# Multi-Attribute Taxi Logistics Optimization

By

**Sonny Li**

A.B. Harvard University
MBA Cornell University

Submitted to the System Design and Management Program
in Partial Fulfillment of the Requirements for the Degree of

**Master of Science in Engineering and Management**

at the

Massachusetts Institute of Technology

June 2006





Signature of Author ______________________________

Sonny Li
System Design and Management Program
May 2006

Certified by ______________________________

David Simchi-Levi
Professor of Civil and Environmental Engineering and Engineering Systems
Co-Director, Leaders For Manufacturing and System Design and Management Programs
Thesis Supervisor

Certified by ______________________________

Patrick Hale
Director
System Design and Management Program

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Sonny Li

Submitted to the System Design and Management Program
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## ABSTRACT

According to U.S. government surveys, 12% of Americans used taxi service in the previous month[1] and spent about $3.7 billion a year for cab fare.[2] Taxi service is one of the major modes of public transportation. Despite providing services 24 hours a day, driving relentlessly with an empty taxicab in search of passengers and answering dispatch calls instantaneously, taxi service is ranked the most unsatisfactory mode of transportation by the public. Charging higher fares than other major modes of transportation and averaging 10 to12 hours work day, taxi drivers have a difficult time to earn a sustainable income.

Approximately half of all the taxi mileage is paid mileage; this means a significant portion of a taxi's time and fuel is spent on non-revenue generating activities, i.e. without passengers. Current taxi allocation is inefficient. The number of taxis and the geographical service areas which they serve are heavily regulated in most cities. With limited competition and strict regulations, taxi service suffers with customers having to endure long wait times and inferior services. The current taxi systems in most U.S. cities may be greatly improved from their current state.

This thesis investigates the factors of inefficiency in the current taxi system, reviews previous taxi efficiency studies, and suggests possible solutions. After extensive literature reviews and field research, a computer simulation model has been built in the MATLAB environment. This computer model tests various attributes that affect logistic optimizations for taxi services. In particular, the effect of taxi fleet size, the quantity of hotspots, and the concentrations of customers at hotspots are analyzed in detail using the

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[1] Bureau of Transportation Statistics. October, 2003. http://www.bts.gov/programs/omnibus_surveys/household_survey/2003/october/

[2] Schechner, S., Cranky Consumer: Hiring a Taxi During Rush Hour, *The Wall Street Journal*, April 26, 2005.

model. The metric of interest includes the customers' wait time, taxi revenue, and costs of operations. Results from the computer simulation experiments, field research, and literature review are analyzed and synthesized. Possible solutions are proposed as part of this thesis.

Thesis Supervisor: David Simchi-Levi
Title: Professor of Engineering Systems Division and Civil & Environmental Engineering

## Acknowledgements

I am grateful for the knowledge, wisdom, insight, and support from my thesis advisor Professor David Simchi-Levi. His guidance provides direction for my research and encourages me to think beyond the traditional boundaries of this topic.

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## Introduction and Thesis Overview

"[New York City taxis] take more than two hundred million passengers [and travel] almost eight hundred million miles a year. They make more than one billion dollars in revenue and drive passengerless for almost a million miles a night. They maintain twenty-four-hour coverage of one of the biggest cities in the world, and they almost always get you where you need to go."[3]

Approximately half of the taxi mileage is paid mileage; this means a significant portion of the taxi's time and fuel are spent on non-revenue generating activities, i.e. without passengers. Current taxi allocation is inefficient. The number of taxis and their geographical service areas are heavily regulated in most cities. With limited competition and strict regulations, taxi service suffers with customers having to endure long wait times and inferior services. The current taxi systems in most U.S. cities have plenty of room for improvement.

From an economic perspective, the supply of taxis (number of hours taxis are available to transport passenger) is not equal to demand of taxis because taxis often drive passengerless in search of customers. From the driver's perspective, the supply of taxis is more than the demand because a significant amount of time (~50%) is spent while the driver is driving an empty taxi looking for potential passengers. From a customer perspective, the demand of taxi service is higher than the supply because customers often have to wait a long time for taxi service. In a free market, the price or fare is determined by the equilibrium of supply and demand. The price (fare) of the taxi is determined by the government in most cities. The government regulates not only the fare structure but also the number of taxi medallions and sometimes even the fee structure between the cab owner and the driver.

[3] *Taxi Dreams*. PBS Documentary. 2001. [http://www.pbs.org/wnet/taxidreams/index.html]

This has created significant economic inefficiency as shown in the graph below.

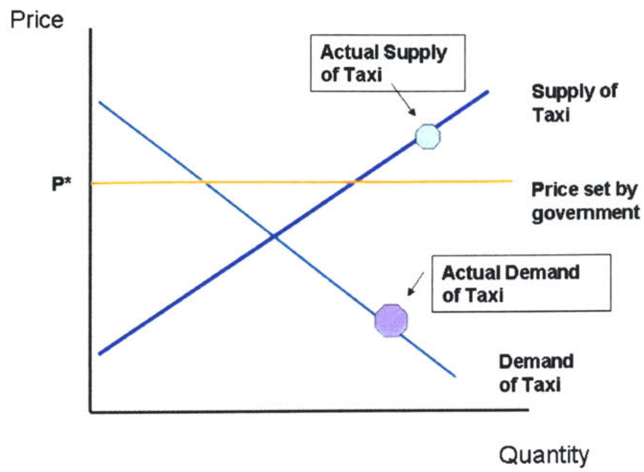



**Figure 1: Taxi demand and supply is <u>not</u> at equilibrium. The price is set by local governments.**

This thesis investigates the factors of inefficiency in the current taxi system, reviews previous taxi efficiency studies, and suggests possible solutions. After extensive literature reviews and field research, a computer simulation model has been built in the MATLAB environment. This computer model tests various attributes that affect logistic optimizations for taxi services. In particular, the effect of taxi fleet size, the quantity of hotspots, and the concentrations of customers at hotspots are analyzed in detail using the model. The metric of interest includes the customers' wait time, taxi revenue, and costs of operations. Results from the computer simulation experiments, field research, and literature review are analyzed and synthesized. Possible solutions are proposed as part of this thesis.

# 1. Industry Background

## A. History

A taxi is a vehicle for hire that transports passengers to *locations of their choice*. It is different significantly from other modes of public transportation where the pick-up and drop-off locations are determined by the service providers.

The history and concept of taxis can be traced back hundreds of years. In the United Kingdom, the first hackney-carriages license, a horse drawn carriage for hire, was issued in 1662. In both London and Paris, royal proclamations dictated the number of carriages allowed.[4] This signifies the beginning of regulations. By the 19$^{th}$ century, the Hansom cab, a horse-drawn carriage that is faster, lighter, and safer than the previous hackney-carriages, became popular and replaced previous carriage designs. In 1891, the taximeter was invented to calculate fare. The first gas-powered and meter-equipped taxi began operation in 1897 in Germany. In the next ten years, this model of taxi proliferated in Paris, London, New York and finally around the world.

The next major invention after the taximeter was the two-way radio in the 1940s. Two-way radio significantly increased the efficiency of dispatching taxis to customers. By the 1980s, computer assisted dispatching (CAD) was introduced to the taxi industry.[5] With CAD, passenger information was entered into the computer and the availability of taxi was displayed for the dispatcher. This facilitated the processing of passenger and taxi data. Today, only a very small minority of taxis is equipped with a small computer, GPS, credit card processing equipment and other technologies.

[4] *Wikipedia*. 2006. http://en.wikipedia.org/wiki/Taxicab.
[5] *Wikipedia*. 2006. http://en.wikipedia.org/wiki/Taxicab.

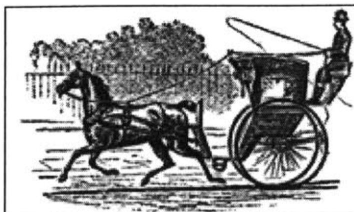
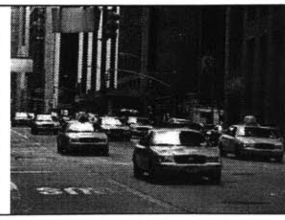
| | |
|---|---|
|  |  |
| 19th Century. Hansom cabs were light, fast and low-slung.[6] | Taxi today in New York City |

**Figure 2: Taxicabs in the 19th century and today**

[6] *Wikipedia*, 2006. http://en.wikipedia.org/wiki/Hansom_cab.

## B. Regulation

Regulations of the taxi industry vary greatly depending on the location. In Chicago, there is a "three-strike" rule for drivers who do not maintain a clean taxi. In Los Angeles, there is a standard on punctuality and customer complaints that cab companies must meet. In New York and Shanghai, there is a rating system for taxi drivers.[7]

Taxis usually are allowed to pick up passengers on the street, at taxi stands, and other locations where they are allowed to operate. On the other hand, other vehicles-for-hire such as livery cars can only pick-up passengers through previous arrangements. Violating passenger pick-up rules can result in revocation of taxi licenses and prosecution.

Regulations in major cities, such as London and New York, are extremely strict. For example, in London, aspiring drivers must pass a grueling geography test as part of licensing requirement. Taxi drivers are required to purchase a medallion in order to own a taxi. The medallion allows the taxi to operate within limited geographic areas. The drivers and/or owners also must also submit to extensive background checks and training.[8] The taxicab has to pass certain inspections and cannot be more than a certain number of years on the road. Finally, the fare structure for passengers, the financial structure between taxi/medallion owner and drivers/lessee are also regulated.

## C. Dispatching

Before the invention of the two-way radio, taxi drivers often go to call-boxes at the taxi stand to contact the central dispatching office. With the invention of two-way radio in the 1940s, taxi drivers can contact their central dispatching office for passenger pick-up information while on the road. This plays an important role in increasing the efficiency of the taxi industry. Today,

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[7] Schechner, S., Cranky Consumer: Hiring a Taxi During Rush Hour, *The Wall Street Journal*, April 26, 2005.

[8] *Wikipedia*. 2006. http://en.wikipedia.org/wiki/Taxicab.

the dispatching of taxis is even more efficient with computer assisted dispatching and GPS. However, new technology is slow to be adopted by the taxi industry.[9]

### D. Fare

Taxi fares are usually measured by a taximeter which calculates the fare based on the combination of distance traveled and waiting time. The fare structure is usually regulated by the government. On a cost per mileage basis, taxis are usually more expensive than other forms of public transportation such as trains, subways, and buses. Depending on the locations/situations, passengers pay a flat fare or while in other settings taxi will take the highest paying passenger.[10] For example, in New York City (NYC), trips originating at JFK Airport have a flat rate range from $40-$50. While on the streets of NYC, the initial fare is $2.50 for the first 1/5 of a mile, 40¢ for each additional 1/5 of mile and waiting time is 40¢ per 2 minutes.[11]

There are differences in regulation, dispatching and fare structure depending on the country or even cities within the same country. For example, taxis in Hong Kong are painted in three different colors (red, green, and blue) designating which areas/districts they can pick up passengers. In contrast, taxis in Washington D.C., there are no meters in the taxi. The city is divided into zones and passengers pay according to which zone they enter and exit the taxi. In general, taxis are concentrated in major cities, business districts, and more affluent communities because of the higher probability of picking up more passengers. This leaves some areas without taxi service. In the U.S., underserved areas are usually served by livery cars or illegal cabs.

[9] *Wikipedia*. 2006. http://en.wikipedia.org/wiki/Taxicab.
[10] *Wikipedia*. 2006 http://en.wikipedia.org/wiki/Taxicab.
[11] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.

## E. Passengers

According to U.S. government surveys, 12% of Americans had used taxi services in the previous month[12] and spent about $3.7 billion for cab fare.[13] Thus taxis are a major mode of public transportation. There are 230,000 active taxi drivers according to the 2000 U.S. Census. However, the number of taxis in each city varies greatly.

In New York City, with 12,779 medallion taxicabs,[14] there were 241 million passengers who took a taxi in 2005 with over 470,000 taxi trips per day which generated $1.82 billion in annual revenue. Taxis transport 25% of passengers traveling within Manhattan. Revenue derives from taxi transport accounts for 45% of the fare paid trips while taxi, bus, subway and black car comprise the balance. The average fare was $10.34 when tips are included.[15] On the average, taxi passengers have stable discretional incomes.

Most of the trips are for work or personal errands. Depending on the time of the day, the purposes of each trip differ. In the morning (7-9 a.m.), 61% of the trips are destined to work. The origins of these trips are primary from the Upper East Side and Upper West Side in NYC, the more affluent neighborhoods. After 8:00 p.m., 50% of the trips are bound for passengers' homes, originating from work or places of entertainments. Overall, 66% of all taxi trips in Manhattan are between work, home, and places of entertainment.[16]

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[12] Bureau of Transportation Statistics. October, 2003. http://www.bts.gov/programs/omnibus_surveys/household_survey/2003/october/

[13] Schechner, S., Cranky Consumer: Hiring a Taxi During Rush Hour, *The Wall Street Journal*, April 26, 2005.

[14] New York City. New York City Taxi & Limousine Commission. *New York City Taxi and Limousine Commission's Annual Report 2005.*

[15] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.

[16] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.

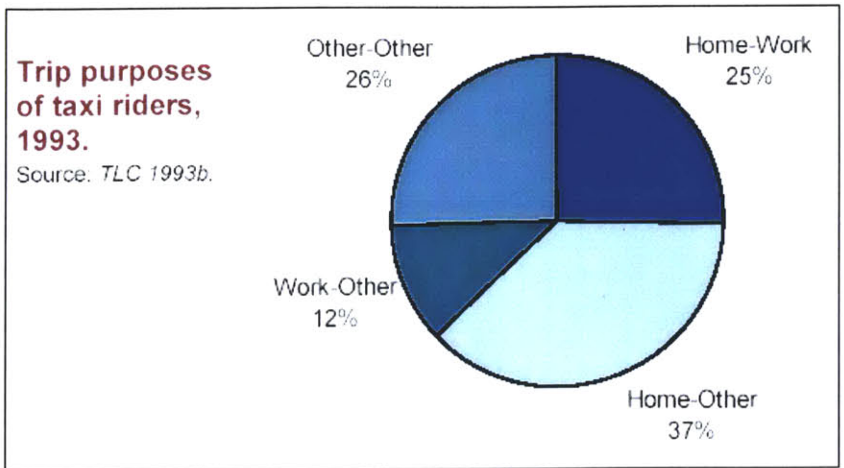


**Figure 3: Purpose of taxi trips in New York City.**[17]

As shown in the figure above, the majority of the taxi trips are either home or work related.[18]

Trips to the airports also accounts for a small portion of total trips. Approximately 30% of air passengers use taxis to get to airports while more than 30% of air passengers use taxis to depart from airports.

As shown in the figure below, most of the taxi passengers are local residents of Manhattan. [19]

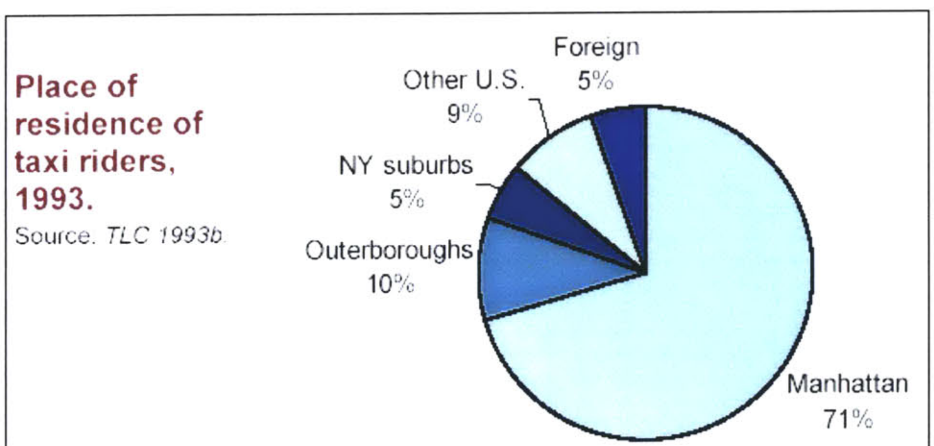


**Figure 4: Residence of taxi riders. New York City study.**[20]

[17] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[18] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[19] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[20] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.

The passenger attributes in New York City taxi riders can be easily extrapolated to other major cities around the world.

### F. Quality of Services

Despite being one of the major modes of transportation, the quality of taxi services ranks much lower when compared to other modes of transportation.

For instance, in New York City, there were 17,350 complaints filed with New York's Taxi & Limousine Commission (TLC) in 2005. The level of satisfaction (6.2 on a scale of 10) was below that of subways and buses. While taxi passengers value the sense of security, comfort, and being in a fast mode of transportation, Most complaints were related to the inability to hail a cab when needed, value for the money, safety from accidents, driver rudeness, and the driver's lack of street and geography knowledge.[21] These fallacies may be improved with training and arming the driver with better technology.

[21] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.

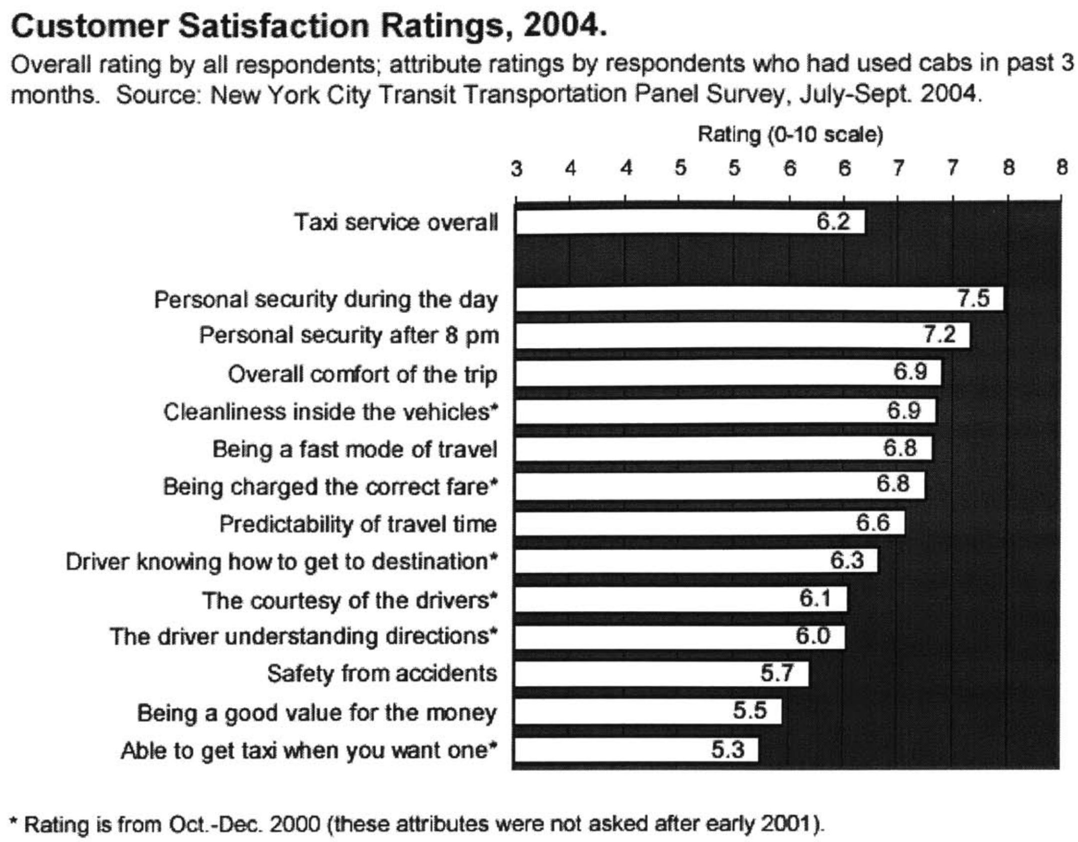


**Table 1: New York Customer Satisfaction Rating of Taxi Services. Taxi has the lowest rating among all public transportations. Unable to get a taxi is the attribute with the lowest rating.**

The graph above shows the attributes that passengers value. Attributes at the top of the chart are factors that customers believe taxis are doing well while those at the bottom of the chart are attributes that need improvement. The overall satisfaction rating (6.2) is below that of subways (7.0) and buses (6.7).[22]

The table on the next page compares the major attributes for taxis, subways, buses, private cars, and car services. It clearly shows that taxi ranks almost last or second to last across all categories.[23]

[22] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[23] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.

**Customer satisfaction ratings, 2004.**

Source: New York City Transit Transportation Panel Survey, July-Sept. 2004.

| | Over all | Being fast mode of travel | Predict-ability of travel time | Overall comfort of trip | Safety from acci-dents | Good value for the money | Per-sonal security during the day | Per-sonal security after 8 p.m. |
|---|---|---|---|---|---|---|---|---|
| Private cars | 8.5 | 8.1 | 7.7 | 8.9 | 7.6 | 7.8 | 8.8 | 8.4 |
| Subway | 7.0 | 7.9 | 7.0 | 6.9 | 7.7 | 7.1 | 7.6 | 6.5 |
| Car service | 6.9 | 7.5 | 7.2 | 7.7 | 6.7 | 6.5 | 7.9 | 7.4 |
| Local bus | 6.7 | 6.4 | 6.4 | 7.2 | 7.6 | 7.1 | 8.1 | 7.4 |
| Taxi | 6.2 | 6.8 | 6.6 | 6.9 | 5.7 | 5.5 | 7.5 | 7.2 |

**Table 2: Customer satisfaction rating of taxi in comparison to other modes of transportation.**[24]

The availability of taxis depends not only on the geographic locations of the passengers and taxis but also on the time of day. As shown in the graph below, demand and availability of taxis varies greatly during a (24) hour cycle.[25]

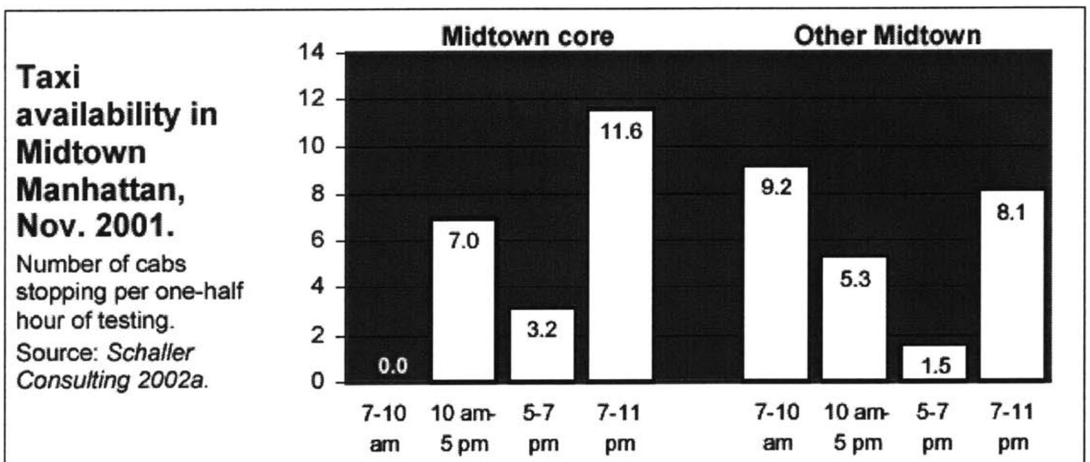


**Figure 5: Availability of taxi is a function of time and location.**[26]

[24] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[25] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[26] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.

