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Electricity Load Forecasting Using a Hybrid Artificial Neural Network and PSO Approach

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Abstract: *Electricity demand forecasting is crucial for effective energy management, particularly in regions with unique consumption patterns like Palangkaraya. This study explores the application of Artificial Neural Networks (ANN) enhanced by Particle Swarm Optimization (PSO) to improve forecasting accuracy. While traditional ANN models offer robust capabilities for handling nonlinear data, their performance is often limited by the challenge of identifying optimal model parameters. By integrating PSO, this research aims to refine parameter selection, thereby enhancing the predictive precision of the ANN model. The study compares the performance of the standalone ANN model and the ANN-PSO hybrid model. Results demonstrate that the ANN-PSO model significantly outperforms the standard ANN, achieving a Mean Absolute Percentage Error (MAPE) reduction from 10.34% to 3.05%, and Root Mean Square Error (RMSE) improvement from 1,061,485.57 to 366,879.94. These findings underscore the capability of the ANN-PSO approach to better capture the intricate patterns in electricity consumption data. The proposed model adapts effectively to the localized energy consumption characteristics in Palangkaraya, offering actionable insights for energy planners. By leveraging the strengths of both ANN and PSO, this research contributes to the development of more accurate and reliable forecasting tools, paving the way for optimized energy management strategies.*

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INTRODUCTION

Electricity demand forecasting is crucial for effective energy management, particularly in regions with unique consumption patterns like Palangkaraya. This study explores the application of Artificial Neural Networks (ANN) enhanced by Particle Swarm Optimization (PSO) to improve forecasting accuracy. While traditional ANN models offer robust capabilities for handling nonlinear data, their performance is often limited by the challenge of identifying optimal model parameters. By integrating PSO, this research aims to refine parameter selection, thereby enhancing the predictive precision of the ANN model. The study compares the performance of the standalone ANN model and the ANN-PSO hybrid model. Results demonstrate that the ANN-PSO model significantly outperforms the standard ANN, achieving a Mean Absolute Percentage Error (MAPE) reduction from 10.34% to 3.05%, and Root Mean Square Error (RMSE) improvement from 1,061,485.57 to 366,879.94. These findings underscore the capability of the ANN-

PSO approach to better capture the intricate patterns in electricity consumption data. The proposed model adapts effectively to the localized energy consumption characteristics in Palangkaraya, offering actionable insights for energy planners. By leveraging the strengths of both ANN and PSO, this research contributes to the development of more accurate and reliable forecasting tools, paving the way for optimized energy management strategies. The rapid population growth in Palangkaraya has led to a significant increase in electricity demand, particularly in the household sector, where consumption patterns are dynamic and exhibit high variability. Peak usage typically occurs during evening hours, but electricity consumption remains relatively high throughout the day, presenting challenges in maintaining a stable and sufficient power supply.

Despite efforts by the local utility company (PLN) to forecast electricity demand, the complex and nonlinear nature of household energy usage necessitates advanced and highly accurate predictive models to support effective energy planning. The inability to account for these nonlinear consumption patterns can lead to inefficiencies in electricity distribution and planning, potentially resulting in underutilization of resources or energy shortages during critical periods. This not only impacts the quality of life for residents but also threatens the functionality of key economic sectors that rely heavily on a stable electricity supply. Artificial Neural Networks (ANNs), which mimic the structure and behavior of biological neural systems, have demonstrated considerable promise in forecasting electricity demand due to their ability to model complex and nonlinear relationships.

However, while ANNs can capture intricate consumption patterns, achieving the highest level of forecasting accuracy requires precise tuning of their parameters. Without proper optimization, even advanced ANN models may fall short in providing the level of precision needed for robust electricity demand planning. To address these challenges, there is a clear need for an advanced forecasting model that integrates ANNs with optimization techniques. Particle Swarm Optimization (PSO), inspired by the social behavior of particle swarms, offers a powerful approach for enhancing ANN performance. By leveraging PSO’s ability to efficiently search for optimal parameter configurations, this integration aims to deliver a highly accurate and reliable model for forecasting household electricity consumption in Palangkaraya. This improved forecasting capability is critical for ensuring sustainable energy planning, optimal resource allocation, and economic resilience in the region.

