

Artificial Neural Network Model for Predicting Direct Solar Radiation for a Single Grid Node by MAT LAB

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Abstract

Due to the climate change the prediction of natural resources like solar radiation and rain are differing each year. Even though lot of arithmetical predictions are available software oriented methods are always more vital. Here we use mat lab for predicting solar energy from 30244 nodes from all over India. The data has been used as the raw material for prediction the solar energy. We are using direct solar readings which is measured from 30244 nodes, with are different Longitudes, Attitude all over the India for the 12 months for the year of 2015.

Keywords: Neural Network, solar energy, Mat lab

INTRODUCTION

A neural network is a massively parallel distributed processor made up of simple processing units that have a natural tendency for storing experiential knowledge and making it available for us. Artificial neural network (ANN) is a type of Artificial Intelligence technique that mimics the behaviour of the human brain [2]. ANNs have the ability to model linear and non-linear systems without the need to make assumptions implicitly as in most traditional statistical approaches. They have been applied in various aspects of science and engineering [3]. ANNs can be grouped into two major categories: feed-forward and feedback (recurrent) networks. In the former network, no loops are formed by the network connections, while one or more loops may exist in the latter. The most commonly used family of feed-forward networks is a layered network in which neurons are

organized into layers with connections strictly in one direction from one layer to another[4]. A study on the solar energy potential of 17 Turkish cities was conducted by [5]. The study used different meteorological and geographical factors (latitude, longitude, altitude, month, averages of sunshine duration and mean temperature) as inputs for the neural networks. Data for 11 stations were used to train the neural networks, while data from the other six stations were used for testing. The results showed a MAPE and absolute fraction of variance (R^2) of 6.7% and 99.89%, respectively. In a similar study carried out by Sozen[6], the solar potential of 12 cities spread over Turkey was predicted using neural networks based on same meteorological and geographical factors. Data for nine stations were used to train the neural networks, and data from the other three stations were used for testing. The results obtained showed values for MAPE and R^2 of 6.78% and 99.78%, respectively. To estimate the global solar radiation for Abha in Saudi Arabia, [7] used air temperature, the number of days and relative humidity as inputs for neural networks. The results showed a mean absolute percentage error of 4.49%. Jiang

ARTIFICIAL NEURAL NETWORKS

ANNs are a computing paradigm that mimics the human brain and nervous system. ANNs can actually mimic natural intelligence because they learn from experience [7] and are superior to other models [8]. Neural networks are “data-driven” as opposed to “model-driven” approaches [9]. They consist of numerous numbers of interconnected processing elements called neurons. ANNs consist of an input layer, a

hidden layer and an output layer [10]. They are able to learn, memorize and create relationships between inputs and outputs [5], which is a capability absent from empirical methods [11]. The learning process of ANNs occurs by adjusting the weights associated with each connection so that the actual output is similar to the desired output [10]. According to [12], ANNs are actually a statistical tool, a type of non-parametric regression model that can be employed in prediction and classification problems. In ANNs, weights are estimated for fitting the model in a similar way that coefficients are estimated when using empirical statistical methods. ANNs have been used to solve complex problems in real life situations [13] and have become an essential part of prediction models applied to situations of uncertainty [8]. While the instrumentation for measuring radiation is costly, there is a need to explore other techniques to accurately measure or predict solar radiation. ANNs are an attractive alternative because they have a high prediction accuracy compared to classical methods [14]. For these and other reasons, ANN techniques have become alternative methods to conventional techniques in a number of solar energy applications.

Definition of the problem

In future all the energy system will be depend upon the PV cells. PV System needs the solar energy as a source .prediction of solar energy is the main criteria for basis of the system..so we design a solar prediction model by MAT lab Neural networks .the figure 2 shows the NERL IAMGE of India direct solar radiation. .In this work, the maximum temperature (°C), mean wind speed(knot), sunshine(hours), mean relative humidity(%) and solar radiation (kWh/m2) for India are provided by NREL INDIA the year of 2015.

DESIGNING AND PROGRAMMING ANN MODELS

Designing ANN models follows a number of systemic procedures. In general, there are five basics steps:

1. Collection of data,
2. processing data,
3. Network building,
4. Training of network,
5. Performance

The design model is as shown in fig 3.

