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NEURAL NETWORK APPLICATIONS IN SOLAR IRRADIANCE PREDICTION

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ABSTRACT

In recent years, introduction of a renewable energy source such as solar energy is expected due to the expected depletion of other conventional energy sources. Solar energy is one of the most promising renewable energy sources. In order to integrate this type of source into an existing power distribution system, system planners need an accurate model that predicts the availability of the generating capacity. However, solar radiation is not constant and power output of photovoltaic (PV) system is influenced by many factors including weather conditions, location of the power plant and irradiation intensity, angle of incidence of the rays, sunshine duration, etc. This work focuses on prediction of solar irradiation, and thus the current/power generated during the day. In order to predict this to a successful extent, an artificial neural network is applied. The irradiation and other training data of one year (December 2012 to November 2013) have been derived from Tata Power Company's Mulshi Solar Power Plant. This paper compares outputs from various neural network models based on supervised learning rules.

KEYWORDS: Artificial Intelligence, Solar Energy, Solar Irradiance, Neural Network, Prediction

INTRODUCTION

The world is facing the threat of depleting fossil fuel resources which could cause a major setback to the world. Researches show that the fossil fuels will get depleted completely in the coming years. The existing system for power generation uses non-renewable resources as a major source which shall soon be depleted. Renewable resources are also being used for power generation but they aren't being used to their full extent.

The energy efficiency of a conventional thermal power station, considered salable energy produced as a percent of the heating value of the fuel consumed, is typically 33% to 48%. As with all heat engines, their efficiency is limited, and governed by the laws of thermodynamics. Generating over the maximum capacity will only reduce the lifespan of the system. Also not generating to the optimal capacity will result in resource loss. So optimization of thermal power plants includes identifying the optimal value of generation. Considering hydro power plants, the proportion of water for generation is almost fixed. The distribution of water for electricity generation and irrigation purposes is fixed and hence the generation is almost fixed. Also the time for which water is available is also fixed.

Wind energy is generally available at night. It should be noted that the cost of unit generated is directly proportional to the demand of energy. In summer seasons, there is hardly any wind while in monsoons a large amount of wind may be available. The time in the day is also unpredictable. Hence, there arises a need of a more reliant renewable source of energy, i.e., Solar Energy.

Solar is a green energy that consumes small streams to generate electricity without depends on any sources of non-renewable energy. Even though the power generated is less but the benefits gained from this energy is the ability to

raise the standard living of residents in remote areas and it does not emit any pollution gas which is able to give an unfavorable effect in the local environment, get free from pollution and helps to maintain sound health.

Solar resources are known to depict a high erraticism in space and time due to the influence of multiple climatic factors such as cloud cover, weather conditions, sunshine duration, etc. The probability distribution of irradiance variations is difficult to predict due to various uncertainties. For efficient conversion and utilization of the solar resource, the solar resource modeling is one of the most essential tools for proper development, planning, maintenance scheduling and pricing of solar energy system.

Solar irradiance is defined as the amount of electromagnetic energy incident on a surface per unit time and per unit area. The energy emitted by the Sun passes through space until it is intercepted by planets, other celestial objects, or interstellar gas and dust. The intensity of solar radiation striking these objects is determined by a physical law known as the inverse square law. Only about 40 %(general level) of the solar energy intercepted at the top of Earth's atmosphere passes through to the surface. The proportion is different under different weather conditions: this proportion is greater than 40% in sunny days, approximately equal to 40–50% in cloudy days and less than 40% in overcast days.

Artificial Neural Networks (ANNs) have been used widely in real world applications, including stock market prediction, flood or disaster prediction, medical diagnostic system, etc. With the advent of the need for efficient reusable energy, ANNs have now also been implemented in Solar Energy Prediction or Solar Irradiance Prediction nowadays.

ANNs are appropriate tools for solving real problems in the cases where classical methods are insufficient. Artificial Neural Networks (ANNs) is an efficient information processing system which resembles in characteristics with a biological neural network. ANNs can easily adapt to changing situations and timely variations. The ANN model that has been proposed in this paper, to estimate solar irradiation in Tata Power Company's Solar Power Plant at Mulshi is based on several input parameters. This study utilizes the commonly available parameter of sunshine hours, irradiation intensity, geographical locations of the power plant, etc. to develop an easy to use ANN model, using data covering a period of one year.

NEURAL NETWORKS & ITS ARCHITECTURES

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. A Neural Network can be defined as an interconnection of neurons, such that neuron outputs are connected, through weights, to all other neurons including themselves; both lag-free and delay connections are allowed.

