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Forecasting industrial electricity demand using hybrid optimization methods

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ABSTRACT

This study presents a hybrid machine learning framework for forecasting industrial electricity consumption by comparing backpropagation neural networks (BPNN) with models enhanced through metaheuristic optimization algorithms. Using 32 years of annual data from APEC economies, the research addresses rising electricity demand driven by economic and infrastructural development. A key limitation in traditional models—underfitting due to complex data patterns—is addressed via feature selection, which identifies the most relevant variables and reduces model complexity. Five metaheuristic algorithms—cuckoo search (CS), differential evolution (DE), harmony search (HS), particle swarm optimization (PSO), and teaching–learning-based optimization (TLBO)—are applied to optimize both feature selection and BPNN training. The proposed approach improves forecasting accuracy by handling noisy inputs and capturing the nonlinear relationships common in energy datasets. Among the tested methods, TLBO consistently delivers superior accuracy and robustness across most evaluated countries. The findings contribute an effective and adaptable forecasting model with significant implications for long-term energy planning and policy development.

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1. INTRODUCTION

Electricity is a fundamental driver of industrial and economic development, with a reliable power supply being essential for sustaining manufacturing and infrastructure growth [1]. In rapidly industrializing economies, electricity demand rises alongside expansion in construction, production, and improvements in living standards [2]. Accurately forecasting industrial electricity consumption is therefore critical for long-term energy planning and effective policy formulation.

Historically, electricity demand forecasting has relied on time series and statistical models. While these traditional approaches are well-established, they often fall short in capturing the nonlinear and evolving patterns typical of industrial energy usage. Their assumptions of linearity and stationarity limit their applicability in dynamic environments influenced by population shifts, economic changes, and policy decisions. Consequently, these models may fail to identify hidden patterns in high-dimensional datasets.

Artificial neural networks (ANNs) have shown superior performance over classical techniques in handling such complexity, thanks to their ability to model nonlinear relationships and learn from multivariable data [3]. Among various ANN architectures, the backpropagation neural network (BPNN) is widely adopted due to its simplicity, ease of implementation, and strong adaptability to structured tabular data such as macroeconomic and industrial indicators. While advanced architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), including long short-term memory (LSTM) models, have demonstrated strong performance in tasks involving spatial or sequential patterns, they often require large volumes of temporally structured data and significantly more computational resources. In contrast, BPNNs are well-suited for regression-based forecasting tasks involving tabular datasets with relatively fewer time steps, which is typical in annual or aggregated economic data. This makes BPNNs a more efficient and interpretable choice for forecasting industrial electricity consumption across multiple economies. However, despite their advantages, BPNNs still face limitations such as underfitting, sensitivity to irrelevant features, and challenges in generalization. These issues are further amplified when handling diverse influencing factors such as economic structure, infrastructure development, and government policies—necessitating further enhancement through optimization techniques [4], [5].

To overcome these limitations, this study proposes a hybrid forecasting framework that combines BPNNs with metaheuristic optimization algorithms. Feature selection is employed to eliminate irrelevant or noisy input variables, reducing dimensionality and improving model focus [6]. At the same time, metaheuristic algorithms optimize both the selected features and the network parameters, helping to prevent underfitting and improve prediction accuracy. Underfitting, where models fail to capture the underlying complexity of data patterns, remains a major challenge in electricity forecasting [7], [8]. This study explores five metaheuristic algorithms—differential evolution (DE), particle swarm optimization (PSO), cuckoo search (CS), harmony search (HS), and teaching–learning-based optimization (TLBO)—each inspired by distinct natural or behavioral processes that enable global search capabilities.

The main contribution of this research is the development of an integrated BPNN framework optimized through metaheuristics for forecasting industrial electricity consumption. This framework is applied across 21 APEC economies to assess its effectiveness in different national contexts. Among the evaluated methods, TLBO consistently demonstrates superior forecasting performance in terms of accuracy and stability. Overall, the proposed methodology offers a scalable and adaptable solution for electricity demand forecasting, providing valuable support for data-driven energy policy and planning in industrial sectors.

