Evaluation of Spare Parts Scheme Based on BP Neural Network

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***Abstract*—Spare parts are one of the most important material resources to ensure the equipment works normally.. Equipment availability and spare parts satisfaction rate are the evaluation indicators of spare parts scheme. Aiming at the problem of the mean time between failures of parts given by manufacturer is not accurate, an evaluation model of spare parts for naval vessels based on BP neural network model is proposed. Firstly, training and testing data are generated by availability simulation model and spare parts satisfaction rate simulation model; then, the parameters of BP neural network model are trained by training data; finally, the prediction results of BP neural network model are tested by test data. Case results show that: The predicted results of the BP neural network model of the two evaluation indicators are consistent with the actual value trend; when the spare parts fill rate is higher than 0.8, the maximum error between the predicted value and the actual value of the BP neural network model is not more than 0.03. The research can be used as a reference for the decision-making of spare parts allocation evaluation of warships or aircraft.**

Keywords- BP Neural Network; Availability; Fill rate; Simulation model

I. INTRODUCTION

Spare parts are one of the most important material resources to ensure the normal operation of naval equipment, which is of great significance to enhance the combat capability of naval vessels. Because quantity of spare parts is related to equipment working intensity, the mean time between failures of spare parts, working time and support force, so how to scientifically and accurately formulate spare parts configuration scheme is of great significance to improve equipment integrity and reduce waste of equipment support resources.

In view of spare parts demand and configuration, many scholars have carried out relevant research. One is the spare parts configuration method based on mathematical modeling, the other is the spare parts configuration method based on machine learning. The spare parts requirement allocation method based on mathematical modeling is mainly based on the classical inventory METRIC model [1-4], which is used to solve the electronic equipment life cycle spare parts allocation problem. One of the important input parameters is the mean time between failures (MTBF). The mean time between failures of most components before delivery are based on equivalent calculation or analogy of the same type components, because it cannot use the subsequent spare parts consumption data, it lacks certain real-time. In this regard, many scholars use machine learning method to study spare parts configuration. Documents [5-6] carried out research on spare parts demand forecasting and classification based on SVM vector regression. In reference [7], BP neural network was used to forecast spare parts demand. Literature [8] Based on LSTM convolution neural network, fault demand prediction is studied. The spare parts demand forecasting method based on machine learning mainly relies on the historical spare parts consumption information to forecast the spare parts consumption in the next

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stage, and less on the joint analysis of spare parts consumption and evaluation indicators.

Aiming at the problem of the mean time between failures of parts given by manufacturer is not accurate, an evaluation model of spare parts for naval vessels based on BP neural network model is proposed. Firstly, training and testing data are generated by availability model and spare parts satisfaction rate model; then, the parameters of BP neural network model are trained by training data; finally, the prediction results of BP neural network model are tested by test data. When the evaluation index is the spare parts fill rate, the predicted value of BP neural network model is very close to the actual value. The research can be used as a reference for the decision-making of spare parts allocation evaluation of warships or aircraft.

II. SPARE PARTS SUPPORT PROCESS AND EVALUATION INDICATORS

A. Spare Parts Support Process

In the field of ship equipment deployment, equipment maintenance personnel usually have certain LRU maintenance capability. When the equipment fails, the maintenance personnel at the equipment deployment site inspect and locate the failure, replace the failure parts with spare parts, repair the replaced failure parts, put the repaired parts back into the spare parts warehouse, and send the unrepairable failure parts to the scrap warehouse. The process of equipment replacement maintenance and support is shown in Figure 1. In the process of replacement maintenance of equipment failure, the assumption of model conditions is the same as that in reference [4].

