ELECTRICITY CONSUMPTION FORECASTING FOR SEAFOOD PROCESSING PLANTS USING A HYBRID ANN–PSO MODEL

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ABSTRACT

The study develops a hybrid ANN–PSO model to forecast the electrical load of a seafood processing plant in Sóc Trăng, where consumption fluctuates strongly due to seasonal production and refrigeration systems. Data were collected from an MFM-384-C meter (1 hour/sample for 1 month) and processed through an HMI WEINTEK MT8071iE on an IoT platform. The ANN–PSO model uses a 1–5–1 structure, with PSO optimizing weights and biases to improve accuracy. Results show very low errors: hourly forecasts are mostly <0.5% (hour 1: actual 315 kWh, predicted 314.52 kWh – 0.15%, maximum 1.20%); weekly forecasts mostly <1% (hour 1: 2141 kWh vs. 2138.54 kWh – 0.11%, maximum 4.29%); monthly errors remain stable, with day 19 at 7524 kWh vs. 7525.41 kWh – 0.02%, and the highest error 1.45% on day 30. Compared to traditional ANN, ANN–PSO performs better, reducing RMSE from 1.45% to 0.53% (hourly) and from 1.85% to 0.78% (monthly). The model proves feasible for accurate energy consumption forecasting and energy management in processing plants.

Keywords: *Energy forecasting, ANN, PSO, hybrid model, seafood industry*

1. INTRODUCTION

In seafood processing plants, electrical load demand often fluctuates significantly due to the seasonal nature of raw materials and the continuous operation of refrigeration systems. These fluctuations lead to power overload during peak hours or energy waste during off-peak periods, posing challenges for energy management and increasing operational costs [1]. Machine learning methods, particularly artificial neural networks (ANN), have been widely applied in time series forecasting, natural language processing, and image recognition. ANN has also been utilized in electrical load forecasting due to its ability to learn nonlinear relationships [2]. However, traditional ANN models often face limitations such as slow convergence speed and a tendency to become trapped in local minima, thereby reducing forecasting accuracy [2, 4]. To address these limitations in convergence and accuracy, many studies have integrated artificial neural networks (ANN) with intelligent optimization algorithms. Among them, the Particle Swarm Optimization (PSO) algorithm, developed by James Kennedy and Russ Eberhart in 1995, has demonstrated high effectiveness in searching for global optima and optimizing network weights [3]. Specifically, PSO updates the velocity and position of "particles" in the search space based on both individual and collective experiences, enabling it to escape local optima and accelerate convergence [3, 4]. Studies applying hybrid ANN–PSO models in electrical energy forecasting have shown superior accuracy compared to traditional ANN models. For example, a study on electricity demand forecasting in Tamil Nadu (India) indicated that an ANN model combined with GA–PSO outperformed standalone ANN–PSO or ANN–GA models [5]. Another study applied ANN–PSO to forecast the electricity consumption of maintenance equipment and reported significantly lower errors compared to conventional ANN models [6]. Meanwhile, recent surveys have identified the seafood processing industry as one of the major electricity consumers in Vietnam, particularly in refrigeration and preservation stages. For instance, a study in Vietnam found that the "processing and preservation of frozen seafood" segment is among the highest energy-consuming subsectors in the food industry in Ho Chi Minh City [7]. Based on this context, this study proposes a hybrid ANN–PSO model to forecast electricity consumption in seafood processing plants. The objective of this paper is to improve forecasting accuracy, support enterprises in proactively planning production, optimizing costs, and achieving sustainable development.

This paper is organized into four sections: the first introduces the research problem; the second presents the methodology and approach; the third discusses the simulation results and analysis; and the final section provides conclusions.

2. METHODOLOGY

2.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are computational models inspired by biological nervous systems, in which artificial neurons (perceptrons) are interconnected through weighted connections to process and transmit information. Each neuron performs a linear transformation combined with a nonlinear activation function to produce an output for the next layer. The basic structure of an ANN consists of an input layer, one or more hidden layers, and an output layer [2].

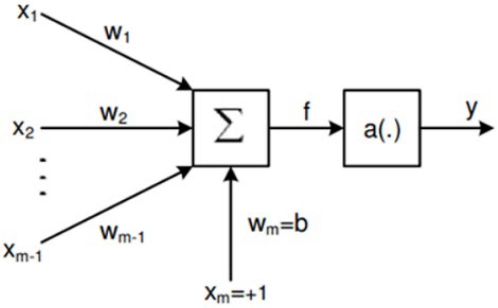

Figure 1. Illustration of an artificial ANN neuron

Let $x_1,..., x_{m-1}$ be input signals and $x_m = +1$ be the bias input with weight $w_m = b$, as shown in the figure. The net input of a neuron is computed as:

$$net = \sum_{i=1}^{m} w_i \,.\, x_i = \sum_{i=1}^{m-1} w_i \,.\, x_i + b \quad [2, 8] \ (1)$$

The neuron output after the activation function is:

$$y = a(net) = a\left(\sum_{i=1}^{m} w_i \,.\, x_i\right) \quad [2, 8] \ (2)$$

Where:

- x_i: the *i*-th input value.
- w_i: weight associated with .
- *b*: bias term that shifts the activation function.
- net: weighted sum of inputs.
- *a*(.): nonlinear activation function (e.g., sigmoid, tanh, ReLU).
- *y*: neuron output.

