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Research Article

Substation Equipment Spare Parts' Inventory Prediction Model Based on Remaining Useful Life

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A large variety of high-value substation relay protection equipment occupies a considerable amount of inventory space and capital in electric power companies. To improve this problem, this study proposes an inventory prediction model based on the remaining useful life (RUL) of equipment. The model acquires the RUL data of equipment by using the support vector regression (SVR) algorithm, and then, by taking this data as the main factor and the environmental factors and human factors during the operation of equipment as secondary factors, the model can realize the prediction of relay protection equipment in the substation. At the same time, the nature of the enterprise and the requirements for safety inventory are considered. The comparison of calculation results and error analysis, as well as the calculation time, all indicate that the RUL-based inventory forecasting is the best one. This model not only has high prediction accuracy but also has strong stability and portability. The model can provide a strong decision basis for improving the inventory management of the enterprise, enhancing the resource allocation capability, and formulating the spare parts procurement plan under the condition that the spare parts inventory reaches the safety stock.

1. Introduction

Safety stock is an important topic in inventory management [1, 2], and its main role is to meet the uncertainty of supply and demand. The definition of safety stock varies from industry to industry. In power systems, the safety stock of spare parts means that the stock level should always be slightly redundant to the actual demand, in case there are no spare parts available when an unexpected event occurs. Spare parts inventory levels are often calculated based on certain historical data and forecasting models. The authors of [3, 4] have summarized the inventory research results of spares, and the forecasting techniques cover everything from early expert system models to the current artificial intelligence models.

The expert meeting method and the Delphi method are less practical and reliable due to their reliance on expert experience. However, this qualitative model, combined with other methods, has an excellent performance in forecasting [5–7]. With the development of computers and the demand for short-term and medium-term forecasting techniques, quantitative forecasting models have taken the dominant position, such as gray forecasting models [8, 9], linear regression [10] and nonlinear regression [11], and autoregressive moving average (ARMA) models [12–14]. These quantitative forecasting approaches tend to have certain data requirements and also have obvious advantages and disadvantages, such as an emphasis on model improvement to improve the prediction accuracy, but less consideration is given to the factors affecting the inventory, and the information contained in the data is not sufficiently mined. With the development of artificial intelligence, forecasting models based on AI techniques began to play an important role, such as machine learning [15, 16], deep learning [17–19], support vector machine (SVM) [20, 21], backpropagation (BP) neural networks [22, 23], and long short-term memory (LSTM) [24, 25]. These intelligent prediction techniques have played an important role in various industries with the help of excellent data processing capabilities.

There is also rich research on inventory forecasting for spare parts in power systems. Zhang [26] established a smart meter inventory demand forecasting model based on analyzing its fault characteristic and installing requirements, and an optimal management strategy [27] was developed. Ding [28] improved the BP neural network model based on the Adam optimization method to forecast the demand for materials in the Guizhou power grid, and the method can significantly reduce the error. In [25], an effective model based on the long short-term memory (LSTM) recurrent neural network was put forward to predict the requirement for maintenance of spare parts. Hamoud and Yiu [29] described a practical reliability model based on a stationary Markov process for assessing the number of spare parts. Yang [30] constructed a deep convolutional neural network based on the graph to realize multicriteria classification for spare parts, which could supply good decision support to control inventory.

As an integral part of the power grid, relay protection equipment has the main characteristics of being diverse, small in size, difficult to obtain monitoring data, and its service life is affected by various factors. Therefore, the advanced prediction techniques mentioned in the above literature, according to our review, found that few prediction models have been applied to this type of equipment. For this reason, in this study, on the basis of analyzing the characteristics of the equipment and its elimination records and safety inventory requirements of electric power enterprises, we make an innovative model of an inventory prediction algorithm according to the RUL of the equipment and applied it to the inventory management system of relay protection equipment in the Changzhou substation. The model implements the following functions:

(i) To improve the prediction accuracy of the model, this study fully considers the factors that have direct and indirect effects on the RUL of equipment; these factors are shown in Section 3.1

(ii) To reduce the computational difficulty, we define the new variable of the life course as the main variable to obtain the RUL of equipment

(iii) To meet the requirement of saving inventory cost and storage space under the condition of achieving inventory safety and to provide decision support for Changzhou Power Supply Company to realize spare parts procurement on a quarterly cycle

Section 1 of this study introduces the current research status of inventory forecasting models and inventory of spare parts in power companies. Section 2 is the inventory forecasting algorithm according to the remaining useful life of equipment, including the algorithm about obtaining the RUL of equipment with the aid of support vector regression and the prediction algorithm of spare parts based on the RUL. Section 3 is a case study for inventory prediction of the central processing unit (CPU) of a substation in Changzhou City. The portability of the model is illustrated by using the predictions for the liquid crystal display (LCD) and DC 220 V Power Supply (DCPS). The validity and stability of the model are indicated by comparing the RUL model with the LSTM, ARMA, support vector machine (SVM), and SVM + BP models. At the same time, the error analyses are given. Section 4 is the conclusions and the perspective.

2. Inventory Prediction Model on the Basis of RUL

The remaining useful life [31] plays an important role in many fields. It can provide strong support for upper-level decision-making, scientifically reduce the operating cost of the system, and enhance the reliability of the system. Especially, with the gradual maturity of AI technology, RUL has been successfully applied to many practical problems [32]. Figure 1 is the main ideation for this study; this framework can demonstrate our research steps.

In this section, we will discuss how to obtain the RUL of substation equipment by using SVR and the construction of an inventory prediction model based on the RUL.

