ANALYSIS OF MACHINE LEARNING BASED RENEWABLE ENERGY SYSTEMS

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ABSTRACT: The present research focuses on the development and optimization of the particle swarm techniques inspired in nature to predict wind speed in renewable energies with real-time wind farm data structures, of unique machine learning architectures for neural networks alongside certain mathematical and stochastic populations. The research work in this article includes six modules, i.e., designing proposed architectures of the neural network with variants based on population stochastic particle swarm (SPS) optimization and developed mathematical parameters in place of hidden neuron numbers to effectively predict the speed of renewable energy systems that reach the set number of neurons. The wind farm data sets are used for training, testing and validation of the proposed model of wind speed predictors. The final prediction model proposed involves the applicability of a neural wavelet network for a predictive wind velocity and the mother wavelet function is used to allow the hidden neurons and to measure the wind speed output with the reduction of the set parameters.

Key words: Renewable energy, stochastic particle swarm (SPS) optimization, Machine learning, wind speed.

1. INTRODUCTION

1.1 GENERAL

The energy crisis in many countries has been a major problem for the last decade, and the use of renewable energy worldwide has become significant. The energy source plays an important role in the increasing economy and produced by wind energy resources that are available in large quantities would contribute to the creation of an energy model and assistance for the proper allocation of resources. Wind is a large accessible natural resource and renewable energy. Wind energy is a renewable energy and pollution-free energy. Wind is essentially distinguished by its direction, speed and time. The wind energy extracted from natural wind flows depends on the wind's intensity or actually wind speed. Wind intensity or wind speed are usually non-linear in nature and fluctuate. Despite its original character, the wind has the potential to produce the requisite energy for the country's daily demands.

For wind energy network systems, the estimation of wind speed is an essential measure. Wind speeds are influenced by few variables, such as humidity, air humidity, air pressure, temperature, rainfall, etc. Predicting precise wind speed helps energy users to schedule the required energy demands accordingly. Different wind speed forecast applications: grid electricity, satellite and rocket launch, agriculture energy, military control module operations and so on. This prediction safeguards the output of secure wind power and allows wind energy to be incorporated into power grids. This research thesis helps to build models for a neural network for the efficient prediction of wind speed.

1.2 NEED FOR NEURAL NETWORK MODELS FOR WIND SPEED PREDICTION

Over the years it was well-known for many prediction applications that artificial neural network models were used (Fu 2003). Artificial neural networks are an intelligent computational technique close to the function of the biological human neural network. Nonlinearity, adaptability, potential for large-scale data and the existence of widespread data are key features of neural networks. The neural system proves to be an efficient tool to accurately predict wind speed, based on the given input parameters because of these integrated features. In various fields such as prediction, identification, processed images, classification, association, control and so forth, neural networks have been used. Several techniques, including physical and mathematical methods, are used (Gieble 2003, Hervas et al. 2012, Junli et al. 2010). The physical method uses basic and higher order equations and contains real-time physical quantities.

In general, because of its nonlinear nature the wind speed varies easily (Ronay et al. 2015, Men et al. 2016, Ahmed Saleh 2016, Hu et al. 2016). In this research thesis, ANN is a versatile and effective method for preaching non-linear wind-prediction system behaviour. The neural networks are fundamentally inspired by the biological work of the brain model, which contains its fundamental element as an artificial neuron (Haykin 2008). ANN does not need math or a mathematical system model, but prefers to automatically minimise the error based upon the available input and output information.

1.3 OBJECTIVES OF THE RESEARCH WORK

In the sector of the renewable energy system, it has been well noted that the wind speed prediction through efficient predictor models is the prime concern. In this case, predictor models must be analysed and built to accurately predict input data from wind farms in the real time. This study proposes therefore to build solutions that guarantee the prediction rate, some architectures in the neural network hybridised with stochastic population-based evolutions algorithms and unique mathematical criteria.This research is focused on the applicability of the proposed neural network architectures and the swarm intelligence algorithm that has proven efficient to predict better.

2. FEED FORWARD NEURAL NETWORKS AND HYBRID NEURO-FUZZY MODEL FOR WIND SPEED PREDICTION

2.1 INTRODUCTION

As the world needs more and more power every day, the demand for effective energy in order to generate power also rises rapidly. This segment focuses on the prediction of wind speed, since wind power generation is affected by this factor, helping in many ways to satisfy demand for electricity. Inputs can typically be used for the prediction models based on the prediction method to forecast wind speed. The inputs used in the prediction models include humids, wind speeds, temperature, humidity content, upstream wind pressure, downstream wind pressure, wind speed etc. In relation to the prediction models, all available inputs and the most prominent inputs which have an extreme role to play and which affect the wind velocity must not be given.