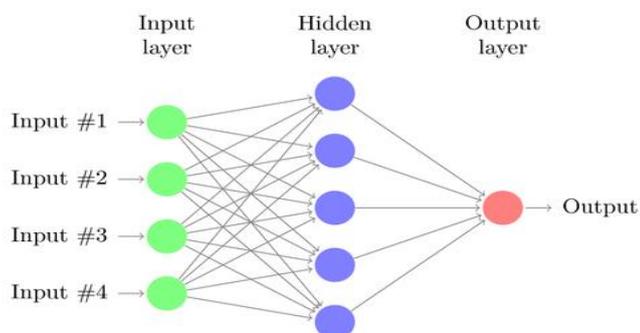


Figure 1: Neural Network

	A	B	C	D	E	F	G	H	I	J
3	74453705	74.45	37.05	3.66112860731	2.66010009766	2.38860009766	2.83600000000	2.79760009766	4.47289990234	6.4638
4	74553705	74.55	37.05	27.95287750850	2.41189990234	2.16139990234	2.72269995117	2.59910009766	4.27900000000	6.5907
5	74653705	74.65	37.05	55.22568441710	2.66330004883	2.46710009766	2.81930004883	3.86400000000	5.04639990234	6.9477
6	74753705	74.75	37.05	37.70858493590	3.51400000000	2.75030004883	4.45310009766	4.31410009766	5.75029980469	6.4551
7	74853705	74.85	37.05	5.09461759641	1.82669995117	2.29910009766	2.95310009766	3.84089990234	4.76170019531	6.1192
8	75153705	75.15	37.05	22.38576636060	2.71610009766	2.58110009766	2.86430004883	4.04069995117	4.82229980469	5.6812
9	75253705	75.25	37.05	65.56430176080	3.61910009766	3.78900000000	4.04160009766	3.79069995117	4.71310009766	5.9496
10	75353705	75.35	37.05	18.89060967650	2.53339990234	2.68769995117	4.01969995117	4.35570019531	4.84570019531	5.7272
11	73653695	73.65	36.95	1.76253667518	1.94559997559	3.67839990234	2.40860009766	2.52000000000	4.30339990234	7.0186
12	73753695	73.75	36.95	0.06234618947	2.00290002441	2.29169995117	2.15360009766	2.41489990234	4.52039990234	7.1190
13	74153695	74.15	36.95	6.14014525897	2.59260009766	2.08930004883	2.69360009766	2.97939990234	4.47770019531	6.7437
14	74253695	74.25	36.95	20.23923785340	3.64910009766	2.43639990234	2.80689990234	2.94600000000	4.96710009766	6.2261
15	74353695	74.35	36.95	79.59098139350	3.27039990234	2.04200000000	2.29400000000	2.69360009766	4.81860009766	6.7500
16	74453695	74.45	36.95	98.82138287300	3.64700000000	2.73239990234	3.05060009766	2.96189990234	5.07970019531	7.0476
17	74553695	74.55	36.95	91.46740301560	3.49969995117	2.85230004883	3.18510009766	4.08200000000	5.59829980469	6.1038
18	74653695	74.65	36.95	98.84685141420	3.62860009766	2.86669995117	3.68539990234	3.88930004883	5.86010009766	6.2948
19	74753695	74.75	36.95	98.84685141420	2.71000000000	2.96500000000	3.91789990234	4.42270019531	5.70210009766	6.5708
20	74853695	74.85	36.95	68.00927426810	2.41230004883	2.35289990234	3.78410009766	3.94289990234	4.90429980469	5.9636
21	74953695	74.95	36.95	66.65841799130	2.62260009766	2.06000000000	2.73210009766	2.99430004883	4.88139990234	6.6867
22	75053695	75.05	36.95	73.75932293210	3.38860009766	2.89239990234	3.90839990234	4.08639990234	5.65210009766	6.0113
23	75153695	75.15	36.95	94.16052857450	3.61330004883	2.72489990234	2.97389990234	3.66460009766	4.56570019531	5.4422