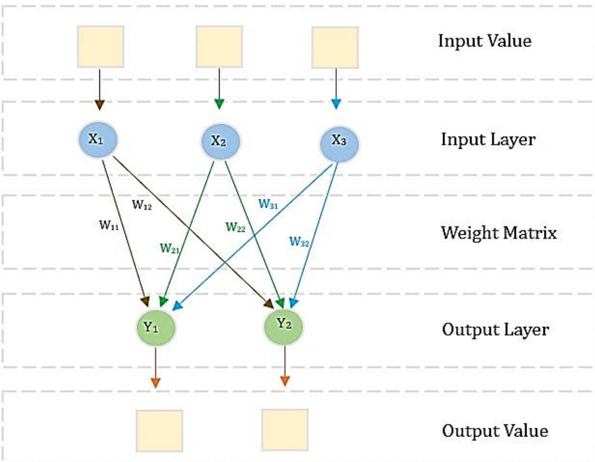
The primary objective of this research is to minimize forecasting errors in electricity consumption predictions by developing an enhanced forecasting model that integrates Artificial Neural Networks (ANNs) with Particle Swarm Optimization (PSO). This integration aims to address the challenges posed by the dynamic and nonlinear consumption patterns observed in the household sector of Palangkaraya. By leveraging the robust pattern-recognition capabilities of ANNs and the efficient optimization potential of PSO, the proposed model seeks to deliver precise and reliable electricity demand predictions, thereby supporting effective energy planning and resource allocation. This research contributes to the field of energy forecasting by advancing the application of hybrid predictive models. Specifically, to enhanced accuracy which the integration of PSO into ANN-based forecasting offers a novel approach to fine-tune model parameters, significantly reducing prediction errors compared to standalone ANN models. Also, the strategic energy planning, by providing more accurate demand forecasts, the research facilitates more efficient energy distribution and resource allocation, mitigating the risk of power shortages and ensuring sustainable energy management.

LITERATURE REVIEW

Electricity demand forecasting is a critical aspect of energy management, ensuring the efficient distribution and supply of electricity while minimizing operational costs. Various forecasting methods have been developed to predict future electricity consumption, utilizing both traditional statistical models and advanced machine learning techniques. Statistical Models for example ARIMA (Auto-Regressive Integrated Moving Average) and Exponential Smoothing, have been widely used for short-term electricity demand forecasting. These models rely on historical data and trends to make predictions. While these methods are effective for relatively stable demand patterns, they often struggle when dealing with complex, nonlinear behaviors or sudden shifts in consumption. Machine Learning Models such as with the advancement of technology, machine learning (ML) methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees have gained prominence in electricity demand forecasting. These models are capable of handling large datasets and can capture intricate patterns in the data, making them more adaptable to fluctuating demand. However, they often require large volumes of data for training and can be computationally expensive. Hybrid methods that combine the strengths of both statistical models and machine learning techniques are also emerging.

Artificial Neural Networks (ANN)

ANNs are computational models inspired by the human brain's structure and function. They are capable of learning complex patterns and relationships from data. The basic structure of an artificial neural network consists of an input layer, a hidden layer, and an output layer.



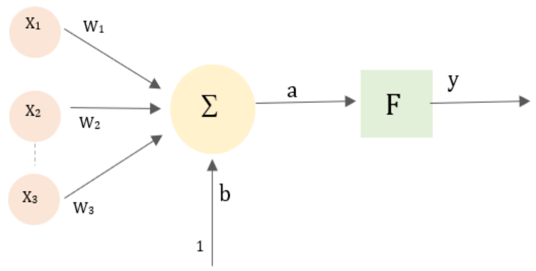
Picture 1. Artificial Neural Networks (ANN)

The functionality of the neural network relies on three key aspects:

a. Connections Between Neurons: Represented as inputs containing information required by the neural network model to arrive at a solution.
b. Training and Learning: This involves computational processes where data is processed

to identify patterns. The model is continuously updated until one of the criteria—number of iterations, error threshold, or processing time is met.

c. Activation Function: This plays a role in activating or deactivating inputs to the neurons. It calculates the inputs and weights, producing the output for the next layer



