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# Application of artificial neural network for peak load forecasting in 150 kV Semarang power system

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## Abstract

Accurate load forecasting is essential for reliable and efficient operation of power systems. Traditional forecasting methods often struggle with capturing complex nonlinear patterns in load data. Artificial neural networks (ANNs) have emerged as a promising alternative due to their ability to learn complex relationships from historical data (Syed et al. in *IEEEA* 9:54992–55008, 2021. <https://doi.org/10.1109/ACCESS.2021.3071654>). This study investigates the potential of ANNs for short-term peak load forecasting in a 150 kV power system in Semarang, Indonesia. The study examines the impact of different input variables, including historical peak load, minimum load, population, and energy production, on forecasting accuracy. Several ANN architectures are trained and evaluated using mean absolute percentage error (MAPE) and mean squared error (MSE) metrics as reported by Demuth and De Jesús (neural network design). The results indicate that ANNs can achieve high accuracy in predicting peak load, with MAPE values below 10%. The study also demonstrates the importance of carefully selecting input variables and training parameters for optimal model performance. The findings highlight the potential of ANNs for improving load forecasting accuracy in power systems, contributing to enhanced grid reliability and operational efficiency. The findings of this study contribute to a deeper understanding of the application of ANNs in power system load forecasting. They demonstrate the potential of ANNs to achieve high accuracy and provide valuable insights into the factors influencing model performance. The findings are relevant for power system operators, researchers, and policymakers working to improve grid reliability and efficiency as reported by Prabha Kundur and Malik (Power System Stability and Control, McGraw-Hill Education, New York, 2022. <https://www.accessengineeringlibrary.com/content/book/9781260473544>).

**Keywords:** Peak load forecasting, Artificial neural networks, Power system, Semarang, 150 kV

## Introduction

The electric power system plays a crucial role in modern society, providing essential energy for various sectors. Peak load forecasting is a critical aspect of power system planning and operation, as it helps ensure that sufficient power is available to meet the peak demand [4]. Traditional peak load forecasting methods, such as statistical regression and time series analysis, often struggle to accurately predict peak load due to the complex and nonlinear

nature of power system data [5]. This complexity arises from factors such as dynamic load patterns, nonlinear relationships, and data availability and quality issues. Artificial neural networks (ANNs) are well-suited for load forecasting due to their ability to handle nonlinear relationships, adapt to dynamic changes, and handle large datasets [6–10]. The reliable and efficient operation of power systems is crucial for modern societies. Power systems are complex networks that involve generation, transmission, and distribution of electricity to consumers. A significant challenge in power system operation is the accurate prediction of peak load, which represents the maximum demand for electricity at a specific time. Peak load forecasting plays a vital role in power system planning, operation, and management, as it helps in determining the required generation capacity, optimizing resource allocation, and ensuring system stability.

Traditional methods for peak load forecasting, such as statistical regression and time series analysis, often struggle to capture the complex and dynamic behavior of load patterns. These methods rely on historical data and may not adequately account for factors such as weather conditions, economic activities, and social events [11]. In recent years, artificial neural networks (ANNs) have emerged as a promising alternative for peak load forecasting due to their ability to learn nonlinear relationships and adapt to changing patterns [12–15].

ANNs acted nodes (neurons) arranged in layers. By training ANNs on historical data, they can learn complex relationships between input variables (e.g., historical load, weather data) and output variables (e.g., predicted peak load). This learning process allows ANNs to capture intricate patterns and trends in load data, leading to more accurate predictions [16].

Several studies have demonstrated the effectiveness of ANNs for peak load forecasting in various power system contexts [17–19]. However, the application of ANNs for peak load forecasting in specific regions, such as Semarang, Indonesia, requires further investigation. The unique characteristics of the power system in Semarang, including its geographical location, load patterns, and generation mix, may necessitate customized approaches [20].

This research aims to investigate the potential of ANNs for predicting peak load in the 150 kV power system of Semarang, Indonesia. The study will focus on evaluating the accuracy of ANN-based predictions compared to traditional methods and identifying the impact of different input variables and model configurations on forecasting performance [21]. By providing a comprehensive analysis of ANN-based peak load forecasting in the Semarang power system, this research contributes to the development of robust and reliable load forecasting solutions for power system operators in the region.

