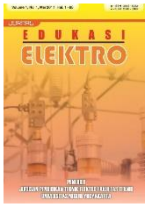
Vol. 9, No. 2, November 2025, pages 214 - 230
JEE
Jurnal Edukasi Elektro
https://doi.org/10.21831/jee.v9i2.91044



Implementation of Neural Networks in Daily PV Power Output Prediction Using Bayesian Regularization Algorithms to Assist Energy Management Systems

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Abstract—Solar power plants have several advantages, namely continuous energy production, reduced electricity demand, and low photovoltaic maintenance, so that PV power output can be optimized with reliable PV power output predictions. Implementation of Artificial Neural Network (ANN) to predict photovoltaic (PV) power output, using the Bayesian Regularization algorithm. Accurate PV power output prediction is very important in power systems. The data used are solar radiation, PV module temperature, ambient temperature, and actual PV power output, with the target being the PV power output for the next day with the PV power output output for the next day. The architecture used in this study is a Cascade Forward Neural Network (CFNN) and an Elman Neural Network (ENN). Both ANN models use daily data sets and performance evaluation using Mean Square Error (MSE). The results of the study show that ENN is more accurate than CFNN. ENN had the lowest MSE of 0.00664 at a configuration of N=8 and R of 0.9922 with a training time of 6.4 seconds, while CFNN recorded the lowest MSE of 0.024306 with N=25. ENN's ability to capture time series patterns in PV is more reliable and effective. Reliable predictions can assist in energy management systems because they help maintain supply balance, reduce the risk of failure, and improve system stability.

Keywords: artificial neural network, elman neural network, cascade forward neural network, bayesian regularization algorithm, mean square error

Article submitted 2025-11-03.
Resubmitted 2025-11-08.
Final acceptance 2025-11-09.
Final version published as submitted by the authors.

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Citation Document:
Mahmudah, N., Delfianti, R., Sigit, F. M., Putra, D. P. E. J., & Nusyura, F. (2025). Implementation of Neural Networks in Daily PV Power Output Prediction Using Bayesian Regularization Algorithms to Assist Energy Management Systems. Jurnal Edukasi Elektro, 9(2), 214-230. https://doi.org/10.21831/jee.v9i2.91044

1. Introduction

The development of electrical energy has increased year by year, in line with population growth and industrial development. Renewable energy, particularly photovoltaic (PV) solar panels, has begun to be utilized to reduce operational costs compared to conventional energy sources that rely on fossil fuels [1][2][3]. The main advantages of PV are that it produces no carbon emissions and has a long lifespan. However, the power output characteristics of PV are significantly influenced by solar radiation and temperature [4][5]. Accurate predictions of PV power output can help minimize the uncertainty associated with PV characteristics. PV power output predictions are important for load management and reducing the risk of intermittency. Photovoltaics are highly influenced by sunlight, and PV power output also fluctuates due to changes in weather conditions. Accurate PV power prediction is vital because large power grids enable managers to regulate electricity supply effectively, whereas in home microgrid systems, electricity usage remains stable and efficient [6][7].

PV power output predictions can assist energy management systems in load processing and minimize the risk of intermittency and regulation in managing backup energy sources efficiently [8][9]. Artificial Neural Networks (ANN) help predict PV power output because they have multi-variable data capabilities, recognize non-linear patterns, and process historical data accurately [10][11].

The Elman Neural Network (ENN) and the Cascade-Forward Neural Network (CFNN) are two architectures of neural networks. ENN is a type of Recurrent Neural Network (RNN) that has the ability to remember historical information due to its feedback structure [12][13], while Cascade Forward Neural Network (CFNN) is a development of Feed Forward Neural Network (FFNN) that has a direct path from input to all layers of the network in sequence, which makes the learning process faster. This improves prediction accuracy, especially for complex PV power outputs [14][15].

A common problem in Artificial Neural Networks is overfitting. Overfitting often occurs when data have high variability, such as PV power output data [16][17]. Overfitting occurs when the model becomes too intensive in learning details, resulting in high noise during training. This leads to rapid data generalization (applicable to unseen data), which causes a decline in training performance accuracy during testing 18][19]. Overfitting in neural networks can be overcome by using the Bayesian Regularization Algorithm. The Bayesian Regularization algorithm employs a probabilistic approach, grounded in the Bayesian principle, which has the advantage of enhancing the ability to reconstruct networks by adjusting network weights. This approach is very effective in overfitting. The Bayesian Regularization algorithm enables the NN model to find the optimal point that balances bias and variance [20][21]. The Bayesian Regularization Algorithm can also accelerate the convergence process of NN models, making them more optimal and efficient, thereby reducing oscillations and achieving convergence quickly and stably [22][23].

The selection of CFNN and ENN architecture was based on theoretical considerations related to the characteristics of PV power output data. CFNN has the advantage of being able to learn complex nonlinear relationships between input and output variables because there are direct connections linking each input layer to all hidden layers and the output. This network pattern enables CFNN to capture the dynamics of non-linear data more effectively than conventional feed-forward networks. On the other hand, the ENN architecture is designed to handle time series data because it has context units and can store information from previous time data, making it very suitable for data that has a time period, such as PV power output characteristics [24].

