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Sustainable Campus Policy Strategy in Estimating CO_2 Emissions at the Universitas Negeri Semarang, Indonesia

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ABSTRACT

In the fight against global warming, various options for reducing CO_2 emissions are being implemented on campus. Furthermore, the management of campus sustainability at the Universitas Negeri Semarang (UNNES), Central Java, Indonesia, should be supported by accurate forecasts of electrical energy consumption. Therefore, this research aims to develop a predictive model to forecast the consumption of electrical energy in reducing CO_2 emissions and to determine the factors triggering the increase. The prediction model is developed using Back Propagation Neural Network Artificial (BP-ANN) architecture. Furthermore, the data on the occupancy of lecturers and education staff as well as on students was obtained from the University's staffing and student affairs bureau. Climatic data such as temperature, humidity, wind speed, the duration of irradiation, and the average intensity of solar radiation were obtained per month from the Meteorology, Climatology, and Geophysics Agency of Semarang, Central Java for the 2013-2019 period as input data. The results of the empirical analysis showed an increase in electrical energy consumption from 2020 to 2025. In March, the consumption decreased but increased from April to June and decreased in July. It then increased until November and December, and it decreased every year. The results of CO_2 emissions calculated by considering the emission factors from Indonesia's RUPTL-PLN in 2020-2025 showed an increase in electrical energy consumption and the ecological consequences affecting the campus area. Furthermore, the main factors causing the high consumption of electrical energy are the occupancy rate, lecturers, students, and campus employees, as well as local climate influences such as temperature, humidity, wind speed, duration of solar radiation, and intensity of solar radiation. Therefore, developing guidelines to reduce power consumption on campus should be a priority

INTRODUCTION

Based on empirical data, several studies have shown an increase in energy demand in campus buildings (Amaral et al. 2020). This is considered unfavorable regarding the environment, especially for unsustainable resources (Ambariyanto et al. 2018). Estimating the energy efficiency of educational buildings needs to consider the composition of research-related factors (Agdas et al. 2019, Yeo & Wang 2019). Currently, the consumption of electrical energy in green campus buildings is an essential factor in the energy system. The construction sector is responsible for most global greenhouse gas emissions and all primary energy consumption (Ahmad et al. 2014, Beceric-Gerber et al. 2014, Rochester University 2015). Therefore, total electrical energy consumption needs to be estimated in planning. This is an essential factor in improving building performance, energy management and saving, fault detection and diagnosis, and optimizing smart buildings (Liu et al. 2019) stated that accurate energy forecasts help building managers prepare future budgets for their management (Amber et al. 2015).

Meanwhile, it stated that an accurate forecast of the electricity consumption of a building is a basis for energy management and shows the energy-saving potential of a building (Ding et al. 2019). The North China University Of Science and Technology, a large customer of electrical energy resources, has conducted actual measurements and simulations of consumption in energy-saving analysis for the campus (Ruijiang et al. 2017, Qiao & Liu 2020, Ghedamsi 2015). The campus is considered an area with a high level of energy use through educational activities, as well as large waste products from the activities of the residents (Meng et al. 2007, Min & Chunga 2014, Hongwei et al. 2014). Subsequently, Universitas Negeri Semarang has different guidelines for implementing sustainable campus management, such as the Green, Clean, and Healthy (H-Bat) program integrated into UI Greenmetric. Campus arrangement and infrastructure provide an overview of tendencies toward a green environment, energy and climate change, waste, water, transportation, and education (Prihanto 2018, Rokhman & Zaenuri 2020, Wahyuningsih et al. 2020). The selection of a suitable forecast model and good results is the basis for significant future research on electrical energy forecasting on campus. Several models have been considered to select the Artificial Neural Network (ANN) model to forecast electrical energy consumption.

