Revenue management method and critical techniques of railway passenger transport

Xinghua Shan, Xiaoyan Lv, Jinfei Wu, Shuo Zhao and Junfeng Zhang
Institute of Computing Technologies,
China Academy of Railway Sciences Corporation Limited, Beijing, China

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Abstract

Purpose – Revenue management (RM) is a significant technique to improve revenue with limited resources. With the macro environment of dramatically increasing transit capacity and rapid railway transport development in China, it is necessary to involve the theory of RM into the operation and decision of railway passenger transport.

Design/methodology/approach – This paper proposes the theory and framework of generalized RM of railway passenger transport (RMRPT), and the thoughts and methods of the main techniques in RMRPT, involving demand forecasting, line planning, inventory control, pricing strategies and information systems, are all studied and elaborated. The involved methods and techniques provide a sequential process to help with the decision-making for each stage of RMRPT. The corresponding techniques are integrated into the information system to support practical businesses in railway passenger transport.

Findings – The combination of the whole techniques devotes to railway benefit improvement and transit resource utilization and has been applied into the practical operation and organization of railway passenger transport.

Originality/value – The development of RMRPT would provide theoretical and technical support for the improvement of service quality as well as railway benefits and efficiency.

Keywords Revenue management, Railway passenger transport, Demand forecasting, Line planning, Inventory control, Pricing strategy

Paper type Research paper

Revenue management (RM) was first applied to the airline business in 1970s, when the multi-level pricing and overbooking strategy were proposed to increase the revenue of airline companies. The concept of RM proposed by Kimes can date back to 1989, of which the aim is to sell the right seats to the right people at the right time at the right price with limited resources to maximize the revenue (Talluri & Van Ryzin, 2004). Since then, the theory has become an effective technique to improve the competitiveness and benefit of airline companies. In the past decades, more and more industries have introduced the concept of RM for the delicacy management of asset operations.

The theory of RM is suitable for products or services with perishability, restricted capacity, market segmentation, pre-booking availability, low variable cost and time-variable demand (Talluri & Van Ryzin, 2004; Marn & Rosiello, 1992). Conventional RM can be carried out at three levels. The first strategic level is to execute market segmentation by product or

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service analysis and make prices by the user responses to pricing; the second tactic level is to assign products and capacity to each submarket based on the market segmentation; the third booking control level is to judge whether to accept the user purchase requests in the sale process to realize booking control.

Similar to the airline business, the products and services of the railway industry also have perishability characteristics, so it is needed to adopt the RM theories to improve railway revenue. Since the railway management and organization in China should consider both economic benefits and social benefits, new theoretical and technical innovations should be made for the RM of railway passenger transport (RMRPT) based on the successful experiences of the RM in airline business.

RMRPT includes diverse research studies which focus on the specific businesses of railway passenger transport. Many researchers have devoted to this work, involving demand forecasting, line planning, seat allocation, dynamic pricing, etc. Travel demand is the basis and source of RM. Li, Lv, and Liu (2011) constructed the forecasting model based on the Radial basis function (RBF) neutral network with the time sequence characteristics of railway passenger flow, where the annual and weekly fluctuation rules were combined to solve the complexity and nonlinearity of the data. Wang, Wang, Jia, and Li (2005) adopted the improved BP neutral network to forecast the railway passenger flow. In order to satisfy the travel demand of passengers, sufficient transit capacity should be provided. Zhao, Wu, and Shi (2021) proposed an approach to optimize line planning problems for high-speed railway time-varying demand by a bi-level programming model based on Stackelberg game theory. Shi, Deng, and Huo (2007) combined line planning, passenger choices, transfer network design and passenger flow assignment to construct the bi-level programming model. Shi, Zhou, Chen, and Deng (2008) incorporated elastic demand into line planning by establishing elastic demand functions and constructed the bi-level programming model based on Stackelberg game theory. Wu, Shan, Sun, Weng, and Zhao (2023) studied daily line planning and traded off demand fluctuation and operation stability, where the thought of “trigger decision, space-time coupling and joint iteration” was proposed to solve the problem. After line planning, seat allocation is to provide specific proper seats for proper passengers. Shan, Zhou, Lv, Zhang, and Wang (2011) studied the dynamic ticket pre-allocation by the principles including “long distance first and then short distance,” “seat first and no seat” and “number-based pre-allocation first and then proportion-based pre-allocation,” by which an information system was established. Based on the forecasted demand, Wang, Lv, Zhou, and You (2013) considered the seat cleavage factors, ticket protective factors and traffic culture factors and established the station-station seat adjustment model and the seat occupancy optimization model to realize reasonable and effective allocation. To realize the revenue maximization, dynamic pricing is the critical phase in RM. Gao, and Si (2001) introduced the application of sensitivity analysis and bi-level programming in railway dynamic pricing. Shi, Zheng, and Gu (2002) proposed the recursion formulation of the optimal strategy and practical strategy of railway dynamic pricing based on the pricing development in China. Chen, and Gao (2003) applied bi-level programming to dynamic pricing where the competition among different transportation modes and passenger choices was involved. Xu, Gao, and Liu (2023) proposed a Pareto-improving seat allocation scheme with time-varying demand and equilibrium travel choices where the model was reformulated into a mixed-integer linear model for solving. Xu, Zhong, Hu, and Liu (2022) extended the model by incorporating pricing to maximize railway revenue, where the model reformulation was also adopted. Luo, Liu, and Lai (2016) established the ticket allocation model according to the first-come, first-serve principle, where the reformulation and simulation were applied and the model was solved by the gradient descend method. Hu, Shi, and Qin (2022) studied the joint optimization of pricing and seat allocation by incorporating the classified pricing strategy by clustering trains with the same O-Ds for large-scale problems.

