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Short-term Wind Power Forecasting Using a Markov Model

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Abstract—— **Large-scale wind power integration to power systems has been significantly increasing since the last decade. However, the reliability of power systems tends to degrade due to the intermittency and uncontrollability of wind power. Future wind power generation forecasts can be used to reduce the impacts of intermittency and uncontrollability of wind power on the reliability of power systems. This paper proposes a Markov chain-based model for the short-term forecasting of wind power. The first-order and second-order Markov chain principles are used as they require lesser memory and have lower complexities. Seasonal variation is also incorporated into the proposed model to further improve the accuracy. Results obtained from both Markov models are validated with real wind power output data and evaluated using evaluation metrics such as Mean Square Error and Root Mean Square Error. The results show that the accuracy of the first-order and second-order Markov models for a high wind regime is 81.33% and 82.61%, respectively and for a low wind regime is 83.50% and 89.27% respectively.**

Keywords——wind power forecast, Markov chain, short-term forecast, wind power

I. Introduction

Renewable power integration, especially wind and solar integration to the power grids has been increasing due to the devastating impacts of fossil fuels and technological advancements in renewable generation. With the shifting of interest of most of the countries from fossil fuels to renewable energy sources, significant attention is paid to wind power generation. As of 2018, the share of wind power generation in the world is accounted for 4.8% amounting to 1,264.84 TWh [1]. Global installed wind generation capacity has increased by 75% in the last 20 years and accounts for 16% of the total electricity generated by renewables [2]. However, large-scale wind power integration tends to reduce the controllability and reliability of the system. This is due to the intermittency and uncontrollability of wind power generation. Unexpected variations in wind power generation may unnecessarily increase the reserve requirement and operating costs, especially when the proportion of wind power in the power grid is large.

The technology related to wind power generation is expanding rapidly to solve the prevailing issues with the integration of wind power into power grids. Wind power forecasting is one such area that can be developed to address the issues of intermittency by predicting the wind power in a very short-term horizon.

Errors in wind power forecasts can result in committing of more costly conventional generators. On the other hand, when the actual wind generation is higher than the forecasted value, the reserving cost of other high-cost generators is a wastage. Therefore, it is necessary to utilize an accurate model for wind power forecasting.

Several wind power forecasting methods can be found in the literature [3-9]. These methods are classified as physical, statistical and hybrid approaches. The physical approach is based on Numerical Weather Prediction (NWP) which is the base source of data. They provide seemingly accurate predictions for very long time horizons. The statistical approach is based on the historical wind data and the hybrid approach combines physical and statistical approaches. In this work, the main emphasis is given to statistical wind power forecasting models.

Wind power can be statistically forecasted using either historical wind speed data in the region or historical wind power generation data of the wind farms. The feasibility studies of future wind farms are carried out using the regional wind profiles and historical wind power forecasting is useful for managing the generator dispatches and ancillary requirements. When the forecasted wind speeds are used to forecast the wind power output of a power plant, the forecasting errors in wind speed are magnified due to non-linear wind speed to power mapping. Wind speed data obtained from meteorological sources may differ from the actual wind speed at the turbines due to vague scenarios which may result in major errors in wind speed predictions and thereby result in errors in power output prediction. Additionally, according to Betz's law, only 59.3% of the kinetic energy present in the wind can be theoretically converted to mechanical power by the turbine. Therefore, wind power forecasts based on historical wind power data are more accurate and useful for system control applications and economic dispatch [3].

Statistical approaches use the relationships of historical values of wind power measurements together with metrological variables to adjust the parameters of the wind power forecasting methods. In a very short time horizon, the correlation between wind speed and wind power generation is high. Therefore, statistical approaches can be accurately used in very short-term wind power forecasting. These approaches can produce deterministic predictions in the form of a single point forecast for some future time or can produce probabilistic predictions in the form of a probability distribution at the future time. A wind power prediction model

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based on a deep-learning method called long short-term memory model which has the advantages of generalization of mass data is proposed in [4]. In [5], the Kalman filter-based time series prediction method is proposed. The results show that the addition of the Kalman filter significantly reduces the forecast errors. A wind power forecasting model based on Least Square Support Vector Mechanism (LS-SVM) is proposed in [6] and the results are compared with classical ARIMA and ANN models. The accuracy of LS-SVM method is higher than that of ARIMA and ANN. In [8], the authors have used principles of nested Markov chains to generate an artificial wind time series that can realistically present a possible chain of events. However, the frequency of obtained wind data is 1 Hz which is not feasible in the practical scenario. Therefore, there is a significant amount of errors in the artificially generated wind time series. Furthermore, SVM enhanced Markov model proposed in [9] does not consider the seasonality and diurnal non-stationarity and only considers normal fluctuations of wind generations. It can be observed that most of the prevailing studies do not take seasonal wind variations into the account [4-9].

