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Research Article

Parking Pricing and Model Split under Uncertainty

Chengjuan Zhu,[1] Bin Jia,[1] Linghui Han,[2] and Ziyou Gao[2]

[1] *State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing 100044, China*
[2] *MOE Key Laboratory for Urban Transportation Complex Systems Theory, Beijing Jiaotong University, Beijing 100044, China*

Correspondence should be addressed to Bin Jia; bjia@bjtu.edu.cn

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In order to investigate different route choice criteria in a competitive highway/park-and-ride (P&R) network with uncertain travel times on the road, a bilevel programming model for solving the problem of determining parking fees and modal split is presented. In the face of travel time uncertainty, travelers plan their trips with a prespecified on-time arrival probability. The impact of three route choice criteria: the mean travel time, the travel time budget, and mean-excess travel time, is compared for parking pricing and modal split. The model at user equilibrium is described as a minimization model. And the analytic solutions are given. Analytic solutions show that both flow and travel time at equilibrium are independent of the price difference of travel expense on money. The main findings from the numerical results are elaborated. While given a confidence level, the flow on the highway changed significantly with the criteria, although the differences of the travel times are small. Travelers can be guided to choose their modes coordinately by improving the quality of the transit service. The optimal parking fees can be affected markedly by the confidence level. Finally, the influence of the log-normal distribution parameters is tested and analyzed.

1. Introduction

Uncertainty is unavoidable in real traffic network. It exists in both supply side (roadway capacity variation) and demand side (travel demand fluctuation). For example, bad weather and traffic incidents can reduce the capacity of the traffic network; population characteristics, special events, and traffic information can lead to the fluctuation of traffic demand. So the travel time of the traffic network is uncertain. Recently, some empirical studies on travel time uncertainty have emerged as an important topic due to its significant impacts on travelers' route choice [1–5]. Abdel-Aty et al. [1] demonstrated that travel time reliability was either the most or second most important factor for most commuters. In the study by Small et al. [2], it is reported that both individual travelers and freight carriers were strongly averse to scheduling mismatches. To model the route choice behavior under stochastic travel times, some of equilibrium-based models adopting maximum utility theory have been presented [6–12], where the disutility function was a combination of some attributes (e.g., expected travel time, travel time variance, or standard deviation, etc.). That is to say, travelers try to make a tradeoff between the expected travel time and its uncertainty. Recently, Watling [13] proposed a late arrival penalized user equilibrium (LAPUE) model using the concept of schedule delay, in which the disutility function comprises the expected generalized travel cost plus a schedule delay term to express the penalty of the late arrival under fixed departure times.

However, the maximum utility theory does not consider the reliability of travel time. To solve the problem, some researchers introduce the concept of travel time budget (TTB) to develop equilibrium model [14–16], in which TTB is defined as the average travel time plus an extra buffer time as an acceptable travel time, such that the probability of completing the trip within the TTB is no less than a predefined reliability threshold (or a confidence level α). But TTB may also be an inadequate risk measure, which could introduce overwhelmingly high trip times (i.e., unreliability aspect of travel time variability) to travelers if it is used solely as a route choice criterion in the network equilibrium-based approach. Chen and Zhou [17] proposed a new α-reliable mean-excess traffic equilibrium (METE) model that explicitly considers both reliability and unreliability aspects of travel time variability in the route choice decision process. The travelers'

choice criterion of METE is to minimize their mean-excess travel time (METT). Zhou and Chen [18] compared three different user equilibrium problem models under stochastic demand.

Recently, park pricing is considered to be an effective means of both managing road traffic demand and raising additional revenue for parking plots construction by both transportation researchers and economists. In present studies on the reliability of travel time, few of those refer to bottleneck traffic model with parking pricing. Bottleneck model studies commuting congestion in a highway between a residential area and a workplace and investigates the effects of various road control measures to alleviate the queue behind the bottleneck [19, 20]. Qian et al. [21] considered how parking locations, capacities, and charges are determined by a private parking market and how they affect travel patterns and network performances. Zhang et al. [22] derived a model to compute the morning commuting pattern when the destination has inadequate parking space to accommodate potential private cars, compare different schemes of distributing parking permits to commuters residing in different origins, and show that parking permits distribution and trading are very efficient in traffic management. Su and Zhou [23] developed a nested logit model to examine the impact of parking management, financial subsidies to alternative modes to drive alone, as well as travel demand management strategies on people's commute mode choices in Seattle based on the Washington State Commute Trip Reduction dataset in 2005.

