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Solar Energy Prediction using LM-Back-propagation in ANN

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Abstract:*Artificial intelligence has made its presence felt ubiquitously in different avenues of research and technology wherein the data is large and complex. In the proposed work, to forecast solar irradiation energy; whose structure uses the back-propagation concept and uses the Levenberg Marquardt algorithm is used. The system used hitherto a single layer of hidden neurons. The averaging approach is also been used with 2, 12- and 24-hour averaging scheme so as to increase the accuracy of prediction. The system attains a MAPE of 2.7%. Hence the accuracy attained is 97%. The mean square error has been chosen as the performance function for the proposed algorithm.*

Keywords: *Solar Energy Prediction, Artificial Neural Network (ANN), Back Propagation, Levenberg-Marquardt (LM) Algorithm, Mean Absolute Percentage Error (MAPE).*

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I. Introduction

Artificial intelligence is a computational technique that is being used in several application where the data size is exhaustive and complicated in nature. The practical way to implement artificial intelligence is the design of artificial neural network that takes the onus of mimicking the very nature and the characteristics of human brain.. In this case, the data is that of solar irradiation. The data being complicated and un-correlated grabs the attention of artificial intelligence-based applications so as to clearly be able to extract meaning out of the complex valued pattern of the data.The mathematical conversion of the ANN can be done by analyzing the biological structure of ANN. In the above example, the enunciated properties of the ANN that have been emphasized upon are:

- Strength to process information in parallel way.
- The power to grasp and learn from weights
- Searching for patterned sets in complex models of data.

To see how the ANN really works, a mathematical model has been devised here, to indicate the functions mathematically.[9]-[11]. Here it is to be noted that the inputs of information parallel goes on into the input layer as specified whereas the end result analysis is marked from the output layer.

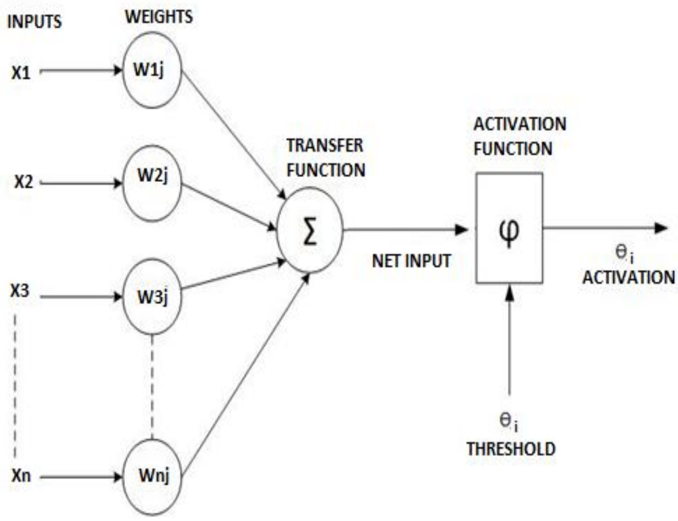

Figure 1 Mathematical Modeling of ANN

The figure above illustrates the ANN mathematical model.

The feature of parallel acceptance and processing of data by the neural network serves a vital role. This ensures efficient and quicker mode of operation by the neural network. Also adding to it, the power to learn and adapt flexibly by the neural network aids in processing of data at a faster speed. **[2]**These great features and attributes make the ANN self dependent without requiring much intervention from humans. The ANN output can be put forth like:

$Y = \sum_{i=1}^{n} X_i . W_i \;\; + \;\; \theta_i$

Here,
Output by ANN marked by y
x signifies the inputs to the ANN
The weights of the ANN shown by w
ϕ denotes the bias.

Training of ANN is of major importance before it can be used to predict the outcome of the data inputs. Many methodologies have been proposed to train ANN, but from them the most useful and apt technique is the way of back propagation. Undoubtedly it is a very good technique to be employed.