In this study, a Markov chain-based probabilistic wind power forecasting model is proposed for very short-term i.e. 1~24 hours ahead wind forecasting. The forecasting model is implemented using the python programming language. Due to the simplicity, fast computing, high precision and low memory requirements of Markov chains [7], authors have utilized first and second-order Markov chain models for wind power forecasting. Seasonal variation of wind power is incorporated into the proposed wind forecasting model. Point power outputs of a wind farm with 15-minute resolution are used to implement the Markov models. Performance measures such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are used to evaluate the proposed wind power prediction models. Furthermore, the predicted and actual wind power generations are compared to identify the accuracy of the proposed wind power forecasting model.

The paper is organized as follows. An overview of the Markov chain principles is presented in section II. In section III, the implementation of the first and second-order Markov chain models is discussed considering mathematical modeling, prediction, and validation methodologies. Section IV describes the model evaluation metrics. The results are discussed in section V. Section VI concludes the paper.

II. Introduction to Markov Chain Theory

Markov chain or Markov model is a special type of discrete model in which the probability of an event occurring only depends on the immediately previous event. The underlying assumption is that the 'future is independent of the past, given the present.' Markov chains can be defined by a set of states and the respective transition probabilities between each of the states. The transition probability is defined as the probability of transition from one state to another [10].

The states of the Markov chain model are defined based on discrete data. Each state must cover a certain predefined range of values that the physical process can undertake. At each instance, the value of the physical process can then be allocated to the relevant state.

A. *First-Order Markov Chain Theory*

The First-Order Markov Chain theory is the basic implementation of the Markov chain model. In a random process where the physical data range is divided into m number of states represented by $[1,2,\dots,\mathrm{m}]$, the first-order Markov chain theory claims that if the process transitions from state i to state j at time t, the probability of this transition only depends on the state at time $t = t-1$. The general mathematical representation of a discrete-time first-order Markov chain model is shown in (1) [11]

$$P(X_t = j \mid X_{t-1} = i) = p_{ij} \tag{1}$$

The element p_{ij} denotes the probability of transitioning to state j at time $t = t$ when the system was at states i at time $t = t-1$.

An $m \; x \; m$ transition matrix can now be obtained as in Fig. 1. The depictions of the number of transitions and the probability are shown in Fig. 2 and please note that this figure is obtained from [12].

B. *Higher-Order Markov Chain Theory*

In the first-order Markov model, only the first lag was considered when obtaining the probability of the next step. In higher-order Markov chains, the last n observations are considered which results in an n$^{\text{th}}$ order Markov chain. This can be mathematically represented by (2).

$$\begin{aligned} P(X_t = j \mid X_{t-1} = i_1, X_{t-2} = i_2, \dots, X_{t-n} = i_n) \\ = p_{i_n i_{n-1} \dots i_1 j} \end{aligned} \tag{2}$$

The element $p_{i_n i_{n-1} \dots i_1 j}$ denotes the probability of transitioning to state j at time $t = t$ when the system was at states i_k at time $t = t-k, \forall k \in [1, n]$. The transition matrix is multi-dimensional with m^{n+1} dimensions for an n$^{\text{th}}$ order Markov chain model. Each dimension corresponds to a previous state of the process and the last dimension corresponds to the next possible state.

When the order of the Markov chain model increases, the number of parameters to calculate the transition matrix increases, and hence, the complexity increases. On the other hand, the accuracy of the prediction increases with the increase in the order of the Markov chain model. Therefore, a trade-off between complexity and accuracy must be considered when implementing the Markov chain model for wind power forecasting.

