

Research Article **Big Data Perspective on Financial Operations Revenue Management Approach**

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Received 21 April 2022; Revised 17 May 2022; Accepted 18 May 2022; Published 2 June 2022

Academic Editor: Wen-Tsao Pan

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For the innovation of financial operation and revenue management work, in the background of the big data era, it should be necessary to establish an information-based financial management system. First, the problems that exist in the construction of information technology are unearthed, and then the information-based financial management system is established according to the requirements and future development plans in the context of big data. This study gives the basic concept of revenue management, takes the revenue management of road shuttle passenger transport as the object of research, establishes the road shuttle passenger transport multizone seat stock control model on the basis of the stock control method based on price, and gives the algorithm of multizone seat stock control. By specifically analyzing the characteristics of applicable revenue management, and then comparing the characteristics of the passenger transport industry, recommendations are made for revenue management methods to improve financial operating performance.

1. Introduction

With the deepening of economic globalization, the era of information technology has come along with it. In the current era of big data, which is characterized by close links and efficient information sharing, opportunities and challenges exist side by side and have an important impact on the development of all sectors [1]. The era of big data has put forward new requirements for financial management work, which requires us to correctly understand the problems and shortcomings in financial management, so as to facilitate the integration of financial management work with big data technology [2] and promote the innovation of financial management work.

Big data is first proposed by Alvin Toffler and then developed rapidly in a short period of time [3]. Big data really took the stage in 2011, for the time being, there is still much room for development regarding the analysis and processing capabilities of big data. The use of big data can enhance the management ability of the capital budget, management of economic activities, management of income and expenditure [4, 5], and the enhancement of internal control ability. It enables financial management to continue to develop in the direction of refined management. It opens up an era of innovation in financial management, realizes the organic combination of internal and external data, enhances the ability to search, analyze, and process, and strengthens the efficiency of financial management departments [6].

Big data technique has strong data collection, processing, and analysis capabilities, which can provide correct decision-making direction for financial management. The traditional decision-making process is based on empirical analysis, and due to the incomplete information, there is a certain lag, which often leads to various problems in the decision-making direction [7]. The application of big data technology can help financial management staff to have the more accurate and clear financial information and to grasp more comprehensive financial data, and it provides effective data support for subsequent financial management work, thus enhancing decision-making in the era of big data [8]. The era of big data has not only brought people accurate data support but also the material basis. More so, it has brought people new service concepts and technological innovation ideas and provided a new financial management model [9]. It has made financial management more intelligent and developed in the direction of precision marketing. The application of big data technology can make full use of data and information to enhance the innovation and efficiency of financial management work, making it one of the core competencies.

In order to reduce the risks that exist in financial management work, big data can enhance the automation level of financial management work, using data analysis ability to improve the accuracy of financial management work [10]. According to the problems in the data, timely information is provided to the financial management personnel in order to prevent in advance and reduce the emergence of financial risks. The development of information technology makes financial management work leaner and data is no longer a constraint to financial management work. Financial management work can be done without the constraints of data, using the integration of data analysis, and then combined with the actual situation to achieve financial work refinement management. In lean management, emphasis will be placed on the value it creates, mainly in areas such as the management and operation of funds. The finance department will provide accurate advice on cost control and decision-making information for the unit's development strategy and continuously create value.

The first step in financial management is constructing a complete management system, which is a prerequisite for effective management [11]. The current financial management system is detached from the actual situation and lacks accurate investigation of the specific situation, making the plans made limited to the form, making it more difficult for the practical operation of the financial management work and weakening the role of the whole financial management system. Moreover, the most problematic part of the whole system is the financial budget, which lacks practicality in budgeting, fails control over the flow of funds, and lacks reasonable planning for the allocation of funds, resulting in the phenomenon of difficult capital turnover at times [12]. This can lead to financial vulnerabilities. Therefore, it is important to plan the financial work clearly and to have a systematic and comprehensive planning of the whole enterprise's finance.

