CHAPTER 5

PREDICTION OF OUTPUT POWER FROM PV PANELS USING AN ARTIFICIAL NEURAL NETWORK (ANN) INTEGRATED WITH BEE COLONY OPTIMIZATION (BCO)

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5.1 INTRODUCTION

Malaysia is increasingly turning to solar photovoltaic (PV) systems to meet growing energy demands in a sustainable way. However, the power output of PV panels is affected by fluctuating environmental conditions such as solar irradiance and temperature. Accurate prediction models are needed to optimize energy generation. Artificial Neural Networks (ANN) can handle nonlinear relationships in data but often require precise tuning. By integrating Bee Colony Optimization (BCO), a nature-inspired algorithm, with ANN, this study aims to improve prediction accuracy while reducing computational complexity. Predicting PV output is difficult due to variable environmental conditions. While ANN can model these complex relationships, it requires extensive data and careful parameter tuning. This tuning process is often time-consuming and computationally expensive.

This study addresses the problem by integrating BCO to optimize ANN parameters, aiming for more accurate, efficient, and practical PV output predictions. The objectives are to develop a predictive model for PV panel output power using ANN, to optimize the ANN parameters using the BCO algorithm for enhancement. To achieve these objectives, this chapter presents a detailed workflow for implementing and evaluating the ANN-BCO model. It includes data collection, ANN training, and BCO optimization for weight and bias adjustment. The performance of the hybrid model is then compared with a conventional ANN using multiple metrics, including daily total power, R^2 scores, regression analysis, time series prediction, and mean squared error (MSE).

5.2 MATERIAL AND METHOD

This section presents the development of a hybrid learning disability prediction model combining ANN and BCO. It covers data collection, ANN training, and BCO parameter optimization, with flowcharts illustrating the workflow and model development process.

5.2.1 ARTIFICIAL NEURAL NETWORK (ANN)

Artificial Neural Networks (ANN) are computer modeling solutions that use the functionality and structure of the human brain. They are composed of input, hidden and output levels which are composed of neurons interconnected with adjustable weights. ANNs are trained using past data and could be used to model nonlinear relationships between the input and the output elements. The ANNs are highly deployed in PV predicted power because of their flexibility and learning capability in analyzing systemic factors like solar irradiance and temperature [1], [2], [3]. Based on the flowchart below it showed how does it works in the coding. Figure 5.1 shows the schematic diagram of arrangement and connection of the system.

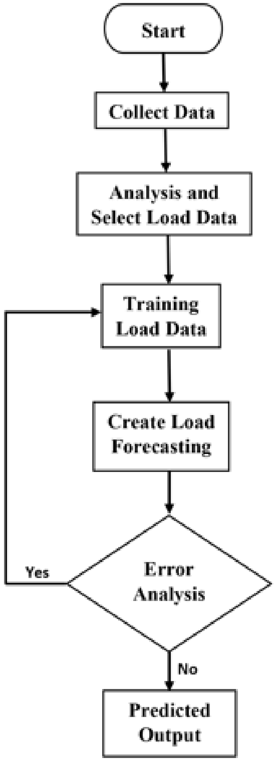

Figure 5.1: Schematic Diagram of Arrangement and Connection of the System.

5.2.2 BEE COLONY OPTIMIZATION (BCO)

Bee Colony Optimization (BCO) is a metaheuristic algorithm, based on the behaviors of honeybee colonies. It resembles the way bees find food, distribute knowledge and decide together. BCO entails exploration of new territories by scout bees, exploitation of familiar food resources by employed bees and assessment of the quality of food sources by onlooker bees and subsequent choice of a given source. This exploration and exploitation trade-off enables BCO to perform rapidly on complex problems. When used in ANN, BCO aids weight and bias adjustment, enhancing the model accuracy in such tasks as output forecasting of PV [4], [5], [6]. Based on the flowchart in Figure 5.2 it shows how does BCO works.