2. METHOD

This study proposes a hybrid forecasting framework that integrates a BPNN with five metaheuristic optimization algorithms to enhance the prediction accuracy of industrial electricity consumption. The integration of metaheuristics addresses the limitations of traditional training methods by enabling more effective parameter optimization and improving the model's ability to generalize from complex, nonlinear data. The proposed methodology is organized into three main components: (1) neural network modeling using a multi-layer perceptron trained via the Backpropagation algorithm; (2) optimization of feature selection and training parameters using five metaheuristic algorithms; and (3) the conceptual framework, which outlines the overall system architecture and illustrates the interaction among data preprocessing, model training, and performance evaluation stages. This integrated approach aims to provide a robust and adaptable forecasting tool for supporting industrial energy planning across diverse economic contexts.

2.1. Neural network

The multi-layer perceptron backpropagation neural network (MLP-BPNN) [9] is a widely used type of artificial neural network (ANN), inspired by the structure and function of biological synapses. In this architecture, dendrites (input fibers) receive signals—analogous to the input units of ANNs—while axons (output fibers) transmit responses, similar to output units. Neural processing occurs in two main stages: summation and transformation [10], during which inputs are weighted, summed, and passed through an activation function to produce outputs [11]. Typically, MLPs consist of three layers: input, hidden, and output.

2.2. Metaheuristic algorithms

Metaheuristic algorithms are a class of optimization techniques designed to find effective solutions to a broad range of optimization problems [12]. Unlike traditional gradient-based approaches, metaheuristics are derivative-free, allowing them to operate in high-dimensional, nonlinear, and non-differentiable search spaces. This makes them more flexible and less susceptible to becoming trapped in local optima, enhancing their suitability for challenging optimization tasks.

These algorithms are inherently stochastic, meaning they begin the search by generating random candidate solutions. This randomness enables broad exploration of the solution space, while the iterative refinement of solutions facilitates exploitation of promising regions. Through this balance of exploration and exploitation, metaheuristics offer a robust mechanism for finding high-quality solutions in diverse problem domains [13].

2.2.1. Cuckoo search

The CS algorithm was developed by Yang and Deb [14], is inspired by the parasitic breeding behavior of cuckoo birds and the random-walk nature of Lévy flights. The algorithm mimics cuckoos laying their eggs in the nests of host birds, selecting optimal solutions based on fitness. CS is particularly notable for its simplicity and efficiency, requiring few parameters and achieving rapid convergence with reduced computational cost. These advantages make it highly effective for solving complex optimization problems [15].

2.2.2. Differential evolution

DE developed by Storn and Price [16], is a population-based evolutionary algorithm known for its straightforward yet powerful search mechanism. It begins with a population of randomly generated vectors and evolves them through mutation, crossover (recombination), and selection processes. A key strength of DE is its use of independent search directions, which helps maintain population diversity and prevents premature convergence. This makes it particularly effective for continuous optimization tasks [17].

2.2.3. Harmony search

The HS Algorithm, introduced by Geem *et al.* [18], draws inspiration from the musical process of seeking harmony. Just as musicians adjust their instruments to find an optimal harmony, HS iteratively refines solutions by mimicking this improvisational process. The quality of a solution is evaluated using an objective function, analogous to musical aesthetics. HS has been widely applied in engineering design and predictive modeling, where it aids in selecting and fine-tuning parameters to enhance model accuracy [19].

2.2.4. Particle swarm optimization

PSO was first introduced by Kennedy and Eberhart [20], simulating the social behavior of bird flocking or fish schooling. Each solution, or "particle," adjusts its trajectory based on its own best-known position and that of its neighbors, promoting convergence toward optimal regions. PSO is known for its simplicity, fast convergence, and effectiveness across a range of linear and nonlinear optimization problems. It is particularly valuable in predictive modeling for parameter tuning and managing high-dimensional data [21].

2.2.5. Teaching-learning-based optimization (TLBO)

TLBO developed by Rao *et al.* [22], is a parameter-free population-based method inspired by the educational dynamics of a classroom. In the teacher phase, the algorithm emulates how a teacher raises the average performance of students. In the learner phase, students improve their knowledge through peer interactions. TLBO effectively balances exploration and exploitation without requiring algorithm-specific parameters. Its success in both continuous and discrete domains, including engineering design, machine learning, and forecasting applications, highlights its versatility and robustness [23].

