

Article

A Novel ANFIS Framework for Energy Consumption Forecasting in Vietnam

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Abstract

Accurate prediction of energy consumption in the future plays an essential role in national energy security and sustainable economic planning in Vietnam. However, the energy consumption data is subject to non-linearity, high fluctuation and complex seasonal variations. To address this problem, this study proposes a novel framework based on an ANFIS model; the proposed models were established by integrating the Denton method, the Adaptive Neuro-Fuzzy Inference System (ANFIS) and meta-heuristic algorithms, namely Particle Swarm Optimization (PSO), the Grey Wolf Optimizer (GWO), and the Whale Optimization Algorithm (WOA). The simulation results demonstrate that the PSO-ANFIS model achieved the best performance, with a Mean Absolute Percentage Error (MAPE) of 4.65% and an R^2 score of 0.7275. Based on this result, this study suggests that the PSO-ANFIS model is a promising candidate for forecasting the energy consumption demand in Vietnam. Energy consumption demand will reach 3108.38 billion kWh by 2030. These findings provide a reliable scientific foundation for grid management and strategic policy-making.

Keywords: energy forecasting; ANFIS; Particle Swarm Optimization (PSO); Grey Wolf Optimizer (GWO); Whale Optimization Algorithm (WOA); Vietnam

1. Introduction

Energy drives economic growth in developing nations like Vietnam, where commercial electricity demand is projected to reach 505.2 billion kWh by 2030 to support 7% annual GDP growth [1]. Therefore, accurate energy demand forecasting is essential for ensuring energy security and maintaining efficient power system operation. However, this task faces two major challenges: capturing highly non-linear fluctuations caused by economic and seasonal factors and overcoming the lack of high-frequency data. Because official energy records are usually updated only once a year, it is difficult to train deep learning models, which require large-scale datasets to avoid overfitting. The Adaptive Network-based Fuzzy Inference System (ANFIS) [2] is highly effective at modeling complex data by combining neural networks with fuzzy logic. However, its standard gradient-based training is often slow and prone to getting stuck in local optima. This is a limitation that motivates the integration of meta-heuristic optimization strategies, as explored in this study.

To resolve these issues, this study proposes a novel, end-to-end forecasting framework. The key contributions of this research are summarized as follows:



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- (1) Developing a novel two-stage hybrid framework that successfully combines temporal disaggregation (the Denton proportional method) with a neuro-fuzzy system (ANFIS).
- (2) Conducting a systematic comparison of three advanced meta-heuristic algorithms (PSO, GWO, and WOA) for ANFIS parameter optimization. Through comprehensive non-parametric statistical testing and residual diagnostics, this study identifies the most robust and stable optimizer for highly fluctuating energy datasets.
- (3) Formulating reliable medium-to-long-term energy demand projections for Vietnam (2026–2030) across multiple macroeconomic scenarios.

2. Related Work

Forecasting highly non-linear energy consumption in developing economies like Vietnam poses significant challenges. Vietnam's energy demand has grown rapidly, yet official statistics remain primarily annual, creating a fundamental data scarcity problem for modeling. While recent studies have shifted toward complex architectures—hybrid deep learning models such as CNN-LSTM-Attention [3] or WIO-SVR [4], which achieve strong short-term forecasting accuracy by capturing high-frequency temporal patterns—these methods generally require large volumes of training data. Wen et al. [5] noted that deep learning models are prone to overfitting and poor generalization unless trained on sufficiently large datasets, and Jang et al. [6] further confirmed that LSTM networks require extensive sequential data to converge reliably. Given that national-level annual energy records in developing economies like Vietnam typically comprise fewer than 50 observations, directly applying such architectures to long-term demand forecasting remains methodologically problematic.

Fuzzy-based methodologies therefore offer a more appropriate alternative. Lee et al. [7] and Blancas et al. [8] demonstrated that fuzzy logic systems outperform standard neural networks in capturing the volatility of power demand. To automate the subjective parameter selection in fuzzy systems, the Adaptive Network-based Fuzzy Inference System (ANFIS) is widely adopted. However, because standard gradient-based ANFIS training frequently gets trapped in local optima, researchers have increasingly integrated meta-heuristic algorithms. Studies by Oladipo et al. [9], Jalaee et al. [10], and Mirboluki et al. [11] demonstrated that algorithms like PSO, WOA, and GWO significantly enhance ANFIS predictive accuracy by balancing global exploration and local exploitation. In the building energy domain specifically, Ngo et al. [4] demonstrated that hybridizing GWO with SVR for short-term load forecasting in Vietnamese non-residential buildings consistently outperformed standalone ML models, reinforcing the effectiveness of meta-heuristic-optimized approaches in local energy contexts.

Despite these algorithmic advances, a systematic comparison of PSO, GWO, and WOA for optimizing ANFIS remains absent in the Vietnamese energy context, where high-frequency data is scarce (official statistics are typically annual). To bridge this gap, temporal disaggregation techniques are essential. The Denton proportional method is a standard econometric approach for converting low-frequency data into high-frequency series. According to Sax and Steiner [12], the Denton method is particularly suitable for unstable economic data because it preserves the underlying trend while breaking down annual figures. This approach has recently gained traction in energy research: Moussa et al. [13] applied a similar two-stage disaggregation-then-forecasting pipeline to renewable energy data across multiple data-scarce countries, demonstrating that proportional disaggregation reliably preserves seasonal structure even when monthly ground truth is unavailable.

To systematically bridge the literature gaps—specifically the fundamental lack of high-frequency datasets and the instability of traditional gradient-based ANFIS training in the context of developing economies—this paper proposes a comprehensive solution. As outlined in our pointwise contributions, rather than merely applying existing techniques,

our approach formulates a complete analytical pipeline: integrating Denton-based temporal disaggregation to resolve data scarcity; conducting a rigorous comparative evaluation of meta-heuristic optimizers (PSO, GWO, and WOA) to ensure model stability; and ultimately delivering validated, scenario-based forecasts to support strategic energy planning.

3. Methodology

3.1. The Denton Proportional Method

To overcome the limitation of annual data, the Denton proportional method, proposed by Denton (1971) [14], is employed to disaggregate the annual energy consumption series into monthly estimates. This technique is mathematically formulated to preserve the fluctuations of a related high-frequency indicator while strictly adhering to annual consistency constraints.

Let A_T be the annual energy consumption for year T (where $T = 1, \dots, M$) and I_t be the corresponding monthly indicator for month t ($t = 1, \dots, 12M$). The primary objective is to estimate the monthly energy series X_t , such that the sum of the estimated monthly values within each year equals the observed annual total. This constraint is formally expressed as:

$$\sum_{t \in T} X_t = A_T, \text{ for } T = 1, \dots, M \quad (1)$$

The Denton method estimates X_t by minimizing the first difference of the ratio relative to the indicator (X_t/I_t). This preserves the high-frequency indicator's volatility, avoiding the artificial smoothing of linear interpolation. The objective function is defined as:

$$\min_{X_t} \sum_{t=2}^{12M} \left(\frac{X_t}{I_t} - \frac{X_{t-1}}{I_{t-1}} \right)^2 \quad (2)$$

Subject to the aggregation constraint defined in Equation (1), solved via quadratic programming, this approach distributes annual residuals without distorting the underlying trend [12]. Consequently, it is particularly suitable for modeling energy consumption, which closely follows economic activities like the IIP.

