Research in Transportation Business & Management 37 (2020) 100548

Contents lists available at ScienceDirect

Research in Transportation Business & Management

journal homepage: www.elsevier.com/locate/rtbm

Evolutionary bi-level model for optimizing ticket fares and operations profit of Taiwan high-speed rail

Jui-Sheng Chou[a,*], Citra S. Ongkowijoyo[b], Ngoc-Tri Ngo[c], Shih-Yun Chen[a]

[a] Department of Civil and Construction Engineering, National Taiwan University of Science and Technology, 43, Sec. 4, Keelung Rd., Taipei, Taiwan
[b] School of Architecture and Built Environment, Deakin University, 1 Gheringhap St, Geelong, Vic 3220, Australia
[c] Faculty of Project Management, The University of Danang – University of Science and Technology, 54 Nguyen Luong Bang, Danang, Viet Nam

ARTICLE INFO

Keywords:
High-speed rail
Bi-level planning
Ticket fare
Operations profit
Passenger flow allocation
Evolutionary optimization

ABSTRACT

The Taiwan High Speed Rail (THSR) has transformed transportation in western Taiwan. Increasing costs of construction and operation have rendered THSR tickets much more expensive than other forms of transportation. The effects of ticket price benefits on the relevant transportation agency and the distribution of passenger flow have been analyzed to improve the profitability of the THSR. However, relying on analysis of passenger flow information alone may be insufficient to the adjustment of ticket fares. An evolutionary optimization model for maximizing the profits of the transportation agency that considers conflicts between executive decision making and passenger flow was developed herein. To resolve these conflicts, the bi-level planning approach was applied to consider both upper-level and lower-level planning and reflect passenger behavior and transportation profit management. Therefore, developing business plans and strategies that maximize cost efficiency while optimally balancing passenger satisfaction and profitability could improve THSR performance. Results indicated that optimal fare rates should be divided into three groups: 3.1, 3.0, and 4.2 NTD/person-km for long, medium, and short distances, respectively. This tool could be used to model and validate THSR fare adjustments and as a reference for authorities when making policy recommendations.

1. Introduction

Railways are a popular mode of transport because of their safety and environmental sustainability (Cordera, Sañudo, dell'Olio, & Ibeas, 2018). Research and development in the field of high-speed railways (HSR) is performed globally to improve intercity links in megaregions (Li, Strauss, & Lu, 2019; Wang, 2018; Zheng, Long, Chang, & Ye, 2019). For instance, Italian and Spanish HSR have been studied to understand the costs and demands of HSR in Europe (Beria, Grimaldi, Albalate, & Bel, 2018). Improving the efficiency of railway systems has been a major concern for several decades in numerous countries (Bai, Zeng, & Chiu, 2019).

As Taiwan's economic development becomes increasingly stable, transportation construction has become a major indicator of socio-economic development. Moreover, public transportation, tourism, and hospitality industries are rapidly developing in Taiwan, and the government has actively implemented policies to encourage overseas tourists to visit Taiwan, prompting the development of public transportation facilities, such as railways and highways.

In recent years, the standard of living and leisure awareness among Taiwanese people have increased, and travelers have demanded higher-quality transportation because of the increased perceived value of time efficiency. However, the high construction and operation costs of the Taiwan high-speed rail (THSR) have led to higher fares compared with the other forms of public transportation (Yu & Johannesson, 2010). The THSR has a smaller number of passengers than the projected plan despite short travel times.

The declining number of passengers in public transportation, such as the THSR, is also caused by the increasing quality of life of Taiwan's residents. Therefore, standing out in this challenging and competitive environment has become critical for the THSR. A novel HSR system can significantly affect the spatial structure and market share of existing transportation modes in certain areas (Hsu, Lee, & Liao, 2010). However, according to the financial analysis of the THSR, the debt level has never dropped despite the continual growth of the recorded revenue.

The THSR must develop strategies to fulfill the passengers' satisfaction to continuously attract loyal customers. There are various factors affecting the passengers' satisfaction, such as staff attitude

* Corresponding author.
E-mail addresses: jschou@mail.ntust.edu.tw (J.-S. Chou), citra.ongkowijoyo@deakin.edu.au (C.S. Ongkowijoyo), trinn@dut.udn.vn (N.-T. Ngo), M10505117@mail.ntust.edu.tw (S.-Y. Chen).

https://doi.org/10.1016/j.rtbm.2020.100548
Received 8 October 2019; Received in revised form 24 August 2020; Accepted 24 August 2020
Available online 21 September 2020

(including the way of handling complaints), convenient ticket purchase and time tabling, train time punctuality, comfortable traveling environment, staff interaction, access to HSR stations, waiting time, line-haul, and egress from HSR stations (Chou & Kim, 2009; Chou, Kim, Kuo, & Ou, 2011; Chou, Kim, Tsai, Yeh, & Son, 2017; Chou & Yeh, 2013; Zhen, Cao, & Tang, 2018; Zhen, Cao, & Tang, 2019).

While there are various factors affecting the passengers' satisfaction as mentioned above, alternative fare strategies (*e.g.,* adjusting ticket prices) have been known as the most effective of all methods offered to the passengers. Importantly, the pricing strategy would reflect the competitive and sustainable business environment faced by the HSR operators. In this view, the price is a significant aspect that directly affects passengers' willingness and decision to consistently choose HSR service (Yang & Zhang, 2012).

Comprehensive strategy toward adjusting the HSR fares is crucial given the role and effect for the HSR market. The challenge lies on the analysis and decision that HSR agency should satisfy public expectations and passenger's satisfaction while maximize organization benefits, considering generalized cost functions. However, as discussed by Chou et al. (Chou, Chien, Nguyen, & Truong, 2018), HSR fares cannot be accepted by the public because of lacking of objective justification based on any theoretical method.

In the conventional model, ticket fares were a function of a single factor, and factors considered were often biased. These conditions hinder the comprehensive analysis of fares. Following this knowledge gap, this research aimed to develop a conceptual bi-level planning model to optimize THSR ticket fares while maximizing operator's annual revenue and ensuring customer satisfaction toward fares and service quality.

This paper is structured as follows: Section 2 reviews the literature on public transportation cost pricing and fare adjustment and assesses the bi-level programming model. Section 3 comprehensively describes the optimization model developed in this research. Section 4 discusses the empirical application of the model by using a THSR case study. The analysis results and findings are explored and discussed in Section 5. The final section draws recommendations and conclusions, presents research limitations, and discusses possible improvements to the presented method and research directions.

2. Literature review

2.1. Pricing theory and time value

The service quality indirectly affects operating costs and other expenses of the THSR (Chou et al., 2017; Chou et al., 2018; THSR, 2018). The operation cost of THSR is affected by several factors, including maintenance costs, development expenses, and employee salaries. Common pricing theories include transportation pricing, target pricing, equilibrium pricing, average cost pricing, and marginal cost pricing. In these theories, average cost pricing and marginal cost pricing are commonly used to set transportation ticket fares.

The theory of average cost pricing is based on the average cost with a certain percentage profit. In contrast, the theory of marginal cost pricing was developed based on providing an economic benefit in exchange for social welfare. This theory is mainly applied to situations in which demand for a mode of transportation is inadequate or when passengers use a mode of transportation during peak hours. The cost–benefits that arise from changes in passenger flow apply to the pricing of railway transportation.

Time value plays a major role in the processes of adjusting ticket fares. Wei (2003) proposed six attributes of time value, namely purposiveness, dual utility, dynamicity, regionality, overlapping, and non-exclusivity. Time value is analyzed using abstraction, simplification, and generalization because of its complexity and multiple attributes. Furthermore, Hultkrantz (2013) considered time value to be a critical parameter that reflects the opportunity cost of time as an input and the direct utility (or disutility) of travel time.

Vickerman (2000) determined that individual income was a crucial element of the standard value of a shortened transportation traveling time that had been neglected in analyses. Therefore, Rothengatter (2000) applied the wage rate method to verify the correlation between time value and gross domestic product in Germany. In the United States, time value calculated using the wage rate method was based on the national average wage rate (Lee, 2000).

China has no single method for calculating time value (Talvitie, 2000). The high level of income inequality in China reduces the accuracy of the wage rate method. However, Börjesson and Eliasson (2019) discussed other factors, such as political factors, that affect time value. Because of the complexity of the public transportation system, considering various aspects for the analysis of transportation fare is crucial.

2.2. Generalized fare cost and passenger flow assignment

Main transportation factors that are of interest to the public are cost, time, comfort, safety, and convenience (Maduwanthi, Marasinghe, Rajapakse, Dharmawansa, & Nomura, 2015). Ma and Gao (2016) analyzed the relative weightings of these five factors by using the fuzzy comprehensive evaluation method and determined that travel cost, time, and comfort were primary factors that affected passenger's choice to use public transportation. Therefore, these factors should be considered crucial variables when establishing a passenger travel choice prediction model.