2.3. Conceptual framework

The conceptual framework for this research is outlined through the steps involved in the research process, as illustrated in Figure 1.

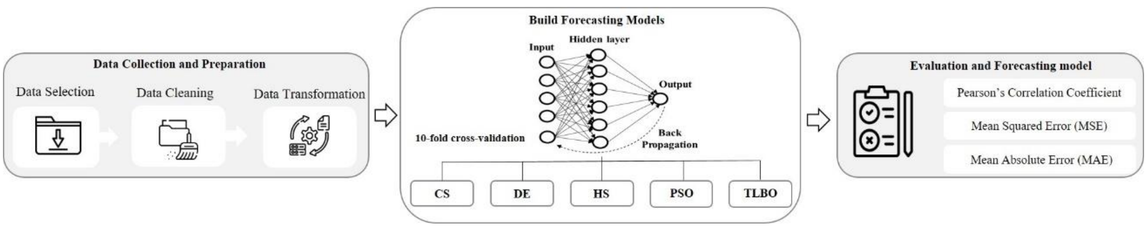

Figure 1. Conceptual framework of the research process

The conceptual framework consists of three stages. The first stage, Data Collection and Preparation, compiles industrial electricity consumption data for APEC economies from 1990–2021 using authoritative sources such as the World Bank, IMF, and APEC Energy Working Group. Key variables include population, GDP, trade indicators, energy production capacity, and total electricity generation. This stage involves data cleaning, handling missing values, normalization, and feature selection supported by Pearson correlation analysis.

The second stage, Build Forecasting Models, develops multi-layer neural networks trained via backpropagation, with 10-fold cross-validation to enhance robustness. To improve generalization and reduce underfitting, five metaheuristic algorithms—CS, DE, HS, PSO, and TLBO—are employed for feature selection and for optimizing BPNN weights and biases. Optimizer parameters are selected based on prior studies and preliminary experimentation to ensure fair and effective comparisons.

The final stage, Model Evaluation and Forecasting, applies a structured set of statistical metrics. Pearson correlation (R) measures the strength of the linear relationship between actual and predicted values, MSE evaluates accuracy with sensitivity to large deviations, and MAE assesses average prediction error on the testing dataset. The model with the lowest MAE is selected as the most reliable. Together, these steps provide a systematic workflow that supports the development of an accurate and robust forecasting system.

3. RESULTS AND DISCUSSION

The results of the correlation coefficient calculations between industrial electricity consumption and the independent variables are presented. The data used for this calculation consists of 10% of the total dataset from each country. This subset is then used to compute the correlation coefficients between industrial electricity consumption and the independent factors. The results are shown in Table 1.

Table 1. Correlation coefficients for industrial electricity demand and economic indicators by country

Country	Population	GDP	Import	Export	Energy production capacity	Total electricity generation
Australia	0.6681	0.6249	0.6126	0.6325	0.8708	0.5696
Brunei Darussalam	0.3645	0.1305	0.5550	0.1541	0.4780	0.4912
Canada	0.0120	-0.0804	0.0073	0.1452	0.2290	-0.0833
Chile	0.9718	0.9167	0.9109	0.9221	0.9828	0.9121
China	0.9304	0.9847	0.9939	0.9937	0.9983	0.9861
Hong Kong, China	-0.9798	-0.9364	-0.9505	-0.9551	-0.6418	-0.4471
Indonesia	0.9649	0.9439	0.8917	0.9036	0.9877	0.9847
Japan	-0.3619	-0.5347	-0.8295	-0.8033	-0.4019	-0.8410
Malaysia	0.9857	0.9417	0.9145	0.8884	0.9891	0.9716
Mexico	0.9830	0.9505	0.9793	0.9831	0.9801	0.9623
New Zealand	0.4870	0.4038	0.4792	0.5035	0.7990	0.6687
Papua New Guinea	0.8540	0.7878	0.7770	0.7763	0.9927	0.5711
Peru	0.9542	0.9723	0.9555	0.9440	0.9979	0.9734
Philippines	0.9803	0.9774	0.9889	0.9837	0.9962	0.6923
Republic of Korea	0.9896	0.9558	0.9535	0.9646	0.9816	0.9518
Russia	0.2103	0.0231	0.0355	0.0115	0.5107	-0.0374
Singapore	0.8682	0.7991	0.8186	0.8222	0.9787	0.8930
Chinese Taipei	0.9921	0.9508	0.9597	0.9675	0.9907	0.9837
Thailand	0.9185	0.9224	0.9223	0.9439	0.9908	0.9498
United States of America	-0.7635	-0.7854	-0.7609	-0.7617	-0.6148	-0.8384
Vietnam	0.9271	0.9935	0.9921	0.9914	0.9994	0.9821