II. Back Propagation in ANN

This method uses the fact of utilizing the feedback of errors sent from the networking domain and again given back to the system. This way, following features are obtained well:
1) Reductionin succession of errors
2) Lessening of errors at a faster paces

Hence the method of back propagation yields in reducing the errors and that also the decrease in the errors is at a rapid rate .The figure underneath has been used to depict the ANN model in a mathematical manner.[7] The method of back propagation feeds the measure of errors back to the network system till the errors don't decrease below a certain threshold or limit. This is termed as the maximum tolerable error. There exists some scenario, if the design of the entire system is such that the amount of the prediction errors of the system does not reduce below the specific error tolerance even after many rounds of iterations of training till he particular epoch, a message of failure is shown by the system. Three widely used methods for back propagation are:
1) Levenberg-Marquardt (LM) algorithm.
2) Bayesian Regularization (BR) algorithm.
3) Scaled Conjugate Gradient (SCG) algorithm.

From among the methods mentioned above, the LM algorithm exhibits minimum number of errors having low time of execution which signifies that it requires lesser number of iterations for getting trained. The flowchart of the LM algorithm is displayed underneath:[11] The attributes of the LM algorithm lie in the fact that it is:
a) Fast
b) Stable

Hence it doesn't render fluctuating errors for time series predictions. The conceptual flow diagram of the back propagation mechanism and the LM algorithm have been shown in the figures below.

