Effect of Taxi Information System on Efficiency and Quality of Taxi Services

UCI-ITS-TS-WP-04-11

Hyunmyung Kim 1
Jun-Seok Oh 2
R. Jayakrishnan 1

1 Department of Civil and Environmental Engineering and Institute of Transportation Studies, University of California, Irvine
hyunmyuk@uci.edu, rjjayakr@uci.edu

2 Department of Civil and Construction Engineering Western Michigan University
jun.oh@wmich.edu

July 2004

Institute of Transportation Studies University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
http://www.its.uci.edu
Effect of Taxi Information System on Efficiency and Quality of Taxi Services

Hyunmyung Kim
Graduate Student Researcher
Department of Civil Engineering and Institute of Transportation Studies
University of California, Irvine
Irving, CA 92697-3600
Tel: (949) 824-5623, Fax: (949) 824-8385, E-mail: hyunmyung@uci.edu

Jun-Seok Oh
Assistant Professor
Department of Civil and Construction Engineering
Western Michigan University
Kalamazoo, MI 49008-5316
Tel: (269) 276-3216, Fax: (269) 276-3211, E-mail: jun.oh@wmich.edu

R. Jayakrishnan
Associate Professor
Department of Civil Engineering and Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600
Tel: (949) 824-2172, Fax: (949) 824-8385, E-mail: rjaya@uci.edu

Word count: 4,122 + 12 × 250 = 7,122

July 30, 2004

Paper for the 84th Annual Meeting of the Transportation Research Board
ABSTRACT

In many major metropolitan areas, taxi services have been playing an important role as a semi-public transportation mode without public support. This study models a taxi service system in urban areas considering taxi drivers' knowledge on the transportation network accumulated from their day-to-day experience. The model considers the stochastic and dynamic transportation network and various levels of drivers' network knowledge. This study analyzes the fleet size of taxi service systems and the effects of taxi company's information systems by considering quality and operational efficiency of taxi services, from both the passengers' and taxi operator's point of view.
INTRODUCTION

In many major metropolitan areas around the world, taxi services have been playing an important role as a semi-public transportation mode without public-sector support. Unlike the dial-and-ride systems and the lower taxi demand cases in some of the US cities, many urban taxi services still rely on the drivers’ experience in seeking passengers, the passengers waiting for taxis on roadside without reservations. Due to the inherent randomness in taxi service systems, there has not been much modeling effort despite its importance in urban transportation systems. While most previous studies have been based on an abstract, aggregate demand and supply model or based on a simplified, specific structural model, recently there have been some studies that model taxi services within mathematical formulations of the transportation network problem.

(1, 2, 3)

Yang and Wong (1) first presented a network model for taxi operations as a mathematical optimization problem. The model was designed to explicitly consider the effects of the taxi fleet size and the uncertainty in the system performances. Wong et al. (2) improved the network model by incorporating variable demand and multi-class vehicle assignment. Their bi-level problem combined both taxi traffic and normal traffic in a network equilibrium model to find the optimal taxi operation pattern. In the same line of their previous work, recently Yang et al. (3) investigated the nature of demand-supply equilibrium in a regulated market for taxi service from a case study for the city of Hong Kong. Their network models contributed to analyzing taxi services by providing a network equilibrium model for the taxi service problem. However, their model framework is based on static equilibrium where time-variant effects are not considered, and the model has limitation in modeling detailed operational characteristics.

One of the major difficulties in modeling taxi services is dealing with uncertainty in both demand and supply. Taxi drivers’ objective is to minimize vacant taxi time; however, they do not know where passengers are. In order to consider the uncertainty in both demand and supply, this study applies a stochastic modeling approach in a dynamic transportation network. Taxi drivers’ decision process is modeled by applying a day-to-day learning process. That is, taxi drivers improve their ability seeking passengers through their own experiences. This modeling approach provides flexibility in modeling the characteristics of taxi operation as well as understanding how taxi drivers’ capability evolves. This study is particularly interested in investigating effects of the taxi fleet size and taxi company’s information systems on quality and operational efficiency of taxi services from both passenger and taxi operator’s point of view.
MODELING A URBAN TAXI SERVICE SYSTEM

This study develops a dynamic urban taxi service model in a stochastic network. In modeling taxi drivers’ learning process, we employ a day-to-day evolution approach that has been introduced by Horowitz (4), Vythoulkas (5) and Cascetta and Cantarella (6). Figure 1 presents the overall structure of the taxi simulation model.

