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Revenue Management for Dedicated Passenger Line Based on Passenger Preference Order

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Abstract: Against the limitations of demand independence hypothesis of traditional revenue management models, adopting preference order to describe passenger choice behavior, taking ticket control strategy vectors as decision variables, a dynamic programming model was constructed to maximize the expected revenue of dedicated passenger line according to Bellman principles and then approximately solved by virtue of heuristic decomposition algorithm. The results show that under the different transfer purchase probabilities, the expected revenues obtained by the choice model are all more than those obtained by demand independence one.

Key words: Revenue management, dedicated passenger line, passenger preference order, dynamic programming

INTRODUCTION

In the 1970s, due to the relaxation of the aviation regulation and price control, RM began to popular in American airlines and now has been indispensable for airline, hotel, rental and many other industries to obtain competitive advantage. According to statistics, the enterprise using RM often has an improvement of 2-8% in revenue (Smith *et al*., 1992).

Application of RM to railway started late. Amtrak is a pioneer in this area, in contract with Sabre, who established the first RM system in railway in 1991, namely the ARROW ticket booking system which achieved a rational allocation of transport capacity and a floating of price. According to statistics, in 2006 the company's railway passenger traffic increased by 23% and revenue increased by 27.2%. In the early 1990s, SNCF the national railroad of France developed railway ticket booking, distribution and integrated decision support system-including RM system (RailRev), schedule plan system (RailPlus) and seat management system (RailCap)-in partnership with SABRF which corresponds to an approximate two percent increase in revenue every year. GNER the Great Britain's Northeast Railway developed IRIS Technology Solutions in 2004 and then in the same year, the revenue increased by 16.6 million pounds which was 40 times compared to 2003.

In addition, DBAG the German railway company developed a new fare system in the late 1990s and established "RM department". The Dutch railway travel industry proposed different dynamic pricing strategies based on the smart card, such as the direction-based pricing strategy according to different traffic in both directions, the time-based pricing strategy according to different demand elastic in the peak and off-peak period and so on which largely alleviate the revenue increase bottleneck. The above operating experience of United States, France, Britain, Germany and other national railway companies show that RM is an effectively way to optimize the transport structure and resource allocation and to enhance competitiveness and revenue of railway.

Research of RM in railway also began late. Strasser (1996) summarized some common characteristics of railway similar to airline and proposes applying RM to railway to balance demand and improve profit. Kraft *et al*. (2000) explored the common and different characteristics between railway and airline and further demonstrated the necessity to study theoretically RM in railway. Abe Itaru (2007) showcased several empirical RM examples in railway in Japan and Portugal and analyzed the adaptability of RM applying to railway.

Bharill and Rangaraj (2008) discussed the elastic pricing strategy of railway when facing competition from other transportation modes such as airline, road and so on. Based on the developing trend of Chinese railway passenger ticket pricing and the summary of western researches, Shi *et al*. (2002) discussed the optimal dynamic pricing policy and developed a practical pricing policy. Shuai and Sun (2006) established a system dynamics model to describe the high-speed railway pricing mechanism. Ciancimino *et al*. (1999) regarded railway RM as a single-fare and multi-leg problem, then explored how to control seat capacity under deterministic and stochastic O-Ds' demand by using a deterministic

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linear programming modal and a probabilistic nonlinear programming model, respectively. You (2008) proposed a constrained nonlinear integer programming model to deal with seat allocation for a railway booking system which assumed that demand for each trip in the network can be divided into two segments, namely a full fare segment and a discounted fare segment. Lan and Zhang (2009) constructed a RM optimization model to maximize the total operation revenue for high-speed passenger railway which is an integrated model that can synchronously optimizes seat inventory allocation and train departure schedule. By transforming the continuous random variables into discrete random variables in the existing seat control model, Xuedong and Yin (2011) optimized operation revenue of the multi-leg and multi-fare railway with less solution difficulty.

The works, especially the models mentioned above provide theoretical support, reference and methodological guidance for implementing RM to railway. However, they make a common simplifying assumption that demand for each ticket is completely independent of the controls applied by the railway firm which are common in the context of traditional RM models. Cooper and Gupta (2006) demonstrated that using strategies which ignore customer choice behavior repeatedly can drive revenue down and result in a phenomenon called the “spiral-down effect”. Zhang and Lan (2012) explored the application of RM to high-speed railway and proposed a RM model with considering customer choice behavior in the case of multi-fare and multi-train railway. Numeral experiments on simulation data show that the total revenue of the model is higher than that of demand independence model and the gain increases with the number of the fare classes.