Big data places higher demands on finance staff, not only in terms of the basic skills of traditional financial management work but also in terms of the skills and literacy of modern financial management [13]. In the era of big data, the cloud computing, which is a new type of technology for financial accounting, has been widely utilized, to promote efficient financial management work, but the development of financial management staff's own quality is slow, and it is difficult to play the real value and role of big data. For their own work, the lack of proper understanding of the importance of their work in the actual operation process is not serious enough to be cautious, and the grassroots staff did not implement in place and play its proper role, resulting in a major loss of results. The financial managers need to have a sense of risk [14, 15], but at present, many financial staff are only concerned with efficiency but easy to ignore the existence of risk, or the grassroots staff think that this is not in

their own scope of thinking just do their own thing, risk awareness is lacking.

The traditional financial management system no longer meets the requirements of the big data era. The innovation of the financial management system is to make up for the defects and shortcomings of the original system and establish a financial management system that is more in line with the actual situation [16]. The establishment of a sound financial budget mechanism, cost accounting system, and information transmission and other systems can make it more in line with the actual development requirements in the context of big data, so as to improve the level of financial management work and provide inexhaustible power for the development of the unit. This study examines financial operations revenue management methods in the context of big data perspectives on revenue management for road shuttle passenger transport. Based on the price-based inventory control method, a multizone seat inventory control model for road shuttle passenger transport is developed and an algorithm for multizone seat inventory control is given. By specifically analyzing the characteristics of applicable revenue management, and then by comparing the characteristics of the passenger transport industry, a financial operational revenue management approach is summarised.

2. Revenue Management

2.1. Definition of Revenue Management. Revenue management is a new business management technique to maximize revenue and was pioneered by the U.S. air transport industry in the 1980s. Revenue management, also known as efficiency management real-time pricing, focuses on maximizing revenue by establishing real-time forecasting models and analyzing demand behavior based on market segmentation to determine the best price for a sale or service.

In 1987, American Airlines' annual report described revenue management as a set of methods to sell the right product to the right passenger at the right time in the right place [17], a process of selectively accepting and rejecting bookings in order to maximize revenue. Revenue management was first implemented in the airline sector, and in the airline passenger sector, it refers to the scientific decision-making theories and tools used by airlines for optimizing and forecasting purposes [18]. It is the process of maximizing revenue by selling products to different types of customers at different prices and at the right time.

Based on the general idea of revenue management, this study defines revenue management as follows: revenue management refers to a set of integrated management and economic techniques designed to solve the problem of pricing and capacity allocation under conditions of fixed capacity and stochastic demand in order to maximize revenue.

2.2. Basic Revenue Management Model. The purpose of revenue management is to maximize the return on flights and can be simply expressed in the following mathematical model:

$$MAX\overline{R} = \sum_{i} \overline{R}_{i}, \overline{R}_{i}(S_{i}) = f_{i} \times \overline{b}_{i}(S_{i}),$$

$$C = \sum_{i} S_{i},$$
(1)

where \overline{R} is the total expected revenue, $\overline{b}_i(S_i)$ is the expected number of bookings for fare class *i*, S_i is the number of seats allocated to that fare class, f_i is the average fare for fare class *i*, and *C* is the total number of seats available.

On the basis of this model, a deep reinforcement learning-based model is proposed. Markov decision [19] processes are mathematical models of sequential decision making used to model the stochasticity of strategies and rewards achievable by the intelligence in an environment where the state of the system has Markovian properties. In stochastic processes, the Markov process is defined as follows:

$$P\{X(t) \le x | X(t_n) = x_1, \dots, x_n\} = P\{X(t) \le x | X(t_n) = x_1\},$$
(2)

where *P* denotes the conditional probability and $X(t_n)$ denotes the distribution of t_n moments *x*. *x* denotes the occupancy rate.

