Paper accepted for presentation at 2009 IEEE Bucharest Power Tech Conference, June 28th - July 2nd, Bucharest, Romania

Short Term Wind Speed Prediction by Finite and Infinite Impulse Response Filters: A State Space Model Representation Using Discrete Markov Process

Noha Abdel-Karim, *Student Member, IEEE,* Mitchell Small, and Marija Ilić, *Fellow, IEEE*[1]

***Abstract*—The importance of Integrating wind power generation into electric power grids has rapidly progressed over the past decade. But the intermittency of wind power presents a special challenge for utility system operations as well as the market structure mechanisms. The problem arises from the uncertainty and variability in wind resources that causes fluctuations in the output of wind power generators. This paper presents a short-term wind speed prediction using linrealized time series model. Wind data are first collected from a weather station in ten minute resolution for a period of one year followed by a fitted two Weibull distribution parameters model being estimated from regression analysis on the logarithms of wind speed data. Transformation from Weibull into normal distribution is then held and linear predictive coefficients calculated using finite impulse response filter (FIR) and infinite impulse response filter (IRR) are evaluated for the normalized wind speed random process. Results of 10 minute ahead, one hour ahead, 12 hours ahead and 24 hours ahead wind speed predictions are presented and model accuracy in each of these time-ahead prediction scale are discussed. Also a remarkable observation of the independencies between future and historical wind speed data allows a state space representation model using discrete Markov Process to best represent the stochastic behavior of wind speed signal. In doing so, optimum quantization parameters are first done for both Weibull and normal wind speed distributions and a transition probability matrices are evaluated in each case showing smooth state transition levels in wind data.**

***Index Terms*—wind speed, short term prediction, filter design, optimum quantization, transition probability, and Markov Process.**

I. Introduction

The intermittent nature of wind power presents special challenges for utility system operators in dealing with system economic dispatch, unit commitment , system energy reserve capacity, control and extension problems, as well as future electricity market participation with increased wind power penetration. There is the expectation of significant increase in the installed wind capacities as energy sources in the United States to 20% by the year 2020. A project conducted between NYISO, General Electric (GE), and Automatic Weather Stations Inc., (AWS) stated that NY State has 101 wind energy potential sites and it should be able to integrate wind generation up to at least 10% of system peak load without further expansion [1]. Moreover, policy regulations have been updated to follow decision strategies to go for increased intermittent renewable by settling1 imbalances generation rulemakings and portfolio standards, the most used one at this time is the production tax credit portfolios.

Therefore, forecasting methods used to predict wind speed and hence wind power take great importance and many intensive literatures have discussed several methods to develop wind power forecasting accuracies in ways to solve or at least to minimize the degrees of uncertainty and variability of its stochastic nature.

C. Lindsay Anderson from Cornell University and Judith B. Cardell from Smith College [2], use an auto-regressive moving average model to estimate the next ten-minute ahead production level for a hypothetical wind farm and investigate the possibility of pairing wind output with responsive demand to reduce the variability in the net wind output.

In [3], the authors develop an Artificial Neural Network (ANN) model to forecast wind generation power with 10-min time step. Current and previous wind speed and wind power generation are used as an input parameters to the network where the output from the ANN is the wind generation power.

M. S. Miranda and R. W. Dunn [4] predicted one-hour-ahead of wind speed using both an auto-regressive model and Bayesian approach.

D. Hawkins and M. Rothleder [5], discuss operational concerns for an increase amount of wind energy in California in the Day-ahead-Market and Hour-ahead-Market for CAISO. They state the importance of forecasting accuracy for unit commitment and ancillary services and the implications of load following or supplemental energy dispatchers to rebalance the system every five minutes.

[1] Noha Abdel-Karim is a PhD student in Engineering and Public Policy Department,Carnegie Mellon University (nabdelga@andrew.cmu.edu)

Mitchell J. Small is a Professor of Environmental Engineering; Professor and Associate Department Head for Graduate Affairs, Engineering and Public Policy; Professor, Civil and Environmental Engineering at Carnegie Mellon University (ms35@andrew.cmu.edu)

Marija Ilić is a Professor of Electrical & Computer Engineering and Engineering & Public Policy, Carnegie Mellon University (milic@andrew.cmu.edu)

978-1-4244-2235-7/09/$25.00 ©2009 IEEE

In [6], the authors propose a probabilistic method to estimate the forecasting error for Spanish Electricity System. They propose cost assessment with wind energy prediction error. The assessment is developed in the sense that wind power generators should pay the costs associated with any energy deviation they cause.

In [7], Dale L. Osborn discusses the impact of wind on the LMP market for Midwest MISO at different wind penetrations. His LMP calculations decrease as an increase of wind energy penetration for the Midwest area.

Authors of [8] describe very short-term wind prediction for power generation, utilizing a case study from Tasmania, Australia. They introduce an Adaptive Neural Fuzzy Inference System (ANFIS) to forecasting a wind time series. Over the very short-term forecast interval, in vector form contains both wind speed and wind direction.

