INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN ECONOMICS & MANAGEMENT SCIENCES

OPEN ACCESS JOURNAL

Vol 14, Issue 4, (2025) E-ISSN: 2226-3624

Techno-Economic Assessment of Solar Farm Output Optimization Using Artificial Neural Networks (ANN): A Case Study from Pahang, Malaysia

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DOI Link: http://dx.doi.org/10.6007/IJAREMS/v14-i4/26869

Published Online: 11 November 2025

Abstract

The integration of Artificial Neural Networks (ANN) into renewable energy management has become increasingly vital for enhancing operational efficiency and supporting sustainable economic development. This study investigates the application of ANN modeling for predicting and optimizing output power at the string level of a large-scale solar farm in Pahang, Malaysia. Using MATLAB-based simulations and real operational data collected from January to November 2023, the study analyzes the relationship between photovoltaic (PV) module temperature and power output to improve prediction accuracy and management decision-making. The optimized ANN model achieved a strong predictive performance with an R^2 of 0.95 and an RMSE of 0.10, demonstrating its capability to capture nonlinear system behavior under tropical climate conditions. The findings suggest that accurate power forecasting not only enhances technical reliability but also contributes to better resource allocation, maintenance planning, and overall economic efficiency in large-scale solar operations. This research provides a scalable framework for integrating intelligent modeling tools into renewable energy asset management strategies, aligning with broader sustainability and energy policy objectives.

Keywords: Artificial Neural Network (ANN), Solar Energy Management, Output Forecasting, Techno-Economic Optimization, Renewable Energy Systems

Introduction

Large-scale solar farms are utility-scale photovoltaic power stations that convert sunlight into electricity. They play a crucial role in meeting the growing energy demand while reducing carbon emissions. However, accurately forecasting the power output of these solar farms is challenging due to the intermittent nature of solar energy and its dependence on various atmospheric parameters (Iskandar et al., 2024a; Iskandar et al., 2024b). Accurate prediction of power demand and generation is essential for modern energy systems to efficiently allocate resources and facilitate energy trading. Improved forecasting techniques provide advantages for electrical energy companies by offering better insights into resource allocation and energy trading. Solar power forecasting enables better management and utilization of renewable energy resources (Iskandar et al., 2024a).

Artificial Neural Networks (ANNs) have emerged as a powerful tool for forecasting solar radiation intensity and power output of photovoltaic (PV) systems. ANNs can be trained to overcome the limaitations of traditional methods, solve complex problems, and model difficult situations that are hard to analyze (Mellit et al., 2013). The "vanilla" feed-forward neural network is a common and simple type of ANN used in solar power forecasting. Various surface parameters and environmental factors influence the energy production of PV solar power plants. These factors include temperature, irradiance, wind speed, and other atmospheric conditions (Sahin et al., 2023). Understanding the relationship between these factors and power output is crucial for improving the efficiency of solar power plants.

MATLAB is a widely used software platform for developing and implementing ANN models. It provides a user-friendly interface and powerful computational capabilities, making it suitable for solar power forecasting applications. The Keras framework, which is compatible with MATLAB, can be used to build and train ANN models for accurate power forecasting (Iskandar et al.,2024b). String-level implementations are widely deployed in grid-tied solar PV systems to improve performance ratio (PR) under non-uniform conditions (Rana et al.,2016). Monitoring and optimizing the power output at the string level is crucial for maximizing the efficiency of large-scale solar farms (Dhoke et al.,2020). Accurately forecasting the power output of individual strings in a solar farm is challenging due to the intermittent nature of solar energy and its dependence on various atmospheric parameters (Gritzbach et al.,2022). Traditional forecasting methods have limitations in modelling complex relationships between environmental factors and string-level power generation.

Artificial Neural Networks (ANNs) have shown promising results in forecasting solar radiation intensity and power output of photovoltaic (PV) systems (Dhoke et al.,2020). ANNs can be trained to learn the complex relationships between input parameters and string-level power output, overcoming the limitations of traditional forecasting techniques (Gritzbach et al.,2022). Developing and implementing ANN models for solar power forecasting requires efficient software tools. MATLAB is a widely used platform that provides a user-friendly interface and powerful computational capabilities for ANN development. However, there is a lack of research focusing on the use of MATLAB and its Keras framework for string-level power forecasting in large-scale solar farms.

The first objective is to develop an Artificial Neural Network (ANN) Model for power output analysis of a Large-Scale Solar Farm. The use of Artificial Neural Networks (ANNs) has been widely explored for solar power forecasting and optimization. Studies have demonstrated the effectiveness of ANN models in predicting the power output of photovoltaic systems, including large-scale solar farms (Solar Power Forecasting Using Artificial Neural Networks, 2015; Kounni et al., 2021; Fahmi et al., 2021). The second objective is to imply the MATLAB software in the development of an Artificial Neural Network (ANN) Model. MATLAB is a widely used software platform that provides a user-friendly interface and powerful computational capabilities for developing and implementing ANN models. Researchers have utilized MATLAB and its compatible frameworks, such as Keras, for building and training ANN models for solar power forecasting applications (Fahmi et al., 2021; Zeng, 2023). The third objective is to investigate the power output performance of the Large-Scale Solar Farm at the String level. Monitoring and optimizing the power output at the string level is crucial for maximizing the efficiency of large-scale solar farms. However, the existing literature lacks experimental research that specifically focuses on the in-situ environmental and ecological impacts of string-level solar PV advancements (Fahmi et al., 2021).

Previous studies on solar power prediction have largely concentrated on system-level or array-level modeling, which, while useful for overall performance assessment, offer limited insights into individual string behavior that is critical for early fault detection and maintenance planning. Furthermore, most of the available literature is based on case studies from temperate climates, leaving a gap in understanding how solar farms operate under tropical conditions characterized by high humidity, intermittent cloud cover, and rapid temperature variations. In addition, although Artificial Neural Networks (ANN) have been widely applied in energy forecasting, many studies employ baseline ANN models without systematic hyperparameter optimization, often resulting in reduced predictive accuracy (Carneiro et al., 2022). These gaps highlight the need for a granular, climate-specific, and optimized modeling framework that can enhance both the accuracy and practical applicability of solar power forecasting. While system-level or array-level modelling is useful, it offers little information into the performance of individual strings that directly impact dependability and maintenance planning (Nwokolo et al., 2002). This is the focus of the majority of current work on solar power prediction. Furthermore, most published research has concentrated on data gathered in temperate settings, which leaves a gap in our knowledge of how solar farms behave in tropical climates with high humidity, sporadic cloud cover, and sharp temperature swings. An Artificial Neural Network (ANN) architecture for string-level power output prediction is developed in this study to fill these gaps (Jathar et.al., 2024). It is optimized by methodical hyperparameter tweaking. Firstly, this work introduces a granular diagnostic approach for string-level performance forecasting, secondly an empirical insight under tropical operating conditions, and thirdly a scalable, adaptable methodology that can be extended to other renewable energy systems by utilizing a year-long dataset from a large-scale solar farm in Pahang, Malaysia.