The activation function determines the nonlinearity of the neuron and influences the convergence speed of training using the backpropagation algorithm [2].

Among ANN architectures, the Multilayer Perceptron (MLP) is the most typical and widely used form. MLP contains at least one hidden layer between input and output layers, allowing it to model complex nonlinear relationships and approximate any continuous function [8]. The training process typically employs the backpropagation algorithm to update weights based on the gradient of the loss function [2].

However, traditional MLP networks may suffer from slow convergence and susceptibility to local minima, reducing forecasting accuracy. Therefore, recent studies have focused on integrating MLP with metaheuristic optimization algorithms such as Particle Swarm Optimization (PSO) [3–5] to enhance weight optimization and improve load forecasting performance [6].

Thanks to its flexibility and strong generalization capability, MLP has been widely applied in pattern recognition, signal processing, and especially electrical load forecasting in industrial systems [5, 6].

2.2 Particle Swarm Optimization (PSO) Algorithm

Particle Swarm Optimization (PSO) was first introduced by James Kennedy and Russell Eberhart in 1995 [9]. The algorithm is inspired by the foraging behavior of bird flocks, where each individual – called a particle – represents a potential solution in the search space.

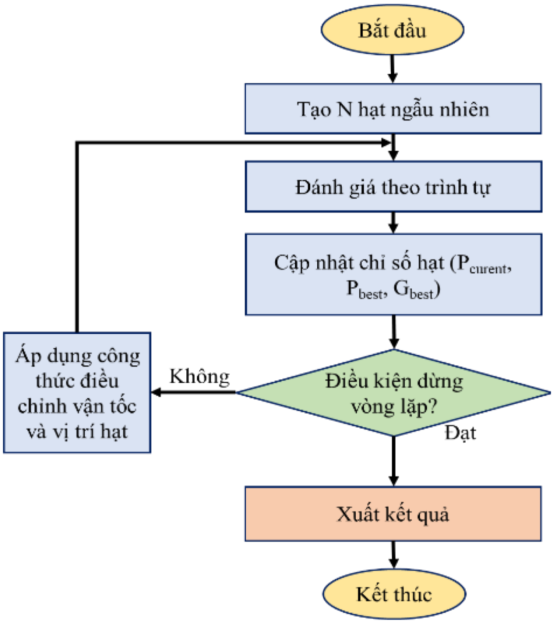

Figure 2. Flowchart of the PSO algorithm [3, 4, 5]

A key advantage of PSO lies in its simple structure, ease of implementation, and high efficiency, making it a powerful optimization tool in many domains, particularly in power systems [10]. Each particle maintains:

+ Current position (representing a candidate solution),

+ Velocity

+ Personal best position (P_{Best}),

+ Global best position (G_{Best}) within the swarm.

During iterations, each particle updates its velocity and position based on both P_{Best} and G_{Best}. As a result, the swarm gradually converges toward regions with better solutions, aiming to minimize the Mean Squared Error (MSE) on the training dataset.

In ANN applications, each particle can be interpreted as a vector of network weights. The particle's movement in multidimensional space corresponds to the optimization process of ANN parameters, helping overcome issues such as slow convergence and local minima.

The classical PSO algorithm consists of the following steps:

- Step 1: Evaluate the objective function for each particle.
- Step 2: Update P_{Best} và G_{Best}.
- Step 3: Update particle velocity and position using standard PSO equations.

The process terminates when the maximum number of iterations is reached or a convergence criterion is satisfied.

Velocity and position updates are defined as:

$$v_i(t+1) = wv_i(t)+c_1r_1[\hat{x}_i(t) - x_i(t)] +c_2r_2 [g(t) - x_i(t)] \text{ ; [3, 4]} \quad (3)$$

After each cycle, the position of each individual is updated as follows:

$$x_i(t+1)= x_i(t) + v_i(t+1) \text{ ; } \quad \text{[3, 4]} \quad (4)$$

Where:

- v_i (t) velocity of particle i at iteration t,
- x_i (t) position of particle i at iteration t,
- w: inertia weight,
- c_1, c_2: cognitive and social learning coefficients,
- r_1, r_2 : random variables in [0,1],
- $\hat{x}_i(t)$: P_{Best} of particle i,
- g(t): G_{Best} of the swarm.

PSO parameters used in this study:

+ w = 0.72 — inertia weight, used to balance local and global search,

+ c_1 = 1.49 — cognitive (individual learning) coefficient,

+ c_2 = 1.49 — social (swarm learning) coefficient,

r_1, r_2 ~ U(0,1) — two random variables uniformly distributed in [0,1],

+ Swarm size = 30,

+ Maximum iterations = 500,

+ Velocity limits: $v_{min} = -1$, $v_{max} = 1$ nhằm tránh bước nhảy quá lớn.

