

Generalized stability of artificial emotional neural network in predicting domestic power peak demand

Suthasinee Iamsa-at, Punyaphol Horata* and Khamron Sunat

Department of Computer Science, Faculty of Science, Khon Kaen University, Khon Kaen 40002, Thailand

ABSTRACT

*Corresponding author:
Punyaphol Horata
punhor1@kku.ac.th

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Predicting an optimal domestic power peak demand is very important for long-term electricity construction planning as the electricity cannot be stored permanently. If the prediction can give a yield close to the actual demand, the electricity suppliers can save their construction costs and provide their customers with a lower cost of electricity. However, accurate predictions still require improvement. This work, therefore, presented the predicting problem using a modified artificial emotional neural network (AENN) based on an improved JAYA optimizer. This study also applied extreme learning machine (ELM) to compute the expanded feature in the AENN. A real case study of Thailand's power peak demand was considered, which was prepared using a rolling mechanism, to demonstrate the performance of a developed predicting model when contrasted with state-of-the-art of AENN models, artificial neural network with Levenberg-Marquardt, AENN methods based on winner-take-all approach, and improved brain emotional learning-based AENN model. Performance analyses demonstrated that the proposed model provided improvements in performance and generalized stability over the comparative models.

Keywords: Domestic power peak demand; artificial emotional neural network; improved JAYA optimization algorithm; extreme learning machine

1. INTRODUCTION

For neutrality of electricity usage, electricity cannot be stored and has to be consumed immediately whenever it is generated. The expected peak electricity demand should be close to the actual demand. The benefit of a minimal error in the expectation is essential information for planning electricity generation in the current or future period. However, the peak of electricity prediction is a challenging problem due to economic conditions and customer usage behavior. Therefore, the demand should be afforded sufficiently in a sustainable way at all times. There is a precise and reliable forecast to determine the country's electricity policy to achieve energy security (Kazemzadeh et al., 2020; McNeil et al., 2019; Sarduy et al., 2016).

Thailand's Office of the National Economic and Social Development Board (NESDB) has stated that Thailand's economy has been positively growing, implying increases in energy consumption (Office of the National Economic and Social Development Board, 2019) as well as greenhouse gas emissions (Sutthichaimethee and Kubaha, 2018). However, electricity demand has dropped in some years. This opposition between economic direction and electricity demand makes forecasting the country's future electricity demands problematic.

Several energy forecasting researches have been conducted in each country to handle power management using different approaches, including auto-regressive integrated moving average (ARIMA) (Zhang, 2003), a conventional approach for time series forecasting. One of

the traditional well-known methods is artificial neural network (ANN) (Lee et al., 1992; Beyca et al., 2019). This method has been introduced for predicting the short-term load of a large power system. Its forecasting error has been reported to be about 2% of the percent relative error and has thus shown promise for the use of the ANN model in load forecasting. A support vector machine (SVM) was used to forecast load (Chen and Chang, 2004). Then, it was developed to be support vector regression (SVR) and utilized for time series or electricity load predicting (Elattar et al., 2010; Hu et al., 2013). Another tool that usually plays an important part in demand forecasting is the grey model (GM). Grey prediction, together with a rolling mechanism, was proposed for forecasting overall and industrial power usage in Turkey (Akay and Atak, 2007). Moreover, new hybrid tools have been proposed by enhancing traditional methods efficiencies with a metaheuristic optimization algorithm. The chaotic particle swarm optimization (CPSO) algorithm in SVR (Hong, 2009) was integrated with a rolling-base forecast procedure to forecast the electric load. The generalized regression neural network (GRNN) model was integrated with particle swarm optimization together with cultural algorithms (Zhao and Guo, 2014). The fruit fly optimization algorithm was integrated with the least-squares support vector machine, LSSVM (Li et al., 2012), and a hybrid model was based on GRNN (Li et al., 2013). A hybrid GM, optimized by ant-lion optimizer (Zhao and Guo, 2016), was one of several hybrid methods (Zhao and Guo, 2014; Li et al., 2012; Li et al., 2013; Zhao and Guo, 2016) that have been used in China's annual energy consumption, in which rolling mechanisms employed the latest data to predict prospective datasets. The GM was maximized by the moth-flame optimization (MFO) algorithm with a rolling mechanism to forecast Inner Mongolia's electricity usage, which was dubbed Rolling-MFO-GM (1,1) (Zhao et al., 2016). The developed shuffled frog leaping algorithm was introduced to maximize ensemble empirical mode decomposition and LSSVM for forecasting power usage in China (Dai et al., 2018). The field peak load, energy peak demand, and energy models forecasting have been collected and reported in the study of Debnath and Mourshed (2018). In order to focus on the research field of energy peak demand forecasting, recent data obtained from the Iran National Electric Energy System using a hybrid method based on the combination of ARIMA, ANN, and SVR techniques have been used (Kazemzadeh et al., 2020).

