Deep Multilayer Perceptron Wind Speed Estimation Based Artificial Immune System For Power Generation Prediction

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DEEP MULTILAYER PERCEPTRON WIND SPEED ESTIMATION BASED ARTIFICIAL IMMUNE SYSTEM FOR POWER GENERATION PREDICTION

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ABSTRACT

Wind energy is fast developing energy resource as it is renewable, pollution free and abundant. The nonlinear and fluctuation of wind are large demand for enhancing the reliability and accuracy of the power system that combines the wind speed. With an exact wind speed data, power system operators predict the power output for system planning and scheduling. Wind speed prediction is an essential factor in forecasting to attain the efficient wind power utilization. But, the prediction time and accuracy performance was not improved using existing techniques. In order to address this problem, Deep Multilayer Perceptron Neural Network based Clonal Selective Optimization (DMLPNN-CSO) technique is introduced. The main objective of DMLPNN-CSO technique is to improve the performance of power generation prediction through wind speed estimation with higher accuracy based on mean air temperature, relative humidity and vapor pressure data. DMLPNN-CSO technique comprises two processes, namely deep multilayer perceptron neural network and clonal data selection algorithm. Initially in DMLPNN-CSO technique, wind turbine is considered as the input and given to the input layer in deep multilayer perceptron neural network. Wind turbine information is extracted and given to the hidden layer 1. In this layer, data preprocessing is performed through the median filter for removing unnecessary data. After that, the preprocessed data is given to the hidden layer 2 to estimate the wind speed. The estimated values are collected and get matched with the pre-stored values in the output layer by using softsign activation function. After estimation of wind speed, the optimal data gets selected by using clonal data selection algorithm for predicting the power generation. Clonal data selection algorithm performs the sorting, cloning and guassian mutation for finding the optimal value in power generation prediction. This in turn helps to improve prediction accuracy and reduce the time consumption. Experimental evaluation of proposed DMLPNN-CSO technique is carried out with respect to number of wind turbine data and data samples. The results showed that DMLPNN-CSO technique produces higher prediction accuracy and wind speed estimation rate when compared to state-of-the-art works.

Keywords: Wind Energy, Renewable, Pollution, Wind Turbine Information, Hidden Layer, Prediction, Optimal Data, Guassian Mutation

1. INTRODUCTION

Wind speed prediction is employed for the power system operators. Prediction is an essential part in the environment. Neural Network (NN) is a computing method that resembles like biological neural network. The key objective of NN is adaptability, nonlinearity and capability to study large data and generalization ability. A linear combination of individual kernel functions constructed the multi kernel ridge pseudo inverse neural network (MK-RPINN) in [1] for improving the forecasting accuracy and stability. But, the prediction time was not reduced.

A neural fuzzy method was introduced in [2] for hourly wind speed prediction. A neural structure was introduced for functional-type single-input-rule-modules (FSIRMs) connected fuzzy inference system (FIS) to join merits of FSIRM connected FIS and neural network. A least square method based parameter learning algorithm was introduced to attain smallest training errors and smallest parameters. However, the prediction accuracy was not improved using the designed algorithm. A new method was introduced in [3] for wind speed estimation with the airborne array radar through combining adaptive processing and compressive sensing. The designed method was introduced to attain the exact wind speed estimation in condition of lesser sampling pulses. But, the wind speed estimation was not carried out in efficient way.

A new approach was introduced in [4] for estimation based hourly wind speed features and power characteristics in actual wind farm. The designed approach used the probability density function for the long-term hourly wind speed data. But, prediction time was not reduced using designed approach. A kernel density estimation (KDE) method was introduced in [5] calculate the probability density function (PDF) of wind speed. The designed method was data-driven approach without fundamental wind speed distribution and uncovered information hidden in the historical data. However, the computational complexity was not reduced using KDE method

A relationship and surface-wind inversion method was introduced in [6] where efficient particle filter was employed to estimate the speed distribution. A forecast model was introduced in [7] for wind speed short-term prediction and wind power through singular spectrum analysis (SSA) and locality-sensitive hashing (LSH). LSH was employed to choose the similar segments of mean trend segments in local forecasting. A new approach called SIE–WDA–GA–SVR was introduced in [8] for short-term wind speed prediction that relates seasonal information extraction (SIE) and wavelet decomposition algorithm (WDA) into hybrid model which combines the genetic algorithm (GA) into support vector regression (SVR). However, the wind speed estimation consumes large amount of time by using GA.The wind speed forecasting by artificial neural networks with the radial basis function, adaptive neuro-fuzzy inference system, artificial neural

network-genetic algorithm hybrid and artificial neural network-particle swarm optimization were introduced in [9] to forecast wind speed data. But, the prediction accuracy was not improved.

The statistical model was introduced in [10] to assist the conclusion about occurrence probability of wind speed depending on the knowledge of low-order flow statistics. But, the speed estimation was not carried out in efficient manner. From the survey, problems identified from existing techniques are minimum prediction accuracy, maximum prediction time, minimum wind speed estimation rate, higher error rate, higher computational complexity, and higher false positive rate and so on. Consequently, there is a need to plan new efficient approach for predicting the power generation with higher accuracy and lesser time.

The main contribution of the work is described as,

- Deep Multilayer Perceptron Neural Network based Clonal Selective Optimization (DMLPNN-CSO) technique is introduced to improve the performance of power generation prediction through wind speed estimation with higher accuracy based on mean air temperature, relative humidity and vapor pressure.
- Wind turbine is considered as the input and given to the input layer in deep multilayer perceptron neural network. Wind turbine information is extracted and given to the hidden layer 1 where the data preprocessing is performed through the median filter for removing the unnecessary data. After that, the preprocessed data is given to the hidden layer 2 to estimate the wind speed. The estimated values are collected and get matched with pre-stored values in output layer by using softsign activation function.
- Clonal data selection algorithm is used in DMLPNN-CSO technique chosen the optimal data for power generation prediction. Clonal data selection algorithm performs the sorting, cloning and guassian mutation for finding the optimal value. This assists to improve the performance of prediction accuracy and reduce the time consumption.

The paper is structured as follows; Section 2 portrays the related works on wind speed estimation. Section 3 describes Deep Multilayer Perceptron Neural Network based Clonal Selective Optimization (DMLPNN-CSO) technique with neat diagram. Section 4 discusses the experimental setting and result analysis of proposed DMLPNN-CSO technique with various parameters. Section 5 concludes the work.

2. RELATED WORKS

A hybrid technique was introduced in [11] depending on Support Vector Regression for wind speed forecasting. Based on autoregressive model termed Time Delay Coordinates, feature selection was carried out through Phase Space Reconstruction process. But, the prediction time was not reduced using hybrid technique. Two Effective Wind Speed (EWS) estimator called kalman filter-based estimator and EKF estimator was introduced in [12]. EWS affected the controller efficiency and the performance gets clarified. But, wind speed estimation rate was not improved.

