State Estimation Based Neural Network in Wind Speed Forecasting: A Non Iterative Approach

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Abstract

Renewable energy sources have gained a lot of importance in today's power generation. These sources of energy are pollution free and freely available in nature. Wind is the most prominent energy source among the renewable energy sources. Increased wind penetration into the existing power system will create reliability problems for grid operation and management. Wind speed forecasting is an important issue in wind power grid integration as it is chaotic in nature. This paper presents a new State Estimation based Neural Network (SENN) for day ahead (24 hours ahead) wind speed forecasting and its performance has been compared with traditional Back Propagation Neural Network (BPNN). SENN is a non iterative technique, where the weights between input-hidden and hidden-output layers are estimated using a Weighted Least Square State Estimation (WLSSE) approach. It accounts noise associated with input and output data, giving accurate results without any iteration. This method is quite efficient and faster compared to conventional Back Propagation Neural Network (BPNN).

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Keywords: Back Propagation Neural Network, State Estimation Neural Network, Wind forecast and Weighted Least Square.

Abbreviations:

BPNN	Back Propagation Neural Network
SENN	State Estimation Neural Network
WLSSE	Weighted Least Square State Estimation
BPA	Back Propagation Algorithm
SVM	Support Vector Machine
ANN	Artificial Neural Network

1 Introduction

The significance of renewable energy sources has recently increased due to multiple factors, including their main property of being eco-friendly. Global warming and limited availability of fossil fuels are also leading to making renewable energy sources the best alternative energy sources. Among the renewable energy sources, wind power is most promising and rapidly expanding worldwide. With the introduction of deregulation in electricity market many new challenges have been taking place by the participants of power industry. Thus, wind speed forecasting is becoming a major issue in deregulated market as wind power is an important contribution to the power industry. Wind speed forecasting reflects directly on power forecasting as wind power is proportional to the cube of wind speed. An accurate wind power forecasting can mitigate undesirable consequences in wind connected power systems and it is also helpful in power system planning studies. As on date, many forecasting methods exist in literature.

A novel hybrid intelligent algorithm has been introduced in [1] for wind power forecasting which uses fuzzy network and wavelet transform, and it is optimized by firefly optimization algorithm. Khosravi et al. [2] Investigated short term forecasting of wind power using two neural network based methods for rapid and direct construction of prediction intervals. A statistical method has also been proposed in [3] for power forecasting where wavelet decomposition is used to predict wind power up to 30 hours. Wavelets are also used for wind speed forecasting in [4–6] and different wavelet functions with various decomposition levels were used to estimate the wind speed. They are also used for energy price forecasting [7]. Sideratos et al. [8] have used a new learning method for radial basis function neural network and

this has been tested on a real wind farm and then compared with state-of-art models. Various wind speed forecasting methods and their significance in the present power system scenario has been discussed in [9, 10]. A day-ahead wind speed forecasting along with direction has been investigated in [11] and results are compared with persistent models. The wind power forecasting is the prerequisite for integrating wind power into the grid as it links the available wind power to the conventional power [12]. In [13] four time series models were examined with different prediction horizons built by data mining algorithm. Barbounis et al. [14] deals with long term wind speed and power forecasting using local recurrent neural networks based on meteorological information. Artificial neural networks have also been used for short-term wind power forecasting [15]. Fuzzy logic and neural network based wind speed forecasting method has been proposed in [16] this method is fast in computation and quite accurate in wind speed prediction. A hybrid forecasting method which is a combination of autoregressive integrated moving average, Artificial Neural Network (ANN), Support Vector Machine (SVM) has been used in [17] for wind speed and power forecasting for different time horizons. A combined approach consisting of ANN, SVM, fuzzy inference system has been used again for wind speed forecasting to improve forecasting accuracy [18]. ANFIS and fuzzy logic techniques have been used extensively for load forecasting [19]. A specific commercial software package has been developed to study wind power forecast in [20] using historical data for this purpose. Finally the wind forecasting also shows its impact on power system reliability and this topic has been extensively discussed in [21] and [22].

