An Examination of the Backpropagation Method for Predicting the Amount of Demand for Power Installations in the North Sumatra UP2D Location Area

Afif Yasri, Zulham Sitorus

Abstract

This study examines the utilization of the Backpropagation method in artificial neural networks to predict the volume of electricity installation requests in the UP2D North Sumatra operational region. The demand for power installations fluctuates due to economic conditions, population expansion, and industrial development, necessitating an accurate forecasting model to enhance capacity planning and energy distribution. This study aims to evaluate the efficacy of the Backpropagation method in forecasting power installation requests using historical data and to determine the precision of the constructed model. The utilized data comprises power installation request records classified by time period (e.g., monthly) sourced from UP2D North Sumatra, and further segmented into training and testing datasets. The modeling process encompasses data preprocessing, specifying the network design (quantity of neurons in the hidden layer), training via the Backpropagation method, and assessing the model. The performance assessment is conducted utilizing error metrics, including Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The research findings indicate that the Backpropagation approach can generate forecasting patterns that closely align with real data and serve as a decision-support tool for planning energy installation requirements at UP2D North Sumatra.

Keywords: Forecasting, Backpropagation, Demand, UP2D North Sumatra

Afif Yasri[1]

[1]Master Student of Information Technology, Universitas Pembangunan Panca Budi, Indonesia
e-mail: afifyasri@gmail.com[1]

Zulham Sitorus[2]

[2]Master of Information Technology, Universitas Pembangunan Panca Budi, Indonesia
e-mail: zulhamsitorus@dosen.pancabudi.ac.id[2]

Introduction

Electrical energy is a crucial necessity for enabling social interactions, business operations, and infrastructural development. The increasing population, development of residential areas, and expansion of industrial and service sectors are driving a substantial demand for more electrical installations over time. Electricity usage is expected to increase over time, although the magnitude of this rise is uncertain. [1]. Electricity providers must meticulously strategize capacity and energy distribution to ensure supply continuity, uphold system reliability, and provide optimal service quality to clients. Artificial Neural Networks (ANNs) are artificial intelligence models based on the structure and function of the human brain, implemented as computer programs that perform several calculations during the learning process. Algorithms utilized in artificial neural networks (ANNs) comprise perceptron, multi-layer perceptron, Kohonen, and backpropagation. [2].

The increasing demand for electrical energy must be met with an adequate supply of electrical power to maintain the stability of the power system and satisfy the needs of all customers. The existence of a high-capacity electrical power source for energy storage is highly significant. The annual fluctuations in electrical load create a unique challenge in producing high-quality electrical power inside the power system to meet these demand variations. Several previous research in electrical engineering have examined the prediction of important indicators inside an electricity company through the utilization of the backpropagation algorithm. The ideal artificial neural network design in that study was structured as 6-100-75-1, attaining an accuracy rate of 83%. [3].

Electricity is essential for promoting development and technological progress. As dependence on electricity as an energy source increases among gadgets, the requirement for reliable and sufficient electrical power systems intensifies. [4]. The State Retail Sukuk (SR) data, classified by professional group, will thereafter be analyzed using an Artificial Neural Network that utilizes the backpropagation method. For the data to be recognized by the Artificial Neural Network, it must be represented numerically within the interval of 0 to 1. This pertains to both the variables and their contents, which function as the input data for State Retail Sukuk (SR) classified by professional group for pattern recognition, as well as the output, which is the projection of State Retail Sukuk (SR) purchases based on professional group obtained from the optimal architectural model during the determination of the best pattern. [5].

UP2D North Sumatra, being an entity responsible for overseeing and administering the distribution system in its area, faces variable dynamics in the need for electricity installations. This demand is influenced by various factors, including regional economic growth, the development of industrial and commercial areas, the government's electrification program, and the rising level of life in the community. Unexpected fluctuations may result in errors in network capacity planning, postponements in material supply, and suboptimal distribution of human resources in installation and customer service functions. Historically, forecasting the volume of electrical installations in diverse operating units has primarily relied on conventional methodologies, such as historical averages, fundamental trends, or the subjective assessments and experiences of decision-makers. This method has limitations in precisely depicting the complex and non-linear relationships among the variables influencing the demand for electrical installations. As a result, the accuracy of the expected results declines, potentially impacting the effectiveness of planning and operational efficiency. This research utilizes the Artificial Neural Network approach with the Backpropagation algorithm and assesses four architectural configurations: 5-10-1, 5-25-1, 5-10-25-1, and 5-25-10-1. The accessibility of electrical energy is a crucial factor, acting as a main determinant of a region's developmental success. [6].

