The use of Markov chains in forecasting wind speed: Matlab source code and applied case study

Ionuț Alexandru Petre[1], Mihai Rebenciuc[2], Ștefan Cristian Ciucu[3]

[1] PhD Candidate, Economic Informatics Doctoral School, The Bucharest University of Economics Studies (Piața Romană 6, București 010374), email: ionut_petre33@yahoo.com

[2] PhD Lecturer, Dept. of Applied Mathematics, The Faculty of Applied Sciences, University Politehnica of Bucharest (Splaiul Independenței 313, București 060042), Romania, email: m_rebenciuc@yahoo.com

[3] PhD Candidate, Cybernetics and Statistics Doctoral School, The Bucharest University of Economics Studies (Piața Romană 6, București 010374), Corresponding author, email: stefanciucu@yahoo.com

Abstract

The ability to predict the wind speed has an important role for renewable energy industry which relies on wind speed forecasts in order to calculate the power a wind farm can produce in an area. There are several well-known methods to predict wind speed, but in this paper we focus on short-term wind forecasting using Markov chains.

Often gaps can be found in the time series of the wind speed measurements and repeating the measurements is usually not a valid option. In this study it is shown that using Markov chains these gaps from the time series can be filled (they can be generated in an efficient way), but only when the missing data is for a short period of time. Also, the developed Matlab programms that are used in the case study, are included in the paper beeing presented and commented by the authors.

In the case study data from a wind farm in Italy is used. The available data are as average wind speed at an interval of 10 minutes in the time period 11/23/2005 - 4/27/2006.

Keywords: *Markov chain, wind speed, Matlab, Chapman-Kolmogorov, forecast*

1. Introduction and literature review

The market of wind energy is under development in the last years and many wind turbines installations are to be constructed in the following period, beeing considered a driver of the economy. This rapid development of the wind energy area is also due to scientifical reseach studies. Among the challenges in the domain are the understanding of the wind speed and applying the gained knowledge in the industry. Knowing the wind behavior in certain wind farms is extremely important for today's power systems, especially in the programming and operating means, wind power becoming an important part of future energy sources.

Futher there will be presented some of the existing models that were studied in modeling of wind speed and a case study on one of these models will be done.

Wind, solar, and biomass are three emerging renewable sources of energy, renewable energy replaceing conventional fuels. One of the benefits of this type of energy is the reduction of the production of CO_2 in the atmosphere. It can be said that global warming is also among the reasons for searching of alternative sources of energy production due to the fact that conventional sources are rich in CO_2 production.

This type of renewable energy can be achieved by installing wind turbines in the areas where the wind is suitable. For this reason, forecasting and analysis of wind speed can lead to the decision whether a wind turbine for a home (micro generation) is suitable or not, or whether to invest or not into so called wind farms which can fill the need of energy.

The problem of forecasting wind speed is quite known and has been dealt a lot in the literature. Among the models used in forecasting of wind speed are: Weibull and Rayleigh distribution (Aksoy 2005; Odo 2012; Ahmad 2009; van Donk 2005; Philippopoulos 2009; Ahmeda 2012), the AR (1) and AR (2) models (Aksoy 2005), the ARMA models (Philippopoulos 2009), Markov chains (Brokish 2009, Song 2011, Chen 2009, Aksoy 2005), wavelet transformation (Aksoy 2005), the Mycielski algorithm (Hocaoğlu 2009; Fidan 2012) and Weibull distribution (Akiner 2008; Ruigang 2011; Zuwei 2008; Isaic-Maniu 1983).

In this paper we propose a short-term simulation of wind speed using Markov chains, namely transition matrices. In the case study it will be noticed that this technique is useful to generate data which is very close to the actual values, which makes us think that Markov chains can be used to fill gaps in the data series, when these gaps are on a short-term. Often, wind speed data sets from wind farms have gaps in measurements due to various reasons.

2. Wind speed forecasts using Markov chains (transition matrices)

Next, we present some theoretical concepts that are used in the case study, namely the Markov chains and the Chapman-Kolmogorov equations. The method of use of Markov chains in order to estimate wind speed will be presented and also, a possible procedure of simulation of the wind speed will be described.

2.1. Markov chains

Definition 2.1. Let $\{X_n, n = 0,1,2, \cdots ,\}$ be a stochastic process that takes a finite number of possible values.