Let the occupancy rate of passenger t on the day booking day a bus be X(t, a) and let us determine whether the following statistical independence assumption holds:

$$P\{X(t, a) = x, X(t, b) = y\} = P\{X(t, a) = x\}$$

$$P\{X(t, b) = y\}, \quad a \neq b,$$

$$P\{X(t, a) = x, X(u, b) = y\} = P\{X(t, a) = x\}$$

$$P\{X(u, b) = y\}, \quad t \neq u.$$
(3)

If equation (3) holds, then a Markov process can be modelled based on check-in days, with each combination of booking day check-in days X(t, a) corresponding to a state, and therefore, a Markov property of X(t, a) can be described independently with the equation:

$$P\{X(t,a) = x | X(t_n) = x_n, \dots, x_1\}$$

= $P\{X(t,a) = x | X(t_n) = x_1\}, \quad t < a.$ (4)

In the above equation, X(t, a) has statistical independence and the assumptions stated above are largely valid [20].

The Markov states in this paper are represented by *s*, which is the concatenation of several different variables, as follows:

- (1) If the date of the ride is t_e , then this parameter remains constant throughout the process.
- (2) The number of days between the booking date and the date of the ride is t_s, and this parameter decreases in a fixed order in each process.
- (3) Objective states that occur at a given date, such as the level of market demand and competitors' prices, are collectively referred to as s_r . These objective states can be viewed as the environment taking random values from a distribution according to the *t*

$$P\{s_r \le x\} = P_s(t_e, t_s, x). \tag{5}$$

(4) The state affected by the strategic action s_m, the number of remaining seats, is the part of s that is affected by the Markovian property and it will vary depending on the decision made. The value fields of these variables do not affect each other, so the total set of states is the outer product of their respective sets of states S:

$$s = \{t_e, t_s, s_r, s_m\},\$$

$$S = T \times T \times S_r \times S_m,$$
(6)

where *T* denotes the set of all dates. Although S_m already exhibits Markovian properties, the addition of the statistically independent parameters t_e , t_s , and s_r corresponds to an orthogonal extension of the Markov decision process (MDP) state space, whose MDP properties remain unchanged and have better variance.

The action is defined as *a* that includes the price of each room type and the number that can be oversold:

$$a = \{a_1, a_2, a_3 \dots\}.$$
 (7)

After each sale, in the updated model, it is possible to discourage further overselling by setting the price very high after the maximum quantity has been sold, but in the daily updated model, such a strategy is not possible, and therefore, the maximum allowable number of oversales must be set in advance. It follows that the regularly updated model is more coarse grained and requires a statistical estimate of the mean value over time.

Since s_r is a stochastic function of t_e and t_s , the MDP property S_m is disregarded and the return prediction for a given day for a given ride day can be defined as $r(t_e, t_s)$. This value is not related to each other and this a priori prediction function is compared with the function approximated by traditional prediction methods that do not take into account the reinforcement learning process.

With the correct definitions of s, a, and r, the complete basis of the reinforcement learning model can be obtained and the definitions of the state spaces S and A and the value functions V and Q can be derived:

$$v_{\pi}(s) = E[G_t|S_t = s],$$

$$q_{\pi}(s, a) = E[G_t|S_t = s, A_t = a].$$
(8)

Based on the nature of the original problem, the appropriate way to take values of s, a, and r is deduced, and a suitable fitting function is chosen.

2.3. Basic Components of Revenue Management. Revenue management is an advanced management idea built on deregulation, multiclass fares, and a free competitive market environment [21], and the core components of which are

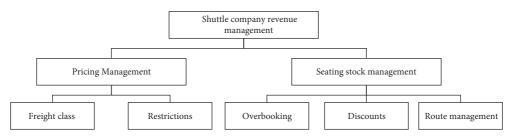


FIGURE 1: Relationship of the components in the revenue management system.

differential pricing and seat stock control. Differential pricing is specifically defined as follows: as the characteristics of different markets are different, transport companies determine the type and quantity of fares based on these differences in characteristics, that is, by the different prices and conditions applicable to the product. Seat stock control aims at the number of seats available in different price classes for each trip and is accomplished through the process of seat overbooking, discounted class allocation, and passenger voyage management. Figure 1 illustrates the components of a revenue management system and how they relate to each other.

