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Research Article

Method of Spare Parts Prediction Models Evaluation Based on Grey Comprehensive Correlation Degree and Association Rules Mining: A Case Study in Aviation

Jun Wang,[1] Xing Pan ,[2] Ligeng Wang,[1] and Wei Wei[1]

[1]*School of Economics and Management, Beihang University, Beijing 100191, China*
[2]*School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China*

Correspondence should be addressed to Xing Pan; panxing@buaa.edu.cn

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Probability of spare parts sufficiency is crucial in the process of the normal operation of businesses, especially for the airline company. However, higher support sufficiency could inevitably lead to the increase of inventory cost of spare parts and restrict a company's efficiency. Therefore, it is important for businesses to reduce material cost on the premise of normal operation in order to accurately predict spare parts requirements based on reasonable models. The purpose of this paper is to solve problems with the evaluation of spare parts prediction models and to improve efficiency of company. Firstly, this paper summarizes a series of prediction models of spare parts requirements and applies the grey comprehensive correlation degree to rank the models. Secondly, the method of association rules mining is used to discover the association relationships between the types of spare parts and the prediction models. Finally, a case study in aviation is given to demonstrate the feasibility of the methodology, and optimal prediction models are recommended for aircraft spare parts. In accordance with the association relationships, the applicable prediction model can be provided in terms of different types of spare parts. This model will greatly enhance the work efficiency of spare parts prediction and improve the prediction tasks for the aircraft companies.

1. Introduction

Spare parts inventory cost is an important part of the operating cost of a company. Therefore, it is necessary to reduce the cost of spare parts and to forecast the demand of spare parts scientifically and reasonably [1]. It is vital for the development of aviation enterprises to improve the operation efficiency of the company by using a scientific forecasting method that forecasts the demand of spare parts and reduces the cost of holding capital of inventory [2].

At present, the study of methods of the demand forecast has been paid much attention by academia in the application fields. Croston [3] raised a method called Croston-CR, which overcame the shortfalls of the exponential smoothing method by evaluating the demanding quantity and the frequency of demand while preventing the shortage of inventory by adjusting the safety stock. Willemain et al. [4] applied Croston's method to predict the intermittent demand for spare parts, which can bring tangible benefits to businesses. Regattieri et al. [5] applied several models to predict the lumpy demands of spare parts. The contribution of Regattieri et al. is that they propose a method of determining the typically unpredictable demand for aircraft spare parts. However, this method cannot be used to predict other types of requirements. Moghadama et al. [6] proposed a new fuzzy EWMA (Exponentially Weighted Moving Average) control chart for fuzzy profile monitoring, which provides us with the possibility of recognizing the causes of process transition from stable mode, so that these causes may be removed and the process stable mode can be restored. However, the setting of fuzzy sets is too subjective to be used in the prediction practice.

These researches made outstanding contributions to improving the efficiency of demanding forecast for spare parts. However, spare parts predictions are very complex, and the demand characteristics of different types of spare parts are not the same [7]. For this reason, the ideal prediction methods differ from one another depending on the spare parts required [8]. Although the above researches can solve the problem of a specific field's spare parts, it is difficult for a spare parts business to select an appropriate model in order to predict a specific type of spare parts. For example, the ABC method is an effective method of selecting the corresponding prediction model which takes deferent categorization scheme that has deferent demand patterns into consideration [9]. Multimodel evaluation and selection methods have brought to spare parts prediction new development and challenges [1, 10], and most spare parts prediction model evaluation methods focus on prediction result or spare parts cost analysis [11]. To get more accurate prediction results, a multimodel prediction method framework based on association rules mining was proposed [12], and this paper extends the method to a method of combining grey comprehensive association degree evaluation and association rule mining.

This paper will put forward a spare parts prediction model autorecommend method based on a multimodel approach that addresses the challenge of predicting quantity demands for spare parts with a single model. The grey comprehensive correlation degree is used to evaluate the prediction accuracy of different spare parts. The models for every prediction are selected according to the given threshold of the grey comprehensive correlation degree and then logged in the prediction records. To lighten the workload of demanding forecast for spare parts and to improve the efficiency of prediction work, the association rules mining method is applied to record the material historical prediction. We mined the association rules between spare parts types and prediction models so that the applicable prediction models can be given based on the association rules after companies accumulating a certain amount of prediction records.

The paper is organized as follows: Section 2 mainly summarizes the analysis and recommendation of alternative prediction models, which are used to predict the demand of spare parts in various fields. Section 3 uses the grey comprehensive correlation degree method to rank the prediction models. Section 4 presents the association rules mining based on the a priori algorithm, which is used to improve the efficiency of forecasting work. In Section 5, a case analysis for airline spare parts is presented in accordance with the spare parts and related data of various companies. Finally, Section 6 conducts a conclusion.

2. Analysis and Recommendation of Alternative Prediction Models

2.1. Analysis of Alternative Prediction Models. The statistical characteristics of different types of demand data for spare parts are different, because there are a great variety of spare parts in different fields. It is difficult for one model to be used and verified for each spare part [8, 10, 13]. To solve the problems, eight prediction models are summarized in this paper to predict spare parts requirements, which are the Poisson distribution model, the linear regression model, the autoregression (AR) model, the integrated autoregressive moving average (ARIMA) model, the automatic ARIMA model, the Holt-Winters model, the grey prediction model GM(1,1), and the support vector machine regression (SVR) model. All of them have been applied in various fields widely, including in aviation spare parts prediction and spare parts prediction based on multimodels in this paper, regarding these models as alternative models.

