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A Modified Neural Network for Predicting the Solar Photovoltaic Power Generation Using Weather and Operational Parameter

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ABSTRACT

Solar PV systems often face challenges feeding power into the local grid due to weather dependence. Although solar PV generation is variable, it is predictable and can help maintain grid stability. In this study, a modified neural network is developed to forecast power generation for a 500-kW solar farm under Thailand's climatic conditions. Year-round operational data from the solar PV plant are used to train the forecasting model, and over 15% of the period is reserved for power generation prediction and validation against the actual power profile. Keras provides an effective interface, with TensorFlow as the backend engine, which is well-suited for high-computation processes. For training and testing, a batch size of 32 and 50 epochs is used as standard parameters, helping avoid overfitting and improving computational efficiency. It was found that during 75% of the sunshine period, the solar PV system generated 50% of its nominal DC capacity, indicating efficient operation. A 0.22 kW average difference between the forecasting model and the actual power profile indicates 99.86% accuracy over the testing period. The difference between actual and predicted power ranged from 2.88 kW to -4.67 kW, and the corresponding MAE, MSE, and RMSE were 0.87, 1.32, and 1.15, respectively. Furthermore, the developed ANN-based forecasting model is highly recommended for commercial use to avoid penalties from the grid authority and enhance grid stability.

INTRODUCTION

The last three decades have been among the most significant periods of technological advancement, and electrical energy has become an integral part of daily life. In the 1990s, energy production relied heavily on fossil fuels, such as coal and petroleum. In the 2000s, following coal, natural gas became the predominant energy source in the United States and other developing countries. Limitations of fossil fuel resources, rising costs, and environmental pollution have led to a reduction in the use of conventional energy sources (Jitoko et al. 2021). Furthermore, the late 2010s saw a forced shift toward renewable energy-based power generation. Coal and other conventional energy sources have declined significantly, with a corresponding increase in renewable energy sources (Dhanraj et al. 2022). Several forms of renewable energy systems are available to meet global energy demand, particularly solar energy, which is widely recognized as an alternative to reduce fossil fuel consumption due to its simplicity of operation and ability to meet conventional loads, ranging from small electronic gadgets to spaceships. Solar Photovoltaic (PV) modules are silicon cells that convert photons into electrical energy through the photovoltaic effect (Karthikeyan et al. 2018, Velmurugan et al. 2022). A solar cell is a p-type and n-type semiconductor that favors exciting electrons and creating electron-hole pairs. The solar cell's internal electric field separates electrons and holes, driving them toward the p-type and n-type junctions. This results in electrons flowing to the external circuit, producing current. The electron flow toward the external circuit depends on the photon energy falling on the solar cells (Techo et al. 2024, Chand et al. 2022). This is the primary concern in solar PV power, as solar irradiance is not continuous and power production follows its trend, leading to grid instability. A large-scale solar PV system often faces penalties from the grid authority division due to power feed that is lower or higher than the expected range (Gandhi et al. 2024).