The progression of computing technology and machine learning presents opportunities to develop more flexible and accurate forecasting models. Artificial neural networks are frequently utilized for modeling nonlinear relationships. The Backpropagation method is a commonly employed learning algorithm for artificial neural networks, distinguished by its ability to

iteratively train the model to minimize the variance between the model's output and the real data. This method can identify trends from complex historical data, perhaps producing forecasts that more accurately reflect real-world conditions. This study utilizes the Artificial Neural Network technique with the backpropagation algorithm and assesses four architectural model configurations: 5-10-1, 5-25-1, 5-10-25-1, and 5-25-10-1. Of the four models, the 5-25-1 architecture was determined to be the most effective, demonstrating a training MSE of 0.0009994101, a testing MSE of 0.0011603685, a total of 520 epochs, and an accuracy rate of 80%. This indicates that the model is exceptionally viable and reliable for data forecasting. [2].

To anticipate the volume of energy installation requests in the UP2D North Sumatra jurisdiction, the application of the Backpropagation method is essential for evaluation and analysis. Historical data on power installation demand can provide a basis for training and testing artificial neural network models to enhance predictive accuracy. Accurate forecasting results can greatly aid management in determining network capacity needs, budget distribution, material acquisition, task scheduling, and improving customer service quality strategies. Electricity is crucial for enabling numerous human activities throughout all sectors of society, including households, workplaces, and industries. The availability of electrical energy is considered a vital necessity for efficient, systematic, secure, and comfortable living activities. [7].

A study is necessary to specifically assess the effectiveness of the Backpropagation method in predicting the volume of electricity installation requests in the UP2D North Sumatra region. This research seeks to evaluate the model's correctness, identify critical parameters in network architecture design, and investigate the potential use of this method as a decision-making tool inside the UP2D Sumut environment. The research findings advance scholarly work in artificial neural networks and forecasting, while also offering practical advantages for the planning and operation of electric power distribution systems.

Literature Review
2.1 Implementation
The implementation occurs at this step through programming. Application development is segmented into discrete modules that will be integrated in the subsequent phase. This stage also entails verifying that the developed modules fulfill the specified functions. These functions will be congruent with the application design. [8] defines implementation as the process of attaining outcomes that correspond with the policy's goals or objectives. The execution of a policy necessitates the performance of an action.

2.2 Artificial Neural Networks
Artificial neural networks (ANNs) represent an information processing framework modeled after biological nervous systems, particularly the cognitive functions of the human brain (Sutojo et al., 2010). Artificial Neural Networks emulate the functioning of the human brain by acquiring knowledge through exemplars. An artificial neural network (ANN) is utilized for particular applications, including data classification, clustering, and forecasting, through a learning process. JST possesses exceptional qualities, namely (Sutojo et al., 2010): (1) extracting insights from intricate data; (2) addressing ambiguous and poorly defined challenges; (3) acquiring knowledge through experiential learning; (4) assimilating information despite uncertainty; (5) generalizing and deriving insights from specific data patterns; (6) formulating knowledge structures through self-regulation or cognitive development; (7) categorizing data inputs into established classifications; (8) elucidating the relationships between entities (association); (9) processing input data independently of a predetermined objective; and (10) identifying optimal solutions to minimize cost functions (optimization). The process of modeling artificial neural networks is typically categorized into four stages: data preparation, selection of network architecture, training (learning), and testing [4]. In the artificial neural network (ANN) methodology, the data must be normalized prior to the data

processing phase. This procedure is termed data preprocessing and seeks to align the data with the standards of the employed methodology. In artificial neural networks, data preprocessing employs the sigmoid activation function for normalization, transforming the data into the interval 0.1 - 0.9. [9].

2.3 Backpropagation

The identification of the backpropagation algorithm with a layered architecture significantly broadened the scope of Artificial Neural Network advancement. The efficacy of numerous applications solvable through backpropagation has heightened the need for Artificial Neural Networks. This technique has been employed across diverse domains, such as finance, handwriting recognition, speech recognition, control systems, medical image processing, and numerous other applications, establishing backpropagation as one of the most dependable computing approaches. [10].

Backpropagation is one of the most commonly employed techniques in artificial neural networks. Backpropagation is a gradient descent technique utilized to minimize the sum of squared errors (Sutojo et al., 2010). The network training process comprises three stages: forward propagation, backpropagation, and the adjustment of weights and biases (Sutojo et al., 2010).