(1) Poisson Distribution Model. The Poisson distribution model is the most widely used model to predict the spare parts demand [11]. Assuming that the spare parts demand is continuous and obeys the parameter λ_t of the Poisson distribution, the probability that the quantity demand of the spare parts is k within the time $(0, t)$ is

$$p_k(t) = \frac{(\lambda_t)^k}{k!} e^{-\lambda_t}, \quad k \in Z^+,\ t > 0 \tag{1}$$

(2) Linear Regression Model. The regression analysis forecast method is to get the corresponding parameters of a system through mathematical statistics and to establish the corresponding regression model to predict the outputs of the system. It is widely used in spare parts prediction and other fields. Godfrey [14] carried out medical research with the linear regression model. Isobe et al. [15] applied the linear regression model to research in astronomy. Liu et al. [16] used the linear regression model to analyze near-infrared spectrum. In addition, Figura et al. [17] applied it to predict underground water temperature. In this paper, we constructed a linear regression model for airline spare parts:

$$Y_i = a + bX_i + \varepsilon_i \tag{2}$$

X_i is parameter set related to the spare parts demand Y_i. When the aircraft spare parts demand is predicted, it includes the parameters of the landing number and flight hour. a and b are regression coefficients, and ε_i is system deviation.

(3) Autoregression (AR) Model. The autoregressive model is a common time series model [11]. In this paper, the autoregressive model is established according to the requirement of spare parts. The AR model is built according to the outbound quantity Y of spare parts.

$$Y(t) = \varepsilon(t) + \sum_{i}^{p} \varphi_i Y(t-i) \tag{3}$$

$\varepsilon(t)$ is a white noise item with a mean of 0 and variance of σ^2.

(4) ARIMA (p,d,q) Model. The autoregressive integrated moving average (ARIMA) model was first presented by Box and Jenkins [18]. It builds and makes predictions through historical time series data. Ramos et al. [19] used the ARIMA model to forecast consumer retail sales. In this paper, the ARIMA (p, d, q) model is used to build a model for spare parts prediction based on the historical requirement of spare parts $Y(t)$. First, the historical requirement of spare parts is $Y(t)$ and get a new time series $X(t)$, which is d (d=0,1,2,. . .,N) order difference for $Y(t)$. Then

$$X(t) = \beta_0 + \sum_{i=1}^{q} \beta_i X(t-i) - \varepsilon(t) - \sum_{j=1}^{p} \alpha_j \varepsilon(t-j) \tag{4}$$

(5) Automatic ARIMA Model. There are hundreds and thousands of varieties of spare parts needed in business. It is impossible for individuals to build models for every time series data. Thus, it is necessary to use the automatic ARIMA model [20], which can automatically identify the patterns of time series and estimate the parameters of models. Li and Wang [21] developed an automatic ARIMA model based on a data aggregation scheme in wireless sensor networks.

(6) Holt-Winters Model. The Holt-Winters model, also called the cubic exponential smoothing model, is one version of the exponential smoothing model. It is suitable for processing a single variable time series with seasonal factors and trends [22]. When the Holt-Winters model is used to predict the spare parts demand, the suitable smoothing parameters should be selected based on the demand of the historical spare parts according to the specific predict cycles.

(7) Grey Prediction Model GM(1,1). The grey system theory is put forward by Deng [23], of which GM(1,1) is one of the most widely used models. Chang et al. [24] predicted the Internet users and the industry revenue of online games. Ou [25] applied GM(1,1) model to forecast the agricultural output. Zhou and He [26] utilized GM(1,1) to predict the output of fuel. In this paper, the GM(1,1) model is used to predict the quantity demand of spare parts, and the model is expressed as follows:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \tag{5}$$

$x^{(1)}$ is a series of cumulative generation of the historical requirement of spare parts, and t is time and a and u are the parameters to be estimated.

(8) Support Vector Regression (SVR) Model. The aim of the SVR model is to provide the mathematic relation between input variables and output variables. The ε-insensitive loss function is introduced in the regression model [27]. The SVR model has already been used to successfully solve regression problems [28, 29]. Yang and Shieh [30] used SVR to predict consumers' affective responses. In this paper, the support vector regression method is used to establish the model for the historical demand of spare parts and the flight hours and the number of landing times, and the model is expressed as follows:

$$f(x) = w^t \phi(x) + b, \quad w \in R^n, \ b \in R \tag{6}$$

The nonlinear regression function $f(x)$ is the demand of the spare parts, and the vector x is the input variable, including the flight hours and the landing times, and $\phi(x)$ is the nonlinear function.

2.2. The Recommended Process of Prediction Models. This paper mainly addresses the problem of multimodels prediction and optimal model determination. The main idea is to determine appropriate prediction models for each type of spare parts. In this paper, the prediction and recommendation of spare parts demand are divided into five steps: (1) preprocessing the data; (2) multimodel prediction (in which eight kinds of prediction models are applied to predict the demand of spare parts); (3) calculation of the grey comprehensive correlation degree (which is used to evaluate the accuracy of prediction models); (4) mining the association rules between spare parts type and prediction models (in which the a priori algorithm is applied to mine the association pattern between spare parts types and prediction models); and (5) prediction model recommendation (optimal model recommendations are given based on the association rules mined by step (4) according to different spare parts). The detailed process is shown in Figure 1.