ANN is inspired biologically to simulate the modeling of a computer program's solution in which the human brain processes (Park et al., 1991; Quan et al., 2013). The neural network with random weights (NNRW) (Schmidt et al., 1992) and the extreme learning machine (ELM) (Huang et al., 2006; Wang et al., 2021) are fast learning algorithms for training single hidden layer feedforward neural networks (SLFNs). The two models were designed by imitating the learning process and function of the human brain. The neuropsychological and perception research of brain emotional learning (BEL), a type of ANN that involves the human emotional brain, has motivated the development of an artificial emotional neural network model (AENN) (Lotfi et al., 2014). BEL-based AENN model has been used in a variety of studies and applications, including classifying, recognizing, as well as forecasting work. AENN trained using stochastic optimization was integrated with a genetic algorithm (AENN-GA) (Lotfi et al., 2014) and later

developed as a winner-take-all emotional neural network (WTAENN(GA)) (Lotfi and Akbarzadeh-T, 2016). The AENN accommodated diverse domains in a variety of problems, such as feature estimation, real-world classification, time series forecast of the Dst index, wind power forecast, as well as classical k-selector problems. In the case of a BEL-based AENN, GA has been used to train the amygdala (AMYG) and orbitofrontal cortex (OFC) input weights. An input of AMYG has been the enlarged attribute which is generally attained by the thalamus module. The attribute can be either the amplitude of each thalamic input (Lotfi and Akbarzadeh-T, 2013) or the average of thalamic input (Lotfi et al., 2014). However, AENN-GA uses the average input as expanded attribute. Meanwhile, WTAENN utilizes the input amplitude as enlarged attribute, both of which have been used in the Australian wind power prediction (Captl_WF) (Quan et al., 2013) and have been reported to have similar root mean square errors (RMSEs). Such findings contrasted with our assumption that the RMSE of WTAENN would be lower than that of AENN-GA. Recently, this bio-inspired BEL model has been applied solely to classification by improving the BEL-based neural network (ImBEL-GA), which adds the bias in the AMYG part of AENN (Mei et al., 2017). We, therefore, considered that the GA problem was appropriate for generating substantial precision BEL-based AENN, whereas the mean of AENN-GA was an ineffective method for capturing the important features of time series prediction problems.

This paper addressed the aforementioned problems using a case study on long-term yearly electricity peak demand prediction of the Electricity Generating Authority of Thailand (EGAT) (Electricity Generating Authority of Thailand, 2020); by applying the ELM as the expanded feature of AMYG, thereby creating a more effective approach for training based on the AENN model. The primary function of JAYA (Rao, 2016) and improved JAYA (IJAYA) (Yu et al., 2017) algorithms was used to determine a greater optimal parameter and to lower the computational burden. Due to its simplicity, the IJAYA optimization algorithm captured our attention. According to studies related to difficult optimization problems, IJAYA outperformed a variety of stochastic optimization methods, such as original JAYA and GA (Rao et al., 2016; Warid et al., 2016).

2. MATERIALS AND METHODS

2.1 Brain emotional neural networks

The BEL-based AENN architecture was inspired by the anatomical structure. The proposed networks characterized the data transmission path in the emotional brain (LeDoux, 1989). Characterized by rapid responses, it has been employed in a variety of engineering projects (Zhao et al., 2019; Nourani et al., 2019; Nourani et al., 2020; Zhang et al., 2022).

The AENN model consisted of two main subsystems based on AMYG-orbitofrontal cortex interconnection. Each of them was linked to the input pattern's dimension. The input pattern was sent to the model's thalamus to determine the imprecise input and send one of the inputs to the amygdala. The other input samples were submitted to the sensory cortex as well as the orbitofrontal cortex, which did not obtain any input sample from the thalamus. AMYG supervised the calculation of the final output.

The input samples were included by vector beginning the learning process. Their signals were transmitted to the thalamus and, subsequently, the sensory cortex. AMYG received the input samples from the sensory cortex as well as the thalamus.

2.2 ELM

ELM was based on the structure of a single hidden feed-forward neural network (SLFNs). The ELM network had 3 layers, including input, hidden, and output layers. The hidden layer was assumed to contain K hidden nodes. The sigmoid, triangular basis, sine, radial basis, or hard limit function could be used as its activation function.

Let $Z = \{(x_i T_i) | x_i \in \mathcal{R}^{1 \times m}, T_i \in \mathcal{R}^{1 \times g}, i = 1, \dots, n\}$ be a sample set, size n refers to the i th the input matrix $X \in \mathcal{R}^{n \times m}$ and T_i stands for i th row of the target matrix. The number of hidden nodes is denoted as p . Thus, ELM includes 3 steps. In the first step, the input weight $W \in \mathcal{R}^{m \times p}$ and bias $b_i \in \mathcal{R}, i = 1, \dots, p$ were randomly generated. The second step was to compute the hidden output matrix of the network defined as $H \in \mathcal{R}^{n \times p}$, the third step was to compute an output weight matrix β which is a solution of the following equation:

$$H\beta = T. \quad (1)$$

where H_{ij} is the output from the j th hidden node of the i th sample, $H_{ij} = g(w_j^T x_i + b_j)$, where g is an activation function, w_i and b_j represent the input weight vector and bias of the j th hidden node, respectively. The output weights β is completed as:

$$\hat{\beta} = H^+ T, \quad (2)$$

where H^+ refers to the Moore-Penrose matrix inverse (MP) of H and is the minimum norm solution. The approximation of ELM is based on the least square concept as $\min \|H\beta - T\|$.

