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# Power Material Demand Forecasting Based on LSTM and Random Forecast

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**Abstract.** This paper takes an electric power company as a case study. Through actual investigation and analysis of the data provided by the company, we found that the material demand forecast of the company is not accurate enough, so that the company cannot effectively arrange the material purchase, resulting in a large backlog of inventory. To improve the reliability and accuracy of the power material demand forecast of the company, this paper proposes a combined forecasting model which combines Long Short-Term Memory Network (LSTM) model and Random Forest (RF) algorithm to predict power material demand. First, the LSTM model is used for preliminary prediction, and then RF algorithm is used to further predict and optimize the residual of LSTM prediction, so as to improve the overall prediction effect. Finally, the combined prediction model proposed in this paper is compared with the single LSTM model and RF algorithm, and it is verified that the combined prediction model has higher prediction accuracy. The research on the demand forecast provides a valuable reference for the company to make material purchase plan and solve the problem of high inventory, and affords a certain reference for the material demand forecast of many similar industries.

**Keywords.** Demand forecasting, LSTM, random forest, power material, combined forecasting model

## 1. Introduction

In recent years, strengthening inventory management has become a key measure for many companies to reduce operating costs, prevent unsalable assets, improve resource allocation efficiency, and enhance market competitiveness. How to improve the accuracy of power material demand forecast, and how to develop more scientific and reasonable inventory strategy, so as to reduce inventory costs, is a big problem for many companies [1,2].

In the field of demand forecasting, there are two main kinds of methods: statistics and machine learning algorithms. Typical statistical methods include time series analysis, gray prediction model, etc. Among machine learning algorithms, typical applications include linear regression (LR), differential autoregressive moving average (ARIMA), neural networks, support vector machines (SVM), extreme gradient boosting (XGBoost), and other algorithms [3]. Feng et al. [4] proposed the ARMIA-XGBoost-LSTM weighted combination algorithm, and concluded that the multivariate prediction method of weighted combination is more accurate. Moghar et al. [5] proposed a recursive neural network (RNN) based on LSTM to predict the future stock market value. The results show that LSTM has high prediction accuracy because it can

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track the evolution of the opening price of assets. Yadav et al. [6] developed an LSTM model and optimized the LSTM model by comparing stateless and stateful models and adjusting the number of hidden layers. The results show that for time series prediction problems, stateless LSTM model is more popular due to its higher stability. Mehtab et al. [7] constructed four deep learn-based regression models for predicting stock prices by using long short-term memory (LSTM) networks, and optimized the hyperparameters of the LSTM model using grid search technology. The results clearly show that, the single variable model based on LSTM is the most accurate model to predict the opening price of the next week with the data of the previous week as the input. Feng [8] proposed a model construction scheme using Ridge regression method to mix support vector regression (SVR) and BP neural network, and carried out automatic optimization of key parameters of SVR model through particle swarm evolution (PSO) algorithm. Experiments showed that the prediction accuracy of the hybrid prediction model was higher than that of the single SVR and BP models. Cai et al. [9] proposed a fault classification method based on the improved whale optimization algorithm to optimize the least square support vector machine (LSSVM), and the results showed that the proposed method had better fault classification performance and higher accuracy. Li [10] proposed an improved SVR short-term traffic flow prediction model, and experimental results show that the improved algorithm has the lowest classification error rate (3.22%). Hou [11] combined ARIMA and SVR models to establish a combined forecasting model and found that the combined forecasting model has better forecasting effect on demand data with volatility. Jing et al. [12] established LGB-LSTM-DRS local optimal fusion prediction model by introducing LightGBM, a lightweight implementation algorithm based on Gradient Decision Enhancement Tree (GBDT), and selecting process fusion method (DRS) as a dynamic regression device to search for local optimal fusion method based on k-nearest neighbor algorithm. Compared to LR, GBDT, and Random Forest (RF) models, it is found that the proposed model has the best performance. Liu et al. [13] used difference and nonlinear perturbation to optimize the whale algorithm, and then used SVM optimized by whale algorithm for prediction. Elsaraiti et al. [14] used ARIMA model to forecast future electricity consumption. The results show that the accuracy and efficiency of the model are relatively high. Liu et al. [15] proposed a short-term PV power generation prediction model based on whale optimization algorithm to optimize support vector machine parameters. The prediction results of the optimized algorithm model are compared with those of SVM, PSO-SVM and ARIMA. The results show that the WOA-SVM algorithm can effectively improve the accuracy of short-term PV power prediction.