3. The Evaluation of Model Based on Grey Comprehensive Correlation Degree

The method of grey relational analysis (GRA) was first presented by Deng [23]. According to the grey relational coefficient between the reference sequence (ideal target sequence) and comparability sequence, this method can judge the similarity between them. The more similar the sequences are, the greater the correlation degree between the corresponding sequences is (Agrawal and Srikant, 1999). Chiang and Hsieh [31] used grey relational analysis to improve the yield of Chrome thin-film sputtering processes in color filter manufacturing. Kuo et al. [32] used the grey relational analysis to solve multiple attribute decision-making problems.

The computing methods of grey relational degrees include Deng's relational degree, absolute relational degree, relative relational degree, and synthetic relational degree [33]. In this paper, the grey comprehensive correlation degree is used to compare the prediction results based on various prediction models and actual historical data. The grey comprehensive correlation degree is the weighted average of the grey absolute relational degree and the grey relative relational degree. As such, before the grey comprehensive correlation degree, the grey absolute relational degree and the grey relative relational degree need to be calculated. On the basis of this, we analyze the pros and cons of predicted results and give four steps to calculate grey comprehensive correlation degrees between actual demand and predicted results using various predict models.

Step 1. Generate reference sequence and comparability sequences.

Firstly, to judge the similarity between the actual demand quantity and the predicted demand quantity by using different predict models, it is necessary to define the reference sequence (actual demand obtained from history data) and comparability sequences (predicted results outputted from predict models) in order to calculate grey relational coefficients among them.

Definition 1. The actual demand quantity of spare parts i in continues n demand cycles is $D_0^i = (d_{01}^i, d_{02}^i, \ldots, d_{0n}^i)$, and the predicted demand quantity of spare parts i is $D_k^i = (d_{k1}^i, d_{k2}^i, \ldots, d_{kn}^i)$ in terms of the prediction method $k = (1, 2, 3 \ldots)$.

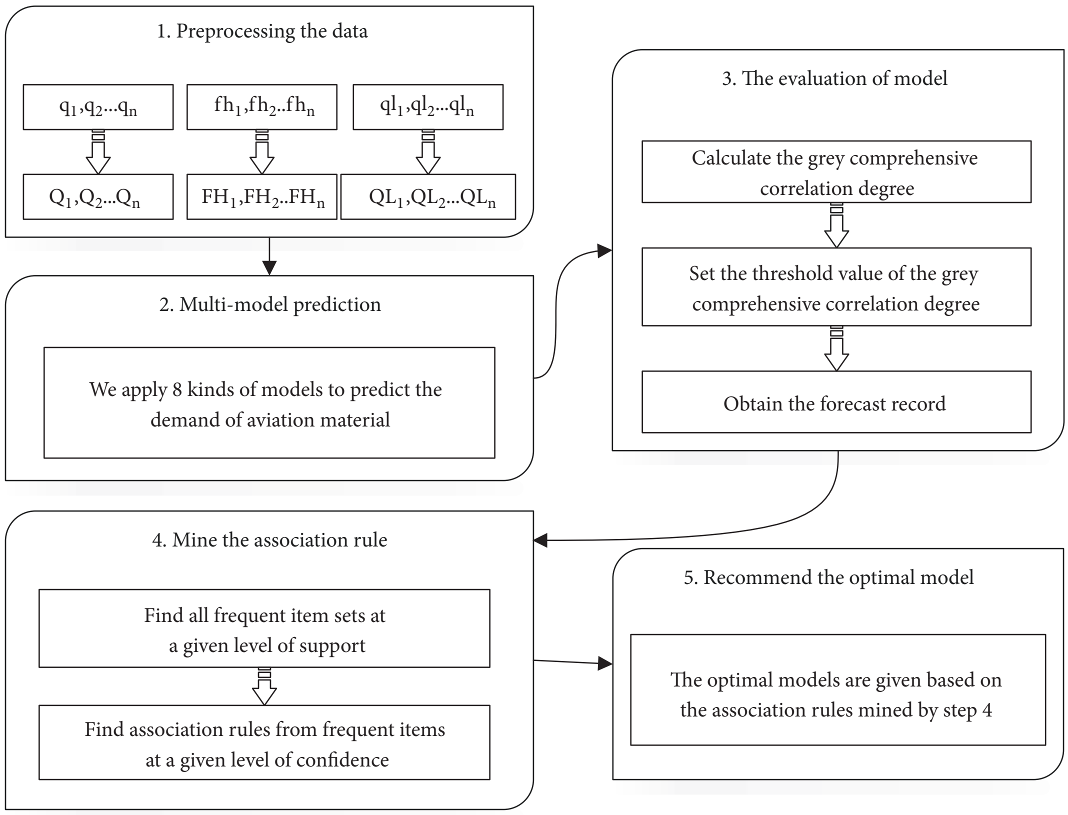

Figure 1: The recommended process of prediction models.

Step 2. Calculate the absolute relational degree.

