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High-speed rail cost recovery time based on an integer optimization model

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SUMMARY

With increasing gasoline prices, electric high-speed rail (HSR) systems represent one means to mitigate overexposure to volatile prices. However, additional research is needed related to funding this infrastructure. In this paper, we develop a new integer optimization model to address this problem and use a hypothetical case study to demonstrate the approach. The objective of the approach is to minimize the time period in which the cost of HSR construction and operation can be recovered. This is an iterative process based on an integer optimization model, whose objective function is to determine the optimum recovery time (ORT), by setting the HSR ticket price and frequency. Embedded in the optimization model is a multinomial logit model for calculating the demand for HSR as a function of these decision variables, thus capturing the effects of level of service on market share. In particular, the optimization model accounts for the role of different types of subsidies toward HSR construction (one-time subsidies at construction, annual subsidies, and subsidies depending on frequency). This method can also help determine whether an HSR system should be built or how much subsidy should be provided given a fixed expected cost recovery time. By integrating the logit model into the objective function evaluation, the effects of ticket price and service frequency on service demand can be directly captured. Copyright © 2014 John Wiley & Sons, Ltd.

KEY WORDS: integer optimization; cost recovery; high-speed rail; multinomial logit model

1. INTRODUCTION

High-speed rail (HSR) has many advantages compared with other transportation modes. First, it is very safe. Until very recently, since the world's first HSR operation in 1964 running between Tokyo and Osaka, there have been only two fatal accidents. Second, it is fast. Trains in France now run routinely at 320 km/h. A record of 575 km/h was set by a French TGV in April 2007. In China, the new JingHu HSR shortens the travel time between Beijing and Shanghai from 10 to 5 h with the highest running speed at about 300 km/h. Third, HSR is energy efficient. The Canberra Business Council reports that with one unit of energy, the number of passengers transported by HSR is 8.5 times the number of passengers transported by air [1]. Finally, HSR also has significant economic effects. The "railway station-based economy" was first pioneered by Japan in the early 20th century. In Kyoto, five hotels, two department stores and several art galleries were built in and around the city's railway station, which is now a major business center with the highest passenger throughput of any area in the city [2].

However, there is also risk in constructing an HSR system. The cost of an HSR is $20m/km in China [3]. Ho [2] concludes: "The debt accumulated by the China Ministry of Railways (MOR) is expected to reach nearly $460bn by 2020, causing the asset-to-liability ratio to rise to more than 70%. If the future operating income of the high-speed rail network is insufficient to repay this debt, the MOR will have to seek other financing channels or potentially explore the possibility of using real estate

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development atop and surrounding railway stations to subsidize its rail operations." Thus, estimating the cost recovery time (RT; the time needed for the HSR company to repay its investment costs) and making the corresponding construction and operation decisions are important questions that need to be answered before the construction of HSR.

Usually, the cost of an HSR system includes infrastructure construction, vehicle purchase and operation. The income of an HSR system includes that from ticket sales, HSR central business district (CBD) leasing and related services (for example, VIP boarding and entertainment services). To minimize the RT is to minimize the cost and maximize the income as far as possible. Clearly, the total costs of vehicle purchase and HSR operation are influenced by travel demand that is determined by the number of travelers and HSR service frequency. Furthermore, HSR income will also be affected by travel demand because the higher the demand, the higher the income from ticket sales. Thus, the RT is undoubtedly influenced by travel demand. As we can imagine, after HSR operations begin, the travel demand by different modes will change because HSR will attract a considerable number of people from other modes. Thus, embedding the mode split calculations into the cost recovery objective is the major contribution of this research. Specifically, we propose an optimization module for setting ticket price and trip frequency, using a multinomial logit (MNL) model to recalculate HSR demand as these attributes vary. As the service frequency (trips per day) must be an integer, we build this model as an integer optimization problem.

The remainder of the paper is organized as follows. Section 2 discusses earlier studies that are related to HSR cost calculation and travel demand calculation. This is followed by the development of our new models in Section 3, in which one integrated integer optimization model is built. MNL models are used in mode split and demand prediction. Following the model design section, we introduce the data and deploy the models in a hypothetical case study in Section 4. Section 5 discusses the case study results, sensitivity analysis and the validity of the method for HSR RT calculation, and Section 6 concludes.

2. OVERVIEW OF EARLIER STUDIES

The US Government Accountability Office (GAO) [4] indicated that travel time, service frequency, safety, and travel distance are key factors in HSR competitiveness. For providing necessary financial support, the federal government needs to fund \$12bn to \$16bn for the proposed high-speed rail line between Los Angeles, California, and San Francisco, California. The GAO also concluded that it is critical to identify expected outcomes of HSR to maximize returns on federal investments.