In congested urban areas parking of cars is time-consuming and sometimes expensive, especially in the center business districts. Urban planners must consider whether and how to accommodate potentially large numbers of cars in the limited geographic areas. Usually the authorities set minimum, or more rarely maximum, numbers of parking spaces for new housing and commercial developments and may also plan their location and distribution to influence their convenience and accessibility. Urban managers usually set reasonable parking fees to regulate the parking market and then to reduce congestion on the ground. The costs or subsidies of such parking accommodations become a heated point in local politics.

The purpose of the present paper is therefore to generalize existing equilibrium assignment approaches to accommodate travelers' reactions to parking fees with variability in traffic conditions. Meanwhile, the impact of parking fees on the social travel cost under uncertain travel times will be studied. How might a conventional traffic assignment model deal with this competitive system? The remainder is organized as follows. The network description and assumptions are elaborated in Section 2. In Section 3, three different route choice criteria are discussed, which can be considered as an extension of the user equilibrium (UE) principle. A bilevel programming model for solving the problem of determining parking fees and modal split is presented. And analytic solutions at user equilibrium are given. Section 4 presents examples and numerical results and shows the effects of parking fees and different route choice criteria on traffic behaviors.

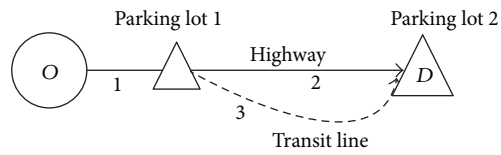

Figure 1: The simple network.

Finally, in Section 5, conclusions are drawn together with further research.

2. Network Description and Assumptions

The traffic network is a many-to-one system. It has several radial corridors (i.e., highways), which is from the urban fringe (origins) to the same city center (destination). There are two parking clusters, one is peripheral on the corridors away from the city center, and the other one is central at the city center. Each cluster has multiple parking lots. One highway, two parking lots belong to different parking clusters. Parking lots within each cluster charged the same fee and had the same space searching and access time. And the part of a corridor from the peripheral parking lot to the city center has a parallel transit line which has fixed travel time for the fixed service frequency. All of OD pairs have the same travel structure, car only or park-and-ride (P&R). Car only travelers must park their cars at the destination. Parking fees at different parking lots are similar to the cordon pricing.

Without loss of generality, the following basic assumptions are made in this paper to facilitate the presentation of the essential ideas.

(A1) Travel demand of each OD pair is invariable, so only one OD pair will be discussed.

(A2) All travelers are identical, having knowledge of the distribution of free-flow travel time variability, which can be acquired from their past commuting experiences or Advanced Traveler Information Systems (ATIS), so travelers make their travel choice decision based on the expected travel costs (which include both on time and on money).

(A3) The free-flow travel time of the highway can be influenced by the reduction of capacity (due to adverse weather). In the face of the travel time uncertainty, travelers plan their trips with a prespecified on-time arrival probability. Furthermore, the free-flow travel time distribution of the highway from the peripheral parking lots to the destination is assumed to follow a log-normal distribution.

(A4) Vehicles maintenance will not be considered. Every traveler uses car, so vehicles maintenance can be ignored. Further, the travel time from the origin to the peripheral parking lots will be considered as zero.

Based on these assumptions, the simple network is shown in Figure 1. There are two parking lots. Parking lot 1 is peripheral, while the parking lot 2 is central. The network has two routes which are denoted by link sequences, route 1: 1-2

and route 2: 1–3. There are two modes that correspond to the two routes: car only and P&R. From the assumption (A4), the travel time of link 1 is zero.