III. Implementation of the Markov Chain Theory

In this work, the Markov chain theory is utilized to forecast the wind power output for a look ahead time at 15-minute intervals. The states for the Markov model are a set of discrete

$$\mathbf{P} = \; \begin{matrix} & S_t \rightarrow \\ S_{t-1} \downarrow & \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \end{matrix} .$$

Fig. 1. m x m transition matrix

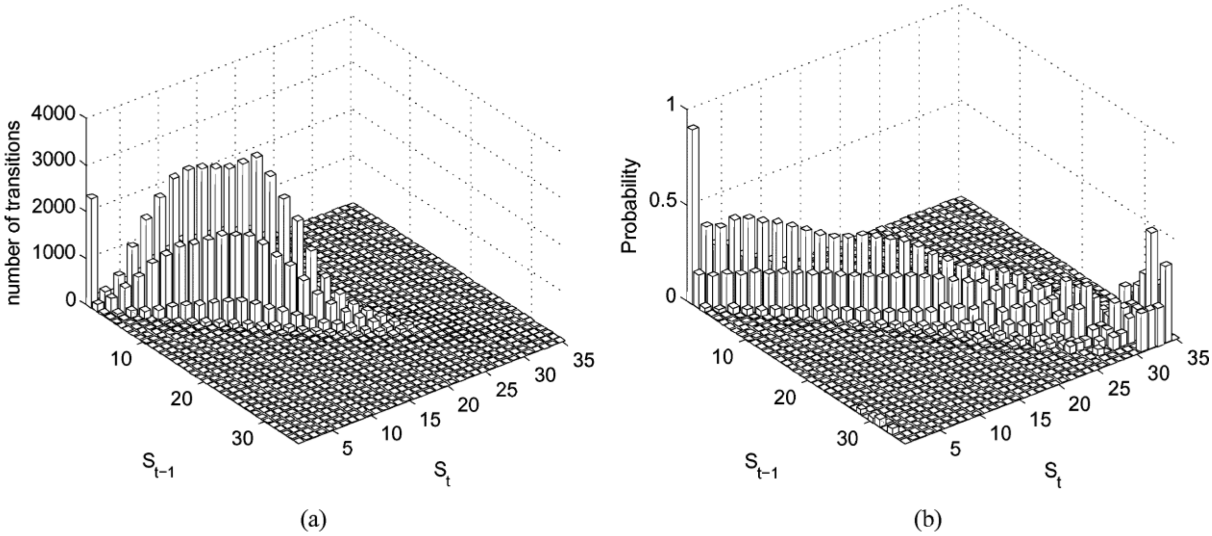


Fig. 1. (a). Number of transitions (b). Transition probabilities [12]

wind power generation values. The number of states is determined by the range of the power output available, and the range of power outputs covered by each state. This is denoted using N in the stated mathematical models. Subsections A and B describe the implementation of the first-order and second-order Markov chain models respectively. Subsection C explains the methodology of using Markov models for wind power forecasting.

A. First Order Markov Model (FOMC)

The initial state matrix $A(t)$ is a matrix that includes the state probability vectors at time $t = t$ as given by (3).

$$A(t) = [A_1 \quad A_2 \quad A_3 \cdots A_{N-1} \quad A_N] \tag{3}$$

At the initial forecasting point, all the elements of the initial state matrix are zero except for the element corresponding to the state at time t, which is set to 1 [13]. Once, the initial state matrix is initialized, the transition probability matrix (P_{FO}) is developed according to the Markov chain mathematical model expressed by (1).

Each row of the matrix represents the current state, and each column represents the next state (i.e., one of the N states of state variables) as shown in Fig. 3. The sum of elements of each row must be equal to unity as in (4) because it corresponds to the probabilities of transitioning from one state to the next state.

$$\sum_j p_{ij} = 1 \tag{4}$$

The individual elements of the first-order transition matrix can be calculated by (5) where n_{ij} represents the number of transitions from state *i* to j.

$$p_{ij} = \frac{n_{ij}}{\sum_{j=1}^{N} n_{ij}} \tag{5}$$

B. Second-Order Markov Model (SOMC)

It is required to define composite states for the implementation of the second-order Markov chain model. For a system with N number of states, the composite states are defined as $\{11, 12, 13, \dots, N1, N2, \dots, (N-1)N, NN\}$. For e.g., the state '12' represents the instance where the state at time $t = (t-1)$ is 1 and the state at time $t = t$ is 2.