In China, dedicated passenger line runs with high density, public transport, flexible organization and other characteristics which results in a variety of optional tickets between the same Origin and Destination (O-D). Facing many optional tickets, a passenger will pick some tickets as his/her purchase intentions according to his/her travel demand and then rank them according to his/her preference-the first is the favorite, followed by the second favorite, the third favorite and so on, to form a list which is called a preference order (Van Ryzin and Vulcano, 2006; Chen and Homem-de-Mello, 2010). When purchasing ticket, if and only if the first option in his/her preference order is not available, the passenger moves to the second option with some probability. If the second option in his/her preference order can’t be obtained either, he/she moves to the third option with some probability and so forth until either the passenger has no other choice but to leave or his /her request is accepted, where the probabilities can be viewed as the transfer purchase probabilities within a preference order.

The concept of preference orders is an effective way to describe passenger choice behavior which embodies the principle of utility maximization and takes “buy-up” into account as well. Indeed, the number of preferred orders will be increase rapidly due to the increasing number of tickets. However, in reality, it is reasonable to distinguish passenger choice behavior by selecting appropriate number of preference orders, on the base of market segments according to the similarities and differences of passengers’ demand and preference. Thus in the study, we study RM in dedicated passenger line with multi-segment, multi-trip and multi-fare based on adopting preference order to describe passenger choice behavior.

MODEL DESCRIPTION

The dedicated passenger line consists of M+1 stations (No.1dontes the original station and the rest are numbered successively) and K tains to serve one single direction. The initial seat capacity of train k (k = 1, 2,…, K) on leg m (m = 1, 2,…, M) (between station m and station m+1) is denoted by c_{km}. Let $C = [c_{km}]_{K\times M}$ be the seat capability matrix.

The dedicated passenger line totally provides n tickets (a ticket is defined by an O-D and fare combination), each ticket j (j = 1, 2,…, n) has an associated fare f_j. Define the incidence matrix B $[b_{jk}]_{n\times K}$. If ticket j take the seat of train k, $b_{jk} = 1$, otherwise, $b_{jk} = 0$. The incidence matrix between tickets and legs is denoted by $Y = [y_{jm}]_{m\times M}$. If ticket j take the seat on leg m, $y_{km} = 1$, otherwise, $y_{km} = 0$. Let A_j be the incidence matrix of ticket j associated with trains and legs and it is easy to get $A_j = B_j^TY_j$, where B_j and Y_j are the jth columns of B and Y, respectively.

As we know, the spare seats in a train may be sold during the run but their values reduce gradually as the train runs forwards and lose completely if they cannot be sold at the last station before the destination. That is to say, for the same train, different station has different presale terminal time. The presale terminal time of train k at station m is denoted by t_{km}. The presale initial time of the dedicated passenger line is denoted by t_0, thus the whole presale range is $[t_0, t_{KM}]$. Paralleling to a practice often used in dynamic control, we divide $[t_0, t_{KM}]$ into τ periods so reasonably that at most a passenger arrives within each period-the probability of more than an arrival is negligible. Period $l(l = 1, 2,..., \tau)$ stands for $[t_{l-1}, t_l]$, where $t_\tau = t_{KM}$.

Let x_{km} be the available seat capacity of train k on leg m in period l. When train k departs from station m, the value of all the spare seats will lose on leg m and train k can no longer meet any subsequent demand of O-Ds associated with leg m, so we might as well appoint that the available seat capacity of train k on leg m is 0, i.e., when $t_{km}<t_{l-1}$, $x_{km} = 0$. The available seat capacities of each train on each leg in period l are denoted by $X = [x_{km}]_{K\times M}$ which is called the network state of the dedicated passenger line. The available seat capacity matrix of ticket j is X_j and it is easy to know that $X_j = [b_{jk}.y_{jm}.x_{km}]$. When $X_j \geq A_j$, if one unit of ticket j is sold, the network state of the dedicated passenger line is updated to $X-A_j$.