Then, calculate the absolute relational degree, and measure the degree of association between the prediction results of k kinds of prediction models and the actual quantity demand of spare parts from the view of the absolute amount. Because the data in the reference and comparability sequences may be different in different dimension and inconvenient for comparison, it is difficult to get the correct conclusion. Therefore, in the grey relational grade analysis, data must be dimensionless. The specific steps could be shown as follows.

Step 2.1. Initialize and achieve the nondimensionalized sequence.

We use actual demand as reference sequence, and the initialization of reference sequence is

$$D_0^{i0} = \left\{ d_{0j}^{i0} = d_{0j}^{i} - d_{01}^{i} \mid j = 1, 2, \ldots n \right\} \tag{7}$$

The predicted demand using method k is comparability sequence, and the initialization of comparability sequence is

$$D_k^{i0} = \left\{ d_{kj}^{i0} = d_{kj}^{i} - d_{k1}^{i} \mid j = 1, 2, \ldots n \right\}, \quad k = (1, 2, 3 \ldots) \tag{8}$$

Step 2.2. Compute $|s^{\mathrm{i}}{}_0|$ and $|s^{i}{}_k|$. Here, $|s^{\mathrm{i}}{}_0|$ is the absolute value of the sum of the initial values in terms of the actual demand sequence for spare parts in benchmarking reference sequences. $|s^{\mathrm{i}}{}_k|$ is the absolute value of the sum of initial values in terms of the prediction results of k kinds of prediction models of comparability sequences.

$$\left| s^{\mathrm{i}}{}_0 \right| = \left| \sum_{j=2}^{n-1} d_{0j}^{i0} + \frac{1}{2} d_{0n}^{i0} \right| \tag{9}$$

$$\left| s^{\mathrm{i}}{}_k \right| = \left| \sum_{j=2}^{n-1} d_{kj}^{i0} + \frac{1}{2} d_{kn}^{i0} \right| \tag{10}$$

Step 2.3. Measure the absolute relational degree between the prediction results of k kinds of prediction models and the actual quantity demanded of spare parts i.

$$\varepsilon^{i}{}_{0k} = \frac{1 + \left| s^{i}{}_0 \right| + \left| s^{i}{}_k \right|}{1 + \left| s^{i}{}_0 \right| + \left| s^{i}{}_k \right| + \left| s^{i}{}_0 - s^{i}{}_k \right|} \tag{11}$$

Step 3. Calculate the relative relational degree.

Then, calculate the relative relational degree. The detailed steps could be shown as follows:

Step 3.1. Initialize and achieve the nondimensionalized sequence.

The initialization of reference sequences is

$$D_0^{i0\prime} = \left\{ d_{0j}^{i0\prime} = \frac{d_{0j}^{i}}{d_{01}^{i}} - 1 \mid j = 1, 2, \ldots n \right\} \tag{12}$$

The initialization of comparability sequence is

$$D_k^{i0\prime} = \left\{ d_{kj}^{i0\prime} = \frac{d_{kj}^{i}}{d_{k1}^{i}} - 1 \mid j = 1, 2, \ldots n \right\}, \quad k = (1, 2, 3 \ldots) \tag{13}$$

Step 3.2. Compute $|s^i{}_0{}'|$ and $|s^i{}_k{}'|$. Here, $|s^i{}_0{}'|$ is the absolute value of the sum of the initial values in terms of the actual demand sequence of spare parts of benchmarking reference sequences. $|s^i{}_k{}'|$ is the absolute value of the sum of initial values in terms of the prediction results of k kinds of prediction models of comparability sequences.

$$\left|s^i{}_0{}'\right| = \left|\sum_{j=2}^{n-1} d_{0j}^{i0\prime} + \frac{1}{2} d_{0n}^{i0\prime}\right| \tag{14}$$

$$\left|s^i{}_k{}'\right| = \left|\sum_{j=2}^{n-1} d_{kj}^{i0\prime} + \frac{1}{2} d_{kn}^{i0\prime}\right| \tag{15}$$

Step 3.3. Measure the relative relational degree between the prediction results of k kinds of prediction models and the actual quantity demand of spare parts i.

$$\gamma^i{}_{0k} = \frac{1 + \left|s^i{}_0{}'\right| + \left|s^i{}_k{}'\right|}{1 + \left|s^i{}_0{}'\right| + \left|s^i{}_k{}'\right| + \left|s^i{}_0{}' - s^i{}_k{}'\right|} \tag{16}$$

Step 4. Calculate the comprehensive relational degree.

Finally, through computing the absolute relational degree and the relative relational degree, we can get the grey comprehensive correlation degree between the actual quantity demanded of spare parts i and the prediction results of k kinds of prediction models.

$$\rho_{0k}^{i} = \theta \varepsilon_{0k}^{i} + (1 - \theta)\, \gamma_{0k}^{i}, \quad \theta \in [0, 1] \tag{17}$$

The value of θ is usually 0.5, which indicates that the absolute relational degree and the relative relational degree are equally important. Therefore, the set of the grey comprehensive correlation degree is $\rho^i = \{\rho_{ok}^i \mid k = 1, 2, \ldots\}$, which indicates the similarity between comparability sequence (predicted result by model k) and reference sequence (actual demand). The prediction models meeting the required accuracy could be found by setting the threshold value of grey comprehensive correlation degree, or appropriate prediction models could be determined as alternative prediction models give a specific grey comprehensive correlation degree threshold. Furthermore, in order to get the best prediction model suitable for the specific type of spare parts, association rules mining also needs to find the optimal prediction model in alternative models.