If the set of possible values is not otherwise stated, it will be indicated by a number of non-negative integer values $\{0,1,2, \cdots\}$. If $X_n = i$, this process is in state i at the time n. We assume that every time the process is in state i , then it is a fixed probability P_{ij} that its next value to be in state j.

Note 2.1.i. Thus we assume that:

$$P\{X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \cdots , X_1 = i_1, X_0 = i_0\} = P_{ij} \quad (1)$$

for all states $i_0, i_1, \cdots, i_{n-1}, i, j$ and all $n \geq 0$. Such a stochastic process is known as a Markov chain.

Note 2.1.ii. Equation 1 can be interpreted to say that a Markov chain distribution in the future conditional status X_{n+1}, being given all the states in the past X_0, X_1,⋯, X_{n-1} and the present state X_n is independent of past states and depends only on the today's condition.

The value of P_{ij} is the probability that a process will be in state i at the next transition will be in state j. Since probabilities are non-negative and because the process must make a transition into a state we have

$$P_{ij} \geq 0, \;\; i,j \;\geq 0; \quad \sum_{j=0}^{\infty} P_{ij} = 1\,, \quad i = 0,1, \cdots$$

P indicates the one-step transition matrix, or otherwise the matrix of order 1 of the Markov chain, of P_{ij} probabilities, thus

$$\mathbf{P} = \left\| \begin{matrix} P_{00} & P_{01} & P_{02} & \cdots \\ P_{10} & P_{11} & P_{12} & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ P_{i0} & P_{i1} & P_{i2} & \cdots \\ \vdots & \vdots & \vdots & \vdots \end{matrix} \right\|$$

2.2. Chapman-Kolmogorov equations

We have already defined the probabilities P_{ij} of one-step transition. We now define the probabilities P_{ij}^n of n-step transition.

Definition 2.2. P_{ij}^n is the probability that a process in the state i, will be in state j after n additional transitions. Meaning

$$P_{ij}^n = P\{X_{n+k} = j | X_k = i\}, \;\; n \geq 0, i, j \geq 0$$

Naturally $P_{ij}^1 = P_{ij}$.

Note 2.2.i. The Chapman-Kolmogorov equations, are giving a method to calculate these n-steps transition probabilities. These equations are:

$$P_{ij}^{n+m} = \sum_{k=0}^{\infty} P_{ik}^n P_{kj}^m \;\; for\ all\ n, m \geq 0, all\ i, j \qquad (2)$$

and are more easily understood by observing that $P_{ik}^{n}P_{kj}^{m}$ is the probability that a process that is in its original state i will arrive in state j in $n+m$ transitions through a path that will lead him to state k to transition n. Therefore, gathering all the k intermediate states, the likelihood that the process is in state j after $n+m$ transitions will be obtained. Formally we have

$$P_{ij}^{n+m} = P\{X_{n+m} = j | X_0 = i\}$$

$$= \sum_{k=0}^{\infty} P\{X_{n+m} = j, X_n = k | X_0 = i\}$$

$$= \sum_{k=0}^{\infty} P\{X_{n+m} = j | X_n = k, X_0 = i\} P\{X_n = k | X_0 = i\}$$

$$= \sum_{k=0}^{\infty} P_{kj}^{m} P_{ik}^{n}$$

Note 2.2.ii. If we note $\mathbf{P}^{(n)}$ as being the n-steps transition matrix with the probabilities P_{ij}^{n}, then Equation 2 can be rewritten as:

$$\mathbf{P}^{(n+m)} = \mathbf{P}^{(n)} \cdot \mathbf{P}^{(m)}$$

Where the dot operator is multiplying matrices. Therefore, in particular, we will have:

$$\mathbf{P}^{(2)} = \mathbf{P}^{(1)} \cdot \mathbf{P}^{(1)} = \mathbf{P} \cdot \mathbf{P} = \mathbf{P^2}$$

and by induction

$$\mathbf{P}^{(n)} = \mathbf{P}^{(n-1+1)} = \mathbf{P^{n-1}} \cdot \mathbf{P} = \mathbf{P^n}$$

Thus, the n-steps transition matrix can be obtained by multiplying the **P** matrix with itself by n times. Several times in this paper we will refer to the n-step transition matrix as the n-order matrix (Ross 2010).

