Research Article

Weixing Song*, Jingjing Wu, Jianshe Kang, and Jun Zhang

Research on maintenance spare parts requirement prediction based on LSTM recurrent neural network

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Abstract: The aim of this study was to improve the low accuracy of equipment spare parts requirement predicting, which affects the quality and efficiency of maintenance support, based on the summary and analysis of the existing spare parts requirement predicting research. This article introduces the current latest popular long short-term memory (LSTM) algorithm which has the best effect on time series data processing to equipment spare parts requirement predicting, according to the time series characteristics of spare parts consumption data. A method for predicting the requirement for maintenance spare parts based on the LSTM recurrent neural network is proposed, and the network structure is designed in detail, the realization of network training and network prediction is given. The advantages of particle swarm algorithm are introduced to optimize the network parameters, and actual data of three types of equipment spare parts consumption are used for experiments. The performance comparison of predictive models such as BP neural network, generalized regression neural network, wavelet neural network, and squeeze-and-excitation network prove that the new method is effective and provides an effective method for scientifically predicting the requirement for maintenance spare parts and improving the quality of equipment maintenance.

Keywords: LSTM, spare parts prediction, neural network, particle swarm

1 Introduction

Equipment are the basis for the improvement of army combat effectiveness. It is necessary for the equipment to be repaired in time to maintain and restore the technical performance. On the one hand, the upgrading of military equipment is accelerating, the level of technology and integration of equipment are constantly improving, and the difficulty of repairing the equipment is increasing; on the other hand, the preparations for combat are accelerating and the use of equipment is frequent. The timeliness of maintenance has become higher and higher. Replacement repair has gradually become the main maintenance method of the grassroots maintenance organizations. To a certain extent, the timely and sufficient supply of equipment spare parts directly determine the maintenance capability of the grassroots maintenance organizations. Requirement prediction is the prerequisite, and foundation of spare parts support work and its role is prominent, attracting more and more research attention now.

The main content of the maintenance spare parts requirement prediction includes the time, type, and quantity. According to the basic relationship of maintenance and supply, the requirement of spare parts should be predicted based on maintenance. Equipment maintenance can be divided into preventive maintenance and corrective maintenance according to the source of the task. Preventive maintenance is to maintain equipment performance according to the corresponding standards of the use time and mileage of the equipment. On reaching a certain threshold, the equipment will be inspected, tested, and replaced by parts, no matter whether it is faulty. According to the scope and degree, preventive maintenance can be divided into major repairs, intermediate repairs, and minor repairs. Corrective maintenance is a maintenance carried out to resume the performance of the equipment after fault. The maintenance time for preventive maintenance can be calculated according to the equipment utilization plan. The content of the maintenance items is also clear

* **Corresponding author: Weixing Song**, Army Engineering University of PLA, Shijiazhuang, 050003, China, e-mail: 88159073@qq.com

Jingjing Wu: Western Theater Army Department of Logistics, 730000, Lanzhou, China, e-mail: 13915292@qq.com

Jianshe Kang: Army Engineering University of PLA, Shijiazhuang, 050003, China, e-mail: jskang201206@126.com

Jun Zhang: Confidential Archives Office of ARSTAF Western Theater, 730000, Lanzhou, China, e-mail: 330773627@qq.com

in accordance with the standard, so it is easier to predict the requirement of the spare parts. Corrective maintenance is triggered by the natural failure of the equipment. As the time, type, and degree of the failure during the use of equipment are very uncertain, and the characteristics and rules are not obvious, the prediction of the spare parts requirement is very difficult. Current research is also focused on this.