This paper presents short term wind speed linear prediction model in state space representation using linear predictive coding (LPC), FIR and IRR filters. 10 minute, one hour, 12 hours, and 24 hours wind speed predictions are evaluated in least square error sense and the prediction coefficients are then used in the state space stochastic formula representing past and future predicted values. One year wind speed data in 10 minute resolution are first fitted by two Weibull distribution parameters and then transformation to normal distribution is done for prediction calculation purposes. Prediction results using various past histories of wind data show independencies. These independencies have been modeled as linear state space discrete Markov process. For that, quantization process is carried to optimize time step between different state levels for both wind speed distributions used. Also state and transition probability matrices are evaluated from the actual representation of wind speed data. Transition probabilities show smooth transitions between states that assert clustering around the diagonal matrices. Section II presents distribution fitting to wind data, and section III demonstrate linear prediction method of wind speed up to one day ahead. Section IV develops linear state space representation of wind speed using discrete Markov process and section and also the results of both prediction method and Markov Process using real data taken from a national weather station in the United States.

II. Wind Speed Prediction Model

A. Wind data distribution models

More than 50 thousands samples representing one year wind speed data in 10 minute resolution are used to determine the best fitted parameters of the Weibull distribution model. Wind speed data are obtained from National weather station in NYISO zonal areas by approximate longitudes and latitudes station's allocation [9]. The empirical cumulative distribution function (CDF) for the wind speed random variable (RV) X is evaluated using n samples based on the statistical Weibull formula

Linear regression is performed between $X = \ln(x)$, where x is the data plotted on the horizontal axis, versus the following CDF metric on the vertical axis:

$$Y = \ln\left(-\ln(1-\hat{F}_X(x))\right) \quad (1)$$

PDF parameters are related to the linear regression slope m and Y-intercept C, as follows:

$$\begin{aligned} &\beta = slope = m \\ &\alpha = \exp(C) \;\; \Leftrightarrow a = \exp(-C/\beta) \end{aligned} \quad (2)$$

The regression results are shown in table I and both empirical and Weibull cumulative distribution functions are plotted in Figure 1 that shows good fit.

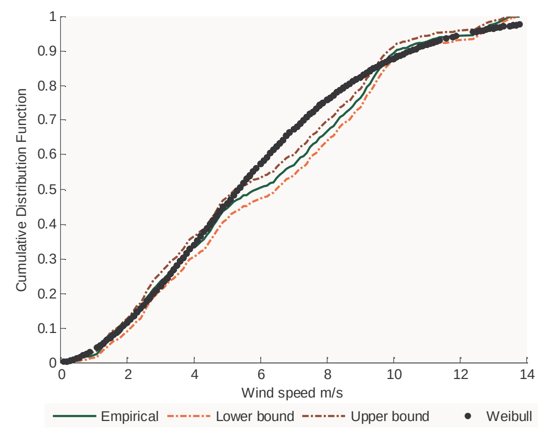

Figure 1 Empirical and Weibull Cumulative Distribution Functions.

TABLE I
LINEAR REGRESSION DEFINES WEIBULL DISTRIBUTION PARAMETERS

α	Slope β	Standard Error (intercept)	Standard error (slope)	R-square
0.0356	1.77	1.4×10^{-3}	8×10^{-4}	99.4%

Next, Transformation to normal distribution with mean zero and variance one is used in both the fitting and prediction processes. Figures 2 and 3 show histograms and wind speed signals representing both Weibull and Normal distributions, respectively. The shape of the actual signal is shifted down with the exact pattern due to the normalization process (Figure 3).

B. Normalization of Wind Speed Data

As an initial step for wind speed prediction, transform from actual wind speed data X to Normal wind speed data X_n (i.e., X_n is a normalized Gaussian RV with zero mean and unit variance) is performed. This transformation is performed using the Normal CDF inversion as follows:

$$\left.\begin{aligned} &F_X(x) = 1 - e^{-\alpha x^{\beta}} \\ &= F_{X_n}(x_n) = G(0,1) \end{aligned}\right\} \quad \Leftrightarrow \quad x_n = F_{X_n}^{-1}\left(F_X(x)\right) \quad (3)$$

Figures 2 and 3 show the histograms and time series, respectively, for both the actual (Weibull) wind speed X

and Normal wind speed X_n. The shape of the Normal signal X_n is shifted down with negative values (Figure 3) compared to the actual signal X due to the normalization process.

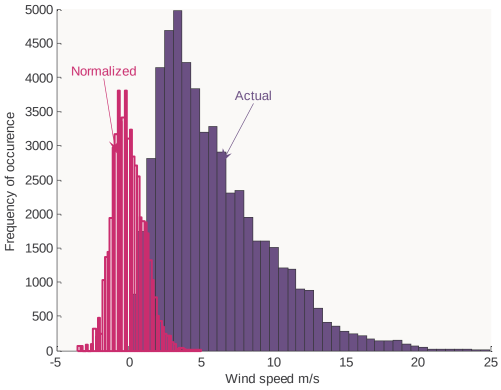

Figure 2 Actual & normalized frequency occurrence of wind speed data.

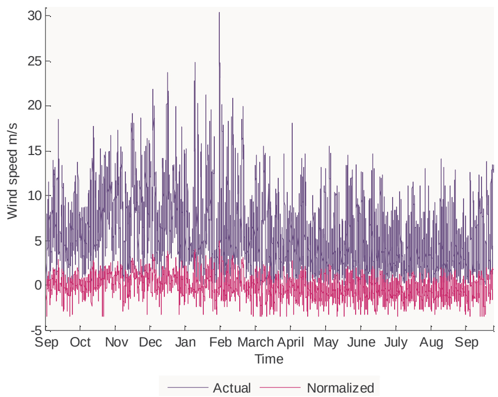

Figure 3 Actual and normalized wind speed data.