2.1. Principle and Algorithm of RUL Based on SVR.

In machine learning [33, 34], SVR is a nonparametric regression model that determines the regression hyperplane by optimizing the distance to nearby support vectors. We first consider the regression hyperplane that achieves the remaining useful life.

For the given training set $D = \{(\mathbf{x}_1, y_1), t(\mathbf{x}_2, y_2)n, q \ldots h,_{(} x_m, y_m)\}$, $y_i \in (0, 1]$, since it is difficult to determine whether the training set is linearly divisible in the original space, let the division hyperplane be

$$f(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x}) + b, \tag{1}$$

where $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m)$, $\phi(\mathbf{x})$ is the eigenvector after mapping $\mathbf{x}$, $\mathbf{w} = \{w_1, w_2, \ldots, w_m\}^T$ is the weight vector, and b is the bias.

The problem of solving the regression hyperplane $f(\mathbf{x})$ can be transformed into the following optimization problem:

$$\min_{\mathbf{w},b} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^{m} l_\varepsilon (f(\mathbf{x}_i) - y_i), \tag{2}$$

where the penalty coefficient $C > 0$ and l_ε is the insensitivity loss function and its expression is

$$l_\varepsilon(z) = \begin{cases} 0, & \text{if } |z| \le \varepsilon, \\ |z| - \varepsilon, & \text{otherwise.} \end{cases} \tag{3}$$

Introducing the slack variables ξ and $\widehat{\xi}$ to normalize (2), we can obtain

$$\begin{gathered} \min_{\mathbf{w},b,\xi,\widehat{\xi}} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^{m} \left(\xi_i + \widehat{\xi}_i\right), \\ f(x_i) - y_i \le \varepsilon + \xi_i, \\ \text{s.t, } f(x_i) - y_i \ge \varepsilon + \widehat{\xi}_i, \\ \xi \ge 0, \quad \widehat{\xi} \ge 0,\ i = 1, 2, \ldots, m. \end{gathered} \tag{4}$$

Introducing the Lagrange multipliers $\mu_i \ge 0$, $\widehat{\mu}_i \ge 0$, $\alpha_i \ge 0$, $\widehat{\alpha}_i \ge 0$, we construct the Lagrange function of (4) as follows:

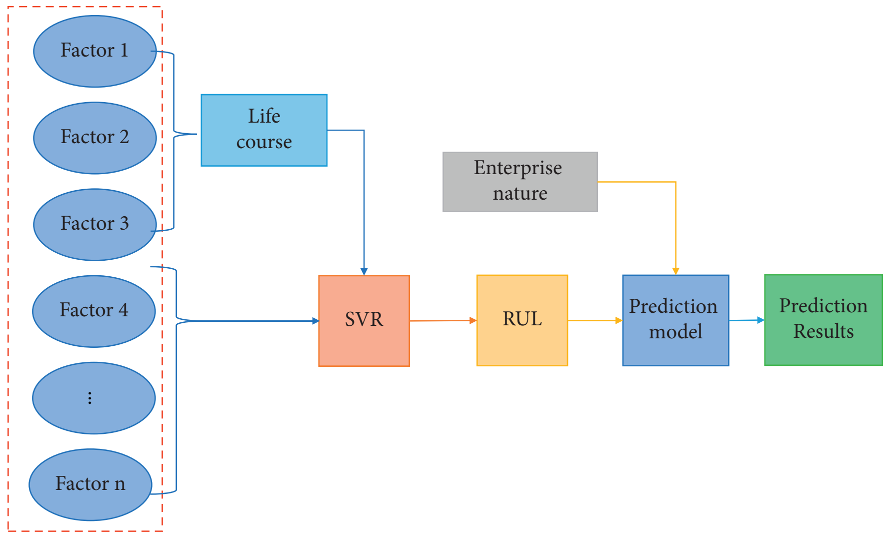

Figure 1: The main ideation and framework of this study.

$$
\begin{aligned}
L\left(\mathbf{w}, \mathrm{b}, \boldsymbol{\mu}_i, \widehat{\mu}_i, \xi_i, \widehat{\xi}_i, \boldsymbol{\alpha}_i, \widehat{\alpha}_i\right) = {} & \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{m}\left(\xi_i + \widehat{\xi}_i\right) \\
& - \sum_{i=1}^{m}\mu_i\xi_i - \sum_{i=1}^{m}\widehat{\mu}_i\widehat{\xi}_i \\
& + \sum_{i=1}^{m}\alpha_i\left(f\left(x_i\right) - y_i - \varepsilon - \xi_i\right) \\
& + \sum_{i=1}^{m}\widehat{\alpha}_i\left(f\left(x_i\right) - y_i - \varepsilon + \widehat{\xi}_i\right).
\end{aligned} \tag{5}
$$

Considering (1), let the derivatives of $L(\mathbf{w}, \mathrm{b}, \mu_i, \widehat{\mu}_i, \xi_i, \widehat{\xi}_i, \alpha_i, \widehat{\alpha}_i)$ with respect to $\mathbf{w}, \mathrm{b}, \xi_i, \widehat{\xi}_i$ be zeros; we can obtain

$$\mathbf{w} = \sum_{i=1}^{m}\left(\widehat{\alpha}_i - \alpha_i\right)\mathbf{x}_i, \tag{6}$$

$$0 = \sum_{i=1}^{m}\left(\widehat{\alpha}_i - \alpha_i\right), \tag{7}$$

$$C = \alpha_i + \mu_i, \tag{8}$$

$$C = \widehat{\alpha}_i + \widehat{\mu}_i. \tag{9}$$

Substituting equation (5)–(8) into (5), we obtain the dual programming problem as follows:

$$
\begin{aligned}
& \max_{\boldsymbol{\alpha}, \widehat{\alpha}}, \sum_{i=1}^{m} y_i\left(\widehat{\alpha}_i - \alpha_i\right) - \varepsilon\left(\widehat{\alpha}_i + \alpha_i\right) - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}\left(\widehat{\alpha}_i - \alpha_i\right)\left(\widehat{\alpha}_j - \alpha_j\right)\mathbf{x}_i^T\mathbf{x}_j, \\
& \text{s.t,}\ \sum_{j=1}^{m}\left(\widehat{\alpha}_i - \alpha_i\right) = 0, \\
& 0 \le \widehat{\alpha}_i,\ \alpha_i \le C.
\end{aligned} \tag{10}
$$