An ultra-short-term wind speed forecasting method with the spatial and temporal correlation model was introduced in [13]. An autoregressive moving average (ARMA) model were introduced with representative time series. The spatial correlation between target wind farm and the reference wind farm were studied with the meteorological data. A multi-objective interval prediction method depending on wavelet neural network (WNN) was introduced in [14] for short-term wind speed forecast. The designed method created the set of Pareto optimal solutions with set of prediction models that construct prediction intervals. However, error rate was not reduced using multi-objective interval prediction method. A genetic algorithm-based non-linear auto-regressive neural network (GA-NARX-NN) model was designed in [15] for short-and medium-term electrical load forecasting with improved accuracy. However, the false positive rate was not reduced.

Two machine learning techniques were introduced in [16] to assess prediction intervals of time-series. The multilayer perceptron neural networks were trained with the multi-objective genetic algorithm. The extreme learning machines were joined with nearest neighbors approach. However, the time consumption was not reduced using learning techniques. A nonlinear control was designed in [17] for region while conventional proportional–integral (PI) control was adapted for region of VSVPWT. The designed controller was joined with the modified Newton Raphson (MNR) wind speed estimator to compute the wind speed. But, the prediction accuracy was not improved. The intelligent ensemble neural model based wind speed forecasting was designed in [18] with forecasted average values from various neural network models with lesser error. Though the error rate was reduced, the computational cost was not minimized.The nonlinear approach was designed for wind turbine (WT) with two-mass model. The key objective of controller in WT was to enhance the energy output at different wind speed. A combination of linear and nonlinear controllers was used in [19] to variable speed variable pitch wind turbines (VSVPWT) system. However, the time consumption was not reduced using linear and nonlinear controllers. Neural Network based hybrid computing model was introduced in [20] for wind speed prediction in

renewable energy systems. But, the computational complexity was not reduced. The SVM-kernel based prediction model is presented in [21&22] but inapplicable for large dataset handing. So, the proposed model introduces a novel deep learning approach for wind speed forecasting in Renewable energy application.

3. METHODOLOGY

The production and consumption of electricity has become the essential indicator level of country's growth. The electricity requirement of developing countries is increasing constantly. The renewable energy sources particularly wind and solar energy sources have attained large attention in recent years. Wind energy is one of the most economical techniques of an electrical power generation. Wind power plants need the continuous and appropriate wind speed for the adequate power generation. For improving reliability of power system, it designed the accurate wind speed prediction technique. In order to address these problems, Deep MultiLayer Perceptron Neural Network based Clonal Selective Optimization (DMLPNN-CSO) technique is introduced for improving the performance of wind speed prediction with higher accuracy based on mean air temperature, relative humidity and vapor pressure. The architectural diagram of DMLPNN-CSO technique is given in Figure 1.

Figure 1 explains the overall flow process of DMLPNN-CSO technique. Wind turbine is considered as the input and given in the input layer. In the input layer, the wind turbine information is extracted and given to the hidden layer 1. In this layer, the data preprocessing is carried out by using median filter for removing the unnecessary data. Then, the preprocessed data is given to the hidden layer 2 to estimate the time interval and wind speed. The estimated values are collected from the output layer by softsign activation function. After estimation of the wind speed, the optimal data gets selected by using clonal selection algorithm for predicting the power generation with higher accuracy and lesser time. The brief explanation of Multilayer Perceptron and clonal data selection algorithm in DMLPNN-CSO technique is given next subsection.

Wind energy is the source of renewable energy with less pollution has large development in recent years. Wind power production depends on the wind speed that varies with the weather conditions. When the variability in wind speed condition is not assessed, power production efficiency and power network operating costs gets increased. In addition, the wind speed estimation and prediction was not carried out in efficient way by using existing techniques.