Backpropagation Algorithm (1). Initialize weights with adequately tiny random values. While the termination condition remains false

a. Stage of forward propagation (1). Each input unit (Xi, where i=1,2,3, …, n) receives the signal Xi and transmits it to all units in the hidden layer. (2). Each hidden unit (Zi, j=1,2,3, …, p) aggregates the input signal weights according to the following equation:

$$z\_in_j = \_v_{0j} + \sum_{i-1}^{n} x_i \; v_{ij}$$

b. Applying the activation function to compute its output signal:

$$z_i = f(z_{inj})$$

c. The activation function employed is often the sigmoid function, which subsequently transmits the signal to all output units.

d. Each output unit (Yki, where K = 1, 2, 3, ..., m) aggregates the weights of the input signals.

$$y\_in_k = w_{ok} + \sum_{i=1}^{p} z_j \; w_{jk}$$

e. Applying the activation function to compute its output signal:

$$y_k = f(y\_ink)$$

Research Methodology

The research stages are a sequence of steps undertaken to address the subject under investigation in this study. The steps are illustrated as a flowchart graphic. The flowchart depicting the research stages for the study of anticipating energy installation numbers is illustrated in the subsequent diagram.
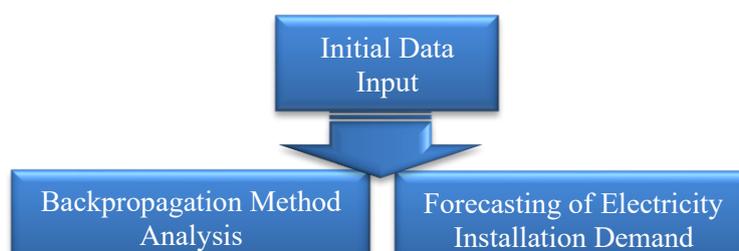
Initial Data
Input

Backpropagation Method
Analysis

Forecasting of Electricity
Installation Demand

Figure 1. Research Stages

Results

The analysis of the backpropagation method encompasses training and testing phases. The network training procedure utilizing this approach commences with the normalization of the training data, succeeded by the establishment of starting parameters for each employed method. The network is subsequently trained until a classifier model is established. Subsequently, the model was evaluated using normalized test data, yielding findings that could be assessed through accuracy and Mean Squared Error (MSE) metrics.

This study utilizes data on the power installation demand index for 2024, encompassing the periods of January to March, April to June, and July to August. The study employs data from periods 1, 2, and 3 of 2024. The index value is determined by the average number of energy installation requests from each sub-category of requests.

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Table 1. Data Input Used

No	Year	Period	Month 1	Month 2	Month 3
1	2024	Period I	12.06	9.77	11.82
2	2024	Period II	11.16	12.33	14.33
3	2024	Period III	9.82	15.60	14.81

The index of power installation requests is derived from the 2024 vaccination period, which is segmented into two phases: Period 1 and Period 2. Period 1 spans three months, commencing in March, followed by April, and concluding in May. Period 2 spans three months, commencing in June, followed by July, and concluding in August. The data from the initial period serves as training data, whilst the data from the subsequent period is employed as testing data. Each interval displays data for a duration of three months.

Table 2. Data Normalization Results from Testing

Data	Data Input			Target
	Month 1	Month 2	Month 3	
Pola 1	0.285	0.447	0.724	0.1
Pola 2	0.447	0.724	0.1	0.9
Pola 3	0.724	0.1	0.9	0.791

Calculate all outputs in the hidden units. Z_j (j = 1, 2, ..., p):

$$Z_{netj} = V_{j0} + \sum_{j=1}^{p} X_i V_{ji}$$

$$Z_{net1} = V_{10} + \sum_{j=1}^{p} X_i V_{ji} = V_{10} + X_1 V_{11} + X_2 V_{12} \quad \ldots \quad X_i V_{ji}$$

$$= 0.2 + (0.2*0.2) + (-0.4*-0.3) + (-0.5*0.1) = 0.35$$

$$Z_{net2} = V_{10} + \sum_{j=1}^{p} X_i V_{ji} = V_{10} + X_1 V_{21} + X_2 V_{22} \quad \ldots \quad X_i V_{ji}$$

$$= 0.5 + (-0.4*-0.4) + (-0.5*0.2) + (0.3*-0.3) = 0.47$$

$$Z_{net3} = V_{10} + \sum_{j=1}^{p} X_i V_{ji} = V_{10} + X_1 V_{31} + X_2 V_{32} \quad \ldots \quad X_i V_{ji}$$

$$= -0.5 + (-0.5*-0.5) + (0.3*0.1) + (-0.4*-0.3) = -0.1$$

$$Z_j = f\left(Z_{netj}\right) = \frac{1}{1+e^{-z\_netj}}$$

$$Z_1 = f\left(Z_{net1}\right) = \frac{1}{1+e^{-z\_net1}} = \frac{1}{1+e^{0,35}} = 0.413382421$$

$$Z_2 = f\left(Z_{net1}\right) = \frac{1}{1+e^{-z\_net1}} = \frac{1}{1+e^{0.47}} = 0.384616243$$

$$Z_3 = f\left(Z_{net1}\right) = \frac{1}{1+e^{-z\_net1}} = \frac{1}{1+e^{-0,1}} = 0.524979187$$

