Markov Models based Short Term Forecasting of Wind Speed for Estimating Day-Ahead Wind Power

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***Abstract*— In order to meet the growing demand of energy, renewable resource utilization has increased in recent years. Wind is the source to a significant percentage of renewable resources and wind farms harvest this energy into electricity with the help of wind turbines. These turbines are very costly to set up and require high amount of maintenance. Accurate short term (from 30 minutes up to 6 hours ahead) wind energy forecasting is therefore important for optimal scheduling of the wind farms. The paper explores the usage of Markov Chains for forecasting wind speed during a short-term period (day-ahead hourly wind generation forecasts for an individual wind farm). The proposed prediction model depends on one variable factor - wind speed, for a specific wind turbine. The geographical location under study is taken at Jodhpur in Rajasthan, India. The performance evaluation of the proposed method is calculated using the different statistical error measures like RMSE, MAPE and MAE.**

Keywords—Markov chain; short term forecasting; wind forecasting; wind farm; wind power.

I. INTRODUCTION

Wind energy constitutes a significant portion of the renewable generation into bulk power grids. Accurate short-term wind speed/power prediction is important for market-driven power systems. The Government of India has set an ambitious target of reaching 175 GW of renewable power capacity in the country by 2022 of which 60 GW has to come from wind. The country has further set a goal of having 40 percent of its installed electric capacity powered by non-fossil-fuel sources by 2030 that would reduce its "emissions intensity". Wind energy being clean energy has to play a major role in achieving these goals to meet the challenges of climate change. Tamil Nadu, Gujarat, Maharashtra, Rajasthan and Kerala are the main states which contribute to wind power. Rajasthan has a 4031.99 MW wind power installed as per 2016 [1].

A lot of research has been carried out for wind speed forecasting using methods based on Numerical Weather Prediction (NWP) models [2], time series models [3], statistical methods [4], or other approaches based on Artificial Intelligence (AI) [5]. [6]

A. *Numerical Methods*: Numerical Methods or Physical methods are the customary methods used for forecasting weather which is done by using Numerical formulae.

B. *Statistical Methods*: In these methods the relation between features is found out and used to predict the wind power. Statistical methods are used when there's an availability of past data and when the relationship between the features and the trend in the data is clearly visible and persistently stable.

C. *AI Methods*: AI methods predict the data without predefined mathematical models. They forecast the data by learning the pattern in between the data and estimate the next value in that pattern.

These methods take into account the different meteorological variables, turbine data etc. However, these methods could not give the accurate wind speed forecasts for short term. Also the probability distribution function based models are either too complex to be applied in practice or based on assumptions.

The simplest Markov chain that can be used for modelling for wind speed forecasting is the First Order Markov Chain. There, however, occurs discrepancy in the results due to the use of first-order Markov chain as a first approximation [7]. Efficiency comes with higher order Markov chain modelling [8], therefore, Second Order Markov Chain is used in modelling short term wind forecasting [9, 10]. Using the transition probability matrix, obtained from Markov chain modelling, the synthetic wind speed time series are generated [11, 12]. There are a variety of wind speed generation schemes used to obtain forecasted wind speeds [13].

In this paper, the potential wind power for a short-term period (day-ahead hourly wind generation forecasts for an individual wind farm) has been predicted using Markov Chain. The trained model is verified using a part of real data and calculating the error between the predicted and the actual value.

II. MARKOV MODELS

Markov Model is a stochastic model which is used to capture randomly changing systems on the basis of Markov Property. The Markov property holds when the current state is dependent only upon the immediate previous state of the system and not on any of other the historical states. Markov chain process is the simplest of the Markov Models. Although the usage of Markov chains and its derivatives is branched

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into various fields, in this paper, we focus on the usage of Markov chain models on wind time series data analysis.

A. Markov Chain

Let S_t {where t = 0, 1, 2, 3...etc.} be a stochastic process with a finite number of values of t. Let the total number of states be N. The notation $S_t = i$, means that the process is in state i at a time t. Lets say in general that if the process is moving from one state i to another state j, then the probability of changing from one state to another state is given by $P_{i,\ j}$.