Machine Learning (ML) is a branch of artificial intelligence, and numerous popular ML forecasting models are frequently used in solar power applications. These models consist of support vector regression (SVR), random forest (RF), K-nearest neighbors (K-NN), long short-term memory (LSTM), and artificial neural networks (ANN). While MATLAB-based ANN techniques have been employed in several studies for PV system modelling, most of them have concentrated on system-level or array-level prediction instead of string-level prediction. For example, Rana et al. (2016) and Dhoke et al. (2020) handled string-level monitoring without incorporating ANN forecasts in MATLAB, whereas Mellit et al. (2013) and Fahmi et al. (2021) focused on overall PV plant production. Comparing string-level MATLAB-based implementations to Python-based frameworks like TensorFlow and Keras, recent reviews (Carneiro et al., 2022; Jathar et al., 2024) further reveal that although ANN applications in solar forecasting are expanding, they are still not well-studied. To address this constraint, the current study contributes by focusing specifically on MATLAB-based ANN applications for string-level forecasting in large-scale solar farms.

Methodology

This study aims to predict the output power generated from String 1 (ipv01) of a large-scale solar farm using an Artificial Neural Network (ANN) method developed with MATLAB software. The methodology involves several key steps, which are detailed below. The solar data were collected from a solar farm in Pahang, Malaysia, spanning the period from January 2023 to November 2023. The primary input variable for the ANN model is the PV module temperature, while the output variable is the power generated from String 1 (ipv01). Data were recorded at hourly intervals from 07:00:00 to 19:00:00 for each day. The raw data were first cleaned to remove anomalies, missing values, or outliers that could affect the performance of the ANN model. After cleaning, the PV module temperature data were normalized to a common scale using the min–max normalization technique to ensure efficient model training. Finally, the processed dataset was segmented into training and testing subsets to evaluate the performance of the ANN model effectively.

ANN Model Development

The ANN model was developed using an output layer that represented the power produced by String 1 (ipv01), one or more hidden layers with an appropriate number of neurones, and an input layer that matched the temperature of the PV module. The training dataset was used to train the model, and the backpropagation algorithm was used to minimize the mean squared error between the actual and predicted power output values. Using a grid search approach, hyperparameters like learning rate, activation functions, number of hidden layers, and number of neurones per layer were methodically optimized to improve model performance.

Flowchart

The flowchart in **Figure 1** outlines a structured process for evaluating the performance of a solar farm using an Artificial Neural Network (ANN). It starts with gathering historical data on key variables such as weather conditions, module quality, shading, temperature, and energy production. This data is then pre-processed to ensure it is clean and consistent, which involves removing any missing values and outliers. Next is feature selection, where important input features for the ANN model, like weather and operational factors, are identified. The ANN model is then developed by designing its architecture and training it repeatedly with the historical data. The model's generalizability and predictive abilities are assessed during the validation and testing phases. Once the model is trained, its performance is analyzed by comparing its predictions with the actual energy output, using metrics like Mean Absolute Error or Root Mean Squared Error. Any inconsistencies or issues identified in this analysis lead to corrective measures. A key element is the implementation of a continuous monitoring and control system that uses the optimized ANN model. This system allows for real-time monitoring and adjustments to ensure optimal operation of the solar farm. The flowchart shows that this is a cyclical process, where the ANN is continually improved, and the solar farm's performance is constantly optimized based on ongoing feedback.

The trained ANN model was used to predict the output power generated from String 1 for the first day of each month from January to November 2023. Predictions were made at hourly intervals from 07:00:00 to 19:00:00. The testing dataset was used to evaluate the ANN model's performance, and several metrics were used to gauge the precision and dependability of the model's predictions. Among these were the Coefficient of Determination (R2), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Squared Error (MSE). The predicted power output values were compared with the actual values recorded from the solar farm to assess the accuracy of the ANN model. The results indicate that the ANN model can effectively predict the output power of String 1 based on the input PV module temperature, with a high degree of accuracy. Detailed analysis of the results is provided in the Results section.

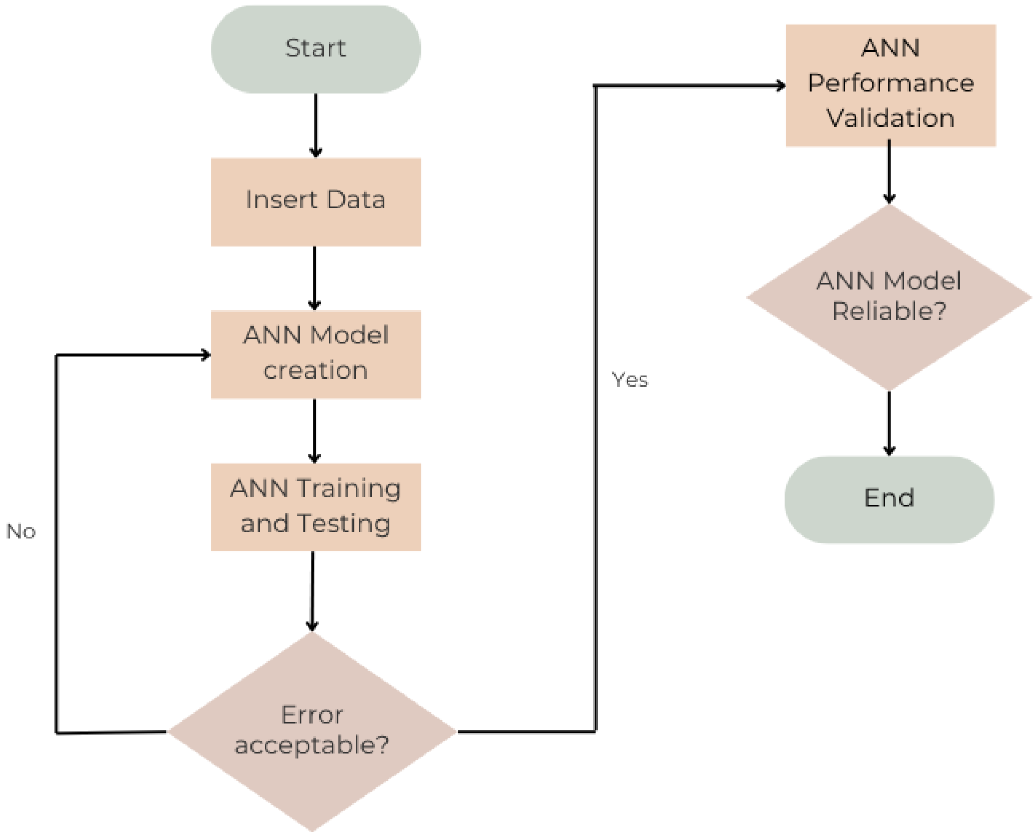

Figure 1: ANN Analysis Flowchart

Results and Discussion

In this investigation, the only input variable for the ANN model was the temperature of the PV module. This decision was made to preserve consistency with the available high-resolution dataset and to separate and assess the effect of temperature on string-level performance under tropical operating conditions. The current analysis did not account for other environmental parameters, such as ambient temperature, wind speed, and sun irradiation, which also affect PV system production. One of the work's limitations is the exclusion of certain criteria. Future research will expand the suggested framework to include more environmental factors, improving the string-level forecasting models' prediction accuracy and resilience.

The differences between the actual and predicted power outputs are relatively small across all three graphs (February 1, 2023, April 1, 2023, and November 1, 2023), as shown in Figure 2, Figure 3, and Figure 4. The small difference between the actual and predicted output power on these three dates indicates that the ANN model has a high accuracy in forecasting the power output. This suggests that the model has been well-trained and validated, capturing the underlying patterns and influences on solar power generation effectively (Premalatha & Arasu, 2016; O'Leary & Kubby, 2017; Lee & Lee, 2023). The primary reason for selecting 1 February 2023, 1 April 2023, and 1 November 2023 is that they exhibit the most similar actual to predicted output power values for the solar farm's power output. This similarity indicates that the ANN model's predictions were highly accurate these days, making them ideal candidates for detailed analysis. The consistent and high accuracy of the model on these dates allows for a comprehensive examination of the factors contributing to the model's performance (Gopi et al., 2022).