2.2 PROBLEM FORMULATION AND ITS IMPORTANCE

The wind turbine generated by a wind farm relies heavily on the stochastic nature of the wind speed and an unexpected wind energy deviation contributes to an increase in electrosystems operating costs. There is a strongly non-linear relationship between wind and wind power. Thus a wind speed forecast error would also lead to a big wind power generation error. This technique increases the output rate functionally. The neural network typically builds on past data and predicts future data with this data. A precise model for wind speed forecasting would allow grid operations to operate economically to meet the needs of the electricity clients. Precise and accurate forecasts of wind speed are therefore a requirement for successful grid activity and advanced control strategy.

The efficiency of the designed model will be applied by calculating the average square error rate in the proposed wind velocity prediction. This square error must be minimal for better accuracy in the prediction model. The Middle Square Error (MSE) for estimation of wind speed is therefore used as the performance metric for learning. MSE parameters are used and described by the following equation in order to evaluate the efficient predictive machine learning model:

$$MSE = \sum_{i=1}^{N} \frac{\left(Y_{predict} - Y_{actual}\right)^2}{N}$$

2.3 WIND INPUT PARAMETERS AND DESCRIPTION OF REAL TIME WIND FARM DATASETS

Wind speed and wind direction play an integral role in assessing the most important wind input parameters. If the wind direction is not changed, there will be no impact on wind speed, and if the wind direction changes suddenly wind speed will change. Wind is considered to be a meteorological phenomenon dependent on changes in the atmosphere and temperatures in the climate. Wind power generation and the wind turbine production are dependent on the wind speed and wind direction variations. The effect of moisture (air density), which is an exponential term for air pressure and temperature, also plays a large role in generating wind power. Therefore, this research includes wind speed, wind direction, temperature and humidity in the wind input parameters considered.

2.4 FEED FORWARD NEURAL NETWORK MODELS FOR WIND SPEED PREDICTION

The development of neural network models began with the start and applicability of feed-forward neural networks for various technological and scientific applications (Sivanandam& Deepa 2007). Neural networks transmit information from the input layer neurons to the centre layer neurons, and from there transmit information to the output layer. They transmit information to the output layer. The information transfer between the layers is carried out in the feed forward way and the layer outputs are determined on the basis of which errors in the training phase are assessed. The convergence of neural feed forward networks is based on the error (above) of minimum value represented by the equation. Feed forward neural networks appears to be stable by their architectural model and the rules of learning followed during the weight update process. This research chapter focuses on the development of a Back Propagation Neural Network (BPN) Model and Radial Base neural network (RBFNN) model to allow efficient wind speed prediction in renewable power systems from the various feeding forward neural architectures used for prediction applications (Sivanandam et al. 2006).This research thesis is focused on wind speed prediction, based on the gradient descent rule used in their training process, which is to select a neural model and a radial function network for back propagation. BPN models are usually used to activate data to address, and RBFNN models are using the Gaussian activation feature to test outputs from the different layers. The following sub-sections describe the training algorithms used for BPN and RBF models in this study.

3. DEVELOPED SUPPORT VECTOR MACHINE NEURAL MODELS FOR WIND SPEED PREDICTION

3.1 INTRODUCTION

In this chapter of the thesis, the emphasis is on developing wind vector forecasting models using the neural support of the vector machine. Basically, Support Vector Machines (SVM) are used as classificators, but SVM variants are used to predict the contribution. In this chapter of the thesis, a built model of a linear vector support machine (LSVM) and a PSVM is proposed to perform a wind speed prediction using existing wind farm data in real-time. This is modelled on both the linear PSVM and non-linear PSVM predictors, in the developed PSVM predictor. The distinction between the linear and non-linear PSVM predictor models is that they are ideal for efficient wind speed predictions by using the kernel functions. The prediction application is implemented in a way that minimises the average square error for the collection of wind farm data at a height of 50m. The training phase for the algorithmic flux of a neural network is carried out using the LSVM, L-PSVM and N-PSVM (Non-linear PSVM) developed to predict wind velocity in renewable energy systems. The compared results of the proposed variants of SVM predictors with other predictors are compared in the literature to show their performance.