"Being able to get a taxi when one needs it" is a major customer complaint. The reasons contributing to being unable to get a taxi include:

- The demand is higher than the availability of taxis
  - Better allocation of taxis can eliminate some non-live mileage (miles on the road without passengers)
  - Better use of other car services, such as livery or black car services, to meet the demand

- Taxis are not at close approximation to the customers
  - Better allocations of taxis will bring taxis closer to the customers

- Taxis are refusing to pick up passengers (service refusal is a major complaint)
  - Financial motivation is one the major reasons customers believe for refusal of service. Upon dropping off passengers, taxi drivers do not want to be stuck in traffic or return with an empty cab
  - Taxi drivers feel safer picking up passengers who called ahead for service than picking up passengers from the street

The refusal of service is closely correlated with the live mileage (miles with passengers). When passengers are plentiful, taxi drivers become more selective, as shown in the figure below:[27]

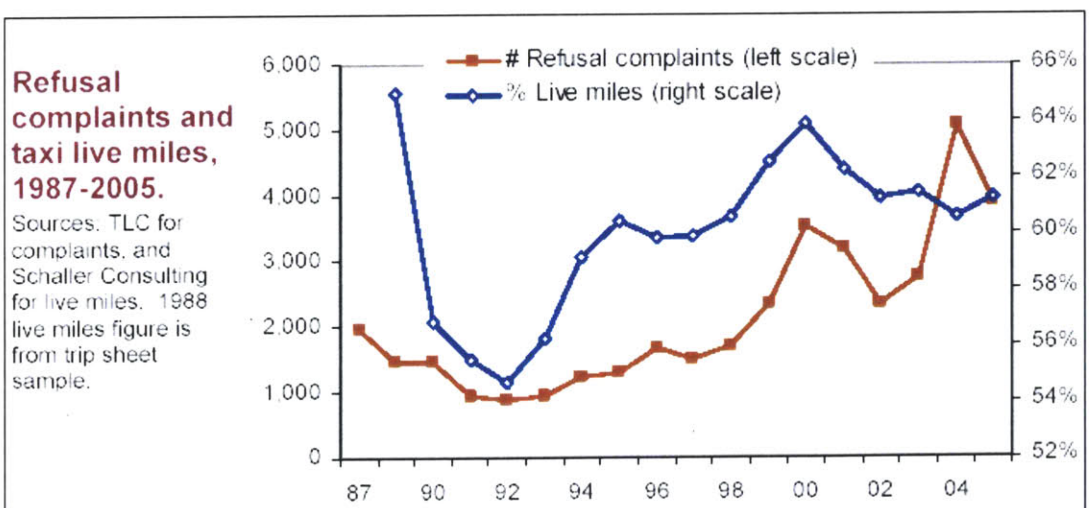


**Figure 6: Comparison of taxi complaints and live mileages.**[28]

[27] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[28] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.

In summary, taxis are a major mode of public transportation that many people depend on it but there is much room for service improvement. This detailed analysis of New York City's highly regulated taxi situation can be applied to other major cities. It is very likely that behaviors needs of passengers in NYC are very similar to other areas. It is clear that the availability of taxi is one of the highest attributes that customers value. Perhaps the level of customer service can be improved with an intelligent, dynamic, centralized taxi allocation system.

## G. Taxi Drivers

The majority of taxi drivers are usually male and foreign-born, especially in major cities. Overall foreign-born drivers represent slightly less than half of all taxi and limousine drivers in the U.S. They usually lease the taxi and pay the medallion owner a portion of the revenue. Driving a taxi requires hard work and long hours. A majority of these immigrant drivers view this as an opportunity to pursue the American dream.

A majority of the taxi drivers are concentrated in seven major U.S. cities this accounts for 36% of all U.S. taxi and limousine drivers. Overall, the growth of the number of drivers has been relatively stable in a tightly regulated industry, as shown in the graph below.[29]

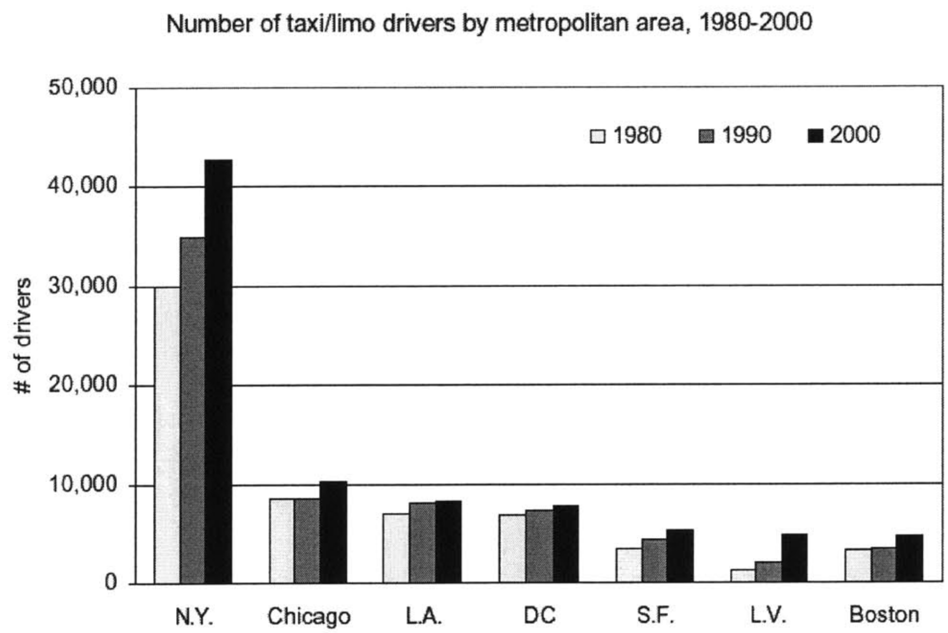


**Figure 7: Distributions of taxi drivers in the U.S.[30]**

[29] Schaller Consulting. *The Changing Faces of Taxi and Limousine Drivers*. July 2004.
[30] Schaller Consulting. *The Changing Faces of Taxi and Limousine Drivers*. July 2004

In New York City, 91% of the drivers are immigrants. The most common countries of origins are Pakistan (14.4%), Bangladesh (13.6%), and India (10.2%).[31] Lack of English skill is one of the major complaints of passengers. New York City also has the highest ratios of taxi drivers to population as shown in the graph below.[32]

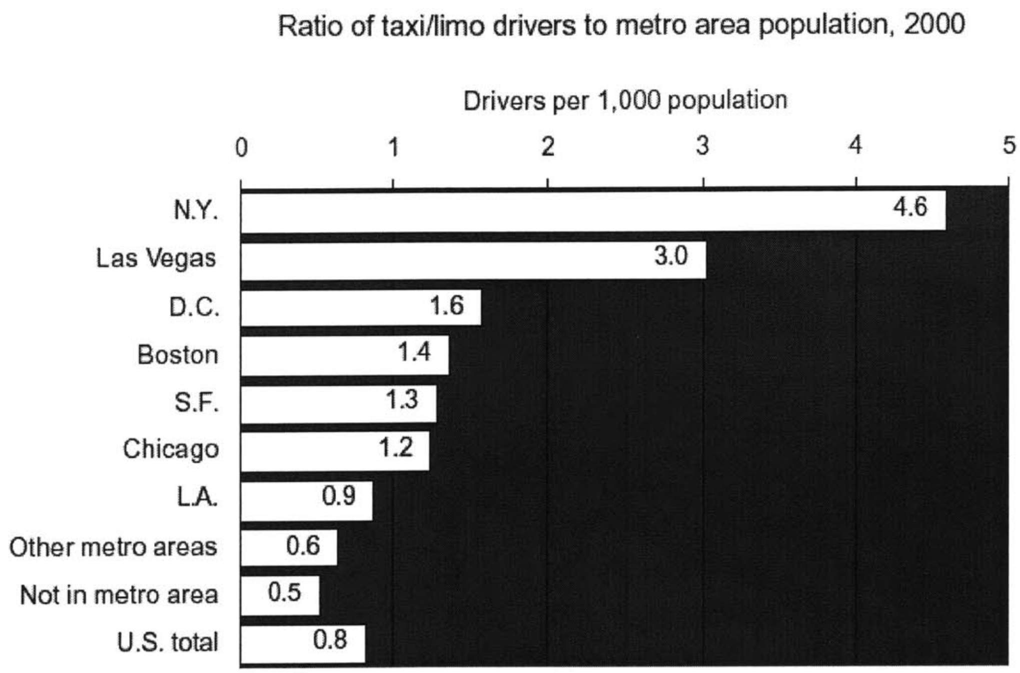


**Figure 8: The ratio of taxi drivers to populations.**[33]

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[31] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[32] Schaller Consulting. *The Changing Faces of Taxi and Limousine Drivers.* July 2004
[33] Schaller Consulting. *The Changing Faces of Taxi and Limousine Drivers.* July 2004

Driving a taxi is a difficult job. Despite 4.6 drivers per 1,000 residents in New York City, drivers only make $158 per shift after paying the lease fee and gas. The average shift is based on 130 miles and 10 hours per day. The drivers average 30 trips and serve 42 passengers each shift with an average fare of $10.34. During the time on the road, only 61% of taxi mileages are transporting passengers. Only 29% of taxis are owner-driven. Thus 71% of the drivers lease their vehicles and pay a portion of the revenue to the medallion owner. As shown in the graph below, drivers only pockets about half of the revenue.[34]

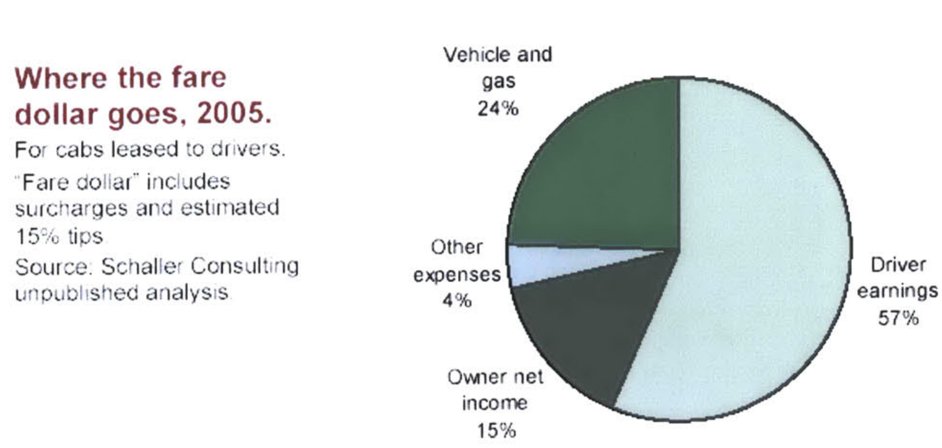


**Figure 9: Taxi driver operation cost distribution.**[35]

Compounding the difficulty of making a living as a taxi driver is the illegal competition from livery car services. By law, livery cars can only pickup passengers from prearrangements. Nonetheless, attempts of livery car trying to pick up passengers on the streets illegally and charge passengers exorbitantly high fares are abundant throughout New York City.

[34] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[35] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.

## H. Medallion Prices

Medallions are one of the major requirements for licensing that give the owner the right to operate a taxi. The number of medallions is limited by the local government and thus is a very sought after commodity.

In New York City, an individual medallion was auctioned off at \$339,000 in October 2005.[36] In Boston, the average sales price in 2000 for medallions at auctioned was \$180,000.[37] The price of medallions has risen significantly over the years. This has become an obstacle for drivers to own a taxi and earn a better living.

## I. Accidents

Accidents are one of the major concerns passengers have when riding a taxi. For example, in New York City, there were 4,270 accidents involving taxicabs in 1999 according to the New York State Department of Motor Vehicles. With better technology that decreases the non-live miles, the number of accidents can be potentially lowered.

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[36] Schaller Consulting. *The New York City Taxicab Fact Book.* March 2006.
[37] Flores-Guri, D., Local Exclusive Cruising Regulation and Efficiency in Taxicab Markets, *Journal of Transport Economics and Policy*, (39) 2, May 2005

## 2. Current Technologies

Taxis identify their potential customers by either picking up passengers on the street or through prearranged agreements.

### A. Street Hail

Hailing a taxi on the side of the street is the most well-known method of hailing a taxi. This method poses several problems:

- Drivers are unable to predict accurately when and where the next passenger will need a taxi.
- Taxi drivers will need to concentrate on both driving and finding the next passenger. This poses danger to the driver, passengers who have to stand onto the road, pedestrians, and other drivers because of potential car accidents.
- Drivers "feel" unsafe because they do not know the passenger. With prearranged fares, the driver will have at least some customer information such as the customer's phone number.
- Passengers have to stand outside exposed to the elements during frigid cold temperature, hot humid day, and sometimes onto the road with on coming traffic in order to hail a cab.
- Taxi drivers cruise certain "passenger-rich" streets and neighborhoods hoping to find passengers. They usually cruise certain neighborhoods based on past experiences. Apparently all other drivers also have similar past experiences; this creates not only an uneven distribution of taxis (supply) and potential passengers (demand) but also generates traffic and potential accidents on the streets.

### B. Taxi Stand

Taxi stands have been in existence for a long time. Taxi stands attempt to have a dedicated place for taxis and passengers to meet. However, it still does not address the critical element of time and the following:

- Time: There is no prearranged time when the passengers and taxis will be there. Based on past experiences and word of mouth from other taxi drivers as which taxi stand will have passengers, the taxis gather there. With a lack of information, both passengers and drivers will be wasting time waiting for each other.

- Passenger will never know when or if a taxi will arrive at a taxi stand.

### C. Prearranged Booking

Passengers usually call a central dispatching office to arrange for pick-ups. This allows the central dispatching office to relay passenger information to their taxis by two-way radio or text messages to the drivers who subscribed to that particular dispatching service. It is then up to the individual drivers to decide whether to accept that passenger. Of the three most common methods of requesting a taxi, this seems to be the most efficient.

For instance, in Singapore, Global Positioning Systems (GPS) based Automatic Vehicle Location and Dispatch System (AVLDS) has been launched to assist in the dispatching of taxis. Companies that employ AVLDS will be able to use GPS to locate its own taxis that are within 10km of the customer. The driver will have the opportunity to accept or ignore the job. Once the job is accepted, the taxi number and expected arrival time is relayed to the passenger.[38]

Prearranged pickups can be classified into two categories, advance and current. Advance pickups are arranged in advance, such as at least 30 minutes in prior or even several hours or days in advance. With advance pickups, drivers have to "block-out" a certain period time prior to the pickup so they can travel to the prearranged passenger. This system has the potential of forgoing passengers who need a cab immediately prior to the prearranged passenger. This also prevents the taxi from accepting other long-haul trips which are profitable but may run into the prearranged passenger's appointment.

Current pickups are pickups that need to occur immediately. It is up to the individual drivers to decide whether to accept the pickups or which driver is able to

[38] Liao, Z. Real-Time Taxi Dispatching Using Global Positioning Systems. *Communications of the ACM*, 46.5 (2003): 81-83.

accept the prearranged pickup first if there is more than one driver competing for that passenger.

With these three most popular modes of requesting taxi services, there is no central monitoring and planning, and a total lack of complete flow of information between the passengers (demand) and taxi drivers (supply) and among the drivers themselves (unable to see competitors' action). This creates significant inefficiency in which almost half of the taxi drivers' time is wasted by cruising the street with an empty taxi. This economic loss has a negative impact to our society. In order to minimize this economic loss, we need to have free flow of complete information between passengers and drivers, minimal regulations, and free competition. However, this is unlikely to happen anytime soon because the industry is politically entrenched and highly resistant to change. The next-best solution is to have central-planning which this thesis proposes by using an efficient taxi allocation system.

# 3. Literature Reviews

Most people view the taxi industry as a dinosaur full of bureaucracy, regulations, and non-customer friendly. Even though taxi is a major mode of public transportation, this industry only draws limited academic interest. It is also an industry that has successfully resisted major changes and improvements that will bring it to the 21st century. For example, several New York City mayors had vowed to improve the system over the course of several decades but the industry is essentially the same as it was in the 1900s. Drivers' real earning today is comparable as they were or sometimes even lower than those in the early 1900s and New Yorkers gave taxis the lowest satisfaction rating among all public transportations.

The following are studies that proposed various methodologies and policies to improve taxi services.

### A. Increased Taxi Service Areas Can Improve Overall Services

*Increase the area where taxis can pickup passengers will benefit consumers without hurting the producers.*

In Daniel Flores-Guri's study, cruising regulations and the efficiency of the taxi market are analyzed. The study examines the cruising regulations and taxi efficiency of two Massachusetts cities, Boston and Cambridge, which are in close proximity to each other. Both Boston and Cambridge have exclusive cruising regulations; Boston does not allow non-Boston taxis to pickup passengers on the streets of Boston. Similarly, Cambridge does not allow non-Cambridge taxis to pickup passengers on its streets. This creates significant inefficiency especially for two cities that are in close proximity and residents travel frequently between these cities. For example, if a passenger originating from Boston wants to go to Cambridge, he would take a Boston taxi. Upon dropping that passenger off in Cambridge, the Boston taxi cannot pickup any Cambridge residents on the streets, except through prearrangements or dispatch calls. The Boston taxi will have to travel back to Boston with an empty cab. This is very inefficient as the Boston taxi not only has to travel back with an empty cab but also has to by pass Cambridge residents who are trying to flag it down for service. Boston taxis are not allowed to service Cambridge residents who are trying to hail cabs on its streets.

In the summer of 2002, Flores-Guri and his team monitored Boston's 1,775 taxis and Cambridge's 255 taxis at the eight bridges that connect Boston and Cambridge. Their results indicate that approximately 90% of the taxis return to their home city with an empty taxi. This is shown in the table on the next page. Those that are returning with passengers most likely are either picking up passengers in the foreign city through the dispatching system, originating from a city other than Boston or Cambridge while en-route to another destination, illegally picking up passengers on the streets of the foreign city, or using that city as a short-cut to some other destination.[39]

[39] Flores-Guri, D., Local Exclusive Cruising Regulation and Efficiency in Taxicab Markets, *Journal of Transport Economics and Policy*, (39) 2, May 2005

*Occupied and Empty Taxicabs*

| *Taxis licensed in:* | | *Boston* | | *Boston* | |
|---|---|---|---|---|---|
| *Entering:* | | *Boston* | | *Cambridge* | |
| *Bridge* | *Weight* | *Empty* | *Occupied* | *Empty* | *Occupied* |
| Anderson | 0.137 | 90.5% | 9.5% | 4.2% | 95.8% |
| B.U. | 0.098 | 75.9% | 24.1% | 19.0% | 81.0% |
| C.R. Dam | 0.113 | 85.0% | 15.0% | 6.5% | 93.5% |
| Elliot | 0.057 | 95.8% | 4.2% | 15.2% | 84.8% |
| Gilmore | 0.040 | 37.9% | 62.1% | 83.3% | 16.7% |
| Longfellow | 0.361 | 95.4% | 4.6% | 7.9% | 92.1% |
| Mass. Ave. | 0.129 | 87.4% | 12.6% | 9.4% | 90.6% |
| Western + River | 0.065 | 81.8% | 18.2% | 13.7% | 86.3% |
| Weighted average | | 87.4% | 12.6% | 12.4% | 87.6% |

| *Taxis licensed in:* | | *Cambridge* | | *Cambridge* | |
|---|---|---|---|---|---|
| *Entering:* | | *Boston* | | *Cambridge* | |
| *Bridge* | *Weight* | *Empty* | *Occupied* | *Empty* | *Occupied* |
| Anderson | 0.137 | 2.1% | 97.9% | 94.1% | 5.9% |
| B.U. | 0.098 | 3.9% | 96.1% | 95.5% | 4.5% |
| C.R. Dam | 0.113 | 5.5% | 94.5% | 93.3% | 6.7% |
| Elliot | 0.057 | 18.2% | 81.8% | 85.7% | 14.3% |
| Gilmore | 0.040 | 9.1% | 90.9% | 96.2% | 3.8% |
| Longfellow | 0.361 | 4.2% | 95.8% | 96.9% | 3.1% |
| Mass. Ave. | 0.129 | 5.1% | 94.9% | 96.6% | 3.4% |
| Western + River | 0.065 | 7.4% | 92.6% | 93.3% | 6.7% |
| Weighted average | | 5.3% | 94.7% | 95.0% | 5.0% |

**Table 3:[40] Top: Approximately 80%-90% of Boston cabs are returning with an empty cab. Bottom: Over 90% of the Cambridge cabs are returning with an empty cab.**

With the fare structure and number of taxis in a city regulated and fixed, this study proposes a model to study the impact of economic efficiency when the cruising regulations are changed. In this model, the demand for taxi service is defined as:

$$Q = Q\ (P+K/V)$$

[40] Flores-Guri, D., Local Exclusive Cruising Regulation and Efficiency in Taxicab Markets, *Journal of Transport Economics and Policy*, (39) 2, May 2005

Where:

Q: the number of occupied taxis

V: the number of vacant taxis

P: price of the ride and cost of waiting time

K: a factor that depends on the cost of waiting time and the size of the area that is serviced by the cab

The cost of operation for all of the taxis is:

$$C = c\ (Q+V)$$

To maximize the difference between the consumers' willingness to pay and the cost of taxi operation, the model proposes the following equations:[41]

$$\max_{Q,V} \int_0^Q \left(Q^{-1}(Q') - \frac{K}{V}\right) dQ' - c(Q+V)$$

And the profit is:

$$\left(Q^{-1}(Q) - \frac{K}{V}\right)Q - c(Q+V) = \Pi$$

This study concludes that merging taxi markets of adjacent cities can increase efficiency. Since price and number of taxis are regulated, the efficiency would be shorter wait-times for passengers and higher revenues for the taxi drivers as they could pickup more passengers in a larger geographic area.