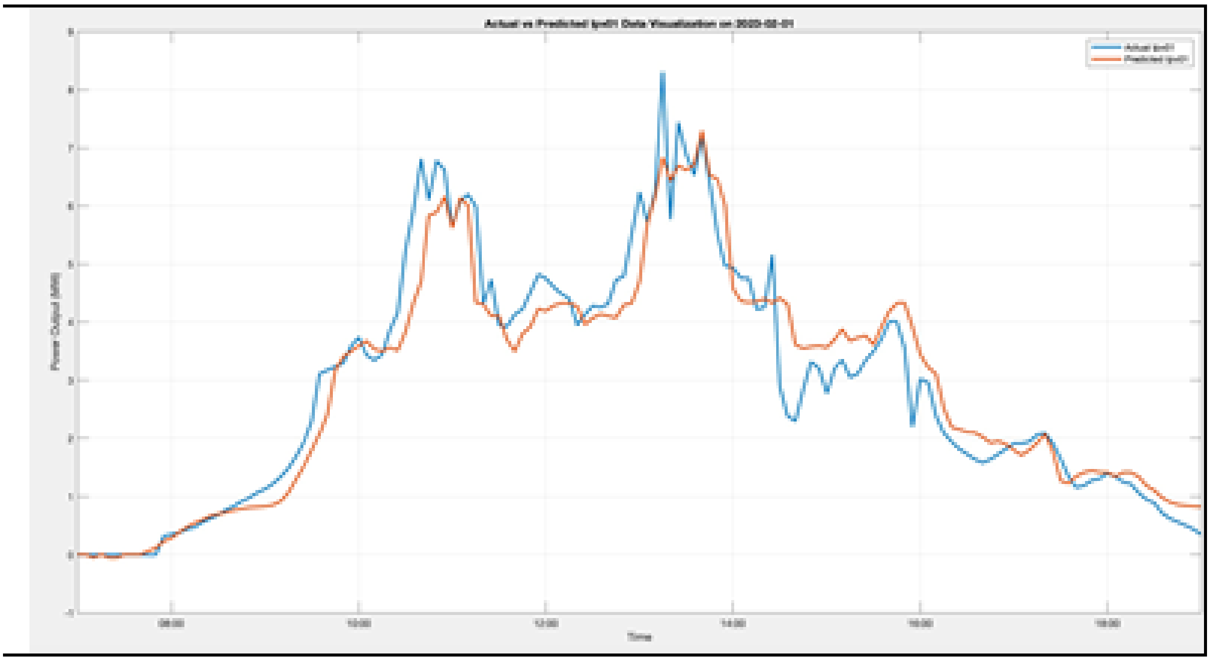

Figure 2: Actual vs predicted output power generated on 1 February 2023 using ANN method

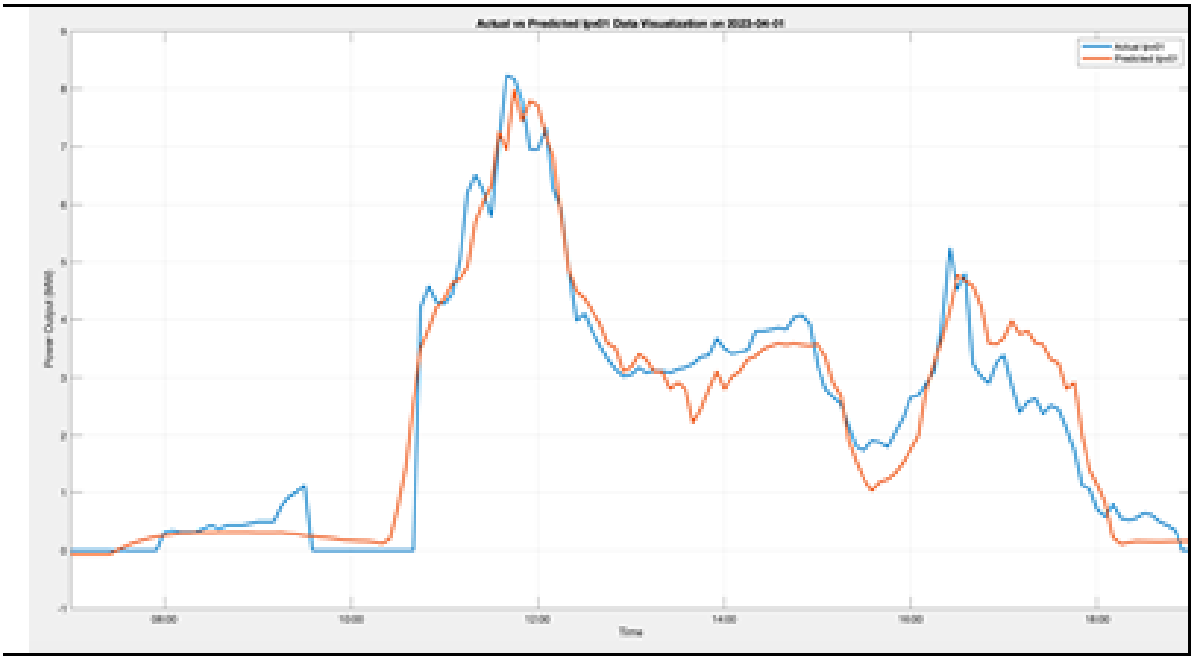

Figure 3: Actual vs predicted output power generated on 1 April 2023 using ANN method

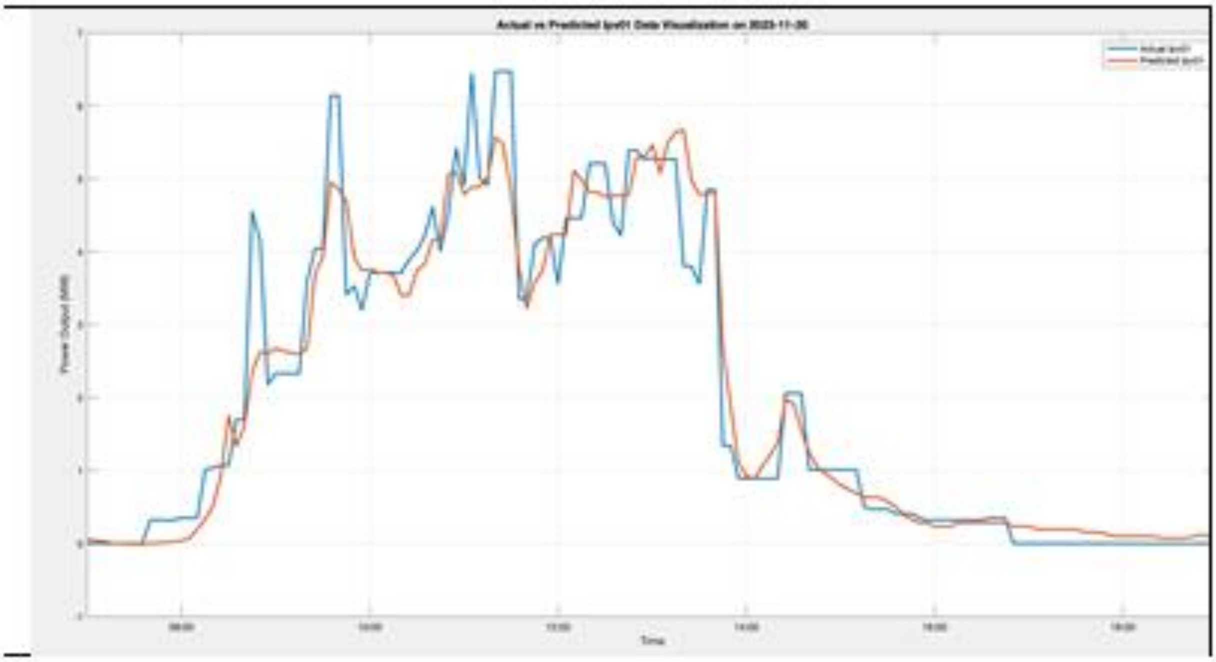

Figure 4: Actual vs predicted output power generated on 1 November 2023 using ANN method

