Design of Machine Learning Based Regression Model for Improved Solar Irradiation Prediction

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Abstract— **Artificial intelligence and machine learning have 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 algorithm is used. The averaging window approach is also been used so as to increase the accuracy of prediction. The performance metrics which have been evaluated are the gradient, combination co-efficients, mean squared error and mean absolute percentage error. The system attains a MAPE of 1.77%. Hence the accuracy attained is 98.23%. The mean square error has been chosen as the performance function for the proposed algorithm.**

Keywords—Solar Energy Prediction, Back Propagation, Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Regression.

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:

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

The mathematical model for the Neural Network is depicted in figure 1.

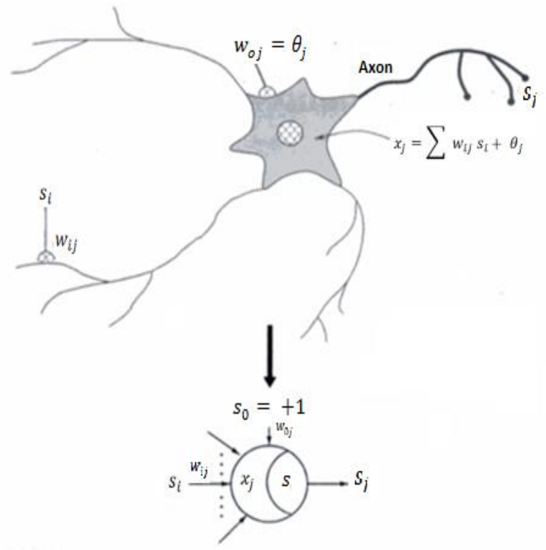

Fig.1 Biological-Mathematical Counterpart of ANN

Solar irradiation forecasting is increasingly critical in today's energy landscape. As the world shifts towards renewable energy sources, solar power has become a key player in reducing carbon emissions and ensuring sustainable energy production. Accurate forecasting of solar irradiation, which refers to the amount of solar energy received per unit area, is essential for optimizing the performance and efficiency of solar power systems. For grid operators and energy managers, solar irradiation forecasting allows for better planning and management of energy resources. By predicting the amount of solar energy that will be generated, they can balance supply and demand more effectively, reduce reliance on non-renewable energy sources, and prevent energy wastage. This is especially important in regions with high solar energy penetration, where variability in solar power can significantly impact grid stability.

II. NEED FOR MACHINE LEARNING FOR SOLAR IRRADIATION FORECASTING

As solar irradiation values are extremely volatile and fluctuating in nature, hence machine learning models are useful for forecasting solar irradiation. The need for solar irradiation forecasting has also driven advancements in technology. Improved models, data analytics, and machine learning techniques are being developed to enhance the accuracy of forecasts. These technologies not only benefit solar power but also contribute to the broader field of renewable energy forecasting, leading to more resilient and adaptive energy systems. Accurate solar irradiation forecasting also plays a role in mitigating environmental impacts. By enhancing the reliability and integration of solar power into the energy grid, it reduces the need for backup power from fossil fuels, thereby lowering greenhouse gas emissions. Moreover, it supports the global transition to a cleaner, more sustainable energy system, which is vital for combating climate change.

On a broader scale, solar irradiation forecasting contributes to the economic viability of solar energy projects. By reducing the uncertainty associated with solar power generation, it helps in lowering operational costs, improving investment returns, and encouraging further investment in solar energy. Additionally, it can assist in the development of energy trading markets, where accurate forecasts are crucial for pricing and decision-making. Machine learning (ML) models have emerged as powerful tools in this domain, offering advanced techniques for predicting solar irradiation with higher precision. These models can analyze vast amounts of data, learn complex patterns, and improve forecasting accuracy over traditional methods, making them indispensable in modern energy management.