Compared with the airline industry, the railway industry has more complex practical factors, such as long transit distance, large-scale demand, complex travel schemes, diverse seat allocation and pricing strategies and so on. Because the existing studies for RMRPT have many assumptions, they are not well suitable for practical RMRPT. In order to improve RMRPT, we should incorporate the practical factors into the existing methods and techniques to improve the railway revenue.

With the government deregulation and the improvement of the economic system, the railway passenger transport in China has had the macro environment of RM research. Meanwhile, due to the high service quality, the railway line planning, seat allocation and pricing have been improved to the market-oriented operation stage, and then it is critical to adopt RM to improve the railway competitiveness, benefits and efficiency based on the China Railway Ticket Information System (including 12306.cn).

1. Revenue management framework of railway passenger transport

Railway passenger transport has similar characteristics to airline business, including product perishability, demand diversity, demand fluctuation, presale attributes, fixed capacity, low marginal cost, high fixed cost, etc. However, as the railway industry has long transit distance, large-scale demand, complex travel schemes, seat allocation and pricing strategies, as well as diverse travel choices, RMRPT should involve these distinct characters to solve its own problems and improve the railway revenue.

Due to the attributes of the railway industry in China, the aim of RMRPT is to improve benefits while decreasing cost, which can be extended into the generalized RMRPT framework. The framework includes market monitoring, demand forecasting, line planning, ticket sale organization, pricing control and so on, where interaction between supply and demand occurs.

(1) Demand forecasting

Demand forecasting is the basis of RMRPT, so precise demand forecasting can benefit maximizing railway revenue. The aim of demand forecasting is to improve the accuracy of demand. Since the external factors would impact the effects and precision of demand forecasting, market monitoring should be adopted to monitor these factors, including the marketing strategies of competitive industries, weather change and passenger behaviors. The forecasting methods mine the passenger travel characters based on historical demand data and forecast the future travel demand by intelligent forecasting models, which can be adjusted by the ticket sales, surplus seats and waiting lists.

(2) Line planning

Line planning is a critical issue of railway planning, which is the process to transform demand flow into train flow. Based on market demand and transit resources, line planning decides the running routes, stop plans, frequencies, capacities and rolling stock circulations. It should not only satisfy the demand fluctuation characteristics, but also improve the capacity utilization and railway benefits.

(3) Ticket sale organization

Ticket sale organization is the distinct strategy of the railway industry to improve the overall revenue. Combined with the long distances, complex stops and diverse travel behaviors, it needs to sell the proper seats to the proper passengers at the proper time to realize the revenue maximization. Conventional ticket sale strategies include ticket pre-allocation, ticket share, seat reuse, sale control and overbooking, which are adopted by combination during the pre-sale period.

