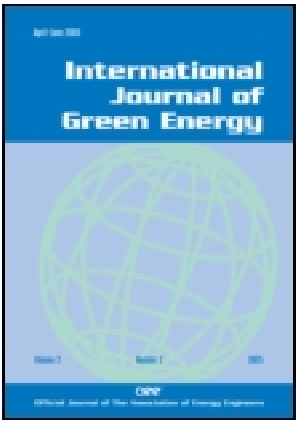

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AN INNOVATIVE HYBRID ALGORITHM FOR VERY SHORT-TERM WIND SPEED PREDICTION USING LINEAR PREDICTION AND MARKOV CHAIN APPROACH

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A new hybrid algorithm using linear prediction and Markov chain is proposed in order to facilitate very short-term wind speed prediction. First, the Markov chain transition probability matrix is calculated. Then, linear prediction method is applied to predict very short-term values. Finally, the results are modified according to the long-term pattern by a nonlinear filter. The results from proposed method are compared by linear prediction method, persistent method and actual values. It is shown that the prediction-modification processes improves very short-term predictions, by reducing the maximum percentage error and mean absolute percentage error, while it retains simplicity and low CPU time and improvement in uncertainty of prediction.

Keywords: ***Linear prediction; Markov chain; Maximum percentage error; Mean absolute percentage error; Wind speed prediction***

INTRODUCTION

Wind power production is increasing and may considerably influence the power quality and the operation of power systems and may become hazardous for the conventional production means. Variations in wind power cause, in general, voltage and frequency fluctuations. Also, a sudden cut-off of wind power due to excessive wind speeds may cause unacceptable shocks in the conventional power units. Therefore, prediction of wind speed and power is important for the efficient load management and operation of the system (Kariniotakis and Pinson 2004).

Very short-term prediction is a subclass of wind speed prediction, which may be used to predict wind speeds for only the next few seconds to minutes of operation. This time scale prediction is useful for control system of a wind turbine, due to the importance of short-term decisions. It could be classified as connection of a load, changing the pitch

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of the blades and/or any other control action which involves delays (Cadenas and Rivera 2007).

Also, advanced control theory known as model predictive control (MPC) is applied in large modern wind turbines to extract maximum available energy (Pourmousavi Kani and Riahy 2008). Since, the behavior of the MPC is predicted based on past measurements and computed future inputs (Pourmousavi Kani and Riahy 2008), very short-term wind speed prediction is an inevitable tool for MPC applications. In literature (Henriksen 2007), a pitch controlled technique is proposed for grid-connected wind turbine in a small power system by Nanayakkara. The proposed pitch controller incorporated the predicted effective very short-term wind speed to minimize effects on the power system while producing optimum wind-generated power. Another operational optimization strategy is introduced at the level of wind park control in Nanayakkara, Nakamura, and Hatazaki (1997) by Moyano. There was assumed that very short-term wind speed prediction values are known for individual wind turbines. This operational strategy was also developed with a concern on the minimization of the connection/disconnection changes of the individual wind generators, for a given time horizon.

Also, there are some existing approaches handling wind speed prediction (Alexiadis, Dokopoulos, and Sahsamanoglou 1998; Shamshad et al. 2005). Most of these studies focused on short-term wind speed prediction and modeled based on minimum mean square error and statistical theories. Hoppmann (Alexiadis et al. 1998) developed a model for short-term maximum wind speed prediction on the basis of continuous wind measurements at distinct locations of a high-speed railway line. In literature (Hoppmann et al. 2002), Kariniotakis introduced a new methodology for assessing the prediction risk of short-term wind power forecasts. This methodology is characterized by two different concepts, the uncertainty and prediction risk estimation. In reference Kariniotakis and Pinson (2004), a novel approach for very short-term wind speed prediction using adaptive neuro-fuzzy inference system is introduced by Potter. That approach verified with a case study from Tasmania, Australia. A same model is proposed by Negnevitsky in Potter and Negnevitsky (2006). Tuning weighting factors of surrounding stations using ANN is proposed for prediction of a pivot station by Oztopal (Negnevitsky and Potter 2006). Geometrical weighting functions are necessary for regional estimation of the regional variable at a location with no measurement, which is referred to as the pivot station from the measurements of a set of surrounding stations. Predictions have been done for a day ahead.

Cadenas in literature Oztopal (2006) compared two techniques for wind speed forecasting in the South Coast of the state of Oaxaca, Mexico. These two methods were Autoregressive Integrated Moving Average (ARIMA) and ANN. Riahy in Cadenas and Rivera (2007) utilized the linear prediction method in conjunction with filtering of the wind speed waveform as a new method for short-term wind speed forecasting. Safavieh (Riahy and Abedi 2008) proposed a new integrated method utilizing Wavelet-based networks and Particle Swarm Optimization (PSO) forecasting very short-term wind speed prediction. PSO algorithm is applied for training a Wavelet networks. The proposed approach is compared with multi layer perceptron networks with Back Propagation training algorithm. Results show that the new approach improved Mean Absolute Percentage Error (MAPE) and Maximum Percentage Error (MPE) as well.

