

IMPLEMENTATION OF THE RADIAL BASIS FUNCTION NEURAL NETWORK METHOD IN PREDICTING SHORT-TERM POWER GENERATED BY PHOTOVOLTAIC

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Article Info	ABSTRACT
<p>Article History: Received: 2026-03-03 Revised: 2026-04-15 Accepted: 2026-04-25 Available online: 2026-04-28</p> <p>Keywords: Clean energy; Forecasting; Photovoltaic; RBF-Neural Network; Renewable energy;</p>	<p>The adoption of photovoltaic (PV) technology in Indonesia offers significant economic and environmental benefits, such as job creation and greenhouse gas reduction. Nevertheless, there are major technological hurdles to overcome, particularly the inherent variability and intermittency of solar energy, as well as severe financial limitations and insufficient policy frameworks, which prevent widespread adoption. Accurate forecasting of PV power is necessary in order to overcome these technical obstacles and maintain grid stability. The Radial Basis Function Neural Networks (RBF-NN) are the primary focus of this study, which assesses cutting-edge prediction techniques using neural networks. The complicated nonlinear mappings used in predicting PV power production are efficiently approximated by this approach using localized receptive fields. With a root mean square error (RMSE) of 3.244, this method produced the best forecasting simulation results in this analysis.</p>
	
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1. INTRODUCTION

The increase in global energy demand, coupled with growing environmental concerns stemming from the depletion of fossil fuels and the associated pollution, necessitates a rapid transition toward sustainable energy sources [1]. This urgency is particularly acute in the power generation sector, where the environmental and health impacts of burning conventional fossil fuels have become a major driver for adopting renewable energy alternatives [2]. In response, photovoltaic (PV) systems have emerged as a promising solution for power generation, attracting significant global attention—including in countries like Indonesia—due to their potential to harness solar energy directly [3]. Furthermore, the strategic geographical locations of many ASEAN countries, including Malaysia and Singapore, offer abundant solar radiation, making photovoltaic technology an attractive and viable option for reducing the ever-increasing energy demand and lowering the carbon footprint [4].

In Indonesia, the implementation of photovoltaic (PV) systems has emerged as a promising alternative, with grid-connected rooftop PV achieving a competitive Levelized Cost of Energy (LCOE) between 0.0491 and 0.0605 USD/kWh, though widespread adoption remains constrained by evolving policy frameworks and financing challenges [5]. Similar trends and obstacles are observed across the ASEAN region; for instance, Malaysia has successfully demonstrated large-scale applications such as a 10 MW floating PV system capable of reducing over 11,000 tons of CO₂ annually, yet it faces persistent challenges related to shading, system degradation, and underperforming incentive schemes [6]. Meanwhile, Singapore's land-scarce environment has necessitated a focus on Building-Integrated Photovoltaics (BIPV), which faces technical and economic barriers due to local environmental sensitivity and non-optimal incentive structures [7].

However, the intermittent characteristics and variability of solar radiation intensity provide significant challenges for grid integration and the operational reliability of PV systems, thereby requiring advanced forecasting methodologies for their power output [8]. To address these challenges, machine learning techniques are increasingly being used to develop accurate short-term photovoltaic power forecasting models, thereby enhancing grid stability and optimizing energy management. Among these techniques, the Radial Basis Function Neural Network (RBF-NN) stands out as a highly effective approach due to its ability to model the complex nonlinear relationships inherent in solar power generation data, thereby offering strong predictive capabilities for short-term power output [9], [10].

Therefore, this study examines the application of the RBF-NN method for short-term PV power output forecasting, detailing its implementation and evaluating its performance compared to conventional forecasting models. Specifically, this study aims to demonstrate how the RBF-NN, with its unique architecture that facilitates rapid learning and strong generalization capabilities, can provide better prediction accuracy for fluctuating solar power generation. This in-depth study will not only contribute to the optimization of PV system operations, but also provide valuable insights for broader renewable energy integration strategies.