[41] Flores-Guri, D., Local Exclusive Cruising Regulation and Efficiency in Taxicab Markets, *Journal of Transport Economics and Policy*, (39) 2, May 2005

## B. Real-Time Demand and Traffic Information in the Taxi's Dispatching Systems

*Trip-Chaining of Taxi's Advance Bookings* and *Incorporating Real-Time Demand and Current Traffic Conditions in Taxi's Dispatching Systems*

There is a study by Der-Horng Lee of National University of Singapore in which Lee proposes to improve the taxi system in Singapore by trip-chaining a taxi's advance bookings[42] and improve a taxi's dispatching system by incorporating real-time demand and current traffic conditions.[43]

In Lee's study of taxi's dispatching systems by incorporating real-time demand and current traffic conditions, Lee studies the current booking systems in Singapore in which Global Positioning Systems (GPS) is used to locate the <u>shortest and direct-line distance</u> between the customer and the taxi. Lee argues that such a system does not necessarily yield the shortest time because of traffic conditions and rules. Lee proposes an alternative dispatching system in which real-traffic conditions are incorporated into the dispatching decisions and the <u>shortest-time paths</u> will be dispatched to the taxi. For instance, one-way streets and rush hour traffic will be incorporated into the proposed dispatching system. Using computer simulations, Lee's study and results showed a 50% reduction in passenger wait time and average distance traveled for the taxi.[44]

## C. Grouping of Taxi's Advance Bookings

Lee also proposes a system in which of taxi's advance bookings are trip-chaining. In advance booking, customers place their taxi bookings more than 30 minutes in advance. Lee proposes to chain several advance bookings into a reasonable span of time, in which each pick-up point is within close proximity of

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[42] Lee, D.H., H. Wang, and R.L. Cheu, Trip-Chaining for Taxi Advance Bookings: A Strategy to Reduce Cost of Taxi Operations, *Proceedings of the 83rd Annual Meeting of the transportation Research Board*, July 12, 2003.

[43] Lee, D.H., H. Wang, R.L. Cheu and S.H. Teo, A Taxi Dispatch System Based on Current Demands and Real-Time Traffic Conditions, Proceedings of the 82nd Annual Meeting of the Transportation Research Board, in CD-ROM, Washington, D.C., U.S., Jan 12-16, 2003.

[44] Lee, D.H., H. Wang, R.L. Cheu and S.H. Teo, A Taxi Dispatch System Based on Current Demands and Real-Time Traffic Conditions, Proceedings of the 82nd Annual Meeting of the Transportation Research Board, in CD-ROM, Washington, D.C., U.S., Jan 12-16, 2003.

the previous drop-off point. Lee's simulation study shows a possible reduction of the fleet size by 87.5% while serving the same level of demand in advance bookings.[45]

**D. Multiperiod Dynamic Model of Taxi Services in Hong Kong**

*"A Multiperiod Dynamic Model of Taxi Services with Endogenous Service Intensity"*[46]

A study is conducted by a group of researchers in China in which they divide the day into a series of subperiods. They believe there is a fluctuation of customer demands during the day thus a dynamic model is needed to model changing demand of customers and supply of taxis. Within each of the subperiods, the supplies of taxis and demand of customers are assumed to be uniform. Using a dynamic model, they model the demand and supply of taxis in Hong Kong. Using this experiment, they concluded that this model more closely reflects the reality of taxi services in Hong Kong.

[45] Lee, D.H., H. Wang, and R.L. Cheu, Trip-Chaining for Taxi Advance Bookings: A Strategy to Reduce Cost of Taxi Operations, *Proceedings of the 83rd Annual Meeting of the transportation Research Board*, July 12, 2003.

[46] Yang, H., Ye, M., Wong, S.C., A Multiperiod Dynamic Model of Taxi Services with Endogenous Service Intensity, *Operations Research*, (53) 3, May-June 2005.

## E. Macroscopic Taxi Model (Passengers, Taxi Utilizations, Level of Services)

*A macroscopic taxi model for passenger demand, taxi utilization and level of services*[47]

In this study, the authors develop a model based on the premise of demand-supply equilibrium of the taxi market. A range of exogenous and endogenous variables are considered and a system of nonlinear simultaneous equations is generated. A model that incorporates all of these factors is developed and used to answer various questions such as the necessary number of taxi licenses, taxi fare structure, range of service quality, and the feasibility of having market demand-supply equilibrium under the constraints of regulations.

This study is conducted in Hong Kong, using Hong Kong data and policies. Like any other major cities, taxi service in Hong Kong is one of the major and important means of transportation that provides flexibility and convenience. They are subject to prevalent regulations such as territorial restrictions, entry restrictions of the quantity of taxis, fare structure control, etc.

The authors develop a model to characterize the demand and supply equilibrium of taxi services in the context of regulations, origin-destination demand patterns, and both vacant and occupied taxi movements on the road. Currently, the "equilibrium quantity (total taxi-hours) of services supplied will be greater than the equilibrium quantity (occupied taxi-hours) demand by a certain amount of slack (vacant taxi-hours). It is this amount of slack that governs the average passenger waiting time."[48]

Thus within a certain taxi market, it is almost always true that the supply (total taxi-hours) is greater than the demand (occupied taxi-hours). Yet, the passengers feel that their demand is not efficiently met, i.e. manifest in the form of

[47] Yang, H., Lau. Y.W., Wong, S.C., Lo, H.K., A macroscopic taxi model for passenger demand, taxi utilization and level of services, Transportation **27**: 317-340, 2000

[48] Yang, H., Lau. Y.W., Wong, S.C., Lo, H.K., A macroscopic taxi model for passenger demand, taxi utilization and level of services, Transportation **27**: 317-340, 2000

long waiting times for a taxi. The length of the waiting time is one of the critical factors that determine the level of customer satisfaction and whether the passenger will take the taxi or not. Thus, the waiting time will have a direct impact on the demand of taxi and affects the market equilibrium.

With price already set by the government, the supply of taxi (vacant taxi-hours) will never be able to reach an equilibrium point where supply equals demand because it takes time (vacant taxi-hours) to reach potential customers. Thus within the taxi industry, the supply is always greater than the demand, yet customers feel that the supply is less than the demand because of waiting time.

In establishing the model, a set of exogenous and endogenous variables are considered: *exogenous variables*—number of licensed taxis, taxi fare, disposable income, population, occupied taxi journey time; *endogenous variables*—daily passenger taxi trips, passenger waiting time, taxi availability, taxi utilization, and average taxi waiting time. The variables are incorporated into a set of nonlinear simultaneous equations. The relationships among the variables are shown on the following page:

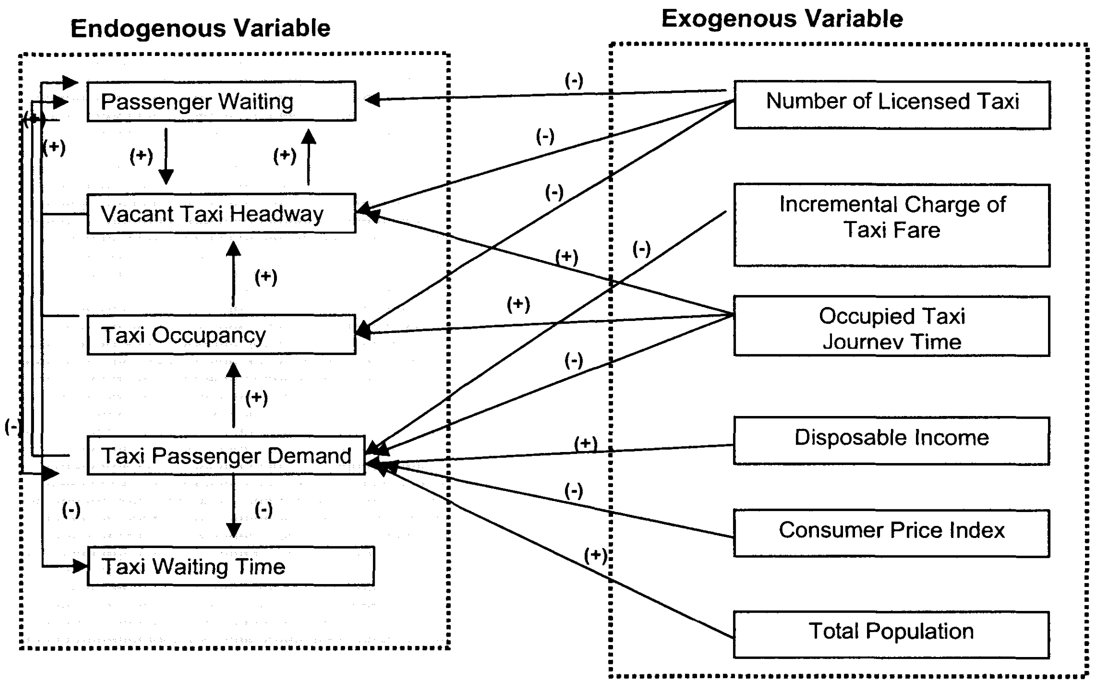


**Figure 10: Relations among the various attributes in this taxi study[49]**

This is an adapted figure from the study[50] that postulated synchronous relationships among the endogenous and exogenous variables in the simultaneous equation model.

The model of simultaneous equations is developed using variable relationships. These equations are further calibrated using survey data. The proposed model is used to predict the impact of various policy changes, the utilization of taxi, and level of services, etc. This study concludes that such a model will help in examining the impact of changes in policy but the real consequence of intervening the supply-demand of the taxi market is still unknown, and better models and further study are needed.

[49] Yang, H., Lau. Y.W., Wong, S.C., Lo, H.K., A macroscopic taxi model for passenger demand, taxi utilization and level of services, Transportation **27**: 317-340, 2000

[50] Yang, H., Lau. Y.W., Wong, S.C., Lo, H.K., A macroscopic taxi model for passenger demand, taxi utilization and level of services, Transportation **27**: 317-340, 2000

## F. GPS-GIS Approach in Fleet Management

*Fleet Management: A GPS-GIS integrated approach*[51]

In this study, the authors evaluated the usefulness of an integrated GPS (Global Positioning System) and GIS (Geographic Information System). The authors studied and concluded that a GPS-GIS system is extremely useful for fleet management-remote vehicle tracking, monitoring use of resources, dynamic trip planning, real-time customer demand, current traffic conditions, and driver behaviors.

In a public transportation setting, an integrated GPS-GIS system can provide information such as vehicle location, speed, distance traveled, and duration of trip. All these data can be used to assess the performance of the fleet and the entire network system. In a real-time setting, the data can be used to dynamically assign vehicles that are closest to the customer demands. The GPS-GIS system is very beneficial in logistics and supply chain planning. For example, given a driver's schedule, one can plan trips that would give the driver time for break and trips that would eventually bring him home at the end of his scheduled shift. In the World Trade Center disaster on September 11, 2001, a GPS-GIS system was used to assist trucks in removing 1.8 million tons of debris from the site. The system helped in preventing long queuing of trucks and traffic bottle necks at the site. It also established a geofencing which could send out alerts if the trucks deviated from their assigned routes. The data stored in the GPS-GIS system also helped in billing and resolving of various disputes relating to the operations.

The study concluded that a GPS-GIS system has many applications in many different situations, such as fleet management. Having such a system in a taxi fleet would significantly increase the current efficiency.

[51] Prakash, S.S.S., Kulkarin, M.N., "Fleet Management: A GPS-GIS integrated approach", Map India Conference 2003.

## G. Scheduling of Network Queues

*Scheduling Networks of Queues: Heavy Traffic Analysis of a Multistation Closed Network*[52]

This study attempts to find an "optimal dynamic priority sequencing policy to maximize the mean throughput rate in a multistation, multiclass closed queuing network with general service time distribution and a general routing structure."[53] This study and many other similar research show that managing the schedules of the servers and customers in the queues can effectively increase the efficiency of a system when compared to a first come, first serve system. For example, rather than assigning the first customer to the first taxi in the queue, it is possible to dynamically analyze the current idle time of the servers, the shortest expected processing time of each customer and the location of the next potential customer; this will increase the efficiency of the entire system. In the taxi system, it is very unlikely that the demand of a significant number of customers is known in advance. In the cases where the demand is heavy and known in advance, it may be appropriate to apply such methodology.

## H. Combinatorial Optimization and Vehicle Fleet Planning

*Combinatorial Optimization and Vehicle Fleet Planning: Perspectives and Prospects*[54]

Studying the complexity of fleet management, the author examines the combinatorial intricacies of vehicle routing and scheduling. The author identifies the complexity of these problems and draws conclusions to other combinatorial optimization studies.

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[52] Chevalier, P.B., Wein, L.M., Scheduling Networks of Queues: Heavy Traffic Analysis of a Multistation Closed Network, OR 219-90, July 1990.
[53] Chevalier, P.B., Wein, L.M., Scheduling Networks of Queues: Heavy Traffic Analysis of a Multistation Closed Network, OR 219-90, July 1990.
[54] Magnanti, T.L., Combinatorial Optimization and Vehicle Fleet Planning: Perspectives and Prospects, *Operations Research* 106-81, 1981.

There are two issues that are very common in today's fleet management: 1) Vehicle routing problem—the routing of vehicles through a series of demands to pickup and deliver goods. 2) Vehicle scheduling problem—the scheduling of vehicles to meet the demands or to meet a set schedule. The author did a comprehensive review of how these two issues are solved in various settings and constraints using a range of different methodologies. A number of these methodologies are derived or influenced by methodologies developed in studying the traveling salesman problem. Various constraints are modified by different studies. For example, in one of the methodologies, three modifications were made to the vehicle routing problem: 1) vehicles are allowed to circulate at their service point upon delivery of service, without returning to the depot; this allows the vehicle to wait at the service point for the next assignment. 2) Allow the vehicle to go to only the most profitable demand points. 3) Create a network that allows combinatorial route selection. Using these modifications, the system became more efficient. Dynamic programming is another approach that seems to be very useful in operational decision making. For example, its algorithm is used to establish a schedule for dial-n-ride situations. It is also used to establish schedules and train station locations in order to maximize revenue while reducing lost sales by minimizing passenger wait time.[55]

The study suggests that there are certain situations where vehicle fleet planning is well-suited for optimization while in other situations heuristic approach is more appropriate. Situation where the network has a well-structured flow and matching type combinatorial models seems to be best suited for optimization. On the other hand, situations where finding an exact solution is more difficult, such as those involved in vehicle routing, a heuristic approach may be more appropriate. Heuristics approach are easier to understand and more accepted by management.

The author concludes that this is a rich field with many challenges and deserves more studies.

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[55] Magnanti, T.L., Combinatorial Optimization and Vehicle Fleet Planning: Perspectives and Prospects, *Operations Research* 106-81, 1981.

## I. Hierarchical Dispatching: Top and Sub-Levels

*Hierarchical dispatching control of urban traffic systems*[56]

This study divided the taxi dispatching into two levels, an upper layer that monitors the overall resource optimization while the lower layer is concentrated in local optimization, dispatching, and vehicle routing within their respective subsystems. However, this system may be effective if most of the trips are localized. If a significant number of trips are outside each of the subsystems, may not be effective are the interface between the subsystems and the upper layer. If the interfaces are not transparent, doubt if the entire system is efficient.

## J. Dynamic Traveling Salesmen Problem

In some respects, optimizing the locations of the taxis to better serve passengers is similar to the classic Traveling Salesman's Problem (TSP), a problem that is well-studied but no effective solution is known for the general case. The traveling salesman problem consists of a salesman finding the shortest route that connects all of the locations that need to be visited. However, taxi allocation is a *dynamic* traveling salesman's problem because the locations of the potential passengers and taxis are neither fixed nor known with certainty in any given time.

## K. The Dynamic Traveling Repairman Problem

There is a study by Dimitris Bertsimas and Garrett van Ryzin in which they study *The Dynamic Traveling Repairman Problem.*[57] In this study, they propose a mathematical model for the dynamic vehicle routing problem. They want to minimize customer wait time in a "stochastic and dynamically changing environment." This is different from the traditional vehicle routing problem or

[56] Gegov, A.E., Hierarchical dispatching control of urban traffic systems, *European Journal of Operational Research*, (71) 2. p235-246, 12/10/1993.
[57] Bertsimas, D., Ryzin, G., (1989), "The Dynamic Traveling Repairman Problem", MIT Sloan School of Management Working Paper No. 3036-89-MS.

traveling salesman problem which seeks to minimize the vehicle travel time in a static environment. In this dynamic traveling repairman problem (DTRP), it is assumed that the demand for service arrives in a Poisson distribution within a region. The demand is then randomly assigned to a location in the region. The objective is to minimize the average wait time each customer spends in the queue.

The approach of the dynamic traveling repairman problem (DTRP) is more realistic than the standard traveling salesman problem (TSP). In the taxi optimization situation, the demands for taxis usually are not known in advance but arrive randomly over time, the dispatching of taxis to meet those demand is a continuous process. In this scenario, it is easier and more relevant to minimize the wait time of the customers. Similarly, this is applicable to emergency vehicle routing where demand for services is not known in advance and the objective is to minimize wait/travel time rather than minimizing the distance travel or cost of the vehicle. Thus the characteristics of the DTRP are:

- "The objective is to minimize waiting time not travel cost
- Information about future demand is stochastic
- The demands vary over time (i.e. they are dynamic)
- Policies have to be implemented in real time
- The problem involves queuing phenomena"[58]

Some of these characteristics have been studied by others. In one study, the probabilistic traveling salesman problem (PTSP) and the probabilistic vehicle routing problem (PVRP) have been analyzed. In this study, "there are *n* known points, and on any given instance of the problem only a subset S consisting of $|S| = k$ out of *n* points ($0 \leq k \leq n$) must be visited. Supposed that the probability that instance S occurs is $p$ ($S$). [The objective is] to find *a priori* a tour through all *n* points. On any given instance of the problem, the *k* points present will then be visited in the same order as they appear in the prior tour. The problem of finding such *a priori* which is of minimum length in the expected value sense is defined as the PTSP. In cases the vehicle has capacity $Q$ then the corresponding problem is the probabilistic vehicle routing problem. It is clear that the policy followed is a

[58] Bertsimas, D., Ryzin, G., (1989), "The Dynamic Traveling Repairman Problem", MIT Sloan School of Management Working Paper No. 3036-89-MS.

real-time policy, but the problem is inherently static, i.e. it is solved *a priori* using only the probabilistic information."[59]

This approach used prior probability information in predicting real-time demand. In developing the DTRP model, the author developed a series of policies and assumptions:

- "When customers are present, the server travels directly from one customer location to the next following a [first come, first serve (FCFS) policy]
- When no [future] customers are present at a service completion, the server waits until the next customer arrives before moving."[60]

Once the base policy is established, the author modified them under different conditions. For example, in light traffic conditions, it was found that the stochastic queue median policy where the server has to travel back to a strategically located depot after finishing its service call seems to be optimal. In heavy traffic conditions, it was found that the nearest neighbor policy works the best where the server is to serve the closest next customer after completion of a service call rather than serving on a FCFS policy.

Thus it seems that the best policy model will be dependant on the current traffic conditions.

## L. Optimal Adaptive Routing and Traffic Assignment

*Optimal Adaptive Routing and Traffic Assignment in Stochastic Time-Dependent Networks*[61]

In this thesis study, the author established a stochastic time dependent (STD) network, a routing policy, and a formal framework for optimal routing policy within STD. Also, variants to traffic networks, travel time, travel schedule changes were incorporated into the model. In the model, a general framework is established

[59] Bertsimas, D., Ryzin, G., (1989), "The Dynamic Traveling Repairman Problem", MIT Sloan School of Management Working Paper No. 3036-89-MS.
[60] Bertsimas, D., Ryzin, G., (1989), "The Dynamic Traveling Repairman Problem", MIT Sloan School of Management Working Paper No. 3036-89-MS.
[61] Gao, S. , Optimal Adaptive Routing and Traffic Assignment in Stochastic Time-Dependent Networks, MIT Thesis 10/24/2004

with three major components: "the optimal routing policy generation module, the routing policy choice model, and the policy-based dynamic network loader." The study found that the adaptation of the different models lead to various levels of time savings.

### M. The Day Activity Schedule Approach to Travel Demand Analysis[62]

This thesis study is developed on the basis that a person's activity schedule can be used to predict travel demand. Travel demand is a mean to meet the needs of various activities on a person's schedule and it is also a major factor in decision making. The study further analyzes the travel demands of different segments of the population by income, work levels, households, and various activity commitments. This study confirms the significance of interactions between daily activity and each person's schedule or daily activity which suggests that travel demand is predictable.

### N. Transportation on Demand

*Transportation on Demand*[63]

An in-depth study was conducted on "Transportation on Demand" (TOD). Transportation on demand is usually concerned with transportation of passengers or goods between the origins and destinations upon at the request of users. The pickup and delivery locations are specified by the users. TOD is usually classified as statistic or dynamic. For static TOD, the requests by the passengers are known in advance, while for dynamic TOD, customer request are in real-time and vehicle routing must be adjusted in real-time to meet demand or re-optimize based on current vehicle locations and customer demands.

[62] Bowman, J.L., The Day Activity Schedule Approach to Travel Demand Analysis, MIT Thesis, May 1998.
[63] Cordeau, J.F., Laporte, G., Potvin, J.Y., Savelsbergh, M.W.P., Transportation on Demand, 10/14/2004.

TOD problems usually involve finding solutions to three conflicting objectives: "maximizing the number of request served, minimizing operating cost, and minimizing user inconvenience. A balance between these objectives is sometime obtained by first maximizing the number of requests that can be accepted given the available capacity and then minimizing the operating costs while imposing service quality constraints."[64] In order to address these three objectives: vehicle scheduling, vehicle routing, and request clustering need to be considered. Vehicle scheduling specifies the time that the vehicle should be at a certain location. Vehicle routing specifies the order of pickups and deliveries that the vehicle should follow. Request clustering bundles a group of requests to be served by the same vehicle.

The author developed a model based on the Vehicle Routing Problem with Pickup and Delivery (VRPPD). The application of the model is examined in the context of "dial-a-ride problem, the urban courier service problem, the dial-a-flight problem, and the emergency vehicle dispatch problem."[65] Similar to other studies, various constraints need to be established and relaxed depending on the situation in order to optimize the objective function.

## O. A Modeling Study of a Taxi Service Operation[66]

In this study, a model is proposed to efficiently allocate taxis for a centrally owned taxi fleet. It is assumed that one has full control of the fleet and central planning is possible. The entire service area is divided into several zones and characteristics of each zone are then determined. For example, there can be residential, business districts, airports and hotels zones, etc. For each of these zones, the typical taxi demand pattern for the entire (24) hours is analyzed. For example, the demand for taxi is high in the morning when people are leaving for work and

[64] Cordeau, J.F., Laporte, G., Potvin, J.Y., Savelsbergh, M.W.P., Transportation on Demand, 10/14/2004
[65] Cordeau, J.F., Laporte, G., Potvin, J.Y., Savelsbergh, M.W.P., Transportation on Demand, 10/14/2004
[66] Deng, C.C., Ong, B.W., Goh, T.N., A Modelling Study of a Taxi Service Operation, *International Journal of Operations & Production Management*, (12) 2, 1992.

during the evenings when people are going home. For business districts, taxi activities are relatively high throughout the entire work day (8:30 a.m. to 5:00 p.m.)