The implementation of CFNN has been applied in research [25] using the algorithm in this study. The smallest Mean Squared Error (MSE) at a learning rate of 0.1 is 0.308%, at a learning rate of 0.05 the MSE error is 0.322%, and at a learning rate of 0.01 the MSE is 0.322%. Researchers [12] employed neural networks with Elman Neural Network (ENN) and Feedforward Neural Network (FFNN) architectures, yielding MSE errors of 0.01471% and 0.00097%, respectively. In study [26], the accuracy of PV prediction was high using historical data and an RNN neural network that prioritized time series prediction during the learning process.

This study aims to implement and compare the performance of the Elman Neural Network (ENN) and Cascade Forward Neural Network (CFNN) architectures in accurately predicting PV power output, utilizing the Bayesian Regularization Algorithm optimization method. This study also provides input to the Energy Management System to obtain accurate and reliable predictions, as well as to evaluate which of the two neural network architectures is superior in terms of accuracy and stability based on the input provided.

2. Method

This study uses MATLAB to process Artificial Neural Networks. The PV power output prediction in this study utilizes data from July 1 to July 7 for training, with a target of 1 day ahead, namely July 8. The target PV power data for the next day is from July 2 to July 8. The data used in this study span from 06:00 to 18:00. The data are sourced from the Pantai Baru Bantul Yogyakarta PLTH. The input and output tables are presented in Table 1.

Table 1. Input and Output Variables

Input	Unit	Target	Output
Solar Radiation	kW	PV Power for the Next Day	One-Day PV Forecast
Ambient Temperature	W/m^2		
PV Module Temperature	$°C$		
PV Output Power	$°C$		

Figure 1 explaining input and output variables. Input variables use four data points, namely solar radiation, ambient temperature, PV module temperature, and PV output temperature, with the target output being PV power for the following day and the output being the predicted PV power output for the following day.

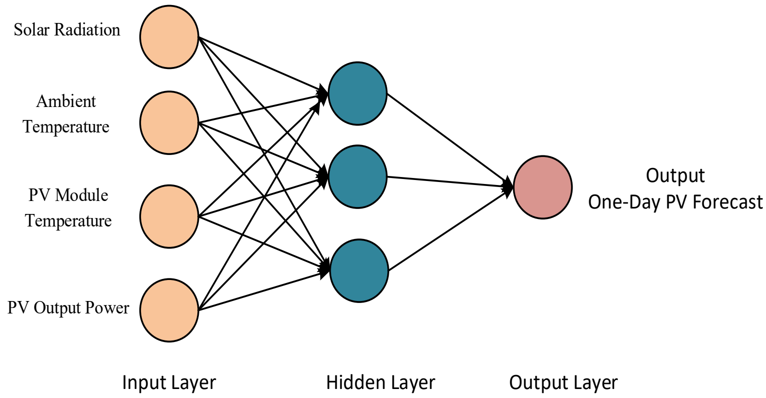

Figure 1. ANN input and output variable architecture

Figure 2 illustrates the process of predicting PV power output using an ANN, starting from the initial stage and importing power. The data will then be divided into two categories: training data and testing data. The ANN training data utilizes the Cascade-Forward Neural Network (CFNN) and Elman Neural Network (ENN) architectures. The algorithm used in both ANN models is the Bayesian Regularization Algorithm to obtain the best model, which will be selected based on the smallest Mean Squared Error (MSE) value. Next, a comparison between the CFNN and ENN models will be conducted. The final step is to analyze the comparison between the prediction results and the actual PV data to assist the energy management system.

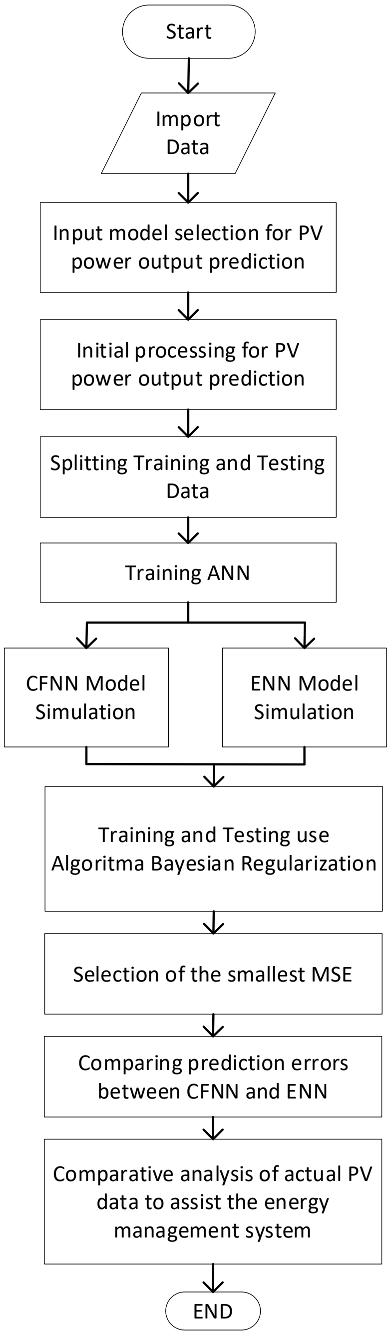

Figure 2. Flowchart for PV power output prediction

2.1. Forecasting PV Power Output with Artificial Neural Networks (ANN)

Renewable energy in this study uses photovoltaics (PV) because each cell can convert solar energy into electrical energy. PV power output predictions are made using actual data. Accurate PV predictions can be made by evaluating several time ranges, including short-term predictions for the next few hours, medium-term predictions for the next week, and long-term predictions (months to years) [27].

