Forecasting Renewable Energy Employing A Regularized Deep Learning Approach

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***Abstract*— Renewable energy prediction has become an important research area due to the increasing demand for clean energy, the depletion of conventional fossil fuels, and the need to reduce greenhouse gas emissions. Among the various renewable energy sources, solar energy has gained considerable attention because of its wide availability, environmental sustainability, and potential for large-scale electricity generation. However, the amount of solar energy generated by photovoltaic (PV) systems depends on several environmental and meteorological factors, including solar irradiance, ambient temperature, humidity, cloud cover, wind speed, and atmospheric conditions. These factors exhibit significant temporal variations, making solar energy prediction a challenging task. The proposed approach combines the DWT and a Bayesian Optimized Deep Neural Network for forecasting renewable energy using solar irradiation dataset. It has been shown that the model attains a MAE of just 3.0 and an MAPE value of 0.03% which clearly outperforms existing baseline techniques in the domain.**

Keywords*—Renewable Energy, Machine Learning, Deep Learning, Neual Networks, Discrete Wavelet Transform (DWT), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE)

I. INTRODUCTION

Conventional statistical methods and machine learning techniques have been widely used for renewable energy prediction, several challenges remain in developing reliable solar energy forecasting systems [1]. Solar energy measurements are inherently nonstationary and may contain noise, abrupt fluctuations, seasonal variations, and complex dependencies on meteorological variables. Conventional neural networks can learn nonlinear relationships, but they may overfit noisy training data or generalize poorly when weather conditions change [2]. Similarly, signal filtration techniques can reduce noise but may remove meaningful short-term variations if their parameters are not selected appropriately. Therefore, a key research gap lies in developing an integrated framework that combines effective signal filtration with a learning mechanism capable of controlling model complexity while preserving important solar energy patterns [3].

While solar power is available in abundance globally, harnessing solar power to generate systems running on solar power requires consideration of a multitude of factors [4]. While solar irradiation exhibits a certain degree of seasonality, global climate change resulting in variability in irradiation characteristics make practical utility (typically for industrial applications) a non-trivial challenge. Still solar power is considered to be the major source of renewable energy due to the potential of harnessing and the share of solar power among all other sources of renewable energy is depicted in figure 1, which is taken from the Renewable Energy Statistics 2022 published by the IREA. It highlights the distribution of renewable energy sources as a percentage of total usage. Here are the key details [5]

- Hydropower: The largest segment, accounting for 59% of renewable energy, represents energy harnessed from flowing water.
- Wind Energy: Wind energy contributes 21% and is the second-largest source.
- Solar Energy: Solar energy makes up 11% and is represented in yellow.
- Bioenergy: Derived from organic materials, bioenergy constitutes 8%.
- Geothermal: Geothermal energy, obtained from Earth's heat, contributes 1%.

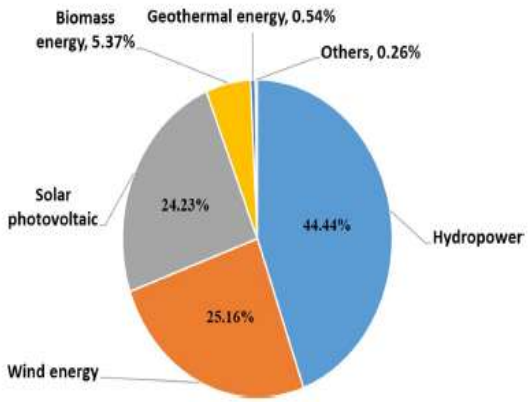


Fig.1 Share of Solar Energy Among Major Renewabel Sources of Enegry

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 [6]. 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 [7].

II. STATISTICAL MODELLING

The proposed integration of DWT and Bayesian Regularized Deep Neural Network addresses this research direction by combining frequency-based signal decomposition with regularized nonlinear learning. Its potential novelty lies in systematically evaluating whether wavelet-based filtration improves the quality of solar energy inputs and whether Bayesian regularization enhances the model's ability to generalize to unseen data. Additional contributions could include selecting the most suitable wavelet family and decomposition level, evaluating alternative thresholding strategies, incorporating relevant meteorological variables, and comparing performance under clear-sky, cloudy, and highly variable weather conditions. The novelty should be established through a review of existing literature and supported by controlled experimental comparisons; the use of DWT and Bayesian regularization together is not, by itself, sufficient to establish that the approach is unprecedented [8].

