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Research on forecasting method of mechanical equipment spare parts demand based on LS-SVM

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Abstract: *In view of the wide variety and quantity of mechanical equipment spare parts, the increasing difficulty of spare parts management, and how to accurately predict the demand for spare parts, the least squares support vector machine (LS-SVM) regression algorithm is proposed to predict the demand for mechanical equipment spare parts. Based on the analysis of the basic principle of least squares support vector machine, a prediction model of mechanical equipment spare parts demand is established. RBF kernel function is selected. LS-SVM is used to study the training samples, train its grid structure parameters, determine the optimal parameters through cross validation and grid search, and use the trained LS-SVM to predict the mechanical equipment spare parts demand, and carry out numerical simulation, The prediction methods such as first-order exponential smoothing, ARMA method and BP neural network are used for comparison. The results show that LS-SVM performs well in the demand forecast of mechanical equipment spare parts.*

Keywords: *Mechanical equipment; Spare parts; Demand forecast; Least squares support vector machine (LS-SVM)*

1. Introduction

With the development of heavy machinery equipment construction in China, more and more new mechanical systems are equipped in the project. However, the variety and quantity of mechanical equipment spare parts make the management of spare parts more difficult. How to accurately predict the demand for spare parts and implement accurate management guarantee for spare parts, so as to meet the demand for spare parts and effectively reduce the supply and storage costs, is an important issue of equipment support work [1,2].

In the past, the forecast of spare parts demand is usually based on mathematical statistics to predict the future varieties and quantities according to past experience. However, there is inevitably a considerable gap between the forecast results and the actual demand for spare parts. In recent years, with the emphasis on equipment spare parts support and the innovation of equipment support to adapt to the new development trend, the supply of spare parts has gradually changed from the traditional prediction based on equipment consumption records to the prediction of the variety and quantity requirements of spare parts based on regular maintenance plans, maintenance manuals and technical specifications of mechanical equipment systems [3-5]. At the same time, it is also recognized that equipment reliability, Mean Time To Failure (MTTF), Mean Time Between Failure (MTBF) and other factors affecting spare parts demand should also be taken into account in the prediction of spare parts demand quantity to improve the accuracy of spare parts demand prediction.[6-8]

After analyzing and studying the demand prediction of spare parts for a certain type of mechanical equipment, this paper combines the mechanical system properties, spare parts life cycle and other parameters, and based on the historical data of spare parts demand and the relevant factors that affect the demand prediction, uses the improved Support Vector Machine (SVM) method to establish the prediction model, and compares the prediction results with the prediction results based on the time series method, and analyzes the applicability of the established model.

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2. Spare parts demand forecasting method based on LS-SVM

2.1 Basic theory of LS-SVM

Support Vector Machine (SVM) is a kind of generalized linear classifier that classifies data in a binary way according to supervised learning. Its decision boundary is the maximum margin hyperplane for learning samples [9].

SVM is one of the common kernel learning methods, which can perform nonlinear classification by kernel method. Different inner product kernel functions in SVM will form different algorithms, and the selection of different kernel functions and parameters has a great impact on the prediction effect of SVR. For example, the common radial basis function (RBF) kernel function:

$$K(x_i, x_j) = \exp(-\gamma \left\| x_i - x_j \right\|^2), \gamma > 0 \qquad (1)$$

So far, the selection of kernel function parameters of support vector machines has only been determined by experiments. Because it is time-consuming and laborious to use cross validation and grid search in parameter determination, RBF kernel function is often directly selected in practice. RBF kernel is different from linear kernel. It maps the sample nonlinear to a high-dimensional space. It can deal with the relationship between nonlinear predictive values and attributes. In addition, the digital complexity of RBF kernel function is small [10].

The least squares support vector machine (LS-SVM) method is an extension of standard SVM. All nodes of LS-SVM can be used as support vectors. In the process of modeling, the nonlinear modeling process is transformed into the solution process of linear equations, which greatly reduces the computational complexity of solving quadratic programming problems. However, the training accuracy of LS-SVM has decreased slightly [11].

For the regression algorithm, we hope to learn the regression equation from the training data:

$$y = W \cdot \varphi(x) + b \qquad (2)$$

The optimization idea of LS-SVR regression model is to minimize the distance between the sample with the largest distance from the regression plane and the regression plane.