The correlation analysis between industrial electricity consumption and six independent variables—population, GDP, imports, exports, energy production capacity, and total electricity generation—shows substantial variation across APEC economies. As summarized in Table 1, Chile, China, Mexico, Peru, the Philippines, the Republic of Korea, Chinese Taipei, Thailand, and Vietnam exhibit consistently strong positive correlations ($R > 0.9$), indicating that industrial electricity demand closely tracks economic expansion. Indonesia and Malaysia show similarly strong but slightly less uniform patterns, while Singapore and Papua New Guinea display mostly positive correlations above 0.75, reflecting moderate alignment between electricity demand and economic indicators.

In contrast, Australia, Brunei Darussalam, and New Zealand present moderate to weak correlations, likely due to more diversified economies. Canada and Russia show low or near-zero correlations, suggesting decoupled or stable industrial electricity trends. Hong Kong, Japan, and the United States display strong negative correlations (often < –0.7), implying that economic growth in these advanced economies coincides with reduced industrial electricity consumption—potentially due to efficiency gains or structural shifts toward service-oriented sectors. Overall, the findings highlight significant heterogeneity in electricity–economy relationships across APEC members, underscoring the importance of country-specific modeling approaches. A 10-fold cross-validation method with five runs was employed, and all simulations used the same number of functional evaluations (maximum generation), with 1000 iterations to divide the data into training and testing sets. The experimental results are shown in Figure 2.