2.3 Jaya optimization algorithm

The JAYA algorithm, introduced by Rao et al. (2016), was claimed to be a novel population-based optimization algorithm to solve restrained and unrestrained optimization issues. Given a specific problem, it would find a solution that reaches the optimal solution while avoiding an inferior solution. JAYA's conceptual foundation differed from that of most of other population-based algorithms. JAYA was solely concerned 2 common variables: population size and generation number. The objective function was determined through Equation (3). If The $x'_{i,j}$ provided a better function value, it was accepted. This $x'_i = (x'_{i,1}, x'_{i,2}, \dots, x'_{i,D})$ was used to utilized to repetitively modify the next solution.

$$x'_{i,j} = x_{i,j} + rand_1 \cdot (x_{best,j} - |x_{i,j}|) - rand_2 \cdot (x_{worst,j} - |x_{i,j}|) \quad (3)$$

where $x_{best,j}$ and $x_{worst,j}$ refer to the variable values that proud to the best and worst solutions. $x'_{i,j}$ stands for the updated value of $x_{i,j}$. $|x_{i,j}|$ represents the absolute value of $x_{i,j}$. The $rand_1$ and $rand_2$ refer to two uniformly distributed random numbers in the ranging of 0 and 1.

2.4 Improved JAYA optimization algorithm

The IJAYA algorithm was developed to define the variables of photovoltaic (PV) models (Yu et al., 2017). According to the

searching process of IJAYA, the IJAYA could be divided into 8 steps as follows:

- Step 1: initialized the main variables of IJAYA; which included the optimum number of function evaluations, the initialized number of population size, and the minimum and optimum limits of design variables (upper and lower bounds).
- Step 2: generated an initially random population size based on the defined variables.
- Step 3: assessed each candidate solution's objective function value.
- Step 4: identified the best and worst solutions among the candidate solutions.
- Step 5: modified all candidate solutions of IJAYA based on the best and worst solutions.

There were three main improvements in IJAYA throughout the j th iteration (generation) and for each candidate solution. First, a self-adaptive weight based on the best and worst function values was applied to modify the tendency to approach the best solution and avoid the worst one. Second, a learning strategy based on the experience of other people was improved and utilized randomly to efficiently increase population diversity. Third, a logistic map was used to increase the quality of the best solution from each generation through chaotic learning. The chaotic sequence was defined by Equation 4, and the best solution, therefore, was adjusted through Equation (5):

$$Z_{m+1} = 4 \cdot (1 - Z_m) \quad (4)$$

$$x'_{best,j} = x_{best,j} + rand \cdot (2 \cdot Z_m - 1). \quad (5)$$

- Step 6: if any design parameter (upper/lower limit) exceeded any updated solutions, the estimated value is replaced with the correlating limit
- Step 7: compared the objective function values $f(x_{best})$ of the previous and updated solutions, for each candidate solution. Wherever the accepted solution was superior to the earlier one, the accepted solution occurred; if not, the previous one was kept.
- Step 8: the optimal solution was terminated and reported if the termination criterion was met; if not, it was returned to Step 4.

2.5 The development of model based on AENN using the Elm expanded feature with IJAYA optimization algorithm

Thalamus generated the AMYG and OFC input weights ((v) and (w) weights) based on the AENN learning process, which should be modified to determine the proper final output. The model proposed in this work is shown in Figure 1. For the expanded feature in the proposed method, ELM would be applied as shown in Equation 6. It could represent the application of the training concept in which the ELM produced the expanded feature called a modified artificial emotional neural network (AENN-ELM) as follows:

$$p_{n=1} = \hat{Y}. \quad (6)$$

$$E_a = \sum_{n=1}^{n+1} (v_n p_n) \quad (7)$$

$$E(\vec{p}) = f(E_a - E_o) = f\left[\sum_{n=1}^{n+1} (v_n p_n) - \sum_{n=1}^n (w_n p_n) + b\right] \quad (8)$$

The expanded feature calculating the use of ELM, was summarized as: calculation of the output \hat{Y} from a training set p_1, p_2, \dots, p_n of Thalamus, and activation of a function $g(x)$, using one of the hidden node. First, the random input weight w_i and bias b_i were assigned based on the number of the hidden node. Second, the hidden layer output matrix $H, H_{ij} = g(q_j^T x_i + b_j)$, was calculated. Third, the output weight β and T , were calculated and the target Y of actual value were determined.

$$\hat{\beta} = H^+T, T=Y \quad (9)$$

The IJAYA based on optimization algorithm was utilized to determine the optimal weights ((v) well (w) weights) to test the capability of introduced set up in learning and generalizing processes. The number of input features (n) was equal to the number of learning weights. Therefore, for each iteration, the number of populations was $2n+2$. Defined to be the model output from each iteration, it was then utilized to compute the weight responses to the i^{th} input pattern. The flowchart of the modified AENN-ELM-IJAYA algorithm is depicted in Figure 2.

In employing IJAYA to optimize AENN variables, the objective function should be first determined. RMSE was used in this study to assess the flexibility of each element of the entire population. The optimization problem determined the

best i parameter within the given range by minimizing the objective of the RMSE(i) equation given by Equation (10):

$$RMSE(i) = \sqrt{\frac{1}{n} \sum_{x=1}^n (E_x - T_x)^2}, \quad (10)$$

where E , refers to the response to the i^{th} input pattern with given weights ((v) of OFC weights and (w) of AMYG weights) and bias of OFC in i . T , represents the targeted value of the i^{th} input pattern and n stands for the number of pattern target pairs.