In view of the issue that Long Short-Term Memory Network (LSTM) is easy to overfit when dealing with small sample data and difficult to learn long-term dependence relationship in time series prediction, this paper proposes a combined prediction model by combining LSTM and RF, to realize the forecast of the demand for power materials. RF can well deal with nonlinear dependence relationship in time series and has strong anti-overfitting ability. The proposed method fully integrates the advantages of the two methods, which can improve the prediction accuracy and provide more reliable decision support for power grid companies.

## 2. Data Preprocessing and Model Evaluation

### *2.1. Data Preprocessing*

The data used in this paper are all provided by an electric power company, including 153,407 records of ex-warehouse data, 80,110 records of im-warehouse data, and 80,110 records of in-warehouse data from January to August 2023. There are 4,517 materials in 13 categories. Because the lead time of most materials of the company is two weeks, this paper divides the data into 17 cycles for demand forecasting. Meanwhile, we select 95 materials that have both ex-warehouse and im-warehouse records within the 17 cycles for forecasting analysis. To be specific this paper takes the materials of "500009917" (infrared thermal imaging instrument), "500023540" (chainsaw), and "500023645" (insulation electrical tool set) as examples to present the analysis results.

### *2.2. Model Evaluation*

In this study, mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are used to evaluate the prediction performance. The evaluation score is the smaller the better. The calculation formulas of these metrics are as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(y_t - z_t\right)^2 \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - z_t\right)^2} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|y_t - z_t\right| \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - z_t}{y_t}\right| \times 100\% \tag{4}$$

Where $y_t$ is the actual value at time $t$, $z_t$ is the predicted value at time $t$, and $n$ is the length of the time series.

In order to eliminate the influence of different orders of values on the evaluation metrics, and to more intuitively reflect and compare the advantages and disadvantages of different prediction models, the values of each feature of these materials are normalized according to MinMaxScaler. After normalization, each value is in [0, 1].

## 3. Demand Forecast

### *3.1. Demand Forecast Based on LSTM*

LSTM is a special type of Recurrent Neural Network (RNN), which controls the accumulation rate of information by introducing a gating mechanism, thereby improving the long-term dependence problem of the original RNN. At present, it is widely used in time series prediction scenarios such as text generation, machine translation, speech recognition, image description, and video annotation.

In this work, the number of units in the LSTM layer is 64. The output layer is a fully connected layer. The Adam optimizer is selected in training, and its default learning rate is 0.001. The loss function is represented by MSE, and the training iteration times are 1000 rounds. The batch size is 1, and other parameters are the default values.

Figure 1 shows the change of MSE value during 1000 training sessions. The horizontal axis represents the number of training sessions, while the vertical axis denotes the MSE value. It can be seen that MSE continues to decrease with the increase of training sessions until it approaches 0, indicating that the training process is convergent.

In this paper, LSTM model is used to fit the original data of the three materials of "500009917", "500023540", and "500023645", and the results are shown in Figures 2, 3, and 4, respectively. It can be seen that LSTM model has achieved good results in the prediction of electric power materials.

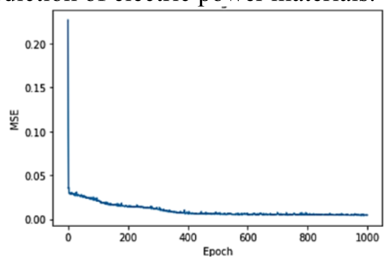


**Figure 1.** MSE of LSTM model training process.

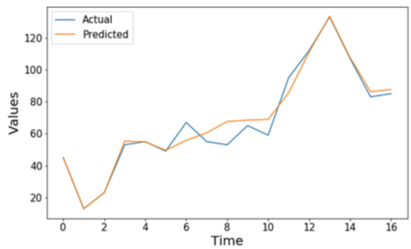


**Figure 2.** Prediction results of material "500009917" based on LSTM.

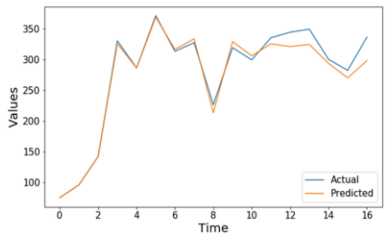


**Figure 3.** Prediction results of material "500023540" based on LSTM.

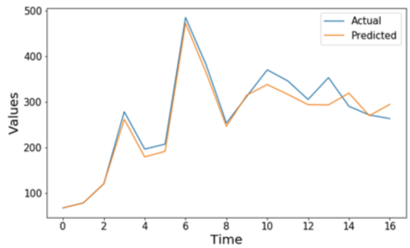


**Figure 4.** Prediction results of material "500023645" based on LSTM.

When LSTM model is used to forecast different materials, there are obvious differences in the fitting curves, and there are some cases that the individual prediction point of a certain material is not effective. The prediction effect of "500023540" obviously better than the other two materials. However, in general, the average error is small.