3.2 SUPPORT VECTOR MACHINE PREDICTOR MODEL – AN OVERVIEW

The support vector machine is essentially a supervised learning network model built on the basis of the planes which clearly define the predicted boundary. A prevision plane or decision plane is called, that separates the level of prediction components from a different class component (Vapnik 2000). SVM model attempts to forecast entities without having an estimation of the likelihood of membership in the data set considered. The fundamental difference between SVM and the multiple regression logistics is this. The two-dimensional SVM Prediction portion is shown in Figure 3.1.

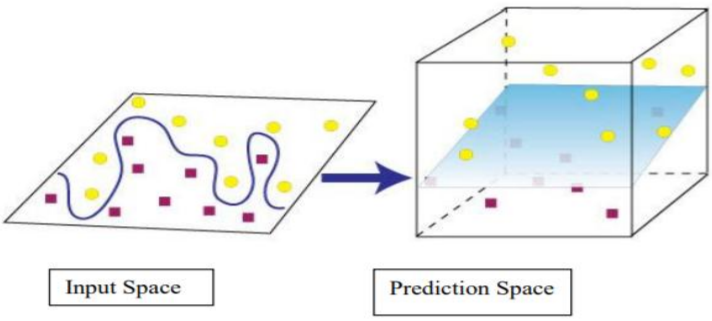

Figure 3.1 SVM Prediction space of two-dimensional datasets

3.3 PROPOSED LINEAR SVM PREDICTOR FOR WIND SPEED PREDICTION

When implementing neural network models for prediction applications, you must choose the best hyper-plane architectural models to achieve the best accuracy of predictions. Several studies were conducted to predict wind speed in renewable energy systems accurately (Peng et al. 2013, Qin et al. 2011, Sajedi et al. 2011, Salas et al. 2009). In order to manage maintenance operations, to establish the optimum power network and to schedule and plan power system networks, it is important for accurate wind speed forecasts in the wind farms. This thesis developed the LSVM neural predictor model to achieve wind speed prediction of wind farm data in real time.

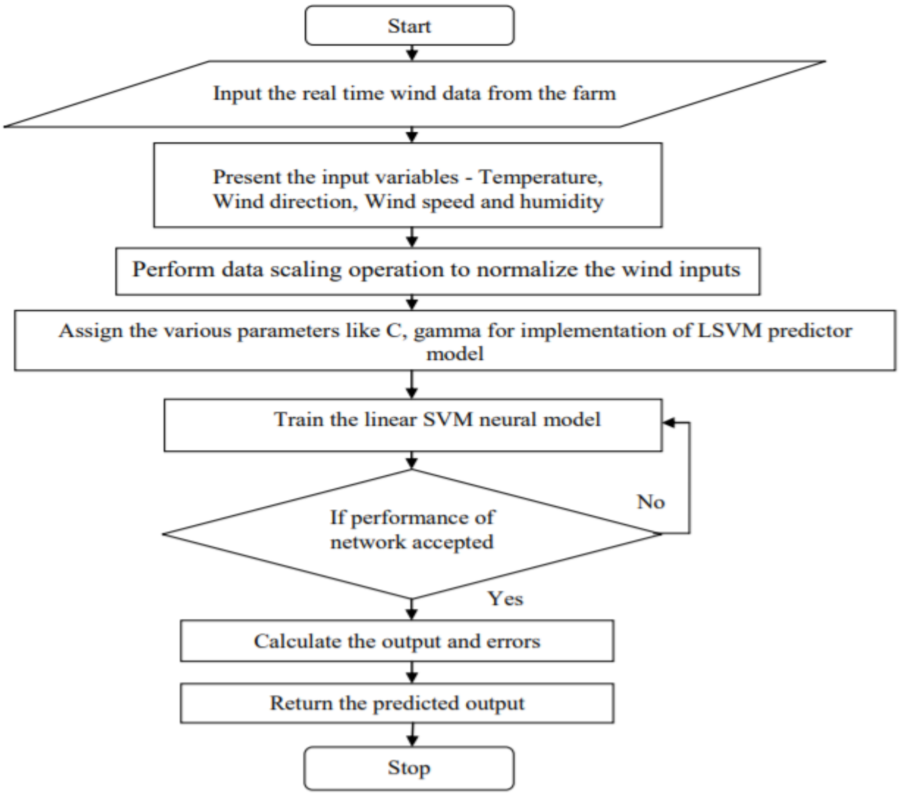

Figure 3.2 Flowchart for the proposed model using LSVM predictor.