3.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System is a hybrid model that combines the learning ability of neural networks with the reasoning capability of fuzzy logic [2]. In this study, we employ a first-order Takagi–Sugeno ANFIS model [15]. Figure 1 illustrates the detailed architecture, showing the flow of information through five processing layers and the specific parameters targeted for optimization.

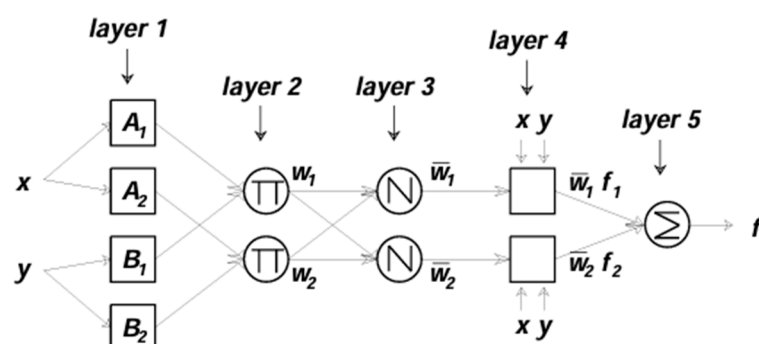


Figure 1. Architecture of the proposed first-order Takagi–Sugeno ANFIS model. The diagram illustrates the five processing layers and highlights the specific parameters targeted for optimization.

As shown in Figure 1, the model processes the input vector to predict energy consumption through five layers:

Layer 1: Fuzzification Layer: Nodes in this layer are adaptive. They transform the numerical inputs into fuzzy values. Specifically, the output of node i indicates how strongly the input x belongs to the fuzzy set A_i (e.g., “low”, “high”). This output is defined as:

$$O_{1,i} = \mu_{A_i}(x), \text{ for } i = 1, 2 \quad (3)$$

In this study, we select the Gaussian membership function because it is smooth and highly effective at capturing non-linear patterns. The mathematical formulation of the Gaussian function is given by:

$$\mu_{A_i}(x) = \exp\left(-\frac{1}{2}\left(\frac{x - c_i}{\sigma_i}\right)^2\right) \quad (4)$$

where $\{c_i, \sigma_i\}$ are the premise parameters (center and width) that are optimized by the meta-heuristic algorithm.

Layer 2: Rule Layer: This layer consists of fixed nodes, labeled as Π . Each node computes the firing strength of a rule by multiplying all incoming signals, effectively performing a fuzzy AND operation:

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1, 2 \quad (5)$$

Layer 3: Normalization Layer: Nodes in this layer are fixed and labeled N . Each node calculates the contribution of the i -th rule relative to the total firing strength of all rules:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \quad (6)$$

Layer 4: Defuzzification (Consequent) Layer: This is the second adaptive layer. Each node calculates the rule's contribution using a linear equation. The output is defined as:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (7)$$

where $\{p_i, q_i, r_i\}$ are consequent parameters. These parameters determine the final forecast value, so tuning them correctly is essential for minimizing prediction errors.

Layer 5: Output Layer: This layer has a single fixed node labeled σ . It calculates the final forecasted output by summing all incoming signals:

$$O_{5,i} = \text{Overall Output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (8)$$

Traditional ANFIS training uses a hybrid method combining gradient descent and least squares. However, gradient-based methods often get stuck in local optima. To solve this, our framework employs meta-heuristic algorithms for global optimization. As shown in the workflow, these algorithms simultaneously tune both the premise parameters (Layer 1) and consequent parameters (Layer 4).

3.3. Meta-Heuristic Optimization Algorithms

The ANFIS learning process is treated as a global optimization problem aimed at minimizing the prediction error. Let Θ represent the complete parameter vector, which comprises both the non-linear premise parameters and the linear consequent parameters:

$$\Theta = \sigma_{ij}, c_{ij}, p_k, q_k, r_k \quad (9)$$

Here, σ and c represent the width and center of the Gaussian membership functions, while p, q, r are the consequent weights.

The optimization objective is to determine the optimal set Θ^* that minimizes the cost function, defined as the Mean Squared Error (MSE):

$$\Theta^* = \underset{\Theta}{\operatorname{argmin}} \left(\frac{1}{N} \sum_{t=1}^N \left(y_{\text{actual}}^{(t)} - y_{\text{forecast}}^{(t)}(\Theta) \right)^2 \right) \quad (10)$$

where N is the sample size, $y_{\text{actual}}^{(t)}$ is the observed value, and $y_{\text{forecast}}^{(t)}$ is the model output.

Because the search space is complex, traditional gradient methods often get stuck in local optima. To solve this, we use three algorithms—PSO, GWO, and WOA. These methods are designed to avoid such traps and find the best global solution.

3.3.1. Particle Swarm Optimization—PSO

Proposed by Kennedy and Eberhart (1995) [16], Particle Swarm Optimization (PSO) is a population-based algorithm that simulates the social behavior of birds. In this study, each “particle” represents a candidate solution vector Θ containing the trainable ANFIS parameters. Assuming a swarm of N particles, at each iteration t , the i -th particle is defined by its position $X_i(t)$ and velocity $V_i(t)$. The movement of each particle is guided by two optimal values: its own best historical position ($P_{\text{best},i}$) and the swarm’s global best position (G_{best}). The velocity and position are updated as follows:

$$V_i(t+1) = w \cdot V_i(t) + c_1 r_1 \cdot (P_{\text{best},i} - X_i(t)) + c_2 r_2 \cdot (G_{\text{best}} - X_i(t)) \quad (11)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (12)$$

In these equations, the weight w is used to balance the search process between exploring new areas and refining current solutions. The coefficients c_1 and c_2 control the influence of the particle’s own history versus the swarm’s global success. Finally, r_1 and r_2 are random values between 0 and 1. Together, these parameters guide the swarm to collaborate and converge toward the solution with the minimum error.

3.3.2. Grey Wolf Optimizer—GWO

Developed by Mirjalili et al. (2014) [17], the Grey Wolf Optimizer (GWO) is a meta-heuristic algorithm inspired by the social hierarchy and hunting behavior of gray wolves. In this study, candidate solutions (ANFIS parameters) are ranked according to their fitness (MSE). The best solution is designated as the leader (α), followed by the second (β) and third (δ) best solutions, while all remaining candidates are classified as followers (ω). The hunting process is modeled by updating the positions of the ω wolves based on the guidance of the three leaders. The distance and movement toward each leader are calculated as follows:

$$\vec{D}_\alpha = \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}(t) \right| \quad (13)$$

$$\vec{D}_\beta = \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{X}(t) \right| \quad (14)$$

$$\vec{D}_\delta = \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{X}(t) \right| \quad (15)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \quad (16)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \quad (17)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \quad (18)$$

The final position of a wolf in the next iteration is determined by averaging the positions indicated by the three leaders:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (19)$$

In these equations, $\vec{A}$ and $\vec{C}$ are coefficient vectors. These values are adjusted throughout the iterations to smoothly transition the search process from global exploration to local exploitation.

3.3.3. Whale Optimization Algorithm—WOA

Proposed by Mirjalili and Lewis (2016) [18], WOA simulates the bubble-net feeding behavior of humpback whales. The algorithm updates the position of search agents using two distinct mechanisms, selected based on a probability p .