Espinosa-Aranda, García-Ródenas, Ramírez-Flores, López-García, and Angulo (2015) investigated user's logic and their preference factors, such as cost and time, and applied them in a simulation model to analyze HSR business strategies. Chen and Gao (2004) reported that higher passenger flow greatly increased the economic benefits of HSR. Additionally, Wu, Luo, and Wang (2010) argued that both ticket fares and passenger flow are influential factors in maximizing public transportation revenue.

Passenger flow was further determined to be highly related to and affected by ticket fares. The relationship between passenger flow and ticket fares has been studied at length. For instance, Du and Si (2005) studied passenger travel choices, which affect the passenger flow, by using the conventional (statistical) method and stochastic model.

Chu (2018) established a novel model based on passenger's travel choices and Wardrop's user equilibrium principle. The model analyzed changes and verified the importance of passenger flow. Moreover, Kurosaki and Alexandersson (2018) revealed that passenger flow was critical in railway operation and management in Japan and Sweden. Therefore, passenger flow should be considered a key factor in the assignment model for railway fare analysis.

Other than these key factors, conventional decision-making methods for adjusting public transport fares generally consider a single expert and do not feature multi-expert perceptions, which can cause poor outcomes. Analyzing and adjusting public transportation fares is a daunting task that requires multi-expert involvement. Several factors must be considered simultaneously to solve the transportation fare problem; thus, the bi-level programming model is discussed in the following section.

2.3. Bi-level programming model for solving transportation problem

The bi-level programming problem arises in the field of transportation (Guo & Wang, 2011). The model consists of upper-level and lower-level models, employed simultaneously to solve the transportation problems. The upper-level model minimizes the total passenger travel cost, and the lower-level model is a random assignment model for passenger arrival time (Zhu, Mao, Bai, & Chen, 2017). Yu, Kong, Sun, Yao, and Gao (2015) applied the bi-level programming model to solve problems with the bus lane network. In the study, the upper-level model was used to analyze the average travel times of passengers and vehicle users, whereas the lower-level model was applied to solve the traffic assignment problem by using the network equilibrium model.

Sun (2016) proposed methods to solve the continuous transportation network design problem. The study developed the objective function of the upper-level model to minimize the total investment budget and total impedance. In particular, the lower-level model was applied as a user equilibrium assignment model. Zito, Salvo, and La Franca (2011) developed operational decision-making methods that simulate the service fees and frequencies of airline services, and the optimal solution is obtained by applying logit analysis. Ghassemi Tari and Hashemi (2016) applied a genetic algorithm (GA) to solve the problem of nonlinear transportation costs. The GA was applied to minimize the transportation cost by considering the assignment in question and the number of vehicles required to deliver products from a manufacturing firm to depots.

When setting highway tolls, an appropriate pricing balance could be obtained based on the destination of users (Dewez, Labbé, Marcotte, & Gilles, 2008). Government agencies use management mechanisms to mitigate problems caused by the concentrated use of roads and terminals. These problems can be solved using the speed-constrained particle swarm optimization (PSO) method (Assadipour, Ke, & Verma, 2016). The bi-level programming model was extended to sustainable intercity transportation. The upper-level model minimized sustainable operational indicators, and the lower-level model represents the ticket fares of all modes of transportation.

Sun, Gao, and Wu (2008) discussed the superiority of bi-level programming. First, the two decisions can be analyzed simultaneously in a decision-making process, even if they have opposing goals. Second, the bi-level programming model can reflect the actual problem because of the availability of various decision-making methods. Third, the model considers the objective values of two decision makers, which leads to an expression of the interaction between decision makers.

In sum, scholars from various countries have used the bi-level programming models to solve a variety of transportation problems similar to that investigated in this research, thus confirming its appropriateness and reliability. Notably, the bi-level programming model influences decision makers. However, it does not interfere with decisions made. Decision makers should identify optimal solutions to the ticket fares problem. The problem of HSR fares is complex because it involves key factors discussed; therefore, the bi-level programming model is applied as the model basis for development.

3. Model development

The proposed model integrates the bi-level programming method with the PSO algorithm to optimize THSR ticket fares. Fig. 1 depicts the model framework. The following subsections provide the fundamentals and discussion of the development of the proposed model.

3.1. Upper-level and lower-level models

Two decision makers must be considered simultaneously in the form of upper-level and lower-level models, with the intention of searching the minimum values. The basic bi-level programming model is mathematically expressed as Eqs. (1) and (2).

$$(U)\min_{x} F(x,y)$$

$$s.\ t.\ \ G(xy) \leq 0 \tag{1}$$

$$(L)\min_{y} f(x,y)$$

$$s.t.\ g(x,y)\ \leq\ 0 \tag{2}$$

where, (U) is the upper-level model, $F(x,y)$ is the objective function of the upper-level model, x is the decision variable in the upper-level model, $G(x,y)$ are the set of constraints on the decision variable in the upper-level model, (L) is the lower-level model, $f(x,y)$ is the objective function of the lower-level model, y is the decision variable in the lower-level model, and $g(x,y)$ is the set of constraints on the decision variable in the lower-level model.

After Eqs. (1) and (2) are performed, the upper-level decision maker affects the lower-level decision-maker by setting the value x to restrict the set of lower-level constraints. However, the lower-level decision maker also influences the upper-level decision-maker by using the value of y. The lower-level decision variable is considered a function of the upper-level decision variable. Colson, Marcotte, and Savard (2005) further suggested several solution methods. Their conditions of use included principal points that should be considered in the bi-level programming model, as described in Table 1.

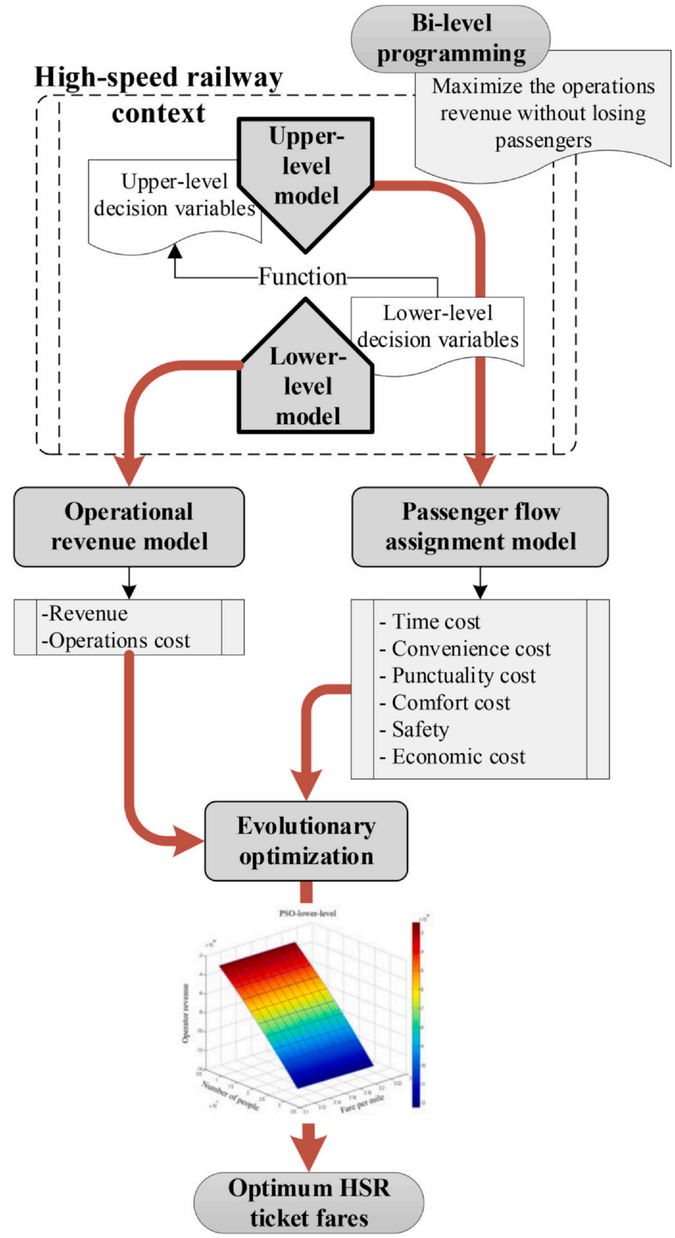

Fig. 1. Flowchart of the proposed model.

3.2. Passenger flow assignment model for ticket fares

Passenger needs, including main reasons for choosing particular

Table 1
Methods for solving bi-level programming model.