2. RELATED WORKS

Several previous studies have examined the forecasting of power generated by PV systems using a variety of methods, ranging from classical to advanced methods. In 2023, Scott et.al have conducted study on energy forecasting for photovoltaic systems using machine learning [11]. The study was conducted to satisfy the standards and necessities of the building management system (BMS), also to determine the forecasting error of PV-generated power using several forecasting methods. Among the various methods utilized, the Random Forest method achieved the lowest RMSE value of 32 compared to other methods such as support vector machine (SVM), artificial neural network (ANN), and linear regression.

Al Shafeey and Csaki have conducted study on PV power forecasting by using ANN and linear regression [12]. In this study, the forecasting models were tested using three types of data: structural, time series, and hybrid. The results of the study indicate that the ANN method achieved better MAE, MSE, and RMSE values of 21.01, 2062.50, and 32.29, respectively.

Furthermore, Yousif and Kazem conducted study on the forecasting of PV thermal (PV/T) systems using ANN [13]. The experiment performed by the researchers involved comparing the power generated by PV/T and standard PV systems while making predictions using three methods: the multilayer perceptron (MLP), the self-organizing feature map (SOFM), and SVM. From the three methods, the SOFM method produced the lowest MSE values: 0.00030 (PV) and 0.00683 (PVT). Based on the previous studies discussed

above, an opportunity has been identified for the application of another neural network-based method, namely the RBF-NN, to forecast short-term PV-generated power.

3. RESEARCH METHODS

3.1 Data Acquisition

The data utilized in this study were obtained from experiments conducted between May and September 2024 in Surabaya. These experiments yielded a total of 1,605 data points, consisting of temperature values, light intensity, generated power, and duration. Table 1 below provides details of the study data.

Table 1. Dataset

Trial	Temperature (°C)	Light Intensity (lux)	Generated Power (W)	Duration
1	26.34	118.2	6.52	7
2	27.74	295	25.46	8
3	29.13	578	45.86	9
4	30.52	762	55.17	10
5	30.62	888	63.85	11
6	30.73	877	62.57	12
7	30.84	560	39.65	13
8	30.31	67	1.65	14
9	29.78	67	1.71	15
10	29.25	59	1.37	16
11	28.58	21	0.18	17
...
1605	29,73	704	53,75	16

3.2 Data Analysis

Numerous procedures involving statistical test were necessary during the data processing phase of this investigation, in order to produce the right judgments and implement forecasting models, resulting in reliable forecast outcomes. Among the tests performed in this study are normality analysis and correlation analysis. Below in Eq. (1-2) are the functions of both.

$$SW = \frac{\sum_{i=1}^n a_i x_{(i)}}{\sum_{i=1}^n (x_i - \bar{x})^2} \tag{1}$$

$$Corr = \frac{\sum_{i=1}^n w_i (X_i - \bar{X}_w)(Y_i - \bar{Y}_w)}{\sqrt{\sum_{i=1}^n w_i (X_i - \bar{X}_w)^2} \sqrt{\sum_{i=1}^n w_i (Y_i - \bar{Y}_w)^2}} \tag{2}$$

3.3 Forecasting Method and Evaluation Metrics

The RBF-NN is recognized as a technique that has simple design, exceptional input noise tolerance, and quick through training [14], [15]. This approach has three levels: input layers, hidden layers, and output layers. The output layers linearly combine the outputs of hidden neurons to produce the network output, while the hidden layers include radial basis functions. The result of the RBF-NN output is expressed as follows:

$$y_i(x) = \sum_{j=1}^k w_{ij} \phi(\|x - c_j\|) \tag{3}$$

Description

x : input vector

y_i : network i -th output

- k : number of neurons in the hidden layer
- c_j : the center of the j -th neuron in the hidden layer
- w_{ij} : the weight of the link from the j -th neuron in the hidden layer to the i -th neuron in the output layer
- \emptyset : Euclidean norm