4. DEVELOPED ENSEMBLE NEURAL NETWORK MODEL FOR WIND SPEED PREDICTION IN RENEWABLE ENERGY SYSTEMS

4.1 MODELING THE PROPOSED ENSEMBLE NEURAL NETWORK ARCHITECTURE

This section presents the modelling proposed for collection of neural networks to be used in renewable energy systems to predict wind speed. In general, no technique is available for selecting the number of hidden neurons in the hidden layer in neural network modelling. In this study, some new requirements are established to fix the hidden neurons for the ensemble network using the convergence theorem's mathematical basis.In the course of training for error reduction any criterion that meets the convergence theorem is evaluated for optimality. The criterion for minimum error in accordance with the convergence theorem is chosen for the optimal criterion in the proposed ensemble model for repairing hidden neurons. The parameters are based on the number of neurons in the input layer (n). As shown in Figure 4.1, the basic block diagram of the proposed ensemble neural network.

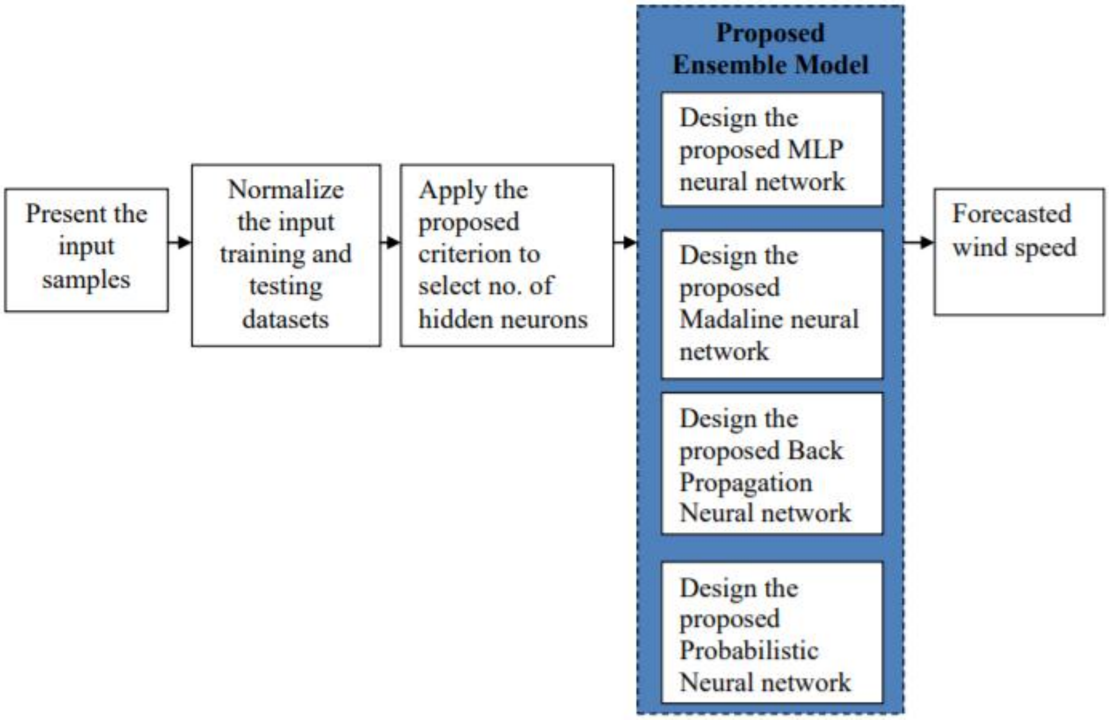

Figure 4.1 Basic block diagram of proposed Ensemble neural network model

4.1.1 Design of proposed Ensemble neural network model

Neural ensemble networks are those which combine the outputs of the independently trained neural networks in modelling of the Artificial Neural Network. The proposed ensemble modelling involves a multi-layer perceptron, multi-layer adaptive linear neuron, neural back propagation network and probability neural network. Each of these independent neural networks (MLP, Madaline, BPN and PNN), together with the criterion proposed to select the hidden neurons integrated, is training using their respective training algorithms.The outcome of each neural network is summed so that the problem under consideration is best generated. This proposed neural network set approach leads to an increase in the stability and potential for generalisation of individual neural systems, avoiding the local optimum problem and delaying network convergence. The neural network ensemble is constructed such that a suitable number of hidden neurons are detected with minimal error and a better precision and faster convergence. As shown in Figure 4.2 the proposed design model of the neural network.