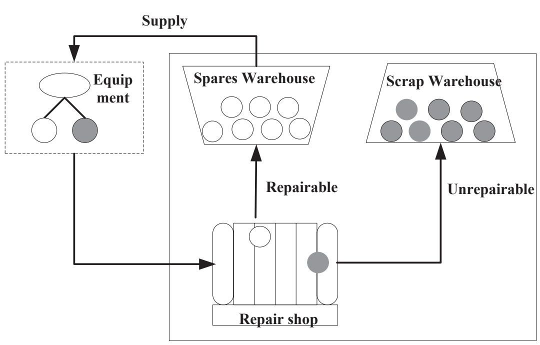


Fig.1 Spare parts support process

B. Spare pare Parts Evaluation Model

Equipment availability and spare parts satisfaction rate are commonly used evaluation indicators for equipment spare parts configuration scheme. The definitions of equipment availability and spare parts support probability are explained below.

According to [4], the availability of LRU in the field of equipment in the time of mission time is as follows:

$$A_l(t) = \frac{1}{t} \bullet \int_0^t BO_l\left(x \le \left(M_l\right), t\right) \bullet dt \qquad (1)$$

In (1), $BO_l\left(x \le \left(M_l\right), t\right)$ is the probability that the number of shortages on the equipment deployment site is less than M_l at time t, and M_l is the number of installed LRU. By default, all components are in series.

According to [9], the relationship between the number of spare parts with the satisfaction rate of spare parts is as follows:

$$P_f(t) = \frac{1}{t} \bullet \int_0^t P(m,t) \bullet dt \qquad (2)$$

In (2), $P(m,t)$ is the guarantee probability when the number of spare parts is m.

The detailed derivation process of (1) and (2) can be found in [4] and [10].

III. BP NEURAL NETWORK MODEL

ANN was proposed to imitate the way of thinking of human brain neurons. Later, error back propagation algorithm was proposed and developed. At present, it is still one of the most successful algorithms in machine learning. The typical ANN network structure is shown in Figure 2. The input layer has n nodes representing n attributes and the output layer has one node.

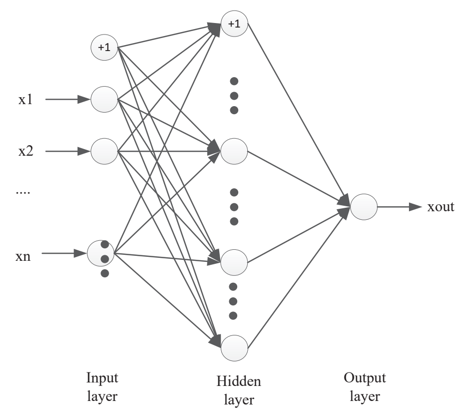


Fig.2 Structure of BP Neural Network

When training the neural network, only the number of input and output nodes, training function, hidden layers, training errors and other parameters need to be adjusted. This paper mainly carries out equipment availability evaluation for spare parts scheme under single-stage and single-layer.

According to the equipment support process in Figure 1, the parameters of BP neural network model need to be input are task time, maintenance time, maintenance probability and spare parts inventory. The output parameter is equipment availability. Reference [9] for the setting of training function and hidden layer. The structure parameters of BP neural network are shown in Table 1.

TAB.1 THE STRUCTURE PARAMETERS OF BP NEURAL NETWORK

Parameter type	Parameters
Input layer nodes	4
Hidden layer number	1
Number of Hidden Layer Nodes	8
Number of Output Layer Nodes	1
Hidden Layer Transfer Function	tansig
Output Layer Transfer Function	logsig
Training algorithm	Levenberg-Marquardt
Training objectives	MSE⩽0.00001
Training steps	500
Learning rate	0.15

IV. CASE ANALYSIS

A. Training and test data

Reference [4] establishes a single-layer equipment availability evaluation model for different tasks and at any level. To this end, the paper generates training data and test data of BP neural network based on equipment availability evaluation model. When generating training and test data, the range of parameters such as input data task time, MTBF, repair time, repair probability and initial spare parts is shown in Table 2.

