Dynamic Demand Forecasting and Ticket Assignment for High-Speed Rail Revenue Management in China

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Revenue management is widely practiced in the airline industry yet rarely applied to high-speed rail (HSR). In the history of the rail and HSR industry, passenger ticket assignment across all stations has often been employed to regulate the supply of seats and demand from rail passengers and thus increase profitability. This study proposes a systematic revenue management approach for HSR passenger ticket assignment with dynamic adjustments. A major advantage of the proposed approach is the integration of dynamic ticket assignment and rigorous short-term demand forecasting; this method can effectively avoid the situation in which passenger tickets are not sufficient at some stations while certain seats remain empty on the train. This novel methodology has three main components. First, it develops a short-term passenger flow forecasting method for dynamic travel demand. Second, it builds a passenger ticket assignment model to allocate passenger tickets during presale periods. Third, it incorporates a dynamic ticket adjustment mechanism to adjust previous passenger ticket assignments. For demonstration purposes, the proposed approach is applied to the HSR system in China. Results show that revenue increases by 13.48% when the existing ticket assignment method is improved by this enhanced revenue management method.

Passenger ticket assignment is an effective way to solve the contradiction between supply and demand of rail passengers and thus increase the total profit. The rational assignment of limited resources with the purpose of profit maximization belongs to the domain of revenue management. Originating with the U.S. domestic aviation industry, revenue management is an effective method for dealing with various disciplines such as marketing, operations research, decision theory, microeconomics, and mathematical programming. Revenue management aims to maximize profit through determining the appropriate sale strategy.

Revenue management mainly includes four research fields—overbooking, demand forecasting, inventory control, and pricing—which are key to maximizing earnings. The earliest method of revenue management implemented was overbooking, in which more reservations existed than actual capacity in order to decrease potential lost revenue from cancellations and other events. Subsequently, after the benefits of revenue management in the aviation industry were realized, many other methods were rapidly developed, including demand forecasting, inventory control, and pricing control. The earliest application of revenue management in the aviation industry achieved many benefits (*1, 2*). Since then, revenue management has developed rapidly in the aviation industry (*3, 4*). To date, many specific methods have been proposed in overbooking, such as the single-leg model (*2*), the multileg model (*5, 6*), and the dynamic programming model (*7, 8*). Demand forecasting methods play a significant role in revenue management, such as the nonhomogeneous Poisson process (*9*), Poisson distribution (*10*), regression analysis (*11*), neural network (*12*), and time series analysis (*13*).

The key to inventory control is whether to accept a reservation request to achieve the maximum income. The methods of inventory control include the expected marginal seat revenue (*5*), adaptive algorithm (*14*), discrete-time dynamic programming (*15*), and probabilistic mathematical programming (*16, 17*). Pricing was to hold to different fare standards according to the customer demand and the fare elasticity. Based on related theories and methods, more specific research in aviation has been explored (*18–20*). Beyond that, revenue management has also been widely used in different service industries, such as hotels (*21–23*), broadcasting (*24*), automobile rental (*25*), Internet service provision (*26, 27*), ocean liner service (*28*), and the nonprofit sector (*29*).

Because of intensified competition in the rail transportation market, some operators in the rail industry have applied revenue management in recent years (*30, 31*). Rail authorities analyzed near-future market situations by using short-term passenger flow forecasting models (*32*). In the passenger rail market, the idea of differential pricing was first proposed by supposing that customers could be divided into different levels (*33*). Some researchers built dynamic pricing models for rail passenger demand forecasting (*34*) and considered the sensitivity of passengers to the fare (*35*). Ticket assignment models were established by using a linear programming method (*36*) and then used to analyze concerns of rail passengers based on statistical data (*37, 38*). Application of these models could raise the ridership on a train.

In China, many studies have focused on how different types of revenue management systems can affect the passenger rail market, such as differential pricing (*39*), group management (*40*), and seat control (*41, 42*). Zhang and Lan studied high-speed rail (HSR) revenue management based on passengers' choice (*43*); dynamic pricing models were used for HSR tickets (*44, 45*). However, more studies are needed on the application of revenue management to HSR. Decision variables include the ticket fare and assignment time. The objective of revenue management can be maximizing revenue subject to capacity constraints. In previous studies, revenue management was evaluated with two cases: floating fares and fixed fares (*46*). Under floating fares, revenue management focused on adopting different pricing

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strategies to satisfy different customer requirements. Under fixed fares, revenue management mainly considered capacity assignment, which could balance the limited market supply and changing demand. However, rail transportation in China has not fully opened fare policy. Therefore, the HSR revenue management approach mainly focuses on assigning tickets to multiple stations in the demand peak.