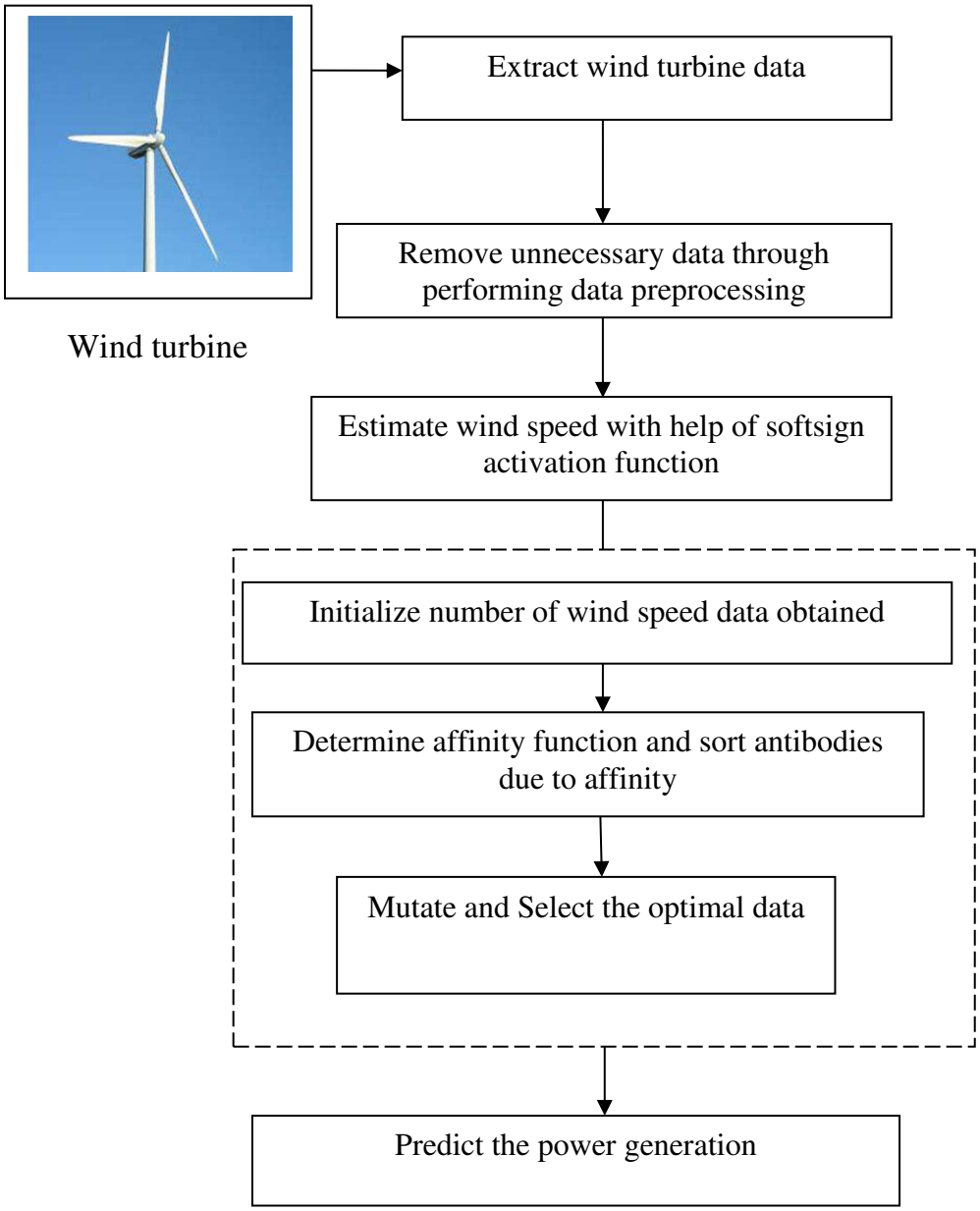

Figure 1 Architecture Diagram of DMLPNN-CSO technique

3.1 Deep Multilayer perceptron Neural Network

Multilayer perceptron (MLP) is one of the perceptron learning rules depending on the computing model in the artificial neural network. MLP comprises three layers of nodes, namely input layer, hidden layer and output layer. Every node is the neuron with the nonlinear activation function. The multiple layers and non-linear activation differentiate the MLP from the linear perceptron. The additional layers allow feature composition from the lower layers. MLP comprises the three or more layers (i.e., input and output layer with more than one hidden layers) of non-linear activating nodes. MLP are fully connected and every node in one layer gets linked with the

weight to every node in the next layer. Deep multilayer perceptron neural network comprises more than one hidden layer for deep analyzing the wind turbine data. The input for the network at the time 't' is represented as the 'a(t)', hidden layer is taken as 'b(t)' and output layer is considered as 'c(t)' as described in Figure 2.

DMLPNN-CSO technique considers the wind turbine 'WT_i' as an input. The input layer 'A' combines the wind turbine with the weights 'ρ_{ab}' and bias term 'α_j'. The neurons activity in input layer '(A)' at the time 't' is formulated as,

$$A(t) = \sum_i WT_i \, \rho_{ab} + \alpha_j \tag{1}$$

From (1), 'A(t)' denotes the activity of neuron in input layer at the time 't' while 'ρ_{ab}' symbolizes the weight between the input and hidden layer. After taking the wind turbine input, the input layer transmits the input wind turbine parameter information to the hidden layer. The first hidden layer collects the wind turbine parameter information and preprocess the collected parameter information of the wind turbine by using the median filter. The median filter in wind turbine is given by,

$$F = \text{median}\{g(s,t)\} \qquad \text{where,} \qquad s,t \in WT \tag{2}$$

From (2), 'F' represents filtered wind turbine parameter data, 's' and 't' represents the previous and next wind turbine data.

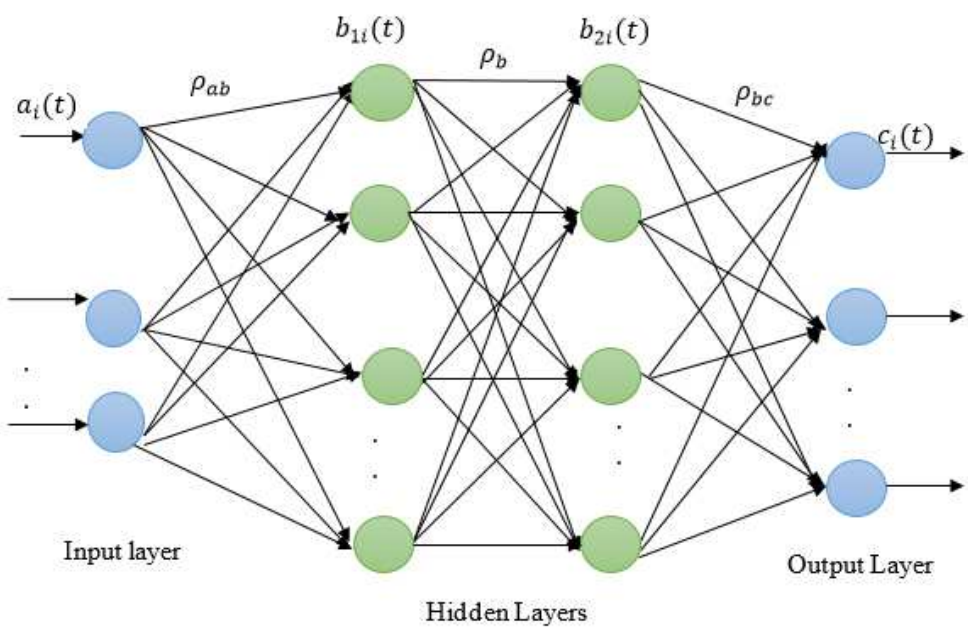

Figure 2 Structure of neural network classifier

In this layer, unnecessary information of the wind turbine are removed and transmitted to the second hidden layer. The neurons activity in the first hidden layer 'B_1' at time 't' is computed as,

$$B_1(t) = F\{\sum A(t)\,\rho_{b_1}\} \tag{3}$$

From (3), 'A (t)' represents the input wind turbine parameter information for one month and 'ρ_{b_1}' symbolizes the weight in the first hidden layer. After that, the essential information of the wind turbine gets extracted and estimated the wind speed and time. In same way, the neurons activity in second hidden layer 'B_2' at a time 't' is computed as,

$$B_2(t) = \{\sum B_1(t)\,\rho_{b_2}\} \tag{4}$$

From (4), 'ρ_{b_2}' represents the weight in the second hidden layer. Wind speed estimation is depending on the principle equation of motion and it is given by,

$$M_a - M_g = J\frac{d\omega}{dx} \tag{5}$$

From (5), the 'M_a' denotes the aerodynamic torque on wind turbine shaft and 'M_g' symbolizes the electromagnetic generator torque. It explains the rotor speed variations as result of the difference between the 'M_a' and 'M_g'. Aerodynamic torque on wind turbine shaft are explained through torque coefficient 'C_q' and it is formulated as,

$$M_a = C_q(\lambda, \beta) * \frac{1}{2}\rho_s \pi R^3 \left(v_w - \dot{x}_{t\_nod}\right)^2 \tag{6}$$

Substituting equation (6) in (5),

$$f(v_w) = C_q(\lambda, \beta) * \frac{1}{2}\rho_s \pi R^3 \left(v_w - \dot{x}_{t\_nod}\right)^2 - M_g - J\dot{\omega} \tag{7}$$