The Matlab 2017a program was used in the simulation. A computer (Intel(R) Core (TM) i7-4771 3.50 GHz CPU, 16 GB RAM, Windows 7 Pro operating system) was utilized to process the data. ELM, a simple model with only one hidden node, was used in the modified AENN models. To fine-tune the optimum weight in the AENN with all algorithms, the variable from all simulations was set to a certain maximum number of population (NP), $2n+2$ populations size, and the certain number of functional assessments (Max generation) was 1000 iterations in each run. Furthermore, each of the comparative models was subjected to 30 independent runs in order to reduce the error.

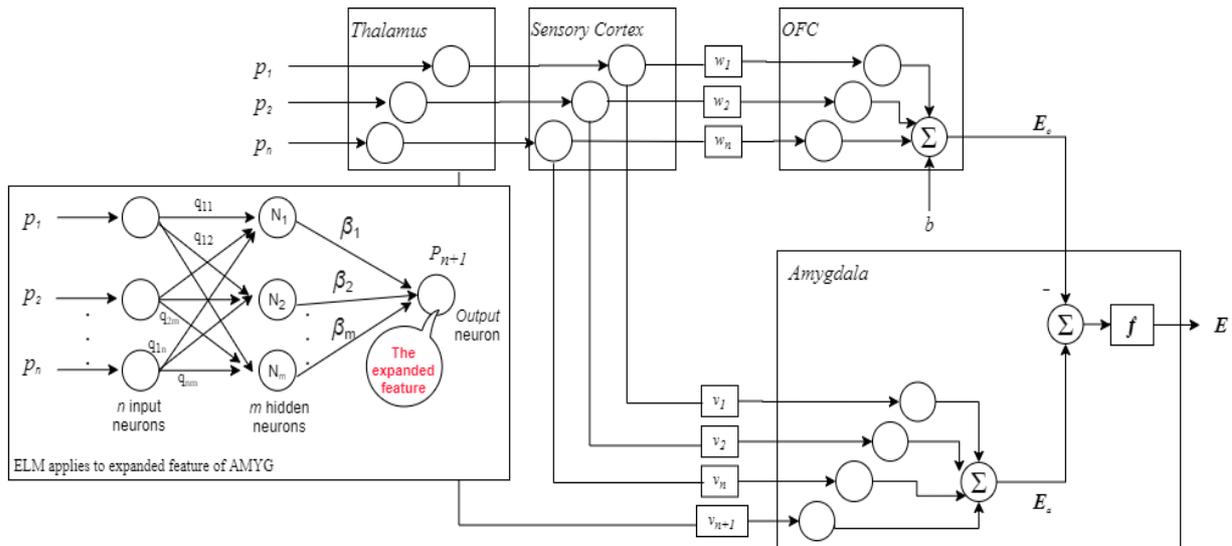


Figure 1. The proposed ELM was applied to calculate the expanded feature (P_{n+1}) of the AENN model inspired by AMYG-OFC interaction

In this study, the sample data were collected from the EGAT. They were gathered from the annual electricity peak demand of Thailand from 1969 to 2017, comprising 49 data points (Figure 3). The sample data were normalized to the range $[0,1]$ and grouped into the training sample and testing data. The pattern variables of AENN models with the rolling mechanism were managed using the last three load data ($L_{n-3}, L_{n-2}, L_{n-1}$) and the output variable (L_n). This process has been proven effective and feasible for the annual electricity load prediction (Li et al., 2013). Since the three-load data were used as the input variables to forecast, the training data started in 1969 and ended in

2012, and the testing sample data were from 2013 to 2017.

Roll-based predicting was used during the training stage. First, the top three load data (from 1969 to 1971) were loaded into the AENN model, so the first load prediction value for 1972 was obtained. Second, the real value of 1972 in the load data was used in the following predicting process. On the other hand, the three-load data input ranged from 1970 to 1972 yielded a predicted value of 1973. The processes were similarly cycled till all the load forecasting values were acquired. The detailed procedures for predicting the electricity peak demand of Thailand are displayed in Figure 4.