For evaluating the performance of forecasting results, the Root Mean Squared Error (RMSE) and R^2 score were employed with following function. Below in Eq. (4-5) are the functions, respectively.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i^{pred} - y_i^{obs})^2} \quad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^m (X_i - Y_i)^2}{\sum_{i=1}^m (\bar{Y} - Y_i)^2} \quad (5)$$

4. RESULTS AND DISCUSSION

4.1 Result of Analysis

Several variables, including temperature, light intensity, generated power, and duration were successfully identified utilizing the data collected from the field study. Additionally, the distribution and patterns that emerged from the measurement data were reidentified. The distribution of all features is presented in Figure 1, while the findings of the descriptive analysis that was carried out are presented in Table 2 below.

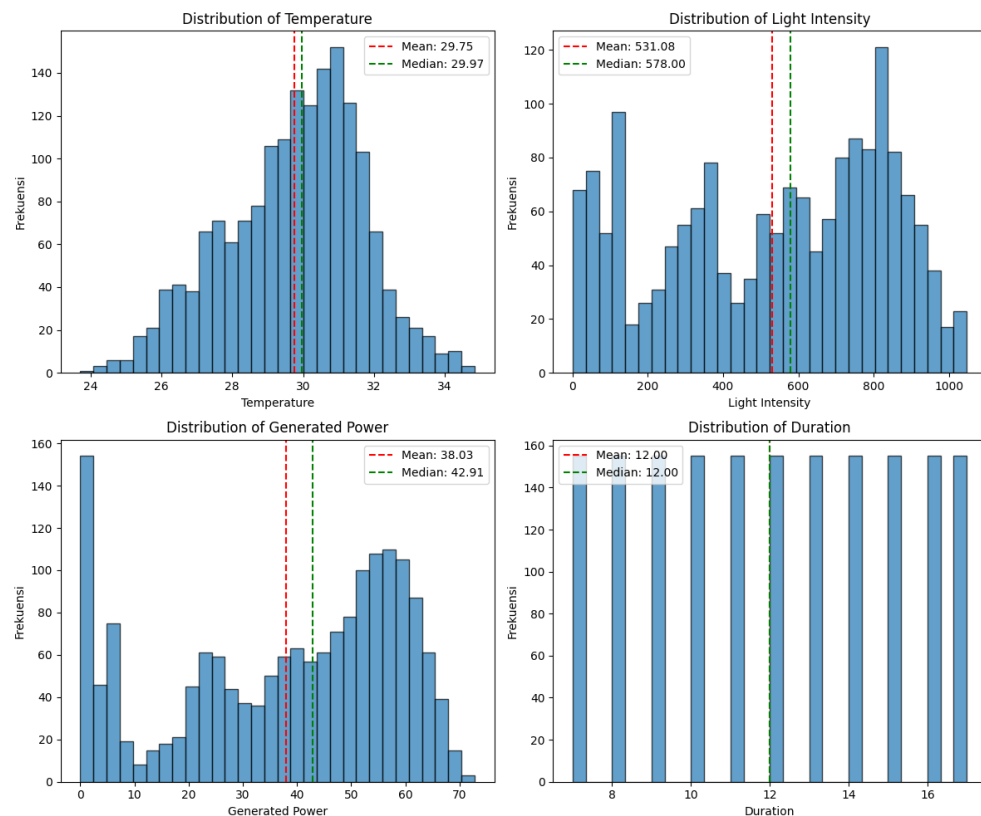


Figure 1. The Distribution of All Features

Table 2. Descriptive Statistics

	Trial	Temperature	Light Intensity	Generated Power	Duration
mean	853	29.74	531.08	38.03	12.00
std	492.33	1.93	295.18	20.82	3.16
min	1.0	23.71	1.00	0.00	7.00
max	1605	34.84	1074.0	72.75	17.00

The data distribution for all features in the dataset is presented in Figure 1 above. The four characteristics are temperature, light intensity, generated power, and duration. Based on the four characteristics presented in the histogram above, it seems that the data as a whole is not normally distributed. A normality test utilizing Shapiro-Wilk (SW) was performed in the next step to further support the findings. Table 3 below presents the detail of the normality test.