2.4. Effectiveness of Revenue Management. Revenue management has achieved brilliant results in the airline industry. According to American Airlines, the use of revenue management systems added 1.4 billion US dollars to the company's revenues between 1989 and 1991 [22, 23]. After-tax profits increased by 892 million U.S. dollars over the same period, Donald Burr, the former CEO of the once-famous American People's Jet Airways, summed it up after the company's 1996 bankruptcy when he said: "We were a dynamic and profitable company from 1981 to 1985, and then we started to fall from the top to a loss of 50 million U.S. dollars a month [24]. Nothing had changed in our company, yet American Airlines had infiltrated their revenue management into every one of our markets. Our days of profitability ended completely when U.S. Airways emerged as the face of the terminator. Because they can always beat our prices or the prices that will be announced."

Revenue management is widely used in business, particularly in countries such as the United States and Europe, where it is beginning to penetrate more business sectors, with the transport industry being a more successful representative.

3. Industry Characteristics of Road Shuttle Passenger Transport

Revenue management is not the prevailing method but has strict restrictions. Although revenue management has not received sufficient attention in the practice of road shuttle passenger transport, the conditions for its implementation are in fact applicable [25].

3.1. Road Shuttle Passenger Products Are Nonstorable and Time-Sensitive. The production and consumption of transport services provided by road shuttles are simultaneous and therefore cannot be stored and are highly time sensitive. If seats on a shuttle bus are not sold prior to departure and seats are left unused, they will not generate revenue for the road shuttle bus or the revenue will be reduced. If seats are not sold after the departure of a direct shuttle bus, the opportunity to generate revenue from these seats is lost; regular shuttle buses may have some intermediate stops, but the value of the seats before they are utilized is similarly lost.

3.2. Market Demand for Road Shuttle Passenger Transport Is Diverse and the Market Can Be Segmented. Road shuttle passenger transport has different characteristics, the needs of passengers are diverse, and their behaviour and habits in purchasing tickets are also different. Road shuttle passenger transport can be divided into a segment of passengers with similar characteristics or needs, and the passenger transport market can be segmented according to the differences in passengers' travel purposes, income levels, and requirements for the timeliness of the shuttle bus.

3.3. Demand for Road Shuttle Passenger Transport Is Highly Volatile. For road shuttle bus passenger transport, the demand for passengers is very high during the spring festival, November, and May day holidays of the year, during which there is a peak in demand, and the shuttle bus passenger transport resources can be fully utilized or even exceed the demand, while in the low season of transport, there is a clear low in demand and the seat resources are idle in a serious situation. Enterprises can take advantage of the volatility of demand by appropriately increasing prices during the high season of demand, prices can be appropriately adjusted downwards or discounts can be taken to stimulate demand and improve the utilization of seats.

3.4. Road Shuttle Passenger Transport Products Can Be Booked. With the formation of ticketing networks, tickets for road shuttle passenger transport can now be booked in advance by means of Internet booking and telephone booking, and road shuttle passenger transport can be reasonably allocated to ticket resources through booking in the same way as air passenger transport.

3.5. Road Shuttle Bus Transportation Is Characterized by Low Marginal Costs and High Fixed Costs. Marginal costs are the increase in expenditure that comes with an increase in

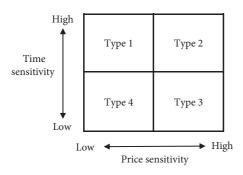


FIGURE 2: Passenger transport market segmentation model.



FIGURE 3: Diagram of the class line.

