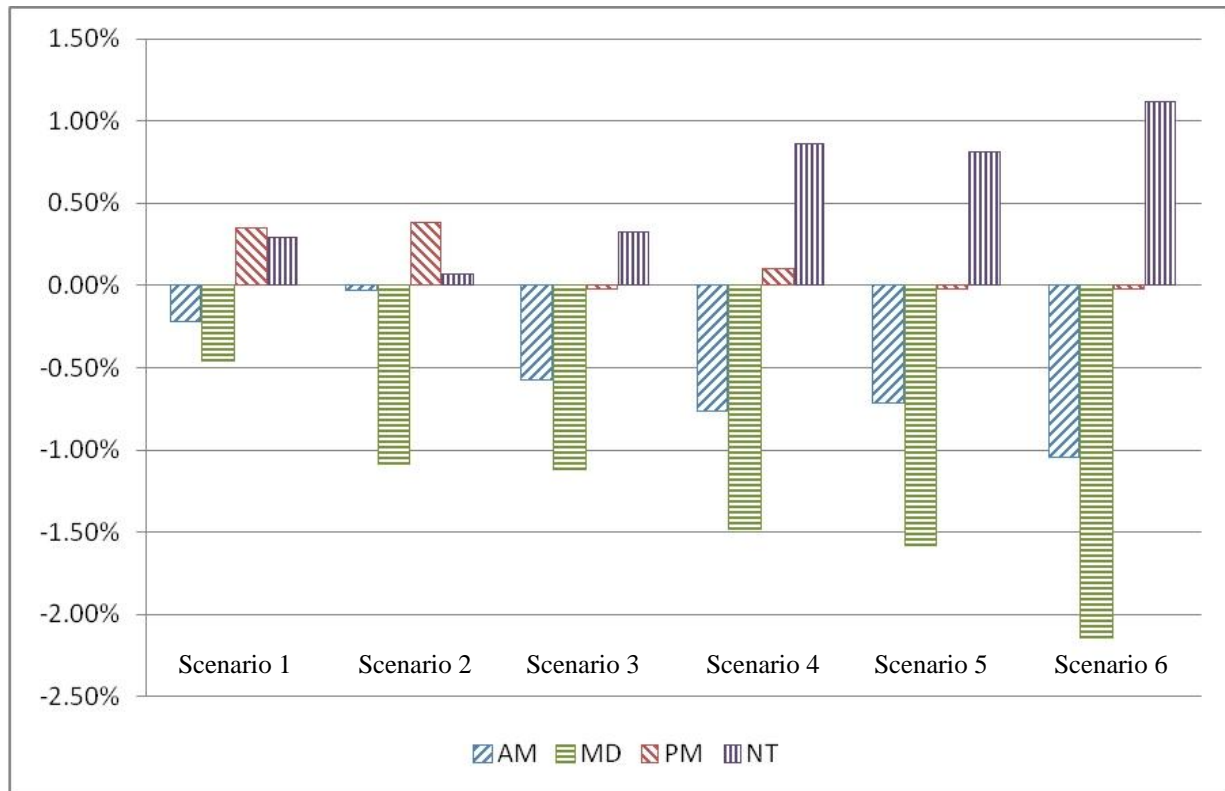
Figure 115: Changes to Average Path Travel Times by Scenario

7.5.5 Regional model/sub-network comparison

A comparison between BPM and the sub-network simulation results is difficult to perform since the TransModeler mesoscopic simulation accounts for results and effects within Manhattan while the BPM aggregates the results of the overall regional network. Moreover, there is some accuracy lost due to the reduction of the area of scope. Even if the results of only the Manhattan links of BPM are compiled, the output will differ from the sub-network links' results due to the interactions with the neighboring regions' links in the larger model. In addition, the results obtained through the TransModeler simulation are path-based, while the BPM provides results at a link level from the traffic assignment nature of the model. In order to perform the comparison TransModeler path-based results obtained have been converted into link based results. Using the information from paths, the total travel times in segments corresponding to the links of the BPM are obtained. These results per link have been aggregated by time period and are presented in Figure 116, as a comparison with the BPM results for the three scenarios (average shifts of 2.93%, 6.90%, and 10.42%) run in both models.

The travel time results are shown for BPM assignment and the sub-simulation, when using link-based and path-based estimates. The results are shown for the NT period, combined daytime periods, and over the 24-hour day. It can be observed that the mesoscopic sub-simulation shows far greater travel time savings during the daytime than the BPM assignment. These differences are also reflected in the 24-hour

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results for all scenarios, where the mesoscopic simulation is observed to provide larger changes, percentage-wise, compared with BPM. The results indicate that the mesoscopic sub-simulation is more sensitive to the reduction in daytime truck traffic than the BPM. These differences are due to how each model manages congestion and the traffic flow model used. For instance, a macro-model, such as BPM, uses a simplified traffic flow model, while the mesoscopic simulator uses a more sophisticated traffic model and accounts for more realistic ways to compute and aggregate delays. During the NT period, this difference is not significant because the period does not have significant congestion. However, the daytime periods have significant congestion, which causes differences in the model output. For the sake of completeness, the results of the path-based results were included, and it can be observed that in general the link-based results of the simulations slightly overestimate the travel time savings. Overall, the mesoscopic model is seen to be more sensitive to the OHD program studied, while the BPM, being a large-scale model, is not as sensitive.
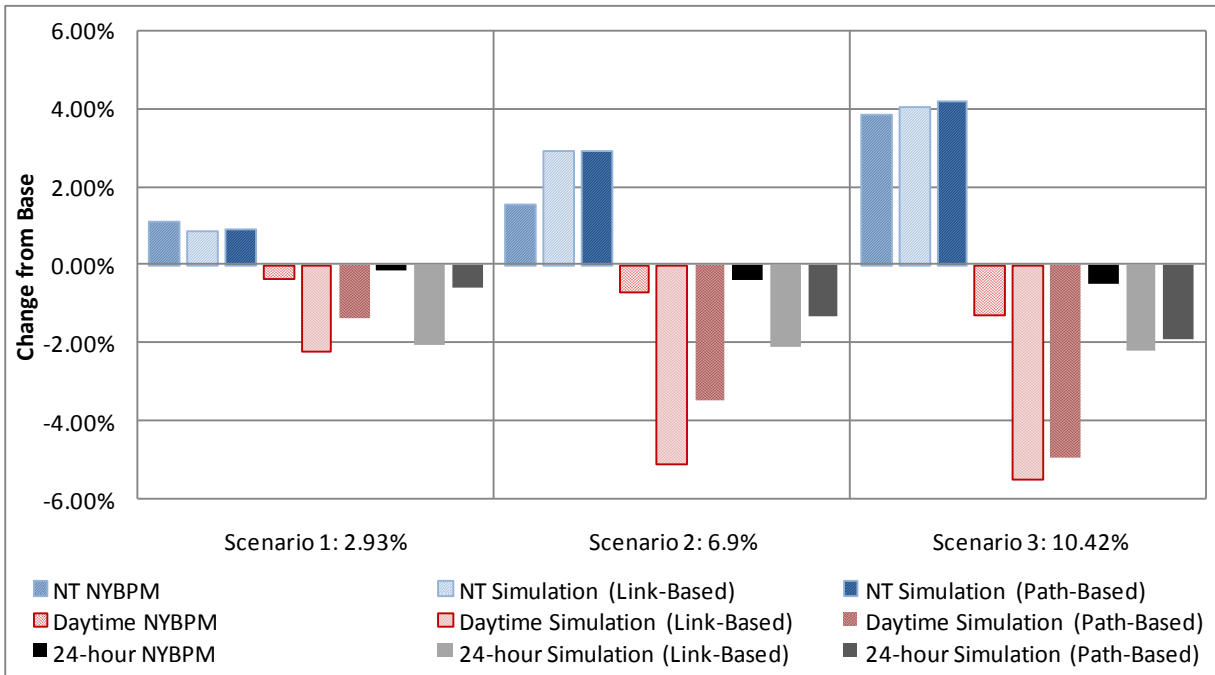
Figure 116: BPM versus Sub-network Comparison (Manhattan Links)

7.6   *Pricing Analysis*

In addition to the other analyses, dynamic pricing measures were implemented within the calibrated sub-area traffic network of Manhattan to test and observe vehicle routing behavior changes in response to tolling strategies accompanying the off-hour delivery shifts of this study. This is done to understand the costs of implementing an OHD program, and to assess an alternative strategy, incorporating static or dynamic pricing, that would render the proposed program cost-neutral. A simple way to do this is by testing ways to increase toll revenues enough to balance the loss in tax revenue due to the tax incentives

given. There are administrative considerations that render this concept impractical; for example, highway tolls are collected by several agencies in the metropolitan area, and they are all locally based, while the incentive comes from the federal government, but it is studied as a way to conduct scenario assessment. Understanding the increases needed to offset the incentive offers a way to analyze the impacts of a certain OHD scenarios. Thus, it is important to emphasize the fact that this is not a policy recommendation but instead a hypothetical scenario meant to study "theoretical" aspects of static and dynamic pricing strategies in the context of OHD scenarios.

7.6.1   Review of dynamic road pricing studies

In the last two decades dynamic road pricing has gained popularity as a method of congestion pricing for diminishing peak period congestion. Instead of a previously determined toll schedule, as in the case of static pricing, dynamic pricing employs variable tolls depending on the congestion level on the tolled lanes or roads. One of the main focuses of this task is to implement and analyze a dynamic pricing application for traffic entering Manhattan. Since static pricing is currently being applied in the tolled bridges and tunnels, static pricing simulations were also run using the same network and inputs as a base case for comparative purposes. The differences between the two tolling schemes are then analyzed.

Congestion pricing is the general term used for the peak hour congestion management method of charging users during the hours when demand is high, to encourage them to either switch their travel times or use less-congested alternative routes. Congestion pricing is mainly implemented in the form of static pricing in real world applications. Road pricing has been successfully implemented in the United States, United Kingdom, Sweden, Norway, Singapore, Italy, and Germany to manage peak period congestion. It has been implemented in different forms, such as distance-based pricing, time-of-day pricing, and cordon pricing (FHWA, 2005; Mn/DOT, 2010; Sandag, 2010; WSDOT, 2010). Dynamic pricing is a form of congestion pricing where the toll rates are determined depending on the real-time traffic conditions. Therefore, tolls are not previously determined but are variable within a previously set range. This is a new area of research and implementation in traffic engineering, thus the number of real world applications is limited. Several traffic parameters can be considered to determine the toll rate in real-time, including prevailing travel speed, occupancy, and delays. Users are informed about the current toll rate at a toll facility with variable message signs and are then allowed to make a route choice, which is usually either a faster tolled road or a free alternative road. Several theoretical studies are available in the literature for dynamic pricing (Wie and Tobin, 1998; Joksimovic et al., 2005; Mahmassani et al., 2005; Friesz et al., 2007; Teodorovic and Edara, 2007; Wie, 2007; Karoonsoontawong et al., 2008; Lu et al., 2008; Zhang et al., 2008; Yin and Lou, 2009).

7.6.2 Static toll model

Prior to running dynamic pricing simulations, a static toll model is also developed and implemented in BPM to study the effects of this study in terms of revenue changes. A simple way to conduct this network analysis is to adjust the tolls in the BPM network of each OHD scenario previously modeled and iteratively conducting assignments to find out what level of toll is required to "pay" for the total tax incentives of a given scenario. Total toll revenue is calculated as the product of the toll level charged to vehicles at a facility and the total flow of vehicles using that facility. To evaluate the proposed toll scenarios, the difference between toll revenue in the base case model and the proposed model is calculated. In order to find the optimal toll level, this net toll revenue must meet the condition that it is at least equal to the total tax incentive given to all receivers participating in the OHD program. This model can be described as follows:

$$\sum \left(T_1^f F_1^f \right) - \sum \left(T_0^f F_0^f \right) \geq \sum \left(TI \times R \right) \tag{27}$$

where, T_1^f = proposed toll to be charged at a facility in a modeled scenario ($)

F_1^f = total flow of vehicles using a facility in a modeled scenario (vehicles per hour)

T_0^f = base toll level for a facility ($)

F_0^f = total flow of vehicles using a facility in the base case simulation (vehicles per hour)

TI = tax incentive offered ($)

R = number of receivers accepting tax incentive and participating in OHD

In order to satisfy Equation 27, iterative assignments are required. In traffic assignment, travel patterns change due to changed toll levels that can result in gained or lost revenue for toll agencies. In addition, the prior modeling shows that traffic conditions generally improve from the program under study, and therefore, toll revenue is likely to be lost by area toll agencies. The net benefit assessment is then done by considering the level of toll revenue from the no-shift, base case as the base line, and requires iterative assignments from gradual increases in toll levels.

Tested scenarios model modified tolls at only the seven inbound tolled entrances to Manhattan from the rest of New York City and New Jersey, similar to previously proposed congestion pricing plans. Additionally, for the sake of simplicity, only existing tolled facilities are modified, thus free inbound crossings remain free. The scenarios are constructed by adding discrete amounts to existing tolls, for example increasing all tolls by $1.00 instead of increasing all tolls 10%, or forcing all tolls to a uniform level, which preserves the existing toll structure maintained by area agencies. Toll increases were only enacted for the three daytime periods in the model (AM, MD, and PM), while NT tolls were left at current levels. Scenarios are modeled where only truck tolls are increased, as well for when tolls are increased for

all vehicles. The following sub-sections show results from these scenarios when applied to the case of two scenarios of incentivized traffic networks.

7.6.2.1 Scenario runs

Several scenarios are tested on the calibrated 2007 BPM. The scenarios are run to find the necessary toll increase in order for the net toll revenue gain over the base case to be equal or greater than the total tax incentive gained by the OHD. It should be noted that net toll revenue gains are taken for all facilities within or connecting to New York City, even though the increases were only for facilities inbound to Manhattan. Due to route choice changes from the toll increases, the toll revenues for other crossings not even connecting to Manhattan can also change.

The scenarios are run for the traffic networks with 2.93% and 6.90% average shifts of deliveries in Manhattan, and for cases where the tolls were increased for only trucks entering Manhattan during the day at existing tolled facilities, as well as all vehicles entering Manhattan during the day at existing tolled facilities. The calculation of the total incentive is summarized in Table 31. The average shift factor comes from two scenarios where tax incentives of $5,000 and $10,000 are offered to receivers in the Food and Retail industries in Manhattan. The data used, including the estimated percentages of receivers accepting the incentive and by extension the estimated loss in tax revenue, was all taken from the BMS. The numbers assumed in the scenarios are only based on estimates of potential demand shifts.