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 [9]. 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 [10]

III. PROPOSED APPROACH

Prior training the Bayesian Model, the DWT is used for data filtration.

The DWT for Data Filtration:

Solar energy data frequently contain noise and irregular fluctuations caused by changing weather conditions, sensor inaccuracies, communication errors, and atmospheric disturbances [11]. These fluctuations may obscure the underlying temporal patterns required for accurate prediction. The Discrete Wavelet Transform (DWT) can be employed as a signal-processing technique to separate solar energy signals into different frequency components. Unlike conventional filtering methods that primarily operate within a fixed frequency range, DWT provides time-frequency localization, enabling the analysis of both rapid fluctuations and slowly varying trends in solar energy measurements [12].

The DWT decomposes an input signal into approximation coefficients and detail coefficients using low-pass and high-pass filtering operations, respectively. The approximation coefficients represent the lower-frequency components associated with broad trends in

solar irradiance or power generation, whereas the detail coefficients capture higher-frequency variations that may contain noise as well as meaningful short-term fluctuations [13]. A suitable wavelet family, such as Daubechies, Symlets, or Coiflets, can be selected according to the characteristics of the dataset. During the filtration process, thresholding can be applied to the detail coefficients to suppress noise while retaining important signal characteristics. The filtered signal is then reconstructed using the inverse Discrete Wavelet Transform [14]. The resulting data preserve the dominant temporal patterns of solar energy generation while reducing unwanted fluctuations. However, careful selection of the wavelet family, decomposition level, and thresholding strategy is necessary because excessive filtration may remove genuine variations associated with sudden cloud cover or rapid changes in solar irradiance [15].

The wavelet transform is an effective tool for removal of local disturbances. Solar energy show extremely random behavior and local disturbances. Hence conventional Fourier methods do not render good results for highly fluctuating data sets. Mathematically, the wavelet transform can be given as [16]:

$$\boldsymbol{Z\,(S,\,P)} = \int_{-\infty}^{\infty} \boldsymbol{z}(\mathrm{t})\;((\boldsymbol{S},\boldsymbol{P},\boldsymbol{t}))\boldsymbol{dt} \qquad \textbf{(1)}$$

Here,
S denotes the scaling operation
P denotes the shifting operation
t denotes the time variable
Z is the image in transform domain
z is the image in the spatial domain

The major advantage of the wavelet transform is the fact that it is capable of handling fluctuating natured data and also local disturbances. The DWT can be defined as [17]:

$$\mathbf{W\Phi\ (Jo,\,k)} = \frac{1}{\sqrt{M}} \sum_n \boldsymbol{S(n).\Phi(n)_{jo\prime k}} \qquad \textbf{(2)}$$

After filtration using the DWT, the deep neural network is trained. Deep learning has evolved as one of the most effective machine learning techniques which has the capability to handle extremely large and complex datasets. It is training neural networks which have multiple hidden layers as compared to the single hidden layer neural network architectures [18].

The architectural view of a deep neural network is shown in figure 1. In this case, the outputs of each individual hidden layer is fed as the input to the subsequent hidden layer. The weight adaptation however can follow the training rule decided for the neural architecture. There are various configurations of hidden layers which can be the feed forward, recurrent or back propagation etc [19].

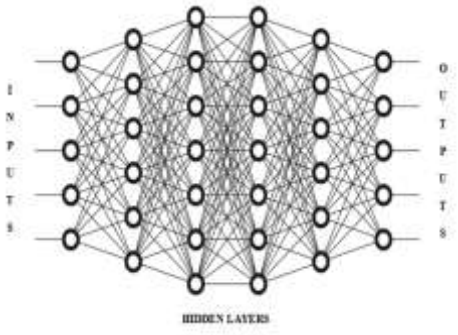


Fig.2 The Deep Neural Network Architecture

The figure above depicts the deep neural network architecture with multiple hidden layers. The output of the neural network however follows the following ANN rule [20]:

$$\boldsymbol{Y = f(\sum_{i=1}^{n} X_i\,.\,W_i \;+\; \theta_i)} \qquad \textbf{(3)}$$

Where,
X are the inputs
Y is the output
W are the weights
Θ is the bias.
Training of ANN is of major importance before it can be used to predict the outcome of the data inputs [21].