In this paper, a State Estimation based Neural Network (SENN) is proposed as a wind forecasting tool and tested on one year real wind data in the Midwest ISO region. SENN based wind speed forecasting method is a novel approach, as it is non iterative. The weights are estimated more accurately with the mathematical approach (which will be explained in the coming sections) at the first instant itself there by forecasting results are more reliable. Moreover, this method is compared with another well-assessed wind speed forecasting method, namely Back-Propagation Neural Network (BPNN). This paper is organized as follows: Section 2 presents traditional BPNN architecture, Section 3 describes the proposed SENN based wind speed forecasting method, Section 4 analyses the results of the two respective methods and Section 5 concludes the paper.

2 BPNN Architecture

In this section application of ANN wind speed forecasting is explained. ANN can utilize past history of data to train the network and forecast future data. ANN based methods are suitable for forecasting compared to traditional methods as they are adaptable in nature. Here, Back Propagation Algorithm (BPA) is used for wind speed forecasting. BPA is a supervised learning technique where the target (output) is known. The main mechanism behind BPA usage consists of back propagating the error and adjusting the weights in proportion to error gradient and this process repeats until error is minimized to the desired level. The considered ANN consists of 3 layers namely the input layer, the hidden layer, and the output layer as shown in Figure 1. Sigmoid function has been used as the activation function in the hidden layer and output layer. Generally a sigmoid function can handle non linear problems effectively and its mathematical expression is given by:

$$\phi(x) = \frac{1}{1 + e^{-x}} \quad (1)$$

The proposed neural network uses 30 inputs, 45 hidden neurons and 1 output node. $X_1, \dots, X_{30}$ are the input samples, IH points from input to hidden and HO points from hidden to output. V_{ij} and W_{ij} represent weights between input to hidden and hidden to output respectively. For training, 1 to 30 data samples are the input and 31st is the output similarly 32nd to 61st data samples are the input and 62nd is the output. This process is continued for 80 patterns, where

Figure 1 Neural network architecture used for both BPNN, SENN.

Figure 2 Conceptual graphic representation of neural network Testing phase.

the 80th training pattern is 2450 to 2479 samples as input and 2480 as the output.

Once the problem converges, the converged weights are used for testing. For testing, sample numbers from 2481 to 2510 have been used as the input and the next 24 samples (2511 to 2534) are the forecasted outputs. At each instant, the forecasted output has been taken as the input for the next pattern. This recursive procedure is then used for the next 24 hours. Figure 2 explains the testing phase of the ANN used. A similar process has been adopted in case of SENN and it is discussed in the Section 3.

3 State Estimation Based Neural Network (SENN)

A State Estimation based Neural Network (SENN) is proposed and used for load forecasting in [23]. SENN is applied to wind speed forecasting in this paper for the first time. State estimation is the procedure of estimating

the reliable state vector of the system from a given set of imperfect measurements made on the power system. A state estimator is able to nullify random errors in meter readings. Generally, this process involves deficient measurements that are redundant and the system state estimating process is involved with statistical approach that estimates actual values of the state variables to reduce the selected error criterion. A commonly used criterion is to reduce the sum of squares of the weighted differences between the “estimated” and “actual” (measured) value of a function as much as possible. Here a weighted least Square State Estimation (WLSSE) technique has been used to estimate the optimal weights between the layers of the Neural Network.

3.1 Weighted Least Square (WLS) State Estimator

In WLS estimation, the objective function is to minimize the sum of squares of the weighted deviations with respect to the true measurements as much as possible. WLS objective function is discussed as follows.

$$\min_{(x_1, x_2 \dots x_{NS})} J(x_1, x_2 \dots x_{NS}) = \sum_{i=1}^{N_m} \frac{[Z_i - f_i(x_1, x_2 \dots x_{NS})]^2}{\sigma_i^2} \quad (2)$$

$$[Z] = [f(x)] + [\eta] \quad (3)$$

$$J(x) = [\eta]^T \cdot R^{-1} \cdot [\eta] \quad (4)$$

$$J(x) = [Z - [f(x)]]^T \cdot R^{-1} \cdot [Z - [f(x)]] \quad (5)$$

Minimization of $J(x)$ would result in

$$x^{est} = [H^T R^{-1} H]^{-1} \times [H^T R^{-1}] Z^{meas} \quad (6)$$

$$[x^{est}] = [H_{effe}]^{-1} \times [Z_{effe}]$$

Where

$$[H_{effe}] = [H^T R^{-1} H]; [Z_{effe}] = [H^T R^{-1} Z^{meas}] \quad (7)$$

$J(x)$ – Objective function

Z – Actual measurements

$f(x)$ – True measurements

$[H]$ – An N_m by N_s matrix consisting of linear function coefficients $f_i(x)$.