2.3 Development of the Hybrid ANN–PSO Model

In seafood processing plants, electricity consumption fluctuates significantly due to seasonal raw materials, inconsistent input quality, and continuous refrigeration system operation. The disparity between peak and off-peak periods leads to overload or energy waste, directly affecting production costs and stability [11]. Therefore, accurate short-term load forecasting is essential for operational optimization. Artificial Neural Networks (ANN) are commonly used for load forecasting due to their ability to model nonlinear relationships.

However, traditional ANN models often suffer from local minima and slow convergence [12]. To address these limitations, the hybrid PSO–ANN model integrates Particle Swarm Optimization to optimize network weights, thereby improving accuracy and convergence speed [13, 14]. This approach has proven effective in building energy forecasting [15] and renewable energy prediction [16], including improved variants such as MPSO-BP.

Based on this foundation, this study proposes applying the PSO–ANN model to forecast electricity consumption in seafood processing plants, aiming to enhance forecasting accuracy, optimize resource allocation, and support sustainable production planning.

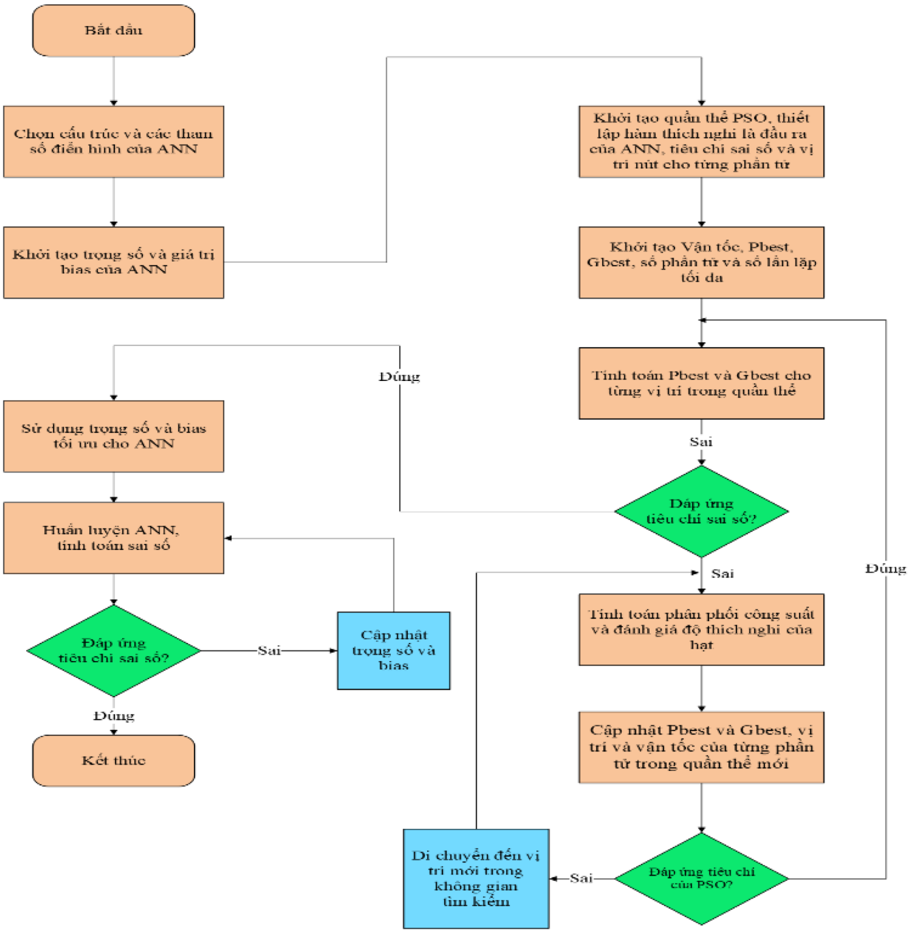

Figure 3. Structure of the hybrid ANN–PSO model

2.4 Mathematical Model

In this study, electrical load is forecasted over a 24-hour period, from which the following equation is established:

- Input dataset

Energy forecasting dataset:

$$D = (x_t, y_t)_{t=1}^{N} \quad ; [2, 8] \ (5)$$

x_t: input variable at time t.

y_t: actual energy consumption (kWh) at time t.

- ANN (MLP) model

+ Architecture: 1 input – 5 hidden neurons – 1 output.

+ Hidden layer:

$$z_i = w_i * x_t + b_i, \quad i = 1..5 \quad ; [2, 8] \quad (6)$$

w_i : weight connecting the input to the i-th hidden neuron.

b_i : bias of the i-th hidden neuron.

+ Activation function (tanh):

$$a_i = tanh(z_i) = \frac{\left(e^{z_i} - e^{-z_i}\right)}{\left(e^{z_i} + e^{-z_i}\right)} \quad ; [2, 8] \quad (7)$$

+ Output layer:

$$\hat{y}_t = b_o + \Sigma_{i=1}^{5} v_i . a_i \quad ; [2, 8] \quad (8)$$

v_i: weight from the i-th hidden neuron to the output.

b_0: bias at the output layer.

