Original Research Article

SOLAR RADIATION VERY SHORT-TERM FORECASTING ON THE ADAPTIVE SOLAR CELLS USING THYBRID MODEL DECOMPOSITION FEED FORWARD NEURAL NETWORK METHOD

ABSTRACT

Variations in solar radiation levels affect the efficiency of solar panels and due to their unpredictability, can cause instability in the generated power and negatively affect the reliability of solar power stations. This study formulates the prediction of solar radiation at short time intervals based on short time series decomposition techniques and Artificial Neural Network - Feed Forward Multi-Layer Perceptron. The prediction method consists of the following steps: data pre-processing, application of the modified FFN model, and evaluation achieved through RMSE, MSE, MAPE and MAE. The experimental results show that the prediction model performs well, exhibiting an MAE value of 3.3823, MSE of 37.0858, RMSE of 6.089, and MAPE of 0.29%. It can be stated that despite the variation between the predictions, ~~and~~ the actual values, and the overall trend of the data yields good accuracy~~,~~ with a deviation of only 5%. These results show that the combination of decomposition and FFNN technique can increase the accuracy of prediction in solar radiation which is crucial for the adaptive solar panel system applications. The next directions of the work are the creation of a more complicated model using greater divisional data and other decomposition methods, which will improve the accuracy of predictions within more rapidly changing weather conditions.

Keywords: Radiation forecasting, Decomposition (FFNN), Adaptive solar cell, Renewable energy.

1. INTRODUCTION

Solar energy is one of the most promising and viable renewable energy sources for generating electricity sustainably[1] . There is a global push towards cleaner energy, and it is for this reason that the technology behind solar power, specifically photovoltaic panels, has advanced drastically. Even with the scientific advances made in the aforementioned field, there is one ever-persistent problem in the form of solar energy's efficiency[2]. Regardless of having a minimal environmental impact or being available in abundance, one key reason for the inefficiency of these photovoltaic systems stems from the amount of energy output solar cells intake. Atmospheric conditions such as air pollution, fog, and even clouds cause this energy input to shift dramatically[3]. Along with these, there is a significant amount of power variability caused due to climatic uncertainties which can further hinder the performance of solar cells. As a byproduct, the reliability and stability of these solar power generation systems take a massive hit. It is self-evidently clear that further research in the field of predicting solar radiation fluctuations, and in general, the performance of solar cells is imperative to solve these issues.

The use of solar tracking systems means that the energy from the sun is harnessed at maximum output because these systems allow the solar panels to follow the sun's motion throughout the day[4]. Adaptive solar cells are an outcome of this advanced technology which enables the solar panels to point in the direction that captures ~~the~~ most solar radiation. However, these systems are only as efficient as the precision of real-time predictions regarding solar radiation intensity.

Solar tracking systems equipped with adaptive controls have the ability to increase energy output significantly by changing the position of the panels in real time[5].

The integration of real-time prediction models with solar tracking technology not only optimizes performance but also Forecasting remains a substantial concern due to the intricate nature of short-term solar radiation and the corresponding meteorological elements such as clouds, humidity, and air pollution. Conventional approaches, for instance, regression models, are unable to adapt to the nonlinear functions and complicated changes of solar radiation[6]. This necessitates the development of novel technologies such as machine learning (ML) as well as hybrid approaches to make more accurate and precise forecasts over shorter periods[7].

Further, high-performance computing alongside intelligent control techniques makes the adaptive solar cells a form of sophisticated solar cells, and several researchers have indeed attempted to create models that allow for the anticipatory estimation of solar radiation, which poses a central requirement for these systems. ~~To illustrate~~ For illustration purpose, a random and nonlinear solar radiation estimator was proposed by Ameera M. et al. through a modified kernel ridge regression approach, which considerably improves accuracy. In addition to this, Wassila Tercha et al. proposed an approach based on hybrid quantum neural networks which allowed for a drastic reduction in absolute error and mean squared error[8]. The performance of the Hybrid Quantum Long Short-Term Memory (LSTM) models surpassed all previous methods by 40%[9].

According to Hammad Ali Khan et al., quantum machine learning can address the issues of traditional methods of forecasting renewable energy systems. This was particularly helpful in scenarios where data was limited. For solar irradiance forecasting, deep learning techniques were applied for the purpose[10]. In a different work by Murugesan S, M. Mahasree et al, a solar energy forecasting system based on machine learning was put into operation with optimization of post-processing and data maintenance, resulting in absolute percentage errors of 4.7% and 6.3% in cold and hot conditions respectively[11]. In this paper, it was discovered by Rajnish et al. that a deep learning algorithm GA-CNN with optimized hyperparameters tuning for photovoltaic energy forecasting turned out to perform much better than LSTM, KNN-SVM, CNN-RNN and other methods which have been evaluated on performance metrics like RMSE, MAE, MSE, R-Square[12].