Artificial Neural Network (ANN) is an approach used for forecasting, considering the ability to study and recognize historical data patterns stated. That it is often applied in studying building energy systems (Sharma & Nijhawan 2015, Kalogirou 2006, Malik et al. 2016), according to Li et al. (2019), Ahmad et al. (2014), Babu et al. (2020) and Deb (2016), ANN is the most widely used artificial intelligence model in the field of building performance optimization because of its speed and high accuracy, and can also handle nonlinear relationships between variables. Furthermore, it is an information-processing system with characteristics similar to biological neural networks. It is inspired by the human brain, where neurons are interconnected in a nonlinear manner. Neurons are the processing units of artificial neural networks, and each neuron receives input, processes it, and sends the result as output (Fausett 1994). The back-propagation algorithm adjusts the weights between neurons to achieve a minimal error between the forecasted and the real output (Lee & Choi 2012, Safi & Bouromi A 2013).

Furthermore, back-propagation neural networks have advantages over other artificial types when supervised training. A neural network is said to be supervised when the expected output is known (Park & Kang 2007, Runge & Zmeureanu 2019, Siregar & Wanto2017, Fang & He 2014). Therefore, this research uses Artificial Neural Network (ANN) back-propagation (Chen & Jain 1994, Olawoyin 2016, Tarigana et al. 2017) to (1) predict the electricity consumption on campus and (2) calculate the CO_2 emission. Based on the researchers' study, it is important to develop a model for forecasting electrical energy consumption in reducing CO_2 emissions on campuses. This is because the current campus is a large user of electrical energy, and the commercial sector has many buildings and many occupancy rates. BP-ANN was chosen as a forecast model with a high accuracy level capable of short-term to long-term forecasts.

MATERIALS AND METHODS

This research was conducted in the eastern area of the UNNES campus in Semarang, Central Java, Indonesia (Fig, 1). It included 6 administrative office buildings, lectures, and laboratories in the Faculties of Education, Economics, Social Sciences, Law, Sports Science, and Engineering. Based on reviews and research, most of which affect the consumption of electrical energy such as the density of building occupants as well as the local climate (Li & Sailor 1995, Lupato 2019, Farah & Whaley 2019, Moazami et al. 2019, Hashimoto & Ihara 2013, Ahmed et al. 2012, Obaidellah & Danaee 2019)