2.3. The use of Markov chains in modelling of the wind speed

The determination of important statistical models for wind speed time series at different time periods is a huge point of interest for the wind power industry, in particular for optimal control of the wind turbines. Also important topics are: establishing of a sending schedule or programming the wind energy, designing and evaluating wind energy and so on.

Time series data for wind speed can be obtained from different sources, such as weather forecasting stations or from wind turbines itself that are equipped with anemometers.

Time series data set of wind speed may be noted as $v_t, t = 0, 1, 2, \cdots, T$ where v_t is the wind speed (discreet) at the time t, t starting at 0 and ending in T. The total number of discrete values of the wind speed for a time series is $T+1$.

Wind speed measurements are continuous values, but to be able to fit into an application of Markov chains, v_t is discreet and can take a finite number of possible states.

Let us suppose that continuous wind speeds can be discretized in r states, $S_i, i = 0, 1, 2, \cdots, r$. For example, S_1 state can be assigned for values of wind speed between 0 and 1 m/s.

The method in which wind speeds are divided in discreet values of r states, is highly dependent on the target application and other factors such as changes in wind speed or specifications of the turbine. In the literature often is used to make this division the range of speeds v_{cut-in} and v_{rated}.

The reason for this range is as follows: a turbine generates zero power as long as wind speed is between 0 and the cut-in speed. When the wind speed is higher than the rated speed, then the turbine will generate a set power (relatively constant), unless the wind is too strong and the wind speed exceeds the cut-out speed, moment that is equivalent with the turbine shutdown in order to protect it from potential damage.

Based on the startup speed and the normal speed of the wind we could define the state S_1 as being wind speeds that range from 0 to v_{cut-in}, meaning $0 \leq v \leq v_{cut-in}$. S_r could be defined as a state comprising wind speed values greater or equal to v_{rated}. Thus S_2 and S_{r-1} could be defined based on different classification schemes of wind speed.

A simple way would be addressing speed range, Δv. Let $\Delta v = 1\, m/s$ be a range, then S_2 is the state containing the following values $v_{cut-in} \leq v \leq v_{cut-in} + 1$. The states from S_3 to S_{r-1} could be defined in the same manner. In this case, the number of possible states is given by the interval Δv, v_{cut-in} and v_{rated}.

For an application of Markov chains with wind speed time series data, the one step matrix P contains probabilities that wind speeds in the state S_i will be in state S_j at the next sampling time. The one step transition matrix (order 1) P can be represented as follows:

$$P = \begin{pmatrix} P_{11} & \cdots & P_{1r} \\ \vdots & \ddots & \vdots \\ P_{r1} & \cdots & P_{rr} \end{pmatrix}$$

each entry of the matrix is a probability and satisfies the condition listed earlier in the definition of Markov chains. It is interesting to see the two step matrix of probabilities, because knowledge of future wind speeds is very important for the wind industry. The two step matrix tells us that a process that is in state S_i will be in state S_j after two additional transitions. In practice, long-term wind forecast with high accuracy can be a very difficult task due to the stochastic nature of the wind.

According to the Chapman-Kolmogorov equations previously presented, the two step matrix P^2 can be easily calculated, multiplying the matrix P with itself. Similarly, the three step matrix P^3 can be easily calculated.

Being given a time series of the wind speed $v_t(t = 0, 1, 2, \cdots, T)$, estimating the transition matrix of a matrix of order 1 is a direct process. Generally, let n_{ij} be the number of speeds that are in state S_i during the time period t (meaning $v_t = S_i$) and in state S_j during the time period $t + 1$ (meaning $v_{t+1} = S_i$), for t between 0 and $T - 1$.

Note 2.3.i. Then the transition probabilities can be estimated as

$$p_{ij} = n_{ij} / \sum_{j=1}^{r} n_{ij} \quad (3)$$

it is known the fact that this equation (3) it is a maximum likelihood estimator that tends towards zero when the sample is very large.

Similarly, the transition matrix of 2nd order can be estimated using the same process described above, only this time n_{ij} is the number of speeds that are in state S_i in the time period t (meaning $v_t = S_i$) and are in state S_j in the time period $t + 2$ (meaning $v_{t+2} = S_i$), for t between 0 and $T - 2$. The process for estimating the transition matrix of the order n can be deduced.

2.4. Procedure to simulate wind forecast

A procedure to generate an average of a simulated hour of a wind speed time series is described below.