Pourmousavi (Safavieh et al. 2007) developed a new model for very short-term wind speed prediction utilizing ANN, Markov Chain and linear regression. In this method, ANN is used to predict primary predictions. Then, second-order Markov Chain is applied to calculate transition probability matrix for predicted values. Finally, a linear regression among

ANN predicted values and Markov Chain calculated probabilities are used for final prediction. The results in comparison with ANN show slightly decreasing in prediction errors. In literature (Shamshad et al. 2005), a new ANN-based methodology is introduced for very short-term wind speed prediction in conjunction with Markov chain approach. The primary predicted values by ANN are modified according to long term pattern in historical wind speed data. Finally, another ANN is utilized among primary predictions and transition probabilities of those values calculated by Markov chain approach. The effectiveness of the proposed approach was illustrated in results in comparison with ANN.

Also, some studies have been carried out for short-term wind speed prediction using Markov chain. Sahin (Pourmousavi Kani et al. 2008) introduced a model to generate hourly wind speed data using first-order Markov chain. For this purpose, the wind speed time series is divided into various states depending on the arithmetic average and the standard deviation. After confirmation of the model, it is then used for generating synthesis series of any desired duration. In literature (Sahin and Sen 2001), Markov chain transition matrix is used to generate Hourly wind speed time series for two meteorological stations in Malaysia by Shamshad. The transition probability matrices have been formed using two different approaches: the first approach involves first-order Markov chain transition probability matrix, and the second one involves a second-order transition probability matrix while the current and preceding values are used to describe the next wind speed value.

Negra (Moyano and Peças Lopes 2009) dealt with a generator for synthetic wind speed time series as input for sequential Monte Carlo simulation. Finally, some statistical issues are considered for verification purposes. Also, a new wind speed data generation scheme based upon wavelet transformation is introduced in Negra et al. (2008) by Aksoy. The proposed method is compared to the existing wind speed generation methods such as first-order Markov chain. Nfaoui in literature (Aksoy et al. 2004) analyzed hourly wind speed data on a statistical basis by applying the Markovian process. Then, Markovian process is applied to generate wind speed time series. The synthetic wind speeds produced via the Markovian process exhibits the same statistical characteristics as the corresponding actual wind speeds. Note that synthetic data generation techniques are used in practice for cases where long wind speed data are required while they are not available by measurement (Negra et al. 2008; Moyano and Peças Lopes 2009). Since basic criteria in the area of wind speed prediction such as MAPE and mean square error (MSE) are not included in the above studies where generation wind speed data is considered using Markovian process independently, it is hard to assess their accuracy of prediction.

In this study, an innovative hybrid algorithm is introduced for very short-term wind speed prediction in wind turbine application. Because of its simplicity and low CPU time, this algorithm can be considered as a tool for on-line prediction. The remainder of this paper is organized in the following manner. In section 2, the detailed process of the new algorithm is presented. In section 3, the linear prediction model and its coefficients estimation approach is reviewed; Markov chain model is described in section 4; the validation experiments and results are presented in section 5. Finally, section 6 contains a summary of the results and conclusions.

INNOVATIVE HYBRID ALGORITHM DESCRIPTIONS

In the proposed algorithm, the short-term patterns in wind speed data are grasped by linear prediction method as well as the long-term pattern by third-order Markov chain. Markov transition probability matrix is calculated from historical wind speed data to modify predicted values concerning long-term patterns. The whole process is divided into three

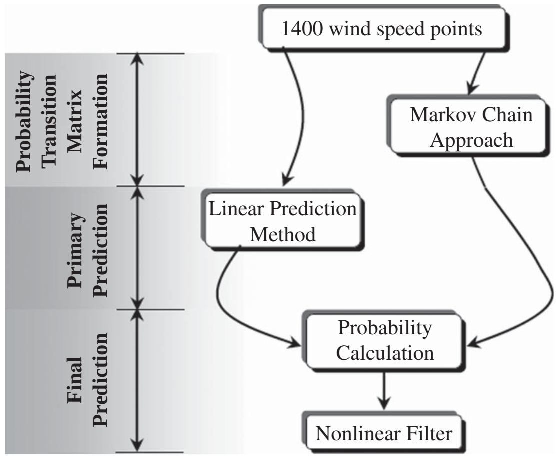


Figure 1 Outline of proposed hybrid algorithm for very short-term prediction.

parts as shown in Figure 1: first, the transition probability matrix is formed using third-order Markov chain with 1,000 data points; second, very short-term values are calculated for remained 4,000 data points by linear prediction method according to prediction horizon; eventually, probabilities for predicted values are calculated. Final prediction is provided by a nonlinear filter, which modifies the primary results based on the probability values from Markov chain transition matrix.

Linear prediction method, Markov chain approach and probability calculation are discussed in detail in the following sections. In order to account for long-term patterns to modify primary predicted values using the Markov transition probability matrix, a nonlinear filter is applied. Here, the nonlinear filter can be modeled as follows (Hoppmann et al. 2002):

$$P_{t+T}^{\text{final}} = \beta.\left[\alpha.P_t^{\text{final}} - (1-\alpha).v_t\right] + (1-\beta).P_{t+T}^{\text{primary}}, \tag{1}$$

where P_t^{final} is the latest modified predicted value by the above filter based on prediction horizon, T;P_{t+T}^{primary} is the future predicted value based on prediction horizon, T;v_t is the latest actual value based on time step; β is the probability value for the primary prediction, P_{t+T}^{primary}, calculated by Markov transition probability matrix and α is a parameter in the nonlinear filter to record the historical performance of the model which is changing between 0 and 1. The more accurate the past prediction, the smaller this parameter is. The value of α is calculated in each prediction as follows:

$$\alpha = \left[P_t^{\text{final}} - v_t\right] \Big/ v_t. \tag{2}$$

Using this filter, the primary prediction is considered unreliable and replaced by a weighted summary of the previous wind speed and the current prediction for the future based on prediction horizon. Hence, the nonlinear filter performs weighted averaging process.