III. Linear Prediction and Filter Design

In this section, finite impulse response (FIR) and infinite impulse response (IRR) filters are being used to determine the prediction coefficients needed to process the normalized wind speed signal X_n, except that we drop the subscript "n" so as not to be confused with the discrete time index. In discrete time, we use the Z-transform of a signal or a filter defined as:

$$g(n)=\sum_i g_i\delta(n-i) \quad \Rightarrow \quad G(z)=\sum_i g_i z^{-i}$$

Where δ(n) is the Kronecker delta function. The wind speed random process x(n) is characterized as wide sense stationary (WSS) Gaussian (Normal) process, and hence will remain Gaussian after any stage of linear filtering. However, the wind speed process is NOT white but can be closely modeled as Auto-Regressive (AR) process as will be shown next.

A. Linear Predictive Coding (LPC) Finite Impulse Response Filter (FIR)

To predict the Normal wind speed, Linear Predictive Coding (LPC) is used based on the autocorrelation method to determine the coefficients of a forward linear predictor by minimizing the prediction error in the least squares sense [17]. The method provides the LPC predictor and its prediction error as follows:

$$\begin{aligned} \hat{x}_{LPC}(n) &= -\sum_{i=1}^{N} b_i\, x(n-i) \\ e_N(n) &= x(n)-\hat{x}_{LPC}(n) = x(n)+\sum_{i=1}^{N} b_i\, x(n-i) \end{aligned} \tag{4}$$

Where N is defined as the prediction order (using N past data samples) and the coefficients $\{b_1, .., b_N\}$ are the fitting coefficients which minimize the mean square (MS) prediction error signal. These coefficients are computed by solving the normal or Yule-Walker equations based on the signal autocorrelation matrix [12]. The LPC predictor has a direct equivalent implementation as an FIR filter if we observe that the error Z-transform is obtained as:

$$\begin{aligned} &\mathbf{E}_N(z)=\mathbf{X}(z)\times\mathbf{B}_N(z) \quad \Rightarrow \quad \mathbf{X}(z)=\mathbf{B}_\mathbf{N}^{-1}(z)\times\mathbf{E}_N(z) \\ &\mathbf{B}_N(z)=1+\sum_{i=1}^{N} b_i\, z^{-i} \end{aligned} \tag{5}$$

Where $B_N(z)$ is the FIR filter transfer function used to compute the output error signal. In other terms, it is also called the prediction polynomial [12]. Figure 4 shows how to obtain the output error signal using two equivalent forms: a) LPC prediction and subtraction, and, b) direct FIR filter design.

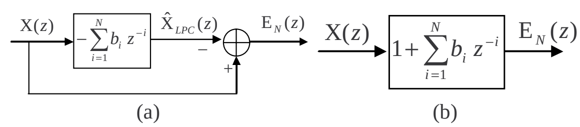

Figure 4. Output prediction error signal using: a) LPC prediction and subtraction. b) Direct FIR filter design.

The main advantage of LPC is that, as the prediction order N increases sufficiently, the prediction error $e_N(n)$ tends to be closely approximated as white noise [12]. This helps in modeling the Normal wind speed as AR signal as will be shown next. Thus, forward LPC is considered an important initial pre-coding step.

B. Auto-Regressive (AR) Model Prediction and Infinite Impulse Response (IIR) Filtering

Equation (5) tells that the true wind speed can be obtained by multiplying the error signal $E_N(z)$ – if it is known – by the inverse of the FIR filter $B_N^{-1}(z)$, which is now an *all-pole* IIR filter. If the error signal is equivalent to white noise for large prediction order N, then the z-multiplication (i.e., convolution or filtering in discrete time) now yields a signal that is modeled as Gaussian Auto-Regressive (AR) process. The AR model block diagram is shown in Figure 5 below, while the reproduced AR signal is obtained by rewriting equation (4) in terms of error as:

$$x(n)=-\sum_{i=1}^{N} b_{i,N}\, x(n-i)+e_N(n) \tag{6}$$

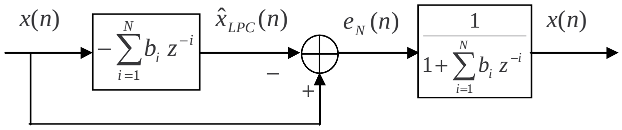

Figure 5 Auto-regression generation process using LPC estimation method

Equation (6) seems to be an ideal reproduction of $x(n)$ by inversion and it assumes the following:

1) The error signal is exactly updated in real time at the prediction time "n". This is a *genie assisted* condition, as $\hat{x}(n)$ is not available yet!

2) All the true N past data samples are available or exactly estimated (measured) by the wind turbine speed meter and reported on time to the prediction algorithm.

3) The prediction coefficients $\{b_1, \ldots, b_N\}$ are computed using the true past data samples and updated for each new prediction.

In a practical prediction algorithm, these genie conditions don't hold. As for the prediction error, different computation models can be used such as:

1) Prediction error is *estimated* as a random generation of white noise of zero mean & unit variance [12].