This study aims to solve the optimization problem of HSR ticket assignment and to compare the optimal policy with the existing assignment policy in China. An approach for passenger ticket assignment and dynamic adjustment is proposed based on revenue management. First, a short-term passenger flow forecasting model is incorporated to predict the passenger travel demand. To avoid large prediction errors that may result from a large time interval, the passenger travel demand is predicted for multiple times including time intervals of 20 days, 10 days, and 1 day in advance. Second, a passenger ticket assignment model is developed with the revenue management theory, and a dynamic adjustment method is proposed according to the ticketing sale analysis. Third, a genetic algorithm (GA) is applied to solve the passenger assignment model and dynamic adjustment models. Compared with existing methods that forecast passenger demand based on historical data, the real-time assignment of a passenger ticket based on short-term passenger flow forecasting is demonstrated to be more accurate and dynamic. After multiple dynamic adjustments, the ticket assignment scheme can better meet the passenger travel demand and achieve more revenue. The approach can effectively relieve the unbalanced problem in which passenger tickets are not sufficient at a station while some seats are empty on the train. For rail authorities, the proposed approach helps maximize revenue and provide adjustment and optimization of HSR operation plans. In total, the approach is easy to implement and does not conflict with existing ticket pricing policies.

In the next section the improved forecasting model, the passenger assignment and dynamic adjustment model, and the solution algorithm (i.e., the GA) are introduced.

METHODOLOGY

A framework of integrating dynamic demand forecasting and ticket assignment for HSR revenue management is proposed. A dynamic adjustment model based on revenue management will be formulated. As illustrated in Figure 1, this approach includes three parts: demand forecasting, ticket assignment, and optimization. First, a short-term passenger flow forecasting approach is proposed, combining ensemble empirical mode decomposition (EEMD) with a gray support vector machine (GSVM) according to the current planning and pricing. Second, a passenger ticket assignment model is built by using the revenue management theory, and a dynamic adjustment method is proposed according to the ticketing sales analysis. Third, a GA is used to solve the passenger assignment model and dynamic adjustment models.

EEMD-GSVM Forecasting of Short-Term Demand

The short-term forecasting of HSR passenger flow provides the daily ridership estimation that accounts for day-to-day demand variations. Short-term demand forecasting is a critical basis of passenger ticket assignment and dynamic adjustment. A hybrid short-term demand forecasting model proposed by Jiang et al. was used to predict short-term passenger flows (*32*).

Passenger Assignment Models

The HSR passenger assignment model is proposed on the basis of short-term passenger flow forecasting results. The primary assumptions of the assignment model are as follows:

- All tickets for a train are allocated among all stations in the operation scope,
- Each passenger only buys one ticket without any discounts, and
- The regularity and stability of passenger travel demand are strong and can be grasped by short-term forecasting.

Maximum revenue can be achieved by improving the income and decreasing the cost. However, HSR operation costs are basically fixed and are not related to the seat occupancy rate, which is the ratio of the number of tickets to the number of seats on the train. Therefore, the maximum HSR revenue is achieved by maximizing the passenger ticket income. Two passenger ticket assignment models are

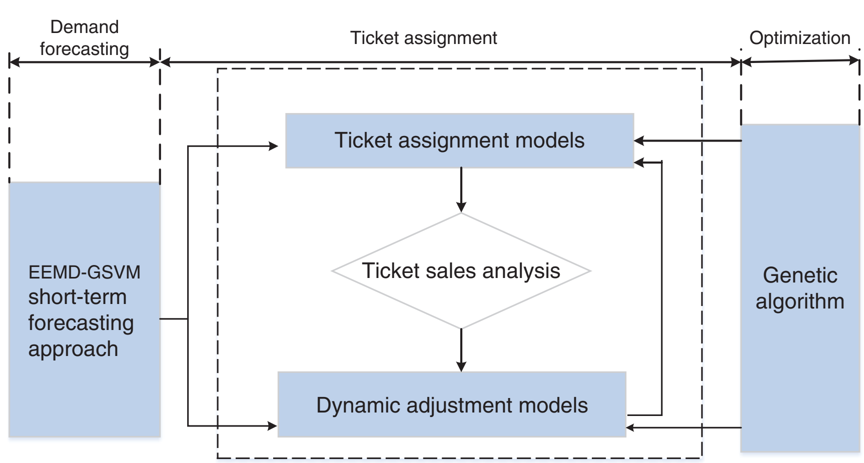

FIGURE 1 Passenger ticket assignment and dynamic adjustment approach.

formulated for trains with enough capacity and inadequate capacity, respectively. For the former case, the passenger ticket assignment objective function is subject to meeting the demand of all stations.