Levinson *et al.* [5] formulated one model to describe HSR cost and income, refer to Equation (1). This model has been widely referenced to calculate HSR cost. In this model, the full long run cost of HSR includes the internal cost of building, operating, and maintaining infrastructure, as well as carrier, user, and external or social costs such as noise, pollution, and accidents. For detail explanation of the parameters, readers can refer to Levinson's paper.

$$FC = ICC + IOC + CCC + COC - CT + UCC + UOC - UT + UTC + SEC + SNC + SAC \quad (1)$$

where

FC — full long run cost of HSR
ICC — capital cost of construction
IOC — infrastructure operating costs
CCC — carrier's capital costs
COC — carrier operating costs
CT — costs of carriers that are transferred to infrastructure
UCC — aggregate of all fees, fares and tariffs paid by users in capital costs
UOC — maintain and operate the vehicle or to ride on a carrier
UT — considered under social costs, this is labeled as user transfers
UTC — the amount of time spent traveling under both congested and uncongested conditions multiplied by the monetary value of time

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SEC — additional net external costs to society as a result of emissions
SNC — additional net external costs to society as a result of noise
SAC — additional net external costs to society as a result of accidents.

Similar research on the calculation of HSR costs can also be found in Nash [6], Martin [7], and Vickerman [8]. Ginés de Rus [9] classified HSR costs into three categories—infrastructure costs, operating costs, and external costs—and investigated their possible ranges based on previous study and some assumptions. Ginés de Rus also designed one model to describe the relationship between HSR benefits and costs, and another model to calculate the benefits of HSR. However, Ginés de Rus made many assumptions, which may not be available in reality and did not evaluate the model with real data.

Armstrong and Meissner [10] provided a summary of papers on both passenger and freight revenue management. Even there already exist many models and algorithms for railway revenue management, they found that there is still room to improve the existed models or design new models. Bharill and Rangaraj [11] illustrated an application of revenue management in the premium segment of Indian Railways. They considered overbooking and cancellation impacts on rail service revenue and tried to construct an accurate model to suggest reasonable ticket price while considering such impacts. Hanne and Dornberger [12] viewed the rail management in a planning perspective. They compared airline planning and railway planning and found that when applying management models on railway, planners cannot simply transfer the method in airline planning to railway management as there are many differences between the two modes. However, none of these researchers considered RT, which can be important in determining how to operate HSR or whether or not to construct HSR.

In the aspect of HSR travel demand analysis, Nash [13] studied the market shares of plane, train and road before and after the introduction of HSR. The impact of introducing HSR on rail market share is very large, particularly in countries like Spain where the improvement in rail journey time was large. Besides, more traffic is extracted from air than road by HSR. Although Nash made deep analysis of the changing of market shares, he did not give explicit theory and method to get market share changing quantity and trends. While doing HSR market share research, the Volpe National Transportation Systems Center (VNTSC) [14] defined many specific options/scenarios, made broad assumptions, and specified detailed inputs to the mode choice modeling process that accounts for market share calculation. Their demand forecasting methodology employed a logit-type diversion (mode split) model structure that operates on each sub-market separately. Although this model could describe the choice behavior between HSR and another mode, it could not describe mode choice behaviors among more than two travel modes. Koppelman and Bhat [15] developed detailed methods about how to model mode choice behavior among more than two modes considering different choice attributes.

While these researchers studied rail cost recovery, demand market share, and operation strategy from different perspectives, this paper presents the first attempt to integrate all of these factors simultaneously. In the following sections, we describe a novel integrated method that endogenously calculates the HSR market share, demand, RT, and optimal ticket price and frequency levels.

3. MODEL STRUCTURE

NOTATION

Symbol Description

INPUT PARAMETERS

I_{CBD} income from business development of HSR infrastructures (million dollars per year)
C_{HSR} the capacity of one set of HSR
C_C HSR construction costs (million dollars)
N sample size
I set of available mode alternatives
j available travel mode, $j \in I$

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X_n	vector value of attributes for individual n
F	total demand between HSR endpoints across all modes
δ	segment travel demand converting factor
θ_o	one-time subsidy for HSR
λ	average special service fee per customer on HSR
N_{flight}	number of flights between the origin and destination
N_{air_seats}	average number of seats in an airplane
f_{load}	average flight load factor
θ_a	annual subsidy for HSR
ε	cost function coefficients, $\varepsilon \in \{\varepsilon_{OMa}, \varepsilon_{OMi}, \varepsilon_V\}$
ε_{OMa}	coefficient of service frequency accounting for annual operating and maintenance costs
ε_{OMi},	coefficient of service frequency accounting for initial operating and maintenance costs
ε_V	coefficient of service frequency accounting for annual vehicle purchase costs.

OUTPUT PARAMETERS

TC	HSR total costs (million dollars)
C_{OMi}	initial operating and maintenance costs (million dollars)
C_{OMa}	annual operating and maintenance costs (million dollars per year)
C_V	annual vehicle purchase costs (million dollars)
t	time (year)
IN	total HSR income (million dollars per year)
I_{tic}	income from selling tickets (million dollars per year)
$I_{service}$	HSR special service fees (million dollars per year)
TD_{HSR}	travel demand by HSR (per day)
$B(t)$	the benefit of running HSR with in time period t
RT	cost recovery time
ORT	optimal cost recovery time
V_{nj}	systematic utility of mode alternative j for individual n
β_j	parameter vector that defines the direction and importance of the effects of attributes of mode j on the utility of an alternative
P_{nj}	probability of decision-maker n choosing alternative j
P_j	market share of mode j; P_{HSR} denotes the market share of HSR
TTD	total travel demand by all modes
TD_{air}	demand by air
y	cost functions, $y \in \{C_{OMa}, C_{OMi}, C_V\}$

DECISION VARIABLES

f_{HSR}	HSR service frequency
TP_{HSR}	ticket price of HSR (dollar).