Assume that the passengers are divided into S segments. The preference order of segment $s(s = 1, 2,\ldots, S)$ is denoted by U_s which contains n_s tickets, where $1\leq n_s\leq n$. Let q^s_h represent the transfer purchase probability from ticket h to ticket h+1 in the preference order U_s, where $1\leq h\leq n_s-1$. When $h = n_s$, we can get $q^s_{n_s} = 0$ from the definition of preference order. Because we only focus on constructing the RM model, q^s_h are just regarded as the input parameters of the model, whose estimation methods can refer to Sven-Eric (1998) and Algers and Beser (2001). Assume that the order of ticket j in U_s is w_{sj}. Let $B_{sj} = \{z\epsilon U_s|w_{sz}<w_{sj}\}$ be the set of tickets which is ranked before j in U_s.

Assume that passengers' arrivals obey Poisson distribution. In order to simplify the model, assume that the possibility of an arrival of segment s is independent of period l and denoted by λ_s. Let $\lambda = \Sigma^s_{s=1}\lambda_s$, $0\leq\lambda\leq 1$. Further assume an arriving passenger books at most a ticket and won't cancel the ticket.

Let $\mu_j(l, X)$ represent the control strategy of ticket j given the network state is X in period l. If $X_j\geq A_j$ and ticket j is on sale in period l, $\mu_j(l, X) = 1$, otherwise, $\mu_j(l, X) = 0$. Because $\mu_j(l, X)$ depends on period l and network state X, for simplicity, we replace $\mu_j(l, X)$ by μ_j without confusion. Let $\mu = (\mu_1, \mu_2,\ldots, \mu_n)$ be the control strategy vector of the tickets within period l when the network state is X. The firm's task is to optimize expected revenue of the dedicated passenger line by dynamical choosing control strategy vector μ during the whole presale range.

MODEL CONSTRUCTION

Let the objective function, denoted $R_l(X)$, be defined as the optimal expected revenue of the dedicated passenger line from period l through to period τ given the network state in period l is X which is closely related to the probability that an arriving passenger buys each ticket.

Let $p_{sj}(\mu)$ mean the probability that ticket j is bought by an arriving passenger of segment s given the control strategies is $\mu.p_{sj}(\mu)$ can be calculated by:

$$p_{sj}(\mu)=\delta_{sj}\prod_{z\epsilon B_{sj}}(1-\mu_z)\prod_{h=0}^{w_{sj}-1}q_h^s \tag{1}$$

where, δ_{sj} is an indicator variable, if $j\epsilon U_s$, then $\delta_{sj} = 1$, otherwise $\delta_{sj} = 0$. $Q^s_0 = 1$, $s = 1, 2,\ldots, S$.

Let $p_j(\mu)$ stand for the probability that ticket j is bought by an arriving passenger given the control strategies is μ. By the formula of full probability, we have:

$$p_j(\mu)=\sum_{s=1}^{S}\lambda_s p_{sj}(\mu) \tag{2}$$

Let $p_0(\mu)$ represent the probability that an arriving passenger buys nothing and by total probability:

$$p_0(\mu)=1-\sum_{j=1}^{n}p_j(\mu)$$

Within period l, if there is no arrival (with the probability $1-\lambda$), the increased expected revenue of dedicated passenger line is $R_{l+1}(X)$. If there is an arrival (with the probability λ), two situations will occur. One is that the arriving passenger purchases one ticket, for example ticket j (with the probability $p_j(\mu)$), correspondingly, the increased expected revenue is $f_j+R_{l+1}(X-A_j)$ and the network state updates to $X-A_j$. The other is that the arriving passenger purchases nothing (with the probability $p_0(\mu)$), correspondingly, the increased expected revenue is $R_{l+1}(X)$. Thus, according to the Bellman optimization principle, the expected revenue optimization problem of dedicated passenger line can be formulated as the following DP:

$$R_l(X)=(1-\lambda)R_{l+1}(X)+\max_{\mu\in\{0,1\}^n}\left\{\sum_{j=1}^{n}\lambda p_j(\mu)\left(f_j+R_{l+1}(X-A_j)\right)+\lambda p_0(\mu)R_{l+1}(X)\right\} \tag{3}$$

further systemized to:

$$R_l(X)=\max_{\mu\in\{0,1\}^n}\left\{\sum_{j=1}^{n}\lambda p_j(\mu)\left(f_j-\Delta R_l(X)\right)\right\}+R_{l+1}(X) \tag{4}$$

The boundary conditions are:

$$R_l(0) = 0,\ l = 1, 2,\ldots, \tau$$
$$R_{\tau+1}(X) = 0,\ \forall X\geq 0$$

where, $\Delta R_l(X) = R_{l+1}(X)-R_{l+1}(X-A_j)$ stands for the opportunity cost of selling one unit of ticket j given the network state in period l is X and $0 = [0]_{K\times M}$.