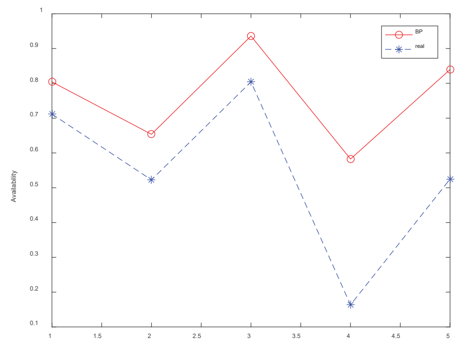
TAB.2 THE RANGE OF PARAMETER VALUES

Parameter type	Scope
Task time（h）	1000–3000
MTBF（h）	30–600
Repair time（h）	100–900
Repair probability	0.3–1
Quantity of spare parts	0–5

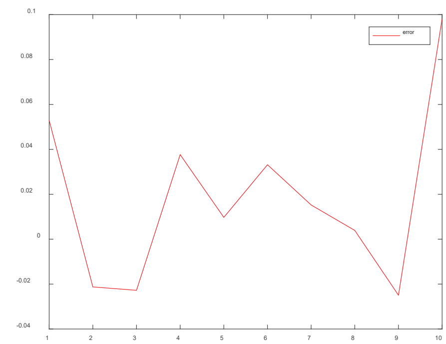
B. Prediction results and errors based on availability

200 input parameters are randomly generated within the above range values, and the corresponding availability of 200 input data is calculated based on the availability model in [4].

When the former 190 data are used as training data and the latter 5 data are used as test data, the predicted value of BP neural network model is compared with the actual value as shown in Figure 3. When the former 170 data are used as training data and the latter 30 data are used as test data, the predicted value of BP neural network model is compared with the actual value as shown in Figure 4. The X-axis in figures 3 to figures 6 represents the number of test data.

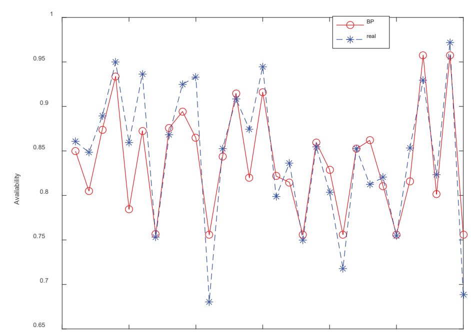


（a）predicted value

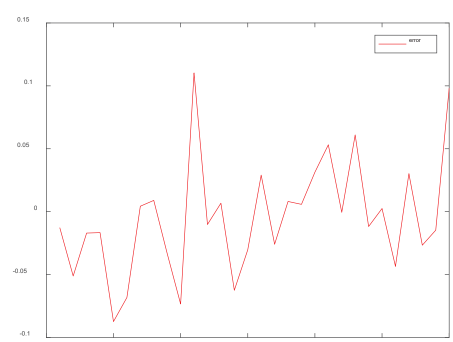


(b) Prediction error

Fig.3 Prediction results and errors



（a）predicted value



(b) Prediction error

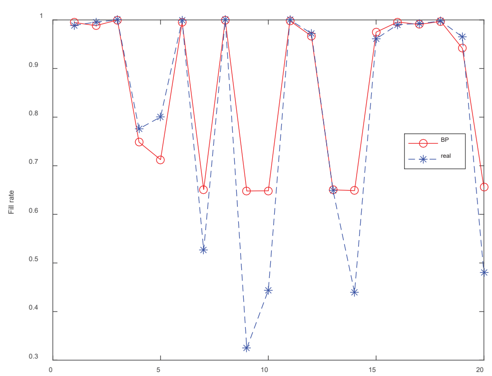
Fig.4 Prediction results and errors

The curve of figure 3 and figure 4 predicted results and actual results shows that the predicted availability by BP neural network algorithm is consistent with the trend of actual availability. When the prediction data is changed from 5 to 30, the maximum error between the prediction results and the actual results becomes larger. For the analysis figure 3 and figure 4, it can be seen that when the actual availability is lower than 0.75 or higher than 0.95, the error between the predicted availability value based on BP neural network and the actual value becomes larger. In the range of 0.75 to 0.9, the predicted results of BP neural network are close to the actual results, but the maximum error is still more than 5%.