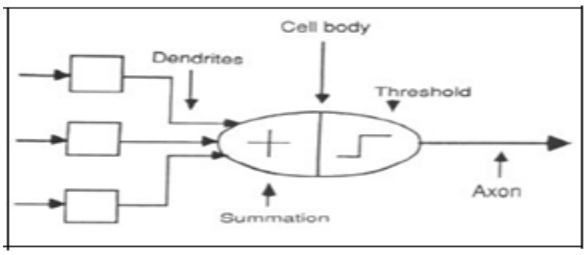

Figure 1: The Neuron Model

Neural network models in artificial intelligence are usually referred to as artificial neural networks (ANNs); these are essentially simple mathematical models defining a function f: X→ Y or a distribution over X or both X and Y, but sometimes models are also intimately associated with a particular learning algorithm or learning rule. A common use of the phrase ANN model really means the definition of a class of such functions (where members of the class are obtained by

varying parameters, connection weights, or specifics of the architecture such as the number of neurons or their connectivity).

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse.

Other Advantages Include

- **Adaptive Learning:** An ability to learn how to do tasks based on the data given for training or initial experience.
- **Self-Organisation:** An ANN can create its own organisation or representation of the information it receives during learning time.
- **Real Time Operation:** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
- **Fault Tolerance via Redundant Information Coding:** Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

Neural networks itself represents a collection of artificial intelligence models which include, multilayer perceptron neural network, recurrent neural network, modular neural network, radial basis network. Each of these models has its own specific structure, training method and area of application. A thorough understanding on each of them is necessary to make the best choice of network structures for solar prediction/forecasting tasks.

Input Connections

Unless the artificial neuron is an input neuron, a neuron is connected to other neurons and depends on them to receive the information that it processes. There is no limit to the amount of connections a neuron may receive information from. The information that a neuron receives from others is regulated through the use of weights. When a neuron receives information from other neurons, each piece of information is multiplied by a weight with a value between -1 and 1, which allows the neuron to judge how important the information it receives from its input neurons is. These weights are integral to the way a network works and is trained: specifically, training a network means modifying all the weights regulating information flow tonsure outputs are correct.

Activation Functions

The activation function helps in achieving the exact output, on applying the net input over the network. The information processing of a processing element can be viewed as consisting of input and output. A function is associated with the input’s processing. This function serves to combine activation, information or evidence from an external source. A non linear activation function is used to ensure that a neuron’s response is bounded. There are several activation functions as:

- Identity Function
- Binary Step Function
- Sigmoidal Function
- Ramp Function

Output Connections

Finally, once the activation function returns a corresponding value for the summed inputs, these values are sent to the neurons that treat the current neuron as an input. The process repeats again, with the current neuron's output being summed with others, and more activation functions accepting the sum of these inputs. The only time this may be ignored is if the current neuron is an output neuron. In this case, the summed inputs and normalized sum is sent as an output and not processed again.

Feed-Forward Networks

A Feed-Forward (FF) neural network is an artificial neural network where connections between the units do not form a directed cycle. This is different from recurrent neural networks. The FF neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network.

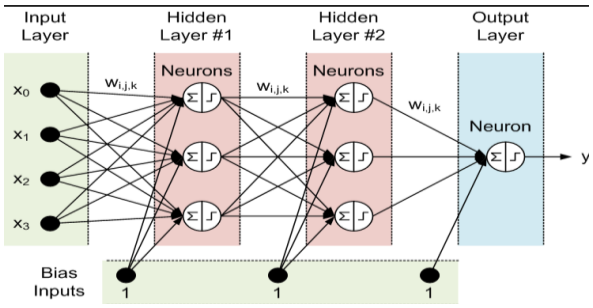

Figure 2: Feed Forward Network

Feed-Forward network models are of 2 types:

- Single layer FF network.
- Multilayer FF network.

The simplest kind of neural network is a single-layer perceptron network, which consists of a single layer of output nodes; the inputs are fed directly to the outputs via a series of weights. In this way it can be considered the simplest kind of feed-forward network. The sum of the products of the weights and the inputs is calculated in each node, and if the value is above some threshold the neuron fires and takes the activated value; otherwise it takes the deactivated value. Neurons with this kind of activation function are also called artificial neurons or linear threshold units. In the literature the term perceptron often refers to networks consisting of just one of these units. A similar neuron was described by Warren McCulloch and Walter Pitts in the 1940s.

A Multilayer FF network is formed by the interconnection of several layers. The input layer is that which receives the input and this layer has no function except buffering the input signal. The output layer generates the output of the network.