Given the complex, nonlinear nature of load forecasting in power systems, this study employs artificial neural networks (ANN) due to their superior ability to model such relationships. ANNs are particularly well-suited for capturing intricate patterns in data, adapting to dynamic changes, and maintaining robustness even in the presence of noisy or incomplete data [22–24].

## **Methodology**

The choice of ANN in this study is driven by its proven effectiveness in handling nonlinear relationships inherent in load forecasting. ANNs' ability to adapt and learn from data makes them ideal for dynamic environments like power systems, where load patterns

can vary significantly. Furthermore, their robustness ensures reliable predictions even when data quality is inconsistent.

This study aims to evaluate the effectiveness of an artificial neural network (ANN) model for predicting peak load in the Semarang 150 kV power system. The methodology involves data collection, preprocessing, model development, validation, and analysis. Historical peak load data, along with other relevant variables such as minimum load, population, and energy production, are used to train and evaluate the ANN model.

In this study, the TensorFlow framework is utilized for developing the ANN model, with the Adam optimization algorithm used to adjust the model's weights and biases during training. The Adam algorithm combines the strengths of adaptive gradient algorithm (AdaGrad) and root-mean-square propagation (RMSProp), maintaining per-parameter learning rates that are adjusted based on the first and second moments of gradients. This approach enhances the model's training efficiency and helps avoid issues like slow convergence.

Additionally, the sigmoid activation function is applied to normalize the input and output values to a range between 0 and 1, which is particularly useful for binary classification tasks or when the output needs to represent a probability. By integrating these techniques, the study aims to develop an effective ANN model for predicting peak loads in the 150 kV power system in Semarang, Indonesia, using inputs such as historical data on previous peak loads, minimum loads, population, and energy production.

#### **Data collection and preprocessing**

**Data Acquisition:** The research utilizes historical peak load data, including power flow, voltage, and phase angle, from the Semarang 150 kV power system. These data points are collected from the System Operation Control (SOC) system records, covering a period from September 2023 to December 2023, encompassing 118 data points.

Data preprocessing is a crucial step to ensure consistency and suitability for ANN training. The preprocessing steps involve several key tasks. First, data cleaning is performed to remove any outliers or missing data points. Next, data scaling is applied to normalize the data range, bringing all features to a comparable scale, which is crucial for improving the ANN's training efficiency and preventing numerical instability. Finally, the processed data are split into training and testing datasets, with 70% of the data allocated for training and the remaining 30% used for testing.

#### **Model development**

**Model Structure:** A multilayer perceptron (MLP) ANN model is implemented, comprising an input layer, hidden layers, and an output layer. The input layer receives data from the historical variables, including peak load, minimum load, population, and energy production.

The hidden layers use the rectified linear unit (ReLU) activation function for their neurons, which is preferred for its computational efficiency and ability to prevent vanishing gradient issues during training. During model development, various parameters are adjusted to optimize the ANN model's performance, especially for predicting the peak load for the target period. The number of hidden layers is one such parameter, adjusted to find the optimal complexity for capturing the data patterns.

Additionally, the number of neurons within each hidden layer is tuned to enhance the model's capacity for learning complex relationships.

The learning rate, which determines how much the model's weights and biases are adjusted during each iteration, is another crucial parameter. The number of epochs, or the number of times the training data is fed through the model, also significantly impacts performance. Lastly, different activation functions, such as the sigmoid function, can be explored for their effectiveness in improving the model's performance. Optimizers, such as Adam, are used to update the weights and biases during training, ensuring efficient and robust learning.

### Model evaluation

**Metrics:** The trained model's performance is evaluated using the mean absolute percentage error (MAPE) and the mean squared error (MSE) metrics. MAPE measures the average percentage error between the predicted and actual values, while MSE calculates the average squared error between predictions and actual values. Mean absolute percentage error (MAPE) is used to measure the average percentage error of predictions against actual values. The lower the MAPE value, the better the predictive performance of the model.