The development of artificial neural networks (ANN) has been widely applied to model and predict PV power output. The advantages of ANN include its ability to recognize complex and non-linear patterns, as well as its capacity to learn from historical data and generalize predictions to new data, thereby enabling the accurate prediction of PV power output[28].

Figure 3 shows the architecture of an Artificial Neural Network (ANN), which has three main parts: the input layer, the hidden layer, and the output layer. The input layer is used to input data containing information, which is then forwarded to the hidden layer. The hidden layer calculates the input data, which is then forwarded to the output layer. ANNs have weights, activation functions, and cost functions. The magnitude of the weights in the hidden layer will affect training.

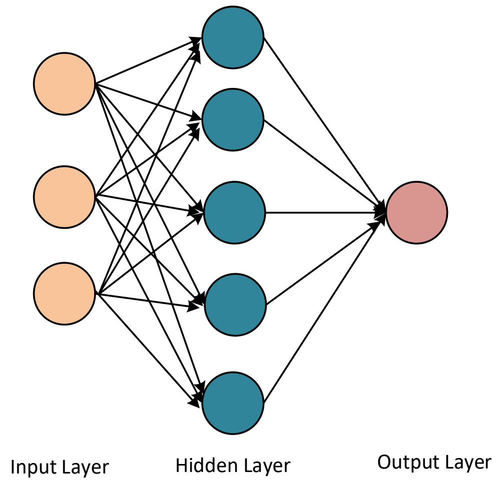

Figure 3. Artificial Neural Network Architecture

2.2. Cascade Forward Neural Network (CFNN)

Cascade Forward Neural Network (CFNN) is a modified form of Feed Forward Neural Network (FFNN). The primary difference between FFNN and CFNN is that in FFNN, the input gradually progresses through the hidden layer until it reaches the output, whereas in CFNN, each neuron in the input layer simultaneously connects to neurons in both the hidden layer and the output layer, resulting in minimal computation time. The mathematical formula for CFNN can be expressed as follows:

$$O = \varphi_1(\textstyle\sum_{i=1}^{n} W_i^n X_i) + \varphi_0 \left[\sum_{l=1}^{k} W_i^n \, \varphi(\sum_{i=1}^{n} W_{li}^n X_i)\right] \quad (1)$$

$$O = \varphi_1(\textstyle\sum_{i=1}^{n} W_i^n X_i) + \varphi_0 \left[B^k + \sum_{l=1}^{k} W_i^n \, \varphi(B^n + \sum_{i=1}^{n} W_{li}^n X_i)\right] \quad (2)$$

Where: 0 is the input, W is the network weight, X is the input signal, B is biased, φ The activation function operates between the input layer and the hidden layer, φ_0 The activation function operates between the hidden layer and the output layer, φ_1 It is the activation function that transfers information from the input layer to the output layer [29].

Figure 4 show the architecture of a cascade forward neural network, with an input layer to receive data inputs (solar radiation, temperature, actual PV power), a hidden layer to process the inputs received, and an output layer to generate predictions as output.

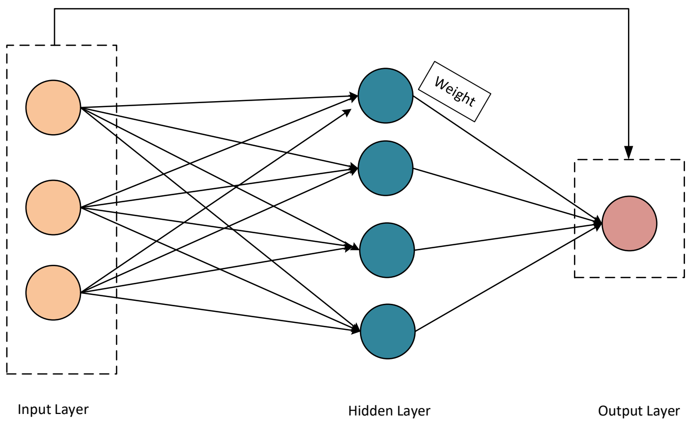

Figure 4. Cascade Forward Neural Network Architecture (CFNN)

2.3. Elman Neural Network (ENN)

Elman Neural Network (ENN) is one type of artificial neural network architecture. The working principle of the Elman neural network involves a context layer that stores memory and activity from the hidden layer, enabling the Elman network to undergo a good learning process by recognizing patterns in data sequences. The ENN stores memory from the hidden layer due to the context layer, enabling it to recognize data sequences effectively and produce accurate predictions because it retains previous data information, thereby improving prediction results [29].