Method	Description
Extreme point search method	The upper-level and lower-level objective functions, including the constraints, must have linear programming and are described as Eq. (3). All optimal solutions appeared at the extreme points of the lower-level model. $\Omega = \{(x,y) : x \in X, G(x,y) \leq 0 \text{ and } g(x,y) \leq 0\}$ (3) where, x is the upper-level variable, and $G(x,y)$ and $g(x,y)$ are the upper-level and lower-level constraints, respectively.
Kuhn–Tucker	This method focuses on the linear bi-level programming model, in which the substitution is performed under Kuhn–Tucker conditions that pertain to the problem of interest. In this method, the bi-level problem is transformed into a single-level nonlinear problem. The corrected nonlinear optimization problem is given by Eq. (4). $\min_x f(x)$ $s.t.\ g(x) \leq 0,\ h(x) = 0$ (4) where, $f(x)$ is the value of the objective function, x is the decision variable, $g(x)$ is the inequality constraint set, and $h(x)$ is the equality constraint set.
Descent method	The search for feasible solutions under the optimal conditions of the lower-level model starts with the assumption that the solution (*i.e., x* and *y*) is an implicit function of x, $y(x)$. In the descent method, the subpoint is obtained using the formula $x + \alpha d$ ($\alpha > 0$). When ensuring the feasibility of the bi-level problem, the F value is reduced to a reasonable extent. This reduction is required to solve the gradient of the objective function in the upper-level model. Notably, the matching method must be identified before the descent method is used, because the solution obtained is generally a local optimal solution to the bi-level programming problem. $\nabla_x F(x,y(x)) = \nabla_x F(x,y) + \nabla_y F(x,y)\nabla_x y(x)$ (5) where, $\nabla_x F(x,y(x))$ is the gradient of the upper-level objective function.
Fuzzy mathematical method	This method applies the concept and characteristic of fuzzy logic to the function of the decision variable of both upper-level and lower-level objective values. The bi-level programming problem is transformed into a single-level optimization problem in which the optimal solution (*i.e.,* single-level linear programming) is applied to replace the satisfactory solution in the bi-level programming problem. The fuzzy mathematical method is used to solve mathematical problems in which the boundaries are neither distinct nor fuzzy.
Non-numerical optimization methods	Non-numerical optimization methods were applied to solve the traffic equilibrium problems, among other things, and included the particle swarm optimization, genetic algorithm, neural network, ant colony optimization, and firefly algorithm.

modes of transportation, must be clarified to obtain the maximum effectiveness of public transportation operational costs. In this study, both time cost and perceived cost were considered fixed values. Therefore, the economic cost and changes in passenger flow were main variables. The upper-level programming model was determined to maximize operator revenue without losing passengers.

The generalized cost indirectly influences passenger flow (Guo and Wang Guo & Wang, 2011). The number of rides does not increase indefinitely with the generalized cost but reaches a state of equilibrium. In a single region, the mode of transportation with the lowest total travel cost experiences an increasing flow of passenger, which in turn increases the generalized cost. However, some passengers still choose different modes of transportation (Hu, Xu, & Jin, 2001). Therefore, Du (2010) concluded that a stable and uniform assignment of passenger flow can be achieved.

The stable state reflects the user equilibrium for passenger flow assignment in actual transportation facilities. This state is divided into first and second principles. The first principle reflects that road users fully understand the traffic conditions and choose what they perceive to be the shortest route, whereas the second principle reflects that in the system equilibrium state, passenger flow along congested roads is determined by minimizing the average or total travel time. The mathematical formula for the passenger flow assignment problem, the upper-level model, is as follows (Du, 2010):

$$\min U_i^{od} = \sum_{i=1}^{n} \int_0^{q_i} F_i(x)dx$$

$$s.\ t.\ \sum_{n\in N} q_i = Q\ q_i \geq 0,\ n \in N \tag{6}$$

where N is the number of modes of transportation, F_i is the generalized travel cost for a randomly selected mode of transportation, q_i is the passenger flow for the i^{th} mode of transportation, and Q is the total passenger flow in section *od*.

3.2.1. Generalized ticket fares and passenger flow

The generalized cost is used in the field of transportation to determine the separation modes of passenger flow in different modes of transportation. The generalized cost function is usually a power or logarithmic function, which is mathematically expressed as follows.

$$F_i(q_i) = aq_i^b + O_i \tag{7}$$

where, O_i is the variable ticket fare for the i^{th} mode of transportation, and a and b represent the service attribute parameters for the i^{th} mode of transportation.

Eq. (7) can be solved using the classic Frank–Wolfe algorithm (Xu & Ma, 2018), which performs an all-or-nothing assignment of the passenger flow to the minimum cost path. The cost of traveling along a road section is assessed based on passenger flow in a particular road section. As the passenger flow on a given road section increases, so does the generalized cost. Therefore, the passenger flow must be assigned to other road sections (Xu, Yun-Chao, & Zi-You, 2008) based on a fixed demand. That is why the addition of a virtual path was proposed to convert the original elastic demand into a fixed demand (Da, 2014).

3.2.2. Determined ticket fare variables

Studies on this topic have employed several variables to analyze and adjust ticket fares in order to satisfy the expectations of travelers, as discussed in Table 2.

3.3. Operational revenue model

The operational revenue model was established to assess the acceptable range of ticket fares among passengers while maintaining operational revenue. The objective was to maximize the profit that was indirectly obtained after deductions of the operational cost for a given mode of transportation. The operational cost refers to various expenses that are incurred by HSR and are directly related to the production and operations during a passenger's journey. This model refers to a management method in which operators seek to sell products to right customers at the right price and the right time (Zhou, Song, & Wang, 2016).

3.3.1. Revenue optimization

To maximize the revenue of HSR, a clear definition of price levels and an understanding of the relationship between demand and selling price are required. The lower-level model begins with maximizing operational revenue. After including the passenger flow and the range of ticket fares that are provided by the upper-level model, the solution is to identify the optimum fare that maximizes operators' benefits, which

Table 2
General ticket fare variables and their descriptions.

Variable	Description
Time cost	The transit time, which is related to travel distance, mode of transportation, and travel speed, affects the cost of travel (Engelson & Fosgerau, 2016). The time cost is given by Eq. (8), and the value of time (*vot*) is converted using Eq. (9). $T_i = \left(\frac{d_i^{od}}{\bar{v}_i}\right) \times vot$ (8) where, T_i is the time cost for the i^{th} mode of transportation, d_i^{od} is the distance traveled from the origin to the destination using the i^{th} mode of transportation, $\bar{v}_i$ is the average travel speed for the i^{th} mode of transportation, and vot is the time value for passengers. Moreover, the time value represents the monetary value of a unit of travel time (Zong et al., 2009). In this research, the wage rate method was used to calculate both the time and travel values per average time unit at the macroeconomic level. The equation of the time value for passengers is expressed as follow. $vot = \frac{GDP}{(P_e \times \bar{t}_e)}$ (9) where, $GDP$is the average gross domestic product, $P_e$is the domestic employed population, and $\bar{t}_e$ is the average number of domestic working hours in a year.
Perceived cost–Convenience cost	Fan et al. (2016) determined that the public perceived public transportation waiting times as longer than actual times (Fan et al., 2016). Waiting time, which serves as a measurement of convenience, can be calculated using Eq. (10) (Osuna & Newell, 1972; Welding, 1957). The waiting time is further converted to time value, and the convenience cost can be obtained using Eq. (11). $W_i = \frac{h}{2}\left(1 + \frac{\sigma^2}{h^2}\right)$ (10) where, h is the average departure time interval, and σ is the standard deviation of the departure time interval. $C_i = \Sigma_1^{i} W_i \times vot$ (11) where, C_i is the convenience cost for the i^{th} mode of transportation, and W_i is the waiting time for the i^{th} mode of transportation.
Perceived cost–Punctuality cost	With an increasing focus on time, passengers are willing to select more punctual modes of transportation. (Wei, Chen, Jiang, Wang, & Shao, 2015) expressed punctuality as the average delay of a mode of transportation. The punctuality cost is expressed as follow: $P_i = t_i \times vot$ (12) where, P_i is the punctuality cost for the i^{th} mode of transportation, t_i is the average delay time for the i^{th} mode of transportation, and *vot* is the value of time.
Perceived cost–Comfort cost	The comfort cost refers to a shorter fatigue recovery time. This approach indicates that higher comfort levels result in higher passenger adaptability during travel. Fatigue recovery time, which is related to the travel time and cabin environment, can be assessed using Eq. (13) (Wei et al., 2015) and Eq. (14) after value conversion. $t_i^{AB} = \frac{H_i}{1 + \alpha_i e^{-\beta_i \left(\frac{d_i^{od}}{\bar{v}_i}\right)}}$ (13) where, H_i is the limiting value of the fatigue recovery time, β_i is the recovery-time intensity coefficient per unit travel time for the i^{th} mode of transportation, and α_i is the minimum recovery time for the i^{th} mode of transportation, for which the recovery time is $\frac{H_i}{1+\alpha_i}$ at $t = 0t = 0$. $A_i = t_i^{AB} \times vot$ (14) where, A_i is the comfort cost for the i^{th} mode of transportation.
Safety	Safety is crucial in the transportation industry (Elms, 2001). In this study, the safety performance, associated with the casualty rate, was used to reflect the operators' credibility. Guo (2012) (Guo, 2012) indicated that safety credibility reflected the safeness of a particular mode of transportation. The safety factor formula is expressed as follows. $S_i = \frac{1}{r_i e^{\alpha_i \beta_i}}$ (15) where, S_i is the safety credibility of the i^{th} mode of transportation, r_i is the casualty rate of the i^{th} mode of transportation, and $e^{\alpha_i \beta_i}$ is the coefficient to be determined.
Economic cost	The economic cost is the principal factor affecting passenger travel choices (Zhang, Zhu, Wu, Shen, & Song, 2014). In general, the economic cost is the sum of ticket fares that are associated with the modes of transportation employed by passengers to reach their destinations. The ticket fare is the product of the unit fare rate and the distance traveled. Therefore, the ticket fare to be paid for the mode of transportation can be used to measure the economic cost (Wei et al., 2015). The economic cost is given by Eq. (16). $E_i = f_i \times d_i^{od}$ (16) where, E_i is the economic cost for the i^{th} mode of transportation, and f_i is the unit fare rate for the i^{th} mode of transportation. In this study, the variable ticket fare model is a part of the upper-level model, whereas the time cost, perceived cost, and economic cost are combined, as in Eq. (17). The economic cost is the main value in the upper-level model. The value of the safety index cannot be converted because safety is considered unique. Therefore, safety is used as the denominator by which the sum of all relevant costs is divided. The principal constraint in the upper-level model is ticket fare because the minimum value of ticket fare cannot be lower than the cost required for operation and the maximum value cannot be higher than the maximum ticket fare rate determined by the government. $O_i = \frac{(E_i + T_i \times \lambda_1 + C_i \times \lambda_2 + P_i \times \lambda_3 + A_i \times \lambda_4)}{S_i}$ (17) where, λ_1, λ_2, λ_3, and λ_4 are the weight parameters that correspond to the service attributes.