There are three main methods for the research of spare parts requirement prediction, which are empirical analysis method, analytical function method, and data regression prediction method. The empirical analysis method is that experts predict the spare parts requirement of the equipment in the future based on the previous spare parts demand of the same or similar equipment, relying on maintenance experience. In ref. [1], experts' forecasts with Markov forecasts were combined and a method of spare parts requirement prediction in wartime was proposed based on fuzzy inference. The analytical function method is to describe and calculate the spare parts requirement by using the analytical function when the life distribution probability of the spare parts is known. In ref. [2], an age replacement strategy and requirement calculation model were proposed for the Weibull distributed equipment spare parts. In ref. [3], the requirement prediction model of special spare parts and shared spare parts were constructed, respectively, on the basic assumption that the daily failure obeyed the exponential distribution and the battle damage-oriented obeyed the binomial distribution. In ref. [4], a prediction model combined with the first, second, and third exponential smoothing methods and three and four term moving average methods were established, making prediction model more accurate. The data regression method is to study and extract the characteristic law of spare parts consumption to predict the requirement of spare parts in the future, by analyzing the consumption data of equipment spare parts in the past period of time. The empirical analysis method has poor stability due to different levels of expert ability. The analytical function method requires the life probability distribution of the spare parts, making its condition and scope restricted [5], and is unsuitable for the grassroots maintenance organization, of which the spare parts reserve is small and the turnover speed is poor. The data regression prediction method has a wide range, such as BP neural network [6], logistic regression [7], support vector machine [8], gray model [9], gray Markov model [10], Bayesian [11], *etc.*

Artificial neural network has outstanding advantages in the research of spare parts requirement prediction due

to its independent learning, associative storage, and super-optimization ability. There are many branches in the application of neural networks for spare parts requirement prediction, such as BP neural network [12], generalized regression neural network [13], radial basis neural network [14], grey neural network [15], *etc.* In order to solve the problems of slow convergence speed and weak global search ability in artificial neural network prediction, some scholars have proposed a composite method combining other intelligent algorithms. In ref. [16], the genetic algorithm was used. In ref. [17], the particle swarm algorithm was used, while in ref. [18], the ant colony algorithm was used to optimize the artificial neural network, in order to improve the speed and accuracy of spare parts requirement prediction. The above research is not very pertinent to the time series characteristics of spare parts requirement data, and does not make good use of the relationship between the data at different time points, thus affecting the predicting effect. According to the time series data of equipment maintenance spare parts consumption, this article proposes a prediction method based on long short-term memory (LSTM) recurrent neural network, which effectively utilizes long and short distance time series information to enhance the accuracy of spare parts requirement prediction.

2 Related theories of LSTM

LSTM recurrent neural network [19], jointly proposed by Hochreiter and Schmidhuber in 1997, is aimed to solve the problem of gradient disappearance, gradient explosion, and insufficient long-term memory ability when recurrent neural network analyzes and processes time series data. It is a new type of neural network model which is the latest and most popular neural network model specially designed for analyzing and processing time series information.

2.1 Net structure

LSTM is a chain-like neural network with repeated network modules. As shown in Figure 1, each module includes a three-layer network structure, including an input layer, a hidden layer, and an output layer. Each layer of the network is composed of a different number of parallel neural units. The input layer is responsible for receiving information. The component data in the current time data information $X(t)$, the module state information

Figure 1: Logical structure diagram of LSTM recurrent neural network.

$C(t-1)$ at the previous time, and the module output information $H(t-1)$ are input into the neural units of the input layer according to different weights. The hidden layer is responsible for calculating and processing the input data information. The output of the output layer includes module status information $C(t)$, module output $H(t)$, and timing output $\hat{Y}(t)$. Each network module carries on data transmission through $C(t)$ and $H(t)$, and timing output $\hat{Y}(t)$ is the calculation output of the network at the current moment.

2.2 Neural unit design and memory realization

The core idea of LSTM is the design of adding unit state $c(t)$ and “gate” structure to the hidden layer neural unit. Figure 2 shows the structure of one neural unit in the hidden layer of the network module at time t . The unit state $c(t)$ serves as the link of information transmission, allowing the information of each time sequence to be transmitted between network modules at successive moments in the entire network, which is equivalent to long-term memory. Through the state information, the information from the earlier time can be transferred to the later time, which overcomes the influence of short-term memory. Forgetting gates, input gates, and output gates are mainly used for the calculation and processing of data information at the current time and state information at the past time, and are a comprehensive application of short-term memory and long-term memory.