The back propagation 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 [22]:

$$\boldsymbol{W_{n+1} = W_n - \alpha \frac{\partial e}{\partial w}} \qquad \textbf{(4)}$$

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 Bayesian Model

A Bayesian Regularized Deep Neural Network (BR-DNN) can be employed to learn the complex nonlinear

relationships between environmental conditions and solar energy generation. A deep neural network consists of an input layer, multiple hidden layers, and an output layer. The input layer receives the preprocessed meteorological features, temporal information, and filtered solar energy measurements. The hidden layers transform these inputs through interconnected neurons and nonlinear activation functions, enabling the network to learn complex relationships among the variables. The output layer produces the predicted solar irradiance, photovoltaic power output, or energy generation value for the desired forecasting horizon [23].

A major challenge in training deep neural networks is overfitting, particularly when the available dataset is limited or contains highly correlated features. Overfitting occurs when a model learns the specific characteristics of the training data rather than the underlying patterns that generalize to unseen observations. Bayesian regularization addresses this problem by combining the prediction error with a penalty on the magnitude of the network weights. The Bayesian Model work on maximizing the posteriori probability for updating weights given by the following function::

$$\boldsymbol{P}\left(\frac{\boldsymbol{X}}{\boldsymbol{X_i},\boldsymbol{k_1},\boldsymbol{k_2},\boldsymbol{M}}\right)=\frac{\boldsymbol{P}\left(\frac{\boldsymbol{X_i}}{\boldsymbol{X},\boldsymbol{k_2},\boldsymbol{M}}\right)\boldsymbol{P}\left(\frac{\boldsymbol{X_i}}{\boldsymbol{k_1},\boldsymbol{M}}\right)}{\boldsymbol{P}\left(\frac{\boldsymbol{X}}{\boldsymbol{k_1},\boldsymbol{k_2},\boldsymbol{M}}\right)} \qquad \textbf{(5)}$$

Here,
P represents probability.
X_i represents weights and bias vectors (combined).
X represents the data to be used for the purpose of training.
M represents data units (neurons) in network.
k_1 *and* $k_2$represents the term responsible for penalty based regularization.
$\rho=\frac{k_1}{k_2}$ is often considered the regularization factor which is acted upon the objective function (J) to me optimized based on the training dataset, and renders the regularized cost function:

$$\boldsymbol{F(w)}=\boldsymbol{\mu w^T w}+\boldsymbol{v}[\frac{\boldsymbol{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}}(\boldsymbol{p_i}-\boldsymbol{a_i})^2] \qquad \textbf{(6)}$$

If $(\pi \ll v)$: errors in training are typically rendered low.

else if $(\pi \geq v)$: errors are typically rendered high needing a weight reduction or Penalty. The training rule is given by [24]:

$$\boldsymbol{w_{k+1}}=\boldsymbol{w_k}-\left[\boldsymbol{J_k J_k^T}+\boldsymbol{\mu' I}\right]^{-1}\boldsymbol{J_k^T e_k} \qquad \textbf{(7)}$$

Here,
w_{k+1} is the weight of the next iteration
w_k is the weight of the present iteration
$\boldsymbol{\mu'}=\boldsymbol{R\mu}$ is the combination co-efficient
$\boldsymbol{R}$ is termed a the Regularization parameter.

In Bayesian regularization, the network parameters are treated probabilistically, and the regularization coefficients can be adjusted using evidence-based estimates. This allows the training procedure to balance model fit against parameter complexity. Consequently, the network can potentially achieve better generalization performance than an otherwise comparable model trained without regularization. Bayesian regularization is particularly relevant to solar energy prediction because meteorological datasets may contain noisy measurements, nonlinear dependencies, and seasonal variations. However, its effectiveness depends on the architecture, dataset characteristics, training procedure, and appropriate evaluation against alternative optimization methods. The proposed algorithm is presented next:

Start
{
Step.1 *Obtain dataset.*

Step.2 *Divide the data into a ratio of 70:30 as training and testing data samples.*

Step.3 *Apply DWT for filtration*

Step.4 *Design a neural network with multiple hidden layers.*

Step.5 *Initialize training with random weights.*

Step.6 *Train models with training data and updated weights based on the back propagation rule as:*

$$\boldsymbol{w_{k+1}}=\boldsymbol{w_k}-\left[\boldsymbol{J_k J_k^T}+\boldsymbol{\mu I}\right]^{-1}\boldsymbol{J_k^T e_k}$$

Step.7 *if (Cost Function J stabilizes over multiple iterations)*
Truncate
else if (iterations==max. iterations defined)
Truncate
else
{
Apply data and update (w, b)
Feedback (e)
}

Step.8 *Calculate error% and Classification Accuracy*

Stop
}

The performance parameters used for evaluation of the algorithm is the accuracy % which is computed as:
Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{M}\sum_{t=1}^{N}\frac{E-E_t|}{E_t} \quad (8)$$

Mean Squared Error (MSE):

$$MSE = \frac{1}{N}\sum_{t=1}^{N} e_t^2 \quad (9)$$

Here,
E_t and E_t~ 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, with more than 30,000 samples. The system has been designed on MATLAB with the functionalities of the deep learning library.
The irradiation parameters for each day and each hour are plotted.

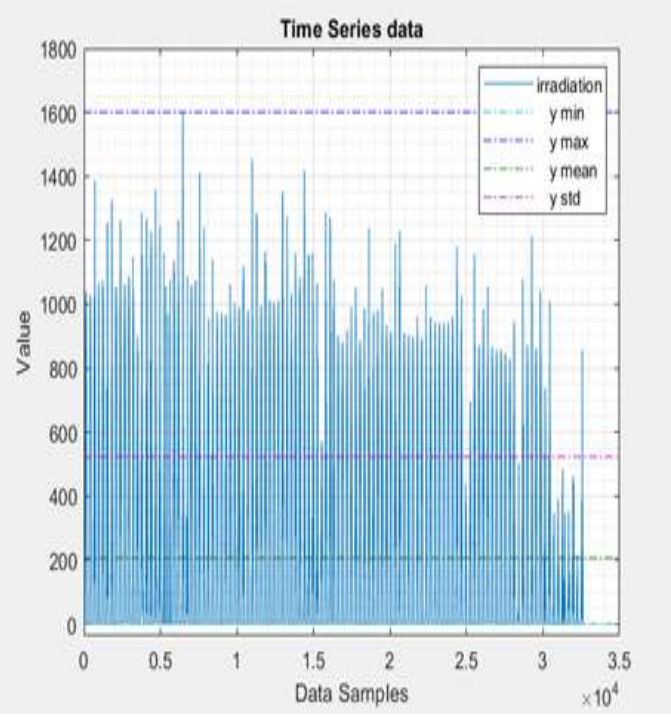


Fig.3 Raw Data

Figure 3 depicts the raw data with the mean, maximum and minimum values marked.

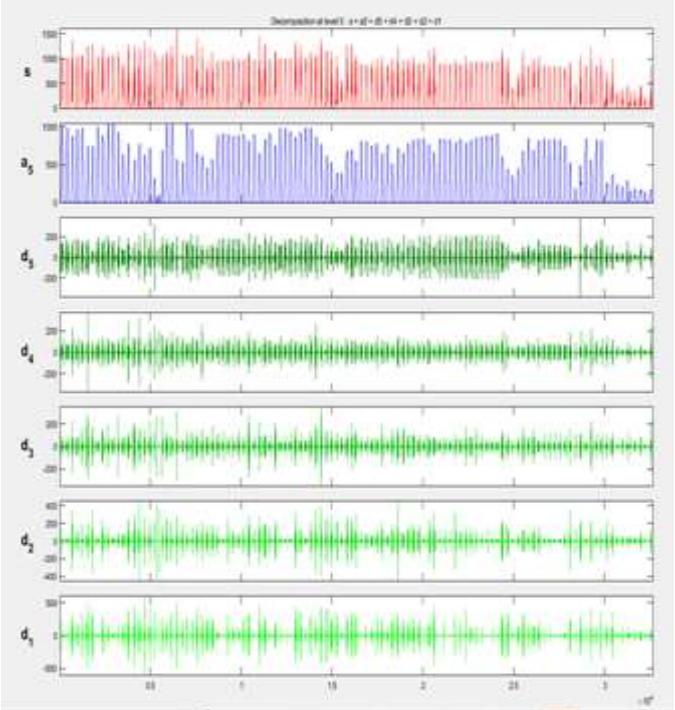


Fig.4 Data Filtration

Figure 4 depicts the data filtration process using the DWT where the CA values are retained while CD values are discarded.

