Power load forecasting and interpretable models based on GS_XGBoost and SHAP

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Abstract: At present, the prediction accuracy of the power load prediction model is not high and the black box model prediction results are not explanatory, so this paper proposes an improved XGBoost based grid search for power load forecasting model (GS-XGBoost), and uses SHAP for model analysis and interpretation to show the impact of the feature set on the model in a visual way according to the marginal contribution of power load feature samples. The impact of the prediction results is shown in a visual way to improve the interpretability of the model, and the key factors affecting the electricity load are identified based on the ranking results of the feature importance to provide decision support for the power system equipment maintenance plan, guide the formulation of strategies related to electricity production, resource procurement and pricing, and avoid market risks. In this paper, the electricity consumption dataset of an enterprise in Jiangsu is used as the research object, and the dataset is pre-processed with unique thermal coding, outlier analysis, null filling, and standardization. Through experimental comparison, the GS-XGBoost load forecasting model has the best prediction accuracy compared to SVR, random forest, decision tree, and XGBoost machine learning models, and then SHAP is applied to interpret the model and improve the model interpretability.

1. Introduction

Power load forecasting plays a crucial role in power system scheduling, maintenance and capacity planning, and is of great significance in guiding the planning and construction of power grids and improving the optimal allocation of power system resources[1]. All along, short- and medium- and long-term power load forecasting has been an important task for power supply enterprises, and various load forecasting methods and researches have emerged, including classical forecasting methods such as time series, neural network, SVM (Support Vector Machine) and gray forecasting method. The mainstream electric load forecasting mainly focuses on regional and industry macro load data. The load data of individual enterprises lack cyclical patterns and are highly volatile due to the influence of uncertain factors such as enterprise production and macro policies, and there are large model prediction errors. In the current context of power reform, grid enterprises can use their technical and data advantages to provide monthly load forecasting results for large industrial users, help enterprises to reasonably choose billing methods, reduce electricity costs and provide value-added services to customers[2].

In this paper, we improve the power load forecasting accuracy and model interpretability based on improved XGBoost model and SHAP model analysis. Using an enterprise electricity consumption dataset in Jiangsu as the research object, preprocessing, feature selection, model training, hyperparameter optimization, performance metrics analysis[3], and SHAP model interpretation are performed to construct a prediction model with excellent performance and high interpretability. The main work focuses on the following two aspects.
An electric load forecasting model based on the GS-XGBoost model is developed and compared with existing load forecasting models (in terms of relevant performance metrics) to verify the superior performance of the model in the paper.

The SHAP model is used to analyze the XGBoost load forecasting model, transform the black-box model into a visual chart, enhance the interpretability of the model, provide decision support for the power system equipment maintenance plan, and guide the formulation of strategies related to electrical energy production, resource procurement, and pricing, thereby effectively avoiding market risks.

2. Analysis of model construction

2.1. Model building process

Process Analysis. After the original training samples are processed for feature engineering such as unique heat coding, outlier analysis, null filling, and data normalization, the data are input into XGBoost to train the model, find the optimal parameters by grid search, and compare with other machine learning models to find the optimal load prediction model, and then analyze by SHAP model interpretation to visually demonstrate the feature set on the model prediction results Impact[4].

2.2. Flow chart

![Figure 1. Flow chart of model construction](image)

3. analysis of real-life examples

3.1. Evaluation indicators

Based on the direction of power load forecasting in this paper, the evaluation indicators use root mean square error (RMSE), mean square error (MSE), mean absolute value error (MAE), and coefficient of determination ($R^2$) where the smaller the three evaluation indicators RMSE, MSE, and MAE represent the smaller the error, and the closer $R^2$ is to 1 represents the higher the degree of explanation of the target variable on the characteristic input and the better the fitting effect [5], the above evaluation The specific formulas of the above evaluation indicators are as follows.