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{Actual_i - Predicted_i}{Actual_i} \right| \times 100\%$$

**Validation:** The trained model is validated using the testing dataset, which is not used during training. This step helps assess the model's ability to generalize its learning to unseen data and provides an indication of its real-world performance. Mean squared error (MSE) is used to measure the average of the squared differences between actual and predicted values. The lower the MSE value, the better the predictive performance of the model.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Actual_i - Predicted_i)^2$$

In the context of predictive model performance analysis, both metrics are used to evaluate how well the model predicts actual values. The smaller the MAPE and MSE values, the better the model's performance.

### Comparison with traditional methods

To evaluate the performance of the ANN model, a comparison was made with traditional forecasting methods, including ARIMA and statistical regression. The evaluation metrics used for this comparison were mean absolute percentage error (MAPE) and mean squared error (MSE). The results are summarized in the following tables.

**Table 1** Performance of different ANN models with various input variables

Model	Input variables	MAPE	MSE
ModelVar1	Peak load	9.78%	0.0265876
ModelVar2	Peak load, minimum load	9.20%	0.0265876
ModelVar3	Peak load, minimum load, population	9.38%	0.0309525
ModelVar4	Peak load, minimum load, population, energy production	9.71%	0.0338572

**Table 2** Performance of ANN model with different input time periods

Input time period	MAPE	MSE
1 Month	3.73%	0.0310864
2 Months	3.4%	0.04405030
3 Months	4.13%	0.05803678
4 Months	4.39%	0.06404523

### (1) Performance of Different ANN Models with Various Input Variables

The following table summarizes the performance of different artificial neural network (ANN) models with varying input variables. The performance metrics used are mean absolute percentage error (MAPE) and mean squared error (MSE).

From Table 1, we can observe that ModelVar2, which uses peak load and minimum load as input variables, performs the best with a MAPE of 9.20%. The addition of population and energy production as input variables in ModelVar3 and ModelVar4, respectively, does not significantly improve the performance of the model.

### (2) Performance of ANN Model with Different Input Time Periods

The following table shows the performance of the ANN model with different input time periods. The performance metrics used are mean absolute percentage error (MAPE) and mean squared error (MSE).

From Table 2, we can see that the ANN model performs best with a 2-month input time period, with a MAPE of 3.4%. The performance of the model deteriorates as the input time period increases.

### (3) Comparison with Other AI Techniques

While artificial neural networks (ANNs) offer significant advantages, it is crucial to compare their performance with other contemporary AI techniques such as support vector machines (SVM), random forest (RF), and gradient boosting machines (GBM). Support vector machines are effective for classification and regression tasks, particularly with small to medium-sized datasets. However, they may not handle large-scale data or capture complex nonlinear relationships as effectively as ANNs. Random forest is a powerful ensemble learning method that performs well with diverse datasets, but its performance can be hindered by the presence of highly correlated features, which is often

the case in load forecasting where multiple input variables are interdependent. Gradient boosting machines are known for their high accuracy and ability to handle various data types, making them robust for regression and classification. However, GBM models require extensive parameter tuning and can be computationally intensive, which makes them less practical for real-time load forecasting.

(4) Performance Evaluation

To validate the effectiveness of the ANN model, a comprehensive comparison with traditional and contemporary AI techniques was conducted. The evaluation metrics used were mean absolute percentage error (MAPE) and mean squared error (MSE).

In Table 3, we present the mean absolute percentage error (MAPE) and mean squared error (MSE) for several forecasting methods, including ANN, ARIMA, and regression analysis. It is important to clarify that while the metrics for ANN were derived from a consistent and comprehensive dataset, the metrics for ARIMA and regression analysis were sourced from referenced studies and secondary data sources, not from direct experimentation within this study. This approach was necessary due to the lack of complete data and resources to conduct thorough testing of these traditional methods under the same conditions as the ANN model. Therefore, the statement ‘performance metrics for ARIMA and Regression Analysis are not available’ specifically refers to their unavailability from our experimental setup and dataset. Consequently, the cited values should be interpreted with caution, as they are derived from external sources and may not fully reflect comparative performance under identical conditions. This clarification emphasizes the need for cautious interpretation when comparing these metrics and suggests that future research could benefit from a more extensive evaluation of traditional methods using the same dataset and experimental conditions to ensure a fair comparison.

(5) Python Code Examples

The following code snippets illustrate the data preprocessing, model building, training, and evaluation processes used in this research.