Radial Basis Function Network (RBFN)

Radial Basis Function Networks (RBFN) consists of 3 layers

- Input layer
- Hidden layer
- Output layer

The hidden units provide a set of functions that constitute an arbitrary basis for the input patterns. Hidden units are known as radial centres and represented by the vectors c1, c2… ch. The transformation from input space to hidden unit space is nonlinear whereas transformation from hidden unit space to output space is linear dimension of each centre for a p input network is p*1.

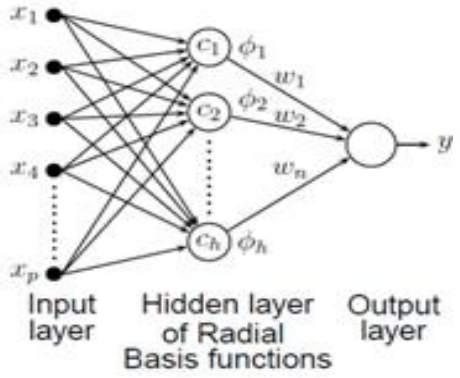

Figure 3: Radial Basis Function Network

Recurrent Neural Network

A recurrent neural network (RNN) is a class of neural network where connections between units form a directed cycle. This creates an internal state of the network which allows it to exhibit dynamic temporal behavior. Unlike FF neural networks, RNNs can use their internal memory to process arbitrary sequences of inputs. This makes them applicable to tasks such as un segmented connected handwriting recognition, where they have achieved the best known results.

Most RNNs have had scaling issues. In particular, RNNs cannot be easily trained for large numbers of neuron units nor for large numbers of inputs units. Successful training has been mostly in time series problems with few inputs.

EXISTING TECHNIQUES

ANN models have been used for various applications including pattern recognition, pattern classification, non-linear mapping, prediction and simulation. Among the different types of networks available currently, one of which implements the multilayer perceptron (MLP) network. A 3-layer multilayer feed forward (MLFF) and a 4-layer MLFF based on back propagation algorithm were developed, trained and tested for estimating monthly mean daily global radiation using the geographical, solar and meteorological parameters. The results obtained in the above mentioned study concluded that the model could be used to predict the monthly mean daily global radiation, since the ANN model had been trained to generalize for any new locations with similar climatic conditions. [1]

Another model was using an ANN based solar irradiance forecasting method, that used statistical feature parameters of irradiance and ambient temperature. Based on the description of solar irradiance variation, the relationship between surface irradiance and extraterrestrial irradiance was figured out. The comparison of measured data with forecasted values shows that the proposed model is both reliable and more effective. Furthermore, the simulation results also illustrated that the forecast accuracy is greatly improved by the new model under changeable weather conditions. [2]

A RBF neural network-based model, which has been compared with two linear models, has also been proposed. Simulation studies were made using the data from the National Solar Radiation Database (NSRDB) at three different sites. First, the proposed RBF neural network-based model had better performance than the Autoregressive (AR) and Local Linear regression (LLR) models in terms of the prediction accuracy. This is due to the RBF neural network's ability of

capturing nonlinear and time-varying nature of the solar radiation data. Second, the proposed model used novel 2D representation for hourly solar radiation, which gave more insight into the solar radiation pattern than the regular 1D representation. In addition, since transmissivity contains extra useful information about meteorological features, the normalization with transmissivity produced lower prediction errors than the sigmoid normalization. Moreover, simulation results indicated the success of using other meteorological variables to improve the Solar Power Prediction (SPP), among which the sky cover is the most important feature. [3]

The works of daily distribution of global solar irradiance for clear days have been predicted by the artificial neural network. In a particular model, the artificial neural network with 30 neurons in the first layer, 10 neurons in the second layer and 1 neuron in the third layer has been used, which contained five inputs and one output. The inputs are calculated extraterrestrial solar irradiation, the day in the year, the solar angle, the temperature and the relative air pressure, while the output parameter is the global irradiance.

For training of the artificial neural network measured data acquired in three years were used. Daily distribution of the global solar irradiance predicted by the trained artificial neural network was acceptable for clear days. However, some more work was needed to improve predicted daily distribution of global solar irradiance for cloudy days. [4]

Another designed ANN has one input parameter, sunshine hours. The ANN architecture that gives the better performance has sixty-five neurons in the hidden layer and the tangent sigmoid as the transfer function. The ANN model made predictions with Mean Bias Error (MBE) and Root Mean Square Error (RMSE), which were superior to the estimates from the empirical model but not to those in the several-parameter ANN model. The sunshine-based ANN model overestimates and underestimates global solar irradiation for a few of the months involved in the study.