With the KKT condition satisfied, the optimal solution of (1) can be obtained as

$$f(\mathbf{x}) = \mathbf{w}^{*T}\phi(\mathbf{x}) + b^*. \tag{11}$$

(11) is the regression hyperplane used to calculate the remaining useful life.

2.2. Variables and Data Processing. Let the data matrix of a certain type of equipment be $\mathbf{Z} = (z_{ij})_{N\times 10}$, where the ith row z_i of $\mathbf{Z}$ denotes the data vector of the ith device of that class of devices and N is the number of devices that have been eliminated. The name and type of the variables in z_i are shown in Table 1.

To facilitate the description, several variables are introduced, and the notation and description of the variables are shown in Table 2.

To improve the accuracy of the prediction results, firstly, the data $\mathbf{Z}$ need to be cleaned, and let $U_l(i) = z_i(9) - z_i(8)$ be the days of usage of equipment, and the mean μ and variance σ^2 of U_l are calculated, and the singular values are screened out using the Z-score method; then, the

Table 1: Variables, notations, and types.

Variables	Notations	Types
Manufacturers	$z_i(1)$	Text variable
Substation name	$z_i(2)$	Text variable
Interval	$z_i(3)$	Text variable
Device	$z_i(4)$	Text variable
O&M shift*	$z_i(5)$	Text variable
Temperature (°C)	$z_i(6)$	Numeric variables
Humidity (hPa)	$z_i(7)$	Numeric variables
Installation date	$z_i(8)$	Time variables
Date of damage	$z_i(9)$	Time variables
Design life/days	$z_i(10)$	Numeric variables

* O&M, operations and maintenance shift.

Table 2: Variables and descriptions.

Notations	Descriptions
U_l	Days of usage of equipment/day
D_{pl}	RUL prediction value of equipment/days
$x_i(8)$	The design life course of equipment
y_{ir}	The actual life course of equipment
D_t	Current date
D_{dl}	Left days of equipment by design life/day
D_{pb}	Predicted damage date of in-service equipment

elimination records containing the singular values are deleted. The formula of the Z-score is as follows:

$$\left|\frac{U_l-\mu}{\sigma}\right| \le z_\theta. \tag{12}$$

Generally, the threshold $z_\theta \in (1,3)$. The data satisfying the above equation are retained, and the new data set matrix is still denoted as $\boldsymbol{Z} = (z_{ij})_{M\times 10}$, where $M \le N$.

Next, we make certain variables labeled and also define a new variable named life course.

The textual variables $z_i(1)$ to $z_i(5)$ are labeled with the regular numerical values and are denoted as $x_i(1)$ to $x_i(5)$. The numerical variables $z_i(6)$ and $z_i(7)$ are denoted as $x_i(6)$ and $x_i(7)$. To reduce the dimensionality of the data and simplify the calculation, the life history course $x_i(8)$ are constructed by using the installation date $z_i(8)$, damage date $z_i(9)$, and design to life $z_i(10)$ as follows:

(i) % M is the number of elimination records of a class of components after cleaning
(ii) % I is the number of interval days
(iii) $J_i = z_i(9) - z_i(8)/I$
(iv) for i from 1 to M
(v) $j=1$
(vi) $D_t = z_i(8) + I$ % Date after installation I days
(vii) while $now < z_i(9)$ % now Indicates the current date
(viii) $r = \sum_{k=1}^{i-1} J_k + j$
(ix) $x_i(8) = D_t - z_i(8)/z_i(10)$ % Design life course of equipment
(x) $y_{ir} = D_t - z_i(8)/z_i(9) - z_i(8)$ % Actual life course of equipment
(xi) $\mathbf{x}_i = (x_i(1), x_i(2), x_i(3), x_i(4), x_i(5), x_i(6), x_i(7), x_i(8))$ % update variable symbols
(xii) $j=j+1$
(xiii) $now = now + I$

where $z_i(9) - z_i(8)$ is expressed by the number of days. If the ith device is active, take $z_i(9)$ means the current date.

Then, the processed data matrix for this type of device is obtained as $\mathbf{X} = (\mathbf{x}_{ij})_{N\times 8}$. The data of the ith device are

$$\mathbf{x}_i = (x_i(1), x_i(2), x_i(3), x_i(4), x_i(5), x_i(6), x_i(7), x_i(8)). \tag{13}$$

2.3. Computation of RUL. Under the above theory and its data characteristics, Algorithm 1 is constructed to predict the RUL of equipment.

With Algorithm 1, the number of days of the RUL of the kth in-service device can be calculated as $D_{pl}(k)$.

2.4. Algorithm for Inventory Forecasting of Spare Parts by RUL. Once the RUL of an in-service device is obtained, we can construct Algorithm 2 to predict the inventory. The main idea of Algorithm 2 is to consider how many components have an RUL less than T in a prediction period T. Also, a correction function is added for tuning to prevent over-prediction and to protect the safety stock.