Based on the observation, the solar farm's actual electricity output on February 1, 2023, was around 8.3 MW at 13:15, but the ANN model's anticipated output was roughly 7.8 MW at the same time (Premalatha & Arasu, 2016; O'Leary & Kubby, 2017). Despite a minor discrepancy during the peak generation phase, this suggests that the model was able to follow the production curve's overall tendency. On 1 April 2023, a similar pattern was noted, with the projected output of about 8 MW at 11:45 and the actual output reaching about 8.2 MW at 11:40 (Premalatha & Arasu, 2016; O'Leary & Kubby, 2017). The predicted and measured values closely match, demonstrating how well the model captures daily fluctuations in very constant weather. The actual production, however, was about 6.4 MW at 11:30 on November 1, 2023, whereas the model anticipated about 5.9 MW at 13:15 (Premalatha & Arasu, 2016; O'Leary & Kubby, 2017). This was a significantly bigger variation than the prediction. This implies that seasonal fluctuations and weather fluctuations might have impacted the model's prediction accuracy, especially when it came to temporal alignment with peak electricity generation. Overall, these findings support the notion that the peak output power is usually recorded between 11:00 and 14:00, during the middle of the day, when solar irradiance is at its highest and the temperature of the PV module reaches a peak of about 50°C. The sun is at its highest point in the sky during this time, which maximizes solar exposure and, as a result, the amount of power that the solar panels can produce (Amer et al., 2023). The influence of high irradiance during this period balances these losses, leading to peak net output, even if temperature increases tend to decrease PV efficiency due to thermal effects. The ANN model can so closely follow string-level performance, with small variations ascribed to seasonal and environmental conditions, as shown by the comparison of real and expected outputs. This emphasizes how crucial it is to include other factors like wind speed and irradiance in subsequent research to increase forecast accuracy even more.

Data Analysis for February 1, April 1, and November 1, 2023

ANN Regression Analysis

The regression graphs for the data on February 1, April 1, and November 1, 2023, as shown in Figure 5, Figure 6, and Figure 7, indicate the relationship between the predicted output power and the actual output power of the solar panels for the specified dates. The weather on February 1, 2023, was cloudy with light rain in the morning, with temperatures between 24°C and 31°C and high humidity all day long (Past Weather in Pahang, n.d.). The weather was mostly clear with little cloud cover on April 1, 2023, which helped to maintain constant solar radiation conditions. The temperature probably fell between the low and mid-30s Celsius (Past Weather in Pahang, n.d.). The temperature was expected to be between 25°C and 33°C on November 1, 2023, with mostly clear skies and sporadic cloud cover (Past Weather in Pahang, n.d.).