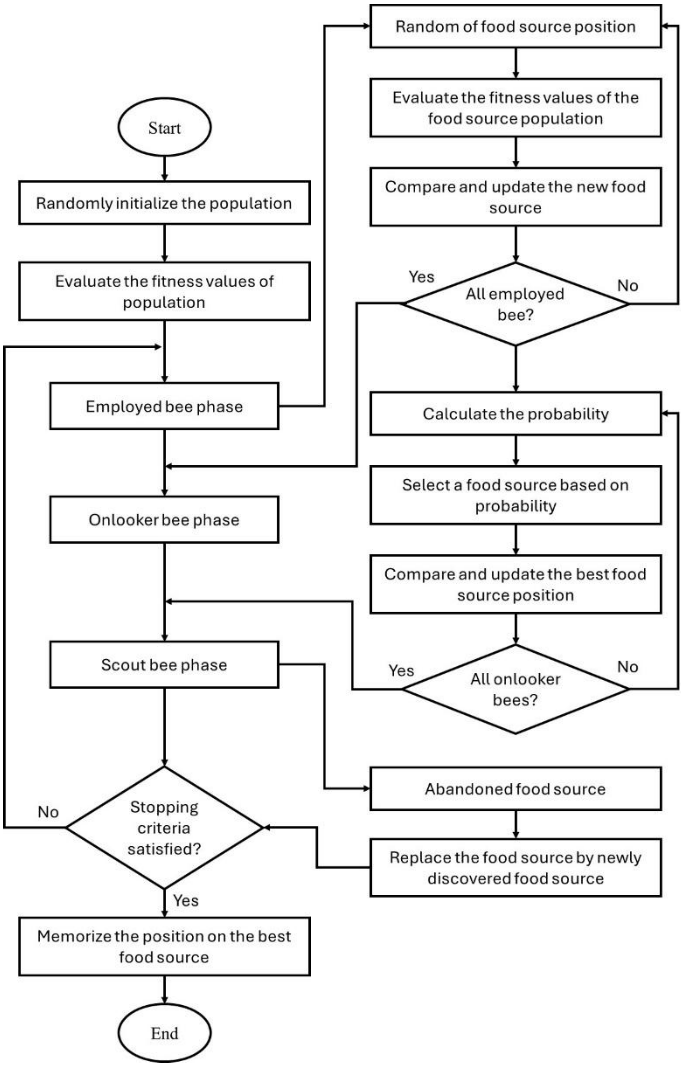

Figure 5.2: Flowchart of BCO.

5.3 RESULTS AND DISCUSSION

In this part, the ANN and ANN-BCO models would be presented and their performance at the prediction of PV panel output examined. It also contrasts the two models with respect to performance figures that include daily total power, R_2 scores, regression analysis, time series forecasts and mean squared error (MSE). Its results indicate that ANN-BCO model consistently outsmarts the regular ANN model in terms of its accuracy as well as being closer to the real power output of PV.

5.3.1 DAILY TOTAL POWER COMPARISON BETWEEN ANN AND ANN-BCO

This graph sums up the daily total power production that both models have forecasts compared to real observed data bringing out the performance of the model in terms of capturing the trends of power productions as shown in Figure 5.3 and 5.4. Based on Figure 5.3 and 5.4 shows the results of predicted of ANN-BCO are much closer to the actual values and while for the ANN it is overestimate than actual value. This shows how good the model of ANN-BCO is predicted than ANN.

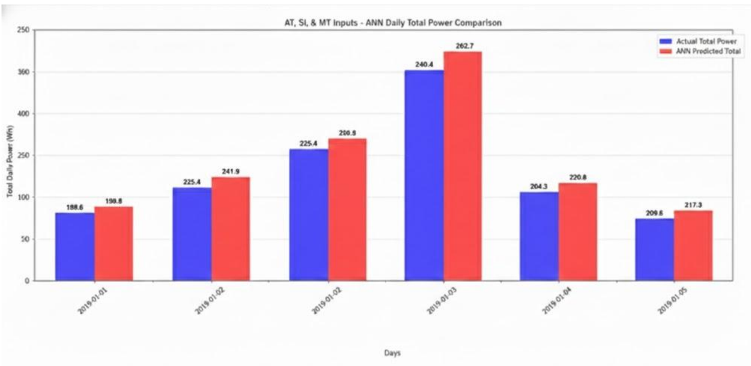

Figure 5.3: ANN Daily Total Power Comparison.

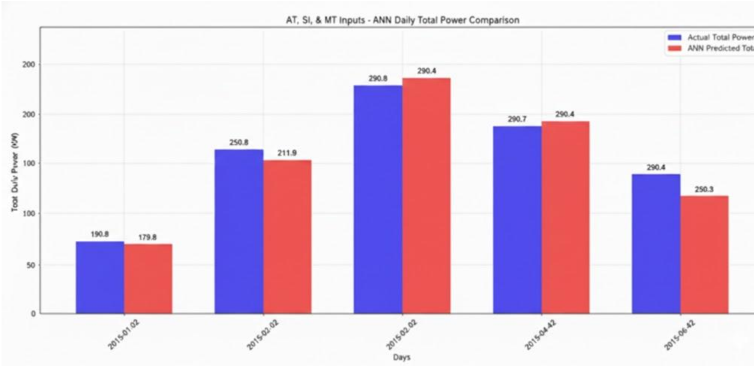

Figure 5.4: ANN-BCO Daily Total Power Comparison.