Picture 2. Activation Function

In the context of wind farm optimization, ANNs are used to predict wake effects and optimize turbine positions by leveraging historical wind data. This results in increased power output and reduced overall turbine count, making the wind farm layout more efficient and sustainable (Wei et al., 2023); (Pareek et al., 2021); (Yadav & Roy, 2023)

ANNs are computational models inspired by the human brain's structure and function. They consist of interconnected nodes called neurons, organized into layers: an input layer, one or more hidden layers, and an output layer. Each neuron processes input data by applying an activation function and then passes the result to the neurons in the next layer. During training, the network adjusts its internal parameters (weights) using optimization algorithms, such as gradient descent, to minimize the difference between its output and the desired output, improving performance over time. (Tarmanini et al., 2023a) (Mateo-Barcos et al., 2024).

Application of ANN in Electricity Demand Forecasting: Pattern Recognition: ANNs can recognize complex patterns in historical electricity consumption data, including daily, weekly, and seasonal trends.

Nonlinear Relationships: They can model nonlinear relationships between various factors affecting electricity demand, such as weather conditions, economic activities, and population growth.

Adaptive Learning: ANNs can adapt to changes in consumption patterns over time, making them suitable for dynamic environments where demand fluctuates. High Accuracy: By learning from large datasets, ANNs can provide highly accurate forecasts, which are crucial for efficient energy management and planning.

Real-time Forecasting: ANNs can be used for real time demand forecasting, helping utility companies to balance supply and demand effectively and reduce operational costs (Dostmohammadi et al., 2024) (Yadav & Roy, 2023), (Pareek et al., 2021)

Particle Swarm Optimization (PSO)

PSO is a computational optimization technique inspired by the social behavior of birds flocking or fish schooling. It is a population-based algorithm where each individual, called a particle, represents a potential solution to the optimization problem.

These particles move through the solution space to find the optimal solution by adjusting their positions based on their own experience and the experience of neighboring particles (El Jaadi et al., 2024), (Yadav & Roy, 2023).

Role of PSO in Optimization Problems: Exploration and Exploitation: PSO balances exploration (searching new areas of the solution space) and exploitation (refining known good solutions) to efficiently find the optimal solution.

Adaptability: PSO can adapt to various types of optimization problems, including continuous, discrete, and multi-objective problems. Simplicity: The algorithm is simple to implement and requires few parameters to adjust, making it accessible for a wide range of applications. Convergence: PSO tends to converge quickly to a good solution, making it suitable for real-time and dynamic optimization problems (Ofori-Ntow Jnr & Ziggah, 2023).

The role of PSO in optimization problems is multifaceted, making it a powerful tool for addressing a variety of challenges. For instance:

- Exploration and Exploitation: PSO effectively balances exploration, which involves searching unexplored areas of the solution space, and exploitation, which refines and enhances existing promising solutions. This dual capability allows it to efficiently navigate complex problem spaces.
- Adaptability: The algorithm is highly flexible and can be applied to a wide range of optimization problems, including continuous, discrete, and multi-objective scenarios, showcasing its versatility across domains.
- Simplicity: PSO is straightforward to implement and requires minimal parameter tuning, making it an accessible and practical choice for researchers and practitioners alike.
- Efficient Convergence: With its inherent ability to converge quickly to near-optimal solutions, PSO is particularly suitable for time-sensitive or dynamic optimization tasks, such as real-time forecasting or scheduling.

The reviewed studies demonstrate a wide application of various forecasting and optimization techniques, including ANN, PSO, and other hybrid methods, to energy management and prediction. However, several gaps remain evident such as limited application of ANN-PSO for Electricity Demand Forecasting in Specific Contexts, while ANN and PSO have been successfully combined for tasks such as aeration efficiency prediction (Yadav et al., 2023) and seed cell optimization (Pareek et al., 2021), their use for electricity demand forecasting, particularly in regions with unique energy consumption patterns like Palangkaraya, remains underexplored. Most studies focus on general energy forecasting or specific energy sources like wind (Mariam el Jaadii et al., 2024) or solar (Mahmood Abdoos et al., 2025). Other studies such as those by (Chafak Tarmanini et al., 2023) and (Florencia Lazzari et al., 2022) use ANN for short-term electricity forecasting but lack adaptation to regional consumption behaviors or unique socio-economic factors, which are critical for accurate demand prediction in localized setting. Emerging methods such as DRL-CNN (Antonio Corte et al., 2024) and hybrid LSTM-ANN-GPR-VAR models (Yu Yang et al., 2023) emphasize increasing forecasting accuracy. However, the direct comparison of ANN-PSO models with these advanced hybrid techniques to highlight relative strengths and weaknesses is limited.