2.2.1 Forgotten gate

The calculation formula of the forget gate is:

$$f(t) = \sigma(w_f h(t-1) + u_f x(t) + b_f), \quad (1)$$

where $x(t)$ is the data input at the current moment, $h(t-1)$ is the output of the neural unit in the hidden layer at the previous moment, u_f and w_f are the weights of $x(t)$ and $h(t-1)$, respectively, b_f is the bias vector, and σ is the Sigmoid function [20].

$$\sigma(x) = \frac{1}{1 + \exp(-x)}. \quad (2)$$

The output value $f(t)$ of the forget gate is between 0 and 1, which is multiplied by the state value $c(t-1)$ at the previous moment, representing whether $c(t-1)$ should be forgotten. The closer it is to 0, the more it should be forgotten, and the closer it is to 1, the more it should be remembered.

2.2.2 Input gate

The calculation formula for the input gate is

$$i(t) = \sigma(w_i h(t-1) + u_i x(t) + b_i), \quad (3)$$

$$c'(t) = \tanh(w_c h(t-1) + u_c x(t) + b_c), \quad (4)$$

$$c(t) = f(t)c(t-1) + i(t)c'(t), \quad (5)$$

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}, \quad (6)$$

Figure 2: LSTM recurrent neural network hidden layer neural unit structure diagram.

where w_i , w_c , u_i , and u_c are weights and b_i and b_c are bias vectors. The value of $i(t)$ in equation (3) is between 0 and 1, which is the input importance factor. Equation (4) uses the $\tanh$ function to distribute the integrated input $c'(t)$ of the output $h(t-1)$ of the hidden layer neural unit at the previous moment and data $x(t)$ at the current moment between -1 and 1 , which plays a role in data centralization. Equation (5) synthesizes the state information $c(t-1)$ of the nerve unit at the previous time and the information at the current time to obtain the state $c(t)$ of the nerve unit at the current time. The input gate determines the degree to which data information $x(t)$ enters the network at the current moment, filters valuable information, and expands and updates the memory of the network.

2.2.3 Output gate

The calculation formula for the output gate is

$$o(t) = \sigma(w_o h(t-1) + u_o x(t) + b_o), \quad (7)$$

$$h(t) = o(t) \cdot \tanh(c(t)), \quad (8)$$

where w_o and u_o are the weights and b_o is the bias vector. In equation (7), the value of $o(t)$ is between 0 and 1, which is the output importance factor; in equation (8), the current state information $c(t)$ is processed by $\tanh$ function and multiplied by $o(t)$ to get the output $h(t)$. The output gate determines how much of the current

neural unit state $c(t)$ is to be output to the hidden layer of the network module at the next moment.

2.2.4 Network timing output

The network timing output is the predicted value of the LSTM recurrent neural network. The sequence output calculation formula in the neural unit is:

$$\hat{y}(t) = v h(t) + c_v, \quad (9)$$

where v is the weight and c_v is the bias vector.

3 Improved LSTM algorithm

As LSTM recurrent neural network is very effective in processing time series data [21], it is currently widely used in handwriting recognition, speech recognition, machine translation, video analysis, and other fields. However, the current application research of LSTM recurrent neural network in the prediction of equipment spare parts requirement is still not seen. After the equipment is repaired and replaced with spare parts, its technical performance will be improved, and the probability of the same failure will be greatly reduced. Therefore, the consumption of spare parts at the previous moment will have

a great impact on the consumption of spare parts at the later time. The spare parts consumption data is a typical time series data, and the LSTM recurrent neural network is very suitable for the prediction of spare parts requirement in theory.

3.1 Algorithm procedure

According to the characteristics of the time series data with equipment spare parts consumption, this article proposes to use LSTM recurrent neural network to predict the requirement of equipment spare parts, in which the technical advantages of LSTM recurrent network will be fully performed. The detailed design of network structure, and the concrete realization of network training and network prediction are shown.

In order to solve the problem that the LSTM recurrent neural network prediction model involves many parameters, which will make the performance of prediction unstable if set artificially, with the goal of minimizing the prediction error, an algorithm of equipment spare part requirement prediction with LSTM recurrent neural network whose parameters are optimized by particle swarm optimization is further proposed. The structural framework of the algorithm is shown in Figure 3.

