International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I6P116
Volume 73 Issue 6, 183-190, June 2025

Original Article

Artificial Neural Networks Based on Optimization Technique for Short-Term Electricity Demand Forecasting: Uttaradit Rajabhat University Data Analysis

Rattapon Dulyala[1], Sitthisak Audomsi[1], Worawat Sa-Ngiamvibool[1*]

[1]*Faculty of Engineering, Mahasarakham University, Kantarawichai, Maha Sarakham, Thailand.*

[*]*Corresponding Author : wor.nui@gmail.com*

Received: 23 December 2024 Revised: 05 April 2025 Accepted: 29 May 2025 Published: 28 June 2025

***Abstract* - *The research examines the efficacy of Artificial Neural Networks (ANNs). When combined, it is accompanied by optimization techniques for predicting electrical load demand. The models include a standalone ANN and an ANN combined with optimization methodologies. The models' performance was assessed utilizing Mean Absolute Percentage Error, and the ANN, accompanied by the Bee Algorithm, demonstrated the highest accuracy and a MAPE of 2.1559%. The standalone ANN had the lowest accuracy, accompanied by a MAPE of 4.3038%. The study found that ANN accompanied by BA effectively matches predicted and actual load values, while the standalone ANN had considerable prediction errors. The study used a notebook with high-end specifications to process and enhance the models, ensuring consistent parameter settings and neural network configurations. The results underscore the importance of combining optimization methods accompanied by ANNs for improved forecasting precision. Future research could explore hybrid optimization methods and expand their applications to additional datasets for more extensive validation.*

***Keywords* - *Artificial Neural Network, Particle Swarm Optimization, Genetic Algorithm, Bee Algorithm, Electrical Load Forecasting.*

1. Introduction

Electricity is an essential resource for industry, technology, and quality of life, significantly influencing social and economic development [1]. The increasing electricity demand, propelled by urbanization and industrialization, varies daily according to consumer behavior. Precise forecasting is crucial to avert system instability, which may jeopardize the long-term sustainability of the electrical grid [2]. Forecasts of energy demand determine effective planning of distribution [3], resource allocation, and network maintenance; thus, they also help to govern power systems. Power systems rely on accurate forecasts to ensure reliability and efficiency, minimizing outage risk and maximising renewable resource use [4]. Through analyzing trends and patterns, utilities can adapt their strategies to meet changing demands and enhance overall service quality. It reduces energy prices, prevents power shortages, and advances future development through production capacity, transmission line upgrades, and protective measures [5]. Artificial Neural Networks (ANN) are adept at organizing complex data, spotting trends, and estimating power use [6]. This paper aims to improve the accuracy of short-term power demand projections by using energy consumption statistics from the Bhumi Ratchapat Building at Uttaradit Rajabhat University. The aim is to build an innovative energy management system that improves the long-term stability and reliability of the electrical.

1.1. Research Inquiries

This study examines the subsequent research questions:

RQ1: Can Artificial Neural Networks (ANNs) accurately predict short-term electricity demand utilizing actual consumption data.

RQ2: What is the effect of optimization techniques-specifically Genetic Algorithm, Particle Swarm Optimization and Bee Algorithm-on the forecasting efficacy of the Artificial Neural Network model.

RQ3: Which ANN-based model produces the most precise and dependable prediction outcomes, as assessed through Mean Absolute Percentage Error.

This inquiry seeks to ascertain the predictive efficacy of Artificial Neural Networks (ANNs) in practical applications and the relative effectiveness of various optimization techniques when combined with ANNs for forecasting electricity demand.

1.2. Limitations of Existing Forecasting Methods

Conventional forecasting models, such as ARIMA, linear regression, and basic artificial neural networks, face various challenges in practical applications:

- Incapability to accurately represent intricate, nonlinear load dynamics, particularly in fluctuating or atypical consumption contexts.
- Vulnerability to variations and anomalies which can considerably distort short-term predictions.
- Suboptimal training performance occurs when unoptimized Artificial Neural Networks (ANNs) converge slowly or become trapped in local minima through diminishing accuracy and generalizability.

These deficiencies underscore the necessity of amalgamating metaheuristic optimization algorithms accompanied by ANN models to improve learning efficiency and predictive performance.

1.3. Novelty and Contribution of the Study

This study diverges from previous research in multiple aspects:

- This study offers a comparative analysis of artificial neural network models combined with diverse metaheuristic algorithms (genetic algorithm, particle swarm optimization, and bee algorithm), whereas most prior research concentrates on a singular approach.
- It employs actual, institution-specific energy consumption data, enhancing the relevance of the findings for facility-level energy management.
- Employing various evaluation techniques (MAPE, visual predictions versus actual comparisons, and scatter plots) augments the reliability and comprehensibility of the findings.