2. METHOD

2.1 Adaptive Solar Cell

The Adaptive solar cells are a unique type of photovoltaics where the cells automatically adjust to the varying intensities of solar radiation in order to maximize the energy output (Tunable Photovoltaics: Adapting)[13]. Unlike traditional static systems, the adaptive solar cells incorporate real-time solar tracking mechanisms that adjust the orientation of the panels throughout the day to align with the sun's position (Dual-axis solar tracker with satellite compass). These systems utilize models to more accurately capture the intensity of solar radiation enabling optimally quicker and more precise adjustments, as reported by Low-cost dual-axis solar tracker. Modern solar tracking systems are now integrated with powerful algorithms that allow adaptive solar cells to operate under optimal panel conditions regardless of the surrounding environmental conditions.

The main breakthrough in the adaptive solar cells arises from the integration of artificial intelligence (AI) and real-time environmental data with the technology. These projections are accomplished by means of hybrid decomposition techniques or FFNN whereby the non-linear distribution of solar radiation is ascertained against meteorological factors such as the cloud cover, humidity, and pollution[14]. This empowers the adaptive solar cells to rapidly adjust to the fluctuations in radiation which leads to a stable and reliable energy output. The dynamic responsiveness of these solar cells in addition to the predictive accuracy is what marks them as an essential step in the pursuit of efficient and sustainable solar energy use.

2.2. Feed Forward Neural Networks (FFNN)

Feed Forward Neural Networks (FFNN) are a type of artificial neural network where the connections between neurons do not form cycles, allowing information to flow in only one direction—from the input layer, through the hidden layers, and finally to the output layer[15]. This form of a neural network is usually used in multi-dimensional problems like regression, classification and pattern recognition tasks. A feedforward neural network is comprised of an input layer, depicted in Figure 1, one or more hidden layers, and an output layer where each layer has a set of nodes or neurons.

1. Input Layer: This layer receives the input features and passes them on to the hidden layers. The number of nodes in the input layer corresponds to the number of input features.

2. Hidden Layer: This layer performs most of the processing within the neural network. Each hidden layer consists of a set of neurons, each applying a non-linear activation function to its input.
3. Output Layer: This layer produces the final output of the network. The number of nodes in the output layer depends on the task at hand; for example, for a regression task, there is typically only one node, while for multi-class classification tasks, the number of nodes corresponds to the number of classes.

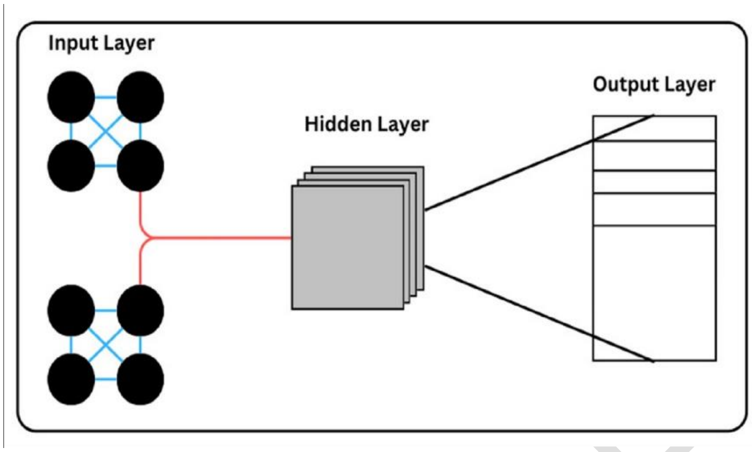

Fig 1. FFNN Architecture

As mentioned previously, feedforward neural networks adjust their weights and biases in order to reduce the gap between the networks (calculated) output and the actual output (target) for the corresponding input[16]. A feedforward neural network is trained via the following procedure;:

1. Forward Propagation: Input is passed through the network, layer by layer, until it reaches the output layer. At each neuron, the weighted sum of the inputs is calculated, the bias is added, and the activation function is applied.

2. Loss Calculation: The loss function measures the difference between the network's output and the correct output. Commonly used loss functions in trading applications include mean squared error (MSE) for regression tasks and cross-entropy loss for classification tasks.

3. Backpropagation: The gradient of the loss function with respect to the weights and biases is calculated using the chain rule of calculus. This step consists of backwards movement through the network as well as the per layer calculation of the gradients.

4. Weight Update: Weights and biases are updated using optimization algorithms such as gradient descent or its variants (e.g., stochastic gradient descent, Adam, or RMSprop). The optimizer adjusts the weights and biases to minimize the loss.

2.3. Decomposition-Feed Forward Neural Network

In the process of constructing a feedforward neural network, a decomposition technique is employed which is known as DFFNN. This technique is instrumental in allowing the network to learn complex and structured data. DFFNN consists of the same architecture as that of the FFNN which is depicted in Figure 2.

1. Input Layer:

   - Represents the raw data features, which could be vectors, time-series data, images, or other forms of structured data.

   - The input may be grouped into subcomponents where each group is handled independently.

2. Decomposition Blocks:

   - These blocks operate on subsets of input data.