After customer demand profiles are determined for each of the zones, the number of taxis required for each zone is determined by modeling the demand pattern as a queuing model. An integer linear program is formulated to construct an optimal schedule for the drivers in each zone. The linear model incorporates the shifts and meal times for the drivers. However, under this model, the drivers are required to return to their original assigned zone upon dropping off the passengers. The authors hope that this model can be applied not only to the taxi industry but also to other situations where fleet management is used.[67]

This model is relatively useful and applicable in many different kinds of situations. However, the idea of having each driver to return to his original assigned zone or location upon dropping off passengers may not be efficient. Even though the drivers are allowed to pick up passengers on the street while en-route to their original assigned locations, there is a very high likelihood that the drivers will drive an empty taxi back to their original assigned locations. Rather than have the driver travel back to his original assigned locations, it may be more efficient if the drivers travel to the nearest location with the highest probability of passenger demands.

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[67] Deng, C.C., Ong, B.W., Goh, T.N., A Modelling Study of a Taxi Service Operation, *International Journal of Operations & Production Management*, (12) 2, 1992.

# 4. Experiments, Modeling, Results

To develop the simulation models, the following approach is applied:

1. Set of attributes that can improve taxi efficiency is outlined.
2. A Model Structure that consists of a set of assumptions that is used to build the computer model is established. This includes the size of the city, the attributes of interested, and the definitions of the variables.
3. Three strategies (Strategy 0 = Base Model, Strategy 1 = Impact of returning to hotspots, Strategy 2 = Hotspot with different demand probability) are defined.
4. Each of these strategies is tested in two different experiments. Experiment 1 examines the effect of taxi fleet size under the three strategies. Experiment 2 investigates the effect of quantity of hotspots and concentrations of customers at the hotspots under the three strategies.

The computer simulation is developed in the MATLAB environment.

Vehicle routing and planning have been extensively studied in the past. Depending on the situation, there are a number of factors that can have different impacts on the performance of the system. However, the results of these studies and methodologies have not been widely applied to the taxi industry. In order to analyze the reasons for the inefficiencies and determine the various attributes that can optimize a taxi's location and efficiency within a city, a base model is developed with a set of common taxi attributes. Subsequent models are built based on modifications of these common attributes and the efficiency of the taxi systems is compared.

The attributes, policies and assumptions that are considered in establishing the model include:

- A time-dependent routing policy is established that specifies which node (location) that a taxi should go, based on current node availability and probability of current passenger demand during that specified time period.
- Customer demand is generated based on a time-dependent Poisson probability distribution. It is the same for all three strategies.
- The speed of the taxi in reaching potential customers or assigned locations, and the duration of transporting passengers are calibrated for each simulation.
- All real-time demand, except those customers booked more than an hour in advance for later service, are on the first come, first serve policy.
- Upon drop-off or completion of service, the taxi will be assigned to the closest location with the highest probability of demand.
- Trips that originate from residential neighborhood usually require a home-bound trip at a later time. The model will consider the probability of another home-bound trip at a later time.
- A sample hourly historical demand and travel patterns are inputted into the model to predict future demand and vehicle routing criteria.
- The model network is time-dependent—customer demand and supply of taxi will vary throughout the entire (24) hour period.
- Every node is considered to be a decision point. A node is defined as a point where customer can request service and a point where the taxi can drop off the passenger.

The objective of the model is to:

- Minimize the waiting time of the passenger;
- Minimize the idle time of the taxi;
- Minimize the non-live mileage (mileage that the taxi travels without passengers);
- Minimize the travel time of the passenger.

However, it is difficult to maximize and/or minimize several objective functions simultaneously. Thus certain criteria, limits, or bounds are placed on certain objectives while maximization/minimization is performed on *one* of the objective functions.

## A. Model Structure

The model is developed in the MATLAB environment. The codes for each model are in the Appendix.

Since passenger waiting time is the highest complaint, this will be one of the major objective functions to minimize in all of the models.

The model is developed with the following attributes:

- **Customer locations**: customers are requesting service from either
  1) hotspots = (airports, hotels, bus and train terminals, etc.)
  2) non-hotspots = (street, restaurants, homes, office.)
- Customers are classified into two types
  1) **Generic customers**: these are customers who request service from non-hotspot locations.
  2) **Hotspot customers**: these are customers who request service from hotspots.
- **Customer Service Demand**: The time and location of customer requesting taxi services are randomly generated.
- The initial taxi locations are randomly generated.
- **City Size**: the shape of the city is a square area with an initial value of 100 units
- **Simulation Durations**: it is the number of iterations.
- **Taxi Speed**: it is the speed that the taxi travel in the city, number of unit distance per iteration
- **Lambda** (Customer Rate): it is the number of customers per unit time or iteration. For example, if lambda =2, there are 2 customers demand taxi services per unit time or iteration. The lambda is further classified into
  1) **General Customer Lambda**: the number of non-hotspot customers per unit time (streets, offices, homes, etc.)
  2) **Hotspot Lambda**: the number of hotspot customers per unit time (airports, hotels, train and bus stations).

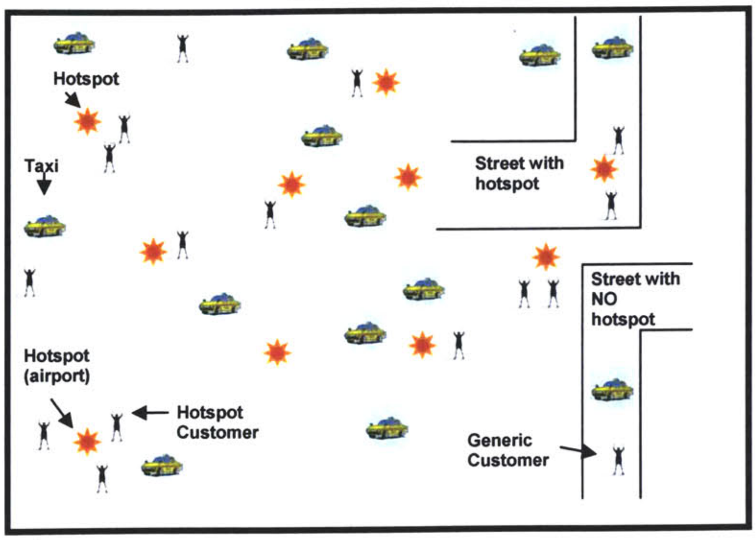


**Figure 11: A sample illustration of a city with taxis, customers, and hotspots**

The output of the model will consist of the following information:

Customer Related Information:

- **Total Customer Wait Time**: The total combined wait time of all of the customers during the entire simulation durations/iterations. The total customer wait time is the sum of the following two components:
    1) **Generic Customer Total Wait Time**: Waiting time of non-hotspot customers.
    2) **Hotspot Customer Total Wait Time**: Waiting time of hotspot customers. (Waiting time at airports, hotels, bus and train stations, etc.)
- Total Number of Generic Customers
- Total Number of Hotspot Customers

Taxi Related Information:

- **Taxi Idling Time**: it is the time that the taxi spends idling, waiting for customers. Since it is not traveling, the fuel consumption should be less than when the taxi is driving, i.e. traveling around in search of customers.
- **Taxing Time**: it is the time that the taxi spends traveling/searching for customers.
- **Taxi Pickup Time**: it is the traveling time when the taxi receives instruction to pickup a customer to the time it actually reaches the potential customer.

- **Taxi Courier (Transportation) Time**: it is the time that the taxi spends driving the customer from the original location to his destination.

## B. Model 1: Base Model and Strategy 0

The base model and Strategy 0 is developed to closely represent the reality where no optimization attributes or policies are implemented.

**Strategy 0**: The taxi will stay at the location where it drop-off the passenger until it is assigned to the next customer.

The following assumptions and attributes are made in the base model:

- The objective is to minimize customer wait time.
- Initial taxis locations are randomly generated. Because taxis are staying at the location where it dropped-off its previous passengers until the next customer is available, the subsequent taxi locations will be at the passenger's drop-off location.
- Customers' demands (both origination and destination) are randomly generated.
- City Size = 100 units (The city is 100 units by 100 units)
- Taxi Speed = 10 per units (Thus it will take the taxi 10 time units (seconds, minutes, etc.) to travel across the city)
- Hotspot = 10. There are ten concentrated hotspots (airports, hotels, train stations, etc. within this city)
- Customer Rate (Lambda) = 26. There are 26 new customer demands for taxi service per unit time. Some of these will be from hotspots (Hotspot lambda) while others will be from non-hotspots (generic lambda)
    - Hotspot Lambda = 24 (24 of the 26 customers are demanding service from hotspots). The lambda for each hotspot is different. Two of the hotspots will have a lambda =10 while the rest will have a lambda of 0.5. In reality, the probability of customers appearing at each hotspot is different and this model tried to emulate that. For example, taxi services demand at airport taxi stands will have higher lambda than service demand at a small hotel.
    - Generic Lambda = 2 (2 of the 26 customers are from non-hotspots, these 2 customers per unit time are evenly distributed across the city at non-hotspots)
- Total Number of Taxis = 200
- Simulation Durations/Iterations = 200 time units

## C. Model 2: Impact of Returning to Hotspots (Strategy 1)

All of the attributes and assumptions are the same as the base model except the following:

For Model 2 (Strategy 1), it is designed to test the impact of customer wait time, taxi driver revenue, cost and profit when the taxi is directed to drive back to the closest hot spot upon dropping off the passengers. All hotspots are assumed to have equal probability (lambda) of passenger demand.

**Expected Results**

**Customer Waiting Time:**

Comparing to the base model, it is expected that this strategy will decrease the waiting time of the potential customers. Because taxis are traveling back to the closest hotspots upon dropping off their passengers, there is a high likelihood that taxi will be able to reach potential customers who are at the hotspots much quickly.

**Taxi Revenue:**

If there are more customers than taxis, it is expected that this strategy is able to serve more customers than the base model, Strategy 0, in the same time period. Thus the revenue is expected to be higher than that of the base model.

**Taxi Cost:**

With better allocations, it is expected that the total cost [sum of non-revenue time = (Taxi Idling Time + Taxing Time + Taxi Pickup Time)] taxi will be lower than the base case, Strategy 0.

**Taxi Profit:**

By transporting more passengers at lower cost, it is expected that this strategy will produce higher profit than the base model, Strategy 0.

## D. Model 3: Hotspot with Different Demand Probability (Strategy 2)

This model was developed to test the impact of customer wait time, taxi driver revenue, cost and profit when the taxi is directed to drive back to the best possible hotspot. Upon dropping off the passenger, the distance from taxi to all hotspots are calculated. The distance to each hotspot is divided by the lambda of the respective hotspots.

All hotspots are subject to the following formula:

**Hotspot = Taxi Distance/Lambda**

The hotspot with the smallest result will be the best possible hotspot. This hotspot has the combined factor of close-distance and has the high probability of customers:

**Smallest Result from Hotspot = Taxi Distance/Lambda**

This will be the next location where the taxi should wait for potential customers.

Each hotspot is assumed to have different probabilities of passenger demand. For example, taxi service demands at airport taxi stands are more likely to have higher demand than those at small hotels. This will more closely reflect reality. The taxi should go to the hotspot that has the lowest value (best possible hotspot) of Taxi Distance divided by Lambda defines as Distance to each hotspot/Lambda of each hotspot.

## Expected Results

### Customer Waiting Time:

It is expected that this strategy will have decreased the waiting time of potential customers more than when compared to the base model (Strategy 1). Because taxis are traveling back to the hotspots that are close, they have high probability of having the next potential customers, there is a high likelihood that the taxi will be able to reach a potential customer more quickly at that particular hotspot.

### Taxi Revenue:

If there are more customers than taxis, it is expected that this strategy will enable taxis to serve more customers than the base model, Strategy 0, or the model in Strategy 1. Thus the revenue is expected to be higher than that both Strategy 0 and Strategy 1.

### Taxi Cost:

With better allocation, it is expected that the total cost [sum of non-revenue time = (Taxi Idling Time + Taxing Time + Taxi Pickup Time)] of the taxi will be lower than the base case, Strategy 0 and Strategy 1.

### Taxi Profit:

With lower cost and transporting more passengers, it is expected that this strategy will produce higher profits than the base model, Strategy 0 and Strategy 1.

## E. Experiment 1: The Effect of Taxi Fleet Size

The objective of this experiment is to analyze the effect of taxi fleet size on the various attributes of taxi optimization. The number of taxis is increased from an initial fleet of 200 to 350 taxicabs in increments of 50 taxicabs. Each of the three strategies (Strategy 0, Strategy 1, and Strategy 2) is tested in this environment. Please refer to the codes in the Appendix for detailed experiment set up. The summary results are shown in the table at the end of this section.

### Results

#### Customer Waiting Time:

As the number of taxis increases from 200 to 350, the waiting time of customers for taxi service decreases significantly as shown in the graph below.

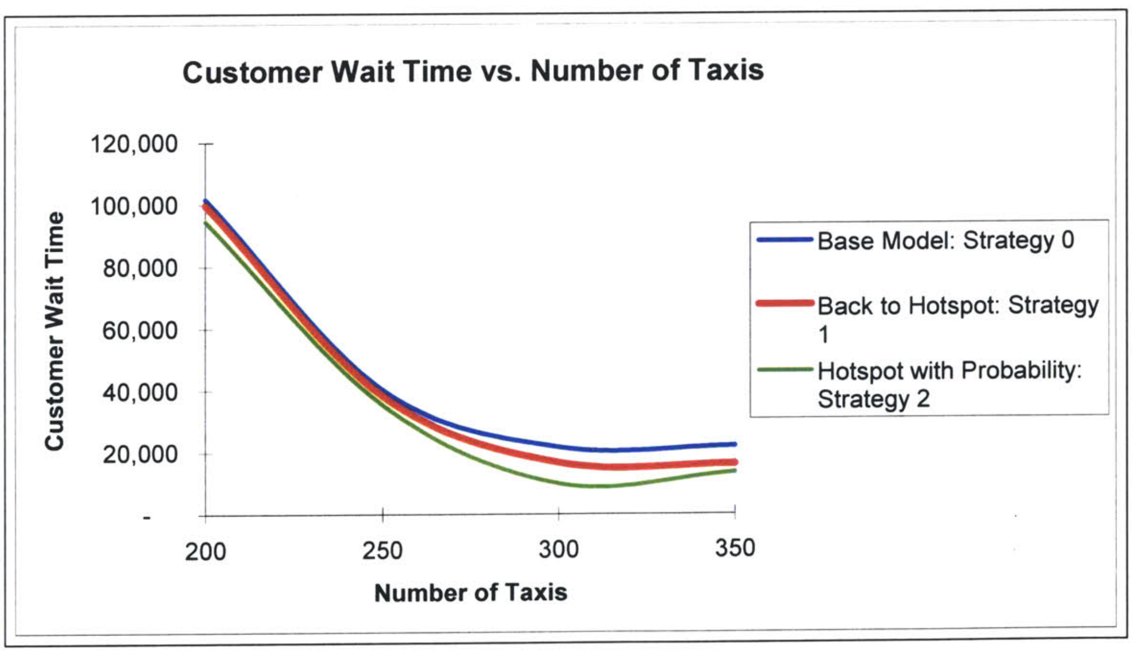


**Figure 12: As the number of taxis increases, the customer waiting time decreases.**

Since long waiting time is the top complaint by customers, it is important to address long waiting times because it is the primary complaint of customers. The results of this experiment indicate that by increasing the number of taxis and assigning them to the best possible hotspot, as indicated by Strategy 2, customer wait times will be decreased.

**Taxi Revenue:**

Because this experiment is designed to test the impact of the taxi fleet size on the attributes of optimization, it is more meaningful to analyze the average revenue per taxi rather than the total revenue of the industry, especially as the number of taxis increases. However, if there are more taxis than passengers, the average will decrease. In order to test Strategies 0, 1, and 2, it is only meaningful if there are more passengers than taxis if the factor of interest is average revenue.

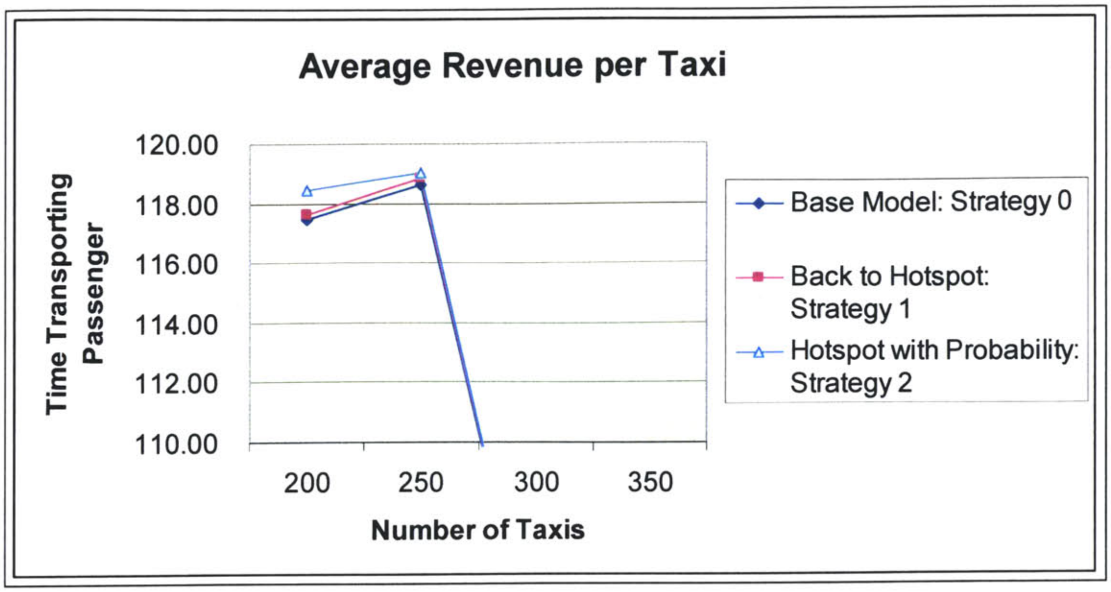


**Figure 13: Average revenue per taxi will increase as long as there are more customers than the availability of taxis. Strategy 2 shows the highest average revenue per taxi because taxis are able to spend more time transporting passengers.**

The figure above shows that both Strategy 1 and Strategy 2 will increase the live-mileage (time transporting passengers) or average revenue for each taxi even as the total number of taxis increase. This will hold true until there are more taxis than passengers (no more passengers at the queue); at that point, average revenue decreases for all strategies. This steep decrease is irrelevant for this experiment because there are more taxis than passengers. The calculation of average revenue for these three strategies becomes less meaningful as the number taxis is exceed customer demand.

**Taxi Cost:**

For this experiment, the taxi cost is defined as time spent not serving passengers. This is the combined time of (Idle Time, Taxing Time, and Pickup Time).

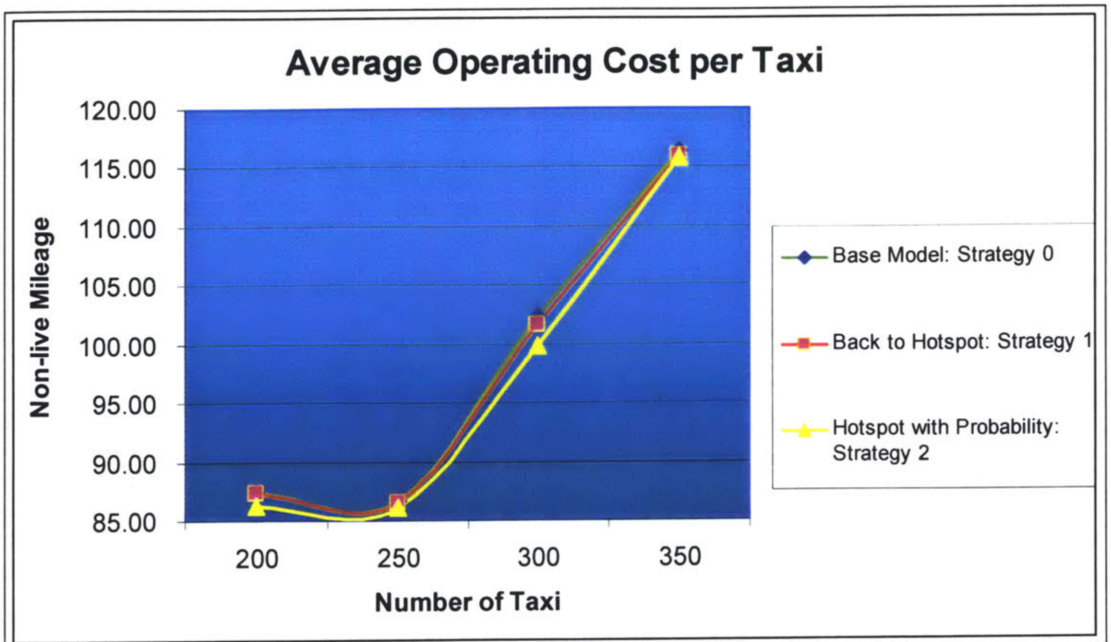


**Figure 14: Non-live mileage (non-revenue generating time) is the lowest with Strategy 2.**

As the graph above shows, Strategy 1 resulted in lower average operating cost per taxi than Strategy 0. Strategy 2 resulted even lower cost than Strategy 1. Thus these strategies will help taxis reduce overall cost.

**Taxi Profit:**

Average Taxi Profit is defined as the average revenue for each taxi minus the average cost. The significance of these number is only valid when the number of customers is more than or equal to the number of taxis. It is obvious that the average profit for each taxi will drop no matter which strategy is in place if there are significantly more taxis than passengers.

**Average Taxi Profit = Average Revenue – Average Cost**

This experiment shows that the Average Profit will be highest with Strategy 2 which directs taxis to go to the next best possible hotspots.

**Conclusions:**

The results of this experiment conclude that with Strategy 1 and Strategy 2, the customer wait time will be shorter than Strategy 0, the base case, where the taxi stays at the passenger drop-off location until the next available customer arrives. With Strategy 1 and Strategy 2, the taxi is directed to the closest hotspots or best possible hotspot respectively, the passenger wait time is the least with Strategy 2. Strategy 1 produces a shorter wait time than Strategy 0. These strategies will decrease passenger wait-time and lead to higher customer satisfactions.