TABLE 1: Fares for each section of the route.

Catagory	В	С
Category	Ticket price	Ticket price
	100	200
А	90	180
	70	140
	0	150
В	0	135
	0	105

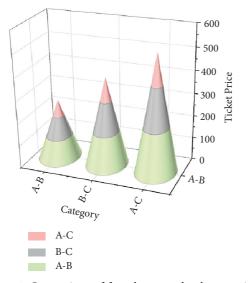


FIGURE 4: Comparison of fares between the three sections.

passengers and are variable. Fixed costs, on the other hand, consist of the fuel consumption, labour, and other costs that must be incurred to operate a road shuttle, and these costs are essentially fixed within the load range. Where there are spare seats, the increase in the cost of adding one or more passengers to a road shuttle bus is negligible. In this respect, the characteristics of road shuttle passenger transport and air passenger transport are identical.

TABLE 2: Random seat booking data.

Experiment	1	2	3	4	5	6	7	8	9
1	5	8	12	6	9	12	7	9	12
2	5	7	8	6	7	9	11	5	13
3	8	4	14	5	7	7	6	14	9
4	9	8	9	6	8	8	8	11	14
5	6	6	8	8	10	6	5	7	12
6	10	8	7	6	9	11	6	8	15
7	7	5	6	9	7	10	9	5	12
8	5	4	5	8	8	7	4	12	9
9	6	5	8	7	5	13	6	5	7
10	7	6	4	4	10	12	8	9	10

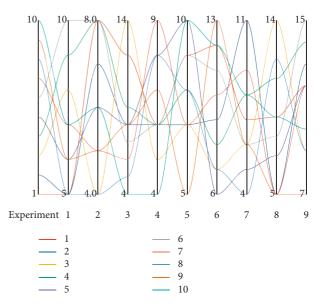


FIGURE 5: Parallel set data distribution of the number of random bookings in the nine experiments.

3.6. Supply Capacity of Road Shuttle Passenger Transport Is Relatively Constant in the Short Term. Compared to airlines or hotels, the supply capacity of road shuttle passenger transport can change relatively easily, but in the short term, the number of vehicles put on board is also fixed and the number of seats that can be provided does not change for a certain period of time. Road shuttle passenger transport cannot change its capacity in the short term to cater for temporary changes in passenger transport demand, unless some additional buses are put on during peak transport periods.

4. Experimental Results and Analysis

4.1. Market Segmentation and Differential Pricing of Road Shuttle Passenger Transport. Differential pricing requires pricing for a segmented market rather than a mass market. Differential pricing can only work effectively if different travel options are offered to different groups of customers. The market segmentation of road shuttle passenger transport means that road shuttle passenger transport enterprises, through market research, divide the entire market of road shuttle passenger transport into different submarkets of

ODF	Average fare for AB zone	Average fare for BC zone	AB interval booking limit	BC interval booking limit	ODF booking restrictions
1	100	150	50	50	110
2	90	135	46	42	90
3	70	105	35	23	70
4	50	75	27	14	50
5	45	50	22	10	33
6	35	45	13	7	9

TABLE 3: Fare sharing and booking limits for each ODF.

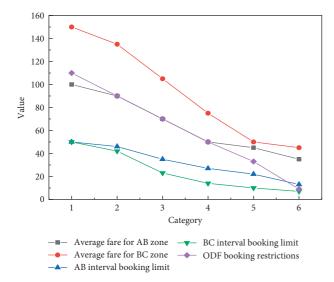


FIGURE 6: Comparison of fare shares and booking limits for each ODF.

passenger groups according to the differences in passenger needs and behavioral habits, each of which has certain similarities in their product transport needs. Differential pricing for road shuttle passenger transport involves setting different prices for different seats on a shuttle bus by analyzing factors such as passengers' willingness to pay and diversity of demand and increasing revenue by exploiting the potential of market segments.