- They might use mathematical transformations, statistical techniques, or specialized neural components to extract relevant features.
- Examples include wavelet transforms, principal component analysis (PCA), or custom neural operations.

3. Hidden Layers:

- The outputs from the decomposition blocks are passed to the hidden layers.
- These layers combine and further process the features extracted from each decomposition unit.

4. Output Layer:

- Represents the final prediction or classification result after the network processes the decomposed data.

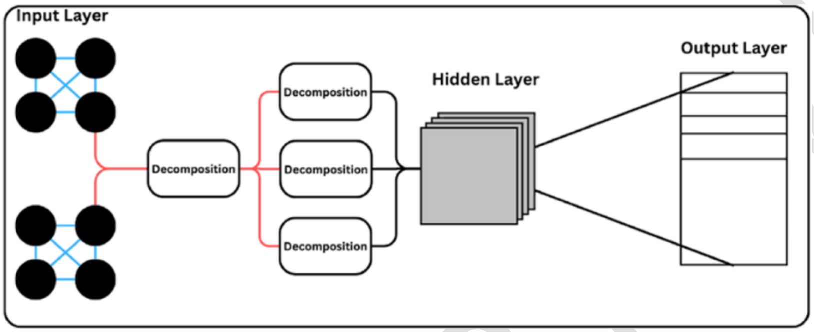

Fig 2. DFFNN Architecture

As outlined in the above figure 2, the decomposition-feed forward neural network technique is carried out by first decomposing the raw data such as solar radiation data or other time series data multiplicatively. (e.g., solar radiation data or other time series data) ~~is~~ are first decomposed using a specific decomposition method (such as STL or Wavelet), so that trends, seasonality and residual components can be isolated. Once the data has been decomposed, each of these separate components is used as input for the Feed Forward Neural Network to make predictions. This leads to improved predictions.

Addressing non-linearity: Decomposition makes the hidden patterns within the data explicit in a structured manner, thus, allowing the FFNNs to capture non-linear relationships present in the data.

2.4. Research Flow

The schematic representation of the research flow is shown in Figure 3. It begins with the gathering of relevant data from sources such as sensors, public datasets, or experiments, which advance the objectives of the research. Then, the raw data is subjected to a pre-processing step where noise is eliminated, normalization is executed, and the layout is altered to the specifications required for the analysis. Subsequently, the data is decomposed. Decomposition entails the partitioning of existing data into smaller forms, more specific components such as trends, seasonality and residuals (for time series) or signal transformations like wavelets. When all necessary data has been collected, the feed forward neural network (FFNN) model is prepared by establishing the network configuration, which consists of the number of layers, neurons, activation functions, and other parameters like detailed modifications. The next step is a training phase, where patterns are categorized with the aid of training data. After the model is trained, a testing phase is conducted where the model is assessed while utilizing test data. During this step, specific evaluation metrics are derived in order to evaluate the performance of the model. After the test has been performed, the results are examined in the evaluation phase, during which the model's outcome is compared with the objective. In instances such as these where the evaluation meets the expected results, the research can be deemed complete. However, if the criteria have not been met, the model must be retrained and tested again from the training stage.

This model verification approach guarantees that the resulting model will be optimal and appropriate for the research goal.

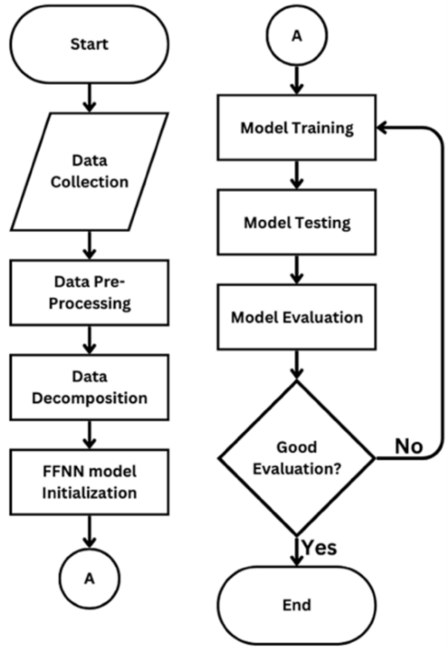

Fig 3. Research Methods

2.5. Methods Evaluation

The model's performance is measured by comparing the predicted output values against actual output values using different error measuring methods. These include, in this particular study, the metrics of Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics are defined as follows:

1. MSE

$$MSE = \frac{1}{M}\sum_{i=1}^{m}(X_i - Y_i)^2 \quad (1)$$

MSE measures the mean value of the difference between the predictions and the actual values and then squares the result. Since this metric incorporates the squared differences, it is vulnerable to outliers. [17].

2. MAE

$$MAE = (\frac{1}{M})\sum_{i=1}^{m}|X_i - Y_i| \quad (2)$$

MAE evaluates the average of absolute errors calculated from actual and predicted values. In comparison to MSE, MAE allows for easier interpretation of errors [18].

3. RMSE

$$RMSE = \sqrt{(\frac{1}{M})(X_i - Y_i)^2} \quad (3)$$

RMSE is easier to understand practically because it is the square root of MSE and has a correlating interpretation with the data itself[19].