While some studies focus on short-term forecasting (Bilal Abu et al., 2022; Chafak Tarmanini et al., 2023), there is a lack of research integrating ANN-PSO for long-term demand forecasting, especially considering changing electricity consumption trends over extended periods. Although optimization techniques such as PSO have been explored in energy contexts, their potential for further integration with feature extraction methods (Eric Ofuri et al., 2023) or adaptive metaheuristics (Wei et al., 2023) in electricity demand forecasting remains underutilized. Few studies, such as those by (Loris A. et al. ,2021), link their findings to actionable insights for energy policymakers. The current study addresses these gaps by focusing on electricity demand forecasting in Palangkaraya, a less-studied region and combining ANN with PSO to enhance predictive accuracy.

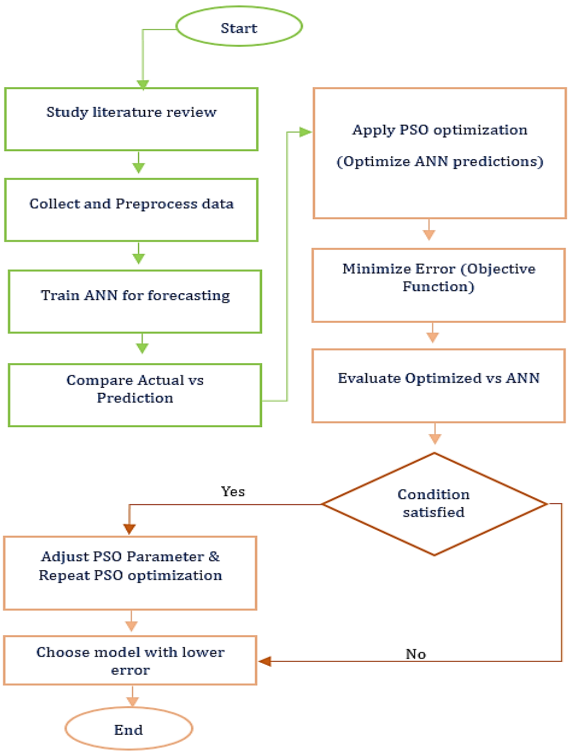
METHODOLOGY

The methodology involves training an Artificial Neural Network (ANN) on historical electricity demand data to generate initial predictions. These predictions are then compared with actual values, and the prediction errors are calculated.

To improve the accuracy of the model, Particle Swarm Optimization (PSO) is applied to minimize these errors by optimizing the ANN's parameters, such as weights and biases.

After applying PSO, the ANN is re-trained with the optimized parameters, and the new predictions are evaluated against the original ANN model.

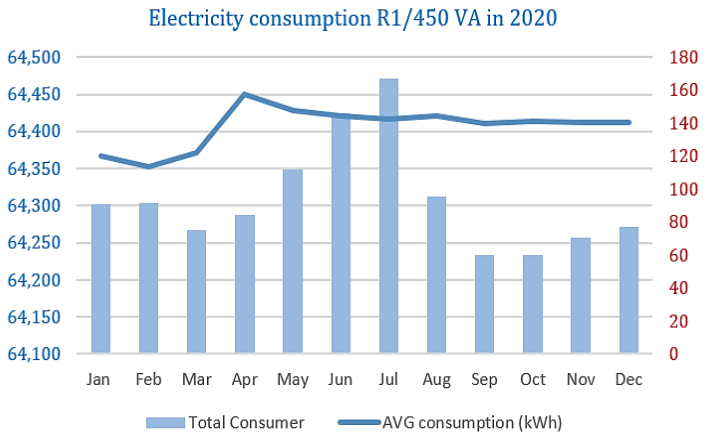
The performance improvement is assessed by comparing the prediction errors before and after optimization, demonstrating the effectiveness of combining ANN and PSO in enhancing forecasting precision.