The first step is to calculate the one step transition matrix. This matrix is a Markov chain so the sum of the probabilities of a single line (of the matrix) is equal to 1. Thus, an initial state is set. The first state, of no wind, S_0 can be considered. Using a random uniform number, the following state of the wind speed can be determined. If S_0 is obtained, then first we check if the wind speed is 0. If the wind speed is not 0, then a random number from the interval of states S_0 is used in order to generate a value. If the highest state is found then a distribution of a gamma parameter is used to calculate the wind speed. For intermediate states, a value is generated of a uniform random number, it is taken from the range that corresponds to the state and it is set as the value of wind speed in that hour (Aksoy 2005).

Note 2.4. A gamma distribution has been used to generate the value of the wind speed in the last state, because this distribution has fitted best for the data set in the study (Aksoy 2005). The explanation is that a distribution without a superior limit should be used in order to choose the values for the biggest state from the Markov chain, so wind speeds bigger than the observed ones can be generated. The main idea is to use the distribution that generates the biggest values for the last state (Aksoy 2005).

3. Matlab source code

In this section of the article the Matlab source code used in the case study is shown and commented. Each of the four programs is custom made by the authors.

3.1. matrix.m

```
%% Data gathering.
WindData =  xlsread('Wind data.xls','unfiltred', 'C2:C22185');
WindDataFuture =  xlsread('Wind data.xls','unfiltred', 'C22186:C22329');
% Removal of the NaN (Not a Number) data
WindData = WindData(isfinite(WindData(:, 1)), :);
WindDataFuture = WindDataFuture(isfinite(WindDataFuture(:, 1)), :);

% General properties
 disp(sprintf('The lowest recorded speed: %f',min(WindData)));
 disp(sprintf(' The highest recorded speed: %f',max(WindData)));
 disp(sprintf('Mean speed: %f',mean(WindData)));

%% The definition of the states.
% Observation! The last state is v > 13 m/s.
states = [0 1;1 2;2 3;3 4;4 5;5 6;6 7; 7 8;8 9;9 10;10 11; 11 12;12 13;13 27];

Markov1 = matrixMarkov(WindData, states, 1);
disp(Markov1);

Markov2calc = Markov1^2;
disp('The 2nd order transition matrix calculated with Chapman-Kolmogorov equations:');
disp(Markov2calc);

Markov2est = matrixMarkov(WindData, states, 2);
disp(Markov2est);

%% Generating data using the obtained Markov chain

% Setting of the last known value
last = WindData(length(WindData));
% The length of the string that we will compare to
l = length(WindDataFuture);

GeneratedWind = generateWind(Markov1, states, last, l);

% The graph
xAxis = 1:l;
plot(xAxis, GeneratedWind, 'b*-', xAxis, WindDataFuture, 'ro-');
legend('Generated wind','Real values');
```

3.2. currentState.m

```
%% Calculates the state in which the given value is assigned
function [stateValue] = currentState(val, states)
%% We initiate with state 1
stateValue = 1;
n = length(states);

for k = 1:n
  if (val > states(k,1) && val <= states(k,2))
    stateValue = k;
  end
end
```

3.3. matrixMarkov.m

```
%% Calculation of the Markov transition matrix of desired order
% @param array data    The time series to analyze
% @param array states  The states for the Markov chain
% @param byte  ordinul The desired order
% @return array Prob  The Markov transition matrix
function [Prob] = matrixMarkov(data, states, ordin)
  stateslength = length(states);

  %% The initialization of the matrix
  Prob = zeros (stateslength, stateslength);

  n = length(data);

  for i=1:n-ordin
    cState = currentState(data(i), states);
    nState = currentState(data(i+ordin), states);
    Prob(cState, nState) = Prob(cState, nState) + 1;
  end

  for i=1:stateslength
    Prob(i,:) = Prob(i,:)/ sum(Prob(i,:));
  end

  disp(sprintf('The estimated matrix of transition of order %d is:',ordin));
end
```

genValueRange.m

```
%% Generates values in a given interval
% @param integer min The minimum value
% @param integer max The maximum value
% @retrun integer val The generated value
function [val] = genValueRange(min, max)
  nr=1;
  val=min+(max-min)*rand(1,1);
end
```