4. Association Rules Mining Based on the a Priori Algorithm

Data mining is a way to find implicit information from a data set and a process of knowledge discovery [34]. Association rules based on the a priori algorithm are widely used in the field of data mining. The association rules algorithm is mainly used to discover the relationship between data sets, and subsequently this relationship can be used to assist in decision-making. Wu et al. [35] used the a priori algorithm for assessing the usability of mining association rules. Wang [36] used association rule mining to identify critical features that formulate customer dissatisfaction. Chougule et al. [37] proposed a novel integrated framework combining association rules mining, case-based-reasoning, and text mining, which can be used to continuously improve service and repair in an automotive domain. Hsu et al. [38] used the association rules to extract good genes and increase gene diversity. Moharana and Sarmah [39] used the association rules technique for finding dependency among spare parts.

4.1. Items Generation for Association Rules Mining. This paper mainly addresses the problem of multimodels prediction. Firstly, the main idea is to generate an alternative prediction model set through grey relational analysis and then use association rules mining to find the best prediction model for the designated spare parts. The process is shown in Figure 1. Before the a priori algorithm is used to mine the association rules for the type of spare parts and the prediction model, the prediction records of the spare parts need to be generated first. Spare parts demand prediction records for association rules mining must be clear, accurate, and complete. It is difficult to get ideal mining effect without full data preprocessing. Therefore, before the analysis of the data, the data needs to be filtrated and consolidated sufficiently.

Spare parts demand prediction data preprocessing and prediction records for association rules mining generation could be divided in 6 steps as follows (see Figure 2).

Step 1. Select the types of spare parts to predict the requirements from the spare parts database. For example, in this paper, the selection of the selected spare parts is type A.

Step 2. Determine the time span of prediction, including annual forecast, quarterly forecast, and monthly forecast. For example, the prediction time span in this paper is monthly forecast.

Step 3. Select prediction time points $(t_1, t_2, t_3, \ldots)$.

Step 4. Use multimodels mentioned in Section 2.1 to predict spare parts demand:

$$M = (\mathit{Poisson}, \mathit{LR}, \mathit{AR}, \mathit{ARIMA}, \mathit{Auto\text{-}ARIMA}, \mathit{Holt\text{-}Winters}, \mathit{GM}, \mathit{SVR}) \tag{18}$$

Step 5. Evaluate models based on grey comprehensive correlation degree.

Step 6. According to the preset grey comprehensive correlation degree threshold, the prediction models satisfying the requirement of the threshold are obtained and the prediction records of the forecast of the spare parts demand are formed. Table 1 gives an example of formed prediction record of spare

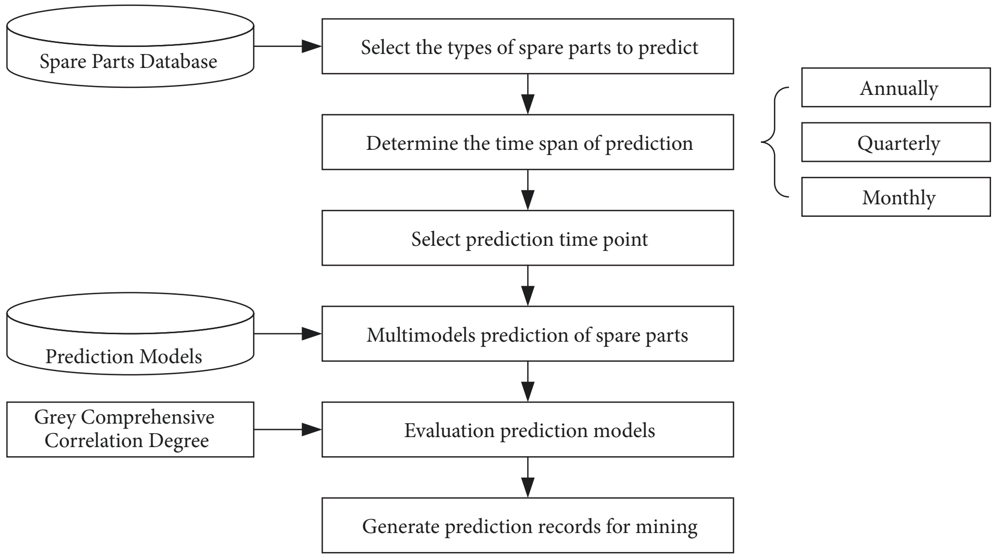

Figure 2: The process of prediction records generation.

Table 1: Item sets example for association rules mining.

Number	Time	Prediction record
1	t_1	{*A*, *Poisson*, *LR*, *Auto-ARIMA*}
2	t_2	{*A*, *LR*, *ARIMA*}
...	...	{*A*, *LR*, *AR*}
...	...	{*A*, *Poisson*, *LR*, *ARIMA*}
...	...	{*A*, *Poisson*, *AR*}
...	...	{*A*, *LR*, *AR*}
...	...	{*A*, *Poisson*, *AR*}
i	t_i	{*A*, *Poisson*, *LR*, *AR*, *Auto-ARIMA*}

part type A according to the threshold of grey comprehensive correlation degree, which is the item set that used to be association rules mined.