The results show that this algorithm outperforms both traditional persistence method and linear prediction method. The MPE and MAPE are decreased significantly in the hybrid algorithm particularly for larger prediction horizon. The accuracy of this algorithm is satisfactory although the significant oscillation exists on wind speed data.

THE LINEAR PREDICTION MODEL

Linear prediction (Makhoul 1975; Cinnéide 2008), is a technique of time series analysis, that emerges from the examination of linear systems. Using linear prediction, the parameters of a linear system can be determined by analyzing the systems inputs and outputs. By definition, a linear time-variant system's outputs are dependant on its current and previous inputs (Cinnéide 2008). A time-varying process is a process where the underlying function of its measured parameters is time variant (Riahy and Abedi 2008). This means a measured parameter of such a process cannot be represented by a unique mathematical function over a long period of time, but rather the equation of the function has to be updated over short periods of time. Therefore, the model coefficients are updated with a moving modeling window for each time step. A wind speed signal typically belongs to a time-varying process which can be modeled as follows (Makhoul 1975; Cinnéide 2008; Riahy and Abedi 2008):

$$\mathrm{y(t)} = \sum_{j=0}^{q} b_j.u(t - j.T) - \sum_{k=0}^{m} a_k.y(t - k.T). \tag{3}$$

This is the general difference equation for any linear system, with output signal y and input signal u, and scalars b_i and a_k, for $j = 1, \ldots, q$ and $k = 1, \ldots, m$ where the maximum of m and q is the order of the system.

By re-arranging Equation $y(t) = \sum_{j=0}^{q} b_j.u(t - j.T) - \sum_{k=0}^{m} a_k.y(t - k.T)$ **(3** and transforming into the Z-domain, the transfer function H(z) of such a system is revealed by the following equation (Makhoul 1975; Riahy and Abedi 2008; Cinnéide 2008):

$$H(z) = \frac{Y(z)}{U(z)} = \frac{\sum_{j=0}^{q} b_j.z^{-j}}{\sum_{k=0}^{m} a_k.z^{-k}}. \tag{4}$$

The coefficients of the input and output signal samples in equation $y(t) = \sum_{j=0}^{q} b_j.u(t - j.T) - \sum_{k=0}^{m} a_k.y(t - k.T)$ **(3** reveal the poles and zeros of the transfer function. Linear prediction follows naturally from the general mathematics of linear systems. As the system output is defined as a linear combination of past samples, future output of the system can be predicted if the scaling coefficients b_j and a_k are known. These scalars are thus also known as the predictor coefficients of the system (Cinnéide 2008).

The general linear system transfer function gives rise to three different types of linear model, dependent on the form of the transfer function H(z) given in Equation.

$$H(z) = \frac{Y(z)}{U(z)} = \frac{\sum\limits_{j=0}^{q} b_j.z^{-j}}{\sum\limits_{k=0}^{m} a_k.z^{-k}}$$

(4 Riahy and Abedi 2008; Makhoul 1975; Cinnéide 2008).

- When the numerator of the transfer function is constant, an all-pole or autoregressive (AR) model is defined.
- The all-zero or moving average model assumes that the denominator of the transfer function is a constant.
- The third and most general case is the mixed pole/zero model, also called the autoregressive moving-average (ARMA) model, where nothing is assumed about the transfer function.

The all-pole model for linear prediction is the most widely studied and implemented of the three approaches, for a number of reasons (Makhoul 1975; Cinnéide 2008). Firstly, the input signal, which is required for ARMA and all-zero modeling, is often an unknown sequence. As such, they are unavailable for use in the derivations. Secondly, the equations derived from the all-pole model approach are relatively straightforward to solve, in sharp contrast to the nonlinear equations derived from ARMA or all-zero modeling. Finally, and perhaps the most important reason why all-pole modeling is the preferred choice of engineers, many real world applications, can be faithfully modeled using the approach (Cinnéide 2008).

All-Pole Linear Prediction Model

Following from the linear system equation $y(t) = \sum\limits_{j=0}^{q} b_j.u(t - j.T) - \sum\limits_{k=0}^{m} a_k.y(t - k.T)$ **(3**, one can formulate the equations necessary to determine the parameters of an all-pole linear system, the so-called linear prediction normal equation (Makhoul 1975; Cinnéide 2008). First, following on from the all-pole model, a linear prediction estimate $\hat{y}(t)$ at time t with preceding wind speed data, $y(t)$, by mth order prediction filter can be given by (Makhoul 1975; Cinnéide 2008):

$$\hat{y}(t) = -\sum_{k=1}^{m} a_k.y(t - k.T). \tag{5}$$

The error or residue between the output signal and its estimate at time t can then be expressed as the difference between the two signals (Makhoul 1975; Cinnéide 2008).