3.4. generateWind.m

```
%% Generating values depending on the matrix of probabilities
% @param array   prob The Markov transition matrix
% @param array   states The states of the Markov chain
% @param integer last   The values that calculates the state of the Markov chain
```

```
% @param integer num   The desired number of values
% @return Generated The generated values
function [Generated] = generateWind(prob, states, last, num)

    lState = currentState(last, states);
    disp(sprintf('State from which we leave: %d ',lState));
    for i=1:num
         %%  Generate a random number
        randomNum = rand(1);
        disp(sprintf('The random value is: %f ',randomNum));

        [c nState] = min(abs(prob(lState,:)-randomNum));

        disp(sprintf('The new state is: %d ',nState));

        Generated(i) = genValueRange(states(nState,1), states(nState,2));
        % Initialize the last state with the new one found
        lState = nState;
    end

    disp('The generated values are:');
end
```

4. Case study

In this study data from a wind farm in Italy is used. The available data are as average wind speed at an interval of 10 minutes in the time period 11/23/2005 - 4/27/2006.

The lowest recorded speed: 0 m/s.

The highest recorded speed 26.08 m/s.

The mean of speeds: 7.1505 m/s.

The states of the Markov chain are defined as:

- state 1: $v \in (0,1]m/s$;
- state 2: $v \in (1,2]m/s$;
- state 3: $v \in (2,3]m/s$;
- state 4: $v \in (3,4]m/s$;
- state 5: $v \in (4\ 5]m/s$;
- state 6: $v \in (5,6]m/s$;
- state 7: $v \in (6,7]m/s$;
- state 8: $v \in (7,8]m/s$;
- state 9: $v \in (8,9]m/s$;
- state 10: $v \in (9,10]m/s$;
- state 11: $v \in (10,11]m/s$;
- state 12: $v \in (11,12]m/s$;
- state 13: $v \in (12,13]m/s$;
- state 14: $v > 13\ m/s$;

In Table 1 the transition matrix of order 1 can be observed. The highest probabilities are on the diagonal of the matrix, meaning that the wind from a certain state is very likely to remain in the same state rather than to change its state. Also it can be observed that if the wind is in state 1, then the furthest it can reach is state 5, and also from state 14 the lowest it can get is state 9. It can be concluded that radical changes in the wind speed (from fast wind speed to low wind speed or from low wind speed to fast wind speed) do not occur in a time interval of 10 minutes.

The Chapman-Kolmogorov equations that calculate the transition matrix of superior order have proven to be of use. By comparing tabel 1 with tabel 2 it can be observed that the 2nd order transition matrix calculated with the Chapman-Kolmogorov equations has similar values with the 1st order transition matrix.. The largest difference between probabilities is 0.06 for the wind to remain in state 13.

Tabel 1. The 1st order estimated transition matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0.6815	0.2713	0.0405	0.0054	0.0013	0	0	0	0	0	0	0	0	0
2	0.1621	0.6032	0.2064	0.0199	0.0038	0.0038	0.0008	0	0	0	0	0	0	0
3	0.0113	0.1734	0.5776	0.1955	0.0284	0.0095	0.0032	0.0013	0	0	0	0	0	0
4	0.0026	0.0175	0.2038	0.5045	0.2283	0.0343	0.0058	0.0013	0.0019	0	0	0	0	0
5	0.0005	0.0066	0.0234	0.1813	0.5358	0.2158	0.0300	0.0030	0.0030	0	0.0005	0	0	0
6	0.0004	0.0013	0.0039	0.0246	0.1896	0.5450	0.1986	0.0289	0.0047	0.0017	0.0013	0	0	0
7	0	0.0004	0	0.0044	0.0265	0.2124	0.5074	0.1950	0.0453	0.0074	0.0009	0	0.0004	0
8	0	0	0	0.0010	0.0035	0.0297	0.2397	0.4726	0.2061	0.0366	0.0094	0.0015	0	0
9	0	0	0	0	0.0006	0.0044	0.0470	0.2456	0.4292	0.2091	0.0498	0.0116	0.0028	0
10	0	0	0	0		0.0006	0.0135	0.0488	0.2510	0.4307	0.2073	0.0347	0.0090	0.0045
11	0	0	0	0	0.0007	0.0007	0.0037	0.0111	0.0656	0.2520	0.4385	0.1850	0.0354	0.0074
12	0	0	0	0	0	0	0	0.0058	0.0087	0.0618	0.2599	0.4473	0.1749	0.0415
13	0	0	0	0	0	0	0.0014	0.0014	0.0014	0.0114	0.0653	0.2798	0.4403	0.1989
14	0	0	0	0	0	0	0	0	0.0005	0	0.0042	0.0244	0.0768	0.8940