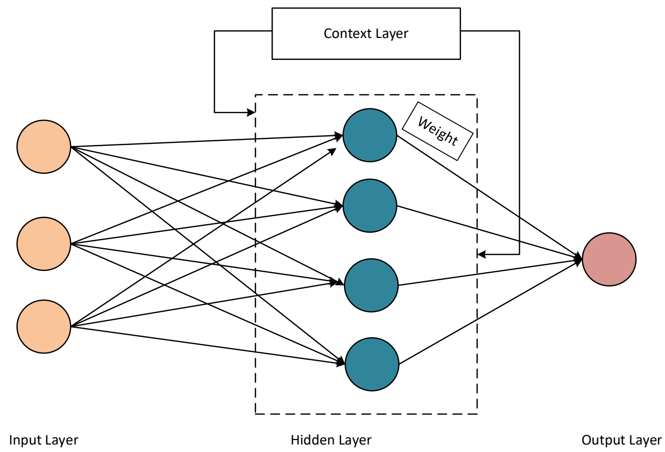

Figure 5. Elman Neural Network Architecture

Figure 5 illustrates the Elman Neural Network (ENN) architecture, which comprises an input layer that receives input datasets, a hidden layer that processes signals from the input layer and produces more optimal weights during the training process. The output layer functions as the final output to generate the prediction from the neural network. Ultimately, the context layer stores the output from the hidden layer and reuses it as input for the hidden layer the next time, forming a feedback loop to remember the previous conditions.

2.4. Bayesian Regularization Algorithm

The Bayesian Regularization algorithm is designed to prevent overfitting. Its primary objective is to produce a neural network with low error values that can effectively respond to novel inputs.

The training process for this algorithm emphasizes adaptation to new data, thereby enhancing the network's ability to generalize. Regularization is critical in this context, as it constrains the magnitude of network weights. Smaller weight values contribute to smoother network responses. In the backpropagation algorithm, the objective is to minimize specific error-related factors. The mathematical formulation for backpropagation is presented below.

$$F = E.d \quad (3)$$

Where:

$$E_d = \sum_{i=1}^{n}(t_i - a_i)^2 \quad (4)$$

Description: n is the total training, t_i is the target for data i, a_i is the output value of the *i-th* data, The Bayesian Regularization algorithm incorporates the standard deviation of the weights and biases, as demonstrated in the following equation:

$$F = \beta E_d + aE_w \quad (5)$$

$$E_w = \frac{1}{n}\sum_{i=1}^{n} W\iota^2 \quad (6)$$

Where: α, β is a parameter of regularization and W_i is the threshold

From equation 4 for ANN error performance, it is necessary to change the smallest weight and threshold, but it is not possible to determine the effective threshold and effective weight[30].

2.5. Mean Square Error (MSE)

Accurate prediction measurements in ANN can be done using several methods, one of which is Mean Square Error (MSE). To calculate MSE, you can use the formula below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_t - F_t)^2 \quad (7)$$

Where: X_t is the actual value at time *t*, F_t is the predicted value at time *t*.

The result obtained by MSE is the smallest MSE value, which indicates accurate prediction capabilities, especially in predicting PV power output[24].

2.6. Setting the Parameter

The Cascade Forward Neural Network (CFNN) and Elman Neural Network (ENN) are trained with the same number of epochs, 2000. The target error value on the ANN network (net.trainParam.goal) is 1e-4. The gradient limit (net.trainParam.min_grad) is set to 1e-7 to ensure that the training process stops when the weight change becomes small. The training status (net.train.show) uses 25 epochs. The adaptive learning rate parameter uses an initial value of mu (net.trainParam.mu_int) of 0.005. The mu reduction factor (net.trainParam.mu_dec) is 0.1 with a mu increase (net.trainParam.mu.inc) of 10. The maximum limit of mu (net.trainParam.mu_max) is set to 1e10, and finally, the learning rate is 0.01. The parameters between CFNN and ENN are the same. The parameter settings for CFNN and ENN are presented in Table 2.

Table 2. Parameter settings for CFNN and ENN

Parameters	Description	Cascade Forward Neural Network (CFNN)	Elman Neural Network (ENN)
net.trainParam.epochs	Number of training epochs	2000	2000
net.trainParam.goal	Network error target or goal	1e-4	0.0001
net.trainParam.min_grad	Minimum gradient for training	1e-7	1e-7
net.trainParam.show	The interval shows the training status.	25	25
net.trainParam.mu_init	Initial value of your parameter (adaptive learning rate)	0.005	0.005

Parameters	Description	Cascade Forward Neural Network (CFNN)	Elman Neural Network (ENN)
net.trainParam.mu_dec	Mu reduction factor	0.1	0.1
net.trainParam.mu_inc	Factors for increasing mu	10	10
net.trainParam.mu_max	The maximum value of mu	1e10	1e10
net.trainParam.lr	Learning Rate	0.01	0.01

3. Results and Discussion

The ANNs used in this study are the Cascade Forward Neural Network (CFNN) and the Elman Neural Network (ENN). Both ANNs are compared to determine the best ANN performance as a reference in predicting PV power output for the next day. The inputs used are solar radiation, ambient temperature, PV module temperature, and current PV power. The data used is 7 days of data, specifically from July 1 to July 7, covering the period from 06:00 to 18:00. The target PV power data, on the other hand, utilizes data from July 2 to July 8.