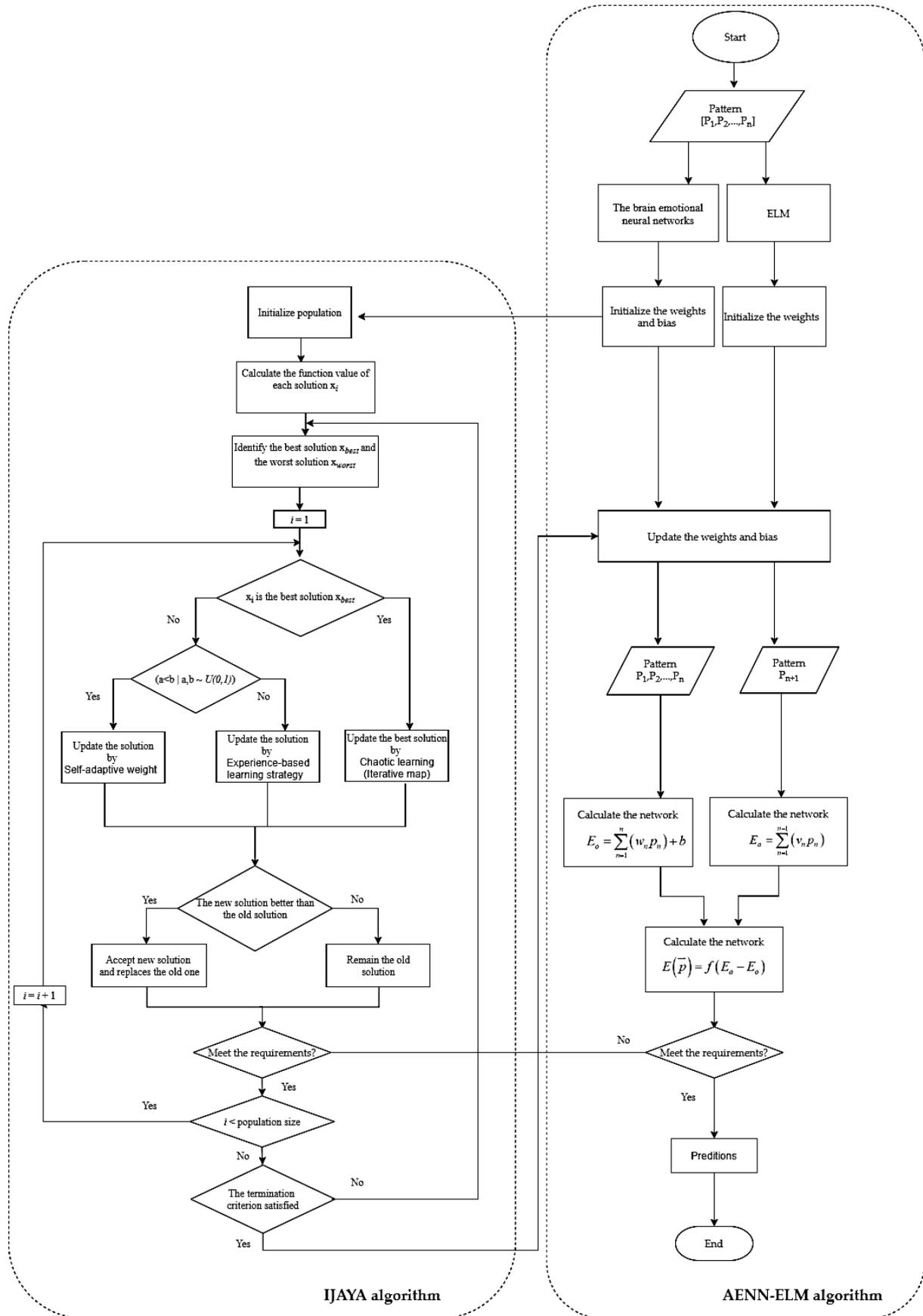


Figure 2. The flowchart of the modified AENN-ELM-IJAYA algorithm

The efficiency of the models for predicting electricity peak demand can be assessed by utilizing mean absolute percentage error (MAPE), mean absolute error (MAE), RMSE, and relative error percentage (REP) (Elattar et al., 2010). These approaches are described as:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{A(i)-F(i)}{A(i)} \right| \times 100\% \quad (11)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |A(i) - F(i)| \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (A(i) - F(i))^2} \quad (13)$$

$$REP = \sqrt{\frac{\sum_{i=1}^N (A(i)-F(i))^2}{\sum_{i=1}^N A(i)^2}} \times 100 \quad (14)$$

where $A(i)$ represents the electricity peak demand at time i , N stands for the size of testing data, and $F(i)$ refers to predicted electricity peak demand at time i .

The prediction efficiency of our introduced model was compared with that of comparative algorithms including ANNs-5nLM (Quan et al., 2013), WTAENN(GA) (Lotfi and Akbarzadeh-T, 2016), ImBEL-GA (Mei et al., 2017), and AENN(GA) (Lotfi et al., 2014).

