Fare Strategies with Premium Service to Improve Travel Time Reliability
所要時間信頼性を向上させるプレミアムサービス運賃戦略に関する研究

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Public transport fare policy remains subject to innovations, not least evident in the Mobility as a Service discussion. Fares and mode integration can be used to increase the attractiveness of PT by compensating for potential delays. This study aims to improve PT travel time reliability by introducing a novel fare strategy. For an origin-destination pair, this study designs a pricing strategy with two fare levels: “Standard” and “Premium”. The Premium fare is higher but allows passengers to use an alternative service free of charge if the PT service is expected to be delayed beyond a certain threshold. This pricing problem is modeled as a nonlinear optimization problem to maximize the operator’s profit. The premium fare and the threshold are employed as decision variables. A logit function is used to describe the choice behavior between the two fares. The incurred non-concavity is addressed by an algorithm incorporating the concept of “path-following”, from the global optimum of an approximated easy-to-solve model to that of the difficult-to-solve true model. In the theoretical case study, the impact of value of time distributions on the optimal solution is investigated.

Keywords: *Public transport, Travel time reliability, Premium fare, Non-concave optimization, Logit model*

1. Introduction

Mass public transportation modes such as trains and buses remain important travel modes though there are more and more newly emerging services such as ride-sourcing, car sharing or bike sharing. However, due to both man-made causes and natural causes travel time delays in public transportation systems happen. Travel time reliability is a crucial factor for evaluating the transport system quality. Passengers’ satisfaction towards the transport system always directly affects their decision-making when they choose a travel mode. Hence, travel time unreliability leads to profit loss for service operators and has negative impacts on the passenger evaluation of a service which then increases the total social cost. Moreover, as the value of time is increasing, the impact of travel time unreliability increases.

In order to maintain the demand and increase the profit, transport operators should properly deal with delays and even improve the reliability. There are several existing methods to deal with the delay which can be categorized as: recovering from delay within the system or with other systems, e.g., substitute bus (Teng and Xu, 2010; Zeng et al., 2012; Zhang and Lo, 2018; Zhang and Lo, 2020), change to other modes (Schimohr and Scheiner, 2021) and compensate for the delay.

Oliveira et al. (2019) concluded that the compensation strategy for delayed or cancelled trains was chosen at the highest rank by passengers as a method to improve the travel experience in the UK. As a practical implementation of this, there are current fare compensation schemes in the UK rail market. For instance, if the delay time is between 15 to 19 minutes, passengers will be able to get a 25% delay repaid when they buy single tickets (website: GWR, 2022). Moreover, in the industry of logistics, there are some pilot projects using compensation services. Meituan company proposed a service called Zhunshibao, which can be regarded as an "insurance" bought in advance. If a delay occurs customers will get compensation according to the actual delay time. For instance, if the delay time is between 10 to 14 minutes, customers are reimbursed 10% of the payment price if they bought the insurance (Meituan, 2018).

Moreover, there are a range of pricing innovations for public transport. For one, Mobility as a Service (MaaS) is at the forefront of attention. Though the forms of MaaS vary, in general, multiple transport services are provided and subsidized jointly through mobility operators (Hietanen, 2014). Related to this, advanced pricing strategies have been explored for many travel modes and these will have impacts on public transport. For example, the dynamic pricing of ride-hailing services and its potential impact on PT in Kyoto have been discussed in Iacobucci and Schmöcker (2021). Chen and Wang (2018) proposed a pricing strategy for a last-mile transportation system. This system provides passengers with transport services from public transportation stations to their destinations. The goal is to maximize the social welfare including the vehicle profit and consumer surplus. They also considered multiple passenger types with different values of time (VOT) and offered a discount for special groups.

These emerging services and improved pricing strategies will offer passengers wider options and more effective travel paths for daily trips which also gives pressure on public transportation operators to improve their services and be attractive among all services. One unneglectable factor in evaluating service level is the time reliability, however, it is not easy to improve since there are various causes including ones that operators cannot predict and prevent. Therefore, instead of direct improvement of time reliability operators can deal with delay by offering alternative modes free of charge which also can improve the overall service reliability. Cost-benefit analysis is necessary for providing compensation service, therefore a proper pricing strategy is needed for public transportation operators.