$\hat{y}_t$: predicted energy value at time t.

+ General ANN prediction:

$$\hat{y}_t = b_o + \Sigma_{i=1}^{5} v_i . tanh(w_i . x_t + b_i); [2, 8] \ (9)$$

- Loss function (optimization objective)

+ Using Mean Squared Error (MSE):

$$L(\theta)=\frac{1}{N}\sum_{t=1}^{N}(y_t-\hat{y}_t)^2 \text{ ; [2, 8] (10)}$$

$\theta = w_i, b_i, v_i, b_0$: the set of all network parameters.

A smaller MSE indicates higher forecasting accuracy.

- Particle encoding

+ Each particle represents ANN parameters:

$$x=[w_1,w_2,w_3,w_4,w_5,b_1,b_2,b_3,b_4,b_5, v_1,v_2,v_3,v_4,v_5,\ b_o] \text{ ;[3, 4] (11)}$$

+ Dimension:

$$D = (d.h) + h + (h.o) + o \text{ ;[3, 4, 9](12)}$$

With d=1 (1 input), h=5 (5 hidden neuron), o=1 (1 output):

D=(1.5)+5+(5.1)+1=16

- PSO - particle pepresentation and update (mathematical formulation):

+ Each particle p corresponds to a position vector $x_p \in R^D$, representing a candidate solution (i.e., a set of weights and biases).

Each particle has a velocity $\mathbf{v}_p \in R^D$

Each particle stores: personal best position $\mathbf{pbest}_p$ (vị trí) and global best position **gbest**

The velocity and position are updated according to the standard PSO equations:

$$v_p(t+1)=\omega v_p(t)+c_1r_1\left(\mathbf{pbest}_p\text{-}\mathbf{x}_p(t)\right)$$
$$+c_2r_2\left(\mathbf{gbest}\text{-}\mathbf{x}_p(t)\right)\text{; [3, 4, 5] (13)}$$

For particle i at iteration t:

Position (ANN parameter set): $x_i(t)$

Velocity: $v_i(t)$

Velocity update:

$$v_i(t+1)=w.v_i(t)+c1.r1.\left(p_i\text{-}x_i(t)\right)$$
$$+c2.r2.\left(g\text{-}x_i(t)\right) \text{ ; [3, 4] (14)}$$

Position update:

$$x_i(t+1)=x_i(t)+v_i(t+1) \text{ ; [3, 4, 5] (15)}$$

Where:

p_i: best solution found by particle

g: best solution found by the entire swarm

w: inertia weight (controls the influence of previous velocity).

c_1, c_2: learning coefficients,

$r_1, r_2 \sim U(0,1)$.

- Data normalization

+ To improve convergence:

$$x_{norm}=\frac{(x\text{-}\mu_x)}{\sigma_x},\ \ y_{norm}=\frac{(y\text{-}\mu_y)}{\sigma_y}\text{; [2, 8] (16)}$$

+ During prediction, denormalization is performed as:

$$\hat{y}=\hat{y}_{norm}.\sigma_y+\mu_y \quad \text{; [2] (17)}$$

- Evaluation metrics

+ RMSE:

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum(X(t)\text{-}\ \hat{X}(t))^2} \text{ ;[5,13] (18)}$$

+ MAPE:

$$\text{MAPE}=\frac{100}{N}\sum\left|\frac{X(t)\text{-}\ \hat{X}(t)}{X(t)}\right| \text{; [5, 13] (19)}$$

+ MAE:

$$\text{MAE}=\frac{1}{N}\sum\left|X(t)\text{-}\ \hat{X}(t)\right| \text{ ; [13] (20)}$$

+ R^2:

$$R^2=1\text{-}\frac{\Sigma(y_t\text{-}\hat{y}_t)^2}{\Sigma(y_t\text{-}\bar{y})^2} \text{ ; [13] (21)}$$

Trong đó:

$X(t)$, y_t: actual values at time t;

$\hat{X}(t)$, $\hat{y}_t$: predicted values at time t;

N: number of samples;

$\bar{y}$: mean of actual values;

RMSE: indicates deviation;

MAPE: relative error;

MAE: absolute error;

R^2: goodness-of-fit of the model;

- Hybrid ANN–PSO model

+ After PSO optimizes the parameter set $\theta^* = w_i^*, b_i^*, v_i^*, b_o^*$, the final prediction model is:

$$\hat{y}_t = b_0^* + \Sigma_{i=1}^{5} v_i^* . tanh\left(w_i^* . x_t + b_i^*\right); \text{ [2, 8] (22)}$$

3. RESULTS

The Artificial Neural Network (ANN) model combined with the Particle Swarm Optimization (PSO) algorithm was applied to forecast the electrical load consumption of a seafood processing plant belonging to Tai Kim Anh Seafood Processing Joint Stock Company in Soc Trang Province. Accurate forecasting of electricity demand enables the plant to proactively manage operations, optimize costs, and improve energy efficiency.

