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Forecasting Electricity Prices Using an Improved Time Series Ensemble Model: A Case Study of the Indian Electricity Market

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ABSTRACT

Forecasting of electricity prices is a need to the actors in the electricity markets which happen to be deregulated. This paper illustrates a new scheme by providing an upgraded time series ensemble forecasting algorithm on Indian electricity market. The manner in which it is executed has the pre-processing of the data to address the missing values, the stationarization of the variance, season and non-stationarization. We considered six baseline time series models, namely the Autoregressive (AR), Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing Model (ESM), Theta, Nonparametric Autoregressive (NAR), and Neural Network Autoregressive (NNA) models. Equal weighting techniques used to develop three ensemble models are in-sample error weighting scheme and out-of-sample error weighting technique. The Ensemble of three samples out of the sample produces the best outcome that is measured with the use of MAE, MAPE, RMSE and others. The given framework is highly accurate and it can be applied to all other energy markets.

1. Introduction

An electricity market in India is the third largest and fastest developing energy sector in the world and is vital in sustaining the economic growth of this country. India is a country with large geographical area, a rapidly increasing population, diversified energy mix and with a unique set of problems and opportunities in generation, distribution and pricing of electricity. During the last decade, the power market has undergone major structural changes such as power generation liberalization, appearance of electricity exchanges, and drastically elevated penetration of renewable generation sources in terms of solar power and wind power. These innovations have caused a high magnitude of complexity in the electricity price dynamics which requires the application of high-level forecasting tools to help the market players in planning, decision-making, and risk avoidance.

The forecasts of the electricity price is a basic input of various interested parties like the generator, retailer, industrial consumers and the policymakers. Precise price forecasts are useful in reducing the cost of bidding strategies, efficient generation of schedule, energy procurement, and grid reliability. Nevertheless, predicting the prices of electricity in such a deregulated and dynamic market is the job in itself that is quite complicated. The electricity spot markets see the presence of an abundance of variables that affect the prices which include changes in demand, fuel prices, the availability of transmission capacity, meteorological, the uncertainty of renewable electricity generation, and the actions of policies. Therefore, price time series are highly volatile, abruptly change and have seasonality and non-stationarity and nonlinear dependencies that create serious difficulties to traditional forecasting models.

Traditional models of forecasting time series are Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing Models (ESM), which statement long has been employed due to its interpretation and easiness to operate. However, such models have a propensity to be dissimilar in managing the irregularities and nonlinearity of the prices of electricity. They cannot record non-linear relationships and structure change of the data since they use linearity assumptions. As a result therefore, these models are normally not applicable in such markets like India that can be very volatile in their electricity prices even though these models can be effectively used on the stable series.

Due to these constraints, the ensemble learning approaches as a powerful alternative have emerged to meet the demands of the situation to capitalize on the strengths of more than one forecasting model. Ensemble methods are achieved by averaging the result of multiple base models - which may represent different factors in the time series distribution - to create a more confident and correct prediction. Ensemble diversities of base models can cover a broad range of time series behaviors due to the variety of base models that include classical linear models, nonlinear and nonlinear machine learning-based modeling. In addition, weighting the models by the extent to which they have been right in the past (either in-sample or out-of-sample) further optimises the end-of-the-day predictions, putting more weight on more accurate predictors.

This paper proposes a new ensemble time series prediction model especially in the Indian electric market. The suggested approach brings on board a set of classical models of statistics as well as machine learning models, such as autoregressive models, neural networks, and smoothing. This is performed by a weighted ensemble approach, and this is done by employing the use of equal, training, and validation weights in order to generate stable and accurate one-month ahead forecasts of the electricity price. In addition to tackling the issues of volatility and nonlinearity, this framework also contains a scalable solution, which can easily be used in other emerging electricity markets.

2. Literature Review

Forecasting electricity price has received major research interest because of deregulation of the power markets and the introduction of renewable energy sources that have caused fluctuation and multifaceted nature in the power price dynamics. Many statistical, machine learning, and ensemble methods have been tried to improve the accuracy of prediction.