Therefore, this research is motivated to focus on the compensation method to deal with travel time delays of public transportation that offers passengers a free alternative mode. We suggest public transport operators could introduce a "Pricing Strategy with Premium Fares (PSwPF) where passengers can choose between "standard" and "premium" tickets. We call this strategy PSwPF in the remainder of this paper. The premium fare is higher than the standard fare but premium passengers are allowed to use an alternative service free of charge if the public transport is expected to be delayed beyond a certain "qualification threshold".

The remainder of this paper is organized as follows. Section 2 reviews the existing pricing strategies for transport services, which are mainly on congestion pricing, and delay compensation and refund strategies for logistics. Section 3 explains the non-linear non-concave optimization model for the proposed pricing problem and the path-following solution algorithm. Input data details and case study settings can be found in Section 4, and case study results with a capacity constraint for alternative mode or not are presented in Section 5. We finally provide the conclusions and further work in Section 6.

2. Literature review

In order to design a compensation strategy, one of the most important aspects is to introduce an effective pricing scheme for both service operators and users. In the study of transport networks, pricing strategy is a popular issue as researchers developed measures to design prices as well as introduced various pricing schemes. There has been an increasing amount of literature on transportation system pricing. Nash (1978) designed the bus transport fare using an optimization problem to maximize the social welfare, passenger mileage or bus mileage subject to a budget constraint. This method improved the performance of unconstrained optimization problems. Further, different fare systems were compared and evaluated quantitatively in the research by Borndörfer et al. (2012). They investigated revenue, profit, demand, user benefit and social welfare maximization model and suggested appropriate models for different types of constraints. Buttazzo et al. (2006) aimed at finding an optimal pricing policy for a public transportation network considering an equilibrium between minimizing the total transportation cost of the population and maximizing the total income of the transport operator. By considering the interaction between road, public transport services and costs for cars and public transport services, Loder et al. (2022) introduced the multi-modal macroscopic fundamental diagram network design problem for network and price design to minimize the total travel time. Moreover, as mentioned before, recently passengers have had much wider travel options, such as ride-sharing and bike-sharing. Correspondingly, particular pricing strategies for these services also have been explored in recent contributions. There are several studies focusing on the pricing schemes with the aim of improving the spatial distribution of vehicles (Jorge et al., 2015; Brendel et al., 2017). Jorge et al. (2015) developed a mixed integer non-linear programming model to solve the pricing problem considering profit maximization. Brendel et al. (2017) proposed the concept of area-based pricing strategy in order to optimize vehicle supply and demand. The price of ride-sourcing services is optimized by considering the negative impact caused by congestion in multimodal transportation networks (Gómez-Lobo et al., 2022).

In the field of logistics, compensation strategies have been explored and several effective measures have been confirmed. Wang and Qin (2015) applied an analytical model to evaluate the compensation service for online shopping delivery delays. In the case of delay, retailers compensate with a certain refund for the consumers who are willing to return the goods after evaluating the utilities of waiting and returning. They concluded that appropriate compensation can effectively decrease the probability of returning the product and increase sellers' profit when a delivery delay occurs. They also found that optimal compensation is related to the time of delay. In the research by Yuan et al. (2022), the characteristics of two compensation strategies are studied by exploring optimal retail price and compensation levels for different online retailers. They concluded that discriminated compensation leads to higher profit for retailers than uniform compensation irrespective of the parametric variations. Pan et al. (2021) studied delivery delay compensation services by evaluating the effect of service attributes on consumer preference. They found consumers prefer a progressive compensation amount to a fixed amount. The existing contributions on compensation strategies in logistics are mainly investigating the refund service which is paid by sellers or shipping platforms. In other words, the delay is compensated within the resource of the system. Similarly, in the field of public transportation, much of the compensation schemes are designed to offer a refund if the system is expected to delay. UL company offers a compensation scheme for delayed journeys (Website: UL). If the journey will be delayed for more than 20 minutes, consumers are entitled to compensation for other transport such as another train or taxi with the expense of up to SEK 1,210 (about US$ 107). By corporation with other travel modes, Liouta et al. (2022) suggested bike-sharing systems can compensate for the restricted capacity of public transport during a pandemic. They are aiming to find the optimal design and operation of bike-sharing systems to maximize the covered demand. Their study can be regarded as a measure to deal with long-term pubic transport disruption considering travel demand.