$$e(t) = y(t) - \hat{y}(t). \tag{6}$$

For further details see Makhoul (1975) and Cinnéide (2008). In order to estimate the coefficients $a_1, a_2, \ldots, a_m$ in equation $\hat{y}(t) = -\sum\limits_{k=1}^{m} a_k.y(t - k.T)$ **(5**, the least squares error method can be incorporated. This error is between the estimated value at time t and the actual measured value at the same instant Park (1981) and Press et al. (1992). In the least squares error method, the energy in the error signal is minimized. It should be mentioned that the error is generated because the linear prediction model cannot be fitted with zero error to the waveform signal. To find the coefficients, $a_1, a_2, \ldots, a_m$, as the elements of matrix A, least squares error method can be applied as follows (Riahy and Abedi 2008; Press et al. 1992):

$$A = (\varphi^T.\varphi)^{-1}.\varphi^T.Y. \tag{7}$$

In equation $A = (\varphi^T.\varphi)^{-1}.\varphi^T.Y.$ **(7)**, φ^T, is the transpose of the matrix ϕ, and $(\varphi^T.\varphi)^{-1}$ is the inverse matrix. Matrix ϕ is arranged as follows by preceding data according to model degree, m, and length of modeling window, w (Riahy and Abedi 2008; Press et al. 1992):

$$\varphi = \begin{bmatrix} y(t-T) & y(t-2T) & \cdots & y(t-mT) \\ y(t-2T) & y(t-3T) & \cdots & y(t-(m+1)T) \\ \vdots & \vdots & \cdots & \vdots \\ y(t-(w+1)T) & y(t-(w+2)T) & \cdots & y(t-(m+w)T) \end{bmatrix} \tag{8}$$

The best values for model degree, m, and length of modeling window, w, is suggested to be the smallest possible value which provides sufficient and acceptable results (Riahy and Abedi 2008). In this study, a sensitivity analysis has been conducted to obtain the best values for model degree, m, and length of modeling window, w, to achieve minimum MAPE and MPE as shown in Figures 2 and 3. To do so, model degree is changed from 1 to 60, while the length of modeling window is changed from 80 to 800 by step of 20.

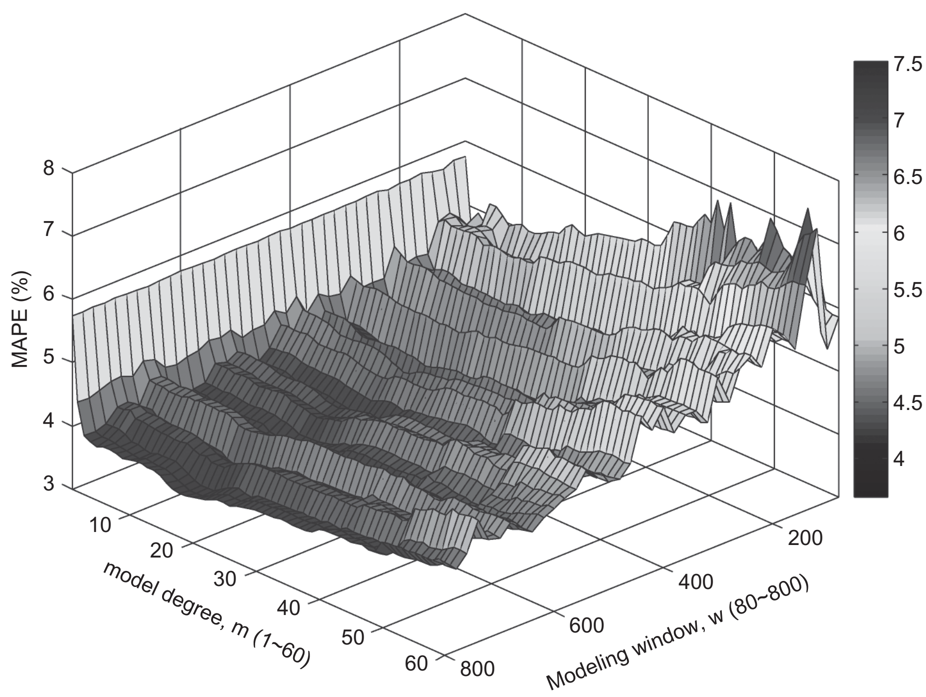


Figure 2 Sensitivity analysis in order to find the best model degree.

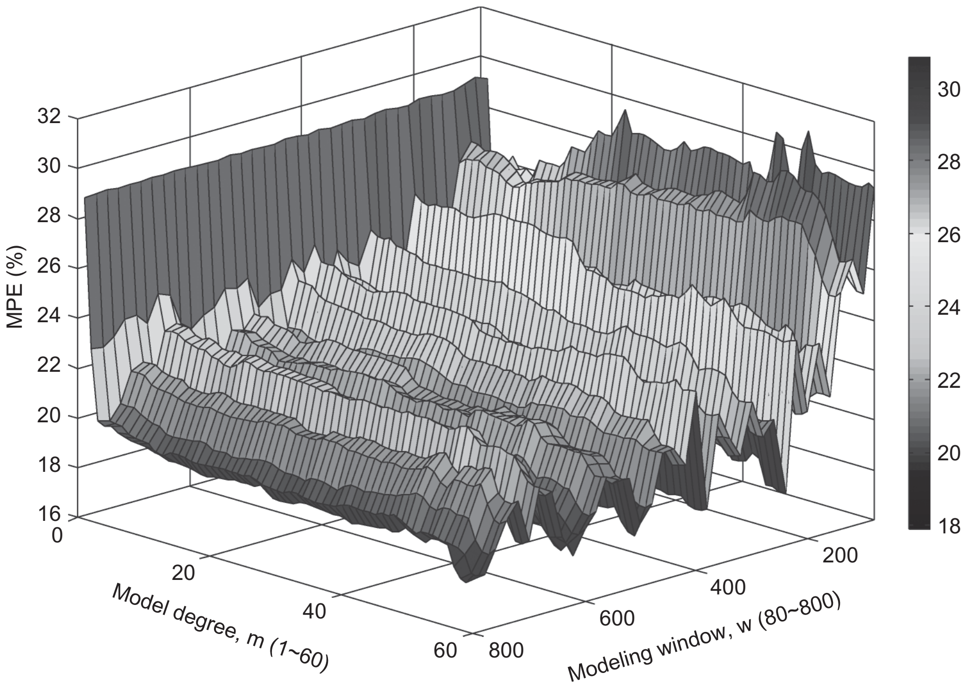


Figure 3 Sensitivity analysis in order to find the best modeling window.

