Forecasting of Korean Electricity Market Price Using Seasonal Decomposition Methods

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Overview

In recent years, there has been an effort to forecast electricity prices. While a prediction of the price of the electricity market is estimated, it is important to reflect the structural characteristics of the market and price, such as calendar data, previous hourly price, fuel costs, seasonal temperature, and electricity demand set of time-series, which are affected by renewable energy generation. The Korean electricity market has a day-ahead market. The market closes at 10 A.M. the day before the operation. The secondary submission of renewable energy generation closes at 5 P.M. The Korean market is a Cost-Based Pool, so each generator must submit such data related to the operating costs nine days before the end of each month. In renewable energy, Solar generation occupies 92% of the variable renewable energy capacity in Korea.

To use the feature of time series, decomposition has been adopted. Some of the important time series elements are demand and renewable energy generation. Using them on point values makes it hard to reflect time series elements or variation. However, using lots of the previous time series elements of the exogenous variable as input data increases the dimension of the input variable and may degrade the prediction performance as overfitting. To solve these problems, decomposition methods have been adopted. They are the Mostly used and recently used methods on decomposition energy: Fourier transform, Wavelet transform, VMD(Variational Modal Decomposition), TBAT(Exponential smoothing state space model with BAT), and MSTL(Multiple Seasonal-Trend Decomposition), STR(Seasonal-Trend decomposition using Regression) based on STL(Seasonal-Trend decomposition procedure based on Loess).[1-3]

There are two benchmark papers. One study comparing AI approaches and statistical techniques shows that DNN, LSTM, and XGBoost outperform complex deep learning models such as CNN and RNN. Furthermore, complex hybrid models based on deep learning or machine learning performed less well than simply averaging compared to hybrid models.[4] Another paper compares multi-seasonal decomposition methods(TBAT, Prophet, AutoSTR, MSTL) to forecasts on univariate sets of related time series using LSTM. On hourly electricity demand forecasting, it is better to use seasonal components & original time series than trends & residuals.[5]

This paper uses seasonal decomposition methods to predict hourly electricity prices in the Korean market. Six forecasting models were compared, STR-LSTM, STR-DNN, STR-XGBoost, MSTL-LSTM, MSTL-DNN, and MSTL-XGBoost, based on the decomposition technique and model. In addition, inputting past SMP values as input values were compared by putting them in a multi-step time series method and a point value.

Methods

The prediction model is divided into feature selection, seasonal decomposition, and training based on the models. The components mentioned above on the Korean electricity market are considered for the variable selection. 32 hours of the forecast was made, using monthly stepwise fuel prices of bituminous coal and natural gas, temperatures, and the size of the observation of each test was 3 months. The critical fuel price and the calendar data were also used as input variables and forecast prices.

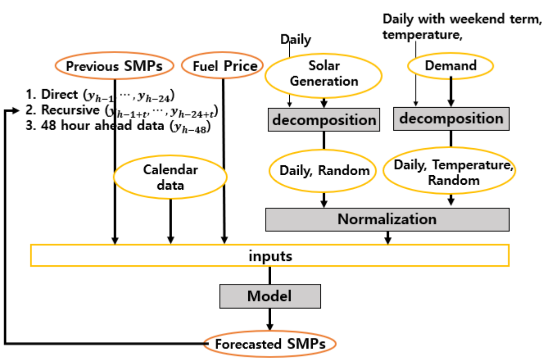

Figure 1. Proposed Method

On the pre-process, this paper calculates feature importance based on Random Forest. In the comparison of dimensions, the demand and the generation[kWh] are much more massive than SMP(System Marginal Price)[won/kWh], so it normalizes the components to decrease the errors.

The seasonal decomposition method is used for the value of demand and solar power generation. MSTL and STR decomposition methods were used, showing accurate performance in power demand prediction[4]. Both models are based on seasonal-trend decomposition. STL extracts the trends, seasonal and residual components by smoothing method using LOESS(local polynomial regression), which can neglect the outliers. MSTL can separate periodicity from time-series elements using smoothness control. It repeats the process of the STL extraction, and elimination for each seasonal component. It can be quickly adopted if the length of the seasonal set is known. STR can extract multiple seasonal components and affect seasonal factors by introducing exogenous variables such as temperature, whether constant or time-vary components. Both models can separate the time-varies values into daily and residual parts. Then we ignored the trend components which tend to be non-oscillate because it hardly affects the short-term price. We choose daily and residual components.

In addition, modeling with LSTM, DNN, and XGBoost was compared, respectively, which are representative models of performing well in demand and price forecasting. Because previous SMPs every 24 hours have high feature importance than the others, this paper uses the 48-hour ahead last data. This paper compared Direct Strategy and Recursive Strategy, which are multi-step time series forecasting strategies.

Results

In the evaluation, the tests were conducted ten times for 32 hours and evaluated based on two methods; MAPE(Mean Absolute Percentage Error) and RMSE(Root Mean Square Error). Each MAPE is calculated for the 32 hours forecast from 16:00 one day before the trading day to 23:00 on the trading day.

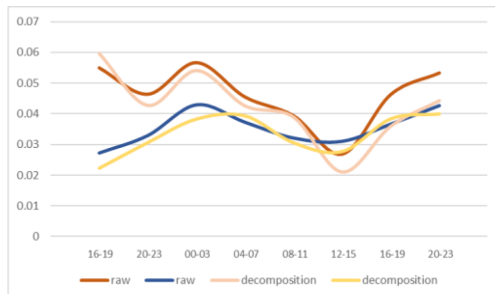

Figure 2. mean of the MAPEs, comparing between using decomposition and non-using

- The performance of XGBoost was recorded as the best in comparison with the other methods, in which the result of XGBoost is 33% to 48% higher in the average of MAPE than DNN, and 4% to 34% higher in the average of MAPE than LSTM.

- Comparing decomposition methods of STR and MSTL, using XGBoost and LSTM, which has a higher accuracy than DNN deep learning models, STR shows a 2% higher an average of MAPE.

- Figure 2 shows the result of comparison with the prediction with decomposition and without decomposition, prediction accuracy improved by 5 to 6% in the total average of MAPE on both models.

- The recursive strategy was 20% lower in an average of MAPE than the direct strategy, while the difference between XGBoost was less than 1%. However, compared to the case with a point-value of 48 hours earlier, the accuracy of the direct strategy is high in the model based on deep learning, but in the case of XGBoost, the model's accuracy with a point-value is higher.

Conclusions

This paper forecasts the Korean electricity market price using seasonal decomposition methods. It shows that the decomposition method is supportable for the prediction. However, this paper assumed the exogenous variables to be the same as the actual value. In future studies, the uncertainty of the external variable will be considered.

References

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