These contributions facilitate the connection between theoretical model development and practical implementation in intelligent energy systems.

1.4. Recent Advancements in Forecasting Methodologies

Recent studies have investigated various methods to enhance the precision of electricity demand forecasting. For example:

- Khairy et al. (2025) suggested a graph neural network model optimized through reinforcement learning for traffic and energy predictions, showing substantial accuracy improvements [2].
- Rhenals-Julio et al. (2025) conducted an economic assessment of microgrid systems in university buildings, demonstrating the relevance of localized energy forecasting [4].
- Jing et al. (2025) applied ANN for load forecasting and scheduling, confirming the effectiveness of ANN-based models when tailored and accompanied by proper optimization [7].

These studies validate the increasing interest in hybrid and intelligent forecasting models, endorsing the application of artificial neural networks in conjunction with metaheuristic algorithms, as analyzed in our research.

2. Elements Influencing the Prediction of Electric Load

Designed through the Provincial Electricity Authority, the Automatic Meter Reading (AMR) technology was applied in the data collection for this project. Aiming to cover electricity use across many scenarios, including peak usage periods (On-Peak), minimal usage periods (Off-Peak), and consumption data during holidays (Holiday), the collected data related to the electricity consumption of the Bhumi Ratchapat Building at Uttaradit Rajabhat University from January 2020 to December 2024.

3. Optimization Technique

Improving the effectiveness of Artificial Neural Network (ANN) models depends critically on optimization strategies [8], especially in complex forecasting situations, including short-term power demand forecasting [9]. To get the best accuracy, these techniques help to change network characteristics, including weights and biases.

3.1. Genetic Algorithm (GA)

Natural selection, mutation, and crossover techniques are used in the Genetic Algorithm (GA) to provide the best solutions for complex or non-linear search fields [10].

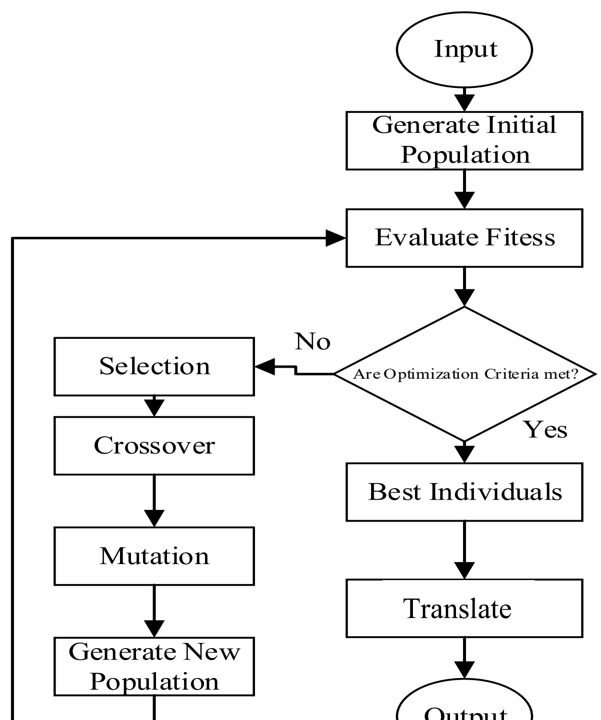

Fig. 1 Genetic algorithm standard process, altered from [12]

While it takes more time to calculate than PSO or BA, it can investigate solutions over the search space. Although they may involve the specification of generating counts and population sizes, genetic algorithms are suitable for complex problems accompanied by large search areas. Figure 1 examines the technique. The figure illustrates how these algorithms operate through iterative processes, showcasing selection, reproduction, and replacement roles in evolving potential solutions. As the algorithm progresses, it converges towards optimal or near-optimal solutions, effectively navigating the complexities of the problem space [11].

3.2. Particle Swarm Optimization (PSO)

Motivated by the collective behavior of animal swarms, like avian or aquatic species, Particle Swarm Optimization (PSO) is an algorithm [13]. This algorithm replicates the social behavior of these animals to identify optimal solutions in intricate search spaces.

Through leveraging interactions among particles, PSO efficiently navigates potential solutions, making it a powerful tool in various fields such as engineering, artificial intelligence, and data analysis. It uses particles to find the best answer based on your and your peers' experiences. For non-linear problems, Particle Swarm Optimization (PSO) shows excellent adaptation to complex search domains. Still, it could be caught at a local optimum, especially in large search areas [14]. Figure 2 examines the technique.