This can be attributed to the fact that the input variable, sunshine hours, fed into the proposed ANN model may not have, entirely, described the nonlinearity nature of global solar radiation. The model needed more training data to increase its accuracy. The study has contributed to the field of prediction of global solar irradiation through design of an ANN model that is a lot easier to use. The several-parameter model is not convenient because it requires availability of all six weather and location. Similar methodology of prediction, that is, use of minimal input parameters, may be extended to other regions of the world. [5]

PROPOSED MODEL

We have proposed a Feed Forward neural network which has an input layer of 8 neurons, 1 hidden layer and an output layer with single neuron. The back propagation algorithm has been used for training the network. The model aims at predicting hourly Irradiance values.

Training Phase

There are two phases in this model architecture. The first phase will be training the model on a set of training data. The training phase can be divided into two parts, the propagation phase and the weight correction phase. In the propagation phase, the input data is normalized and fed to the network input nodes. A weighted sum of the inputs is calculated and fed to each hidden layer neuron.

The hidden layer neurons will use the sigmoid activation function for its calculation. After that, each hidden layer neuron passes the output to the output layer neuron. The output that is obtained (Irradiance value) is then compared with the desired output and the error signal is thus calculated. The error is generated from the Propagation Phase is used to update the weight.

The Prediction Phase

After the neural network has been trained for a given amount of training sets, it is then ready for prediction. After training with acceptable error, the weights are set into the network. We then give the trained network the input data set of the hour we want to predict the solar irradiance for. The trained network then predicts the hourly irradiance value using the input data set.

Input DATA

Geographical Position

The geographical position of the solar power plant plays an important role in determining the solar irradiance since it is more towards the equator than the poles. Hence, a mix of latitude and longitude of the plant will be used in the model.

Weather Conditions

The cloud cover and temperature of the surrounding area of the plant will be an essential input. As surrounding temperature increases, general solar irradiance values increase. On the same hand, the cloud cover determines if the sun rays will be falling on the PV panels or not.

Solar Tilt Angle

The optimum tilt (inclination) of solar collector with respect to user is an important subject from application of thermal / electrical energy point of view. By utilizing maximum solar energy through the optimum tilt, we are able to harness the energy needed without polluting our environment. Solar radiation data is usually measured in the form of global and diffuse radiation on a horizontal surface at the latitude of interest. Flat-plate solar collectors are tilted so that they capture the maximum radiation and the problem of calculating solar radiation on a tilted surface is in determining the relative amount of beam and diffuse radiation contained in the measured horizontal global radiation.

Previous Day Solar Irradiance

The solar irradiance value on the same time on the previous day would be considered as an input to get a trade-off between hourly/daily short term forecasting.

30 Minutes before Solar Irradiance

A 30 minute earlier solar irradiance value is useful in the case of short term predicting of the same.

45 Minutes before Solar Irradiance

A 45 minute earlier solar irradiance value is useful in the case of short term predicting of the same.

1 Hour before Solar Irradiance

Solar irradiance value of the hour before is useful in the case of short term predicting of the same.

Mean Sunshine Duration

Sunshine duration or sunshine hours is a climate logical indicator, measuring duration of sunshine in given period (usually, a day or a year) for a given location on Earth. It is a general indicator of cloudiness of a location.

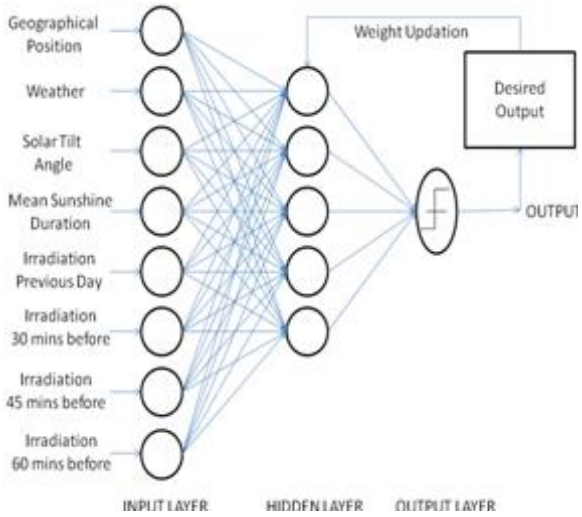

Figure 4: ANN for Solar Irradiation Prediction

CONCLUSIONS

The ANN model as discussed above has considered many essential input parameters which were not taken into perspective in previous papers. The advantage of taking these inputs is that the network would give an efficient prediction of irradiation, close to real values and thus help in optimising the power generation from solar plants.

In future models, there is a scope for including more input parameters if possible with different network architecture. Also things like condition based cleaning and automating the cleaning processes for solar panels can be implemented to further optimize the solar energy generation from the solar plants.

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