2) For initial or limited time intervals, the error can be *exactly computed* using true available data samples to investigate the tracking of the algorithm, but not for long term prediction.

3) The prediction error can be *estimated* from exact measurements but up to a delay of one or more samples, i.e., measurement at time $(n - L)$ applies at time "n". For example, if the prediction update interval is 10 minutes and the measurement delay is 1 hour, then the sample count delay is $L = 60/10 = 6$ samples. The minimum estimation delay is $L = 1$.

In our work we excluded the white noise generation alternative and considered the two other alternatives for wind speed forecasting.

IV. The Prediction Algorithm for Wind Speed

A. *Linear Prediction Phases*

In this research, more than 50,000 data samples have been collected at 10-minute intervals. For prediction, a time reference is set at $n = N_S$, where $N_S \leq 50000$, to mark the end of known data and start of prediction. The remaining samples can be used for tracking the algorithm.

We assume a data measurement reporting interval of L samples and that there is no error in the measurement or the reporting process. At time epochs $n = N_S + m\,L$, where m is an integer, the L measurements $x(n - L + 1)$, $x(n - L + 2)$, …, $x(n)$ are reported and will be available to use at the next epoch, $(N_S + m\,L + 1)$. Depending on L, two extreme cases can result as follows:

$L = 1$: $\rightarrow$ Point estimator case.
$L = \infty$: $\rightarrow$ Time series case, i.e., no measurements at all.

Further, we define the following signals and associated time epochs for prediction purposes:

$x(n)$: True Normal signal known within $0 \leq n \leq N_S$ or whenever measurement is available as above.

$\hat{x}(n)$: Predicted signal using IIR filter or AR recursion.

$x_{REF}(n)$: Reference signal used to produce $\hat{x}(n)$.

$x_{REF}(n) = x(n)$ within $0 \leq n \leq N_S$ or whenever measurement is available

$e_N(n) = x(n) - \hat{x}(n)$: True prediction error, only known if $x(n)$ & $\hat{x}(n)$ are known.

$\hat{e}_N(n)$: Prediction error estimate, either white noise or delayed measurement.

The prediction algorithm can be summarized as follows:

a) ***Training phase*** within $0 \leq n \leq N_S$: Apply the LPC algorithm on the true samples $x(0)$, … , $x(N_S)$ to obtain the prediction coefficients $\{1, b_1, \ldots, b_N\}$. Then FIR filter is used to filter the same samples using the FIR coefficients $\{-b_1, \ldots, -b_N\}$ to compute the predictor $\hat{x}(n)$ and true prediction error $e_N(n) = x(n) - \hat{x}(n)$ within $0 \leq n \leq N_S$. Further, we pre-load the reference signal $x_{REF}(n) = x(n)$ within $0 \leq n \leq N_S$.

b) ***Prediction phase*** for $n \geq N_S + 1$: The AR model of equation (6) is applied after computing the error estimate $\hat{e}_N(n)$. The same prediction coefficients obtained in the training phase are used if we plan short-term prediction, which is our case. Otherwise, prediction coefficients have to be updated for long-term prediction. The steps for prediction at epoch "n" are given by:

1) Compute the prediction error estimate using:

$$\begin{aligned} \hat{e}_N(n) &= x_{REF}(n-1) - \hat{x}(n-1) \quad \textbf{if} \quad x_{REF}(n-1) = x(n-1) \\ &= \hat{x}(n-2) - \hat{x}(n-1)\,, \quad \textbf{if} \quad x_{REF}(n-1) = \hat{x}(n-1) \end{aligned} \tag{7}$$

We can set $\hat{e}_N(n)$ as randomly generated white noise or also import a snapshot from the past true prediction error series obtained in the training phase.

2) By inspecting equation (6), we compute the predicted signal via the AR recursion:

$$\hat{x}_{AR}(n) = -\sum_{i=1}^{N} b_{i,N}\; x_{REF}(n-i) + \hat{e}_N(n) \tag{8}$$

3) Update the reference signal entries as follows:

If $n \neq N_S + m\,L$ $\rightarrow$ $x_{REF}(n) = \hat{x}_{AR}(n)$

If $n = N_S + m\,L$ $\rightarrow$ b $[x_{REF}(n - L + 1), x_{REF}(n - L + 2), \ldots, x_{REF}(n)] = [x(n - L + 1), x(n - L + 2), \ldots, x(n)]$

4) Update the prediction coefficients if needed by running the LPC on the reference signal. It is best to make such update at $n = N_S + m\,L$ because $x_{REF}(n)$ would be just updated by measurements.

5) Increment n and go back to step 1.

Figure 5 shows prediction process phases

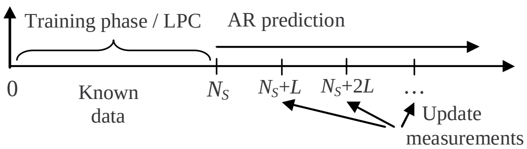

Figure 5. The two phases of prediction process.

B. *Wind speed prediction results*

Ten minute wind speed data from Dunkirk weather station in the west zone of New York State have been used for the stochastic prediction of wind speed [9].