To improve grid stability and maintain the lifespan of the load, the local grid authority monitors alternative energy sources on a day-ahead and hourly basis using forecasting tools (Sankari & Kumar, 2023). In recent years, solar PV power forecasting has become essential for medium- and large-scale solar PV power plants. Several forecasting methods exist, including conventional mathematical modeling, machine learning, deep learning, and Artificial Neural Networks (ANNs) (Ahmed et al. 2020, Liu & Du, 2023). Faizan Tahir et al. developed a bidirectional long- and short-term memory model to predict solar PV power generation for the 10 MW Masdar project in the UAE. The Bayesian optimization technique was adopted to maintain higher prediction accuracy. Historical data, including solar irradiance, PV module temperature, ambient temperature, angle of incidence, sun zenith angle, sun altitude, and air mass ratio, were used to train the forecasting model. Notably, hyperparameter tuning played a significant role in improving the accuracy of the power prediction, with Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Error (MAE) of 3.2560%, 21.252%, and 1.2310%, respectively (Tahir et al. 2024). Distributed solar PV power forecasting was conducted for the Netherlands location for the day ahead using 12 different models. Ensembles and deep-learning forecasting models were found to attain lower MAE, effectively eliminate unnecessary parameters, and capture efficient information from predictor variables. Second, the physical model shows its importance for day-ahead energy trading by delivering higher profits. By comparison, random forest and LSTM models are effective for technical performance and reliable for both single and aggregated solar PV systems (Visser et al. 2022). Unlike other forecasting models, ANN is simpler to compute and requires less computational power. The faster training time makes this prediction model efficient for solar PV power forecasting and applicable to real-time applications (Tavares et al. 2022, Pazikadin et al. 2020). Ledmaoui et al. developed a hybrid system in which solar power forecasting is performed by an Artificial Neural Network (ANN), and the energy meter is connected to the Internet of Things (IoT) to monitor the forecasted power and real-time power fed into the grid. The IoT is integrated with energy meters, as the solar PV system is located in the industrial area of Benguerir, Morocco, where energy demand is high. The developed ANN model exhibits accurate power prediction, making it versatile for energy trading and increasing the power plant's income. The correlation, MAE, and RMSE were found to be 0.694, 9.913, and 13.447, respectively (Ledmaoui et al. 2023). Forecasting power production for bifacial solar PV systems is challenging, as computing the bifacial solar PV and cooling roof system for different albedos is required. The examined system features a roof cooling system, as the bifacial solar system is situated in a desert region with higher PV module temperatures than in other tropical regions. With the help of the ANN model, the microgrid power system operates efficiently and reduces power curtailment with balanced demand-side management. The albedo surface significantly impacts power production; for example, an albedo range of 0.2 to 0.5 resulted in a 7.75% power enhancement, and further increasing the albedo to 0.8 resulted in a 14.96% power enhancement. The MSE for the different albedos of 0.2, 0.5, and 0.8 was 1.19540e-1, 1.95796e-1, and 1.60751e-1, respectively, and the correlation coefficients were 9.92416e-1, 9.88912e-1, and 9.91884e-1, respectively (Ghenai et al. 2022). Furthermore, to analyze the forecasting accuracy for hot climatic conditions, a 4 kW solar PV system from Shaqra, Saudi Arabia, was used to predict the DC power and PV module operating temperature. The hybrid model combines Multilayer Feedforward Neural Networks (MFFNNs) with a Genetic Algorithm (GA) and a Multiverse Optimizer (MVO) to enhance forecasting accuracy. Second, GA and MVO with MFFNNs favor controlling local minima and optimizing the network parameters. It was found that the Normalized Root Mean Square Error (NRMSE), MSE, MAE, and coefficients of determination were 2.78e-3, 1.30e-1, 1.07e-2, and 0.997222 for MFFNNs-GA and 7.11e-4, 3.33e-2, 7.22e-3, and 0.999289 for MFFNNs-MVO, respectively (Talaat et al. 2022). Sahin et al. examined a 500 kW solar PV power plant under Turkey's environmental conditions to find the relationship between weather and power production. Principal Component Analysis (PCA) improves the forecasting accuracy by controlling the feature dimension, and ANN captures the complex relationship between features and efficiency. The developed ANN model achieved lower RMSE and MAE values of 23.89 and 25.09, respectively, compared to the Multiple Linear Regression (MLR) model, which had R^2 values of 0.9628 and 0.901 (Sahin et al. 2023). According to the literature above, it is evident that forecasting solar PV power generation has become an essential process for maintaining grid stability. Several forecasting models are in practice, among which ANN models have gained popularity due to their ease of computation, high prediction accuracy, and the ability to train the model with fewer parameters. The main objective of the present study is given below:

- This study developed a modified neural network called SPFNet, specifically designed to perform the regression task for Thailand's geographical conditions.
- A dynamic model architecture is created based on neural layers, activation functions, and kernel initializers to forecast solar PV power generation.
- The dependent and independent variables of solar PV systems are obtained from the NREL open-source data and analyzed statistically to understand their operational behavior.
- A comparative analysis is performed for the actual and predicted power generations, and the error metrics of MAE, MSE, and RMSE are used to validate the accuracy of the forecasting model.

