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RENEWABLE ENERGY SYSTEMS FOR MACHINE LEARNING

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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. 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 the exact wind speed aids energy users in planning their energy needs. Numerous uses for wind speed forecasts: grid electricity, satellite and rocket launches, agricultural energy production, military control module operations, etc. This forecast ensures reliable wind power output and allows for the integration of wind power into electrical grids. Models for a neural network used to accurately predict wind speed can be built with the help of this research thesis.

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).

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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

A wind farm's wind turbine is heavily reliant on the stochastic nature of wind speed, and an unexpected wind energy deviation raises electrosystems' operating costs. When it comes to wind, the relationship is decidedly non-linear. This means that an incorrect wind speed forecast will also lead to an incorrect amount of wind power generated. This method functionally raises the output rate. An artificial neural network works by learning from the past and making predictions about the future. If wind speed forecasting models were more accurate, grid operations could run more efficiently to meet customers' demand for electricity. Precise and accurate forecasts of wind speed are therefore a requirement for successful grid activity and advanced control strategy.

When making a wind velocity prediction, the model's accuracy will be evaluated by calculating the average square error rate. The prediction model's square error must be kept to a minimum if it is to be accurate. As a result, the MSE for wind speed estimation is used as a learning performance metric.MSE parameters are used and described by the following equation in order to evaluate the efficient predictive machine learning model:

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

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.

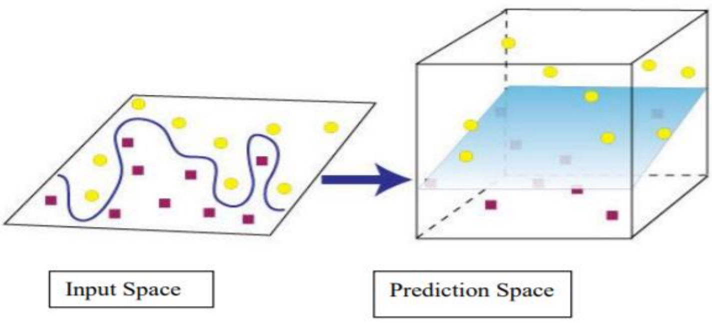

Figure 3.1 SVM Prediction space of two-dimensional datasets

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.