Calculate the sum of errors from the hidden units. $(= \delta)$

$$\delta_{netj} = \sum_{k=1}^{m} \delta_k W_{kj}$$

$\delta_{net1} = \delta_k. W_{11} = (-0,14). (-0,011) = 0.0016$
$\delta_{net2} = \delta_k. W_{12} = (-0,14). (-0,011) = 0.0014$
$\delta_{net3} = \delta_k. W_{13} = (-0,14). (-0,015) = 0.002$
Error factor δ in the hidden unit:
$\delta_j = \delta_{netj} \; f'(Znet_j) = \delta_{net} Z_j (1-Z_j)$
$\delta_1 = \delta_{net1} Z_1 (1-Z_1) = 0.0016.(0,41). (1-(0,41)) = 0.00038$
$\delta_2 = \delta_{net2} Z_2 (1-Z_2) = 0.0014.(0,41). (1-(0,41)) = 0.00035$
$\delta_3 = \delta_{net3} Z_3 (1-Z_3) = 0.002.(0,41). (1-(0,41)) = 0.00051$
Weight change to hidden unit: $\Delta Vji = \alpha \; \delta jxi$
1. $\Delta V_{ji} = \alpha \; \delta_j x_i = 0.2* 0.00038*0.2 = 0.0$
2. $\Delta V_{ji} = \alpha \; \delta_j x_i = 0.2* 0.00035*-0.4 = 0.0$
3. $\Delta V_{ji} = \alpha \; \delta_j x_i = 0.2* 0.00051*-0.5 = 0.0$

A use case or use case diagram is a model that delineates the behavior of an information system intended for development. A use case delineates the interaction between one or more actors and the system. The following is a use case diagram representing the system that predicts the volume of electricity installation requests.
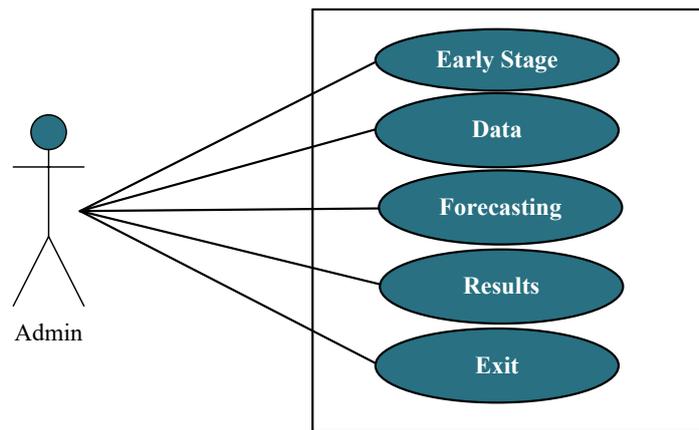
Figure 1. Use Case

Conclusion

The study and testing conducted indicate that the backpropagation approach can be effectively employed as a forecasting tool for the number of energy installation requests in the UP2D Sumut jurisdiction. The training of an artificial neural network with historical power installation demand data can create a model that accurately represents the temporal patterns of demand fluctuations. This capability is evidenced by the comparatively low error value and a sufficient accuracy level for decision-making.

The data standardization procedure, selection of network design (including the number of neurons in the hidden layer), and determination of training parameters such as learning rate, number of epochs, and error threshold significantly impact the model's performance. The test results utilizing the test data indicate that the backpropagation model not only adheres to historical trends but also generates forecasts for the number of power installation requests that closely approximate the actual values. Consequently, this model may serve as a reference for capacity planning, work schedule formulation, and more systematic and proactive resource management for power system administrators at UP2D Sumut.

This study, however, possesses several drawbacks. The input variables remain concentrated on historical demand statistics and do not incorporate external factors such as customer growth, electricity tariff policies, or area economic situations. Consequently, future research should focus on enhancing the model by incorporating additional supporting variables, evaluating the efficacy of the backpropagation method against alternative forecasting techniques (such as ARIMA, LSTM, or hybrid models), and extending the temporal scope of the data utilized to achieve a more dependable and precise forecasting model that aids in the planning and decision-making processes within the electricity sector.

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