More specifically, $P_{i,\ j}$ denotes the probability of the system changing from state i at at time t to state j at time $t+1$.
Transition probability is given by:

$$P\ \{S_{t+1} = j \mid S_t = i,\ S_{t-1} = i_{t-1},...,\ S_1 = i_1,\ S_0 = i_0\} = P_{i,\ j} \quad (1)$$

where $t \geq 0$ for all states, this process is known as Markov chain.
The state at S_{t+1} does not depend upon states at S_0, S_1 …… S_{t-2}, S_{t-1} but only on previous state at S_t. Transition matrix or Markov matrix is a square matrix which is used to represent the transitions of the Markov process. Each entry in the transition matrix is a non-negative number. Since the total of transition probability from a state i to all other states must be 1, the sum of each row is 1.[7]

$$\sum_{j=1}^{N} P_{i,j} = 1 \quad (2)$$

$$P_{\ i,j} = \begin{pmatrix} P_{1,1} & \cdots & P_{1,N} \\ \vdots & \ddots & \vdots \\ P_{N,1} & \cdots & P_{N,N} \end{pmatrix} \quad (3)$$

B. Higher order Markov Chains

Higher order Markov chains are Markov chains that use more than one preceding states in the process of Markov chain modelling. For example, a second order Markov Chain would use two preceding states to obtain the transition probability matrix. Higher order Markov chain is useful for efficient prediction in the wind data as they provide additional memory regarding the data, which is same as increasing the features in training the model [8]. Thus, here we can build more memory into our states by using higher order Markov chain model.

In this paper, the second order Markov model is used. Second order Markov transition matrix can be obtained by using the Chapman-Kolmogorov equation. Chapman-Kolmogorov equation suggests that, the n-step transition matrix can be obtained by multiplying the transition probability matrix with itself n times. In order to get second order matrix ([9], [10]), the transition probability matrix is multiplied twice to get 2-step matrix.

$$P^2 = P * P \quad (4)$$

$$P^{\ 2} = \begin{pmatrix} P_{1,1} & \cdots & P_{1,N^2} \\ \vdots & \ddots & \vdots \\ P_{N^2,1} & \cdots & P_{N^2,N^2} \end{pmatrix} \quad (5)$$

III. Proposed Methodology

A. Categorizing the Wind Data into Groups

The data used here is for the year 2015. It is found by observing the data that there is a lot of variability and inconsistency when longer periods are considered. The change in daily values also vary over the months. Hence, there is a need to group together those months/periods which show similar daily fluctuation. This problem is addressed by grouping the consecutive months into one category if the similarity of the average wind speed for the months is greater or lesser than a certain threshold θ.

B. Categorization of States

1. Random states

Let $V_{\min}$ be the minimum wind speed and $V_{\max}$ be the maximum wind speed in the data set for one year. The states are defined according to these extreme values. States are taken in regular intervals with a common difference as 1m/s [9]. The first state categorizes all data points in which the wind speed lies between 0m/s and 1m/s. Similarly, the second state categorizes all data points in which wind speed lies between 1m/s and 2m/s. This continues till we reach our maximum wind speed in the dataset. If we have our maximum wind speed as 8m/s, we'd have 9 states in total.

2. States based on mean and standard deviation

Let m be the mean and s be the standard deviation of the wind speed data. All the states (except the first state) will have an interval of s. For example, if the first state will have an interval of $(0,\ m - s]$, the second state will have an interval of $(m - s,\ m]$ and so on.

C. Transition probability matrix estimation

Let T be the total time period in the Markov process. For a given time series of the wind speed V_t (t = 0, 1, 2,..., T), estimation of the transition probability matrix/Markov matrix of order 1 is a simple process. Let $R_{i,\ j}$ be the number of speeds/data that are in state S_i during the time period t and in state S_j during the time period $t + 1$, for t between 0 and $T-1$. Then the $P_{i,\ j}$ is given by the mathematical expression:

$$P_{i,j} = R_{i,j} \,/\, \sum_{j=1}^{T} R_{i,j} \quad (6)$$

The above expression is known as the likelihood estimator which tends to zero for large sample [12].