σ – Standard deviation

η – Noise vector

N_m – Number of measurements

N_s – Number of Training Samples

$[R^{-1}]$ = Weight matrix (it is a diagonal matrix with $\frac{1}{\sigma_i^2}$ as diagonal element)

In the proposed forecasting method, WLSSE technique is used between input layer to hidden layer, and hidden to output layers. In this technique, the weight matrices between the layers have been estimated like the states as $X_1, X_2, \dots, X_n$. Thus to train the three layered neural network, a state estimation approach has been applied between input-hidden and hidden-output individually.

3.2 SENN Based Wind Speed Forecasting

SENN construction is similar to BPNN structure: except for the weight vector estimation, remaining actions and structure like normalization, de-normalization, training period, node structure etc. remain unchanged. In SENN method weights need not be initialized randomly. As anticipated a sigmoid function has been used as activation function in the hidden layer. In this architecture again 30 input nodes, 45 hidden nodes and one output node are set, and the same network has been used for ANN based wind speed forecasting. A total number of 80 patterns are used and each pattern consists of 30 samples therefore a total of 2400 samples are ($80 \times 30 = 2400$) used for training.

3.3 Mathematical Approach for SENN

In this section the complete mathematical set of equations involved in SENN referring to Figure 1 and their formulation have been explained. Each individual training sample output is given by

$$\begin{aligned}
 V_{11} \times x_1^{(1)} + V_{21} \times x_2^{(1)} + V_{31} \times x_3^{(1)} + \dots + V_{301} \times x_{30}^{(1)} &= y_1^{(1)} \\
 V_{11} \times x_1^{(2)} + V_{21} \times x_2^{(2)} + V_{31} \times x_3^{(2)} + \dots + V_{301} \times x_{30}^{(2)} &= y_1^{(2)} \\
 &\vdots \\
 &\vdots \\
 &\vdots \\
 V_{11} \times x_1^{(80)} + V_{21} \times x_2^{(80)} + V_{31} \times x_3^{(80)} + \dots + V_{301} \times x_{30}^{(80)} &= y_1^{(80)}
 \end{aligned} \tag{8}$$

The matrix form referred to above equations is given as below:

$$\begin{bmatrix} x_1^{(1)} & x_2^{(1)} & \cdots & x_{30}^{(1)} \\ x_1^{(2)} & x_2^{(2)} & \cdots & x_{30}^{(2)} \\ \vdots & \vdots & \cdots & \vdots \\ x_1^{(80)} & x_2^{(80)} & \cdots & x_{30}^{(80)} \end{bmatrix}_{(80 \times 30)} \times \begin{bmatrix} V_{11} \\ V_{21} \\ \vdots \\ V_{301} \end{bmatrix}_{(30 \times 1)} = \begin{bmatrix} y_1^{(1)} \\ y_1^{(2)} \\ \vdots \\ y_1^{(80)} \end{bmatrix}_{(80 \times 1)}$$

This can be represented dimensionally as:

$$[A]_{(80 \times 30)} \times [V]_{(30 \times 1)} = [Z]_{(80 \times 1)} \quad (9)$$

and expressed in terms of state estimation, it becomes:

$$[A]_{(80 \times 30)} \times [V]_{(30 \times 1)} + [\eta]_{(80 \times 1)} = [Z]_{(80 \times 1)} \quad (10)$$