From (7), 'v_w' represents the estimated effective wind speed, 'J' is the total moment of inertia of rotor and generator, '$\dot{\omega}$' denotes the rotor acceleration, 'R' symbolizes the rotor radius, 'ρ_s' is the air density and '$\dot{x}_{t\_nod}$'is tower nodding speed. After that, the estimated information is transmitted into the output layer for performing the wind speed prediction. The output layer is given by,

$$C(t) = S * \left[\sum B_2(t)\, f(v_w)\rho_{b_2}\right] \tag{8}$$

From (8), the estimated information are obtained. 'S' symbolizes the softsign activation function and it is formulated as,

$$S = \frac{B_1(t)}{1+|B_1(t)|} \tag{9}$$

From (9), 'S' denotes the softsign activation function. It is the function of one fold from the previous layer. The output layer matches the output with the pre-defined results to predict the power generation using softsign activation function. From output layer, the wind speed estimation is computed for predicting the power generation. The algorithmic process of deep multilayer perceptron neural nework wind speed estimation is explained as,

\\ Deep Multilayer Perceptron Neural Network Wind Speed Estimation Algorithm

Input: Number of data samples

Output: Minimal power loss and Improved stability performance

Step 1: Begin

Step 2: Deep neural network initialized with random weights

Step 3: **While** (termination criteria attained) **do**

Step 4: **For** each data

Step 5: Extract input data from wind turbine in input layer and transmit to the hidden layer 1

Step 6: Perform data preprocessing using median filter in hidden layer 1

Step 7: Estimate time interval and wind speed

Step 8: The output layer generates result 'c(T)' with help of softsign activation function

Step 9: **End for**

Step 10: **End while**

Step 11: End

Algorithm 1 Deep Multilayer Perceptron Neural Network Wind Speed Estimation Algorithm

Algorithm 1 describes the algorithmic process of deep multilayer perceptron neural network wind speed estimation to improve the accuracy and to reduce the time consumption. DMLPNN-CSO technique initializes the neural network with the random weights.

Every extracted wind turbine data at input layer is transmitted to the hidden layer 1. Then, hidden layer 1 preprocesses the wind turbine data and transmits the analyzed performance results to the hidden layer 2. In this layer, the wind speed gets estimated and transmitted to the output layer. The output layer matches the output with the pre-stored results to predict the power generation using softsign activation function. This in turn helps to enhance the prediction results of power generation with higher accuracy and lesser time.

3.2 Clonal Data Selection Algorithm

The artificial immune system (AIS) is employed to map the structure and function of immune system to the computational system for addressing the engineering and information technology issues. Artificial immune system is introduced to address the bioinformatics issues and modeling biological process through immune algorithm. AIS are a developing area in the

computational intelligence. Clonal selection principle is the popular AIS model. Clonal Selection Principle describes the fundamental traits of immune reaction to antigenic stimulus.

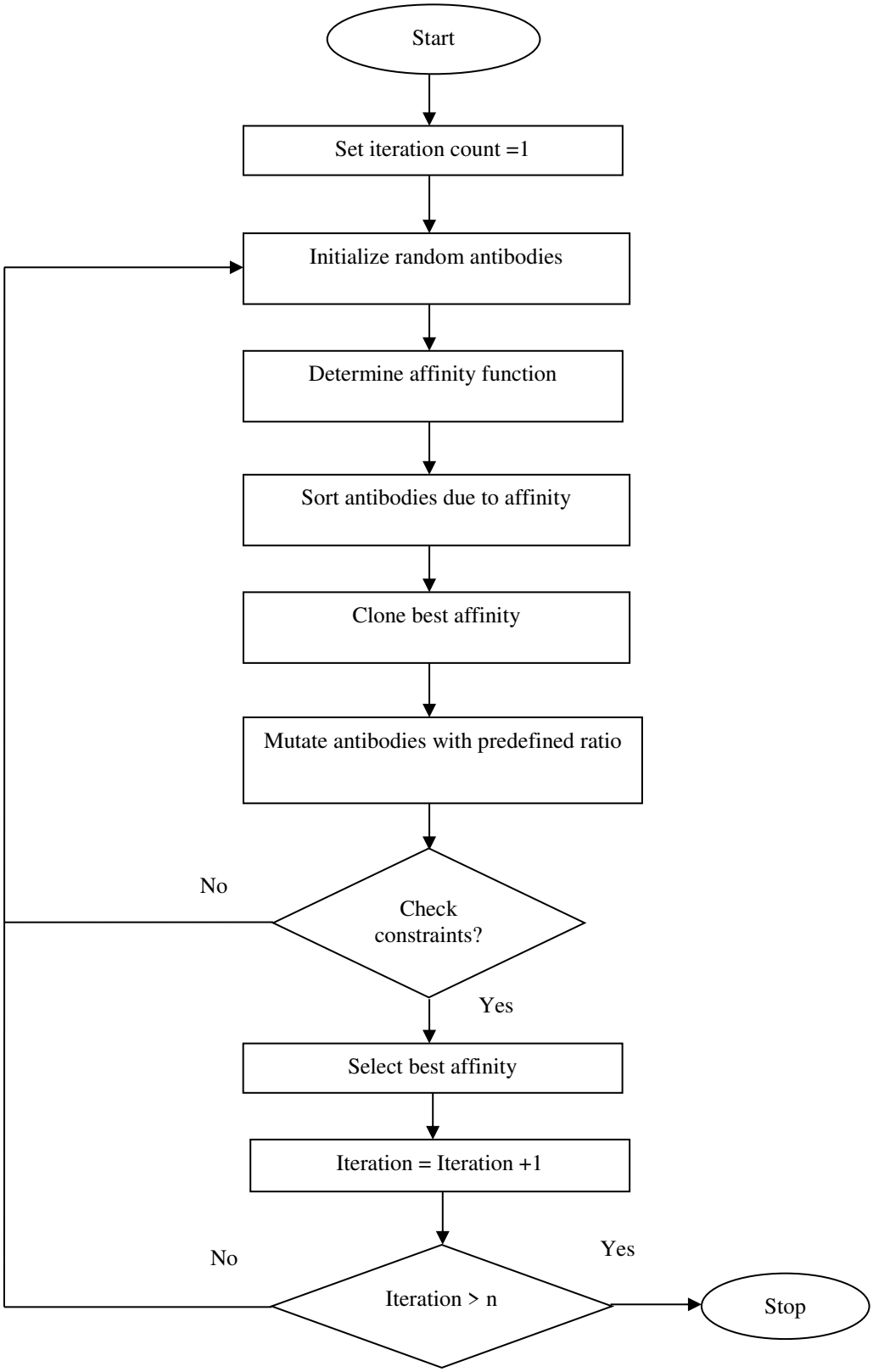

Figure 3 Flow process of Clonal Data Selection Algorithm

In the proposed research work, the optimal data is selected by using clonal data selection algorithm for power generation prediction in wind turbine. In clonal selection algorithm, initially, set of random antibodies (i.e., wind turbine data) are generated that are current candidate solutions of the objective function (i.e., speed estimation). After that, the affinity values (i.e., power created based on the wind turbine speed estimation) of every candidate solutions are calculated through evaluating the objective function by every candidate. Then, arrange the antibodies from the lowest affinity to the highest affinity and clone better matching antibodies with predefined ratio. Finally, mutate the antibodies with the predefined ratio where better matching clones mutated less and lesser matching clones gets mutated more to attain the optimal solution (i.e., to predict power generation). The flow process of the clonal data selection algorithm is given in the Figure 3.