Traditional and Hybrid Time Series Models.
The first forecasting attempts were mostly based on linear forms that included ARIMA and exponential smoothing. Shah et al. (2022) observed the higher accuracy of several time series approaches to electricity demand and price forecasting and pointed out that such nonlinear trends cannot be fully understood with the use of a purely linear pattern. To overcome these difficulties, the hybrid models that integrate both decomposition methods and conventional statistical models providing have been proposed. As an example, the authors presented the

hybrid model of both wavelet transforms and ARMA and extreme learning machines meant to better model short-term and long-term dependencies (Yang et al., 2017).

Ensemble Learning Approaches.
Another strong intervention to this problem of achieving higher predictions is the use of ensemble techniques where several forecasting models are used together. The more efficient time series ensemble method was suggested by Mancha Gonzales et al. (2024) and consisted of weighting mechanisms that contributed to Six base models**.** In their work, the researchers indicated that the ensemble method worked much better than individual models in predicting monthly prices of electricity in the Peruvian market. In a similar fashion, Ribeiro et al. (2020) used self-adaptive decomposition and heterogeneous ensemble learning to forecast electricity prices, pointing at the versatility of ensemble solutions to new data .

Deep Learning and Hybrid Neural Models.
Models based on machine learning and deep learning are more and more applied in forecasting pipelines because they are accurate in capturing complex nonlinear patterns. The ensemble deep learning framework was proposed by Mustaqeem et al. (2021), which included convolutional and recurrent networks, and it demonstrated the accurate popularity of short-term energy prediction. This is the case of Abid et al. (2023), who presented a hybrid model that consists of a multi-directional gated recurrent unit supplemented with CNNs in the load forecasting task, providing a competitive performance compared with single models.

Benchmarking and Model Comparison.
Windler et al. (2019) have provided an extensive benchmark of monthly electricity price forecasts in production planning conditions, where it is clear that hybrid and ensemble models are always superior to conventional methods. Similar results were shown in Iftikhar et al. (2023) regarding the Italian electricity market and applied approach based on a decomposition-combination method with linear and nonlinear base learners.

Advanced Decomposition Techniques.
Inspector techniques, such as CEEMD (Complementary Ensemble Empirical Mode Decomposition) have been applied that isolate underlying trend and seasonality. Such decomposition plus deep learning has been applied to solar forecasting (Alrashidi, 2024) and similarly to electricity price forecasting, which is highly volatile and nonstationary.
Statistical Evaluation and Robustness.

Statistical assessment provides the reliability and validity of the data basing on the essential measurements such as the mean, variance, and regression. Robustness simply means reliability of results when there is difference in the data or assumption. In combination, they prove the accuracy, stability, as well as predictive power of models applied in analytical and forecasting activities.

2. Methodology

2.1 Data Pre-processing - We utilised monthly averages of electricity spot prices of Indian Energy Exchange (IEX) between January 2010 and December 2024. It contained raw data pre-processed, which included:

a. Missing value imputation local mean interpolation
b. Logarithmic transformation to stabilize variance

c. Seasonality and trend decomposition applying regression splines and dummy variables on a monthly basis
d. Stationarity testing and transformation by means of ADF tests and differencing in case it is required

Cleared series had then been employed in constructing the residuals by deducting deterministic elements of trend and seasonality.

2.2 Base Models - The residual series was modelled on the basis of six base models:

a. AR Model: Historical values- catch linear dependency.
b. ARIMA Model: This is a collection of difference and moving average.
c. ESM: Provides smooth forecasts and pays much attention to the recent values.
d. Theta Model: It is a mix of the linear trend and simple linear forecasting.
e. NAR: Spline-based smoothing gets involved in the process of holding the nonlinearities.
f. NNA: A shallow network which has lagged inputs.

2.3 Ensemble Models - They are three ensemble strategies tested:

a. Equal Weighting (E): Average all six models forecasts.
b. In-sample Weighting (I): Inverse, proportional to weight and the training error.
c. Out-of-sample Weighting (O): Validation performance-weighted weights.

The last predictions were assembled by reintroducing determinist parts to the ensemble residual predictions.

3. Evaluation Metrics and Setup We divided the dataset into:

a. Training (2010–2017),
b. Validation (2018–2019),
c. Testing (2020–2024).