A test data set consist of 1,000 wind speed data is applied for sensitivity analysis. The minimum occurred for MAPE when model degree is 20 and length of modeling window is 400. Also, the best values of model degree and length of modeling window for MPE is almost as same as MAPE. At the rest of the paper, all results are reported for 20 as model degree and 400 for modeling window.

Since linear prediction method apply short time preceding data, long-term patterns in time-variant processes will not be recognized by the linear method. Due to this problem, it can be seen in the results that the linear prediction method shows largest errors when the wind spectrum changes abruptly. Applying a method to consider long-term patterns will reduce the errors of linear prediction method.

MARKOV CHAIN APPROACH

Markov chains are stochastic processes which can be parameterized by empirically estimating transition probabilities between discrete states in the observed systems (Sahin and Sen 2001). The order of the chain represents the number of time steps in the past which influence the present state's probability distribution. For example, a Markov chain of first-order is one for which each subsequent state depends only on the immediately preceding state. Markov chains of second, third or higher orders are the processes in which the next state depends on two or more preceding ones.

Let *X(t)* be a stochastic process, possessing discrete states space $S = \{1,2,\ldots, K\}$. In general, for a given sequence of time points $t_1 < t_2 < \cdots < t_{n-1} < t_n$, the conditional probabilities should be (Sahin and Sen 2001):

$$\Pr\{X(t_n) = i_n | X(t_1) = i_1, \cdots, X(t_{n-1}) = i_{n-1}\} = \Pr\{X(t_n) = i_n | X(t_{n-1}) = i_{n-1}\}. \quad (9)$$

The conditional probabilities $\Pr\{X(t) = j | X(s) = i\} = P_{ij}(s, t)$ are called transition probabilities of order $r = t\text{-}s$ from state i to state j for all indices $0 \leq s < t, with 1 \leq i \, and \, j \leq k$. They are denoted as the transition matrix P. For k states, the first-order transition matrix P has a size of $k \times k$ and takes the form (Sahin and Sen 2001):

$$P_{\text{transition}} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,k} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,k} \\ \vdots & \vdots & \vdots & \vdots \\ p_{k,1} & p_{k,2} & \cdots & p_{k,k} \end{bmatrix} \quad (10)$$

The state probabilities at time t can be estimated from the relative frequencies of the k states. If n_{ij} is the number of transitions from state i to state j in the sequence of speed data, the maximum likelihood estimates of the transition probabilities is (Shamshad et al. 2005):

$$p_{ij} = n_{ij} \Big/ \sum_j n_{ij}. \quad (11)$$

The following properties of the transition matrix are valid by definition. Any state probability varies between zero and one. Notationally,

$$0 < p_{i.j.k,l} < 1.0. \quad (12)$$

On the other hand, the row summation in the transition matrix is equal to 1 and hence notationally,

$$\sum_{l=1}^{n} p_{i.j.k,l} = 1.0. \quad (13)$$

Third-Order Transition Matrix Formation

Initially, the wind speed time series were converted to wind speed states, which contains wind speeds between certain values. In Sahin and Sen (2001) wind speed states determined according to the average $\overline{V}$ and standard deviation S_v of the available wind speed time series. In Shamshad et al. (2005) the wind speed states have been adopted with an upper and lower limit difference of 1 m/s of wind speed, Based on the visual examination of the histogram of the wind speed data. Such a state categorization may be rather arbitrary depending on the purpose and the real wind speed data used for verification (Shamshad et al. 2005). In this study, sensitivity analysis has been carried out for different strategies. Categorization with an upper and lower limit difference of 1 m/s, 0.1 m/s and according to the average, $\overline{V}$, and standard deviation, S_v, of wind speed is considered. Finally, the best results are obtained from categorization with an upper and lower limit difference of 1 m/s. Based on state matrix, it is possible to find the number of transition from three past states, for third-order transition matrix, in the sequence of speed data to another state at time $t+mT$. Finally, the transition probabilities are calculated according to Equation (11).