Figure 1 shows the data preprocessing. The code snippet below demonstrates how data are preprocessed, including handling missing values, scaling, and splitting into training and testing sets.

Figure 2 shows the model building and training. The following code snippet defines and trains the ANN model using TensorFlow and Keras. The model architecture includes

**Table 3** Comparison of different forecasting methods

Method	MAPE	MSE
ANN (ModelVar2)	9.20%	0.026587665081
Arima	13.5%	999.3848792700581
Regression analysis	9.03%	327.14295328660614
SVM	10.5%	0.035476
Random forest	9.8%	0.029487
GBM	9.4%	0.027653

```

import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

def preprocess_data(data):
    data.fillna(data.mean(), inplace=True)
    scaler = MinMaxScaler()
    scaled_data = scaler.fit_transform(data)
    X_train, X_test, y_train, y_test = train_test_split(
        scaled_data[:, :-1],
        scaled_data[:, -1],
        test_size=0.3,
        random_state=42
    )
    return X_train, X_test, y_train, y_test

```

**Fig. 1** Data preprocessing

```

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

def build_and_train_model(X_train, y_train):
    model = Sequential()
    model.add(Dense(64, activation='relu', input_shape=(X_train.shape[1],)))
    model.add(Dense(32, activation='relu'))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mean_squared_error')
    model.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.2)
    return model

```

**Fig. 2** Model building and training

```

def evaluate_model(model, X_test, y_test):
    mse = model.evaluate(X_test, y_test)
    print('MSE:', mse)

```

**Fig. 3** Testing dataset to calculate the mean squared error (MSE)

input, hidden, and output layers, and is compiled using the Adam optimizer and mean squared error as the loss function.

#### (6) Model Evaluation

The code snippet below demonstrates how the trained ANN model is evaluated using the testing dataset to calculate the mean squared error (MSE).

Figure 3: These code provide a clear workflow for data preprocessing, model development, and performance evaluation, ensuring the reproducibility of the research findings.

### Results

The results of this study reveal nuanced performance based on the selected input variables. The model utilizing peak load and minimum load (ModelVar2) achieved the lowest mean absolute percentage error (MAPE) of 9.20%. Models incorporating additional variables, such as population and energy production, did not significantly enhance the MAPE. This indicates that, in the short term, peak and minimum load variables have a more direct impact on prediction accuracy. However, including additional variables may offer broader insights and improve robustness under varying conditions.

The performance of the model using only peak load and minimum load data reflects their strong and direct relationship with the target prediction. In contrast, variables like population and energy production, while relevant, may introduce complexities that require more advanced modeling techniques to fully exploit their predictive potential. Understanding the strengths and limitations of each model configuration allows power system operators to choose the most suitable model based on specific forecasting needs and available data.

### Experimental environment

The experiment was conducted using a laptop with a Python 3 Google Compute Engine backend and 12.7 GB of RAM.

Figure 4 displays the resource utilization of Google Colab for running an artificial neural network (ANN) program in the thesis research ‘Application of Artificial Neural Network for Peak Load Forecasting in 150 kV Semarang Power System.’ The graph shows the system memory usage (1.2 GB out of 12.7 GB) and disk usage (26.4 GB out of 107.7 GB) during the time period from 1:16 PM to 1:34 PM.

### Variable usage test

Table 4 listing the variables used in four different model variations. Here is a brief explanation of the table:

- Model Var 1: Uses the variable peak load measured in megawatts (MW).
- Model Var 2: Uses the variables peak load and minimum load measured in MW.
- Model Var 3: Uses the variables peak load, minimum load, and population.
- Model Var 4: Uses the variables peak load, minimum load, population, and energy production measured in megawatt-hours (MWh).