In the flow diagram, initially, set of wind turbine data are randomly generated. Let, the randomly generated wind turbine data be '$WT_1, WT_2, WT_3, WT_4 \ldots, WT_n$'. For every wind turbine data, estimate the wind speed by using equation (10). After that, the power generated based on the wind speed is calculated by,

$$P_g = \rho_s * v_w * b_d * \alpha \tag{10}$$

From (10), the total amount of power generated based on the wind speed is calculated. 'ρ_s' denotes the air density, 'v_w' denotes the wind speed, 'b_d' denotes the diameter of the blade. 'α' symbolizes the proportionality constant term. After that, sort the power generated value from lowest to the highest level. After that, clone the power generated value for performing the gaussian mutation. The gaussian mutation of the wind turbine is given by,

$$f_g = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-WT^2}{2\sigma^2}} \tag{11}$$

From (11), the gaussian mutation is calculated. After that, the optimal data value is selected for predicting the power generation. The algorithmic process of clonal data selection is described in Algorithm 2.

From algorithm 2, the clonal data selection process is explained for power generation prediction with higher accuracy and lesser time consumption. Initially, the set of data are generated randomly. After that, the affinity values are estimated for every antibody. Then, the clones are generated with the highest affinity value. The guassian mutation mutates the data and identifies the optimal value to predict the power generation. By this way, based on the wind speed estimation, the power generation is predicted with higher accuracy and lesser time.

\\Clonal Data Selection Algorithm

Input: Number of random data

Output: Find optimal value for power generation prediction

Step 1: Begin

Step 2: Create initial random set of antibodies

Step 3: **For** every antibodies

Step 4: Determine affinity with each antibodies

Step 5: Generate clones of antibodies with highest affinity

Step 6: Mutate the antibodies by using guassian mutation function

Step 7: Replace lowest affinity antibodies

Step 8: **End for**

Step 9: End

Algorithm 2 Clonal Data Selection Algorithm

4. SIMULATION SETTINGS AND RESULT ANALYSIS

The designed Deep Multilayer Perceptron Neural Network based Clonal Selective Optimization (DMLPNN-CSO) technique is simulated in the MATLAB R2009 environment and implemented in Intel Core 2 Duo Processor with 2.27GHz speed and 2.00GB RAM with wind power dataset https://www.thewindpower.net/store_manufacturer_turbine_en.php?id_type=7. The experiment of proposed technique is carried out in Siahpoush Wind Farm. The farm includes the 18 wind turbines with the capacity of 3.4 MW produced by Siemens with the new gear-less technology. The ability to supply electricity for more than 75,000 households and avoids from producing more than 110 thousand tons of greenhouse gas per year. The produced electricity is transmitted to the power Grid through power plant direct 230/33 KV substation. The proposed technique is compared with two existing methods, namely MK-RPINN and Neural Fuzzy Method. The efficiency of DMLPNN-CSO technique is evaluated along with the metrics such as prediction accuracy, prediction time and wind speed estimation rate.

Wind Manufacturer Name :

i) Enercon

ii) Gamesa

iii) Nordex

iv) Repower

v) Vestas

Turbine Name and Id:

i) E82/2300 -ID 495

ii) G128/4500 –ID 81

iii) N90/2500 – ID 7

iv) MM82- ID 16

v) V112/3000 – 413

4.1 Wind Speed Estimation Rate (WSER)

Wind speed estimation rate is defined as the ratio of total number of data that are correctly estimated the wind speed to the total number of data. It is measured in terms of percentage (%). It is formulated as,

$$\text{WSER} = \frac{\text{Number of data that are correctly estimated wind speed}}{\text{Total number of data samples}} \tag{12}$$

From (12), wind speed estimation rate is calculated. When the wind speed estimation rate is higher, the method is said to be more efficient.

Sample calculation:

- **MK-RPINN:** the number of wind turbine data that are correctly estimated is 3 and the total number of wind turbine data is 10. After that, wind speed estimation rate is determined as,

$$\text{Wind Speed Estimation Rate} = \frac{6}{10} * 100 = 60\%$$

- **Neural Fuzzy Method:** the number of wind turbine data that are correctly estimated is 7 and the total number of wind turbine data is 10. After that, wind speed estimation rate is determined as,

$$\text{Wind Speed Estimation Rate} = \frac{7}{10} * 100 = 70\%$$

- **Proposed DMLPNN-CSO technique:** the number of wind turbine data that are correctly estimated is 8 and the total number of wind turbine data is 10. After that, wind speed estimation rate is determined as,

  - $\text{Wind Speed Estimation Rate} = \frac{8}{10} * 100 = 80\%$

Table 1 explains the wind speed estimation rate of three different methods, Deep Multilayer Perceptron Neural Network based Clonal Selective Optimization (DMLPNN-CSO) technique, Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) and Neural Fuzzy Method for different number of wind turbine data ranging from 10 to 100. From the table, it is clear that, the

wind speed estimation rate of DMLPNN-CSO technique is higher than other two existing methods. The graphical representation of wind speed estimation rate is described in Figure 4.

Table 1 Tabulation for Wind Speed Estimation Rate

Number of data samples (Number)	Wind Speed Estimation Rate (%)		
	MK-RPINN	Neural Fuzzy Method	DMLPNN-CSO technique
10	60	70	80
20	50	55	80
30	60	67	83
40	55	68	93
50	68	76	92
60	78	83	92
70	74	84	93
80	75	84	94
90	77	80	96
100	76	80	94

Figure 4 describes the wind speed estimation rate performance for different number of wind turbine data. From the above graph, number of wind turbine data is taken in 'X' axis and the wind speed estimation rate is considered in the 'Y' axis. From Figure, the green color line symbolizes the wind speed estimation rate of DMLPNN-CSO technique where blue color line and red color line denotes the wind speed estimation rate of Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) [1] and Neural Fuzzy Method [2]. Deep multilayer preceptron neural network is carried out to estimate the wind speed after performing the extraction and preprocessing from the wind turbine. The wind turbine is considered as an input. The data are extracted from the wind turbine for performing the wind speed estimation and transmitted to hidden layer 1. After the data extraction, median filter is used to perform the preprocessing task in hidden layer 1. The wind speed gets estimated in the hidden layer 2. The output layer matches the output with the pre-stored results to predict the power generation using softsign activation function. This in turn helps to improve the wind speed estimation rate.