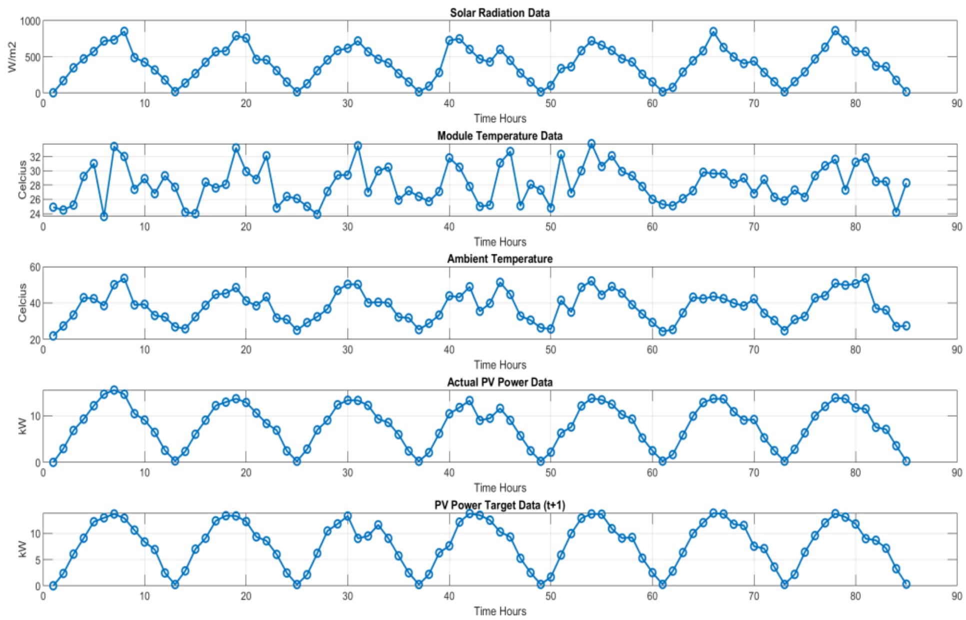

Figure 6. Solar radiation

Figure 6 shows the input and target graphs used in this study. The first input data includes solar radiation data, PV module temperature data, ambient temperature data, and actual PV power output data. The target used is the PV power output for the following day.

The solar radiation input data used is 7 days of data from 6:00 a.m. to 4:00 p.m. The peak solar radiation of 863 W/m² indicates clear weather conditions that are optimal for solar panels. Solar radiation of 0 W/m² indicates nighttime conditions. The data was obtained from the Pantai Baru Bantul Micro Hydro Power Plant, located at coordinates Longitude -7.987706244605494 and Latitude 110.22199483118821.

PV module temperature data, with the lowest recorded temperature of 21.9 °C and the highest of 53.6 °C. The temperature on the PV module increases during the day when solar radiation is high and decreases at night. The correlation between PV module temperature data is important because high operating temperatures can reduce the conversion efficiency of PV modules, meaning that when the temperature on the PV module is high, the efficiency of the electrical energy produced will decrease.

Ambient temperature data around the PV, with a maximum temperature of 33.8°C and a minimum temperature of 23.6°C. The higher the ambient temperature around the PV, the lower its efficiency in converting sunlight into electricity. This means that even though solar radiation is high, if the temperature is too hot, the power generated by the PV will be low. Ambient temperature is an additional input that increases the accuracy of PV predictions.

Actual PV power data in kilowatts (kW), with the highest PV power peak of 15.3 kW occurring during the day, while dropping to almost 0 kW at night.

Target PV power data for the next day (t+1). This data is very important in determining the performance of the neural network model. The neural network will learn from the predicted power data to be generated the next day by considering other input data, namely solar radiation, the temperature around the PV (ambient), the temperature on the PV module, and actual PV data.

3.1. Simulation Result of the CFNN

PV power forecasting predictions using the Bayesian Regularization Algorithm use input from solar radiation, ambient temperature, PV module temperature, and actual PV data. The training target is the PV power for the following day. The training and testing processes were carried out 10 times with an epoch of 2000. Figure 7 shows a graph of training using CFNN to predict PV power output. The blue curve shows actual PV power, and the red curve shows the PV prediction. The graph indicates that the CFNN model has successfully internalized the PV power pattern accurately during the training process.

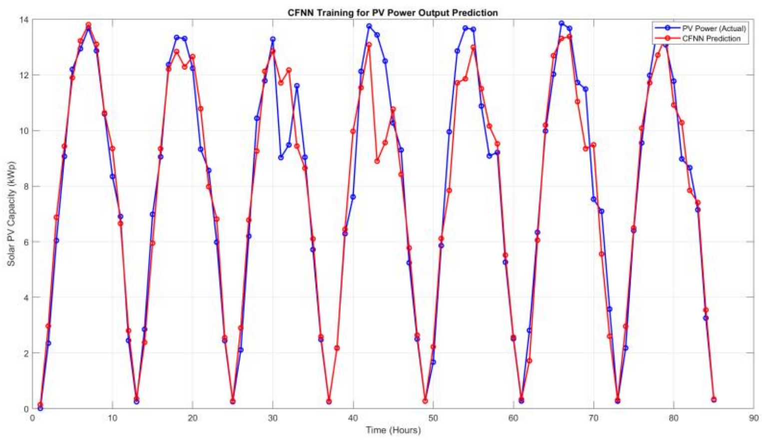

Figure 7. CFNN Training

Figure 8 illustrates the CFNN linear regression, which represents the relationship between the output value of the CFNN model and the target during training, testing, and overall evaluation. In the graph, the data points cluster closely around the blue line, which has a high correlation value (R) of 0.97505, indicating that the CFNN can predict the data well.

