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Solar Irradiance Prediction using Neural Model

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ABSTRACT

The accurate prediction of solar irradiation has been a leading problem for better energy scheduling approach. Hence in this paper, an Artificial neural network based solar irradiance is proposed for five days duration the data is obtained from National Renewable Energy Laboratory, USA and the simulation were performed using MATLAB 2013. It was found that the neural model was able to predict the solar irradiance with a mean square error of 0.0355.

Keywords--- ANN, Prediction, Solar, Neural, Forecast

I. INTRODUCTION

In the field of photovoltaic generation, solar radiation forecasting is a leading requirement for better control of power production. In fast decades of solar generation scenarios, there is a rapid rise and need for detailed and pertinent modeling along with proper methods for accurate prediction and estimation of solar irradiance.

Some of the regular models for computation comprise of regression models, models derived from satellite information and neural network-based models for identification of atmospheric parameters. The hourly diffuse solar radiation [1] is dependent on the sigmoid function, hence a regressive model is utilized for the irradiation estimation. It applies the index of clarity along with the forecaster as the relative optical mass on previous occasions, many solar irradiation models were used which were further categorized into physical and statistical models [2], [3]. Mathematical equations were the requirement of physical models, describing the physical situation and vibrant motion of the atmosphere. These physical models were found to be exceedingly complex and required significantly high computing power in order to come to a convergence [4]. Hence further numerical methodology was applied which could obtain estimated solutions of equations and they came to be identified as numerical weather prediction (NWP) models [5]– [8] however it is not in common usage. In NWP, the solar irradiance forecasting model varies greatly on the location of testing and different climate conditions along with the dynamic changing atmospheric conditions. The statistical models comprise satellite imaging models, models based on time series, wavelet decomposition, sky imaging and ANN models [9]. They depend on images taken from sky and satellite data which observe the structure of clouds and motion vector fields. Cloud index images are taken from two consecutive readings of sky image which yields important information about the cloud movement. The images from the sky and data from satellite yield errors which increment when the sun is at a low height, low irradiance conditions and large variation in spatial conditions. Statistical models are known to have a less complex structure, even lesser than physical models in their requirement of less information and short computational time. There are two basic requirements for these forecast model evaluations which includes the input to the model as information and the accuracy, the complexity of the forecasting mechanism [10], [11]. Features like satellite imaging are not available easily. Some meteorological parameters like relative humidity, ambient temperature, wind speed, the direction of sun and index of clarity are accessible with ease hence the convention based solar model is using only the basic parameters. The solar time scale utilizes the two parts of forecasting based on the ultra-short term (4-7 hour ahead) and short-term (24-72 hour forward) forecasting [12] [13]– [15]. The 24 hours ahead estimate can be used for the dispatch of power used in grid-connected optimization of PV plants and the link between storage devices and the PV systems. The most customary short-term forecast is 24 hours overnight. There are three types of solar forecasting models for various time scales which use ANN techniques and deliver better than the conventional NWP and satellite imaging systems. Among these three techniques, the first technique predicts the solar irradiance using meteorological information. The second technique is based on the use of historical data patterns to get the future values of input for solar irradiance. The third technique is a combination of the previously discussed methods. Due to non-availability of meteorological data for forecasting purposes, the multi perceptron model can be used as an ideal replacement for the 24 hours ahead forecasting.

Leaving aside the non-violent fluctuations which may be due to a storm [16], these models show good performance of solar irradiance prediction. The input data vector defines the suitability and competence of the input information. The input vector may contain additional factors which may make the model complex and lead to higher errors in forecast values, however insufficient data for input may cause variations between the input and output data and not representing the true values. A proper balance is needed between the model complexity and the trueness of forecasting information. This is needed and is necessary for model formation.

Solar irradiance may be outlined as the total quantity of electromagnetic energy which falls on a surface per unit time per unit area. The solar concentration on earth's surface follows the inverse square law. Only 38% of the solar irradiation approximately passes the earth' atmosphere to reach the earth and form the input for solar energy harvesting. This can exceed 38% on sunny days can reach up to 50% on cloudy days and on overcast days it can reach below 38%. This data is collected using meteorological instruments.