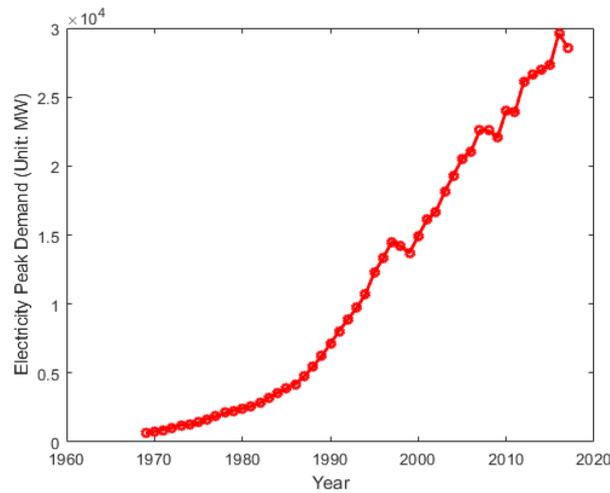


Figure 3. Time plot of annual electricity peak demand for Thailand

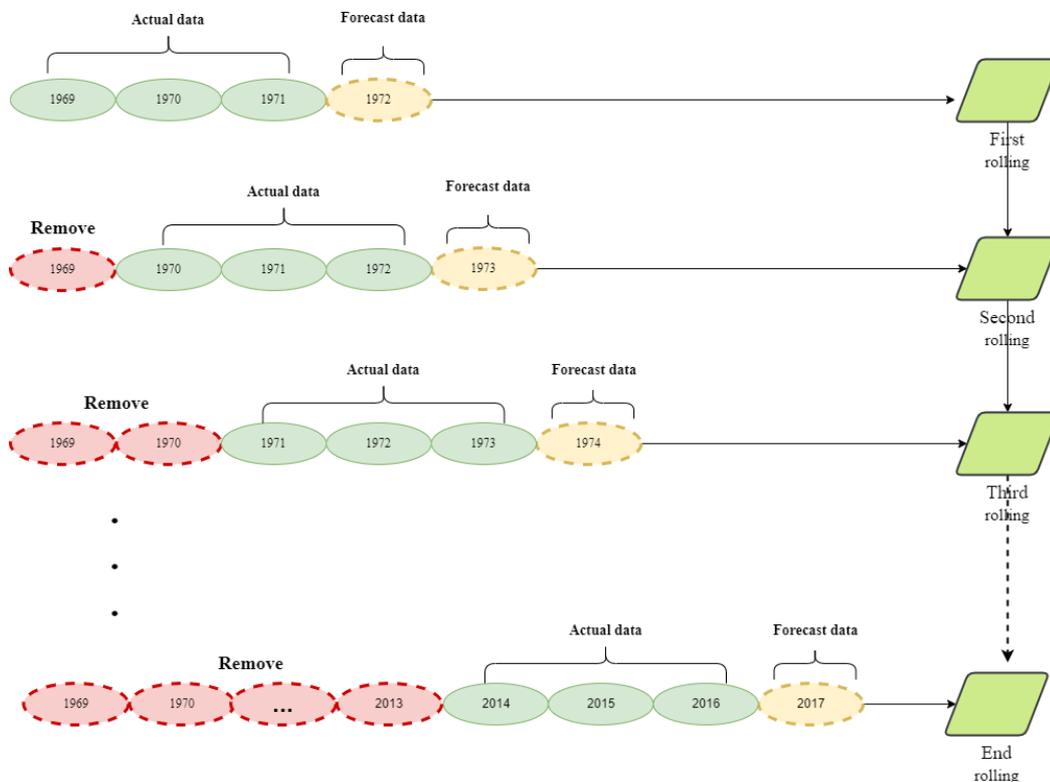


Figure 4. Predicting procedure of Thailand's electricity peak demand feeding input data into models with rolling mechanism

3. RESULTS AND DISCUSSION

Table 1 and Figure 5 present the predictions for annual electricity peak demand using the ANN-5nLM, WTAENN, ImBEL-GA, AENN-GA, AENN-ELM-GA, AENN-ELM-JAYA, and AENN-ELM-IJAYA models. The best ANNs-LM architecture for predicting the electricity peak demand in Thailand was acquired using five hidden neurons. Under the same conditions, comparisons were made with the AENN-ELM-IJAYA model developed herein, predicting the demands of the previous five years. The MAPE of

Thailand's five-year electricity peak demand prediction (2013-2017) is summarized in Table 2. According to Figure 5, the deviation between the prediction results of the seven predictive models and the actual value could be captured. The actual values from 2013 to 2015 increased by an average of 249.22 units. Meanwhile, the actual value from 2015 to 2017 reached their highest peak in 2016 at +2,273 units and declined in 2017 at -1,040.4 units. However, in terms of the prediction results, the gap between actual value and output value in 2016 displayed the worst predicting performance of all the predicting models.

Table 1. Predicted results of Thailand's annual electricity peak demand models based on AENN (unit: MW)

Year	Actual value	Model						
		ANN-5n LM	WTAENN GA	ImBEL GA	AENN GA	AENN-ELM GA	AENN-ELM Jaya	AENN-ELM IJaya
2013	26598.14	24501.88	25372.22	39641.48	24894.55	24636.98	24394.64	24877.94
2014	26942.1	23813.93	26902.63	41863.43	27478.14	27122.08	26757.95	26773.76
2015	27345.8	23612.49	26987.80	42331.55	27979.72	27621.98	27247.23	27225.13
2016	29618.8	23083.32	25608.08	42810.58	27859.36	27845.54	27483.86	27448.15
2017	28578.4	23394.42	26595.04	43376.66	28880.22	28253.08	27988.51	28495.13