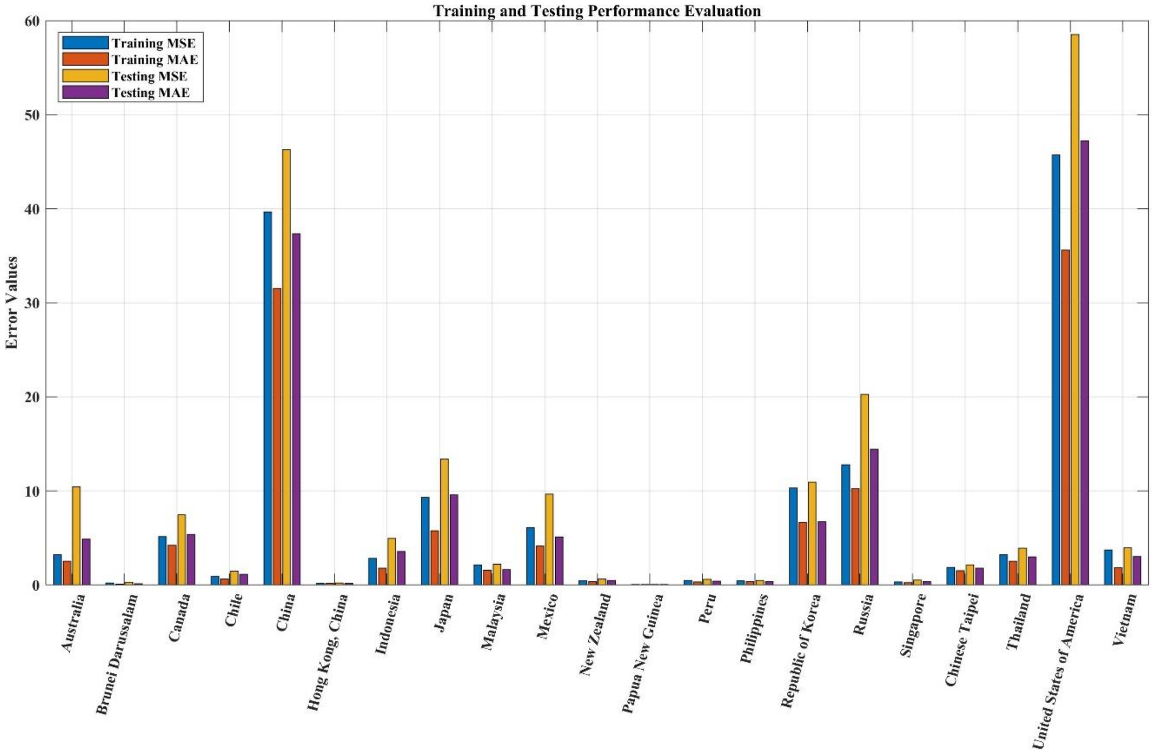

Figure 2. Performance evaluation of BPNN model using 10-fold cross-validation

The BPNN model, evaluated using 10-fold cross-validation over five runs, exhibited substantial performance variation across the 21 APEC economies. Countries with complex and volatile industrial electricity consumption—such as China (testing MSE 46.2801), Japan (13.3956), and the United States (58.5218)—recorded notably higher errors, indicating challenges in capturing their dynamic patterns. In contrast, economies with more stable demand profiles, including Brunei Darussalam (0.3030), Papua New Guinea (0.0653), and Singapore (0.5299), showed consistently lower errors. Across all cases, MSE exceeded MAE due to the squared penalty applied to larger deviations, as seen in China's high MSE (46.2801) relative to its MAE (37.3604). These results confirm that while BPNN performs adequately in stable contexts, it struggles with variability and is sensitive to initialization and convergence issues. Similar challenges have been reported in prior studies, where gradient-based BPNNs often fell into local minima—limitations mitigated through metaheuristic-assisted optimization such as PSO [24]. Recent work has therefore emphasized hybrid models, and our findings align with evidence that TLBO offers stable convergence and superior generalization [25].

To ensure a fair comparison between BPNN and the metaheuristic-based hybrid neural network models, all models were trained under a standardized experimental setup using a population size of 20 and a maximum of 100 generations, with five independent runs for statistical reliability. Training MSE served as the primary criterion for evaluating accuracy and consistency. A heatmap visualization as shown in Figure 3 was used to present the training MSE across all models and economies, where lighter shades indicate lower error and stronger performance. This visualization clearly highlights cross-country and cross-model performance differences, revealing the superior stability and accuracy of the TLBO-NN model relative to CS-NN, DE-NN, HS-NN, and PSO-NN.

The heatmap, derived from the final MSE matrix, shows that most models achieved relatively low training mean squared error (MSE) values across the APEC economies, indicating strong convergence behavior and reliable predictive performance. Nonetheless, notable differences are observed among the models. For instance, the DE-NN model exhibits a significantly higher MSE for Canada (0.1176), suggesting challenges in capturing the underlying data patterns for that country. In contrast, countries such as Vietnam, Peru and Chinese Taipei, and Malaysia consistently display very low MSE values across all models, indicating high data predictability and model stability in those regions. Among the evaluated models, TLBO-NN and PSO-NN demonstrate superior performance, characterized by consistently lower and more stable MSE values across a wide range of countries, underscoring their robustness and generalization capability. Overall, the heatmap based on the final MSE matrix serves as an effective visual tool for evaluating and comparing model performance across diverse geographic datasets, helping identify both high-performing models and outliers that may warrant further investigation. The strong convergence behavior observed in TLBO-NN and PSO-NN aligns with prior studies [24], [25], which have shown that teaching–learning-based and swarm intelligence algorithms tend to exhibit superior global search capabilities compared to classical evolutionary techniques such as DE or HS when optimizing ANN models for forecasting tasks.