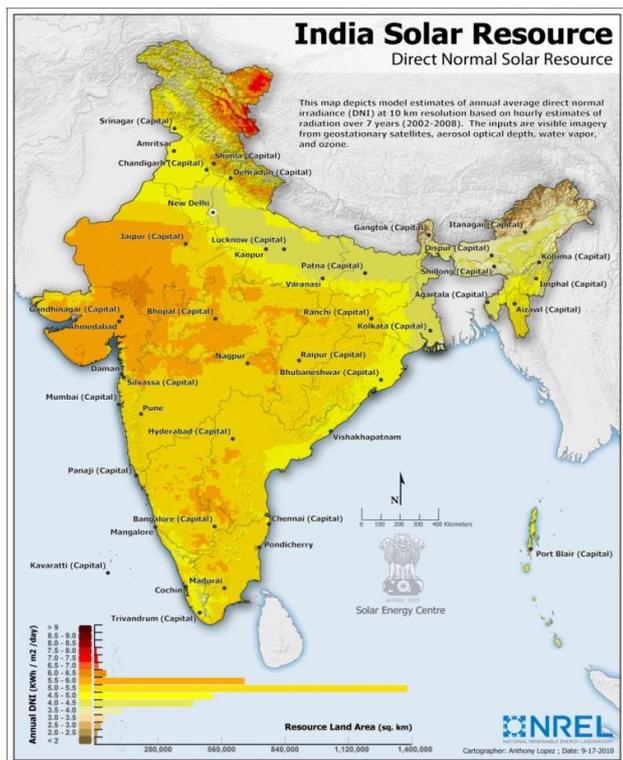


Figure 2: Direct solar radiation of INDIA

Collection of data

The data is collect with longitude and latitude with different sea level from 30244 grids, for 12 months is measured. This data is raw source for neural network in to Excel sheet.

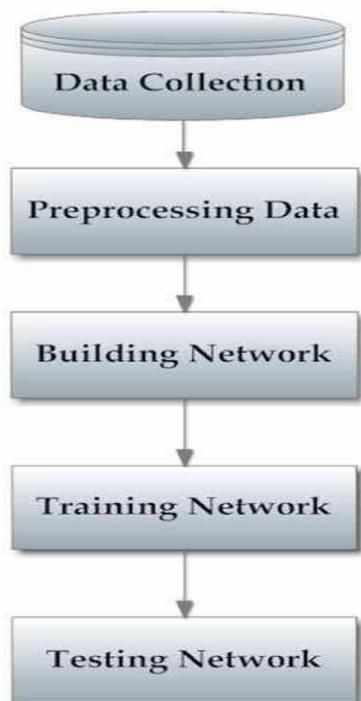


Figure 3: Design steps for ANN

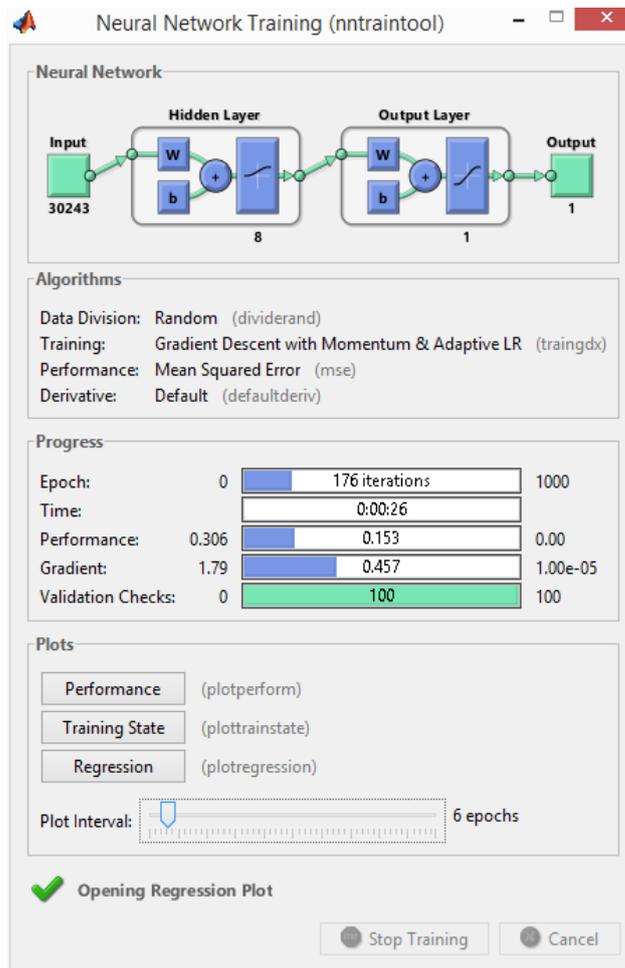


Figure 4: Net work Mat lab trainer

Processing Data

The methods followed for processing the data are

- (1) Solving the missing data,
- (2) Normalizing the data
- (3) Data randomizing.