(4) Pricing control

Railway pricing control includes static pricing control and dynamic pricing control. Static pricing control needs to decide the periodical prices of each train or segment with low pricing frequencies, while dynamic pricing control is a short-term multi-level pricing decision process based on the change in travel demand.

(5) Data platform support

The big data platform of railway passenger transport collects the whole ticket pre-sale data that can well reflect the travel characters of passengers. Meanwhile, it also includes the access data of 12306.cn, the check-in data, extended service data, external data and so on. These data can be applied to the portrait of railway passengers and products, where more data values can be mined to support RMRPT.

2. Railway passenger transport market and demand forecasting

Oriented to the railway passenger transport market, the portrait of railway passengers and products is made to mine the travel behaviors and segment market, then it can support the short-term and real-time demand forecasting for existing trains and newly designed trains.

2.1 Portrait of railway passengers and products

(1) Railway production portrait

Based on the actual railway production data, railway production portrait adopts statistic and artificial intelligence (AI) techniques to mine the distinct characters of railway production, which can support the railway production design.

The railway stations are the basic elements of the railway system. The portrait is constructed by the following labels: physical attribute, passenger flow character, service feature, transportation planning, economic level, city development, geographic location, etc. We adopt the natural breakpoint classification to classify stations into different categories based on the passenger flow, while the K-means clustering algorithm is applied to cluster different city regions.

Train portrait is constructed by labels such as train class, train type, train number, stop plan, train O-D, travel speed, O-D segment, load factor, revenue, break-even point, etc.

(2) Railway passenger portrait

Railway passenger portrait reflects the diverse travel behaviors of travel demand. It can benefit the segmentation of different travel groups and differentiated design of railway production.

Passenger travel characters can be classified into static characters (natural attributes) and dynamic characters (travel behaviors). Meanwhile, more external characters should be involved, such as travel distances, travel aims, service requests and social relationships. Passengers' travel behaviors can be illustrated by the concept of travel chain, which consists of actual travel behaviors and invisible travel behaviors. By travel chains, we can obtain the whole travel trajectory of each passenger and classify passengers into different groups. Using the concept of the loyalty index, we can also analyze the competitiveness among different modes on segments.

2.2 Short-term demand forecasting of high-speed railway

Due to the change and fluctuation of travel demand, it is needed to adjust the line plan that is being executed to better satisfy the travel desires of passengers (Li *et al.*, 2011; Wang *et al.*, 2005; Littlewood, 1997). It is indicated that the precision of demand forecasting becomes more and more critical. Due to the interaction between railway supply and demand, the adjustment of railway line planning would lead to the fluctuation of travel demand, resulting in the error of demand forecasting.

Conventional forecasting methods include time series forecasting, machine learning, neutral network, etc. Due to the frequent adjustments and unstable passenger flow, we need to improve the conventional historical time series forecasting. The improved method adopts the XGBoost method based on the O-D type classification of each train. The method searches the best reference train according to the deviation of travel time, and then the XGBoost method is adopted to forecast the target passenger flow.

(1) Flow matching

Flow matching is aimed to obtain the reasonable historic reference passenger flow in trains. In a specific transit corridor, the historic travel time and departure time between an O-D pair within a year are, respectively, denoted by x_i and y_i, while those of the target train are denoted by x_α and y_α, and then the best reference train is

$$\begin{cases} \min_i |y_i - y_a|, if\, |x_i - x_a| > 30 \\ \min_i |x_i - x_a|, \qquad otherwise \end{cases} \tag{1}$$

It means that if the deviation of travel time is within 30 min, then the best reference train is that with the most approximate departure time to the target train; otherwise, it is the train with the most approximate travel time.

Using the reference trains, we can adopt the corresponding train flows as the revised historic reference train flows to forecast the passenger flow in the target train.

(2) Demand forecasting based on XGBoost

XGBoost is an efficient supervised-learning boosting algorithm. Assume the data set $D = \{(x_i, y_i)\}$ $(|D| = n, x_i \in \mathbb{R}^m, y_i \in \mathbb{R})$ where m is the feature vector and n is the sample volume. The tree model is consisted of K trees, which is formulated as follows:

$$\hat{y}_i = \varphi(x_i) = \sum_{k=1}^{K} f_k(x_i), f_k \in F \tag{2}$$

where $F = \{f(x) = \omega_q(x)\}$ $(q: \mathbb{R}^m \to T, \omega \in \mathbb{R}^T)$ is the forecasting result of x_i by the Kth tree, T is the volume of the leaf nodes in the tree model, and w_t is the weight of the tth leaf node.

