Day-ahead and intra-day wind power forecasting based on feedback error correction

Akshita Gupta1 | Arun Kumar2 | Kadhirvel Boopathi3

1 Hydro and Renewable Energy Department, Indian Institute of Technology Roorkee, Roorkee, Uttarakhand, India
2 Hydro and Renewable Energy Department, Indian Institute of Technology Roorkee, Roorkee, Uttarakhand, India
3 Research & Development, Resource data Analytics & Forecasting And Solar Radiation Resource Assessment, National Institute of Wind Energy (NIWE), Chennai, India

Correspondence
Hydro and Renewable Energy Department, Indian Institute of Technology, Roorkee, Uttrakhand
247667, India
Email: 26akshita@gmail.com

Abstract
The major hindrance in the development of large-scale grid integration of wind energy into the power system is the production of intermittent and variable power. A large-scale integration requires a forecasting mechanism to support the power system operators while operating the grids. This study forecasts the day-ahead and intra-day wind power using the wavelet decomposition, followed by the autoregressive integrated moving average. The forecasting has been attempted on two datasets, actual and error wind power. The forecasting using the wavelet decomposition employs the discrete wavelets consisting of 16 wavelets, grouped into 5 families. The optimum length of the past data used for the model formulation has also been examined for the various scenarios. The forecasting results have been compared based on various performance metrics. The results of the forecasted values have been compared with the reference ARIMA model to see the effectiveness of the proposed wavelet-ARIMA model. The results indicate that the feedback mechanism used in the error dataset have improved the forecasting efficiency over the use of actual data in both the day-ahead and intra-day forecasting. Also, it has been observed that some of the wavelet families outperformed the other families in terms of accuracy and speed.

1 | INTRODUCTION

The increasing environmental concerns and demand for electricity has led to a world-wide increase in renewable energy deployment. The most cost-effective and readily developed renewable energies being wind and solar, which are highly penetrating the power systems all over the world. For the past two decades, the wind energy deployment over the world has increased from 17.4 GW in the year 2000 to about 650 GW in the year 2019, accounting for about 25% of the total electricity mix [1, 2]. The major hindrance in the path of large-scale penetration into the electrical grid is the inherent intermittent and variable nature of the wind energy. The sustenance of high wind energy penetration in the grid requires a suitable energy storage system on the system side and an accurate wind power forecasting on the utility side. An accurate forecasting can lead to reducing the overall operating cost of the system.

The wind power forecasting has been performed using the different techniques and can be grouped coarsely into three categories; (1) a statistical modelling approach, (2) physical modelling approach, and (3) combination of both the methods. The statistical approach deals with the development of the models that use historical datasets like wind power, wind speed, wind direction etc. as the predictors for the forecasting of the wind power. These approaches can be of two types: heuristic and classical. The heuristic techniques include artificial intelligence models like neural network [3–5], machine learning [6, 7], deep-learning [8, 9], support vector regression [10, 11], particle swarm optimization [12] and bird swarm optimization [13]. The classical techniques, on the other hand, include time-series analysis models like ARIMA and seasonal ARIMA models [14, 15]. The GARCH method has been applied to model the volatility of the wind power generation [16, 17], but the model assumes that positive and negative shocks have the same effects on volatility. In practice, it is well known that the response to positive and negative shocks is different [18, 19].

The physical models employ different meteorological and topological components for the forecasting of the wind speed which is further analysed with the wind farm data for conversion into wind power. The physical approach provides accurate
The combination approach combines the two and produces results that provide better wind power forecasting than the individual technique [24]. The physical and the statistical approaches are used for the long term and short-term wind power forecasting respectively. Apart from this, the use of decomposition algorithms like Kalman filters and wavelet decomposition [25] with the various techniques have provided better forecasting accuracies. The wavelet decomposition has been applied to the forecasting applications in multiple fields involving finance, sales, medicine, among other ones. Therefore, the time series is decomposed into different constituent components. The application of this decomposition in wind power forecast have provided some promising results and thus proves useful in the forecasting application [26]. The determination of the mother wavelet in the wavelet decomposition process that provides accurate forecast is an important step while using the decomposition algorithm.

The feedback mechanism (or feedback error correction) deals with the improvement of the existing wind power forecasting models so as to reduce the error in the subsequent forecasting [27], thus improving the existing model. The studies involving the use of wind error data has a wide area of application which includes the estimation of the penalties in the modern liberalized markets [28], economic dispatch of power [29], unit commitment [30], power system operation [31], operating and reserve capacity planning [32, 33], forecasting of ramping events [34], storage requirements [35] and balancing requirements [36]. In [37,38] the quantitative impact of wind power forecasting on the overall economy and the public shows encouraging results in terms of living standards and growth of the economy.