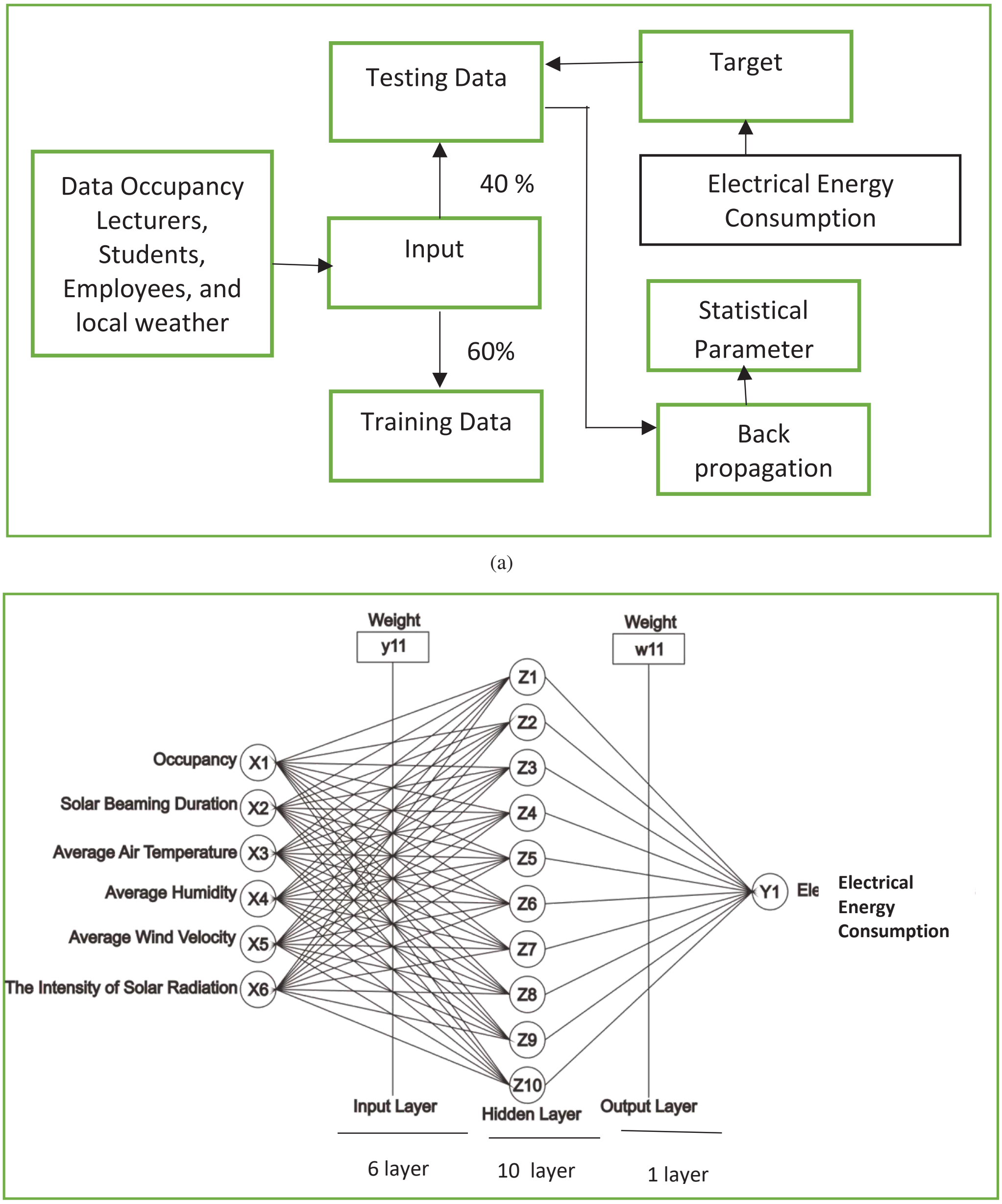
Fig. 1: Research location map.

Meanwhile, the staffing and student affairs office obtained data on the monthly building occupants consisting of lecturers, education staff, and students. The monthly data on temperature, humidity, wind speed, duration of irradiation, and average solar radiation intensity per month from January 2013 to December 2019 were collected from the Office of the Meteorology, Climatology, and Geophysics Agency in Semarang, Central Java, Indonesia.

Modeling of Back Propagation Artificial Neural Network

Data Preprocess

The monthly data on learning used as a reference was 40% of the initial ones for 2013-2019. It was adjusted to the input and output patterns determined as follows: (1) Input Pattern, BP-ANN learning input data for 72 months from 2013-2019 divided into 2 parts, namely learning patterns using 60%



(a)

(b)

Fig. 2: (a) Consumption energy electricity prediction model; (b) Network topology.

data and 40% for testing of the total initial data. The training process used a pattern of 6 inputs, 10 hidden, and 1 output layer (Fig. 2). Therefore, the output from this training data was analyzed, and the value of Mean Square Error (MSE) was the measure of forecasting accuracy. The best MSE value (smallest error value) from several trainings was used for simulation with test data. The formation of an artificial neural network used the Feedforward Back-propagation model, and the training process used the Traingdm function. Furthermore, the analysis step in building the best architecture was determined from several parameters such as (1) Logsig activation function used to bridge the comparison between the sum of the values of all future weights and the input with a threshold value available in the Matlab toolbox (Howard 2000), (2) In this study, the best result was indicated by the epoch value of 10000. (3) the best learning result using goal performance with a value of 0.001. (4) the more hidden layers, the better the learning and the longer it takes. This research used 10 hidden layers with values of 20 and 50 to slow the learning rate, while hidden layers of less than 10 shorten the learning rate with high error values. Furthermore, (5) research conducted by Trainingdm used the Gradient Descent learning function with Momentum and Adaptive Learning Rate (GDM / Traingdm). The traingdx algorithm updates the weight according to the gradient descent method with an adaptive learning rate combined with momentum to accelerate the network learning rate. In addition, the network learning process (Train Network) within the specified epoch or error value will automatically stop.