MATERIALS AND METHODS

Study Description

This study developed an ANN forecasting model for a 500-kW solar PV power plant in Thailand equipped with monocrystalline PV modules and fixed-array tracking systems. Given the local geography, the PV modules are mounted at a 20-degree tilt and a 180-degree azimuth, which favors higher power generation and shorter payback periods. For solar power forecasting, meteorological and plant performance data are obtained from the NREL open-source dataset. The raw data include 24-hour timestamps (hourly intervals) of beam irradiance, diffuse irradiance, POA irradiance, ambient temperature, solar cell temperature, and DC array output for one year. Furthermore, to improve forecasting accuracy, the models are trained using only daylight periods.

ANN Model Training

Importing libraries: Solar PV power forecasting uses open-licensed Anaconda Navigator to create a controlled environment. Furthermore, the Jupyter Notebook processes the data and performs the modeling. Initially, libraries are imported to build an ANN model for predicting solar power. Pandas and NumPy are used for data manipulation and to handle large datasets for numerical operations. TensorFlow and Keras are used to leverage layers for building and training the ANN model. TensorFlow is more suitable for complex computations and offers greater built-in deployment support than PyTorch. Secondly, Scikit-learn is widely used for linear regression but is less effective for deep learning models and has poor scalability, especially in PV system power forecasting. Furthermore, Matplotlib and Seaborn are used to visualize the dataset, as they are widely used for solar PV power forecasting. After importing the libraries, a dataset is loaded using the 'd.read_csv' function for preprocessing and modeling tasks.

Dataset: A one-year dataset of solar PV power plant data is imported to build and train the ANN model at an hourly frequency. The main parameters in the dataset include beam irradiance, diffuse irradiance, and plane-of-array irradiance, as well as ambient temperature, PV cell temperature, and power output. Except for power output, all parameters are independent variables, as power generation depends on the irradiance and temperature. profile. Furthermore, converting the dataframe to a numpy array facilitates splitting the dataset into X and y, where X contains the independent variables and y contains the dependent variable.

Splitting, training and test sets: For training and testing the dataset, the train_test_split function from sklearn. model is used to split X and y into X_train and y_train for training, and X_test and y_test for testing the model. In this model, 15% of the data is used for testing by setting the parameter to 0.15, which helps ensure the robustness of the developed forecasting model. The random_state parameter was set to 42 to guarantee the reproducibility of the split. To ensure data distribution across the training and testing sets, the shapes are printed as X_train.shape, y_train.shape, X_test.shape, and y_test.shape.

Feature scaling: To normalize the data, StandardScaler from the 'sklearn.preprocessing' module is used, as it is essential for determining the features and preparing the variables in a comparable state. In this case, StandardScaler is employed for both the input and output variables of the forecasting. The training data are fitted and transformed to have a mean of 0 and a standard deviation of 1; the same conditions are applied to the testing data, respectively.

Creating a neural network: The neural network forecasting model is developed using the create_spfnet function, and solar PV power plant generation is predicted using TensorFlow and Keras. The list of neuron counts for each layer, activation functions, and kernel initializers plays a significant role in initializing the model. Dense layers are added to the neuron count, and the input dimensions are initialized. As a result of the forecasting, a final dense layer is added to the neuron count and predicts the power output.

Train and test: Following the development of the neural network, data training is performed with a batch size of 32 and running 50 epochs. A batch size of 32 indicates the number of samples used at a time for computing the gradient and updating the model. The epoch 50 means the model will learn the training data pattern 50 times. The primary reason for selecting 50 epochs is to prevent overfitting. Secondly, increasing the epochs beyond 50 could lead to higher accuracy in solar power forecasting, but the computational cost is comparatively higher. As an effective method, several studies have adopted 50 epochs as the standard setpoint. Validation occurs for each training session to evaluate the neural network's performance and continually monitors the outcome. The verbose and history functions ensure the display of the progress and error metrics for each epoch, indicating performance and convergence over time.