For the wind speed data which is used in this study, the third-order autocorrelation coefficients are significant rather than first and second order autocorrelation coefficients. Therefore, higher accuracy can be expected by third-order Markov chain. Therefore, third-order Markov chain is considered in this study for higher accuracy. Third-order transition probability matrix for k state can be shown symbolically as below:

$$P_{transition} = \begin{bmatrix} p_{1.1.1,1} & p_{1.1.1,2} & \cdots & p_{1.1.1,k} \\ \vdots & \vdots & \vdots & \vdots \\ p_{1.1.k,1} & p_{1.1.k,2} & \cdots & p_{1.1.k,k} \\ p_{1.2.1,1} & p_{1.2.1,2} & \cdots & p_{1.2.1,k} \\ \vdots & \vdots & \vdots & \vdots \\ p_{1.k.k,1} & p_{1.k.k,2} & \cdots & p_{1.k.k,k} \\ p_{2.1.1,1} & p_{2.1.1,2} & \cdots & p_{2.1.1,k} \\ \vdots & \vdots & \vdots & \vdots \\ p_{k.k.k,1} & p_{k.k.k,2} & \cdots & p_{k.k.k,k} \end{bmatrix}. \quad (14)$$

In this matrix, the probability $p_{i.j.k,l}$ is the probability of the next wind speed state l if the current wind speed state is k and the previous wind speed states were j and i. It has a size of $k^3 \times k$. This is how the probability of making a transition depends on the current state and on the three preceding states. The transition matrix contains long-term patterns from wind speed changes. It is used in nonlinear filter to modify primary prediction values by linear prediction method.

PERSISTENT METHOD

The persistent technique is based upon the high correlation between the present wind speed and the wind speed in the immediate future (Potter and Negnevitsky 2006). This method was developed by meteorologists as a comparison tool to supplement a numeric weather prediction. Because the accuracy of very short-term prediction was historically deemed unimportant, the persistent method was considered sufficient. In fact, this simplified method proved to be more effective than a numeric weather prediction model for very short-term predictions (Potter and Negnevitsky 2006).

VALIDATION EXPERIMENTS

For verification purposes, one set of data is utilized from a site located in Manjil, Iran to evaluate performance of the new algorithm. Local wind speed sampled every 2.5 s. The proposed algorithm is applied to predict one and two steps ahead wind speed prediction (2.5 and 5 s ahead, respectively). Also, categorization with an upper and lower limit difference of 1 m/s is considered. 400 s modeling window and model degree of 20 is set for linear prediction as the best value obtained from sensitivity analysis. The first 1,000 points are used to form Markov Chain transition matrix. So, prediction of wind speed is done for 4,000 data points for two different prediction horizons. Also, transition matrix is updated along the simulation by new preceding data.

In order to test the accuracy of new algorithm, the experimental results are compared with those of primary values predicted by linear prediction and persistent methods. For comparison purposes, two criteria are applied. As first criteria, Mean Absolute Percentage Error (MAPE) is used to measure the performance of different strategies. Its definition is as follows:

$$MAPE = \frac{1}{n}\sum_{t-1}^{n}\left|\left(\frac{y_t - F_t}{y_t}\right) \times 100\right|, \tag{15}$$

where y_t is the actual observation at given time t, F_t is the prediction at the same time and n is the number of prediction.

Another criterion, called MPE, is also used. In wind turbine control applications, it is very important to reduce maximum error of prediction because; a great prediction error may create an unstable condition for wind turbine because of wrong control command. So, a sudden cut-off of wind power due to unstable condition may cause unacceptable shocks in the conventional power units. Since the prediction has been done for a specific number of values with different time steps, the MPE is calculated as follows:

$$MPE(\%) = \max\left\{\left(\frac{y_t - F_t}{y_t}\right) \times 100, t = 1, \ldots, n\right\} \tag{16}$$

The results for different strategies in comparison with measured data for one step-ahead prediction are shown in Figure 4. For better resolution, the results are illustrated for 60 data points in Figure 4. It can be seen from Figure 4 that the hybrid algorithm shows slightly better prediction in some points while it saves linear prediction method accuracy in other points.

The performance comparison for different strategies is shown in Table 1. It shows that the results provided by hybrid algorithm are slightly better than others. By applying the

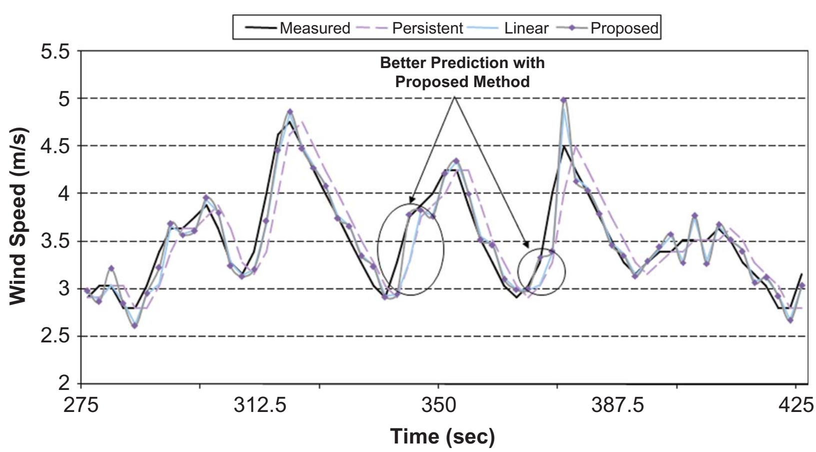
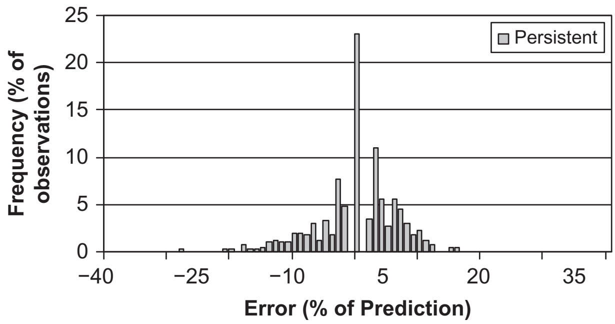


Figure 4 Wind speed waveforms for measured data, persistent, linear methods and proposed hybrid algorithm for one step-ahead horizon (for 60 data points only).