Even though the overall structure of the model is based on the day-to-day evolution approach, the taxi model includes a within-day learning process as well to reflect the nature of taxi drivers’ repeated travel. In the model, drivers acquire knowledge on network and passenger demand only from their experience, and their knowledge is inductively updated. The taxi drivers’ passenger seeking behavior is modeled based on their expected travel time and expected waiting time.

<< Insert Figure 1 here >>

Stochastic Network and Demand

Time-dependent Link Travel Times

In our model, link travel times are time-variant, but independent of taxi traffic. We assume a daily link travel time pattern with two peak periods (7 – 9 A.M. for morning peak and 5 – 7 P.M. for evening peak period), non-peak period, and transition periods (one hour between peak and non-peak) during the 18 hour from 6 AM to midnight. Link travel times for every 5-minute interval are generated based on traffic pattern with uncertainty by applying random disturbances as follows.

\[ t_i^d(k) = t_i^{avg}(k) + \epsilon_i \]  

- \( t_i^d(k) \) = the travel time of link \( i \) for the time step \( k \) on day \( d \).
- \( t_i^{avg}(k) \) = the average travel time of link \( i \) for the time step \( k \) on day \( d \).
- \( \epsilon_i \) = the random disturbance of link \( i \).
Probabilistic Passenger Generation

Passengers waiting for taxi services are generated time-dependently based on the
assigned passenger arrival rate at each node, and their destinations are assigned based
the trip distribution ratio (\(\psi r s\)) between origin \(r\) and destination \(s\).

\[
N^t_{r \rightarrow s} = O^t_{r \rightarrow s} \cdot \psi^{r s}
\]

(2)

\[
N^r_{s \rightarrow r \text{ peak}} = O^r_{s \rightarrow r \text{ peak}} \cdot \psi^{r s}
\]

(3)

where

- \(N^t_{r \rightarrow s}\) is the number of passengers to travel between OD pair \(rs\) during peak hour,
- \(O^t_{r \rightarrow s}\) is the number of passengers generated at origin node \(r\) during peak hour, and
- \(\psi^{r s}\) is the trip ratio to destination \(s\) for passengers from node \(r\).

The model generates passengers at each node each time interval, and
probabilistically assigns passenger’s destination based on the trip ratio. Therefore, in the
model, the number of passengers at each node and their destinations are determined as
follows.

\[
n^t_{r \rightarrow s}(k) = \frac{N^t_{r \rightarrow s} \cdot \Delta t}{60} = n + \xi
\]

(4)

\[
n^r_{s \rightarrow r \text{ peak}}(k) = \frac{N^r_{s \rightarrow r \text{ peak}} \cdot \Delta t}{60} = n + \xi
\]

(5)

where

- \(n^t_{r \rightarrow s}(k)\) is the number of passengers to travel between \(rs\) during the time interval \(k\),
- \(\Delta t\) is length of the simulation time interval in minute,
- \(n\) is an integer value, and
- \(\xi\) is a real value between 0 to 1 indicating probability of having one additional
  passenger.
Inductive Learning Model

The core element of the model is incorporating taxi drivers’ inductive learning behavior based on their previous trip experience. In the model, drivers update their knowledge instantly whenever they acquire new knowledge.

Taxi Drivers’ Prior Knowledge and Information

We postulate four variables for taxi driver’s passenger seeking behavior: 1) expected link travel times, 2) expected taxi queues at nodes, 3) expected passenger arrival headways at nodes, and 4) expected passenger queues at nodes. We assume taxi drivers perceive their knowledge based on three periods—peak period, non-peak period, and transition period, and have initial (or prior) information on these variables for each period. Drivers’ prior knowledge on link travel times is modeled by combining random disturbance for each link for each driver as follows:

\[ i^p_{a,m} = a^{m\rightarrow a} \cdot t_i^f (1 \pm \epsilon_{a,m}^{m\rightarrow a}) \]  
\[ i^{peak}_{a,m} = [a^{m\rightarrow a} + a^{a\rightarrow m}] \cdot t_i^f (1 \pm \epsilon_{a,m}^{a\rightarrow m}/2) \]  
\[ i^{non-peak}_{a,m} = a^{a\rightarrow m} \cdot t_i^f (1 \pm \epsilon_{a,m}^{a\rightarrow m}) \]

where

- \( t_i^f \) is the expected link travel time of link \( i \),
- \( a \) is a congestion factor (\( a^{peak} > a^{m\rightarrow a} \)),
- \( t_i^f \) is the free-flow travel time of link \( i \), and
- \( \epsilon_{a,m} \) is random disturbance of link \( i \) for taxi driver \( m \).