The results also demonstrate that both Strategy 1 and Strategy 2 will increase the average revenue of each taxi as long the number of taxis is greater than the number of customers. Similarly, both of these strategies will decrease the non-live mileage (non-revenue generating time) of each taxi.

Strategy 2 will result in the highest profit among all three strategies. Strategy 1 will outperform Strategy 0. By implementing Strategy 2, taxi allocation can be optimized.

## Summarized Data:

The following is a summary of the results from this experiment:

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Taxi Fleet Size Experiment** | | | | | | | |
| **Model Attributes:** | | Units | | | | | | |
| | Simulation Iterations | 200 | | | | | | |
| | City Size | 100 | | | | | | |
| | Number of Hotspot | 10 | | | | | | |
| | Number of Taxi | | | | | | | |
| | Initial number of Taxi | 200 | | | | | | |
| | Incremental Number of | | | | | | | |
| | Taxi Increase for Each Run | 50 | | | | | | |
| | Final Number of Taxi | 350 | | | | | | |
| | Taxi Speed | 10 | | | | | | |
| | Generic Lambda | 2 | | | | | | |
| | Hotspot Lambda | Lambda | | Lambda | | | | |
| | Hotspot 1 | 10 | Hotspot 6 | 0.5 | | | | |
| | Hotspot 2 | 10 | Hotspot 7 | 0.5 | | | | |
| | Hotspot 3 | 0.5 | Hotspot 8 | 0.5 | | | | |
| | Hotspot 4 | 0.5 | Hotspot 9 | 0.5 | | | | |
| | Hotspot 5 | 0.5 | Hotspot 10 | 0.5 | | | | |
| | | | **Passenger Attributes** | | | | | |
| | | **Total Customer Wait Time** | **Generic Customer Total Wait Time** | **Total Number of Generic Customers** | **Hotspot Customer Total Wait Time** | **Total Number of Hotspot Customers** | **Total Wait Time of Customers Still Waiting for Service** | **Total Number of Customers Still Waiting for Service** |
| Taxis | | | | | | | | |
| 200 | **200 Taxis** | | | | | | | |
| | Base Model: Strategy 0 | 101,628 | 7,438 | 407 | 94,190 | 4,809 | 25,587 | 1,157 |
| | Back to Hotspot: Strategy 1 | 99,571 | 7,271 | 407 | 92,300 | 4,809 | 25,411 | 1,153 |
| | Hotspot with Probability: Strategy 2 | 94,510 | 6,883 | 407 | 87,627 | 4,809 | 24,108 | 1,123 |
| 250 | **250 Taxis** | | | | | | | |
| | Base Model: Strategy 0 | 40,218 | 2,457 | 397 | 37,761 | 4,823 | 611 | 170 |
| | Back to Hotspot: Strategy 1 | 38,226 | 2,271 | 397 | 35,955 | 4,823 | 520 | 157 |
| | Hotspot with Probability: Strategy 2 | 35,334 | 2,220 | 397 | 33,114 | 4,823 | 475 | 150 |
| 300 | **300 Taxis** | | | | | | | |
| | Base Model: Strategy 0 | 21,559 | 785 | 393 | 20,774 | 4,829 | 0 | 0 |
| | Back to Hotspot: Strategy 1 | 16,571 | 1,128 | 393 | 15,443 | 4,829 | 0 | 0 |
| | Hotspot with Probability: Strategy 2 | 9,723 | 1,680 | 393 | 8,043 | 4,829 | 0 | 0 |
| 350 | **350 Taxis** | | | | | | | |
| | Base Model: Strategy 0 | 21,873 | 793 | 392 | 21,080 | 4,877 | 0 | 0 |
| | Back to Hotspot: Strategy 1 | 16,097 | 1,614 | 392 | 14,483 | 4,877 | 0 | 0 |
| | Hotspot with Probability: Strategy 2 | 13,306 | 1,933 | 392 | 11,373 | 4,877 | 0 | 0 |

**Table 4: Taxi Fleet Size experiment: Passenger related results.**

| | | Taxi Attributes | | | | |
|---|---|---|---|---|---|---|
| | | Total Idle Time of All the Taxis | Total Taxing Time of All the Taxis | Total Pickup Time of All the Taxis | Total Transporting Time of All the Taxi | Total Non-Revenue Time of All Taxis |
| Taxis | | | | | | |
| 200 | **200 Taxis** | | | | | |
| | Base Model: Strategy 0 | 803 | 0 | 16,685 | 23,496 | 17,488 |
| | Back to Hotspot: Strategy 1 | 282 | 611 | 16,587 | 23,523 | 17,480 |
| | Hotspot with Probability: Strategy 2 | 102 | 835 | 16,311 | 23,683 | 17,248 |
| 250 | **250 Taxis** | | | | | |
| | Base Model: Strategy 0 | 1,245 | 0 | 20,402 | 29,646 | 21,647 |
| | Back to Hotspot: Strategy 1 | 518 | 1157 | 19,942 | 29,717 | 21,617 |
| | Hotspot with Probability: Strategy 2 | 177 | 1843 | 19,493 | 29,752 | 21,513 |
| 300 | **300 Taxis** | | | | | |
| | Base Model: Strategy 0 | 9,346 | 0 | 21,362 | 30,669 | 30,708 |
| | Back to Hotspot: Strategy 1 | 3,588 | 10,304 | 16,571 | 30,669 | 30,463 |
| | Hotspot with Probability: Strategy 2 | 1,651 | 18,586 | 9,723 | 30,669 | 29,960 |
| | | | | | | - |
| 350 | **350 Taxis** | | | | | - |
| | Base Model: Strategy 0 | 18,818 | 0 | 21,873 | 30,563 | 40,691 |
| | Back to Hotspot: Strategy 1 | 10,443 | 14,011 | 16,097 | 30,563 | 40,551 |
| | Hotspot with Probability: Strategy 2 | 6,074 | 21,110 | 13,306 | 30,563 | 40,490 |

**Table 5: Taxi Fleet Size experiment: Taxicab related results.**

## F. Experiment 2: The Effect of Quantity of Hotspots and Concentration of Customers at Hotspots

This experiment is designed to test the effect of quantity of hotspots and concentrations of customers at hotspots on the various attributes of taxi optimization. The number of hotspot will increase from 6 to 18 in increments of 2 while the concentration of customers at hotspots will change from 90% to 10% at increments of 10%. The total number of customers will remain constant throughout the entire experiment, only the distributions of customers between hotspots and non-hotspots will be different. For example, if there were 70% customer concentration at hotspots that mean 30% of the customers are located at non-hotspots. Of the 70% customers at hotspots, their distribution will be according to the lambda associated with that hotspot and the total number of hotspots. The impact of these changes will be analyzed under the three strategies (Strategy 0, 1, and 2). All other model attributes, such as number of taxicabs, are constant.

For Strategy 2, there are two hotspots that have twice the lambda value as the rest of the hotspots. Two of the hotspots have twice the lambda in order to illustrate some of the hotspots such as airports will have more customers demanding services than those at hotels. For example, with total lambda value of 25 (at any unit of time, there will be 25 customers requesting taxi services. If there are 6 hotspots and 90% of the customers are at hotspots, two of the hotspots will have 5.625 customers each while the other 4 hotspots will 2.8125 customers each.

[90% * 25 = 22.5];
[22.5/(6+2) = 2.8125];

The attributes analyzed include customer wait time, taxi driver revenue, profit, and cost under the three strategies within the design of the experiment. Please refer to the codes in the Appendix for detailed experiment set up. The summary results are also shown in the table at the end of this section.

## Results

### Customer Waiting Time:

### Strategy 0:

Under Strategy 0, where the taxi driver stays at the drop-off location until arrival of the next customer, the minimum wait time is <u>2.315</u> time units when there are 8 hotspots and 10% of the customers are at hotspots. As shown in the graph below, the minimum wait times are generally distributed at the concentration in the 10% range with 8 to 18 hotspots. The results are consistent with Strategy 0 because the taxis are distributed all over the city. When the customers are not concentrated at hotspots (10%), it is easier for taxi to pick up passengers because both customers and taxicabs are widely distributed. Please see the graph below for detailed analysis.

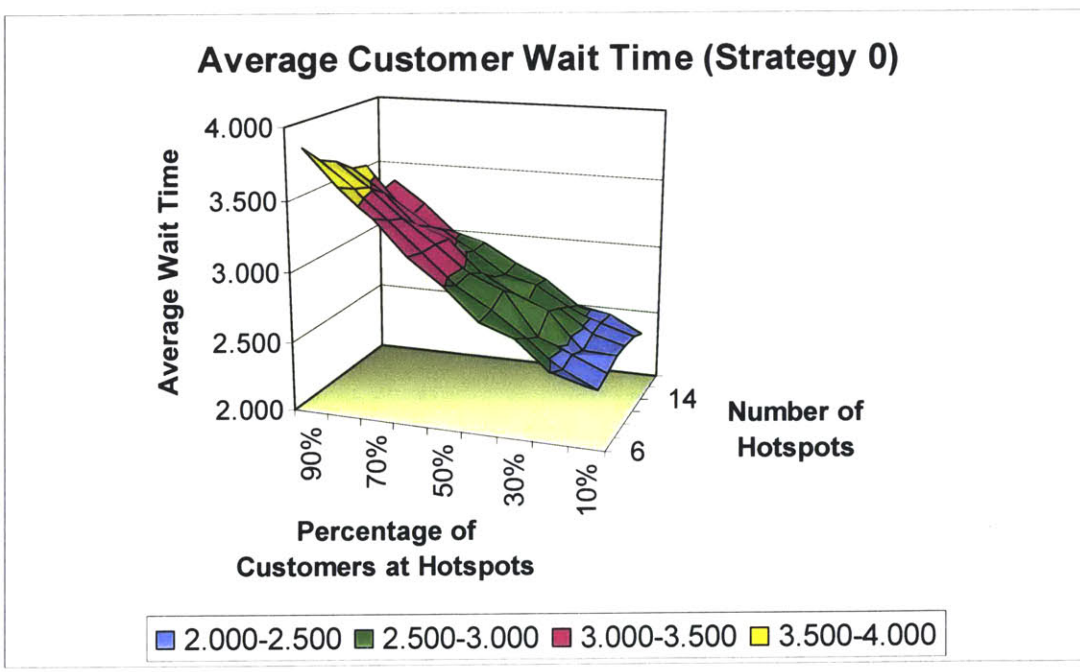


**Figure 15: Average customer wait time under Strategy 0. Wait times are minimal when 10% of customers are at hotspots.**

**Strategy 1:**

Under this strategy, the minimum customer wait time is 2.438 time units when the number of hotspots is 6 and 90% of the customers are concentrated at hotspots. The maximum customer concentration and minimum number of hotspots is the best policy with this strategy. Since all of the taxicabs are returning to the closest hotspots, with a fixed number of taxicabs, when customers are concentrated and the number of hotspots is at minimum, this will result in the shortest wait time. The results are shown in the graph below.

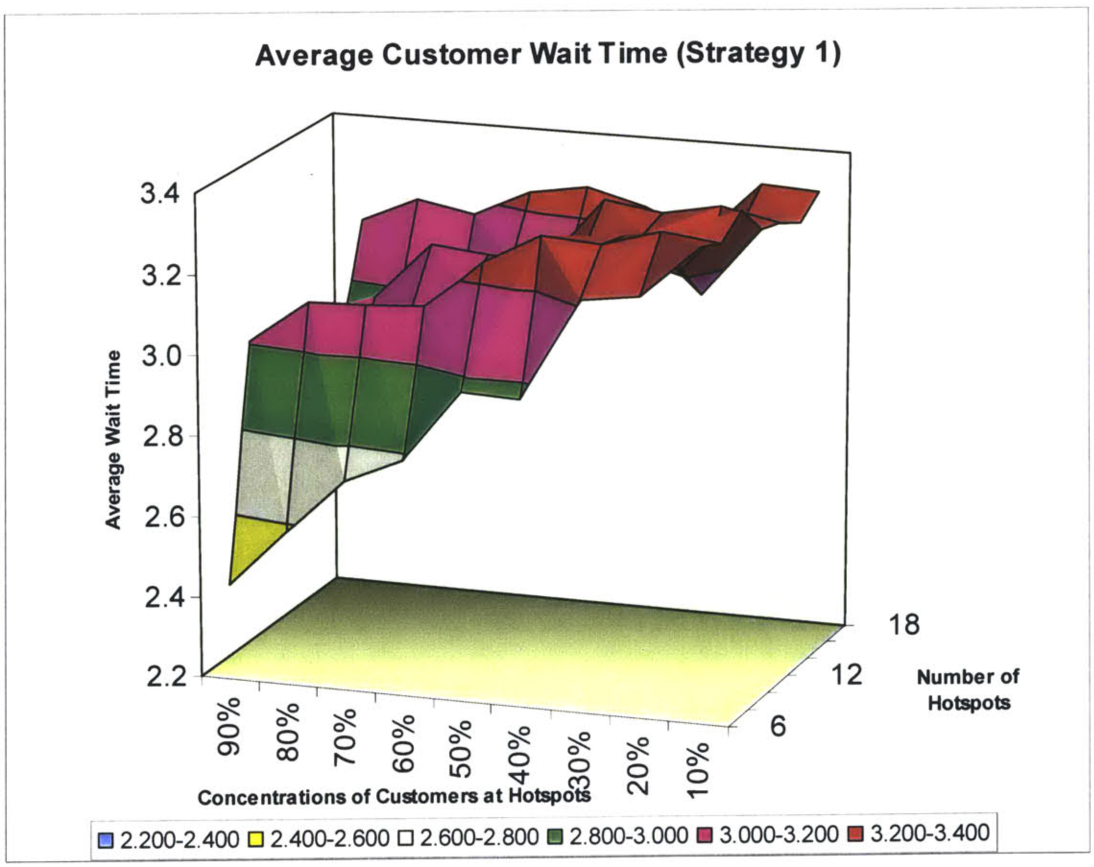


**Figure 16: Average customer wait time under Strategy 1.**

**Strategy 2:**

With Strategy 2, where the taxicab must return to the hotspot with the best possibility of potential customers, the minimum wait time 2.498 time units. This is achieved when the number of hotspots is 6 and 80% of the customers are concentrated at hotspots. In general, the minimum wait time is where the concentration of customers at hotspots is high and the number of hotspots is minimal as shown in the graph below.

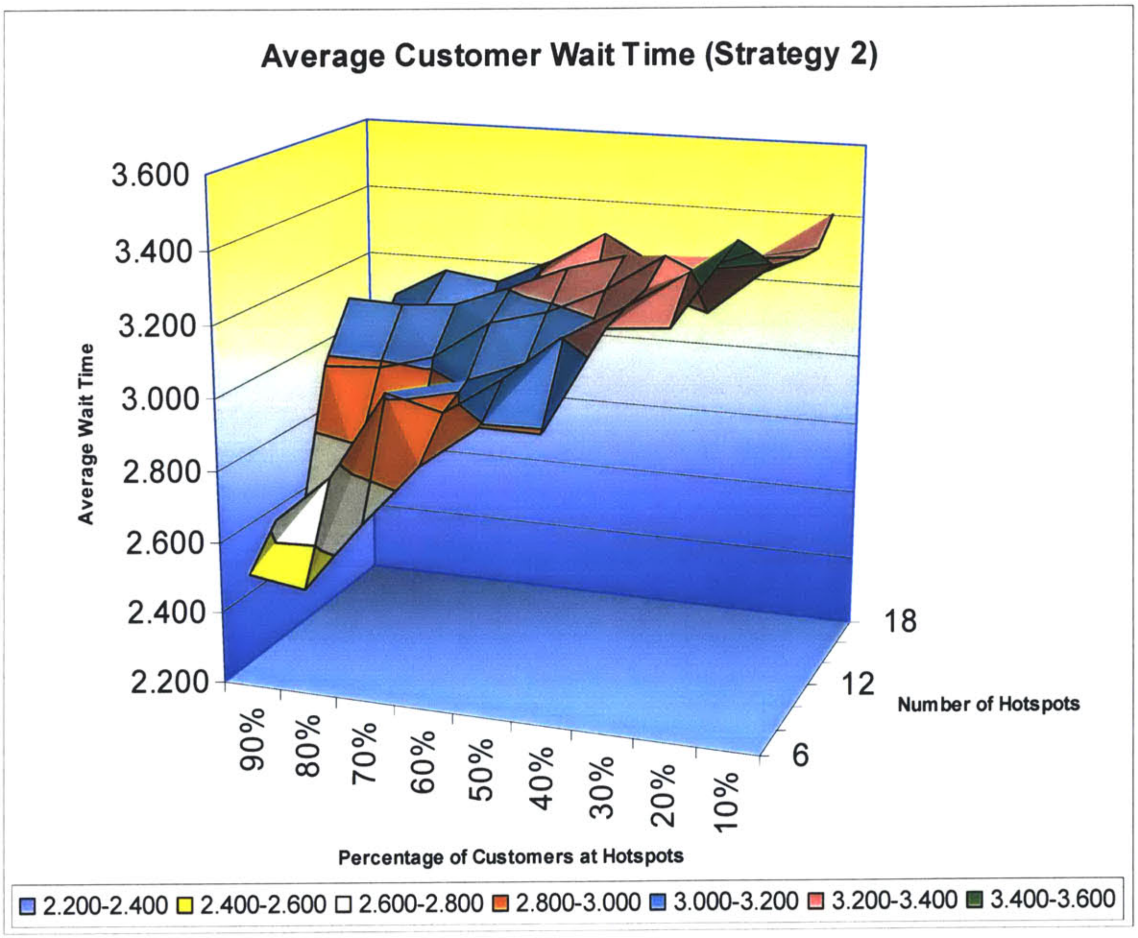


**Figure 17: Average customer wait time under Strategy 2.**

In order to minimize customer wait time, the results of this experimental simulation run indicate that:

1. If taxis remain at where they drop-off passengers (Strategy 0), it is best that customers do not concentrated at hotspots but instead disperse themselves across the city.
2. In general, if taxis are returning to hotspots, it is preferable if the customers are concentrated at hotspots and that the numbers of hotspots are minimal.

**Taxi Revenue:**

The revenue for taxis will be depended on the number of customers that the taxis are able to serve. In the analysis below, the results for both the generic customers (non-hotspot customers) and hotspot customers are shown. The results are the same for all three strategies because all customers were served and there were no customers waiting in the queue.

The graph below indicated that more customers are being served when they are less concentrated. The results are very similar across the range of the number of the hotspots.

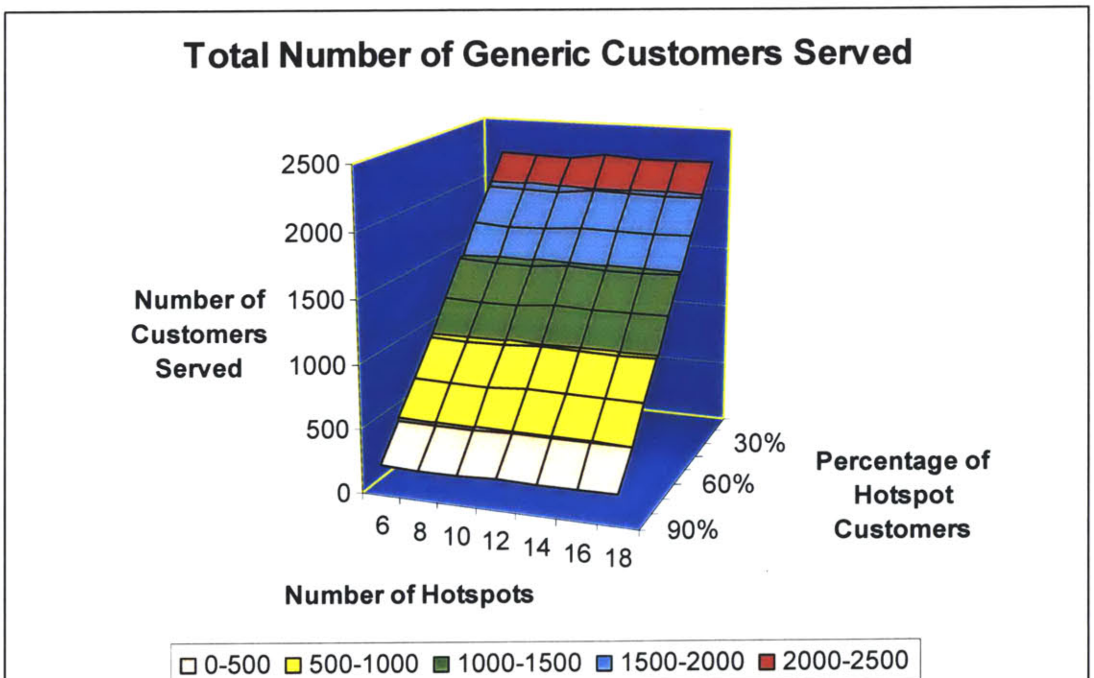


**Figure 18: The total number of generic customers (non-hotspot customers) served. The graphs are the same for all three strategies because there are no customers in the queue.**

The graph below shows the total number of hotspot customers being served. Since the customers are at hotspots, most of the customers that are being served are at the hotspots. Since no customers are in the queue at the end of the simulation runs, because all customers are being served.