- Data monitoring and storage system:

+ Electric load data were directly collected from the MFM-384-C multifunction meter, a specialized device for measuring electrical parameters in industrial systems. The measured values were displayed and monitored via the WEINTEK MT8071iE HMI screen, with the interface designed using EasyBuilder Pro software. In addition, the system supported remote monitoring and data access through an IoT platform using EasyAccess 2.0 software.

+ Data were collected at a frequency of one sample per hour, ensuring continuous monitoring of the plant's electrical load. In this study, historical data over a one-month period were used.

Input of the ANN–PSO Model: The input variable of the model was time in hours (from 1 to 24) within a day. This variable reflected the production cycle and operational schedule of equipment in the plant. These input values were obtained directly from the MFM-384-C meter and were normalized before being fed into the training model to improve convergence speed and ensure optimization stability.

- Output of the ANN–PSO Model: The output of the model was the electrical energy consumption (kWh) at each hour. This is the target variable to be forecasted for energy management purposes. The predicted values were compared with actual data to evaluate error and model accuracy.

Figure 4. IoT-based electrical energy data acquisition system

- ANN–PSO Model Architecture

+ The forecasting model was constructed using a 1–5–1 neural network architecture, including:

• Input layer: 1 neuron representing the hour value.

• Hidden layer: 5 neurons responsible for extracting and learning nonlinear relationships between time and electricity consumption.

• Output layer: 1 neuron providing the predicted kWh value.

- During training, the PSO algorithm was used to optimize all weights and biases of the ANN. PSO plays the role of a global optimization method, enabling the model to achieve the lowest forecasting error compared to actual data.

- In this study, the entire dataset was randomly divided into three independent sets in the ratio of 70% – 15% – 15%. 70% of the data was used to train the ANN-PSO network; 15% was used as a validation set to adjust parameters and avoid overfitting; and the remaining 15% was used as an independent test set, completely uninvolved in the training process. The model was trained entirely offline on the 70% set, and then its performance was evaluated using the 30% untrained data. Only when the model achieved high accuracy on the test set was the ANN-PSO used for the power load forecasting problem.

- Daily, monthly, and yearly energy consumption data were presented in Table 1 and Table 2.

Table 1. Daily energy consumption (24 hours)

Hour	Actual data (kWh)	Hour	Actual data (kWh)	Hour	Actual data (kWh)	Hour	Actual data (kWh)
1	315	7	332	13	332	19	321,66
2	302	8	325	14	215	20	338,52
3	267	9	327	15	339	21	328,13
4	248	10	292	16	332	22	340,17
5	325	11	272	17	313,22	23	331,29
6	306	12	337	18	265,75	24	301,45

Table 2. Monthly energy consumption (30 days)

Day	Actual data (kWh)	Day	Actual data (kWh)	Day	Actual data (kWh)
1	7025	11	7220	21	7737
2	6986	12	7248	22	7116
3	6930	13	7425	23	6219
4	7422	14	7210	24	7084
5	6323	15	7031	25	6182
6	5918	16	6395	26	6027
7	7419	17	7736	27	7527
8	6530	18	7771	28	7238
9	6344	19	7524	29	6974
10	7771	20	8040	30	6549

The simulation process was implemented on the MATLAB platform. The error between actual and predicted values was calculated as:

$$\varepsilon = \frac{|X(t) - \hat{X}(t)|}{X(t)} \times 100\% \qquad (23)$$

The energy consumption curve over a 24-hour period was shown in Figure 5, representing a non-stationary signal.

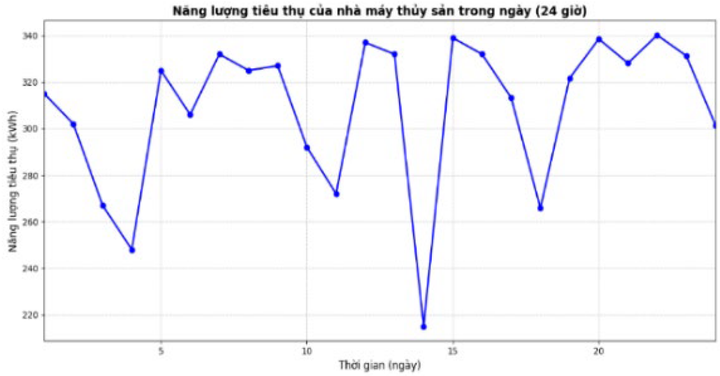

Figure 5. Energy consumption of the seafood processing plant over 24 hours

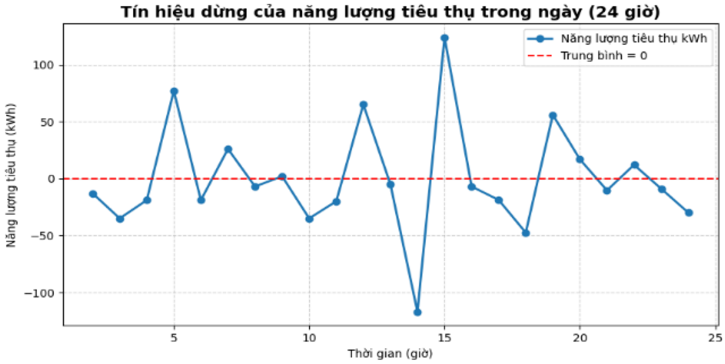

Figure 6. Stationary signal of daily (24-hour) energy consumption

The results of applying the hybrid ANN–PSO algorithm for hourly energy forecasting were presented in Figure 7.