As in the first-order Markov chain model, the initial state matrix $B(t)$ must be obtained and it can be represented by (6).

However, an initial matrix cannot be obtained straightforwardly as in the first-order Markov chain model. The initial matrix of the second-order Markov model is

$$B(t) = [B_1 \quad B_2 \quad B_3 \cdots B_{N-1} \quad B_N] \tag{6}$$

obtained by (7).

$$B_i(t) = \sum_{l=1}^{N} B_{li}(t-1, t) \tag{7}$$

where $i = 1, 2, \dots N$ and

$$B_{li}(t-1, t) = P(X_{t-1} = l, X_t = i) \; \forall \; l, i \tag{8}$$

		Next State (t+1)				
		1	**2**	**. . .**	**N-1**	**N**
Current State (t)	**1**	p_{11}	p_{12}		$p_{1,(N-1)}$	p_{1N}
	2	p_{21}	p_{22}		$p_{2(N-1)}$	p_{2N}
	. . .					
	N-1	$p_{(N-1)1}$	$p_{(N-1)2}$		$p_{(N-1)(N-1)}$	$p_{(N-1)N}$
	N	p_{N1}	p_{N2}		$p_{N(N-1)}$	p_{NN}

Fig. 2. Transition matrix of first order Markov model

In the second-order Markov chain model, the subsequent step of a stochastic model depends on two of its immediately previous states. This can be mathematically presented as in (9).

$$P(X_{t+1} = j \mid X_t = i, X_{t-1} = l) = p_{ijl} \quad (9)$$

Where p_{ijl} refers to the probability of the system being in state j at time $\mathrm{t} = \mathrm{t} + 1$ given that the system is in state i at time $\mathrm{t} = \mathrm{t}$ and in state l at time $\mathrm{t} = (\mathrm{t} - 1)$.

Considering the data of the sliding window, a 'one-step transition probability matrix' (P_{SO}) is developed. This one-step transition probability matrix has an advantage. As can be seen in the 3-state transition matrix shown in Fig. 4, many elements of one-step transition probability matrices are zeros and this results in easy computation.

As in the first-order Markov chain implementation, the sum of elements of the last dimension of the matrix should be equal to 1 as shown in (10).

$$\sum_j p_{i_n i_{n-1} \dots i_1 j} = 1 \quad (10)$$

The individual elements of the one step transition probability matrix can be calculated by (11).

$$p_{li,ij} = \frac{n_{li,ij}}{\sum_{j=1}^{N} n_{li,ij}} \quad (11)$$

C. Wind Power Forecasting

For the first-order Markov chain implementation, the prediction for the state at time $t = t + 1$ is obtained by the estimated state matrix $A(t+1)$ given by (12).

$$A(t+1) = A(t) \times P_{FO} \quad (12)$$

Thus, for the first-order Markov chain model, point power forecasts for a look-ahead time can be obtained by (13).

$$A(t+k) = A(t) \times {P_{FO}}^k \quad (13)$$

When considering the second-order Markov chain model, once the transition matrix is obtained, the predictions can be obtained. The predictions for the states at time $t = t + 1$ can be obtained by the estimated state matrix $B(t, t+1)$ by using (14).

$$B(t, t+1) = B(t-1, t) \times P_{SO} \quad (14)$$

Where P_{SO} is the transition matrix of the second-order Markov model, and $B(t-1, t)$ is the auxiliary state probability vector. In the auxiliary state probability vector, all the elements are zero except for the element corresponding to the state at time t and $t - 1$, which is set to 1.

However, in this work, it is required to obtain the state probability vector $B(t+1)$ as follows (15).

$$B_j(t+1) = \sum_{i=1}^{N} B_{ij}(t, t+1) \quad (15)$$

Where $j = 1, 2, \dots N$ and

$$B_{ij}(t, t+1) = P(X_t = i, X_{t+1} = j) \; \forall \, j, i \quad (16)$$

The state probability vector $B(t+k)$ is used to obtain the predictions at time $t = t + k$ as shown in (17).

$$B_j(t+k) = \sum^{N} B_{ij}(t+k-1, t+k) \quad (17)$$

where $j = 1, 2, \dots N$.