First, the Shrinking Encircling Mechanism is triggered when $p < 0.5$. In this phase, whales move toward the best solution found so far ($\vec{X}^*$), similar to the behavior in GWO but relying on the single best leader:

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (20)$$

Second, the Spiral Updating Position mechanism occurs when $p \geq 0.5$. Here, the whales approach the prey following a logarithmic spiral path, defined as:

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) \quad (21)$$

In this equation, $\vec{D}' = |\vec{X}^*(t) - \vec{X}(t)|$ represents the distance to the prey, b is a constant defining the spiral shape, and l is a random number in $[-1, 1]$. WOA is highly regarded for its ability to balance global exploration and local exploitation, effectively preventing the ANFIS model from getting trapped in local optima.

3.4. Proposed Forecasting Framework

As discussed in the previous sections, forecasting energy consumption faces major challenges with limited data and non-linear patterns. While the Denton proportional method effectively resolves the low-frequency data limitation by preserving underlying economic trends, the standard ANFIS model—despite its strong fuzzy reasoning capabilities—often gets stuck in local optima during training. To overcome these inherent limitations and combine the strengths of each individual method, this study proposes a novel hybrid forecasting framework based on integrating Temporal Disaggregation and optimizing the ANFIS model by meta-heuristic algorithms. Using three algorithm optimizations, we establish three distinct variations: Proposed Model 1 (PSO-ANFIS), Proposed Model 2 (WOA-ANFIS), and Proposed Model 3 (GWO-ANFIS). All three models are executed through the same fundamental pipeline, differing only in the optimization phase. The

detailed workflow is illustrated in Figure 2, and the process is carried out through the following steps.

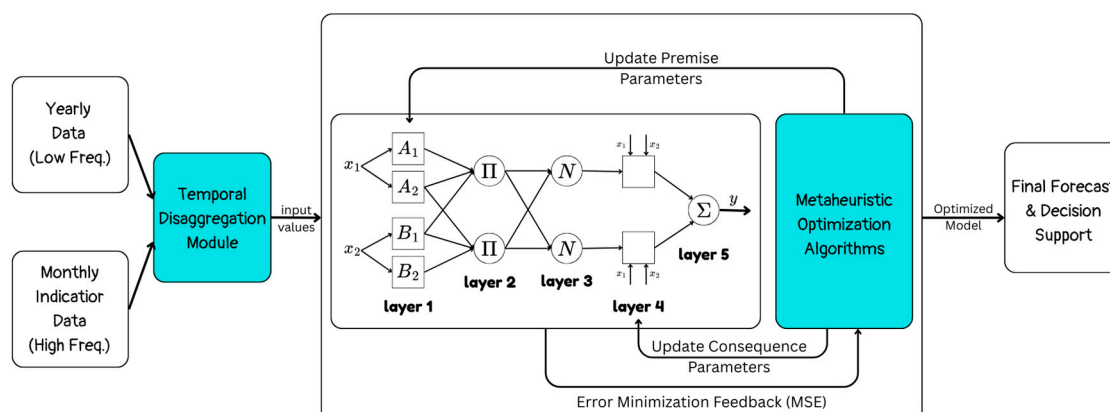


Figure 2. The proposed hybrid neuro-fuzzy forecasting framework. The system integrates Denton-based temporal disaggregation with a meta-heuristic optimization loop that specifically tunes the premise (Layer 1) and consequent (Layer 4) parameters of the ANFIS structure.

Step 1: Data Preparation. The Denton method uses monthly economic indicators (e.g., IIP and FDI) to convert annual energy data into a detailed monthly time series.

Step 2: Model Setup. This monthly data is fed into an ANFIS model. We use Gaussian functions to help the model capture complex, non-linear patterns.

Step 3: Optimization. This is where the models differ. Depending on the selected variation, a specific algorithm (PSO, WOA, or GWO) is applied to globally optimize the ANFIS parameters. This minimizes the error (MSE) and prevents the model from getting stuck during training.

Step 4: Forecasting and Evaluation. The optimized model generates the final energy predictions, which are evaluated against actual data using standard metrics (RMSE, MAE, MAPE, and R^2).

3.5. Performance Evaluation Metrics

To evaluate the proposed model, we used four standard statistical metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). These metrics evaluate both the size of the errors and how well the model fits the data. The mathematical formulations of these metrics, which are standard in the forecasting literature [19–22], are defined as follows:

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (22)$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (23)$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (24)$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (25)$$

where

- n is the total number of observations.
- y_i is the actual energy consumption value for the i -th period.
- $\hat{y}_i$ is the forecasted energy consumption value for the i -th period.
- $\bar{y}$ is the mean of the actual energy consumption values.

3.6. Statistical Significance Tests

To ensure the reliability of the performance evaluation, a comprehensive statistical analysis framework was employed. Because the performance metrics obtained from 30 independent runs may not follow a normal distribution, non-parametric statistical methods were adopted for model comparison. First, the Friedman test [23] was applied to determine whether significant performance differences existed among the three hybrid models. When the Friedman test indicated statistical significance ($p < 0.05$), the Wilcoxon Signed-Rank test [24] was subsequently applied to examine pairwise differences among the models. In addition, Cliff's Delta (δ) was calculated to measure the effect size, providing further insight into the magnitude of performance differences beyond statistical significance alone [25].

To further validate the robustness of the selected forecasting model, residual diagnostic tests were also performed. The Durbin–Watson (DW) test [26] was used to examine first-order auto-correlation in the residuals, where values close to 2.0 indicate error independence. Meanwhile, the Shapiro–Wilk [27] test was conducted to assess the normality of the residual distribution. A p -value greater than 0.05 suggests that the residuals satisfy the normality assumption, thereby supporting the statistical reliability of the forecasting results and confidence intervals.

4. Results and Discussion

4.1. Data Collection and Preprocessing

4.1.1. Data Sources and Validation

This study uses data from January 2009 to December 2024. The main target variable is Total Energy Consumption, obtained annually from Our World in Data [28]. Since the data are only available by year, we use monthly Commercial Electricity Output from the Ministry of Industry and Trade (MOIT) [29] as a reference. This allows us to estimate monthly energy values using the Denton method, as electricity usage closely reflects total energy trends.

We selected two key inputs for the forecasting model. First, the Index of Industrial Production (IIP) from the General Statistics Office [30], as industry dominates Vietnam's energy consumption. Second, Foreign Direct Investment (FDI) from the Ministry of Planning and Investment [31], as Vietnam's manufacturing heavily relies on foreign capital, directly driving energy demand. Table 1 and Figure 3 present the descriptive statistics and historical trends of the raw datasets before temporal disaggregation.

Table 1. Descriptive statistics of the raw datasets (2009–2024).

Variable	Frequency	Obs.	Mean	Std.	Min	Max
Energy Consumption (TWh)	Yearly	16	933.54	322.95	462.68	1457.18
IIP (Index)	Monthly	192	101.45	46.04	36.9	176.2
FDI (Million USD)	Monthly	192	1376.15	594.62	300.0	3671.0

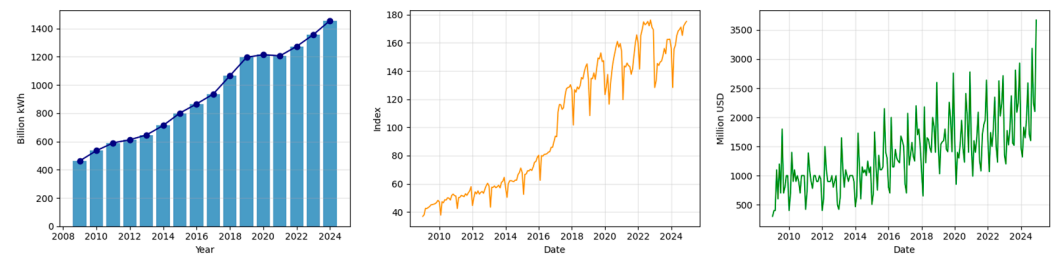


Figure 3. Historical trends of the raw datasets from 2009 to 2024. **(Left)** Annual Total Energy Consumption; **(Middle)** Monthly Index of Industrial Production (IIP); **(Right)** Monthly Foreign Direct Investment (FDI).

