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Multivariate Forecasting of Electricity Consumption for Sustainable Energy Planning

Lukmanul Hakim*, **Hery Dian Septama**

Electrical Engineering and Informatics Department, Faculty of Engineering, Universitas Lampung, Jl. Soemantri Brojonegoro No. 1, Bandar Lampung, 35145, Indonesia.

ABSTRACT

Forecasting accurate consumption of electricity is crucial for energy security of a rapidly grown region. Prior study proves that there is a positive relationship between electricity consumption, population and economic growth. Nevertheless, only a few have applied the multivariate model within a regional context for the long-term electricity forecasting. This study tries to bridge the gap in forecast reliability by using machine learning to support regional sustainable energy planning in the Lampung Province. The methodology includes data preprocessing, integration, and cleaning, and model training and validation using time-series data. The Vector Autoregressive (VAR) was employed to predict electricity consumption from 2024 to 2030 based on historical data from 2010 to 2023. The model demonstrated a robust predictive performance, with a low MAPE of 0.57%, RMSE of 37.74, and a high R^2 value of 0.998. This instills confidence in the findings of the research and the future use of the VAR for electricity forecasting. The model suggests that the trend of energy consumption in Lampung Province is continuously increasing. The study also stresses the need for renewables to meet future electricity needs, ensuring energy infrastructure tackles socio-economic growth and the energy transition agenda with regard to the development of Lampung Province.

Keywords

Multivariate;
Forecasting;
Electricity;
Machine learning;
Energy planning

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1. Introduction

In today's fast-paced world of economic development, the availability of adequate and affordable electrical energy is a key constraint to economic development. Rural electrification plays an important role in providing access to electricity. Since the 1950s, Indonesia has improved its electrification ratio through its rural electrification program. As of 2023, the program had achieved an electrification ratio of 99.78%, as reported by the Ministry of Energy and Mineral Resources (MEMR) of Indonesia. Issues related to this rural electrification program have been reported previously [1]. Implementing a sound and broad-minded electricity supply plan is key to economic stability, technological innovation, and environmental sustainability. Governments, policymakers, and industries in energy sector must develop a framework that not only meets current demands but also prepares for the future challenges in energy demands [2].

The development of an electricity supply plan stands at the core of ensuring energy security in the future. An electricity supply plan forecasts the future energy requirements of the region and provides a detailed strategy for their fulfillment [3]. The planning of electricity supply networks requires significant time and effort due to the long lead times involved in developing new power plants and transmission lines. This planning has to be adapted as a result of costs, prices, technology, and public policies [4,5].

The projection of future energy requirements should consider population growth, industrial expansion, technological advancement, changing pattern of energy use, and sustainability. Moreover, the strategies must also

*Corresponding author – e-mail: lukmanul.hakim@eng.unila.ac.id

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include the utilization of renewable energy from the viewpoint of sustainability and environmental issues. Technological advancements in renewable energy like solar energy and wind energy are critical for the future. These technologies can reduce the environmental impact and improve energy sustainability [6].

These renewable energy sources are designed to take over from fossil-fueled power stations. Sustainable energy transition involves three important technological shifts, *i.e.* energy savings on the demand side, generation efficiency on the production side, and fossil fuel substitution through renewable energy sources and low-carbon nuclear option [7]. Several studies have been conducted to analyze and forecast energy sources for sustainable electricity generation in Indonesia. Energy sources are ranked for sustainable electricity generation in Indonesia using multi-criteria decision analysis in [8]. It reveals that solar, hydro and oil are the top three alternatives for sustainable electricity generation in Indonesia.

The study by [9] shows that Indonesia is facing a growing gap between energy supply and demand. This study also shows an increasing reliance on fossil fuels and a stagnating share of new/renewable energies. This study also notes that despite ambitious national targets for a higher share of renewables by 2025 and 2050, the actual trends suggest the country is not moving toward those targets. At last, the significant challenges of planning lie in balancing the incorporation of green energy with all existing infrastructure and keeping it affordable to the consumers [10]. In order to cope with its electricity demand until 2030, Indonesia, through the MEMR has updated the National Electricity Supply Business Plan 2021 – 2030 [11]. This revised plan seeks not only to add to the country's power generation capacity but also to bring in a more diverse array of energy mix, especially renewables and other state-of-the-art clean technologies. The plan aims to enhance energy security, competitiveness of the economy and environmental sustainability. Further, it also calls for modernizing grid infrastructure and adopting effective policies and regulatory frameworks to enable efficient power distribution. In the end, these strategies aim to ensure that Indonesia can provide electricity to its people and industry while advancing the country toward a more sustainable, enduring energy future.