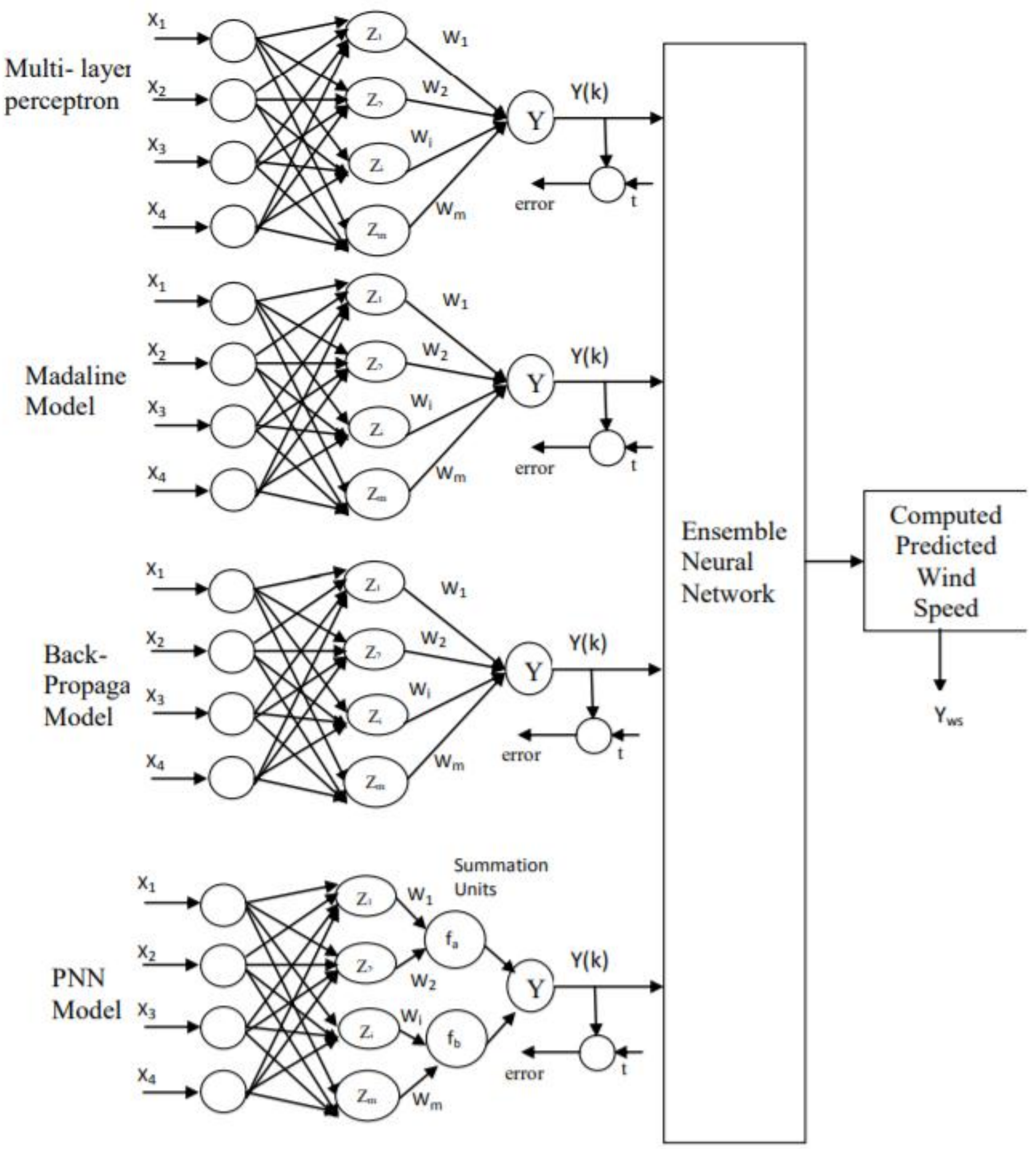

Figure 4.2 Proposed architectural model of Ensemble neural network.

Proposed training algorithm of Ensemble neural network

The proposed training algorithm for the neural network ensemble is as follows:

Step 1: Initialize the necessary MLP, Madaline, BPN and PNN network parameters.

Step 2: Implement the proposed criterion in each training algorithm of individual neural network model to assess the number of hidden neurons.

Step 3: Present the input and target vector pairs for the neural network models of each ensemble. When training is started and the tested data sets are used to test the trained network, the input - target vector pair is the training data sets.

Step 4: Compute the net input of each network by using the activation over the computed net input and obtain the corresponding output. YMLP, YMadaline, YBPN, YPNN and the different networks are denoted as H MLP, H Madaline, Hbpn, HPNN, the outputs determined for each network.