Basic Model Without Limited Stations

$$\max\ R = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{l=1}^{L}\sum_{k=1}^{K} p_{ijl}x_{ijlk} \tag{1}$$

subject to

$$\sum_{i=1}^{m}\sum_{j=i+1}^{n}\sum_{l=1}^{L}\sum_{k=1}^{K} x_{ijlk} \le C \tag{2}$$

$$0 \le \sum_{k=1}^{K} x_{ijlk} \le d_{ijl} \tag{3}$$

$$x_{ijlk} \in Z \tag{4}$$

where

- R = total revenue;
- p_{ijl} = ticket fare of l type seat between station i and station j;
- x_{ijlk} = decision variables, number of allocated tickets of l type seat on train k between station i and station j;
- L = number of seat types;
- K = number of trains;
- n = section number;
- $m = n - 1$;
- C = number of seats offered by train;
- d_{ijl} = travel demand between station i and station j of l type seat; and
- Z = nonnegative integer set.

Model with Limited Stations

When the train capacity is not enough, tickets are allocated to satisfy long-distance demands with priority by restricting a number of stations. The restricted number of stations F can be directly determined by maximizing the total travel distance of all passengers. The model is given by

$$F^* = \arg\max_{F} D(F) = \arg\max_{F} \sum_{i=1}^{F}\sum_{j=F+1}^{n}\sum_{l=1}^{L} d_{ijl}D_{ij} \tag{5}$$

subject to

$$1 \le F \le n \qquad F \in Z \tag{6}$$

where

- D = kilometers traveled by all passengers,
- F = limited station number (decision variable),
- F^* = optimal limited station number, and
- D_{ij} = distance from station i to station j.

Then F^* is substituted in the revenue model given by

$$\max_{x_{ijlk}} R = \sum_{i=1}^{F^*}\sum_{j=F+1}^{n}\sum_{l=1}^{L}\sum_{k=1}^{K} p_{ijl}x_{ijlk} \tag{7}$$

subject to

$$\sum_{i=1}^{F^*}\sum_{j=F+1}^{n}\sum_{l=1}^{L}\sum_{k=1}^{K} x_{ijlk} \le C \tag{8}$$

$$0 \le \sum_{k=1}^{K} x_{ijlk} \le d_{ijl} \tag{9}$$

$$x_{ijlk} \in Z \tag{10}$$

Dynamic Adjustment Model

The default forecasting time interval for HSR demand is 20 days; however, such a large interval inevitably produces large prediction errors. The model is refined by predicting 10-day and daily demands. Then the dynamic adjustment ticket assignment is given by

$$\max R = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{l=1}^{L}\sum_{k=1}^{K} p_{ijl}x'_{ijlk} \tag{11}$$

subject to

$$\sum_{i=1}^{m}\sum_{j=m+1}^{n}\sum_{l=1}^{L}\sum_{k=1}^{K} x'_{ijlk} \le C \tag{12}$$

$$0 \le \sum_{k=1}^{K} x'_{ijlk} \le d'_{ijl} \tag{13}$$

$$x'_{ijlk} \in Z \tag{14}$$

where x'_{ijlk} is the adjusted ticket number between station i and station j, l type seat, k train; and d'_{ijl} is the predicted travel demand after the adjustment.

Solution Algorithm

Powell resolved a number of dynamic vehicle allocation problems by establishing stochastic functions that lent themselves readily to the Frank–Wolfe algorithm (*47–49*). Compared with the Frank–Wolfe algorithm, the GA has stronger adaptability, better robustness, and extensive applicability in seeking for global optimization. The GA is applied to solve models proposed in the sections on the passenger assignment and dynamic adjustment models. It takes the number of passenger tickets predicted by the EEMD-GSVM method as an initial population. The process of the GA consists of the following steps:

Step 1. Create an initial set of potential solutions. Set the maximum generation T equal to 40 and the population size of each generation equal to 200. Use passenger tickets predicted by EEMD-GSVM as the initial group, $P(0)$.

Step 2. Calculate the fitness of each individual in group $P(t)$ of the iteration t to find the best individual. The fitness values are the objective function values. The larger the fitness value is, the better the individual performs.