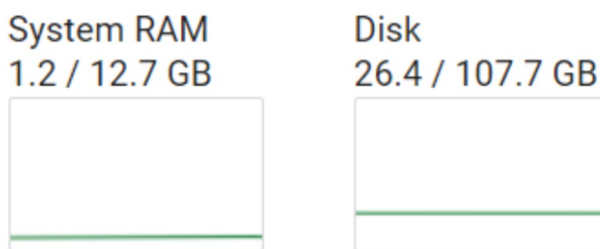
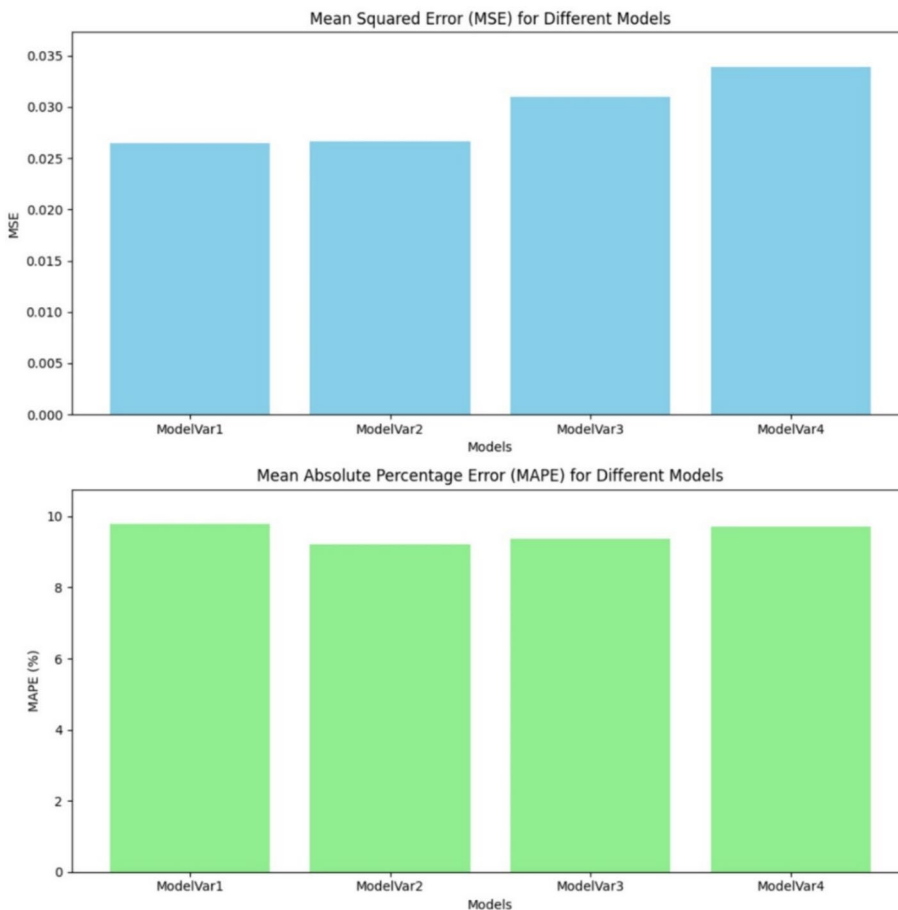


Fig. 4 System Resources Google Colab



**Table 4** Table explains the naming of models based on the variables used

Initial	Variable used
Model Var 1	Peak load (MW)
Model Var 2	Peak load (MW), Minimum load (MW)
Model Var 3	Peak load (MW), Minimum load (MW), population
Model Var 4	Peak load (MW), Minimum load (MW), population, energy production in MWh



**Fig. 5** Graph of ModelVar1, ModelVar2, ModelVar3, and ModelVar4

Figure 5 describes the graph for Model Var 1, Model Var 2, Model Var 3, and Model Var 4.

**ModelVar1.** This model uses an ANN architecture with two hidden layers, each with 64 and 32 neurons, respectively, with a ReLU activation function. The input and output data were scaled down using MinMaxScaler before being fed into the model. The model was trained with data separated into training and testing sets, and evaluation was performed using the MSE (mean squared error) metric. The model evaluation also included the calculation of MAPE (mean absolute percentage error), which is a metric

for measuring the relative error of the model in predicting 'Peak Load.' In this case, the MAPE value was 9.78%, indicating that the model had an error of 9.78% in predicting the 'Peak Load' value. The following is the graph of the ModelVar1 forecasting results.