From the Markov chain theory and (16), we can derive (18) to obtain point power forecasts for a look-ahead time.

$$B_{ij}(t+k-1, t+k) = B(t-1, t) \times {P_{SO}}^k \quad (18)$$

Once the point power forecasts are obtained, wind power generation in the considered look-ahead time can be estimated. In order to formulate conditional point predictors, the mean values of the forecasts are calculated by (19).

$$Mean = \sum_{i=1}^{N} s_i * C(t+k) \quad (19)$$

Where $C(t+k)$ is the point power forecasts obtained for the FOMC model by using (13) and for SOMC model by using (18) for the second-order Markov model. s_i refers to the i[th] state.

IV. Evaluation Metrics

Performance measures can be used to quantify the accuracy of the proposed Markov models. The model prediction error can be defined as the difference between the measured values of the wind power output and the predicted values of the same. In this work, the model prediction error is calculated using two metrics, namely MSE and RMSE[14].

$$P_{SO} = \begin{pmatrix} p_{11,11} & p_{11,12} & p_{11,13} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & p_{12,21} & p_{12,22} & p_{12,23} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & p_{13,31} & p_{13,32} & p_{13,33} \\ p_{21,11} & p_{21,12} & p_{21,13} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & p_{22,21} & p_{22,22} & p_{22,23} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & p_{23,31} & p_{23,32} & p_{23,33} \\ p_{31,11} & p_{31,12} & p_{31,13} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & p_{32,21} & p_{32,22} & p_{32,23} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & p_{33,31} & p_{33,32} & p_{33,33} \end{pmatrix}$$

Fig. 3. One step transition matrix of second order Markov model

Table I shows the equations of the aforementioned performance measures.

V. Application Study and Discussion

The wind power generation dataset used in this work is obtained from [16]. The dataset consists of wind generation data in a 15-minute resolution with an accuracy of 0.1 scale. The data in the period starting from 1st January 2013 to 31st January 2013 is considered as the training range for high wind regime and the data from 1st July 2013 to 31st July 2013 is taken as the training range for the low wind regime. This accounts for 2976 data points as the sliding window of each scenario. The higher the data points, the higher the accuracy. However, a trade-off between accuracy and complexity exists and hence the sliding window has to be compromised. The range of the wind power output in the selected period is from 0 to 931 MW. Therefore, the states of the Markov model were defined as integer values between 0 and 931. Then this dataset is used to forecast the wind power as can be seen in the block diagram of the model is shown in Fig. 5.

The seasonality of the region is also considered in this application study. Separate Markov chains are used for different wind seasons to get a better accuracy.

The proposed models are validated as follows. Forecasted point power values obtained from the FOMC model and the SOMC model are compared with the actual output of the wind farm. The wind power forecasts for a 25-hour look-ahead period are obtained from developed models. Fig. 6 shows the wind power predicted by first-order and second-order Markov models and the actual power output of the wind farm. Moreover, the performance measures are tabulated in Table II for the predictions of the aforementioned Markov chain models.

When comparing the error metrics of the two Markov chain models developed in this work, it can be seen that the error metrics are low for the second-order model. Therefore, the results show that the forecasting accuracy of the model increases as the order of the Markov chain increases and this is compatible with [17].

TABLE I. Evaluation Metrics

Metric	Equation
Mean Squared Error (MSE)	$\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$
Root Mean Square Error (RMSE)	$\sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n}}$