Picture 3. Demonstrating the Effectiveness

RESULTS AND DISCUSSION

Data as figured in graph 1.1 as training data and data as figured 1.2 as testing data and the source is from PLN Palangkaraya.



Graph 1.1 Data source PLN Palangkaraya
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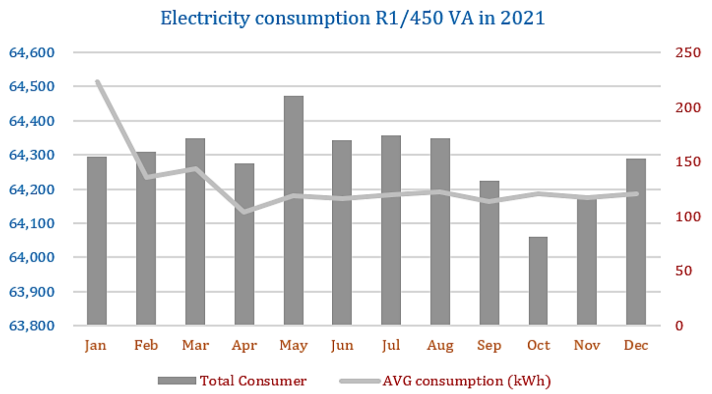

Graph 1.2 Data source PLN Palangkaraya
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Artificial Neural Network (ANN) Framework

This study used a feed-forward backpropagation neural network (FFBP) in MATLAB to predict monthly electricity consumption.

a. Structure: The network had two layers: a hidden layer with 5 neurons and an output layer. The input was historical electricity consumption, and the output was the predicted consumption for the next 12 months.
b. Activation Functions:
Hidden Layer: tansig (hyperbolic tangent sigmoid), mapping inputs between -1 and 1 to capture non-linear patterns. Output Layer: Linear activation for continuous value prediction.
c. Training Parameters:
TRAINLM: Levenberg-Marquardt optimization for fast convergence.
LEARNGDM: Gradient descent with momentum for weight updates. Performance Metric: Mean Squared Error (MSE).

On ANN simulation process using normalization to reduce the scale of data without losing the original characteristic with formula as follows:

$$X' = 0.8 * \frac{(X - a)}{(b - a)} + 0.1$$

X': Normalized data for binary sigmoid
X: Initial data
a: Initial minimum value
b: Initial maximum value

Particle Swarm Optimization (PSO) Integration

Particle representation as set of adjusted predictions:

$$x_i = \left[y_{PSO,1}, y_{PSO,2}, \dots, y_{PSO,12}\right]$$

Velocity update of each particle as

$$v_i(t+1) = w.v_i(t) + c_1 * r_1 * \left(p_{best,i} - x_i(t)\right) + c_2 * r_2 * \left(g_{best} - x_i(t)\right)$$

r_1, r_2 : Random numbers in [0,1].
$p_{best,i}$, : Best position of particle i.
g_{best}, : Best position found by the swarm.

Particle initialization for each represents as a potential solution that initialized as slightly version of initial prediction and velocity vectors are randomly initialized to dictate how particles move through the solution space.

Position update: $x_i(t+1) = x_i(t) + v_i(t+1)$ which updated position are clipped to $\mathrm{x_i(t+1)} \in [7.000.000, 10.000.000]$.

The fitness of each particle is using MSE with constraints function this shows the measure of MSE between particle's prediction and actual values.

For updating personal and global best each particle tracks its own best solution based on its fitness and the swarm tracks globally best solution with the lowest fitness across all the particles.

Over the iterations (T=100), particles converge to the global best position, representing an optimized set of predictions that minimize MSE under the constraints.

Objective Function and Constraints

The objective is to minimize the prediction error of an Artificial Neural Network (ANN) using Particle Swarm Optimization (PSO). The error is quantified as Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE).

