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# Power Grid Material Demand Forecasting Based on Pearson Feature Selection and Multi-Model Fusion

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The demand projection of power grid materials can furnish an effective support for the management of power grid materials. Due to variations in the data distribution of individual districts and diversity of materials, a single forecasting model is incapable of accurately predicting the demand for all types of materials. Moreover, for the data-driven network model, the effect of the model has a strong correlation with the quality of its input parameters. To address these problems, this study proposes a power grid material demand forecasting model based on feature selection and multi-model fusion. The first step in this regard is the usage of Pearson coefficient in the selection of main characteristic parameters from original parameters and using them as the input of the network model. Then, stacking fusion algorithm is used to fuse multiple basic models. At last, the proposed method mentioned in this study is tested on a real dataset. The results depict that the proposed method can fully integrate the advantages of various basic models with higher accuracy and generalization ability.

**Keywords: power grid materials, demand prediction, feature selection, fusion algorithm, gradient boosting decision tree, eXtreme gradient boosting tree, long- and short-term memory network**

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## INTRODUCTION

A power grid system is one of the preeminent pillars for national economic development. Any sort of issue in power equipment might cause large-scale power outage of the power grid, thus leading to huge negative impacts. At present, the material management of power grid has several problems including "the material data fragmentation, material reserves mechanization, and main responsibility ambiguity." The accuracy, correctness, and integrity problems existing in most of the historical demand data of electric power materials, which leads to the demand of material, cannot be predicted (Lai et al., 2016; Oliveira et al., 2021), thereby causing inadequate refinement of material management. Therefore, in order to achieve higher efficiency and precision of material management, the material demand forecasting has been researched deeply throughout the world.

According to the references (Pan et al., 2016; Wang and Gu, 2016; Zhao et al., 2017; Wang et al., 2019; Dong et al., 2020; Ming et al., 2021), most of the prediction models for power grid materials are presently using a single model structure having the problem of either over-fitting or under-fitting and also have poor generalization for different scenarios. However, the data model requires a high quality of input parameter information. As a result, the input parameter information should be screened. According to the reference (Yang et al., 2022a), this research is a pioneer study for SCUC problems

that proposes an expanded sequence-to-sequence (E-Seq2Seq) based data-driven SCUC expert system for dynamic multiple-sequence mapping samples; it can accommodate the mapping samples of SCUC and consider the various input factors that affect SCUC decision-making, possessing strong generality, high solution accuracy, and efficiency over the traditional method.

Aiming at the aforementioned problems, this study proposes a power grid material prediction model based on feature selection and multi-model fusion. First, the Pearson coefficient will be used to calculate the relevant characteristic parameters. After removing the irrelevant parameters, the important characteristic parameters related to the problem will be extracted as the input of the subsequent network model. Afterward, the multiple base models will be fused using stacking fusion. The basic model will utilize gradient boosting decision tree (GBDT), extreme gradient boosting tree (XgBoost), and long- and short-term memory network (LSTM), portraying excellent regression learning ability. The multi-model fusion network is able to fulfill the advantages of each basic model, through high prediction accuracy as well as improvement in the generalization ability.

## STATISTICAL ANALYSIS OF POWER GRID MATERIAL FAULTS AND DEFECTS

First of all, this study presents a statistical analysis of the defect levels of a certain bureau of China Southern Power Grid Corporation from 2015 to 2019. The defect levels can be categorized into four types: emergency, major, general, and others accounting for 46, 9, 42, and 3%, respectively. Based on various types of defects, the current material demand can be bifurcated into three categories, namely, daily materials (defect level is general), major defect materials, and emergency defect materials (Gong, 2013; Ke et al., 2017; Dong, 2018; Chai, 2020; Shen and Raksincharoensak, 2021; Yang et al., 2022b).

The main factors responsible for these defects include the quality of the product design, the quality of construction, the quality of operation and maintenance, the service time of products, the overload state of equipment, and the natural environment.