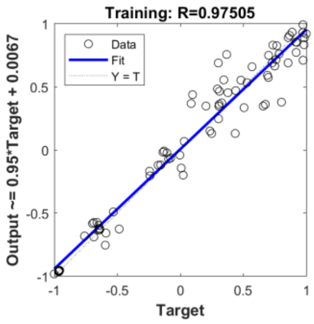

Figure 8. Linear regression CFNN

Table 3 shows the results of CFNN training with varying neurons. An R value close to 1 indicates that CFNN can make good predictions, meaning that the predicted output of PV power and actual PV power are as expected. The smallest MSE in training is 0.02431 with 25 neurons, and the smallest MSE percentage is around 2.431%.

Table 3. Training results using CFNN

Neuron	R	Time (s)	MSE Training
8	0,968	5,5	0,02526
10	0.9684	4,3	0,02497
15	0,9685	4,3	0,02493
20	0,9684	6,6	0,02495
25	0,9684	8,8	0,02431
30	0,9683	5,6	0,02509
35	0,9681	7,4	0,02532
40	0,9685	5,6	0,02492
45	0,9684	6,2	0,02496
50	0,9683	6,8	0,02594

Figure 9 shows the CFNN testing results. The blue line indicates the actual PV power, while the red line indicates the predicted PV power output. The prediction line (red) closely follows the actual PV power (blue), indicating that CFNN can accurately capture changes in PV power. Although there are some differences between the predicted PV and actual PV power values, CFNN demonstrates that it can accurately predict PV power output.

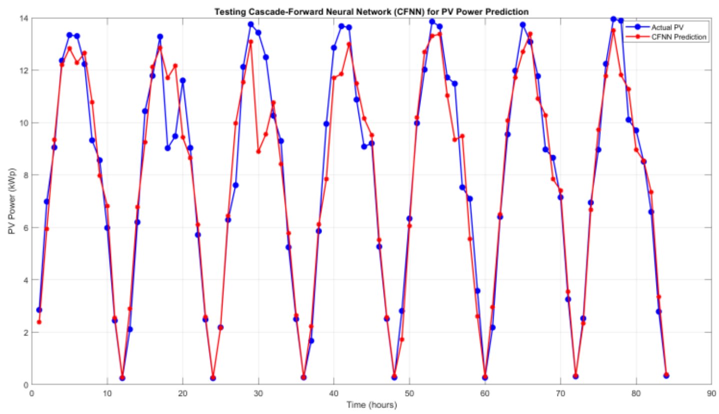

Figure 9. CFNN Testing

Table 4 shows the test results using CFNN. The smallest MSE at N=25 is 0.024306, which indicates accurate predictions with small quadratic errors. The highest MSE value at N=10 is 0.02597 with a time of 4.9 seconds. The average MSE value of 2.5% is still within the acceptable range, which is below 10%.

Table 4. Testing results using CFNN

Neuron	R	Time (s)	MSE Training
8	0,9666	4,8	0,025532
10	0,9662	4,9	0,025897
15	0,9665	5,5	0,025676
20	0.9664	9,2	0,025645
25	0,9694	7,7	0,024306
30	0,9663	7,1	0,02585
35	0,9665	9,9	0,025424
40	0,9662	7,3	0,025753
45	0,9666	6,2	0,025575
50	0,9661	5,48	0,025944

3.2. Simulation Result of the ENN

The PV power output prediction uses ENN with the Bayesian Regularization Algorithm. The training data used are solar radiation, ambient temperature, PV module temperature, actual PV data, and target PV power for the next day. During the training process, 10 training sessions were conducted with varying neuron numbers.

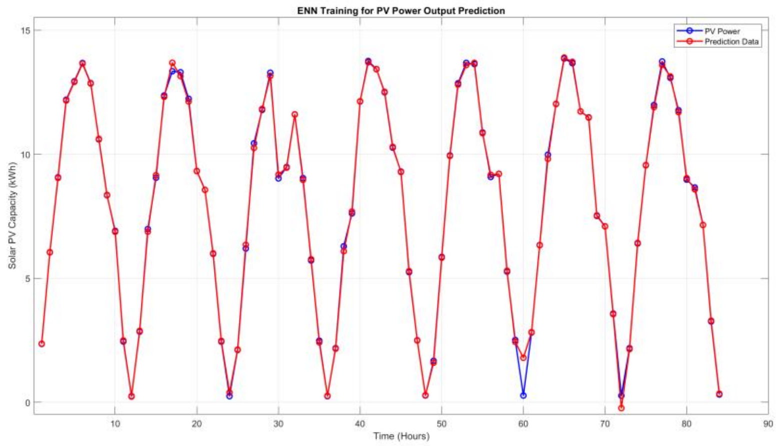

Figure 10. ENN Training

Figure 10 shows the results of ENN training in predicting PV power output. The blue line shows the actual PV power value, while the red line shows the prediction results using ENN. This graph shows that the prediction is close to accurate, because the prediction line (red) follows the PV power line (blue).

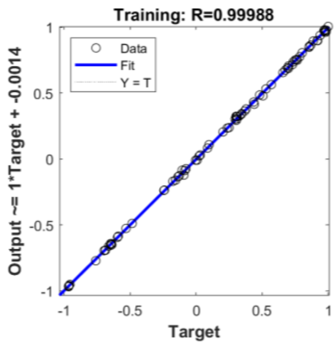

Figure 11. Linear regression Elman Neural Network

Figure 11 shows the regression line of ENN, with small circles representing actual data points. The blue line (Fit) represents the regression line generated by the model, with black data points clustered closely around it, indicating accurate predictions. The line Y=T is the ideal line where the output equals the target. R shows a value of 0.99988; the closer R is to 1, the more accurate the prediction.