Table 31: Total Tax Incentive per Year by OHD Scenario

Scenario	Average Shift	Participating Receivers		Estimated Tax Revenue Loss
		Retail	Food	
1	2.93%	986	2253	$ 16,195,324
2	6.90%	2240	5368	$ 76,071,530

7.6.2.2 Necessary toll increase

The toll increase needed to neutralize the revenue lost from tax incentives can be found by iterative assignments, or can be approximated from the results of the assignments conducted. Although vehicular flows at toll facilities unpredictably change in each scenario due to network effects, the net toll revenue added corresponds linearly to the toll increase enacted. From this linear approximation, the toll increase necessary can be calculated at the total tax incentive paid amount. A summary of the results can be seen in Table 32, noting that the required increases would be for trucks or all vehicles, not both.

Table 32: Required Toll Increases by OHD Scenario for Trucks Only and for All Vehicles

Scenario	Truck Only Toll Increase	Scenario	All Vehicle Toll Increase
1	$ 7.36	1	$ 0.25
2	$ 34.34	2	$ 1.19

While raising truck tolls seems acceptable to incentivize truckers to move to the off-hours, increased tolls for autos is justified due to their experiencing better conditions during the daytime hours, with less trucks on the road and less congestion. However, it can be seen that the first scenario can be paid for with a much smaller truck surcharge than the second scenario (due to higher incentive and much higher receiver participation). Similar results can be expected for the larger incentive scenarios. In either case, the toll increases needed to cover the incentives of the OHD are minimal relative to other toll increases enacted in the region. In the next sub-section, the analysis conducted by this toll model is compared with the results of the dynamic pricing simulations.

7.6.3   Dynamic pricing in TransModeler

TransModeler was previously discussed as part of the sub-network simulation of this study. TransModeler offers both static and dynamic pricing capabilities for a given network under the high occupancy toll (HOT) lane editor. Dynamic pricing, on the other hand, can be performed under the "traffic responsive" type of tolling capability provided by TransModeler's HOT lane editor (Caliper Corporation). In this case, toll rates vary over time, but rather than following a pre-determined schedule, they change in response to real-time traffic conditions. One or more sensors measure the occupancy and travel speed on specified lanes or links that are subjected to tolling. The data received from the sensors are used to update the toll rates within a previously determined time cycle. When the threshold values for minimum occupancy and/or maximum speed are reached, the rates are automatically changed. An example traffic responsive dynamic tolling algorithm can be as seen in Equation 28:

$$TOLL = \begin{cases} if\ t_{occ} \geq 40\%\ or\ u_{max} \leq 40\ mph\ then\ SOV:2.25, HOV2:1.5, HOV3+:1.1 \\ if\ t_{occ} \geq 30\%\ or\ u_{max} \leq 45\ mph\ then\ SOV:2.0, HOV2:1.2, HOV3+:0.8 \\ if\ t_{occ} \geq 20\%\ or\ u_{max} \leq 50\ mph\ then\ SOV:1.75, HOV2:0.8, HOV3+:0.5 \\ if\ t_{occ} \geq 10\%\ or\ u_{max} \leq 55\ mph\ then\ SOV:1.5, HOV2:0.5 \\ else\ SOV:1.0 \end{cases} \quad (28)$$

where, t_{occ} = the measured occupancy of the lane or the link depending on the sensor type (%),

   u_{max} = the maximum speed on the link (mph),

   SOV, HOV2 and HOV3 = different classes of users which are subjected to different toll rates.

Dynamic pricing was extensively tested establishing its suitability for the analysis of this study. Both dynamic and static congestion pricing scenarios are modeled with a primary focus on charging tolls to

enter Manhattan Island. Static pricing, which is currently applied at the crossings, is the case when toll rates are fixed throughout the day. Traffic conditions do not affect the toll rates in real-time as they do in the dynamic pricing case.

The extracted sub-network of the BPM focusing on Manhattan used for pricing simulations is shown in Figure 117. This network is an extended version of the Manhattan sub-area network which was previously used for behavioral module implementation. Since pricing is expected to affect users' route decisions, the Manhattan-only sub-network previously extracted was extended to include alternative links connecting the crossings into Manhattan from New Jersey for entering Manhattan from the west side and crossings from Bronx and Brooklyn for entering from the east side. This enables simulated drivers to select a different path to enter Manhattan to either save money due to different toll costs or travel times as a result of congestion in the paths that they regularly use.

Figure 117: Extended Manhattan Sub-network for Mesoscopic Simulation

7.6.3.1   Simulation study area selection

The crossings used in the simulation network (shown in Figure 118) are:

- Manhattan-Brooklyn/Queens Crossings
- Triborough Bridge (Tolled)
- Queensboro Bridge (Free)
- Queens Midtown Tunnel (Tolled)
- Williamsburg Bridge (Free)
- Manhattan Bridge (Free)
- Brooklyn Bridge (Free)
- Brooklyn Battery Tunnel (Tolled)
- Manhattan-New Jersey Crossings
- George Washington Bridge (Tolled)
- Lincoln Tunnel (Tolled)
- Holland Tunnel (Tolled)

Figure 118: Crossings and Routes Used in the Simulation Network[6]

Manhattan-New Jersey crossings (George Washington Bridge, Lincoln Tunnel, and Holland Tunnel), which allow entering Manhattan from the west side, are ideally positioned for a dynamic pricing simulation. In the simulation, two connecting roads are included between the crossings for users who

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[6] http://maps.yahoo.com accessed on 02/19/2010

want to use an alternative route to cross to Manhattan. These two routes are New Jersey Turnpike (NJTPK) and Route 1-9 which carry the complexity of the network one step further since one of these connecting roads (NJTPK) is tolled and the other one (Route 1-9) is free. NJTPK is a major highway with speed limits of 55 mph while Route 1-9 is an arterial with traffic lights and much lower speeds. It should be noted that all of the traffic carried by these three crossings is assumed to be using or have an option to use one of the two routes before using crossings.

To enter from the east side of Manhattan, there are seven different alternatives in the simulation (Triborough Bridge, Queensboro Bridge, Queens Midtown Tunnel, Williamsburg Bridge, Manhattan Bridge, Brooklyn Bridge, and Brooklyn Battery Tunnel). All the bridges and tunnels are located close enough to constitute alternatives for each other. However, different from the west side crossings of Manhattan, among these seven alternatives only three are tolled. Free crossings remain un-tolled in the simulations and tolled ones are dynamically priced. I-278 (Brooklyn-Queens Expressway) is provided to link the alternative crossings.

The simulation study area is focused on Manhattan crossings; therefore, some possible alternative routes are not considered in the network. New Jersey-Staten Island crossings (Goethals Bridge, Outerbridge Crossing) and Verrazano-Narrows Bridge to connect NJTPK and Interstate 278 would offer a system that enables users to enter Manhattan even from a different side (e.g., from the east side instead of the west side). Although this may not be the case for most of the users whose destinations are inside Manhattan, it may be a possible alternative for through trips. However, the limited traffic data for network calibration forces the simulation team to make assumptions for the traffic distributions in the connection points of the roads and this may result in more unrealistic or unreliable results. For example, in such a configuration aggregated traffic in the connecting roads must be realistically distributed to all crossings (e.g., similar traffic volumes as in real traffic counts) for the base case where the tolls remain static. TransModeler has specific features for route choice depending on the value of time of users but the distributions do not match the real counts in most of the meso-scale simulations. Therefore, it needs to be recalibrated to get realistic traffic volumes in each crossing.

Calibration for the extended dynamic sub-network model is done by either modifying route characteristics (e.g., free flow speed or number of lanes) to adjust the total cost of travel time or putting a fake toll to match the real costs of travel in the selected route. Both ways are useful in terms of simulation purposes for obtaining real traffic counts in the crossings, but the network dynamics are also changed by these modifications and, as a consequence, reality of the network is lost for some links. Therefore, instead of using these methods to simulate a larger network, network construction was finalized with inclusion of the previously stated crossings only.

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7.6.3.2 *Dynamic pricing network calibration*

For dynamic pricing simulations that allow users to select their route to enter Manhattan among different crossings, traffic volumes for all crossings are aggregated at several demand generating points. These points have connections to all possible crossings in one side via the connecting roads (NJTPK and Route 1-9 on New Jersey side, I-278 on Brooklyn/Queens side). For the static case, network calibration is performed to make sure the traffic volumes are realistically distributed to the crossings. A schematic flow chart for the calibration procedure is given in Figure 119.
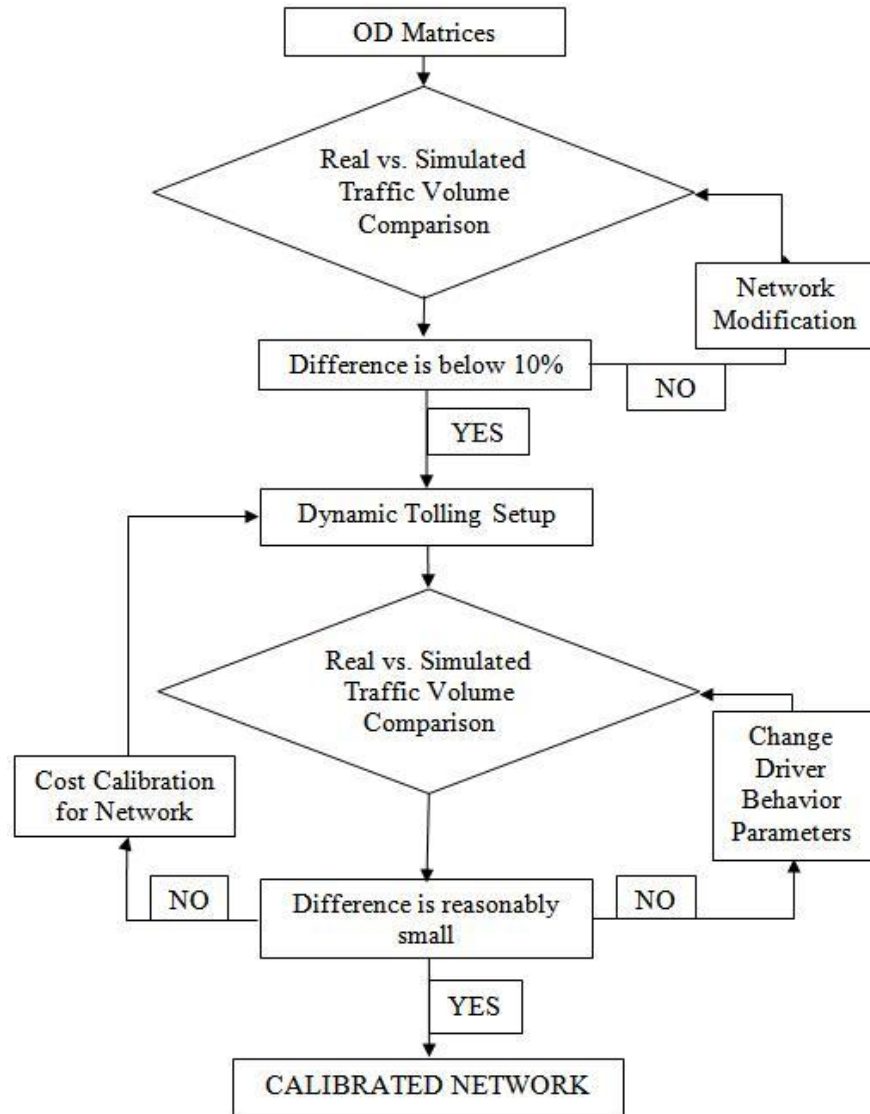
Figure 119: Dynamic Pricing Network Calibration Procedure

Simply adding connecting roads on both sides of the Manhattan simulation network created unrealistic traffic volume distributions in some of the crossings. However, for the static case, the main objective is to simulate the real highway network as accurately as possible to use as a base for comparison of the results with dynamic pricing simulation. Several sensors are set up in the network including all connecting roads and crossings to measure what portion of the traffic changes its route in the static case due to the additional links between crossings (e.g., NJTPK, Route 1-9, and I-278). Traffic volumes from the simulation were compared with the real volume counts (NYCDOT, 2007; PANYNJ) and the network was calibrated by modification of the link characteristics (e.g., free flow speed, speed limit, lane width etc.) for the sections where significant disparities in traffic volumes were observed. After several calibration trials, all the crossings were set to have at most a 10% error in traffic volume compared with the expected counts. Table 33 shows the values obtained after the final calibration.

Table 33: Error between Expected and Simulated Volumes after Dynamic Calibration

Facility	ERROR
Holland Tunnel	4.1%
Lincoln Tunnel	-4.7%
George Washington Bridge	-0.1%
Triborough Bridge	0.0%
Queensboro Bridge	0.8%
Queens-Midtown Bridge	4.4%
Williamsburg Bridge	-6.7%
Manhattan Bridge	-0.8%
Brooklyn Bridge	4.8%
Brooklyn Battery Tunnel	-0.3%
TOTAL	**0.2%**

7.6.4   Scenarios modeled

After network calibration was complete, the broad-based OHD scenarios previously discussed are implemented in the network. Two different cases are run for all hours separately for a typical day: (1) using static pricing in the crossings to Manhattan with the toll rates given in Table 34 held constant throughout the day; and (2) using dynamic pricing. Toll rates in static pricing are defined differently by vehicle class. Since not all vehicle classes are defined in the simulation, average values for each class were used for toll rates.

In static pricing, driver behavior is not influenced by the toll rate since they are the same for all hours and for all alternative routes. In this case, travel times are the decisive factor for the route choice of users. The main purpose of running this case is to use it as a base case and analyze the differences from the results obtained from the dynamic pricing case. In the dynamic pricing case, a robust tolling model is needed to meet driver satisfaction, by offering them acceptable toll rates to travel and to meet the

minimum requirements for a previously set level of service for traffic. As stated, TransModeler offers dynamic pricing using two decision parameters namely, "minimum occupancy" and "maximum speed". However, the data obtained after running the static pricing scenario for different time periods showed that there was no reason to implement an algorithm for dynamic pricing using the two parameters together. Therefore, only occupancy level was considered in determining the real-time toll rates since this approach was found to work well given the simulation tool used and the network characteristics.