The loss function is

$$L(\Phi) = \sum_i l\left(\hat{y}_i - y_i\right) + \sum_k \Omega(f_k)$$

$$s.t.\, \Omega(f) = \gamma T + \frac{1}{2}\lambda\|w\|^2 \tag{3}$$

l is the mean squared error (MSE) between the forecast values and the actual values and Ω is the penalty term.

The nonlinear objective function is the sum of the loss function and the regularization term. We need to adopt forward distributed learning to solve it. By splitting the decision trees, the weak learner iterations are repeated to solve the model.

3. Railway line planning optimization

The line plan is actually a set of trains with diverse routes, stop patterns, fleet sizes and estimated starting times (Zhao *et al.*, 2021; Shi *et al.*, 2007; Shi *et al.*, 2008; Wu *et al.*, 2023).

To match the demand fluctuation, line plans are needed to be adjusted in a regular cycle. Given the high-speed railway (HSR) network $G = (V, E)$ where V, E are the station set and section set, respectively, travel demand fluctuation and operation parameters, daily line planning is to adjust the reference line plan Ψ_0 based on the base line plan $\overline{\Psi}$ according to the demand fluctuation, then the newly adjusted daily line plan $\Psi = \{T = (L_T, S_T, B_T)\}$ is obtained to ensure the defined level of service for demand and the limit of transit capacity allocation on the network, with the trade-off between the system cost and the adjustment deviation.

3.1 Constraints

(1) Constraint of section capacity

The number of passing trains T_e of a section $e \in E$ during a day should not exceed the section capacity C_e.

$$T_e \le C_e, \quad e \in E \tag{4}$$

(2) Constraint of starting/ending capacity

Similarly, the number of trains starting from or ending at a station $v \in V$ cannot exceed the corresponding starting and/or ending capacity C_v for safety security. If the station is not a starting station, then $C_v = 0$.

$$\left|\left\{T \in \Psi \middle| v = v_1^T\right\}\right| \le C_v, v \in V \tag{5}$$

$$\left|\left\{T \in \Psi \middle| v = v_{n_T}^T\right\}\right| \le C_v, v \in V \tag{6}$$

(3) Constraint of common train proportion

To ensure operation stability, the adjusted line plan cannot excessively deviate from the overall structure of the reference line plan. It means some trains in the reference line plan should be remained to ensure the space-time coupling relationship between the two line plans. The common trains of the two line plans should account for a certain proportion in the reference line plan, which satisfies the lower limit α.

$$|\Psi \cap \Psi_0| / |\Psi_0| \ge \alpha \tag{7}$$

(4) Constraint of candidate set of space-time segments

The space-time segments of a daily line plan should be selected from the candidate set in the base line plan. Let denote the candidate set of space-time segments by $\overline{L} = \{(V_T, D_T) \middle| T \in \overline{\Psi}\}$, then each space-time segment in the adjusted line plan L_T, $T \in \Omega$ should belong to the candidate set.

$$L_T \in \overline{L}, \quad T \in \Psi \tag{8}$$

(5) Constraint of the range of starting/ending times

Let denote the operation period of a day by $[t_1, t_2]$, then the estimate starting time and final ending time should be in the operation period.

$$t_1 \le D_T, a_{n_T}^T \le t_2, \quad T \in \Psi \tag{9}$$

(6) Constraint of transit allocation

The transit capacity allocation should satisfy the travel requirement of passengers, which means the total travel demand should be transported and no passenger is detained. Considering the spatial distribution of detained passengers, we adopt the detained passenger kilometers to evaluate the transit capacity allocation. It should satisfy

$$\sum_{(r,s)\in RS} q_{rs}^{0} l_{rs} = 0 \tag{10}$$

where q_{rs}^{0}, l_{rs} are the detained passenger number and the shortest path length between the O-D pair (r, s).