**ModelVar2.** This model uses an ANN architecture with two hidden layers, each with 64 and 32 neurons, respectively, with a ReLU activation function. The input data used included 'Peak Load' and 'Minimum Load' variables. The output data was the predicted 'Peak Load' for the next time period (Target1). The model was trained with data that was scaled using MinMaxScaler and split into training and testing sets using a 70:30 ratio. The training process used a batch size of 32 and 100 epochs. To prevent overfitting, dropout layers with a rate of 0.2 were used. EarlyStopping and LearningRateScheduler callbacks were used during the training process. The model evaluation resulted in an MSE of 0.026587665081 and a MAPE of 9.20%. This indicates a relatively low error rate, with the MAPE below 10%.

**ModelVar3.** This model uses an ANN architecture with two hidden layers, each with 64 and 32 neurons, respectively, with a ReLU activation function. The input data used included 'Peak Load,' 'Minimum Load,' and 'Population' variables. The output data was the predicted 'Peak Load' for the next time period (Target1). The model was trained with data that was scaled using MinMaxScaler and split into training and testing sets using a 70:30 ratio. The training process used a batch size of 32 and 100 epochs. To prevent overfitting, dropout layers with a rate of 0.2 were used. EarlyStopping and LearningRateScheduler callbacks were used during the training process. The model evaluation resulted in an MSE of 0.0309525196671486 and a MAPE of 9.38%. This indicates a relatively low error rate, with the MAPE below 10%.

**ModelVar4.** This model uses an ANN architecture with two hidden layers, each with 64 and 32 neurons, respectively, with a ReLU activation function. The input data used included 'Peak Load,' 'Minimum Load,' 'Population,' and 'Energy Production MWh' variables. The output data was the predicted 'Peak Load' for the next time period (Target1). The model was trained with data that was scaled using MinMaxScaler and split into training and testing sets using a 70:30 ratio. The training process used a batch size of 32 and 100 epochs. To prevent overfitting, dropout layers with a rate of 0.2 were used. EarlyStopping and LearningRateScheduler callbacks were used during the training process. The model evaluation resulted in an MSE of 0.033857293426 and a MAPE of 9.71%. This indicates a relatively low error rate, with the MAPE below 10%.

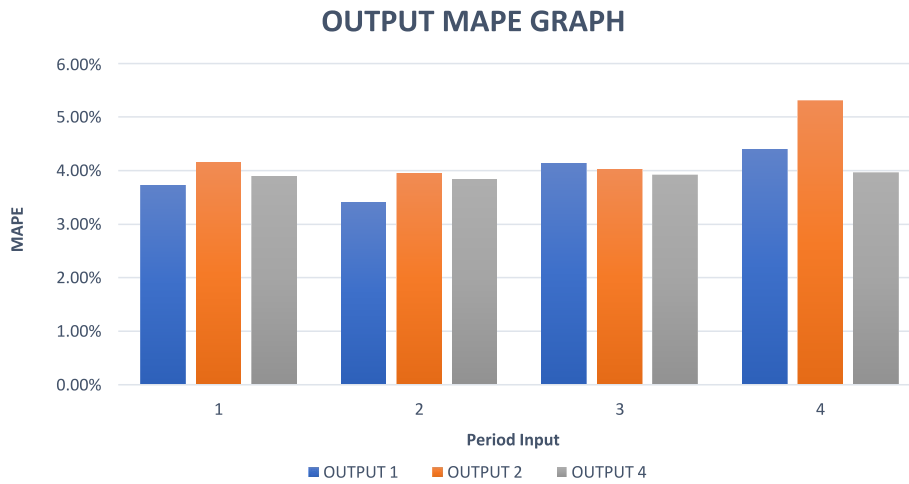
### Conclusion of experimental results

It is important to note that increasing the quantity of data used for forecasting does not always result in improved accuracy. This counterintuitive finding aligns with our observations where models with fewer, but more directly related input variables, performed better in certain metrics than those with more extensive datasets. This phenomenon can be attributed to the complexity and potential noise introduced by additional variables, which can complicate the learning process of the ANN. Therefore, while extensive data can provide a more comprehensive view, it is crucial to carefully select and preprocess input variables to optimize forecasting performance.