Model Evaluation

The method of Mean Absolute Percentage Error (MAPE) forecasting is used to determine the absolute error of each period. It is then divided by the observed value for that period and averaging the absolute percentage. Furthermore, MAPE states the percentage of error forecasting against actual results over a certain period. It is the average absolute error over a certain period multiplied by 100% to obtain a percentage result. This approach is useful when the size or magnitude of the forecast variable is important in evaluating the accuracy of the forecast. MAPE compares the weight of the error in guessing to the real value. Mathematically (Chen et al. 2007), it is given as:

$$\text{MAPE} = \sum_{t=1}^{n} \left| \frac{y_i - \hat{y}_i}{\hat{y}_i} \right| \times 100\%$$

Where:

MAPE = Mean Absolute Percentage Error

n = the number of data

y = actual yield value

ŷ = forecast value

The resulting MAPE value has the following interpretation :

1. MAPE < 10% : highly accurate
2. 10% ≤ MAPE < 20% : good accurate
3. 20% ≤ MAPE <≤ 50% : reasonable accurate
4. MAPE 50% : inaccurate

RESULTS AND DISCUSSION

Electrical Energy Consumption Forecast Using BP-ANN

In the energy management and climate change program, the campus makes policies through the office of the implementing unit for conservation tasks. This was conducted by implementing energy efficiency on campus for new renewable energy, such as using solar modules to replace electricity sources from PLN (Perusahaan Listrik Negara/ (State Electricity Enterprise), automatic control applications for lighting, air conditioning, and other equipment electricity. Furthermore, it includes conducting energy audits for campus electrical systems and training employees on energy audits and electric power systems. However, the results of observations from the campus household showed a yearly increase in electricity costs. Therefore, the monthly increase and the cost of electricity consumption should be examined. This research used BP-ANN to predict errors in training since it recognizes the pattern and produces an accurate input-output relationship. It also used a feedforward back propagation algorithm with one hidden layer, and the number of neurons was developed in this BP-ANN method. In addition, several structural MLP (Multi-layer Perception) efforts have been trained and developed in Matlab software. This structure showed the number of neurons in the input, hidden, and output layers. The comparison of measured and predicted values was checked according to the Mean Average Percentage Error (MAPE) with equation (6). The results showed that the BP-ANN model achieved a significant agreement between the estimated value and the average monthly electricity consumption with MAPE, which is 9.6105% below 10% and has a high prediction accuracy (Lewis 1982, Tayman & Swanson 1999). An estimator can achieve MAPE with the structure of MLP consisting of 6, 10, and 1 neuron in the input, hidden, and output layers.

The measured or forecasted values of electrical energy consumption in green campuses are presented in Table 1.

Table 1: The results of the measurement value with the target value of electrical energy consumption using BP-ANN.

Month	Monthly electricity consumption [kWh]	Monthly electricity consumption predicted [kWh]	Error [kWh]	Error [%]	MAPE
January	218028,230	218626	597,7696	0.071142	0.096105
February	198498,260	199467	968,7396	-0.01653	
March	176182,273	175897	285,273	-0.16102	
April	267692,607	269987	2294,393	0.008223	
May	244261,746	246789	2527,254	0.009057	
June	249430,670	250243	812,3296	0.002911	
July	181879,404	178748	3131,404	-0.01122	
August	209176,099	210239	1062,9	0.003809	
September	229160,837	227034	2126,837	-0.00762	
October	261834,830	263748	1913,17	0.016856	
November	269313,258	269849	535,742	0.02192	
December	259735,610	258839	896,6098	-0.00541	

The validity results showed that the MAPE price was below 10%. Because of that, the BP-ANN model is feasible to use to estimate electricity consumption in green campuses, as illustrated in Fig. 3.