The increasing competitiveness in the energy markets all over the world has resulted in the reduction of the market settling time as well as giving rise to the different segments of energy markets like day-ahead markets (DAM), real time markets (RTM) etc. All these markets require different horizons of power forecasting, e.g., a day-ahead market requires the forecast for a day ahead in advance, a real time market on the other hand requires forecast in 1 or 2 h in advance based on the guidelines of the energy markets. It becomes imperative to have a forecasting system that could provide accurate forecasting for the specific market. The wind power forecasting in the literature has provided an insight into the forecasting techniques and its applications in power system management. In this study, wind power forecasting has been conducted by breaking wind power series using the wavelet decomposition technique and then forecasting the resulting components using autoregressive integrated moving average (ARIMA) method. The ARIMA is selected for forecasting because the combination of wavelet decomposition and ARIMA has been limitedly reported in the literature, and the ARIMA model requires a small input data for the forecasting. The significant contributions that are made in this paper are as follows:

1. The wind power forecasting on the wind error data strengthens the existing wind power forecasting model and a comparison with the forecasting of actual wind power data provides the usefulness of the feedback error mechanism.
2. The day-ahead and intra-day wind power forecasting model using the wavelet-decomposition and ARIMA generates several forecasting scenarios based on different wavelets and selects the best wavelet generating the most accurate wind power forecasts.
3. The length of the wind power data series used for training the forecasting model for the different scenarios for both day-ahead and intra-day models have been optimized and the one providing the best accuracy is obtained.
4. The use of wavelet decomposition to the extent that could be utilized in the future forecasting studies directly without applying all the possible wavelets for forecasting has been extended.

The day-ahead and intra-day wind power forecasting using the wavelet-ARIMA has been performed using the error wind data and compared with the forecasting using the actual wind data. Also, the forecasting is compared using the forecasting done by the ARIMA model. The rest of the paper has been organized as follows: Section II provides the introduction of the preliminaries that have been used in the proposed forecasting model, including ARIMA and wavelet decomposition. In Section III, the proposed forecasting model is applied for numerical simulation and analysis. The conclusion of the study has been provided in Section IV.

## 2 | DESCRIPTION OF BASIC METHODOLOGIES USED IN THE PROPOSED SYSTEM

This section presents the description of the methods used in wind power forecasting model along with the various performance evaluation tools applied to obtain the best results.

### 2.1 | Time-series analysis

A time series is defined as a set of values of a variable in an ordered sequence that is spaced at equal time intervals. The time series models have two major usages: (1) to understand the data by obtaining the underlying forces and structure, (2) to fit the model based on the observation, which can be further used for forecasting and monitoring. The time series analysis has been applied in a number of day to day applications like sales forecasting, analysis of the stock market, the study of inventory, quality and process control, census analysis etc. [39]. There are many models that have been used for the time-series forecasting, but the most popular and readily used is the autoregressive integrated moving average (ARIMA) model, developed by Box-Jenkins in 1994. This comprises of three components: (1) Autoregressive, (2) integrated and (3) moving average, each signifying separate elements of the time-series. An autoregressive model is a linear regression model of current values of the time-series against one or more past values of the series. The
A moving average model on the other hand is a linear regression of a variable window for scanning the frequency spectrum is the main characteristic of this transform, which increases the temporal resolution of the analysis. A general wavelet is represented by Equation (2).

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}} \varphi\left(\frac{t-b}{a}\right)$$

where $a$ is the scale parameter of continuous wavelet parameter, $b$ is the translation parameter of continuous wavelet parameter and $\varphi(t)$ is the mother wavelet.

The wavelet decomposition is achieved using wavelet transform and can be categorized into two categories: (1) Continuous wavelet transform (CWT) and (2) discrete wavelet transform (DWT). The CWT of the continuous signal $\chi(t)$ can be defined as per Equation (3) [44].

$$(\text{CWT})(a,b) = \int_{-\infty}^{+\infty} \chi(t) \varphi_{a,b}(t) dt = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} \chi(t) \varphi\left(\frac{t-b}{a}\right) dt$$

where $\chi(t)$ is the test signal.