Table 34: Static Pricing Simulation Toll Rates Used

MANHATTAN-NEW JERSEY CROSSINGS (George W. Bridge, Lincoln Tunnel, Holland Tunnel)	
Vehicle Class	Toll Rate
Passenger Car	$8.00
Trucks	$27.00
Small Commercial Vehicles	$13.00
MANHATTAN-BROOKLYN/QUEENS TOLLED CROSSINGS (Triborough Bridge, Queens-Midtown Tunnel, Brooklyn Battery Tunnel)	
Vehicle Class	Toll Rate
Passenger Car	$5.50
Trucks	$24.00
Small Commercial Vehicles	$11.00

Six scenarios are initially selected to test broad-based OHD program of shifting Manhattan-bound commercial vehicles to the off-hours. For this task, the first three scenarios are implemented and tested in the sub-network. The OD matrices of truck and commercial vans, grouped as CMV, are updated to accurately represent the shifted traffic volumes of vehicles entering Manhattan. Three different demand-shift simulation scenarios are run and compared with two base case scenarios:

1. Scenario A describes runs with observed traffic demands when the crossings into Manhattan are tolled with static pricing (existing conditions).
2. Scenario B, which is also stated as the dynamic pricing-only scenario, refers to the simulation runs with observed traffic demands when the crossings are tolled using a dynamic pricing strategy.

The outputs for Scenario A and Scenario B are first obtained for the existing base case network.

Traffic volumes on the crossings into Manhattan are compared and the average occupancy values measured by virtual sensors located in the simulation network on each crossing link for all three pricing scenarios. Both occupancy and traffic volume parameters give an idea about the congestion mitigation as a result of the off-hour shift and dynamic pricing, which are the two methods tested for controlling peak-hour congestion. Although application of the commercial vehicle demand shifts and the dynamic pricing methods together makes it difficult to explain the results for individual benefits gained from each method, triple comparison with static pricing and existing conditions with base demands, dynamic pricing without

demand shifts, and dynamic pricing with off-hour demand shifts helps to understand the effect each of the changes has on traffic conditions.

7.6.5 Dynamic pricing simulation results

Table 35 shows the weighted average of percentage differences in average occupancy and traffic volumes in the demand shift scenarios compared to the base static scenario (Scenario A) and dynamic pricing scenario (Scenario B). The numbers indicated in red show a decrease in the stated quantity in the demand shift scenario when compared to the two other scenarios, Scenario A and Scenario B. Seven crossings are combined into three categories as Hudson River Crossings (e.g., Holland Tunnel, Lincoln Tunnel and George Washington Bridge), East River Free Crossings (e.g., Queensboro Bridge, Williamsburg Bridge, Manhattan Bridge, Brooklyn Bridge) and East River Tolled Crossings (e.g., Triborough Bridge, Queens Midtown Tunnel, Brooklyn Battery Tunnel) and the average percentage changes are presented. East River Crossings are analyzed in two categories since the behavior in tolled and free crossings differs significantly when the demand shifts are applied with dynamically priced tolls.

Table 35: Percent Occupancy and Percent Volume Changes from Dynamic Pricing

		vs SCENARIO A			vs SCENARIO B		
OCCUPANCIES		Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
AM	Hudson River Crossings	-1.2%	-0.8%	-0.8%	-0.9%	-0.5%	-0.5%
	East River Free Crossings	1.3%	0.9%	0.7%	0.1%	-0.3%	-0.5%
	East River Tolled Crossings	-2.8%	-3.1%	-2.8%	-0.7%	-1.0%	-0.7%
MD	Hudson River Crossings	-0.4%	-0.5%	-0.5%	0.0%	-0.1%	-0.2%
	East River Free Crossings	0.8%	0.6%	0.1%	-0.2%	-0.4%	-0.9%
	East River Tolled Crossings	-1.0%	-0.9%	-1.1%	0.1%	0.1%	0.0%
PM	Hudson River Crossings	0.4%	0.5%	0.5%	-0.2%	-0.3%	-0.3%
	East River Free Crossings	0.4%	0.6%	0.5%	-0.2%	0.0%	-0.1%
	East River Tolled Crossings	-1.3%	-1.4%	-1.4%	0.0%	-0.1%	0.0%
NT	Hudson River Crossings	-0.3%	-0.2%	-0.2%	-0.1%	0.0%	0.0%
	East River Free Crossings	-0.3%	0.2%	0.7%	0.1%	0.5%	1.0%
	East River Tolled Crossings	-0.4%	-0.4%	-0.2%	-0.1%	-0.1%	0.1%
		vs SCENARIO A			vs SCENARIO B		
VOLUMES		Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
AM	Hudson River Crossings	-6.1%	-3.6%	-3.8%	-4.2%	-1.8%	-1.9%
	East River Free Crossings	8.9%	8.8%	8.3%	0.2%	0.1%	-0.4%
	East River Tolled Crossings	-10.4%	-10.2%	-10.6%	-0.9%	-0.6%	-1.1%
MD	Hudson River Crossings	-1.4%	-1.6%	-2.0%	-0.5%	-0.7%	-1.1%
	East River Free Crossings	5.5%	4.2%	5.1%	-0.1%	-1.5%	-0.5%
	East River Tolled Crossings	-7.9%	-8.0%	-9.0%	1.0%	0.8%	-0.2%
PM	Hudson River Crossings	0.0%	0.0%	-0.3%	-0.2%	-0.3%	-0.1%
	East River Free Crossings	8.0%	8.6%	8.6%	-0.2%	0.4%	0.3%
	East River Tolled Crossings	-0.9%	-2.1%	-0.5%	-0.9%	-2.1%	-0.5%
NT	Hudson River Crossings	4.6%	5.3%	5.5%	0.6%	1.2%	1.4%
	East River Free Crossings	0.5%	1.8%	3.5%	0.5%	1.8%	3.5%
	East River Tolled Crossings	-9.7%	-8.4%	-7.2%	-5.6%	-4.2%	-2.9%

The results show that the average occupancies in tolled crossings in daytime periods (AM, MD, and PM) decrease for most of the crossings with shifted CMV traffic. The impact of dynamic pricing can be observed with the comparison of average percentage changes within the same demand shift scenario with different pricing practices. For the AM Peak period, the results show that there is a significant difference in the demand shift scenario traffic volumes when compared with the static pricing base case scenario. However, the average values in the same demand shift scenarios do not differ significantly when compared to the dynamic pricing-only scenario. This is an indication that the main factor decreasing the traffic volumes was dynamically priced tolls for AM period.

When the demand shifts are applied in the AM period, average occupancies increased in free crossings when compared with the base case. The reason can again be stated as the different pricing strategies. This is also shown by the fact that, in scenarios with dynamic pricing, average occupancies decrease in most of the crossings when demand shifts to the off-hours. For the MD period, average occupancies increased in free East River crossings when compared to the base case as a result of the traffic shifting from tolled crossings. Similar to the AM period, percent traffic volumes using the crossings decreased for most of the tolled crossings in MD period. In the PM period, average occupancies decreased for both tolled and free crossings of the East River for all demand shift scenarios. Similarly, in Hudson River crossings, average occupancies and the number of vehicles using the crossings decreased for all demand shift scenarios. In the NT period, as a result of the shifted commercial van and truck traffic volumes, average occupancies increased in most of the crossings, except the tolled crossings of the East River. The main reason for the decrease in traffic volumes and average occupancies on those crossings is that most of the users shift to the free alternatives to avoid tolls.

7.6.5.1 *Facility analysis*

According to the simulation results, improvements in traffic conditions in the crossings to Manhattan are not solely due to the number of vehicles shifting to the off-hours. Percentage differences in traffic volumes in each crossing are different depending on the real-time toll rates and the number of vehicles shifted to the NT period. Observed differences between dynamic pricing-only simulations and dynamic pricing with demand-shift simulations are depicted in the following figures for the three Hudson River crossings into Manhattan from New Jersey. The results are shown for each of the scenarios run: Scenario 1 (2.93% average shift), Scenario 2 (6.90% average shift) and Scenario 3 (10.42% average shift).
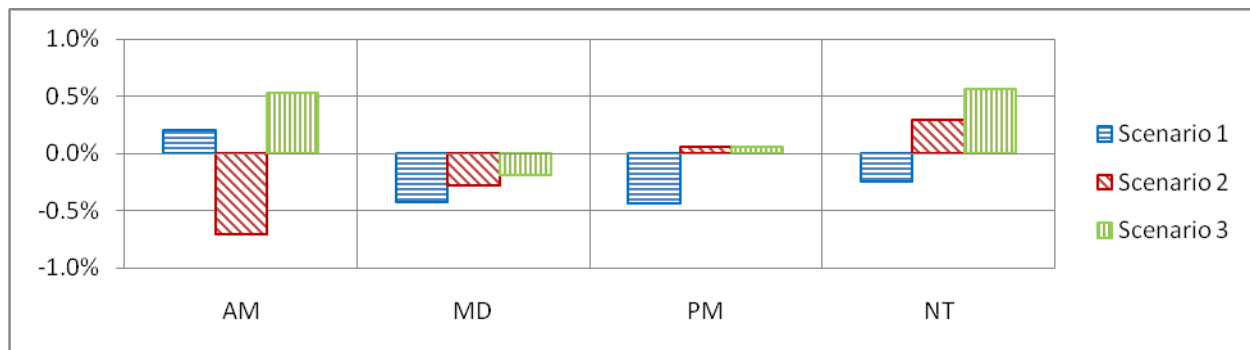
Figure 120: Holland Tunnel Percent Volume Change by Dynamic Pricing Scenario

Figure 121: Lincoln Tunnel Percent Volume Change by Dynamic Pricing Scenario
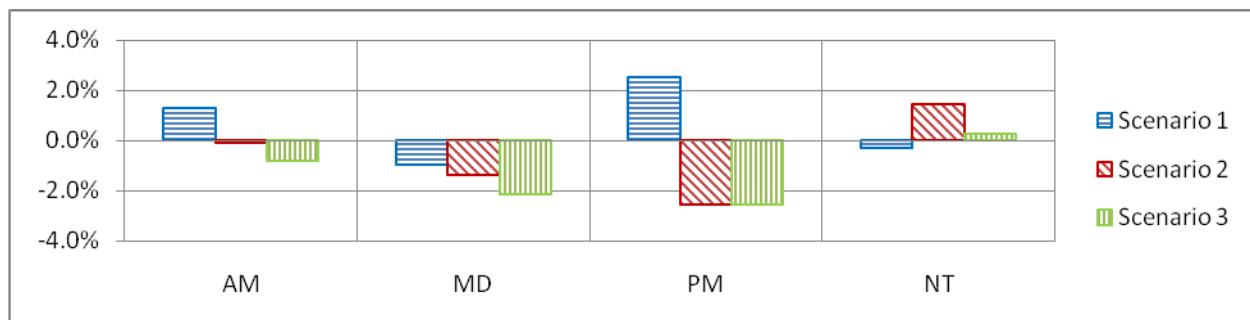
Figure 122: G.W. Bridge Percent Volume Change by Dynamic Pricing Scenario

Figure 120 shows the percent changes in traffic volume in the Holland Tunnel. The results show that traffic volumes decreased significantly in the AM period for all scenarios modeled. Scenario 2 and Scenario 3 gave similar results when daytime traffic decreased and the overnight traffic increased. However, in Scenario 1 traffic volumes in all time periods decreased, meaning that there were shifts to the other crossings as a result of dynamic pricing. Figure 121 shows the percent changes in traffic volume in Lincoln Tunnel. All scenarios gave similar results except the AM period of Scenario 1 when the decrease in traffic volume was excessively high due to the dynamic tolling (as discussed in the previous section). Changes in traffic volumes are observed in similar ways in all other periods for different scenarios.

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Percent differences in traffic volumes for the George Washington Bridge are given in Figure 122. For all tested scenarios, traffic volumes in the selected crossings are very heavy and thus the effect of relatively low demand shift due to OHD incentives is not too high. However, pricing affects all users, thus its effects appear to be more significant. This is the reason for the increase in traffic volume in the PM period in Scenario 1. It should be also noted that all three Hudson River crossings to Manhattan are tolled and there is no free alternative. Since they are all dynamically priced, some irregular changes in traffic volumes can be observed because of the different time-dependent toll rates. Therefore, drawing a conclusion about the effectiveness of each scenario is not attempted.