4. MAPE

$$MAPE = 100\%\ x(\frac{1}{M})\sum_{i=1}^{m}|\frac{Y_i - X_i}{Y_i}| \quad (4)$$

Because MAPE captures error in relative percent form, it can be useful for benchmarking the performance of the model trained on datasets of varying sizes [20].

Parameters:

M: Total number of data points (samples).

X_i : Actual value (observed).

Y_i : Predicted value.

3. RESULT AND DISCUSSION

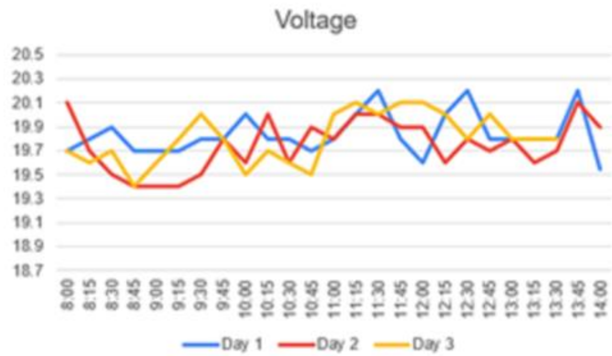

Fig 4. Voltage Data Graph

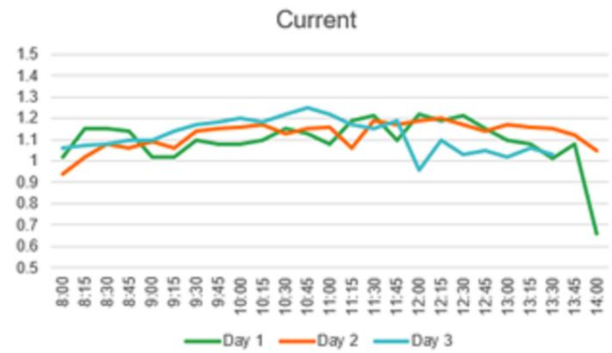

Fig 5. Current Data Graph

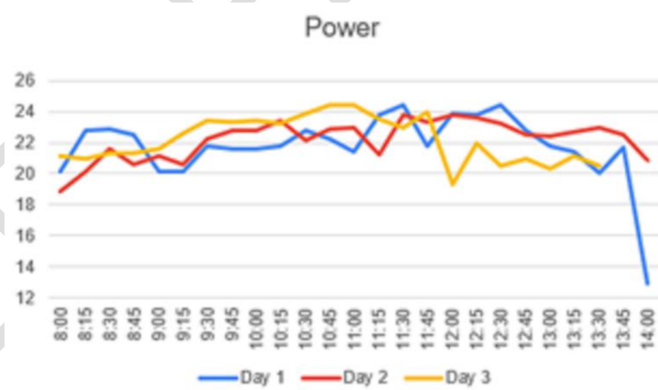

Fig 6. Power Data Graph

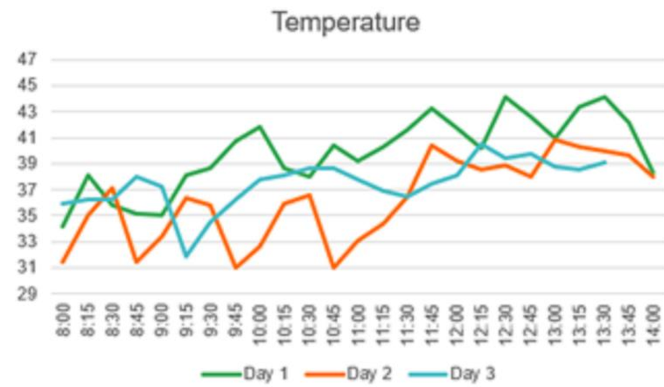

Fig 7. Temperature Data Graph

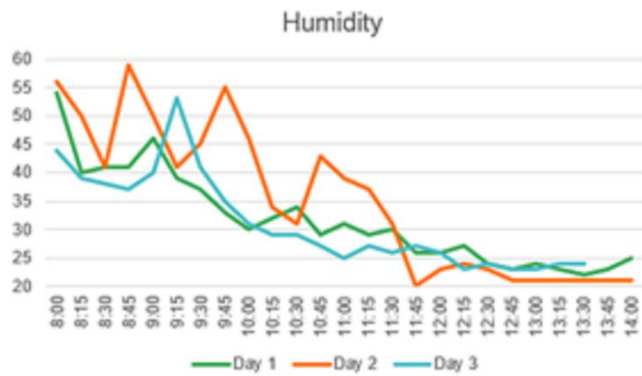

Fig 8. Humidity Data Graph

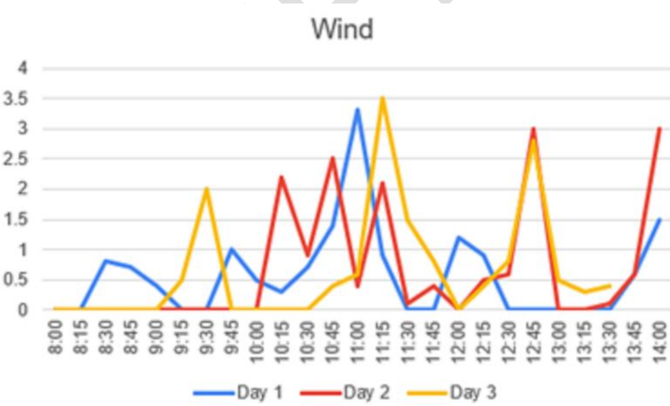

Fig 9. Wind Data Graph

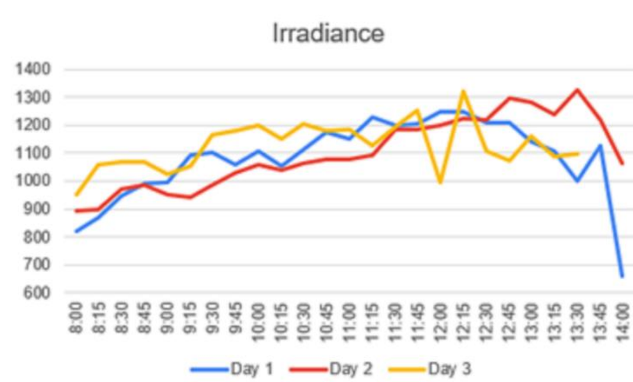

Fig 10. Irradiance Data Graph

Figures 4 to 10 present the graphs of the sensor data from the solar tracker system. The recordings for this data were made on the 29th and 30th of September as well as on the 1st of October 2024. These recordings provide a comprehensive understanding of the environmental and operational conditions during this ~~time~~ period and will be used as the preliminary dataset for training the Feed Forward Neural Network (FFNN) modelling approach.

In order to increase the FFNN model's effectiveness, this dataset will be transformed. This includes a singular decomposition method which separates inputs into a trend component, seasonal component, and ~~a~~ residual component. By separating the data into different components, it will provide the model with better insight into the data and lead to improved model performance and accuracy in the output predictions.

The data that includes features such as voltage, current, power, temperature, wind and humidity are very important data that help with the pattern identification process for the target label which in this case is the radiation data. It is expected that these features will give additional components that influence radiation and thus enhance the model's generalization and prediction capability.

Through careful observation of datasets, it can be said that changes within variations of coma data have a demonstrable impact on radiation data. This explains the reason why the selected coma feature data are of great significance and are likely with the variable of interest. Therefore, those features will probably increase the robustness of the predictive model that needs to be coupled with the highly variable solar radiation dynamics.