Objective function:

$$f(y_{PSO}) = MSE\ (y_{PSO}, y_{actual}) + Penalty$$

Where:

$$MSE(y_{PSO}, y_{actual}) = \frac{1}{n}\sum_{i=1}^{n}(y_{PSO,i} - y_{actual,i})^2$$

When the penalty is applied if any prediction violates the error constraint:

$$Penalty = \begin{cases} 0 & if\ maximum\left(\left|y_{PSO,i} - y_{actual,i}\right|\right) \le 0.01 * y_{actual,i,}, \forall i \\ 10^{10} & otherwise \end{cases}$$

Constraints

Prediction is bounded $7.000.000 \leq y_{PSO,i} \leq 10.000000 \quad \forall i$
Maximum error which is allowed $|y_{PSO,i} - y_{actual,i}| \leq 0.01 * y_{actual,i,}, \forall i$
PSO parameters
Number of particles (n_p): 30
Iterations (T): 100 as stopping criteria.
Inertia weight (w):0.5 to control the particle's tendency to continue moving in its current direction.

Weight for a particle's own best position and weight for the swarm's best position represents as c_1 *and* c_2.
Cognitive coefficient (c_1): 1.6
Social coefficient (c_2): 2.0
3.5 Performance Metrics

Optimized predictions (y_{PSO}) which represent the predictions after minimizing error. Performance metrics used to evaluate model performance
Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE)

$$MSE: \frac{1}{12}\sum_{i=1}^{12}\left(y_{PSO,i} - y_{actual,i}\right)^2$$

$$MAPE: \frac{1}{12}\sum_{i=1}^{12}\frac{|y_{PSO,i} - y_{actual,i}|}{y_{actual,i}} * 100$$

Error improvements for each month: $|y_{initial,i} - y_{actual,i}| - |y_{PSO,i} - y_{actual,i}|$
evaluating prediction accuracy:

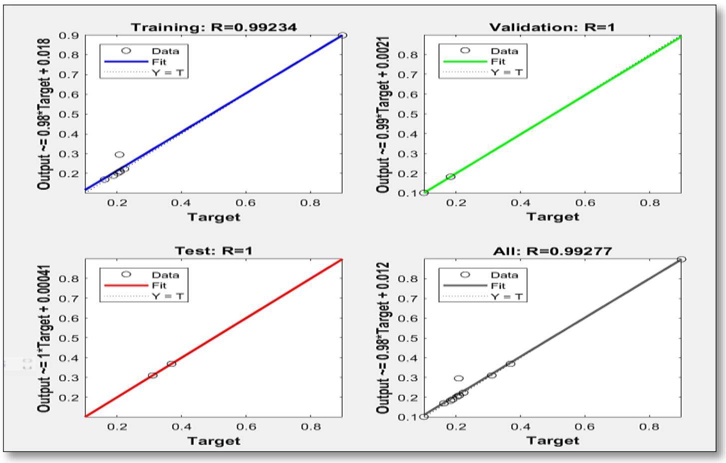
- < 10%: Very good forecasting accuracy. Predictions are highly accurate and acceptable for most applications.
- 10% - 20%: Good forecasting accuracy.
  Predictions are reliable but may have slight deviations; still useful for decision-making.
- 20% - 50%: Reasonable but requires improvement.
  Forecasting accuracy is moderate, and the model may need refinement or additional data.
- 50%: Poor forecasting accuracy.
  Predictions are highly inaccurate and not suitable for practical use; significant changes to the model or method are required.

The experimental setup involves using MATLAB for training the Artificial Neural Network (ANN) and Python for implementing the Particle Swarm Optimization (PSO) algorithm. The ANN was trained to predict 12 months of electricity consumption based on historical data. PSO with Python that the initial predictions from the trained ANN were optimized using PSO implemented in Python and the PSO algorithm aimed to minimize MSE with error constraints. Optimization was performed with 30 particles over 100 iterations to refine the predictions further.