To ensure the reliability of this datasets, we validated the indicator before applying the Denton disaggregation method. A strong linear relationship is essential for accurate temporal distribution. As shown in Figure 4, the scatter plot shows a high correlation ($R \approx 0.9977$) between the annual Total Energy Consumption and the aggregated Commercial Electricity Output. This statistical evidence confirms that electricity output captures the underlying trend of total energy demand.

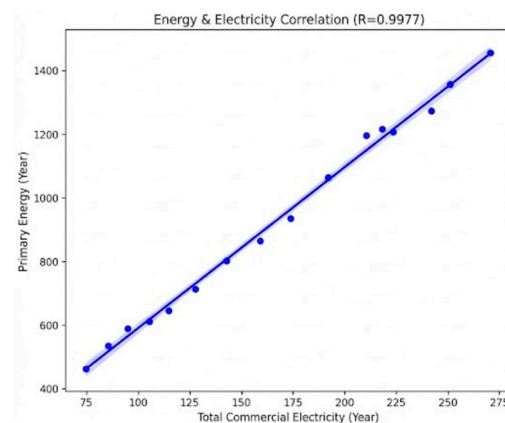


Figure 4. Linear correlation between energy and electricity.

4.1.2. Disaggregation Results

To prevent data leakage, the annual datasets and reference indicators were partitioned into training (2009–2021) and testing (2022–2024) sets prior to any mathematical transformation. The Denton disaggregation was then executed independently on each subset, ensuring the training data contained no forward-looking information. To ensure strict accuracy, the generated monthly values were aggregated back to the annual level. The validation results confirmed that the aggregated monthly values perfectly matched the original annual totals. The calculation error was extremely small, with a Maximum Absolute Error of only 2.27×10^{-13} billion kWh and a Maximum Relative Error of 0.00%.

Beyond numerical precision, this temporal disaggregation successfully preserved the long-term growth of the original yearly records while introducing realistic seasonal fluctuations. To empirically validate the superiority of the Denton proportional approach over naive disaggregation techniques, we conducted a comparative quality assessment against a standard linear interpolation baseline. While both methods perfectly satisfy the annual aggregation constraint, their intra-year distributions differ significantly. As demonstrated in Figure 5, linear interpolation generates an artificially flat series (Coefficient of Variation, $CV = 0.77\%$) that fails to capture real-world seasonality. Conversely, the Denton method actively inherits the seasonal dynamics of the high-frequency indicator, achieving a realistic seasonal shape ($CV = 6.90\%$) and a near-perfect correlation ($r = 0.9974$) with the reference electricity output.

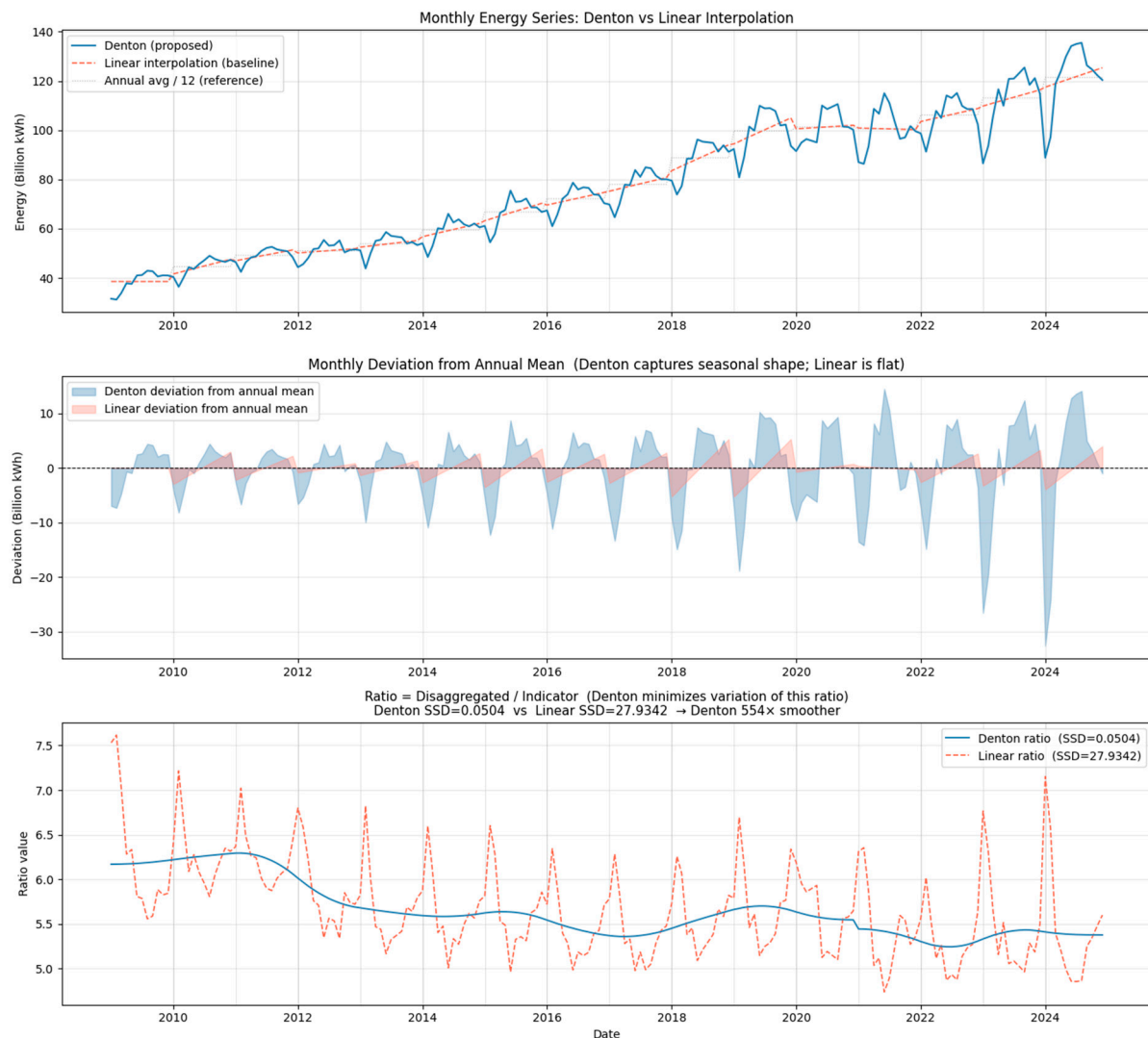


Figure 5. Comparative quality assessment between Denton disaggregation and linear interpolation: **(Top)** monthly energy series overlay; **(Middle)** monthly deviation from the annual mean demonstrating seasonal capture; and **(Bottom)** disaggregated-to-indicator ratio smoothness.