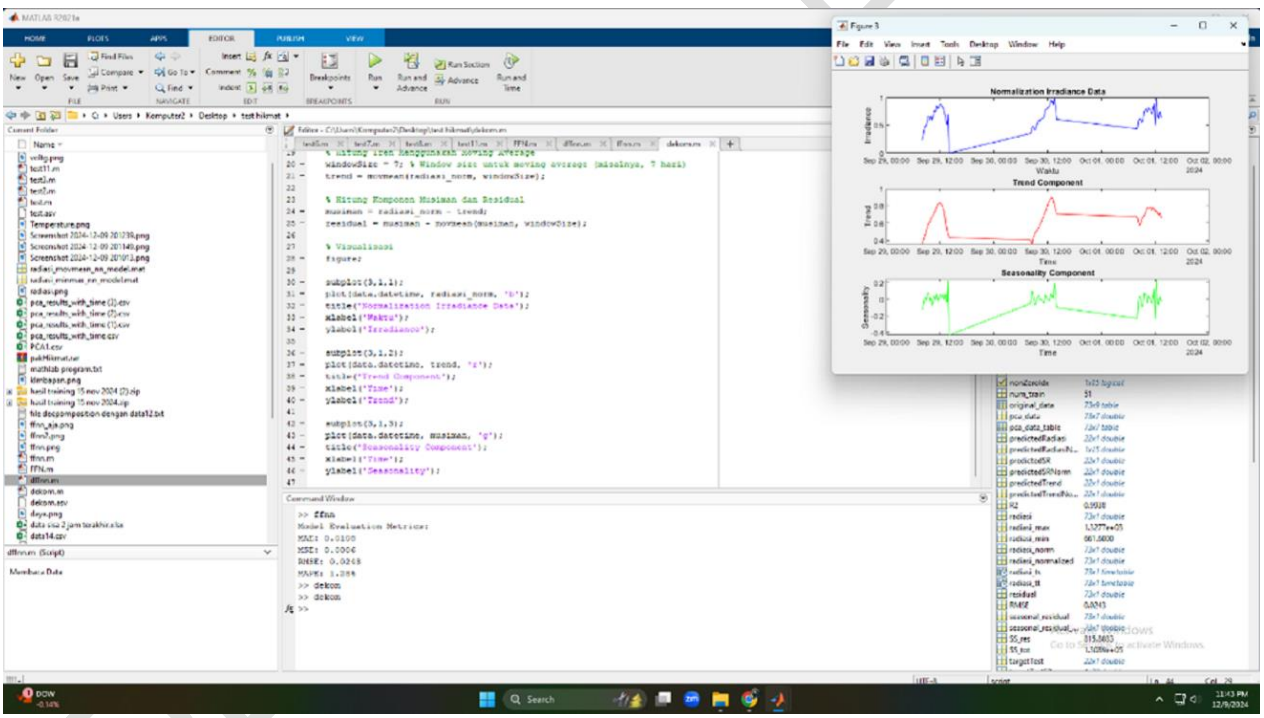

Fig 11. Decomposition Result

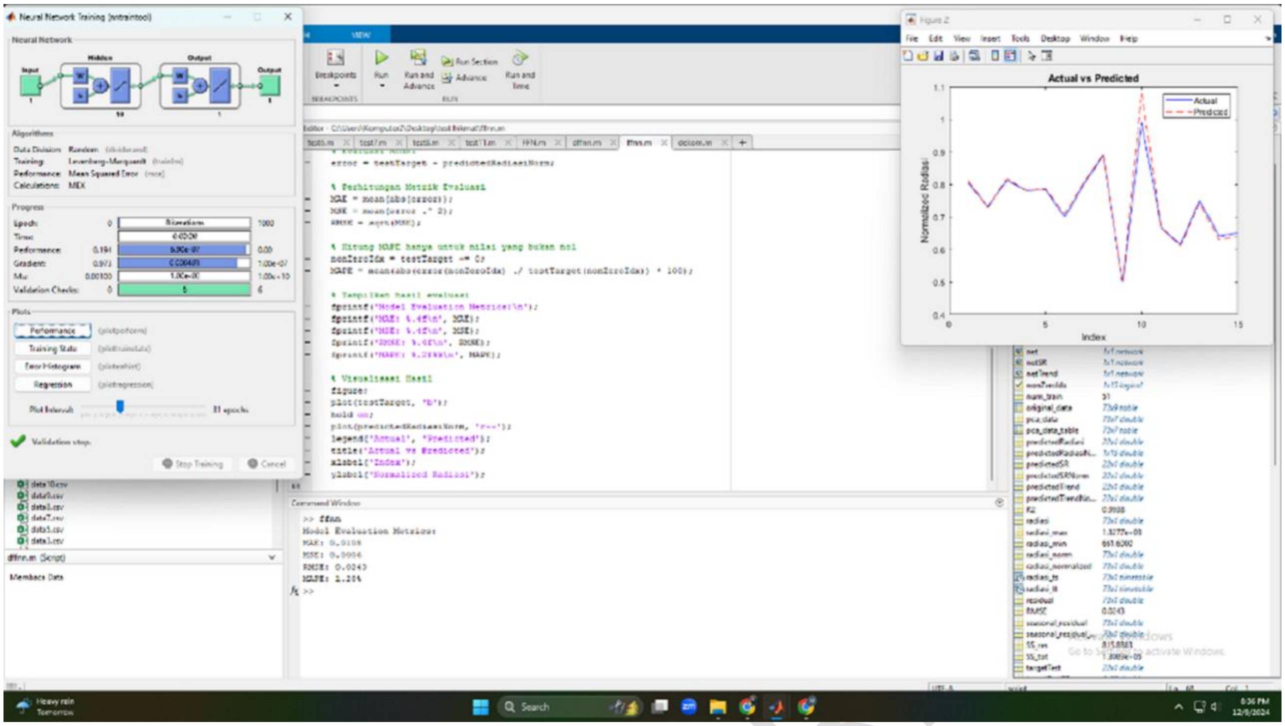

Fig 12. FFNN Training Result

In Figure 11, the C++ C compiler is used in MATLAB to implement the decomposition technique. Because MATLAB does not have a decomposition library, the program has to use the movement approach. The movement method is a built-in function of MATLAB and so this method has been chosen to implement the decomposition technique in MATLAB. The figure contains three graphs: the blue one presents the normalized original data, the red one shows the data which has had the trend extracted from it, and the green one shows the seasonality component. From the results, it is clear that the decomposition process is functioning properly and the variability is being enhanced. This, in turn, gives more options for the FFNN model to work with.

This research utilised the Feedforward Neural Network (FFNN) model as its base model. It is a rather simple deep learning model, and therefore quite useful as an efficient model for predictive tasks such as radiation data prediction. In figure 12, a graph is presented that is remarkably accurate, depicting a 97% correlation to the actual data. MAE, MSE, RMSE, and MAPE gave similar results, which are illustrated in Table 1. After performing the evaluation, the models made predictions that did not enormously deviate from the actual values, meaning it performed exceedingly well for a dataset of this scale.