Figure 6 Ten minutes and one hour prediction using 10 minute past value

Figures 6 and 7 assist that the prediction model insensitive to the prediction order which is defined as the number of observed data (history) used in the prediction. 10 minute wind speed prediction model shows persistence for all prediction orders used.

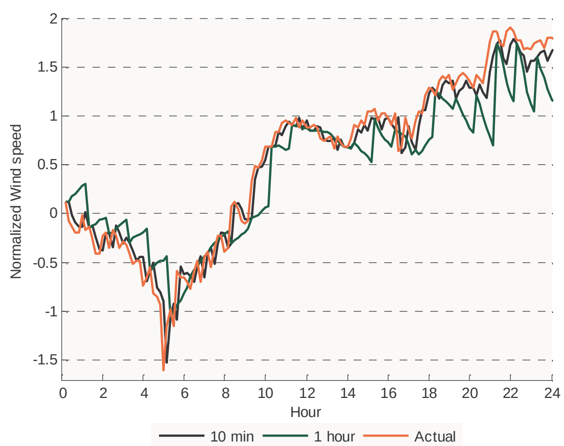

Figure 7 Ten min and one hour prediction using 1 hour past values

Figure 8 shows the effect of how the increase in the number of present and past wind speed sample data does not significantly reduce the root mean square error (RMSE). This led us to an interesting valuation of data structuring and modeling. If only can one recent sample random variable captures stochastic statistics of wind signal to predict future values, then time and memory reductions in presenting such signal can be modeled as a discrete Markov process; the process that stated generally the independencies between past and present values to present signal statistics and structure using state and transition probabilities that will be discussed in detail in the next section below.

V. Wind Model Using Discrete Markov Process

The interesting results obtained above shows Independencies from past observed data except for the nearest one. Model representation using Markov process is then valid, which is defined as the likelihood of next wind speed value in state *k* is conditioned on the most recent value of wind speed in state *m*. Equation (9) defines this likelihood – state relationship.

$$P(X_k=i|X_m=x_m,x_{m-1},\ldots,X_1=j)=P(X_k=i|X_m=x_m) \tag{9}$$

However, to identify state levels and state values, uniform midrise quantization process is carried out to discretize wind speed signal to state levels with optimum threshold or cutoffs values.

A. *Design of optimum Uniform Quantizer*

A midrise uniform Quantizer is implemented that minimizes the mean square quantization error given a set of M states; we define $x=[x_1\, x_2 \cdots x_M]$ as a state value vector, and $x_t=[x_t(1)\, x_t(2)\cdots x_t(M-1)]$ as a quantized threshold levels or partitions vector. x is the original analog wind speed signal and x_q is the quantization signal. The quantization step Δ is defined as;

$$\Delta = x(m+1)-x(m)=x_t(m+1)-x_t(m) \tag{10}$$

The operation of the Quantizer is as follows:

$$x_q=\begin{cases} x(1) & if \quad x \le x_t(1) \\ x(M) & if \quad x \succ x_t(M-1) \\ x(m) & if \; x_t(m-1) \prec x \le x_t(m) \end{cases} \tag{11}$$

B. *State and Transition probabilities in discrete state space Markov model*

Given the initial and final boundaries of each state; state probabilities can now be defined as:

$$\begin{aligned} P(m) &= P\left[x_i(m) \prec x \le x_f(m)\right] \\ &= P[x(m)] = \int_{x_i(m)}^{x_f(m)} f_X(x)\, dx \\ &= F_X(x_f(m) - F_X(x_i(m)) \end{aligned} \tag{12}$$

Where m = 1, 2, …, M, is the state index. Equation (13) presents the Markov linear state space model that takes into account the prediction coefficients, error signal modeled as disturbance d, and a regeneration time τ in which the signal is updated (e.g., 1 sample in 10 minutes or 6 samples in one hour).