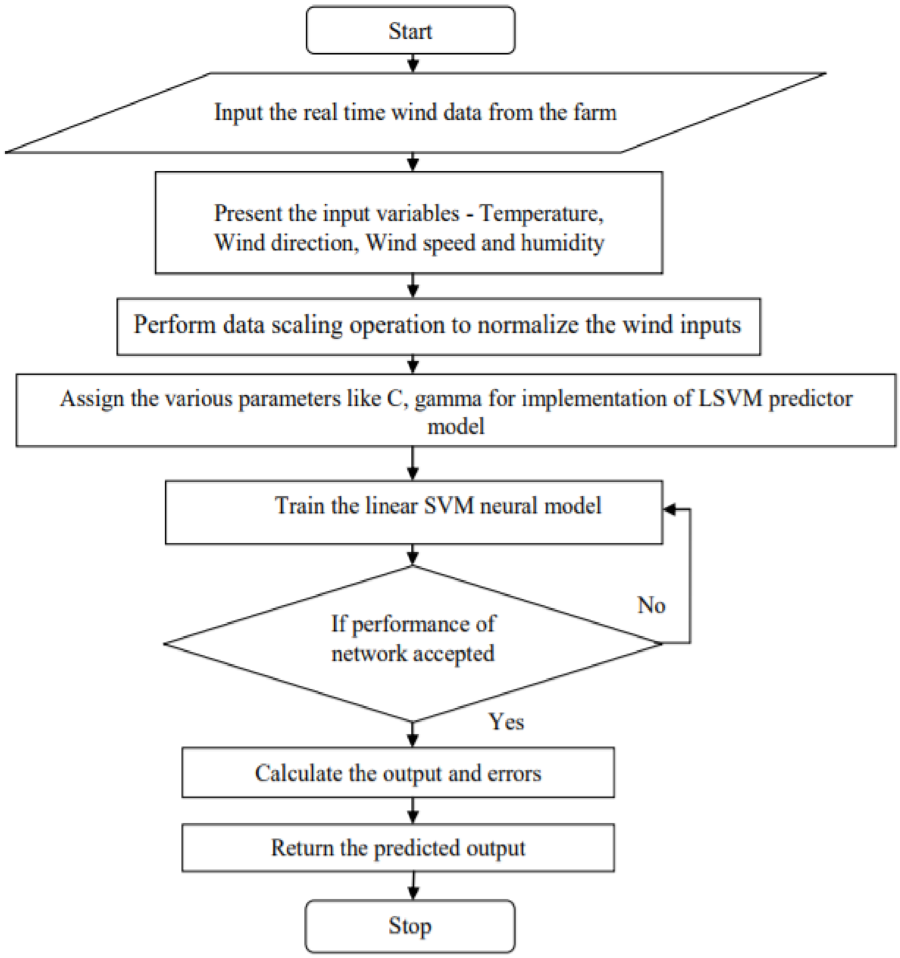

Figure 3.2 Flowchart for the proposed model using LSVM predictor.

4. 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 4.1 offers an overview of the parameters of the linear and nonlinear neuronal vector machine established support for wind speed predictions.

Table 4.1 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.

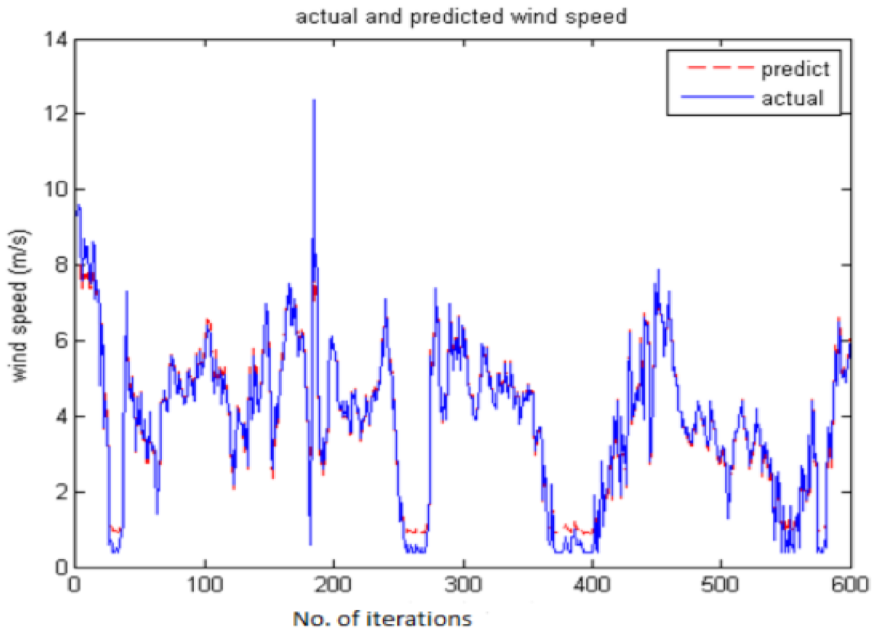

Figure 4.1 Actual and Predicted wind speed output waveform in LPSVM neural model.