3.1. *Optimum cost recovery time model*

In this model, we assume that the costs of HSR include construction, operation and maintenance, and vehicle purchase (refer to Equation (2)). Different from Levinson *et al*. [5], we classify costs into only four types—construction C_C, initial operations and maintenance C_{OMi}, annual operations, maintenance C_{OMa} and annual vehicle purchase cost C_V. This does not lose generality because model users can easily incorporate other costs into any of the four types of costs depending on their own understanding of the characteristics of the costs. Government subsidies or other incentives can be incorporated into these or other terms, as appropriate, as demonstrated in the numerical study. The total cost is given by

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$$TC(t) = C_C + C_{OMi} + C_{OMa} \cdot t + C_V \cdot t \tag{2}$$

The total income of HSR includes ticket sales I_{tic}, CBD rent I_{CBD}, and special service fees $I_{service}$ (refer to Equation (3)). Ticket sales can be calculated by multiplying ticket price by travel demand (refer to Equation (4)). The CBD rent income is assumed to be a fixed value. Special service income covers all the earnings from specific customer services, like priority boarding, on board entertainment, food and beverage service, and so forth. Suppose that each HSR customer will pay an average of λ dollars on special services per trip. Then, the special service income can be calculated as in Equation (5).

$$IN = I_{tic} + I_{CBD} + I_{service} \tag{3}$$

$$I_{tic} = 365 \cdot 10^{-6} \cdot TD_{HSR} \cdot TP_{HSR} \tag{4}$$

$$I_{service} = 365 \cdot 10^{-6} \lambda \cdot TD_{HSR} \tag{5}$$

Notice that both I_{tic} and $I_{service}$ depend on the HSR travel demand, so in order to get the two values, we first need to forecast the travel demand of HSR after its operation. This forecasting process is detailed in Section 3.2 with the logit model.

The benefits of running HSR then can be calculated as subtracting total costs from total income:

$$B(t) = IN \cdot t - TC(t) \tag{6}$$

$B(t)$ is the total benefit of running the HSR in t years. Because recovery time is the time interval from the beginning of HSR construction to the moment that benefits change from negative to positive, so solving $B(t)=0$, we would get the break even time or recovery time RT.

$$RT = (C_C + C_{OMi})/(I_{tic} + I_{CBD} + I_{service} - C_{OMa} - C_V) \tag{7}$$

The objective of this study is to minimize RT to get an optimum recovery time (ORT). The decision variables are service frequency f_{HSR} and ticket price TP_{HSR}, both of which we require to be integers. Thus, the integer optimization framework is

$$ORT = Minimize\ RT = (C_C + C_{OMi})/(I_{tic} + I_{CBD} + I_{service} - C_{OMa} - C_V) \tag{8}$$

$$s.t.\ f_{min} \leq f_{HSR} \leq f_{max} \tag{9}$$

$$2C_{HSR} f_{HSR} \geq (1+\delta) TD_{HSR} \tag{10}$$

$$TP_{HSR} \leq TP_{MAX} \tag{11}$$

$$I_{tic} + I_{CBD} + I_{service} - C_{OMa} - C_V > 0 \tag{12}$$

$$TP_{HSR} > 0 \tag{13}$$

$$TP_{HSR}, f_{HSR} \ \text{integer} \tag{14}$$

The following sections expand on this framework, showing how demand modeling and subsidies are integrated. In this model, the first constraint assures that the service frequency satisfies the minimum and maximum frequency requirements. The second constraint means that the HSR capacity must satisfy the travel demand requirement. In this constraint, C_{HSR} denotes the capacity of one set of HSR. The coefficient 2 accounts for the two directions of an HSR line. The coefficient δ accounts for demand of people who are traveling through just a portion of the HSR line. It is used to transfer trip demand on segment of the HSR line to demand on the entire line. For instance, if there are 10 trips from the middle point of the OD pair to the destination, after transferring, it equals 5 trips from the origin to the destination that means $\delta = 0.5$ for these trips. The third constraint guarantees that the HSR ticket price does not exceed the highest ticket price requirement. The fourth constraint requires the denominator of the objective function to be positive because RT is undefined if the system is operating at a loss. The fifth constraint ensures the ticket price is positive.

Solving the integer programming problem, we can get the optimum service frequency and ticket price. Nevertheless, I_{tic} and $I_{service}$ are influenced by HSR travel demand that must be calculated as part of the integer programming problem; however, the demand level is clearly influenced by the choice of train frequency and ticket price. Thus, we use an iterative process to get ORT. This process is detailed in Section 3.3.