The wavelet coefficient is an expansion and a particular shift is a representation of the dilation and translation of the mother wavelet in comparison to the original signal $\chi(t)$. Thus, the wavelet representation of the original signal $\chi(t)$ in relation to the mother wavelet is provided by the coefficient group of $\text{CWT}(a,b)$ associated with a particular signal. The representation of the signal provided by CWT is redundant because the entire support of $W(a,b)$ is not required in order to recover $f(t)$. Another approach that translates and scales the mother wavelet using certain scales and positions generally based on the powers of two, is known as DWT, and compared to CWT, this scheme is more efficient and accurate. The DWT can be described by Equation (4).

$$\text{DWT}(m,k) = \frac{1}{\sqrt{a^n}} \sum_{n} \chi(n) \psi\left(\frac{k-nb a^m}{a^n}\right)$$

where $m$, $k$ are the discrete wavelet parameters and $n$ is the number of observations.

In DWT analysis and reconstruction of a signal is achieved using multiresolution filter banks and special wavelet filters. A filter bank consists of the filters that separates a signal into different frequency bands. An example of a filter bank is shown in Figure 1, which represents a three-level filter bank with both the analysis and synthesis phases. In the analysis phase, a discrete time signal $\chi(k)$ enters the bank and is filtered using the filters $L(\tilde{z})$ and $H(\tilde{z})$, that separates the frequency content of the input signal into the frequency bands of equal width with the low-pass and high-pass components respectively and retrieves
the approximations and details of the signal $x(k)$. The two outputs together consist of the same frequency content as the input signal, but the amount of data becomes twice. Therefore, the outputs of the filters in the analysis bank are down sampled by a factor of two which is denoted by $\downarrow 2$. The level of the filter bank depends on the desired resolution and accordingly can be expanded to an arbitrary level. The coefficient $c_l(k)$ consists of half the number of samples and represents the lowest half of the frequencies in $x(k)$. In the second level, the outputs of $L(z)$ and $H(z)$ have a decreased frequency content and double time resolution, thus the window width is increased.

The original signal can be reconstructed using the synthesis filter bank, shown in Figure 1(b). In this the signals are up sampled ($\uparrow 2$) instead of down sampled and then passed through the filters $L'(z)$ and $H'(z)$, which are based upon the filters in the analysis bank. The outputs of the filters in this are then summed, thus leading to the reconstructed signal $y(k)$ [45]. This study uses 106 discrete wavelets from 5 different families. These wavelets along with their families are listed in Table 1.

### 2.3 Performance evaluation tools used in the study

This section gives a comprehensive description of the different statistical metrics for assessing the performance of the forecasting system for the forecasting of wind power and obtain the best results in case of different wavelets.

The different evaluation metrics that have been employed in the study are mean absolute percentage error (MAPE), mean absolute error (MAE), root mean square error (RMSE), normalized mean square error (NMSE), and index of agreement of forecasts (IA).

![Figure 1: DWT as the filter banks in wavelet decomposition](image)

| S. No. | Family | Wavelets                      |
|-------|--------|-------------------------------|
| 1.    | Bior   | bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8 |
| 2.    | Coif   | coif1, coif2, coif3, coif4, coif5, coif6, coif7, coif8, coif9, coif10, coif11, coif12, coif13, coif14, coif15, coif16, coif17 |
| 3.    | Db     | db1, db2, db3, db4, db5, db6, db7, db8, db9, db10, db11, db12, db13, db14, db15, db16, db17, db18, db19, db20, db21, db22, db23, db24, db25, db26, db27, db28, db29, db30, db31, db32, db33, db34, db35, db36, db37, db38, haar, dmey |
| 4.    | Rbior  | rbio1.1, rbio1.3, rbio1.5, rbio2.2, rbio2.4, rbio2.6, rbio2.8, rbio3.1, rbio3.3, rbio3.5, rbio3.7, rbio3.9, rbio4.4, rbio5.5, rbio6.8 |
| 5.    | Sym    | sym2, sym3, sym4, sym5, sym6, sym7, sym8, sym9, sym10, sym11, sym12, sym13, sym14, sym15, sym16, sym17, sym18, sym19, sym20 |

The interpretation of each of these parameters are quite different from each other, as discussed below:

1. **MAPE** comes in handy when the data cannot be interpreted from the error measure and gives a good idea of the relative error. The problem with this approach is when the forecast series can have small denominators and hence there might be chances of zero division or the value blowing up. MAPE also puts a substantial penalty on negative errors and as a consequence, when MAPE is used to compare the accuracy of predictions it will select a method whose forecasts are too low.