By doing so, each taxi driver perceives different link travel times. However, we assumed that all drivers have the same initial perception for other variables: the expected taxi queue (\( \bar{q}_{a,m}^{m\rightarrow a} \)), the expected passenger arrival headway (\( \bar{h}_{a,m}^{a\rightarrow m} \)), and the expected passenger queues (\( \bar{q}_{a,m}^{a\rightarrow m} \)). Same as the link travel times, random disturbances are applied to these variables. Here \( m \) denotes a taxi driver, and \( n \) denotes \( \epsilon \) node.

Although the notation is omitted here, these variables vary by period.
Taxi Drivers’ Learning Model

In this study, taxi drivers’ knowledge is assumed imperfect and limited, but is updated only from their experience. Thus, we model taxi drivers’ learning mechanism as a process. In the model, taxi drivers update their network and demand knowledge—
including link travel times, taxi queues, passenger arrival rates, and passenger queues—through post-evaluation process after their experience. Unlike other day-to-day approaches (4, 6, 7, 8, 9, 10, 11, 12), drivers update their knowledge not only day-to-
day but also every time they acquire information. That is, this learning model also
includes a within-day learning process as well.

The updating process of driver’s link travel time is as follows.

\[ i_{mn,k}^{l, t^{-1}} = (1-s) i_{mn,k}^{l,t} + s \cdot i_{mn,k}^{l,t}(k) \quad \forall \, k, m, n \quad (9) \]

where \( s \) denotes a learning rate (0≤s≤1), and \( d \) denotes the number of visits rather than
day in this case. For simplicity, we abbreviate the period (eg. peak, non-peak, and
transition).

Similarly to link travel time, the expected taxi queue and the expected passenger queue at each node are also updated when the taxi driver visit the node. That is, a taxi
driver updates his/her knowledge on the taxi queue and the passenger queue at the node
whenever he/she travel the node as follows:

\[ q_{mn,k}^{ex,k,t^{-1}} = (1-s) \cdot q_{mn,k}^{ex,k,t} + s \cdot q_{mn,k}^{ex,k,t}(k) \quad \forall \, k, m, n \quad (10) \]

\[ q_{mn,k}^{pass,k,t^{-1}} = (1-s) \cdot q_{mn,k}^{pass,k,t} + s \cdot q_{mn,k}^{pass,k,t}(k) \quad \forall \, k, m, n \quad (11) \]

The taxi driver’s knowledge on the passenger arrival headway at a node is also
updated with similar manner, but only with the driver’s direct experience. It is because
the information cannot be gathered unless the taxi driver spends some time to acquire it
unlike the information on taxi and passenger queues. The expected passenger headway
at node \( n \) for driver \( m \) is updated as follows:

\[ h_{mn,k}^{ex,k,t^{-1}} = (1-s) \cdot h_{mn,k}^{ex,k,t} + s \cdot \left( \frac{\sum_{m' \in N_{mn,k,t}} h_{m'k}^{ex,k,t}}{N_{mn,k,t}} \right) \quad \forall \, m, n \quad (12) \]

where \( N_{mn,k} \) is the number of time steps that driver \( m \) stayed until he/she picks up a
passenger, and \( h(k) \) is the observed passenger headway during the time step \( k \).
Taxi Driver’s Decision Making

Basically, the taxi driver’s passenger searching problem is a destination choice problem to minimize his/her idling time (travel time + waiting time). When a taxi becomes vacant, the taxi driver will search for a new node (new destination) to minimize his/her idling time. The objective function for destination choice for driver m at node r can be formalized as follows.

\[ \arg \min \left[ t^{m}_{r} + \Phi_{m}, \tau_{m,r} \right] \]  

(13)

where \( t^{m}_{r} = 0 \) if \( r = s \).

The decision model includes three attributes: expected travel time, expected waiting time, and taxi driver’s node preference. The following subsections explain how to calculate the expected waiting time and the taxi driver’s node preference.