Through selecting optimal control strategy vector in each period, model Eq. 4 optimizes the expected revenue of dedicated passenger line from the discrete viewpoint. By observation, each decision variable in the solution space is related to presale period and network state. Although the presale range of dedicated passenger line is relatively short, the characteristics such as consisting of multiple legs and serving multiple O-Ds' demand will lead to very large model size, so it is necessary to design the effective algorithm.

MODEL SOLUTION

In order to overcome large scale problem of the network RM model, we refer to the approximate decomposition heuristic put forward by Talluri and van Ryzin (2004a) which has obtained good numerical analysis results.

Deterministic approximation: Deterministic approximation is applicable way to simplify high-dimensional optimization problems, in which stochastic quantities are replaced by their mean/expected values and seat capacity and demand are assumed to be continuous, then from aggregate viewpoint the total time (the amount of periods) of each control strategy vector adopted during the whole presale range is taken as decision variable to achieve the optimization of objective value.

Let $R(\mu)$ denote the expected revenue of dedicated passenger line generated from an arriving passenger when the control strategies is μ. It's easy to know:

$$R(\mu)=\sum_{j=1}^{n} f_j p_j(\mu)$$

Let $Q_{km}(\mu)$ denote the probability that the passenger use a seat in train k on leg m. Obviously:

$$Q_{km}(\mu)=\sum_{j=1}^{n} b_{jk}\cdot y_{jm}\cdot p_j(\mu)$$

The seat consumption probabilities are denoted by the matrix $Q(\mu) = [Q_{km}(\mu)]_{K\times M}$. The total time that control strategy vector μ is adopted during the whole presale range is represented by $t(\mu)$ which is allowed to be continuous by further relaxation. Thus we can construct the following Choice-based Deterministic Linear Programming (CDLP):

$$\max \sum_{\mu\in\{0,1\}^n} \lambda R(\mu) t(\mu) \tag{5}$$

$$\text{s.t.} \sum_{\mu\in\{0,1\}^n} \lambda Q(\mu) t(\mu) \le C \tag{6}$$

$$\sum_{\mu\in\{0,1\}^n} t(\mu) \le \tau \tag{7}$$

$$t(\mu)\ge 0,\ \forall \mu\in\{0,1\}^n \tag{8}$$

where, the inequality Eq. 6 stands for the seat capacity constraint, Eq. 7 stands for the ticket booking deadline constraint, Eq. 8 stands for nonnegative constraint of the total time. DP model focuses on dynamic matching between control strategy and presale period while CDLP model focuses on the total time that each control strategy vector is adopted. Their starting points differentiate but their solutions relate, the latter is equivalent to the integration of the former. Talluri and van Ryzin (2004a) have proved CDLP to be asymptotic optimality that ensures its approximation effect.

Solving CDLP by column generation algorithm: As noted, it is very difficult to solve CDLP Eq. 5 exactly because the number of its decision variables is 2^n which is far greater than the number of its constraints. Column generation algorithm has been proved to be an efficient technique to solve such models. Roughly speaking, we first choose a limited number of control strategy vectors (a control strategy vector corresponds to a column of coefficient matrix) and then solve a reduced CDLP only using these control strategy vectors. Next we check to see if any control strategy vector left has a positive reduced cost relative to the dual solutions of the reduced CDLP. If so, the control strategy vector with maximal positive reduced cost is added and the reduced CDLP is resolved. If there are no such control strategy vectors with positive reduced cost, then the current solution is optimal.