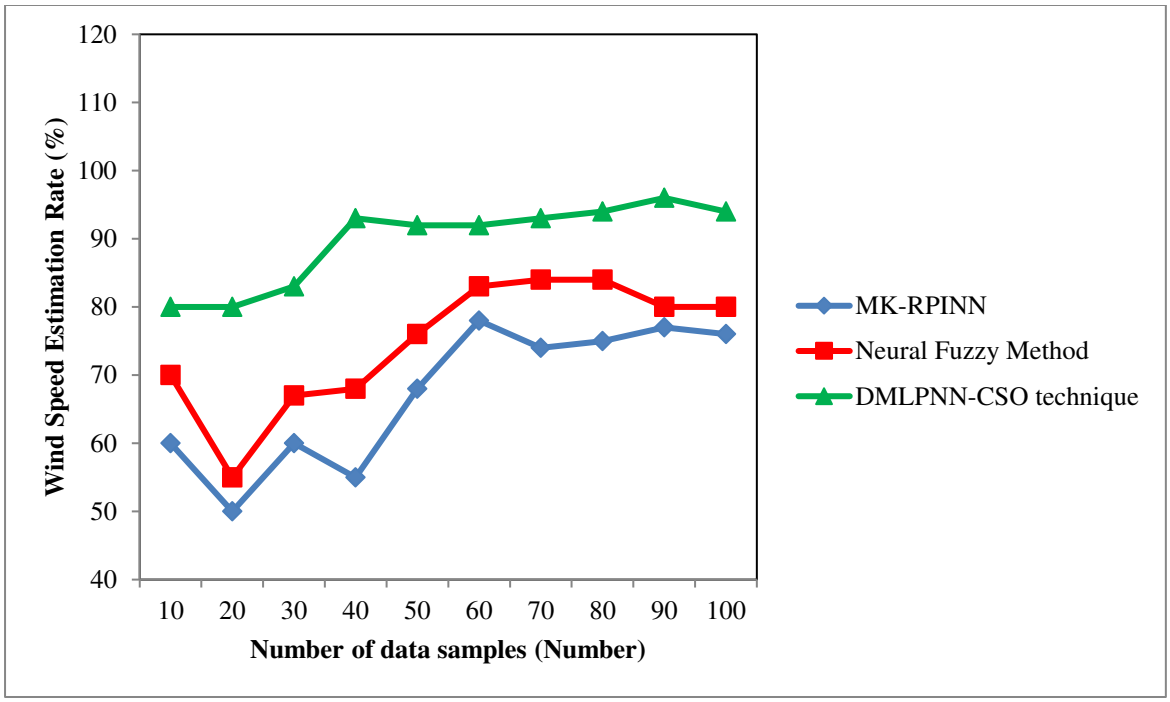

Figure 4 Measurement of Wind Speed Estimation Rate

Let us take the number of instance as 10 for predicting the power generation performance. For each iteration, the number of wind turbine data gets varied. When number of wind turbine data is taken as 30 for simulation work, the wind speed estimation rate of DMLPNN-CSO technique is 83% while Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) [1] and Neural Fuzzy Method [2] attains 60% and 67% respectively. The wind speed estimation rate of DMLPNN-CSO technique is increased by 35% and 21% when compared to existing Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) [1] and Neural Fuzzy Method [2] respectively.

4.2 Prediction Accuracy

Prediction accuracy is defined as the ratio of number of data samples that are correctly predicted for power generation to the total number of data samples. It is measured in terms of percentage (%). It is formulated as,

$$\text{Prediction Accuracy} = \frac{\text{Number of data samples that are correctly predicted}}{\text{Total number of data samples}} \qquad (13)$$

From (13), prediction accuracy of power generation is calculated. When the prediction accuracy is higher the method is said to be more efficient.

Sample calculation:

- **MK-RPINN:** the number of data samples that are correctly predicted is 3 and the total number of data samples is 5. After that, prediction accuracy is determined as,

$$\text{Prediction accuracy} = \frac{2}{5} * 100 = 40\%$$

Table 2 Tabulation for Prediction Accuracy

Number of data samples (Number)	Prediction Accuracy (%)		
	MK-RPINN	Neural Fuzzy Method	DMLPNN-CSO technique
10	40	60	80
20	70	80	90
30	80	87	93
40	75	80	90
50	84	88	96
60	8	90	93
70	89	91	94
80	90	93	90
90	91	93	96
100	92	94	96

- **Neural Fuzzy Method:** the number of data samples that are correctly predicted is 3 and the total number of data samples is 5. After that, prediction accuracy is computed as,

$$\text{Prediction accuracy} = \frac{3}{5} * 100 = 60\%$$

- **Proposed DMLPNN-CSO technique:** the number of data samples that are correctly predicted is 4 and the total number of data samples is 5. After that, prediction accuracy is measured as,

$$\text{Prediction accuracy} = \frac{4}{5} * 100 = 80\%$$

Table 2 describes the prediction accuracy of three different methods, Deep Multilayer Perceptron Neural Network based Clonal Selective Optimization (DMLPNN-CSO) technique, Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) and Neural Fuzzy Method for different number of data samples ranging from 5 to 50. From the table, it is clear that, the prediction accuracy of DMLPNN-CSO technique is higher than other two existing methods. The graphical representation of prediction accuracy is explained in figure 5.