3. Model and Formulation

3.1. Three Choice Criteria. Next, the differences of using the mean travel time (MTT), TTB, and METT as the route choice criterion in a competitive traffic network will be shown. All travelers are assumed to have a same confidence level, that is, prespecified on-time arrival probability. The log-normal distribution $\log n(\mu, \sigma)$ is a nonnegative, asymmetrical distribution and has been adopted as a more realistic approximation of the stochastic travel time [17, 24]. The probability density function (PDF) is shown as below:

$$f(x \mid \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma x} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right), \quad \forall x > 0. \quad (1)$$

The variability of travel time could come from the free-flow travel time, the link capacity, or the link flow [17]. We describe that the travel time variability comes from the free-flow travel time which is due to various nonroutine events such as weather, road conditions, or traffic delays. The free-flow travel time of highway of link a, t_a^0, is a random variable. It follows the log-normal distribution $\log n(\mu, \sigma)$. The mean and variance are $E[t_a^0] = \exp(\mu + \sigma^2/2)$ and $\mathrm{Var}[t_a^0] = \exp(\mu+\sigma^2/2)(\exp(\sigma^2)-1)$, respectively. We also can get

$$\begin{aligned} \mu &= \ln\left(E\left[t_a^0\right]\right) - \frac{1}{2}\ln\left(1 + \frac{\mathrm{Var}\left[t_a^0\right]}{E\left[t_a^0\right]^2}\right), \\ \sigma^2 &= \ln\left(1 + \frac{\mathrm{Var}\left[t_a^0\right]}{E\left[t_a^0\right]^2}\right). \end{aligned} \quad (2)$$

Let us consider the widely adopted Bureau of Public Road (BPR) link performance function as follows:

$$t_a = t_a^0\left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right), \quad (3)$$

where t_a, v_a, and c_a are the travel time, flow, and capacity of link a. t_a is also a random variable. Let $y = 1 + \beta(v_a/c_a)^n$, $t_a = yt_a^0$; highway travel time follows a log-normal $\log n(\mu', \sigma')$. According to the formula (2), μ' and σ' can be calculated as follows:

$$\begin{aligned} \mu' &= \ln\left(E\left[yt_a^0\right]\right) - \frac{1}{2}\ln\left(1 + \frac{\mathrm{Var}\left[yt_a^0\right]}{E\left[yt_a^0\right]^2}\right) \\ &= \ln y + \ln\left(E\left[t_a^0\right]\right) - \frac{1}{2}\ln\left(1 + \frac{\mathrm{Var}\left[t_a^0\right]}{E\left[t_a^0\right]^2}\right) \\ &= \mu + \ln y = \mu + \ln\left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right), \\ \sigma'^2 &= \ln\left(1 + \frac{\mathrm{Var}\left[yt_a^0\right]}{E\left[yt_a^0\right]^2}\right) \\ &= \ln\left(1 + \frac{y^2\,\mathrm{Var}\left[t_a^0\right]}{y^2 E\left[t_a^0\right]^2}\right) \\ &= \ln\left(1 + \frac{\mathrm{Var}\left[t_a^0\right]}{E\left[t_a^0\right]^2}\right) \\ &= \sigma^2. \end{aligned} \quad (4)$$

So, the highway travel time distribution follows $\log n(\mu+\ln(1+\beta(v_a/c_a)^n), \sigma)$.

3.1.1. Mean Travel Time. In this simple network, the highway (i.e., route 1) travel time is equal to the travel time of link $a = 2$, and the expected travel time criterion can be derived analytically as follows:

$$\begin{aligned} \zeta(v_a) &= E\left[t_a^0\left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right)\right] \\ &= \left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right) \cdot \exp\left(\mu + \frac{\sigma^2}{2}\right) \\ &= \left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right) \cdot l_E, \end{aligned} \quad (5)$$

where $l_E = \exp(\mu + \sigma^2/2)$.

3.1.2. Travel Time Budget. The TTB ξ is defined by the travel time reliability chance constraint at a confidence level α on link a as follows:

$$\xi(\alpha, v_a) = \min\{\xi \mid \Pr(t_a \le \xi) \ge \alpha\}. \quad (6)$$

Under the assumption of the log-normal distributed route travel time, the TTB for the route 1 can be analytically computed [17] as follows:

$$\begin{aligned}\xi(\alpha, v_a) &= \exp\left(\mu + \ln\left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right) + \sqrt{2}\sigma \operatorname{erf}^{-1}(2\alpha - 1)\right) \\ &= \left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right) \cdot \exp\left(\mu + \sqrt{2}\sigma \operatorname{erf}^{-1}(2\alpha - 1)\right) \\ &= \left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right) \cdot l_T,\end{aligned} \tag{7}$$

where $l_T = \exp(\mu + \sqrt{2}\sigma \operatorname{erf}^{-1}(2\alpha - 1))$ and $\operatorname{erf}^{-1}(\cdot)$ is the inverse of the Gauss error function defined as:

$$\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x \exp\left(-t^2\right) dt. \tag{8}$$