In summary, delay compensation is an effective measure to attract users and maintain operator profit. The existing delay compensation strategies in logistics and passenger transport systems generally provide a certain amount of refund. Existing pricing strategies have been explored mainly for objective optimization including profit, social welfare and demand etc. We are focusing on the short-term disruption and compensation pricing strategies which are major concerns of public transport operators.This paper contributes to this literature by explicitly aiming to define the value of the compensation. We will show that this leads us to a comprehensive evaluation of service reliability as the value of the compensation also depends on the value of the alternative mode.

3. Methodology

In this study, we develop and design the PSwPF by exploring the optimal fare level and qualification threshold. Hence, these two variables are employed as decision variables. The first part of this study is to evaluate the impact of fare level and threshold on the public transport operator's profit. Then, the price level of premium fare and qualification threshold are optimized based on constant standard fares and static demand. Further, we test our model using different VOT distributions.

3.1 Premium service and passenger decision making

To explain the main idea, consider a train line as an example. The passenger pays for the premium service to the public transport operator. If the train is delayed, the passenger can either choose to take the alternative mode such as a taxi or wait for the delayed train. The cost for the alternative mode such as the taxi cost will be paid by the public transport operator to the taxi operator so that passengers can use the taxi free of charge. This strategy can increase premium passengers' travel time reliability as they are willing to pay an additional fare. It might also be beneficial for standard fare passengers as the higher fare for the premium class can lead to reduced fares for the standard class passengers.

We presume that passengers have already decided from where to where they want to use public transport. Passengers then choose between premium fare and standard fare depending on the expected generalized travel cost which includes fare and their perception of the potential delay. This can be evaluated by passengers' experience or past data such as the annual report published on the public transport website.

3.2 Model

In this study, a base model is developed for the network considering a specific pair of origin (O) and destination (D) which are both public transport stations. As for the delay time distribution, $h_k(t)$, which is regarded as input data, reasonable distributions are generated. The details can be found in Section 4. Given the delayed time distribution, and standard class fare F^s, we are aiming to find the optimal premium class fare, F^p, and the qualification threshold, z, considering the operator profit maximization problem.

The profit is calculated by the difference between revenue and cost shown as Eq. (1)-(3). The revenue includes the income from both standard fare and premium fare. The cost of the public transport operator is considered as the alternative mode cost paid to the alternative mode operator for each ride that is provided to passengers who experienced delay and chose to use the alternative mode under the premium fare scheme. With regards to the fare class choice (modal share), we consider the binary logit model based on the generalized expected travel cost of two classes shown as in Eqs. (9) and (10).

Generalized travel cost equals the sum of fare and time cost. For passengers with a premium ticket, they are qualified to take the alternative mode if the delay time is longer than $z \times \check{t}_k$ and taking the alternative mode is more time-effective, $\widetilde{H}_k < g(t)$, i.e., $\check{t}_k \gamma + \beta < t$. Otherwise, passengers wait and take public transport though they bought the premium ticket. Hence, the generalized travel cost of premium class can be calculated as Eq. (8). The generalized travel cost of the standard class is also calculated by time and monetary cost as Eq. (7). With this, we can calculate the profit of passengers with two class fares for a certain VOT, O_m. For the regulation of two fare levels, it is obvious that the premium fare is always higher than the standard fare. In addition, we set an upper bound to the premium fare which is also reasonable since public transport operators cannot set an extremely high value that few people can afford. Therefore, the constraints for the premium fare are shown in Eq. (4).