Step 3. Genetic operators include the selection operator, crossover operator, and mutation operator. Among these, the selection operator selects the best individual to form a new population from the old population according to the fitness values. The higher the fitness value is, the larger the selection probability is. The crossover operator randomly selects two individuals from the population and then exchanges and combines partial genes between them with a crossover probability $p_c = .6$. The mutation operator randomly selects one individual from the population and then changes the value of the individual gene with a mutation probability $p_m = .01$. Thus, the group $P(t + 1)$ is obtained for the next generation.

Step 4. If the maximum generation is reached (i.e., $t = T = 40$), output the individual with the maximum objective function value as the near-optimal solution and terminate. Otherwise return to Step 2.

DATA AND CASE STUDY

The Beijing–Shanghai HSR is a line 1,318 km (819 mi) long connecting two major economic zones in China (Figure 2). It is the world's longest HSR line ever constructed in a single phase and the first one designed for a maximum speed of 380 km/h (236 mph) in commercial operation. The travel time is expected to be 3 h and 58 min, that is, on average 329 km/h (204 mph).

There are 24 stations along the line. HSR operates at two service speeds: G-trains, 300 km/h, and D-trains, 250 km/h. The fastest 300-km/h G-trains have only one intermediate stop (Nanjing South) and take 4.8 h for a trip. However, most G-trains have six or seven intermediate stops and take between 5.33 h and 5.5 h. Different trains have different intermediate stops, but almost all 300-km/h trains will stop at the Jinan and Nanjing stations. The D-trains have more intermediate stops and take between 7.86 h and 9 h to complete the full journey from Beijing to Shanghai.

FIGURE 2 Beijing–Shanghai HSR line.

The Beijing–Shanghai HSR line is typical to test the passenger assignment and dynamic adjustment models. For short-term passenger flow forecasting, daily passenger volume data were collected through the ticketing and reservation system during the period from July 1, 2011, to November 30, 2012 (519 days in total). There were 1,069,148 passengers in 2011 and 1,987,608 passengers in 2012.

By comparing the passenger flows between each origin–destination pair, 10 rail stations with the largest passenger flows were selected: Beijing South, Cangzhou West, Dezhou East, Jinan West, Taian, Xuzhou East, Nanjing South, Wuxi East, Suzhou North, and Shanghai Hongqiao. The spacing between stations and corresponding ticket fares of the 10 stations are shown in Table 1. The 10 stations in a single direction mutually constituted 45 sections. Only southbound trains were analyzed in this study. Table 1 is an upper-right triangular matrix.

RESULTS

Short-Term Forecasting

According to the data described in the previous section, first the original data for the time periods of 20 days, 10 days, and 1 day were merged. Three groups of two-dimensional data were obtained followed by the corresponding matrices of 26×45, 52×45, and 519×45. Forecasts were made for 20 days, 10 days, and 1 day in advance, with the data of 519 days as the original data. Then the EEMD method was applied to decompose the preliminary processed data into intrinsic mode functions, which were classified and predicted with the GSVM model. Finally, the GSVM model was used again with the predicted values of each intrinsic mode function as the test set to achieve the predicted value of the original sequence after model reconstruction.

Figure 3 shows the day-to-day HSR demand forecasting results of three representative origin–destination pairs. After the intrinsic mode functions were trained in the GSVM, the model reconstruction was conducted by applying the SVM to each section. Table 2 shows the training and prediction errors and goodness of fit of the model reconstruction process. The shorter the prediction period is, the higher the prediction precision and the smaller the errors in the results. The day-to-day prediction can be more accurate and better describe demand fluctuations. The section from Beijing South to Shanghai Hongqiao is taken as an example (other sections are omitted due to length restrictions).

As is shown in Table 2, the errors of the three groups increase successively while the correlation coefficients decrease; this result means that the prediction accuracy decreases. This phenomenon is mainly due to merging the data for 20 days or 10 days. It is equivalent to a simple irregular processing of the original data, resulting in more instability and greater volatility of the data. The rail passenger flow generally shows periodic fluctuations of 7 days. The HSR tickets are sold 20 days in advance. Taking these factors into account, the comparison results in Table 2 are reasonable.