Calculation of Expected Waiting Time

The expected waiting time is calculated in two different ways depending on the situation at the node. The expected waiting time at the node is 0 if the expected passenger queue at the node is larger than 1. On the other hand, if the taxi driver expects no passenger is waiting at the node, the expected waiting time at the node is calculated based on the expected passenger arrival headway and the expected taxi queues at the node.

\[ \bar{W}_{r,s} = \begin{cases} 0 & \text{if } \bar{W}_{r,s}^{\text{ex}} \geq 1 \\ \frac{1 + \bar{W}_{r,s}^{\text{ex}}}{\bar{W}_{r,s}^{\text{ex}}} & \text{otherwise} \end{cases} \]  

(14)

Modeling Driver’s Node Preference

In this paper, driver’s preference behavior is included in the driver’s decision process. This preference reflects driver’s habitual or irrational behavior as introduced by Nakayama et al. (6) for their route preference study. In our case, this preference model reflects reliability of driver’s expectation at nodes as a result of all decision variables combined together. Taxi driver’s node preference is developed by his/her post-evaluation process, and updated through the inductive learning process. That is, driver’s preference for a node increases if he/she experiences shorter idling time than expected,
and vice versa. To simplify the model, we consider only drivers’ node preference, and so the preference is determined only by the waiting time at the node. As described in Figure 2, the preference function, \( \psi() \), includes an indifference band (\( \epsilon \)) where drivers ignore the minor discrepancy in their expectation, and the slope (sensitivity, \( \sigma \)) could vary by driver. Driver’s node preference is updated as follows:

\[
\Phi_{n,m}^{s+1} = (1 - s)\Phi_{n,m}^{s} + s \cdot \psi(w_{n,m}, \bar{w}_{n,m})
\]

where

\[
\Phi_{n,m}^{s}
\]

denotes driver \( m \)'s preference for node \( n \) at iteration \( s \), and

\[
\psi(w_{n,m}, \bar{w}_{n,m})
\]

is preference as a function of the expected waiting time (\( \bar{w}_{n,m} \)) and the experienced waiting time (\( w_{n,m} \)).

<< Insert Figure 2 here >>

Dynamic Simulation Model for Urban Taxi Service

This section briefly describes how taxis move to pick up passengers. Although the model developed in this study reports taxis’ movements and passengers’ arrivals in a discrete time interval, it determines individual taxis’ movement and statistics including pick-up decisions and pick-up time in a continuous time dimension. When there are multiple vacant taxis on upstream links and a passenger waiting for service at the downstream node, the model decides which taxi to pick up the passenger by the order of arrival. In our model, all taxi drivers always try to minimize their idling time without predicting future condition, so they pick up passengers whenever available. Figure 3 shows the procedure how to determine the taxi to pick up a passenger and how to calculate the passenger’s waiting time.

<< Insert Figure 3 here >>
SIMULATION EXPERIMENT

Test Network and Scenario

The developed model is tested in a test network. As shown in Figure 4, the network consists of 16 nodes and 52 links. All nodes are assumed centroids where passengers are generated. Nodes are classified into three groups by the level of demand: downtown (node 1), sub-centers (nodes 2, 3, and 4), and suburban areas (node 5 – node 16).

In our model, passenger trips are generated based on the demand rate at each node during the periods (peak hours and non-peak hours) and the trip distribution pattern. We assume that the trip generation rate during the non-peak is a half of the peak hour’s while the trip distribution pattern remains same. Finally, passengers are generated every 5 minute interval.

For each driver’s initial perception on link travel times, we assume that the congestion factors are 1.0 and 2.0 for non peak-period (\(\alpha^{*} = 1.0\)) and peak period (\(\alpha^{*} = 2.0\)), respectively. We also apply a random disturbance factor (\(\varepsilon_{n}\)) of 10%. That is, initial link travel times during peak hours are twice longer than those during non-peak hours, and each driver’s perception on link travel times vary by ±10%.

The initial values for the expected taxi queue (\(Q_{n}^{T} \)) and the expected passenger queues (\(Q_{n}^{p} \)) are assumed to be same at all nodes, but vary by period. We apply 0.5 for non-peak period and 1.0 for peak-period on average. For the average expected passenger arrival headway (\(H_{n}^{a} \)), we apply the average of the passenger arrival headway at each node. Based on these average values, we randomly assign individual drivers’ perception error up to ±50%.