The specific steps are as follows:

Step 1: Standardize the experimental data and divide it into a training set and a testing set.

Step 2: Set particle swarm algorithm parameter learning factors c_1 and c_2 , maximum inertia weight $w_{\max}$, minimum $w_{\min}$, number of iterations N_{iter} , and number of populations pop_size . Setting parameters such as the number of neural units in hidden layer of LSTM recurrent neural network size_h , prediction interval T , the number of training data subsets MiniBatchSize , and the initial learning rate η as state vectors, initialize the state and velocity of each particle in the population.

Step 3: To each particle, construct an LSTM recurrent neural network according to its four-state vector values, use the training set data to train the network, use the testing set data to test the network, and use the mean square error as the fitness value of each particle.

Step 4: Determine the extreme value p_{best} of the individual and the extreme value g_{best} of the population according to the fitness value of each particle in the population.

Step 5: According to p_{best} and g_{best} , update the state and velocity of each particle in the population.

Step 6: Calculate the fitness value of each particle in the population, and update p_{best} and g_{best} .

Figure 3: PSO optimizes the LSTM to predict the spare parts requirement.

Step 7: Repeat steps 4 to 6, and after reaching the number of iterations, use the four-state vectors of particle g_{best} as parameters to construct an LSTM recurrent neural network to predict the requirement of maintenance spare parts.

3.2 Data processing and network construction

The spare parts consumption data is the time series data $P = \{p_1, p_2, \dots, p_t, \dots, p_n\}$ with monthly intervals, p_t represents the consumption of spare parts in t th month. $p_t = \{k_1^t, k_2^t, \dots, k_m^t\}$ and k_m^t represent the consumption quantity of the m th kind of spare parts in t -month. In order to accelerate the convergence of weight parameters when training the network, first use method of z-score to normalize p_t . The calculation formula for standardization of time series data is:

$$p'_t = \frac{p_t - \bar{p}}{s}, \quad (10)$$

$$\bar{p} = \frac{1}{n} \sum_{i=1}^n p_i, \quad (11)$$

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (p_i - \bar{p})^2}. \quad (12)$$

The standardized data set P' is divided into training set $P'_{tr} = \{p'_1, p'_2, \dots, p'_x\}$ and testing set $P'_{te} = \{p'_{x+1}, p'_{x+2}, \dots, p'_{x+y}\}$, $x + y = n$, $x < y$.

As the requirement for m kinds of spare parts is predicted based on the consumption data of m kinds of spare parts, the number of neural units in the input layer is m , and the number of neural units in the output layer is also m . The number of hidden layer neural units is $size_h$, theoretically the larger the number, the higher the prediction accuracy, but it will increase the amount of network calculations, which can be optimized and determined by the particle swarm algorithm.

3.3 Network training

Set the network training parameters, the number of training cycles $MaxEpochs$, the number of training data subsets $MiniBatchSize$, the prediction interval T , and the initial learning rate η . For the training set $P'_{tr} = \{p'_1, p'_2, \dots, p'_x\}$, take T time data $\{p'_1, p'_2, \dots, p'_T\}$ initiating from p_1 to calculate the network sequence output $\{\hat{y}(1), \hat{y}(2), \dots, \hat{y}(T)\}$ at time $1 \sim T$ through the forward calculation of equations (1)–(7). Then, check $\{\hat{y}(1), \hat{y}(2), \dots, \hat{y}(T)\}$ with $\{p'_2, p'_3, \dots, p'_{T+1}\}$ at time $2 \sim T + 1$ in the training set. Use the mean square error loss function (13) to calculate the error loss value.