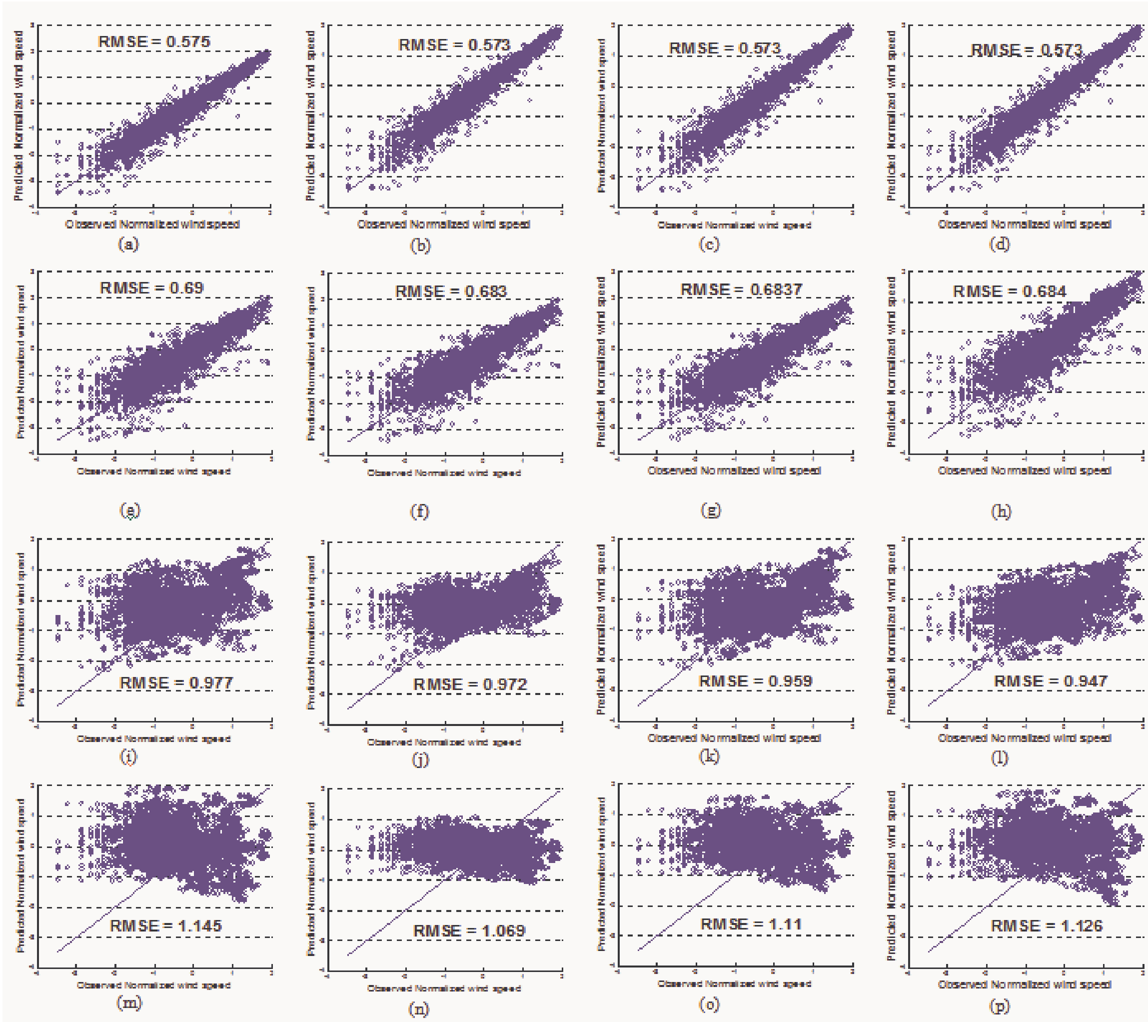

Figure 8 Wind speed prediction using various past wind speed data in 10 minute resolution:

1st raw: 10 minute prediction using: (a) 10 min, (b) one hour, (c) 12 hours, and (d) 24 hours past data.
2nd raw: 1 hour prediction using: (e) 10 min. , (f) one hour, (g) 12 hours , and (h) 24 hours past data.
3rd raw: 12 hours prediction using: (i) 10 min. , (j) one hour, (k) 12 hours , and (l) 24 hours past data.
4th raw: 24 hours prediction using: (m) 10 min. , (n) one hour, (o) 12 hours , and (p) 24 hours past data.

$$x_{\tau}(n)=\sum_{j=1}^{N} a_j x(n-j)+d_j(n) \tag{13}$$

The processing time from $\tau_o \rightarrow \tau$ is represented by a rectangular function. Equations (14) and (15) define subsequent use of the state space representation.

$$x_{j,\tau}(n)=\sum_{j=1}^{N+1} a_{j+1} x(n-j)+d_j(n) \tag{14}$$

$$\bar{x}_{j,\tau}(n)=[A]\times\bar{x}_{j-1,\tau}(n)+d_j(n) \tag{15}$$

Where $[A]$ is the prediction coefficient matrix. Transition probabilities are calculated based on the counting method discussed in [11], for which we define:

$N_{trans}(k\,|\,m) \equiv$ The number of transitions from state m to state k in the time series,(m is the originating state, k is the next state)

$N_{state}(m) \equiv$ The number of occurrences of state m in the time series signal.

Both state and transition counters are related by (16) and the total size of the time series is defined in (17)

$$N_{state}(m)=\sum_{k=1}^{M} N_{trans}(k\,|\,m) \tag{16}$$

$$N=\sum_{m=1}^{M} N_{state}(m)=\sum_{m=1}^{M}\sum_{k=1}^{M} N_{trans}(k\,|\,m) \tag{17}$$

Using the statistical counter values of $N_{state}(m)$ and $N_{trans}(k\,|\,m)$, the transition and state probabilities can be statistically computed as:

$$P_{trans}(k\,|\,m)=\frac{N_{trans}(k\,|\,m)}{N_{state}(m)} \tag{18}$$

$$P_{state}(m)=\frac{N_{state}(m)}{N} \tag{19}$$

Where, *K = 1,…, M and, m= 1,…, M.* Note that (19) represent the statistical (actual) state probabilities of wind speed signal while (12) represent the theoretical state probabilities defined be either Weibull or Normal probability density functions. The probability state space representation is defined as:

$$P(\bar{x}_{j,\tau}(n)) = [P_{trans}] \times \bar{x}_{j-1,\tau}(n) \quad (20)$$

Where $[P_{trans}]$ is the transition probability matrix.