3. Experiment and Analyses

3.1. Elimination Record. The data on the defect elimination records stored in Changzhou Power Supply Company contain 10 field variables, which are listed in Table 1. The spare parts in this research are installed in relay protection equipment of the substation. They share the following common features:

(i) A wide variety and distribution, high value, and integration.
(ii) It is difficult to obtain monitoring data since they are board-like devices of small size. The operation and maintenance (O&M) processes require a lot of manpower. It has a long procurement cycle.
(iii) Service life is influenced by many kinds of factors listed in Table 1.

3.2. Prediction Results Based on RUL, Comparison, and Its Error. First, we make forecasts for the CPU inventory. Combining with the proposed procurement cycle of Changzhou Power Supply Company, we set the prediction period $T = 90$ days and the interval days $I = 10$ days and make $z_\theta = 2.5$ in the Z-score during data screening and parameter $s = 2$ in the correction function $Q_s(t)$. Figure 1 shows the prediction results of CPU spare parts based on the RUL.

In Figure 2, the horizontal coordinate indicates the quarter and the vertical coordinate indicates the prediction result about CPU. From it, we can see that the prediction curve of the CPU with the quarterly cycle has almost the same trend as the real value, which means that the RUL-

Input: $\mathbf{x}_i = (x_i(1), x_i(2), x_i(3), x_i(4), x_i(5), x_i(6), x_i(7), x_i(8))$.
Output: the RUL value of the kth component $D_{pl}(k)$.
Step 1. The data matrix $\mathbf{x}$ is assigned to training set $\mathbf{x}_{\text{train}}$ and test set $\mathbf{x}_{\text{test}}$ in the ratio of 4 : 1.
Step 2. Get the prediction model by the training data. The regression hyperplane expression is obtained by inputting a certain class of components processed data $\mathbf{x}_{\text{train}}$ into equation (2), i.e., $f(\mathbf{x}) = \mathbf{w}^{*T}\phi(\mathbf{x}) + b^*$.
Step 3. Validity test, let T_{test} be the number of rows of test data, for the given $\Delta > 0$, if $1/T_{\text{test}} \sum_{r=1}^{T_{\text{test}}} |\mathbf{y}_{\text{test}}(r) - f(\mathbf{x}_{\text{test}}(\mathbf{r}))| < \Delta$. go to Step4, otherwise, go to (2), and adjust the penalty coefficients C and ε until they are satisfied.
Step 4. Substitute the kth data of the in-use device$\mathbf{x}_k = (x_k(1), x_k(2), x_k(3), x_k(4), x_k(5), x_k(6), x_k(7), x_k(8))$ into (14) and output $f(\mathbf{x}_k)$. This is the value of the life course of the actual life of the kth component.
Step 5. Calculate the damage date $D_{pb}(k)$ of the kth in-service spare part: $D_{pb}(k) = x_k(8) + D_t - x_k(8)/f(\mathbf{x}_k)$.
Step 6. Compute the number of days $D_{pl}(k)$ left in the life of the kth in-service spare part: $D_{pl}(k) = D_{pb}(k) - D_t$.

Algorithm 1: Computation of RUL by SVR.

Input : RUL of the kth equipment $D_{pl}(k)$
Output : the demand for spare parts Q in the next cycle T.
Step 7. Calculate the number of days remaining in the design life of the kth component $D_{bl}(k)$: $D_{bl}(k) = x_k(8) + z_k(10) - D_t$.
Step 8. Set the correction function to$Q_s(t) = 1 - \tanh st = 2e^{-st}/1 + e^{-st}$, $\quad (s > 1,\ t \in R)$
Step 9. Predicting the inventory level of a certain type of component spare parts, the algorithm pseudocode is as follows:

(i) % Q is the demand for a class of components.
(ii) % Sum is the number of components of this class being operated in the system
(iii) % T is the forecast period
(iv) $Q = 0$
(v) for $k = 1$: sum
(vi) If $D_{pl}(k) \le T$
(vii) $Q = Q + 1$
(viii) If $D_{pl}(k) > T$ and $D_{bl}(k) \le T$
(ix) $Q = Q + Q_s(t)$
(x) Output Q % the demand for spare parts in the next cycle.

Algorithm 2: Prediction algorithm by RUL.

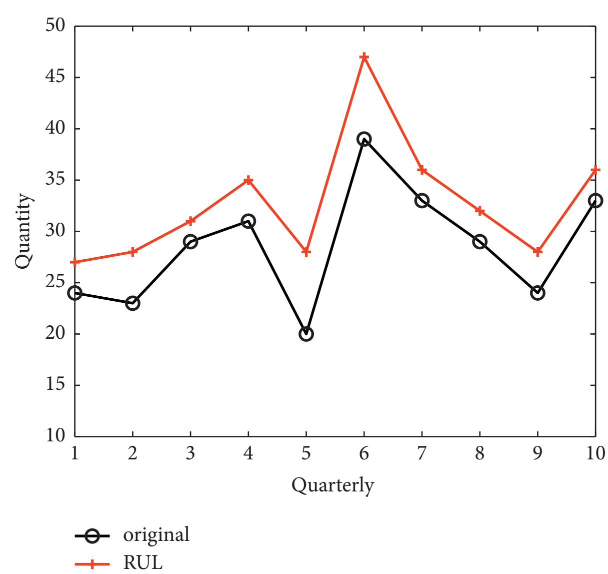

Figure 2: The prediction results of CPU based on RUL.

based prediction method is effective. In the graph, we will also notice that the predicted value is slightly larger than the true value, which is intended to make the spare parts slightly more available in case there are no spare parts available when an unexpected event occurs, i.e., it is beneficial to the stability of the power system.