Table 5 shows that the smallest value of 0.0008 indicates that the ENN model with 50 neurons has a low prediction error rate, achieved with a training time of 234.5 seconds. In contrast, the highest MSE of 0.0052 is obtained with 40 neurons and a training time of 139.7 seconds. All neuron variations have low MSE values with efficient computation times.

Table 5. Training results using ENN

Neuron	R	Time (s)	MSE Training
8	0,9966	5,3	0,0030
10	0,9943	5,9	0,0044
15	0,9977	5,4	0,0019
20	0,9955	10,2	0,0037
25	0,9968	19,2	0,0025
30	0,9964	26,8	0,0030
35	0,9959	53,2	0,0034
40	0,9935	65,7	0,0052
45	0.9960	139,6	0,0031
50	0,999	234,5	0,0008

Figure 12 shows the ENN testing results. The red line (ENN prediction results) follows the actual PV power pattern (blue line), which indicates that the Elman Neural Network (ENN) is capable of accurately predicting PV output power.

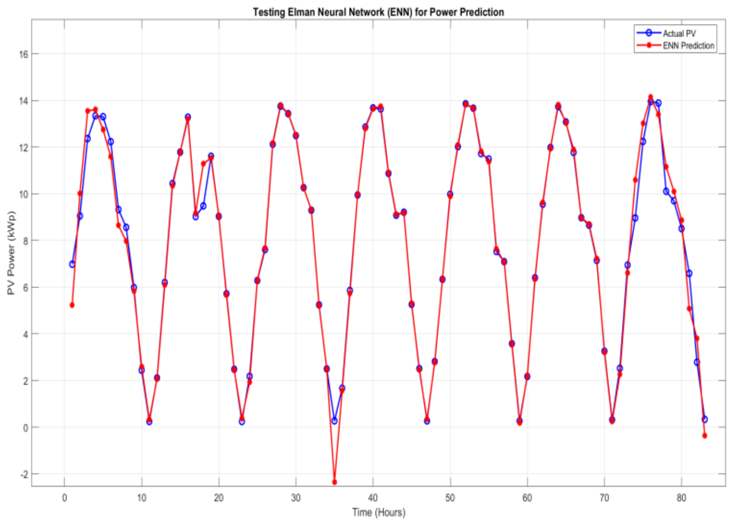

Figure 12. Testing of ENN

Table 6 shows the lowest MSE value at N=8 of 0.00664, R=0.9922, with a time of 6.4 seconds, while the highest MSE value is at N=30 with an MSE value of 0.01752, R=0.9789, with a time of 5.1 seconds. The average MSE error of 1.2% is still acceptable because it is below 10%.

Table 6. Training results using ENN

Neuron	R	Time (s)	MSE Training
8	0,9922	6,4	0,00664
10	0,9868	4,9	0,01097
15	0,9876	4,1	0,01013
20	0,9859	4,6	0,01133

Neuron	R	Time (s)	MSE Training
25	0,9663	5,7	0,01061
30	0,9789	5,1	0,01752
35	0,98801	4,8	0,01084
40	0,9845	5,9	0,012463
45	0,9798	4,9	0,016693
50	0,9834	4,9	0,016693

3.3. Comparison of CFNN and ENN

This study compares the performance of ANNs, namely Cascade Forward Neural Network (CFNN) and Elman Neural Network (ENN), to obtain recommendations for the best prediction performance. Figure 16 shows a comparison between actual power, CFNN prediction power, and ENN prediction power. Figure 13 Shows a comparison of PV power output predictions. The blue line (Actual PV Power) represents the actual power generated by the solar panels. The red line (ENN Prediction) represents the predicted PV power using the Elman Neural Network (ENN), while the green line (CFNN Prediction) represents the predicted PV power output using the Cascade Forward Neural Network (CFNN). The results of this study indicate that the use of the Elman Neural Network (ENN) is superior to that of the Cascade-Forward Neural Network (CFNN). In ENN, during testing, the smallest error was 0.00664 with 8 neurons and a time of 6.4 seconds. In contrast, in CFNN, the smallest MSE was 0.024306 with 25 neurons and a time of 7.7 seconds. This indicates accurate predictions because it is less than 10%. Therefore, the use of ENN with the Bayesian Regulation Algorithm is more recommended in predicting PV power output to assist energy management systems because it has a better mean square error (MSE) value than using CFNN.