In WLSSE method A_{effe} and Z_{effe} are calculated as:

$$\begin{aligned} [A_{effe}]_{(30 \times 30)} &= [A^T]_{(30 \times 80)} \times [R^{-1}]_{(80 \times 80)} \times [A]_{(80 \times 30)} \\ &= [A^T]_{(30 \times 80)} \times [A]_{(80 \times 30)} \end{aligned} \quad (11)$$

$$\begin{aligned} [Z_{effe}]_{(30 \times 1)} &= [A^T]_{(30 \times 80)} \times [R^{-1}]_{(80 \times 80)} \times [Z]_{(80 \times 1)} \\ &= [A^T]_{(30 \times 80)} \times [Z]_{(80 \times 1)} \end{aligned} \quad (12)$$

In this approach R^{-1} is considered to be the identity matrix:

$$[A_{effe}]_{(30 \times 30)} \times [V]_{(30 \times 1)} = [Z_{effe}]_{(30 \times 1)} \quad (13)$$

Using gauss elimination, vector $[V]$ can be found as:

$$[V]_{(30 \times 1)} = [A_{effe}]_{(30 \times 30)}^{-1} \times [Z_{effe}]_{(30 \times 1)} \quad (14)$$

It may be noted that the weight vector $[V]_{(30 \times 1)}$ is estimated directly in a non iterative approach using WLSSE technique. The above mentioned process is applied to calculate remaining weights between inputs to hidden neurons. The above process demands the output of hidden layer. The following section discusses the calculation of output of hidden nodes.

3.4 Calculation of Hidden Nodes Output

Since the hidden node values are not known, mean values of input sample would be treated as hidden nodes output.

$$[Z]_{(80 \times 1)} = \begin{bmatrix} y_1^{(1)} \\ y_1^{(2)} \\ \vdots \\ y_1^{(80)} \end{bmatrix}_{(80 \times 1)} = \begin{bmatrix} \bar{x}^{(1)} \\ \bar{x}^{(2)} \\ \vdots \\ \bar{x}^{(80)} \end{bmatrix}_{(80 \times 1)}$$

Here $x^{-(i)}$ = Average value of i^{th} sample $x_1^{(i)}, x_2^{(i)}, x_3^{(i)}$ etc.
And at node 2 output values are given as

$$\begin{bmatrix} y_2^{(1)} \\ y_2^{(2)} \\ \vdots \\ y_2^{(80)} \end{bmatrix}_{(80 \times 1)} = \begin{bmatrix} r_t \cdot \bar{x}^{(1)} \\ r_t \cdot \bar{x}^{(2)} \\ \vdots \\ r_t \cdot \bar{x}^{(80)} \end{bmatrix}_{(80 \times 1)}$$

Where, r_t is a random number taken between 0.8 to 1.2, which varies for each x_i^j . A similar approach is adopted for the hidden layer nodes. Each individual $[x^{-(i)}]$ is multiplied with random value (r_t) in order to obtain the output of hidden node $[y^{(i)}]$.

$$[y_i^{(j)}]_{(80 \times 45)} = \begin{bmatrix} \bar{x}^{(1)} & r_t \cdot \bar{x}^{(1)} & \dots & r_t \cdot \bar{x}^{(1)} \\ \bar{x}^{(2)} & r_t \cdot \bar{x}^{(2)} & \dots & r_t \cdot \bar{x}^{(2)} \\ \vdots & \vdots & \dots & \vdots \\ \bar{x}^{(80)} & r_t \cdot \bar{x}^{(80)} & \dots & r_t \cdot \bar{x}^{(80)} \end{bmatrix}_{(80 \times 45)}$$

Weights between hidden-output nodes in terms of output equations are:

$$\begin{aligned} W_{11} \times y_1^{(1)} + W_{21} \times y_2^{(1)} + \dots + W_{451} \times y_{45}^{(1)} &= Out_1^{(1)} \\ W_{11} \times y_1^{(2)} + W_{21} \times y_2^{(2)} + \dots + W_{451} \times y_{45}^{(2)} &= Out_1^{(2)} \\ \vdots & \\ \vdots & \\ W_{11} \times y_1^{(80)} + W_{21} \times y_2^{(80)} + \dots + W_{451} \times y_{45}^{(80)} &= Out_1^{(80)} \end{aligned} \quad (15)$$