As shown in Table 1, the average values of MSE, RMSE, MAE, and MAPE for the above three materials are 2.31, 4.74, 2.81, and 3.87, respectively. From the overall situation, the prediction effect is quite ideal.

**Table 1.** Prediction accuracy of LSTM model for three materials.

| Materials | MSE (×0.001) | RMSE (×0.01) | MAE (×0.01) | MAPE (%) |
|---|---|---|---|---|
| 500009917 | 3.33 | 5.77 | 3.15 | 5.57 |
| 500023540 | 1.5 | 3.88 | 2.51 | 2.29 |
| 500023645 | 2.09 | 4.57 | 2.78 | 3.75 |
| average | 2.31 | 4.74 | 2.81 | 3.87 |

### *3.2. Demand Forecast Based on RF*

RF is a classic Bagging model whose weak learner is the decision tree model, which is often used for regression and classification tasks. It does this by building multiple decision trees and making regression by combining the prediction results of these trees. Compared to a single decision tree model, RF integrates multiple decision trees, and thence its prediction is more accurate and not prone to overfitting.

The number of decision trees is an important factor affecting the performance of RF. More decision trees generally improve the performance of the model, but also increase the computational cost. In order to set a reasonable number of decision trees and improve the prediction effect of RF, we experimentally determine the number of decision trees in a certain range.

Figure 5 shows that when the number of decision trees is 5, the MSE of material "500009917" is the smallest, and Figure 6 shows the corresponding prediction results of RF. Figure 7 shows that the number of decision trees for "500023540" should be set to 10. Figure 8 shows the corresponding prediction results of RF. Figure 9 shows that the number of decision trees for "500023645" should be set to 30 However, considering that there is only little difference of MSE when the number of decision trees is set to 15 and 30, and larger number of decision tree is more time consuming, the number of decision trees for material "500023645" is set to 15. Figure 10 shows the corresponding prediction results of RF.

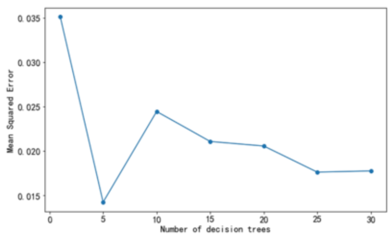


**Figure 5.** MSE for material "500009917".

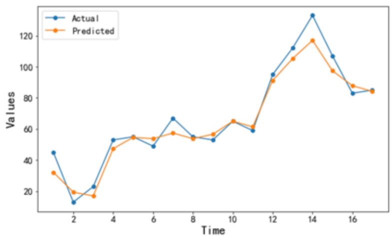


**Figure 6.** Prediction results of material"500009917" based on RF.

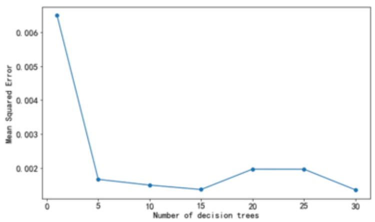


**Figure 7.** MSE for material "500023540".

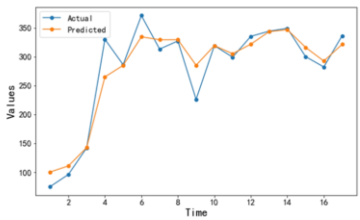


**Figure 8.** Prediction results of material "500023.

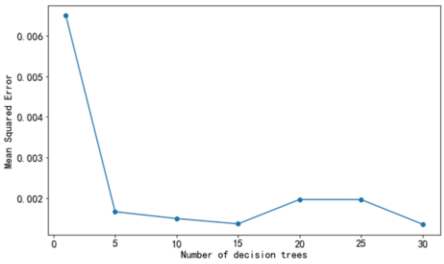


**Figure 9.** MSE for material "500023645".

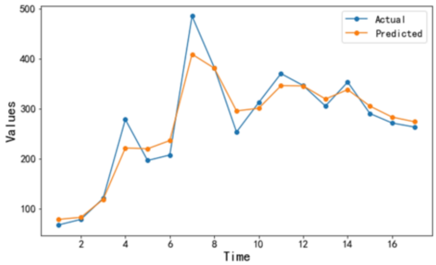


**Figure 10.** Prediction results of material "500023 645" based on RF.

Like LSTM, RF does not necessarily work for all materials. As shown in Table 2, the prediction performance of RF on material "500009917" is better than that of the other two materials. The average value of MSE, RMSE, MAE, and MAPE for the above three materials is 5.18, 7.11, 5.07, and 8.97, respectively. RF is not as effective as LSTM.