Step 5: Build the neural network collection to combine the model and calculate the final wind velocity predicted by the neural network.

5. RESULTS AND DISCUSSION

Implementation results of proposed PSVM neural model for predicting wind speed

This section presents the simulation results determined when the proposed L-PSVM and N-PSVM model is implemented in renewable energy systems to predict the wind speed of the wind farm. The proximal hyper-planes have the predictive data points, which are calculated by the final performance. Table 5.1 offers an overview of the parameters of the linear and nonlinear neuronal vector machine established support for wind speed predictions.

Table 5.1 Parameters for the proposed L-PSVM and N-PSVM Predictor

Parameters	PVSM Predictor
Kernels	i) Linear Kernel- For linear PVSM predictor ii) Gaussian or RBF kernel- For non-linear PVSM predictor
Learning rate	1
No. of Neurons in input and output layers	Based on data sets considered
Maximum Iteration	600

For the 600 iterations of proposed LPSVM and N-PSVM, the figures 5.1 and 5.2 display the real and expected wind speed plot.

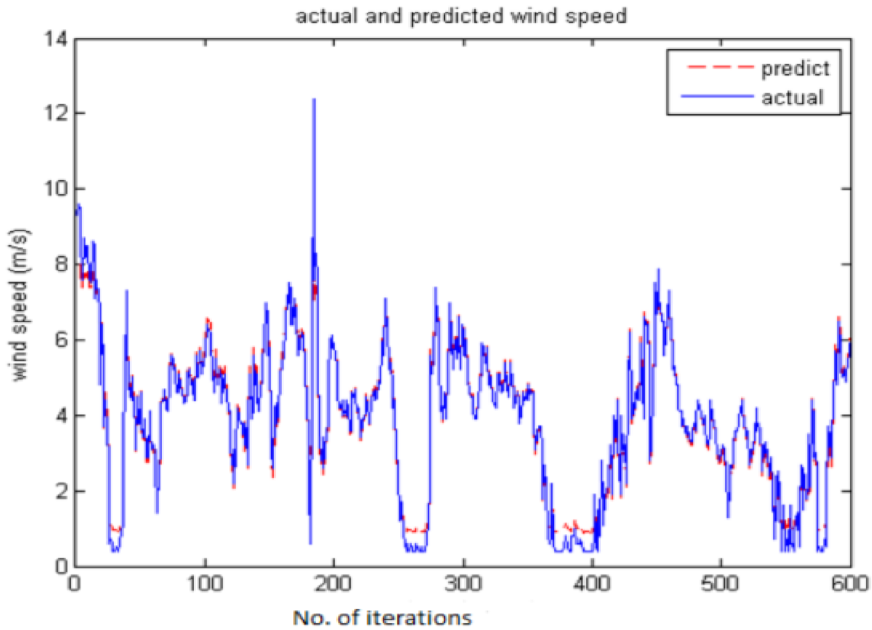

Figure 5.1 Actual and Predicted wind speed output waveform in LPSVM neural model.

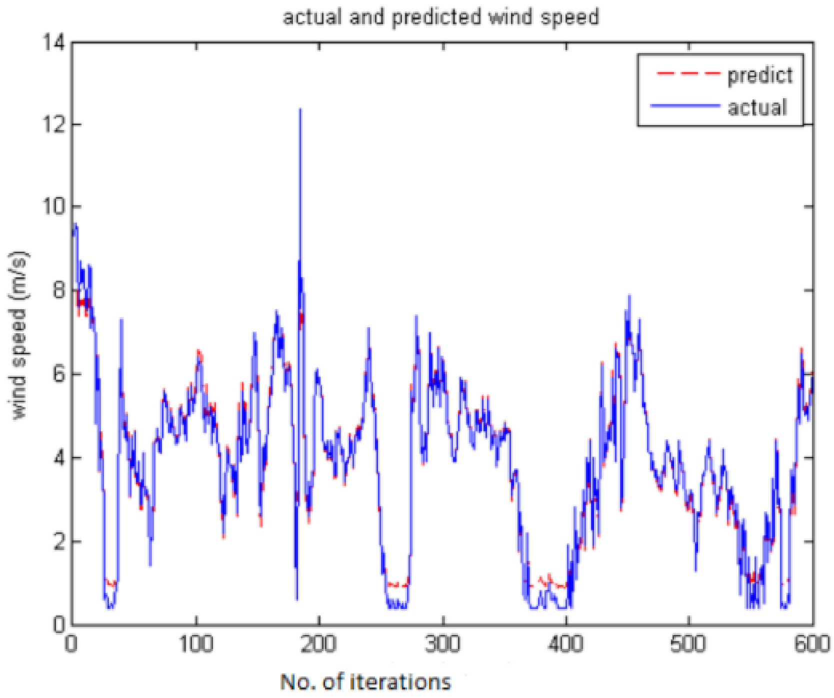

Figure 5.2 Actual and Predicted wind speed output waveform in NPSVM neural model.