Error metrics: These error metrics are important parameters in solar PV power forecasting, indicating the accuracy of the forecasting model and how it differs from actual power generation. Generally, MAE, MSE, and RMSE are primary error metrics that need to be evaluated to quantify the accuracy and robustness of a forecasting model.

***Mean Absolute Error*:** MAE is directionless and does not indicate that the predicted values are higher or lower than the actual value. It simplifies the average error magnitude, and the absolute value of the error is taken to treat all errors as a positive contribution, as expressed in Eq. (1).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad \ldots(1)$$

where, y_i = actual value, $\hat{y}_i$ = predicted value, and n = total number of predictions.

***Mean Square Error (MSE)*:** MSE is one of the standard error metrics widely used for analysing the prediction error following MAE. It is the square of the errors and is often validated against the actual power generation, as expressed in Eq. (2). The MSE is sensitive to outliers, where larger errors are penalised more, and is often used to train the regression model.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad \ldots(2)$$

***Root Mean Square error (RMSE)*:** RMSE is the square root of MSE as expressed in Eq. (3). RMSE is sensitive to the large errors following MSE because large errors can significantly change the outliers of the error pattern, leading to lower forecasting accuracy. It is noted that the RMSE is non-negative, and when the value is zero, the prediction and actual values are identical.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad \ldots(3)$$

RESULTS AND DISCUSSION

Input Parameters

This study predicts 500 kW of solar PV power production for the Thailand location. To forecast power production, one year of meteorological data, including irradiance and ambient temperature, along with plant performance data such as solar cell temperature and power production (as shown in Fig. 1), is used to train the ANN forecasting model. To improve forecasting accuracy, beam, diffuse, and Plane of Array (POA) irradiance are utilized. Fig. 1 shows raw data in a 24-hour format and is further processed into 12-hour segments for training the forecasting model. In Thailand, daylight periods naturally begin at 6:00 AM on most days of the year. The annual average diffuse irradiance at the examined site is 54.05 W/m² and 112.55 W/m², lower than the beam irradiance and POA, respectively, due to fewer clouds and other physical obstacles. On the other hand, peak POA irradiance is recorded at 1096.85 W/m², which gives solar PV farms greater potential to generate higher electrical energy. Under tropical climatic conditions, increased solar irradiance generates higher power but also raises solar cell temperature due to the high ambient temperature. Notably, peak ambient and solar cell temperatures reached 38.1°C and 75.26°C, respectively, which exceed standard test conditions and considerably deteriorate power generation. It is well known that solar PV power generation is discontinuous, and higher solar cell temperatures worsen plant operation and economic stability. In this case, a high ambient temperature significantly reduces the DC power output during the summer. This study does not focus on reducing solar cell temperature. However, solar cell temperature patterns are trained with the ANN model to achieve temperature-corrected power prediction.

Statistical Analysis

As mentioned above, the raw solar PV power plant data are processed into a 12-hour format, which contains a total of 4,408 irradiance values, ambient temperatures, cell temperatures, and DC array power outputs used to train the ANN forecasting model to predict the DC power output. The mean POA irradiance was recorded as 431.41 W/m², and the corresponding DC power was 165.07 kW. In year-round performance, for 25% of the period, the solar farm generates 56.90 kW; notably, the mean and 50% reached 165 kW. Notably, over 75% of the time, the solar farm generates more than 50% of the installed DC capacity, indicating that it is operating on a profitable scale. Diffuse irradiance is lower than beam and POA irradiance in all conditions due to the best absorption. The solar cell is a current generator; an increase in solar irradiance increases both the current profile and the power profile simultaneously. Due to the nature of the solar irradiance pattern, power generation is sinusoidal, and a wide variation is observed over the 12 hours of daytime operation, with a standard deviation (SD) of 114224.17. The difference between beam