**Table 2.** Prediction accuracy of RF for three materials.

| Materials | MSE (×0.001) | RMSE (×0.01) | MAE (×0.01) | MAPE (%) |
|---|---|---|---|---|
| 500009917 | 3.43 | 5.86 | 4.63 | 11.18 |
| 500023540 | 7.4 | 8.6 | 5.67 | 7.76 |
| 500023645 | 4.71 | 6.87 | 4.91 | 7.98 |

### *3.3. Demand Forecast Based on LSTM-RF*

A single prediction method can only reflect the characteristics of a certain aspect of the data and cannot process the characteristic information from different aspects. As a consequence, it is difficult to obtain ideal prediction performance. However, if multiple prediction models are combined, different models can complement each other and thence reduce the prediction error. Therefore, considering the excellent fitting performance of RF to the nonlinear part of the data, this paper puts forward the LSTM-RF, a combination model, to forecast the demand of electric power materials. LSTM-RF uses RF to forecast and optimize the residual error of the predicted result of LSTM.

Just like using RF algorithm alone, the number of decision trees is first determined, and then the prediction is made according to the number of optimal decision trees. The residual prediction of the three materials is shown in Figures 11, 12 and 13.

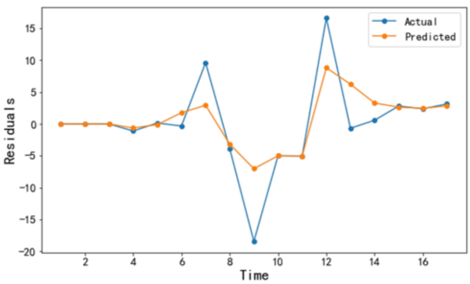


**Figure 11.** Residual prediction of material "500009917".

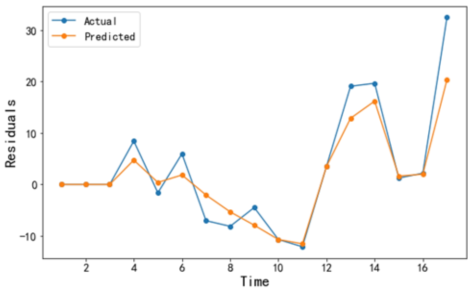


**Figure 12.** Residual prediction of material "500023540".

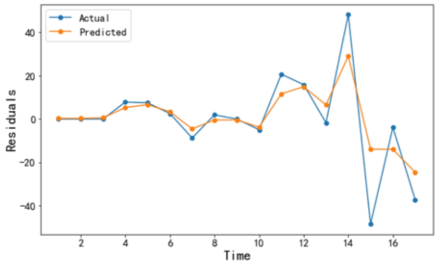


**Figure 13.** Residual prediction of material "500023645".

As can be seen from the above figures, the secondary prediction using RF algorithm reduces the large prediction error of LSTM model, which also indicates that the selection of RF in this paper is correct, especially for materials with large changes in demand, RF optimization prediction is very necessary.

## 4. Model Application

### *4.1. Data Preparation*

Input data: $X = (x_1, x_2, x_3, \ldots, x_n)$, representing a material demand residual data series over a historical step, namely $x_i$ represents the difference between the actual value of the corresponding time and the LSTM prediction.

Output data: $Y = (y_1, y_2, y_3, \ldots, y_n)$, representing the residual data series of material demand in the future time step, that is, the residual prediction result of LSTM prediction at the corresponding time.

The final prediction result: $Z = (z_1, z_2, z_3, \ldots, z_n)$, where $z_i$ is the sum of the LSTM prediction results and the residual results predicted by RF, and the final prediction result is shown in Figures 14, 15 and 16.