$$\underset{F^p, z}{\mathrm{Max}} \qquad O_m = O_m^p + O_m^s \tag{1}$$

$$O_m^p = \left(\check{d}_k F^p - \tilde{c}_k \sum_{t=\max(z\check{t}_k,\, \check{t}_k\gamma+\beta)}^{\infty} h_k(t) \right) \times M_m^p \tag{2}$$

$$O_m^s = \check{d}_k F^s \times M_m^s \tag{3}$$

Subject to:

$$F^s \leq F^p \leq F^p_{max} \tag{4}$$

$$g(m,t) = m \times t \tag{5}$$

$$\widetilde{H}_k(m) = m \times (\check{t_k} \times \gamma + \beta) \tag{6}$$

$$E^s_{km} = \check{d}_k F^s + \int_{\check{t}_k}^{\infty} g(m,t)\, h_k(t)\, dt \tag{7}$$

$$E^p_{km} = \check{d}_k F^p + \int_{\check{t}_k}^{\max(z\check{t}_k,\, \check{t}_k\gamma+\beta)} g(m,t) h_k(t)\, dt + \int_{\max(z\check{t}_k,\, \check{t}_k\gamma+\beta)}^{\infty} \widetilde{H}_k(m) h_k(t)\, dt \tag{8}$$

$$M^p_m = \frac{1}{1+\exp\,(E^p_{km} - E^s_{km})} \tag{9}$$

$$M^s_m = \frac{1}{1+\exp\,(E^s_{km} - E^p_{km})} \tag{10}$$

3.3 Solution approach

The problem leads to a non-concave problem. The incurred non-concavity is addressed by an algorithm incorporating the concept of "path-following", from the global optimum of an approximated easy-to-solve model to that of the difficult-to-solve true model. The idea was introduced in the study by Hanson and Martin (1996) as they artificially changed the choices to more random and less responsive attributes. Based on this idea, we introduce a new parameter, r, to the logit model to reduce the sensitivity of expected travel cost. Hence, the modal share can be calculated as Eq. (11). Firstly, we set r to a relatively large value, and find the optimal solution. Then this solution will be taken as the initial point for the next iteration and we find the optimal solution by setting a lower r. Gradually, we repeat the above process until r is reduced to the target value which means, that is the original problem that we are aiming to solve. Finally, we can obtain the correct global optimum. The adjusted concept and solution-finding path are illustrated in Fig. 1.

$$M^{p,r}_m = \frac{1}{1+\exp\,((E^p_{km} - E^s_{km})/r)} \tag{11}$$

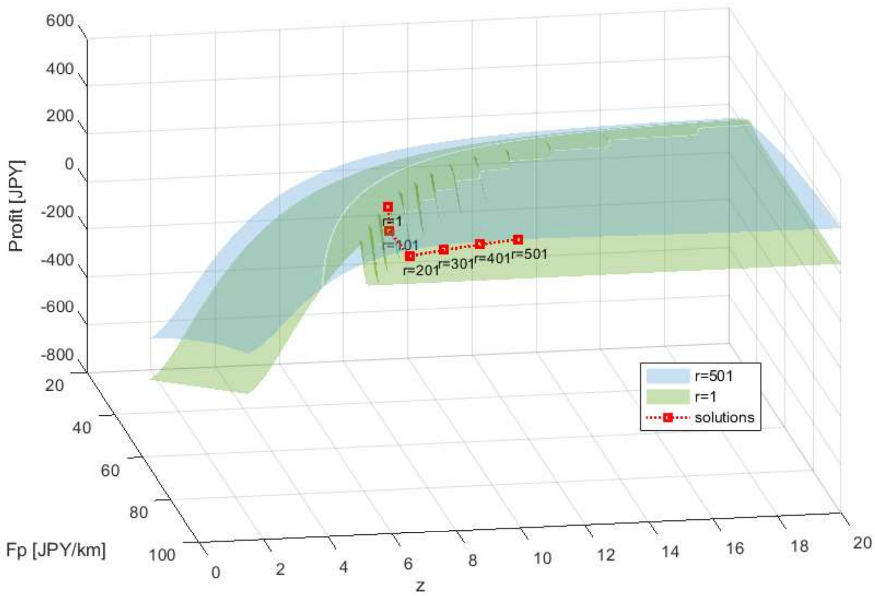

Fig. 1. Solution finding path: The blue surface shows the solution domain of the problem in the first iteration with $r = 501$, and the green surface shows that of our origin problem, i.e., $r = 1$. (Surfaces of intermediate iterations are omitted). The red dots are global solutions at each iteration with different r, and the red line indicates the solution-finding path.