3.2. *Multinomial logit model*

As mentioned in Section 3.1, MNL model can be used to forecast HSR demand before its operation. Usually, there are many modes between an origin–destination pair, and for a long distance trip, rail is one of the available mode choices. We assume that after an HSR begins operation, conventional rail will no longer be in service for travelers; consequently, after HSR's operation, the total number of available modes is the same as before. Let I denote the set of all available mode alternatives, $j \in I$ one of the alternatives, n the individual traveler n, X_n the vector value of attributes of individual n, β_j the regression parameter vector corresponding to the attributes of mode j, V_{nj} the systematic utility of mode j for individual n, P_{nj} the probability of decision-maker n choosing mode j, and P_j the market share of mode j. Based on random utility theory, we can formulate the following general MNL model:

$$V_{nj} = \beta_j \cdot X_n \tag{15}$$

$$P_{nj} = \exp(V_{nj}) / \sum_{i=1}^{I} \exp(V_{ni}) \tag{16}$$

$$P_j = \sum_{n=1}^{N} P_{nj} / N \tag{17}$$

The parameter vector β_j can be estimated for the before-HSR MNL model. However, for the after-HSR case, because of a lack of available data, the parameter vector β_j MNL model cannot be estimated directly. Considering that travelers will not significantly change their sensitivities to the attributes X_n, we simply assumed that the two models share the same value of β_j in which the HSR mode will share the β_j values of conventional rail mode.

In this paper, we use F to denote the total demand for intercity travel along the HSR line (among all modes). For convenience, we assume that this is measured in terms of trips between the endpoints of the HSR line; Section 3.1 has shown how to accommodate trips starting and ending at intermediate stops. In general, F is a function that can be calibrated from intercity trip generation modeling. While there are many models on urban trip generation, very few studies focus on intercity trip generation. Li [16] classified existing intercity trip generation models into three classes: regression method, cross-classification method and discrete choice-based method. All these methods need large quantity of data that is usually very hard and expensive to get.

Because trip generation is not this paper's focus, we instead assume that the total number of intercity trips by all modes is a constant and that HSR demand can be determined as the relative share of intercity trips it attracts:

$$TD_{HSR} = P_{HSR} F \tag{18}$$

P_{HSR} denotes the market share of HSR. As will be discussed in section 3.3, P_{HSR} is a function of HSR service frequency f_{HSR} and the ticket price TP_{HSR} and will be recalculated based on the updated frequency and price values.

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3.3. Integrated optimum cost recovery time model and the solution algorithm

Incorporating the MNL market share model and the travel demand projection model into the cost recovery model (8), along with subsidy terms defined in the succeeding texts, the integrated optimum cost recovery time model is

$$Minimize\ RT = \frac{C_C + C_{OMi}(f_{HSR}) - \theta_o}{365\cdot 10^{-6}(1+\delta)P_{HSR}(TP_{HSR}, f_{HSR})F\ (TP_{HSR}+\lambda) + \theta_a\ + I_{CBD} - C_{OMa}(f_{HSR}) - C_V(f_{HSR})} \tag{19}$$

$$s.t.\ f_{min} \le f_{HSR} \le f_{max} \tag{20}$$

$$2C_{HSR}f_{HSR} \ge (1+\delta)TD_{HSR} \tag{21}$$

$$TP_{HSR} \le TP_{MAX} \tag{22}$$

$$365\cdot 10^{-6}(1+\delta)P_{HSR}(TP_{HSR}, f_{HSR})F(TP_{HSR}+\lambda) + \theta_a + I_{CBD} - C_{OMa}(f_{HSR}) - C_V(f_{HSR}) > 0 \tag{23}$$

$$TP_{HSR} > 0 \tag{24}$$

$$TP_{HSR}, f_{HSR}\ \ integer \tag{25}$$

The coefficient $365 \cdot 10^{-6}$ accounts for the conversion of unit of dollars per day to unit of million dollars per year. Considering that cost recovery for HSR is difficult without government subsidy, the objective function also includes subsidy terms. The one-time subsidy θ_o is for construction, land acquisition, or other up-front costs, and θ_a is a continuing subsidy (perhaps tax rebates or toward operations and maintenance expenses). Because the frequency can highly impact C_{OMa}, and C_V, we assume that they are functions of f_{HSR}. Furthermore, we assume that C_{OMi} is also a function of f_{HSR} because increasing f_{HSR} would increase the one-time investment in infrastructure, training people, and so forth. We assume that C_{OMa}, C_{OMi} and C_V are all linear with trip frequency and has the form $y = \varepsilon \cdot f_{HSR}$ where $y \in \{C_{OMa},\ C_{OMi},\ C_V\}$ and $\varepsilon \in \{\varepsilon_{OMa},\ \varepsilon_{OMi},\ \varepsilon_V\}$. ε_{OMa}, ε_{OMi} and ε_V account for the linear coefficients of f_{HSR} for C_{OMa}, C_{OMi} and C_V, respectively.

The objective is a highly nonlinear function, because P_{HSR} is itself a function of f_{HSR} and TP_{HSR}, calculated through the logit model. In order to get the optimal solution, we need to iteratively calculate the values of f_{HSR}, TP_{HSR} and P_{HSR}. In this paper, we solve this model using the simulated annealing metaheuristic developed by Kirkpatrick *et al*. [17]. Because the optimization model is nonconvex and discontinuous, classic optimization solution algorithms will not work. Simulated annealing is a common choice of metaheuristic for this type of problem.