(7) Constraint of service frequency

To serve the passengers from or to each station, the services for each station should satisfy the required service frequency. Denote n_v^0 as the lower limit of service frequency for station $v \in V$, the following constraint should be satisfied.

$$\left|\left\{T \in \Psi | \exists i, v = v_i^T, x_i^T = 1\right\}\right| \geq n_v^0, v \in V \tag{11}$$

3.2 Objectives

We adopt Electric Multiple Unit (EMU) kilometers to evaluate the train cost that is described by the multiple of EMU kilometers.

$$Z_1 = \sum_{T\in\Psi} \sum_{i=1}^{n_T - 1} \eta_T m_{Ti} \tag{12}$$

As for train $T \in \Psi$, if the train is a short-marshalling train, then $\eta_T = 1$; otherwise, $0 < \eta_T < 1$.

Given time-varying demand, the whole passenger itineraries include the travel adjustments, on-board travels and transfer processes, so the total travel cost is related to the boarding deviation time T_1, on-board time T_2 and transfer time T_3. Combined with diverse time values w_1, w_2, w_3, the total passenger travel cost is

$$Z_2 = w_1 T_1 + w_2 T_2 + w_3 T_3 \tag{13}$$

when $w_1 = w_2 = w_3 = 1$, the total travel cost is exactly the total travel time.

We further introduce weights for the above objectives and construct the bi-level programming formulation.

$$\min Z(\Omega) = \sum\nolimits_{i=1}^{2} \alpha_i Z_i \tag{14}$$

s.t. formulas (4)–(11)

Where $LF, \tau_b, \tau_r, \tau_h, q_{rs}^0$ are obtained by passenger flow assignment.

In the line planning process, the interaction and conflicts between railway companies and passengers are generated sequentially in line planning decisions and travel choices, which would influence the two sides until reaching equilibrium. We adopt the bi-level programming formulation to describe the daily line planning process. In the upper level, the reference line plan is adjusted subject to relevant constraints and the base line plan and then the lower level is to assign the passenger flow to the adjusted line plan by the schedule-based passenger flow assignment approach in reference (Zhao, Shi, Hu, Xu, and Shan, 2018; Zhao *et al.*, 2021; Wu *et al.*, 2023).

3.3 Solving algorithm

The solving algorithm is designed based on the Simulated Annealing Algorithm (SAA) framework and the base line plan, including the following procedures where (4)-(5) are repeatedly executed to adjust the daily line plan until the end condition (Wu *et al.*, 2023). Figure 1 illustrates the flow chart of the algorithm.

(1) Trigger decision. Based on the current travel demand and the reference line plan, calculate the deviation of travel demand from the demand before adjustment, then determine whether to adjust the reference line plan according to the threshold of the trigger decision.

(2) Initial solution generation and evaluation. If the trigger condition is satisfied, then set the reference line plan as the initial line plan and evaluate the initial solution by the passenger flow assignment to obtain the initial objective value and other indexes.

(3) Space-time coupled train set partition. According to the evaluation results of the initial solution, select the space-time coupled trains that need to be remained and determine the fixed train set and the adjusted train set.

(4) Neighborhood solution searching and evaluation. Based on the base line plan and space-time coupled train set partition, search for the neighborhood solution by the searching strategies (deleting, fleet size adjustment, adding and stopping adjustment)

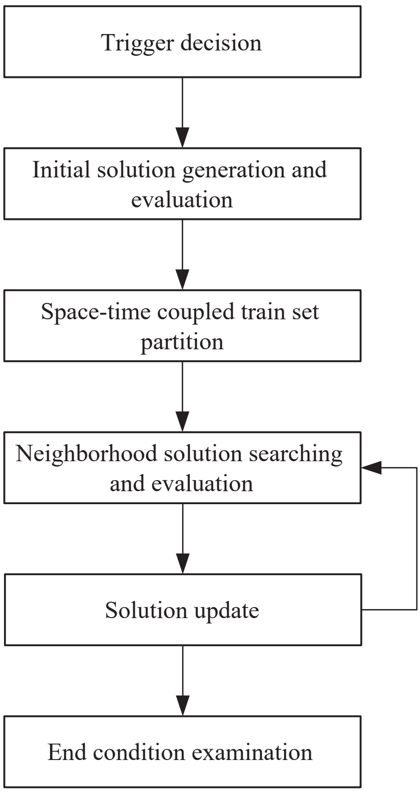

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Figure 1. Illustration of the line planning solving algorithm

and evaluate the neighborhood solution by the passenger flow assignment to obtain the objective value of the neighborhood solution and other indexes.