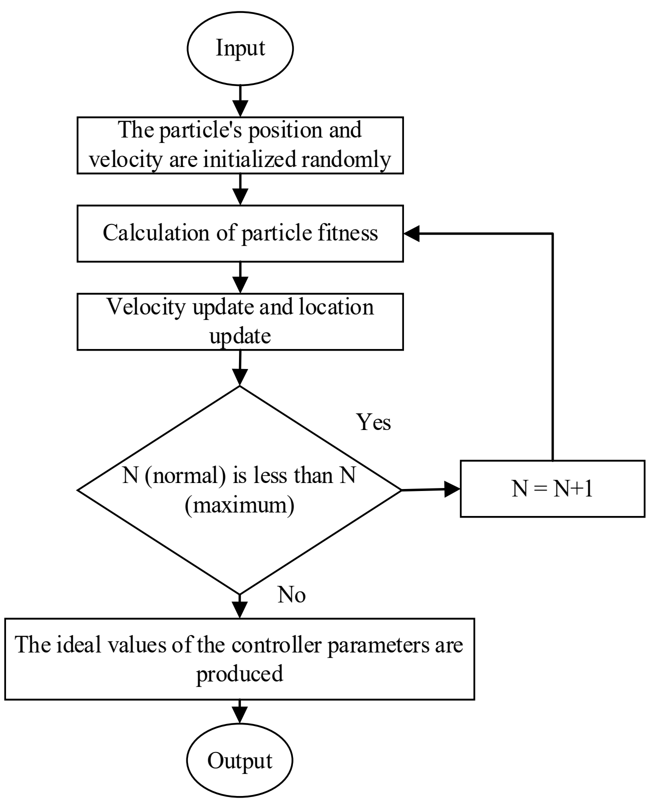

Fig. 2 Particle Swarm Optimization standard process, altered from [15]

3.3. Bee Algorithm (BA)

Derived from the foraging behavior of bees, the flexible optimization approaches the Bee Algorithm (BA): Every Bee aims to find the area accompanied by the best goal value and represents the response value inside the search space [16]. Bees disseminate their acquired knowledge to fellow bees to enhance the likelihood of identifying the optimal solution. Although the bee algorithm is good at avoiding local optima, properties like the bee population and search radius call for calibration [17]. It could be insufficient for problems accompanied by a large search space but suitable for complex parameter optimization problems.

Using optimization techniques in Artificial Neural Networks can help to reduce forecasting errors [18], including Mean Absolute Percentage Error [19], and improve the learning consistency of ANN networks accompanied by data and complex situations in short-term power forecasting research [20]. Thus, optimization techniques are seen as necessary tools to increase the model's reliability for application in high-precision environments, like future power management, and thus enhance the capabilities of artificial neural networks [21].

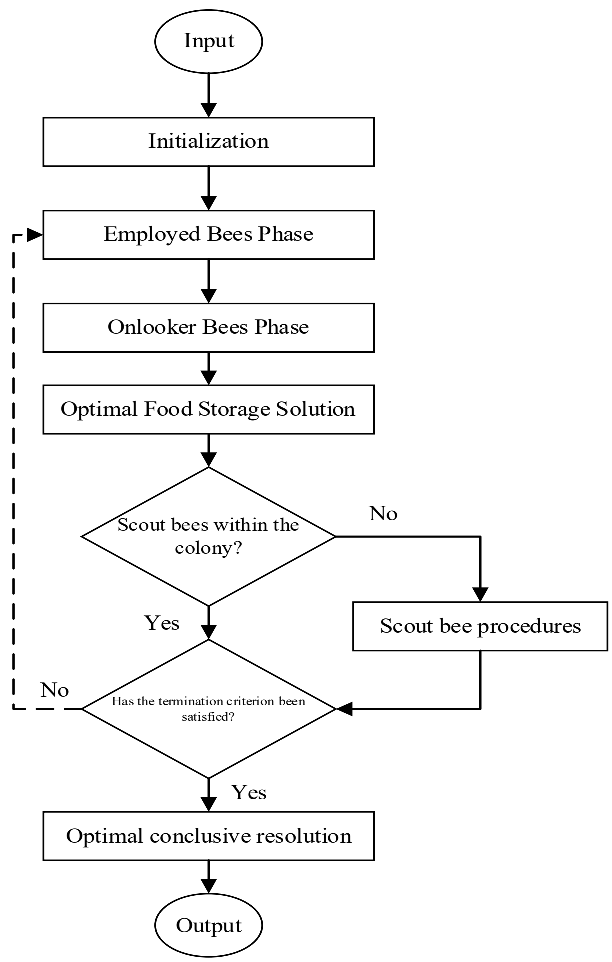

Fig. 3 Bee algorithm standard process, altered from [22]

4. Objective Function Employed in the Optimization Procedure

4.1. Mean Absolute Percentage Error (MAPE)

Calculated through the average percentage of absolute error (Absolute Percentage Error) [23] between the projected value ($\overline{y}_t$) and the actual value (y_t) Overall samples, this statistic evaluates the accuracy of a forecasting model. MAPE has advantages, as equation (1) shows, as its results are stated as a percentage, which makes simple comparisons easier [24].