2.2 LS-SVM training and test steps

1) Normalize the data and convert it to the data format required by support vector machine;

2) Input normalized data into support vector machine for training;

3) Use different kernel functions and compare the results to select the better kernel function;

4) Use Cross-Validation and Grid-Search to select the optimal parameters of the kernel function;

5) Input all training sets for training to obtain LS-SVM predictor;

6) Use LS-SVM predictor to predict and evaluate various parameters of the results.

3. Forecasting Model of Spare Parts Demand Based on LS-SVM

The demand for spare parts is affected by many factors such as equipment maintenance, operating environment, operating load, etc. In order to improve the accuracy of spare parts prediction, first of all, it is necessary to identify the main reasons for the occurrence of spare parts demand. During the use of equipment, there will be a lot of information related to spare parts requirements. The prediction effects of different models and methods are compared by using case analysis.

This paper selects a certain type of equipment spare parts for analysis and modeling. The main factors that affect the consumption of spare parts are: the life cycle (F1), the number of equipment maintenance (F2), the equipment startup time (F3), the number of misoperations by operators (F4), the duration of bad weather (F5), and the duration of special tasks (F6),

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3.1 Basic steps of prediction

The SVR prediction model of influencing factors takes the factors affecting the occurrence of spare parts demand as the input and the demand of spare parts as the output. The basic steps of its modeling are as follows:

1) Analyze the influencing factors related to equipment spare parts demand. In addition to some factors affecting reliability, it should also include factors such as repair at all levels and daily maintenance in equipment daily management.

2) Determine the explanatory variables of the influencing factors. Explanatory variables should be linked with various influencing factors. The change of spare parts demand caused by its change is consistent, and its value is easy to determine.

3) Input samples to train SVR, and use descriptive variables as input parameters, while output parameters are the demand for spare parts.

4) Input new spare parts demand samples or spare parts demand samples under different conditions into the support vector machine model for training.

5) Add new samples to the support vector regression prediction model for learning to continuously improve the accuracy of spare parts demand prediction.

3.2 Data preparation

This paper selects the 36-month data of spare parts of a certain type of equipment as the modeling interval of demand prediction. The sampling period is one month. The data of each month is taken as a sample. The training sample is the data of the first 24 months, and the test sample is the data of the last 12 months. Some data are shown in Table 1.

Table 1: Summary of partial collected data.

Sample type	Sample number	Influence factor						
		F1(m)	F2	F3(h)	F4	F5(h)	F6(h)	Requirement
Training sample	1	48	2	67	2	18	24	0
	2	48	2	59	1	15	19	0
	3	48	4	63	0	16	20	0
	4	48	2	83	3	22	26	1
	…							
	21	48	0	86	3	25	29	1
	22	48	1	82	2	20	34	2
	23	48	3	60	0	16	23	1
	24	48	4	58	0	18	20	0
Test sample	25	48	3	63	1	19	20	0
	26	48	2	61	1	18	21	0
	…							
	35	48	4	86	2	23	26	1
	36	48	4	84	2	25	30	2

4. Simulation experiment and result analysis

The kernel function of LS-SVM selects RBF, input influence factor matrix and output matrix, and use cross-validation and grid-search to select the optimal parameters of the kernel function gamma=1500, sig2=4. Train with trainlssvm function. The results are shown in Table 2:

Table 2: Prediction Results of LS-SVM.

Number	25	26	27	28	29	30
True value	0	0	0	1	2	0
LS-SVM	0.2405	0.003406	0.55556	1.3001	1.3979	-0.14581
Number	31	32	33	34	35	36
True value	1	2	0	0	0	0
LS-SVM	1.4328	1.6464	-0.43516	-0.12825	0.19223	0.50157

As can be seen from Figure 1, the overall prediction effect of LS-SVM is satisfactory, and the

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prediction of demand occurrence time and specific quantity is relatively accurate.