(5) Solution update. Determine whether to update the neighborhood solution according to the update condition.

(6) End-condition examination.

4. Inventory control technologies

4.1 Railway inventory control framework

Inventory control is the conventional method in RM to assign the limited capacity (space, seats and inventory) to customers with different price classes. Different from airline business, railway transit belongs to the multi-segment network pattern (Belobaba Peter, 1989; Shan *et al.*, 2011; Wang *et al.*, 2013). The object of railway inventory control is train seats, so the seats based on multiple stop patterns have their own attributes: (1) one seat can correspond to multiple O-D pairs, (2) the subsequent passenger flow of a partial ticket is uncertain and (3) the seat values gradually decrease after the train departs.

The factors of railway inventory control include passenger flow and seat. Based on the forecasted demand, we can decide the O-D ranges, pre-sale times and pre-sale volumes of segment tickets by the inventory control method. Meanwhile, based on the seat inventory change curve, the deviation outliers between the allocated seats and forecasted passenger flows are monitored, which is fed back to the inventory control process for deviation revision to realize the match between seat allocation and travel demand.

4.2 Inventory control with passenger flow patterns

Passenger flow pattern is the matching pattern in the passenger's journey that describes the utilization process of train seats. Based on historical passenger flow data and demand forecasting, inventory control with passenger flow patterns is aimed to maximize transit capacity utilization and demand travel satisfaction by reasonable seat allocation.

Passenger flows in trains generally consist of three categories: passenger flows with the origin segment, passenger flows with passing segments and passenger flows with the destination segment. Passenger flow patterns include three terms: dominated by starting passenger flows, dominated by exchange passenger flows and balanced passenger flow distribution. Let denote X, Y and Z as the utilization ratios of the origin station, passing stations and destination station, respectively, then the passenger flow pattern $H(X, Y, Z)$ can be

$$X = INT\frac{\frac{\sum_{j=2}^{n} x_{1j}}{F} \times 100}{10} \tag{15}$$

$$Y = INT\frac{\frac{\frac{\sum_{k=2}^{n-2}\left(\sum_{i=1}^{k}\sum_{j=k+1}^{n} x_{ij}\right)}{F}}{n-3} \times 100}{10} \tag{16}$$

$$Z = INT\frac{\frac{\sum_{i=1}^{n-1} x_{in}}{F} \times 100}{10} \tag{17}$$

$$H(X, Y, Z) = 100min(X\ , 9) + 10min(Y\ , 9) + min(Z\ , 9) \tag{18}$$

where n is the stop number, x_{ij} is the passenger volume from the ith station to the jth station and F is the train capacity, the function INT is adopted to execute the round operation.

Due to the complex demand fluctuation, the practical ticket pre-sale techniques are adopted based on the fuzzy conditions where the available seats would be allocated more than once by a nested mode. Inventory control with passenger flow patterns can be executed by the method of matching pre-allocation. This method divides the available seats based on the forecasted O-D passenger flows, and then it is needed to set the boarding station, the station available for sale and its subsequent stations for each ticket.

Let denote f_{ij} as the forecasted demand from the ith station to the jth station, and $f_{ij}^{\prime m}$ as the allocated ticket volume from the ith station to the jth station in the mth matching, a_{ij}^{m} is the pre-allocated ticket volume from the ith station to the jth station with m matching processes. The allocated results with the origin station and destination station is

$$A_0 = \left(a_{ij}^{0}\right)_{(n-1)\times n} \tag{19}$$

$$a_{1n}^{0} = f_{1n} = f_{1n}^{\prime 0} \tag{20}$$

If the whole journey consists of two matching processes, then the pre-allocated tickets need to be divided again, i.e.

$$A_1 = \left(a_{ij}^{1}\right)_{(n-1)\times n} \tag{21}$$

$$a_{1k}^{1} = a_{kn}^{1} = \min(f_{1k}, f_{kn}) \tag{22}$$

5. Railway dynamic pricing

Transport price is the monetary expression of transport values, which is consisted of transport cost, tax and profit. Railway dynamic pricing is executed based on the existing prices to better match the actual travel demand and improve the whole revenue (Gao & Si, 2001; Shi *et al.*, 2002; Chen & Gao, 2003).