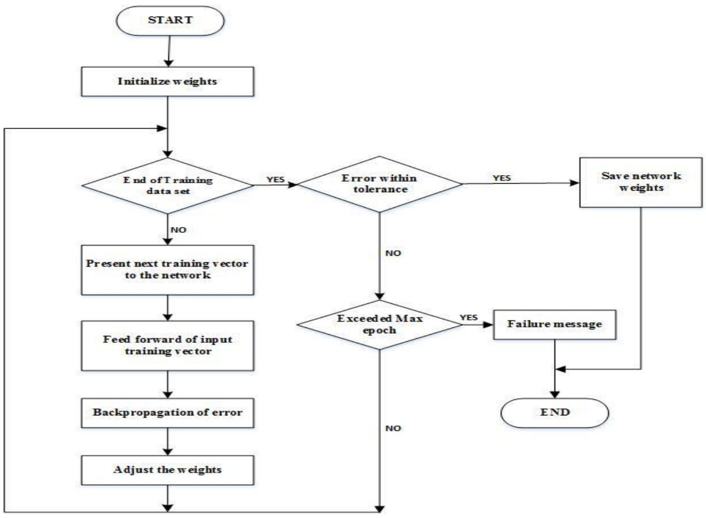

Figure 2. Flowchart of Back Propagation

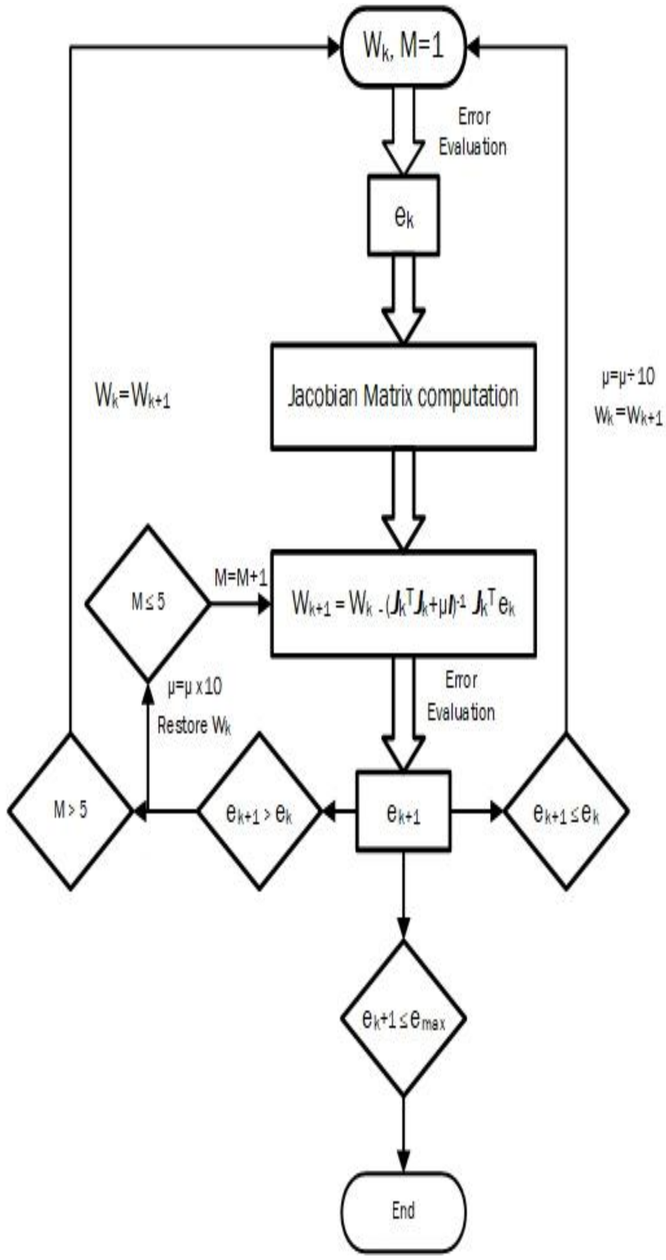

Figure 3 Flow diagram of LM Algorithm

The biggest merit of LM Algorithm is that it happens to be a mix of two power techniques namely:
1) Steepest descent technique and
2) The Gauss-Newton Technique

Algorithm	**Rules**	**Convergence**
Gradient Newton algorithm	$W_{k+1} = W_k - \alpha g_x,\ \alpha = \frac{1}{\mu}$	Stable, slow
Gauss – Newton algorithm	$W_{k+1} = W_k - [J_K{}^T J_k]^{-1} J_K{}^T e_k$	Unstable, fast
Levenberg – Marquardt (LM) algorithms	$W_{k+1} = W_k - [J^T{}_k J_k + \mu I]^{-1} J_k e_k$	Stable, fast

Table.1 Comparative Analysis of LM algorithm

The LM algorithm gives both speed and also makes the error prediction stable. That conveys-
1) Lesser time is required to train the ANN utilizing LM Algorithm
2) There is reduction in errors with subsequent numbers of iterations that reflects decay in mse. A integral ground of this algorithm is computing the Hessian matrix deploying the Jacobian matrix that stands for the second order rate of change of errors relative to number of weights.
The Levenberg –Marquardt algorithm is in actuality a mix of the steepest descent method and the Gauss–Newton algorithm. The relation for LM algorithm computation is indicated as follows:-

$$W_{n+1} = W_n - [J_n J_n^T - \mu I]^{-1} e_n J_n^T$$

Where,
I depicts an identity matrix
W_n depicts weight of iteration n,
W_{k+1} depicts weight of iteration n+1
E_n is the weight of iteration n
μ is indicated as the step size that formulates number of parallel inputs to the ANN architecture.

III. System Design

This prevalent system of data utilizes data from the data centre located at the place of Texas :(http://mrcc.isws.illinois.edu/CLIMATE/Hourly/StnHourBTD2.jsp) for a time domain of 28 months (in hourly intervals)
The data has been priory processed and then formulated according to:
1) Set of missing values.
2) Set of values that not feasible.
In addition to that the data is modified to be fed to the ANN in and as:
1) one hour data in the final hour
2) two hours data in the final time domain
2) Last 24 hours' set of data

The data is then broadly divided into a training data set and another is the testing data set. 70% training & 30% testing;of the data is deployed for testing. The LM algorithm is implemented for simulation and training of the ANN structure in an effective way.
Following illustrate the performance metrics pertinent to the system designed based on the ANN topology:
1) Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{M} \sum_{t=1}^{N} \frac{E - E_t|}{E_t}$$

Here E_t and $E_t^{\sim}$ stand for the predicted and actual values respectively.
The number of predicted samples is indicated by M.
2) Regression
The amount of similarity between the predicted and actual value set is referred as Regression. The maximum regression value is 1 signifying complete similarity whereas the minimum value is 0 that shows no similarity.