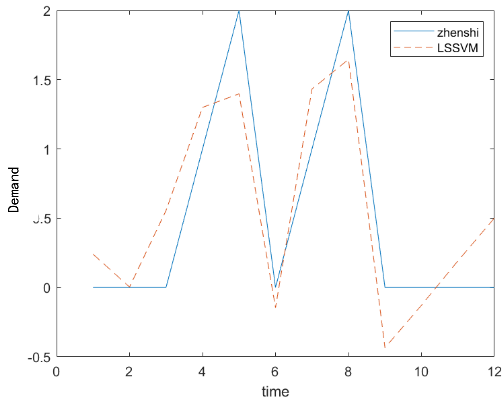

Figure 1: Prediction results of LS-SVM.

The LS-SVM algorithm is used to predict the demand for spare parts. In order to evaluate its prediction effect and applicability, BP neural network and traditional time series prediction methods are introduced here for comparison. The prediction results are shown in Figure 2.

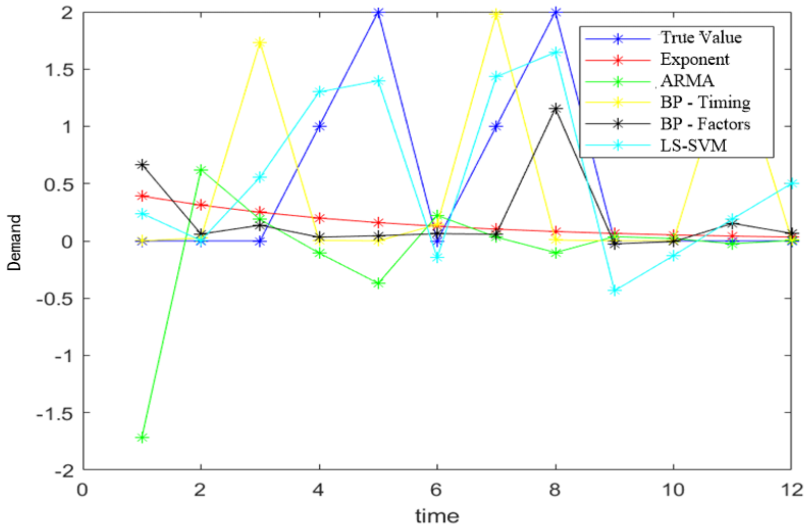

Figure 2: Comparison of prediction results.

It can be seen from the prediction results that although the exponential smoothing method is the most widely used, applicable to small sample data, and easy to calculate, because its long-term impact is gradually weakened, it can only be used for short-term prediction.

Although the prediction results of the autoregressive moving average method extend the past trend to the future, in fact, the parameter estimation of the ARMA model is nonlinear, and the accurate estimation of its parameters is difficult to obtain, and the calculation amount is large, and the convergence cannot be guaranteed. Therefore, in the actual prediction results, the prediction results of the model are also relatively volatile.

When the BP neural network algorithm is used for prediction, the initial weights and thresholds are random in the training process of the network, resulting in the network training is difficult to reach the best, and there is no sufficient explanation for the model, that is, using the same network input and transfer function, the trained network will also be very different, and the training process is huge, but the trained network has good fitting effect, and its trend in the long-term prediction is more consistent with the actual situation. Especially when the interval length is enlarged, the long-term prediction effect is good.

When BP neural network algorithm predicts by influencing factors, its prediction results get rid of the influence of time periodicity, and the overall prediction results are good, but the training process lacks sufficient in-depth interpretation, and it is also difficult to converge to a satisfactory network model in the training process.

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The LS-SVM algorithm has sufficient theoretical support and mature algorithm model. The previous prediction methods for small samples often have poor fitting effect due to the lack of data. However, the LS-SVM method can better achieve the prediction of intermittent demand for spare parts after determining parameters through cross validation.

5. Conclusion

According to the above analysis, the exponential smoothing method is usually simple and effective in short-term prediction of small sample data. When forecasting data in the long term, both ARMA method and BP neural network can maintain the long-term trend, and the trained neural network method is better than ARMA method, but the uncertainty of the network in the training process is large, and the results of different training networks vary greatly. When forecasting according to the influencing factors, BP neural network can also be used as a simple method to save the process of parameter calculation, but it still needs to make decisions in a large number of training networks, sometimes falling into local optimum. When the LS-SVM method is used to predict the influencing factors, it can achieve ideal results when appropriate parameters are obtained.

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