5.3.2 DAILY R^2 SCORES BETWEEN ANN AND ANN-BCO

This indicator shows both model scores are estimated daily, and the scores measure how much variance in power output is reflected by the model predictions shown in Figure 5.5 and 5. 6.

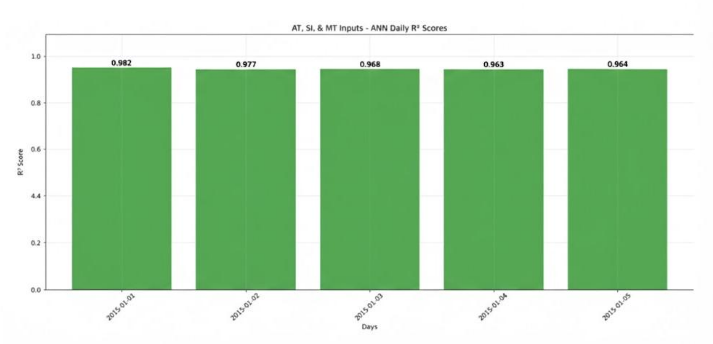

Figure 5.5: ANN Daily R^2 Scores.

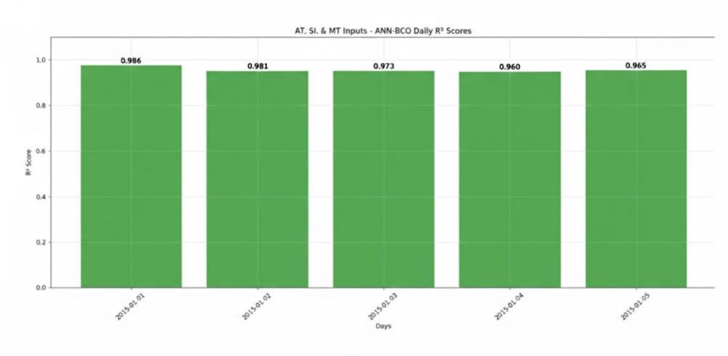

Figure 5.6: ANN-BCO Daily R^2 Scores.

5.3.3 REGRESSION ANALYSIS BETWEEN ANN AND ANN-BCO

This is the regression plot of both models that illustrates a correlation between expected and actual values of power output to evaluate the linear fit and the dispersion of the error shown 5.7 and 5.8. From Figure 5.7 and 5.8 the regression line for ANN-BCO is much closer to the actual value than regression line for ANN is slightly much further than actual value line. The value for overall $R2$ is ANN-BCO value is much better which is 0.9735 than ANN value is 0.9705.

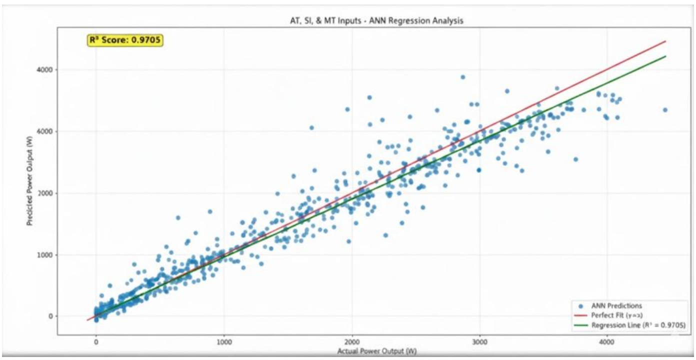

Figure 5.7: ANN Regression Analysis.

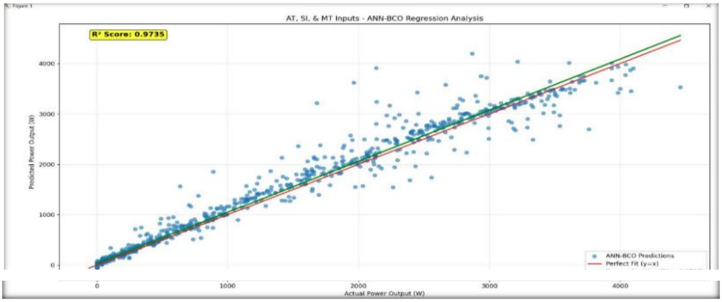

Figure 5.8: ANN-BCO Regression Analysis.

