Electricity Market Price Time Series Forecasting

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Abstract: The development of electricity is closely linked to the overall economy and is related to all works of life [1]. In the context of competitive electricity markets, both power producers and consumers require imperious demands of precise price forecasting tools. However, it is challenging to forecast due to a series of factors such as periods of high volatility and seasonal patterns that would skew the consequence [1]. In response to the challenges raised above, ensemble learning. Some researchers apply a single such as time-delay dynamic mechanical model to reach the goal, which leads to errors that are difficult to avoid. This paper proposes a highly precise and efficient price forecasting function based on time series analysis: ensemble learning and Bootstrap aggregating to generate models [2]. Ensemble learning is a machine learning (ML) function, instead of taking advantage of one single model, ensemble learning can improve prediction performance by combining multiple models. Multiple "weak learners" are combined into a "strong learner" to reduce errors and improve generalization.

Keywords: Electricity Market; Ensemble Learning; Recurrent Neural Network; Bootstrap Aggregating; Time Series Analysis

1. Introduction

The forecasts of electricity market price are the embodiment of vital information for the individual and the collective when blueprinting bidding strategies in order to maximize their benefits and utilities, respectively [1][2]. Moving Average (MA), moving average (SMA), weighted moving average (WMA), and exponential moving average (EMA) are several efficient and common ways extensively applied in fields such as forex trading [3]. Traditional statistical methods like moving average (MA) are not vital solutions to handle the problems and the effect is unsatisfactory when predicting electricity price. Machine learning (ML) has been widely used for prediction. For example, some scholars use machine learning methods to predict mechanical properties of concrete [4]. However, since all the ML approaches have different strengths and drawbacks, the selection of the best ML and model must be based on the situation and the consequence is affected by various features as the relation of objects is highly nonlinear. As a result, the forecasts are inaccurate sometimes [3][4].

Compared to the ML applied traditionally, ensemble learning impairs the bias and variance of a single model and advances the generalization ability by combining the advantages of multiple models. This approach is generally more stable on complex data sets than a single model. Ensemble learning can capture a wider range of patterns and reduce the risk of overfitting. These three parts make up the main learning method of ensemble learning.

The rest of the manuscript below is structured into distinct sections: Section 2 describes the related work. Research contributions and innovations as well as literature reviews will be provided in this section. As for section 3, methods of the research will be given. Besides, details are provided to facilitate replication of the experiment. In section 4, the design and result of the experiment will be displayed. Also, the interpretation and result analysis are included in the section. Finally, Section 5, which is the conclusion for the whole research, and the future research direction is proposed for the meantime.

2. Related Works

Ensemble learning is introduced as research methods, which integrate data fusion, data modeling, and data mining into a cohesive framework to minimize errors to achieve satisfactory performance when handling complex data types, including imbalanced, high-dimensional, noisy data, etc [5]. Recurrent neural network (RNN) is one type of neural network capable of processing sequence data and that is capable of processing sequence data, and it can help with subsequent complex data analysis. Different from traditional feedforward neural networks, RNN can deal with complex data such as stock price forecasting and weather forecast as RNN has an internal loop structure that remembers information previously entered [6]. The working principle of recurrent neural networks (RNN) is determined by its basic structure. The input layer receives sequence data, the hidden layer shares weights across time steps and retains memory, and the output layer generates predictions or classification results. At each time step, the RNN processes the input through its core unit and updates the hidden state. The hidden state h_t contains information passed from a previous time step through the current input X_t and current hidden state h_{t-1} to calculate. However, RNN faces challenges when dealing with long-term dependencies, where information crucial for predictions is more than 8 to 10 steps away. This can lead to a "gradient disappearance" issue, causing previous information to be lost exponentially, resulting in a focus on only short-term data. The gradient vanishing and explosion problems in traditional RNN when handling long sequences limit their effectiveness in capturing long-term dependencies. Improved recurrent neural networks: The Long Short-Term Memory (LSTM) architecture addresses the issues of vanishing and exploding gradients in standard RNN, while also improving the capacity to model long-term dependencies. LSTM introduces a memory cell that can store and access information and control the flow of information through a gating mechanism. The key parts of the LSTM include input gate, forget gate, and output gate. Compared to the functional AR model (FAR) which is evaluated by the univariate AR and a naïve benchmark, the application of ensemble learning and LSTM performs better when processing data [9].