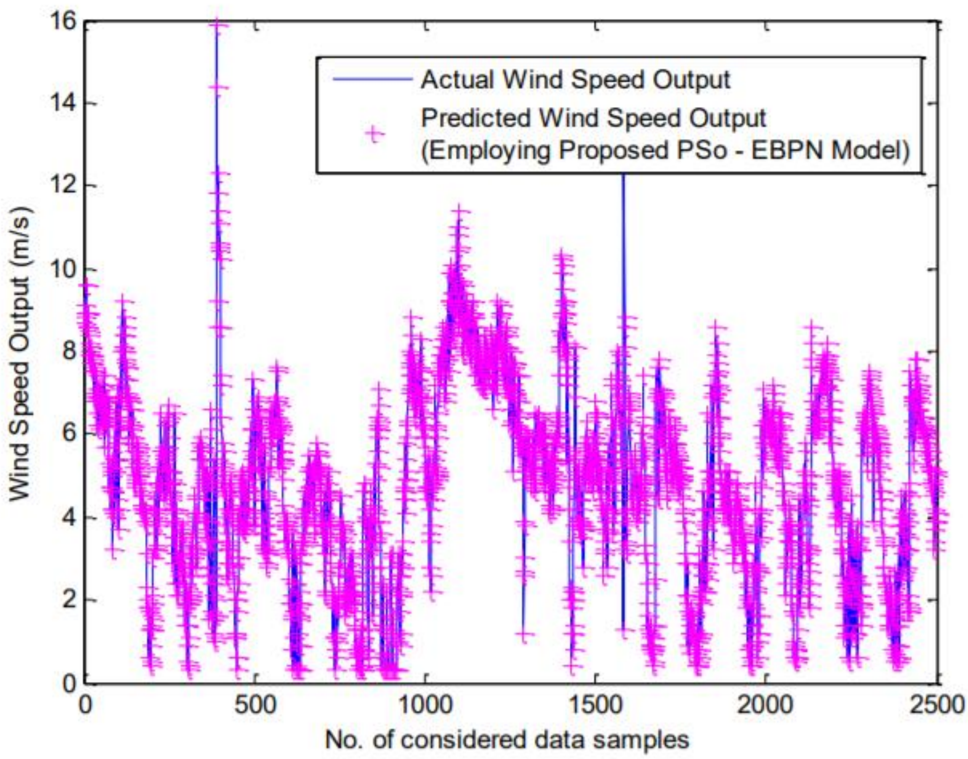

Figure 5.3 Actual and Predicted wind speed output waveform employing proposed PSO – EBPN model.

Figure 5.3 shows that the model proposed predicts wind speed to be in line with the actual wind speed production from real-time data sets, which is well understood by the user.