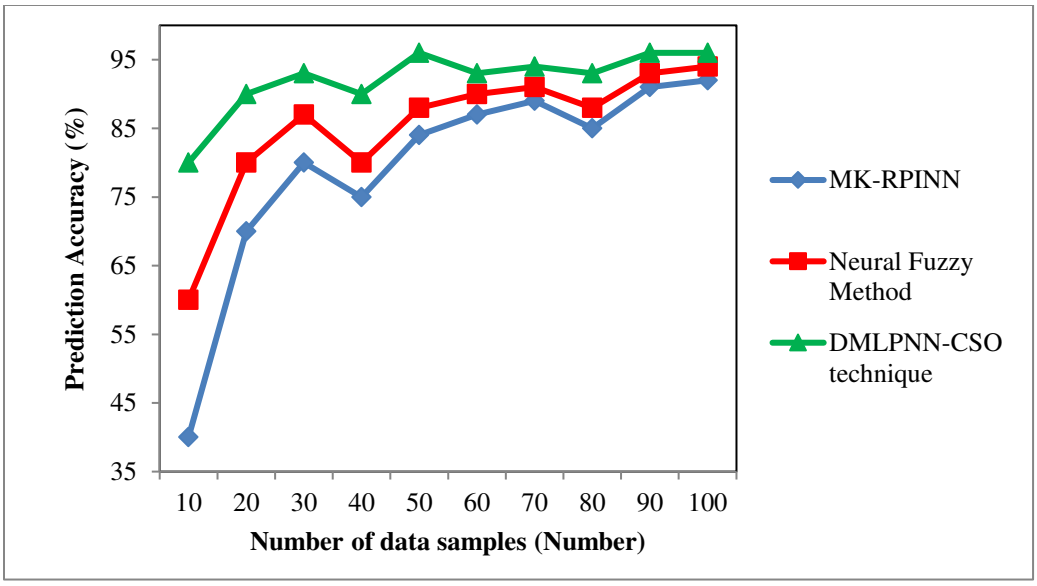

Figure 5 Measurement of Prediction Accuracy

Figure 5 illustrates the prediction accuracy performance for different number of data samples. From the above diagram, number of data samples is taken in 'X' axis and the prediction accuracy is taken in the 'Y' axis. In above graph, the green color line represents the prediction accuracy of DMLPNN-CSO technique where blue color line and red color line denotes the prediction accuracy of Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) [1] and Neural Fuzzy Method [2]. In DMLPNN-CSO technique, deep multilayer preceptron neural network is built to estimate the wind speed of the turbine after performing the data extraction and preprocessing tasks. The median filter performs the preprocessing task for estimating the wind speed to predict the power generation using softsign activation function. Then, the clonal data selection algorithm chooses the optimal data value for predicting the power generation through sorting, cloning and guassian mutation process. This in turn helps to improve the prediction accuracy. Let us consider the number of instance as 10 with different number of the data samples. When the number of data sample is considered as 20 for performing the simulation work, the prediction accuracy of DMLPNN-CSO technique is 90% while Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) [1] and Neural Fuzzy Method [2] consumes 75% and 80% respectively for performing the prediction of power generation.

The prediction accuracy for power generation of DMLPNN-CSO technique is increased by 21% and 9% when compared to existing Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) [1] and Neural Fuzzy Method [2] respectively.

4.3 Prediction Time

Prediction time (PT) is defined as amount of time consumed for predicting the data samples. It is defined as the difference of starting time and ending time of data sample prediction for power generation. It is measured in terms of milliseconds (ms). It is given by,

$$\text{PT} = \text{Ending time} - \text{Starting time of data sample prediction for power generation} \quad (14)$$

From (14), the prediction time is calculated. When the prediction time is lesser, the method is said to be more efficient.

Sample calculation:

- **MK-RPINN:** the starting time of data sample prediction is 0 and the ending time of data sample prediction is 65ms. Then, prediction time is calculated as,

$$\text{Prediction time} = 65\text{ms} - 0 = 65\text{ms}$$

- **Neural Fuzzy Method:** the starting time of data sample prediction is 0 and the ending time of data sample prediction is 51ms. Then, prediction time is calculated as,

$$\text{Prediction time} = 51\text{ms} - 0 = 51\text{ms}$$

- **Proposed DMLPNN-CSO technique:** the starting time of data sample prediction is 0 and the ending time of data sample prediction is 45ms. Then, prediction time is calculated as,

$$\text{Prediction time} = 45\text{ms} - 0 = 45\text{ms}$$

Table 3 Tabulation for Prediction Time

Number of data samples (Number)	Prediction Time (ms)		
	MK-RPINN	Neural Fuzzy Method	DMLPNN-CSO technique
10	65	51	45
20	68	54	47
30	71	57	50
40	74	59	52
50	72	56	49
60	68	53	46
70	65	51	44
80	67	54	47
90	70	57	50
100	75	61	53

Table 3 describes the prediction time of three different methods, Deep Multilayer Perceptron Neural Network based Clonal Selective Optimization (DMLPNN-CSO) technique,

Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) and Neural Fuzzy Method for different number of data samples ranging from 10 to 100. From the table, it is observed that, the prediction time of DMLPNN-CSO technique is lesser than other two existing methods. The graphical representation of prediction time is illustrated in Figure 6.

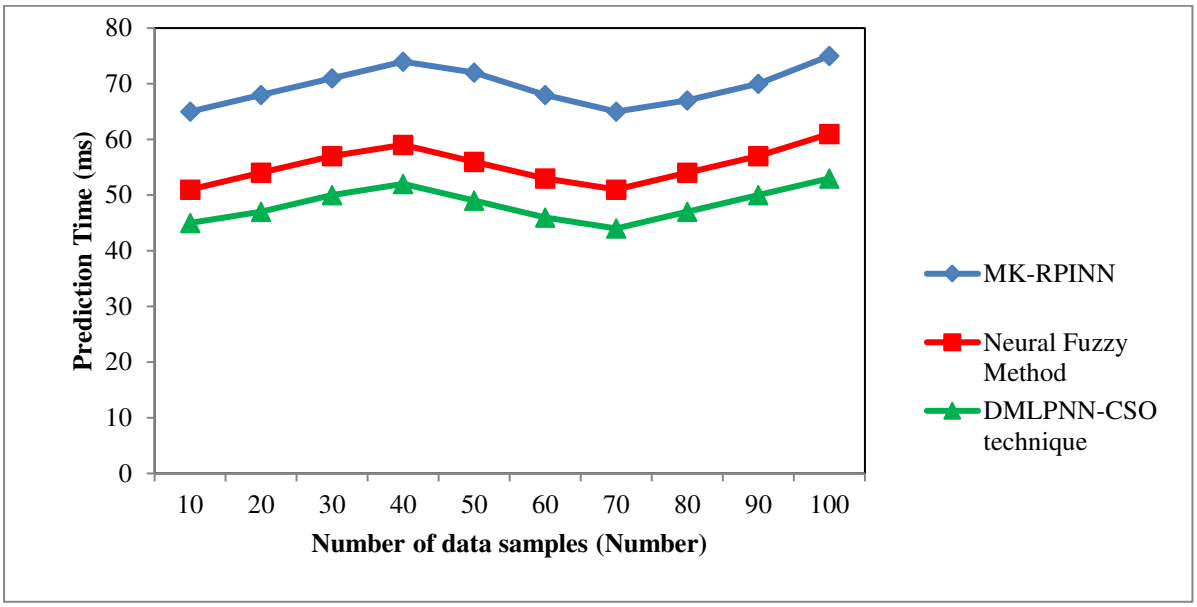

Figure 6: Measurement of Prediction Time

Figure 6 explains the prediction time performance for different number of data samples. From Figure, number of data samples is taken in the 'X' axis and the prediction time is taken in the 'Y' axis. In the graph, the green color line represents the prediction time of DMLPNN-CSO technique where blue color line and red color line symbolizes the prediction time of Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) [1] and Neural Fuzzy Method [2]. DMLPNN-CSO technique uses the deep multilayer preceptron neural network and clonal data selection algorithm for predicting the power generation. Deep multilayer preceptron neural network is performed to estimate the wind speed after performing the data extraction and preprocessing from wind turbine. Median filter is employed to perform the preprocessing task and wind speed gets estimated in the hidden layer. The output layer matches the output with pre-stored results to predict the power generation using softsign activation function. After that, clonal data selection algorithm is used to select the optimal data for predicting the power generation by performing the sorting, cloning and guassian mutation process. This in turn helps to reduce the prediction time. Let us take the number of instance as 10 with different number of data samples. When the number of data sample is taken as 40 for performing the simulation work, the prediction time of DMLPNN-CSO technique is 47ms while Multi Kernel Ridge Pseudo Inverse Neural

Network (MK-RPINN) [1] and Neural Fuzzy Method [2] consumes 67ms and 54ms respectively for performing the prediction. The prediction time for power generation of DMLPNN-CSO technique is reduced by 31% and 13% when compared to existing Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) [1] and Neural Fuzzy Method [2] respectively.