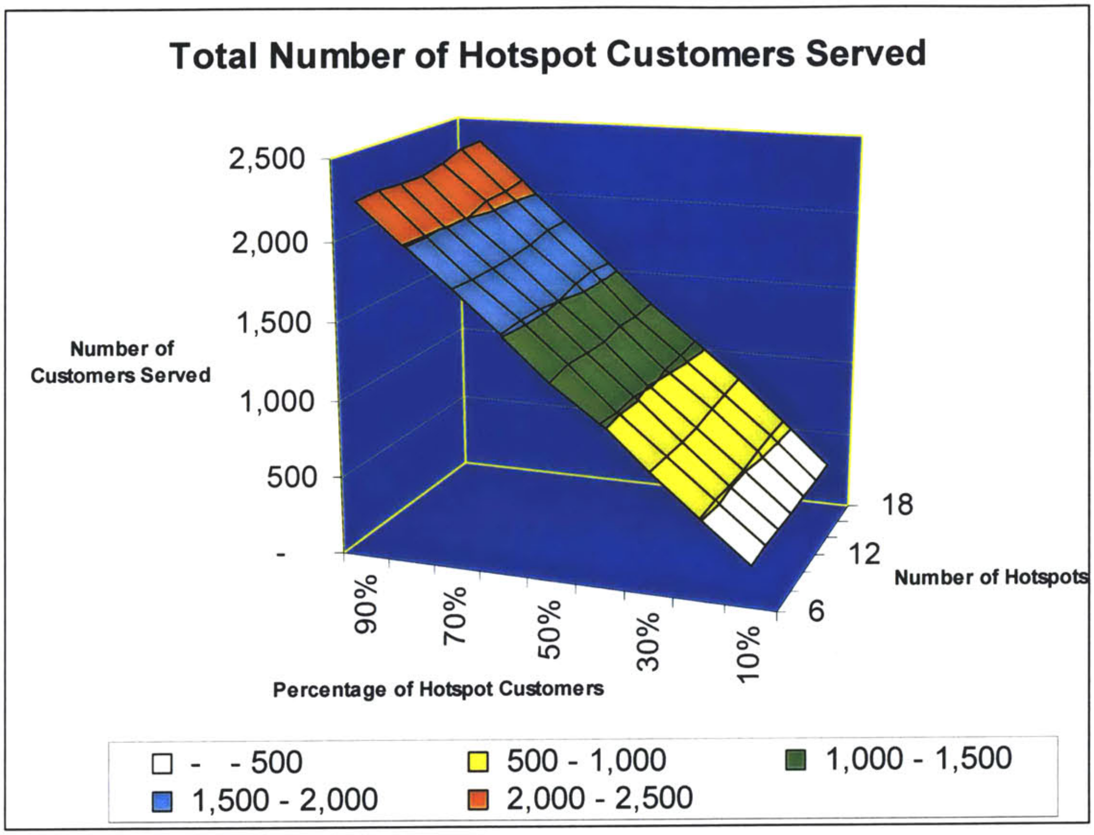


**Figure 19: The total number of hotspot customers served. The graphs are the same for all three strategies because there are no customers in the queue.**

**Taxi Cost:**

The cost of taxi operation consists of several components:

Taxi Operation Cost = [Idle Time Cost + Taxing Time + Pickup Time]

(Transporting Time has been excluded for this calculation because this is also revenue generating time and would complicated the calculation)

As shown in the graph below with Strategy 0, idle time is the least when there are high concentrations of customers.

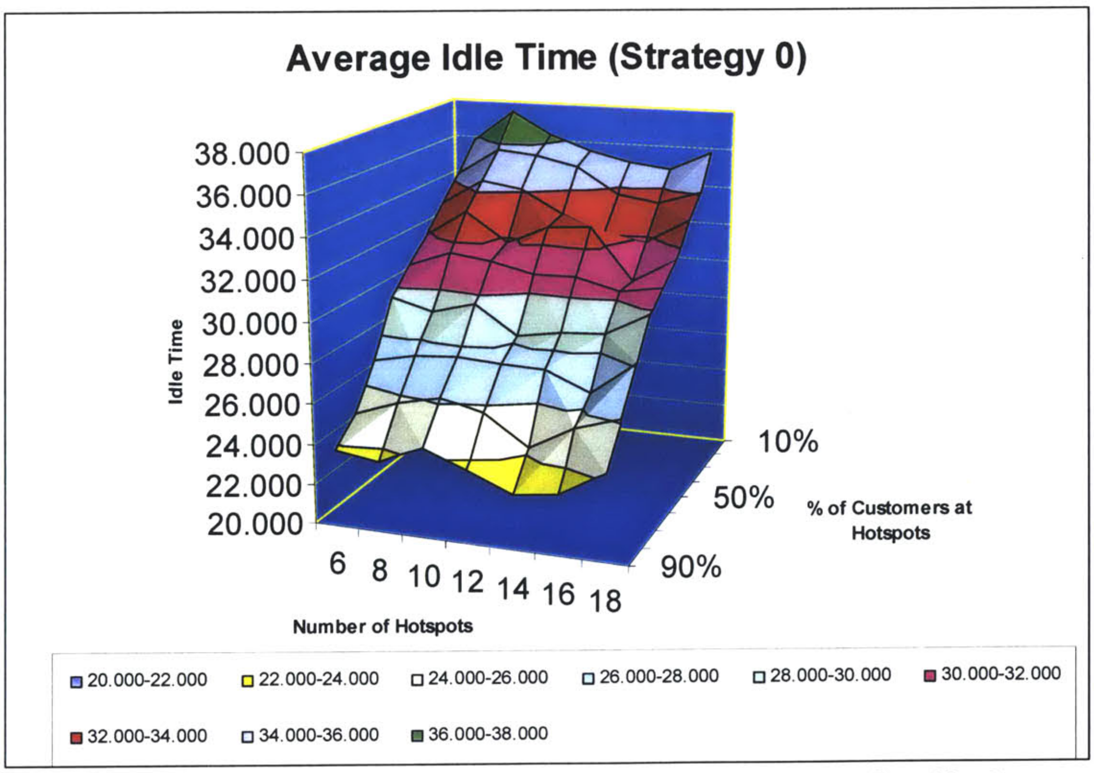


**Figure 20: Average Idle Time is one of the cost components. The taxicab idles while waiting for passengers.**

For both Strategies 1 and 2, the idle time results are very similar. Please see the table at the end of this section for details. The graphical result for Strategy 1 is represented below. The idle time for the taxi driver is less when the customers are concentrated at hotspots and the numbers of hotspots are minimal.

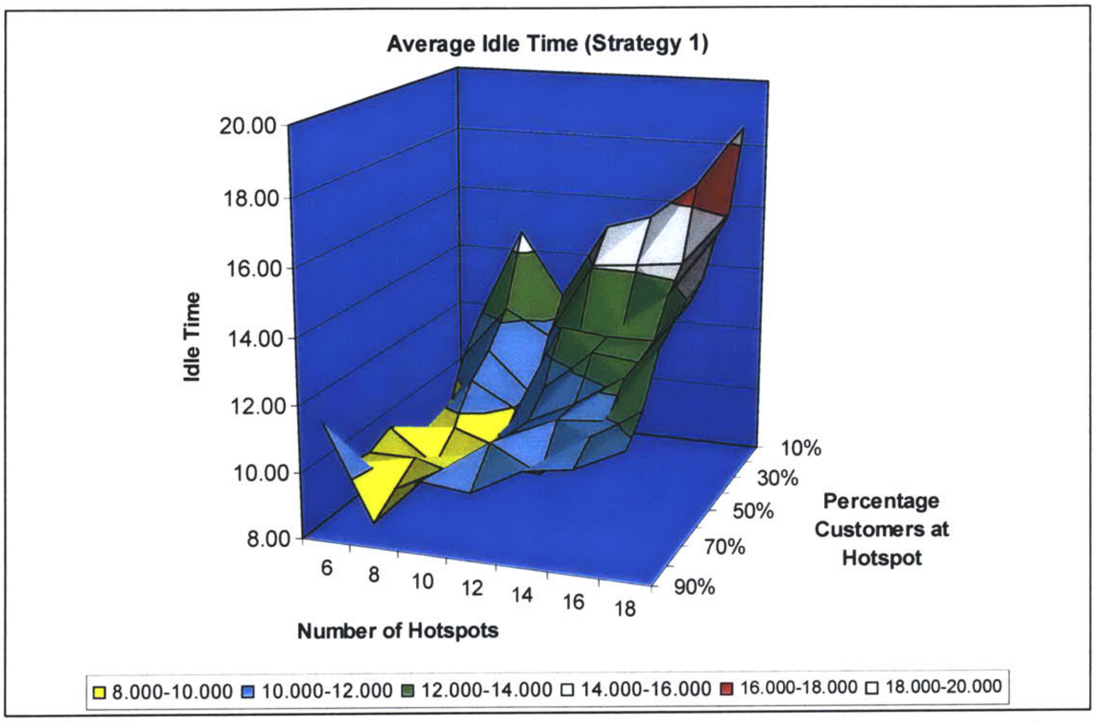


**Figure 21: Average idle time under Strategy 1. Idle time is less when customers are concentrated at hotspots and the numbers of hotspots are minimal.**

Another cost factor to consider is taxing time; which is the time that the taxi drives passengerless in search of potential customers. This cost variable is not applicable to Strategy 0 because the taxi stays at the location where it dropped-off its previous passengers. The analysis for Strategies 1 and 2 shows that the taxing time is less when the concentration of customers is low and the number of hotspot is high. If the concentration of customer is at the minimal, the implication is that one should employ Strategy 1 or 2 to decrease taxing time. This is shown in the graph below.

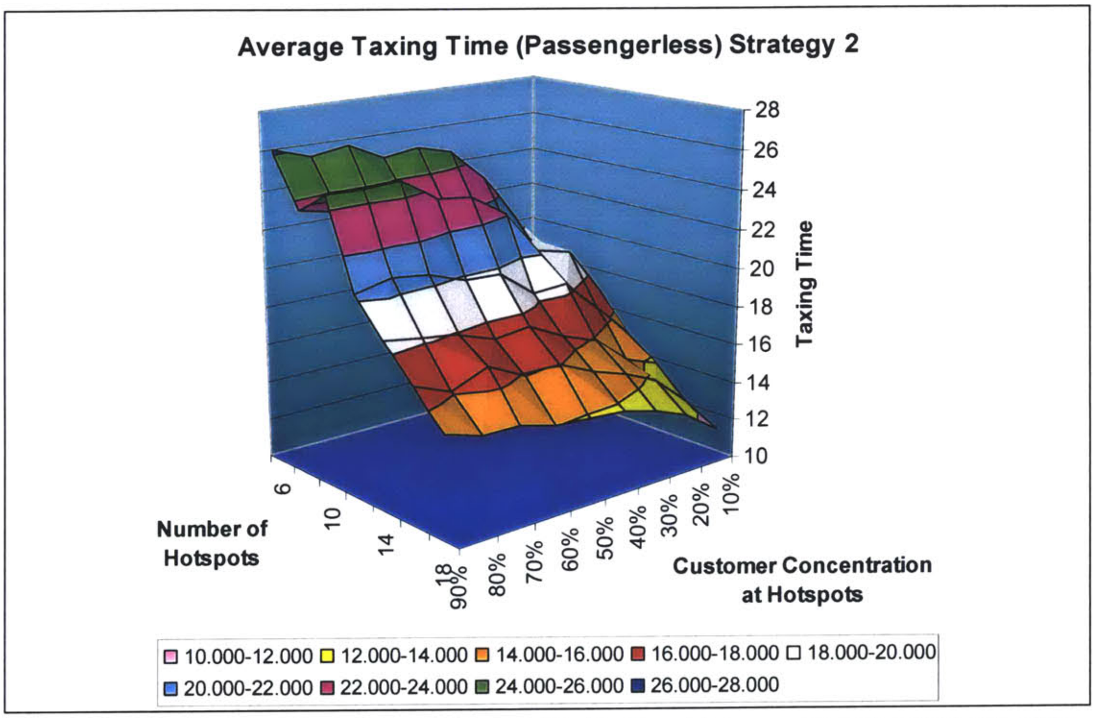


**Figure 22: Average taxing time under Strategy 2. It is the time driving passengerless in search of the next potential customer.**

Pickup time is the final component of the cost function to be considered in this experiment. With Strategy 0, the minimum pickup times occur when the customers are less concentrated irrespective the number of hotspots because taxis are already located at the previous customer's drop-off location.

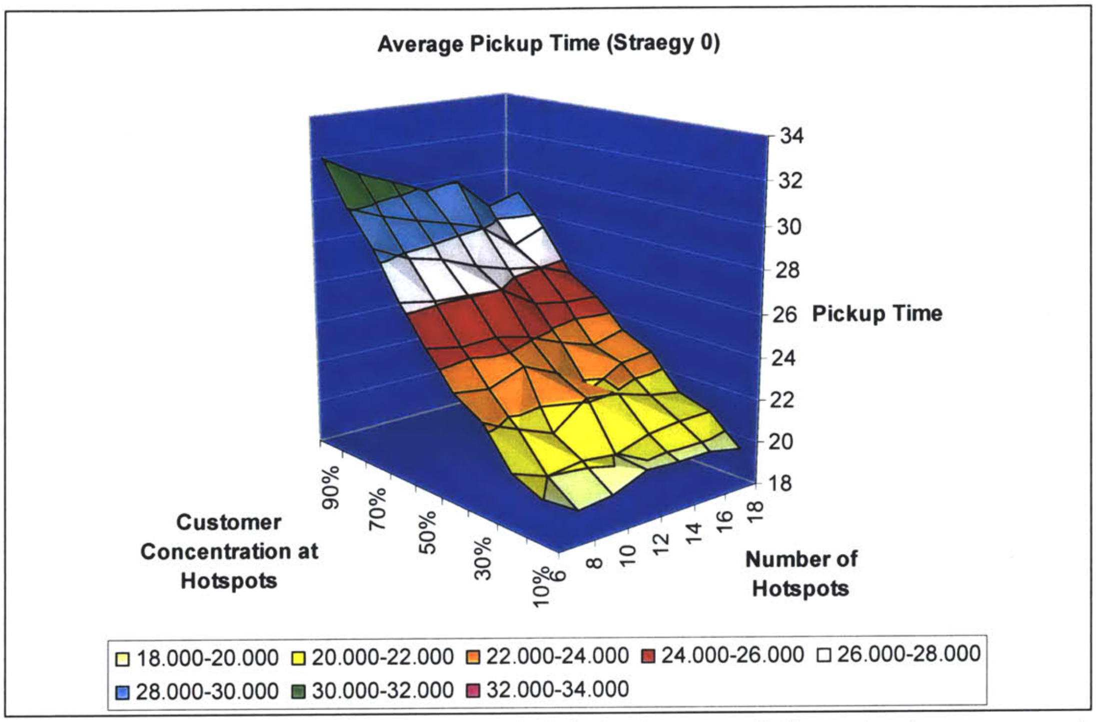


**Figure 23: Average pickup time under Strategy 0. It is the time to reach the next customer upon receiving the request for services.**

Under Strategy 2, the results of the experiment indicate that the pickup time will be minimal when customers are concentrated at hotspots. The results for Strategy 1 are very similar to that of Strategy 2. Please see the summarized results at the end of the section.

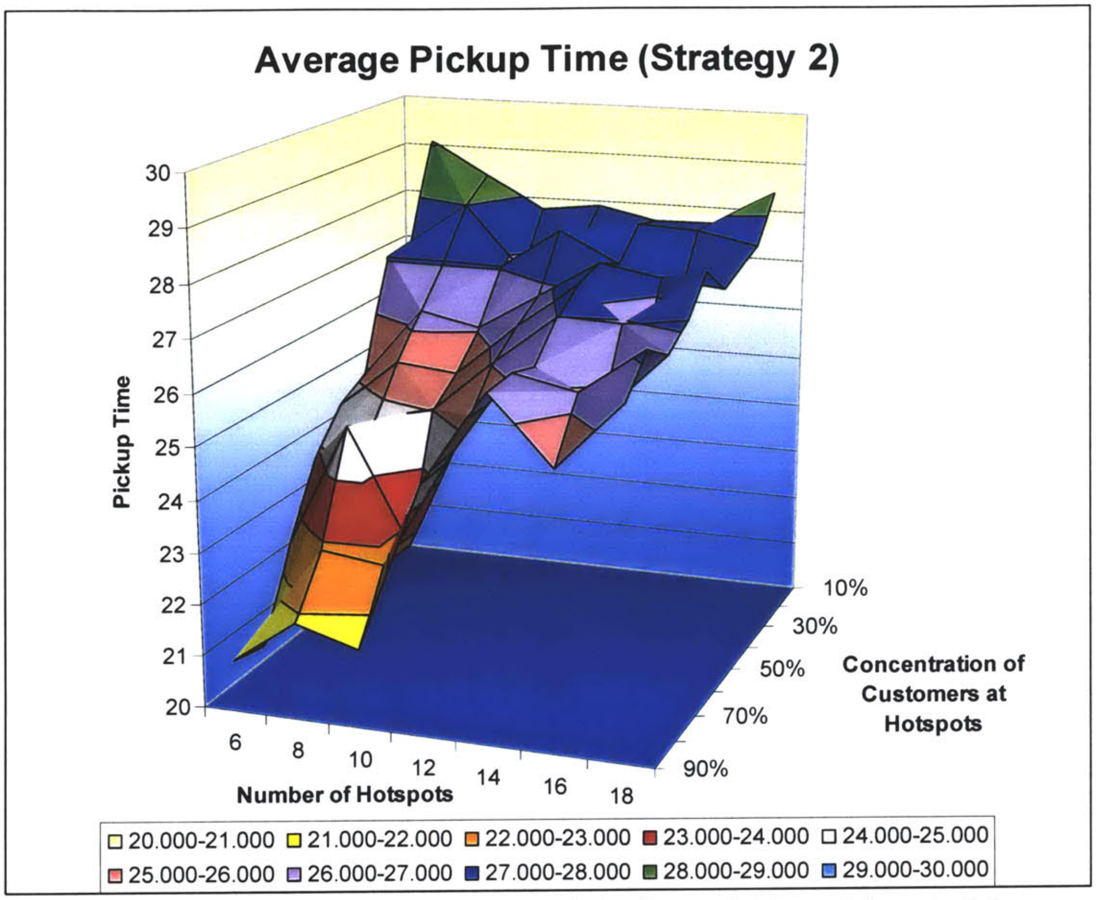


**Figure 24: Average pickup time under Strategy 2. It is the time needed to reach the potential customers upon request of service.**

**Taxi Profit:**

Taxi profit is defined as revenue minus cost. In this experiment, the taxi profit is significant when the number of customers is more than or equal to the number of taxis. Otherwise, under any of these strategies, the revenue would be the same because taxis would be able to transport all of their customers before the end of the simulations. This was the case in this experiment. Thus, if the revenue is the same, in order to analyze profit, one needs to compare the cost of operations. The costs among the three strategies are different under the various circumstances, thus the profit will differ.

**Conclusions:**

The results of this experiment show that there are significant cost differences among the three strategies, the number of hotspots, and the concentrations of customers at hotspots. Depending on the circumstances, one strategy is preferably better than the others. For example, during the morning rush hours, it is likely that there are lower concentrations of customers as people leave their individual homes and depart for work. However, in the early evening hours when people are leaving work from concentrated business districts, the origin of customers are more concentrated than during the morning. In this instance, one strategy may have an advantage over the others.

## Summary of Experiment Results:

| Model Attributes: | Units |
|---|---|
| Simulation Iterations | 100 |
| City Size | 100 |
| Initial Number of Hotspots | **6** |
| Hotspot Incremental | **2** |
| Final Number of Hotspots | **18** |
| Number of Taxi | 300 |
| Taxi Speed | 10 |
| Total Lambda | 25 |
| Two of the hotspot will have twice the lambda value | |