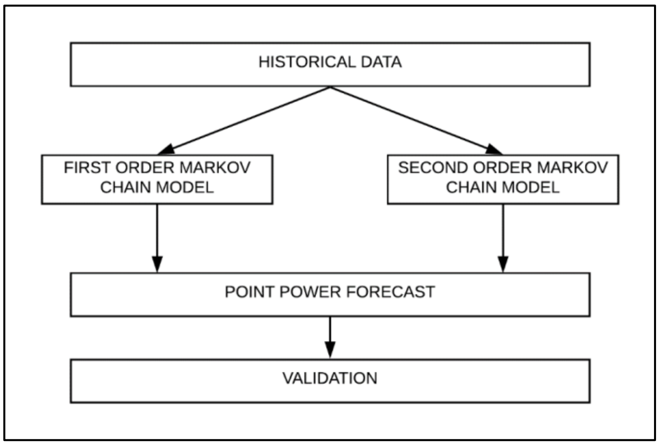
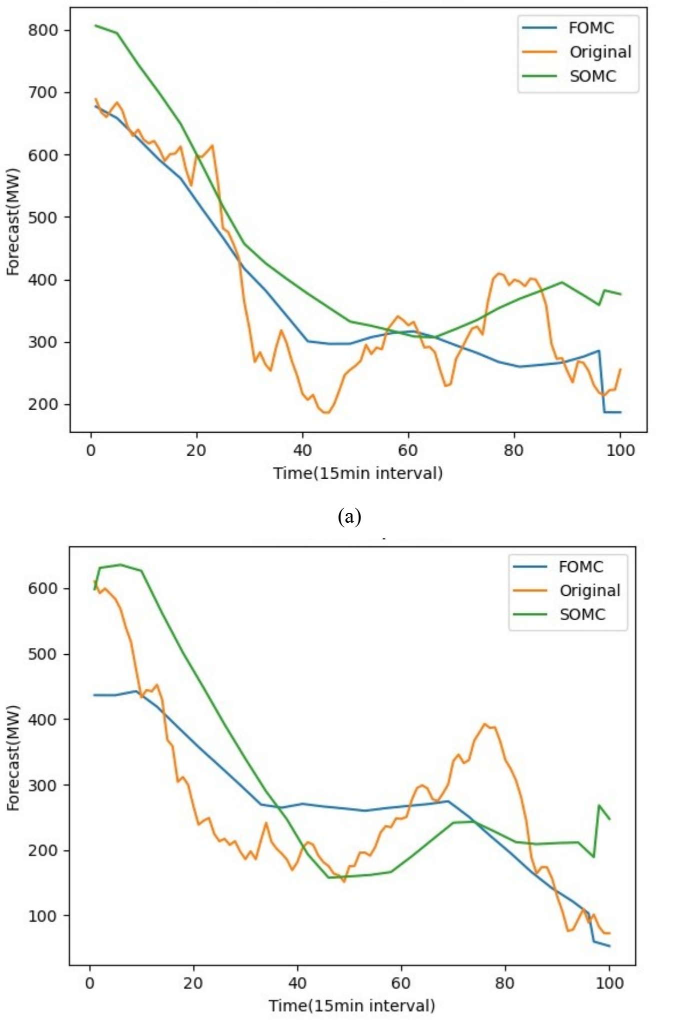


Fig. 5. Block diagram for application of Markov models for wind power forecasting



(b)

Fig. 4. Forecasts of the First order Markov Chain (FOMC) model and the Second Order Markov Chain(SOMC) model and the actual wind power output for (a) high wind regime. (b) low wind regime

The accuracy of the predictions of low wind regime is higher than that of the high wind regime. Forecast error depends on the variability of the wind speed. Variability is large in high wind regimes compared to low wind regimes and that is the reason for getting a low forecast error in the low wind regime.

The results show that the proposed wind power forecasting models can be used to predict the wind power generation with an accuracy higher than 80%.

VI. Conclusion

In this work, a wind power forecasting algorithm is proposed using Markov chain principles. Historical wind power data for 62 days in two different seasons are used to forecast the wind power output for 25 hours at a 15-minute resolution. Seasonal variations at the location of the wind farm are incorporated into the algorithm via a manual clustering system. The results show that the accuracy of the proposed Markov models is over 80% with respect to actual power

TABLE II. ERROR MATRICS OF THE MODELS

Metric	High wind regime		Low wind regime	
	First-order model	*Second-order model*	*First-order model*	*Second-order model*
Mean Squared Error (MSE)	38.76	22.46	23.47	11.41
Root Mean Square Error (RMSE)	18.67	17.39	16.50	10.73

generation data used for both models in high wind and low wind regimes.

The proposed model would support the power system operators to solve the issues that occur due to the intermittency of wind power generation under high levels of wind penetration by predicting the wind power output with high accuracy. In the future, it may be possible to further increase the accuracy of the proposed wind forecasting model by using clustering algorithms to cluster the historical wind power data.

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