3.1.3. Mean-Excess Travel Time. The METT η is defined with the conditional expectation of travel time exceeding the corresponding TTB at a confidence level α on link a; that is,

$$\eta(\alpha, v_a) = E\left[t_a \mid t_a \geq \xi(\alpha, v_a)\right]. \tag{9}$$

According to the log-normal distribution, the METT for the route 1 can be analytically calculated [17] as follows:

$$\begin{aligned}\eta(\alpha, v_a) &= \exp\left(\mu + \ln\left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right) + \frac{\sigma^2}{2}\right) \\ &\quad \cdot \frac{\Phi\left(-\sqrt{2}\operatorname{erf}^{-1}(2\alpha - 1) + \sigma\right)}{(1 - \alpha)} \\ &= \left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right) \cdot \exp\left(\mu + \frac{\sigma^2}{2}\right) \\ &\quad \cdot \frac{\Phi\left(-\sqrt{2}\operatorname{erf}^{-1}(2\alpha - 1) + \sigma\right)}{(1 - \alpha)} \\ &= \left(1 + \beta\left(\frac{v_a}{c_a}\right)^n\right) \cdot l_M,\end{aligned} \tag{10}$$

where $l_M = \exp(\mu + \sigma^2/2) \cdot \Phi(-\sqrt{2}\operatorname{erf}^{-1}(2\alpha - 1) + \sigma)/(1 - \alpha)$ and $\Phi(\cdot)$ is the standard normal cumulative distribution function (CDF).

3.2. Travel Costs and Model. The mean travel cost of travelers by car only (route 1) can be expressed as

$$C_1 = P_1 + m \cdot \kappa(\alpha, f_1). \tag{11}$$

The travel cost of travelers by P&R (route 2) can be expressed as

$$C_2 = P_2 + F + m \cdot t_s, \tag{12}$$

where $\kappa(\alpha, f_1)$ is the route choice criterion (i.e., $\zeta(f_1)$, $\xi(\alpha, f_1)$, $\eta(\alpha, f_1)$) of route 1; f_1 and f_2 are the flow on route 1 and route 2; m is the unit cost of the travel time; t_s and F are the travel time and fare of the transit; P_1 and P_2 are the parking fees of the destination and the P&R (the peripheral parking lot), respectively.

The total social cost (TSC) defined in this paper is the sum of all costs borne by operators and all travelers but excluding fares and parking fees. We develop a bilevel programming model for the optimal parking fees

$$\begin{aligned}\min \quad & \mathrm{TSC}(P_1, P_2) = m \cdot t_s \cdot f_2 + m \cdot f_1 \cdot \kappa(\alpha, f_1) \\ \min \quad & \int_0^{f_1} (m \cdot \kappa(\alpha, x_1) + P_1)\, dx_1 \\ & + \int_0^{f_2} (m \cdot t_s + P_2 + F)\, dx_2 \\ \text{s.t.} \quad & f_1 + f_2 = d, \\ & f_i \geq 0, \quad i = 1, 2.\end{aligned} \tag{13}$$

The total social cost of the competitive system is given by the objective function of the problem (13). The first constraint describes the conservation condition of demand and the second proves the nonnegative of the route flows. The lower level is something like UE for different route criteria. Travelers cannot unilaterally reduce their travel cost by changing their route choice. When the system reaches the equilibrium with equivalent route travel costs, the bilevel programming can be described as the following minimization model:

$$\begin{aligned}\min \quad & \mathrm{TSC}(P_1, P_2) = m \cdot t_s \cdot f_2 + m \cdot f_1 \cdot \kappa(\alpha, f_1) \\ \text{s.t.} \quad & m \cdot \kappa(\alpha, f_1) + P_1 = P_2 + F + m \cdot t_s \\ & f_1 + f_2 = d, \\ & f_i \geq 0, \quad i = 1, 2.\end{aligned} \tag{14}$$