This heuristic was developed to solve optimization problems lacking favorable mathematical properties (such as linearity, differentiability, or even continuity) and is a probabilistic descent method: Given an incumbent solution, the algorithm randomly generates a “neighboring” solution and evaluates the objective function. If it represents an improvement over the incumbent solution, the new solution becomes the incumbent solution; if it is worse, the new solution still becomes the incumbent solution with some probability. In this way, the algorithm can avoid being trapped at local optima. The probability of accepting a worse solution depends on a “temperature” parameter: The higher the temperature, the higher the probability of accepting a disimproving move. As the algorithm proceeds, the temperature is reduced until this probability becomes small. The words temperature and

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"annealing" are meant to give an analogy to the cooling process in metallurgy. The following pseudocode demonstrates the calculation process, as applied to the integer optimization model we described in the preceding texts.

In this iteration process, neighboring solutions are generated by randomly increasing or decreasing f_{HSR} and TP_{HSR} by one unit, checking that the constraints are satisfied. For each updated f_{HSR} and TP_{HSR}, a new P_{HSR} value and a temporary ORT value are calculated. If the temporary ORT value satisfies the simulated annealing criterion, this value will be given to the updated ORT value. This process will continue until the temperature reaches a specified threshold and the algorithm terminates.

Pseudocode *Simulated annealing for iteratively calculating optimal high speed rail frequency and ticket price*

Initialization

Initialize frequency f_{HSR}, ticket price TP_{HSR}, temperature t, temperature reduce tr, convergence temperature ct, iteration number n. Let N denote the iteration limit per temperature.

While $t > ct$ **do**

Reduce temperature according to cooling schedule.

While $n < N$ **do**

Increment n

Generate neighboring solution (randomly increase or decrease f_{HSR} and TP_{HSR} by one unit)

Set f_{temp} and TP_{temp} to boundary values if f_{temp} and TP_{temp} are infeasible;

Calculate P_{HSR} through the MNL model, TD_{HSR} and ORT_{temp} (the recovery time for the new solution)

Let $ORT_{\Delta} = ORT_{temp} - ORT$

If ((ORT_{Δ}**or** randUniform (0, 1)) $\exp\left(\frac{ORT_{\Delta}}{t}\right)$)

Then $f_{HSR} = f_{temp}$; $TP_{HSR} = TP_{temp}$; $ORT = ORT_{temp}$;

If ($ORT < ORT_{\boldsymbol{best}}$) $f_{best} = f_{temp}$; $TP_{best} = TP_{temp}$; $ORT_{best} = ORT_{temp}$

4. DEMONSTRATION AND DATA

4.1. The data and formulation

The demonstration considers a proposed HSR line in Canada connecting Toronto, Ontario and Montreal, Quebec. This section details how we assembled the necessary parameters to implement our model and the additional assumptions made. This section is just a demonstration of our model based on limited available data and some assumptions, so this demonstration is not intended to evaluate the actual performance of this hypothetical HSR line (which would require a major data collection effort beyond the scope of this paper). Section 4.2 reports the results from the demonstration.

Megarail Transportation Systems Incorporation indicates that building a new HSR line costs \$12 to \$50m/km [18,19]. Based on the consumer price index (CPI), we assume the present construction cost of HSR with a speed range of 240 to 320 km/h to be \$30m/km. For the case study, we assume that CBD rent income is \$20m/year and that each HSR customer pays \$10 on average for special services. We further assume that the minimum and maximum service frequencies are 1 and 20 trips per day, respectively, and that the maximum allowable ticket price is \$300. The capacity of one set of HSR vehicles is assumed to be 600 passengers. Because there are two directions between Toronto and Montreal, the capacity of HSR per day equals $600 \cdot 2 \cdot f_{HSR}$ (Table I).

The MNL model was estimated with data drawn from the 1989 Rail Passenger Review conducted by VIA Rail (the Canadian National Rail Carrier). After removing unreasonable survey results, there are 3593 travelers left in the data set who traveled in the Toronto–Montreal corridor. The data includes the following attributes of each traveler: demographic variables, trip-making characteristics, and level of service variables. In particular, the level of service variables include travel cost (ticket price or gas cost), service frequency, in-vehicle travel time and out-of-vehicle travel time. In total, there are 78 attributes for each customer. While some the attributes are significant in the MNL models, the others are not. Using a *t*-test to identify the significant parameters, 10 attributes were included in the utility

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Table I. The best operation strategies for the HSR company.

Average ticket price	Frequency	Optimal market share			ORT
\$2010, one way	Times per day per direction	HSR	Air	Drive	Years
39	20	0.43	0.25	0.32	38

functions that are used in the MNL model. Table II shows the 10 attributes and their corresponding coefficients in the utility functions. Notice the number of parameters is 15, not 10 because for attributes *travel alone*, *gender*, *income*, *living location and traveling in weekend*, each attribute corresponds to two different parameters in two different mode utility functions.