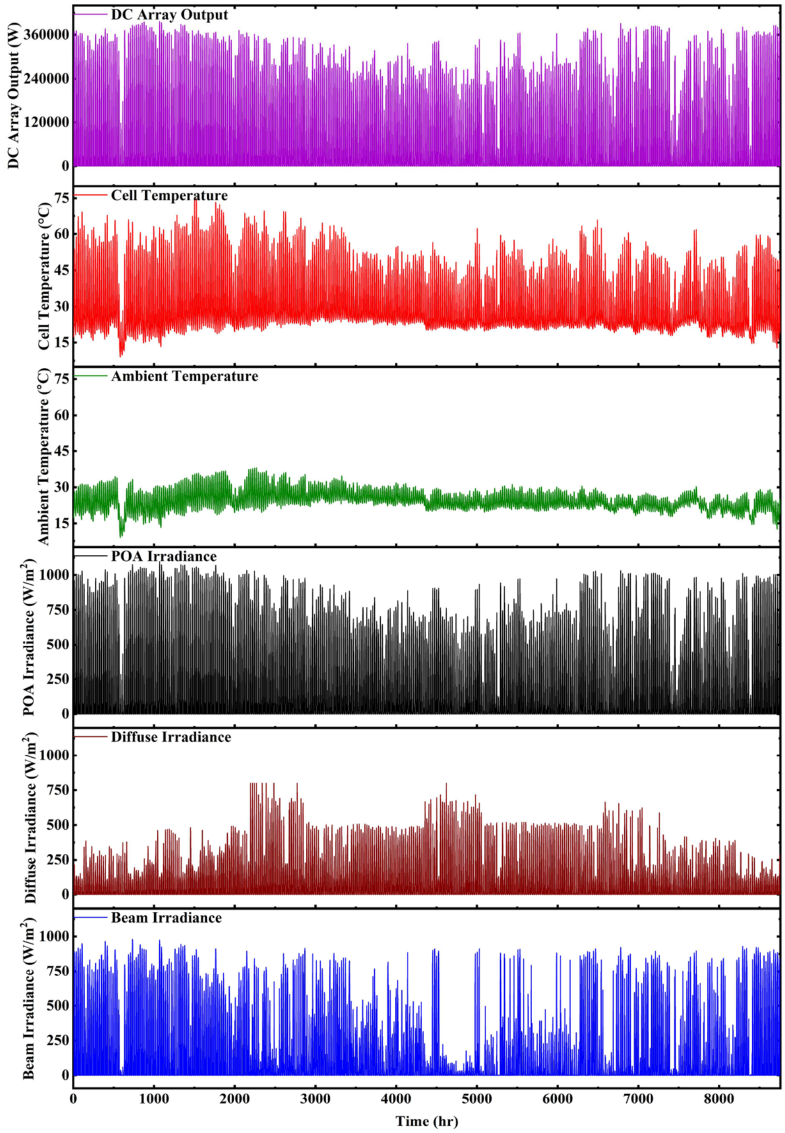

Fig. 1: Meteorological and plant performance data.

Table 1: Statistical analysis of meteorological and solar farm data.

	Beam Irradiance [W.m^{-2}]	Diffuse Irradiance [W.m^{-2}]	Ambient temperature [°C]	Plane of Array Irradiance [W.m^{2}]	Cell Temperature [°C]	DC Array Output [W]
count	4408.00	4408.00	4408.00	4408.00	4408.00	4408.00
mean	315.16	207.74	26.92	431.41	39.69	165070.88
min	0.00	1.00	9.80	0.93	10.48	0.00
25%	34.00	89.00	24.40	147.71	29.60	56909.29
50%	201.00	159.00	26.80	416.45	39.11	165067.66
75%	592.00	308.00	29.30	674.66	48.63	258488.94
max	980.00	800.00	38.10	1096.85	75.27	396421.24
SD	304.12	161.91	3.88	305.66	11.88	114224.17

and POA irradiance is 1.56, but a higher difference in SD is noted with diffuse irradiance. Comparatively, the ambient temperature attained a 3.88°C deviation, indicating that the solar farm operates under severe thermal stress, resulting in a higher solar cell temperature with a deviation of 11.88°C.