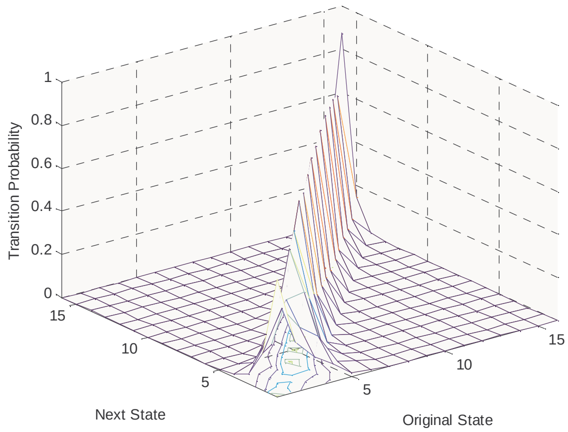

Figure 9 Gaussian transition probability for M = 16 states

Figures 9 through 14 show the transition probability plots being clustered around the diagonal which means smooth transitions between states and suggesting that the data does not exhibit frequent wind gusts. Also the difference between theoretical and actual (statistical) state probabilities as shown in Figures 15 and 16 is due to the use of the uniform quantization while we conjecture that a non-uniform quantizer will achieve a better match between the actual and theoretical probabilities.