Figure 123: Triborough Bridge Percent Volume Change by Dynamic Pricing Scenario
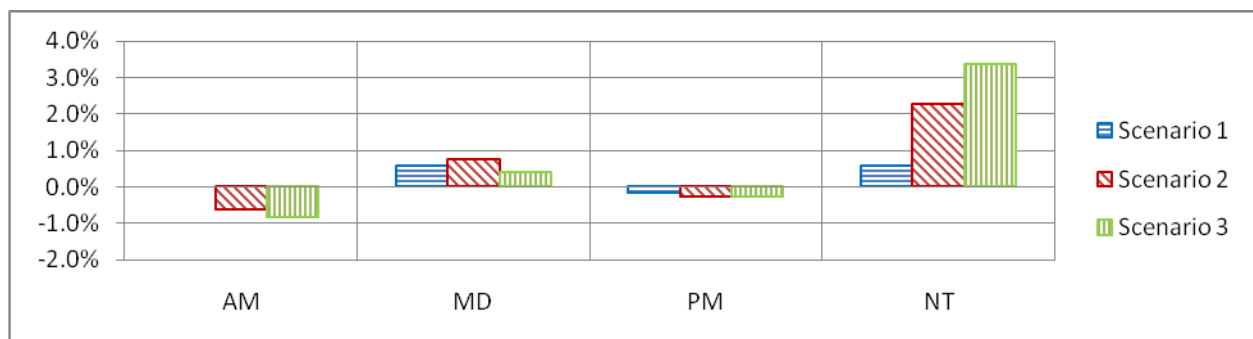
Figure 124: Queensboro Bridge Percent Volume Change by Dynamic Pricing Scenario

Figure 125: Queens-Midtown Tunnel Percent Volume Change by Dynamic Pricing Scenario

Figure 126: Williamsburg Bridge Percent Volume Change by Dynamic Pricing Scenario
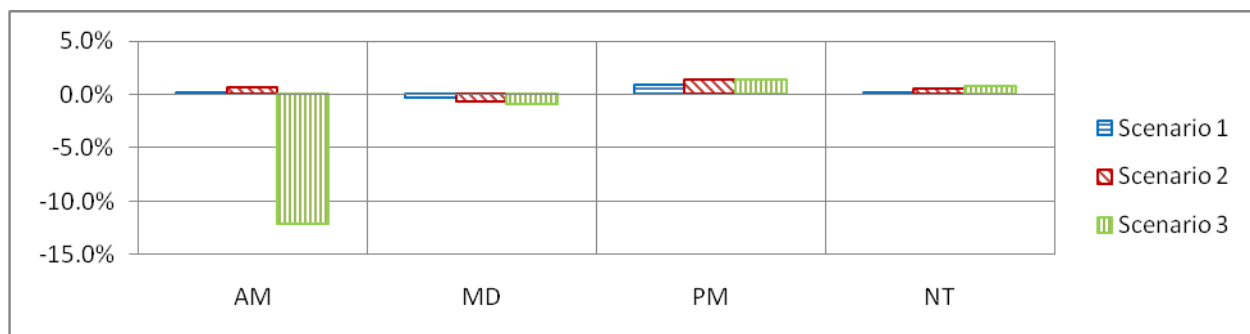

Figure 127: Manhattan Bridge Percent Volume Change by Dynamic Pricing Scenario
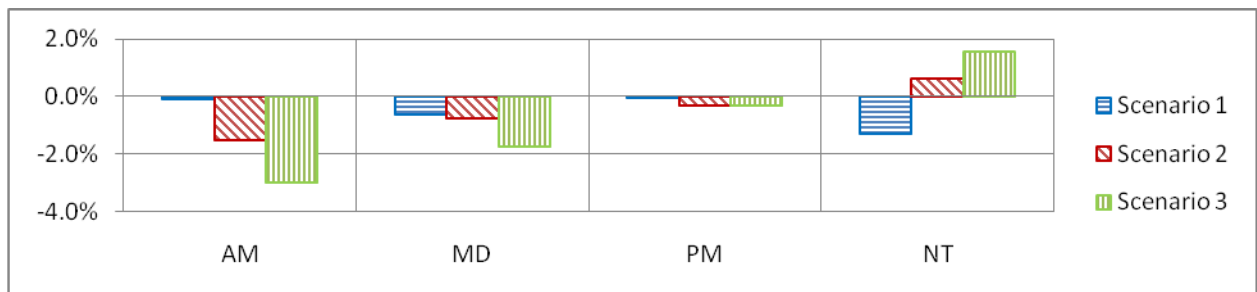
Figure 128: Brooklyn Bridge Percent Volume Change by Dynamic Pricing Scenario

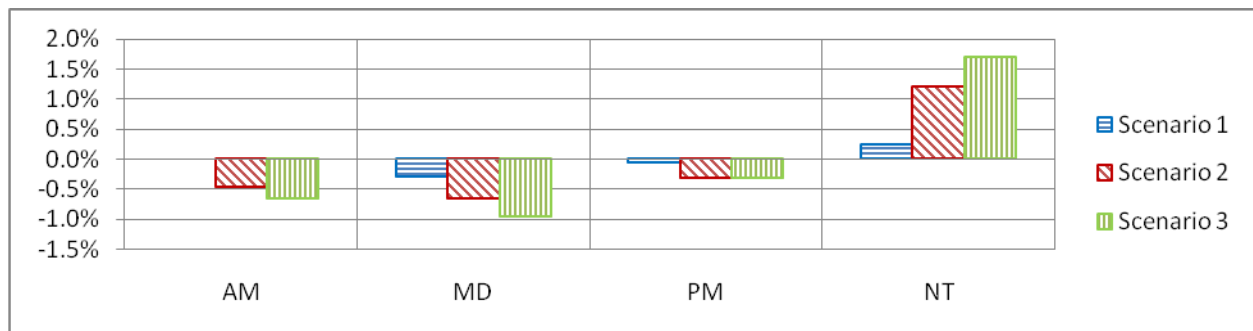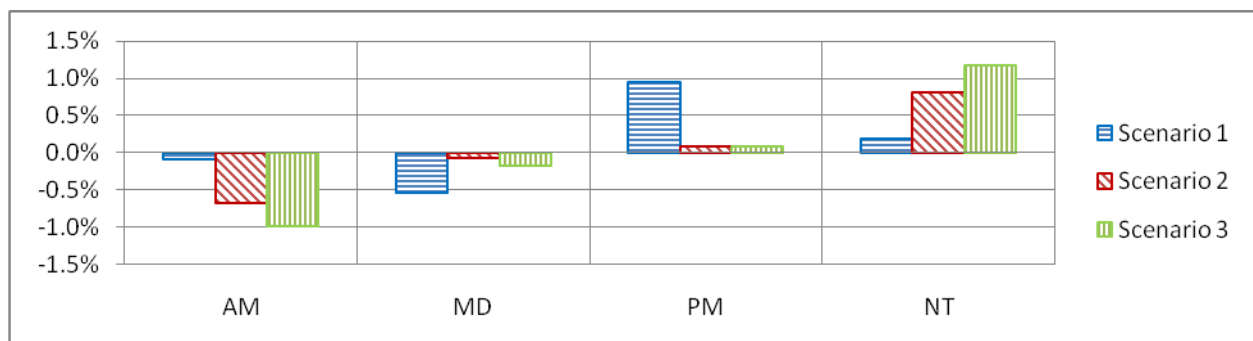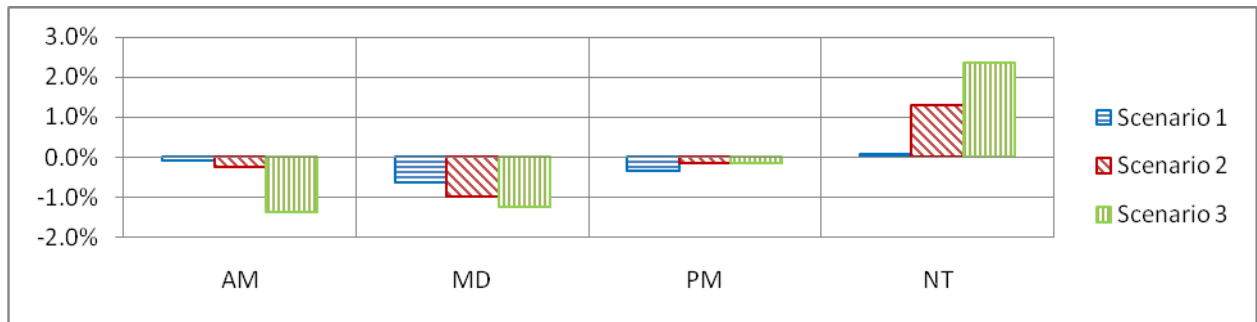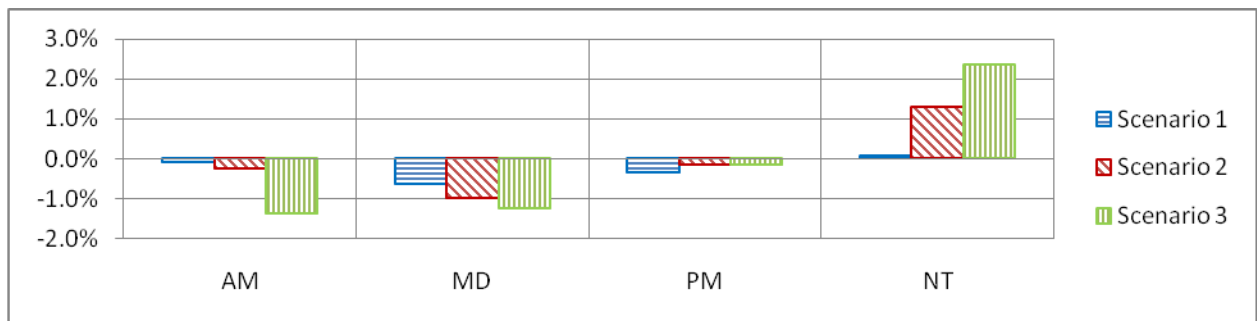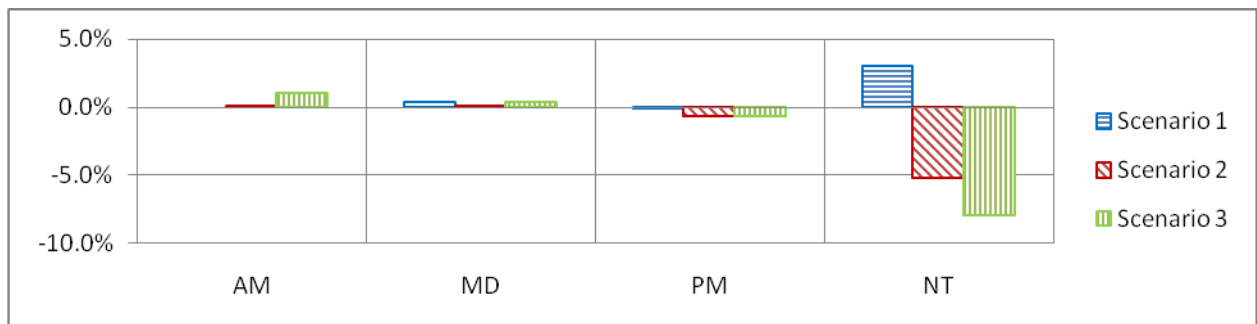**Figure 129: Brooklyn Battery Tunnel Percent Volume Change by Dynamic Pricing Scenario**

Figure 123 shows percent changes in traffic volumes for the Triborough Bridge (entering Manhattan) for different demand shift scenarios. Triborough Bridge is a tolled bridge and the distance between the closest free alternative, Queensboro Bridge, is approximately five miles. It was observed throughout the simulation that very few users changed their path to save travel time. As a result, the effect of dynamic pricing is minimal and the change in traffic volumes was mainly controlled by changes due to the demand shifts. It can be seen that the change in traffic volumes is directly proportional to the magnitude of the demand shift for this crossing, as the percentage gets higher more vehicles shift to the NT period. Traffic volume changes in the Queensboro Bridge are depicted in Figure 124. Queensboro Bridge is a free crossing between Queens and Manhattan which attracts traffic from tolled bridges when the toll rates are high. Thus, the increase in traffic volumes in daytime periods can be explained by the users who tried to avoid high tolls and changed their paths. Among the three scenarios tested, Scenario 2 showed the highest differences in traffic volumes.

Figure 125 shows the percent changes in traffic volumes for the Queens-Midtown tunnel. For all demand shift scenarios, AM period traffic volumes decreased, and the only scenario where traffic volumes for NT period increased is Scenario 3. Although a portion of vehicles in MD and PM periods shifted to the NT period, for Scenario 1 and Scenario 3 there were increases in traffic volumes. Queens-Midtown Tunnel is a tolled crossing, and one of the reasons for the increase is the decrease in average occupancy levels in several time intervals, and accordingly the time-dependent decrease in toll levels. For the Williamsburg Bridge, the difference in traffic volumes does not change in a regular way related to the demand shifts, as seen in Figure 126. Therefore, the route decisions were mainly controlled by dynamically priced toll rates of the alternative crossings. The best performance was observed in Scenario 3 where the AM, MD, and PM period traffic volumes decreased while the NT period increased.

Figure 127 depicts the change in traffic volume percentages on the Manhattan Bridge with different demand shift scenarios. It can be seen that the traffic volume is not directly related to the shifted demands only. Midday period traffic volumes using the bridge increased in Scenario 1 and Scenario 2. For Scenario 3, in all daytime periods there were fewer users and the increase in traffic volume in the NT period is the highest. The percent change in Brooklyn Bridge traffic volumes are shown in Figure 128. For all tested scenarios, NT period traffic volumes increased. Scenario 2 was the scenario where the highest percent changes were observed in MD and NT periods. In other periods different behavior was observed with different off-hour shift values. The difference in daytime periods also results from the traffic shifting from the closely located tolled alternatives. Figure 129 shows the Brooklyn Battery Tunnel traffic volume differences by percent change. Some of the users changed their path to avoid tolls. The differences in volumes mainly resulted from different toll rates depending on average occupancy levels measured in real-time.

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7.6.5.2 Dynamic pricing OHD scenario assessment

Simulation results show that Scenario 1 (2.93% average shift) did not change the traffic conditions significantly, due to the minimal demand shift. However, the percentage differences in traffic volumes show irregularities when compared to other scenarios for some crossings. The results show that dynamic pricing was the main reason for the differences in most of the crossings in this scenario. Although collected toll revenue is higher than the base static scenario, there were no major improvements observed in traffic conditions.

For some of the crossings, Scenarios 2 and 3 ran as expected (i.e., decreasing traffic volumes in daytime, increasing traffic volume in nighttime) and gave higher differences in traffic volumes compared to Scenario 1. However, there were again irregularities in changing patterns. They did not follow a smooth pattern, e.g. the percentage of traffic volume decrease is not always increasing with higher shift factors. For some crossings, such as Triborough Bridge and Williamsburg Bridge, increased shift factors for trucks and other commercials created better traffic conditions in the daytime periods for all vehicles. It was observed from the simulation results that the estimated toll revenues collected in Scenario 3 are slightly higher than the other two scenarios tested.

7.6.5.3 Toll revenues

Estimated toll revenues changes from the simulation of the seven tolled crossings are given in Table 36. The first three columns compare the dynamically-priced OHD scenarios with the statically-priced base case (existing conditions). The next three columns compare the OHD scenarios with a dynamically-priced base case. It can be seen that while dynamically-priced tolls are projected to increase toll revenues overall, the increase is slightly tempered by shifting CMVs to the off-hours. The reasons are the higher toll rates in peak periods and the different throughputs in different periods. Trucks and commercial vans pay high toll rates compared to passenger cars and during peak periods dynamically-priced tolls are at their highest values. Therefore, shifting a portion of trucks and commercial vans to the nighttime period, where the average occupancies are lower (e.g., lower toll rates), decreases total daily revenue.