Denoting the collection of the chosen control strategy vectors by $\mu^r = \{\mu_1, \mu_2,..., \mu_\beta\}$ where $1\le\beta\le 2^n$, the reduced CDLP is formulated as following:

$$\max \sum_{\mu\in\mu^r} \lambda R(\mu) t(\mu),\ \ \text{st} \sum_{\mu\in\mu^r} \lambda Q(\mu) t(\mu) \le C,$$
$$\sum_{\mu\in\mu^r} t(\mu) \le \tau,\ t(\mu)\ge 0,\ \forall \mu\in\mu^r$$

Let $\pi = [\pi_{km}]_{K\times M}$ and σ be the dual prices for the first and second constraints, respectively, of the reduced CDLP. To check to see if these values are feasible for CDLP Eq. 5, we can solve the following column generation sub-problem:

$$\max_{\mu\in\{0,1\}^n} \left\{\lambda R(\mu)-\lambda\sum_{k=1}^{K}\sum_{m=1}^{M}\pi_{km}\cdot Q_{km}(\mu)\right\}-\sigma \tag{9}$$

i.e.:

$$\max_{\mu\in\{0,1\}^n} \left\{\lambda\sum_{s=1}^{S}\lambda_s\sum_{j=1}^{n}(f_j-\sum_{k=1}^{K}\sum_{m=1}^{M}\pi_{km}\cdot b_{jk}\cdot y_{jm})\cdot\mu_j\delta_{sj}\prod_{z\in B_{sj}}(1-\mu_z)\prod_{h=0}^{w_{sj}-1}q_h^s\right\}-\sigma \tag{10}$$

If the optimal value of Eq. 10 is non-positive, then $\pi = [\pi_{km}]_{K\times M}$ and σ are dual feasible and the current solution to the reduced CDLP is in fact optimal for CDLP Eq. 5. Otherwise let μ^* be the optimal solution to Eq. 10, then we add μ^* to the collection $\mu^r = \{\mu_1, \mu_2,..., \mu\beta\}$ and repeat the above process until the optimal solution is obtained.

Decomposition heuristic: Let π^*_{km} be the optimal dual solutions obtained from the above sections. At a given train k and a given leg m, we approximate the objective function by:

$$R_1(X) \approx R_1^{km}(x_{km}) + \sum_{i \neq k} \sum_{v \neq m} \pi^*_{iv} x_{iv} \tag{11}$$

where, $R^{km}_l(x_{km})$ represent a dynamic (time-dependent) and non linear approximation of the seat capacity of train k on leg m, $\pi^*_{iv}x_{iv}$ are static (time-independent) and linear approximation of the value of the else seat capacity. Thus the opportunity cost of selling one unit of ticket j can be approximated by:

$$R_1(X) - R_1(X - A_j) \approx b_{jk} \cdot y_{jm} \left(\Delta R^{km}_{l+1}(x_{km}) - \pi^*_{km}\right) + \sum_{i \neq k} \sum_{v \neq m} b_{ji} \cdot y_{jv} \pi^*_{iv}, \tag{12}$$

in which $\Delta R^{km}_{l+1}(x_{km}) = R^{km}_{l+1}(x_{km}) - R^{km}_{l+1}(x_{km}-1)$. Then by substituting Eq. 11 and 12 into 5, we obtain:

$$R_l^{km}(x_{km}) = \max_{\mu \in \{0,1\}^n} \left\{ \sum_{j=1}^{n} \lambda p_j(\mu) G_{jklm} \right\} + R^{km}_{l+1}(x_{km}) \tag{13}$$

with the boundary conditions:

$$R_l^{km}(0) = 0, \forall l$$
$$R_{\tau+1}(x_{km}) = 0, \forall_{km} \geq 0$$

Where:

$$G_{jklm} = f_j - b_{jk} \cdot y_{jm} \left(\Delta R^{km}_{l+1}(x_{km}) - \pi^*_{km}\right) - \sum_{k=1}^{K} \sum_{m=1}^{M} b_{jk} \cdot y_{jm} \cdot \pi^*_{km}$$

Obviously, model Eq. 13 is a one-dimensional DP and can be solved relatively easy, thus we approximate $R_l(X)$ by:

$$R_l(X) \approx \frac{1}{KM} \sum_{k=1}^{K} \sum_{m=1}^{M} \left(R_l^{km}(x_{km}) + \sum_{i \neq k} \sum_{v \neq m} \pi^*_{iv} x_{iv} \right) \tag{14}$$