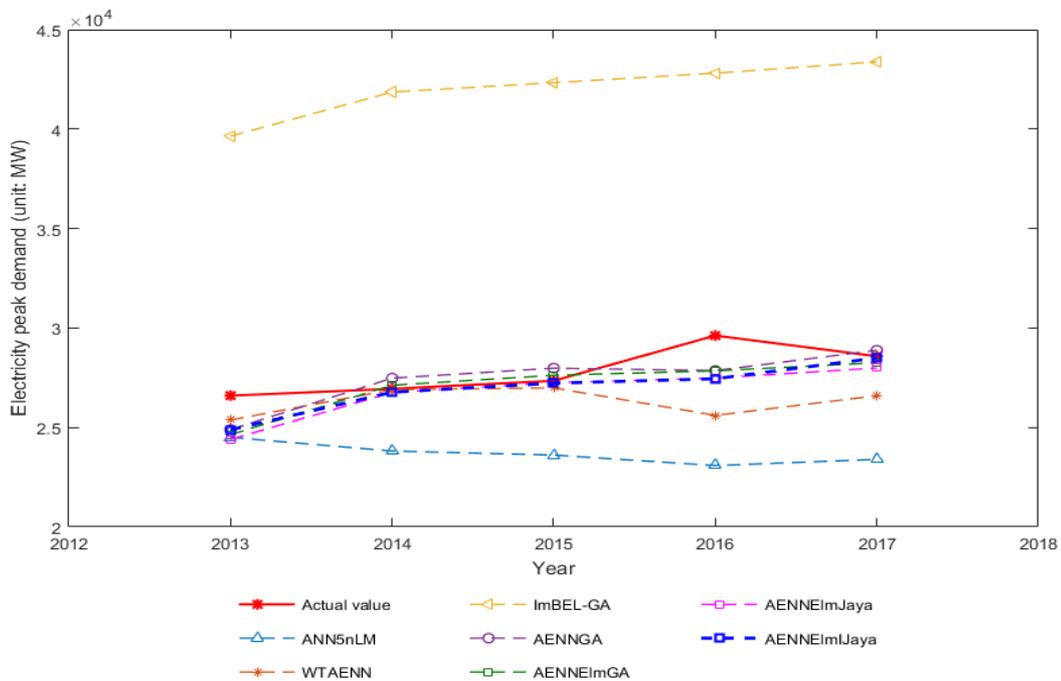


Figure 5. A plot of Thailand's real electricity peak demand value and the predicted demands from 2013 to 2017 of the different comparative models

Table 2. Yearly average MAPE of different predictive models

Model	Year	Year				
		2013	2014	2015	2016	2017
ANN-5n	LM	8.3253	11.9028	13.9027	22.0653	18.5082
WTAENN	GA	9.6489	6.8633	6.5451	13.5411	8.9928
ImBEL	GA	49.3412	55.3830	54.8009	44.8316	51.7813
AENN	GA	6.4049	2.4273	2.7975	5.9403	4.0125
AENN-ELM	GA	8.4227	3.1752	3.4393	7.3269	6.9073
AENN-ELM	Jaya	8.2844	0.7131	0.4341	7.2081	2.0641
AENN-ELM	IJaya	6.4674	0.8237	0.6925	7.3286	1.2108

Table 3 demonstrates the prediction efficiency of the developed model and comparative algorithms. The proposed AENN-ELM-IJAYA model had an efficiency (2.03) greater than all comparative models. Moreover, AENN-ELM-IJAYA showed lower RMSE than ANN-5n-LM, WTAENN, ImBEL-GA, AENN-GA, and AENN-ELM-JAYA, respectively.

The MAPE values for predicting the domestic power peak demand are shown in Table 3 and Figure 6. It could be seen that the AENN-ELM-IJAYA model outperformed the ImBEL-GA, AENN-GA, WTAENN, ANN-20n-LM, AENN-ELM-GA, and AENN-ELM-JAYA models by 3.30, 51.23, 4.32, 9.12, 14.94, 5.85, and 3.74, respectively.

Table 3. Testing errors in predicting electricity peak demand

Model		RMSE (MW)		MAE (MW)		MAPE		REP	
		avg.	SD	avg.	SD	avg.	SD	avg.	SD
ANN-5n	LM	4559.35	3307.12	4209.57	3186.10	14.94	11.36	15.01	11.52
WTAENN	GA	3170.34	1871.12	2557.21	1522.80	9.12	5.46	5.10	3.01
ImBEL	GA	14355.40	9507.48	14221.55	9577.06	51.23	34.49	23.08	15.29
AENN	GA	1452.00	346.15	1205.74	318.03	4.32	1.15	2.33	0.56
AENN-ELM	GA	1976.19	800.85	1636.08	709.29	5.85	2.52	3.18	1.29
AENN-ELM	Jaya	1402.43	72.75	1047.83	86.46	3.74	0.31	2.25	0.12
AENN-ELM	Ijaya	1264.85	95.94	929.64	95.39	3.30	0.35	2.03	0.15

The average training computational times of the proposed AENN-ELM-IJAYA model and all comparative models were achieved by utilizing the commands “tic” and “toc” in the MATLAB program; lower computational times indicated better results. Table 4 demonstrates the faster learning speed

of AENN-ELM-IJAYA versus the comparative algorithms, though they had the same population size and maximum number of iterations. Additionally, the IJAYA algorithm demonstrated superior performance in terms of computational time when compared with the traditional JAYA algorithm.

Table 4. Average training computational time of each model

Training time (s)	ANN-5n	WTAENN	ImBEL	AENN	AENN-ELM		
	LM	GA	GA	GA	GA	Jaya	Ijaya
	2.027	17.8901	9.5895	0.7676	0.7723	1.3455	0.0819