3.4 Notation

Table 1. Notation

Decision variable	
F^p	Fare per km for passengers in Premium class
z	Multiplier of minimum travel time that qualifies the traveler of class p to use the alternative mode free of charge

Parameters and input data		
$h_k(t)$	$input\ data$	Probability of travel time t on OD pair k
β	3min	Transfer penalty when travelers choose to take an alternative mode
γ	1.2	Multiplier of travel time for an alternative mode
$\widetilde{d_k}$	8 km	Fare relevant distance for OD pair k (the minimum distance on any route)
$\breve{t_k}$	10 min	Minimum, undelayed travel time on OD pair k
F^s	30 JPY\km	Fare per km for passengers in Standard class
$\widetilde{c_k}$	1000 JPY	Expected cost of the operator for offering alternative transport options for OD pair k
m	$input\ data$	Value of time
$l(m)$	$input\ data$	Probability of value of time level m

Dependent variables	
E_{ck}	Expected travel cost for passenger travelling with fare class c on OD pair k
M_m^p	Percentage of passengers who purchase fare class c with a certain VOT level m
M^p	Percentage of passengers who purchase fare class c for all VOT levels
$g(m,t)$	Perceived disutility converted into monetary units associated with a travel time t for passenger (currently assumed to be a linear function of time) with a certain VOT level m
$\widetilde{H}_k(m)$	Expected travel cost on alternative mode for OD pair k given (note, in future might be also depending on public transport travel time is t) with a certain VOT level m
O	Total profit of public transport operator
O_m	Profit from the passengers with a certain VOT level m
O_m^c	Profit from passengers who purchase fare class c with a certain VOT level m
T	Percentage of passengers who use alternative mode

4. Case study settings

4.1 Network

We implement our model between one OD pair. In this case study, we consider values for a trip between Katsura station and Shijokawaramachi station on Hankyu railway line in Kyoto city. The distance d is about 8km, and the minimal travel time without delay is 10 minutes. If passengers change from taking a train to taking the alternative mode, an extra transfer time is needed. Therefore, we set the transfer penalty as 3 minutes. With regard to the travel time of the alternative mode, a multiplier is applied considering that, generally, the alternative mode is slower than the train. The multiplier is set as 1.2, so the alternative mode travel time is $1.2 \times 10 = 12$ minutes. The other input parameters are as follows:

$$F_s = 30\,JPY/km, \quad \tilde{c_k} = 1000\,JPY$$

4.2 Delay time

In the absence of good delay distribution data for our example OD pair, we consider a general typical delay distribution. Yang et al. (2019) explored the statistical distribution using actual China's high-speed railway (HSR) operational data considering several types of delay events. Among these, it is found that the most suitable distribution for the delay caused by bad weather is a lognormal distribution with $\mu_t = 3.469$ min and $\sigma_t = 0.793$ min. (Yang et al., 2019). We consider this distribution as our delay time distribution since bad weather is also a common cause in Japanese railway systems. Note that we use the total travel time as the input including delay time and travel time, and we assume that the public transport will not arrive ahead of the schedule. Thus as shown in Fig. 2, the x-axis of time distribution, i.e. total travel time, starts from the minimal travel time, $\breve{t_k} = 10\,min$. And total mean travel time equals to:

$$10 + e^{3.469+\frac{0.793^2}{2}} \approx 53.97\,min$$

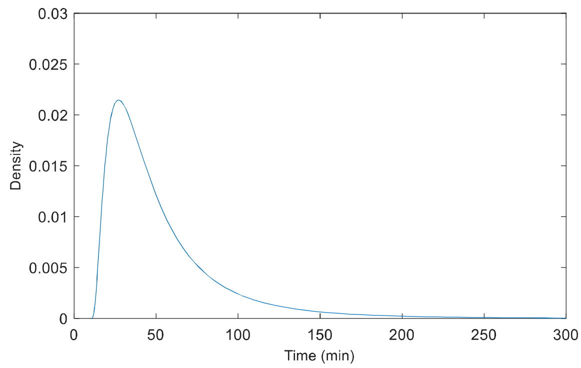

Fig. 2. Total travel time distribution including delay

4.3 VOT distribution

Since VOT is a crucial factor when evaluating the generalized travel cost, we investigate the optimal solutions for different VOTs. Passengers always have different levels of VOT related to sociodemographic factors, trip types, etc. We consider a non-uniform distribution of VOT for passengers, since generally passengers evaluate VOT based on many factors such as travel type, income and time of day e.g. morning peak. For the group of passenegers with a certain VOT, the operator's profot, O_m has been calculated as Eq. (1) in section 3.2. Then, in order to obtain the total operator's profit, we integrate this with respect to each VOT level. Therefore, the objective function has been adjusted as shown in Eq. (12).

$$\underset{F^p,z}{\text{Max}} \qquad O = \int_0^{inf} O_m l(m) dm \qquad (12)$$

In this case study, we generate a VOT distribution according to the household income data in Japan. Given the frequency distribution of each annual income level, we convert the annual income into the value of time per minute. Finally, we fit the data into a lognormal distribution with $\mu_{\text{VOT}} = 2.5262$ JPY/min and $\sigma_{\text{VOT}} = 0.6183$ JPY/min as shown in Fig. 3. We note that this mean of around 908 JPY/h is clearly a too low estimate for business hours as the calculation is based on every minute of a day and considering the whole population. In further work, these values can be adjusted according to the target population. The scaling up of the VOT and the fare will, however, not influence the general tendencies observed in the following.

Based on these parameters, we vary the value of μ_{VOT} and σ_{VOT} to explore the impact of VOT distributions in the following sections.

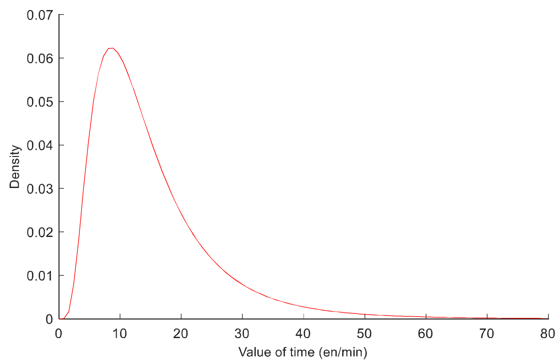

Fig. 3. Value of time distribution

5. Results

We consider two schemes in this case study. Firstly, we will apply our model to a basic scenario where there is no constraint except the lower and upper bound for z and F_p. Then we add an alternative mode capacity constraint to the model which means the public transport operator sets the premium fare and the qualification threshold at a level so that the number of passengers who finally can take the alternative mode will not exceed the threshold. For each scheme, we are aiming to explore the optimal z and F_p and evaluate the public transport operator profit, the modal share of each fare class and the number of passengers who take alternative mode.

5.1 Case study with no alternative mode capacity constraint

Under this scheme, we apply our model to different VOT distributions by fixing μ_{VOT} or σ_{VOT} to explore the impact of the other one.

In Table 2 we vary σ_{VOT} with μ_{VOT} set to the fitted value of the original distribution. Note that a larger σ_{VOT} means more heterogeneous VOT among passengers. The optimal z and F_p and other evaluation measures are shown in the table. We can find that when σ_{VOT} is low, i.e., a more concentrated VOT distribution, the premium fare is set at a relatively low value. Since under this μ_{VOT} value, overall VOT is not high which means the operator needs to control the fare level for attracting more premium service users to maintain the revenue, thus we can find a high premium class modal share. On the other hand, in order to maximize the profit, the operator also needs to control the alternative mode cost which is affected by the z value. Hence, z should be set at a high value to limit the number of passengers taking the alternative mode. Further, as σ_{VOT} becomes larger, there will be more passengers with high VOT who are willing to pay high fares. Therefore, the premium fare level increases until it reaches the upper bound. At that point, the operator needs to increase the z value to control the cost and maximize profit.