Ticket Assignment and Adjustment

Figure 4 is a flowchart of the adjustment procedures. Ticket assignment and adjustment contain the following two steps:

Step 1. Prediction of the merged data of 20 days is used as the constraints of the 10-day ticket assignment model, and the GA is applied

TABLE 1 Station Distances and Ticket Fares of Beijing–Shanghai HSR Line

	Station								
Station	CZW	DZE	JNW	TA	XZE	NJS	WXE	SZN	SHHQ
BJS									
Distance (km)	219	327	419	462	688	1,018	1,201	1,227	1,302
Fare (RMB)	94.5	144.5	184.5	214	309	443.5	513.5	523.5	553
CZW									
Distance (km)	—	108	200	243	469	799	982	1,008	1,083
Fare (RMB)		49.5	89.5	114.5	219	359	433.5	443.5	473.5
DZE									
Distance (km)	—	—	92	135	361	691	874	900	975
Fare (RMB)			39.5	69.5	174.5	314	393.5	403.5	438.5
JNW									
Distance (km)	—	—	—	43	269	599	782	808	883
Fare (RMB)				24.5	129.5	279	354	364	398
TA									
Distance (km)	—	—	—	—	226	556	739	765	840
Fare (RMB)					104.5	254	329	344	374
XZE									
Distance (km)	—	—	—	—	—	330	513	539	614
Fare (RMB)						149.5	239	249	279
NJS									
Distance (km)	—	—	—	—	—	—	183	209	284
Fare (RMB)							84.5	99.5	134.5
WXE									
Distance (km)	—	—	—	—	—	—	—	26	101
Fare (RMB)								9.5	49.5
SZN									
Distance (km)	—	—	—	—	—	—	—	—	75
Fare (RMB)									34.5

NOTE: 1 RMB = US$0.16 in June 2015. RMB = renminbi; CZW = Cangzhou West; DZE = Dezhou East; JNW = Jinan West; TA = Taian; XZE = Xuzhou East; NJS = Nanjing South; WXE = Wuxi East; SZN = Suzhou North; SHHQ = Shanghai Hongqiao; BJS = Beijing South; — = not available.

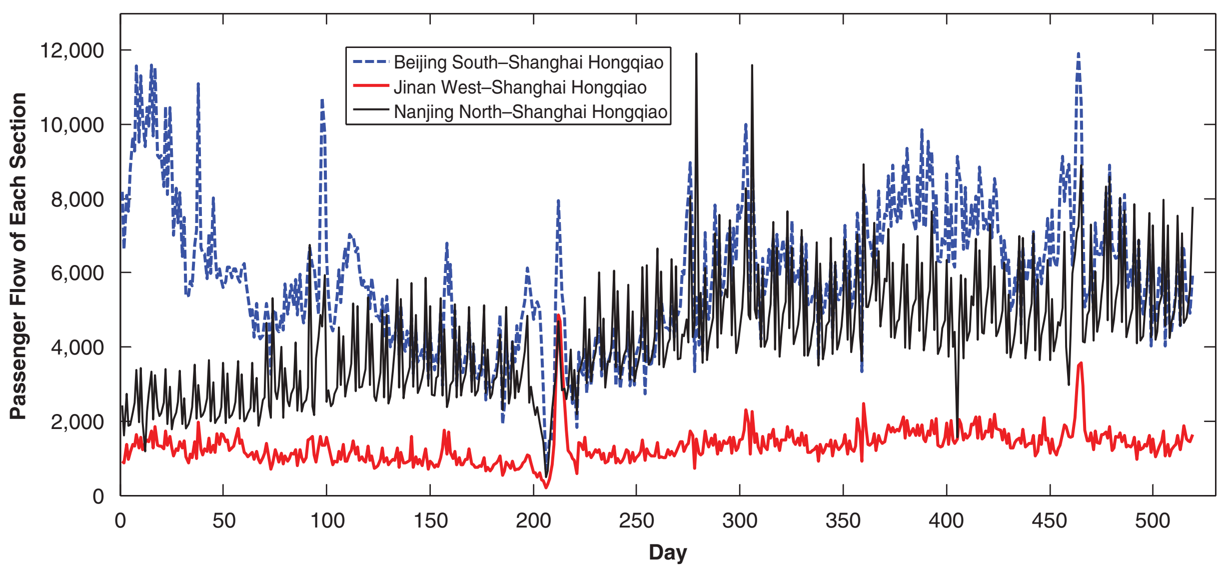

FIGURE 3 Passenger flow forecasting results (day to day).

TABLE 2 Modal Reconstruction Error of Three Time Groups

Measurement of Effectiveness	Daily		10 Days		20 Days	
	Train_set	Test_set	Train_set	Test_set	Train_set	Test_set
MSE	3.56 E-05	8.32 E-04	8.68 E-05	9.95 E-04	2.64 E-03	1.50 E-02
R^2	.97	.94	.92	.89	.84	.82
MAPE	9.31	9.62	11.83	13.15	13.31	14.91

NOTE: MSE = mean square error; R^2 = correlation coefficient; MAPE = mean absolute percentage error.

to obtain the optimal 10-day ticket assignment scheme. Comparing the scheme with the prediction of the merged data of 10 days, the preliminary dynamic adjustment is conducted in the ticket assignment scheme.