The results of the forecasted electrical energy consumption can be presented in Table 2.

Fig. 4 shows the results of forecasting electrical energy consumption using the BP-ANN model in 2020 - 2025 in the green campus building at Universitas Negeri Semarang, Indonesia. The electricity consumption in green campuses was different every month and was quite high in February and March, then low in June, July, August, and September. It increased from October to November and then decreased in December. This finding allows managers to consider strategies for saving electricity, energy conservation, electricity system management, and support for the environment in reducing carbon emissions in the future. The relevant research (Lee & Choi 2013) shows that back-propagation neural networks have other advantages over other artificial neural networks, namely back-propagation artificial neural networks using supervised training. The neural network is supervised if the expected output is known beforehand and concludes that the accuracy of back-propagation ANN forecasts is 81.43% greater than the accuracy of multivariate discriminant analysis, which is 74.82%. The ANN model can be applied to forecast building energy consumption and is suitable for all buildings (Deb

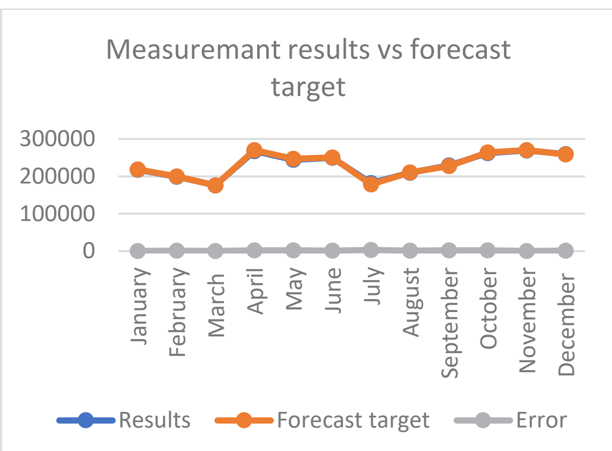


Fig. 3: Graph of validation of measurement results versus forecast targets.

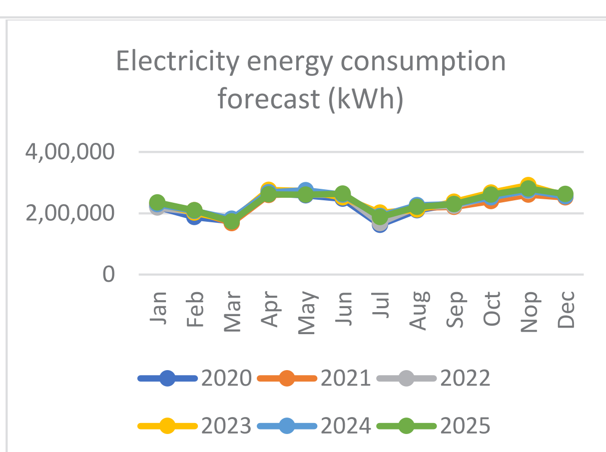


Fig. 4: Graph of electrical energy consumption forecast (kWh) in 2020-2025.

Table 2: Estimated results of electrical energy consumption (kWh) in green campuses in 2020 -2025 using the BP -ANN model.