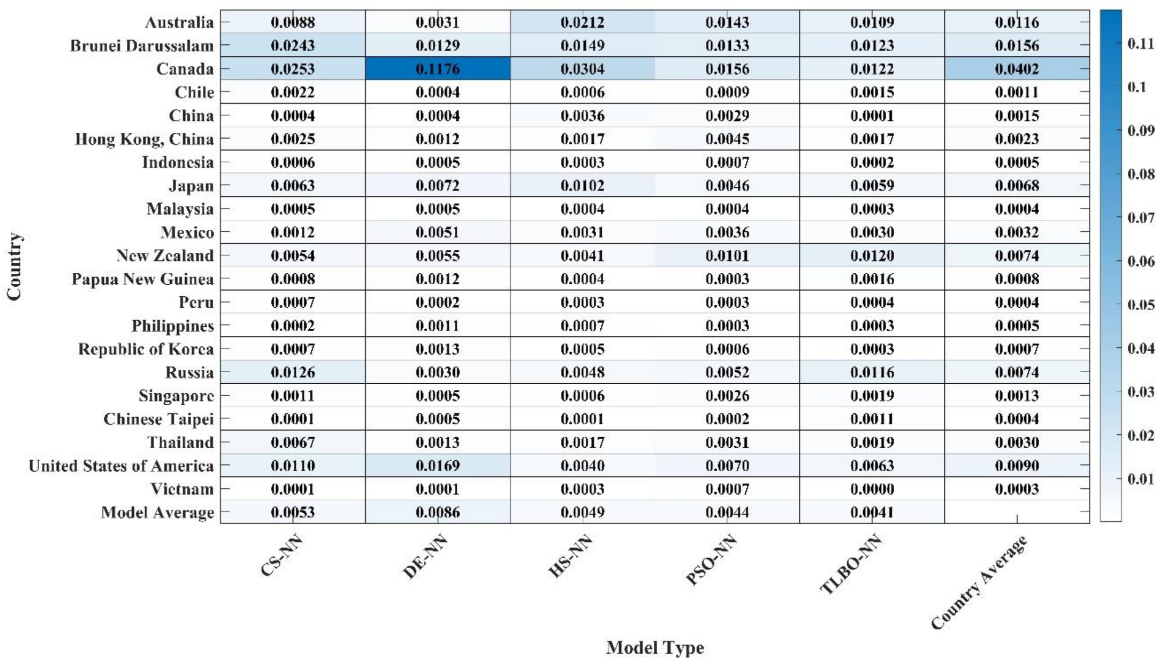

Figure 3. Comparison of training MSE for different models

The testing MAE provides a clearer understanding of the model's predictive performance on unseen data, highlighting its accuracy in capturing absolute errors. To further analyze the distribution and variability of errors, a Boxplot is used, as it effectively visualizes the spread, median, and potential outliers of MAE values across different models. Figure 4 illustrates the comparison of testing MAE across different models using a Boxplot representation.

The boxplots in Figure 4 reveal notable differences in model performance across regions, indicating that the effectiveness of each metaheuristic algorithm in minimizing MAE varies by country. This suggests that certain algorithms may be better suited to specific regional datasets. To enhance the interpretation of the MAE results, the SD is also considered, as it reflects the stability or variability of model predictions—where lower SD values indicate more consistent and reliable performance. MAE is emphasized in this analysis due to its straightforward interpretation, as it quantifies the average magnitude of prediction errors without accounting for their direction. A comprehensive comparison of the five models, including the average MAE values and corresponding rankings across all countries, is presented in Table 2 to support a deeper evaluation of model effectiveness.

Using both MAE and SD provides a balanced evaluation of forecasting performance. MAE measures the average prediction error, while SD reflects the variability of those errors across regions. Low MAE indicates high accuracy, and low SD indicates consistent behavior; thus, a model with low values for both metrics is both precise and robust—an essential quality when forecasting heterogeneous datasets such as those of the APEC economies. Table 2 summarizes the MAE and SD of five metaheuristic-optimized neural networks across 21 economies. TLBO-NN achieves the lowest average MAE (0.0518) and SD (0.0354), demonstrating superior accuracy and stability. DE-NN and PSO-NN perform comparably (average MAE 0.0534), though DE offers slightly better consistency. HS-NN also performs competitively, while CS-NN shows the highest average error and variability, indicating lower reliability. Overall, the results highlight TLBO as a robust optimization method for neural network training and clarify how different metaheuristics influence forecasting accuracy and consistency in the complex industrial electricity sector.