Most importantly, evaluating the core objective function—the Sum of Squared Differences (SSD) of the disaggregated-to-indicator ratio—reveals that the Denton method ($SSD = 0.0504$) is approximately 554 times smoother than the linear baseline ($SSD = 27.9342$). This mathematically minimizes ratio variations and effectively eliminates the artificial step-changes at year boundaries that plague linear methods. Consequently, this indicates that the generated monthly datasets provides a more mathematically consistent and realistic foundation for training the ANFIS architecture. However, it must be explicitly acknowledged that the monthly series generated via the Denton method constitute model-derived estimates rather than directly observed measurements. As noted by Sax and Steiner [12], the reliability of temporally disaggregated series is fundamentally dependent on the strength of the reference indicator; accordingly, the residual uncertainty inherent in this procedure may propagate into subsequent forecasting outputs. The reported model performance metrics should therefore be interpreted within the context of this methodological constraint.

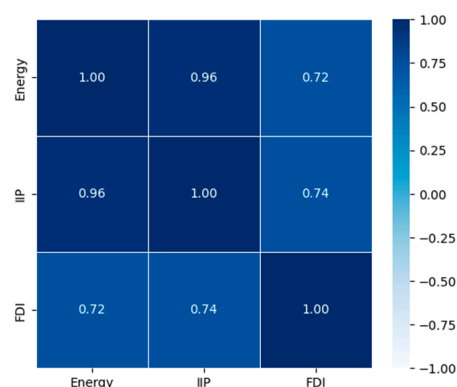
Table 2 summarizes the detailed descriptive statistics of the resulting monthly datasets, making it highly suitable for training the ANFIS model.

Table 2. Descriptive statistics of the monthly datasets after Denton disaggregation (2009–2024).

Variable	Frequency	Obs.	Mean	Std.	Min	Max
Energy Consumption (TWh)	Monthly	192	77.80	27.08	31.23	135.50
IIP (Index)	Monthly	192	101.45	46.04	36.9	176.2
FDI (Million USD)	Monthly	192	1376.15	594.62	300.0	3671.0

4.1.3. Correlation Analysis and Feature Engineering

After generating the monthly data, we analyzed its relationship with the economic indicators (IIP and FDI). Figure 6 displays the correlation matrix of these variables. The results showed a strong positive linear relationship between energy consumption and the industrial production index. This confirms that industrial activity is the primary determinant of energy demand in Vietnam.

**Figure 6.** Correlation heat map of the studied variables.

To ensure the model receives stable inputs, we tested the stationarity of the energy time series using the Augmented Dickey–Fuller (ADF) test [32]. The results showed an ADF Statistic of 0.7872 and a p -value of 0.9914. Since the p -value is significantly higher than the standard threshold ($\alpha = 0.05$), the test confirms that the monthly energy consumption series is non-stationary and follows a stochastic trend.

Using non-stationary data directly causes significant problems for ANFIS. Since the model relies on fixed membership functions, a shifting trend would cause future data to drift outside the learned ranges, making the rules ineffective. To fix this, we apply First-Order Differencing (Δ) to make the series stationary. We validated this transformation using the ADF test, which results in a p -value of 0.0261 (< 0.05). This result confirms that the data is now stable and suitable for modeling. Therefore, the final input vector (X) uses these monthly variations rather than absolute values. The final input vector (X) uses monthly variations to ensure stationarity. Side-by-side with these inputs, we unified the algorithm hyper-parameters ($N = 80$, $T = 200$, $Runs = 30$) to ensure a fair comparison. The detailed setup is summarized in Table 3.

Table 3. Model input variables (left) and hyper-parameter configurations (right).

Role	Variable	Rationale	Algorithm	Parameter	Value
Target	ΔEnergy_t	Monthly variation	Common	N, T, Runs	80, 200, 30
Inputs	$\Delta \text{Energy}_{t-1}$	AR trend	PSO	w, c_1, c_2	$0.9 \rightarrow 0.4, 1.5$
	$\Delta \text{Energy}_{t-12}$	Seasonality	GWO	a	$2 \rightarrow 0$
	ΔIIP_{t-1}	Industrial impact	WOA	b, p	$1, [0, 1]$
	ΔFDI_{t-1}	Investment impact			

These parameters were set based on the standard guidelines to balance global exploration and local exploitation, ensuring the model runs efficiently without excessive computation time.

4.1.4. Optimization Convergence and Stability Analysis

To establish a robust baseline, we first evaluated the standard gradient-based ANFIS model. While it successfully captured the general trend, its reliance on local search mechanisms left room for accuracy improvement. Therefore, we tracked the optimization process of the proposed hybrid models—denoted as Proposed Model 1 (PSO-ANFIS), Proposed Model 2 (WOA-ANFIS), and Proposed Model 3 (GWO-ANFIS)—over 200 iterations (Figure 7). Given the stochastic nature of swarm intelligence, Table 4 presents a statistical summary of the Mean Squared Error (MSE) across 30 independent runs. The results show that GWO-ANFIS achieved the best convergence quality during optimization, with the lowest mean MSE of 0.0108. PSO-ANFIS also performed well, obtaining a similar mean MSE of 0.0130. In addition, both models exhibited high stability, as reflected by their low standard deviations (0.0012 and 0.0013, respectively). In contrast, WOA-ANFIS produced a much higher variance, suggesting less stable and less consistent convergence behavior.

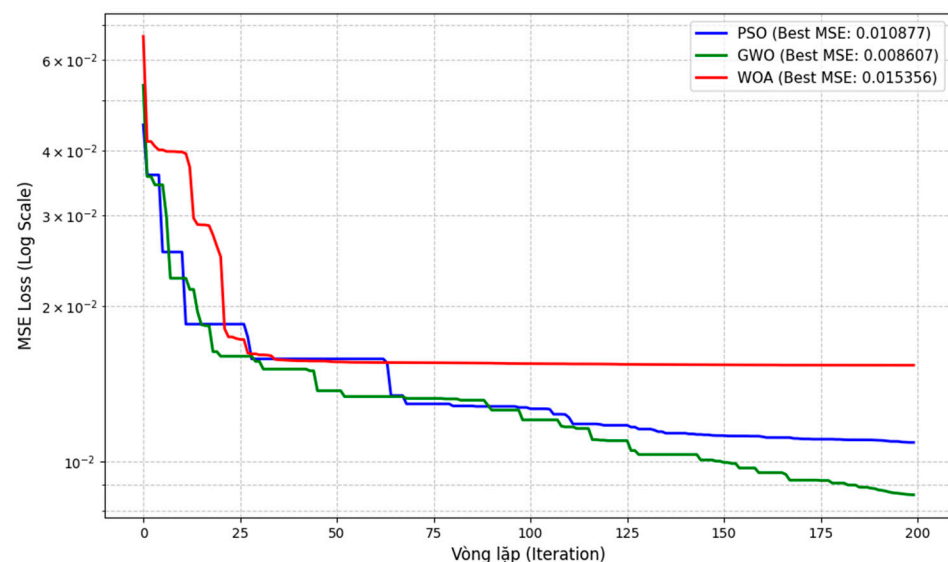


Figure 7. Convergence characteristics over 200 iterations.

Table 4. Statistical analysis of MSE over 30 independent runs.

Model	Best (Min)	Worst (Max)	Mean MSE	Std. Dev
Proposed Model 1 (PSO)	0.0109	0.0149	0.0130	0.0012
Proposed Model 2 (WOA)	0.0154	0.0678	0.0311	0.0135
Proposed Model 3 (GWO)	0.0086	0.0145	0.0108	0.0013

4.2. Forecasting Performance Comparison

To rigorously validate our proposed approach, we compared its predictive performance against standard benchmarks, including the statistical ARIMAX model and machine learning baselines such as SVR and LSTM. For these benchmarks, we ensured reproducibility through systematic parameter tuning: the ARIMAX order was determined via an automated search based on the Akaike Information Criterion (AIC) to minimize information loss, while SVR and LSTM hyperparameters were optimized using TimeSeriesSplit cross-validation (grid search). The optimal SVR configuration ($C = 100$, $\gamma = 0.1$, $\epsilon = 0.001$)

and LSTM architecture (hidden size = 32, 1 layer, $lr = 0.005$) were utilized, with all models applying a sliding window of length 3.