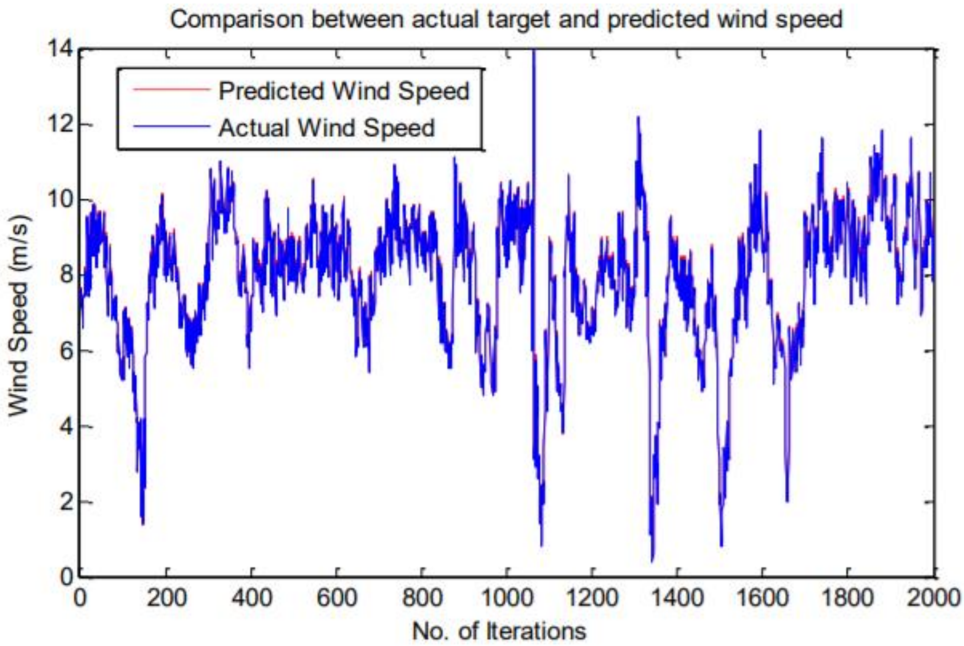

Figure 5.4 Comparison between the predicted and actual wind speed employing proposed Ensemble model

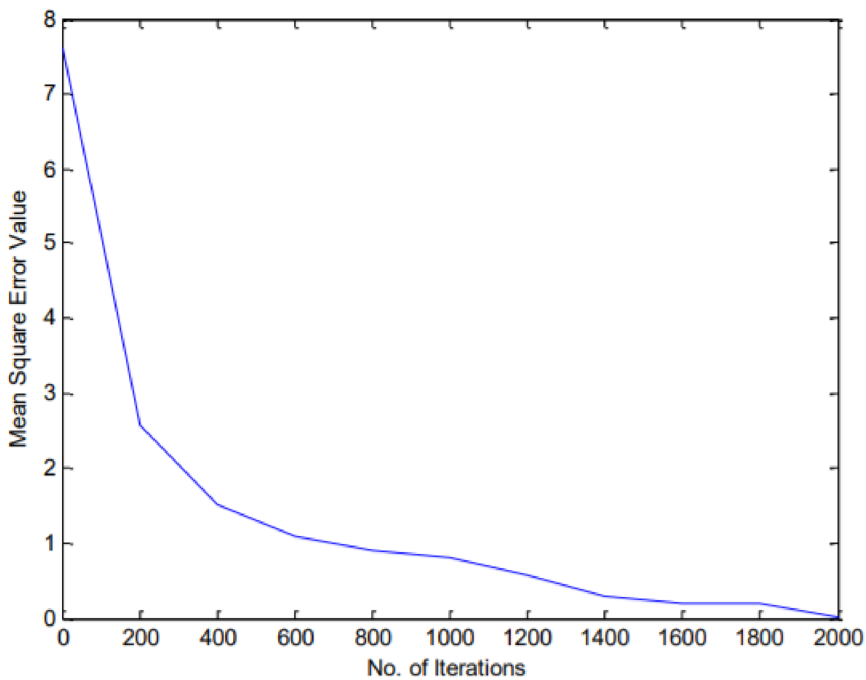

Figure 5.5 Computed MSE value using the proposed Ensemble NN model.

The variance of the mean square error value with regard to the number of iterations using the proposed ensemble neural network model is shown in Figure 5.5. Figure 5.5 shows that, for the proposed ensemble model with the hidden neuron criterion selected, the MSE reaches at least 0.01515. Previous studies and error rule for estimating the number of hidden neurons to be put in the neural network were used from literature.

CONCLUSION

With the fast growing modelling of renewable energy systems more relevant to wind energy generation, wind speed prediction using efficient predictor models is a major concern. It was also well noted. At this point wind speed prediction models are needed to evaluate and improve to perform an effective wind speed prediction based on the attributes for real-time data sets. Thus, this study aims at providing better solutions that ensure the prediction rate, including some neural network architectures and these swarm hybridised architectures. The proposed model of the predicting network for neurons included: BPN, RBFNN, Hybrid Neuro–Fuzzy, EBPNN and ERBFNN, EBPNN, PSO–ERBFNN, LSVM and PSVM predictors; Ensemble NN model; PSO–Ensemble NN model; and WNN models, with a robust and effective prediction of real-time wind farm dataset in numerical simulation. All these proposed models of predictors for neural networks seek to increase the ability of wind farm data sets to learn and generalise. Each of these predictors follows its own mechanism, to train the considered architectures of the neural network to achieve better prediction rates and the solution point. All NN-based predictor models carry out their quest in an aggressive and supportive way.. Instead. Each of the proposed and implemented neural network architectures is reliable and demonstrates their increased convergence rate in the solution space.

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