For the sake of fairness, only the problem (14) is concerned with following. And for simplicity, we set $n = 2$ in the following study. Solve the constraints, we get

$$f_1 = c_a \sqrt{\frac{m \cdot t_s - m \cdot l - \Delta}{m \cdot \beta \cdot l}}, \tag{15}$$

where $\Delta = P_1 - (P_2 + F)$ is the price difference of travel expense on money for the two routes, $l = l_E, l_T, l_M$. The solution of the model (14) is

$$\Delta = \frac{2}{3} m \cdot (t_s - l), \tag{16}$$

$$f_1 = c_a \sqrt{\frac{t_s - l}{3l \cdot \beta}}. \tag{17}$$

The modal split at equilibrium are f_1 and $f_2 = d - f_1$. Equation (17) shows that the number of car travelers is dependent on t_s but independent of the parameter m. Substituting (16) into the cost constraint at equilibrium, we can get the following expression:

$$\kappa = \frac{t_s}{3} + \frac{2}{3} l, \tag{18}$$

Table 1: Equilibrium travel time on route 1 for different route choice criteria.

Scenarios	MTT (min)	TTB (min)	METT (min)
1	26.1846	27.9729	29.5712
2	21.1846	22.9729	24.5712

Table 2: Equilibrium flows on route 1 for different route choice criteria.

Flow on route 1	UE	RUE	METE
Scenario 1	773.3948	683.1355	613.5801
Scenario 2	529.3781	439.0619	362.5719

Table 3: Optimal parking fees.

Δ	UE	RUE	METE
Scenario 1	18.8154	17.0271	15.4288
Scenario 2	8.8154	7.0271	5.4288

where the equilibrium travel time is only depending on the transit travel time t_s and the confidence level α while given the log-normal distribution, but is independent of the flow distribution the highway capacity c_a, and the price difference of travel expense on money Δ and parameter m.

4. Examples and Numerical Results

4.1. Case 1. The free-flow travel time distribution of the road link is assumed to follow logn(2.80, 0.20), the travel demand $d = 1000$ unit, and $m = 1$. We set $c_a = 400$ unit/h, $t_s = 45$ min for scenario 1; $c_a = 400$ unit/h, $t_s = 30$ min for scenario 2; and $c_a = 600$ unit/h, $t_s = 30$ min for scenario 3. Increase of the capacity can be achieved by removing parking on the road, channelizing traffic at intersections, increasing the isolation facility to regulate pedestrian crossing, and so on.

Specially, in this experiment, the travelers are assumed to have an 80% confidence level of on-time arrival. The effects of the change of the transit travel time on various route choice models are analyzed, and the results are compared. Reducing the transit travel time can be achieved by increasing the service frequency or reducing the walking time by transit. We give the equilibrium travel times, flows, and Δ on route 1 in Tables 1, 2, and 3, respectively. The reduction of the equilibrium travel times is equivalent, as well as Δ, which coincide with (16) and (18). Therefore, both reliability and unreliability aspects of travel time should be considered in the route choice behavior, as well as in the development of the parking price. In Table 1, the difference between the MTT and the TTB is not large, but the flow on route 1 varies significantly, as shown in Table 2. The similar situation occurs in the TTB and the METT. It is shown that the reliability and the unreliability of the travel time have significant impact on travelers' route choice behavior. In Table 2, it is clear that the three user equilibrium models induce quite different equilibrium flow patterns, and reducing the transit travel time can adjust the flow on route 1 effectively. So, from the point of traffic managers' view, improving the quality of transit service can guide travelers to choose their modes coordinately.

Without loss of generality, we let the confidence level vary from 0.55 to 0.95. We show the flows on route 1, total social cost, and Δ on different route choice models in scenario 1 in Figures 2 and 3. RUE equilibrium flows tend to UE with a lower confidence level, while with a higher confidence level, the RUE equilibrium flows deviate from the UE markedly, which are shown in Figure 2(a). The flows on route 1 decrease sharply with the increasing of the confidence levels at RUE and at METE. The confidence levels have no effect on the travelers' travel behaviors at UE, so the flows on route 1 and total social costs remain unchanged. The total social costs have the opposite change tendency, as is shown in Figure 2(b). Owing to the TTB and METT increase with the confidence levels, the total social costs increase. When the confidence level is higher than 0.55, the social total cost is always higher than that at UE.

Confidence levels versus the price difference of travel expense on money are shown in Figure 3. The optimal price difference of travel expense on money decreases with the increasing of the confidence levels; and the difference between RUE and METE is getting smaller, which are coinciding with Figure 2(a).