In this simulation experiment, we apply the learning parameter (\(\gamma\)) of 0.05, and drivers’ initial node preference (\(Q_{n}^{i}\)) of 1.0. In the preference function, \(\gamma(\cdot)\), we assign a random value between 0 to 6 3 to each driver as a sensitivity parameter (\(\sigma\)), and assume the indifference band (\(\epsilon\)) ±10%. To obtain stable results, we simulate the model for 200 days.
Taxi Drivers’ Learning Behavior in a Dynamic Stochastic Network

We first investigate the taxi drivers’ learning behavior in a dynamic stochastic network. In our simulation approach, taxi drivers’ travel knowledge is updated through their day-to-day within-day experience. In this experiment, we assume that there are sixty taxis in the network and that the drivers rely only on their experience.

First, we investigate how accurately taxi drivers can predict travel times. As shown in Figure 5, the error in their expected travel time decreases as drivers accumulate their experience. Through their experience, drivers were able to predict travel times within an error rate of 15%. Considering the maximum link travel time variability of 10%, the error range is quite an accurate level.

<< Insert Figure 5 here >>

Next, we investigate if taxi drivers can improve their capability in predicting passenger queues at nodes. This capability is important for taxi drivers’ efficient operation. By improving this capability, taxi drivers will be able to seek passengers more efficiently. Figure 6 shows changes in taxi drivers’ capability in predicting passenger queue. While the error in their expectation during the non-peak period fluctuated day-to-day without significant improvement, minor improvements were observed during the peak period. It seems because drivers could acquire meaningful knowledge only when there were enough passengers to satisfy statistical significance. During the non-peak period, drivers were not able to develop their significant knowledge from the random trend due to the lack of data.

<< Insert Figure 6 here >>

Although we can find some intuition on the operational efficiency from the taxi drivers’ capability in predicting passenger queue in Figure 6, the ratio of vacancy in time is a direct measure of taxi operational efficiency. Figure 7 shows how the operational efficiency changes as taxi drivers’ experience increases. We were not able to observe any improvement in the taxi operational efficiency. Another important index
in taxi service is passengers' waiting time that represents quality of taxi service from passengers' point of view. Figure 8 shows changes in passengers' average waiting time. Unfortunately, we do not observe any improvement in the figure despite taxi drivers' more experience in the network.

<< Insert Figure 7 here >>

<< Insert Figure 8 here >>

In summary, even though taxi drivers can improve their network knowledge from their day-to-day experience, such experience does not necessarily improve operational efficiency or quality of taxi service. It is mainly because the taxi demand is not enough to develop significant passenger statistics and taxis' destinations are dependent on passengers' trip not drivers' choices.

Effect of Taxi Fleet Size on Taxi Services

From previous section, we observed that taxi drivers' day-to-day experience would not significantly affect taxi services despite taxi drivers' improved capability in travel time prediction. In this section, we investigate the effects of the fleet size on taxi services. In this experiment, we do not attempt to investigate the optimal fleet size. Rather, we are interested in the effects on the operational efficiency and the quality of service with respect to the taxi fleet size under fixed taxi passenger demand. That is, the model is applicable as a performance predictor rather than an optimizer.

Figure 9 compares the number of rides per taxi each day and the ratio of vacant travel time with respect to the fleet size. Obviously, as the fleet size increases, the taxi operational efficiency decreases with the number of rides reducing and the vacant travel increasing. On the other hand, as shown in Figure 10, passengers' average waiting time decreases as the fleet size increases. However, changes in the passengers' average waiting time are more sensitive when the fleet size reduces.

<< Insert Figure 9 here >>

<< Insert Figure 10 here >>
Effect of Taxi Information System on Taxi Services

In this section, we investigate the effectiveness of taxi information systems. Various kinds of taxi information systems are possible. A common information system in transportation is one that provides travel time information for better route choice. However, as we observed in the previous section, taxi drivers could predict recurrent traffic congestions quite well from their travel experience, and such a capability may not significantly improve their operational efficiency, other than under unexpected conditions. Another finding from the taxi driver's learning model is that taxi drivers may be able to improve their knowledge with passenger location information, which leads to needs for such a capability in taxi information systems. Therefore, in this study, the taxi information system provides taxi drivers with passenger location information. To reflect a real situation, we assume that only instantaneous information (that does not involve any prediction) is available. This means that the number of passengers waiting at a location could change by the time the driver arrive at the location. That is, the instantaneous information does not guarantee accuracy, but it plays an important role in improving the operational efficiency by helping drivers find a desirable location.