5.1 Railway pricing control

Railway pricing is impacted by three main factors: transport cost, transport market and government economic policies. Firstly, transport cost is the cost railway companies spend to transport travel demand during a specific period, which consists of operation cost, management cost and financial cost. The pricing needs to cover the whole transport cost. Secondly, the transport market is the external factor of railway pricing, which includes the supply and demand relationship as well as the market structure pattern. Because supply and demand interact with each other, the travel demand generally shows elastic characters to the existing prices. Railway pricing would impact the competitiveness among different transportation modes. It is needed to decide competitive prices based on the price relations and market positioning. Thirdly, railway pricing is impacted by the government's economic policies, and the prices should be set in the framework of the national pricing policy.

The change of pricing would lead to the change of travel cost. When the prices increase or decrease, travel demand would perform the corresponding changes, i.e. decrease or increase. This would result in demand elasticity, which is used to describe the sensitivity level of passengers to the change of supply or other factors. It can be quantified by the percentage of demand change when the prices change by 1%, i.e.

$$e_d = \frac{\Delta Q/Q}{\Delta P/P} \tag{23}$$

where e_d is the price elasticity, $\Delta Q/Q$ is the change percentage of demand and $\Delta P/P$ is the change percentage of price.

If $e_d > 1$, then it is indicated that the pricing is elastic, and the pricing change would dramatically impact travel demand; if $e_d < 1$, then the pricing lacks elasticity and travel demand would change a little; if $e_d = 1$, then demand would present the unit elasticity character.

5.2 Dynamic pricing strategies and model

In the transport market, the pricing strategies are the pricing-decision-oriented strategies that can improve the competitiveness in the transport market based on transit resource and transport service attributes. The common pricing strategies includes bundle sale, demand elasticity strategy, differential pricing, discount strategy, dynamic pricing, psychological pricing, etc.

Due to the interaction between supply and demand, the theory of user equilibrium is introduced to construct the bi-level programming model. The model can not only minimize the travel cost of passengers but also maximize the profit of railway companies. The upper level model is

$$(U)\, max\, F = \sum_{w \in W} q_r^w \left(u_r^w\right) u_r^w \tag{24}$$

$$s.t.\, u_e^{\omega(\min)} \leq u_r \leq u_r^{\omega(\max)} \tag{25}$$

The lower level model is

$$(L) \min Z(q, q(u)) = \sum_{w \in W} \sum_{w \in W} \int_0^{q_n^w} f(x) dx \tag{26}$$

$$s.t. \sum_{w \in N} q_n^w \left(u_n^w\right) = Q^w, w \in W \tag{27}$$

$$q_n^w \geq 0, n \in N, w \in W \tag{28}$$

where q_r^w and u_r^w are the passenger volume of segment w, $u_r^{\omega(\min)}$, $u_r^{\omega(\max)}$ are the transport cost and the highest price of segment w, $f(x)$ is the passenger generalized cost function and Q^w is the total passenger volume on segment w. The constraint (25) ensures the price should be in the reasonable range.

The solving algorithms of the bi-level programming model include five categories: peak searching algorithm, direct searching algorithm, descending algorithm, Karush-Kuhn-Tucker (KKT) transform and optimization. Nonnumeric optimization algorithms include the Simulated Annealing Algorithm, Genetic Algorithm, Chaos Optimization Algorithm, Ant Colony Algorithm, etc.

6. Revenue management system of railway passenger transport

6.1 System framework

Revenue management system of railway passenger transport (RMSRPT) can serve multi-level users including China State Railway Group Co., Ltd, railway bureaus and specific stations or segments. The system framework illustrated in Figure 2 consists of five layers: (1) an external data layer for big data processing, (2) an accumulation layer for distributed