Training Model

In this ANN forecasting model, the dataset is split into training and testing subsets to ensure robust predictions. Over 365 days, 85% of the data is used to train the ANN model, and the remaining 15% is used to test and validate the model against actual data. Using 310 days of dependent and independent variables from solar farm data helps the model learn the relationships among parameters, delivering accurate predictions in the testing phase. Furthermore, the mean and SD from the training data are applied to both the training and testing sets, which helps prevent data leakage and maintain consistency.

Error and Epochs

Each layer of the developed neural network is processed iteratively, with the first layer conFig.d with a specified number of nodes, an activation function, and an initializer. The final layer is appended with a single node to produce the predicted DC array power output. In this case, a neural network with two hidden layers, containing 32 and 64 nodes, is used. Training data is processed over 50 epochs with a batch size of 32 to fit the model. Over the 50 training epochs, the training and validation RMSE values improve substantially. Initially, the training set's RMSE stood at 0.4569, indicating higher prediction errors. However, as training continued, the RMSE consistently decreased, reaching a final value of 0.0093 by epoch 50. Similarly, the validation RMSE experienced a significant reduction, starting at 0.0842 and ending at 0.0101.

Training and Testing the Model with Ambient Temperature and Beam Irradiance

As mentioned earlier, ambient temperature plays a crucial role in power generation, as an increase in ambient temperature naturally restricts heat dissipation from the PV module, thereby increasing the temperature of the solar cell. Power training and testing models are plotted against ambient temperature, reflecting their importance in power generation. It is found that higher power production periods are widely observed at ambient temperatures above 20°C, whereas temperatures below this threshold typically occur before effective sunshine hours (a typical day in winter).