Month	Year					
	2020	2021	2022	2023	2024	2025
January	221.098	226.678	218.307	232.259	229.469	235.049
February	187.337	209.939	204.079	201.289	206.870	209.660
March	174.507	167.811	178.972	176.182	181.762	173.391
April	264.903	259.322	273.274	276.064	267.693	262.113
May	258.215	263.795	261.005	272.166	274.957	261.005
June	246.640	257.802	260.592	251.105	260.592	263.382
July	162.347	170.718	167.928	201.412	190.251	187.460
August	209.177	218.106	220.339	211.968	225.919	220.339
September	229.162	220.791	223.581	237.533	229.162	229.162
October	250.672	239.511	253.463	267.414	251.788	260.997
November	263.734	260.944	272.105	291.637	274.895	280.476
December	257.559	251.978	260.349	257.559	254.769	263.140

Table 3: CO_2 emission factors for the Java-Bali electricity system in 2020-2025.

Year	Emission Factor (EF) [$kgCO_2/kWh^{-1}$]
2020	0.854
2021	0.854
2022	0.871
2023	0.871
2024	0.871
2025	0.759

CO_2 emissions = EF x Electricity production, given in ($kgCO_2/kWh$) per month: (Source: ESDM of Republic of Indonesia 2016)

2016, Ghedamsi 2015).

The Relationship between Electrical Energy Consumption and CO_2 Emissions on Campus

The amount of CO_2 emissions can be determined from the equation based on the results of forecasting electricity consumption in the location:

CO_2 emissions = EF x Electricity production (IPCC 2006). The Emission Factor (EF) of electricity was determined from the electricity emission factor of the Java–Bali system. The factors of CO2 emissions in Java and Balli over the year are given in Table 3.

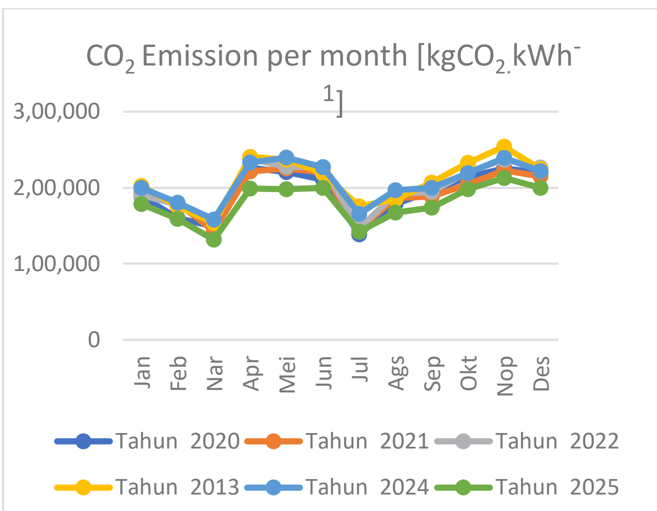


Fig. 5: Graph of the amount of CO_2 emissions per month ($kgCO_2$ kWh^{-1}) in 2020-2025.

Fig. 5 and Table 4 show the quantity of CO_2 emissions per month ($kgCO_2.kWh^{-1}$) on a green campus in 2020-2025. These predictions and calculations support policies to reduce electricity consumption and greenhouse gas emissions. The future implications of this electrical energy forecast can provide an overview of CO_2 emissions in green campuses. (Presekal et al. 2018, Robinson et al. 2015, Riddel et al. 2009, Babatunde et al. 2020). The estimated electrical energy demand (kWh) results affect the CO_2 emissions generated in 2020-2025.

CONCLUSION

The development of sustainability policies oriented toward reducing campus electricity consumption should be prioritized. Furthermore, implementing the BP-ANN model for predicting electrical energy consumption in the State University of Semarang green campus building showed good accuracy with a MAPE value of 9.6105%. Therefore, it was “feasible” to be used as a model for forecasting electricity consumption. In addition, the makers of green campus policies can obtain information on CO_2 gas emissions from electrical energy consumption to investigate the amount.

Several things that require further research are related to electrical energy data during the COVID-19 pandemic to estimate electrical energy on campus and the reduction in CO_2 emissions due to reduced occupancy rates. Future work on the results of electrical energy forecasts in reducing CO2 emissions is one of the aspects taken into account for the achievement of SDGs in higher education institutions

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