First, we analyze the taxi operational efficiency as the number of taxi drivers receiving information increases. As before, the ratio of vacant travel time is regarded as an index for operational efficiency. As shown in Figure 11, the overall efficiency improves slightly as more taxi drivers receive information. However, taxi drivers with information can reduce their vacant driving compared to those without information. The benefit of taxi drivers with information reduces as more drivers receive the information. Similar tendency has been identified in many studies on information systems. In our case, although information receivers are at an advantage relative to the normal drivers, only minor improvement in overall operational efficiency was observed. That is, in terms of the unoccupied travel time, it was a zero-sum game between drivers with information and those without information.

<< Insert Figure 11 here>>

Another important measure of operational efficiency is vacant taxi travel distance. Although very similar, the ratio of vacant taxi travel distance is a little different from that of vacant taxi travel time in that the distance is measured only when the taxi is moving. Figure 12(a) compared the travel distance traveled without passenger. The figure shows similar pattern as the ratio of vacant travel time in Figure 11.

However, unlike the case of vacant travel time, the average vacant travel distance
decreases as more taxis receive information. When more than 60% of taxis receive information, approximately 10% of the vacant travel distance can be reduced. It is because taxi drivers with information take advantage in seeking passengers and improve their knowledge from the information as well. As shown in Figure 12(b), informed taxi drivers’ occupied travel distance, which is almost equivalent to the taxi revenue, is 24% greater than non-informed taxi drivers when only 10% of drivers receive information. The average value is same regardless of the percentage of informed drivers in our case where the taxi demand is fixed. Figure 12(c) shows changes in average travel distances. It shows that informed drivers travel less than non-informed drivers although their occupied travel distance is longer than that of the uninformed drivers. Another interesting finding is that information reduces overall taxi travel distance. It is because information helps taxi drivers reduce unnecessary rambling travel. This implies that information is also beneficial to the general traffic system by reducing the unnecessary taxi travel.

<< Insert Figure 12 here >>

Lastly, we investigate effect of information on passengers’ waiting time reduction. This measures the quality of taxi service from the passenger’s point of view. As shown in Figure 13, the passengers’ average waiting time decreases as more taxis receive information. Especially during the non-peak period, the waiting time can be drastically reduced. However, the benefit is relatively small during the peak period. On average, when more than 20% of taxi drivers use information, more than 15% of the passengers’ average waiting time can be saved. This benefit is equivalent to providing 20% more taxis under no information.

<< Insert Figure 13 here >>

CONCLUSION

In this paper, we developed a simulation model for urban taxi services in a dynamic and stochastic network. The model is based on a simple learning model to represent driver’s destination choice behavior. The developed simulation model gives good insights for urban taxi service in dynamic situation.

Through a simulation experiment, this study identified several interesting points for taxi information system. First, from a drivers’ day-to-day learning behavior analysis,
it was found that taxi drivers could improve their capability in predicting non-recurrent traffic condition, but they could not acquire enough knowledge on taxi demand. Second, despite taxi drivers’ improved knowledge on network condition from their experiences, the operational efficiency and the quality of taxi service may be not improved. Third, the taxi information system helps drivers efficiently seek passengers and reduces unnecessary travel. Lastly, the taxi driver information system can provide benefit equivalent to increasing the number of taxis by 20% in terms of the quality of taxi service.

This study provides another modeling approach for taxi service systems. As shown in paper, the simulation approach is helpful in understanding drivers’ behavior as a process. The model developed in this study is flexible in its nature, and can be further improved by incorporating taxi fare system and elastic demand.

REFERENCES

2. Wong, K. I., S C. Wong, and H.Yang, Modeling urban taxi services in congested road networks with elastic demand, Transportation Research part B. vol. 35., 2001, pp. 819-842


Figure 1. Overall structure of taxi simulation model
Figure 2. Preference model based on post-evaluation

Figure 3. Determination of a taxi to pick-up and passenger’s waiting time
Figure 4. Test network

Figure 5. Improvement of taxi drivers' link travel time prediction capability
Figure 6. Improvement of taxi drivers’ passenger queue prediction capability

Note) Thicker lines are polynomial trend lines.

Figure 7. Changes in taxi operational efficiency
Figure 8. Changes in passengers' average waiting time

Figure 9. Changes in average passenger and vacant taxi time by taxi fleet size
Figure 10. Passenger waiting time vs. taxi fleet size

Figure 11. Effect of taxi information system on vacant travel time
Figure 12. Effect of information on taxi travel distances
Figure 13. Effect of information on passenger waiting time reduction