4.2. Market Demand Segmentation Model. Among the theories of transport market segmentation, the representative one is the market demand segmentation model proposed by Belobaba, which takes into account the time sensitivity and price sensitivity of passengers, according to which the passenger transport market can be segmented into four types. The specific distribution is shown in Figure 2.

4.3. Case Study. As revenue management methods are still in the preliminary research stage in the field of road shuttle passenger transport, it is difficult to obtain actual data. Therefore, this study takes a particular shuttle bus seat stock control on a three-site shuttle route as an example, carries out seat stock control according to the shadow price-based stock control method proposed in this section, and compares it with no seat stock control, the interval-based stock

TABLE 4: Final number of accepted bookings for the price method.

ODF	Number of bookings received
1	5
2	8
3	10
4	6
5	9
6	12
7	7
8	9
9	7

TABLE 5: Final number of bookings accepted without seat stock control.

ODF	No seat stock control on the number of bookings accepted
1	3
2	8
3	12
4	1
5	9
6	17
7	2
8	9
9	12

control method, and the virtual nesting method, respectively.

As shown in Figure 3, there are three stations A, B, and C on a road service, where station A is the starting station and station C is the end station, with two sections, AB and BC, and three passenger flows, AB, BC, and AC. The fares for each section are listed in Table 1.

A comparison of fares between the three sections is shown in Figure 4. It can be seen that the fares between A and C are the highest and in high demand, with the next highest fares directly between B and C and the lowest fares between A and B.

Based on the given demand data, 10 sets of random seat bookings were generated using Matlab, as listed in Table 2. It is assumed that the booking period is 10 days and each day is a booking phase, making a total of 10 booking phases. The following section compares this method with the no seat stock control, interval-based stock control, and virtual nesting methods based on the above data to test the effectiveness of the price stock control method.

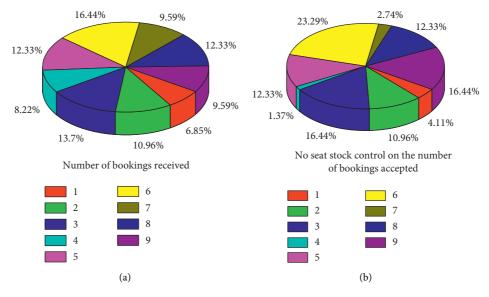


FIGURE 7: Pie chart comparing the number of tickets booked under the price method and without seat stock control. (a) Number of bookings received. (b) No seat stock control on the number of bookings accepted.

TABLE 6: Comparison of price and no seat stock control benefits.
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Experiments	Price method	No seat stock control	Earnings growth rate (%)
1	9420	8835	6.62
2	9585	9030	6.15
3	9070	8690	4.37
4	9280	8745	6.12
5	9780	9460	3.38
6	9820	9235	6.33
7	9770	9190	6.31
8	9375	8900	5.34
9	9340	8790	6.26
10	9040	8420	7.36

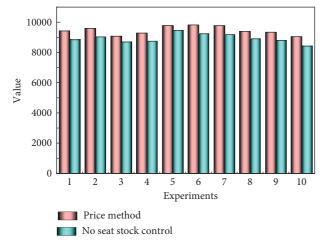


TABLE 7: Virtual class classification.

Virtual grades	Ticket price	ODF
	100	1
1	200	4
	150	7
	90	2
2	180	5
	135	8
	70	3
3	140	6
	105	9

FIGURE 8: Comparison of data between the price method and the benefits of no seat stock control.

The comparative data for the number of random bookings in the nine experiments are shown in Figure 5. It can be seen in Figure 5 that there is no clear pattern in the results of the experiment, and the data are random and scattered in each experiment. These conditions are a prerequisite for the experiment to proceed, and the randomness of the data can be clearly seen in the parallel set plots.