4.2. Association Rules Definition and Mining. Association rules are defined as follows.

Define $I = \{i_1, i_2, \ldots, i_m\}$ as an m-items set. Define D as a set of transactions in the database, where each transaction T is a nonempty subset of I. An association rule can be expressed as $(X \in T) \longrightarrow (Y \in T)$, where $X \in I, Y \in I$, and $X \cap Y \neq \varnothing$. Whether the association rule $X \longrightarrow Y$ belongs to the data set is determined by the degree of support and confidence. According to the main idea in Figure 1, the purpose of this paper is to determine optimal predict model based on spare parts type. In previous section, items for association rule mining have been generated. Therefore, the association rules between spare parts type and prediction model being used to predict spare parts multimodels could be described as $X \longrightarrow Y$, where X indicates spare parts type that we need to determine appropriate prediction model and Y indicates prediction models belonging to M = (*Poisson*, *LR*, *AR*, *ARIMA*, *Auto-ARIMA*, *Holt-Winters*, *GM*, and *SVR*).

The degree of support of the rule $X \longrightarrow Y$ in the transaction set D can be expressed as $Sup(X, D)$, which means the percentage of X in D. The degree of support is used to measure the importance of a transaction in a transaction set D. The greater the value of the support is, the more important the transaction in the data set D is. $Sup(X \cup Y, D)$ represents the proportion of $X \cup Y$ in the transaction set D.

The confidence of the rule $X \longrightarrow Y$ in the transaction set D can be expressed as $Conf(X \Longrightarrow Y)$, which means the percentage of X and Y in the transaction set D. Given a transaction set D, mining association rules finds all transactions at the given level of support and confidence [40].

The a priori algorithm is a mining association rules method [41]. The method can be broken down into the following two steps:

(1) Finding all the frequent item sets at a given level of support

(2) Mining the association rules from frequent items at a given level of confidence

5. Results of the Case Study

To verify the multiprediction models and the model recommendation methods, the monthly data of spare parts A of an airline company from January 2000 to July 2014 were selected, including the consumption quantity of spare parts A, the number of flight hours, and landing times. The detailed calculation and analysis results will be presented in the following section of this paper.

5.1. The Results of the Prediction Models. Here, the monthly data of the spare parts A of an airline company from January 2000 to July 2014 were selected. Because the parameters of the model need a certain amount of data, the first 12 months of the data are used to estimate of the model parameters,

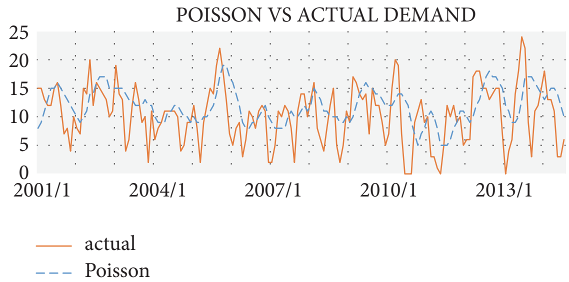

Figure 3: The results of the Poisson model.

instead of forecasting the demand. Figure 3 and the figures in the appendix show the comparison of the monthly outbound quantity of spare parts A in terms of eight kinds of prediction models from January 2001 to July 2014.

From the comparison of the actual demand (spare parts delivery quantity from inventory) with the forecasted results, among the eight models, the accuracy of the grey prediction model GM(1,1) is the worst. Based on the analysis of the application of GM(1,1) in the grey forecasting model, it is shown that the necessary condition for obtaining high precision with the GM(1, 1) model is an equal time interval, the nonnegative value, and the monotonicity. Although the demand of A is satisfied with an equal time interval and the nonnegative value, it is not satisfied with the monotonicity. Therefore, the prediction accuracy of the grey model GM(1,1) is poor. In contrast, the time series methods and the support vector machine regression model could predict more accurately. However, it should be noted that this conclusion is only applicable to spare parts type A. For other types of spare parts, different results may be presented, since different materials have differing demand characteristics. A detailed evaluation of the accuracy of the prediction models will be conducted in the next section of this paper.

5.2. Evaluation Results of the Grey Comprehensive Correlation Degree. In this paper, the grey comprehensive correlation degree is used to evaluate varying prediction models. From February 2001 to July 2014, the actual demand (spare parts delivery quantity from inventory) of spare parts type A and eight kinds of forecasting results were selected to calculate the grey comprehensive correlation degree. For example, in order to get the grey comprehensive correlation degree of the actual demand and eight kinds of prediction results in February 2001, the actual demand of the spare parts type A and eight kinds of prediction results from January 2001 to February 2001 were selected. Similarly, in order to get the grey comprehensive correlation degree in July 2014, the actual demand and eight kinds of prediction results from January 2001 to July 2014 were selected.

It should be noted that the calculation of the grey comprehensive correlation degree requires that the length of the time series be not less than 2, so this paper begins with calculation of grey comprehensive correlation degree in February 2001. Taking the calculation process of the grey comprehensive correlation degree in December 2011 as an example, the specific analysis process is as follows.