Supervised learning models, such as linear regression, support vector machines (SVM), and decision trees, are commonly used for solar irradiation forecasting. These models require historical data on solar irradiation, weather conditions, and other relevant variables to train the model. Once trained, they can predict future solar irradiation levels based on new input data. For instance, decision trees and random forests have been particularly effective in capturing non-linear relationships in data, making them popular choices in solar forecasting. Artificial Neural Networks (ANNs) have shown great promise in solar irradiation forecasting due to their ability to model complex, non-linear relationships in data. ANNs, inspired by the human brain, consist of interconnected neurons that process inputs and produce outputs. When applied to solar forecasting, ANNs can handle large datasets, such as historical weather data, satellite images, and solar irradiation records, to generate highly accurate predictions. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which are specialized forms of ANNs, are particularly effective in time-series forecasting, making them ideal for predicting solar irradiation

III. NEURAL NETWORKS AND BACK PROPAGATION

To see how the ANN really works, a mathematical model has been devised here, to indicate the functions mathematically.. 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.

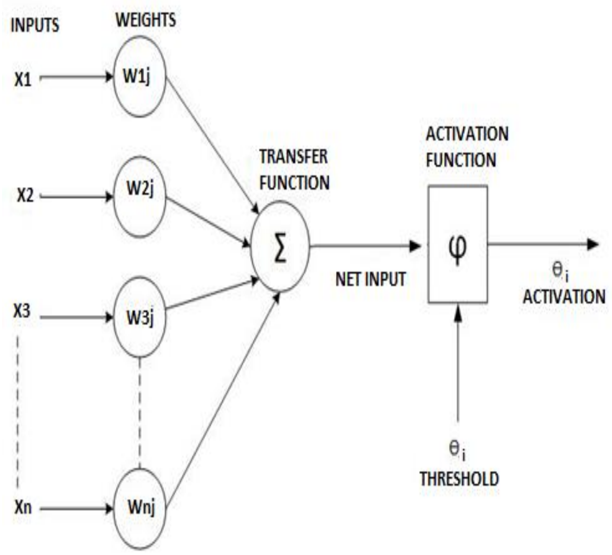

Fig.2 Mathematical Modeling of ANN

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:

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

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.
f denotes the activation function.

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. 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) Reduction in 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. 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.

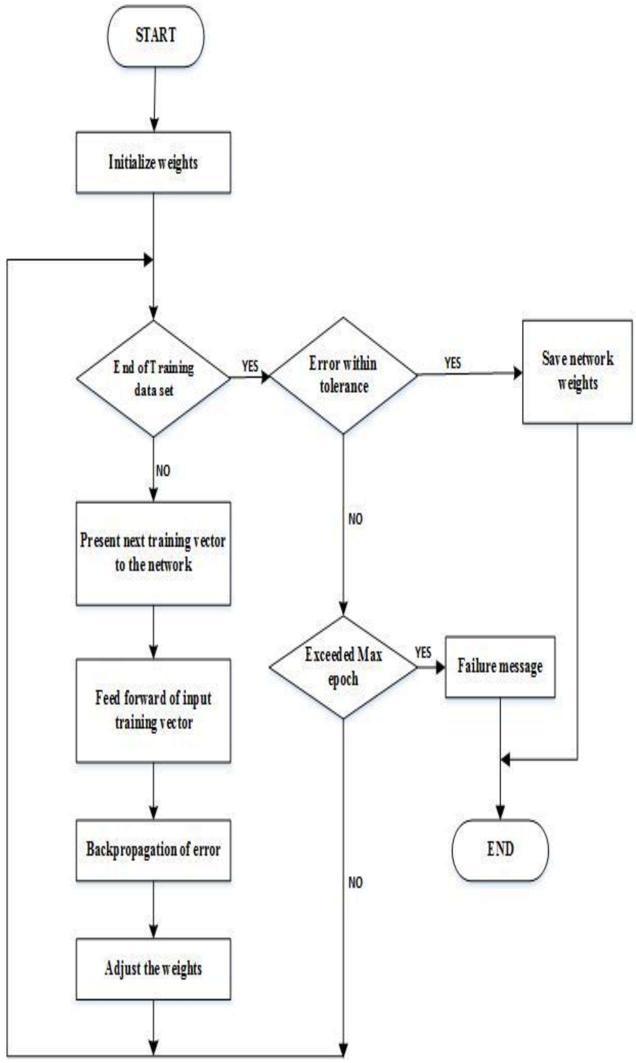

Fig.3 Flowchart of Back Propagation

The BP algorithm gives both speed and also makes the error prediction stable. That conveys-

1) Lesser time is required to train the ANN utilizing back propagation.