Tabel 2. The 2nd order transition matrix calculated with Chapman-Kolmogorov equations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0.5089	0.3556	0.1081	0.0200	0.0051	0.0019	0.0004	0.0001	0	0	0	0	0	0
2	0.2106	0.4440	0.2545	0.0640	0.0157	0.0080	0.0025	0.0006	0.0001	0	0	0	0	0
3	0.0429	0.2114	0.4103	0.2204	0.0788	0.0248	0.0077	0.0026	0.0009	0.0001	0	0	0	0
4	0.0083	0.0569	0.2297	0.3370	0.2501	0.0885	0.0206	0.0048	0.0032	0.0006	0.0003	0	0	0
5	0.0025	0.0152	0.0652	0.1988	0.3709	0.2462	0.0761	0.0162	0.0063	0.0015	0.0010	0.0001	0	0
6	0.0009	0.0040	0.0141	0.0618	0.2160	0.3819	0.2220	0.0700	0.0207	0.0055	0.0024	0.0004	0.0002	0
7	0.0002	0.0010	0.0024	0.0146	0.0696	0.2354	0.3494	0.2087	0.0856	0.0241	0.0068	0.0014	0.0006	0.0001
8	0	0.0002	0.0004	0.0034	0.0158	0.0828	0.2512	0.3234	0.2067	0.0804	0.0270	0.0068	0.0016	0.0003
9	0	0	0	0.0007	0.0035	0.0219	0.1068	0.2416	0.2928	0.2024	0.0921	0.0278	0.0081	0.0023
10	0	0	0	0.0001	0.0009	0.0062	0.0370	0.1108	0.2404	0.2943	0.2028	0.0744	0.0223	0.0107
11	0	0	0	0.0002	0.0010	0.0024	0.0128	0.0403	0.1243	0.2450	0.2983	0.1834	0.0664	0.0257
12	0	0	0	0	0.0002	0.0004	0.0038	0.0136	0.0417	0.1238	0.2551	0.3004	0.1682	0.0927
13	0	0	0	0	0.0001	0.0004	0.0021	0.0048	0.0113	0.0440	0.1334	0.2657	0.2605	0.2775
14	0	0	0	0	0	0	0.0001	0.0004	0.0013	0.0036	0.0170	0.0550	0.1069	0.8156

Tabel 3. The estimated 2nd order transition matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0.5628	0.3090	0.0958	0.0229	0.0081	0.0013	0	0	0	0	0	0	0	0
2	0.1904	0.4817	0.2508	0.0466	0.0145	0.0084	0.0046	0.0015	0.0015	0	0	0	0	0
3	0.0309	0.2208	0.4416	0.2145	0.0587	0.0215	0.0082	0.0013	0.0019	0.0006	0	0	0	0
4	0.0110	0.0375	0.2199	0.3849	0.2490	0.0712	0.0175	0.0039	0.0032		0.0013	0.0006	0	0
5	0.0025	0.0152	0.0569	0.1899	0.4058	0.2489	0.0543	0.0142	0.0071	0.0020	0.0020	0.0005	0.0005	0
6	0.0013	0.0022	0.0116	0.0478	0.2111	0.4326	0.2176	0.0526	0.0151	0.0052	0.0022	0	0.0004	0.0004
7	0.0004	0.0017	0.0026	0.0144	0.0540	0.2180	0.3808	0.2232	0.0757	0.0200	0.0061	0.0022	0.0009	0
8	0	0	0.0010	0.0064	0.0188	0.0583	0.2650	0.3465	0.2012	0.0712	0.0252	0.0049	0.0005	0.0010

9	0	0.0006	0	0	0.0066	0.0210	0.0846	0.2378	0.3258	0.2052	0.0885	0.0177	0.0088	0.0033
10	0	0	0	0.0006	0.0019	0.0051	0.0353	0.0950	0.2548	0.3267	0.1861	0.0668	0.0186	0.0090
11	0	0.0007	0	0.0007	0	0.0037	0.0111	0.0398	0.1032	0.2351	0.3287	0.1945	0.0590	0.0236
12	0	0	0	0	0	0.0010	0.0029	0.0126	0.0367	0.1053	0.2696	0.3237	0.1778	0.0705
13	0	0.0014	0	0	0	0	0	0.0014	0.0043	0.0469	0.1080	0.2813	0.3224	0.2344
14	0	0	0	0	0	0	0.0016	0.0016	0.0005	0.0053	0.0154	0.0445	0.0864	0.8447

By using the 1st order transition matrix, we made a wind speed forecast for 24h. We compared the forecast with the real data from that day, and a graphical comparison can be seen in figure 1.