Neighbouring data is used solving the missing data. Normalization procedure before presenting the input data to the network is usually used, since mixing 6 .decimal numbers are minimized to 4 decimal values are minimized to 4 decimal values.

Network building

Network building specifying the mat lab number of hidden layer we are setting the hidden layer to 8. The neurons are set to 10. Ant train the system for 1000 epoch levels this will decide the iterations level to 1000. Two training function, weight/bias learning function, and performance function are used.

The Training Of network

Weights are adjusted during the process. For predicted output near to the target. 1 year date 30524 grid nodes for 12 months are time has taken.

Testing the network

The network is tested using network synthesizer. As shown in the Figure 4. The output graphs are plotted.

1. Performance
2. Training state
3. Regression

EXPERIMENTAL RESULTS

1. Performance

The performance graph Figure 5 shows the blue line training of network, red line shows tested data, dotted line best performance of the network of a particular grid of node.

2. Training state

The training state is shown in Figure 6. This graph shows the training state gradient, validation, epoch's level of the network

3. Regression

Fig 7 gives the regression graphs. Solar radiation variables are set to the statistical processes using regression Analysis. It shows the plots of trained data in blue, dotted lines show the predicted energy from the network.

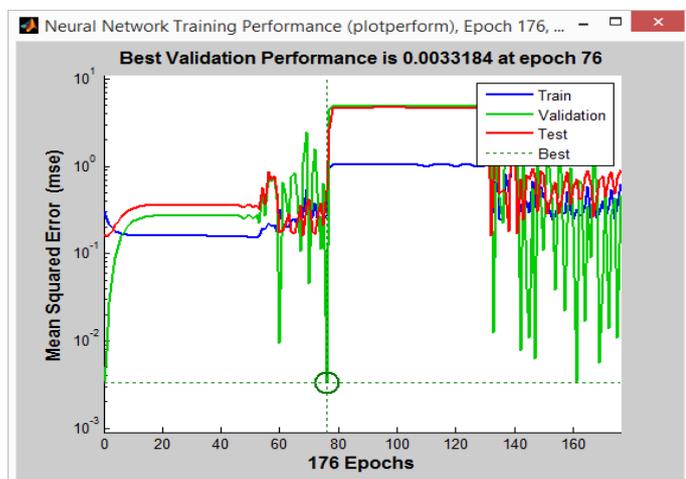


Figure 5: Performance graph

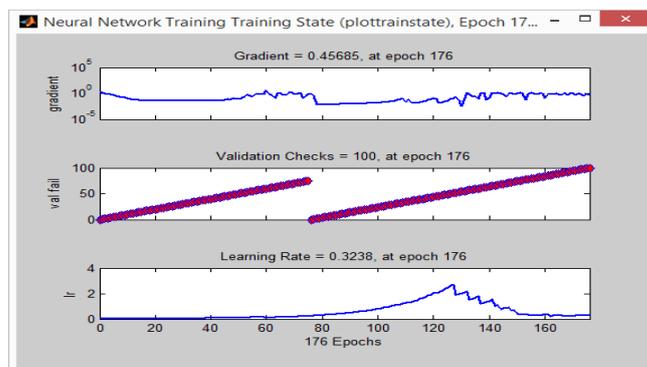


Figure 6: Training state

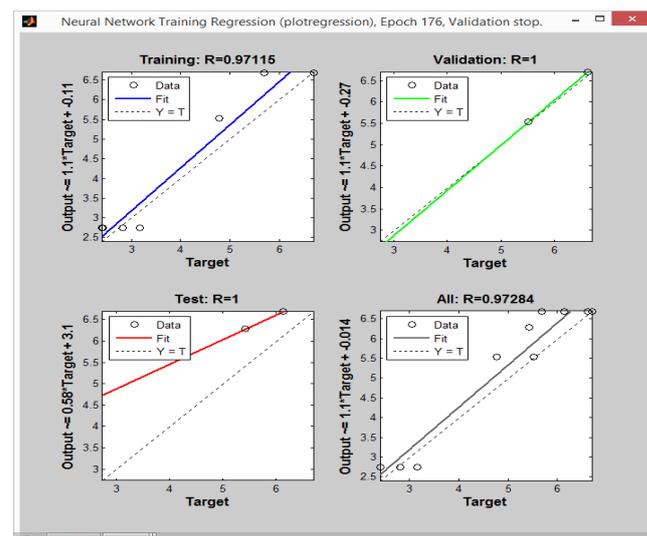


Figure 7: Regression graphs

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