$$E_t = \sum_{t=1}^n \text{sum}((\hat{y}(t) - p'_{t+1})^2). \quad (13)$$

According to the loss function value E_t , the reverse transfer algorithm of error data items [22] is used to calculate the adjustment values dU_f , dW_i , dU_i , dW_c , dU_c , dW_o , dU_o , dV , db_f , db_i , db_c , db_o , and db_v of the weights W_f , U_f , W_i , U_i , W_c , U_c , W_o , U_o , and V and the bias vectors b_f , b_i , b_c , b_o , and b_v . Continue to take T time data $\{p'_2, p'_3, \dots, p'_{T+1}\}$ initiating from p_2 to calculate the network timing output value $\{\hat{y}(2), \hat{y}(3), \dots, \hat{y}(T + 1)\}$ forwardly, then check it with the data $\{p'_3, p'_4, \dots, p'_{T+2}\}$ at time $3 \sim T + 2$, apply error loss function and reverse transfer algorithm to get the adjustment value of each weight and bias vector, respectively, accumulated with

the adjustment value of the previous moment. Follow this method in sequence. After $MiniBatchSize$ times calculation, the weights and bias vectors of the network are updated. The updated value is the cumulative adjustment value multiplied by the learning rate, such as $U_f = U_f + \eta \times dU_f$, and the adjustment value will return to zero after the update is completed. After $MiniBatchSize$ time data are calculated again, the network weights and bias vectors are updated again. Once the data reaches p'_{x-T+1} , one training process ends. After repeating $MaxEpochs$ training cycles, the network training is complete. In the training process, the improved Adam optimization algorithm [23] is used to adaptively adjust the learning rate η to make the network training converge as soon as possible, according to the gradient.

3.4 Network prediction

To test the effectiveness of the network, the trained LSTM recurrent neural network and the testing set data $P'_{te} = \{p'_{x+1}, p'_{x+2}, \dots, p'_n\}$ are used to predict data. Starting from p'_{x+1} , take T time data $\{p'_{x+1}, p'_{x+2}, \dots, p'_{x+T}\}$ to calculate the output $\hat{y}(x + T)$ at time $x + T$ according to the equations (1)–(7), continue to take T data from p'_{x+2} to calculate $\hat{y}(x + T + 1)$ until the output $\hat{y}(n - 1)$ at time $n - 1$ is completed. The prediction output set $Y = \{\hat{y}(x + T), \hat{y}(x + T + 1), \dots, \hat{y}(n - 1)\}$ is de-normalized to obtain the prediction data set P'' according to equation (13), and the network prediction is completed.

$$P'' = Y \times s + \bar{p}. \quad (14)$$

3.5 Parameter optimization

The LSTM recurrent neural network uses the training set data to train the network, optimizes, and adjusts the weight parameters and bias vectors of the input layer, hidden layer, and output layer to obtain a network structure suitable for the prediction object. After the network training is completed, use the testing set data to test the network prediction effect. In the procedure of LSTM recurrent neural network prediction and training, there are four key parameters that affect the quality of the algorithm, which are the number of hidden layer neural units $size_h$, the prediction interval T , the number of training data subsets $MiniBatchSize$, and the initial learning rate η . The influence of these parameters on the algorithm is complicated, and setting by experience

is often ineffective. Taking the minimum mean square error of the prediction data set P'' and the testing set data P'_{te} as the objective function, this article proposes to use the adaptive inertial weight particle swarm algorithm to optimize the four parameters, and use Matlab to implement the algorithm.

4 Calculation case

4.1 Experimental data and parameter settings

This article takes 48 months consumption data of three main types of maintenance spare parts of a maintenance

Figure 4: Consumption of three types of spare parts in a maintenance organization.

organization as an example to show the procedure of prediction. The consumption of three types of spare parts is shown in Figure 4.

The particle swarm algorithm is used to optimize the LSTM recurrent neural network to predict the requirement of equipment maintenance spare parts. The main initial parameter settings of the algorithm are shown in Table 1. Among them, in order to reduce the calculation time, the network training times is set as 100 when using the particle swarm to optimize the LSTM recurrent network parameters, and is set as 300 to enhance the prediction accuracy when using the optimal parameters to construct the network for prediction.