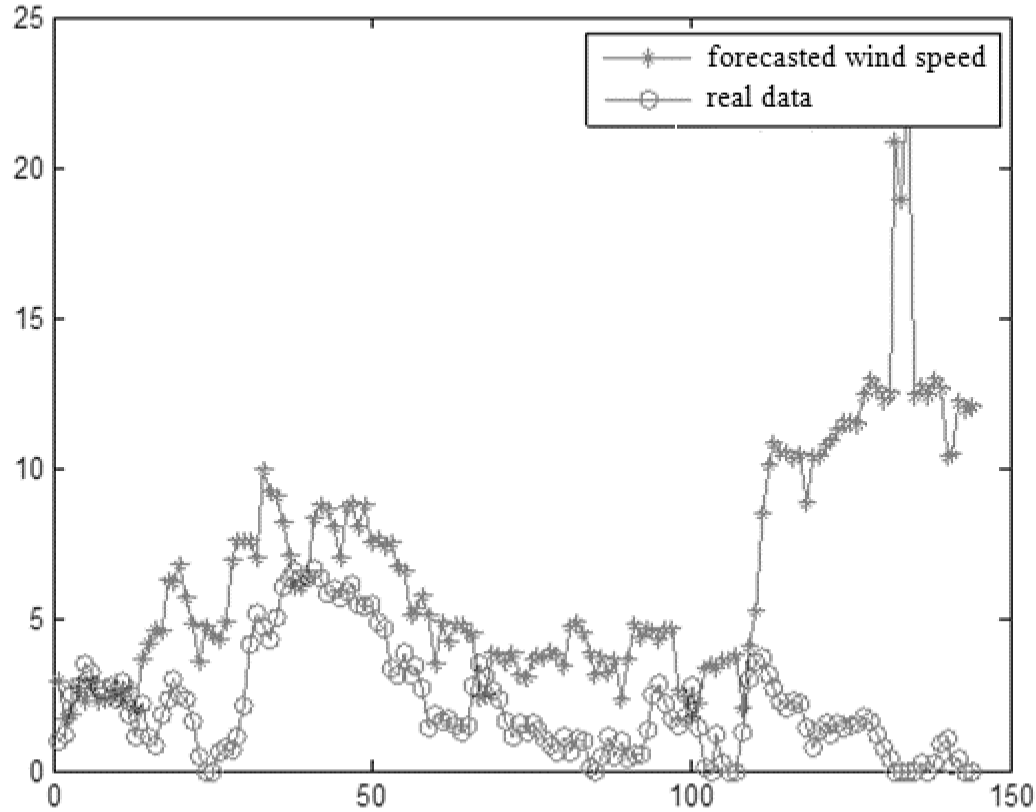

Figure 1. Graphical comparison between forecasted wind speed (represented with blue and stars) and real data (represented with red and circles)

Some metrics may be used to express more precisely the vicinity between the estimated and actual wind.

5. Conclusions

In this paper it is presented the importance of knowing the wind speed and the reasons why a good forecast is needed. The future investments in creating wind turbines in order to generate wind energy depend on proper wind analysis.

We have presented some of the models that have been used until the present days and we have conducted a case study using Markov chains. The result of the comparison between forecasted wind speed and real data for the selected wind farm indicates that this model is not the best, being very precisely on short term (the first hour) but after that it can take very different values.

It is important to underline the fact that this method, due to a good forecast on the short term, can be used to fill in gaps in the time series, when these gaps are not for a long period of time, because the Markov chains lose their precision. The filling of gaps is a subject of interest, because many times the re-measurement is not possible, or it is costly or unpractical.

Due to space limitation, the actual paper did not allow measurement with certain metrics of the vicinity of forecasted and actual values.

Acknowledgments

The authors would like to thank Mr. Radu Porumb (University Politehnica of Bucharest, Faculty of Power Engineering, email: radu.porumb@upb.ro, Splaiul Independenței nr. 313, București, România) for providing the data used in the case study.