## THE MODEL OF POWER GRID MATERIAL DEMAND

### Gradient Boosting Decision Tree Algorithm

The gradient boosting decision is made to superimpose M sub-trees to achieve regression prediction:

$$F(x, w) = \sum_{m=0}^{M} \alpha_m h_m(x, w_m) = \sum_{m=0}^{M} f_m(x, w_m). \tag{1}$$

In the formula shown previously, x represents the input sample, $w_m$ represents the model parameter, h represents the classification regression tree, and $\alpha$ signifies the weight of each tree. The core concept of GBDT algorithm is based on the weighted sum of multiple weak learners (Chen et al., 2015; Son et al., 2015; Sheridan et al., 2016; Rao et al., 2019; Wu et al., 2020; Yang et al., 2021a; Yang et al., 2021b; Shen et al., 2021). This study initializes several weak learners in the beginning:

$$F_0(x) = \arg\min_c \sum_{i=1}^{N} L(y_i, c). \tag{2}$$

Then, building M trees, $m = 1, 2, \ldots, M$:

1) For the sample $i = 1, 2, \ldots, N$, the negative gradient corresponding to the number M tree is calculated by pseudo-residual:

$$r_{m,i} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x)}\right]_{F(x)=F_{m-1}(x)}. \tag{3}$$

2) For the sample $i = 1, 2, \ldots, N$, the number M regression tree is obtained by using data $(x_i, r_{m,i})$, and its corresponding leaf node region is $R_{m,j}$, and $j = 1, 2, \ldots, J_m$.
3) For $J_m$ leaf nodes region $j = 1, 2, \ldots, J_m$, the best fitting value is calculated as follows:

$$C_{m,j} = \underset{c}{\operatorname{argmin}} \sum_{x_i \in R_{m,j}} L(y_i, F_{m-1}(x_i) + c). \tag{4}$$

4) Renewing the learner $F_m(x)$, we get:

$$F_m(x) = F_{m-1}(x) + \sum_{j=1}^{J_m} c_{m,j} I\left(x \in R_{m,j}\right). \tag{5}$$

5) The final expression of the strong learner $F_M(x)$ is:

$$F_M(x) = F_0(x) + \sum_{m=1}^{m} \sum_{j=1}^{J_m} c_{m,j} I\left(x \in R_{m,j}\right). \tag{6}$$

The model of GBDT has many parameters, such as the number of base learners, the learning rate, the number of subsamples, and the maximum depth of each base learner (decision tree). Due to the limited number of defect data samples, the maximum depth of the tree should not be too deep.

### Extreme Gradient Boosting Tree

Extreme gradient boosting algorithm is an ensemble learning algorithm based on gradient boosting. It calculates the final regression result by integrating multiple basic trees. It has advantages pertaining to high efficiency and accuracy in regression tasks. On the basis of GBDT, XgBoost introduces the loss function of the second derivative of the predicted results. It adds the tree model complexity into the objective function as a regular term. This can prevent over-fitting and improve the generalization performance of the model. In this study, the XgBoost prediction function is constructed as follows (Malhotra et al., 2015; Sikora and Al-Laymoun, 2015; Xu et al., 2015):

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), f_k \in F. \tag{7}$$

Since the model is additive, the current prediction results need to be added to calculate in each iteration.

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{t-1} + f_t(x_i)\right) + \Omega(f_t). \tag{8}$$

The overall objective function is:

$$L_\phi = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k). \tag{9}$$

The $\Omega(f)$ is the regular term, which is expressed as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \|w\|^2. \tag{10}$$

.

Taylor expansion of $L^{(t)}$is:

$$\begin{aligned} \bar{L}^t &= \sum_{i=1}^{n}\left[g_i f_t(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right] + \gamma T + \frac{1}{2}\lambda\sum_{j=1}^{T} w_j^2 \\ &= \sum_{j=1}^{T}\left[\left(\sum_{i\in I_j} g_j\right)w_j + \frac{1}{2}\left(\sum_{i\in I_j} h_j + \lambda\right)w_j^2\right] + \gamma T. \end{aligned} \tag{11}$$

Then, the ideal weight of leaf node j in round t should be

$$w_j^* = -\frac{\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i + \lambda}. \tag{12}$$

The quality score of the tree in round t is marked by the following formula:

$$\bar{L}^t(q) = -\frac{1}{2}\sum_{j=1}^{T}\frac{\left(\sum_{i\in I_j} g_i\right)^2}{\sum_{i\in I_j} h_i + \lambda} + \gamma T. \tag{13}$$

For all leaf nodes to be split in this round, $I_L$ and $I_R$ represent the set of assumed leaf nodes after splitting, so the loss reduction after splitting can be measured by the following formula illustrated as:

$$L_{\text{split}} = \frac{1}{2}\left[\frac{\left(\sum_{i\in I_L} g_i\right)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{\left(\sum_{i\in I_R} g_i\right)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{\left(\sum_{i\in I} g_i\right)^2}{\sum_{i\in I} h_i + \lambda}\right] - \gamma. \tag{14}$$

Compared to GBDT, XgBoost algorithm is a further optimization design, which can reduce model variance through row sampling. Also, it reduces over-fitting through learning rate setting. Moreover, it controls the tree growth through early stopping to avoid over-fitting.