Step 2. In the same way, prediction of the merged data of 10 days is used as the constraints of the 1-day ticket assignment model to achieve the optimal 1-day ticket scheme. Comparing the scheme with the 1-day prediction results, the second dynamic adjustment is processed.

After the steps of forecasting and adjustment, the final results are obtained. The average demand satisfaction rates of the major stations along the Beijing–Shanghai HSR line in one day are shown in Figure 5. As is shown, the number of tickets is converted to normalized values as the *y*-axis, and the sections with large passenger flows are selected as the *x*-axis. The trends of the three lines are similar, but since this finding is not clear in Figure 5, the lines between Sections 27 and 29 are enlarged, as shown in the inset to Figure 5. It can be seen that the forecasting data of tickets in one day are basically in accordance with the original ticket data, which means that the results of short-term forecasting model have a high accuracy. Through the ticket assignments and two adjustments, the average demand satisfaction rates of stations along the Beijing–Shanghai HSR line are increased because the change trend of the ticket assignment curve is in accordance with the change of the original ticket data. The ticket assignment and adjustment model is proved to better satisfy the passenger demand.

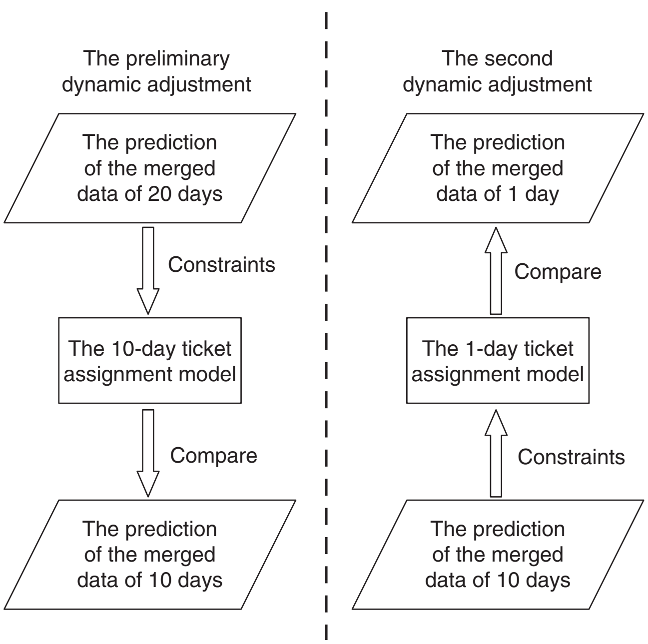

FIGURE 4 Flowchart of adjustment procedures.

Comparison with Existing Ticket Assignment Method

On the basis of the historic passenger flow, rail authorities forecast the passenger flow for different sections and then assign the long-term planning tickets in each section. The fixed ticket policy cannot realistically reflect the passenger demand and does not make full use of rail resources; this result eventually leaves some stations' tickets in short supply and some stations' tickets in oversupply.

In order to compare the ticket assignment results with the existing policy, the ticket revenue during the whole forecasting period was calculated. The comparison of revenue is shown in Table 3. "Ticket Assignment Revenue" means the prediction of the merged data of 20 days as input of the ticket assignment model to acquire the maximum return by a GA. "Revenue After First Adjustment" means the prediction of the merged data of 20 days as the constraints of the 10-day ticket assignment model to acquire the maximum return. "Revenue After Second Adjustment" means the prediction of the merged data of 10 days as the constraints of the 1-day ticket assignment model to acquire it with the same method.

In the results of the initial assignment model (as shown in the fourth column of Table 3), the revenue of all stations increases by 5.98% in comparison with the existing ticket assignment. This study makes full use of the dynamic adjustment to meet actual passenger ticket demand, and thus the two dynamic adjustments get the best results of passenger ticket assignment (as shown in the last column of Table 3). Although the revenue of some stations is reduced after the first adjustment, the total revenue increases by 9.01% more than the existing ticket assignments. For example, the revenue of Beijing South to Jinan West (BJS-JNW) is reduced by 37.89 million renminbi (RMB) (yuan) (1 RMB = $0.16 in June 2015), and the revenue of Xuzhou East to Nanjing South (XZE-NJS) is reduced by 8.53 million RMB. Though the revenue of some sections also decreases based on the second adjustment (e.g., BJS-SZN, JNW-SHHQ), the total return of the second adjustment increases by 13.48%. The increased revenue shows that the assignment results can better reflect actual passenger demand and reduce the waste of rail resources. Thus, the method that combines the short-term prediction of passenger flow, passenger ticket assignment, and dynamic adjustment is feasible for the Beijing–Shanghai HSR line.