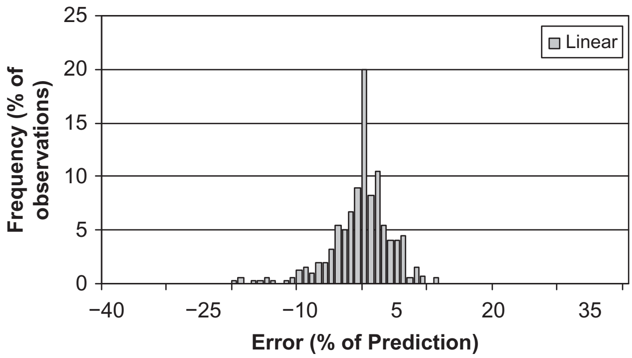
Table 1 2.5 s ahead prediction comparison.

	Linear prediction	Persistent method	Proposed method
MPE* (%)	21.5431	29.7119	18.4544
MAPE** (%)	3.7652	4.9649	3.2672

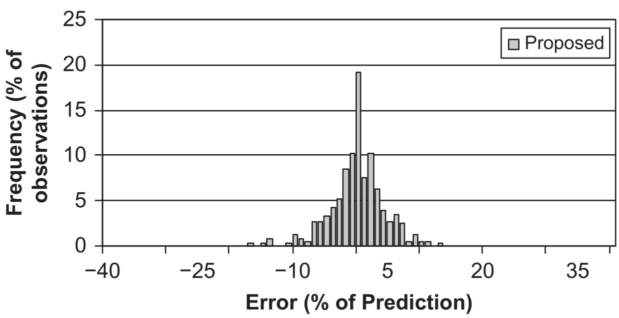
*Maximum Prediction Error, MPE.
**Mean Absolute Percentage Error, MAPE.



(a) Persistent method.



(b) Linear prediction method.



(c) Proposed hybrid algorithm.

Figure 5 Error distribution of wind speed prediction for one step-ahead (2.5 s) obtained by: (a) Persistent, (b) Linear and (c) new algorithm.

nonlinear filter, both errors are reduced against linear prediction. Also, the hybrid algorithm improved results even better than persistent method.

In Figure 5 the error distributions (difference between actual and predicted values) for one step-ahead prediction is illustrated. The MPE obtained from different strategies have been used to find the number of errors in each bins. The histogram clearly shows the reduction of the MPE. Also, it is more symmetrical for hybrid algorithm than others. So, the hybrid algorithm leads to a sharper distribution of the errors. In other words, the forecasts obtained with new hybrid algorithm present a lower uncertainty (Louka et al. 2008).

New hybrid algorithm shows higher efficiency when it is applied for larger prediction horizons. As previous case study, 5,000 observations are used for both formation of Markov transition matrix and prediction for 5 s ahead. Figure 6 illustrates the results of different strategies in comparison with actual data for 5 s horizon. In the points of data which the linear method shows unstable prediction with high frequency changes, the non-linear filter in conjunction with Markov chain approach shows significant effect on the final prediction since the difference between the last predicted and measured data is increased in Equation (1).

MPE and MAPE values for different strategies are also summarized in Table 2. It also shows the improvement of prediction by hybrid algorithm along the leading time. Both errors are reduced significantly, therefore it can be concluded that the new hybrid algorithm shows higher performance. Since the data resolution is 2.5 s, the persistent method show better prediction than linear method in longer horizon. But, the new algorithm improved linear method prediction significantly, even better than persistent method.

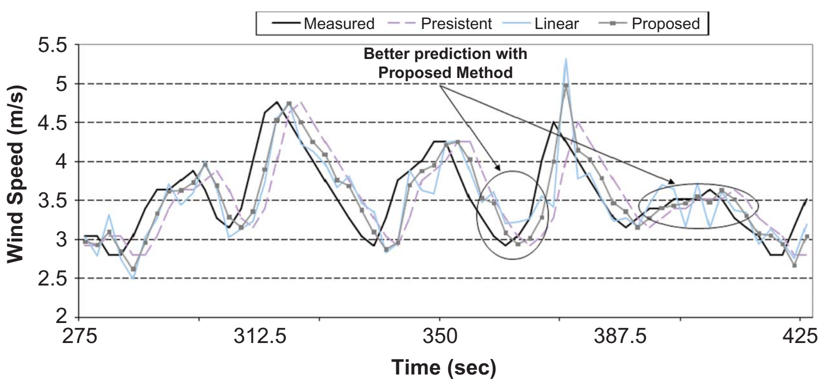


Figure 6 Wind speed waveforms for measured data, persistent, linear methods and hybrid algorithm for two steps-ahead horizons (for 60 data points only).

Table 2 5 s ahead prediction comparison.

	Linear prediction	Persistent method	Proposed method
MPE* (%)	42.6566	40.1029	37.0017
MAPE** (%)	9.1197	7.5560	6.7671

*Maximum Prediction Error, MPE.
**Mean Absolute Percentage Error, MAPE.