Table 36: Total Daily Toll Revenues for Different Demand Shift Dynamic Pricing Scenarios

Facility	vs BASE STATIC			vs BASE DYNAMIC		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
Holland Tunnel	14.2%	14.1%	14.0%	-2.3%	-2.3%	-2.4%
Lincoln Tunnel	12.3%	17.8%	16.9%	-2.8%	1.9%	1.2%
George Washington Bridge	27.5%	25.9%	25.8%	-0.5%	-1.8%	-1.9%
Triborough Bridge	0.0%	-4.2%	-0.7%	-0.7%	-4.9%	-1.4%
Queens-Midtown Tunnel	-18.1%	-18.7%	-15.1%	-1.4%	-2.1%	2.2%
Brooklyn Battery Tunnel	18.6%	20.1%	19.2%	-0.3%	1.0%	0.3%
TOTAL	**15.6%**	**15.5%**	**15.9%**	**-1.2%**	**-1.4%**	**-1.0%**

7.6.6   Dynamic pricing conclusion

Pricing strategies are tested in conjunction with the proposed off-hour delivery program to investigate ways to recoup the incentives of the proposed off-hour delivery program and to analyze the effect of pricing on proposed shift scenarios. The BPM was used for static pricing tests of incremental toll increases, and an extracted Manhattan sub-network was used to study dynamic pricing in a mesoscopic simulation. The results of the pricing adjustments in the BPM showed that only minor toll increases would be needed to make up for the potential total incentive given out by the proposed program.

OD matrices were created for each demand shift scenario to shift CMVs from daytime periods (AM, MD, and PM) to the NT period, as studied in the previous behavioral analysis tasks of this study. Mesoscopic simulations using the traffic simulation software TransModeler were then performed to study dynamic pricing. The results of each demand shift scenario were compared to the results obtained in previous tasks for static pricing and dynamic pricing simulations. Comparison of the results showed that increasing the demand shift to the night period enhances the traffic conditions under the application of dynamic pricing on the crossings. Total toll revenues, on the other hand, decrease when more trucks and commercial vans are shifted to the NT period. Among the three scenarios considered in this task, better performances were observed in Scenarios 2 and 3 in terms of the effects on traffic conditions compared to Scenario 1. Toll revenues generated in each scenario were close to each other and all were higher than the base static scenario. Dynamic pricing has been demonstrated to improve traffic conditions, thus were any toll increase to be enacted to support the OHD program, deployment with dynamic pricing has potential to be highly effective.

7.7   Targeted OHD Program Analysis – Large Traffic Generators

While the majority of the modeling of this study focused on the broad-based OHD program—incentives provided to Manhattan receivers in the food and retail industries—traffic assignments are also run for a more targeted program. An assessment of the effect of shifting traffic from LTGs is also conducted. Large traffic generators are defined as specific facilities that house a significant number of businesses that collectively receive a large number of daily deliveries. This group of facilities may include and is not limited to government offices, colleges and universities, hospitals, and large buildings (i.e., the Javits Center, Madison Square Garden, and Grand Central Terminal), among others. The estimation of the number of their daily deliveries and truck trips produced (considering only freight related SICs) is quantified. The BMS research team has identified them using landmark buildings already included in GIS databases as having their own postal code (referred as LTG). In addition, the number of establishments with more than 250, 500, and 1000 employees (which will be referred to as 250+) are identified and the number of deliveries received and trucks trip produced using the trip generation estimates are calculated.

These scenarios tested results from shifting truck and other commercial vehicles from these LTGs, and for the LTG and the establishments with 250+ employees to the overnight period.

7.7.1 Shifting factors

The shifting factors were provided by the BMS team and are summarized in Table 37 and Figure 130. The data corresponds to the percentage of deliveries of the LTGs and companies with 250+ employees per ZIP code, assuming a 100% shift to the off-hours. For this assessment, it has been assumed that these percentages represent the shifting truck and other commercial vehicles traffic shifted to the NT period. In the models, the shifting percentages have been applied to all zones or centroids belonging to a particular ZIP code. As in the broad-based scenarios, the shifting percentages have been equally applied for all time period matrices. The resulting two scenarios correspond to when only LTGs traffic has been shifted, and also when both LTG and companies with more than 250 employees (LTG & 250+) are shifted.

Table 37: Targeted Program Shift Percentages

ZIP Code	% Shift - LTG	% Shift to (LTG &250+ employees)	ZIP Code	% Shift - LTG	% Shift to (LTG &250+ employees)
10001	7.11%	8.83%	10019	8.13%	14.62%
10002	0.00%	0.30%	10020	20.49%	30.25%
10003	0.14%	6.74%	10021	0.40%	2.08%
10004	6.11%	6.86%	10022	6.04%	13.93%
10005	7.31%	7.31%	10023	1.94%	7.22%
10006	0.81%	1.47%	10024	0.67%	0.67%
10007	12.07%	13.32%	10027	0.85%	2.23%
10009	0.00%	0.00%	10028	0.00%	0.83%
10010	0.64%	3.53%	10029	4.97%	4.97%
10011	0.16%	3.12%	10031	0.00%	0.61%
10012	0.00%	1.54%	10032	0.00%	0.45%
10013	0.00%	0.95%	10035	0.00%	1.14%
10014	0.00%	1.36%	10036	0.59%	2.22%
10016	10.47%	14.33%	10038	0.12%	0.79%
10017	16.88%	20.43%	10128	0.67%	0.91%
10018	0.72%	2.09%	10280	67.45%	67.45%
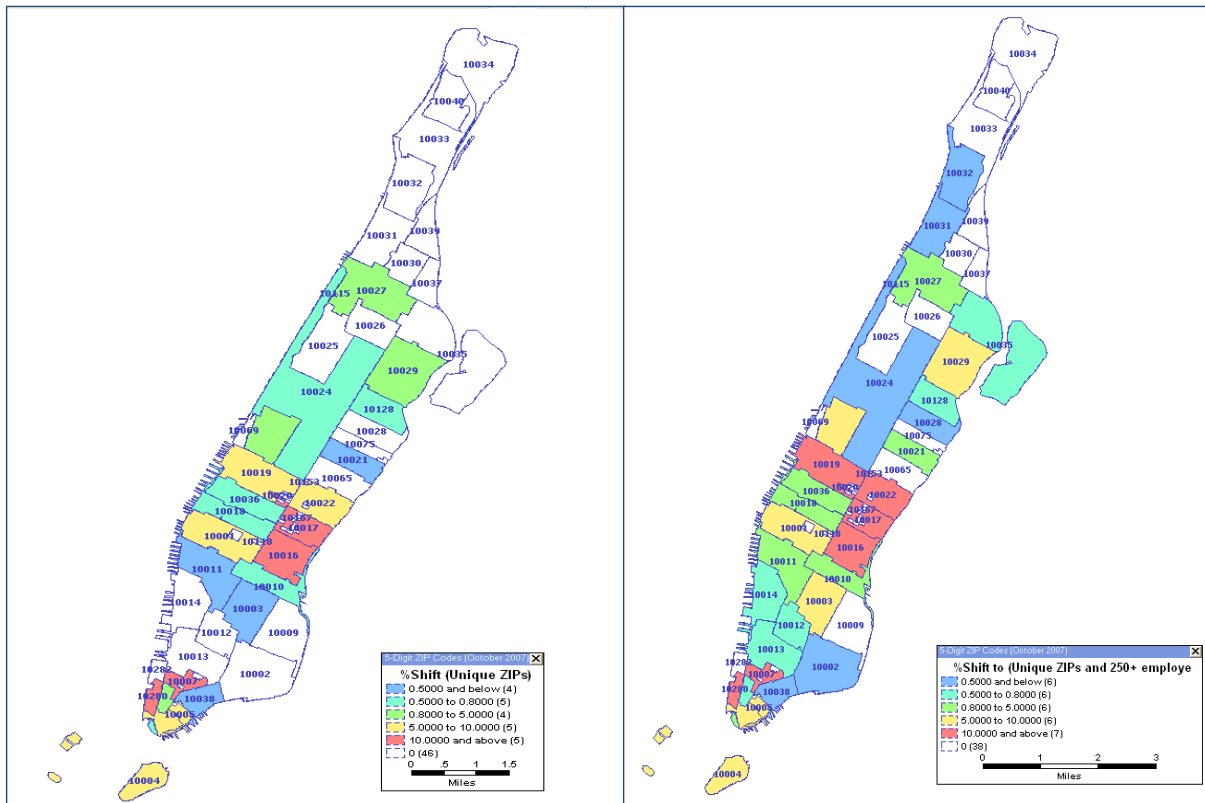
Figure 130: Shifting Percentages Distribution by ZIP Code

7.7.2 Targeted program results

7.7.2.1 Macroscopic model results

The same methodology used for the broad-based OHD program modeling is implemented for the targeted program, with the only difference being the destination zones shifted and their shift percentages. Figure 131 shows the change to VHT when links within Manhattan are aggregated, and Figure 132 shows the change to VHT when all links throughout the network are aggregated. The results indicate the targeted program has a beneficial impact on the traffic networks by reducing congestion. Compared to the broad-based incentive program, since much fewer businesses are considered, the effects are tempered. Both the LTG and LTG&250+ scenarios consider a 100% shift of deliveries to the off-hours; however, the reduction in vehicle hours traveled over the 24-hour day are observed to be similar to the benefits of Scenario 1 of the broad-based program, which assumed a 4.59% shift in the food sector and a 22.21% shift in the retail sector.
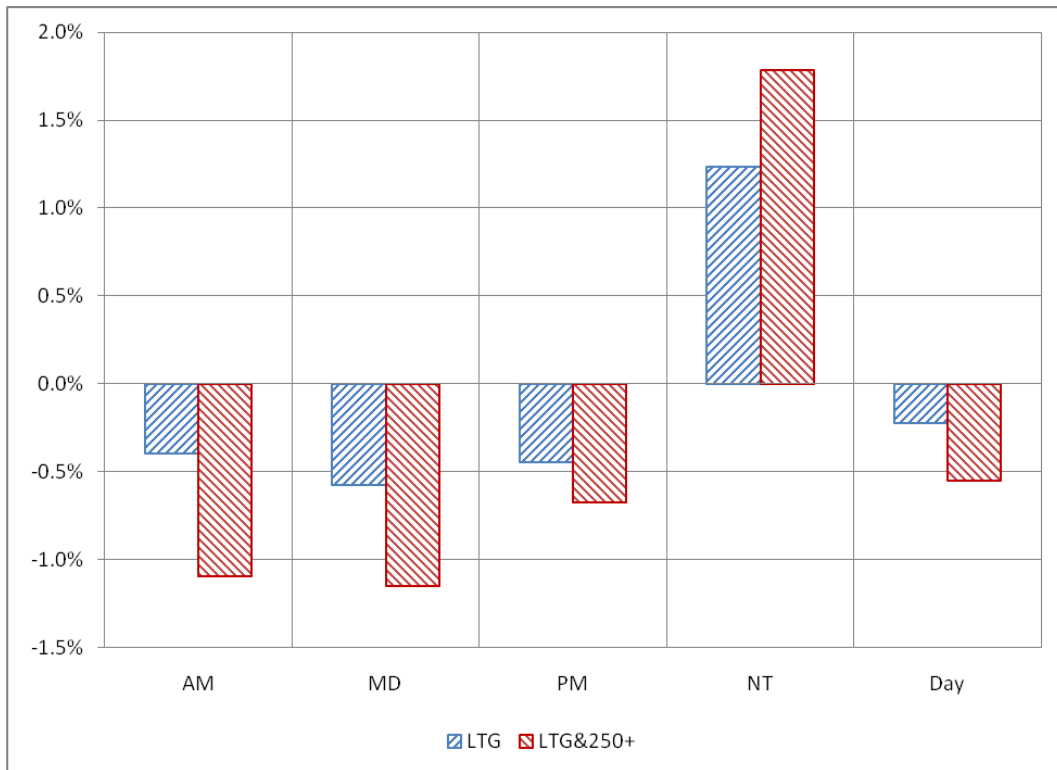
Figure 131: Targeted Program BPM VHT Changes – Manhattan Links
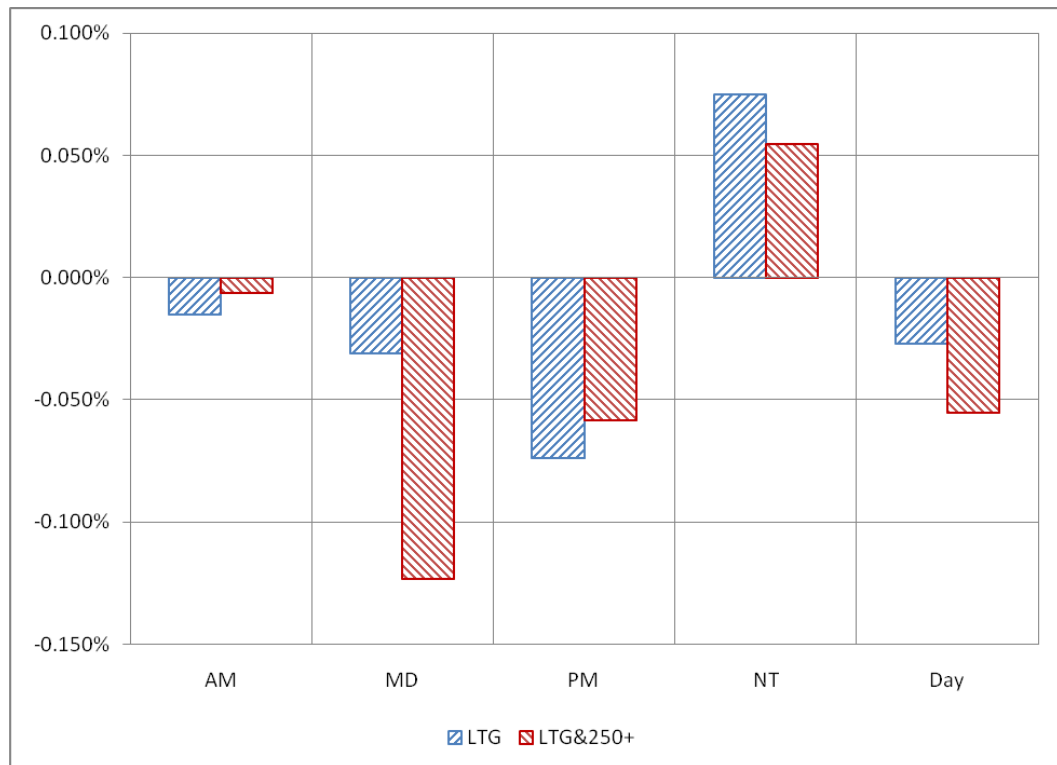
Figure 132: Targeted Program BPM VHT Changes – All Network Links