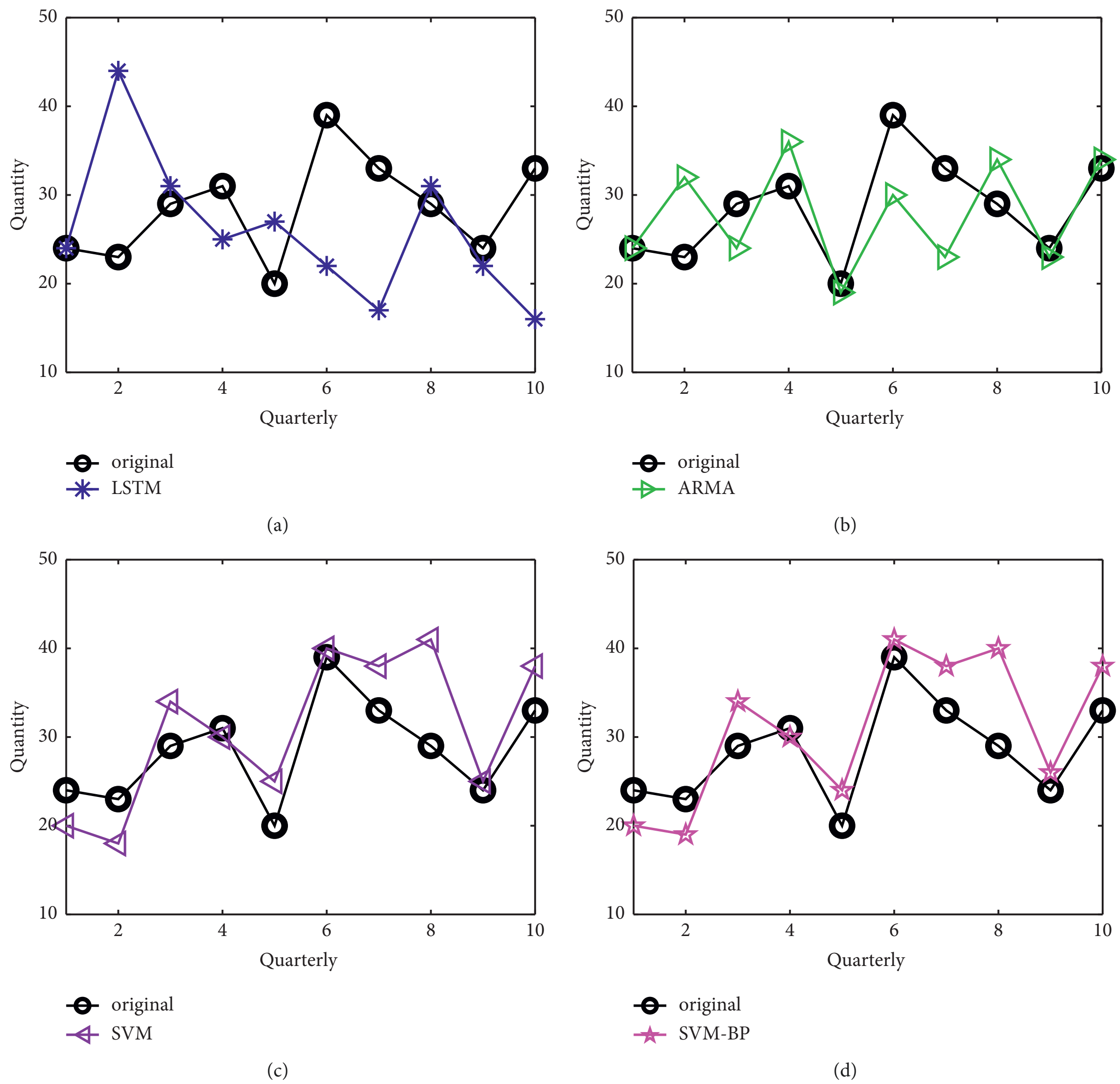

Figure 3: (a) to (d) The prediction results of the CPU based on LSTM, ARMA, SVM, and BP-SVM, respectively.

Second, to illustrate the effectiveness of the algorithm, we employ LSTM, ARMA, SVM, and a combined model of BP and SVM to predict the CPU inventory, and a comparison of the predicted results with the true values is shown in Figure 3.

As we can see from Figure 3, although the prediction results of these four forecasting models are the same as the true values in some quarters, the overall prediction results are not suitable for electric power companies mainly because the difference between the predicted and true values is positive and negative, which leads to the inability of Changzhou Power Supply Company to achieve the goal of purchasing by quarters, and the safe and stable operation of the electric power system cannot be guaranteed under such prediction results.

Finally, the errors of five forecasting models are compared, the root mean square error (RMSE) and mean absolute error (MAE) corresponding to the forecast values under different models are discussed, and the formulas are as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_a(i) - x_p(i)\right)^2},$$
$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|x_a(i) - x_p(i)\right|, \tag{14}$$

where x_p and x_a are the predicted and true values, respectively. If the values of RMSE and MAE of an algorithm are smaller, it means that the algorithm is more effective. The RMSE and MAE of the five method prediction methods are shown in Table 3.

From Table 3, it can be seen that the RUL-based prediction results have the smallest RMSE and MAE among the above five prediction models. It further illustrates the effectiveness of RUL-based CPU prediction.

Table 3: RMSE and MAE of CPU prediction results on different prediction models.