In Figure 4, flow increments on route 1 and total social costs decrements from scenario 2 to scenario 3 with different confidence levels are shown. When the capacity increases from scenario 2 to scenario 3, more and more travelers are willing to choose P&R with the increasing of the confidence level. Because the variation of the highway capacity only has effect on the flow on route 1 but has no effect on the equilibrium travel time, total social costs decrease. However, in Figure 5, total social costs increase with the confidence levels, which are coinciding with Figure 2(b).

4.2. Case 2. The input parameters of this case are $d = 1000$ unit, $m = 1$, $c_a = 400$ unit/h, $t_s = 45$ min. The free-flow travel time distribution of the road link is assumed to logn(μ, σ) and the travelers are assumed to have an 80% confidence level of on-time arrival.

Let $\sigma = 0.20$, μ vary from 3.20 to 2.80; numerical results are shown in Table 4 at UE, Table 5 at RUE, and Table 6 at METE.

Let $\mu = 2.80$, σ varying from 0.10 to 0.35; numerical results are shown in Table 7 at UE, Table 8 at RUE, and Table 9 at METE.

From these tables below, the distribution of travel time affects the travel behavior dramatically, especially at METE. Both the optimal Δ and flow on route 1 decrease with μ and σ, but travel time at equilibrium with different choice criteria and TSC has the opposite trend. The decrease of μ and σ means the reduction of the free-flow travel time on highway further induced the reduction of the travel time at equilibrium with different choice criteria, finally the decrease of the TSC. From Table 4 to Table 9, all results listed almost are changing linearly with μ and σ, increasing or decreasing. The target of the model and assumptions about the network structure as well as the form of the BPR function may induce

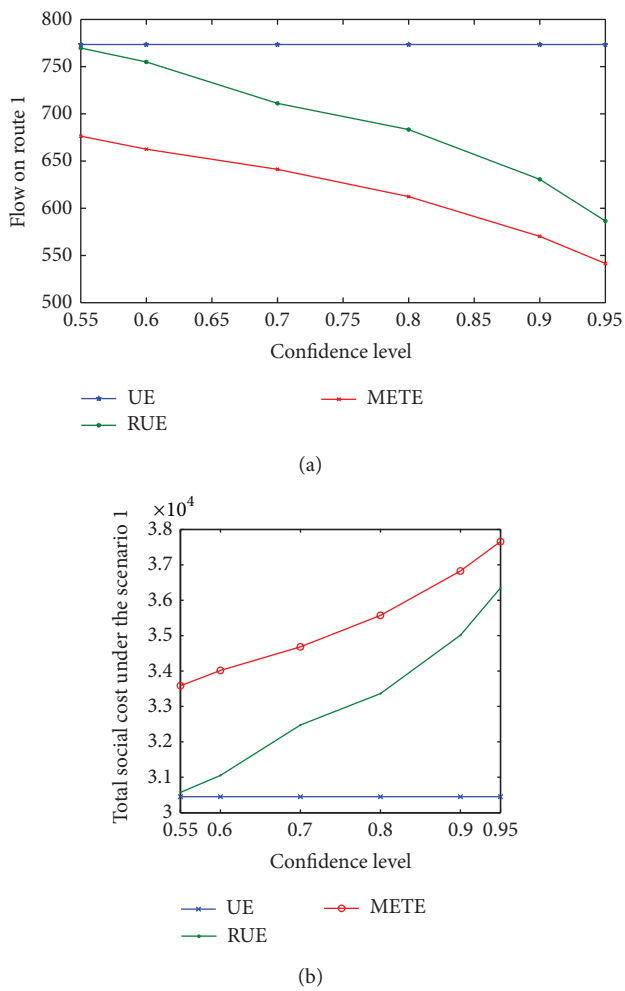

Figure 2: Flow on route 1 and TSC under the scenario 1.