is expressed as follows.

$$max\, L_i^{od} = q_i^{od} \times d_o^{od} \times (f_i - C_t)$$

$$s.\ t.\ \ f_{min} \le f_i \le f_{max} \tag{18}$$

where, q_i^{od} is the passenger flow for the i^{th} mode of transportation and C_t is the unit cost per kilometer of the i^{th} mode of transportation.

3.3.2. Operational cost

Operational expenses refer to all monetary expenses incurred by the HSR company in conveying passengers to their destinations (Guo, 2009). Zhao and Ren (2015) proposed an algorithm to optimize costs, which comprises four components that consider the number of kilometers per vehicle. The four components are the annual depreciation and maintenance cost (C_1), the annual total personnel cost (C_2), the annual cost to operate and manage train stations and routes (C_3), and all other costs (C_4).

The average operational costs are allocated to each passenger for a particular mode of transportation over each kilometer, which produces an algorithm of the average passenger–kilometer cost formula, announced by the Taiwan Railways Administration (TRA), Ministry of Transportation and Communications (MOTC, 2020). The operational cost equation is as follows.

$$C_t = \frac{C_1 + C_2 + C_3 + C_4}{\sum_{i=1}^{N} d_i^{od} \times q} \tag{19}$$

where q is the passenger flow for the mode of transportation.

3.4. The optimization algorithm

In this research, the PSO method is applied to solve the bi-level programming problem. The PSO can maximize the profits of the transportation agency by considering conflicts between executives and passengers by reflecting the perspectives of both passenger behavior and transportation profit management, respectively. Zhao, Wang, and Huang (2013) suggested the PSO method, which has a relatively simple structure; thus, parameters are easy to control compared with other algorithms. Hereafter, the PSO method is suitable for this study. The general steps of the PSO algorithm are as follows.

(1) Initialize the particle swarm, including its characteristics, speed, and position.
(2) Find a suitable function to define each particle based on the problem to be optimized.
(3) Compare the redefined particles with the original values. If the redefined particles are more favorable to the historical optimal solutions, update and redefine the particles as the current optimal solutions.
(4) After all the particles have been updated, update the particle whose adaptability exceeds the global optimal solution as the optimal solution.
(5) Repeatedly update particle speed and position by performing the loop iteration until the objective condition is met; then, stop the iterative process.

The PSO algorithm is updated for each iteration by using Eq. (20). Several parameters are critical during the optimization processes. The first parameter is the number of particles and iterations. The second parameter is the inertia weight (ω), which determines the proportion of the original speed in the next iteration, given by Eq. (21). The third parameter is learning factors (c_1 and c_2), which generally take the value of 2 because it is the weight of random acceleration terms for each particle as it flies to both local optimal and global optimal positions (Zhao, Gu, & Li, 2007).

$$\begin{aligned} v_i^{(t+1)} &= \omega \times v_{i-1}^{(t)} + c_1 \times rand(1) \times (p_{best} - p_{i-1}^{(t)}) + c_2 \times rand(1) \\ &\quad \times (g_{best} - p_{i-1}^{(t)}) \\ s.\ t.\ \ p_i^{(t+1)} &= x_{i-1}^{(t)} + v_i^{(t+1)} \end{aligned} \tag{20}$$

where, v is particle velocity, p_i is the current position of the particle i, and $rand$ is a random number that lies between zero and one.

$$\omega = \omega_{\text{Max}} - iter \times \frac{\omega_{\text{Max}} - \omega_{\text{Min}}}{iter_{\text{Max}}} \tag{21}$$

where, ω_{Max} is the maximum weighting coefficient, ω_{Min} is the minimum weighting coefficient, $iter$ is the number of current iterations, and $iter_{\text{Max}}$ is the total number of iterations.

The traditional PSO algorithm is easily trapped at local optimal solutions (Fan & Jen, 2019). A random perturbation parameter enables the algorithm to escape from local traps. Therefore, applying a random perturbation parameter is beneficial to facilitate the search for a globally optimal solution (Zhao et al., 2013). Meanwhile, to increase the probability of obtaining the global optimal solution, the mutation is performed on g_{best}, which is expressed in Eq. (22).

$$g_{best} = g_{best} \times (1 + \eta \times 0.5) \tag{22}$$

where, η is a random variable with the standard normal distribution $\eta \sim N(0,1)$.

In this study, the values of perturbation parameters are set into the PSO algorithm to obtain a solution that matches the model optimally. The upper and lower-level models are then initialized, and data related to the upper-level model are collected. The passenger flow assignment model is then initiated. After the model has been processed, the relevant decision variables are introduced to the lower-level model. The improved PSO algorithm is then employed to obtain the overall optimal solution. If results do not reach the expected upper-level, the steps are repeated until optimization results completely correspond to both upper-level and lower-level optimal solutions.

4. Empirical applications

The present study employed the developed model to identify and determine optimal fares for THSR by considering passenger flow satisfaction, the growth of annual operator profits, and the overall gains of the THSR Corporation (THSRC).

4.1. Taiwan high speed rail corporation and its system

The THSR was constructed in the western part of Taiwan with an average speed of 250 km/h, 12 stations, and a total length of 345.2 km. The complete THSR map is depicted in Fig. 2. The THSR system is now operated by a private corporation (THSRC) under a 35-year BOT contract until 2033, after which the system's operational ownership will transfer back to Taiwan's government (Cheng, 2010). The BOT project was completed by the private sector, based on plans by the THSRC, rather than under the constraints of the government's budgeting process.

The THSRC has the right to construct and operate commercial development on the land near HSR stations for 50 years. This BOT model enables THSRC to incur profits and losses during the time it operates the system. The benefits for THSRC of the BOT contract come in the form of support from the government, including land acquisition, financial loan acquirement, alleviation of environmental concerns (vibration and noise), and integration with the local transportation system.

The THSRC offers a non-reserved seat service at lower ticket fares without seat reservations for specific boarding of carriages 9, 10, 11, and 12. Passengers can only purchase non-reserved seat tickets on the date of travel at ticket windows and ticket vending machines at HSR stations. The non-reserved seat service permits the sale of standing tickets, which may cause dissatisfaction with service quality. The non-reserved seats' transportation volume is much higher than that of reserved seats, mainly because of the more economical ticket price for non-reserved seats.

Passengers in business cars, all of which are reserved seats, pay higher prices for a much more comfortable onboard service, which includes free snacks, drinks, and magazines. The standard class car offers two kinds of services: reserved seats and non-reserved seats. There is currently one car for business passengers, four cars for non-reserved seats, and seven cars for reserved seats. THSRC offers a price discrimination strategy between reserved seats and non-reserved seats.