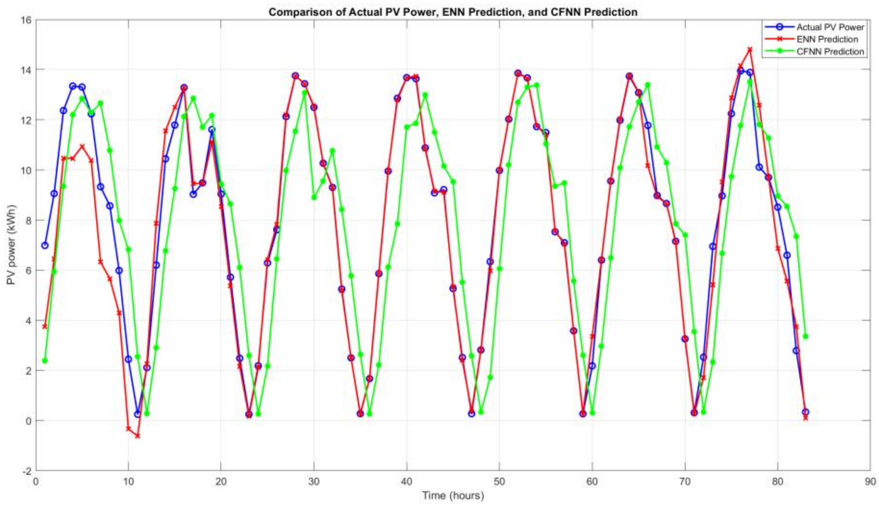

Figure 13. Comparison of Actual PV Power, ENN Prediction, and CFNN Prediction

The graph in Figure 14 compares the mean square error (MSE) of the CFNN and ENN models as the number of neurons varies from 8 to 50. The MSE value in the ENN model is lower than that of the CFNN. These findings demonstrate that ENN outperforms CFNN in predicting time series data patterns, thereby enabling it to retain information from previous instances.

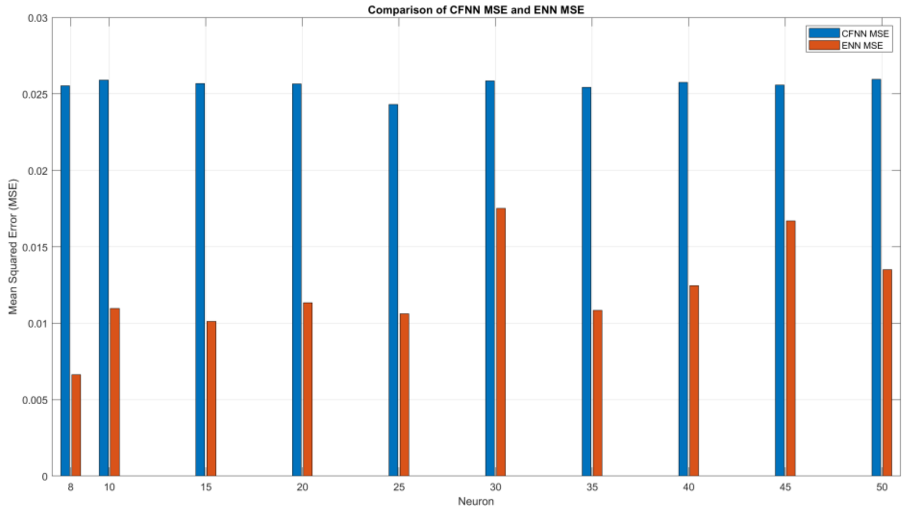

Figure 14. Comparison of CFNN MSE and ENN MSE

3.4. Discussion

The findings in this study indicate the presence of overfitting, characterized by high accuracy in the training data and low accuracy in the testing data. The selection of neural networks with numerous parameters, layers, and neurons can also lead to overfitting [11][25], Nevertheless, this study successfully demonstrated the effectiveness of overcoming the problem of overfitting by utilizing the Bayesian regularization algorithm. In equation (6), E_w which is the mean square error, prevents the weights from overfitting too much by controlling α (alpha) and β (beta). This happens automatically when using the Bayesian Regularization algorithm (trainbr). The Bayesian Regularization algorithm prevents noise by increasing α to strengthen the weights and prevent the neural network from simply memorizing the training data, and by increasing β (beta) so that the neural network focuses on learning relationship patterns rather than just memorizing them. Neural networks that utilize the Bayesian regularization algorithm possess robust capabilities and continue to learn patterns without compromising accuracy.

The advantage of this research lies in the implementation of the Bayesian regularization algorithm for training two architectural models: the Elman neural network and the cascade forward neural network. This research compares two different ANN models, namely CFNN and ENN. The performance results of both ANNs show that the ENN performs very well, with a low MSE of 0.00664 during testing, achieved with 8 neurons and a time of 6.4 seconds. This compares favorably to the CFNN, which exhibits the smallest error during testing of 0.024306 and the largest error of 0.025944, still within the permissible range. The results of this study support energy management systems by providing accurate predictions, enabling informed energy planning, reducing losses, and enhancing operational efficiency.

This study also has limitations, namely that the ANN parameters are set to an epoch of 2000, a learning rate of 0.01, and only 10 different neuron variations, with a maximum of 50 neurons. If the parameter limits were broader, a more optimal configuration would be obtained. Only two ANN architectures were tested, so other architectural models, such as LSTM and GRU, were not compared.

4. Conclusion

In this study, the use of the Elman Neural Network (ENN) demonstrated better performance compared to the Cascade-Forward Neural Network (CFNN). In ENN, the smallest MSE value obtained was 0.00664 with a number of neurons N=8, a correlation value of R=0.9922, and a time of 6.4

seconds. In the CFNN model, the smallest MSE value was obtained with N = 25, yielding an MSE value of 0.024306. ENN was able to produce more accurate prediction results. The increase in the accuracy of PV power output prediction allows the system to adapt more quickly to fluctuations in PV power production, making it more optimal.

5. Acknowledgment

We would like to thank the Center for Research and Community Service at Madura State Polytechnic for their support in completing this research. This research was funded by the Canter for Research and Community Service under the 2025 Early Career Faculty Research Scheme.

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