The product of the origin to destination and the fare class is abbreviated as ODF. The fares are apportioned proportionally according to the derived fare apportionment factor. The ODF numbered 5 has a fare of 45 in AB and 105 in BC. The ODF numbered 6 has a fare of 35 on AB and 105 on BC, as listed in Table 3.

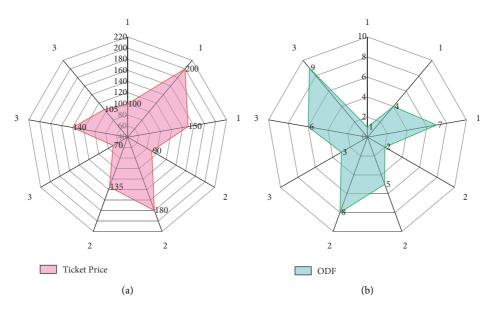


FIGURE 9: Relationship between virtual class and ticket price and ODF. (a) Ticket price. (b) ODF.

A comparison of the data for the five mixed cases is shown in Figure 6. As can be seen in Figure 6, the fare apportionment value for the BC interval is always at the top end, which is determined by both the distance between BCs and the fare. The booking limit for the BC interval is always at the bottom end, where its booking limit is at a minimum.

Based on the booking restrictions and the random number of bookings generated by Matlab and the assumption that passenger arrivals follow a Poisson distribution, 10 sets of booking experiments can be carried out and for the first set of booking data, the final number of bookings accepted by each ODF for the price method is calculated and the results are listed in Table 4.

In the absence of seat stock control, the final number of bookings accepted by each ODF was obtained based on the first set of random bookings generated by Matlab, following the first-come, first-served principle, and the results are listed in Table 5.

A comparison of the pie charts of the number of bookings received for the two scenarios is shown in Figure 7.

Based on the number of bookings in Tables 4 and 5, it is possible to calculate the revenue, which is 9420 for the price method and 8835 for the interval fare sharing method, an increase of 585 or 6.62%. For the other nine trials, a comparison table between the price method and no seat stock control gains is listed in Table 6.

A comparison of the data for the price method and for no seating stock control gains is shown in Figure 8.

The virtual nesting method is a common method for dealing with multisector, multifare class seat stock control. While the zone-based stock control method and the shadow price method proposed in this study are both apportionment methods based on a certain percentage, the virtual nesting method is a nonapportionment method. Seating stock control using the virtual nesting method is generally divided into three steps. First, the virtual classes are divided; second, the predetermined limits for each virtual class are found, and finally, seat stock control is implemented. In this example, it is assumed that each ODF has three price classes, namely, full price, 10% discount, and 30% discount tickets. The three full-fare ODFs are classified as the same virtual class, the three 10% discount ODFs are classified as the same virtual class, and the three 7% discount ODFs are classified as the same virtual class. The classification of virtual classes is listed in Table 7.

A comparison of fares and ODF for the three virtual classes is shown in Figure 9, which shows that the fare for class 1 reaches the highest and the fare for class 3 the lowest, with the ODF value showing an opposite trend to the fare. It is suggested that road passenger transport companies can combine both differential pricing and stock control methods in order to increase their revenue.

5. Conclusion

In the new era, financial management has moved from a simple management to the mining, analysis, and decisionmaking of data. Big data should be used to manage financial information and understand unit costs of inputs, economic activities, and revenues from profits. In this study, based on the price-based inventory control method, a multizone seat inventory control model for road shuttle passenger transport is developed and an algorithm for multizone seat inventory control is given. To verify the validity of the model, a simple example is used to compare the price-based stock control method with no seat stock control and the virtual nesting method. The calculation results show that the price-based stock control method can significantly increase the revenue of road shuttle passenger transport enterprises, and the revenue increase is greater compared with the virtual nesting method. This study's research on financial management under big data is based on road shuttle data. Future research should apply this approach to other industries to enhance the persuasiveness of the proposed method and give specific recommendations for financial operations revenue management based on the results.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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