2. **MAE** is defined as the average of the absolute values of the deviation and is useful when measuring prediction errors in the same unit as the original series. It is quite robust to outliers. Hence if the data is homogeneous, this error measure can be used to compare different models.

3. The **RMSE** metric favours that model whose individual errors have a consistent magnitude because a large variation in error increases the RMSE. And as the error is squared, only a few poorly predicted values could increase the RMSE.

4. The **NMSE** facilitates the comparison between models with different scales. Thus, the NMSE can be interpreted as a fraction of the overall range that is typically resolved by the model.

5. **IA** is defined as a standardized measure of the degree of model prediction error and is represented by the ratio of the mean square error and the potential error. The value of this varies between 0 and 1, where the value of 1 indicates a perfect forecast, and 0 indicates no agreement of the forecast at all. It can easily detect the additive and proportional differences present in the observed and simulated means and variances.

The formulas of these evaluation metrics are shown in Table 2. This study utilizes all these evaluation metrics for checking the performance of the different wavelets and the best
### TABLE 2  
Evaluation metrics used in the study

| Metric | Equation |
|--------|----------|
| MAPE   | $MAPE = \frac{1}{N} \sum_{i=1}^{N} |\frac{A_i - F_i}{A_i}| \times 100$ |
| MAE    | $MAE = \frac{1}{N} \sum_{i=1}^{N} |A_i - F_i|$ |
| RMSE   | $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (A_i - F_i)^2}$ |
| NMSE   | $NMSE = \frac{1}{N} \sum_{i=1}^{N} \frac{(A_i - F_i)^2}{A_i F_i}$ |
| IA     | $IA = 1 - \frac{\sum_{i=1}^{N} (A_i - F_i)^2}{\sum_{i=1}^{N} |A_i - \bar{A}| + |F_i - \bar{A}|)}$ |

wavelet in a specific category is the one that provides the best results for maximum number of metrics.

### 3  
NUMERICAL SIMULATIONS AND RESULT ANALYSIS

In this section, the proposed forecasting model is simulated numerically by applying the wind power datasets from India in order to verify its performance. Also, the analysis of the results for day-ahead and intra-day forecasting of wind power in this study is conducted using the actual and the error wind power data. Thus, the performance analysis of the proposed model corresponding to the best wavelet is described.

#### 3.1  
Study data

Wind power forecasting has been performed on the wind power data of a state in India, which has been provided by the National Institute of Wind Energy (NIWE). The data has been a high-resolution data with 15 min interval. The two sets of wind power data have been obtained from NIWE, actual wind power data and the model wind power data developed by NIWE. The forecasting is performed using the actual wind power data and error wind data, which is the difference between the actual and model wind power data. Both the datasets are available for a duration of a year starting from April 2018 to March 2019. The data has been checked for the outliers and missing data has been replaced using the 5-moving average method. The day-ahead and intra-day forecasting have been implemented on day wise basis, i.e. for every 24 h and the revision is sought at 90 min prior to the reference time. The length of the training data is taken as a variable in the interval of 5 blocks (1 block = 15 min) prior to the reference time, starting from 150 till 400 blocks. The difference in the operation of day-ahead and intra-day forecasting mechanisms is shown in Figure 2.

All the experimental simulations in this study has been performed on the Python platform at Windows 10 with 3.40 GHz Intel Core i7-4590HQ 64-bit and with 16 GB RAM.

#### 3.2  
Forecasting length selection

The selection of the length of past data for the training purpose of the wavelet-ARIMA model is an important step in the forecasting process. In this study the different lengths of past data have been used to obtain forecasting. The different forecasting data lengths used in the study are 150, 200, 250, 300, 350 and 400 blocks. The results of the best forecasting length for intra-day and day-ahead wind power forecasting using the actual and error wind dataset are shown in Table 3. The forecasting length selection is based on the evaluation based on the performance metrics of Table 2.

#### 3.3  
Intra-day wind power forecasting

The intra-day wind power forecasting is used in the purpose of dispatching and scheduling of power from the wind generators. This has been performed primarily in literature for one-hour
or two-hour ahead forecasting [46]. Apart from this intra-day wind power forecasting also finds application in coordinating with other resources [47, 48] and bidding strategy facilitation in the intra-day market [49, 50]. A limited work has been reported in the literature and time lag has been limited to one-hour and not minutes.