Table 2. Results for different σ_{VOT} with μ_{VOT} = 2.5262 JPY/min

σ_{VOT}	0.1	0.3	0.5	0.7	0.9	1.1
F^p	47.34	52.02	70.01	100.00	100.00	100.00
z	10.35	9.49	7.52	6.00	6.48	6.92
O	282.11	272.93	278.41	293.36	310.29	324.65
T	0.089	0.110	0.186	0.288	0.250	0.220
M^p	1.000	0.999	0.916	0.704	0.630	0.583

When we increase μ_{VOT} to a larger one such as $\mu_{VOT} = 3.5$ JPY/min, the results are shown in Table 3. We can find that under this higher μ_{VOT}, the premium fare can be set to a high level to the upper bound for all σ_{VOT} because passengers with higher VOT will show a higher willingness to pay for premium service. Therefore, the premium class modal share can be maintained, although the fare level is high. Under the same fare level, we can find that the optimum z value firstly decreases and then increases as we raise σ_{VOT}. This is due to the tradeoff between reducing cost by increasing z and increasing premium class modal share by decreasing z to maximize profit. Note that increasing z will control the number of premium service users who are qualified to take the alternative mode, which means it can control the cost of the public transport operator and lead to a higher profit. When σ_{VOT} is low, increasing the modal share is more effective while, as σ_{VOT} becomes larger, increasing z has a better performance to increase profit.

Table 3. Results for different σ_{VOT} with μ_{VOT} = 3.5 JPY/min

σ_{VOT}	0.1	0.3	0.5	0.7	0.9	1.1
F^p	100.00	100.00	100.00	100.00	100.00	100.00
z	7.28	6.83	7.02	7.33	7.66	7.99
O	585.37	504.33	470.01	455.46	449.07	446.44
T	0.199	0.226	0.214	0.196	0.179	0.163
M^p	0.957	0.791	0.665	0.592	0.548	0.521

Table 4 shows the results of fixing σ_{VOT} at 0.6183 and varying μ_{VOT}. A higher μ_{VOT} indicates all passengers have a relatively higher VOT and as described previously, their willingness to pay for premium service is high. Hence, as μ_{VOT} increases, the premium fare can be increased and when it reaches the upper bound, the operator has to control z value to reduce cost and increase profit.

Table 4. Results for different μ_{VOT} with σ_{VOT}= 0.6183 JPY/min

μ_{VOT}	1.5	2	2.5	3.0	3.5	4
F^p	43.33	58.94	86.57	100.00	100.00	100.00
z	11.36	8.55	6.51	6.35	7.20	8.37
O	243.43	253.32	283.57	355.73	460.01	565.27

T	0.070	0.140	0.248	0.260	0.203	0.147
M^p	1.000	0.998	0.845	0.677	0.581	0.498

5.2 Case study with alternative mode capacity constraint

We now add a constraint for the capacity of the alternative mode. The main motivation for doing so is that in practice there is likely to be a queue or supply shortage if the number of passengers taking the alternative mode is large. In order to cope with this problem, we consider a capacity constraint for the alternative mode. We set it as 20% by giving an upper bound for $\boldsymbol{T}$ in this study. We evaluate the above results under this constrained condition. Here, we only show the results of two cases, varying σ_{VOT} and μ_{VOT} respectively as shown in Tables 5 and 6.