5.3.4 TIME SERIES PREDICTION COMPARISON BETWEEN ANN AND ANN-BCO

Figure 5.9 and Figure 5.10 displays how well both models make a time series prediction compared to the actual values and thus shows how the model can follow temporal trends in power generation. From Figure 5.9 and 5.10 the ANN-BCO prediction is much closer to the actual value than ANN. From the start of times which 0 minutes until 1400 minutes the prediction of ANN- BCO consistent near the actual value than ANN is also consistent but further than actual value. Based on both graph the prediction of ANN-BCO is improved because it enhanced accuracy to optimize the ANN parameters more effective, adapt in dynamic during training and also make generalization to new data.

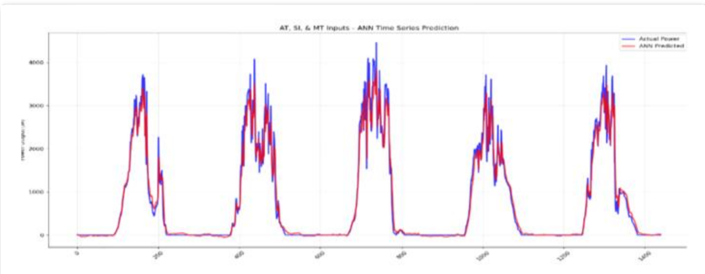

Figure 5.9: ANN Time Series Prediction.

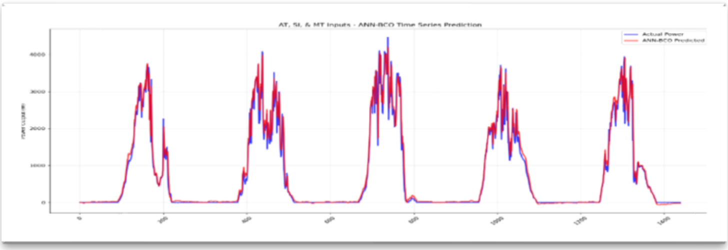

Figure 5.10: ANN-BCO Time Series Prediction.

5.3.5 MSE COMPARISON BETWEEN ANN AND ANN-BCO

This Figure 5.11 highlights how the Mean Squared Error (MSE) of ANN and ANN-BCO models obtained at various conditions of input variables (AT, SI, MS) have the capacity to yield less prediction errors with ANN-BCO model. From Figure 5.11 shows the comparison for ANN and ANN-BCO models with the lower values for MSE is ANN-BCO (3.33) which meaning it have much more accurate in predicting PV power output than ANN (3.65). The lower MSE means, it much closer with the actual power output values by reducing forecasting errors.

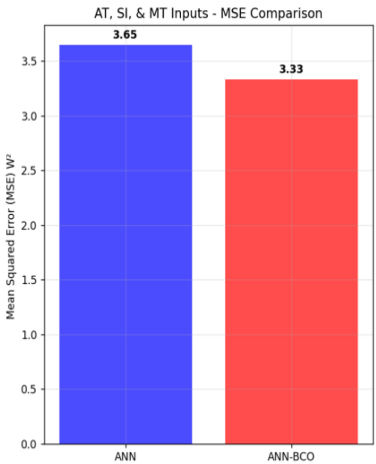

Figure 5.11: MSE Comparison Between ANN and

ANN-BCO.

5.4 CONCLUSION

The ANN-BCO model effectively predicts PV panel output by combining the ANN's ability to model complex non-linear relationships with BCO's optimization capabilities. This integration enhances prediction accuracy and efficiency, outperforming traditional models. BCO helps ANN converge to optimal structures, reducing errors and improving generalization.

The study supports the use of bio-inspired algorithms to improve machine learning in renewable energy. Future work could explore other meta-heuristics or adaptive learning to boost performance in large-scale solar plants. The ANN-BCO model offers a reliable tool for energy planners and grid operators to optimize solar energy use and system efficiency.

BIBLIOGRAPHY

[1] V.V.Coury,D.C.Jorge, IEEE Transaction on Power Delivery,Vol 13,No.1,Janury 1998

[2] C. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," Bulletin of Mathematical Biophysics, vo1.5, pp.115-133 (1943)

[3] D.O. Hebb, The Organization of Behaviour, John Wiley, New York, 1949

[4] Karaboğa, D. (2005). An Idea Based on Honeybee Swarm for Numerical Optimization.

[5] Čubranić-Dobrodolac, M., Švadlenka, L., Čičević, S., Trifunović, A., & Dobrodolac, M. (2021). A bee colony optimization (BCO) and type-2 fuzzy approach to measuring the impact of speed perception on motor vehicle crash involvement. Soft Computing, 26(9), 4463–4486.

[6] Kruekaew, B., & Kimpan, W. (2020). Enhancing of Artificial Bee Colony Algorithm for Virtual Machine Scheduling and Load Balancing Problem in Cloud Computing. International Journal of Computational Intelligence Systems, 13(1), 496.