7.7.2.2   Mesoscopic model results

Similar to BPM, the shifting factors shown in Table 37 are applied to all centroids attached to a ZIP code in the mesoscopic sub-network. The resulting CMV traffic has been shifted and added evenly to the NT period. Figure 133 shows that the reduction in the daytime period (-1.47%) drives an overall reduction in travel time for the 24-hour day of 0.64% in the LTG scenario. In the LTG&250+ scenario, the 24-hour effect is a travel time reduction of 0.16% Since the reduction in the daytime period (-2.28%) is higher than the scenario with only LTGs, the increase in the NT, which almost doubles the effect of the first scenario, reduces the overall benefits to a 1.1% reduction. Contrary to the broad-based program, where congestion is reduced throughout Manhattan, in the targeted program the reduction is basically in the delays but not in the vehicle miles traveled (see Figure 134). In other words, the congestion in the targeted program is reduced along the segments and routes that are used connected to the LTG and establishments, which are fewer than the broad tax incentive scenarios.
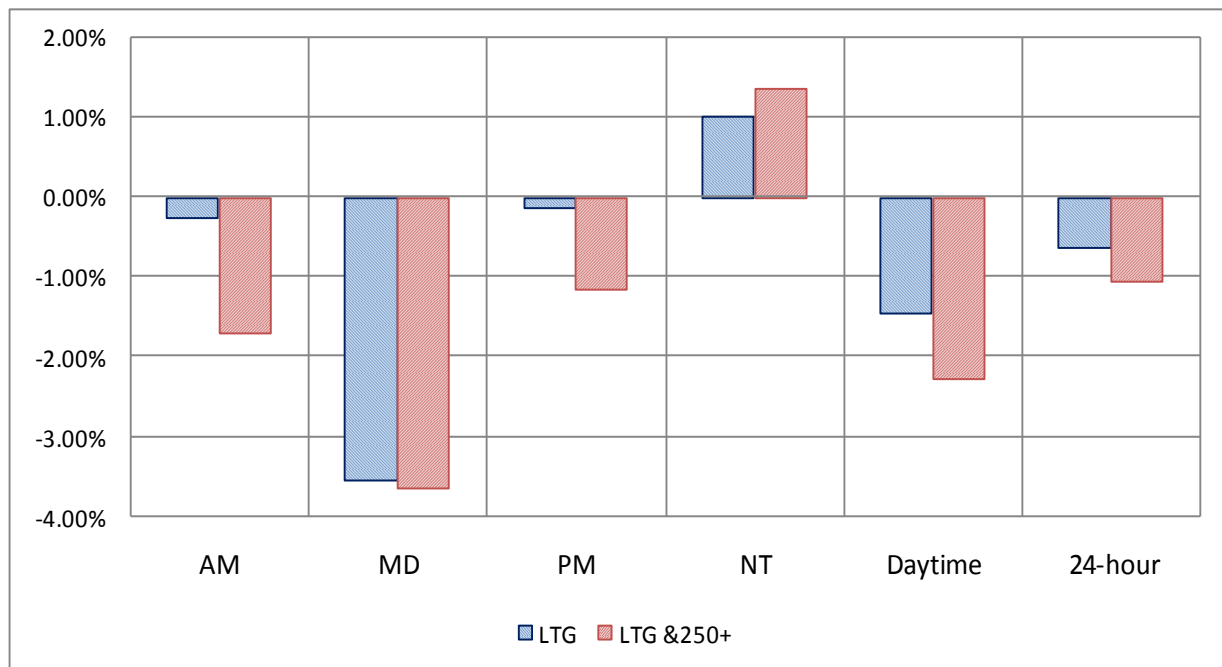
Figure 133: Targeted Program Travel Time Effects by Time Period
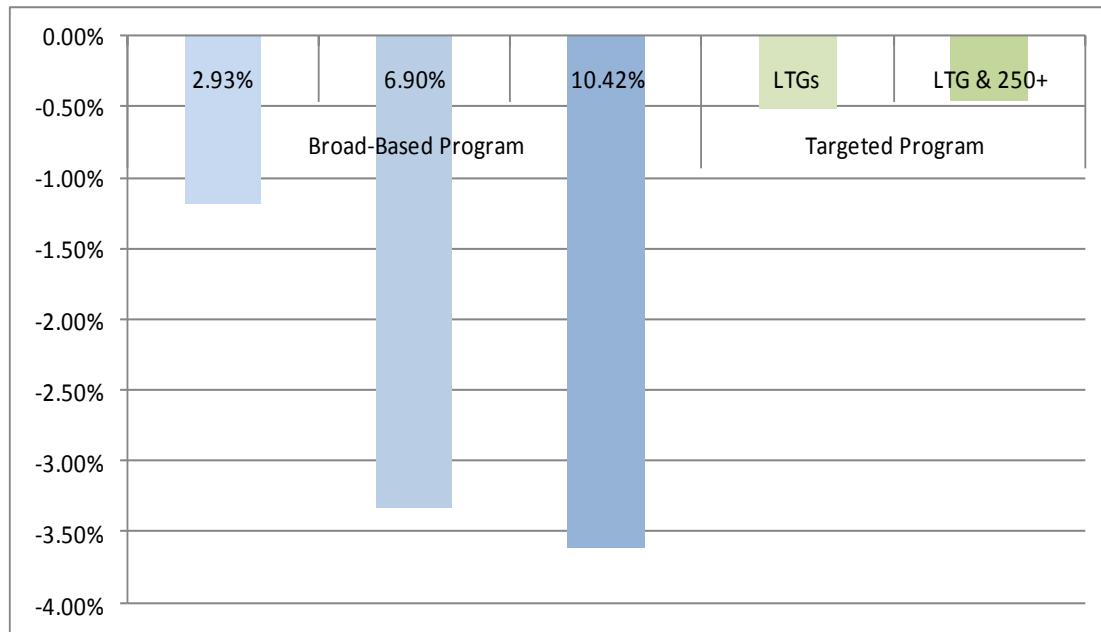
Figure 134: Sub-network VMT Changes by Scenario

7.8   *References*

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8.   ECONOMIC IMPACTS

The team used the results from both the regional network model (BPM), and the mesoscopic traffic simulation (MTS) to estimate the economic impacts in terms of travel time savings and air pollution reductions. The estimates are based on the use of a composite value of time, and economic valuations of the criteria pollutants. The analyses focus on three different cases:

- Financial incentives to establishments in the food and retail sectors. This is the policy identified by the NYSDOT project as the most effective one. It provides a financial incentive to be received in exchange for their commitment to accept OHD.

- Targeted programs aimed at Large Traffic Generators (LTGs). These policies focus on the major generators of truck traffic, which include large buildings that house scores of individual establishments, and large establishments (defined as those with more than 250 employees). Two sub-cases are considered: (1) Large buildings, which only include those buildings that have a unique ZIP code, which is a subset of the total; and (2) Large buildings and Establishments with more than 250 employees.

- Unassisted deliveries. This group considers policies that encourage OHD without the intervention of the staff from the receiving establishment. These concepts have great potential as they could lead to economic benefits comparable to those produced by the financial incentives, at a fraction of the cost. Together with policies targeting LTGs, unassisted deliveries must be the subject of further research.

In all cases, the results are aggregated to obtain the annual economic benefits of the scenarios. Benefits are obtained as the monetization of travel time savings plus additional benefits due to the reduction of externalities. For this report, only the costs and externalities that can be reasonably estimated using the traffic simulation outputs have been considered such as the travel time savings, vehicle operation costs, environmental costs, and safety costs.

8.1   Value of Time

There are different sources for estimates of the value of time in the New York City metropolitan area. In 2005, the New York Metropolitan Transportation Council (NYMTC) released a report that assumed a value of time (VOT) for 2001 at $20.46/hr and for 2005 at $23.00/hr on average for all vehicles (NYMTC; Partnership for NYC, 2006). According to the most recent empirical results obtained from travel survey data for users of Port Authority of New York and New Jersey facilities, the VOT is around $16.50/hr for EZ-Pass peak users, and around $15.15/hr for EZ-Pass off-peak users (Yanmaz-Tuzel et al., 2010). However, these numbers may be underestimating the VOT for the peak-hour conditions. The reason is that, because of the large percentage of work related trips, the value of time is expected to be the same as the hourly wage, which according to the US Bureau of Labor Statistics 2009 data for New York-

Newark-Bridgeport area[7] are between \$26.56/hour and \$33.66/hour. Similar uncertainty surrounds the value of time for commercial vehicles. The only estimate available for the region suggests \$34/hour for light trucks to \$55/hour for semi-trailers (Holguín-Veras and Brom, 2008). No estimates were found for transit vehicles.

However, due to the uncertainty associated with the exact composition of the traffic in the entire network, the results are presented for a range of values of the composite VOT. Assuming a traffic composition of 83% passenger cars, 13% small trucks, 3% large trucks, and 1% buses; and values of time of \$24 (which assumes an average occupancy of 1.2 passengers/vehicle), \$35, \$55, and \$750 (which includes the time value of all passengers plus driver and vehicle) per vehicle class, respectively, leads to a composite value of \$33.62/vehicle-hour. Different assumptions of traffic composition and VOT lead to composite value of time as low as \$25/vehicle-hour, and as high as \$40/vehicle-hour.

8.2   Costs of Externalities

In the case of the estimates produced by the BPM, the computation of the economic value of the reductions in environmental pollutants was conducted using the methodology developed by Ozbay et al. (2007) that estimated the true costs of travel in Northern New Jersey (part of the New York City metropolitan region). These costs include vehicle ownership costs, travel time and congestion costs, accident costs, air pollution costs, noise costs, and others. Based on previous studies and data collected, functions were developed to estimate the full costs of travel for a highway network with a number of input variables, including distances, speeds, travel times, volumes, and values of time. A tool, ASSIST-ME (RITSL, 2009), was then developed to take the output of transportation planning models, such as BPM, and estimate the link costs for all or some links in the network. Using this tool, network costs for each of the scenarios simulated in the BPM were calculated. These costs included operating, congestion, accident, air pollution, and noise costs. By taking the difference between the costs for each scenario and the base case scenario, the traffic results can be put into monetary terms. These costs were developed based on available information in the literature, and compare with the cost estimates used to calculate savings from the mesoscopic sub-model.

The calculation of benefits estimated by the mesoscopic traffic simulation model required the use of a different methodology than the one used to analyze the BPM results. This is because the ASSIST-ME approach is only applicable to link-based results. Instead, a new set of functions to calculate externalities for the sub-network are employed. These externality costs have been obtained from the literature, and are estimated in terms of savings of vehicle miles traveled (VMT). The costs were obtained from the averages of the Victoria Transport Institute estimates (VTPI). They are: air pollution (\$0.06 per mile), greenhouse

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[7] Based on: http://www.bls.gov/ncs/ocs/sp/ncbl1405.txt

gas –GHG ($0.016), vehicle operation ($0.22 per mile), and external crash ($0.055 per mile) for a total of $0.351/mile. Again, due to the sensitivity in the assumptions, two additional values of externality costs were selected (+/- 20%).

8.3   *Computation of Economic Costs and Benefits*

The estimation of the economic impacts associated with policies to foster OHD was done in accordance to standard practices of economic analysis. The key components are:

- **Benefits and costs to road users (passenger cars, buses, trucks)**
  - o Reductions in travel time and environmental pollutants enjoyed by the traffic stream in the regular hours. This captures the increase in welfare for regular-hour roadway users brought about by the trucks that shift to the off-hours.
  - o Increases in travel time and environmental pollutants accrued by the traffic stream in the off-hours. This represents the loss of economic welfare for off-hour roadway users associated with the increase in travel times and pollution during the off-hours. The estimates show that this is relatively small component.

- **Benefits and costs to receivers**
  - o The receivers are likely to accrue additional costs. However, since these additional staff costs are compensated with the financial incentive, or bypassed altogether if policies such as unassisted deliveries are implemented, these costs are assumed to be equal to zero.
  - o Some receivers are likely to benefit from off-hour deliveries. The interviews conducted after the pilot test revealed the case of a receiver that, because of the uncertainty in the delivery times (the carrier could not guarantee a narrow delivery time window because of the randomness of traffic conditions), had to have staff idle for up to four hours (6 - 10 AM) waiting for the delivery truck to arrive. With OHD, however, the staff is certain that the products are available when they arrive to the store. However, due to the lack of data about how general this case is, and in the interest of being conservative in the economic analyses, the team decided to assume that the receivers do not receive any economic benefit from OHD.

- **Benefits to carriers**
  - o Reductions in the travel time associated with the delivery tour. As a consequence of the faster travel speeds, the carriers accrue significant economic benefits. This component assesses the economic value of the total travel savings to the industry.