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2}$$  (1)

Expected Variance (EVS)

$$EVS(y, \hat{y}) = 1 - \frac{\text{Var}\{y - \hat{y}\}}{\text{Var}\{y\}}$$  (2)

Mean absolute percentage error (MAPE)

$$MAPE = \frac{100}{m} \sum_{i=1}^{m} \left| \frac{\hat{y}_i - y_i}{y_i} \right|$$  (3)
Coefficient of determination \((R^2)\)

\[
R^2 = \frac{\sum_{i=1}^{m} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{m} (y_i - \bar{y})^2}
\]

where \(m\) is the number of samples predicted

3.2. **Optimal feature selection**

The values of the prediction evaluation indicators for the optimal set of features selected for the prediction model at different number of features are shown in Figure 2, and it can be seen that: different combinations of features lead to different biases in the prediction model, and when the number of feature combinations is 6, all four error evaluation indicators are better than other combinations.

![Figure 2. Comparison of errors under different combinations of feature numbers](image)

3.3. **Predictive model performance comparison**

| Model      | RMSE    | MAPE    | \(R^2\) | EVS   | Prediction time/s |
|------------|---------|---------|---------|-------|-------------------|
| SVR        | 174.533 | 6.519%  | 0.775   | 0.780 | 0.04              |
| RF         | 86.575  | 2.784%  | 0.945   | 0.946 | 0.26              |
| DTR        | 253.860 | 8.437%  | 0.525   | 0.529 | 0.01              |
| XGBoost    | 90.408  | 2.963%  | 0.940   | 0.950 | 0.02              |
| GS_XGBoost | 36.928  | 1.069%  | 0.989   | 0.989 | 0.02              |

From Table 1, we can see that: compared with the XGBoost prediction model with direct input features, the RMSE of the GS-XGBoost optimal feature combination method decreases by 59.2%, and the three error evaluation metrics of MAPE, \(R^2\), and EVS are better than the comparison model. Overall, the GS_XGBoost model has the best performance with short prediction time, highest prediction accuracy and best fitting ability.

The comparison of the prediction curve of this method with the real curve in different prediction models is shown in Fig. 3, which can visualize the fitting of each prediction model to the real load curve, and the figure can clearly reflect the load prediction of each model, in which GS_XGBoost load model fits the real load curve the best.
4. SHAP interpretive analysis

SHAP is a method used to interpret predictions that are based not only on the importance of features based on a complex training model, but also on the predictions of the current test sample [6].

The overall SHAP feature summary analysis was conducted in the SHAP framework, and the GS-XGBoost model variable importance rankings and the positive and negative effects affecting the results are shown in the SHAP summary graph. As can be seen in Figure 4, the y-axis ranks the previous day's electricity consumption, current day's holiday condition, previous two days' holiday condition, current day's minimum temperature, previous day's holiday condition, and current day's temperature difference according to the importance of the input features, from largest to smallest. x-axis indicates the SHAP values corresponding to the features. The point of each feature in the graph represents a sample of features in the corresponding dataset, and the change in color from Low to High indicates the sample feature array from small to large, and the positive and negative SHAP values indicate the positive and negative correlation between the features and the prediction results [7].

5. Conclude

In this paper, GS-XGBoost method is adopted to study power load forecast. The main conclusions can be summarized as follows: (1) the GS-XGBoost model has a great improvement in the accuracy of load
prediction compared with other models. (2) There are many factors affecting load prediction, the input of different feature combinations has a great influence on the accuracy of the prediction model and the generalization ability of the model, and the optimal combination of features can be obtained without losing the amount of data information by the quantitative selection of the input features, which can further improve the precision and generalization of the machine learning load prediction model. (3) The SHAP analysis framework is introduced to explain the GS-XGBoost prediction black box model, to explain the importance of input features in the prediction process, and to qualitatively analyse the value size of feature samples and load prediction worthy of positive and negative correlation. (4) To explains the reasons for the load forecasting model to make corresponding predictions of load values, increases the credibility of the forecast results, and provides an analytical basis for power dispatchers to formulate strategies. In terms of the future work, Add other associated factors as features should be carried out to enhance power load prediction accuracy.

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