Matrix representation to the above equations are given below

$$\begin{bmatrix} y_1^{(1)} & y_2^{(1)} & \dots & y_{45}^{(1)} \\ y_1^{(2)} & y_2^{(2)} & \dots & y_{45}^{(2)} \\ \vdots & \vdots & \dots & \vdots \\ y_1^{(80)} & y_2^{(80)} & \dots & y_{45}^{(80)} \end{bmatrix}_{(80 \times 45)} \times \begin{bmatrix} W_{11} \\ W_{21} \\ \vdots \\ W_{451} \end{bmatrix}_{(45 \times 1)} = \begin{bmatrix} Out_1^{(1)} \\ Out_1^{(2)} \\ \vdots \\ Out_1^{(80)} \end{bmatrix}_{(80 \times 1)}$$

$Out_1^{(1)}, Out_1^{(2)}, \dots, Out_1^{(80)}$ are the output of node 1 at output layer for all selected 80 patterns. Here weights are considered as state variables and their representation is given below:

$$[B]_{(80 \times 45)} \times [W]_{(45 \times 1)} = [Z_o]_{(80 \times 1)} \quad (16)$$

Above equation in terms of state estimation is

$$[B]_{(80 \times 45)} \times [W]_{(45 \times 1)} + [\eta]_{(80 \times 1)} = [Z_o]_{(80 \times 1)} \quad (17)$$

The effective values from WLSSE method is:

$$\begin{aligned} [B_{eff}]_{(45 \times 45)} &= [B^T]_{(45 \times 80)} \times [R^{-1}]_{(80 \times 80)} \times [B]_{(80 \times 45)} \\ &= [B^T]_{(45 \times 80)} \times [B]_{(80 \times 45)} \end{aligned} \quad (18)$$

$$\begin{aligned} [Z_{eff}]_{(45 \times 1)} &= [B^T]_{(45 \times 80)} \times [R^{-1}]_{(80 \times 80)} \times [Z_o]_{(80 \times 1)} \\ &= [B^T]_{(45 \times 80)} \times [Z_o]_{(80 \times 1)} \end{aligned} \quad (19)$$

From Equation (16) we have

$$[B_{eff}]_{(45 \times 45)} \times [W]_{(45 \times 1)} = [Z_{eff}]_{(45 \times 1)} \quad (20)$$

$$[W]_{(45 \times 1)} = [B_{eff}]_{(45 \times 45)}^{-1} \times [Z_{eff}]_{(45 \times 1)} \quad (21)$$

The weight matrix between hidden and output is obtained from (21). The network is now fully trained with input wind samples and ready for testing on wind speed forecasting. For example if input node is taken as $[X_i]_{(1 \times N)}$ then hidden and output layer are given by

$$[Y]_{(1 \times NH)} = [X_i]_{(1 \times N)} \times [V]_{(N \times NH)} \quad (22)$$

$$[Out]_{(1 \times No)} = [Y]_{(1 \times NH)} \times [W]_{(NH \times No)} \quad (23)$$

Finally the forecasted output is obtained from Equation (23).

3.5 Detailed SENN Algorithm steps

1. Read the Neural Network data

$N \rightarrow$ No. of Input layer nodes

$NH \rightarrow$ No. of Hidden layer nodes

$NO \rightarrow$ No. of Output layer nodes

$NTS \rightarrow$ No. of Testing Samples

$NS \rightarrow$ No. of Training Samples

2. Store all the training samples of input in the matrix form as $[A]_{(80 \times 30)}$.
Similarly store the training samples of output in matrix $[T]_{(80 \times 1)}$.

$$[A]_{(80 \times 30)} = \begin{bmatrix} X_1^{(1)} & X_2^{(1)} & X_3^{(1)} & \dots & X_{30}^{(1)} \\ X_1^{(2)} & X_2^{(2)} & X_3^{(2)} & \dots & X_{30}^{(2)} \\ X_1^{(3)} & X_2^{(3)} & X_3^{(3)} & \dots & X_{30}^{(3)} \\ \vdots & \vdots & \vdots & \dots & \vdots \\ X_1^{(80)} & X_2^{(80)} & X_3^{(80)} & \dots & X_{30}^{(80)} \end{bmatrix}_{(80 \times 30)}$$

$$[T]_{(80 \times 1)} = \begin{bmatrix} Out_1^{(1)} \\ Out_1^{(2)} \\ Out_1^{(3)} \\ \vdots \\ Out_1^{(NS)} \end{bmatrix}_{(80 \times 1)}$$