As an extension to the decomposition and FFNN training results, this research combines both techniques into a single model called D-FFNN. This hybrid model breaks down the dataset into its constituent parts, namely trend, seasonality, and residuals before feeding the data into the FFNN model. This increases the diversity of the training dataset of the FFNN model enabling it to perform more effective learning. Despite the advantages, the decomposition approach has a significant flaw in that it is more prone to noise due to the increased variability in the dataset. Thus, more attention needs to be paid to the details of the computations. Table 1 contains the model evaluation results, while Figure 13 shows the graph deformed with the actual data which have close to perfect regression curves. The evaluation metrics suggest that the model was aptly trained which shows its capacity to handle large scale data due to the decomposition approach.

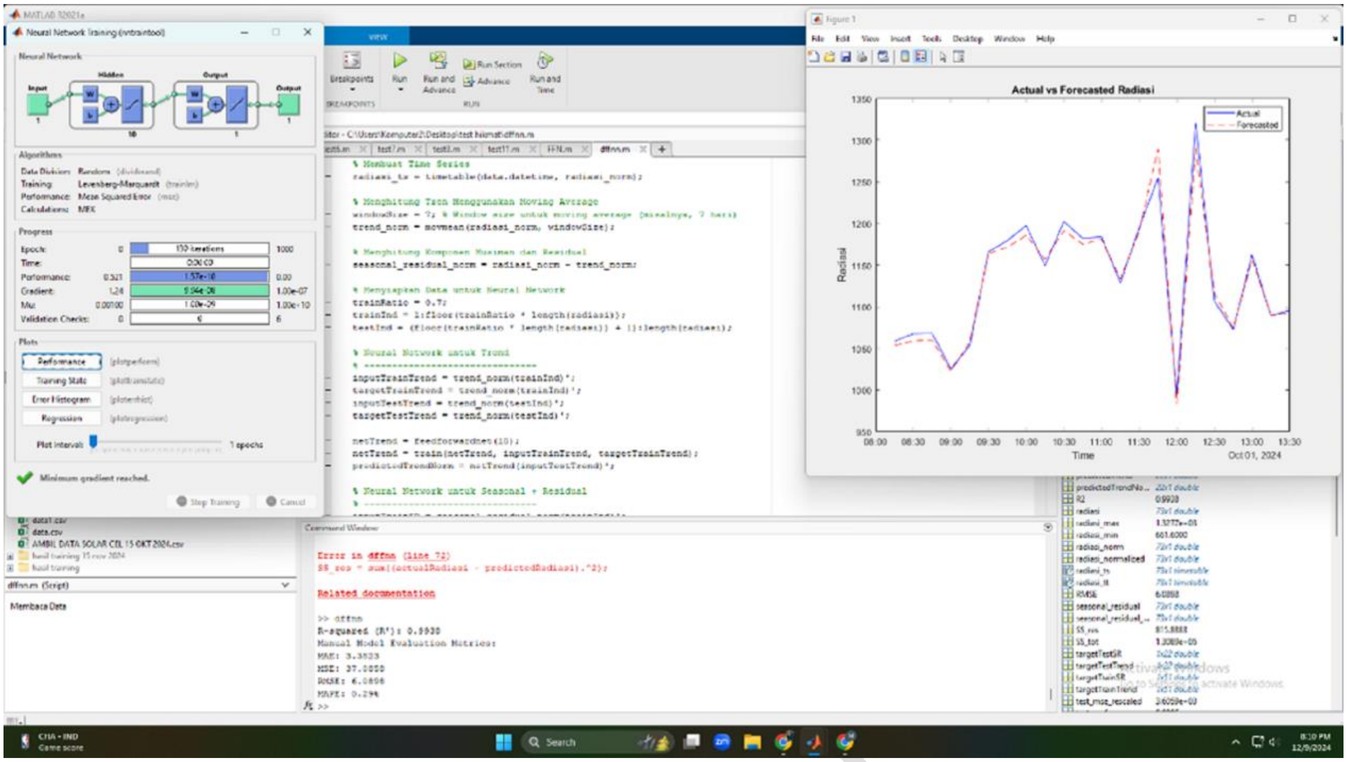

Fig 13. D-FFNN Training Result

Table 1. Model Evaluations.

Method	MAE	MSE	RMSE	MAPE(%)
D-FFNN	3.3823	37.0858	6.089	0.29
Authors	0.0108	0.0006	0.0243	1.28

The comparison of evaluation metrics for the D-FFNN and FFNN models is shown in Table 1. Analysis of the table demonstrates that the FFNN model has lower error values. This is due to the scale of the dataset that was used. In contrast, the D-FFNN model remarkably has higher error values because of the scale of data which was previously processed in comparison to the base model. Regardless, both evaluation results are considered acceptable with respect to their dataset scale.

Table 2. Forecasting Result.