Model Performance

Table 1. Data Electricity Consumption to simulate using ANN in MATLAB

Period	1	2	3	4	5	6	7	8	9	10	11	12
1	0.2192	0.1	0.2526	0.9	0.7268	0.663	0.6307	0.6604	0.5731	0.5967	0.5845	0.5917
2	0.1	0.2526	0.9	0.7268	0.663	0.6307	0.6604	0.5731	0.5967	0.5845	0.5917	0.9
3	0.2526	0.9	0.7268	0.663	0.6307	0.6604	0.5731	0.5967	0.5845	0.5917	0.9	0.3106
4	0.9	0.7268	0.663	0.6307	0.6604	0.5731	0.5967	0.5845	0.5917	0.9	0.3106	0.3689
5	0.7268	0.663	0.6307	0.6604	0.5731	0.5967	0.5845	0.5917	0.9	0.3106	0.3689	0.1
6	0.663	0.6307	0.6604	0.5731	0.5967	0.5845	0.5917	0.9	0.3106	0.3689	0.1	0.2028
7	0.6307	0.6604	0.5731	0.5967	0.5845	0.5917	0.9	0.3106	0.3689	0.1	0.2028	0.1825
8	0.6604	0.5731	0.5967	0.5845	0.5917	0.9	0.3106	0.3689	0.1	0.2028	0.1825	0.2081
9	0.5731	0.5967	0.5845	0.5917	0.9	0.3106	0.3689	0.1	0.2028	0.1825	0.2081	0.2233
10	0.5967	0.5845	0.5917	0.9	0.3106	0.3689	0.1	0.2028	0.1825	0.2081	0.2233	0.1623
11	0.5845	0.5917	0.9	0.3106	0.3689	0.1	0.2028	0.1825	0.2081	0.2233	0.1623	0.2087
12	0.5917	0.9	0.3106	0.3689	0.1	0.2028	0.1825	0.2081	0.2233	0.1623	0.2087	0.189

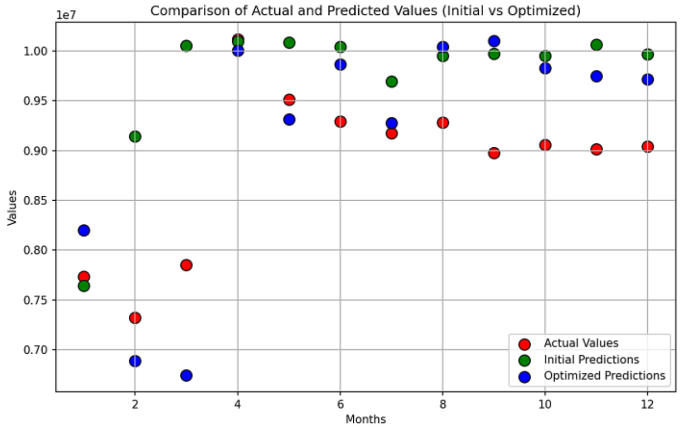


Graph 1.3 Training regression result (ANN)

Output: [0.89807 0.31059 0.36881 0.10095 0.20279 0.18248 0.2953 0.22332 0.16962 0.20876 0.18903 0.2099].

These results are denormalized once these raw outputs are generated by the ANN, the next step would involve optimizing the model using PSO. The role of PSO is to adjust the ANN's internal parameters (like weights and biases) to minimize the prediction errors and produce more accurate outputs. By using PSO, the optimization process refines these values to get closer to the actual values, effectively improving the prediction accuracy of the model.

Percentage error from prediction ANN vs actual (in percentage): [1.18 24.94 0.25 6.02 8.08 5.62 7.20 11.10 9.85 11.62 10.24] with average error 10.34%. Based on the results, the average Mean Absolute Percentage Error (MAPE) of 10.34% indicates that the prediction accuracy of the ANN falls within the "10% - 20%" range, which, according to the given rule, is categorized as having "good forecasting ability". However, it does not meet the standard of "very good forecasting ability" (<10%), meaning there is room for improvement. This result suggests that while the ANN provides generally reliable predictions, it struggles to achieve the highest level of accuracy.