| | | # of Hotspots | Percentage of Customers at Hotspot | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 90% | 80% | 70% | 60% | 50% | 40% | 30% | 20% | 10% |
| **Strategy 0** | Average Customer Total Wait Time (Served) | 6 | 3.869 | 3.617 | 3.423 | 3.187 | 3.008 | 2.785 | 2.703 | 2.496 | 2.427 |
| | | 8 | 3.745 | 3.555 | 3.361 | 3.149 | 2.947 | 2.794 | 2.626 | 2.427 | 2.315 |
| | | 10 | 3.683 | 3.517 | 3.309 | 3.146 | 2.966 | 2.858 | 2.557 | 2.459 | 2.346 |
| | | 12 | 3.590 | 3.432 | 3.204 | 3.127 | 2.899 | 2.771 | 2.673 | 2.403 | 2.393 |
| | | 14 | 3.561 | 3.308 | 3.140 | 2.963 | 2.807 | 2.602 | 2.619 | 2.451 | 2.385 |
| | | 16 | 3.320 | 3.150 | 3.061 | 2.918 | 2.756 | 2.697 | 2.551 | 2.457 | 2.378 |
| | | 18 | 3.358 | 3.194 | 2.987 | 2.917 | 2.780 | 2.678 | 2.493 | 2.448 | 2.321 |
| **Strategy 1** | Average Customer Total Wait Time (Served) | 6 | 2.438 | 2.582 | 2.721 | 2.785 | 2.967 | 2.963 | 3.217 | 3.235 | 3.369 |
| | | 8 | 3.007 | 3.114 | 3.120 | 3.129 | 3.248 | 3.324 | 3.314 | 3.358 | 3.341 |
| | | 10 | 2.540 | 2.712 | 2.793 | 2.914 | 3.063 | 3.061 | 3.300 | 3.230 | 3.387 |
| | | 12 | 2.994 | 2.892 | 3.028 | 3.102 | 3.078 | 3.227 | 3.270 | 3.132 | 3.307 |
| | | 14 | 2.931 | 3.021 | 3.164 | 3.152 | 3.142 | 3.311 | 3.290 | 3.316 | 3.286 |
| | | 16 | 2.875 | 2.960 | 2.911 | 3.093 | 3.114 | 3.133 | 3.094 | 3.235 | 3.254 |
| | | 18 | 3.136 | 3.200 | 3.172 | 3.240 | 3.261 | 3.225 | 3.156 | 3.304 | 3.295 |
| **Strategy 2** | Average Customer Total Wait Time (Served) | 6 | 2.521 | 2.498 | 2.695 | 2.871 | 2.992 | 2.991 | 3.276 | 3.290 | 3.523 |
| | | 8 | 2.622 | 2.757 | 3.013 | 2.971 | 3.081 | 3.204 | 3.295 | 3.396 | 3.461 |
| | | 10 | 2.590 | 2.755 | 2.738 | 3.018 | 3.081 | 3.161 | 3.304 | 3.255 | 3.392 |
| | | 12 | 2.977 | 2.983 | 3.031 | 3.138 | 3.182 | 3.255 | 3.359 | 3.285 | 3.368 |
| | | 14 | 3.139 | 3.132 | 3.144 | 3.205 | 3.271 | 3.317 | 3.255 | 3.330 | 3.345 |
| | | 16 | 2.941 | 3.090 | 3.001 | 3.190 | 3.100 | 3.267 | 3.171 | 3.305 | 3.337 |
| | | 18 | 3.074 | 3.160 | 3.139 | 3.213 | 3.304 | 3.213 | 3.232 | 3.257 | 3.400 |
| **Strategy 0** | Average Generic Customer Wait Time (Served) | 6 | 1.983 | 1.831 | 1.903 | 1.953 | 2.083 | 2.101 | 2.242 | 2.231 | 2.310 |
| | | 8 | 1.838 | 1.878 | 1.983 | 1.953 | 1.934 | 2.067 | 2.210 | 2.192 | 2.237 |
| | | 10 | 2.180 | 2.172 | 2.039 | 2.154 | 2.179 | 2.239 | 2.159 | 2.227 | 2.243 |
| | | 12 | 1.780 | 1.957 | 1.776 | 2.062 | 2.050 | 2.131 | 2.247 | 2.172 | 2.310 |
| | | 14 | 2.062 | 2.202 | 2.004 | 2.074 | 2.121 | 2.029 | 2.276 | 2.264 | 2.312 |
| | | 16 | 1.931 | 2.045 | 1.980 | 2.100 | 2.206 | 2.185 | 2.200 | 2.265 | 2.291 |
| | | 18 | 1.956 | 2.026 | 1.878 | 2.192 | 2.182 | 2.174 | 2.114 | 2.268 | 2.252 |
| **Strategy 1** | Average Generic Customer Wait Time (Served) | 6 | 4.252 | 4.307 | 4.183 | 4.078 | 4.093 | 3.905 | 3.948 | 3.716 | 3.624 |
| | | 8 | 4.231 | 4.195 | 4.089 | 4.110 | 4.102 | 3.986 | 3.905 | 3.780 | 3.562 |
| | | 10 | 4.597 | 4.509 | 4.264 | 4.325 | 4.196 | 4.016 | 3.984 | 3.647 | 3.634 |
| | | 12 | 4.029 | 4.085 | 4.186 | 4.062 | 3.968 | 3.965 | 3.808 | 3.533 | 3.511 |
| | | 14 | 4.128 | 3.986 | 4.072 | 4.075 | 3.959 | 3.963 | 3.811 | 3.648 | 3.523 |
| | | 16 | 4.000 | 3.868 | 3.910 | 3.941 | 4.063 | 3.837 | 3.605 | 3.642 | 3.462 |
| | | 18 | 3.992 | 4.208 | 3.951 | 4.013 | 3.927 | 3.818 | 3.652 | 3.712 | 3.524 |
| **Strategy 2** | Average Generic Customer Wait Time (Served) | 6 | 4.718 | 4.637 | 4.481 | 4.296 | 4.288 | 4.131 | 4.105 | 3.849 | 3.811 |
| | | 8 | 3.953 | 4.195 | 4.183 | 3.962 | 4.018 | 4.017 | 3.880 | 3.809 | 3.720 |
| | | 10 | 4.403 | 4.338 | 4.120 | 4.132 | 4.224 | 4.058 | 3.905 | 3.673 | 3.634 |
| | | 12 | 3.959 | 4.016 | 4.181 | 4.078 | 4.058 | 4.026 | 3.869 | 3.658 | 3.559 |
| | | 14 | 4.103 | 3.947 | 3.931 | 3.903 | 3.864 | 3.872 | 3.677 | 3.649 | 3.571 |
| | | 16 | 4.098 | 4.020 | 4.096 | 4.019 | 3.987 | 3.893 | 3.728 | 3.714 | 3.557 |
| | | 18 | 4.124 | 4.061 | 3.981 | 4.098 | 4.087 | 3.851 | 3.741 | 3.697 | 3.652 |
| **Strategy 0** | Total Number of Generic Customers served | 6 | 238 | 485 | 732 | 979 | 1220 | 1468 | 1716 | 1970 | 2212 |
| | | 8 | 234 | 477 | 723 | 966 | 1208 | 1454 | 1702 | 1955 | 2195 |
| | | 10 | 233 | 477 | 723 | 965 | 1206 | 1453 | 1701 | 1953 | 2194 |
| | | 12 | 245 | 494 | 742 | 988 | 1233 | 1482 | 1732 | 1987 | 2229 |
| | | 14 | 243 | 489 | 735 | 978 | 1224 | 1471 | 1718 | 1973 | 2215 |
| | | 16 | 245 | 491 | 736 | 978 | 1224 | 1472 | 1720 | 1974 | 2216 |
| | | 18 | 249 | 495 | 739 | 982 | 1231 | 1479 | 1726 | 1981 | 2224 |
| **Strategy 1** | Total Number of Generic Customers served | 6 | 238 | 485 | 732 | 979 | 1220 | 1468 | 1716 | 1970 | 2212 |
| | | 8 | 234 | 477 | 723 | 966 | 1208 | 1454 | 1702 | 1955 | 2195 |
| | | 10 | 233 | 477 | 723 | 965 | 1206 | 1453 | 1701 | 1953 | 2194 |
| | | 12 | 245 | 494 | 742 | 988 | 1233 | 1482 | 1732 | 1987 | 2229 |
| | | 14 | 243 | 489 | 735 | 978 | 1224 | 1471 | 1718 | 1973 | 2215 |
| | | 16 | 245 | 491 | 736 | 978 | 1224 | 1472 | 1720 | 1974 | 2216 |
| | | 18 | 249 | 495 | 739 | 982 | 1231 | 1479 | 1726 | 1981 | 2224 |
| **Strategy 2** | Total Number of Generic Customers served | 6 | 238 | 485 | 732 | 979 | 1220 | 1468 | 1716 | 1970 | 2212 |
| | | 8 | 234 | 477 | 723 | 966 | 1208 | 1454 | 1702 | 1955 | 2195 |

**Figure 25: Summary of Experiment 2 results. Both concentrations of customer at hotspots and numbers of hotspots are tested.**

## 5. Solutions and Recommendations

Many attributes that were studied in these taxi optimization simulations are applicable to general vehicle fleet management. Thus applications of this study can be applied to school bus routing, garbage truck pickups, courier services, mail delivery, emergency vehicle planning, public transportation management, etc.

Taxi optimization involves many factors, some of which can be easily quantified while others cannot. To achieve optimization, an approach that combines mathematical optimization and heuristic methodologies seem to be the best solution—an approach that integrates the elements of optimization-based heuristics, continuous approximation, and probabilistic analysis.

To have efficient taxi services that benefit passengers, drivers, and other intermediaries, the following elements are critical:

1. Establish a time-dependent routing policy based on the probability of hourly demand of potential customers, the availability of hotspots/nodes, and current traffic conditions.
2. Incorporate real-time demand and current traffic conditions in the taxi's dispatching system. These include rush hour traffic, one-way streets, construction zones, etc.
3. Trip-chaining of taxi's advance bookings
4. Increase geographical areas where taxis are allowed to pickup passengers.
5. Analyze the customer demand profiles for each location within each time period of the day. (Taxi demand at business districts, at 5:00 p.m.) Incorporate this information to predict future demand and vehicle routing criteria.
6. Assign drivers based on current taxi location and the highest probability of where the next closest passenger will be located. This

will be a dynamic model that will change throughout the day and depends on the locations of empty taxis.

7. Adapt a GPS-GIS system to taxi fleet management. Such as a system will significantly increase taxi efficiency by providing real-time information on current taxi locations. This system will also reduce manual data entry required by the drivers to keep track of the passengers. It will also provide dynamic scheduling of taxi fleets, and location/driving information for the drivers, in the form of maps and directions.
8. Many taxi trips are round-trips with returns, especially those originating from residential areas where a home-bound trip is very likely to occur in the near future. It is wise to book such trip and incorporate it in the planning.

# 6. Conclusions

Taxi logistics optimization encompasses a range of factors; some of these can be quantified while others are regulatory in nature. In this study, a number of experiments were conducted using computer simulations. The results indicate that the best strategy largely depends on the objective or attributes that one wants to optimize and the circumstances or nature of the environment.

The results of the experiments indicate that as the number of taxis increases, the customer wait time will decrease. This is applicable across all three strategies with Strategy 2 providing the least wait time. For example, in Experiment 1 when there are 300 taxis, Strategy 2 will decrease customer wait time by 55% when compared to Strategy 0. As the number of taxis increases, the average revenue of each taxi will also increase; this will be true as long as customer demand is greater than or equal to the supply of taxis. Strategy 2 provides the best average revenue and the lowest operating cost.

With regard to the quantity of hotspots and concentration of customers, Strategy 2, the best strategy will depend on the objectives and circumstances of the environment. For example, if the objective is to minimize customer wait time and the customers are highly concentrated at a limited numbers of hotspots, then Strategy 2 will be the best strategy. An example of this would be traveling from hotels to the airport. On the other hand, if the objective is to minimize the average customer pickup time, and the customers are widely distributed, then Strategy 0 is the best strategy. This is illustrated by the demand for taxis for trips that originated from home to the office during weekday mornings.

Another critical aspect of optimization are policies involving institutional changes, such as incorporation of real-time demand and current traffic conditions into taxi's dispatching system as well as adoption of a GPS-GIS system to taxi fleet management. These will significantly improve overall efficiency.

The computer simulation that was developed in this study along with the policies outlined above may be applied to real situations to achieve optimal solutions. The more information regarding customers, drivers and current driving conditions that are available will be greatly beneficial to the accuracy of taxi allocation optimizations.

# 7. Appendix

## A. Model Codes

The followings are the actual codes written in MATLAB environment to build the models and experiments. The codes are structured into two parts: 1) **RunSim**, this is the main program. For each of the experiments, the variables that are being tested, the changes are made in this main program. 2) **TaxiSim**, this is the subprogram and also the core of the program. This subprogram stays the same during all the experimental simulations.

## B. Taxi Simulation Codes: TaxiSim (Codes)

These are the codes for the taxi simulation programs. These codes stay the same for each of the experiments.

```
function [uStat, taxiStat] = taxiSim(param,hotspotLambda,strategy,seed)
% TAXISIM randomly generates a city, hotspots, taxis, and
%       customers (customers by Poisson distribution) and
%       simulates the taxi services for a period of time
%       based on a decided on strategy
%
%       The general form of taxiSim is
%       [uStat, taxiStat] = taxiSim(param,hlambda,strategy,seed)
%
%       INPUT parameters are formatted as follows
%       Param = [P1 P2 P3 P4 P5 P6]
%               P1 = simulationDuration    P2 = citySize    P3 = numberOfHotspots
%               P4 = numberOfTaxis        P5 = taxiSpeed    P6 = generalCustomerLambda
%       HotspotLambda = [R1 R2 R3 ... RM ... RN] where N = number of Hotspots
%               in the city and RM is the lambda for hotspot #M, a positive real number
%       Strategy = choice of strategy to test out.
%               0: taxi waits after dropping off customer. (base case)
%               1: taxi travels towards nearest hotspot
%                 (distance factor NOT scaled by hlambda) but picks up calls
%               2: taxi travels towards nearest hotspot
%                 (distance factor scaled by hlambda) but picks up calls
%       Seed = randomNumberSeed
%
%       OUTPUT parameters are formatted as follows
%       UStat = [U1 U2 U3 U4 U5 U6 U7], a matrix of 7 unitary statistics
```

```
%	U1 = totalCustomerWaitTime		U2 = genericCustomerTotalWaitTime
%	U3 = totalNumberOfGenericCustomers	U4 = hotspotCustomerTotalWaitTime
%	U5 = totalNumberOfHotspotCustomers
%		U6 = totalWaitTimeOfCustomersStillWaiting
%		U7 = numberOfCustomerStillOnQueue
%		U8 = numberOfGenericCustomersServed
%		U9 = numberOfHotspotCustomersServed
%	TaxiStat = [taxiTimeSpentOnIdling; taxiTimeSpentOnTaxing;
%		taxiTimeSpentOnPickup; taxiTimeSpentOnCouriering]
%		where each is a [1 numberOfTaxis] matrix.
%		Idling   is wasted time waiting around but minimal fuel is expended
%		Taxing is wasted time moving around to a new location, fuel is expended
%		Pickup   is time spend traveling to get to the customer
%		Courier  is actual productive and profitable time driving customerS around

% GLOBAL CONSTANTS AND SETUP
%display('	*** RUN OF taxiSim.M ***  ');

rand('state',seed);

simDur = param(1);		% num iterations of simulation
citySize = param(2);		% citySize > 1; number of nodes in the city.
numHotspot = param(3);	% hotspots are places like hotels, airports, &c.  Where there
are high likelihood of a customer
numTaxi = param(4);		% number of taxis serving the city
taxiSpeed = param(5);% speed of the taxis.  number of unit space traversed per unit time
lambda = param(6);	% mean num of general city customer per iteration (lambda in
poisson distribution)
% mean num of customer at each hotspots per iteration (lambda in poisson distribution)
hlambda = hotspotLambda;		% NOTE:  ONE ENTRY PER HOTSPOT
% strategy:
%	0: do nothing during taxi idling
%	1: move to nearest HS location
%	2: move to nearest HS location, including lambda

% DIMENSION VARIABLES
cusQc = 6;	% number of columns in cusQ; [timeWaiting origX origY destX destY
hotSpot(=1)?]

% INITIALIZE STATISTICS STORAGE VARIABLES
taxiIdle = zeros(1,numTaxi); % taxi time idling for customer
taxiTaxing = zeros(1,numTaxi);			% taxi time driving around taxing and looking
for customers
taxiPickup = zeros(1,numTaxi);			% taxi time going to pickup customer
taxiCour = zeros(1,numTaxi);			% taxi time driving customer around
cusWaitTime = 0;				% total customer waiting time
```

```
genWaitTime = 0;      genCus = 0;             % total number of general customers
hotWaitTime = 0;      hotCus = 0;             % total number of general customers
genCusServed = 0;  hotCusServed = 0;        % total number of X customers served
sQWaiting = 0;          % which customer still waiting for taxi

% GENERATE CITY [simpliest city, distance as crow flies]
% nothing to do because no need to create an actual "city" under this circumstance

% GENERATE CUSTOMERS
% create hotspots
hotspot = ceil(citySize*rand(numHotspot,2));          % hs data struct: r = index, c = [x y]
coord

% GENERATE HOTSTANDBY LOCATIONS
% create a list of good places for taxi's to go during standby

% GENERATE TAXI
% place taxi in initial locations
taxi = [zeros(numTaxi,1) , ceil(citySize*rand(numTaxi,2))];
% taxi data struct: r = index, c = [outOfServiceTime x-coord y-coord]; oOSTime = time
before avail again, 0 if avail

% GENERATE CUSTOMER QUEUE
genQ = rot90(poisr(lambda,simDur));
for m = 1:numHotspot,          hotQ(m,:) = rot90(poisr(hlambda(m),simDur));   end; % for
m
hotCus = sum(sum(hotQ));    genCus = sum(genQ); % calculate number of customers
totalQ = sum([genQ; hotQ]);  % number of customers along timeline (e.g. [0 3 0 0 0 2])

cusQ = [];
for m = 1:simDur,
  % generate genQ for time M
  tempGenQ = [zeros(genQ(m),1) ceil(citySize*rand([genQ(m) 4])) zeros(genQ(m),1)];
        % tempGenQ finished being created
  % generate hotQ for time M by iterating thru each hotQ             % note lasts 0 is
hotspot? boolean
  tempHotQ = [];
  for n = 1:numHotspot,
    o = hotQ(n,m);     % num hotQ customers at hotspot location N at time M
    for p = 1:o,           % make a tempQ only if something's there, otherwise creates a
corrupted data struct
      tempHotQ = [tempHotQ ; 0 hotspot(n,:) ceil(citySize*rand([1 2])) 1];          %
NOTE:  LAST 1 MEANS IS HOTSPOT*****
    end% for p
  end   % for n% tempHotQ finished being created
```

```
  cusQ = [cusQ ; tempHotQ ; tempGenQ];   % HotQ before GenQ for comparison model
  tempHotQ = [];        tempGenQ = [];                              % clear temp variables
end     % for m         % cusQ finished being created, how have a list of all customers and
destinations

% START
SIMULATION %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

presentQ = []; % customers currently waiting to be served; starts off empty

for m = 1:simDur,

  %     reinitialize certain temporaray matrix that should be empty at start of time M
  taxi2cus = [];          serviceQ = []; a = []; ai = []; b = []; bi = [];

  % append new customers onto presentQ and shorten cusQ (the remaining customers)
  if totalQ(m) > 0       % there are new customers on this round of time M
    presentQ = [presentQ ; cusQ(1:totalQ(m),:)];              % [timeWaiting origX origY
destX destY hotSpot(=1)?]
    [cQr cQc] = size(cusQ);
    cusQ = cusQ((totalQ(m)+1):cQr , :);              % chop of front of cusQ; now cusQ
only has future customers
  end   % if totalQ(m)

  % do we have available taxi to serve customers?
  numAvailableTaxi = 0;
  for n = 1:numTaxi,
    if taxi(n,1) == 0
      numAvailableTaxi = numAvailableTaxi+1;
    end% if taxi(n,1)
  end   % for n

  % decide the number of customers to serve; serviceQ is the portion of presentQ we're
going to serve
  [pQr pQc] = size(presentQ);
  serviceQ = presentQ(1:(min([numAvailableTaxi pQr])) , :);
  presentQ = presentQ((min([numAvailableTaxi pQr])+1):pQr , :);
  % serviceQ and presentQ are ready for use



  % is there something to do or can be done this round?  if so, do it.
  [sQr sQc] = size(serviceQ);

  if sQr > 0     % there is a number of servicable customers and taxis to serve them
```

```
% calculate distance from each taxi to each customers in serviceQ
for n = 1:numTaxi,                    % taxi index
  if taxi(n,1) == 0            % taxi available (outOSTime == 0)
    for o = 1:sQr,             % customer index
      a = abs(taxi(n,2) - serviceQ(o,2));  % x-vector distance between taxi N and
hotspot O
      b = abs(taxi(n,3) - serviceQ(o,3));  % y-vector distance between taxi N and
hotspot O
      taxi2cus(n,o) = sqrt(a^2 + b^2);                % c = sqrt(a^2 + b^2)
    end     % for o
  else                                                % taxi not available so take it out from
consideration via Inf.
    for o = 1:sQr, taxi2cus(n,o) = Inf; end; % for o
  end       % if taxi
end% for n



a = []; b = [];        % re-initialize variables
% finds nearest customer for each taxi
[a ai] = sort(taxi2cus,2);   % determine distances; sorting by column, cus #ai
[b bi] = sortrows(a);                 % determine taxi assignment, taxi #bi

% assign taxi to pickup a customer
sQWaiting = ones(1,sQr); % initalize all customers as still waiting
for n = 1:numTaxi,                    % for each taxi (which is >= servicable customer)...
  if taxi(bi(n),1) == 0      % nth closest taxi available (OOSTime == 0), pick up
customer; do nothing if not avail

    % for nth closest taxi, look at oth closest customer.  if customer served, look at next
customer...
    for o = 1:sQr,             % for each customer O...find one waiting, serve, then break
out of loop

      if sQWaiting( ai(bi(n),o) ) == 1      % customer AI(O) still unserved...
        % serve this customer with taxi BI(N)
        sQWaiting( ai(bi(n),o) ) = 0;                % customer is served; taken out of
future consideration
        % calculate total out of service time and update stats
        a = abs(serviceQ(ai(bi(n),o),2) - serviceQ(ai(bi(n),o),4));        % x-vector
distance
        b = abs(serviceQ(ai(bi(n),o),3) - serviceQ(ai(bi(n),o),5));        % y-vector
distance
        pickupTime = ceil( (taxi2cus(bi(n),ai(bi(n),o)) / taxiSpeed) );
        courierTime = ceil( (sqrt(a^2 + b^2)) / taxiSpeed );
```

```
            outOfServiceTime = pickupTime + courierTime;
        % total taxi out of service time


            % taxi taken out of service; no longer available; and new location = cus
destination
            taxi(bi(n),:) = [outOfServiceTime  serviceQ(ai(bi(n),o),4)
serviceQ(ai(bi(n),o),5)];
            numAvailableTaxi = numAvailableTaxi-1;                % taxi taken out of
service because serving customer
            taxiPickup(bi(n)) = taxiPickup(bi(n)) + pickupTime;     % inc pickup stat for
that taxi
            taxiCour(bi(n)) = taxiCour(bi(n)) + courierTime;                % inc courier
stat for that taxi
            % cusWaitTime is a little redundant but that's ok.  doesn't add too much
overhead.
            cusWaitTime = cusWaitTime + serviceQ(ai(bi(n),o),1) + pickupTime; % inc
cusWaitTime stat var
            if serviceQ(ai(bi(n),o),6) == 1              % hotspot customer
              hotWaitTime = hotWaitTime + serviceQ(ai(bi(n),o),1) + pickupTime;
        % inc hotWaitTime stat var
              hotCusServed = hotCusServed+1;
            else
              genWaitTime = genWaitTime + serviceQ(ai(bi(n),o),1) + pickupTime;
        % inc genWaitTime stat var
              genCusServed = genCusServed+1;
            end%        if serviceQ
            % break out of for o loop
            break;
          end   % if sQWaiting
        end     % for o

      end       % if taxi(bi(n),1) == 0
    end% for n
  end   % if sQr > 0

  if numAvailableTaxi > 0     % we have idle taxis and no one to serve
    switch strategy      % any strategy what to do with idle taxis?
    case 0
      % do nothing, leave the taxis where they stopped
      for n = 1:numTaxi,
        if taxi(n,1) == 0         % taxi is idling
          taxiIdle(n) = taxiIdle(n) + 1;          % increment idling time
        end     % if taxi(n,1) == 0
      end       % for n
```

```
    case 1      % move to nearest hotspot regardless of lambda
      % calculate distance from each taxi to reach hotspot
      for n = 1:numTaxi,                % taxi index

        if taxi(n,1) == 0               % taxi available (outOSTime == 0) and therefore, idle,
move it
          taxiN2hs = [];                % init taxiN2hs
          % calculate distance to each hotspot
          for o = 1:numHotspot,                 % hotspot index;
            a = abs(taxi(n,2) - hotspot(o,1));  % x-vector distance between taxi N and
hotspot O
            b = abs(taxi(n,3) - hotspot(o,2));  % y-vector distance between taxi N and
hotspot O
            taxiN2hs(o) = sqrt(a^2 + b^2);              % c = sqrt(a^2 + b^2)
          end   % for o

          a = []; ai = []; nearestHS = []; % re-initialize variables
          % finds nearest hotspot for each taxi
          [a ai] = sort(taxiN2hs);      % determine distances; sorting by column, cus #ai
          dist2hs = taxiN2hs(ai(1));            % ai(1) is the closest distance
          nearestHS = hotspot(ai(1),:);         % ai(1) is the index of the nearest hotspot
          %
          fracMove = ceil(dist2hs/taxiSpeed);           % ceiling on how many time units it
takes to move there
          if fracMove > 0       % if there's any place to actually go..
            moveX = (taxi(n,2) - nearestHS(1)) / fracMove; % number of units to move in
X dirn
            moveY = (taxi(n,3) - nearestHS(2)) / fracMove; % number of units to move in
X dirn
            if moveX > 0, moveX = ceil(moveX); else moveX = floor(moveX); end
        % if moveX
            taxi(n,2) = taxi(n,2) - moveX;      % move it
            if moveY > 0, moveY = ceil(moveY); else moveY = floor(moveY); end
        % if moveY
            taxi(n,3) = taxi(n,3) - moveY;      % move it
            % increment time taken for taxi to taxi around to new location
            taxiTaxing(n) = taxiTaxing(n)+1;
          else taxiIdle(n) = taxiIdle(n) + 1;   % increment idling time
          end  % if fracMove
        end     % if taxi(n,1) == 0

      end       % for n

    case 2      % move to nearest hotspot scaled by lambda
      % calculate distance from each taxi to reach hotspot
      for n = 1:numTaxi,                % taxi index
```

```
    if taxi(n,1) == 0                  % taxi available (outOSTime == 0) and therefore, idle,
move it
        taxiN2hs = [];        taxiN2hsScaled = [];  % init taxiN2hs, taxiN2hsScaled
        % calculate distance to each hotspot
        for o = 1:numHotspot,                  % hotspot index;
          a = abs(taxi(n,2) - hotspot(o,1));  % x-vector distance between taxi N and
hotspot O
          b = abs(taxi(n,3) - hotspot(o,2));  % y-vector distance between taxi N and
hotspot O
          taxiN2hs(o) = sqrt(a^2 + b^2);              % c = sqrt(a^2 + b^2)
          taxiN2hsScaled(o) = taxiN2hs(o)/hlambda(o);            % create scaled
distances
        end   % for o

        a = []; ai = []; nearestHS = []; % re-initialize variables
        % finds nearest hotspot for each taxi
        [a ai] = sort(taxiN2hsScaled);        % determine distances; sorting by column, cus
#ai
        dist2hs = taxiN2hs(ai(1));            % ai(1) is the closest distance
        nearestHS = hotspot(ai(1),:);         % ai(1) is the index of the nearest hotspot
        %

        %taxi(n,:)
        % move taxi towards that destination
        fracMove = ceil(dist2hs/taxiSpeed);          % ceiling on how many time units it
takes to move there
        if fracMove > 0      % if there's any place to actually go..
          moveX = (taxi(n,2) - nearestHS(1)) / fracMove;  % number of units to move in
X dirn
          moveY = (taxi(n,3) - nearestHS(2)) / fracMove;  % number of units to move in
X dirn
          if moveX > 0, moveX = ceil(moveX); else moveX = floor(moveX); end
      % if moveX
          taxi(n,2) = taxi(n,2) - moveX;      % move it
          if moveY > 0, moveY = ceil(moveY); else moveY = floor(moveY); end
      % if moveY
          taxi(n,3) = taxi(n,3) - moveY;      % move it
          % increment time taken for taxi to taxi around to new location
          taxiTaxing(n) = taxiTaxing(n)+1;
        else taxiIdle(n) = taxiIdle(n) + 1;   % increment idling time
        end  % if fracMove
    end     % if taxi(n,1) == 0

  end       % for n
```

```
    otherwise disp('Something wrong with Strategy switch statement');
    end% switch strategy
  end   % if numAvailableTaxi > 0

  % STATS UPDATES  now that we've dealt with the customers, time for statistics
updates.
  % update customer time waiting for being assigned a taxi
  [pQr pQc] = size(presentQ);
  if pQr > 0     % if there is any one still unserved...
    presentQ(1:pQr, 1) = presentQ(1:pQr, 1) + ones(pQr,1);% increment unserved
customer wait times
  end   % if pQr

  for n = 1:numTaxi,  % upate taxi stats
    if taxi(n,1) > 0      % taxi is not available
      taxi(n,1) = taxi(n,1) - 1;          % decrement taxi unavailable time by one
    end% if taxi(n,1)
    % NOTE: if taxi is available, the taxi Taxing or Idling time is taken care of in switch
statement
  end   % for n

end     % for m          % next time cycle.

% DISPLAY/ASSIGN STATISTICS VARIABLES
%cusQ
[pQr pQc] = size(presentQ);
stillWaiting = sum(presentQ(:,1));
taxiStat = [taxiIdle; taxiTaxing; taxiPickup; taxiCour];
uStat = [cusWaitTime genWaitTime genCus hotWaitTime hotCus stillWaiting pQr
genCusServed hotCusServed];
%sQWaiting   % which customer still waiting for taxi
%display('      *** FINISHED taxiSim.M ***   ');
```