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{y_t - \overline{y}_t}{y_t}\right| \quad (1)$$

5. Results

5.1. Neural Network Architecture and Experimental Setup

This study employs an Artificial Neural Network (ANN) comprising:

- Input layer: Three neurons representing features derived from time-series consumption data (e.g., date/time, historical demand values).
- Hidden layer: One layer comprising 15 and 30 neurons, assessed individually for performance.
- Output layer: a single neuron indicating the forecasted electricity demand.
- Activation function: The sigmoid function is utilized in hidden layers, and the linear function is employed in the output layer.

The models underwent training via backpropagation accompanied by a learning rate of 0.01 over 200 epochs. The dataset was partitioned into 70% for training and 30% for testing. Optimization methodologies (GA, PSO, BA) were employed to refine the weights and biases. The efficacy of each model was evaluated using the Mean Absolute Percentage Error (MAPE). Supplementary validation was conducted by comparing actual versus predicted values and scatter plots to illustrate model accuracy. Hardware configuration: The simulations were performed on a laptop with an Intel Core i5-12400F CPU, 16.0 GB DDR4-3200 RAM, and an NVIDIA GeForce RTX 4060 GPU.

5.2. Compare Model Accuracy

The mean error (MAPE) of every model is shown in Table 1. This shows that the traditional ANN model shows lower accuracy than the integrated model accompanied by the optimization technique.

Table 1. Mean Absolute Percentage Error (MAPE)

ANN + Optimization Technique	Value (%)
Artificial Neural Network	4.3038
Artificial Neural Networks accompanied by Genetic Algorithm	2.2198
Artificial Neural Network accompanied through Particle Swarm Optimization	3.8130
Artificial Neural Network accompanied through Bee Algorithm	2.1559

Using Mean Absolute Percentage Error, the study revealed that conventional Artificial Neural Network (ANN) models show less accuracy in estimating electricity consumption than models augmented accompanied by optimization techniques.

Accompanied throughout augmentation measures, the conventional ANN model has a MAPE of 4.3038%, the most significant inaccuracy among the tested approaches. On the other hand, the model improved using optimization methods shows a much-reduced error; the ANN coupled with Particle Swarm Optimization (PSO) achieves a MAPE of 3.8130%, indicating a significant increase in accuracy.

Accompanied by a MAPE of 2.2198%, the ANN integrated accompanied by Genetic Algorithm (GA) shows better performance than other approaches relative to PSO. Accompanied by a MAPE of just 2.1559%, the ANN, accompanied by the Bee Algorithm (BA) model, shows exceptional performance, indicating the highest electrical load forecasting accuracy.

5.3. Analysis of Actual Versus Predicted Workloads

The graphs shown in Figures 4 to 7 show a comparison between the predicted values (Predicted Load) produced from many models, particularly ANN, ANN accompanied through GA, ANN accompanied through PSO, and ANN accompanied through BA, and the actual measured values (Actual Load).

The findings of every graph show how well the models predict demand for electrical loads throughout the assigned sample period. Figure 4 shows the predictions of the conventional ANN model, which show clear deviations at some time intervals, especially in samples 6–8 and 13–15, where the forecasted values fail to reflect the variations of the actual values fairly, so stressing the flaws of traditional ANNs in the lack of optimization techniques.

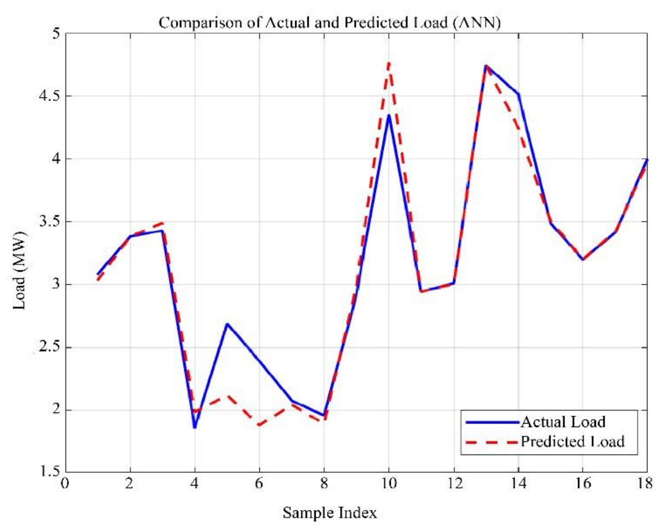

Fig. 4 Comparison of actual and predicted load (ANN)