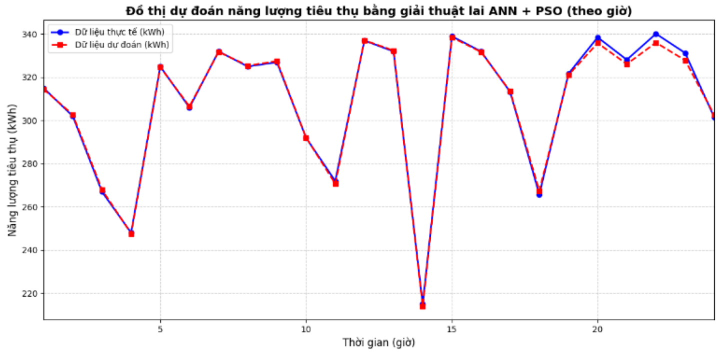

Figure 7. Energy consumption forecasting using the ANN–PSO hybrid algorithm (hourly data)

To clarify the model's accuracy in hourly load forecasting, Table 3 presented detailed errors obtained during training and validation using the ANN–PSO algorithm.

Table 3. Hourly energy forecasting errors (24 hours) using ANN–PSO

Hour	Actual data (kWh)	Predicted data (kWh)	% Error	Hour	Actual data (kWh)	Predicted data (kWh)	% Error	Hour	Actual data (kWh)	Predicted data (kWh)	% Error
1	315	314,5	0,15	9	327	327,5	0,16	17	313,2	313,5	0,1
2	302	302,7	0,23	10	292	292,1	0,04	18	265,8	267,4	0,63

Hour	Actual data (kWh)	Predicted data (kWh)	% Error	Hour	Actual data (kWh)	Predicted data (kWh)	% Error	Hour	Actual data (kWh)	Predicted data (kWh)	% Error
3	267	268	0,36	11	272	270,8	0,46	19	321,7	321	0,19
4	248	247,6	0,15	12	337	337,2	0,05	20	338,5	335,9	0,78
5	325	324,7	0,11	13	332	332,4	0,12	21	328,1	326,1	0,61
6	306	306,6	0,18	14	215	214,1	0,44	22	340,2	336,1	1,2
7	332	331,8	0,07	15	339	338,5	0,14	23	331,3	327,9	1,03
8	325	325,4	0,13	16	332	331,7	0,08	24	301,5	302,6	0,36
Average hourly error											**0,32**

Results in Table 3 showed that the hybrid ANN–PSO model achieved high accuracy in hourly load forecasting. Forecasting errors remained very low, with some time points such as hour 10 (0.04%) and hour 12 (0.05%). Most hours had errors below 0.5%. Although a few peak hours (e.g., hours 22 and 23) showed slightly higher errors of about 1–1.2%, they were still within acceptable limits. Overall, errors mainly ranged from 0.1% to 0.4%, confirming the model's stability and reliability in capturing electricity consumption patterns, making it suitable for practical energy management applications.

Table 4. Average evaluation metrics of the 24-hour energy forecasting model

Evaluation metrics	RMSE (kWh)	MAE (kWh)	MAPE (%)	R²
Average value	1.43	1.00	0.32	0.9980

The hourly forecasting model demonstrated very high accuracy, with minimal errors (MAE = 1.00 kWh, MAPE = 0.32%), RMSE = 1.43 kWh, and R^2 = 0.9980, indicating that predictions closely matched actual data.

Similar to hourly forecasting, the model could be extended to weekly and monthly predictions. The corresponding results were shown in Figures 8 and 9.

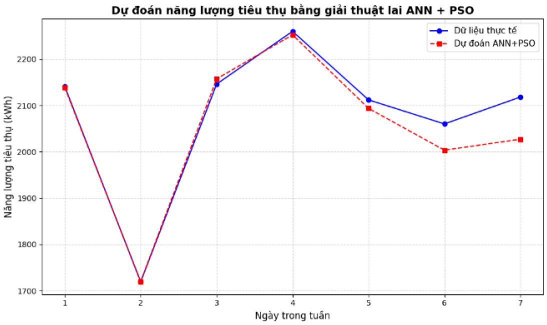

Figure 8. Energy consumption forecasting using ANN–PSO (weekly data)

The error levels during the training process were summarized in Table 5, providing a clear view of prediction performance and model fitting capability.