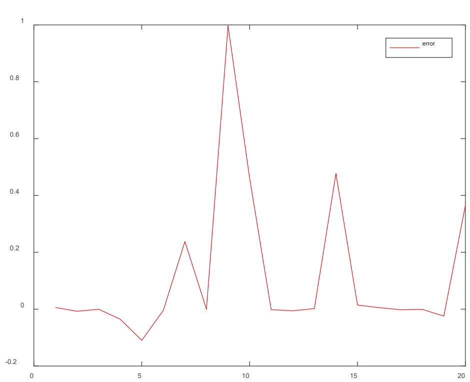
C. Prediction Results and Errors Based on Spare Parts fill Rate

A Monte Carlo simulation model based on discrete events is established in [2], which generates 200 data with the spare parts satisfaction rate as the calculation result.

When the former 180 data are used as training data and the latter 20 data are used as test data, the predicted value of BP neural network model is compared with the actual value as shown in Figure 5. When the former 150 data are used as training data and the latter 50 data are used as test data, the predicted value of BP neural network model is compared with the actual value as shown in Figure 6.

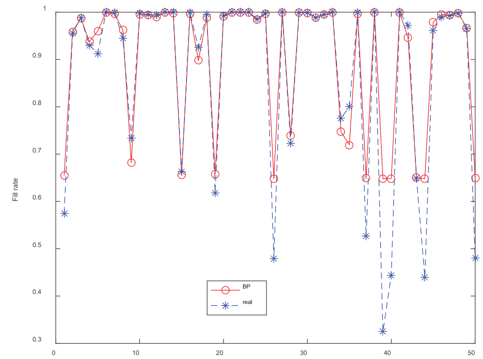


（a）predicted value

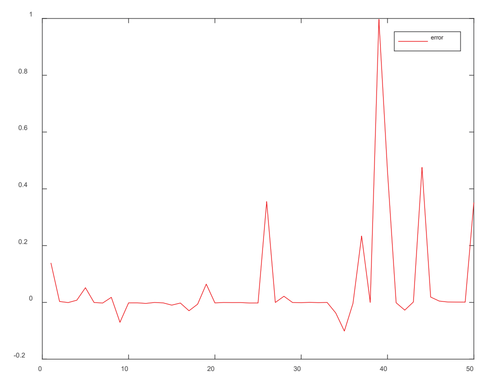


（b）Prediction error

Fig.5 Prediction results and errors



（a）predicted value



（b）Prediction error

Fig.6 Prediction results and errors

Analysis of Figures 5 and Figures 6 shows that when the satisfaction rate is higher than 0.8, the predicted value of the BP neural network model is extremely consistent with the actual value. Except for individual points, the maximum error between the predicted value and the actual value does not exceed 0.01. When the fill rate of spare parts is less than 0.7, there is a big error between the predicted value and the actual value of BP neural network model. With the decrease of the satisfaction rate, the error value will become larger. In the process of spare parts configuration on board, the requirement of spare parts satisfaction rate is higher than 0.8. Therefore, when the spare parts satisfaction rate is selected as the evaluation index of spare parts scheme, the BP neural network model is feasible.

V. CONCLUSION

Spare parts are one of the most important material resources to ensure the integrity of equipment. Aiming at the problem of inaccurate the mean time between failures of components in engineering practice and the inability of traditional equipment availability model to update the subsequent spare parts consumption information, an evaluation model of spare parts for naval vessels based on BP neural network model is proposed. Through case analysis, the following conclusions can be drawn:

- The predicted results of the BP neural network model of the two evaluation indicators are consistent with the actual value trend, and the fill rate is better than the predicted value with availability as the evaluation index;
- when the spare parts fill rate is higher than 0.8, the error between the predicted value and the actual value of the BP neural network model is not more than 0.01. The research can be used as a reference for the decision-making of spare parts allocation evaluation of warships or aircraft.

In this paper, the exponential life components are studied, and the predictive effect of BP neural network model for normal or Weibull life components is not considered, which will be further studied in the future.

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