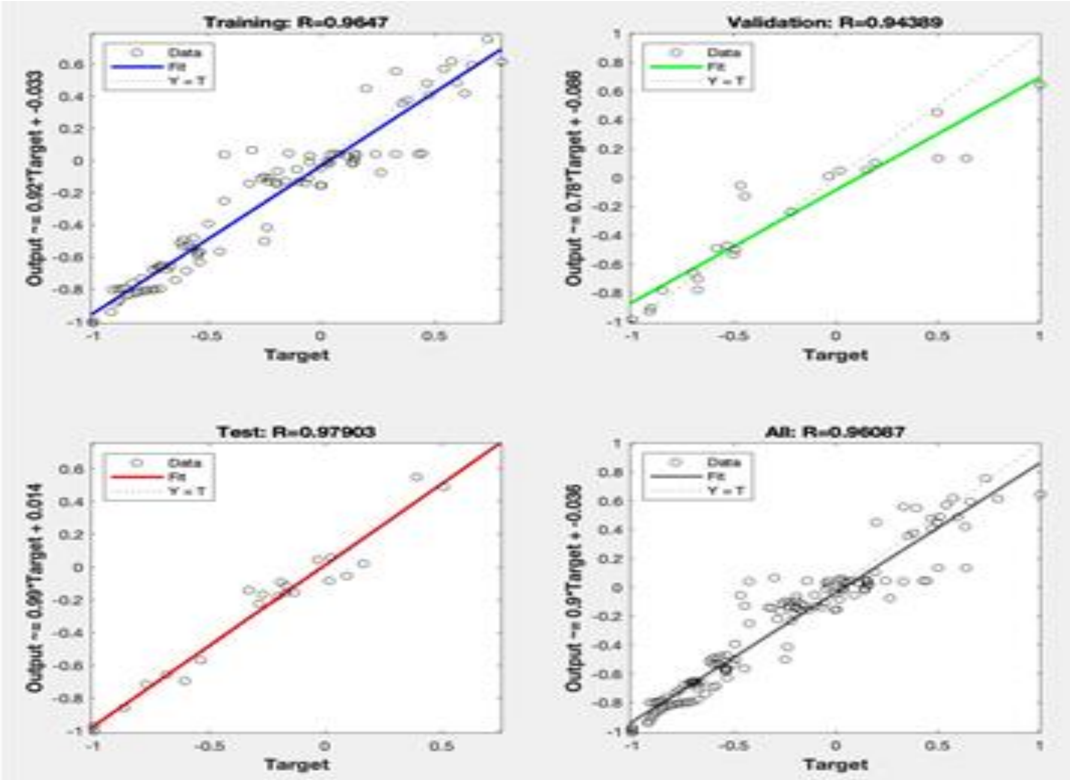

Figure 5: ANN regression for training, testing, validation on 1 February 2023

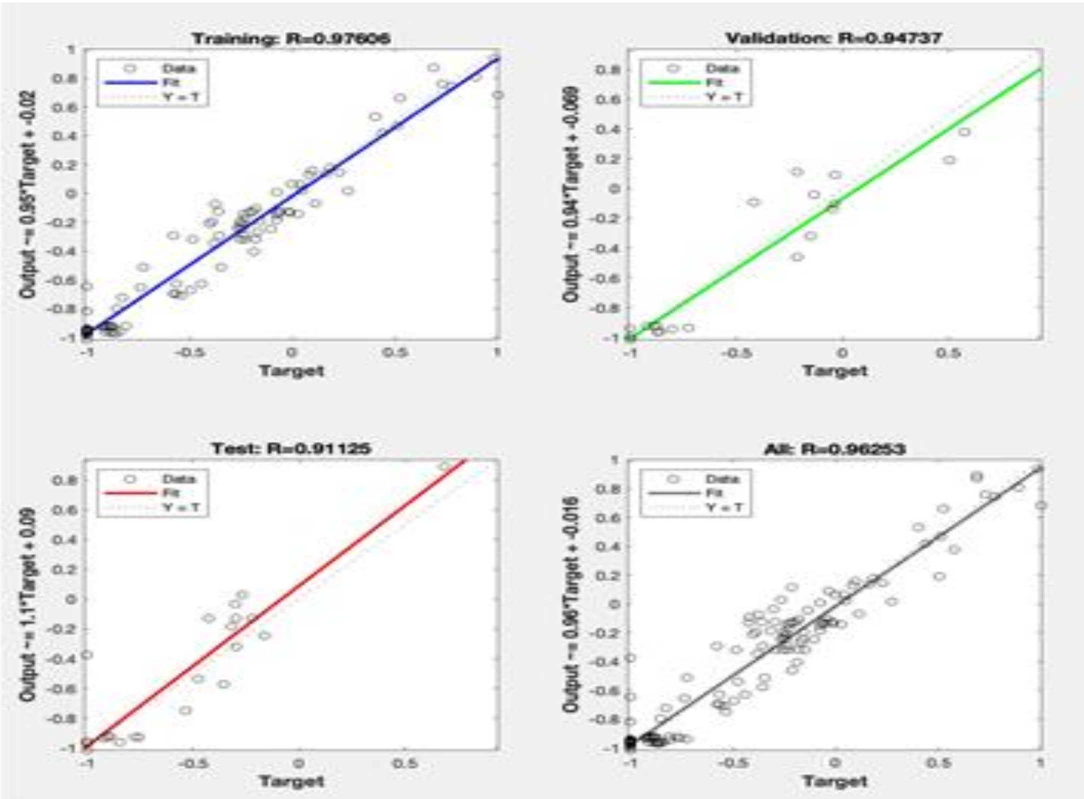

Figure 6: ANN regression for training, testing, validation on 1 April 2023

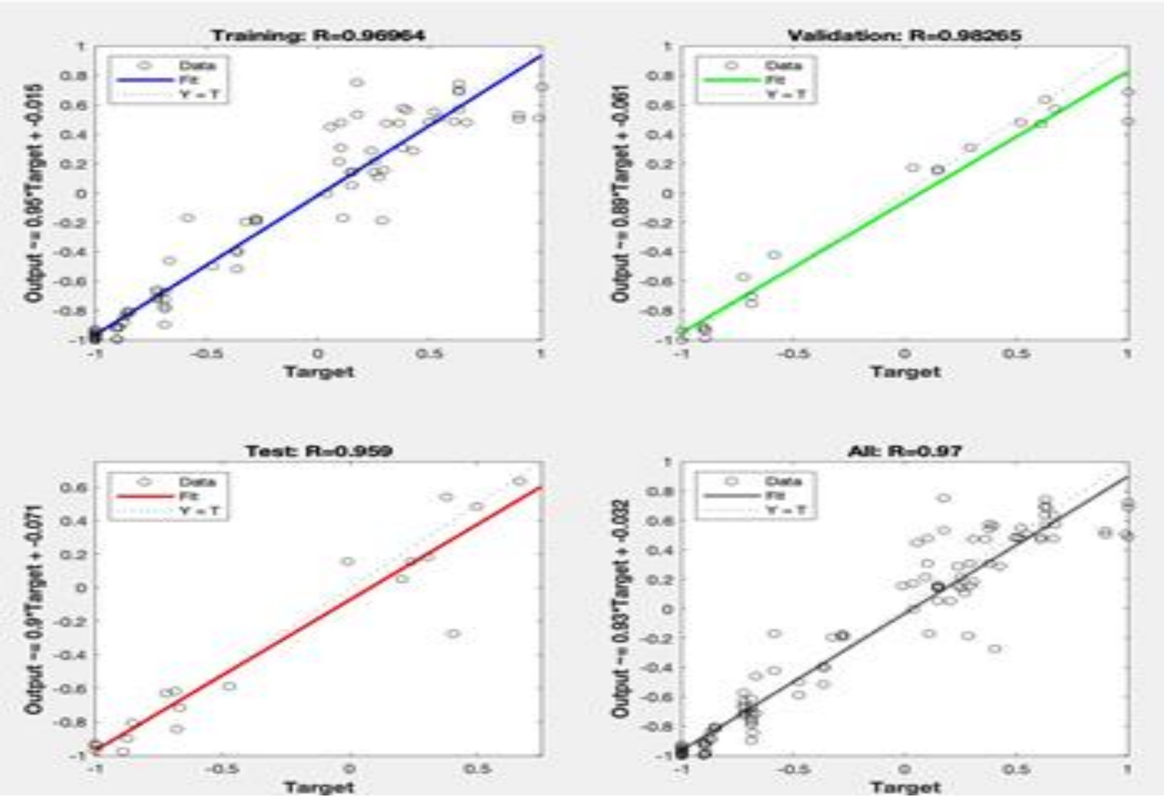

Figure 7: ANN regression for training, testing, validation on 1 November 2023

ANN Model Evaluation
The high R-values across all datasets (training, validation, and testing) indicate a strong linear relationship between the predicted and actual values. An R-value greater than 0.96 signifies that the ANN model can accurately capture the patterns and variability in the data. Several important aspects affected the ANN model's performance. First, the quality of the training data was crucial since it allowed the model to learn underlying patterns accurately and generalize well because the dataset used for training, validation, and testing was extensive and representative of a range of scenarios (Nau, 2019). Second, by choosing pertinent inputs like PV module temperature, which have a direct impact on solar power generation and give the model useful data for precise forecasts, effective feature engineering was used (Nau, 2019). Third, in order to improve the learning capacity of the model, the ANN design was refined, including the number of neurones and hidden layers, and the Levenberg–Marquardt backpropagation training function was implemented (Nau, 2019). Fourth, data normalization made sure that targets and inputs were on the same scale, which accelerated convergence, increased training efficiency, and improved overall performance (Nau, 2019). Fifth, the dataset was divided into training, validation, and testing subsets to implement a robust training process. This prevented overfitting and enabled precise assessment of model performance on unseen data (Nau, 2019). Finally, the model's efficacy was also greatly enhanced by high-quality meteorological data, since precise power output projections were made possible by precise records of conditions like those in Pahang, Malaysia, on February 1, April 1, and November 1, 2023 (Nau, 2019).

In regression analysis, the coefficient of determination, R^2, represents the proportion of the variance for the dependent variable that is explained by the independent variables in the model. An R^2 value close to 1 indicates that a large proportion of the variability in the response variable has been accounted for by the regression model. In this context, the R values greater than 0.96 across all the datasets suggest that the ANN model provides a good fit to the data (Nau, 2019).

Output Power Graph Analysis

As the graphs in Figure 8, Figure 9 and Figure 10 show, there are notable discrepancies between the actual and expected output power for Ipv01 on March 1, 2023, June 1, 2023, and August 1, 2023. These three dates were particularly picked for analysis because they showed the least amount of overlap between the actual and expected power outputs, providing a chance to look more closely at the differences and pinpoint the underlying causes. There are several causes for the output power changes. The most important element is weather variability, where variations in temperature, cloud cover, and solar irradiance have a big impact on how well solar panels work (Gopi et al., 2022; Navothna & Thotakura, 2022). Furthermore, the ANN model's shortcomings might have played a role, since it might not have been trained with enough varied data to precisely capture abrupt or erratic weather pattern shifts (Gopi et al., 2022). Additionally, mistakes in recorded actual values compared to projected ones may result from measurement errors that occur throughout the data gathering procedure (Navothna & Thotakura, 2022).