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 that stands for the second order rate of change of errors relative to number of weights. The weight updating rule for the back propagation algorithm is presented next:

$$W_{n+1} = W_n - \alpha \frac{\partial e}{\partial w}$$

Where,

W_n depicts weight of iteration n,

W_{k+1} depicts weight of iteration n+1

α depicts the learning rate.

$\frac{\partial e}{\partial w}$ denotes the gradient.

The algorithm for the proposed work is given by:

Start
{

Step.1: Extract dataset.

Step.2: Divide Data into training and testing samples.

Step.3: Define maximum number of iterations as $maxitr$.

Step.4: Define least squares (LS) cost function to be minimized as:

$$f_{cost} = \underbrace{min}_{maxitr} \frac{1}{n}\sum_{i=1}^{n}(t_i - \hat{t}_i)^2$$

Step.5: Design a neural network and initialize weights randomly.

Step.6: for i=1:maxitr,
{
Update weights as:

$$\boldsymbol{w_{i+1} = w_i - \alpha \nabla f_{cost}(w_i) - \left[\begin{bmatrix} \frac{\partial^2 e_1}{\partial w_1^2} & \cdots & \frac{\partial^2 e_1}{\partial w_m^2} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 e_n}{\partial w_1^2} & \cdots & \frac{\partial^2 e_n}{\partial w_m^2} \end{bmatrix} * \begin{bmatrix} \frac{\partial^2 e_1}{\partial w_1^2} & \cdots & \frac{\partial^2 e_1}{\partial w_m^2} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 e_n}{\partial w_1^2} & \cdots & \frac{\partial^2 e_n}{\partial w_m^2} \end{bmatrix}^T + \alpha I\right]_i^{-1} * (t_i - \hat{t}_i)}$$

}

Step.7: if ($i == maxitr$ or f_{cost} stabilizes over k-fold, validation)
{
Truncate training
else
Update weights
}

Step.8: Computer forecasting error and accuracy at convergence.
}
Stop.

Here,
The least square optimization is considered as the cost function.
I is an identity matrix.
α is the learning rate.
t_i and $\hat{t}_i$ are the target and predicted values.

Following illustrate the performance metrics pertinent to the system designed based on the ANN topology:
1) Mean Absolute Percentage Error (MAPE)

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

Mean Squared Error (MSE)

$$MSE = \frac{1}{N}\sum_{t=1}^{N} e_t^{\,2}$$

Here,
E_t and $E_t^{\sim}$ stand for the predicted and actual values respectively.
The number of predicted samples is indicated by M.

IV. EXPERIMENTAL RESULTS

This data utilized has bene extracted from Kaggle with each day and each hour data.
In addition to that the composite data, a moving window of samples just prior to the testing samples has been computed separately to render recent information to the model for more accurate prediction. The following section presents the experimental results obtained through the simulation.