The load factor in carriages offering non-reserved seat service is relatively high because of the ticket price discount. Passengers in carriages for non-reserved seats account for 40% of total train passengers on weekdays and 50% during weekends. Fares for certain tickets, including senior, disabled person, and children tickets, are 50% off from the fare regulated by the Ministry of Transportation and Communications. Senior citizens, disabled persons, and one accompanying passenger and children are all eligible to purchase tickets at half price. Group discounts are offered to groups purchasing 11 or more adult tickets. The discount rate for group tickets is 10%.

The basic fare rate approved by the government is adjusted according to the consumer price index, expressed in Eq. (23). The THSRC is allowed to adjust the standard fare rate (F_g) after approval from the government. However, the annual fare increment rate cannot exceed

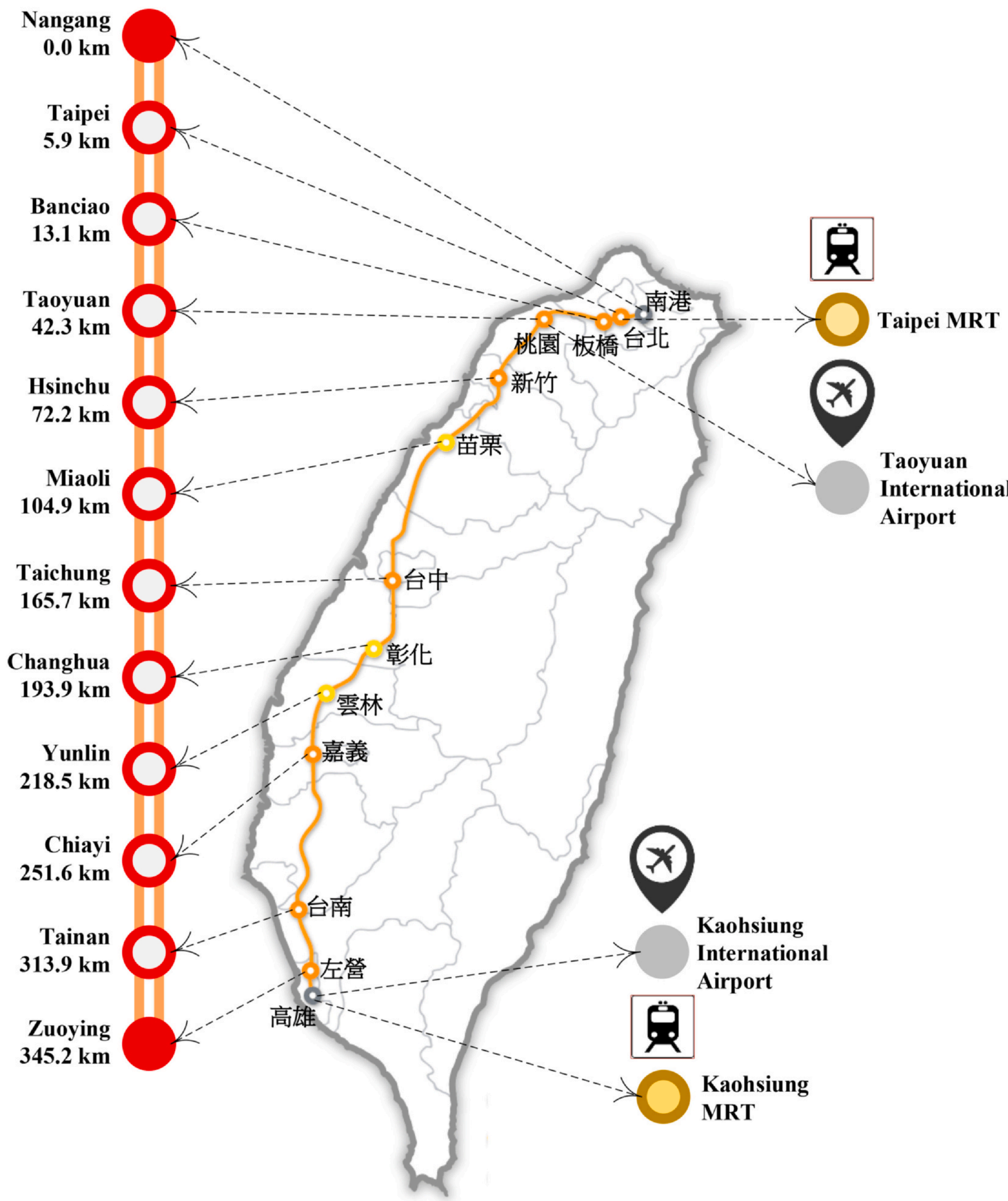

Fig. 2. THSR map and distance between stations.

20%. Although the revenue from the THSR is increasing, benefits to the transportation agency are still limited (Hsu et al., 2010).

$$F_{g,t+1} = F_{g,t} \times (1 - X_t\%) \ldots X_t\% = \frac{GICP_t - GICP_{t-1}}{GICP_{t-1}} \tag{23}$$

where *GICP* is the consumer price index in Taiwan.

4.2. Constructing the upper-level model

Although revenue collected by the TRA is gradually increasing, the debt of the company has only slightly declined (Yu & Johannesson, 2010), which indicates that the overall revenue has not reached the operator's expected revenue. Therefore, a passenger flow model that satisfies passenger needs was constructed and used as a basis for developing the upper-level model while maximizing annual operator revenue.

The basic generalized cost following the THSRC principle for calculating ticket fares is 4.386 NTD per km for each passenger. The THSR passengers can be categorized into three groups based on the distance traveled: long-distance, medium-distance, and short-distance passenger groups. The first group undertakes long-distance travel from Taipei to Zuoying. The highest and lowest numbers of THSR passengers were assumed to be 92,957,423 and 34,637,399 per year, respectively.

A virtual path was added to convert the original elastic demand into a fixed demand. The demand function is represented in Eq. (24), and the cost-sensitive parameter is assumed to be 10 (Da, 2014). The impedance function is represented as Eq. (25), and the impedance function obtained from the maximum and minimum values was $0.1q_2$. The passenger flow was divided based on the original fare rate (q_0), the current model (q_1), and the remaining selected paths (q_2). Accordingly, the upper-level formula was Eq. (26).

$$Q_{max} - \theta F_i = 92{,}957{,}423 - 10F_i \tag{24}$$

where, $Q_{max}$was the maximum number of passengers required; θ is the

Table 3
Analytical results of fare rates and passenger flow in the first upper-level model.

Rate (NTD/person-km)	Original passenger flow q_0 (thousand people)		Research model traffic q_1 (thousand people)		Remaining path traffic q_2 (thousand people)	
	Max	Min	Max	Min	Max	Min
2.0	31,719	8208	36,822	10,411	24,415	16,017
2.5	32,620	8509	35,622	9910	24,715	16,217
3.0	33,621	8909	34,421	9310	24,915	16,417
3.5	34,521	9310	33,321	8709	25,116	16,617
4.0	35,522	9610	32,120	8208	25,316	16,818
4.5	36,322	10,010	31,019	7608	25,616	17,018
4.7	36,723	10,110	30,619	7408	25,616	17,118

cost-sensitive parameter (*i.e.,* $\theta > 0$), and F_i is the minimum generalized travel fare.

$$D^{-1}(Q) = 9{,}295{,}742.3 - 0.1Q = 9{,}295{,}742.3 - 0.1(92{,}957{,}423 - q_2) = 0.1q_2 \tag{25}$$

$$\min U_i^{od} = \int_0^{q_o} (2q_i^{0.4} + 339.28 \times 4.386) dq + \int_0^{q_1} (2q_i^{0.4} + 339.28 \times f + 406.19)dq + \int_0^{q_2} (0.1q_i)dq$$

$$s.\ t.\ \ q_0 + q_1 + q_2 = 92{,}957{,}423 \ and \ q_i \geq 0,\ i = 0, 1, 2 \tag{26}$$

Table 3 presents the result of the passenger flow analysis by using the first upper-level model. Passenger flow was determined to change with the fare rate between 3.0 and 3.5 NTD/person-km. Integrating the analysis result into the lower-level analysis yielded a maximum operational cost at a fare rate of 3.5 NTD/person-km. However, narrowing the scope of passenger flow assignment is crucial to accurately determine changes in passenger flow.

Table 4 presents the results of the second passenger flow assignment, which indicated that passenger flow changed significantly at fare rates of 3.1 and 3.2 NTD/person-km. The corresponding costs were calculated based on this fare rate interval to yield the overall operational income.