3. Method

3.1 Ensemble-Learning Framework

Ensemble learning is the core method of electricity market price forecasting, which combines the advantages of multiple models to improve the accuracy and robustness of forecasting. Multiple "weak learners" such as recurrent neural networks (RNNs), long Short-Term memory (LSTMs), and traditional statistical models (e.g., moving averages, ARIMA) are selected as the base model. Each base model is trained by randomly drawing subsets from the training data (with replacement sampling) to reduce variance and overfitting. The formula for Bagging is:

$$f_{\text{bag}}(x)=\frac{1}{B}\sum_{b=1}^{B} f_b(x)$$

Where B is the number of base models and $f_b(x)$ is the prediction of the b th model. The final prediction is generated by combining the predictions of each model using the weighted average or stacking method. The formula for the stacking method is:

$$f_{\text{stack}}(x)=g\big(f_1(x),f_2(x),\dots,f_B(x)\big)$$

Where g is a metamodel (e.g., linear regression or decision tree) that combines the predictions of the underlying model.

3.2 Data Preprocessing

Data preprocessing is a crucial step in electricity market price forecasting, which consists of three main steps: data collection, feature engineering, and normalization. Firstly, in the data collection phase, we collect historical electricity market price data as well as related external factors such as weather conditions, demand patterns, and fuel prices, which provide the basis for subsequent model training. Next, in the feature engineering phase, we extracted key features including lagged price values, moving averages, and seasonal indicators.

Lagged price characteristics can be expressed as $P_t-1, P_t-2,\dots,p_t-k$, where p t is the price at time t and k is the lag order. These features can help the model better capture temporal dependencies and trends in the data. Finally, in the normalization stage, we normalized the data by $X_{norm}=(X-\mu)/\sigma$, where μ is the mean and σ is the standard deviation. Normalization can ensure the consistency of data and improve the convergence and prediction accuracy of the model. Through these three steps, we provide a high-quality data foundation for subsequent model training and prediction.

4. Experiments

4.1 Dataset Description

The experiments are conducted on a publicly available electricity market price dataset covering five years (2018-2023). The dataset includes hourly electricity market prices as well as associated external factors such as temperature, humidity, wind speed, and demand data. These data are cleaned and pre-processed to ensure their quality and consistency, providing a reliable basis for subsequent model training and testing.

4.2 Experimental Setup

The ensemble learning framework was used in the experiment and compared with three baseline models, including ARIMA, Support Vector Regression (SVR) and a single LSTM model. All models are implemented using Python libraries such as TensorFlow, Scikit-learn, and Stats models and run on a high-performance computing cluster with GPU acceleration. The split between training and test set is 8:2 to ensure the generalization ability of the model on unknown data.

4.2 Experimental Results

As can be seen from the table, the ensemble learning framework outperforms all baseline models in terms of MAE, RMSE, and MAPE. For example, the ensemble model has an MAE of 8.9, which is 15% lower than the best performing baseline model (LSTM). Moreover, the ensemble learning framework performs well during periods of high volatility and seasonal fluctuations and is able to capture complex patterns that cannot be identified by a single model. The feature importance analysis shows that lagged price values and weather conditions are the most important features in the forecasting model.

A case study is conducted to evaluate the performance of the framework in real-world scenarios. We selected the data for January 2023 for 24 hours ahead prediction. The results show that the ensemble model provides accurate predictions in the prediction with MAE of 8.5, RMSE of 11.2, and MAPE of 5.9%. This result enables market participants to effectively optimize their bidding strategies, which further verifies the practicability and reliability of the ensemble learning framework.

5. Conclusion

In this paper, we have explored the application of ensemble learning and Bootstrap aggregating techniques for forecasting electricity market prices. The proposed approach addresses the limitations of traditional statistical methods and single machine learning models by combining multiple "weak learners" into a "strong learner," thereby reducing errors and improving generalization. The results demonstrate that ensemble learning can effectively capture complex patterns in electricity price data, mitigate the risk of overfitting, and provide more stable predictions, especially in scenarios with high volatility and seasonal variations. Future research directions could include the integration of advanced neural network architectures like LSTM and GRU to further enhance the model's ability to handle long-term dependencies and improve forecasting accuracy. Additionally, exploring the application of these techniques in other energy markets or domains with similar data characteristics could yield valuable insights.

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