3. Normalize each sample of the input and output.
4. Evaluate the transpose matrix $[A]_{(80 \times 30)}^T$.
5. From WLSSE approach calculates $[A_{eff}]_{(30 \times 30)}$ using Equation (13).
6. Evaluate output of each node at hidden layer using following relation

$$[y_i^{(j)}]_{(80 \times 45)} = \begin{bmatrix} \bar{x}^{(1)} & r_t \cdot \bar{x}^{(1)} & \dots & r_t \cdot \bar{x}^{(1)} \\ \bar{x}^{(2)} & r_t \cdot \bar{x}^{(2)} & \dots & r_t \cdot \bar{x}^{(2)} \\ \vdots & \vdots & \dots & \vdots \\ \bar{x}^{(80)} & r_t \cdot \bar{x}^{(80)} & \dots & r_t \cdot \bar{x}^{(80)} \end{bmatrix}_{(80 \times 45)}$$

7. Calculate Z_{eff} using Equation (12)

$$[Z_{eff}]_{(30 \times 1)} = [A^T]_{(30 \times 80)} \times [Z]_{(80 \times 1)}$$

8. Using Gauss elimination technique calculate the weight matrix $[V]_{(30 \times 1)}$ between input to hidden node using Equation (14) and repeat this procedure for remaining hidden nodes.
9. Compute the weights between hidden and output layer, by representing hidden layer output and target output in matrix form as shown below:

$$\begin{aligned} [B]_{(80 \times 45)} &= [y]_{(80 \times 45)} \\ [Z_o]_{(80 \times 1)} &= [T]_{(80 \times 1)} \end{aligned}$$

10. Compute the $[B_{eff}]$ and $[Z_{oeff}]$ matrices using Equations (18) and (19).
11. Using gauss elimination technique calculate the weights $[W]_{(45 \times 1)}$ between hidden and output node using Equation (21).
12. Load the test samples from test input file.
Input sample = $[X_i]_{(1 \times 30)}$; Target Output = $[T(O)]_{(1 \times 1)}$
13. Normalize the input samples and actual output.
14. Calculate output of hidden layer by multiplying with weights $[V]_{(30 \times 45)}$ using following relation

$$[y]_{(1 \times 45)} = [x_i]_{(1 \times 30)} \times [V]_{(30 \times 45)}$$

15. Output results of output layer is calculated by multiplying with weights $[W]_{(45 \times 1)}$ using following relation

$$[Out]_{(1 \times 1)} = [y]_{(1 \times 45)} \times [W]_{(45 \times 1)}$$

16. De-normalize the forecasted output and repeat this procedure for next 24 hours.

4 Results and Discussion

In this paper, in order to perform the forecasting analysis, practical wind speed data has been taken from National Renewable Energy Laboratory (NREL) website [24]. In this section BPNN, SENN based wind speed forecasting results have been compared and discussed. For both BPNN and SENN same network architecture has been used for forecasting application. For BPNN network, learning rate = 0.8, momentum factor = 0.2, epsilon (tolerance) = 0.0001 and maximum numbers of iterations are set as 400. Number of training patterns is 80 and testing patterns are 24 in both cases. In this problem BPNN has converged in 340 iterations [25]. Using single statistical parameter analyzing forecasting efficiency is not much effective, so in this section set of statistical parameters are considered to evaluate forecasting accuracy.

Forecasting accuracy is evaluated by following statistical parameters such as:

- Absolute Percentage Error $APE = \left| \frac{AW - FW}{AW} \right|$
- Mean Absolute Percentage Error $MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{AW - FW}{AW} \right| * 100$
- Mean Absolute Error $MAE = \frac{1}{n} \sum_{i=1}^n |AW - FW|$
- Root Mean Square Error $RMSE = \sqrt{\frac{\sum_{i=1}^n (AW - FW)^2}{n}}$
- Correlation Coefficient $R = \frac{R_{AF}}{Std(A) * Std(F)}$

In the above equations the following symbols are used, namely AW = Actual wind speed, FW = Forecasted wind speed, n = Number of wind samples, R_{AF} = Covariance between Actual and Forecasted wind speed, $Std(A)$ = Standard deviation of Actual wind speed, $Std(F)$ = Standard deviation of Forecasted wind speed.