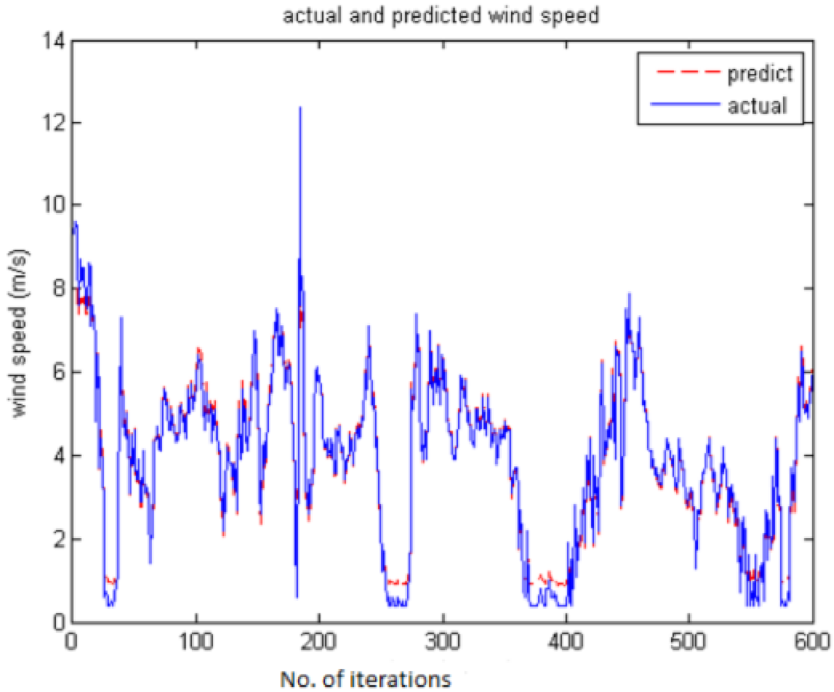

Figure 4.2 Actual and Predicted wind speed output waveform in NPSVM neural model.

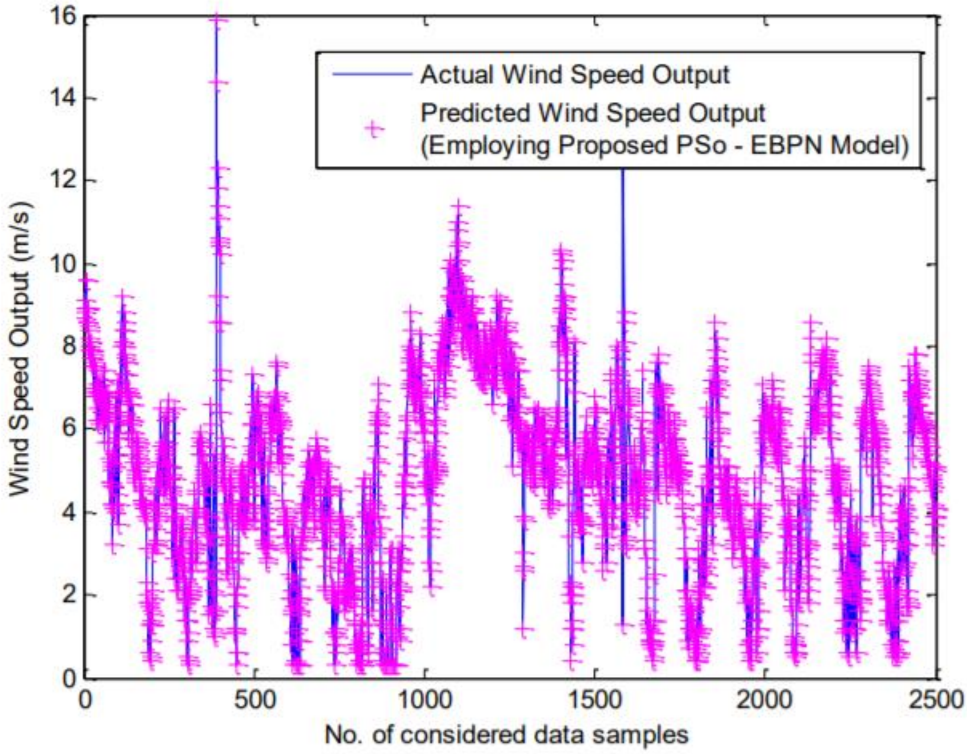

Figure 4.3 Actual and Predicted wind speed output waveform employing proposed PSO – EBPN model.

Figure 4.3 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.