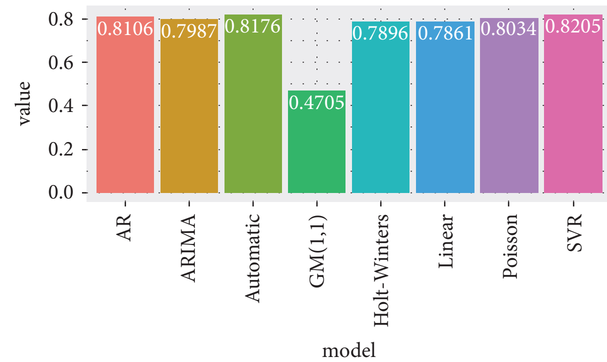

Figure 4: Grey comprehensive correlation degree, December 2011.

(1) Select the evaluation indexes.

In this paper, the actual demand of the spare parts type A and the results of different models are selected, including the Poisson distribution model, linear regression model, autoregression (AR) model, integrated autoregressive moving average (ARIMA) model, automatic ARIMA model, Holt-Winters model, grey forecasting model GM(1,1), and support vector machine regression (SVR) model. Respectively, the corresponding time series is set to X_0, X_1, X_2, X_3, X_4, X_5, X_6, X_7, and X_8.

(2) Set the weight of the grey absolute correlation degree and the grey relative correlation degree θ to 0.5.

(3) Get the grey comprehensive correlation degree, as shown in Figure 4.

According to the order of grey comprehensive correlation degrees from largest to smallest, the prediction accuracy of the support vector machine regression model outperforms other forecasting models in December 2011. The predictive effect of automatic ARIMA model is worse than the support vector machine regression model, but it is better than other models. Consistent with the conclusion from the last section, the accuracy of grey forecasting model GM(1,1) is the most unsatisfactory one.

(4) Obtain the forecast record according to the presetting threshold of the grey correlation degree.

According to the characteristics of aircraft demand and the requirement of aircraft management, set the threshold value of the grey comprehensive correlation degree to 0.8. Set the prediction model as an alternative model with a grey comprehensive correlation degree of more than 0.8. The forecast record in December 2011 is expressed as follows:

$$\{A, SVR, AR, Automatic\text{-}ARIMA, Poisson\} \tag{19}$$

However, due to differing demand characteristics, the above results may not be applicable to other types of aircraft. At the same time, due to the changing demand characteristics of the same type of aircraft, the results obtained in different years may not be the same. Figure 5 shows the calculation results of the grey comprehensive correlation degree of spare parts type A in December 2013.

According to the threshold value of the same grey comprehensive correlation degree, the prediction models whose grey comprehensive correlation degree is more than 0.8 are

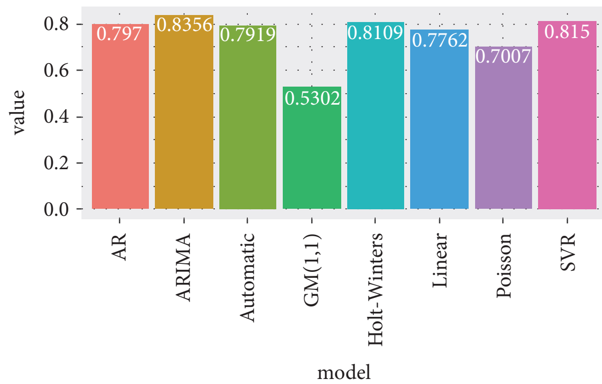

Figure 5: Grey comprehensive correlation degree, December 2013.

Table 2: Association rules.

Number	Association rules	Support	Confidence
1	$\{A\} => \{Automatic\ ARIMA\}$	0.74	0.92
2	$\{A\} => \{SVR\}$	0.55	0.85

set as the alternative models. The forecast record in December 2013 is shown as follows:

$$\{A, SVR, ARIMA, Holt\text{-}Winters\} \quad (20)$$

The results from Figure 5 show that, regarding December 2013, the ARIMA model is better than other prediction models, with the exception of the support vector machine regression model, caused by changes in the characteristics of the demand of spare parts. Therefore, at different time points, the optimal forecasting model is not the same. At each time point, the eight prediction models need to be recalculated, along with the grey comprehensive correlation degree between the actual demand and the forecast results of the eight models. Although that can get the best prediction model at each time point, such a process will inevitably lead to low efficiency of forecast work, which is not conducive to the development of spare parts demand forecasts. Therefore, this paper introduces this method of association analysis to improve the efficiency of aircraft demand forecasting.

5.3. The Association Rules between the Spare Parts Types and Prediction Models. Here, the confidence level is set to 0.8, and the support level is set to 0.5, according to the relationship between spare parts types and alternative prediction models. The association rules in Table 2 can be obtained by mining the 162 monthly forecast records from February 2001 to July 2014.

According to the association rules obtained from Table 2, for spare parts type A, the automatic ARIMA is the most applicable one compared to other forecast models, and the next is the SVR model. Businesses can simply select the automatic ARIMA model to predict the future demand of spare parts type A, which will make a significant improvement in their efficiency.

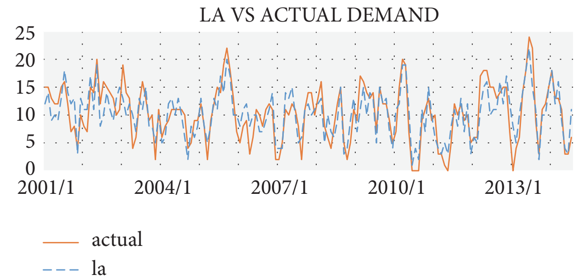

Figure 6: The results of linear regression.