Table 5. Weekly (7-day) energy forecasting errors using ANN–PSO

Day	Actual data (kWh)	Predicted data (kWh)	% Error
1	2141	2138,54	0,11
2	1719	1719,55	0,03
3	2146	2157,31	0,53
4	2260	2252,44	0,33
5	2112	2093,66	0,87
6	2060	2003,34	2,75
7	2118	2027,07	4,29
Average weekly error			**1,27**

The results indicated that daily load forecasting using the ANN–PSO model achieved high accuracy compared to actual data. In the first few days, errors were very small (Day 1: 0.11%; Day 2: 0.03%), demonstrating strong learning capability during stable periods. Subsequent days maintained errors below 1% (Day 3: 0.53%; Day 4: 0.33%; Day 5: 0.87%), indicating high reliability. However, errors increased on Days 6 and 7 (2.75% and 4.29%) due to significant load fluctuations, although predictions still followed the actual trend closely. Overall, ANN–PSO provided stable results and shows strong potential for practical applications in energy forecasting and management.

Table 6. Average evaluation metrics of the weekly (7-day) energy forecasting model

Evaluation metrics	RMSE (kWh)	MAE (kWh)	MAPE (%)	R^2
Average value	41.41	26.83	1.27	0.9309

The weekly forecasting model also achieved high accuracy, with low average errors (MAE = 26.83 kWh, MAPE = 1.27%). RMSE = 41.41 kWh reflected some higher deviations on certain days, while R^2 = 0.9309 indicated that the model explained approximately 93% of the variance in actual data.

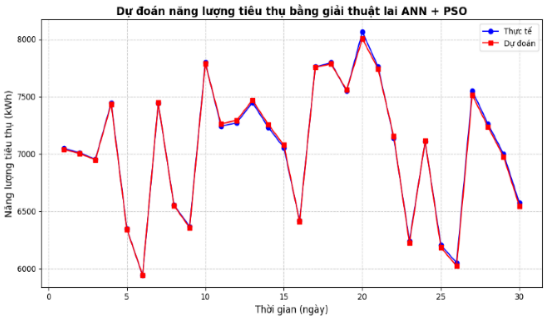

Figure 9. Energy consumption prediction using the hybrid ANN–PSO algorithm (monthly data)

Table 7 summarized in detail the errors generated during the training process of the algorithm, clearly illustrating the accuracy level of monthly energy consumption forecasting when applying the hybrid ANN–PSO method.

Table 7. Monthly (30-day) energy consumption forecasting errors using the hybrid ANN–PSO algorithm

Day	Actual data (kWh)	Predicted data (kWh)	% Error	Day	Actual data (kWh)	Predicted data (kWh)	% Error	Day	Actual data (kWh)	Predicted data (kWh)	% Error
1	7025	7006,48	0,26	11	7220	7239,41	0,27	21	7737	7719,06	0,23
2	6986	6972,57	0,19	12	7248	7267,47	0,27	22	7116	7124,05	0,11
3	6930	6921,48	0,12	13	7425	7438,43	0,18	23	6219	6193,44	0,41
4	7422	7429,44	0,1	14	7210	7231,69	0,3	24	7084	7080,94	0,04
5	6323	6308	0,24	15	7031	7059,38	0,4	25	6182	6128,12	0,87
6	5918	5863,99	0,91	16	6395	6429,59	0,54	26	6027	5943,12	1,39
7	7419	7430,3	0,15	17	7736	7728,92	0,09	27	7527	7495,7	0,42
8	6530	6550,01	0,31	18	7771	7759,1	0,15	28	7238	7204,1	0,47
9	6344	6365,4	0,34	19	7524	7525,41	0,02	29	6974	6922,44	0,74
10	7771	7776,79	0,07	20	8040	7997,73	0,53	30	6549	6453,93	1,45
Average monthly error											**0,39**

Table 7 showed that the monthly energy consumption forecasting errors produced by ANN–PSO remained very low, with many days nearly matching the actual values. For instance, the error on day 19 was only 0.02%, day 24 was 0.04%, and day 10 was 0.07%. During the consecutive days from day 1 to day 5, the errors fluctuated only between 0.10% and 0.26%, demonstrating that the model was stable and closely followed the real data. On some days, the errors were slightly higher, such as day 6 (0.91%), day 25 (0.87%), or the highest values on day 26 (1.39%) and day 30 (1.45%); however, these values still remained within acceptable limits and were significantly lower than those of non-optimized models. Overall, the average error remained below 0.5% for most days, confirming that ANN–PSO was effective, accurate, and applicable in practice for monthly load forecasting.

Table 8. Average evaluation indices of the 30-day energy consumption forecasting model

Evaluation metrics	RMSE (kWh)	MAPE (%)	MAE (kWh)	R²
Average value	198.32	2.47	172.37	0.8787

The forecasts were relatively accurate, with low average errors (MAE = 172.37 kWh, MAPE = 2.47%), while RMSE = 198.32 kWh indicated that some days exhibited larger deviations, and R² = 0.8787 showed that the model explained approximately 88% of the variation in the actual data.