	RUL	LSTM	ARMA	SVM	SVM-BP
RMSE	4.7434	11.7132	5.8310	5.3666	5.0299
MAE	4.3201	9.0611	4.6517	4.411	4.3603

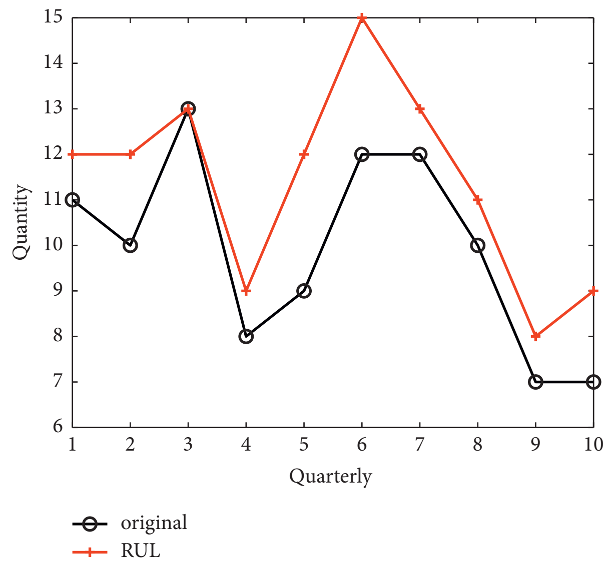

Figure 4: The prediction results of LCD based on RUL.

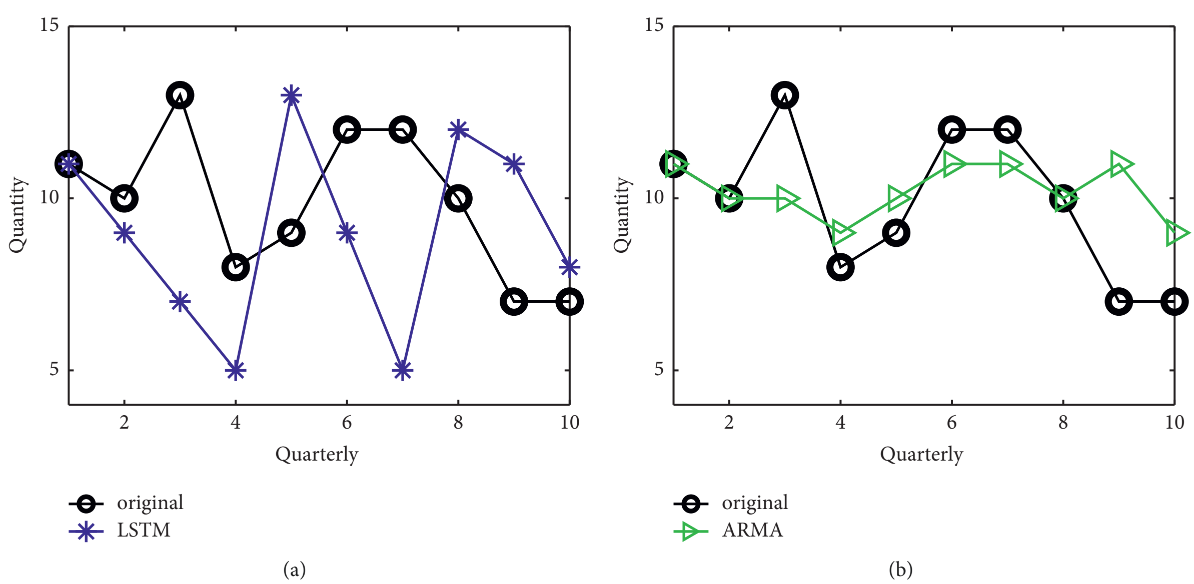

Figure 5: Continued.

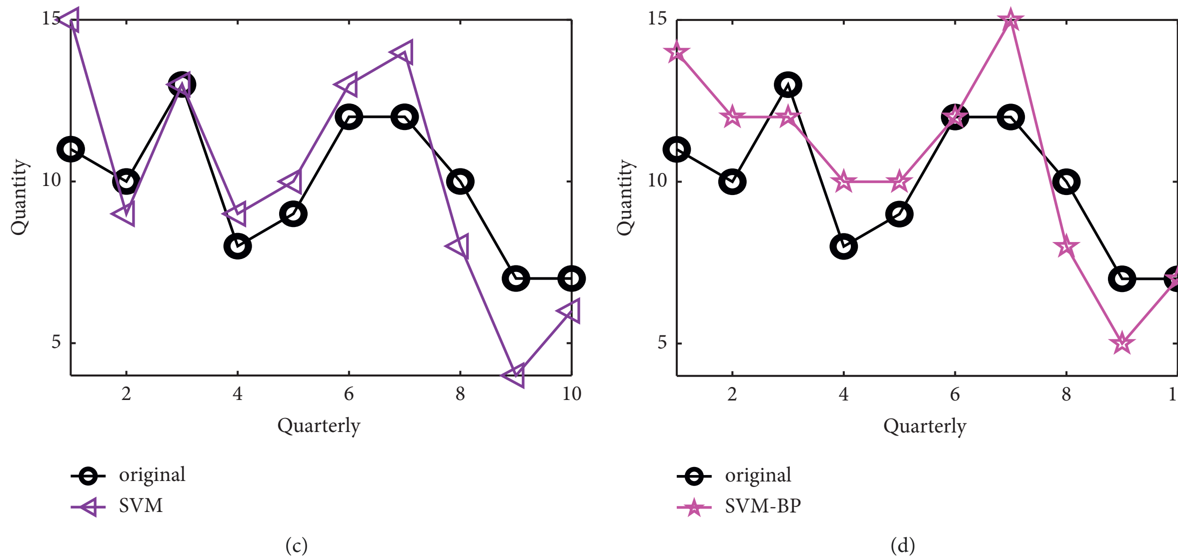

Figure 5: (a) to (d) Prediction results of LCD based on LSTM, ARMA, SVM, and BP-SVM, respectively.