$R_l(C)$, the expected revenue of dedicated passenger line during the whole presale range is formulated approximately as:

$$R_1(C) \approx \frac{1}{KM} \sum_{k=1}^{K} \sum_{m=1}^{M} \left(R_1^{km}(c_{km}) + \sum_{i \neq k} \sum_{v \neq m} \pi^*_{iv} x_{iv} \right) \tag{15}$$

NUMERICAL EXAMPLE

A dedicated passenger line consists of three stations and runs three trains in one single direction during morning, noon and evening, respectively. The trains are numbered in the order 1, 2, 3 and their operation schemes are different as shown in Fig. 1. Each train has eight carriages and offers 560 seats on each leg. The firm sells tickets by 15 days in advance, the ticket presale terminal time of each station (not including the destination) is listed in Table 1 and the whole presale range is divided finely into 3000 periods.

A total of 24 products are offered with their descriptions shown in Table 2 and passengers are divided into 12 segments with their characteristics, arriving probabilities and preference orders shown in Table 3. To simplify the calculation, we assume passengers' transfer purchase probabilities in each preference order are equal.

To test the influence of passenger preference order on the expected revenue of the dedicated passenger line, we choose the expected revenue obtained under the demand independence assumption as the benchmark. In demand independence case, the optimal dual prices applied to approximately decompose DP Eq. 4 are achieved by solving a deterministic linear programming model (Talluri and van Ryzin, 2004b), in which, the expected demand of ticket j is calculated by:

$$\tau \sum_{s=1}^{S} \lambda_s \delta_{sj} \prod_{h=0}^{w_{sj}-1} q_h^s (1 - q^s_{w_{sj}})$$

With the help of MATLAB and CPLEX software, the expected revenues of the dedicated passenger line

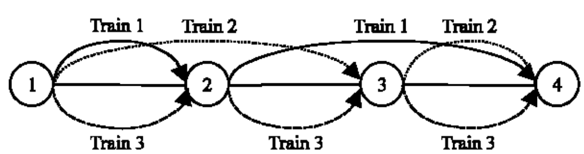

Fig. 1: Dedicated passenger line network

Table 1: Ticket presale terminal time of stations

Train	Station	Terminal time
1	1	8:30
	2	9:20
2	1	11:50
	3	13:10
3	1	18:30
	2	19:40
	3	20:20

Table 2: Description of dedicated passenger line tickets

Ticket	O-D	Motor car	Fare (yuan)
1	1→2	1	60
2	1→2	1	40
3	1→4	1	225
4	1→4	1	150
5	2→4	1	150
6	2→4	1	100
7	1→3	2	120
8	1→3	2	80
9	1→4	2	225
10	1→4	2	150
11	3→4	2	90
12	3→4	2	60
13	1→2	3	48
14	1→2	3	32
15	1→3	3	96
16	1→3	3	64
17	1→4	3	180
18	1→4	3	120
19	2→3	3	60
20	2→3	3	40
21	2→4	3	120
22	2→4	3	80
23	3→4	3	72
24	3→4	3	48

Table 3: Description of dedicated passenger line passenger segments

Segment	Characteristics	Arriving probability	Preference order
1	Time-sensitive (1→2)	0.10	{1, 2}
2	Price-sensitive (1→2)	0.06	{14, 2, 13}
3	Time-sensitive (1→3)	0.09	{7, 8}
4	Price-sensitive (1→3)	0.06	{16, 8, 15}
5	Time-sensitive (1→4)	0.15	{3, 4, 9, 10}
6	Price-sensitive (1→4)	0.10	{18, 4, 10, 17}
7	Time-sensitive (2→3)	0.06	{19, 20}
8	Price-sensitive (2→3)	0.06	{20, 19}
9	Time-sensitive (2→4)	0.08	{5, 6}
10	Price-sensitive (2→4)	0.10	{22, 6, 21}
11	Time-sensitive (3→4)	0.06	{11, 12}
12	Price-sensitive (3→4)	0.06	{24, 12, 23}

Table 4: Expected revenue under different transfer purchase probabilities

Transfer purchase probability	Expected revenue (yuan)		
	Preference order	Demand independence	Gain (%)
0.1	313030	298411	4.67
0.2	325451	309081	5.03
0.3	330778	313379	5.26
0.4	344168	322898	6.18
0.5	347469	322347	7.23
0.6	349680	323629	7.45
0.7	352926	317351	10.08
0.8	356854	312248	12.50
0.9	360716	313642	13.05
1	365393	313653	14.16

associated with different transition purchase probabilities are obtained (as shown in Table 4). We can see from Table 4 that the expected revenues of the dedicated passenger line obtained by the model taking consideration of passenger preference order are improved compared to the demand independence model. Meanwhile, as passengers' transfer purchase probability increases, the gain of the model based on passenger preference order related to the demand independence model is more significant. This does more visually show the limitations of the demand independence assumption in traditional RM models. Therefore, in RM practice, we should fully consider the influence of passenger choice behavior which will help to further improve the profitability.