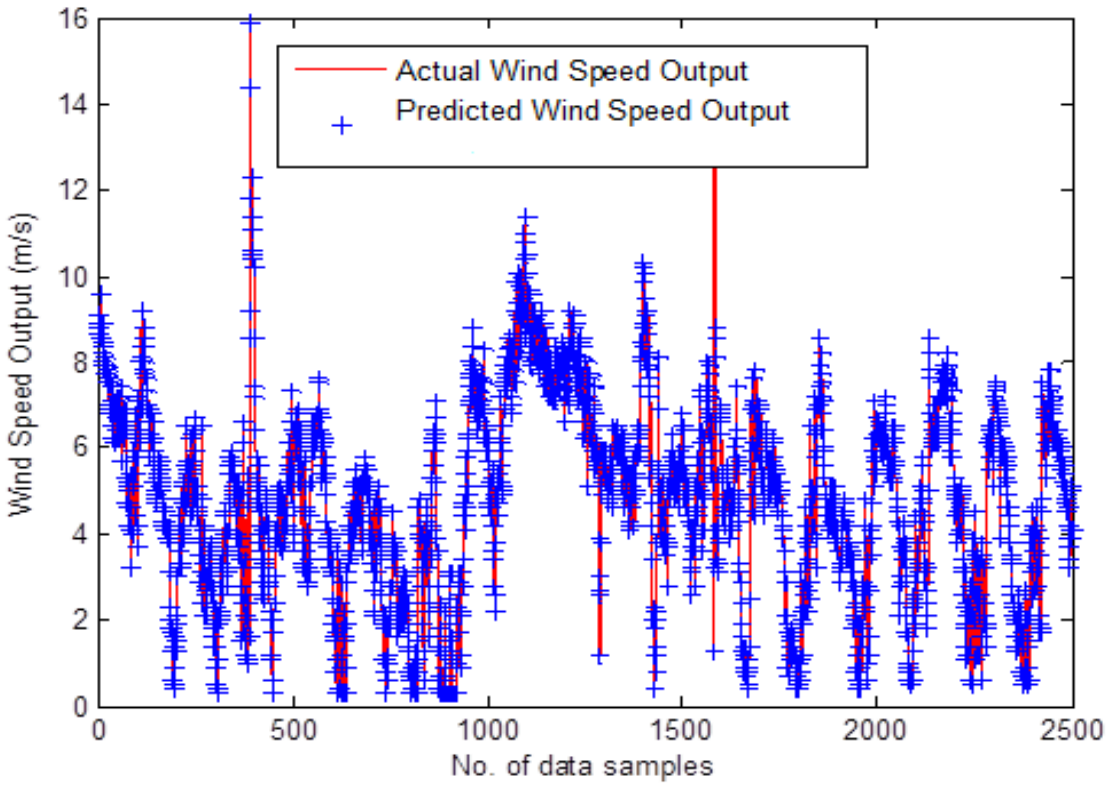

Figure 7: The mapping of actual and predicted data of the proposed DMLPNN-CSO Technique

4.4 Prediction Metrics: RMSE, MSE, MAPE

The mapping of actual and predicted values are plotted in Figure 7 for the proposed DMLPNN-CSO technique. In addition to the above metric analysis the model is also evaluated by employing other metric parameters such as Root Mean Square Error and Mean Absolute Percentage Error. The obtained results for Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) [1] , Neural Fuzzy Method [2] and the proposed DMLPNN-CSO technique are depicted in Table 4.

$$RMSE = \frac{1}{N}\sum_{t=1}^{N}(Y_t' - Y_t)^2 \quad (13)$$

$$MAPE = \frac{100}{N}\sum_{t=1}^{N}|(Y_t' - Y_t)/|\,Y_t' \quad (14)$$

Table 4 Performance metric analysis of the proposed model

Model Under Study	RMSE	MAPE
(MK-RPINN) [1]	2.314E-3	4.214E-3
Neural Fuzzy Method [2]	1.0945E-3	5.149E-4
Proposed DMLPNN-CSO technique	**1.0011E-5**	**1.0121E-4**

Further, the model is evaluated by statistical analysis to demonstrate the significance of the proposed model for handling of stochastic nature of model parameters. The statistical analysis is made with correlation value (r) and coefficient of determination (R^2), when the obtained value is near l then the model is validated for its effective wind speed estimation. The obtain results is not influenced by stochastic parameters, instead the reported variation in result is actual model performance. In Tabe 5 the statistical analysis is reported, it is demonstrated that the proposed DMLPNN-CSO algorithm has better statistical results than that of other models under comparison.

Table 5 Statistical Analysis of the proposed model

Model Under Study	Correlation Value, r	Coefficient of Determination R^2
(MK-RPINN) [1]	0.8991	0.8083
Neural Fuzzy Method [2]	0.8972	0.8049
MLP-CSO	0.9094	0.8270
DLNN	0.9134	0.8343
Proposed DMLPNN-CSO technique	**0.9729**	**0.9465**

5. CONCLUSION

An efficient technique called Deep Multilayer Perceptron Neural Network based Clonal Selective Optimization (DMLPNN-CSO) technique is introduced to improve the performance of the power generation prediction through wind speed estimation with higher accuracy based on mean air temperature, relative humidity and vapor pressure data. In DMLPNN-CSO technique, wind turbine is taken in the input layer. The wind turbine information is extracted and transmitted to the hidden layer 1 where the data preprocessing is performed through the median filter for removing unnecessary data. After that, the preprocessed data is transmitted to the hidden layer 2 to estimate the wind speed. The estimated values are collected and get matched with the pre-stored values in the output layer through softsign activation function. After estimation of wind speed, the optimal data gets selected by clonal data selection algorithm for predicting the power generation. Clonal data selection algorithm performs the sorting, cloning and guassian mutation for finding the optimal value in power generation prediction. This in turn helps to improve the prediction accuracy and minimize the time consumption. Experimental evaluation is carried out with the

parameters such as prediction accuracy, prediction time and wind speed estimation rate. The results analysis of DMLPNN-CSO technique improves prediction accuracy and wind speed estimation rate with minimal prediction time than the state-of-art methods.

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Authors Contribution:

Vinothkumar.T & S.Tamizharasi : Methodology, Software Development, Model Framing And Validation.

Deepa S N: Supervision, Model Framing and Evaluation.

Yogambal Jayalakshmi N: Writing and Software Development.

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