The second group investigated was medium-distance passengers who traveled from Taipei to Taichung. Based on the recorded numbers of passengers who depart from Taichung station, the maximum and minimum numbers of passengers were assumed to be 16,005,991 and 5,744,008 people per year, respectively. The formula for generalized cost was $\int_o^{q_1}(2q_i^{0.4} + d_i^{od} \times f + 221.1)dq$, in which the variable ticket fare is 221.1 NTD. A distance of 159.83 km from Taipei to Taichung was substituted into this formula. The first analysis revealed a change in passenger flow with a fare rate between 3.0 and 3.5 NTD/person-km. However, the second analysis revealed changes in passenger flow within a fare rate interval of 3.0–3.1 NTD/person-km.

Table 4
Analytical results of fare rates and passenger flow in the second upper-level model.

Rate (NTD/person-km)	Original passenger flow q_0 (thousand people)		Research model traffic q_1 (thousand people)		Remaining path traffic q_2 (thousand people)	
	Max	Min	Max	Min	Max	Min
3.0	33,621	8909	34,421	9310	24,915	16,417
3.1	33,820	8910	34,221	9210	24,915	16,178
3.2	34,021	9010	33,920	9110	25,015	16,518
3.3	34,221	9110	33,720	8910	25,015	16,618
3.4	34,321	9210	33,520	8810	25,115	16,618
3.5	34,521	9310	33,321	8709	25,116	16,617

The third group in this study was short-distance passengers who traveled from Taipei to Banqiao. Records of numbers of passengers who depart from Banqiao station report the maximum and minimum numbers of passengers of 6,049,514 and 3,435,956 people, respectively. The formula for generalized cost was$\int_o^{q_1}(2q_i^{0.4} + d_i^{od} \times f + 58.7)dq$, in which the variable ticket fare was 58.7 NTD.

A distance of 7.22 km from Taipei to Banqiao was substituted into this formula. The first analysis revealed that the passenger flow primarily changed with a fare rate between 4.0 and 4.5 NTD/person-km. However, a second analysis revealed that the passenger flow changed within the fare rate interval from 4.2 to 4.3 NTD/person-km. Incorporating these three groups into the lower-level model yielded the overall operational status for various distances.

The five previously discussed variables involved in ticket fares were also applied to calculate variable ticket fares and obtain optimum ticket fares that are accepted and satisfy public expectations. Table 5 describes the specific variables related to THSR ticket fares. The ranges of rates that incur major changes in the number of passengers were included in the lower-level model for analysis. The analysis results of ticket fare adjustment on passenger expectation satisfaction were evaluated to determine whether the THSR operator's overall benefits exceeded rates that were previously set.

4.3. Developing the lower-level model

The upper-level model indicated that passenger flow from Taipei to Zuoying in the first group mostly changed in fare rates between 3.0 and 3.5 NTD/person-km. Within this range, the maximum and minimum passenger flows were determined to be 34,421 and 8,709 thousand people, respectively. The PSO algorithm was used to evaluate the maximum operator profit. Therefore, the lower-level model formula was modified so that the maximization of operational income became the minimization. The modified formula is presented in Eq. (27).

$$\min L_i^{od} = -q_i^{od} \times d_i^{od} \times (f_i - C_t) \tag{27}$$

Parameters in the algorithm must be defined before execution. Particle size was assumed to be 50 ($n = 50$); Inertia weight was determined to be 0.1 ($\omega = 0.1$), and the maximum number of iterations was 50 (iterMax = 50); learning factors generally take the value of 2 (c_1, $c_2 = 2$); and the perturbation coefficient was set to 0.005 ($\eta = 0.005$) (He & Cheng, 2017; Zhao et al., 2013). The passenger flow and ticket fare rates obtained from upper-level programming were incorporated into the lower-level model.

When the unit fare rate was 3.5 NTD/person-km, the operational revenue travel from Taipei to Zuoying was higher. To reflect variations in passenger flow after a change of ticket fare, a simulation was performed using the upper-level model. The fare rate interval in the second simulation was between 3.1 and 3.2 km/h. This interval was then incorporated into the lower-level model for analysis. The revenue was maximized for a fare rate of 3.2 NTD/person-km.

The calculations of variable costs revealed that the fare rate obtained from the second simulation was 3.2 NTD/person-km, and the revenue from the deducted cost rate was 89.4 billion NTD. However, this result does not satisfy the optimization condition of the upper-level passenger flow assignment model. Therefore, to enable both the upper and lower-level to reach optimum states, the fare rate was modified to 3.1 NTD/person-km.

The number of passengers who selected this ticket fare in the upper-level model reflected passenger satisfaction, whereas the lower-level model satisfaction represented revenue that exceeded the expected THSR revenue. Therefore, a greater distance traveled corresponded to a greater effect on overall revenue. The optimal fare rate of the first group was selected as the standard in setting all ticket fares. Table 6 provides the corresponding ticket fares.

To determine the operator's income, costs were classified as

Table 5
Applied THSR ticket fare variables and their descriptions.

Variable	Description
Time cost	The official website of the Executive Yuan and National Statistics states that a calculation of time value must consider the average gross domestic product, domestic employed population, and average annual domestic working hours. The value of time for 2017 was thus calculated to be 707 NTD/person–hour.
Perceived cost–Convenience cost	Based on the concept of convenience cost, passengers perceive the waiting time as the convenience cost. The timetable announced by the THSRC was organized and relevant calculations were performed before the time value was converted to the convenience cost.
Perceived cost–Punctuality cost	The THSR has always outperformed in punctuality. The THSRC has confidence in its targeted and average punctuality, which is provided on the official website every month. The punctuality cost in 2017 was 1.24 NTD. The annual amount spent was close to zero, indicating that passengers did not incur extra expenses because of lateness.
Perceived cost–Comfort cost	Comfort is related to both travel time and cabin environment, which is reflected in fatigue recovery time. The maximum fatigue recovery time (H_l) is 15 h, and the minimum recovery time (α_i) and recovery-time intensity coefficient (β_i) are reported in the study by (Wei et al., 2015). Longer distances traveled result in a longer fatigue recovery time. Therefore, perceived comfort costs will also be higher.
Safety	Safety is a significant factor when selecting a mode of transportation. Failure to embrace and prioritize safety will inevitably damage the operator's reputation which causes passengers to be reluctant in choosing a particular mode of transportation. In this study, safety was quantified as safety credibility. Following the data announced by THSRC, the number of deaths and casualties in 2017 were both zero, so safety credibility for that year was 1.
Economic cost	Another crucial factor that affects passenger travel choices is ticket fare. The HSR ticket fare rates are set according to the passenger flow. Following the combination of time cost, perceived cost, and safety factors, the variable ticket fare model was substituted into the upper-level model to obtain the number of passengers affected by these costs. Based on the service attribute parameters proposed by (Zhang et al., 2014), the weights of service attribute parameters were $\lambda_1 = 0.3607, \lambda_2 = 0.2692, \lambda_3 = 0.1896,$ and $\lambda_4 = 0.1805$. Because the economic cost can be obtained using both upper-level and lower-level models, each value must be combined with the economic cost to obtain the total cost of travel in the variable ticket fare model.

operational costs, operational expenses, and other expenses. These cost categories were then divided by the passenger flow at relevant rates, followed by the comprehensive evaluation of the formula provided by the TRA (Eq. 28). The relevant data were then incorporated into the computation to generate the total operational cost in 2017, which was 2.98 NTD. After the PSO algorithm was applied to the annual cost rate, the operator's total revenue from deducted costs could be obtained as follows.

$$C_t = \frac{\text{Operation cost+Operation expenses+Other cost}}{\sum_{i=1}^{N} d_i^{od} \times q_1} \tag{28}$$

In the second group analysis, which comprised medium-distance travelers from Taipei to Taichung, the first fare rate at which the passenger flow changed was between 3.0 and 3.5 NTD/person-km. When the fare rate approached 3.5 NTD/person-km, the operational revenue was optimal. Based on the second analysis, the range of fare rates was 3.0–3.1 NTD/person-km. The operational revenue was reached the optimal value when the fare rate was 3.1 NTD/person-km. However, to satisfy the upper-level and lower-level, the fare rate was adjusted to 3.0 NTD/person-km.

For the third group, which comprised short-distance travelers from Taipei to Banqiao, the first fare rate at which passenger flow changed was between 4.0 and 4.5 NTD/person-km. The maximal operational revenue was determined to occur at a fare rate of 4.5 NTD/person-km. The second analysis indicated that the range of fare rates was between 4.2 and 4.3 NTD/person-km. Therefore, the operational revenue was maximized when the fare rate was 4.3 NTD/person-km. However, to satisfy both levels, the fare rate was adjusted to 4.2 NTD/person-km. The adjustment is performed to prevent the operator from losing passengers.

5. Findings and discussion

The analyses revealed that optimal fare rates were divided into three groups by distance traveled. In the first group, the optimal fare rate for long distances was 3.1 NTD/person-km; in the second group, the optimal fare rate for medium distances was 3.0 NTD/person-km; and in the third group, the optimal fare rate for short distances was 4.2 NTD/person-km. The original generalized cost to use the THSR was approximately 4.4 NTD/person-km for all three groups.