3.3. Portability and Stability. There are many other CPU-like devices in substations that have similar characteristics to CPUs. To exemplify the portability of the model, we apply the model to the LCD and DCPS inventory predictions, respectively. The parameter settings are unchanged. Figure 4 shows the prediction results based on the RUL model for LCD. Figure 5 presents the inventory prediction results for LCD based on LSTM, ARMA, SVM, and BP-SVM. Figure 6 illustrates the prediction results of DCPS based on the RUL model. Figure 7 demonstrates the inventory prediction results for DCPS based on LSTM, ARMA, SVM, and BP + SVM. Table 4 is the error comparison of the responses.

From Figures 4 and 6, we can notice that the trend of the predicted and true values is almost the same, and the predicted values are also slightly larger than the true values, thus indicating that the RUL-based prediction model has strong portability and also strong stability. This prediction model is suitable for the corporate requirements of Changzhou Power Supply Company and the requirements for power system stability.

From Figures 5 and 7, the predicted and true value curves intersect several times. Although, in some quarters, the predicted results are almost the same as the true ones, this does not satisfy the enterprise requirements.

In Table 4, it can be found that the RMSE and MAE of the forecast results based on RUL are the smallest, except for the MAE of the forecast based on the ARMA model for LCD. For this exception, the result of our analysis is that LCDs are durable equipment in substations with a long service life, resulting in small data for elimination records and data with a strong linear nature, while the ARMA model has a high advantage in dealing with this type of prediction problem.

The purpose of forecasting on a quarterly cycle is to provide a decision basis for the procurement of spare parts for Changzhou Power Supply Company to save storage space as well as improve capital utilization.

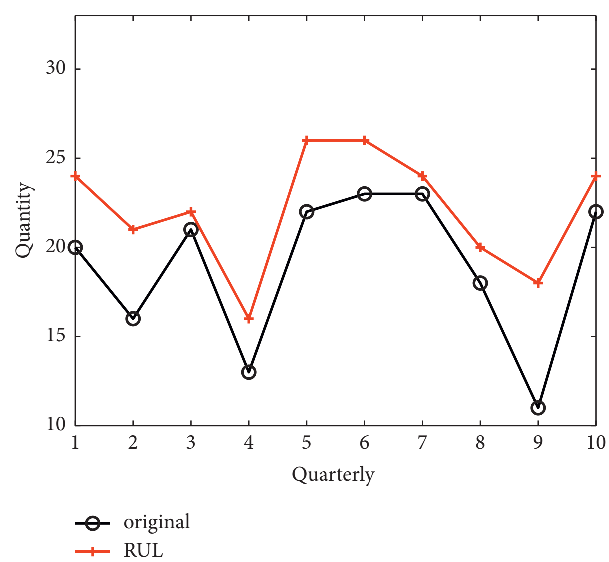

Figure 6: The prediction results of DCPS based on RUL.

3.4. Computation Time. The elapsed time of a model is affected by several aspects, such as the complexity of the algorithm, the dimensionality of the variables, and the code, and therefore, it is often used as a metric to assess the efficiency of the model. In this study, the elapsed time of the five algorithms involved is statistically measured, and the results are shown in Figure 8.

Figure 8shows the time consumption for the computation of the RUL-based prediction model is not the most or the least. Combined with the previous prediction results, we can consider this time consumption to be acceptable for the following reasons: (1) For this study, we are pursuing the accuracy of the prediction and the conformity of the prediction results to the nature of the enterprise; (2) the engineering environment in which the algorithm is applied is not in a time-critical circumstance but has a very sufficient amount of time.