CONCLUSION

By using dynamic programming model, we explored the RM problem of dedicated passenger line under the influence of passenger preference order in this study. The difficulty of large model size was overcome by means of decomposition heuristic to realize approximate optimization of the expected revenues of dedicated passenger line. Results show that the expected revenue based on passenger preference order is higher than that based on demand independence assumption which further demonstrates the limitation of the demand independence assumption in traditional RM models. Our research enriches the theory results of railway passenger RM and provides a reference and a new perspective for implementing RM to dedicated passenger line.

REFERENCES

Abe Itaru, S.M., 2007. Revenue management in the railway industry in Japan and Portugal: A stakeholder approach. M.S. Thesis, Massachusetts Institute of Technology (MIT), Cambridge, MA., USA.

Algers, S. and M. Beser, 2001. Modelling choice of flight and booking class: A study using stated preference and revealed preference data. Int. J. Serv. Technol. Manage., 2: 28-45.

Bharill, R. and N. Rangaraj, 2008. Revenue management in railway operations: A study of the Rajdhani Express, Indian Railways. Transp. Res. A: Policy Pract., 42: 1195-1207.

Chen, L.J. and T. Homem-de-Mello, 2010. Mathematical programming models for revenue management under customer choice. Eur. J. Operat. Res., 203: 294-305.

Ciancimino, A., G. Inzerillo, S. Lucidi and L. Palagi, 1999. A mathematical programming approach for the solution of the railway yield management problem. Transp. Sci., 33: 168-181.

Cooper, W.L. and D. Gupta, 2006. Stochastic comparisons in airline revenue management. Manuf. Serv. Operat. Manage., 8: 221-234.

Kraft, E.R., B.N. Srikar and R.L. Phillips, 2000. Revenue management in railroad applications. J. Transp. Res. Forum, 39: 157-176.

Lan, B.X. and L. Zhang, 2009. Revenue management model for high-speed passenger railway. Chinese J. Manage. Sci., 17: 53-59.

Shi, F., G.H. Zheng and Q. Gu, 2002. Optimal dynamic pricing of railway passenger ticket. J. China Railway Soc., 24: 1-4.

Shuai, B. and C.Y. Sun, 2006. System dynamics model for pricing of high-speed railways. J. Southwest Jiaotong Univ., 40: 206-209.

Smith, B.C., J.F. Leimkuhler and R.M. Darrow, 1992. Yield management at American airlines. Interfaces, 22: 8-31.

Strasser, S., 1996. The effect of yield management on railroads. Transp. Q., 50: 47-55.

Sven-Eric, A., 1998. Passenger choice analysis for seat capacity control: A pilot project in Scandinavian Airlines. Int. Transp. Operat. Res., 5: 471-486.

Talluri, K. and G. van Ryzin, 2004a. Revenue management under a general discrete choice model of consumer behavior. Manage. Sci., 50: 15-33.

Talluri, K. and G. van Ryzin, 2004b. The Theory and Practice of Revenue Management. Kluwer Academic Publishers, Boston, MA., USA., ISBN-13: 9780387243764, Pages: 714.

Van Ryzin, G. and G. Vulcano, 2006. Computing virtual nesting controls for network revenue management under customer choice behavior. Manuf. Serv. Operat. Manage., 10: 448-467.

Xuedong, D. and M. Yin, 2011. Seat control model research on railway passenger transport. Res. J. Inform. Technol., 3: 140-145.

You, P.S., 2008. An efficient computational approach for railway booking problems. Eur. J. Operat. Res., 185: 811-824.

Zhang, L. and B.X. Lan, 2012. Revenue management model for high-speed railway based on traveler choice. Operat. Res. Manage. Sci., 21: 116-125.