Table 1 shows comparison of actual and predicted wind speed using BPNN and SENN where MAPE is obtained as 13.221 and 8.173 respectively and individual APE also been calculated for each (total 24) wind sample. Figure 3 is the graphical representation of Table 1. Table 2 reports the comparison of statistical measures such as MAPE, MAE, RMSE, Correlation coefficient (R) and the execution time.

Figure 3 Actual and forecasted wind speed for BPNN and SENN.

Table 1 Comparison of actual and forecasted wind speed using BPNN, SENN

S.No.	Actual Wind Speed(m/s)	Forecasted Speed BPNN (m/s)	Forecasted Speed SENN (m/s)	APE BPNN	APE SENN
1	9.563	8.762	8.824	8.376	7.727
2	9.972	9.203	10.578	7.712	6.077
3	6.352	7.655	5.948	20.513	6.360
4	6.909	6.624	6.634	4.125	3.980
5	7.328	7.117	7.516	2.879	2.565
6	2.905	3.321	2.443	14.320	15.903
7	3.838	2.625	4.015	31.605	4.611
8	7.175	7.671	6.985	6.912	2.648
9	2.65	3.327	3.065	25.547	15.660
10	7.175	7.7471	8.011	7.973	11.651
11	4.894	5.216	3.875	6.579	20.821
12	10.788	9.346	9.415	13.366	12.727
13	3.246	3.365	3.424	3.666	5.483
14	5.367	5.656	4.895	5.384	8.794
15	11.406	9.224	9.725	19.130	14.737
16	5.547	5.859	4.955	5.624	10.672
17	7.403	5.971	7.724	19.343	4.336
18	3.267	4.001	3.435	22.467	5.142
19	3.32	2.57	3.187	22.590	4.006
20	7.107	5.668	6.862	20.247	3.447
21	7.406	8.417	7.855	13.651	6.062
22	2.531	2.208	2.314	12.761	8.573
23	9.525	9.349	10.218	1.847	7.275
24	3.868	4.668	4.135	20.682	6.902
MAPE				13.221	8.173

Table 2 Comparison of statistical parameters using BPNN and SENN

Statistical Measures	BPNN Forecast	SENN Forecast
MAPE	13.221	8.173
MAE	0.753	0.504
RMSE	0.910	0.635
R	0.904	0.933
Execution Time	68 sec.	29 sec.

Comparison of all statistical measures prove that, SENN based wind speed forecasting method is showing better performance when compared to BPNN based wind speed forecasting method. In particular, statistical data prove that SENN based forecasting are more accurate and they have more correlation to the original wind samples. Indeed, Figure 3 shows that SENN based forecasting method results are coinciding with actual wind speed values

more closely where as BPNN results are deviating to the original wind speed values. In BPNN, weights are estimated randomly and error is back propagated to adjust the weights. In SENN technique weights are estimated accurately based on weighted least square approach. SENN is a non iterative technique and it will take less time of training for same error when compared with BPNN method. Run time for SENN is low when compared to BPNN because of non iterative nature and deterministic weight approach of SENN, which is reduced to 57.3% as compared to that of BPNN.

5 Conclusion

In this paper day ahead (24 hours) wind speed forecasting has been carried out using BPNN and SENN based methods. Both these methods have been tested with practical data from NREL website. Statistical measures illustrate that SENN method has least error and an improved correlation factor so that forecasting results are more accurate and coinciding with actual wind values. In BPNN weights are initialized randomly and error is back propagated to adjust the weights. In SENN technique weights are estimated accurately based on the weighted least square approach because of which this method is more accurate. BPNN is a traditional forecasting method where the weights are updated based on error and back propagated to reach desired value and it suffers with local minima problem. SENN is a complete mathematical approach and weights are estimated between layers accurately using weighted least square technique, therefore error is reduced. Execution time (training as well as testing) for SENN is comparatively low as that of BPNN since SENN method is a non-iterative technique and it can be used for online studies like contingency analysis.

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