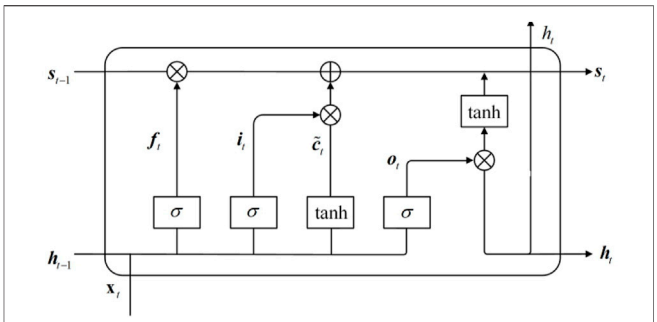


**FIGURE 1 |** Unit structure of LSTM.

## Long- and Short-Term Memory Network

**Figure 1** illustrates the unit structure of LSTM. At every moment t, the weight calculated by LSTM is linked back to itself. The input to the LSTM unit is the previous state $h_{t-1}$ and the current input $x_t$. The function of storing and forgetting information is realized through four fully connected neurons, namely, $f_t$, $i_t$, $\tilde{c}_t$, and $o_t$. Specifically, the forgetting gate $f_t$ determines how much previous information is transmitted forward; input gate $i_t$ controls the input information level; the forgetting gate $o_t$ determines the output of this time step (Singh, 2017; Hu et al., 2018). The formula for calculation is described as follows:

1) Input the sequence value $x_t$ at time t and the hidden layer state $h_{t-1}$ at time t-1, and determine the discarded information through activation function. At this time, the output is as follows:

$$f_t = \sigma\left(W_f \cdot h_{t-1} + W_f \cdot x_t + b_f\right). \tag{15}$$

In the previously stated formula, $f_t$ is the result of the forgetting gate state, and $W_f$ and $b_f$ are the residual weight matrix and bias, respectively. $\sigma$ is the activation function, usually the tanh or sigmoid function.

2) The input gate state formula is illustrated as follows:

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$$i_t = \sigma(W_i \cdot h_{t-1} + W_i \cdot x_t + b_i); \tag{16}$$

$$\tilde{c}_t = \tanh(W_c \times h_{t-1} + W_c \times x_t + b_c); \tag{17}$$

$$c_t = i_t \circ \tilde{c}_t + f_t \circ c_{t-1}. \tag{18}$$

In the aforementioned formula, $i_t$ is the result of the input gate state, and $\tilde{c}_t$ is the input unit state at time t. $W_i$ and $W_c$ are input gate weight matrix and input unit state weight matrix, repectively, and $b_i$ and $b_c$ are the corresponding input gate bias and input unit state bias, respectively. tanh is activation function, and $\circ$ stands for multiplying by elements.

3) Output information of LSTM is determined by the output gate and unit state as shown in the following equation:

$$o_t = \sigma(W_o \cdot h_{t-1} + W_o \cdot x_t + b_o); \quad (19)$$

$$h_t = o_t \circ \tanh(c_t). \quad (20)$$

In the formula, $o_t$ is the output gate state result, and $W_o$ and $b_o$ are the weight matrix and output bias, respectively.

## Stacking Fusion Algorithm

Stacking fusion algorithm reduces the generalization error of the whole model and improves the classification accuracy of the model via building a two-layer learner. This makes the second-layer model to learn the classification results of the first-layer model. Among them, T basic classification models are first used in the first layer. After inputting the original data, a result with the same data size is outputted as the input of the second-layer network. The output of each basic learner is used as input when training the second-layer learner, and the function of the second-layer learner is to integrate the output of the basic learner.

## Power Grid Material Prediction Based on Pearson Feature Selection and Multi-Model Fusion

In this study, the integrated feature scoring model is used to evaluate, and the total score is averaged to avoid the limitations of single feature selection and finally optimizes the effect of feature selection. With the help of classical Pearson correlation coefficient analysis and selecting high linear correlation attributes, we can roughly find out the relevant attribute categories that have a great impact on material defects. The Pearson correlation coefficient formula is shown in **Eq. 21** and **Eq. 22**. Through this formula, Pearson correlation coefficient can be obtained by dividing the covariance by the standard deviation of two related variables, which is used to make up for the weak performance of the covariance value in the correlation degree of random variables.