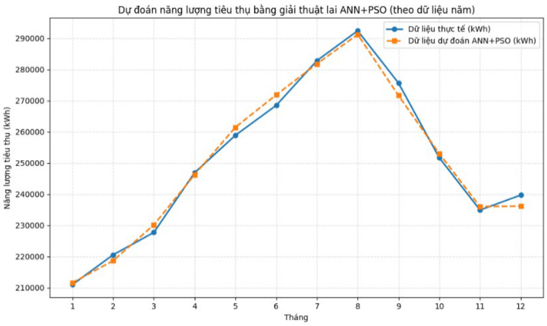

Figure 10. Energy consumption prediction using the hybrid ANN–PSO algorithm (yearly data)

To evaluate the accuracy of the hybrid ANN–PSO model in annual energy consumption forecasting, the errors between predicted values and actual data were calculated for each month. The detailed results were compiled and presented in Table 9, reflecting the model's closeness to actual data and its reliability over the 12-month cycle.

Table 9. Annual (12-month) energy consumption forecasting errors using the hybrid ANN–PSO algorithm

Month	Actual data (kWh)	Predicted data (kWh)	% Error	Month	Actual data (kWh)	Predicted data (kWh)	% Error
1	210921	211544,83	0,3	7	282825	281800,85	0,36
2	220508	218614,79	0,86	8	292413	291200,27	0,41
3	227698	230112,64	1,06	9	275635	271652,71	1,44
4	246873	246211,32	0,27	10	251667	253000,52	0,53
5	258857	261432,51	0,99	11	234889	236000,71	0,47

Month	Actual data (kWh)	Predicted data (kWh)	% Error	Month	Actual data (kWh)	Predicted data (kWh)	% Error
6	268444	271823,04	1,26	12	239683	236143,22	1,48
Average annual error							**0,79**

The results showed that the hybrid ANN–PSO model achieved high accuracy in forecasting energy consumption, with an average annual error of 0.79%. Most months recorded errors below 2%, indicating that the model closely followed real trends and maintained good stability. The largest error occurred in December (1.48%); however, this value was still low and within the acceptable range for energy forecasting problems. Overall, the ANN–PSO model demonstrated reliable predictive capability and was suitable for application in annual load forecasting.

Table 10. Average evaluation indices of the 12-month energy consumption forecasting model

Evaluation metrics	RMSE (kWh)	MAPE (%)	MAE (kWh)	R^2
Average value	2276,97	0,79	1979,34	0,9913

Both RMSE and MAE remained low relative to the load scale, indicating small deviations between predicted and actual values. MAPE reached 0.79%, confirming the model's high accuracy in forecasting energy consumption. The coefficient of determination (R^2 = 0.9913) indicated that the model explained more than 99% of the variation in the actual data. This demonstrated that the hybrid ANN–PSO algorithm was highly suitable for annual load forecasting.

To evaluate the effectiveness of the ANN–PSO model, the results of this study were compared with several previously published works that applied similar models for load forecasting. Table 11 presented a comparison of key error metrics (MAE, RMSE) across related studies.

Table 11. Comparison of ANN–PSO model results with related studies

Research	Model	RMSE (%)	MAE (%)
Anand & Suganthi (2017)[17]	ANN–PSO (Linear, Quadratic)	2.5–3.2	1.5–2.8
Bayat (2015) [18]	ANN–PSO	≈1.2	≈0.9
This research	ANN–PSO (1–5–1)	0.53	0.42

The comparison results in Table 11 showed that the hybrid ANN–PSO model in this study achieved superior accuracy compared to previous works. RMSE decreased to 0.53% and MAE to 0.42%, significantly lower than those reported in the models of Anand & Suganthi (2017), Bayat (2015), and Rahmoune & Chettih (2021). This confirmed the effectiveness of applying PSO to optimize network weights under nonlinear and highly fluctuating real-world data conditions, such as those in seafood processing plants.

4. CONCLUSION

Based on the analysis of load forecasting results using ANN–PSO across multiple time scales, the model demonstrated high accuracy and stability. On an hourly basis, the error was mostly below 0.5%, with the lowest at 0.04% and the highest around 1%. On a weekly basis, the average error remained below 1%, with many values nearly matching actual data. On a monthly basis, despite longer and more fluctuating data, the error was still mainly below 0.5%, with the highest ranging from approximately 1.39% to 1.45%. This indicated that ANN–PSO closely tracked data in both short-term and long-term forecasting. Compared to traditional ANN, ANN–PSO showed clear superiority: MAE/RMSE were 0.42%/0.53% (hourly), 0.48%/0.61% (daily), and 0.65%/0.78% (monthly), whereas ANN exhibited significantly higher values (1.12%–1.85%). This confirmed that ANN–PSO not only reduced errors but also improved stability. From a theoretical perspective, ANN was effective in learning nonlinear relationships but was prone to being trapped in local optima due to random initialization. The integration of PSO enabled global optimization through swarm intelligence mechanisms, allowing better identification of optimal weights and thresholds. As a result, ANN–PSO improved both accuracy and generalization capability. In conclusion, the hybrid ANN–PSO model is an optimal solution for energy load forecasting in industrial contexts, particularly in seafood processing plants in Soc Trang. This method ensures low error rates, maintains stability from short-term to long-term forecasting, and provides a foundation for developing more advanced intelligent energy forecasting models in the future.