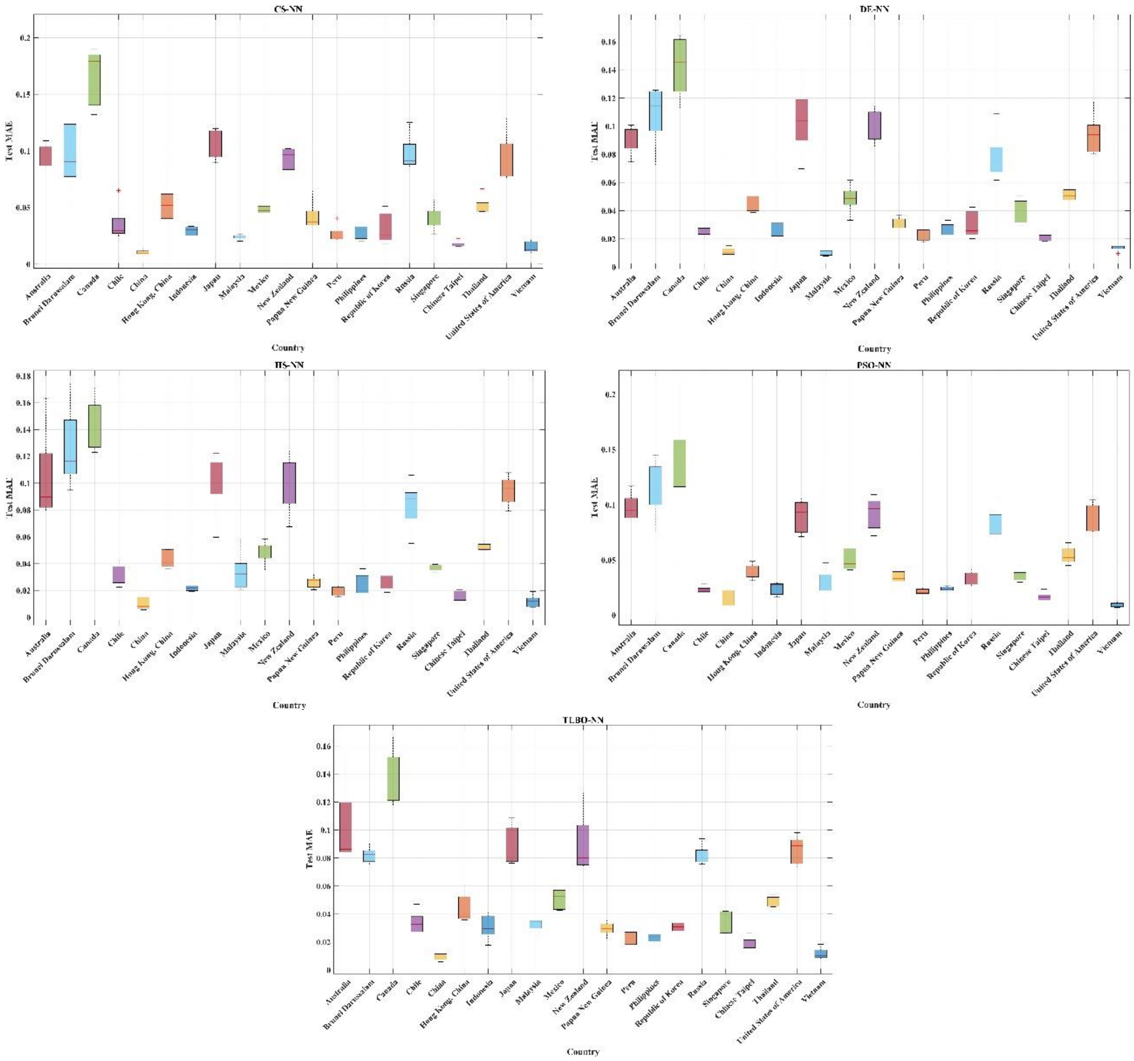

Figure 4. Evaluation of model performance across regions using MAE

Table 2. Evaluation of model performance across countries based on MAE and SD

Country	Models									
	CS	SD	DE	SD	HS	SD	PSO	SD	TLBO	SD
Australia	0.0944	0.0576	0.0908	0.0613	0.1048	0.0960	0.0981	0.0600	0.1027	0.0707
Brunei Darussalam	0.0969	0.1084	0.1083	0.1302	0.1271	0.1390	0.1145	0.1548	0.0821	0.0863
Canada	0.1655	0.0969	0.1424	0.0772	0.1424	0.0965	0.1440	0.1071	0.1356	0.0614
Chile	0.0359	0.0414	0.0254	0.0174	0.0322	0.0308	0.0230	0.0119	0.0338	0.0296
China	0.0105	0.0093	0.0111	0.0093	0.0109	0.0194	0.0145	0.0157	0.0093	0.0105
Hong Kong, China	0.0536	0.0606	0.0446	0.0233	0.0434	0.0240	0.0398	0.0197	0.0443	0.0265
Indonesia	0.0292	0.0253	0.0268	0.0217	0.0220	0.0141	0.0241	0.0236	0.0308	0.0295
Japan	0.1050	0.0645	0.1047	0.0781	0.1008	0.0141	0.0895	0.0472	0.0885	0.0541
Malaysia	0.0240	0.0133	0.0097	0.0078	0.0338	0.0342	0.0301	0.0378	0.0326	0.0249
Mexico	0.0486	0.0299	0.0486	0.0299	0.0486	0.0285	0.0506	0.0359	0.0509	0.0305
New Zealand	0.0931	0.0383	0.0994	0.0505	0.0998	0.0577	0.0921	0.0513	0.0904	0.0604
Papua New Guinea	0.0424	0.0355	0.0314	0.0215	0.0262	0.0142	0.0340	0.0211	0.0297	0.0226
Peru	0.0266	0.0347	0.0222	0.0202	0.0198	0.0163	0.0214	0.0137	0.0217	0.0158
Philippines	0.0273	0.0412	0.0272	0.0148	0.0254	0.0217	0.0240	0.0145	0.0232	0.0132
Republic of Korea	0.0318	0.0217	0.0302	0.0254	0.0263	0.0257	0.0339	0.0349	0.0307	0.0299
Russia	0.0981	0.0887	0.0778	0.0567	0.0836	0.0593	0.0835	0.0535	0.0820	0.0495
Singapore	0.0407	0.0307	0.0405	0.0378	0.0370	0.0192	0.0359	0.0218	0.0343	0.0233
Chinese Taipei	0.0177	0.0140	0.0209	0.0140	0.0159	0.0116	0.0168	0.0090	0.0188	0.0155
Thailand	0.0514	0.0356	0.0513	0.0292	0.0529	0.0268	0.0542	0.0291	0.0486	0.0269
United States of America	0.0958	0.0531	0.0940	0.0679	0.0945	0.0627	0.0871	0.0502	0.0857	0.0471