Original data model derived from meteorological information is treated as a data input vector fed to the ANN. There may be lapses in the available information which may affect the generalization capability of the ANN. In this paper, the generalization capability is progressed in various aspects which include the input features of the vector, constructed using the meteorological information and to avail more existing data features and neural optimization.

II. ARTIFICIAL NEURAL NETWORK

The artificial neural network can be seen as a type of node. The computational model discussed is inspired by the human neuron structure and is called the artificial neuron. These neurons receive signals through synapses which are surrounded by dendrites or neuron membrane. The inward signals which are strong enough and may exceed the threshold, then get activated and now can emit a signal through the axon. This received signal may be transferred to another axon or synapse and this acts as an activation impulse for other neurons [17]– [19].

A simple neuron is shown in Figure 1.

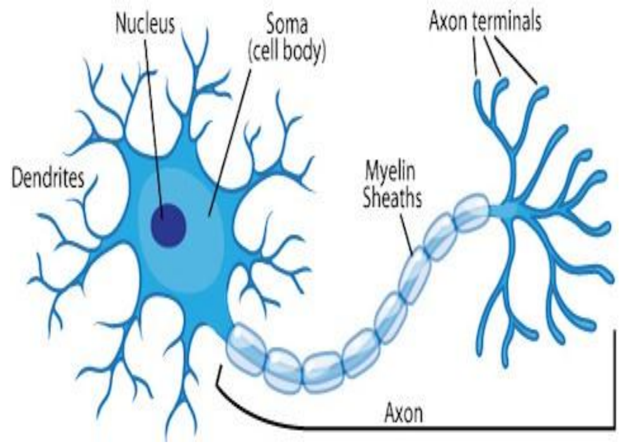

Fig 1: A biological neuron

The central unit of the artificial neural network is formed by the neurons which utilize a transfer function to generate the output. Then every input in the ANN is multiplied with the weight and which acts as a connection between the input and output between several neurons. Then all the weight units are combined and later, the bias unit is added to the summed units of weighted inputs. When the neuron applies the transfer function to the neuron, the output is obtained. An Artificial Neural network structure is shown in Figure 2.

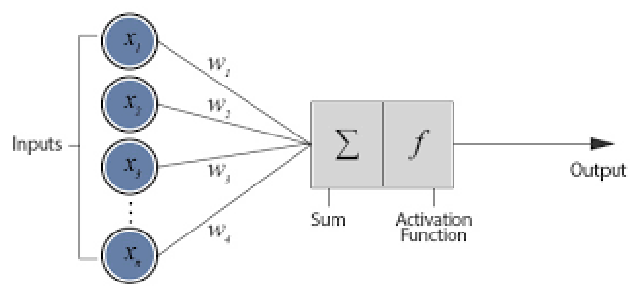

Fig 2: Artificial neural network

Artificial neural networks map with the biological neural systems. These ANN models are utilized for several purposes like classification, pattern recognition, mapping of nonlinear networks, simulation and prediction. A multilayer perceptron (MLP) network is utilized for several networks. A neural network is like a paralleled processor which can store and operate on experimental knowledge and can be used for different purposes.

The neural network functions similar to the human brain in several ways which include

1. The learning process gives birth to the network which acquires the knowledge.

2. The weights or inter-neuron connection strengths are used as a carrier or storage for data.

Artificial neural networks have the capability to manage complex huge systems which have several interrelated values. It attenuates the unwanted data and focuses well on the inputs and the parameters. The backpropagation algorithm is the commonly used algorithm in which the output is fed back to the input for better achievement of training goals. It works on the error stabilizing rule. It consists of both the forward pass and backward pass algorithm. The input vector matrix is applied at the forward pass rule and it conceives its result across the neuron hidden layers. In the forward pass network, synaptic weights are immobile and in backward pass network, the synaptic weights are arranged according to the backpropagation mechanism. With the backward production of the error signal between the desired and actual values of output, the network is trained. The ANN network comprises of the several input layers, one hidden layer and the activation function here chosen as tan-sigmoid. A linear activation function 'PURELIN' was used for the output layer. Lavender Marquardt algorithm is used to train the neural model owing to its high efficiency. The Nonlinear autoregressive (NAR) method was utilized in which the outputs are fed back to the input time series.