D. Short Term Wind Forecasting

The first and foremost step in order to generate wind speed is to calculate the transition probability matrix (both first order and second order) which we've done in the previous step. A random number from the specific state interval is used to generate a value ([12]). For the intermediate state, the random number is generated using a uniform distribution taken from that specific state interval range ([7], [11]). For higher state values, a gamma distribution [13] is used to generate the random number. Ultimately this random number is the estimated predicted wind speed.

IV. SIMULATION AND RESULTS

The proposed method for predicting the day ahead wind power is carried out for geographical location at Jodhpur (26.2389°N, 73.0243°E) in Rajasthan, India. The meteorological data is collected from Dark Sky [14]. The hourly data for wind speed for the location of Jodhpur for the year 2015 is extracted. The data is grouped into seasons or categories in this paper and then the model is trained. Based on the similarity of average wind speeds of the month, the consecutive months are categorized into one group. Here the threshold θ is taken to be 0.5m/s as suitable to the data. The Fig. 1. shows the box plot of the wind speed data. The five groups obtained according to this are:

Group 1 - January, February, March, April
Group 2 - May, June
Group 3 - July
Group 4 - August, September
Group 5 - October, November, December

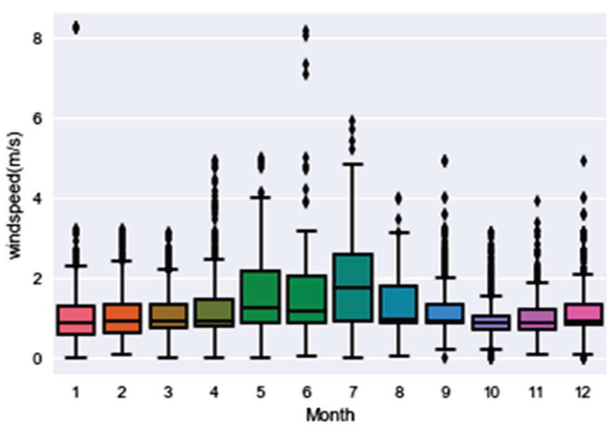

Fig.1. *Average wind speeds given as per month (2015)*

For numerical accuracy assessment of the wind speed forecasts, different error measurements are used. Root-Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are employed for evaluating the forecasting accuracy. The prediction error of a model is defined as the difference between the predicted values and the measured data. Let $G(t)$ be the predicted value and $M(t)$ be the measured value. N be the length of total forecast horizon at time t.

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N} (G(t) - M(t))^2} \tag{7}$$

$$MAPE = \frac{1}{N}\sum_{j=1}^{N} \frac{|G(t) - M(t)|}{M(t)} \tag{8}$$

$$MAE = \frac{1}{N}\sum_{j=1}^{N} |G(t) - M(t)| \tag{9}$$

Mean Absolute Error (MAE) is the easiest to interpret. In Root Mean Square Error (RMSE), the errors are turned positive by raising it to the square, with the advantage of being easy to handle. The Mean Absolute Percentage Error (MAPE) calculates the percentage error and compares two models. MAPE provides an indicator of percentage deviation of the predicted values with the real values of the time series.

Table i. Performance Evaluation of Each Group with 8 States

Categories *(8 states)*	**RMSE**	**MAPE**	**MAE**
Group 1	0.7854	0.2614	0.6817
Group 2	0.4785	0.1997	0.3768
Group 3	**0.3656**	**0.1136**	**0.2994**
Group 4	0.5085	0.2525	0.4366
Group 5	0.6174	0.2299	0.5612

Table ii. Comparison Between Number of States for Group 3

Categories	**RMSE**	**MAPE**	**MAE**
Group 3 (4 states)	0.5957	0.2299	0.4978
Group 3 (6 states)	0.4079	0.1693	0.3696
Group 3 (8 states)	0.3656	0.1136	0.2994
Group 3 (10 states)	0.4588	0.1382	0.3681
Group 3 (12 states)	0.4545	0.1470	0.3775