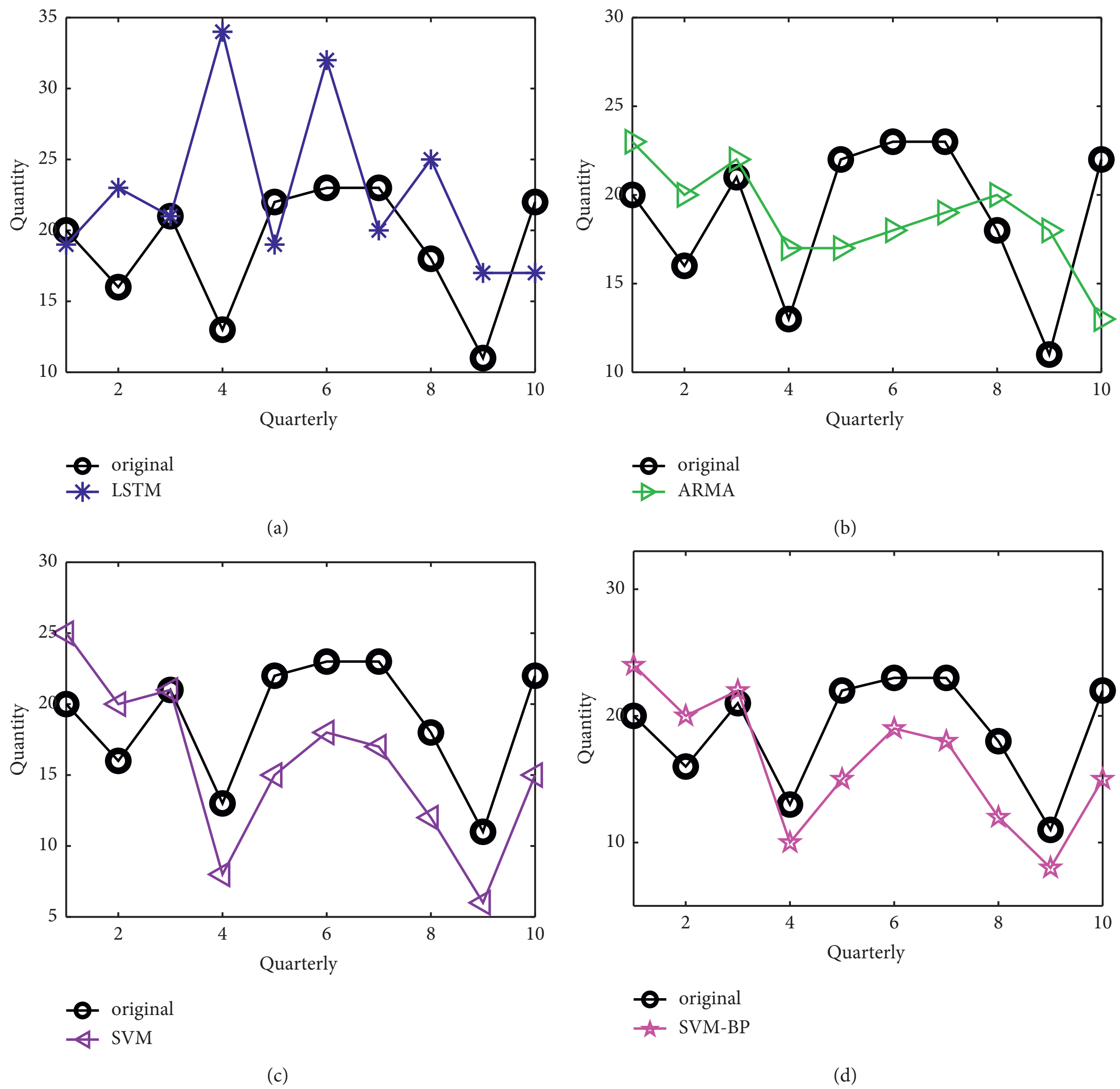

Figure 7: (a) to (d) Prediction results of DCPS based on LSTM, ARMA, SVM, and BP-SVM, respectively.

Table 4: Comparison of the errors of different models for LCD and DCPS prediction results.

		RUL	LSTM	ARMA	SVM	SVM-BP
LCD	RMSE	1.7607	3.7757	1.8166	1.9494	1.8974
	MAE	1.5123	3.2411	1.3301	1.6221	1.6000
DCPS	RMSE	3.6606	8.3666	4.9193	5.3479	4.7539
	MAE	3.202	6.2817	4.4709	5.01	4.4212

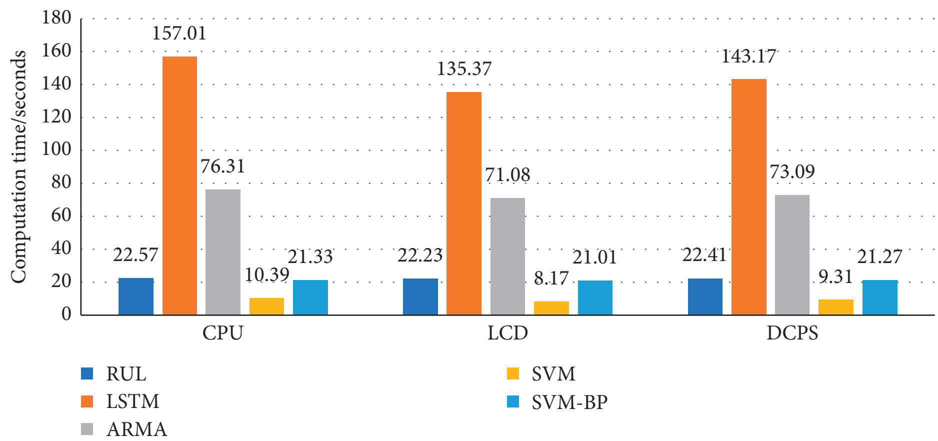

Figure 8: Computation time.

4. Conclusions and Perspective

In this study, a spare parts inventory forecasting model based on the remaining useful life of in-service equipment is proposed for the nature of electric power company enterprises, spare parts characteristics, and data. From the results of the case study, the model is suitable for inventory forecasting in electric power companies. The comparison of the model, the analysis of the error, and the computation time illustrate the validity, stability, and portability of the model.

According to the forecasting algorithm, the quarterly cycle is used for forecasting, which avoids the randomness of data brought by a small cycle and the large forecast error caused by a large cycle. At the same time, the quarterly cycle does not affect the annual procurement plan, while inspiring us to provide a feasible procurement proposal, i.e., to pay and supply according to the quarter, which can save inventory space and reduce holding costs.

The value of the forecasting model used in this study is reflected in three aspects: (1) accurate calculation, portability, and stability; (2) improving inventory management capability and saving inventory cost and storage space; (3) the model idea has certain generalizations, such as applying to the primary variable equipment of power system and enriching the whole life cycle management of power equipment.

The inability to obtain monitoring data makes it difficult to operate and maintain (O&M) relay protection equipment, and usually, routine maintenance does not reduce the failure rate of the device. Currently, the best maintenance strategy is predictive O&M [35–37]. An essential prerequisite for predictive O&M is to have information about the status of the health of the equipment, and the remaining useful life is an influential parameter for assessing the operational status of equipment. Therefore, we can utilize RUL to assess the health of equipment and provide a reliable basis for predictive maintenance.

Data Availability

All data included in this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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