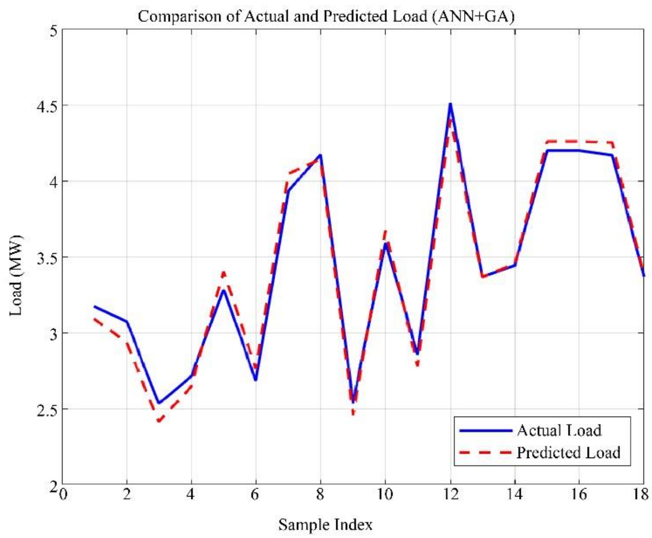

Fig. 5 Comparison of actual and predicted load (ANN accompanied through GA)

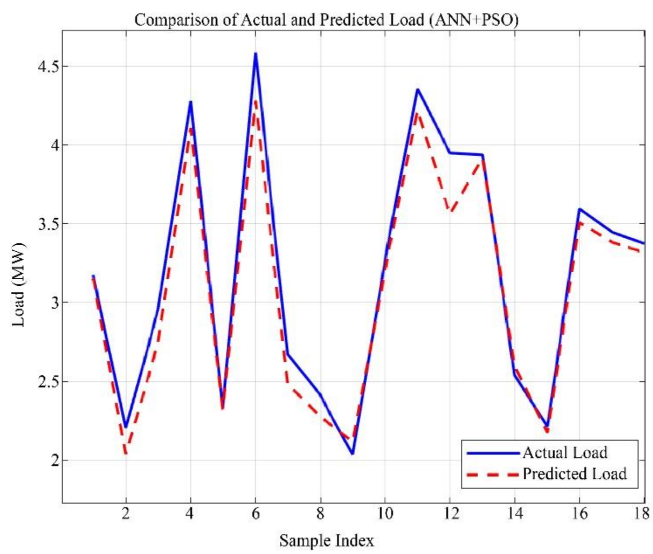

Fig. 6 Comparison of actual and predicted load (ANN accompanied through PSO)

Compared to the traditional ANN, Figure 5 shows the Artificial Neural Network (ANN) forecasting results and a Genetic Algorithm (GA), showing a significant variation between actual and anticipated values reduced.

While some variations exist in some instances, as shown in Examples 4–5, the expected values more precisely follow the pattern of the actual values in almost every sample period.

Though significant deviations exist in some regions, including Examples 6–7 and Examples 15–16, the graph in Figure 6 demonstrates the ANN's predicting outcomes coupled with Particle Swarm Optimization (PSO), surpassing the conventional ANN. Still, the predicted values resemble absolute values more than those obtained using ANN.

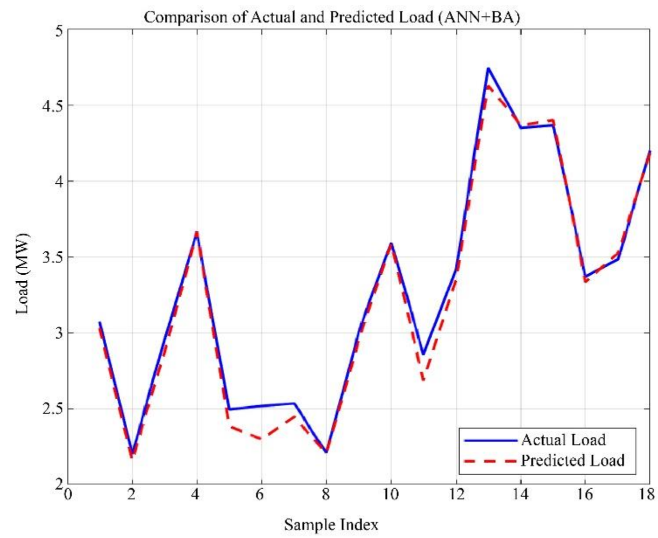

Fig. 7 Comparison of actual and predicted load (ANN accompanied through Bee)

Among the evaluated models, the graph in Figure 7 displays the highest predicting ability by showing the ANN outcome coupled with the Bee Algorithm (BA).