The bi-level programming model yields optimal ticket fares from Taipei to Zuoying (longest distance) and from Nangang to Taipei (shortest distance) of 1,110 and 75 NTD, respectively. For shorter distances, the optimal ticket fare was close to the original THSR ticket fare. Therefore, public satisfaction should be observed for short-distance trips because the current THSR fares are close to the optimal ticket fare (*e.g.,* Taipei to Banqiao or Nangang to Taipei).

The analysis also demonstrated that the optimal ticket fare becomes increasingly lower than the current THSR ticket fare as distance traveled increases. For certain trips, higher mileage corresponds to greater gains. Therefore, the relevant agency should promote long-distance trips. For instance, Taiwanese people select THSR for long-distance

Table 6
Ticket fares between stations.

Station	Nangang	Taipei	Banqiao	Taoyuan	Hsinchu	Miaoli	Taichung	Changhua	Yunlin	Chiayi	Tainan
Nangang											
Taipei	75										
Banqiao	98	81									
Taoyuan	188	171	177								
Hsinchu	281	264	270	187							
Miaoli	382	365	371	289	214						
Taichung	571	554	560	477	403	325					
Changhua	658	641	647	565	490	412	207				
Yunlin	734	718	723	641	566	488	283	230			
Chiayi	837	820	826	744	669	591	386	332	234		
Tainan	1030	1013	1019	937	862	784	579	525	427	321	
Zuoying	1127	1110	1116	1034	959	881	676	623	525	418	187

Unit: NTD.

traveling because of its convenience, frequency, and rapidity. According to analytical results, the current THSR pricing policy encourages passengers to select short-distance service.

The optimal fare rates for medium and long distances are lower than the current ones, implying that the current fare rates are higher than passengers expect them to be. Although the THSR remains the optimal choice of passengers for medium and long distances trips, the policy does not attract new customers or maintain loyal customers, because the high fare rate fails to meet customer expectations. Therefore, the THSRC should improve the service quality as well as providing concession tickets for both medium-distance and long-distance trips to meet passengers' expectations.

Following the findings discussed above, the bi-level optimization model has proven to be robust comparing to the previous analysis model. The model is capable to generate optimal ticket fares based on the distance traveled. Accordingly, the simulation outputs from the model not only generate the optimum ticket fares but also consider the trade-off of ticket fares for the travelers between stations allocated by THSRC.

The optimization model and evolutionary algorithm were designed to solve the fare issue considering different travel distance and travel volume. The evolutionary bi-level model shows that the perturbation parameter that has been applied within the optimization processes enables the algorithm to reaching a globally optimal ticket fares. Compared to the original THSR ticket fares approved by the TRA, the model gave lower ticket fares.

The difference between the proposed optimization model and other relevant ones is that it takes HSR capacity, different distance, passenger volume, operations cost, and current ticket fare constraints into consideration. The analytical case demonstrates that the pricing strategy based on the proposed model can increase the agency revenue as well as stimulate the potential travel demand.

6. Concluding remarks

An evolutionary optimization model for assessing the optimum HSR ticket fare was developed by applying a bi-level programming method. Passenger flow assignment was applied in the optimization analysis as the baseline for analyzing optimal ticket fares adjustment while examining the operator's overall revenue. The constructed model can quantify operator revenue in terms of various factors, such as ticket fare rates and travel volume, to provide quantitative justification on the effects of adjustment of ticket fare rates on operational revenue.

The analysis revealed that upper and lower-level models were mutually constrained. Subsequently, both the rights and interests of passengers were unaffected by operational revenue. Applying the proposed model on the THSR case study yielded optimal ticket fares of 1,110 and 75 NTD for Taipei to Zuoying and from Nangang to Taipei, respectively. For shorter distances, the optimal ticket fare was close to the original HSR ticket fare.

As the distance traveled increases, the optimal ticket fare becomes increasingly lower than the current THSR ticket fare. Higher mileage generally corresponds to higher earnings. Therefore, the relevant agency should promote long-distance trips. The case study demonstrates both the feasibility and superiority of the bi-level programming model. Empirical application on the THSR case confirmed the effects of changing ticket fares on agency revenue.

This research has two limitations. First, this investigation considers the transportation agency as the main stakeholder and passenger satisfaction as the key factor. Second, both the transportation agency and passengers' weight value are disregarded within the analysis. Further work should modify the bi-level programming model into trilateral game theory and verify or calibrate the model with a survey or stakeholders' perception information that considers various stakeholders with their divergent weight values (including operator, passengers, and government agencies) to investigate and analyze other modes of public transportation ticket fare in more detail.

There are certainly many potential directions for future research in this area, such as expanding the optimization of ticket fares for multiple trains considering the passengers' choice behavior among these train services. Another research direction is to dynamically determine when to open each fare grade based on the available seats and time left. Future work can also determine ticket price for HSR by expanding multiple objectives with the proposed evolutionary bi-level planning model.

In sum, this study contributes practical tools for decision makers because the structured procedure, indicators, and series of key factors can be used to assess and determine public transportation ticket fares while considering passengers' satisfaction and operations performance. Furthermore, the proposed model could assist in decision making related to the governance of public transportation through a more comprehensive understanding of the transportation market and by aiding in achieving breakthroughs in the adjustment of ticket fare intervals by policymakers.

Declaration of Competing Interest

None.

Acknowledgements

The authors would like to thank the Ministry of Science and Technology, Taiwan, for financially supporting this research under contract MOST 108-2221-E-011-003-MY3.

References

Assadipour, G., Ke, G. Y., & Verma, M. (2016). A toll-based bi-level programming approach to managing hazardous materials shipments over an intermodal transportation network. *Transportation Research Part D: Transport and Environment, 47*(0), 208–221.

Bai, X.-j., Zeng, J., & Chiu, Y.-H. (2019). Pre-evaluating efficiency gains from potential mergers and acquisitions based on the resampling DEA approach: Evidence from China's railway sector. *Transport Policy, 76*, 46–56.

Beria, P., Grimaldi, R., Albalate, D., & Bel, G. (2018). Delusions of success: Costs and demand of high-speed rail in Italy and Spain. *Transport Policy, 68*, 63–79.

Börjesson, M., & Eliasson, J. (2019). Should values of time be differentiated? *Transport Reviews, 39*(3), 357–375.

Chen, J. H., & Gao, Z. Y. (2004). Optimal railway passenger-ticket pricing and train speeding-up. *Journal of Management Sciences in China, 4*, 49–55.

Cheng, Y.-H. (2010). High-speed rail in Taiwan: New experience and issues for future development. *Transport Policy, 17*(2), 51–63.

Chou, J.-S., Chien, Y.-L., Nguyen, N.-M., & Truong, D.-N. (2018). Pricing policy of floating ticket fare for riding high speed rail based on time-space compression. *Transport Policy, 69*, 179–192.

Chou, J.-S., & Kim, C. (2009). A structural equation analysis of the QSL relationship with passenger riding experience on high speed rail: An empirical study of Taiwan and Korea. *Expert Systems with Applications, 36*(3 Part 2), 6945–6955.

Chou, J.-S., Kim, C., Kuo, Y.-C., & Ou, N.-C. (2011). Deploying effective service strategy in the operations stage of high-speed rail. *Transportation Research Part E: Logistics and Transportation Review, 47*(4), 507–519.

Chou, J.-S., Kim, C., Tsai, P.-Y., Yeh, C.-P., & Son, H. (2017). Longitudinal assessment of high-speed rail service delivery, satisfaction and operations: A study of Taiwan and Korea systems. *KSCE Journal of Civil Engineering, 21*(6), 2413–2428.

Chou, J.-S., & Yeh, C.-P. (2013). Influential constructs, mediating effects, and moderating effects on operations performance of high speed rail from passenger perspective. *Transport Policy, 30*, 207–219.

Chu, Y.-L. (2018). Implementation of a new network equilibrium model of travel choices. *Journal of Traffic and Transportation Engineering (English Edition), 5*(2), 105–115.

Colson, B., Marcotte, P., & Savard, G. J. O. (2005). *Bilevel programming: A survey.* 3(2) 87–107.

Cordera, R., Sañudo, R., dell'Olio, L., & Ibeas, Á. (2018). Trip distribution model for regional railway services considering spatial effects between stations. *Transport Policy, 67*, 77–84.

Da, J. (2014). *Study on the formulation of high-speed railway fare based on competition of different modes of transport.* Southwest Jiaotong University pp. 1-z.

Dewez, S., Labbé, M., Marcotte, P., & Gilles, S. (2008). New formulations and valid inequalities for a bilevel pricing problem. *Operations Research Letters, 36*(2), 141–149.