Table 3. Normality Test

Feature	Result
Temperature	stat = 0.9873, p-value = 0.0000
Light Intensity	stat = 0.9403, p-value = 0.0000
Generated Power	stat = 0.9164, p-value = 0.0000
Duration	stat = 0.9384, p-value = 0.0000

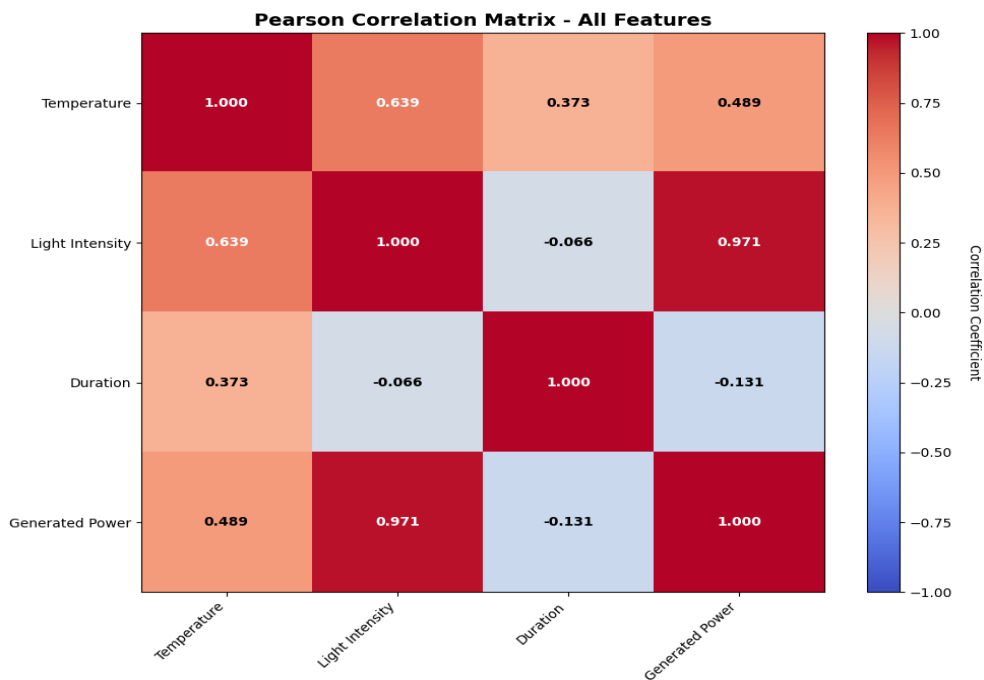


Figure 2. The Heatmap of Correlation Test

This correlation experiment will analyze how feature values in the dataset are related to each other. In Figure 2, the correlation coefficient between the light intensity and generated power features is 0.971, indicating that the two variables are closely related. Nevertheless, the correlation coefficient of temperature and generated power is 0.489, indicating minimal association. In contrast to the characteristics mentioned above, the generated power feature presents a negative correlation with the duration feature. According to this observation, as the experiment progresses, PV generated power drops and is likely due to a decrease in sunlight as daylight diminishing in the afternoon. These three features (temperature, light intensity, and duration) can be thought as input variables for calculating the PV power, according to the result of this correlation analysis.

4.2 Hyperparameter Tuning

The findings of all simulations that have been performed using the suggested approaches will be discussed at the time. Prior to that, Table 4 below lists a number of explanations pertaining to hyperparameter tuning for the RBF-NN approach.