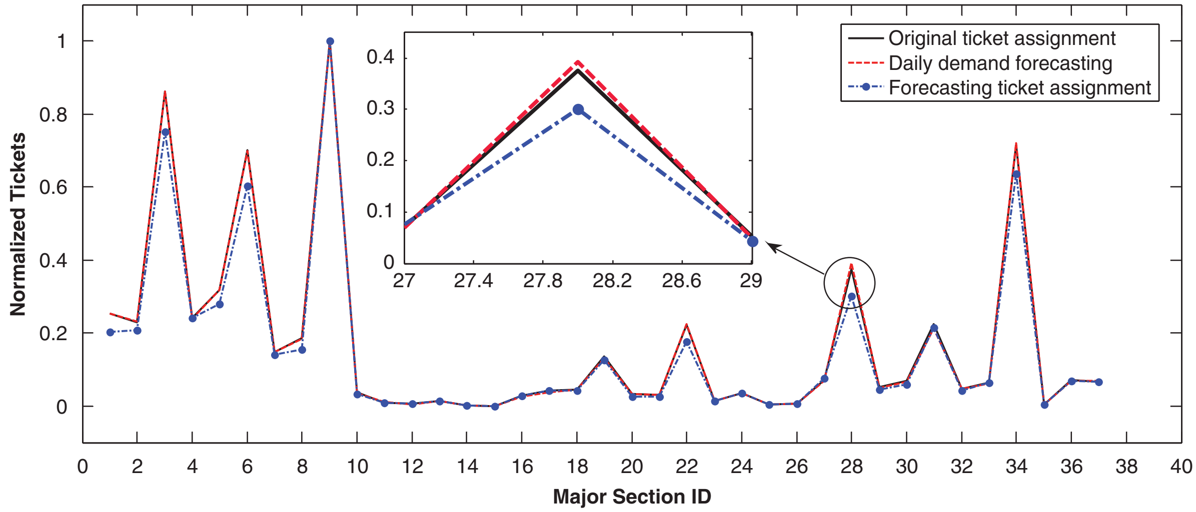

FIGURE 5 Average demand satisfaction rates of major stations along Beijing–Shanghai HSR line.

TABLE 3 Comparison of Results

Section	Fare (RMB)	Revenue (RMB millions) Existing Ticket	Ticket Assignment	After First Adjustment	After Second Adjustment
BJS-CZW	94.5	73.90	*68.76*	*67.06*	**111.58**
BJS-DZE	144.5	103.31	**107.50**	**125.19**	**138.06**
BJS-JNW	184.5	486.95	**491.90**	*449.06*	**520.66**
BJS-TA	214	159.93	**185.42**	**198.32**	**233.31**
BJS-XZE	309	303.83	**309.17**	**373.23**	**328.51**
BJS-NJS	443.5	953.84	*950.76*	**1,017.42**	**1,077.07**
BJS-WXE	513.5	237.98	**263.42**	**244.34**	**297.38**
BJS-SZN	523.5	305.81	*292.91*	**316.22**	**413.70**
BJS-SHHQ	553	1,690.39	**1,959.58**	**1,898.55**	**1,890.06**
CZW-DZE	49.5	1.04	**1.06**	**1.13**	**2.08**
CZW-JNW	89.5	4.54	**4.60**	**5.03**	**7.47**
CZW-TA	114.5	2.11	**2.38**	**2.82**	**4.60**
CZW-XZE	219	7.19	*6.46*	**7.94**	**16.20**
CZW-NJS	359	22.18	**23.96**	**23.90**	**51.75**
CZW-WXE	433.5	8.77	**10.26**	**8.82**	**22.15**
CZW-SZN	443.5	5.10	*4.65*	**6.59**	**16.33**
CZW-SHHQ	473.5	37.49	**38.00**	**45.16**	**58.39**
DZE-JNW	39.5	5.09	**5.19**	**5.23**	**6.79**
DZE-TA	69.5	3.11	**3.22**	**4.19**	**7.74**
DZE-XZE	174.5	5.43	**5.73**	**5.57**	**9.25**
DZE-NJS	314	17.51	**20.16**	**24.88**	**29.54**
DZE-WXE	393.5	8.50	*7.89*	**10.42**	**16.84**
DZE-SZN	403.5	5.59	*5.41*	**8.42**	**14.82**
DZE-SHHQ	438.5	43.66	**50.19**	**67.03**	**63.01**
JNW-TA	24.5	3.43	**4.03**	**4.29**	**5.15**
JNW-XZE	129.5	19.49	**20.94**	**24.97**	**24.13**
JNW-NJS	279	119.85	**127.01**	*117.18*	**166.02**
JNW-WXE	354	41.30	*37.54*	*36.63*	**52.46**
JNW-SZN	364	38.76	**39.32**	**39.14**	**55.94**
JNW-SHHQ	398.5	274.79	*254.64*	**323.31**	**293.91**