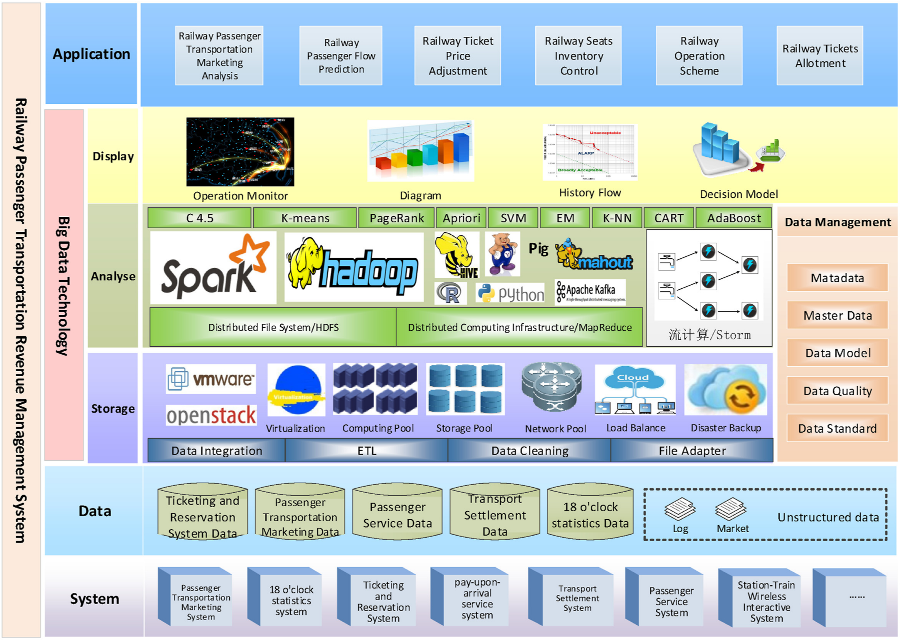

Figure 2.
Framework illustration of RMSRPT

Source(s): Authors' own work

memory, (3) an analysis layer for comprehensive analysis, (4) a presentation layer for data presentation and (5) an application layer for railway passenger transport business decisions.

RMSRPT adopts the data management technique, data acquisition and pre-processing technique and analysis and mining technique to manage railway passenger transport data and external data, process and analyze data and support the business models.

6.2 System functions

RMSRPT has six function applications, i.e. demand forecasting, transit resource management and capacity calculation, line planning, benefit evaluation, ticket pre-sale and pricing decision.

(1) Demand forecasting application adopts demand forecasting models and algorithms, involves historical data and diverse impact factors and provides demand forecasting results with different periods, granularities and dimensions. The demand forecasting techniques in Section 2 are applied in this module.

(2) The transit resource management and capacity calculation application realizes transit resource management and visibility, capacity calculation and simulation to provide the constraint data for business decisions.

(3) The line planning application adopts optimization theory, machine learning and a neutral network to obtain the elements of the line plan based on the transit resource data and demand data, which can support partial optimization and dynamic optimization. The adopted optimization methods are introduced in Section 3.

(4) The benefit evaluation application constructs the benefit calculation method based on total income and total cost, realizes real-time monitoring and comprehensive analysis of train benefits and comprehensively evaluates the benefits of potential trains.

(5) The ticket pre-sale application can decide the pre-sale segments, ticket volumes and periods based on the historical data, forecasting demand and train diagraph to maximize the whole revenue. The adopted optimization methods are introduced in Section 4.

(6) The pricing decision application focuses on the differentiated pricing for different trains and dates and provides adjustment suggestions for railway pricing strategies, i.e. the adjustment of discount ratios for different dates, trains, segments or periods. The adopted optimization methods are introduced in Section 5.

7. Conclusion

This paper introduces the theory and critical techniques of RMRPT in China. The critical techniques in RMRPT, involving demand forecasting, line planning, inventory control, pricing strategies and information systems, are all studied and elaborated. Because the aim of railway passenger transport is to satisfy travel demand, demand forecasting becomes the basis of RMRPT to provide demand data for subsequent businesses. With the forecasted demand, line planning designs enough transit capacity to balance supply and demand, and then inventory control methods are adopted to provide proper seats and tickets for passengers. Combined with the elasticity between pricing and demand, railway pricing decides proper pricing strategies to improve railway competitiveness. The corresponding techniques are integrated into the RMSRPT to support practical businesses in railway passenger transport. The combination of the whole technique devotes to railway benefit improvement and transit resource utilization.

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Corresponding author
Xinghua Shan can be contacted at: shanxinghua@rails.cn