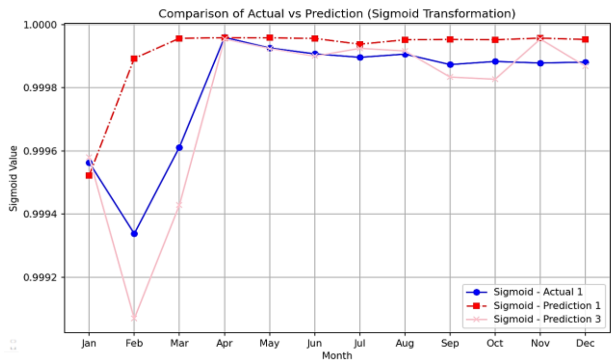


Picture 4. The Simulation ANN-PSO

The simulation ANN-PSO result:
Initial MAPE (ANN) : 10.34%
Optimized MAPE (ANN-PSO) : 3.05%
MAPE Improvement: 7.29%

Overall, the optimization showed a significant reduction in error across most months, with Mape improving from 10.34% (initial model) to 3.05% (optimized model). This translates to an improvement of 7.29%, demonstrating that the application of PSO optimization made a substantial difference in the prediction accuracy. Month 2nd (February) and Month 3rd (March) displayed the largest improvements, showing reductions in error, respectively. These months were highly successful, where the predictions after optimization were much closer to the actual values. Month 4th (April) was showing a slight decrease in performance. This might suggest the need for further tuning or adjustments in the optimization parameters to improve consistency and months with smaller errors, like May, June, and December, demonstrated relatively stable and significant improvements, showcasing the consistency and effectiveness of the ANN-PSO model.

The ANN-PSO model consistently outperforms the initial ANN model, especially in reducing the absolute error and improving the prediction accuracy across most months. The largest improvements were observed in the early months (February and March), while April was an outlier. Overall, the optimization significantly enhanced the model's ability to forecast electricity consumption, achieving a final MAPE of 3.05%, which is a substantial improvement over the 10.34% MAPE of the initial ANN model.



Graph 1.6 Comparison Actual, ANN, ANN-PSO.

In the context of simulation, Particle Swarm Optimization (PSO) significantly improved the forecasting precision model, which was aimed at predicting electricity consumption for a 12 months period. By leveraging PSO, the model's performance, as indicated by the Mean Absolute Percentage Error (MAPE), was around 10.34%.

However, after applying PSO, the optimized model reduced the MAPE to 3.05%, demonstrating a clear improvement in prediction accuracy.

CONCLUSION

In this study, the performance of the proposed model (ANN optimized using Particle Swarm Optimization, PSO) with other forecasting methods found in the literature, with other methods like linear regression, simple ANN, and other optimization techniques, such as Genetic Algorithms (GA), have been widely used in energy consumption forecasting.

However, the proposed ANN-PSO model outperformed these existing methods in terms of accuracy, as demonstrated by a significant reduction in the Mean Absolute Percentage Error (MAPE) from 10.34% to 3.05%.

For instance, when compared to the performance of a basic ANN model or other methods, the PSO-optimized model showed improved precision in predicting monthly electricity consumption, offering more reliable insights for energy management.

The findings of this study have significant practical implications for energy management in Palangkaraya. Accurate forecasting of electricity demand is crucial for efficient resource allocation, infrastructure development, and reducing energy shortages. The proposed model, with its enhanced forecasting accuracy, can assist local policymakers and energy planners in making more informed decisions, ensuring that the energy supply meets the growing demand. By adopting this model, energy planners can optimize the generation, distribution, and consumption of electricity, contributing to sustainability and cost efficiency.

This research demonstrates that the combination of Artificial Neural Networks (ANN) and Particle Swarm Optimization (PSO) offers a robust approach to forecasting electricity consumption. The proposed model significantly improved prediction accuracy compared to traditional forecasting methods, as evidenced by a reduction in error metrics such as MAPE and RMSE.

These findings validate the utility of the ANN-PSO model in real-world energy forecasting applications, particularly in Palangkaraya, where accurate predictions are essential for effective energy management. While the proposed model delivered promising results, surely there were several limitations in this study. One of the main constraints was the availability and quality of historical energy consumption data. Limited data or noisy data can affect the accuracy of the model, and future studies could benefit from more comprehensive and richer information for datasets.

Although the ANN-PSO model worked well for a year-long forecasting period, its performance could potentially degrade with larger datasets or longer time horizons, and more detail and specific data which highlighting the need for further optimization and testing.

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