Du, X.-D., & Si, B.-F. (2005). Bi-level programming model of srochastic equilibrium traffic flow distribution based origin-destination estimation and its new algorithm. *Journal of Shandong University of Science and Technology, 24*(3), 86–89.

Du, Y.-l. (2010). A Bi-level programming model for ticket fare pricing of rail transit.

Transport Standardization, 15, 201–203.
Elms, D. (2001). Rail safety. *Reliability Engineering & System Safety, 74*(3), 291–297.
Engelson, L., & Fosgerau, M. (2016). The cost of travel time variability: Three measures with properties. *Transportation Research Part B: Methodological, 91*, 555–564.
Espinosa-Aranda, J. L., García-Ródenas, R., Ramírez-Flores, M.d. C., López-García, M. L., & Angulo, E. (2015). High-speed railway scheduling based on user preferences. *European Journal of Operational Research, 246*(3), 772–786.
Fan, S.-K. S., & Jen, C.-H. J. M. (2019). An enhanced partial search to particle swarm optimization for unconstrained optimization. *Mathematics, 7*(4) 357.
Fan, Y., Guthrie, A., & Levinson, D. (2016). Waiting time perceptions at transit stops and stations: Effects of basic amenities, gender, and security. *Transportation Research Part A: Policy and Practice, 88*, 251–264.
Ghassemi Tari, F., & Hashemi, Z. (2016). A priority based genetic algorithm for nonlinear transportation costs problems. *Computers & Industrial Engineering, 96*(Supplement C), 86–95.
Guo, C.-J., & Wang, H.-J. (2011). Model and algorithm for adjustment of high-speed railway service properties basd on market demand. *Journal of the China Railway Society, 8*, 7–12.
Guo, J. J. (2012). Study on the diversion of passenger volume of railway passengers along the highway. *Urban construction theory research, 25* c-c.
Guo, S. Y. (2009). Exploration of cost optimization of high-speed railway. *Occupational Circle, 21*, 74–75.
He, P. H., & Cheng, S. R. (2017). Application of particle swarm optimization in solving railway bilevel programming model. *Computer Knowledge and Technology, 2017*, 238–242.
Hsu, C.-W., Lee, Y., & Liao, C.-H. (2010). Competition between high-speed and conventional rail systems: A game theoretical approach. *Expert Systems with Applications, 37*(4), 3162–3170.
Hu, Y.-c., Xu, J.-m., & Jin, W.-z. (2001). Application of logit model in evaluation passenger transport charges. *Journal of Highway and Transportion Research and Development, 6*, 130–133.
Hultkrantz, L. (2013). A note on high-speed rail investments and travelers' value of time. *Journal of Rail Transport Planning and Management, 3*(1–2), 14–21.
Kurosaki, F., & Alexandersson, G. (2018). Managing unprofitable passenger rail operations in Japan - lessons from the experience in Sweden. *Research in Transportation Economics, 69*, 460–469.
Lee, D. B. (2000). Methods for evaluation of transportation projects in the USA. *Transport Policy, 7*(1), 41–50.
Li, H., Strauss, J., & Lu, L. (2019). The impact of high-speed rail on civil aviation in China. *Transport Policy, 74*, 187–200.
Ma, Y., & Gao, Y. (2016). Passenger transportation structure optimization model based on user optimum. *Procedia Engineering, 137*, 202–209.
Maduwanthi, R. A. M., Marasinghe, A., Rajapakse, R. P. C. J., Dharmawansa, A. D., & Nomura, S. (2015). Factors influencing to travel behavior on transport mode choice. *International Journal of Affective Engineering, 15*(2), 63–72.
MOTC (2020). *Monthly transportation report.* Ministry of Transportation and Communication.
Osuna, E. E., & Newell, G. F. (1972). Control strategies for an idealized public transportation system. *Transportation Science, 6*(1), 52–72.
Rothengatter, W. (2000). Evaluation of infrastructure Investments in Germany. *Transport Policy, 7*(1), 17–25.
Sun, H., Gao, Z., & Wu, J. (2008). A bi-level programming model and solution algorithm for the location of logistics distribution centers. *Applied Mathematical Modelling, 32*(4), 610–616.
Sun, Z. (2016). Continuous transportation network design problem based on bi-level programming model. *Procedia Engineering, 137*(Supplement C), 277–282.
Talvitie, A. (2000). Evaluation of road projects and programs in developing countries. *Transport Policy, 7*(1), 61–72.
THSR (2018). *Taiwan high speed rail*.
Vickerman, R. (2000). Evaluation methodologies for transport projects in the United Kingdom. *Transport Policy, 7*(1), 7–16.
Wang, L. (2018). High-speed rail services development and regional accessibility restructuring in megaregions: A case of the Yangtze River Delta, China. *Transport Policy, 72*, 34–44.
Wei, L., Chen, H., Jiang, J., Wang, H., & Shao, H. (2015). Study on bi-level programming model of high-speed rail fares based on generalized cost function. *Journal of Railway Science and Engineering, 2*, 250–256.
Wei, Z. (2003). Time value of passengers. *Journal of Traffic and Transportation Engineering, 3*, 110–116.
Welding, P. I. (1957). The instability of a close-interval service. *Journal of the Operational Research Society, 8*(3), 133–142.
Wu, W.-G., Luo, X.-Q., & Wang, Y. (2010). A study on a bi-level programming model for urban metro ticket fare. *Humanities & Social Sciences Journal of Hainan University, 2*, 63–66.
Xu, J., & Ma, Q. (2018). Multi-label regularized quadratic programming feature selection algorithm with Frank–Wolfe method. *Expert Systems with Applications, 95*, 14–31.
Xu, M., Yun-Chao, Q., & Zi-You, G. (2008). Implementing frank-wolfe algorithm for traffic assignment problem under different flow update strategies and line search technologies. *Journal of Transportation Systems Engineering and Information Technology, 3*, 14–22.
Yang, H., & Zhang, A. (2012). Effects of high-speed rail and air transport competition on prices, profits and welfare. *Transportation Research Part B: Methodological, 46*(10), 1322–1333.
Yu, B., Kong, L., Sun, Y., Yao, B., & Gao, Z. (2015). A bi-level programming for bus lane network design. *Transportation Research Part C: Emerging Technologies, 55*(Supplement C), 310–327.
Yu, P. K.-h., & Johannesson, J. (2010). Near-bankruptcy of the Taiwan high speed rail corporation: What went wrong? *International Journal of Business and Management, 5*(12), 14.
Zhang, L., Zhu, L.-H., Wu, X.-Y., Shen, B.-B., & Song, Y.-X. (2014). *Analysis on examples of high-speed railway ticket pricing mechanism based on floating pricing model railway transport and economy*.
Zhao, J., & Ren, M. (2015). Empirical study on passenger market segmentation and ticket marketing strategy of Beijing-Shanghai high-speed railway. *Railway Economics Research, 6*, 28–30.
Zhao, Z.-g., Gu, X.-y., & Li, T.-s. (2007). Particle swarm optimization for bi-level programming problem. *System Engineering Theory andPractice, 27*(8), 92–98.
Zhao, Z.-g., Wang, W.-q., & Huang, S.-y. (2013). Bi-level programming problem based on improved particle swarm algorithm. *Computer Science, 2013*, 115–119.
Zhen, F., Cao, J., & Tang, J. (2018). Exploring correlates of passenger satisfaction and service improvement priorities of the Shanghai-Nanjing High Speed Rail. *Journal of Transport and Land Use, 11*(1), 559–573.
Zhen, F., Cao, X., & Tang, J. (2019). The role of access and egress in passenger overall satisfaction with high speed rail. *Transportation, 46*(6), 2137–2150.
Zheng, L., Long, F., Chang, Z., & Ye, J. (2019). Ghost town or city of hope? The spatial spillover effects of high-speed railway stations in China. *Transport Policy, 81*, 230–241.
Zhou, Y., Song, X.-M., & Wang, H.-X. (2016). Research on high-speed railway pricing mechanism based on revenue management and its application strategy. *Railway Transport and Economy,* (5), 10–14.
Zhu, Y., Mao, B., Bai, Y., & Chen, S. (2017). A bi-level model for single-line rail timetable design with consideration of demand and capacity. *Transportation Research Part C: Emerging Technologies, 85*(Supplement C), 211–233.
Zito, P., Salvo, G., & La Franca, L. (2011). Modelling airlines competition on fares and frequencies of service by bi-level optimization. *Procedia - Social and Behavioral Sciences, 20*(Supplement C), 1080–1089.
Zong, F., Juan, Z.-c., Zhang, H.-y., & Jia, H.-f. (2009). Calculation and application of value of travel time. *Journal of Transportation Systems Engineering and Information Technology, 3*, 114–119.