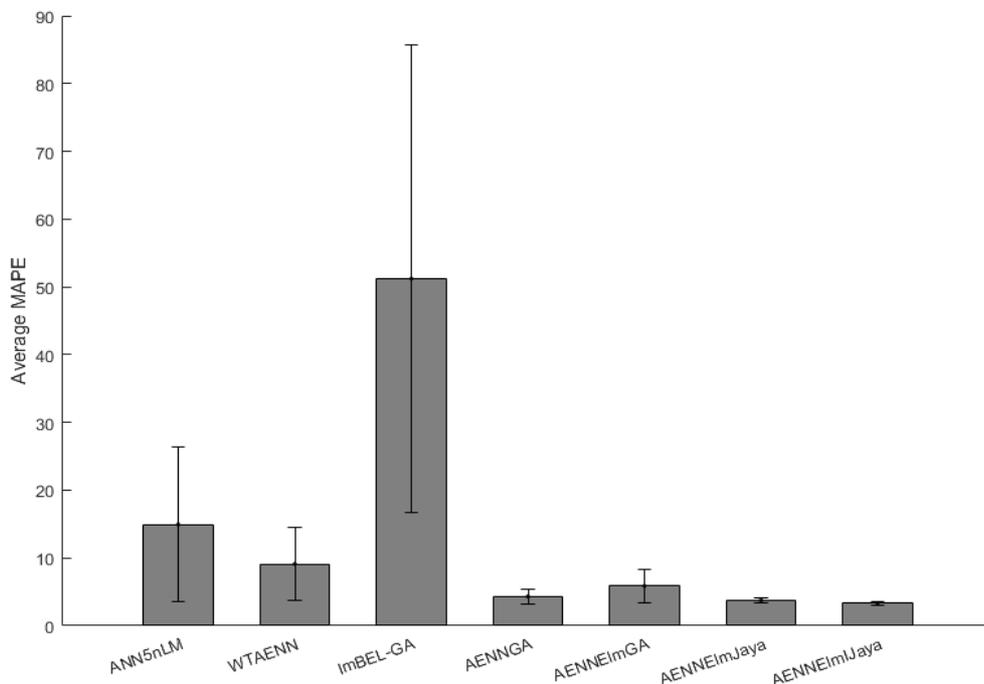


Figure 6. Average MAPE (%) for predicting electricity peak demand using the proposed AENN-ELM-IJAYA and comparative models

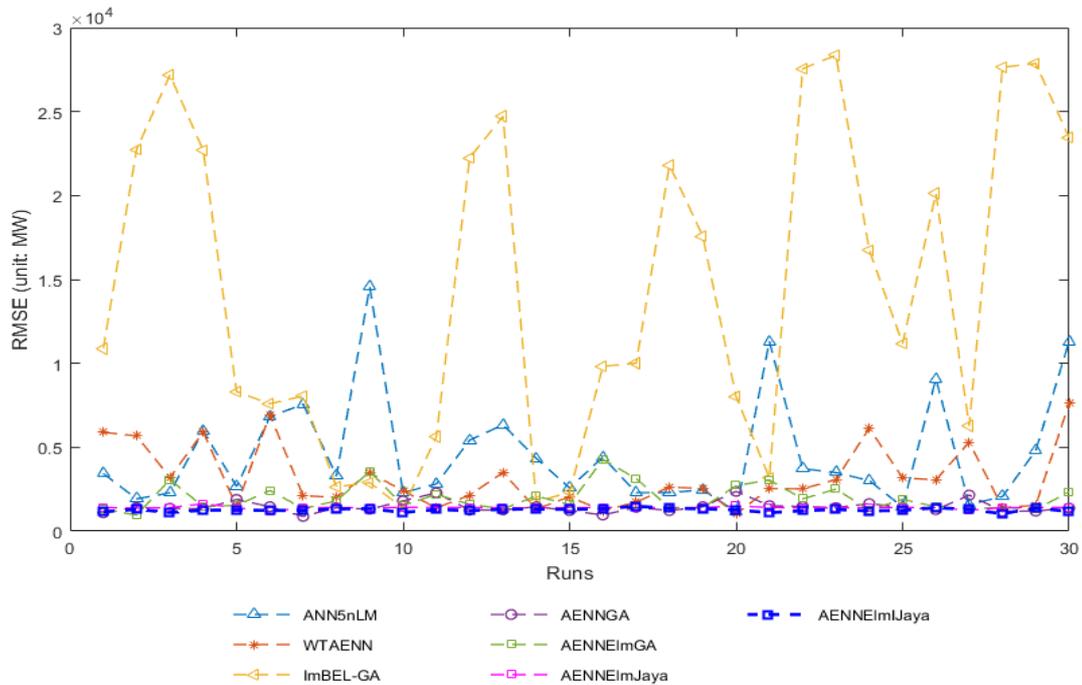


Figure 7. Comparison of the testing RMSE curves for 30 independent runs of comparative models in predicting the electricity peak demand of Thailand

To verify the effects of the different comparative models proposed to predict electricity peak demand, the experiment used of several runs for the ANNs-5nLM, WTAENN(GA), ImBEL-GA, AENN-ELM-JAYA, and AENN-ELM-IJAYA. The experiment results are given in Figure 7, which illustrates the RMSE curves of each learning algorithm in predicting electricity peak demand. In this problem, the RMSE curves for ANN5nLM, WTAENN, and ImBEL-GA comprised many sharp spiking events. On runs 3, 13, 18, 23, and 29, the ImBEL-GA was deemed sensitive. In all runs, the testing RMSE curves for the proposed model and AENN-GA were comparable; both had a lower score than the other comparative algorithms. The effectiveness of AENN-ELM-IJAYA outperformed all other models in terms of generalized stability for RMSE values in each iteration.

4. CONCLUSION

Peak load demand predicting is important in electric utilities as technological development and energy policies are causing an increase in peak demand. Thus, accurate peak load predicting plays a critical role in preventing a blackout or loss of energy. This paper presented a new, innovative method for predicting long-term (yearly) domestic power peak demand in Thailand. The two new models were proposed: AENN-ELM-JAYA, and AENN-ELM-IJAYA that modified using the input AMYG (v) weight as well as OFC (w) weight as well as bias value. The results demonstrated that the two proposed models, AENN-ELM-JAYA and AENN-ELM-IJAYA, outperformed the comparative models in terms of minimal error rates and generalized stability. AENN-ELM-IJAYA, in particular, outperformed the comparative models in forecasting domestic power

peak demand. Furthermore, the proposed model AENN-ELM-IJAYA required significantly less computational training time than other comparative models.

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