III. RESULTS

The proposed neural model consists of 7 hidden layers and one delay unit as shown in Fig 3. The data was split into 70 % training and 30% validation and test units respectively. The error histogram for the trained model is discussed in Fig 4. It is centered along the mean which depicts good performance. The best validation performance before training stops was found to be 0.037359 as shown in Fig 5.

From the given data the actual solar irradiation (Watt/m2) was plotted wrt time axis for a period of 5 days as seen in Fig 6. The forecasted values using ANN wrt the actual values are shown in Fig 7 which shows close approximation between the input and output [11].

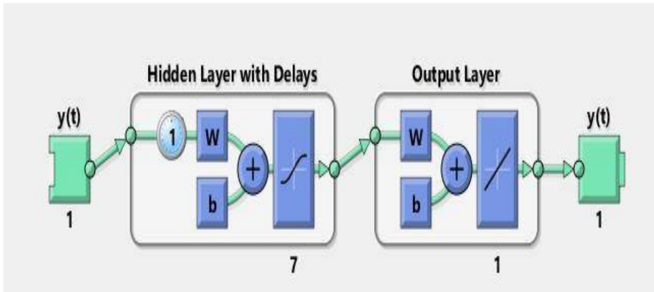

Fig 3: Proposed Neural model

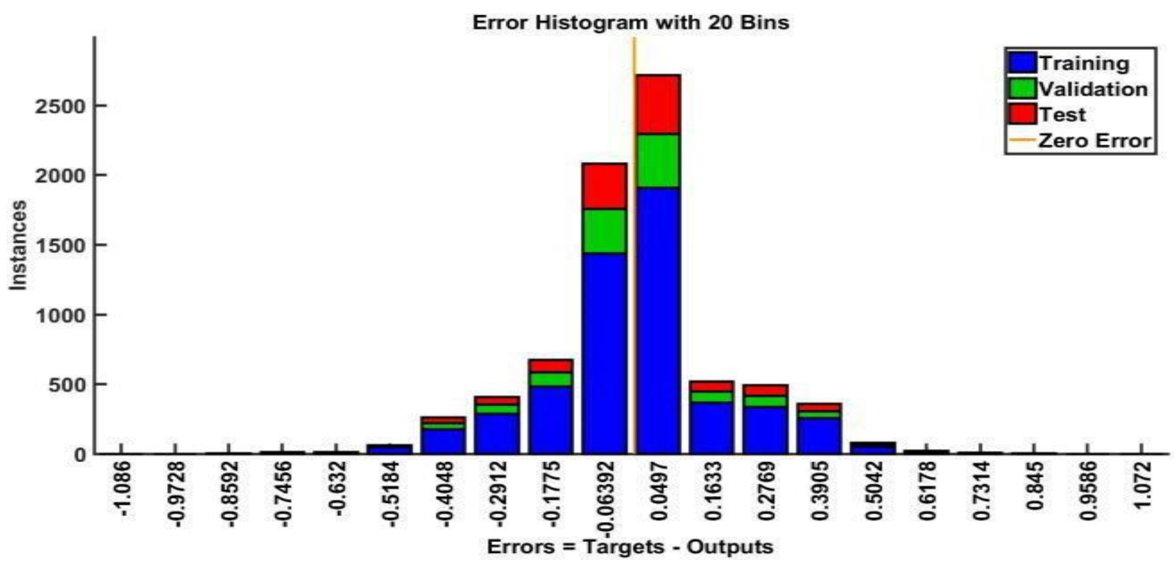