.

$$cov(x, y) = \frac{\sum_n^{i=1}(x_i - x)(y_i - y)}{n-1}; \quad (21)$$

$$Pearson = corr(x, y) = \frac{cov(x, y)}{\sigma_x \sigma_y} = \frac{E\left[(x - \mu_x)\left(y - \mu_y\right)\right]}{\sigma_x \sigma_y}. \quad (22)$$

The range of the Pearson coefficient is $[-1, 1]$. The larger the absolute value is, the more linearly related the two random variables are. Pearson = 1 means that the random variables are completely positively correlated, Pearson = −1 means that the random variables are completely negatively correlated, and Pearson = 0 means that there is almost no linear correlation between the two variables [Feng et al., 2019; Li et al., 2021a; Li et al., 2021b].

**TABLE 1 |** Comparison of different basic models and fusion model algorithms for emergency defective material prediction.

| Model and method | *RMSE* | *Err* (%) |
|---|---|---|
| XgBoost | 11.2 | 41.2 |
| GBRT | 8.9 | 33.4 |
| LSTM-1 | 13.4 | 29.9 |
| LSTM-2 | 15.6 | 38.4 |
| LSTM-3 | 9.7 | 43.1 |
| LSTM-4 | 7.8 | 40.7 |
| Multi-model fusion | 6.6 | 27.5 |
| Multi-model fusion with feature optimization | 4.7 | 18.3 |

# EXAMPLES ANALYSIS

The sample dataset provided by the power supply bureau of China Southern Power Grid Corporation was selected for training and testing. The defect data from 2015 to 2019 were initially used to train the model, and then the data from 2020 were tested to verify the prediction effect of the model.

## The Method of Model Evaluation

In order to comprehensively evaluate the validity and accuracy of the proposed method in power grid material forecasting, the following two evaluation indexes are selected:

The value of the root mean square error (RMSE) between the real value of the test set and the predicted value of the model is expressed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{T}(\tilde{x}_i - x_i)^2}{T}}. \quad (23)$$

The average relative error between the real value and the predicted value, *Err*, is expressed as:

$$Err = \frac{1}{T}\sum_{i=1}^{T}\left|\frac{\tilde{x}_i - x_i}{x_i}\right| \times 100\%. \quad (24)$$

## The Result of Examples Analysis

In this study, the prediction results of emergency defect materials are compared and analyzed, taking overhead wire as an example.

The number of sub-trees of XgBoost is set at 300, and the learning rate is kept at 0.04, while the penalty factors $\gamma$ and $\lambda$ of tree model complexity are taken as 0.01 and 0.9, respectively. Furthermore, the number of sub-trees of GBDT too is set at 300 along with the learning rate at 0.04. The network layers of four kinds of LSTM networks (LSTM-1, LSTM-2, LSTM-3, and LSTM-4) are set at 3, 3, 4, and 4, respectively; the number of corresponding neurons is set to 128, 128, 256, and 256, respectively, and the learning rate is set at 0.01.

**Table 1** shows the prediction results of different base models, multi-model fusion, and multi-model fusion with feature optimization for emergency materials. The results of the basic model are obtained directly from their own network without the second layer fusion of the proposed network.

The results of the evaluation index reveal that a single model cannot achieve the best effects. After using the multi-model fusion algorithm, it can make full use and give full play to the prediction advantages of each basic model in one aspect. Moreover, it improves the overall prediction accuracy of the algorithm. It also avoids the phenomenon of over-fitting along with enhanced stability of prediction. On the basis of multi-model fusion, this study also uses Pearson coefficient to optimize the input parameters and selects the most important characteristic parameters as the input of the network. Therefore, after the feature optimization of the original input parameters, the main influencing feature parameters can be selected. Following this, the feature parameters of irrelevant factors can be eliminated, so that the subsequent learning model can better fit the historical data. Therefore, based on the aforementioned observations, it can be concluded that the multi-model fusion algorithm of feature optimization proposed in this study has high accuracy in the prediction of power grid materials.

## CONCLUSION

Focusing at the problem of material prediction in the power system, a prediction method based on feature selection and multi-model fusion is proposed in this study. Starting by calculating the Pearson coefficient, the irrelevant parameters are removed from the original parameters. The main characteristic parameters are then selected as the input of the subsequent network model. Furthermore, three excellent data-driven models are identified as the basic model followed by the application of the stacking method for fusion. The fusion algorithm can not only make full use of the advantages of each basic model to improve the prediction accuracy but also improve the generalization ability of the model. Hence, the predicted power grid material demand can provide an effective data support for the management of power grid materials.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

## AUTHOR CONTRIBUTIONS

ZD put forward the research technical route of the manuscript; GW reviewed the scientificity of the manuscript; and RB and CD completed the data analysis of the manuscript.

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