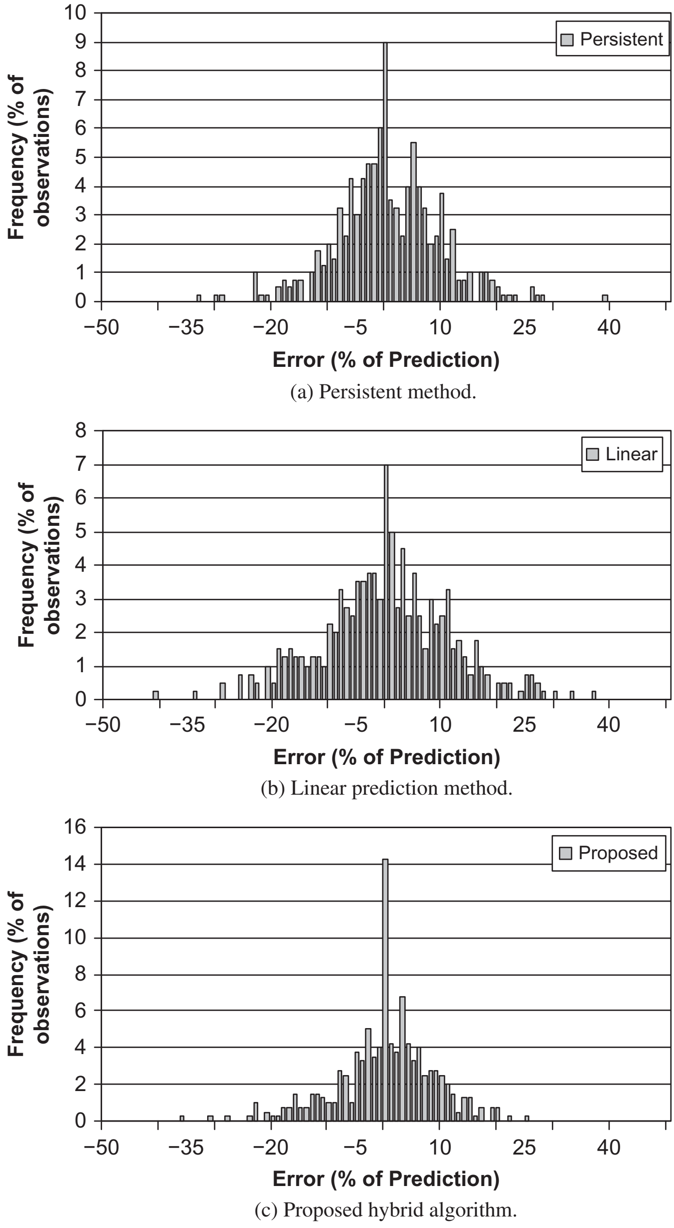


Figure 7 Error distribution of wind speed prediction for one step-ahead (5 s) obtained by: (a) Persistent, (b) Linear and (c) new algorithm.

In Figure 7 the error distributions (difference between actual and predicted values) for 5 s-ahead predictions are illustrated. The hybrid algorithm shows more symmetry than other approaches. Therefore, the hybrid algorithm leads to a sharper distribution of the errors and lower uncertainty (Louka et al. 2008). Lower uncertainty can be illustrated by analyzing the number of prediction errors inferior to a certain error margin. Table 3 represents the number of predictions between ±5%, ±15%, and ±30% error margins for

Table 3 Number of wind forecast errors between ±5%, ±15%, and ±30% for different approaches.

	Horizon (2.5 s)			Horizon (5 s)		
	Persistent	Linear	Hybrid algorithm	Persistent	Linear	Hybrid algorithm
±5%	56.15	73.77	75.02	41.15	35.75	49.00
±15%	90.34	95.03	99.79	78.36	70.29	83.23
±30%	100	100	100	91.82	86.20	95.72
	% of Errors in each margin			% of Errors in each margin		

different methods for comparison. For example, for 5 s horizon, 35.75% of the errors are between ±5% measured values for linear prediction method. Also, 41.15% of the errors are in this margin for persistent method, whereas for the new hybrid algorithm, 49% of the errors are in the same error margin for the same prediction horizon. This trend is true for 2.5 s horizon with smaller improvement in the new algorithm rather than others. It can be observed from Table 3 that the new hybrid algorithm reduces the number of error for higher margins. In other words, the most errors in the new hybrid algorithm are limited to the first narrower margin. It means that the new algorithm is reduced the uncertainty of prediction as well as reducing prediction errors.

It is observed that with larger prediction horizon, the hybrid algorithm significantly will improve the final prediction.

CONCLUSION

In this paper, a new hybrid algorithm is proposed and verified for very short-term wind speed prediction. The proposed method involves linear prediction model together with Markov chain approach. The linear prediction model is applied to grasp short-term pattern and Markov chain approach is utilized to consider long-term patterns on final prediction. The manners in which linear prediction method and Markov chain approach can be used to predict wind speed is described. A nonlinear filter is introduced for final prediction as a new algorithm based on the results of primary approaches. To provide more comparison, persistent method is described and applied for the same prediction horizons and data set.

It is concluded from results that the proposed hybrid algorithm obtained a higher accuracy. Also, it is shown that this method can reduce the uncertainty in wind speed prediction. Further, it can be more effective when it is applied for longer prediction horizons. Since the new hybrid algorithm is very fast, it can be easily applied for on-line prediction which is necessary in wind turbine control applications. Finally, it can be concluded that 'linear prediction' model in conjunction with the Markov chain approach utilizing a nonlinear filter, can perfectly demonstrate a novel method for predicting with speed in wind energy applications.

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