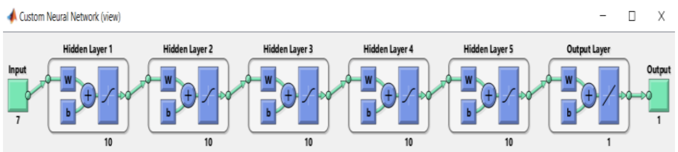

Fig.4 Designed Model

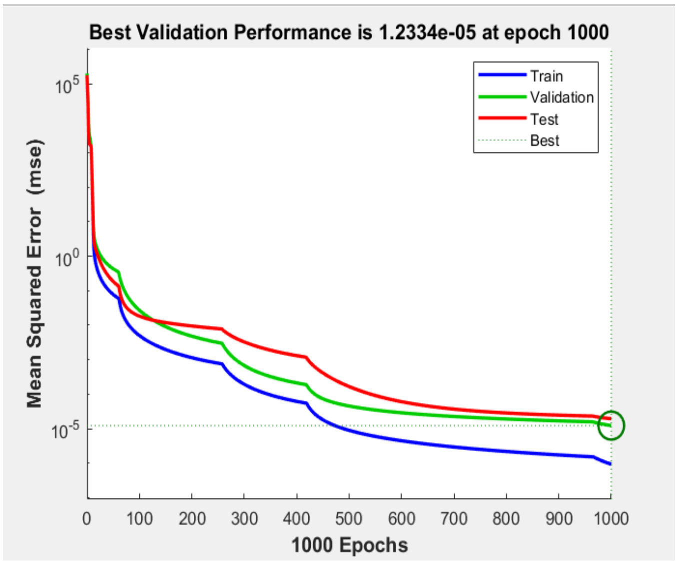

Fig.5 Iterations to convergence

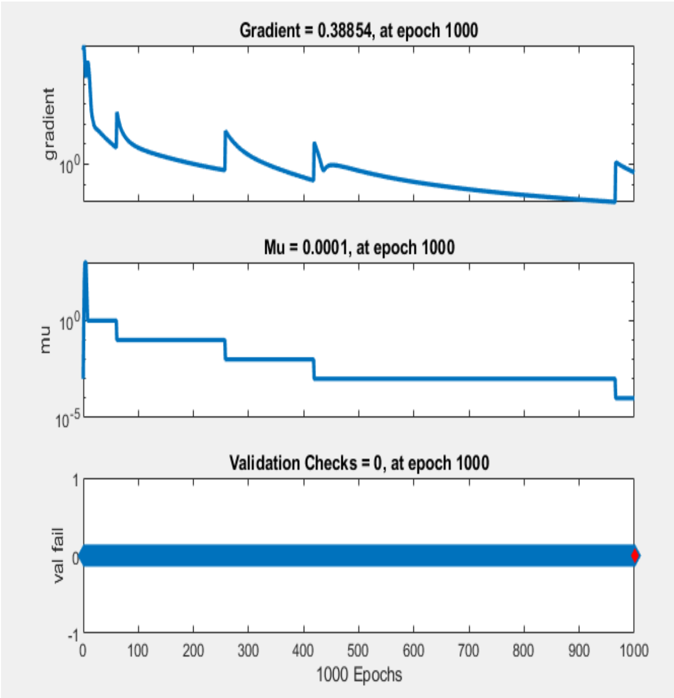

Fig.6 Training Parameters

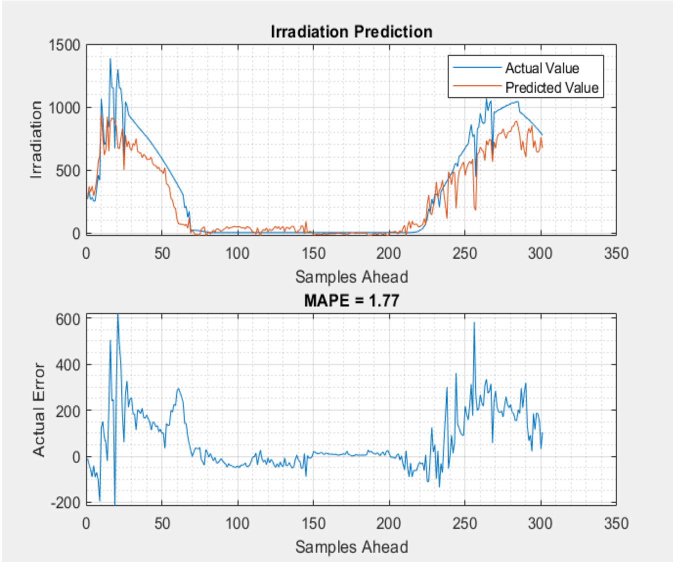

Fig.7 Prediction Results

Figure 4 depicts the machine learning model designed. Figure 5 depicts the iterations to convergence. Figure 6 depicts the training parameters. Figure 7 depicts the prediction results in terms of actual and predicted values. The MAPE of the previous work [1] is a mean error of 4% which the present work beats the performance with an error % of 1.77%.

V. CONCLUSION

Machine learning models have significantly advanced the field of solar irradiation forecasting, offering more accurate and reliable predictions than traditional methods. From supervised learning models and ANNs to ensemble techniques and deep learning, these models are transforming how we predict and manage solar energy. As technology continues to evolve, further innovations in machine learning will likely enhance the accuracy and efficiency of solar forecasting, contributing to the broader goal of sustainable energy management. The work presented in this paper combines a moving window of recent values along with the back propagation based neural network model. It has been shown that the proposed work attains improved prediction performance compared to existing work in the domain.

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