Table 5. Results with constraint for different σ_{VOT} with μ_{VOT} = 2.5262 JPY/min

σ_{VOT}	0.1	0.3	0.5	0.7	0.9	1.1
F^p	47.34	52.02	70.01	83.01	98.49	100.00
z	10.35	9.49	7.52	7.26	7.26	7.26
O	282.11	272.93	278.41	**291.12**	**307.42**	**324.12**
T	0.089	0.110	0.186	**0.200**	**0.200**	**0.200**
M^p	1.000	0.999	0.916	0.741	0.586	0.563

Table 6. Results with constraint for different μ_{VOT} with σ_{VOT}= 0.6183 JPY/min

μ_{VOT}	1.5	2	2.5	3.0	3.5	4
F^p	43.33	58.94	77.65	92.56	100.00	100.00
z	11.36	8.55	7.26	7.26	7.26	8.37
O	243.43	253.32	**283.09**	**349.69**	**459.96**	**565.27**
T	0.070	0.140	**0.200**	**0.200**	**0.200**	**0.147**
M^p	1.000	0.998	0.868	0.659	0.577	0.498

By comparing the results in Table 5 with Table 2 and Table 6 with Table 4. We highlighted in bold in Tables 5 and 6 where the results are impacted by the capacity constraint and are worthy to discuss. We can find public transport operator increases the qualification threshold z and decreases premium fare F^p when there is a capacity constraint. However, these changes do not lead to a significant decline in the operator's profit. This indicates that though in the practice there is probably a limit of passengers who can finally use an alternative mode, the operator can always maintain the profit. In other words, alternative mode capacity does not have a negative impact on this pricing strategy's performance.

6. Discussion and conclusion

We developed a novel fare strategy with two fare levels, premium and standard. This pricing strategy is aiming to improve the travel time reliability by integrating multiple travel modes. The premium fare is higher but allows passengers to use an alternative service free of charge if the public transport is expected to be delayed beyond a certain threshold. This pricing problem is modeled as a nonlinear optimization problem to maximize the operator's profit by finding the optimal premium fare and the threshold. A logit function is used to describe the choice behavior between the two fares. The incurred non-concavity is addressed by an algorithm incorporating the concept of "path-following". In the theoretical case study, the impact of the value of time on the optimal solution is investigated.

In general, we can conclude that PSwPF can lead to win-win situations for passengers and operators. For passengers, it improves the travel time reliability. Integrating an alternative mode such as taxi and public transport can decrease the travel time if a delay occurs. From the perspective of passengers, the generalized travel cost can be reduced. On the other hand, the public transport operator can increase the profit if they introduce a premium ticket. The numerical studies find that both standard deviation and mean of VOT distribution have an impact on the optimum solution and system performance results. In general, passengers with high VOT have more tolerance for higher fares while lower VOT passengers will not choose public transport if the fare is high. Hence, for a group of passengers with low VOT operator has to control the fare below a low level to attract enough consumers. When there are a sufficient number of people with high VOT, the operator can raise the fare to increase revenue. At the same time, the operator raises the qualification threshold z to control the cost. When the fare has been raised to the upper bound the only control for the operator is to adjust z. The results show the ambivalent role of z: Reducing z can be good to increase the premium service modal share and revenue; increasing z to reduce the passengers taking the alternative mode and cost. We show that the results depend on the mean and the deviation of the population's VOT.

Further, by setting a capacity to the alternative mode we investigate the situation where there is a limit on the alternative mode as, for example, taxi capacity is likely not sufficient to cater to a specific station with a suddenly occurring large demand. We can conclude that in our network, the operator can adjust premium fare and qualification threshold accordingly to avoid the profit decrease under constrained alternative mode capacity.

In future work, we will firstly illustrate the effect of different costs for the alternative modes. This will further illustrate that the premium fare can also be understood as a general value of network reliability. In unreliable networks with few alternative modes, the premium fare can be high whereas in reliable networks with good alternatives passengers will not be willing to pay much of an "insurance fee".

Furthermore, we will expand this single OD pair network into a more complex network with multiple nodes and traffic lines. Also, the total demand can be dynamic. For instance, other travel modes such as private cars and walking can be introduced into the network. Then there will be competition between other travel modes and public transport, in other words, demand will be affected by both standard and premium fares.

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