Table 5 presents the predictive performance metrics on the testing datasets (2022–2024). Standard ANFIS achieved an R^2 of 0.58. In comparison, both PSO-ANFIS and GWO-ANFIS significantly outperformed the standard ANFIS baseline. PSO-ANFIS achieved the best overall performance with an R^2 of 0.73 and MAPE of 4.65%, while GWO-ANFIS obtained nearly identical accuracy ($R^2 = 0.72$, MAPE = 4.65%). By contrast, WOA-ANFIS underperformed with an R^2 of only 0.45. Furthermore, the PSO-ANFIS model tightly follows the actual trend, capturing key seasonal variations most accurately. To visualize this tracking accuracy, Figure 8 compares the predictive outputs against the actual data.

Table 5. Forecasting performance on the testing set (2022–2024).

Model	RMSE (Billion kWh)	MAE (Billion kWh)	MAPE (%)	R^2
Standard ANFIS	8.26	5.94	5.53	0.58
ARIMAX	8.97	6.55	6.18	0.50
SVR	6.76	5.25	4.86	0.72
LSTM	8.28	6.45	5.69	0.55
Proposed Model 1 (PSO-ANFIS)	6.64	5.03	4.65	0.73
Proposed Model 2 (WOA-ANFIS)	9.24	6.91	6.38	0.45
Proposed Model 3 (GWO-ANFIS)	6.76	5.04	4.65	0.72

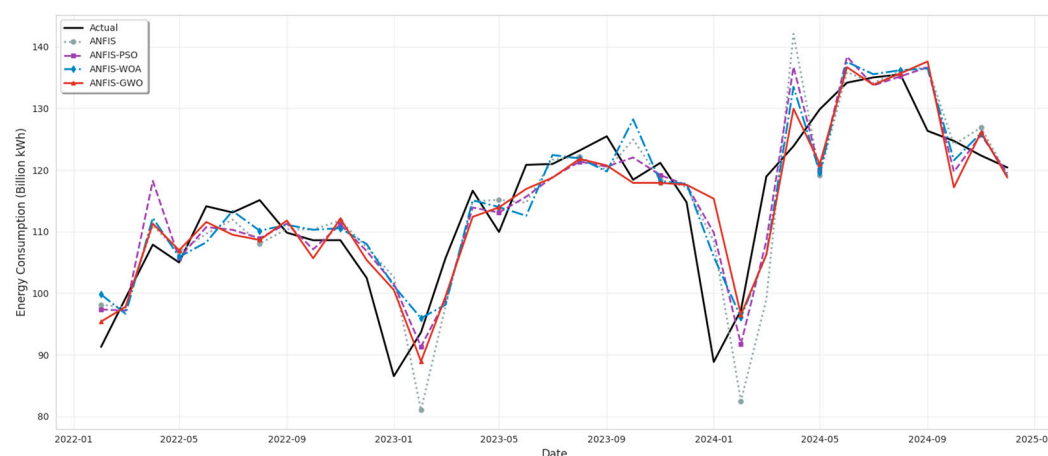


Figure 8. Predicted values vs. actual data.

To ensure a reliable performance comparison, we conducted statistical analyses over 30 independent runs. The Friedman test produced a significant result ($\chi^2 = 40$, $p = 0.000$), indicating that the three models differ significantly in performance. Pairwise Wilcoxon signed-rank tests further showed that PSO-ANFIS and GWO-ANFIS achieved statistically similar results ($W = 214.0$, $p = 0.7151$). However, PSO-ANFIS performed significantly better than WOA-ANFIS ($W = 2.0$, $p < 0.001$). This finding is also supported by Cliff's Delta analysis, where the effect size between PSO and GWO was negligible ($\delta = -0.02$), while the difference between PSO and WOA showed a large effect size ($\delta = 0.90$). Furthermore, in terms of win rate, PSO-ANFIS also outperformed WOA-ANFIS by achieving better results in 96–100% of runs across all evaluation metrics. In contrast, PSO-ANFIS and GWO-ANFIS showed highly comparable performance, with win rates ranging from only 46% to 50%, further reinforcing the statistical equivalence between the two models. Table 6 presents the mean $\pm$ std across 30 runs.

Table 6. Comparison of prediction results between different hybrid ANFIS models.

Model	RMSE (Billion kWh)	MAE (Billion kWh)	MAPE (%)	R ²
Proposed Model 1 PSO-ANFIS	6.6428 ± 0.3489	5.0280 ± 0.2034	4.6510 ± 0.2011	0.7275 ± 0.0295
Proposed Model 2 WOA-ANFIS	9.2407 ± 2.1133	6.9144 ± 1.4639	6.3795 ± 1.3188	0.4474 ± 0.2985
Proposed Model 3 GWO-ANFIS	6.7553 ± 0.4357	5.0426 ± 0.2840	4.6482 ± 0.2588	0.7178 ± 0.0373

Although the Wilcoxon test suggests statistical equivalence in mean performance between PSO-ANFIS and GWO-ANFIS, a deeper stability analysis reveals that PSO-ANFIS is the more robust candidate. As shown in Table 7, PSO-ANFIS consistently achieved the lowest Coefficient of Variation (CV) across all metrics (ranging from 4.05% to 5.25%), which is more stable than GWO-ANFIS (5.63% to 6.45%). Furthermore, the Interquartile Range (IQR) for PSO-ANFIS is narrower (e.g., MAE IQR of 0.23 vs. 0.26 for GWO), indicating a higher density of high-quality predictions. Given its superior consistency and lower risk of performance fluctuations, PSO-ANFIS is selected as the optimal model for deployment.

Table 7. Stability analysis of hybrid ANFIS models across 30 times.

Model	IQR			CV (%)		
	MAE	MAPE	RMSE	MAE	MAPE	RMSE
Proposed Model 1 PSO-ANFIS	0.23	0.26	0.42	4.05	4.32	5.25
Proposed Model 2 WOA-ANFIS	1.71	1.42	2.10	21.17	20.67	22.87
Proposed Model 3 GWO-ANFIS	0.26	0.26	0.36	5.63	5.57	6.45

Following its selection as the most robust candidate, residual diagnostics were performed to further validate the PSO-ANFIS model (Figure 9). A Durbin–Watson statistic of 2.41 (close to 2.0) indicates no significant auto-correlation in the residuals, ensuring their independence. Furthermore, the Shapiro–Wilk test indicates that residual distribution remains within acceptable bounds, with no systematic bias detected. These diagnostic results confirm that the model satisfies the key assumptions required for reliable forecasting.