Table 4. Tuning for RBF-NN method

Method	Hyperparameter	Value
RBF-NN	gamma	0.1
	n_components	100
	random_state	42

4.5 Result of Simulations

This section discusses the results of the forecasting simulation using the RBF-NN method. The simulation conducted in this study utilized several splits of training and test data. These data splits were intended to assess the effectiveness of the method in forecasting based on the error rates produced. Table 5 below provides details of the data splits.

Table 5. Data Split

Percentage (%)	Number of Data Training	Number of Data Testing
70 : 30	1123	482
80 : 20	1284	321
90 : 10	1444	161

Furthermore, the visualization of the short-term power forecast results generated by the PV system is illustrated in Figure 3-5 below.

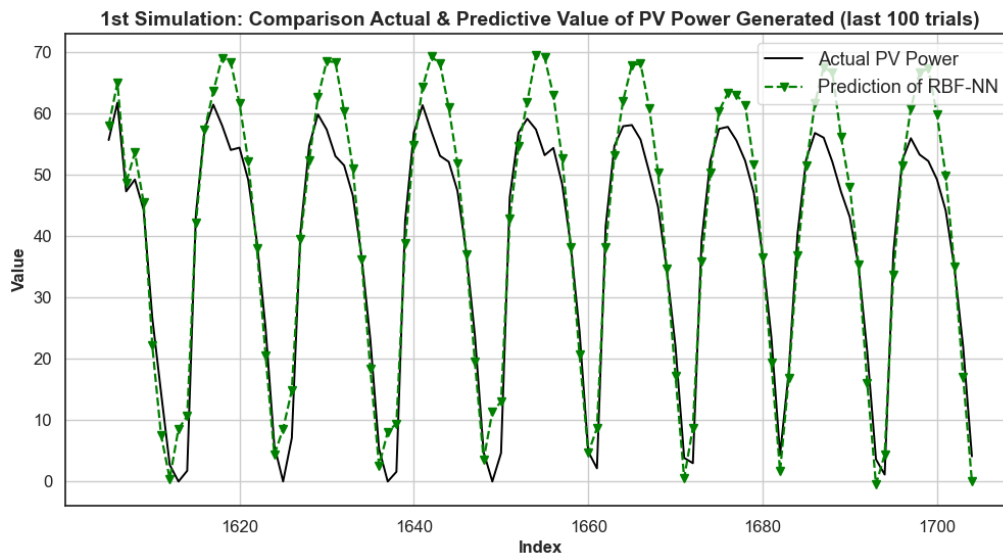


Figure 3. The Result of First Simulation

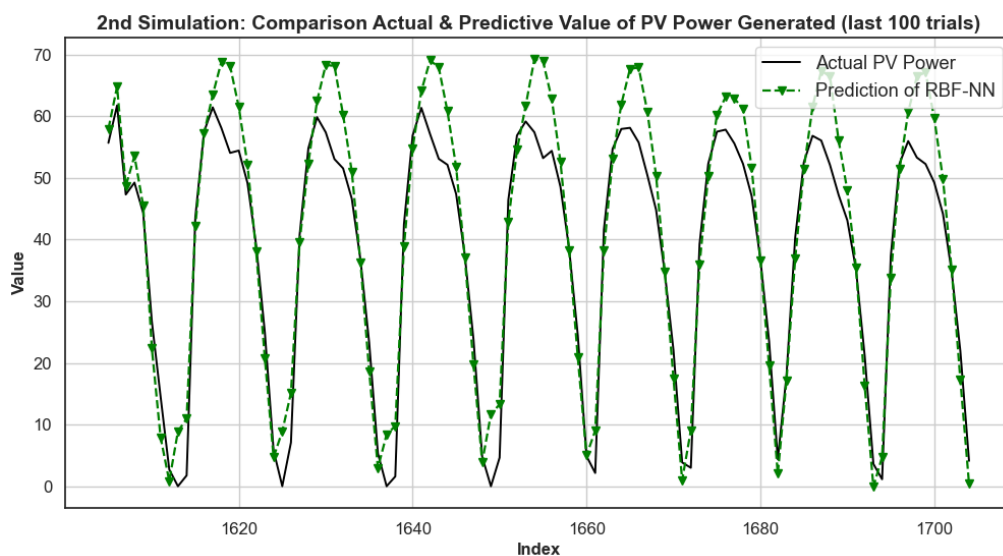


Figure 4. The Result of Second Simulation

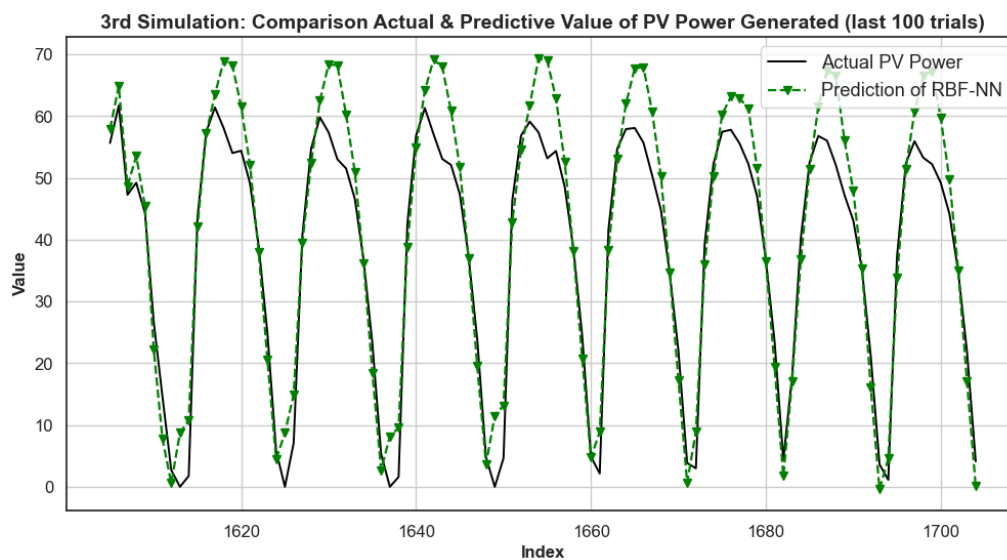


Figure 5. The Result of Third Simulation

As demonstrated by Figures 3 to 5 above, the RBF-NN method were able to successfully approach the line at the actual value, thereby producing excellent results. In addition, the forecast result produced by this method in Figure 3 had an RMSE value of 3.401 and R^2 score of 0.972. The circumstances presented in Figure 4 also seem to be fairly similar to the result of the first simulation. In this second simulation, the forecast results produced by this method approach an RMSE value of 3.262 and R^2 score of 0.975, which was 0.139 points lower than in the first simulation. Finally, Figure 5 demonstrates that the RMSE value of the forecast result achieved an RMSE value of 3.244 and R^2 score of 0.975, representing of 0.018 points improvement over the second simulation.

Based on the results of the three simulations above, the RBF-NN method experienced positive improvement as the amount of training data increased. These results are evident in the decreasing RMSE and the increasing of R^2 score. In addition, these results are also supported by the significant influence of the light intensity feature as a predictor variable, which can compensate for the shortcomings of the other two features. The results of this simulation also successfully demonstrated that the RBF-NN method is capable of handling the nonlinearity issues present in PV power measurement data.

5. CONCLUSION

Based on the results of this study, it can be concluded that the RBF-NN method is capable of accurately forecasting short-term power generated by PV systems while also satisfying the objectives of this study. This new approach also offers a new alternative for conducting forecasts in a practical and resource- and time-efficient manner. In future research, the study will be expanded to include more complex methods and larger datasets.

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