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o <u>Reductions in service times.</u> The GPS data collected clearly indicate that service times in the off-hours are much shorter than in the regular hours. As shown in Figure 135, the median service time for deliveries at 10 AM is about 1.8 hours, compared to half an hour after 10 PM. Although there may be other factors (e.g., differences in shipment size) that may play a role, the industry representatives interviewed as part of the project did report significant savings in service times. The reasons reported for longer regular-hour service times include the need for drivers to: share elevators with building visitors (a major source of delays in large buildings with no cargo elevator), wait for the loading docks to be available, find/wait for store managers to review the shipments and sign the paperwork, coordinate the actual delivery at times when the store staff is busy with other chores, among others. During the off-hours, in contrast, these sources of delay all but vanish. However, since there is some uncertainty about how much of the observed service times reduction are directly attributable to the shift to the off-hours, the team decided to assume that service times during the off-hours are only 15 minutes faster than in the regular hours. This extremely conservative assumption means that a truck with the average number of 5.5 delivery stops would save 1.38 hours if it shifts to the off-hours. These estimates suggest that, for a sizable portion of the delivery industry, the reductions in service times would be larger than the travel time savings.
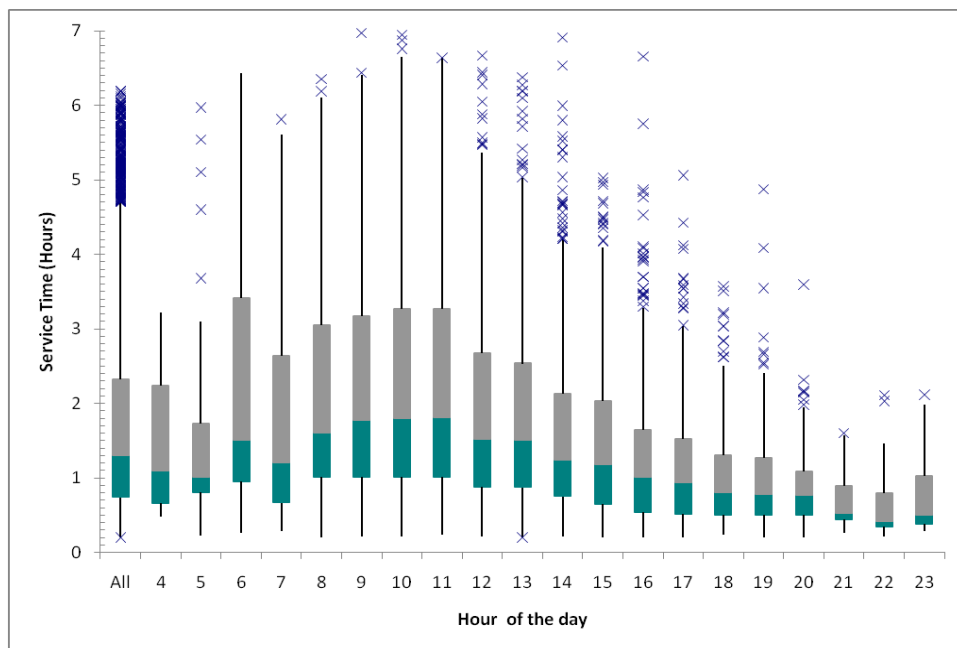
Figure 135: Service Times vs. Time of Day

The total benefits and costs for the various stakeholders are shown in Table 38 (roadway users), Table 39 (Carriers) and Table 40 (Receivers and Public Sector). Since there are no data about the incentive costs or the benefits in some of the alternatives, question marks have been added to the corresponding cells. As shown in these tables, the magnitude of the economic impacts depends on the value of times used in the analyses. For reference purposes, the values considered by the team as the most likely ones have been shaded. These values correspond to \$30/hour for the composite VOT of roadway users, and \$40/hour for the VOT for delivery trucks (large and small).

Table 38: Summary of Economic Impacts: Roadway Users

		Annual Benefits (millions) [1]								Public Sector Incentives (millions)
		Composite Value of Time (passenger cars, buses, and trucks) [2]								
		\$20/hr		\$25/hr		\$30/hr		\$35/hr		
	Trips Shifted	BPM [3]	MTS [4]	BPM [3]	MTS [4]	BPM [3]	MTS [4]	BPM [3]	MTS [4]	
Financial incentives to Food and Retail Sectors										
\$5,000	7,262	\$38.61	\$20.68	\$47.89	\$23.95	\$57.10	\$27.23	\$66.34	\$30.51	\$0.00
\$10,000	15,982	\$57.58	\$51.23	\$70.96	\$58.74	\$84.42	\$66.25	\$97.84	\$73.76	\$0.00
\$15,000	23,617	\$68.24	\$65.50	\$84.24	\$76.11	\$100.24	\$86.72	\$116.23	\$101.94	\$0.00
\$20,000	28,634	\$99.27		\$122.71		\$146.15		\$169.58		\$0.00
Targeted programs aimed at Large Traffic Generators										
Large Buildings [5]	8,345	\$24.36	\$17.68	\$30.23	\$21.28	\$36.10	\$24.87	\$41.97	\$25.18	?
Large Bldgs. & 250+ [5]	17,878	\$53.60	\$26.86	\$67.33	\$32.84	\$81.07	\$38.82	\$94.81	\$41.87	?
Unassisted deliveries										
Security incentives	?	?	?	?	?	?	?	?	?	?
Bonded deliveries	?	?	?	?	?	?	?	?	?	?
Double doors	?	?	?	?	?	?	?	?	?	?

Notes:

[1] Estimated based on changes to congestion, operating costs, noise, and air pollution assuming 250 days/year.

[2] The benefits depend on the composite value of time estimate used.

[3] BPM refers to Best Practice Model. Benefits are calculated for links covered by the 28-county NYMTC region.

[4] MTS refers to Mesoscopic Traffic Simulation. Benefits are calculated based on links located only within Manhattan as part of the extracted sub-model.

[5] Assume 100% participation in off-hour deliveries.

Table 39: Summary of Economic Impacts: Carriers

		Annual Benefits (millions)								Public Sector Incentives (millions)
		Average Value of Time Carriers that Shift to the Off-hours								
	Trips Shifted	$30	$35	$40	$45	$50	$55	$60	$65	
Financial incentives to Food and Retail Sectors										
$5,000	7,262	$21.54	$25.13	$28.72	$32.31	$35.90	$39.49	$43.08	$46.67	$0.00
$10,000	15,982	$47.40	$55.30	$63.20	$71.10	$79.00	$86.90	$94.80	$102.70	$0.00
$15,000	23,617	$70.05	$81.72	$93.39	$105.07	$116.74	$128.42	$140.09	$151.77	$0.00
$20,000	28,634	$84.93	$99.08	$113.23	$127.39	$141.54	$155.70	$169.85	$184.01	$0.00
$25,000	32,856	$97.45	$113.69	$129.93	$146.17	$162.41	$178.65	$194.90	$211.14	$0.00
Large Buildings 5	8,345	$24.75	$28.88	$33.00	$37.13	$41.25	$45.38	$49.50	$53.63	?
Large Bldgs. & 250+ 5	17,878	$53.02	$61.86	$70.70	$79.54	$88.37	$97.21	$106.05	$114.89	?
Unassisted deliveries										
Security incentives	?	?	?	?	?	?	?	?	?	?
Bonded deliveries	?	?	?	?	?	?	?	?	?	?
Double doors	?	?	?	?	?	?	?	?	?	?

Assumptions:

Travel time saved (hours/tour):	0.80	Days per year:	250.00
Service times savings (hours/delivery):	0.25	Delivery stops/tour:	5.50

Table 40: Summary of Economic Impacts: Receivers and Public Sector

	Trips Shifted	Annual Cost to Receivers (millions)[1]	Public Sector Incentives (millions)[2]
Financial incentives to Food and Retail Sectors			
$5,000	7,262	($16.20)	$16.20
$10,000	15,982	($76.07)	$76.07
$15,000	23,617	($172.91)	$172.91
$20,000	28,634	($284.13)	$284.13
$25,000	32,856	($413.72)	$413.72
$50,000	47,605	($1,244.39)	$1,244.39
Targeted programs aimed at Large Traffic Generators			
Large Buildings 6	8,345	$24.75	?
Large Bldgs. & 250+ 6	17,878	$53.02	?
Unassisted deliveries			
Security incentives	?	?	?
Bonded deliveries	?	?	?
Double doors	?	?	?

Notes:

[1] Assumed to be equal to the incentive.

[2] Calculated by multiplying the number of receivers expected to participate by the incentive amount.

Table 41 and Figure 136 show summaries of the economic impacts to stakeholders for the case in which the composite VOT of roadway users is $30/hour, and the average value of time of delivery trucks is $40/hour. As noted previously, the costs to receivers have been assumed to be equal to the incentive cost. As shown, the economic benefits to carriers and roadway users increase with receiver participation in OHD. However, the rate at which these benefits grow decreases as the incentive amount and the resulting number of establishments participating in OHD increases. The cost to receivers, and consequently the associated incentive costs, increases at an accelerating pace due to the effect of the incentive amount and the number of establishments that take the incentive.

Table 41: Economic Analysis Results

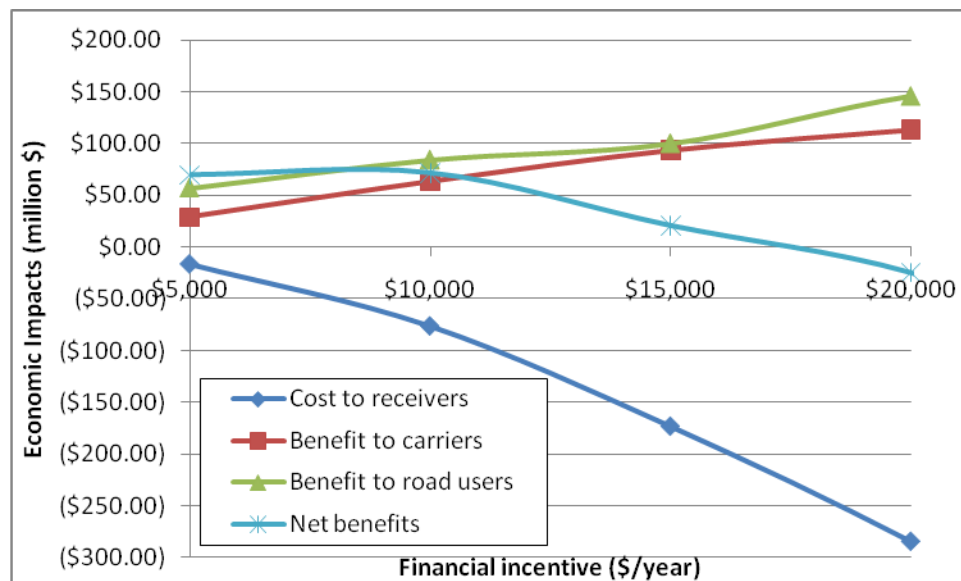|	Cost to receivers	Benefit to carriers	Benefit to road users	Total benefits	Total Incentive Costs	Net benefits	Marginal B/C (ΔB/ΔC)
Financial incentive to food and retail sectors							
$5,000	(16.20)	$28.72	$57.10	$85.81	($16.20)	$69.62	5.30
$10,000	(76.07)	$63.20	$84.42	$147.62	($76.07)	$71.55	1.03
$15,000	(172.91)	$93.39	$100.24	$193.63	($172.91)	$20.72	0.48
$20,000	(284.13)	$113.23	$146.15	$259.38	($284.13)	($24.75)	0.59
Targeted programs aimed at Large Traffic Generators							
Large Buildings 6	?	$24.75	$24.36	$49.11	?	?	?
Large Bldgs. & 250+ 6	?	$53.02	$53.60	$106.62	?	?	?
Unassisted deliveries							
Security incentives	?	?	?	?	?	?	?
Bonded deliveries	?	?	?	?	?	?	?

Figure 136: Cost and Benefits

These analyses show that beyond the $15,000/year incentive, the total costs outweigh the benefits brought about by OHD. However, the optimal amount of incentive is about $10,000/year. The table shows the marginal benefit/cost ratio. This economic indicator measures the ratio of the increase in benefits brought about by a given alternative, with respect to the increase in costs. It is optimal when the marginal benefits equal marginal costs, for a $\Delta B/\Delta C = 1$. As shown in the table, increasing the financial incentive leads to a marginal benefit of $61.81 million/year ($147.62 million/year - $85.81 million/year), at a marginal cost of $59.87 million/year ($76.07 million/year - $16.1 million/year). This translates into a $\Delta B/\Delta C$ of 1.03.

The results indicate that:

- Both the BPM and MTS produce consistent results, though they cover different areas and are built on different assumptions.

- In all cases, the economic benefits associated with increasing off-hour deliveries exhibit diminishing returns though the incentive costs continue to grow.

- The optimal financial incentive is about $10,000 per year, depending on the composite value of time. Depending on the combination of financial incentive and composite value of time, the economic benefits exceed the total incentive cost.

- Policies aimed at increasing off-hour deliveries at large traffic generators have great potential. As shown, switching to the off-hours the truck traffic generated by the 88 large buildings that have their own ZIP code (which are only a fraction of all large buildings in Manhattan), produces economic benefits comparable to the ones for the $5,000 incentive at only a small fraction of the cost.

- Policies that also target large establishments with more than 250 employees could produce significant economic benefits. As shown, shifting all truck-trips produced by these LTGs to the off-hours would lead to economic benefits comparable to the ones for the $10,000 incentive at, yet again, a fraction of the cost.

- Unassisted deliveries represent a huge opportunity, thought not much is known about their market potential. However, a small survey of the receivers that participated in the pilot test indicated that 80% would do unassisted deliveries if the liability issues are satisfactorily addressed. Should this finding be confirmed by future research, it could lead to a situation in which a small public investment could produce economic benefits similar to the ones brought about by the financial incentives.

- Future research must tackle the design of policies and quantification of market potential, and implementation costs for both LTGs and unassisted deliveries. Both concepts offer the potential to shift significant number of truck-trips to the off-hours at a fraction of the cost. This must be a high priority research area.

It should be noted that the economic impacts estimated here are the ones associated with reducing truck traffic in the regular hours. Since in the absence of complementary policies, passenger car traffic is

likely to increase to take advantage of the road capacity made available by the trucks that switched to the off-hours (as part of a process of induced demand), congestion may again increase. This does not mean, however, that OHD have not produced these economic benefits. Instead, the correct interpretation is that these economic losses (due to the increased congestion produced by the induced passenger car traffic) are the cost of not having appropriate passenger car demand management. The key implication is that coordinated demand management policies—targeting both passenger car traffic and freight deliveries— are a must.

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9. CONCLUSIONS AND SUGGESTED NEXT STEPS

This project has been lauded by the freight industry, agencies, and the research community, as a path-breaking effort to be emulated and expanded. In essence, the work done has clearly and unambiguously established that the proposed concept: (1) is effective in inducing a shift of urban deliveries to the off-hours; (2) enjoys broad-based industry support; (3) would bring about substantial reductions in congestion and environmental pollution thus increasing quality of life; and (4) would increase the competitiveness of the urban economy. The fact that this is a win-win concept that benefits all the participants in urban deliveries provides a unique opportunity for expansion and full implementation.

It is important to stress that the focus of the project was on urban deliveries, i.e., the transportation of cargo to urban locations. The main reason being that they represent the bulk of the freight traffic in urban areas, most likely accounting for more than 80% of the entire freight traffic, and the natural target for freight demand management programs aimed at reducing the congestion they produce. Other segments, e.g., external-external flows that pass through the urban area, are not discussed. This must be kept in mind as urban deliveries are quite different than other segments of the freight industry. As a result, the conclusions and methodologies developed here should be assumed to be valid only for the urban delivery case. Further research must be conducted to assess how valid they are for application in other types of freight operations.