4.2 Simulation result analysis

With the minimum mean square error as the target, the particle swarm algorithm is used to perform 100 iterative calculations, in order to optimize the four key parameters of the LSTM recurrent neural network. The training process is shown in Figure 5. It can be seen that the algorithm converges after 58 iterations, and the optimal mean square error is 3.8524. The four key parameters of the LSTM recurrent neural network are preferably: $size_h = 275$, $T = 3$, $MiniBatchSize = 10$, and $\eta = 0.3187$.

The LSTM recurrent neural network is constructed using the four optimal parameters, and the network is trained 1,000 times with 36 months consumption data of three types of spare parts. The values of the loss function in the training process are shown in Figure 6.

It can be seen that the convergence of the algorithm is good, and the loss function value is low. Using 12 months consumption data to test the trained network, the comparison between the predicted value and the actual consumption value is shown in Figure 8, and the

Table 1: Algorithm parameter settings

	Parameter	Value
Particle swarm	Learning factor c_1, c_2	0.5, 0.5
	Maximum inertia weight w_{max} , minimum w_{min}	3, 0.2
	Number of iterations N_{iter}	100
	Number of populations pop_size	100
LSTM	Number of neural units in input layer $size_i$	3
	Number of neural units in output layer $size_o$	3
	Number of training cycles $MaxEpochs$ (optimization procedure)	100
	Number of training cycles $MaxEpochs$ (prediction procedure)	300
	Months of training set	36
	Months of testing set	12

Figure 5: The training process of PSO optimizing the key parameters of LSTM.

mean square error is 3.3611. The error of the spare parts prediction in August is relatively large because the equipment was suddenly used in large quantities during that period, which was inconsistent with the previous two years.

In order to verify the predominant prediction performance of the LSTM recurrent neural network, comparative experiments are performed. Four widely used neural networks currently, BP neural network, generalized regression (GRNN) neural network, wavelet neural network, and squeeze-and-excitation networks (SENet) are used to predict the requirement of spare parts too, using the same training set and testing set. After 1,000 times of network

Figure 6: Loss function values in LSTM recurrent neural network training.

Figure 7: Legend of Figures 8–11.

training, 12 months requirement for 3 types of maintenance spare parts was predicted, and the comparison between the 3 kinds of neural network prediction values and actual consumption values were obtained, as shown in Figures 9–12. The mean square errors of the four neural

Figure 8: Comparison of LSTM.

Figure 9: Comparison of BP neural network.

Figure 10: Comparison of GRNN.

Figure 12: Comparison of SENet.

Figure 11: Comparison of wavelet neural network.

networks are shown in Table 2. From the comparison of the predicted value and the actual consumption value curve and the mean square error value, it can be seen that the LSTM recurrent neural network has the highest prediction accuracy and has obvious advantages in predicting the requirement of maintenance spare parts with time series characteristics.

5 Conclusion

This article summarized the important significance and current research situation of equipment maintenance

Table 2: Comparison of the mean square error of four kinds of neural network

LSTM	BP	GRNN	Wavelet	SENet
3.3611	8.4722	6.5833	7.9444	4.5812

spare parts requirement prediction, analyzed the time series characteristics of equipment maintenance spare parts consumption data, and the principle and advantages of LSTM algorithm processing time series data, and proposed an equipment maintenance spare parts prediction method based on LSTM recurrent neural network. The procedure of algorithm implementation was designed. The methods of data standardization and application classification, the key issues of network training and network prediction as well as the construction procedures of network input layer, hidden layer, and output layer were expounded. It focused on the method of applying particle swarm algorithm to optimize the four important parameters of the LSTM recurrent neural network, including the number of hidden layer neural units, the prediction interval, the number of training data subsets, and the initial learning rate. Finally, the algorithm was implemented using Matlab programming. The algorithm was verified using 48 months consumption data of 3 types of maintenance spare parts of a certain unit, and the performance of the BP neural network, GRNN, wavelet neural network, and SENet were compared to verify the reliability and accuracy of the algorithm. The limitation of the method is that the complexity is relatively high, the time-consumption is relatively long, and it needs a lot of

data to support training. In the next step, it is necessary to further collect long-term and large-scale maintenance spare parts consumption data, and to improve the algorithm experimentally.

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