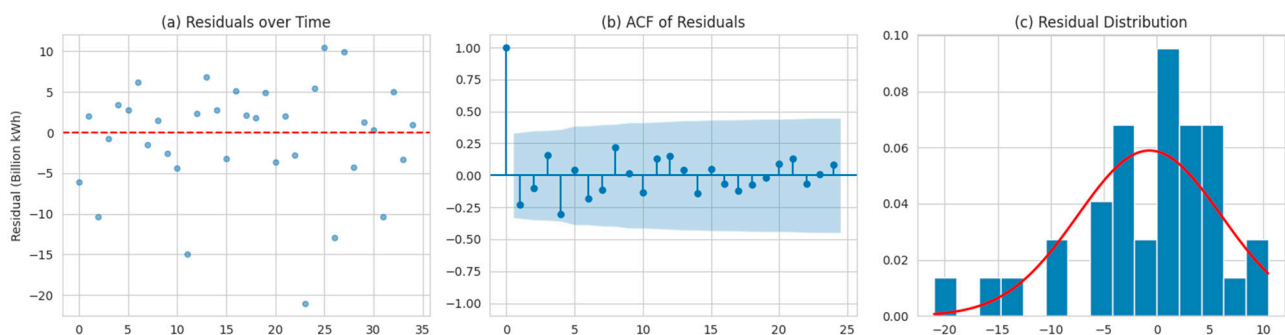


Figure 9. Residual diagnostic plots for the PSO-ANFIS model: (a) residuals over time showing random distribution; (b) Auto-Correlation Function (ACF) plot confirming independence; (c) histogram of residual distribution with a fitted normal curve.

4.3. Future Energy Demand

4.3.1. Input Scenario Construction

Due to the lack of official forecasts for 2025–2030, we generated future IIP and FDI inputs using a two-step simulation. First, annual values were projected using CAGR

under three scenarios: low (3.5%), base (6.0%), and high (8.0%)—which were derived from historical growth patterns, including past average and peak performance. Second, we applied the Denton–Cholette method to convert these annual figures into monthly data. By using 2024 as a seasonal reference, this approach preserves historical patterns, ensuring the inputs reflect realistic economic dynamics rather than simple linear trends. It is acknowledged that relying on fixed CAGR values is a limitation of this simulation, as it may not fully capture sudden macroeconomic shocks. However, within the medium-term horizon (5 years), this method provides a stable baseline for the ANFIS model to demonstrate its predictive capability.

Visual inspection confirmed that the Denton method successfully preserved the structural characteristics of the historical data. The generated input series logically maintained the seasonal patterns while firmly adhering to the long-term upward growth trends defined by the macroeconomic CAGR scenarios.

4.3.2. Short-Term Forecasting Results

To validate the model’s applicability for short-term operational planning and grid management, we examined the monthly forecasting results for the year 2026. As observed, the forecasted demand showed a clear seasonal pattern consistent with Vietnam’s climatic characteristics. Under the base scenario, consumption starts at its lowest in January (133.29 billion kWh) and rises steadily, reaching a peak in June (172.70 billion kWh) due to high cooling loads during the summer, before gradually stabilizing towards the end of the year. This specific range provides grid operators with a quantifiable margin of safety for capacity planning.

4.3.3. Long-Term Forecasting Results

To provide a comprehensive outlook for national energy security and strategic policy-making, we extended the forecasting horizon to 2030. The aggregated annual results under three scenarios are detailed in Table 8.

Table 8. Projected total annual energy consumption (2026–2030) (unit: billion kWh).

Year	Low	Base	High
2026	1923.70	1929.20	1931.69
2027	2191.61	2217.74	2224.24
2028	2447.90	2511.74	2533.77
2029	2694.99	2807.25	2850.02
2030	2943.91	3108.38	3179.10

The results show a clear increase in energy demand driven by economic growth. In the base scenario, total consumption is expected to rise from 1929.20 billion kWh in 2026 to 3108.38 billion kWh in 2030. The gap between the low and high scenarios gets wider over time, reflecting the uncertainty of future economic conditions. It is crucial to note that while these fixed CAGR assumptions (3.5%, 6%, and 8%) provide structured baseline trajectories aligned with national development targets, they do not explicitly account for unpredictable exogenous shocks. These deterministic scenarios cannot perfectly anticipate sudden extreme volatility in international energy markets, abrupt macroeconomic crises, or radical shifts in environmental policies. Therefore, these projections should be interpreted as strategic reference points rather than absolute forecasts.

Furthermore, it is essential to clarify that the forecasted values in this study represent total primary energy consumption—encompassing all energy carriers, such as petroleum products, coal, natural gas, and biomass—rather than Commercial Electricity Output alone. This distinction is important when comparing these results with national benchmarks. For

instance, Vietnam's Power Development Plan VIII (PDP8) projects a Commercial Electricity Output of 505.2 billion kWh by 2030 [1]. The significantly higher figures in our base scenario (3108.38 billion kWh) account for direct energy use in transportation, heavy industry, and heating, alongside system-wide conversion inefficiencies and transmission losses (typically estimated at 8–10% of generated electricity). Therefore, these projections are consistent with the broader total energy demand trajectories reported by international agencies for Vietnam's industrializing economy.

To further illustrate the forecasting behavior, Figure 10 presents the transition from historical observations (2023–2024) to future monthly forecasts (2025–2030). The forecast curve connects smoothly with the historical data at the beginning of 2025, indicating stable model continuity. Moreover, as energy demand increases over time, seasonal fluctuations become more pronounced. Overall, the model successfully captures long-term growth trends while preserving realistic seasonal patterns observed in the historical data.



Figure 10. Seamless transition of monthly energy forecasts from historical observations (2023–2024) to future scenarios (2025–2030).

5. Conclusions

This study successfully developed a comprehensive forecasting framework for Vietnam's energy demand. First, by applying the Denton method, we effectively addressed the scarcity of high-frequency data, transforming annual statistics into a robust monthly datasets. Then, we developed a hybrid model by integrating ANFIS with meta-heuristic optimization algorithms (PSO, GWO, and WOA). The experimental results demonstrate that PSO-ANFIS is the superior model overall, achieving the highest R^2 (0.73) and the lowest MAPE (4.65%) on the test set while also demonstrating the best stability across 30 independent runs (Std. Dev = 0.0012, CV $\approx$ 4–5%). GWO-ANFIS achieved comparable accuracy but exhibited higher variability. WOA-ANFIS showed the weakest and most inconsistent performance.

Using the optimal PSO-ANFIS model, we projected energy consumption for the 2026–2030 period under three growth scenarios. The forecast indicates a significant upward trend, with total demand in the base scenario reaching 3108.38 billion kWh by 2030. Importantly, the model accurately captures complex seasonal variations, including summer peaks and holiday reductions, ensuring realistic and practical projections.

These findings provide a scientific basis for energy policy-making. The proposed model offers a robust tool for grid operators and authorities to plan for capacity expansion, ensuring national energy security amidst rapid economic growth. Despite the robust predictive performance of the proposed framework, this study acknowledges certain methodological limitations. Primarily, the 192-month dataset generated via the Denton method constitutes synthetic (pseudo-monthly) data rather than truly observed high-frequency

records. This inherently introduces potential risks of error propagation, where initial disaggregation biases could cascade into the forecasting phase. Furthermore, it presents a risk of the neuro-fuzzy model overfitting to mathematically generated variance rather than actual physical economic behaviors. While these risks were actively mitigated in this study by anchoring the disaggregation to a highly correlated reference indicator ($r = 0.9974$) and employing strict out-of-sample validation, these constraints should be noted.

Future work should aim to validate and fine-tune this framework using ground-truth high-frequency macroeconomic datasets as they become officially available. Additionally, future studies could extend this framework by incorporating renewable energy factors or external climate variables to further enhance long-term forecasting precision.