The analyses conducted by the team indicate that:

- Financial incentives to receivers will be effective in inducing a shift of carriers to the off-hours. Once the receivers are compensated for the extra costs of off-hour deliveries they have an incentive to switch to the off-hours; while the carriers—that benefit from off-hour work because of the lower delivery costs and parking fines—happily follow suit. The analyses indicate that, depending on the industry segment and incentive provided, the shift could be between 10% and 20% of the truck traffic in these segments.

- The traffic simulations indicate that the switch of truck traffic to the off-hours brings about substantial economic benefits. The estimates produced by the team indicate that the optimal financial incentive is slightly higher than $10,000 a year. This incentive would be accepted by about 7,600 establishments at total cost of $76 million. The economic benefits would range between $83 and $129 million, depending on the value of travel time used in the calculations. Beyond the $10,000 incentive, the marginal benefits get smaller while the incentive costs continue to increase.

- The GPS devices installed in the participant vehicles indicate that, on average, a truck traveling in the off-hours achieve speeds of about 8 miles per hour, while in the regular hours they typically fall below 3 miles per hour. A truck that travels 10 miles delivering from customer to customer would save 1.25 hours per each tour shifted to the off-hours.

- There are substantial reductions in service times during the off-hours. In the regular hours, due to the combined effects of longer walks from parking to customer, elevator congestion,

waiting for customers to check deliveries and the like, service times exceeding 1.5 hours per customer are common. In the off-hours, all these impediments to expedient deliveries all but disappear, leading to service times that average half an hour. Since delivery trucks serve the needs of multiple customers in the same tour, the total service time savings are bound to be substantial, and likely larger than the time savings.

In spite of the concept's great promise and the encouraging results obtained in this project, there are a number of important questions that need to be answered before proceeding to a full implementation. These questions are related to: (1) noise impacts on surrounding communities; (2) statistical validity of the results obtained in the small pilot test conducted; (3) the potential role of targeted programs aimed at large traffic generators; (4) fostering of unassisted OHD; and (5) inter-agency coordination and policy development. These are important questions to be addressed because:

- Noise impacts were not assessed during the project. Although no community complaints were received during the execution of the small pilot test, it is natural to expect that community members would be concerned about noise impacts. In this context, it is important to both assess noise impacts, and define appropriate mitigation strategies should noise be deemed a potential obstacle for implementation. The goal here is to ensure that local communities are not negatively impacted.

- The small size of the pilot test conducted does not support the estimation of statistically representative results. Although a significant and important effort, the test conducted is minuscule when compared to the number of deliveries made in New York City. An increase in the size of the pilot will lead to greater insight into how best to integrate remote sensing into a workable prototype, and to assess the overall benefits attributable to off-hour deliveries. It is important to mention that the size of the pilot test has been recognized as an issue by both team members and USDOT. At the end of 2008, an expansion of the pilot test was considered though USDOT, and the team ended up deciding against it because the economic climate prevailing at the time—in the midst of the collapse of the finance industry—was not conducive for business participation in such research efforts. However, the marked improvement in economic conditions, the stability of financial markets, and the success of the project provide a unique opportunity to conduct another path-breaking effort by expanding the pilot test.

- About 4-8% of all deliveries to New York City are generated by Large Traffic Generators. As a result, inducing LTGs to do off-hour deliveries could have a noticeable impact on traffic congestion. Equally important is that since the number of LTGs is small (between 90 and 500, depending on what definition of LTG is used), the coordination effort is insignificant when compared to the potential payoff. It is therefore possible that the City of New York could play a key role in convincing the owners of the LTGs to switch to the off-hours as part of the City's sustainability efforts.

- Unassisted deliveries could play a key role as part of a sustainability strategy involving off-hour deliveries. Unassisted off-hour deliveries provide a unique opportunity to achieve the benefits attributable to financial incentives, at a fraction of the cost. In this context, public

sector programs that successfully address the liability issues that deter businesses from doing unassisted off-hour deliveries will increase off-hour activity. Over time, as the business sector gets accustomed to unassisted off-hour deliveries, more establishments will join the practice. As an illustration of the potential of the concept, it suffices to mention that 80% of the participating receivers indicated that they would do unassisted off-hour deliveries if the liability issues were resolved.

- <u>Inter-agency coordination of efforts will facilitate implementation.</u> As established in the project, off-hour deliveries have significant economic, environmental, and energy consumption impacts. For that reason, it is natural to involve all agencies whose primary mission is to promote economic development, environmental improvements, and energy conservation. Involving these agencies in the definition of a common off-hour delivery strategy is bound to lead to robust policies and a smooth implementation of the concept.

Fostering OHD at large traffic generators and fully exploiting the use of unassisted deliveries are extremely important because they eliminate the need (and the cost) for the receiver to be present when the OHD are made. As a result, they are very cost-effective as they only require a fraction of the incentives required by the broad-based OHD. However, in spite of their considerable potential, major questions remain concerning policies to foster OHD at large traffic generators and use of unassisted deliveries. This includes: (1) how to integrate remote sensing elements to ensure compliance; (2) liability issues; (3) cost/benefits to participants; and (4) effectiveness of alternative policies, among others.

Both macroscopic and mesoscopic traffic models show beneficial impacts in terms of congestion reductions and improved environmental conditions. Both the regional and sub-regional models showed benefits though the estimates produced by each differed. The integration of two levels of models is essential in order to realistically assess different types of impacts such as dynamic traffic impacts at the facility level. Modeling has also focused mainly on short-term impacts of the proposed program, with long-term network-wide impacts requiring a more significant process of data collection and study. Moreover, an extended pilot test will allow the team to collect and have access to more data, and ensure a better calibration of the models. The use of these simulation models is crucial for better understanding of various scenarios, to quantify their impacts, and to garner support of the involved agencies. The research team is now in a unique position due to the extensive experience it has gained to expand these simulation studies beyond what has been done so far.

All of this suggests the steps outlined below:

- <u>Research and design:</u>
  - ○ Conduct behavioral research to identify and select the most cost-effective incentive policies to foster unassisted off-hour deliveries, and off-hour deliveries at large traffic generators.
  - ○ Expand and improve the traffic simulation models to ensure they provide a meaningful representation of the transportation network in New York City.

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- o Engage the city and state agencies and stakeholder groups that could collaborate in the full implementation of such policies to define their potential roles as part of a comprehensive implementation. This could include: New York City Economic Development Corporation, New York State Energy Research and Development Agency, Real Estate Board of New York, among others.

- o Launch a publicity campaign to get industry support and sign up potential participants in an expanded pilot test.

- o Conduct research on noise impacts and potential mitigation strategies.

- o Design community feedback programs to ensure concerns are properly addressed.

- o Design and establish compliance verification mechanisms.

- Expanded pilot test and Implementation:

  - o Roll out a comprehensive set of incentive policies; recruit participants.

  - o Design a monitoring plan involving: the use of GPS devices to assess performance of delivery operations before and after the pilot; the installation of noise measuring devices to assess noise impacts; the use of the GPS data currently being collected by NYCDOT to monitor network-wide impacts.

  - o Launch and monitor the expanded pilot test.

  - o Use behavioral models to predict participation in the implementation phase.

  - o Use the traffic simulation models to assess the network impacts of both the expanded pilot test, and a full implementation.

  - o Organize community hearings and gather stakeholder input.

  - o Decide on implementation.

The team is of the opinion that an expansion of the pilot test, combined with the steps outlined above, could bring about an enhanced understanding of the potential benefits of integrating cutting edge remote sensing technology as part of a novel freight demand management concept. Furthermore, a revised focus on LTGs and unassisted deliveries could provide much needed empirical evidence on the practical challenges as well as the benefits and costs of what is likely to become a business-friendly way to do freight demand management in congested cities.

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APPENDIX

Participating Receiver Management Satisfaction Survey

February 10, 2010

Dear Store Manager,

We would like to thank you for your participation in this important pilot test. At this point we would like to get your feedback regarding the pilot test. Please fill out the following survey and return it to us via e-mail (bromm@rpi.edu) or fax (518-276-4833).

IMPORTANT: When responding to the survey, please assume that the additional costs corresponding to the staff working in the off-hours have been taken care of by means of a financial incentive from the city, or any other incentive that compensate the store for the additional costs.

How many employees does your store have working on a typical day? _____

Of those employees, how many are dedicated to receiving and stocking goods? _____

What was your impression of off-hour deliveries? _____

1) Very Favorable 2) Favorable 3) Neutral 4) Unfavorable 5) Very Unfavorable

How much did receiving off-hour deliveries affect your operations? _____

1) Drastic Changes 2) Significant Changes 3) Moderate Changes 4) Few Changes 5) No Change

In what way?

If it were up to you, how likely are you in the future to request deliveries from your vendors (not only Sysco) in the off-hours? _____

1) Very Likely 2) Likely 3) May or May Not 4) Unlikely 5) Very Unlikely

What did you like about receiving deliveries in the off-hours?

What did you dislike about receiving deliveries in the off-hours?

If all liability issues were addressed, would you be interested in receiving unassisted deliveries (e.g. driver places goods in a secure storage location at your establishment)? _____

1) Very Interested 2) Interested 3) Neutral 4) Uninterested 5) Very Uninterested

If you would like more information about this request, please contact Mr. Matthew Brom at 518-203-3831 (bromm@rpi.edu). I look forward to hearing from you.

José Holguín-Veras, Ph.D., P.E., Principal Investigator, Professor
Civil and Environmental Engineering

Participating Carrier Management Satisfaction Survey

Rensselaer

February 17, 2010

Dear Manager,

We would like to thank you for your participation in this important pilot test. At this point we would like to get your feedback regarding the pilot test. Please fill out the following survey and return it to us via e-mail (bromm@rpi.edu) or fax (518-276-4833).

How many employees does your business have working on a typical day?   _____

   Of those employees, how many are drivers?   _____

What was your impression of off-hour deliveries? _____

1) Very Favorable 2) Favorable 3) Neutral   4) Unfavorable 5) Very Unfavorable

How much did making off-hour deliveries affect your operations? _____

1) Drastic Changes 2) Significant Changes 3) Moderate Changes 4) Few Changes 5) No Change

   In what way?

How did making off-hour deliveries affect your costs? _____

1) Moderate Increase 2) Slight Increase 3) No Change 4) Slight Decrease 5) Moderate Decrease

   In what way?

If it were up to you, how likely are you to make deliveries during the off-hours if requested from your customers? _____

1) Very Likely 2) Likely 3) May or May Not 4) Unlikely 5) Very Unlikely

What did you like about making deliveries in the off-hours?

What did you dislike about making deliveries in the off-hours?

If you would like more information about this request, please contact Mr. Matthew Brom at 518-203-3831 (bromm@rpi.edu). I look forward to hearing from you.

José Holguín-Veras, Ph.D., P.E., Principal Investigator, Professor
Civil and Environmental Engineering

Participating Carrier Driver Satisfaction Survey

Rensselaer

February 17, 2010

Dear Delivery Driver,

   We would like to thank you for your participation in this important pilot test. At this point we would like to get your feedback regarding the pilot test. Please fill out the following survey and return it to us via e-mail (bromm@rpi.edu) or fax (518-276-4833).

Considering your experience with making deliveries in the off-hours (before 6AM or after 7PM) rather than the regular hours (6AM to 7PM), how were the following aspects affected? *Please circle your response.*

Availability of Parking

1) Large Increase 2) Some Increase 3) No Change 4) Some Decrease 5) Large Decrease

Average Travel Speed

1) Much Higher 2) Somewhat Higher 3) No Change 4) Somewhat Lower 5) Much Lower

Level of Congestion

1) Much More Congested 2) More Congested 3) No Change
4) Less Congested 5) Much Less Congested

Level of Stress From Driving

1) Much Higher 2) Somewhat Higher 3) No Change 4) Somewhat Lower 5) Much Lower

Amount of Time Needed to Complete the Delivery Route

1) Much Higher 2) Somewhat Higher 3) No Change 4) Somewhat Lower 5) Much Lower

Length of Time Needed at Each Stop to Deliver Goods

1) Much Higher 2) Somewhat Higher 3) No Change 4) Somewhat Lower 5) Much Lower

How Safe Do You Feel Making Off-Hour Deliveries

1) Much More Safe 2) More Safe 3) No Change 4) Less Safe 5) Much Less Safe

Personal Preference of Delivery Time

1) Strongly Prefer Off-Hour 2) Somewhat Prefer Off-hours 3) No Preference
4) Somewhat Prefer Regular hours   5) Strongly Prefer Regular hours

What did you like about making deliveries in the off-hours?

What did you dislike about making deliveries in the off-hours?

   If you would like more information about this request, please contact Mr. Matthew Brom at 518-203-3831 (bromm@rpi.edu). I look forward to hearing from you.

José Holguín-Veras, Ph.D., P.E., Principal Investigator, Professor
Civil and Environmental Engineering

Foot Locker Satisfaction Survey

Rensselaer

November 23, 2009

Dear Store Manager,

We would like to thank you for your participation in this important pilot test. At this point we would like to get your feedback regarding the pilot test. Please fill out the following survey and return it to us.

How many employees does your store have working on a typical day? _____

Of those employees, how many are dedicated to back room operations? _____

What was your impression of off-hour deliveries? _____
1) Very Favorable   2) Favorable   3) Neutral   4) Unfavorable   5) Very Unfavorable

How much did receiving off-hour deliveries affect your operations? _____
1) Drastic Changes   2) Significant Changes   3) Moderate Changes   4) Few Changes   5) No Change

In what way?

If it were up to you, how likely are you in the future to request deliveries from your vendors in the off-hours? _____
1) Very Likely   2) Likely   3) May or May Not   4) Unlikely   5) Very Unlikely

What did you like about receiving deliveries in the off-hours?

What did you dislike about receiving deliveries in the off-hours?

If you would like more information about this request, please contact Mr. Matthew Brom at 518-203-3831 (bromm@rpi.edu).

I look forward to hearing from you.

Yours truly,
José Holguín-Veras, Ph.D., P.E.

Principal Investigator, Professor
Civil and Environmental Engineering