## C. Experiment 1 - The Effect of Taxi Fleet Size: (Codes)

The following are codes written for simulations to analyze the effect of taxi fleet size on the various attributes of taxi optimization. This program (**RunSim**) calls the TaxiSim program for various calculations.

```
clc;
format;
%display(' *** RUN OF runSim.M *** ');
clear;
diary('strategy.txt');
diary on;

% The general form of taxiSim is
% [uStat, taxiStat] = taxiSim(param,hlambda,strategy,seed)
%
% INPUT parameters are formated as follows
% Param = [P1 P2 P3 P4 P5 P6]
% P1 = simulationDuration    P2 = citySize    P3 = numberOfHotspots
% P4 = numberOfTaxis    P5 = taxiSpeed    P6 = generalCustomerLambda
% HotspotLambda = [R1 R2 R3 ... RM ... RN] where N = number of Hotspots
%         in the city and RM is the lambda for hotspot #M, a positive real
%         number
% Strategy = choice of strategy to test out.
%         0: taxi waits at the drop-off location after dropping off customer.
%               (base case)
%         1: taxi travels towards nearest hotspot
%           (distance factor NOT scaled by hlambda) but picks up calls
%         2: taxi travels towards nearest best possible hotspot
%           (distance factor scaled by hlambda) but picks up calls
% Seed = randomNumberSeed
%
% OUTPUT parameters are formated as follows
% UStat = [U1 U2 U3 U4 U5 U6 U7], a matrix of 7 unitary statistics
%         U1 = totalCustomerWaitTime
%         U2 = genericCustomerTotalWaitTime
%         U3 = totalNumberOfGenericCustomers
%         U4 = hotspotCustomerTotalWaitTime
%         U5 = totalNumberOfHotspotCustomers
%         U6 = totalWaitTimeOfCustomersStillWaiting
%         U7 = numberOfCustomerStillOnQueue
%         TaxiStat = [taxiTimeSpentOnIdling; taxiTimeSpentOnTaxing;
%                 taxiTimeSpentOnPickup; taxiTimeSpentOnCouriering]
%         where each is a [1 numberOfTaxis] matrix.
```

```
%          Idling is wasted time where the taxi is waiting around but minimal
%                fuel is consumed since it is not moving
%          Taxing is wasted time moving around to a new location with an
%                empty taxicab, fuel is consumed
%          Pickup is time spend traveling to get to the customer
%          Courier is actual productive and profitable time driving customerS
%                around

% PARAMETER RANGE (low, step, high)
% Param
simDurL = 200
simDurS = 10;           simDurH = simDurL;          % simulation duration
citySizeL = 100
citySizeS = 20;         citySizeH = citySizeL;      % citySize
numHSL = 10
numHSS = 2;             numHSH = numHSL;            % number of hotspots
numTaxiL = 200
numTaxiS = 50
numTaxiH = 350                                      % number of taxis
taxiSpeedL = 10
taxiSpeedS = 5;         taxiSpeedH = taxiSpeedL;    % taxi traveling speed
genLambL = 2
genLambS = 0.1;         genLambH = genLambL;                  %
lambda of generic customer
% HotspotLambda
for s = 1:numHSL, hlamb(s) = 5/numHSL; end  % for m
hlamb(1) = 10;
hlamb(2) = 10;
hlamb             % for displaying in output
% Strategy
%strg = 1;
% Seed
rSeed = 0;

%**** **** **** **** **** **** **** **** **** **** **** **** **** ****
%display(' *** RUN OF STRATEGY 0 ***  ');

ti = 0; ui = 0; vi = 0; wi = 0; xi = 0; yi = 0;
for t = simDurL:simDurS:simDurH,
  ti = ti+1;
  for u = citySizeL:citySizeS:citySizeH,
    ui = ui+1;
    for v = numHSL:numHSS:numHSH,
      vi = vi+1;
      for w = numTaxiL:numTaxiS:numTaxiH,
        wi = wi+1;
```

```
for x = taxiSpeedL:taxiSpeedS:taxiSpeedH,
  xi = xi+1;
  for y = genLambL:genLambS:genLambH,

    % Strategy
    disp('*****************STRATEGY 0*******************');
    strg = 0

    yi = yi+1;
    param = [t u v w x y];
    [uSt, tSt] = taxiSim(param,hlamb,strg,rSeed);
    %uStat(ti,ui,vi,wi,xi,yi,:) = uSt;
    %tStat(ti,ui,vi,wi,xi,yi,:,:) = tSt;

<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<
    uSt
    %tSt
    sum(tSt,2)

    % Strategy
    disp('**********STRATEGY 1***************');
    strg = 1

    yi = yi+1;
    param = [t u v w x y];
    [uSt, tSt] = taxiSim(param,hlamb,strg,rSeed);
    %uStat(ti,ui,vi,wi,xi,yi,:) = uSt;
    %tStat(ti,ui,vi,wi,xi,yi,:,:) = tSt;

<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<
    uSt
    %tSt
    sum(tSt,2)

    % Strategy
    disp('****STRATEGY 2************************');
    strg = 2

    yi = yi+1;
    param = [t u v w x y];
    [uSt, tSt] = taxiSim(param,hlamb,strg,rSeed);
    %uStat(ti,ui,vi,wi,xi,yi,:) = uSt;
    %tStat(ti,ui,vi,wi,xi,yi,:,:) = tSt;

<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<
    uSt
```

```
            %tSt
            sum(tSt,2)

          end       % y
          yi = 0;
        end         % x
        xi = 0;
      end   % w
      wi = 0;
    end     % v
    vi = 0;
  end       % u
  ui = 0;
end% t
ti = 0;

display('    ************** FINISH runSim.M **************   ');
display('    ************** FINISH runSim.M **************   ');

diary off;
```

## D. Experiment 2: The Effect of Quantity of Hotspots and Concentration of Customers at Hotspots (Codes)

The following are codes written to analyze the effect of quantity of hotspots and the concentrations of customers on the various attributes of taxi optimization. This program (**RunSim**) calls the TaxiSim program for various calculations.

```
clc;
%format short e;
format;
%display('      *** RUN OF runSim.M ***  ');
clear;
diary('numberHS_PercentageHSDIARY.txt');
diary on;

%       The general form of taxiSim is
%       [uStat, taxiStat] = taxiSim(param,hlambda,strategy,seed)
%
%       INPUT parameters are formated as follows
%       Param = [P1 P2 P3 P4 P5 P6]
%       P1 = simulationDuration    P2 = citySize    P3 = numberOfHotspots
%       P4 = numberOfTaxis         P5 = taxiSpeed   P6 = generalCustomerLambda
%       HotspotLambda = [R1 R2 R3 ... RM ... RN] where N = number of Hotspots
%       in the city and RM is the lambda for hotspot #M, a positive real number
%       Strategy = choice of strategy to test out.
%               0: taxi waits after dropping off customer.  (base case)
%               1: taxi travels towards nearest hotspot
%                  (distance factor NOT scaled by hlambda) but picks up calls
%               2: taxi travels towards nearest hotspot
%                  (distance factor scaled by hlambda) but picks up calls
%       Seed = randomNumberSeed
%
%       OUTPUT parameters are formated as follows
%       UStat = [U1 U2 U3 U4 U5 U6 U7], a matrix of 7 unitary statistics
%               U1 = totalCustomerWaitTime
%               U2 = genericCustomerTotalWaitTime
%               U3 = totalNumberOfGenericCustomers
%               U4 = hotspotCustomerTotalWaitTime
%               U5 = totalNumberOfHotspotCustomers
%               U6 = totalWaitTimeOfCustomersStillWaiting
%               U7 = numberOfCustomerStillOnQueue
%               U8 = numberOfGenericCustomersServed
%               U9 = numberOfHotspotCustomersServed
```

```
%       TaxiStat = [taxiTimeSpentOnIdling; taxiTimeSpentOnTaxing;
%               taxiTimeSpentOnPickup; taxiTimeSpentOnCouriering]
%               where each is a [1 numberOfTaxis] matrix.
%               Idling is wasted time waiting around but minimal fuel is expended
%               Taxing is wasted time moving around to a new location, fuel is
%                consumed.
%               Pickup is time spend traveling to get to the customer
%               Courier is actual productive and profitable time driving customers
                around

% PARAMETER RANGE (low, step, high)
% Param
simDurL = 100;
simDurS = 10;        simDurH = simDurL;              % simulation duration

citySizeL = 100
citySizeS = 20;              citySizeH = citySizeL;        % citySize

numHSL = 6
numHSS = 2
numHSH = 18;                                              % number of hotspots
disp('7 hotspot range to test--ROW');

numTaxiL = 300
numTaxiS = 50;               numTaxiH = numTaxiL;      % number of taxis

taxiSpeedL = 10
taxiSpeedS = 5;              taxiSpeedH = taxiSpeedL;  % taxi driving speed

totalLambda = 25;            % total lambda for all customers

genLambL = 0.1
genLambS = 0.1
genLambH = 0.9               % percentage of lambda is generic customer
disp('9 hotspot lambda percentage to test--COLUMN');

% Seed
rSeed = 0;

%**** **** **** **** **** **** **** **** **** **** **** **** **** ****
**** **** **** **** **** **** **** **** ****
%display('      *** RUN OF STRATEGY 0 ***  ');

ti = 0; ui = 0; vi = 0; wi = 0; xi = 0; yi = 0; uSt0 = []; uSt1 = []; uSt2 = [];
% setup saving vars
```

```
avgTotalWait0 = []; avgTotalWait1 = []; avgTotalWait2 = [];
        % average wait time for served customers

avgGenWait0 = []; avgGenWait1 = []; avgGenWait2 = [];
        % average wait time for served gen customers

totalGenServed0 = []; totalGenServed1 = []; totalGenServed2 = [];
        % total number of gen customers served

avgHSWait0 = []; avgHSWait1 = []; avgHSWait2 = [];
        % average wait time for served HS customers

totalHSServed0 = []; totalHSServed1 = []; totalHSServed2 = [];
 % total number of HS customers served

avgQWait0 = []; avgQWait1 = []; avgQWait2 = [];
        % average wait time for customers still on Q

totalQWait0 = []; totalQWait1 = []; totalQWait2 = [];
        % total number of HS customers still on Q

avgIdle0 = []; avgIdle1 = []; avgIdle2 = [];
        % average time idle for a taxi

avgTaxing0 = []; avgTaxing1 = []; avgTaxing2 = [];
        % average time taxing for a taxi

avgPickup0 = []; avgPickup1 = []; avgPickup2 = [];
        % average time picking up customer for a taxi

avgCourier0 = []; avgCourier1 = []; avgCourier2 = [];
        % average time transporting customer for a taxi

for t = simDurL:simDurS:simDurH,
  ti = ti+1;
  for u = citySizeL:citySizeS:citySizeH,
    ui = ui+1;
    for v = numHSL:numHSS:numHSH,
      vi = vi+1;                                % number of hotstpos--X-
AXIS <<<<<<<<<<<<<<<<<<<<<
      for w = numTaxiL:numTaxiS:numTaxiH,
        wi = wi+1;
        for x = taxiSpeedL:taxiSpeedS:taxiSpeedH,
          xi = xi+1;
          for y = genLambL:genLambS:genLambH,
```

```
        yi = yi+1;          % percentage generic lambda--Y-AXIS
<<<<<<<<<<<<<

        % Clear variables just in case...
        uSt0 = []; uSt1 = []; uSt2 = [];

        % HotspotLambda
        hlamb = [];
        % first two hotspots takes up 25% each, leaving 50% to be divided
among rest
        hsfrac = (totalLambda*(1-y))/(v+2);
        hlamb = hsfrac*ones(1,v);
        hlamb(1) = hlamb(1)+hsfrac;
        hlamb(2) = hlamb(2)+hsfrac;
        hlamb

        param = [t u v w x totalLambda*y]

        % Strategy
        disp('******STRATEGY 0*******************************');
        strg = 0;
        [uSt0, tSt0] = taxiSim(param,hlamb,strg,rSeed);
        %uStat(ti,ui,vi,wi,xi,yi,:) = uSt;
        %tStat(ti,ui,vi,wi,xi,yi,:,:) = tSt;
        %   variable display for DEBUGGING
<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<
<<<<<<
        uSt0
        %tSt
        totalTaxiStat0 = sum(tSt0,2)

        % Strategy
        disp('**********STRATEGY
1******************************');
        strg = 1;
        [uSt1, tSt1] = taxiSim(param,hlamb,strg,rSeed);
        %uStat(ti,ui,vi,wi,xi,yi,:) = uSt;
        %tStat(ti,ui,vi,wi,xi,yi,:,:) = tSt;
        %
      <<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<<
<<<<<<<<<<<
        uSt1
        %tSt
        totalTaxiStat1 = sum(tSt1,2)

        % Strategy
```

```
disp('**********STRATEGY
2*****************************');
strg = 2;
[uSt2, tSt2] = taxiSim(param,hlamb,strg,rSeed);
%uStat(ti,ui,vi,wi,xi,yi,:) = uSt;
%tStat(ti,ui,vi,wi,xi,yi,:,:) = tSt;
uSt2
%tSt
totalTaxiStat2 = sum(tSt2,2)

% Store data in a variable to be saved for analysis
avgTotalWait0(vi,yi) = uSt0(1)/(uSt0(8)+uSt0(9));
% avg wait time for a customer (served)

avgTotalWait1(vi,yi) = uSt1(1)/(uSt1(8)+uSt1(9));
avgTotalWait2(vi,yi) = uSt2(1)/(uSt2(8)+uSt2(9));

avgGenWait0(vi,yi) = uSt0(2)/uSt0(8);
% avg wait time for a gen customer (served)

avgGenWait1(vi,yi) = uSt1(2)/uSt1(8);
avgGenWait2(vi,yi) = uSt2(2)/uSt2(8);

totalGenServed0(vi,yi) = uSt0(8);
    % total number of gen customers served

totalGenServed1(vi,yi) = uSt1(8);
totalGenServed2(vi,yi) = uSt2(8);

avgHSWait0(vi,yi) = uSt0(4)/uSt0(9);
% average wait time for served HS customers (served)

avgHSWait1(vi,yi) = uSt1(4)/uSt1(9);
avgHSWait2(vi,yi) = uSt2(4)/uSt2(9);

totalHSServed0(vi,yi) = uSt0(9);
% total number of HS customers served

totalHSServed1(vi,yi) = uSt1(9);
totalHSServed2(vi,yi) = uSt2(9);

if uSt0(7) ~= 0     % to avoid a DIV/0 error
  avgQWait0(vi,yi) = uSt0(6)/uSt0(7);
    % average wait time for customers still on Q (NOT served)

  totalQWait0(vi,yi) = uSt0(7);
```

```
    % total number of HS customers still on Q (NOT served)
else
  avgQWait0(vi,yi) = -1;
  totalQWait0(vi,yi) = -1;
end% if uSt0(7)

if uSt1(7) ~= 0
  avgQWait1(vi,yi) = uSt1(6)/uSt1(7);
    % average wait time for customers still on Q (NOT served)

  totalQWait1(vi,yi) = uSt1(7);
    % total number of HS customers still on Q (NOT served)
else
  avgQWait1(vi,yi) = -1;
  totalQWait1(vi,yi) = -1;
end% if uSt0(7)

if uSt2(7) ~= 0
  avgQWait2(vi,yi) = uSt2(6)/uSt2(7);
    % average wait time for customers still on Q (NOT served)

  totalQWait2(vi,yi) = uSt2(7);
    % total number of HS customers still on Q (NOT served)
else
  avgQWait2(vi,yi) = -1;
  totalQWait2(vi,yi) = -1;
end% if uSt0(7)

avgIdle0(vi,yi) = totalTaxiStat0(1)/w;
    % average time idle for a taxi

avgIdle1(vi,yi) = totalTaxiStat1(1)/w;
avgIdle2(vi,yi) = totalTaxiStat2(1)/w;

avgTaxing0(vi,yi) = totalTaxiStat0(2)/w;
    % average time taxing for a taxi

avgTaxing1(vi,yi) = totalTaxiStat1(2)/w;
avgTaxing2(vi,yi) = totalTaxiStat2(2)/w;

avgPickup0(vi,yi) = totalTaxiStat0(3)/w;
    % average time picking up customer for a taxi

avgPickup1(vi,yi) = totalTaxiStat1(3)/w;
avgPickup2(vi,yi) = totalTaxiStat2(3)/w;
```

```
            avgCourier0(vi,yi) = totalTaxiStat0(4)/w;
                % average time transporting customer for a taxi

            avgCourier1(vi,yi) = totalTaxiStat1(4)/w;
            avgCourier2(vi,yi) = totalTaxiStat2(4)/w;

          end  % y
          yi = 0;
        end    % x
        xi = 0;
      end      % w
      wi = 0;
    end% v
    vi = 0;
  end  % u
  ui = 0;
end    % t
ti = 0;

avgTotalWait0
avgTotalWait1
avgTotalWait2

avgGenWait0
avgGenWait1
avgGenWait2

totalGenServed0
totalGenServed1
totalGenServed2

avgHSWait0
avgHSWait1
avgHSWait2

totalHSServed0
totalHSServed1
totalHSServed2

avgQWait0
avgQWait1
avgQWait2

totalQWait0
totalQWait1
totalQWait2
```

```
avgIdle0
avgIdle1
avgIdle2

avgTaxing0
avgTaxing1
avgTaxing2

avgPickup0
avgPickup1
avgPickup2

avgCourier0
avgCourier1
avgCourier2

display('      ******************************************** ');
display('      ************** FINISH runSim.M ************** ');
display('      ******************************************** ');

save 'numberHS_PercentageHS.txt' avgTotalWait0 avgTotalWait1 avgTotalWait2
avgGenWait0 avgGenWait1 avgGenWait2 totalGenServed0 totalGenServed1
totalGenServed2 avgHSWait0 avgHSWait1 avgHSWait2 totalHSServed0
totalHSServed1 totalHSServed2 avgQWait0 avgQWait1 avgQWait2 totalQWait0
totalQWait1 totalQWait2 avgIdle0 avgIdle1 avgIdle2 avgTaxing0 avgTaxing1
avgTaxing2 avgPickup0 avgPickup1 avgPickup2 avgCourier0 avgCourier1
avgCourier2 -ASCII;
save 'numberHS_PercentageHS.mat' avgTotalWait0 avgTotalWait1 avgTotalWait2
avgGenWait0 avgGenWait1 avgGenWait2 totalGenServed0 totalGenServed1
totalGenServed2 avgHSWait0 avgHSWait1 avgHSWait2 totalHSServed0
totalHSServed1 totalHSServed2 avgQWait0 avgQWait1 avgQWait2 totalQWait0
totalQWait1 totalQWait2 avgIdle0 avgIdle1 avgIdle2 avgTaxing0 avgTaxing1
avgTaxing2 avgPickup0 avgPickup1 avgPickup2 avgCourier0 avgCourier1
avgCourier2;
diary off;
```

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