(continued on next page)

TABLE 3 *(continued)* **Comparison of Results**

Section	Fare (RMB)	Revenue (RMB millions) Existing Ticket	Ticket Assignment	After First Adjustment	After Second Adjustment
TA-XZE	104.5	6.16	**6.54**	**7.04**	**10.48**
TA-NJS	254	31.75	**34.32**	**33.62**	**50.90**
TA-WXE	329	9.46	**10.34**	*9.12*	**16.40**
TA-SZN	344	11.53	**11.69**	**14.11**	**21.22**
TA-SHHQ	374	85.95	**105.13**	**107.64**	**122.91**
XZE-NJS	149.5	173.20	*160.51*	*164.67*	**213.74**
XZE-WXE	239	40.61	*40.53*	**41.81**	**55.12**
XZE-SZN	249	56.16	*54.48*	**61.20**	**78.08**
XZE-SHHQ	279	194.99	**215.66**	**252.24**	**212.26**
NJS-WXE	84.5	13.60	**13.98**	**14.63**	**25.21**
NJS-SZN	99.5	20.83	**23.47**	*20.60*	**32.45**
NJS-SHHQ	134.5	294.25	**304.09**	*273.84*	**444.53**
WXE-SZN	9.5	0.25	*0.23*	**0.25**	**0.61**
WXE-SHHQ	49.5	11.25	**12.57**	**13.00**	**17.07**
SZN-SHHQ	34.5	7.47	**8.62**	**8.28**	**14.58**
Total revenue (million RMB)	na	5,948.32	**6,304.23**	**6,484.10**	**6,750.44**

NOTE: Increased revenue is in bold type and decreased revenue is in italics. na = not applicable. Incremental rate of revenue compared with existing ticket assignment: ticket assignment = 5.98%; after first adjustment = 9.01%; after second adjustment = 13.48%.

CONCLUSIONS

It is well known that optimizing passenger ticket assignment can significantly increase the revenue of rail authorities. In this study, an approach of passenger ticket assignment and dynamic adjustment was proposed on the basis of revenue management theory and applied to HSR in China.

- A forecasting approach integrating EEMD with GSVM was applied to predict short-term passenger flows for 20 days, 10 days, and 1 day. Compared with the previous methods that forecast passenger demand on the basis of historical data, the real-time assignment of passenger tickets based on short-term passenger flow forecasting was shown to be more accurate and dynamic.
- To obtain the maximum total revenue during the operating time, a revenue management model was proposed by taking into account ticket fare and passenger demand between origin–destination pairs. The merged short-term passenger flow predicted by EEMD-GSVM in advance of 20 days and 10 days was taken as the constraint conditions to allocate passenger tickets in 10 days and 1 day, respectively, and was adjusted twice through comparison with the merged predicted passenger flow in groups of 10 days and 1 day. This procedure made the passenger ticket assignment more accurate and effective and had the practical value to meet real-world requirements. After the two adjustments, the average demand satisfaction rates of stations along the Beijing–Shanghai HSR line increased. In conclusion, the proposed ticket assignment and adjustment model better satisfied passenger demand.
- The passenger ticket assignment and dynamic adjustment models were applied to the Beijing–Shanghai HSR line on the basis of revenue management theory. The total revenue comparison results showed that during the forecasting period of 519 days (from July 1, 2011, to November 30, 2012), the total revenue after application of the ticket assignment and dynamic adjustment models increased by 13.48% compared with the existing ticket assignment method. The ticket assignment and adjustment models could significantly improve the revenue. The case study demonstrated that the ticket assignment and dynamic adjustment models were applicable and effective in the revenue management of HSR in China.
- A GA was applied to solve the proposed models and got a satisfactory solution, since the GA was simple to implement. However, there may be other, better algorithms to solve the problems in this study. In future the authors will develop more advanced algorithms better than the GA or design a new hybrid algorithm by combining a GA with other optimization algorithms.

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