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References

1. Prime Minister of Vietnam Decision No. 500/QĐ-TTg: Approving the National Power Development Plan for 2021–2030, with a Vision to 2050; Government of Vietnam: Hanoi, Vietnam, 2023.
2. Jang, J.-S.R. ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Trans. Syst. Man Cybern.* **1993**, *23*, 665–685. [\[CrossRef\]](#)
3. Lin, Z. A Hybrid CNN-LSTM-Attention Model for Electric Energy Consumption Forecasting. In *Proceedings of the 2023 5th Asia Pacific Information Technology Conference*; ACM: New York, NY, USA, 2023; pp. 167–173.
4. Ngo, N.-T.; Truong, T.T.H.; Truong, N.-S.; Pham, A.-D.; Huynh, N.-T.; Pham, T.M.; Pham, V.H.S. Proposing a Hybrid Metaheuristic Optimization Algorithm and Machine Learning Model for Energy Use Forecast in Non-Residential Buildings. *Sci. Rep.* **2022**, *12*, 1065. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Wen, X.; Liao, J.; Niu, Q.; Shen, N.; Bao, Y. Deep Learning-Driven Hybrid Model for Short-Term Load Forecasting and Smart Grid Information Management. *Sci. Rep.* **2024**, *14*, 13720. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Jang, J.; Kim, B.; Kim, I. Comparative Analysis of Deep Learning Techniques for Load Forecasting in Power Systems Using Single-Layer and Hybrid Models. *Int. Trans. Electr. Energy Syst.* **2024**, *2024*, 5587728. [\[CrossRef\]](#)
7. Lee, M.; Ser, Y.; Selvachandran, G.; Thong, P.; Cuong, L.; Son, L.; Tuan, N.; Gerogiannis, V. A Comparative Study of Forecasting Electricity Consumption Using Machine Learning Models. *Mathematics* **2022**, *10*, 1329. [\[CrossRef\]](#)
8. Blancas, J.; Noel, J. Short-Term Load Forecasting Using Fuzzy Logic. In *2018 IEEE PES Transmission & Distribution Conference and Exhibition-Latin America (T&D-LA)*; IEEE: Piscataway, NJ, USA, 2018; pp. 1–5.
9. Oladipo, S.; Sun, Y.; Amole, A.O. Investigating the Influence of Clustering Techniques and Parameters on a Hybrid PSO-Driven ANFIS Model for Electricity Prediction. *Discov. Appl. Sci.* **2024**, *6*, 265. [\[CrossRef\]](#)
10. Jalaei, M.S.; GhasemiNejad, A.; Jalaei, S.A.; Amani Zarin, N.; Derakhshani, R. A Novel Hybrid Artificial Intelligence Approach to the Future of Global Coal Consumption Using Whale Optimization Algorithm and Adaptive Neuro-Fuzzy Inference System. *Energies* **2022**, *15*, 2578. [\[CrossRef\]](#)
11. Mirboluki, A.; Mehraein, M.; Kisi, O. Improving Accuracy of Neuro Fuzzy and Support Vector Regression for Drought Modelling Using Grey Wolf Optimization. *Hydrol. Sci. J.* **2022**, *67*, 1582–1597. [\[CrossRef\]](#)
12. Sax, C.; Steiner, P. Temporal Disaggregation of Time Series. *R J.* **2013**, *5*, 80–87. [\[CrossRef\]](#)
13. Mbasso, W.F.; Farh, H.M.H.; Harrison, A.; Al-Shamma’a, A.A. Strategic Renewable Energy Forecasting and Monthly Disaggregation in Data-Scarce Regions: A Cross-Continental SARIMA-Based Framework for Policy Planning. *Stoch. Environ. Res. Risk Assess.* **2025**, *39*, 6075–6108. [\[CrossRef\]](#)

14. Denton, F.T. Adjustment of Monthly or Quarterly Series to Annual Totals: An Approach Based on Quadratic Minimization. *J. Am. Stat. Assoc.* **1971**, *66*, 99–102. [\[CrossRef\]](#)
15. Takagi, T.; Sugeno, M. Fuzzy Identification of Systems and Its Applications to Modeling and Control. *IEEE Trans. Syst. Man Cybern.* **1985**, *SMC-15*, 116–132. [\[CrossRef\]](#)
16. Kennedy, J.; Eberhart, R. Particle Swarm Optimization. In *Proceedings of ICNN'95—International Conference on Neural Networks*; IEEE: Piscataway, NJ, USA, 1995; Volume 4, pp. 1942–1948.
17. Mirjalili, S.; Mirjalili, S.M.; Lewis, A. Grey Wolf Optimizer. *Adv. Eng. Softw.* **2014**, *69*, 46–61. [\[CrossRef\]](#)
18. Mirjalili, S.; Lewis, A. The Whale Optimization Algorithm. *Adv. Eng. Softw.* **2016**, *95*, 51–67. [\[CrossRef\]](#)
19. Chai, T.; Draxler, R.R. Root Mean Square Error (RMSE) or Mean Absolute Error (MAE)?—Arguments against Avoiding RMSE in the Literature. *Geosci. Model Dev.* **2014**, *7*, 1247–1250. [\[CrossRef\]](#)
20. Willmott, C.J.; Matsuura, K. Advantages of the Mean Absolute Error (MAE) over the Root Mean Square Error (RMSE) in Assessing Average Model Performance. *Clim. Res.* **2005**, *30*, 79–82. [\[CrossRef\]](#)
21. Lewis, C.D. *Industrial and Business Forecasting Methods: A Practical Guide to Exponential Smoothing and Curve Fitting*; Butterworth-Scientific: London, UK, 1982.
22. Chicco, D.; Warrens, M.J.; Jurman, G. The Coefficient of Determination R-Squared Is More Informative than SMAPE, MAE, MAPE, MSE and RMSE in Regression Analysis Evaluation. *PeerJ Comput. Sci.* **2021**, *7*, e623. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Friedman, M. The Use of Ranks to Avoid the Assumption of Normality Implicit in the Analysis of Variance. *J. Am. Stat. Assoc.* **1937**, *32*, 675–701. [\[CrossRef\]](#)
24. Wilcoxon, F. Individual Comparisons by Ranking Methods. *Biom. Bull.* **1945**, *1*, 80–83. [\[CrossRef\]](#)
25. Cliff, N. Dominance Statistics: Ordinal Analyses to Answer Ordinal Questions. *Psychol. Bull.* **1993**, *114*, 494–509. [\[CrossRef\]](#)
26. Durbin, J.; Watson, G.S. Testing for Serial Correlation in Least Squares Regression. I. *Biometrika* **1950**, *37*, 409–428. [\[CrossRef\]](#)
27. Shapiro, S.S.; Wilk, M.B. An Analysis of Variance Test for Normality (Complete Samples). *Biometrika* **1965**, *52*, 591–611. [\[CrossRef\]](#)
28. Ritchie, H.; Rosado, P. *Energy*; Our World Data: Oxford, UK, 2025.
29. Ministry of Industry and Trade of Vietnam (MOIT). *Report on Power Production and Business Activities*; Ministry of Industry and Trade of Vietnam (MOIT): Hanoi, Vietnam, 2024.
30. General Statistics Office of Vietnam. *Statistical Data: Index of Industrial Production (IIP)*; General Statistics Office of Vietnam: Hanoi, Vietnam, 2024.
31. Ministry of Planning and Investment (MPI). *Situation of Foreign Direct Investment (FDI) in Vietnam*; Ministry of Planning and Investment (MPI): Hanoi, Vietnam, 2024.
32. Dickey, D.A.; Fuller, W.A. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica* **1981**, *49*, 1057–1072. [\[CrossRef\]](#)

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