This study uses the intra-day wind power forecasting to forecast the wind power without explicitly using the forecasted data for 90 min into the next forecasting interval. Thus, forecasted data is not used for forecasting of subsequent values and instead the data from the actual values is used. The forecasting is performed using the wavelet-ARIMA model. To show the effectiveness of this model it is compared with the forecasting using the ARIMA for a typical day. The intra-day wind power forecasting results using the actual wind power dataset with the best wavelet and the optimum length of the past data is shown in Figure 3. The best wavelet using the actual data comes out to be db6 for the 250 blocks of past data.

The intra-day wind power forecasting using the error data, i.e. the dataset resulting from the difference of actual data and the model data for the best wavelet and the optimum length of the past data is shown in Figure 4. The best wavelet in this case comes out to be rbio1.3 at an optimum length of 200 blocks of past data.

The forecasting using the two datasets shows that the wind power forecasting using the actual wind power data gives a step response, unlike the forecasting using the error data which gives a smoother and close response. The forecasting using the ARIMA model follows a similar trend as the wavelet-ARIMA but the forecasting using the wavelet-ARIMA model is closer produces lowest error. This fact for intra-day wind power forecasting can be observed from Table 4, which shows that for both the datasets wavelet-ARIMA model performs better than the ARIMA model.

### 3.4 Day-ahead wind power forecasting

The day-ahead wind power forecasting has been performed in the literature to cater the needs of day-ahead market and also to plan the wind resources for the grid [51, 52]. The day-ahead forecasting has been performed mostly for the one-day ahead interval, but the use of two-day and three-day ahead interval has also been reported [53]. The day-ahead market has been very popular and hence this forecasting is quite popular [54, 55]. The time between two forecasts is mostly on the hourly basis in the literature and has not been reported seldom for reduced duration.

The day-ahead wind power forecasting has been used in this study for forecasting the wind power by explicitly using the forecasted data for 90 min into the next forecasting interval, thus using the previously forecasted data into the forecasting of the subsequent values. The forecasting is performed using the wavelet-ARIMA model and compared with the forecasting using the ARIMA model for a typical day. The day-ahead wind power forecasting results using the actual wind power dataset with the best wavelet and the optimum length of the past data is

**FIGURE 3** Intra-day forecasting using the actual dataset

**FIGURE 4** Intra-day forecasting using error dataset

**TABLE 4** Comparison of performance metrics for intra-day

| Metrics    | Actual ARIMA | Wavelet-ARIMA | Error ARIMA | Wavelet-ARIMA |
|------------|--------------|---------------|-------------|---------------|
| MAPE (%)   | 24.91        | 21.68         | 15.78       | 14.67         |
| MAE (MW)   | 338.25       | 300.00        | 207.98      | 207.85        |
| RMSE (MW)  | 409.60       | 367.03        | 282.56      | 272.83        |
| NMSE       | 55.58        | 6.23          | 3.34        | 3.32          |
| IA         | 0.94         | 0.95          | 0.95        | 0.96          |
shown in Figure 5. The best wavelet using the actual data comes out to be db6 for the 250 blocks of past data.

The intra-day wind power forecasting using the error data, i.e. the dataset resulting from the difference of actual data and the model data for the best wavelet and the optimum length of the past data is shown in Figure 6. The best wavelet in this case comes out to be rbio1.1 at an optimum length of 300 blocks of past data.

The forecasting using the two dataset shows that the wind power forecasting using the actual wind power data gives a response which is irregular in nature and does not follow the actual trend at all unlike the error dataset which follows the actual wind power data trend. The forecasting using the ARIMA model follows a similar pattern as the wavelet-ARIMA model but the wavelet-ARIMA model forecasting follows the actual values closely in terms of trend as well as magnitude. The performance of wavelet-ARIMA model compared to the ARIMA model for the day-ahead in terms of different performance metrics is shown in Table 5. It can be observed that wavelet-ARIMA model reduces the error for both the datasets compared to the ARIMA model.

### 3.5 Performance metrics and wavelet analysis

The summary of all the performance metrics for the best forecasting length values obtained for both intra-day and day-ahead forecasting using the wavelet-ARIMA model is shown in Figure 7. It can be observed from Tables 4 and 5 that for the error data all the performance metrics had better values compared to the actual data for both day-ahead and intra-day forecasting. The fit of the error dataset is better compared to the actual dataset.

The wavelet decomposition uses 106 discrete wavelets for wind power forecasting which are categorized into 5 families. The best wavelet for the intraday and day-ahead wind power forecasting corresponding to the optimum length of past data is shown in Table 6. It can be observed that the best wavelets belong to two wavelet families, db and rbio. The other wavelet families do not provide a satisfactory result as compared to these families.