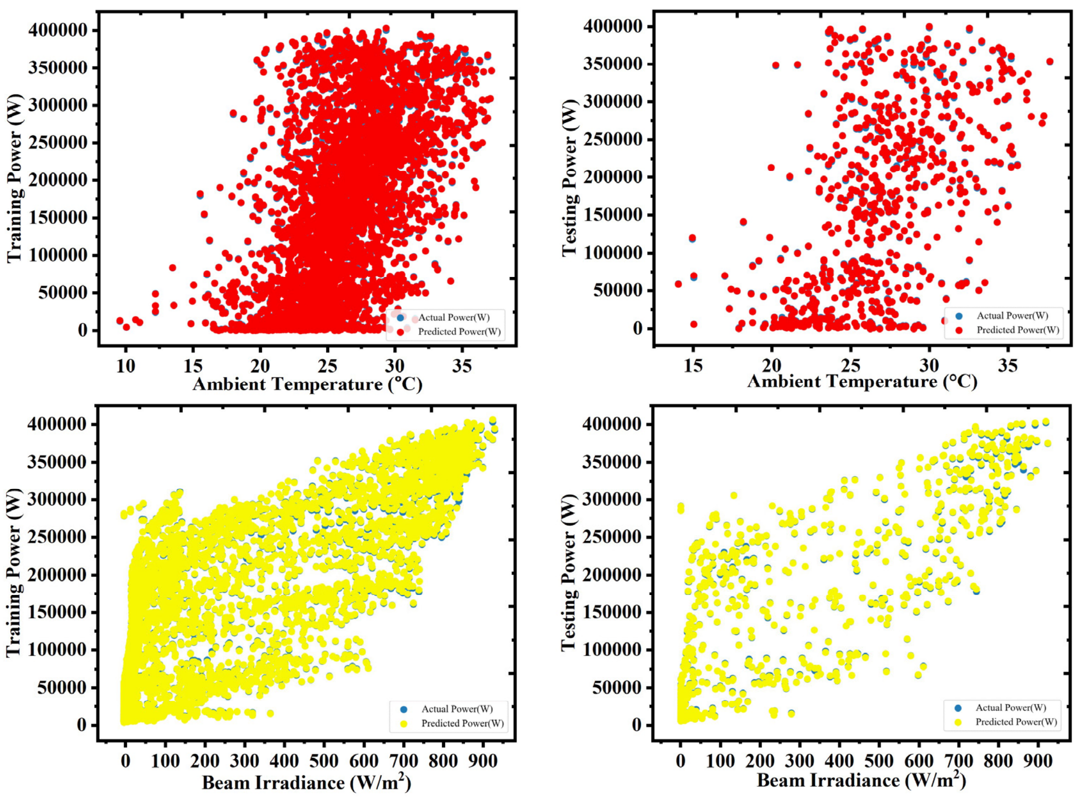

Fig. 2: Power training/testing model for ambient temperature and beam irradiance.

By comparison, the difference between actual and predicted power is negligible, as the developed ANN model was trained using 310 days of solar power generation data, along with other plant performance and meteorological data, providing accurate predictions, as shown in Fig. 2. A similar pattern is observed when testing the model against the correlation with ambient temperature. Furthermore, a training and testing model is performed against beam irradiance to understand energy generation, as beam irradiance represents the amount of solar irradiance received by the Earth. Although the higher count of power generation noted was less than 200 W/m², solar farms failed to meet 50% of the total installed DC capacity, as solar cells are current generators and higher solar irradiance favors higher power generation. Secondly, irradiance above 600 W/m² favors delivering 350 kW, and, beneficially, a second higher power generation count is noted between 750-850 W/m². This indicates that the solar farm effectively converts solar irradiance into electrical energy and attains higher performance efficiency. The training and testing model of the power profile shows that beam irradiance and ambient temperature follow a similar pattern. The dependent variable, DC power output, maintains a similar pattern to the independent variables of beam irradiance and ambient temperature. These findings indicate that the developed ANN forecasting model accurately predicts power generation for Thailand's location.

Actual and Predicted Power

As mentioned earlier, 85% of the dataset is used to train the ANN forecasting model, while the remaining 15% is used to test and validate the developed model. Fig. 3 shows the actual and predicted power generation for the 500-kW solar farm. The actual average power output of the testing model was 166.296 kW, and the developed ANN forecasting model predicts a power generation of 166.516 kW, which is 0.22 kW higher than the actual power generation. Based on 663 hours of power prediction testing, the model is 99.86% accurate and highly reliable for commercial solar farms to avoid penalties from grid authorities. The power prediction differences range from 2.88 kW to -4.67 kW, which is reasonably negligible. Although the power prediction differences are negligible, the high oscillation is mainly attributed to sudden fluctuations in solar irradiance, such as an unexpected cloud passing. In Fig. 3, a 36-hour insight view of actual and predicted power is plotted to visualize the error percentage in the developed ANN forecasting model, which is nearly zero or negligible. Under certain unpredictable weather conditions, forecasting errors can be observed, but these fluctuations are typically short-lived and often overlooked in real-time applications.

Error Metrics

The error metrics for the developed ANN model indicate an MAE of 0.87, with the actual and predicted power