IV. Results

The results have been evaluated based on: The results have been evaluated based on the following parameters:
1. (MAPE)
2. Regression
3. MSE w.r.t. the number of epochs

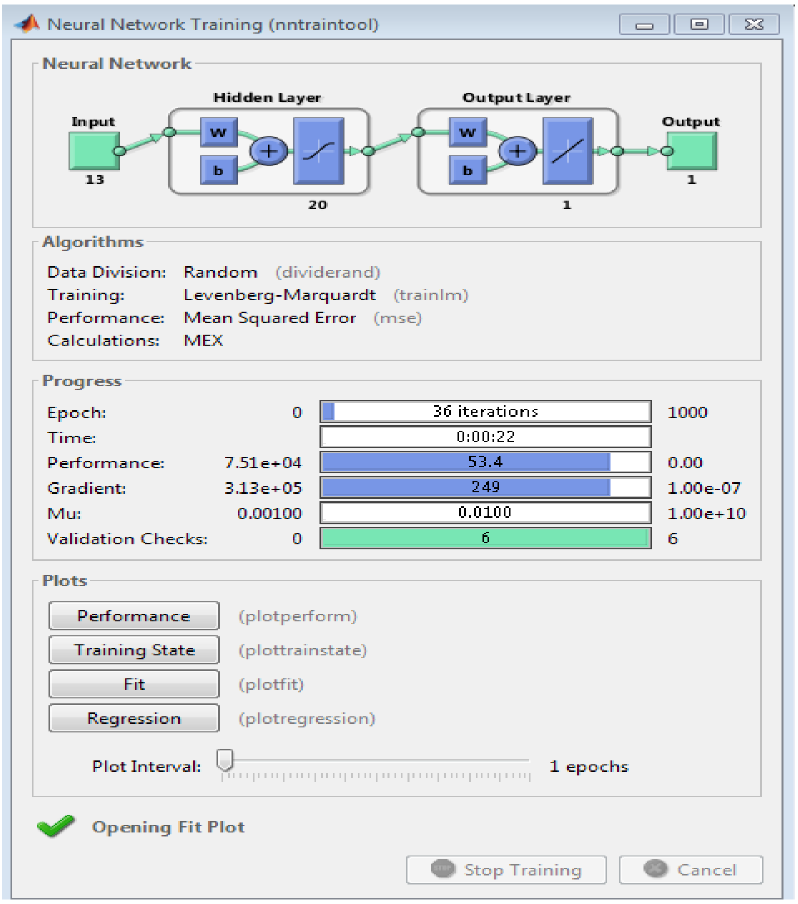

Figure 4 Designed ANN Structure

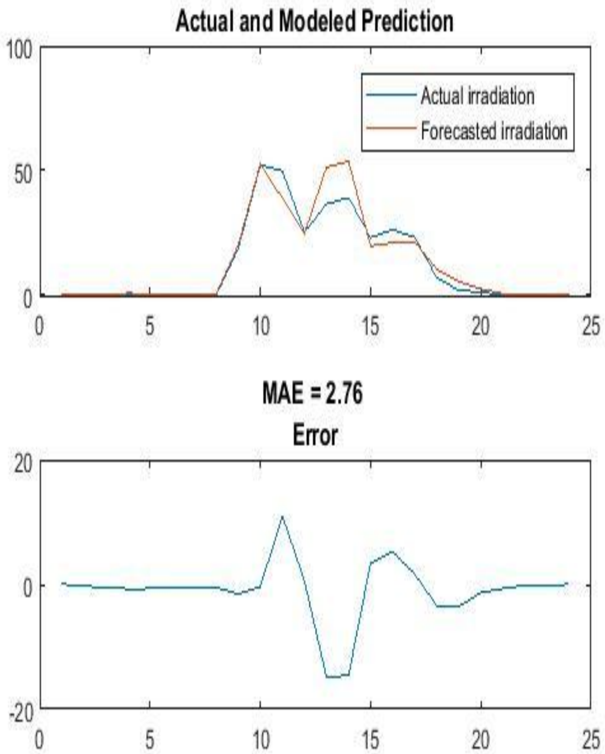

Figure5. Predicted and Actual Solar Irradiation

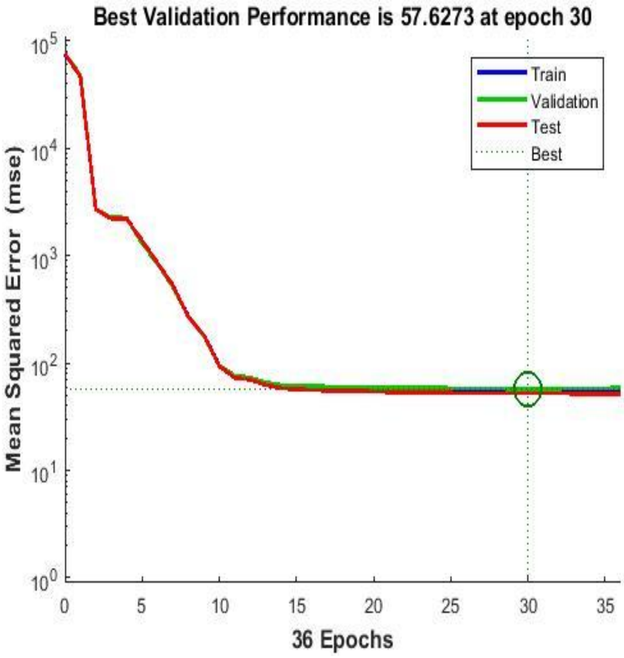

Figure6. Reduction of MSE with respect to epochs

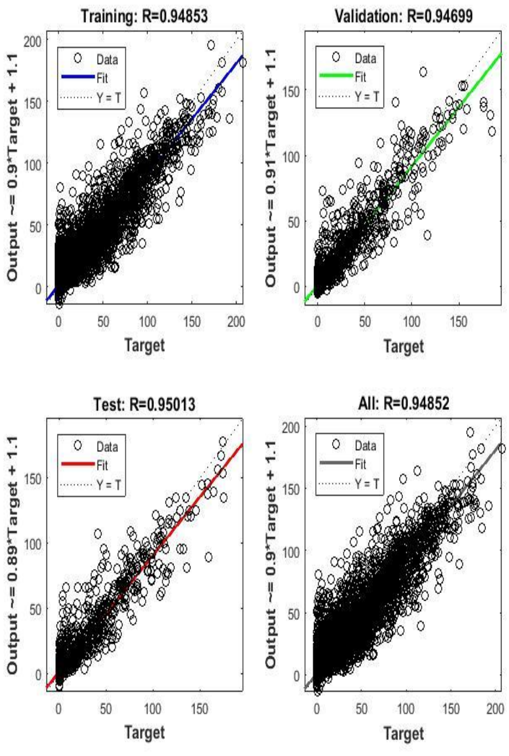

Figure7 Regression Analysis of proposed system

V. Conclusion

The approach used in the paper uses the efficacy of back propagation to forecast solar energy irradiation, wherein the Levenberg-Marquardt training rule is applied for machine learning. An averaging as well as penultimate approach has been used to enhance the accuracy of the system. The accuracy attained is approximately 97% by dint of the low MAPE value. Thus it can be conceded that the proposed approach is an effective mechanism for complex data analysis pertaining to solar irradiation for accurate prediction.

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