Data Analysis for March, June, and August 2023

In terms of peak performance, the model expected a lower production of 2.6 MW around 14:40, but the highest output power generated on March 1, 2023, was roughly 3.4 MW around 16:15. In contrast to the projected output of 7.7 MW at 13:35 on June 1, 2023, the actual output reached approximately 8.7 MW at 13:55. Likewise, on August 1, 2023, the output was significantly lower at 6.6 MW at 12:55 than the expected figure of 8.3 MW at 13:15. The observed variations were also significantly influenced by the weather on these dates. Temperatures in Pahang ranged from the mid-20s to the low-30s Celsius on March 1, 2023, with partly cloudy conditions and sporadic sunshine (Past Weather in Pahang, n.d.). On the other hand, the weather on June 1, 2023, was primarily sunny, had high solar irradiance, and was between 30°C and 35°C, which encouraged the production of more energy (Past Weather in Pahang, n.d.). Finally, the observed differences between actual and expected power output were also influenced by the combination of sunshine and cloud cover on August 1, 2023, with temperatures ranging from 25°C to 33°C (Past Weather in Pahang, n.d.).

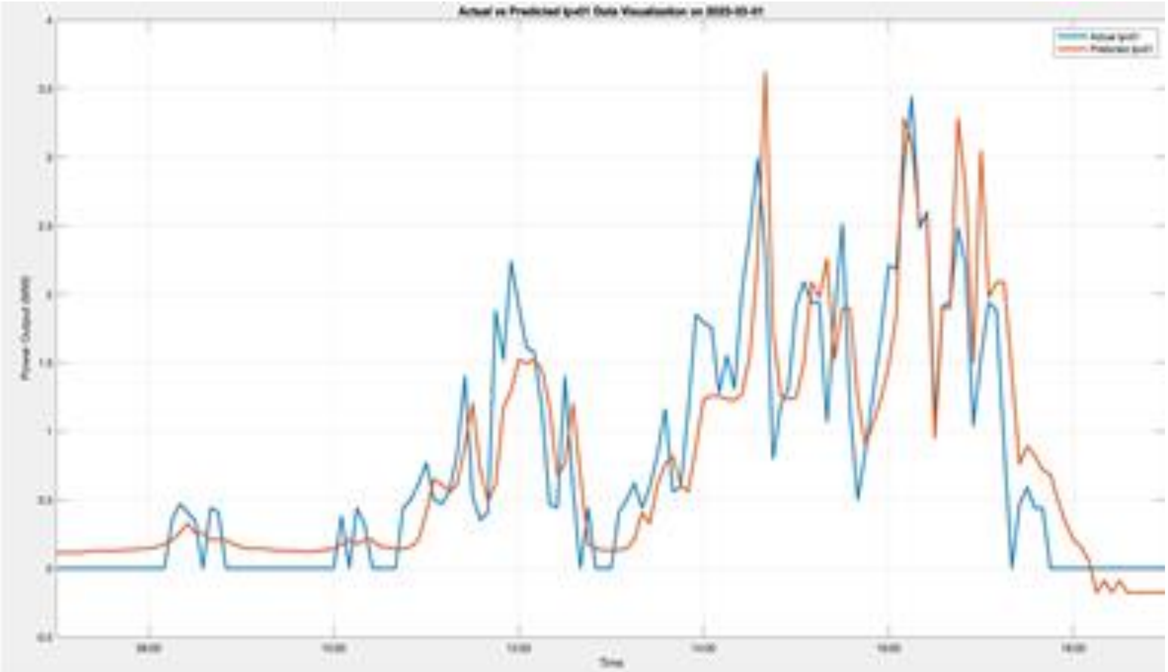

Figure 8: Actual vs predicted output power generated on 1 March 2023 using ANN method

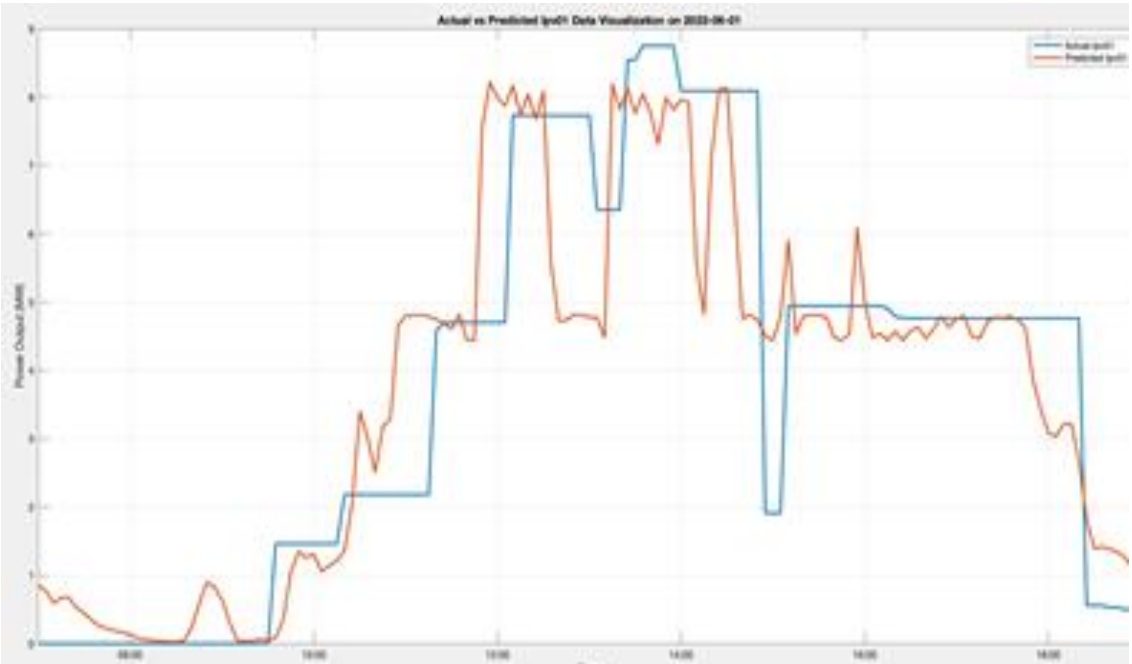

Figure 9: Actual vs predicted output power generated on 1 June 2023 using ANN method

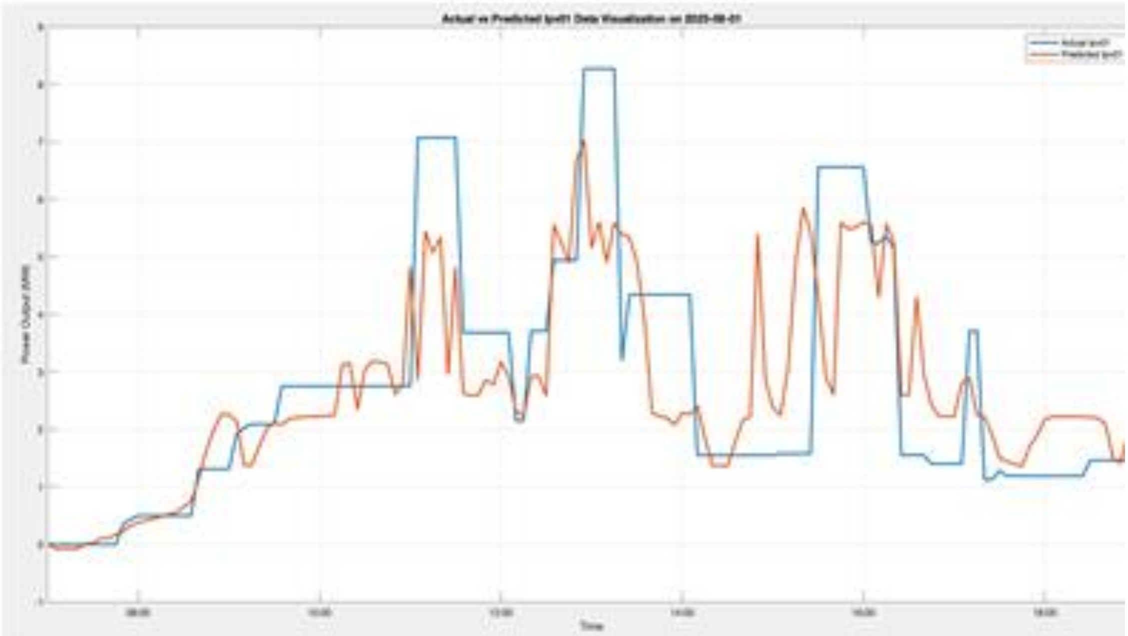

Figure 10: Actual vs predicted output power generated on 1 August 2023 using ANN method