In every sample period, the expected values are nearer than the actual values. Compared to other techniques, the divergence is quite minimal, which indicates that ANN, accompanied by BA, can manage data volatility and generate reliable forecasts.

Figures 8 through 11 show the results of the Scatter Plot graph, which uses many models-ANN, ANN accompanied through GA, ANN accompanied through PSO, and ANN accompanied through BA-that contrast the actual load versus the projected load. Data points close to or on the dotted line suggesting the best link show more forecast accuracy in every graph.

Figure 8 shows the traditional Artificial Neural Network (ANN) forecasting result. Particularly in the low and high load zones, the data points show dispersion from the dotted line throughout multiple ranges, therefore illustrating the limitations of typical artificial neural networks in precisely simulating the complex connection between input elements and electric power demand.

The Artificial Neural Network (ANN) linked accompanied by a Genetic Algorithm (GA) shown in Figure 9 prediction results.

The data points indicate improved forecast accuracy as they follow the dotted line more precisely than the traditional ANN. Especially inside the medium load demand range, the data points usually line up along the dotted line more consistently.

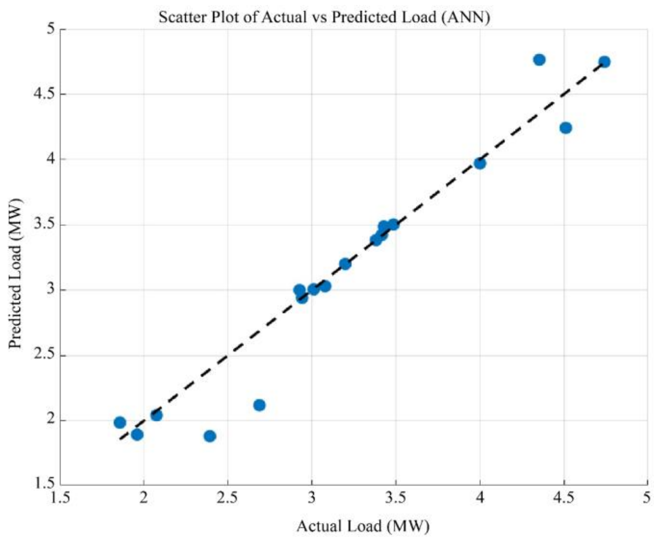

Fig. 8 Scatter plot of actual and predicted load (ANN)

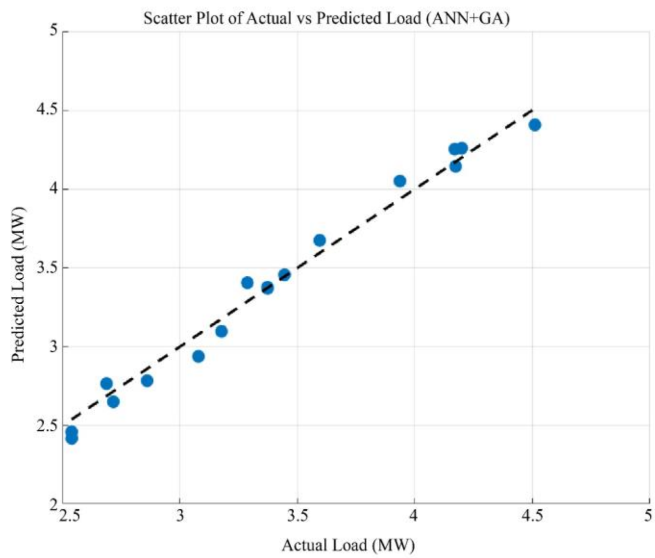

Fig. 9 Scatter plot of actual and predicted load (ANN accompanied through GA)

Although there remains a dispersion of data points from the dotted line in some areas, especially inside the high load spectrum, Figure 10 shows the predictive outcomes of the Artificial Neural Network (ANN) integrated accompanied through Particle Swarm Optimization (PSO), demonstrating better accuracy than the conventional ANN. This improvement shows PSO's ability to improve the ANN's accuracy, yet it has limits in some cases.

Figure 11 shows the Artificial Neural Network (ANN) coupled with the Bee Algorithm (BA) forecasting result. Among all the models, the data points most precisely line the dotted line. The minimum mean error (MAPE) observed in the experimental results supports the great accuracy of ANN+BA in forecasting electric power demand, as indicated by the consistency of the data points aligned along the dotted line.