Times	MAE
13.45	1289.5
14.00	1046.14
14.15	1322.97
14.30	1157.14
14.45	1123.84
15.00	1206.73
15.15	1133.12
15.30	1140.11

The forecasting results obtained via the D-FFNN model are detailed in Table 2, which displays values that reasonably follow the pattern of the actual data. At 13:45 and 14:00, the actual radiation data for the day in consideration was 1076.1 and 786.2, respectively. The loss was forecasted and amounted to 1289.5 at 13:45 and 1046.14 at 14:00, marking a notable discrepancy of about 19%. This difference occurs as a consequence of the model not just examining the most recent information, but also evaluating the entirety of the data set. For example, during the preceding day, the radiation data hovered around 1217, with a mere 5% deviation. Further, variabilities in the radiation data can be impacted by persistent factors such as changeable weather and cloud cover that shield sunlight. The model, thus, assumes that while a certain degree of variation is permitted, swift changes might result in sudden dissimilarities. This means that once again, the most recent dataset is taken into consideration with the previous forecasting data set, aligning it to the presumed pattern shown in Figure 14. This is so much so that it isn't just the dataset that has altered; it is also the changes noted in the real world, in this case with degree differences in solar radiation measurements. With all this taken into consideration, there indeed seems to be order in the data pattern, and yet, its modelling and practical application does yield PP deviations, which the degree differences previously identified suggest.

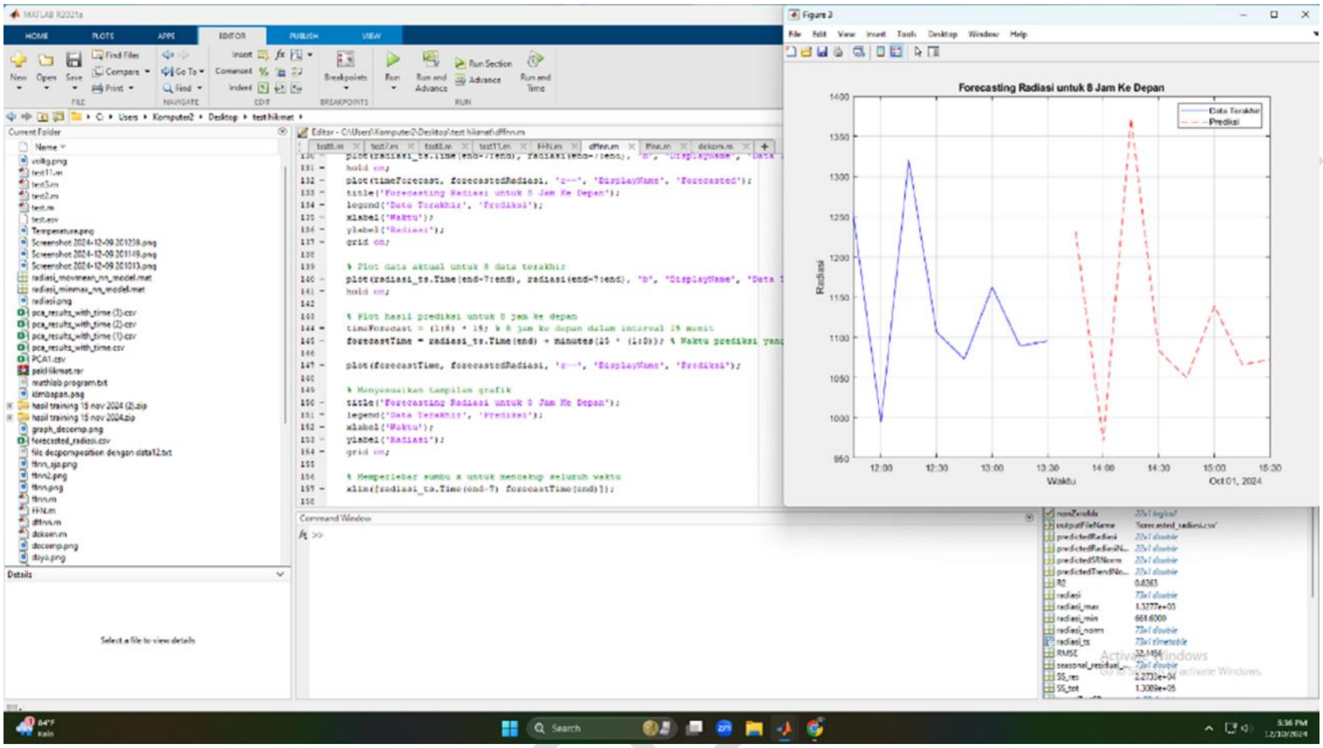

Figure 14. Irradiance Forecasting

4. CONCLUSION

In this study, a new methodology for short-term solar radiation forecasting utilizing decomposition and FFNN approaches is proposed. Using trends and recent data, the method has produced a reasonably accurate prediction of 1289.5 at 13:45 and 1046.14 for 14:00, which has a deviation of 19%. Based on the results, the model achieved MAE, MSE, RMSE, and MAPE values of 3.3823, 37.0858, 6.089, and 0.29 respectively. The model forecasting the solar radiation showed low error rates, which points to the model's reliability. Having low error rates confirms the model's usefulness in predicting solar radiation, which is necessary in order to enhance the stability and efficiency of solar power systems. This methodology is verified in this study using six forecasting datasets.

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