ANN Regression Analysis

The regression graphs for the data on March 1, June 1, and August 1, 2023, indicate the relationship between the predicted output power and the actual output power of the solar panels for the specified dates as shown in Figure 11, Figure 12 and Figure 13. Regression findings showed that the ANN model did reasonably well in the validation phase on March 1, 2023, with an R value of 0.95281, indicating a significant connection between the actual and projected values. However, the performance was lower in the testing (R = 0.89871) and training (R = 0.87589) phases, indicating some discrepancies in the prediction abilities across various data subsets. A R score less than 0.9 indicates that although the model could accurately estimate output power trends, it was less successful in doing so, pointing to possible areas for improvement.

With an overall R value of 0.8898, the regression values for June 1, 2023, were like those from March. The model did not achieve high levels of accuracy, although performing reasonably consistently throughout the months. Specifically, the validation phase's R value of 0.87314 suggests that the ANN may have overfitted, learning training patterns but finding it difficult to generalize to new data. The ANN model's performance peaked on August 1, 2023. The model may have had trouble making correct predictions on this date, as evidenced by the much lower regression values for both the validation (R = 0.55645) and testing (R = 0.59698) phases when compared to March and June. A weak correlation between the expected and actual outputs is further indicated by the overall R value of 0.71742, which highlights significant errors and the necessity of model modifications. The decreased accuracy of the regression results on March 1, June 1, and August 1, 2023, could have been caused by a number of variables. Variations in cloud cover, precipitation, or abrupt changes in solar irradiation can have a substantial impact on the actual output of PV systems, making it difficult for the ANN to effectively capture such oscillations. Therefore, inconsistent weather patterns were probably one of the main culprits (Gallo, 2015).

An additional concern is model overfitting, in which the ANN may have learnt patterns or noise in the training dataset instead of recognizing the broad underlying correlations. This may help to explain why the model performed better during training but less well during testing and validation (Gallo, 2015). Furthermore, a lack of training data might have hindered the model's capacity to generalize. The model is less exposed to a range of scenarios when the dataset is not diverse in terms of weather or does not cover longer time periods. Predictive performance may be improved by enlarging the dataset to incorporate longer history records and a wider variety of weather patterns (Gallo, 2015). Lastly, this dataset may not have been optimized for hyperparameter settings like learning rate, number of hidden layers, or number of neurones per layer. The ANN's capacity to identify intricate patterns in solar output may be limited by suboptimal parameter adjustment. The overall performance of the model may be enhanced by methodical testing with various hyperparameter combinations (Gallo, 2015).