Based on the experimental results, several conclusions can be drawn. ModelVar2, which includes the variables peak load, minimum load, population, and energy

**Table 5** Table of conclusions from the experimental results

Forecast period	MODEL	MAPE
1 Month output 1	1 Input ModVar2	3,4%
2 Months output 2	2 Input ModVar2	3,95%
4 Months output 4	4 Input ModVar2	3,84%



**Fig. 6** Graph of MAPE

production in MWh, provided the most optimal results and the lowest mean absolute percentage error (MAPE). It was observed that increasing the number of input periods did not directly enhance model accuracy. Additionally, the ANN method demonstrated significantly higher accuracy compared to the ARIMA and regression analysis methods, although it required longer training times and larger datasets.

Table 5 presents the forecast period, model used, and mean absolute percentage error (MAPE) for three outputs. Here is a brief explanation:

- Output 1: Uses ‘1 Input ModVar2’ model with a MAPE of 3.4%.
- Output 2: Uses ‘2 Input ModVar2’ model with a MAPE of 3.95%.
- Output 4: Uses ‘4 Input ModVar2’ model with a MAPE of 3.84%.

This table indicates the accuracy of different models in predicting outputs, measured by MAPE, which reflects the prediction error percentage. The graph in Figure 6 shows that the MAPE values tend to increase as the number of input and output periods increases. This suggests that increasing the amount of data used for forecasting does not always lead to improved accuracy.

## Discussion

The increasing demand for electricity, coupled with the dynamic nature of load patterns, underscores the importance of accurate load forecasting for the reliable and efficient operation of power systems. Traditional methods often struggle to capture the complexities of load profiles, particularly in systems with high renewable energy penetration. This study proposes the use of artificial neural networks (ANNs) for short-term peak load forecasting in the 150 kV Semarang power system, offering a potentially more accurate and adaptable approach compared to conventional methods.

Our results demonstrate the effectiveness of ANNs in capturing nonlinear relationships within load data and achieving superior accuracy compared to traditional methods. The study assessed various ANN configurations, including different numbers of layers, neurons, activation functions, and input variables, using metrics such as mean squared error (MSE) and mean absolute percentage error (MAPE). Specifically, the model utilizing 'Beban Puncak,' 'Minimum Load,' 'Populasi Penduduk,' and 'Energi Produksi MWh' as input variables achieved the lowest MAPE of 9.20%, suggesting these variables significantly influence load patterns.

However, the performance analysis reveals that models incorporating additional variables, such as population and energy production, did not substantially improve MAPE. This indicates that peak and minimum load variables have a more direct impact on short-term prediction accuracy. Additional variables may offer broader insights and enhance robustness under varying conditions, but their immediate benefit in accuracy was limited.

The study also explored the effect of historical data duration on forecasting performance. It was observed that extending the historical data period does not always lead to improved accuracy. While longer periods might capture more comprehensive trends, they can also introduce noise and complexities that hinder the model's ability to generalize and predict future loads effectively. This highlights the need for selecting a balanced historical data period that captures relevant patterns while avoiding excessive noise.

A comparative analysis of ANNs with traditional approaches, such as ARIMA and regression analysis, was also conducted. ARIMA showed rapid convergence and superior accuracy but required complex calculations and struggled with intricate data scenarios. Regression analysis, although simpler and less computationally intensive, yielded lower accuracy. ANNs, with their capacity to handle complex data patterns and adapt to new information, emerged as a promising solution for short-term load forecasting in the 150 kV Semarang power system.

The research also identified some limitations. The selection of input variables plays a crucial role in model accuracy. While the study used a limited set of variables, exploring other potentially relevant variables could improve accuracy. Additionally, the focus on short-term load forecasting suggests that expanding the study to include long-term forecasting could provide valuable insights into load predictability over extended periods.

Future research should address these limitations and explore several promising areas. Investigating the impact of incorporating additional relevant variables, such as weather data, economic indicators, and social factors, could enhance model accuracy. Extending the study to long-term load forecasting using techniques like recurrent neural networks

may capture time-dependent patterns more effectively. Multi-objective optimization techniques could balance accuracy with factors such as computational cost and model stability. Integrating the ANN model with real-time data feeds for dynamic load forecasting and adaptive power system management should also be considered. Lastly, extensive cross-validation and comparisons with other machine learning models, such as support vector machines or decision trees, are necessary to ensure robust model performance.