6. Conclusion

In this paper, we analyzed the problems of spare parts demand forecasting and summarized the eight kinds of demand forecasting models, such as the Poisson distribution model. Then, the grey comprehensive correlation degree between the predicted results of each model and the actual consumption was calculated. According to the threshold value of the grey comprehensive correlation degree, the forecast model was selected, and the forecast record was obtained. Finally, the a priori algorithm was introduced, and the association rules between the spare parts type and the prediction models were obtained by mining the forecast records.

Additionally, we analyzed the characteristics of the demand of airline spare parts A through a case study. According to the order of the grey comprehensive correlation degree from largest to smallest, the prediction accuracy of the support vector machine regression model outperforms other forecasting models in December 2011 and the ARIMA model outperforms other prediction models in December 2013. According to the association rules, the applicability of the automatic ARIMA model is better than other forecast models for spare parts type A. In the future, the optimal forecasting model will be directly given according to the association rules and the type of spare parts, which would greatly improve the efficiency of the demand forecasting.

Here, the grey comprehensive correlation degree was used to evaluate eight prediction models. Although it makes up for deficiencies in absolute degrees of grey incidence and the relative degree of incidence, there is no reliable basis for determining the weight between the grey absolute correlation and the relative correlation, which is mainly adjusted according to experience and historical data. Future study will focus on the weight evaluation between the grey absolute correlation and relative correlation (the two correlations), so that better scientific standards could be defined.

Appendix

See Figures 6, 7, 8, 9, 10, 11, and 12.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

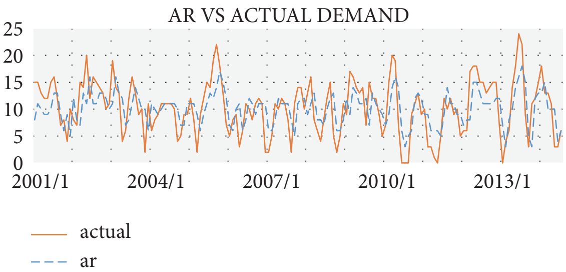

Figure 7: The results of AR.

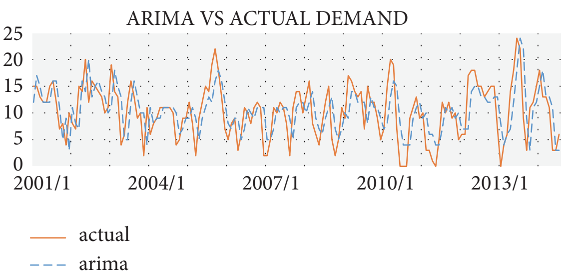

Figure 8: The results of ARIMA.

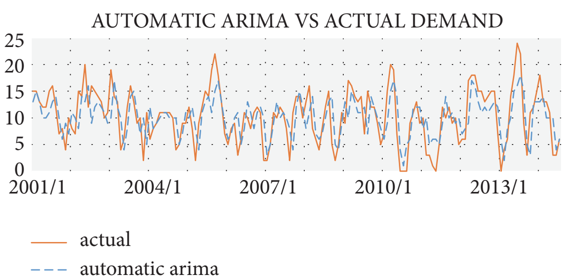

Figure 9: The result of automatic ARIMA.

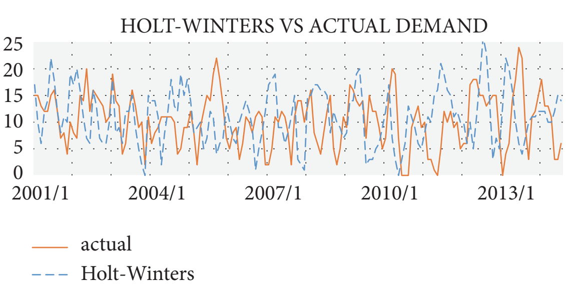

Figure 10: The results of Holt-Winters.

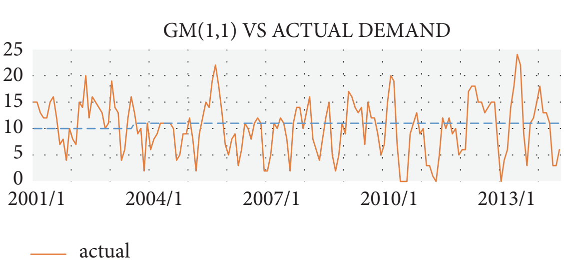

Figure 11: The results of GM(1,1).

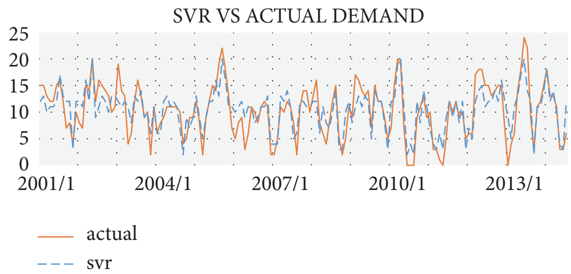

Figure 12: The results of SVR.

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