References

[1] Ahmad, S. / Wan Hussin, W. M. A. / Bawadi, M. A. / Mohd. Sanusi, S. A.: "Analysis of Wind Speed Variations and Estimation of Weibull Parameters for Wind Power Generation in Malaysia". *Working Paper, Universiti Sains Malaysia,* http://eprints.usm.my/id/eprint/10959, Accessed 16 May 2015, 2009.

[2] Ahmeda, S. A. / Mahammed, H. O.: "A Statistical Analysis of Wind Power Density Based on the Weibull and Ralyeigh models of "Penjwen Region" Sulaimani/ Iraq". *Jordan Journal of Mechanical and Industrial Engineering* 6(2), ISSN 1995-6665, 2012, pp. 135-140.

[3] Akiner, T. / Zuwei, Y. A.: "Theoretical Analysis on Parameter Estimation for the Weibull Wind Speed Distribution". *IEEE Transactions on Power Systems* 23(3), doi: 10.1109/PES.2008.4596167, 2008, pp. 1-6.

[4] Aksoy, H. / Fuat Toprak, Z. / Aytek, A. / Erdem Ünal, N.: "Stochastic generation ofhourly mean wind speed data". *Renewable Energy* 29(14), 2004, pp. 2111–2131.

[5] Brokish, K. / Kirtley, J.: "Pitfalls of Modeling Wind Power Using Markov Chains". *Power Systems Conference and Exposition, PSCE '09. IEEE/PES,* doi: 10.1109/PSCE.2009.4840265, 2009, pp. 1-6.

[6] Chen, P. / Berthelsen, K. K. / Bak-Jensen, B. / Chen, Z.: "Markov Model of Wind Power Time Series Using Bayesian Inference of Transition Matrix". *Industrial Electronics. IECON '09. 35th Annual Conference of IEEE,* doi: 10.1109/IECON.2009.5414993, 2009, pp. 627 – 632.

[7] Fidan, M. / Hocaoğlu, F. O. / Gerek, O. N.: "Improved synthetic wind speed generation using modified Mycielski approach". *Int. J. Energy Res.* 36(13), doi: 10.1002/er.1893, 2012, pp. 1226–1237.

[8] Hocaoğlu, F. O. / Fidan, M. / Gerek, O. N.: "Mycielski approach for wind speed prediction". *Energy Conversion and Management* 50(6), 2009, pp. 1436–1443.

[9] Isaic-Maniu, Al.: *Metoda Weibull. Aplicații* (en: *The Weibull Method. Applications*). Ed. Academiei Republicii Socialiste România: București 1983.

[10] Odo, F. C. / Offiah, S. U. / Ugwuoke, P. E.: "Weibull distribution-based model for prediction of wind potential in Enugu, Nigeria". *Advances in Applied Science Research* 3(2), 2012, pp. 1202-1208.

[11] Philippopoulos, K. / Deligiorgi, D.: "Statistical simulation of wind speed in Athens, Greece based on Weibull and ARMA models". *International journal of energy and environment* 4(3), 2009, pp. 151-158.

[12] Ross, S. M.: *Introduction to Probability Models.* Tenth Edition. Elsevier 2010.

[13] Ruigang, W. / Wenyi, L. / Bagen, B.: "Development of Wind Speed Forecasting Model Based on the Weibull Probability Distribution". *Computer Distributed Control and Intelligent Environmental Monitoring (CDCIEM), International Conference* doi: 10.1109/CDCIEM.2011.333, 2011, pp. 2062-2065.

[14] Song, Z. / Geng, X. / Kusiak, A. / Xu, C.: "Mining Markov chain transition matrix from wind speed time series data". *Expert Systems with Applications* 38(8), 2011, pp. 10229–10239.

[15] van Donk, S. J. / Wagner, L. E. / Skidmore, E. L. / Tatarko, J.: "Comparison of the Weibull model with measured wind speed distributions for stochastic wind generation". *American Society of Agricultural Engineers,* ISSN 0001−2351, 48(2), 2005, pp. 503−510.

[16] Zuwei, Y. / Akiner, T.: "Wind Speed Modeling and Energy Production Simulation with Weibull Sampling". *Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century,* doi: 10.1109/PES.2008.4596166, 2008, pp. 1-6.