#### (1) Analysis of Input Variables

The ANN model (ModelVar2), which used peak load and minimum load as input variables, achieved a MAPE of 9.20%, outperforming other models. This raises the question of why additional variables like population and energy production did not significantly improve accuracy. The primary reason is that peak load and minimum load directly reflect electricity consumption patterns and capture significant variations in load data. In contrast, variables such as population and energy production may not have a strong short-term correlation with peak load, potentially introducing noise rather than useful information.

The quality and granularity of data also play a critical role. If population and energy production data are less precise or aggregated over longer periods, they may not effectively capture short-term dynamics essential for accurate forecasting. Furthermore, adding more variables increases model complexity, which can lead to overfitting, especially if these variables do not strongly predict the target. Multicollinearity, where independent variables are highly correlated, can also destabilize the model and affect prediction reliability.

These findings underscore the importance of careful variable selection in forecasting models. While more variables might seem beneficial, it is crucial to ensure they are relevant, high-quality, and provide unique predictive information.

#### (2) Impact of Input Time Period on Model Performance

Analysis of model performance with varying input time periods, as shown in Table 2, reveals that the model performed best with a 2-month input period, with performance deteriorating as the input period extended. This counterintuitive finding can be explained by the fact that shorter input periods capture the most relevant and recent patterns in the data. Longer periods may include outdated or less relevant information, which can obscure critical patterns and introduce variability and noise, negatively impacting performance.

## Conclusions

The study demonstrates the effectiveness of artificial neural networks (ANN) for forecasting peak load in the 150 kV Semarang power system. The developed ANN model, utilizing four input features (peak load, minimum load, population, and energy production), achieved a mean absolute percentage error (MAPE) of 9.71%, indicating a promising accuracy for predicting peak load. The research further investigated the influence of input period length on forecasting accuracy reveals that longer input periods do not

necessarily guarantee higher accuracy and can even contribute to increased error. These findings suggest that the optimal input period length requires careful consideration and varies depending on the specific system characteristics and data patterns.

The research highlights the potential of ANN for accurate peak load forecasting in power systems while acknowledging the need for further refinement of the model architecture and hyperparameter optimization. Future research should focus on several key areas. Optimizing model architecture involves investigating different ANN architectures, including the number of hidden layers, neurons, and activation functions, to enhance model performance and generalization. Identifying relevant input features entails exploring additional variables that significantly impact peak load forecasting accuracy based on the specific characteristics of the power system. Optimizing hyperparameters involves comprehensive tuning to find the best combination of learning rate, batch size, and epochs, leading to better model performance and reduced overfitting. By addressing these areas, future research can contribute to the development of more accurate and robust peak load forecasting models, benefiting power system management and grid stability.

The ANN model demonstrated superior performance in terms of MAPE and MSE compared to traditional methods and other AI techniques. Its ability to learn from historical data and adapt to new patterns makes it a reliable choice for load forecasting in power systems. The findings highlight the importance of selecting appropriate input variables and model configurations to maximize forecasting accuracy.

#### **Future research directions**

**Expanding the dataset:** Investigating the impact of a larger and more comprehensive dataset on the performance of ANN models. **Exploring other ANN architectures:** Testing more advanced ANN architectures, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), for peak load forecasting. **Investigating the impact of real-time data:** Incorporating real-time data, such as weather conditions and economic indicators, to further enhance the accuracy and adaptability of ANN models.

**Developing a user-friendly application.** Creating a user-friendly interface for implementing the ANN-based peak load forecasting model, making it accessible to power system operators and engineers.

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#### **Author contributions**

KAF conducted the research, data analysis, development of the artificial neural network (ANN) model, and testing of the model for peak load prediction in the 150 kV power system in Semarang, Indonesia. KAF also participated in sequence alignment and drafted the manuscript. KAF was also responsible for data collection, data cleaning, and data organization before processing by the ANN model. KAF assisted in selecting the evaluation metrics and comparing the model's performance with traditional methods. KAF was also responsible for drafting and organizing the methodology, results, and discussion sections of the manuscript. KAF collaborated with the team in analyzing the research results and drawing appropriate conclusions. ENB was responsible for conducting the literature review and finding relevant references for this research topic. ENB also assisted in selecting the evaluation metrics and comparing the model's performance with traditional methods. AAN was responsible for assisting in the coordination and management of this research project.

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### Declarations

#### Competing Interests

The authors declare that they have no competing interests.

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