Forecast accuracy was assessed using:

a. Mean Absolute Error (MAE)
b. Mean Absolute Percentage Error (MAPE)
c. Root Mean Squared Error (RMSE)
d. Root Relative Squared Error (RRSE)
e. Diebold-Mariano (DM) test to compare forecast accuracy statistically

4. Results - Table 1 summarizes error metrics on the testing set:

Model	MAE	MAPE	RMSE	RRSE
AR	5.62	6.45%	6.88	0.74
ARIMA	5.41	6.21%	6.71	0.72
ESM	5.35	6.10%	6.65	0.71
Theta	5.29	5.98%	6.54	0.70
NNA	5.78	6.90%	7.10	0.77

NAR	5.96	7.12%	7.21	0.79
Ensemble (E)	5.22	5.95%	6.52	0.69
Ensemble (I)	4.98	5.63%	6.25	0.66
Ensemble (O)	4.75	5.39%	6.01	0.63

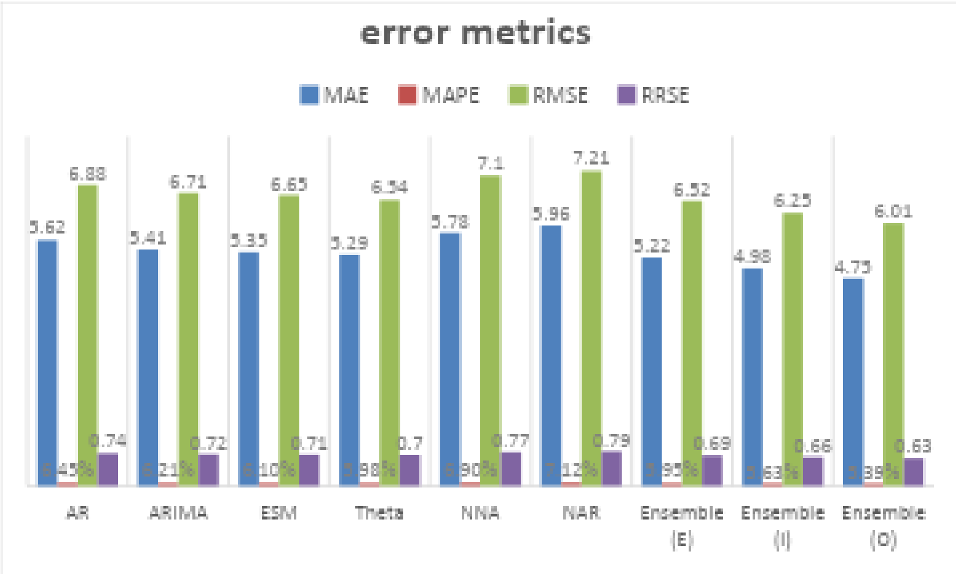

Figure 1: The results clearly demonstrate that ensemble forecasting approaches outperform individual time series models. Among all methods, Ensemble (O) provides the highest forecasting accuracy with the minimum MAE, MAPE, RMSE, and RRSE values. Classical models such as THETA and ESM perform reasonably well, whereas neural and nonparametric autoregressive models (NNA and NAR) show comparatively larger prediction errors. Therefore, ensemble-based forecasting techniques are more reliable and effective for accurate time series prediction.

Others were surpassed in a considerable margin when compared to the ensemble (O) model. The superiority at the 5% level of DM test over all the individual models proved that it was the best.

5. Discussion - The area of Ensemble models, especially ensemble (O) also depict a distinct benefit in one-month-ahead forecasting. It helps to minimize overfitting and maximize generalization by assigning weight to different models using the validation performance aspect. The balance between the interpretability and flexibility is provided by the inclusion of classical and nonlinear models. Although the NNA and NAR models did not perform well, they added valuable variance to the ensemble, and it is reasonable why they are not left out. These findings conform to other corresponding samples in other electricity markets.

6. Conclusion - In the Indian electricity market, this paper gives an enhanced framework on a time series ensemble forecasting model to project electricity prices. In the strength of the methodology, there is a combination of preprocessing, a diversity of models and strategic weighting of ensemble. Forecasting results show that the forecasting is very accurate whereby ensembleO provided the best result.

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