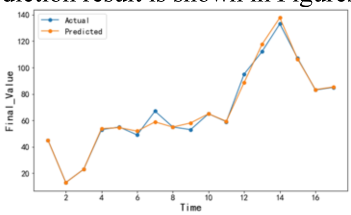


**Figure 14.** Final prediction of material "500009917"

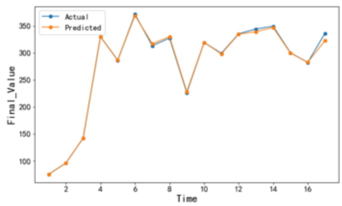


**Figure 15.** Final prediction of material "500023540"

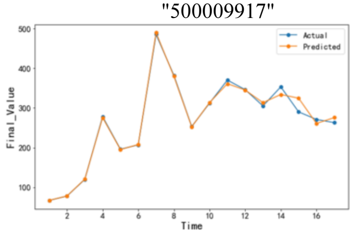


**Figure 16.** Final prediction of material "500023645"

### 4.2. Model Prediction

In order to reflect and compare the advantages and disadvantages of the model more directly, this section will compare the predicted results of three materials using three methods respectively, as shown in Table 3.

**Table 3.** Prediction accuracy of LSTM-RF model.

| Materials | 500009917 | | | 500023540 | | | 500023645 | | |
|---|---|---|---|---|---|---|---|---|---|
| | *LSTM* | *RF* | *LSTM-RF* | *LSTM* | *RF* | *LSTM-RF* | *LSTM* | *RF* | *LSTM-RF* |
| MSE (×0.001) | 3.33 | 3.43 | 0.59 | 1.5 | 7.4 | 0.24 | 2.09 | 4.71 | 2.01 |
| RMSE (×0.01) | 5.77 | 5.86 | 2.43 | 3.88 | 8.6 | 1.54 | 4.57 | 6.87 | 4.48 |
| MAE (×0.01) | 3.15 | 4.63 | 1.61 | 2.51 | 5.67 | 0.97 | 2.78 | 4.91 | 2.22 |
| MAPE (%) | 5.57 | 11.18 | 2.73 | 2.29 | 7.76 | 0.95 | 3.75 | 7.98 | 2.98 |

For material "50009917", compared with only using LSTM model, the MSE, RMSE, MAE and MAPE predicted by the proposed model decreased by 2.74, 3.34, 1.54 and 2.84 respectively. For material "500023540", compared with only using LSTM model, the MSE, RMSE, MAE and MAPE predicted by the proposed model decreased by 1.26, 2.34, 1.54 and 1.34 respectively. For material "500023645", compared with the single LSTM model, the MSE, RMSE, MAE and MAPE predicted by the model proposed in this paper decreased by 0.08, 0.09, 0.56 and 0.77 respectively. It can be seen from the above data that the performance of LSTM-RF is significantly better than that of LSTM and RF. It is not difficult to understand that using RF algorithm to predict the residual of LSTM model can reduce the prediction error of LSTM to a certain extent, so as to make the final prediction result more accurate.

Because of the data itself, the same method works differently for different materials. For example, the LSTM-RF model shows some differences in the prediction of the three materials. Specifically, the optimization prediction effect of "500023645" is not as good as that of the other two materials, which may be due to the strong linear correlation of the data itself. The LSTM model has captured the dependence relationship and achieved a good prediction effect. So the RF algorithm doesn't play a big role.

The LSTM-RF model performed best, followed by the LSTM algorithm, and RF performed worst. LSTM-RF achieves better prediction effect because RF reduces the prediction error of LSTM, so it is better than the other two algorithms. LSTM is a deep learning algorithm based on recurrent neural networks, which can capture the long-term dependence and nonlinear characteristics of time series well, and thus has a good performance, so it is also the most widely used model in the field of time series prediction. RF algorithm is an integrated learning algorithm based on decision tree, with a relatively simple structure. In this paper, the prediction effect of materials with large demand fluctuations, such as "500023540", is obviously inferior to that of the other two materials with relatively stable demand, and the performance is generally poor.

## 5. Conclusions

In this paper, according to the actual situation of an electric power company, a combination forecasting model that is composed of LSTM model and RF algorithm is proposed to perform the power material demand forecasting. This method make full use of the advantages of both LSTM and RF, and improves the accuracy of material demand forecasting. To be specific, LSTM is good at capturing long-term dependencies in time series, while RF is better at dealing with nonlinear dependencies and overfitting. Accurate demand forecasting will help the company make reasonable purchasing plans and solve the problem of high inventory, so as to improve the efficiency of business operations and reduce costs.

There are still many shortcomings in the research of this paper. First, RF is selected subjectively to predict the residual error of LSTM just because RF has strong nonlinear data processing ability. Other algorithms with better prediction performance can be considered, such as ARIMA and Bayesian neural network, to predict the residual error. Secondly, the parameters of LSTM are not optimized, and the influence of different time window sizes on the prediction performance is not considered. Whale algorithm and Sparrow algorithm can be used to optimize the key parameters of LSTM.

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