Two MNL models needs to be developed to describe the before-HSR and after-HSR travel conditions. Both MNL models include the 10 attributes in Table II. (This choice of factors was based on the data set used in the case study; the model itself is general and can be tailored to available data.) Particularly, the location of residence indicates whether a traveler is living in large city or not; service frequency indicates how many times a day one particular mode will provide service; travel cost means air ticket purchase, gas purchase, rail or HSR ticket purchase for air, car, rail or HSR, respectively.

In this case study, the MNL models are employed based on the assumption that the travel demand by air is already available. This assumption is reasonable because from the public data, it is easier to get the travel demand by air compared with demands by other travel modes. For instance, the demand by air can be estimated by the product of the number of flights N_{flight} traveling between two cities, the number of seats N_{air_seats} of an airplane and the average load factor f_{load}. Let TD_{air} denote the travel demand by air per day, F the total travel demand per day, and TD_{HSR} denotes the travel demand by HSR per day. Let P_{HSR} denote the market share of HSR, and P_{air} denote the market share of air. Both P_{HSR} and P_{air} can be calculated through Equation (15) to Equation (17). Then, the TD_{HSR} can be determined by the following equations:

$$TD_{air} = N_{flight} N_{air\_seats} f_{load} \tag{26}$$

$$F = TD_{air}/P_{air} \tag{27}$$

$$TD_{HSR} = F \cdot P_{HSR} = N_{flight} N_{air\_seats} f_{load} P_{HSR}/P_{air} \tag{28}$$

Incorporating Equation (28) to our integrated optimization model (19), we obtain the objective function as specialized for the case study:

$$ORT = Minimize\ RT = \frac{C_C + C_{OMi}(f_{HSR}) - \theta_o}{365 \cdot 10^{-6}(1+\delta) TD_{HSR}\,(TP_{HSR} + \lambda) + \theta_a + I_{CBD} - C_{OMa}(f_{HSR}) - C_V(f_{HSR})} \tag{29}$$

The number of flights between Toronto and Montreal comes from survey on Canada airlines' website [20]. The load factor was assumed based on the load factor report submitted by Centre for Asia Pacific Aviation [21]. This projection involves several assumptions: Most air planes traveling from Montreal to Toronto are Boeing 737 with 120 seats (N_{air_seats}) on average, and the load factor f_{load} is 0.8; currently, there are about 60 flights (N_{flight}) between Toronto and Montreal per day; the travel demand from Toronto to Montreal equals the travel demand from Montreal to Toronto. In this case study, we assume that initial operation cost, annual operation cost and annual vehicle purchase cost are all linear with trip frequency and set the coefficient values ε_{OMa}, ε_{OMi} and ε_V at 70, 50 and 3.5, respectively. The values of ε_{OMa}, ε_{OMi} and ε_V are chosen through properly estimation based on VNTSC [14]. The VNTSC did an evaluation of high-speed rail options for the Macon-Atlanta-Greenville-Charlotte Rail Corridor in 2008. In their study, the estimation of construction, operating and

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Table II. The estimation results of before-HSR MNL parameters.

Parameters	Corresponding attribute	Parameters' meanings	Value	T test
ASC_AR		Estimation constant for air mode	0.0743	0.1600
ASC_RL		Estimation constant for rail mode	−0.7850	−2.5400
B_ALON_AR	Travel alone	Parameter of travel alone effects on air mode choice	0.3380	2.9200
B_ALON_RL	Travel alone	Parameter of travel alone effects on rail mode choice	0.2650	2.0800
B_COSINC	Total travel cost over income	Parameter of effects of travel cost divided by income	−0.1220	−2.3900
B_COST	Travel cost	Parameter of cost effects	−0.0351	−9.8100
B_FEM_AR	Gender	Parameter of gender effects on air mode choice	0.5800	4.1700
B_FEM_RL	Gender	Parameter of gender effects on rail mode choice	1.2400	9.4500
B_FREQ	Service frequency	Parameter of service frequency effects	0.0745	18.3400
B_INC_AR	Income	Parameter of income effects on air mode choice	0.0197	4.6400
B_INC_RL	Income	Parameter of income effects on rail mode choice	−0.0053	−1.6300
B_IVTT	In-vehicle travel time	Parameter of in-vehicle time effects	−0.0104	−16.3600
B_LCIT_AR	Living location	Parameter of living location effects on air mode choice	0.7190	5.0900
B_LCIT_RL	Living location	Parameter of living location effects on rail mode choice	1.1100	7.5500
B_OVTT	Out-vehicle travel time	Parameter of out-vehicle time effects	−0.0304	−13.5000
B_WEKD_AR	Traveling in weekend	Parameter weekend-travel effects on air mode choice	0.6400	4.8600
B_WEKD_RL	Traveling in weekend	Parameter weekend-travel effects on rail mode choice	1.8000	13.9700

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maintenance costs are explored. These estimations are based on existing reports, papers and experts' judgments. Although the function θ_a could depend on many factors, for instance, political issues, public welfare, rail service level, running cost, and so on, we assume that it is a constant value at \$1200m/year in this case study. We also assume the one-time subsidy is \$1865m.