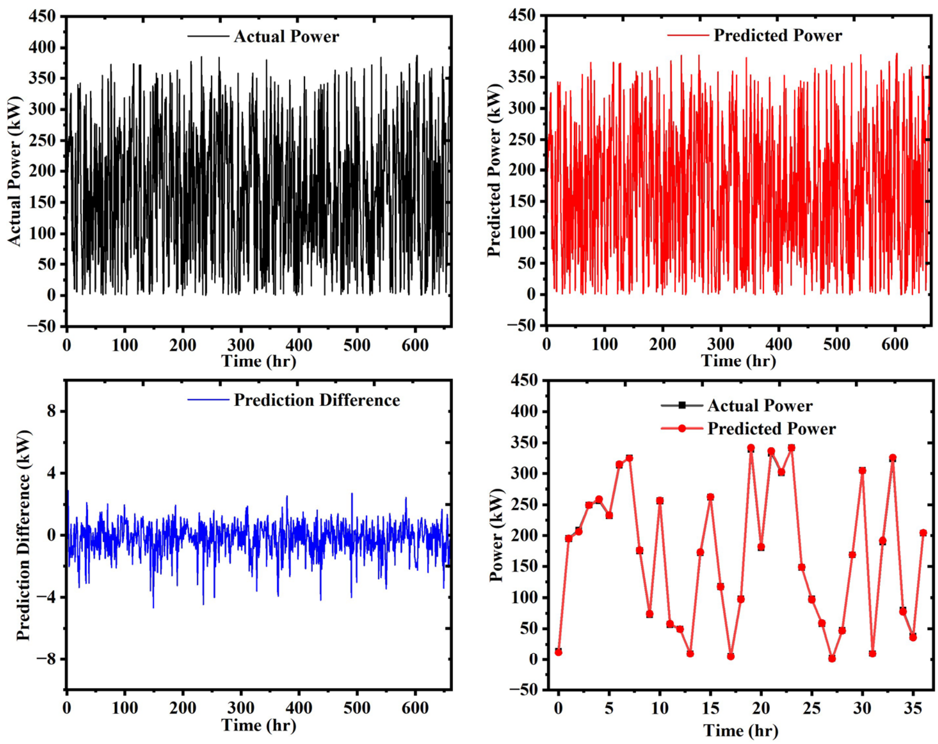

Fig. 3: Actual and predicted power profile using ANN model.

following a similar trend and minor variations in power generation. Following that, the MSE and RMSE are 1.32 and 1.15, respectively. The small difference between the MAE and RMSE indicates that the forecasting model is efficient and less affected by outliers. However, the MSE may yield a noticeable error, which is acceptable, and the forecasting model operates in a stable mode. The RMSE is critical whenever significant outliers are present; in this case, an RMSE of 1.15 is considered a minor error in forecasting accuracy. These error metrics indicate that the prediction deviated slightly by 0.87 kW from the actual power generation profile. Overall, the developed ANN forecasting model is suitable for solar farms in Thailand, and it is recommended that it be utilized for large-scale solar PV systems to prevent incurring surplus charges from the grid authority.

CONCLUSIONS

In this study, a modified neural network is developed to predict power generation for a 500-kW solar farm in Thailand. Raw data from the solar farm are processed and aggregated into 12-hour intervals to minimize prediction errors, as power generation is zero at night. The dataset is split into X (independent variables) and y (dependent variable). Both variables undergo training and testing with a 0.15 parameter setting, meaning 15% of the data is reserved for prediction. The ANN model is trained with a batch size of 32 and 50 epochs to enhance prediction accuracy through iterative optimization. The statistical analysis indicates that the maximum cell temperature reached 75.27°C, which is above the STC. During 75% of the period, the DC power output exceeded 258488.94 W, indicating that the solar farm is operating under severe thermal stress. The developed forecasting model predicts power generation with an average difference of 0.22 kW. Over 663 hours of testing, the model's actual and predicted power generation sums are 110088 kW and 110233.9 kW, respectively. The modified neural network achieves MAE, MSE, and RMSE values of 0.87, 1.32, and 1.15, respectively. According to these error metrics, the predictions are effective and reliable for large-scale and commercial implementation. Furthermore, it is recommended that future studies consider additional independent variables, such as humidity and atmospheric pressure, to enhance the accuracy of the forecasting model.

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NOMENCLATURE

ANN	Artificial Neural Network
DC	Direct Current
GA	Genetic Algorithm
IoT	Internet of Things
kW	Kilowatt
LSTM	Long Short-Term Memory
MFFNNs	Multilayer Feedforward Neural Networks
MVO	Multiverse Optimiser
MAE	Mean Absolute Error
MSE	Mean Square Error
MLR	Multiple Linear Regression
NRMSE	Normalised Root Mean Square Error
NREL	National Renewable Energy Laboratory
N	total number of predictions
PCA	Principal Component Analysis
PV	Photovoltaic
POA	Plane of Array
RMSE	Root Mean Square Error
SD	Standard deviation
UAE	United Arab Emirates
y_i	actual value
$\hat{y}_i$	predicted value

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