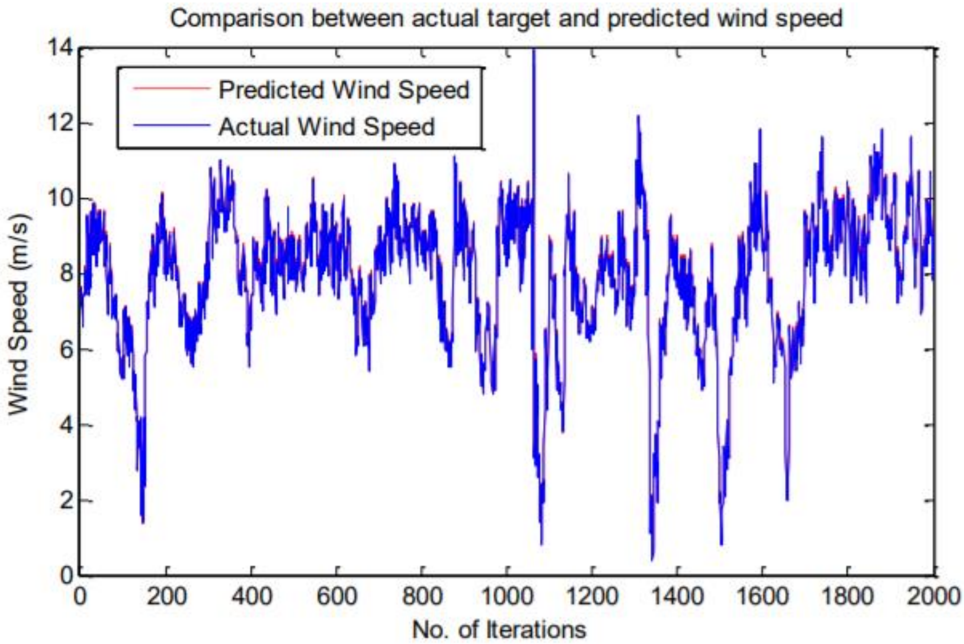

Figure 4.4 Comparison between the predicted and actual wind speed employing proposed Ensemble model

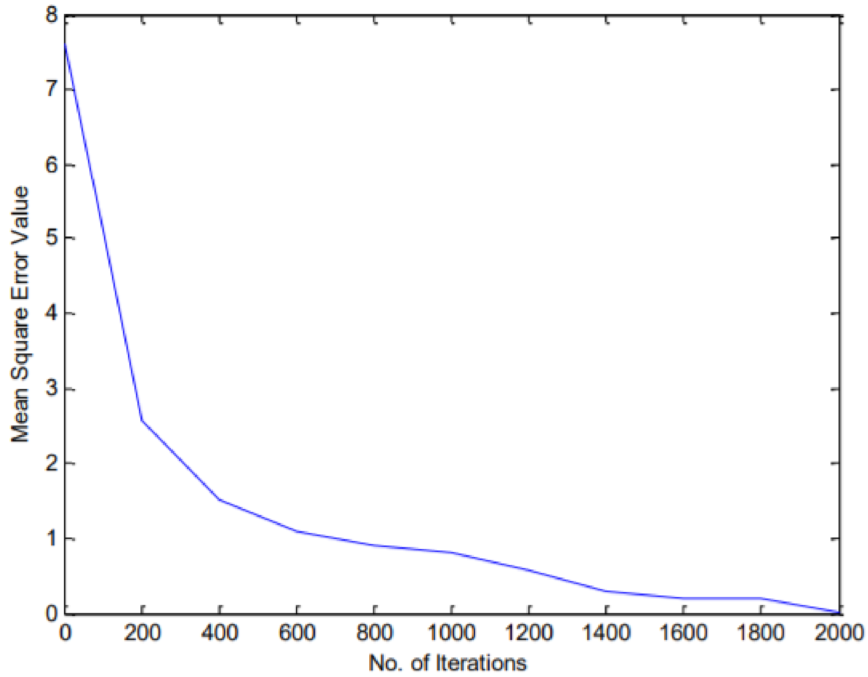

Figure 4.5 Computed MSE value using the proposed Ensemble NN model.

According to the proposed ensemble neural network model, the variance of the mean square error value increases with the number of iterations (Figure 4.5). Figure 4.5 shows that the MSE is at least 0.01515 for the proposed ensemble model using the hidden neuron criterion. The number of hidden neurons to be included in the neural network was estimated using previous studies and an error rule derived from the 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.In order to train the neural network's considered architectures for better prediction rates and the solution point, each of these predictors follows its own mechanism. All NN-based predictor models are aggressive and supportive in their search for knowledge.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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