Vietnam	0.0150	0.0201	0.0136	0.0123	0.0119	0.0131	0.0096	0.0112	0.0117	0.0149
Average	0.0573	0.0439	0.0534	0.0384	0.0552	0.0393	0.0534	0.0392	**0.0518**	**0.0354**

4. CONCLUSION

This study evaluated the effectiveness of hybrid BPNN models enhanced with five metaheuristic algorithms for forecasting industrial electricity consumption across 21 APEC economies. Integrating metaheuristics improved BPNN performance by enhancing convergence and reducing the risk of local minima. Models were evaluated under a consistent setup of 1,000 iterations and five independent trials, using training MSE, testing MAE, and SD to measure accuracy and stability. Results indicated that TLBO-NN and PSO-NN achieved the lowest and most consistent training errors, while boxplots of testing MAE highlighted TLBO-NN's superior generalization, with the lowest average error and variance. DE-NN and PSO-NN were competitive, whereas CS-NN and HS-NN exhibited higher variability, performing well in some regions but lacking consistent reliability. In summary, metaheuristic optimization significantly enhanced forecasting accuracy and robustness, with TLBO emerging as the most effective strategy across diverse economies. Future research could explore advanced deep learning architectures, incorporate higher-resolution temporal data and additional external factors, and develop adaptive metaheuristic frameworks for dynamic parameter tuning, aiming to further improve convergence efficiency, generalization, and predictive performance in complex and volatile electricity consumption scenarios.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Tidarat Luangrungruang		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study will be available in https://www.egeda.ewg.apec.org.

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