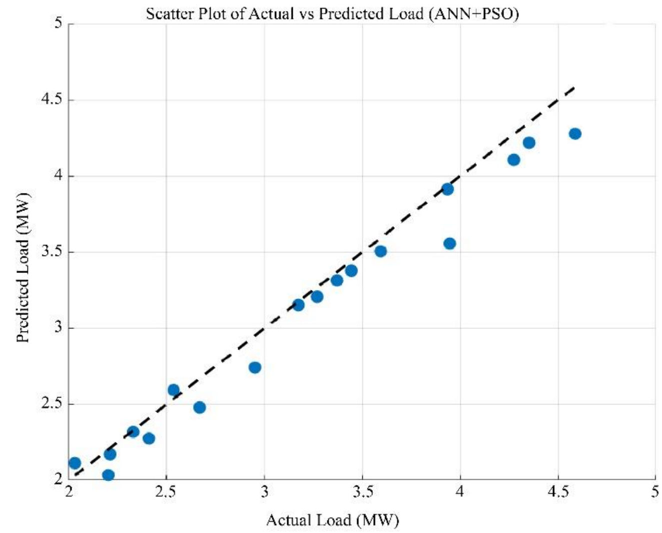

Fig. 10 Scatter plot of actual and predicted load (ANN accompanied through PSO)

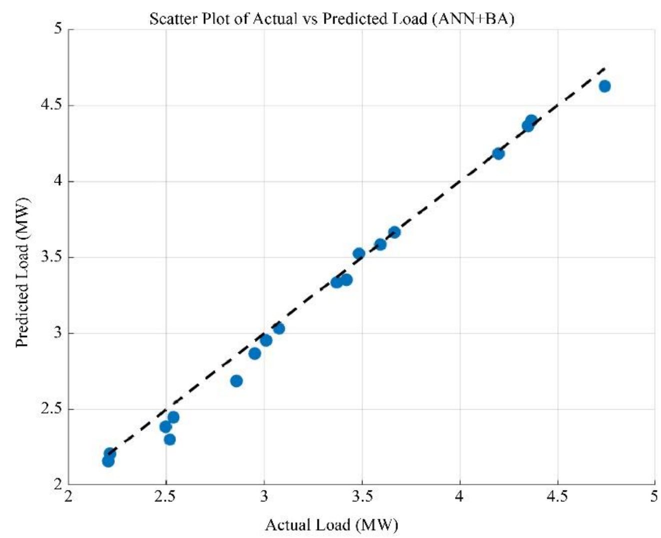

Fig. 11 Scatter plot of actual and predicted load (ANN accompanied through Bee)

6. Discussion and Conclusion

The study shows that Artificial Neural Networks (ANNs) for electrical loads significantly improve their forecasting ability using optimization techniques. Approaches including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Bee Algorithm (BA) provide ANN+BA models accompanied by the lowest Mean Absolute Percentage Error (MAPE) of 2.1559%, therefore surpassing both ANN+GA and ANN+PSO. Accompanied through a MAPE of 4.3038%, the independent ANN indicated reduced forecasting accuracy. While the solo ANN struggled to capture complicated load patterns throughout optimization, the scatter plot investigation revealed that ANN+BA showed the best accuracy in linking predicted load values accompanied by actual load values. The study emphasizes the need to combine artificial neural networks accompanied by optimization methods in load demand forecasting, as using models such as ANN+BA may produce accurate and good forecasts. Future research might look at hybrid methodologies or other optimization techniques to improve forecast performance.

Acknowledgments

The author appreciates the engineering faculty at Mahasarakham University and Uttaradit Rajabhat University, Thailand, for their indispensable assistance in this research.