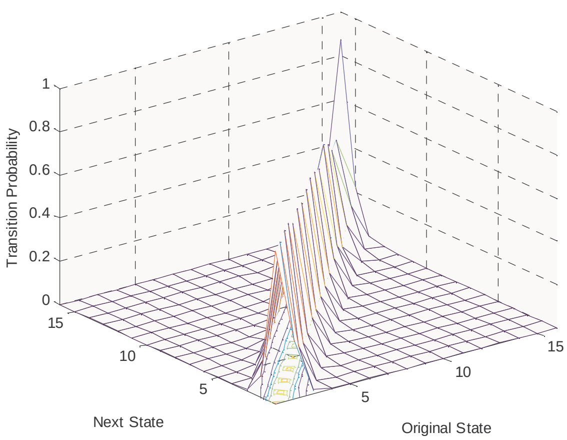

Figure 10 Weibull transition probability for M = 16 states

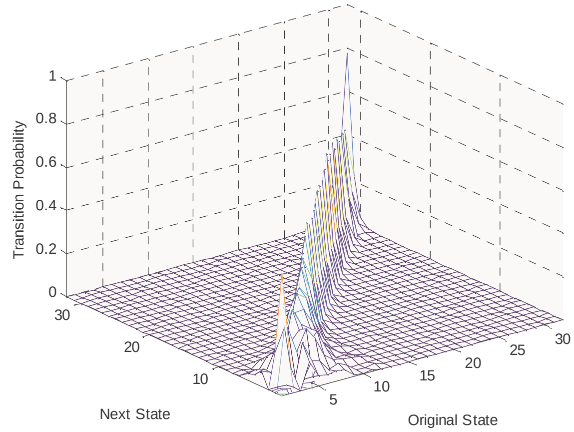

Figure 11 Gaussian transition probability for M = 32 states

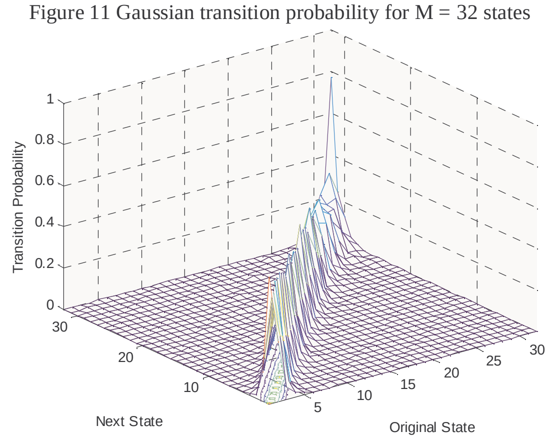

Figure 12 Weibull transition probability for M = 32 states

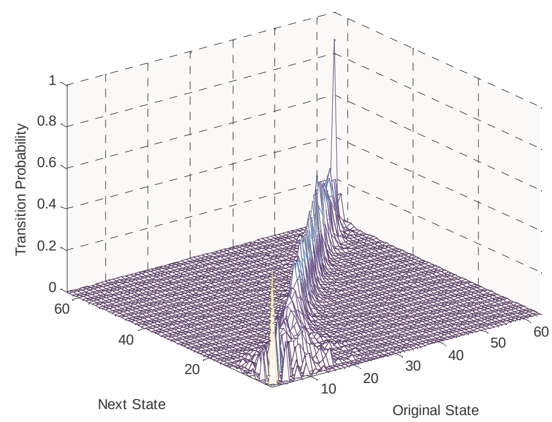

Figure 13 Gaussian transition probability for M = 64 states

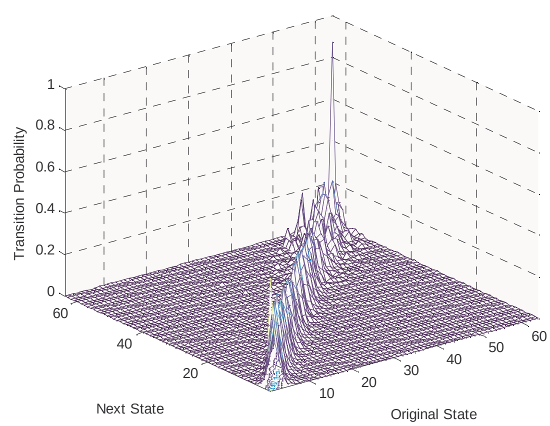

Figure 14 Weibull transition probability for M = 64 states

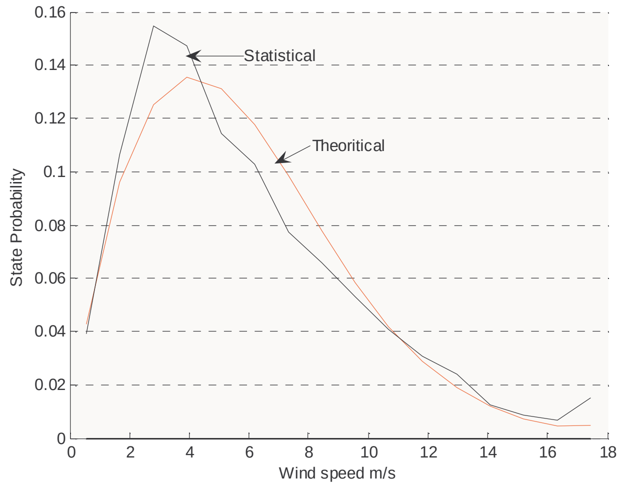

Figure 15 Weibull state probability for M = 16 states

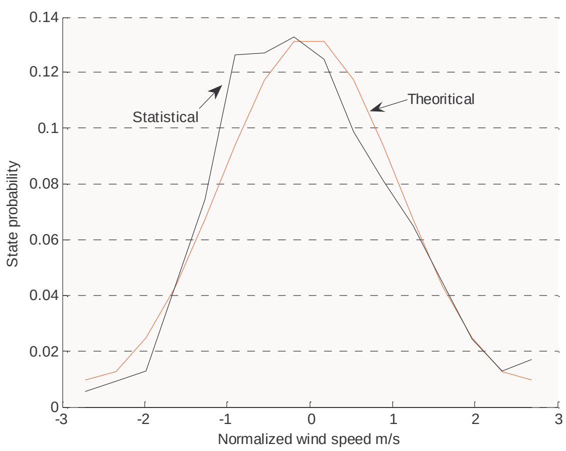

Figure 16 Gaussian state probability for M = 16 states

VI. Conclusion

Linear prediction with FIR and IIR filtering has been used to predict wind speed signals transformed from Weibull to Normal PDF. Linear state space representation has been performed and the prediction results show that a small prediction order based on the most recent data is sufficient for a good accuracy. A uniform quantization algorithm using Weibull and Normal PDF's has been used to discretize the signal for representation as a discrete Markov process. The state probabilities of the Markov process have been calculated both statistically (by counting the time series data) and theoretically (by integrating the modeled signal PDF) with a good match for both Weibull and Normal distributions that can be further improved by using non-uniform quantization. The computed transition probability matrix of the Markov process is shown to be clustered around the diagonal, which indicates the absence of frequent wind gusts in the used time series.

VII. References

[1] GE Energy, Report on "*The Effects of Integrating Wind Power on Transmission System Planning, Reliability, and Operations*" Prepared for: The New York State Energy Research and Development Authority, March, 2005. Available online: http://www.nyserda.org/publications/**wind_integration**_report.pdf

[2] C. Lindsay Anderson, Judith B. Cardell, "Reducing the Variability of Wind Power Generation for Participation in Day Ahead Electricity Markets," *Proceedings of the 41st Hawaii Inter national Conference on System Sciences, IEEE*, 2008.

[3] Kittipong M., Shitra Y., Wei Lee, and James R. "An Integration of ANN Wind Power Estimation Into Unit Commitment Considering the Forecasting Uncertainty," *IEEE Transactions On Industry Applications*, Vol., 43, No. 6, Nov. 2007.

[4] Marcos S. Miranda, Rod W. Dunn, "One-hour-ahead Wind Speed Prediction Using a Bayesian Methodology," *IEEE* 2006.

[5] D. Hawkins, M. Rothleder, "Evolving Role of Wind Forecasting in Market Operation at the CAISO," *IEEE PSCE*, pp. 234 -238, 2006.

[6] Alberto F., Tomas G., Juan A., Victor Q., "Assessment of the Cost Associated With Wind Generation Prediction Errors in a Liberalized Electricity Market," *IEEE Transactions on Power Systems*, Vol. 20, No. 3, pp. 1440-1446, August 2005.

[7] Dale L. Osborn, "Impact of Wind on LMP Market," *IEEE PSCE*, pp. 216-218, 2006.

[8] Cameron W. Potter, Micheal Negnevistsky, "Very Short-Term Wind Forecasting for Tasmanian Power Generation", IEEE, TPWRS Conference, 2005

[9] National weather station, available online, http://www.ndbc.noaa.gov/data/5day2/DBLN6_5day.cwind

[10] B. A. Shenoi, "Introduction to Digital Signal Processing and Filter Design" John Wiley & Sons, Inc. 2006

[11] F. Castellanos," Wind Resource Analysis and Characterization with Markov's Transition Maatrices," IEEE Transmission and Distribution Conf., Latin America, Aug. 2008

[12] P. P. Vaidyanathan, *The Theory of Linear Prediction*, California Institute of Technology, 1st ed., Morgan & Claypool, 2008