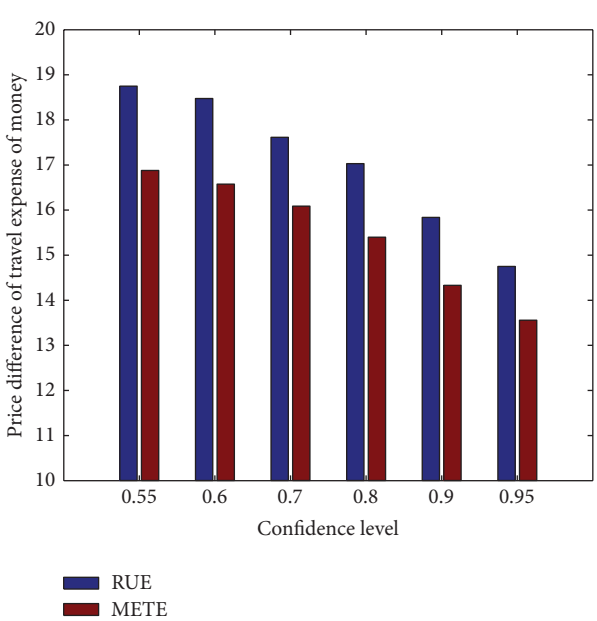

Figure 3: Confidence levels versus the price difference on money.

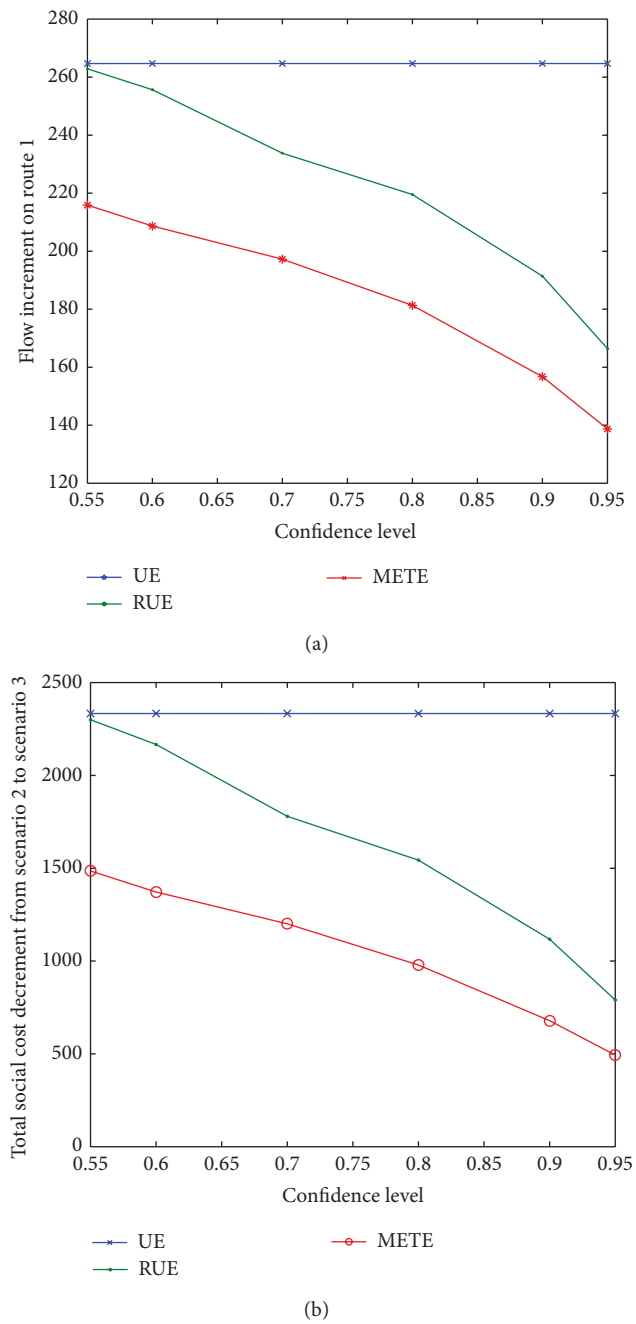

Figure 4: Route 1 flow increment and TSC decrement from scenario 2 to scenario 3.

that results. Parameters analysis will be discussed in our further research when the route travel times followed other distributions.

5. Conclusions and Further Research

In this study, a model under stochastic travel times is proposed. The model explicitly considers both travelers' preferences of risk and parking fees in a competitive system. Numerical examples were also provided to illustrate the route