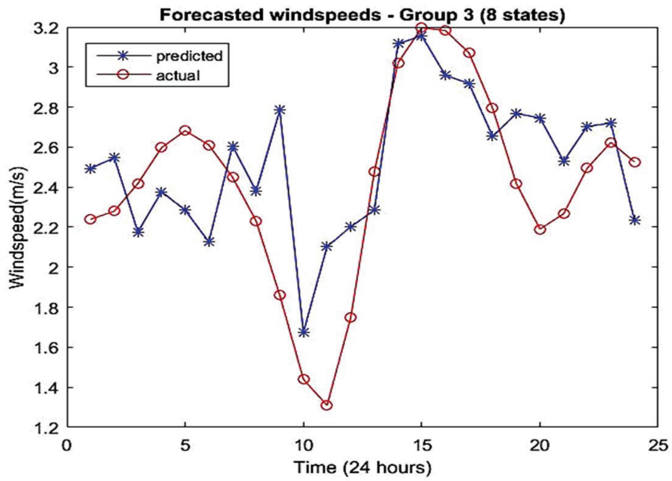

Fig.2. *Forecasted and actual wind speeds for Group 3 (8 states)*

For analyzing the wind energy potential of the study area the data of a typical wind turbine is taken. Power output from a wind turbine is directly proportional to third power of wind speed. Each turbine model has a unique site-dependent power curve which shows relation between wind speed and power. Due to high variability in wind speed, the turbine power output changes continuously. Table III shows the specifications of a SUZLON model S95-2.5 MW wind turbine, where these turbine model is located in present wind farm site.

Table III. Specifications of the Wind Turbine

Specifications	***S 97***
Rated Power	2100 kW
Rotor Diameter	97 m
No.of Blades	3
Swept area	7386 m^2
Air density	1.225 kg/m^3
Rotational speed	variable 12-15.7 rpm
Cut in wind speed	3.5 m/s
Rated wind speed	11 m/s
Cut out wind speed	20 m/s

Using the above specifications, wind power generated can be found out by using the below equation

$$P = 0.5\, \rho A C_p V^3 \qquad (10)$$

where P is the power in W, V is the wind speed in m/s, C_p is the dimensionless factor i.e., power coefficient, ρ is the air density in kg/m3, A is the turbine rotor area in m^2.

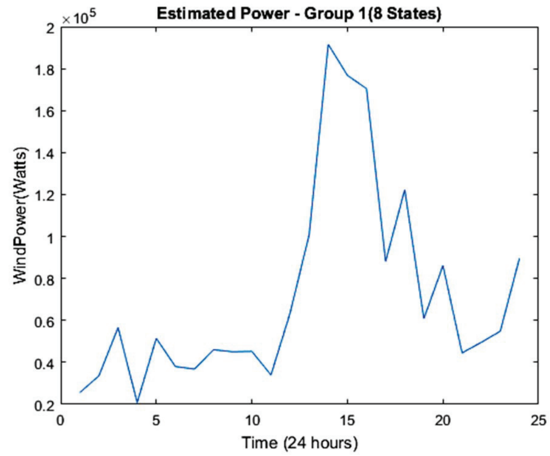

Fig.3. *Estimated Power for Group 1 (8 states)*

V. Conclusions

In this paper, the Markov chain model is used for predicting short term day-ahead wind power using wind speeds for wind farms. Markov Models are a more suitable choice because of their robustness in sequential data modelling. These are based on few non-restrictive hypotheses and can be calibrated and applied on the real data. With proper analysis, the wind speed data can be grouped into different seasons/groups so that it can be trained and processed most efficiently. Only one variable – wind speed, is used for training. The model is validated by using real measured data for the duration of one year (2015) for the region Jodhpur, Rajasthan, India. The results are measured by calculating the error, the difference between the real data and the predicted data, using performance parameters such as RMSE, MAE and MAPE.

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