Fig 4: Error histogram for neural model

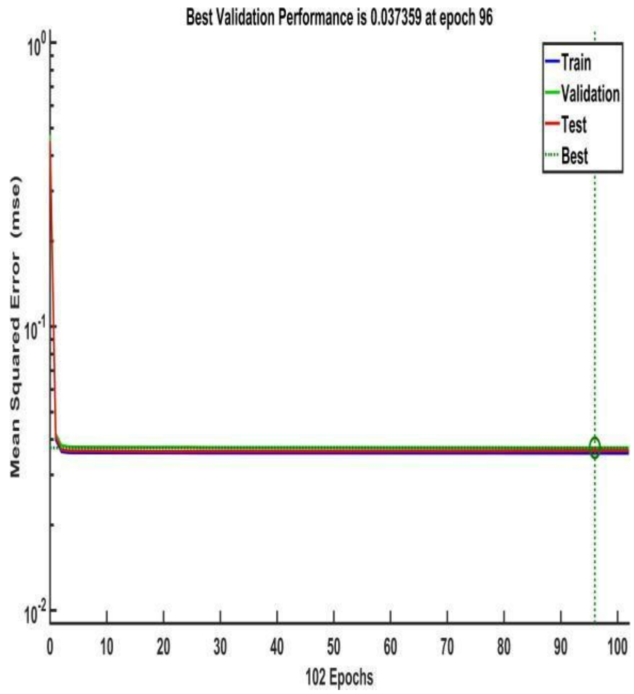

Fig 5: Performance of the neural model

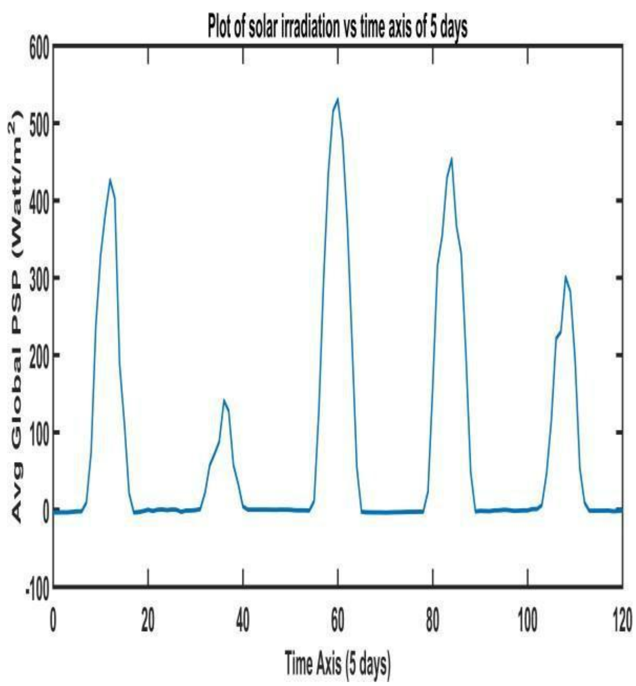

Fig 6: Irridation vs time

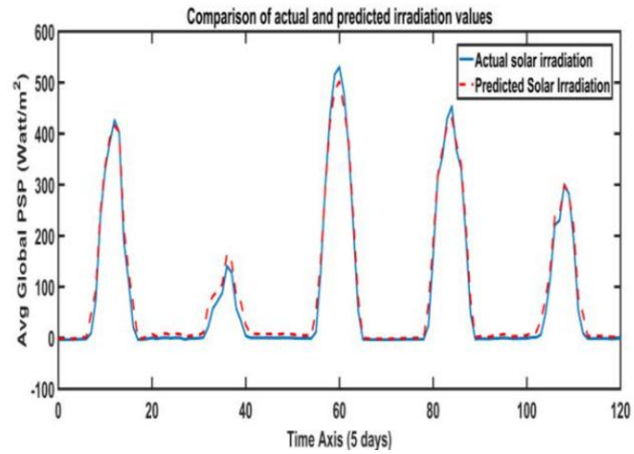

Fig 7: Plot of actual and predicted solar irradiation over a period of 5 days

IV. CONCLUSION

The prediction of average global radiation for a period of five days was undertaken based on the data collected from the sources mentioned. The predicted data gave close approximation to the actual measurement data and the mean square error for the trained model was found to be 0.0357. Further studies may include the effect of shading on the efficiency of the neural model.

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