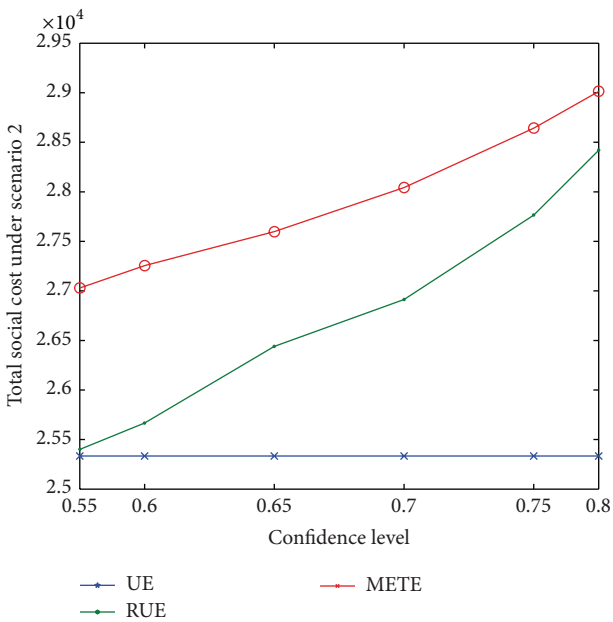

Figure 5: TSC under the scenario 2.

Table 4: Results with different μ at UE.

μ	Flow on route 1	MTT	Δ	TSC
3.20	532.6588	31.6854	13.3146	37907.8686
3.10	592.4180	30.0976	14.9024	36171.5413
3.00	652.1226	28.6609	16.3391	34344.8776
2.90	712.3085	27.3609	17.6391	32435.4889
2.80	773.3948	26.1846	18.8154	30448.2419

Table 5: Results with different μ at RUE.

μ	Flow on route 1	TTB	Δ	TSC
3.20	442.2686	34.3532	10.6468	40291.2668
3.10	503.5546	32.5115	12.4885	38711.3710
3.00	563.5860	30.8451	14.1550	37022.4864
2.90	623.2404	29.3372	15.6628	35238.3242
2.80	683.1355	27.9729	17.0271	33368.1532

Table 6: Results with different μ at METE.

μ	Flow on route 1	METT	Δ	TSC
3.20	367.6179	36.7377	8.2623	41962.6382
3.10	432.1460	34.6691	10.3309	40535.5446
3.00	493.7458	32.7973	12.2027	38974.9880
2.90	553.9116	31.10370	13.8963	37302.6774
2.80	613.5801	29.5712	15.4288	35533.2135

flows and optimal parking fees at different route choice criteria with different confidence levels. The log-normal distribution parameters affect the route flow, optimal parking fees, travel time at equilibrium, and the total social cost linearly. Improving the quality of the transit service can guide travelers to choose their modes coordinately. For the traffic network with multiple routes, the lower-level of the model is a standard UE problem, so, the model can be solved by an algorithm for bilevel problems.

Table 7: Results with different σ at UE.

σ	Flow on route 1	MTT	Δ	TSC
0.10	782.6575	26.0181	18.9819	30143.6347
0.15	778.7946	26.0871	18.9129	30270.7589
0.20	773.3948	26.1846	18.8154	30448.2419
0.25	766.4663	26.3111	18.6889	30675.5911
0.30	758.0189	26.4677	18.5323	30952.1670
0.35	748.0641	26.6556	18.3444	31277.1961

Table 8: Results with different σ at RUE.

σ	Flow on route 1	TTB	Δ	TSC
0.10	734.0778	26.9257	18.0743	31732.0693
0.15	708.5286	27.4383	17.5617	32557.0131
0.20	683.1355	27.9729	17.0271	33368.1532
0.25	657.8691	28.5304	16.4696	34165.1702
0.30	632.6970	29.1119	15.8881	34947.6716
0.35	607.5838	29.7185	15.2815	35715.1825

Table 9: Results with different σ at METE.

σ	Flow on route 1	METT	Δ	TSC
0.10	699.5494	27.6244	17.3756	32844.9064
0.15	656.6104	28.5589	16.4411	34204.5845
0.20	613.5801	29.5712	15.4288	35533.2135
0.25	570.2645	30.6688	14.3312	36827.4403
0.30	526.4151	31.8598	13.1402	38082.8031
0.35	481.7015	33.1532	11.8468	39293.3727

Many further works are worthy of exploring based on this work. From the comprehensive point of view, urban multimodal traffic networks composed by multiple arcs and bus lines need to be developed and tested, and more efficient solution algorithms are followed. Moreover, a stochastic multimodal traffic network with two perfectly competitive parking lots, which have insufficient parking spaces, will be concerned. We will obtain a more empirical model and get a better understanding of the travelers' risk preference and then study the flow distribution on the network.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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