References

[1] Carmen Valor, Valeria Karina Moreno, and Leonor Ruiz, "Schemes for Flexibility Provision Among Residential Consumers: Value Propositions for Automated Flexibility," *Current Sustainable/Renewable Energy Reports*, vol. 12, no. 1, pp. 1-8, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[2] Mohammed Khairy, Hoda M.O. Mokhtar, and Mohammed Abdalla, "Adaptive Traffic Prediction Model using Graph Neural Networks optimized through Reinforcement Learning," *International Journal of Cognitive Computing in Engineering*, vol. 6, pp. 431-440, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[3] Linfeng Li et al., "Optimal Planning of Renewable Energy Infrastructure for Ports Under Multiple Design Scenarios Considering System Constraints and Growing Transport Demand," *Journal of Cleaner Production*, vol. 477, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[4] Jesús D. Rhenals-Julio et al., "Economic Assessment of the Potential for Renewable Based Microgrids Generation Systems: An Application in a University Building," *International Journal of Energy Economics and Policy*, vol. 15, no. 1, pp. 206-212, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[5] Najwa Aaraj et al., "FANNG-MPC: Framework for Artificial Neural Networks and Generic MPC," *IACR Transactions on Cryptographic Hardware and Embedded Systems*, vol. 2025, no. 1, pp. 1-36, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[6] Jin Rong Tan et al., "Application of Deep Learning Algorithms in Classification and Localization of Implant Cutout for the Postoperative Hip," *Skeletal Radiology*, vol. 54, no. 1, pp. 67-75, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[7] Zuriani Mustaffa, and Mohd Herwan Sulaiman, "A Hybrid Prediction Model for Short-Term Load Forecasting in Power Systems," *ECTI Transactions on Computer and Information Technology (ECTI-CIT)*, vol. 18, no. 4, pp. 568-578, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] Soham Chakraborty et al., "Emergency Power Supply System for Critical Infrastructures: Design and Large Scale Hardware Demonstration," *IEEE Access*, vol. 11, pp. 114509-114526, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Mingxing Zhang et al., "Integrated Sensing and Computing for Wearable Human Activity Recognition with MEMS IMU and BLE Network," *Measurement Science Review*, vol. 22, no. 4, pp. 193-201, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Jun Li et al., "Multi Objective Optimization Algorithm for Hybrid Quantum Harmonic Oscillator and its Application in Rotor System Optimization," *Scientific Reports*, vol. 15, no. 1, pp. 1-16, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[11] Osama Moh'd Alia, "Optimizing Multilevel Image Segmentation with a Modified New Caledonian Crow Learning Algorithm," *Systems and Soft Computing*, vol. 7, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Priya Banerjee et al., *Chapter 3 - Review of Soft Computing Techniques for Modeling, Design, and Prediction of Wastewater Removal Performance*, Soft Computing Techniques in Solid Waste and Wastewater Management, pp. 55-73, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[13] M.A. Ebrahim et al., "Electric Eel Foraging Optimization based Control Design of Islanded Microgrid," *Scientific Reports*, vol. 15, no. 1, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[14] Shuai Ma et al., "Application of Fuzzy Inference System in Gas Turbine Engine Fault Diagnosis Against Measurement Uncertainties," *Chinese Journal of Mechanical Engineering*, vol. 38, no. 1, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Yang Sun et al., "Trajectory Tracking Control Design for 4WS Vehicle Based on Particle Swarm Optimization and Phase Plane Analysis," *Applied Sciences*, vol. 14, no. 9, pp. 1-25, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Yong Wang, "An Intelligent Path Planning Algorithm for Dynamic Football Training Environments," *Expert Systems with Applications*, vol. 277, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] Fan Ye et al., "An Enhanced Artificial Bee Colony Algorithm with Self-Learning Optimization Mechanism for Multi-Objective Path Planning Problem," *Engineering Applications of Artificial Intelligence*, vol. 149, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Kübra Yılmaz et al., "Sustainable Textile Manufacturing Accompanied through Revolutionizing Textile Dyeing: Deep Learning-Based, for Energy Efficiency and Environmental-Impact Reduction, Pioneering Green Practices for a Sustainable Future," *Sustainability*, vol. 16, no. 18, pp. 1-18, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Jiangbo Jing et al., "Optimization of Power System Load Forecasting and Scheduling based on Artificial Neural Networks," *Energy Informatics*, vol. 8, no. 1, pp. 1-20, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[20] Alessandro Filippo et al., "Application of Artificial Neural Network (ANN) to Improve Forecasting of Sea Level," *Ocean & Coastal Management*, vol. 55, pp. 101-110, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[21] Benjamin F. Hobbs et al., “Artificial Neural Networks for Short-Term Energy Forecasting: Accuracy and Economic Value,” *Neurocomputing*, vol. 23, no. 1-3, pp. 71-84, 1998. [CrossRef] [Google Scholar] [Publisher Link]

[22] Hamid Bouyghf, Bachir Benhala, and Abdelhadi Raihani, “Analysis of the Impact of Metal Thickness and Geometric Parameters on the Quality Factor-Q in Integrated Spiral Inductors through Means of Artificial Bee Colony Technique,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 4, pp. 2918-2931, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[23] Sungil Kim, and Heeyoung Kim, “A New Metric of Absolute Percentage Error for Intermittent Demand Forecasts,” *International Journal of Forecasting*, vol. 32, no. 3, pp. 669-679, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[24] Sudhakar Uppalapati et al., “Precision Biochar Yield Forecasting Employing Random Forest and XGBoost with Taylor Diagram Visualization,” *Scientific Reports*, vol. 15, no. 1, pp. 1-16, 2025. [CrossRef] [Google Scholar] [Publisher Link]