4.2. The optimal solution for the case study

With the integer optimization model and the simulated annealing algorithm, we calculated the best operation strategy in terms of ticket price and service frequency (refer to Table I). The first column in Table I indicates the average ticket price for a traveler who travels from Toronto to Montreal or from Montreal to Toronto. For travelers who travel within the Toronto–Montreal corridor, the ticket prices can be estimated by interpolation. The second column indicates the total service frequency per day in one of the two directions between Toronto and Montreal. The third column gives the optimal market share. The last column indicates the RT with a ticket price of \$39 and frequency of 20. With this operation strategy, the HSR investor can recover their investment in a little more than 38 years.

The simulated annealing algorithm itself was implemented in C and run on a Windows 7 machine with an Intel (R) Core (TM) i3 processor and 4 GB memory. Based on a tuning process, the best cooling schedule was found to result when the initial temperature parameter is 10, the temperature is reduced by 10% after 1000 inner iterations *N*, and termination occurs when the temperature is 3. Figure 1 shows the performance of the algorithm, reporting the best solution found as a function of the computation time involved. The figure shows that this algorithm converges relatively quickly to the best solution this heuristic can obtain and that the model is fast enough to allow comparative analysis of a large number of scenarios despite the complexity of embedding the logit model into an integer program.

5. SENSITIVITY ANALYSIS

Government subsidies could result in a lower construction or operation cost. As a result, it is important for the HSR company to consider these factors when they estimate the possible RT. This section presents a sensitivity analysis on potential subsidies and how they affect the recovery time.

Figure 2 shows that if the initial one-time subsidy increases, the ORT will decrease in a nearly linear manner. This makes sense as adding more initial subsidy to the construction process will lead to less total cost and will help the investor recover the cost quicker.

As in the preceding discussion, the annual subsidy can depend on many factors. Here, we assume that the annual subsidy is linear in the frequency (representing, for instance, subsidies toward maintenance and operation expenses). We want to see how the per-train-trip subsidy impacts the ORT. Figure 3 shows that if the annual subsidy per train-trip increases, the ORT will also decrease. Notice that there is a steep drop when the subsidy value changes from \$55 000 to \$68 000 per trip. This threshold represents a point at which the rail operator's optimal strategy is to run as many trips as possible, in order to receive a higher subsidy. Before this point, the ORT has almost a linear relationship with the

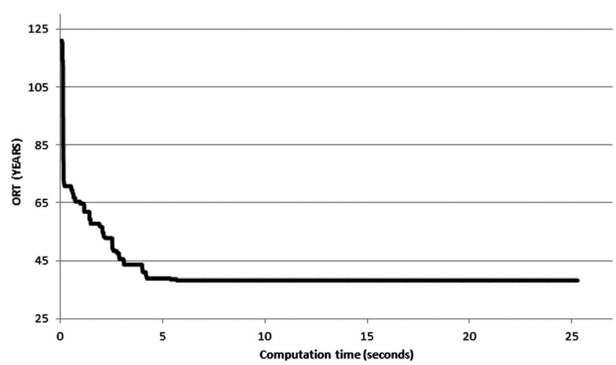

Figure 1. Convergence process of the simulated annealing algorithm.

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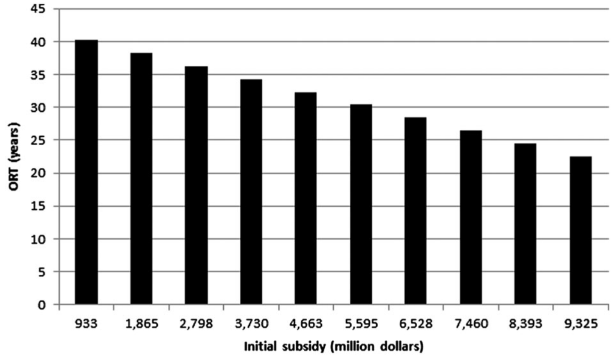

Figure 2. Relationship between ORT and initial subsidy.

subsidy, while after this point, the ORT has a convex change with the subsidy increasing. Below this threshold, increasing the subsidy will cause the change in both service frequency and ticket price. The combination of the effects of the subsidy and the two variables leads to a linear relationship between the ORT and the subsidy; while above this threshold, the service frequency will always be at the boundary value and the ticket price is fixed, so the subsidy itself becomes the only factor that causes the reduction of the ORT. This is why the ORT has a convex change with the subsidy increasing from this point.