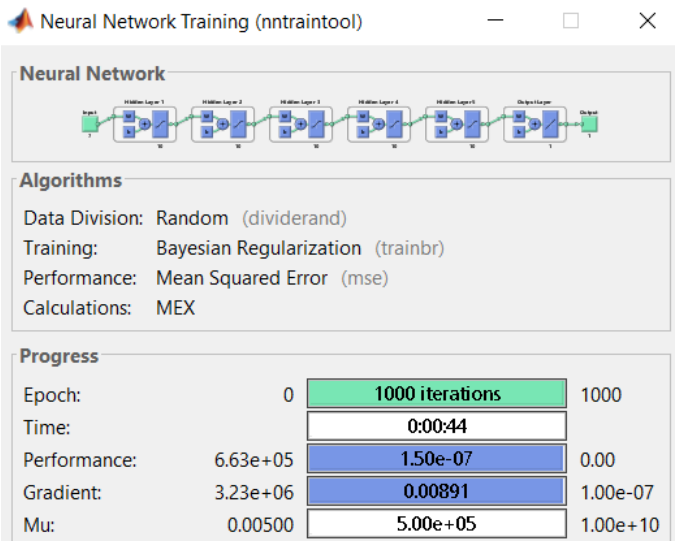


Fig.5 The Bayesian Model

Figure 5 depicts the Bayesian Model which is trained with the training data. The training to testing split has been kept at 70:30. The model can be seen to be trained in 1000 iterations.

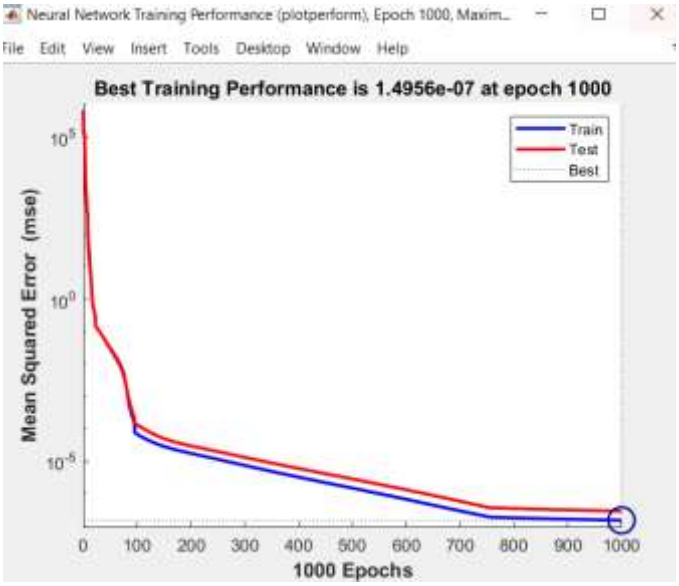


Fig.6 Iterations to convergence

Figure 6 depicts the iterations to convergence, and the variation of the cost function. A smooth dip in the cost function can be observed indicating the stability of the approach.