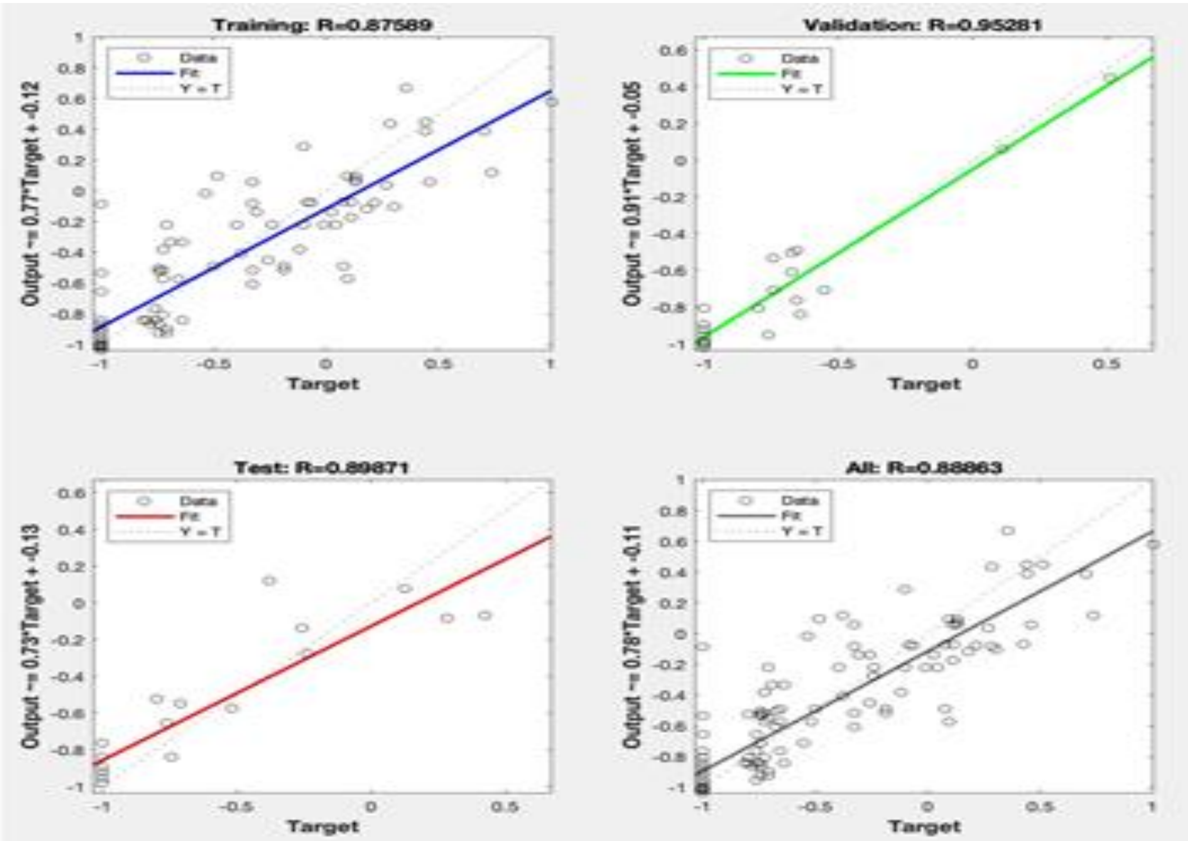

Figure 11: ANN regression for training, testing, validation on 1 March 2023

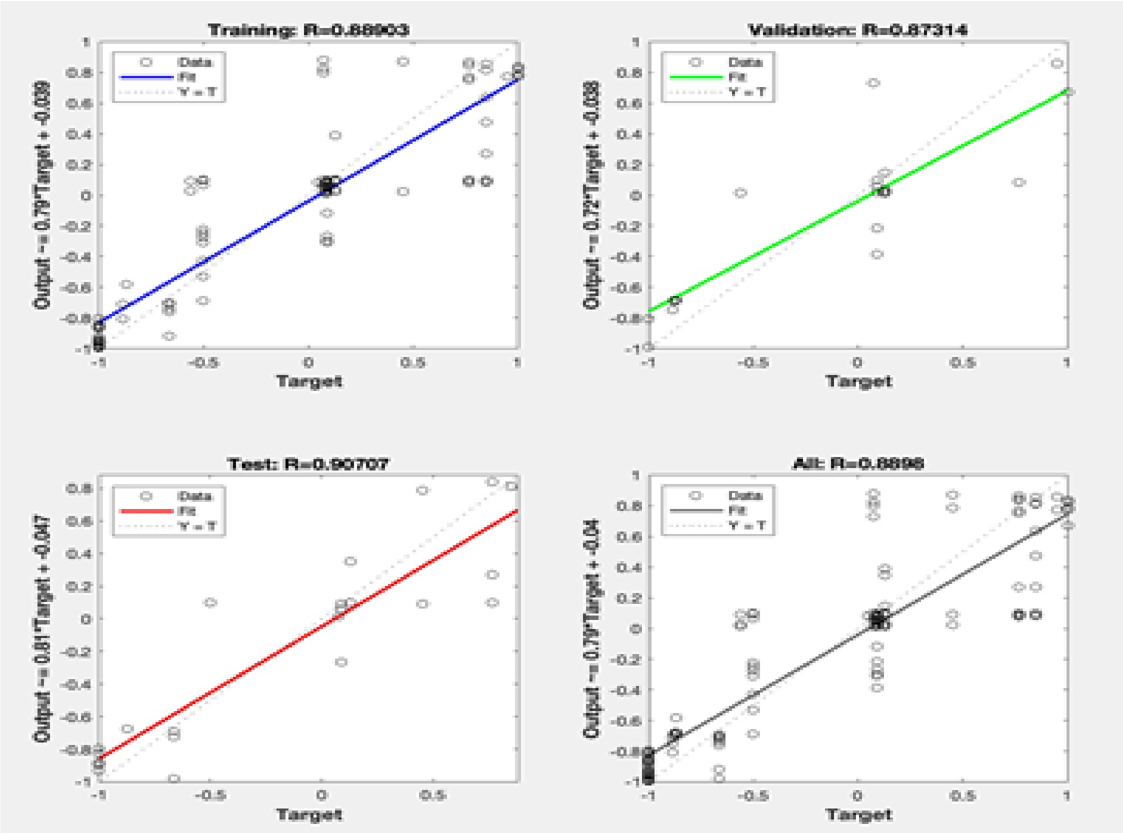

Figure 12: ANN regression for training, testing, validation on 1 June 2023

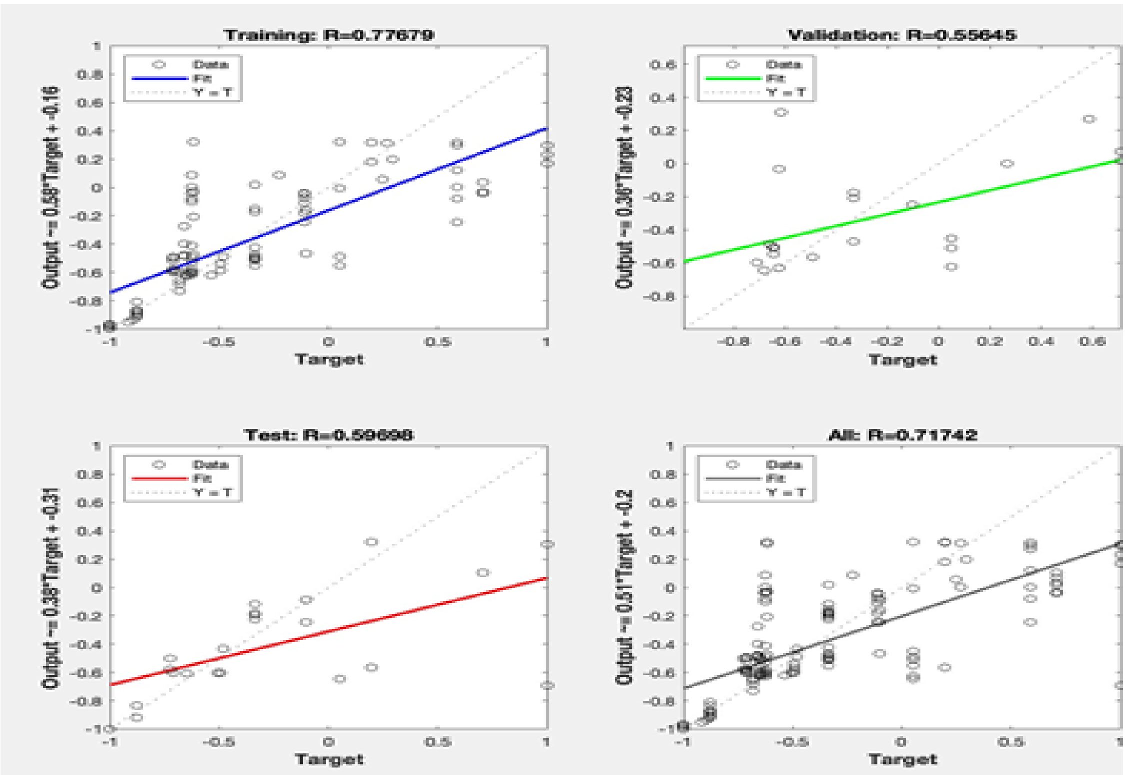

Figure 13: ANN regression for training, testing, validation on 1 August 2023

Overall, several enhancement techniques can be used to raise the ANN model's accuracy and performance. First, the model's capacity to generalize and function dependably in a variety of situations would be reinforced by expanding the training data by gathering more thorough and varied historical records, covering a range of meteorological circumstances (Gandhi, 2018). Second, feature engineering is essential for increasing predictive power; adding more environmental factors that directly affect solar power generation, like humidity, wind speed, and cloud cover, would enable the model to pick up more detailed patterns (Gandhi, 2018). Third, the use of regularization strategies like L2 regularization or dropout might improve the model's resilience to dataset noise and assist avoid overfitting (Gandhi, 2018). In addition, hyperparameter tweaking by systematic approaches like grid search or random search and perhaps more advanced methods such as Bayesian optimization can ensure that the architecture and learning process of the ANN are properly tuned for the given dataset (Gandhi, 2018). Finally, applying cross-validation specifically, k-fold cross-validation can offer a more trustworthy evaluation of the model's performance across various data subsets, lowering the risk of overfitting and enhancing the process's robustness (Gandhi, 2018).

Conclusions

This study demonstrates the potential of Artificial Neural Networks (ANN) as a practical and cost-effective tool for improving the management and operational performance of large-scale solar farms. By accurately forecasting output power at the string level, the ANN model enables energy managers to optimize maintenance schedules, minimize production losses, and enhance the economic returns of solar investments. The high predictive accuracy achieved under tropical conditions highlights the model’s adaptability and relevance to emerging solar markets in Southeast Asia. Furthermore, the proposed framework supports data-driven decision-making that can inform energy policy development and promote sustainable energy management practices. Future work could extend this research by integrating financial parameters and policy scenarios to further quantify the economic impact of predictive analytics in renewable energy operations.

Acknowledgements

The author would like to acknowledge the financial support provided by grant awarded under 100-TNCPI/INT 16/6/2 (003/2024), titled “Fungal Innovations for Synergy of Zero Hunger and Affordable Energy for Sustainable Development (Fuse)” and Solar Research Institute (SRI).

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