Now, let us assume that the subsidy has two parts: subsidy on vehicle purchase (as reflected by changing this parameter directly) and subsidy on all other costs. Assume that the second part of subsidy is fixed and equal to \$500m. Figure 4 shows how changing subsidy only on vehicle purchase impacts the ORT. The horizontal axis indicates how much the subsidy is per every dollar used for

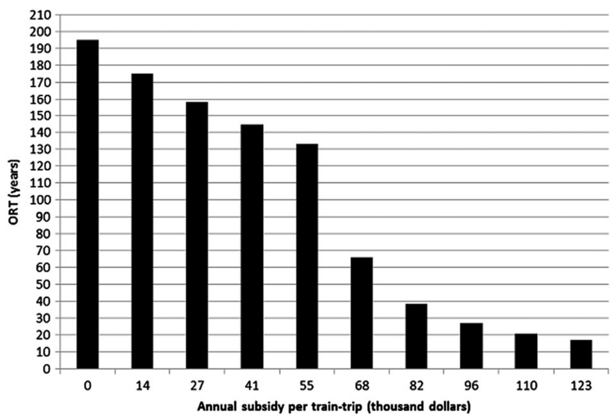

Figure 3. Relationship between ORT and annual subsidy.

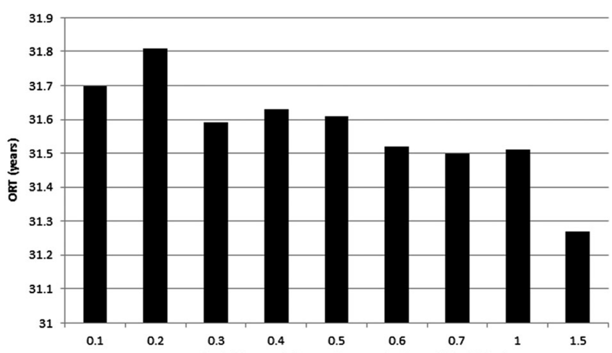

Figure 4. Relationship between ORT and vehicle purchase-based annual subsidy.

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purchasing vehicles. Roughly speaking, ORT decreases as the vehicle purchase-based subsidy increases. However, this trend is not uniform, and there is some fluctuation as subsidy increases; in any case, while the trend is downward, the slope is not steep. This occurs because the vehicle purchase cost is a small part of the whole HSR cost, so subsidies on vehicle purchase does not help much to recover the total cost, and because the simulated annealing algorithm is not exact—when the objective is less sensitive to a given parameter, the approximation error from using a heuristic produces more "noise" in trends than when a parameter has a larger impact.

Generally, if the government wants more companies to invest into the HSR businesses, it needs to provide more subsidies. Meanwhile, if the HSR investors want to recover their cost as soon as possible, they have to get as many subsidies from the government as possible. Specifically, with the increase of one-time construction subsidy, the investor can expect a linear reduction in RT. If increasing the annual subsidy, the RT will also decrease. The difference is that there is a threshold point where when the subsidy gets just bigger than this point, the RT has a big drop, but when the subsidy is bigger than this threshold point, the more subsidies, the less incremental RT decreases where incremental RT means the cost recovery time caused by introducing a unit of subsidy. The sensitivity analysis also shows that the vehicle purchasing subsidies has the least impact on the RT.

6. CONCLUSION AND FUTURE STUDIES

This paper contributes a new optimization model to facilitate the analysis of HSR deployment. This model includes methods to iteratively calculate market share changes and RT for HSR. To demonstrate the presented approach, a hypothetical case study was presented. Based on the analysis results (and the noted modeling assumptions) of the hypothetical case study, without any subsidy, the optimal recovery time is quite long, suggesting that incentives and subsidies have a major impact on RT and financial viability. The model and case study analysis also demonstrate that with known subsidies, the investor can determine the best ticket price and service frequency to recover cost within the least time. Another contribution of this model is that given a pre-set cost recovery due time, the investor can figure it out whether they are able to find a feasible ticket price and service frequency to achieve this payback period. On the other hand, the model could be used by the government to judge how much subsidy should be provided so that an HSR's construction and operation will be attractive to investors. Given several alternative subsidy plans, the model can be used to determine which plan is the best choice. To do so, run the model with different subsidy plans as inputs then compare between the plans and identify which plan can give the minimum RT. Future research will develop a more sophisticated optimization program in which an optimal subsidy level will be determined alongside the service frequency and ticket price. This model can also be applied to other HSR projects if the input parameters, which are listed in the notation part, are provided.

Future research should identify the optimum value for other attributes, such as travel time, in addition to frequency and ticket price. Note that our model assumed that all other attributes of mode choice were constant regardless of the presence of HSR, even though these attributes may change. Thus, it is necessary to analyze how these attributes would influence the value of RT, which can help design better models in the future. Further extensions to the mode choice model would include incorporating more sophisticated discrete choice models, such as nested or mixed logit models, and investigating the resulting improvements in accuracy. Many papers [22–25] show that accurate and comprehensive data is necessary to get accurate nested logit model results. However, the data currently available to us is not comprehensive enough to support nested logit model construction. Those papers also show that there are many kinds of nesting strategies and only through thoroughly investigation, the best one or ones can be found. This needs much more effort than it can be included in this paper. The previous reasons are why we do not do comparison across different discrete choice models in this paper. The model can also be extended to include trip generation as well as mode choice. From the standpoint of practice, additional factors can be added to reflect peaking effects or within-day variation in demand rates or more explicit dependence of total demand (across all modes) on rail level of service. More generally, as new data, behavioral insights, and economic models becomes available, the presented approach can be extended to employ such new developments.

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