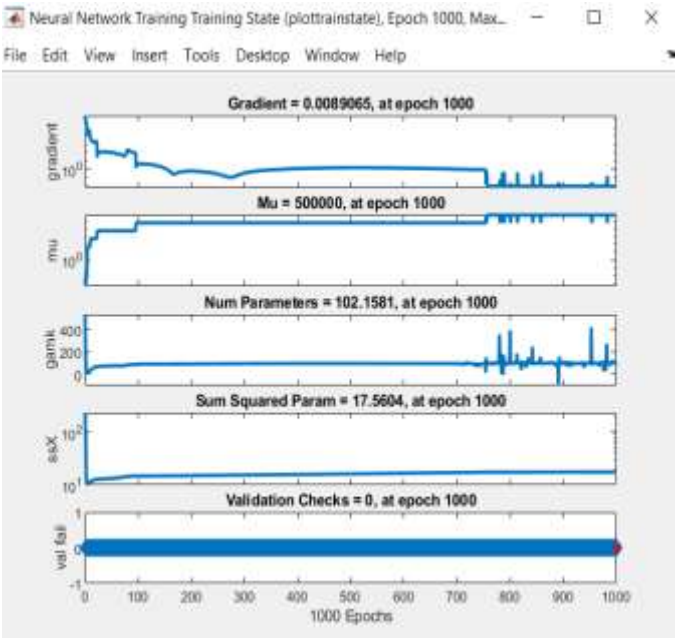


Fig.7 Training Parameters

Figure 7 presents the training states with additional parameters such as gradient, learning rate and validation checks.

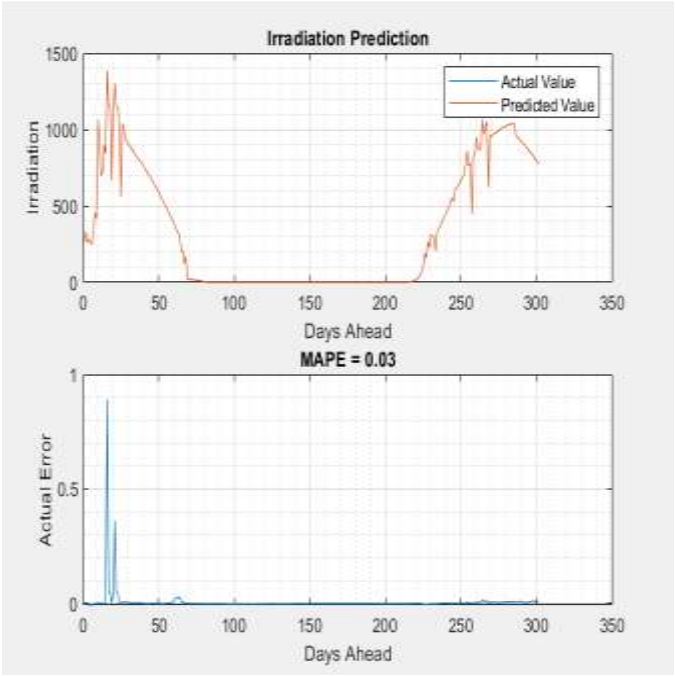


Fig.8 Actual and Predicted values

Figure 8 presents the predicted and actual values on prediction. It can be observed that the model attains an MAPE of just 0.03% or MAE of 3.0. Comparing it with existing work in the domain, it is extremely less.

Table 1. Summary of Results

S.No.	Parameter	Value
1	Dataset	Kaggle
2	Samples	32,000
3	Training Testing Split	70:30
4	Filtration	DWT
5	ML Model	Deep Neural Network
6	Training Algorithm	Bayesian Regularization
7	Iterations to Convergence	1000
8	Training Time	44s
9	MAE (Proposed Work)	3.0
10	MAE (Previous Work, Hossain et al.), LSTM, [25]	16.44 (avg)

The summary of results is presented in Table 1. It can be clearly observed that the proposed work clearly outperforms the baseline model with LSTM in terms of prediction MAE making it a much more accurate model for predicting renewable energy.

V. CONCLUSION

It can be concluded that forecasting renewable energy is a critical need of the present times. The proposed DWT-BR-DNN framework can support different solar energy forecasting applications. In short-term forecasting, the model can predict solar power generation over the next several minutes or hours, supporting real-time power dispatch, grid balancing, and battery management. In day-ahead forecasting, the model can estimate expected solar energy production for the following day, enabling electricity scheduling and energy market planning. In longer-term applications, the framework may support energy assessment and operational planning when suitable historical data and relevant seasonal information are available. The prediction model can also be integrated with smart-grid management systems to estimate the expected contribution of photovoltaic installations to the electricity supply. The proposed approach combines DWT-BRDNN and attains an MAE value of just 3.0 clearly outperforming baseline approaches in the domain.

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