The comparison of the computational time for different length of data for both the intra-day and day-ahead forecasting is shown in Table 7. It can be observed that the computational

| Table 5 | Comparison of performance metrics for day-ahead |
|---------|-----------------------------------------------|
| Metrics | Actual | Wavelet-ARIMA | Actual | Wavelet-ARIMA |
| MAPE (%) | 69.29 | 43.82 | 20.52 | 15.23 |
| MAE (MW) | 805.20 | 592.06 | 322.37 | 269.89 |
| RMSE (MW) | 939.82 | 690.02 | 413.46 | 369.05 |
| NMSE | 43.77 | 19.73 | 6.52 | 3.88 |
| IA | 0.48 | 0.69 | 0.92 | 0.93 |

| Table 6 | Best-wavelets for the wavelet-ARIMA model |
|---------|-----------------------------------------|
| Intra-day | Day-ahead |
| Length | Actual | Error | Actual | Error |
| 150 | db5 | db3 | db8 | rbio1.1 |
| 200 | db6 | rbio1.3 | db6 | rbio2.2 |
| 250 | db6 | db5 | db7 | rbio3.1 |
| 300 | db3 | db7 | rbio1.1 | |
| 350 | db5 | rbio2.2 | db4 | db2 |
| 400 | db5 | db4 | rbio3.1 | rbio3.1 |

| Table 7 | Computational time (in s) for the wavelet-ARIMA model |
|---------|-----------------------------------------------|
| Length | Intra-day | Day-ahead |
|        | Actual | Error | Actual | Error |
| 150 | 31 | 42 | 43 | 51 |
| 200 | 34 | 47 | 45 | 54 |
| 250 | 33 | 44 | 46 | 58 |
| 300 | 37 | 46 | 49 | 60 |
| 350 | 39 | 50 | 47 | 62 |
| 400 | 44 | 54 | 55 | 65 |
time varies between 30 and 70 s. The computational time for the actual time series is less compared to the error time series and also intra-day computation is faster compared to day-ahead forecasting.

4 CONCLUSION AND FUTURE SCOPE

In the scenario of high penetration of wind power into the electrical grid, forecasting can be really useful to increase the reliability and stability of the grid. The integration of large wind farms requires an accurate wind power forecasting. The deregulated market environment requires a forecasting system that is robust and accurate as well as the forecast for the intervals suitable for the market. This study proposed the wavelet-ARIMA model for the intra-day and day-ahead wind power forecasting using the error and actual wind power data. The results indicate that the feedback mechanism provided by the error wind power data increase the accuracy of the existing model data. Also, the forecasting done using the error data follows the trend and magnitude better than the forecasts using the actual data. The comparison of the ARIMA and wavelet-ARIMA model shows that the decomposition increases the forecasting accuracy and follows the actual data trend closely in both the intra-day and day-ahead forecasting. The wavelet decomposition uses the discrete wavelets that are sub-divided in 5 families and consists of 106 wavelets. Out of these only two wavelet families, i.e. db and rbio were found to obtain the best accuracy under all the scenarios. The length of the past data blocks for forecasting impacts the accuracy of the forecasting and does not remain the same for all the scenarios. The computational time of the algorithm is within a minute and thus for 15-min forecasting interval does not impact the working of future algorithm. The future research could include the probabilistic forecasting into the existing model as well as use the weighted average method to combine the results of different wavelets to obtain more refined forecasts.

ACKNOWLEDGMENTS

The author would extend a sincere gratitude to Mr. A. G. Ranagaraj from NIWE for providing assistance in NIWE model and data input. Also, sincere thanks to the Ministry of Human Resources and Development (MHRD) for providing the financial and technical support to carry out the research work at the Indian Institute of Technology (IIT), Roorkee.

List of Acronyms

| Acronym | Description |
|---------|-------------|
| ARIMA   | Autoregressive integrated moving average |
| CWT     | Continuous wavelet transform |
| DAM     | Day-ahead market |
| DWT     | Discrete wavelet transform |
| GARCH   | Generalized autoregressive conditional heteroskedasticity |
| IA      | Index of agreement |
| MAE     | Mean absolute error |
| MAPE    | Mean absolute percentage error |
| NMSE    | Normalized mean square error |
| RMSE    | Root mean square error |
| RTM     | Real time market |

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