The link between how the specific region's population, jobs, and energy infrastructure interact will inform how electricity planning should be done accurately. As the population increased in the regions and the industrial and service sectors diversified, electricity demand has become varied and complex. At the same time, technological development, especially the deepening digitalization and integration of digital technologies across sectors, is going to reshape the integration of renewable energy. The changing landscape requires strong analytical methods to guarantee power supply reliability, efficiency, and sustainability to meet present needs and future growth pathways.

This paper investigates the machine learning application for predicting the increasing demand of energy in the future. As a result, governments and policymakers can plan for sustainable development using these forecasting results. This study is conducted in the Lampung Province region due to its unique regional characteristics. Predicting the electricity consumption of a rapidly growing and developing region like Lampung Province of Indonesia is of great importance in the coming year. Consistent with our discussion above, the paper applies the multivariate forecasting model of the Vector Autoregressive (VAR) model.

The current study will provide an analysis of the correlation between electricity consumption, population, and Gross Regional Domestic Product (GRDP) as an accurate prediction of electricity demand in Lampung Province over the next seven years for the purpose of regional energy policy planning. This analysis focuses on regions and their GRDP instead of using Gross Domestic Product (GDP). As GRDP refers to the total value of goods and services produced in a region during a certain period, it makes GRDP as a good indicator of regional economic activity in billion Indonesian Rupiah (IDR). On the other hand, GDP reflects the national economic output as a whole, which may mask key regional differences that are vital for effective energy planning at subnational levels. In addition, this research study undertakes an investigation of renewable energy sources and their relevance to electric development strategies in light of the province's net-zero emissions targets.

2. Literature review

A significant long-term positive correlation characterizes the relationship between electricity consumption and GDP growth in developed economies [12]. Research indicates that electricity consumption is an essential production factor supporting economic growth [13,14]. These are evidenced by studies involving advanced economies where a consistent positive association was found between electricity consumption and GDP growth over extended periods [15]. A cross-sectional analysis of OECD countries also confirms that electricity consumption impacts economic growth more than the reverse impact. Electricity consumption has positive, significant and strong effect on economic growth [16,17].

Studies indicate that past electricity consumption is productive for current economic growth. However, a study on the U.S. noted some variations with regard to feedback effects [13]. According to Zhu, the relationship between electricity consumption in a country and GDP growth has a long-term equilibrium. However, this relationship specifically with reference to developed economies was not explained [18]. Some studies indicate that electricity consumption may not be a consequence of national income in developed economies which suggests complex interplay between the two variables [19].

Electricity consumption can also be affected by population. Energy consumption rises due to increase in population. Its impact differs by sector and over time [20,21]. According to estimates, the world's population will grow to between 9 and 13 billion by the year 2100. Furthermore, it is expected that the energy demand will rise at least three to five times more than today [22]. The patterns of demand can be influenced by the density, age composition and urbanization of the population [23]. It is also important to provide equity to electricity access as well as efficient use of electricity due to its direct bearing on socioeconomic development and allows for mitigating the negative impact of population growth on resource consumption [24,25]. Consequently, it is critical for policymakers to implement sustainable energy policies to ensure energy efficiency, continuous economic development, and electricity access [26].

Forecasting the electricity requirement is an important task. Various studies have been conducted on forecast for either price and either demand predictions [27,28]. To make forecasting more accurate, various methodologies have been developed. Many studies use probabilistic approaches by using improved algorithms and neural networks. Regression analysis effectively forecasts electricity demand using variables like Net State Domestic Product and sector-wise domestic savings. The study accurately predicts future domestic sector demand [29]. Roman's research makes a systematic literature review from 1993 to 2020 that uses ANN-based Machine Learning Algorithms for Electricity Demand Forecast [30]. The study findings suggest that there is an opportunity to enhance electricity demand forecasting using ANN and other machine learning techniques despite considerable progress. Pallonetto et al. study Long Short-term Memory Networks and Support Vector Machines, among other machine learning models. The work deals with short-term load forecasting, indicating the method's utility for handling nonlinear load data characteristics [31]. This machine learning model could lead to more robust models that can handle the complexities of modern electricity demands.

VAR models offer several benefits for forecasting, particularly in the context of multivariate time series data. The application of VAR models spans various fields, including climate [32], economics [33,34], energy consumption [35], electricity and internet forecasting [36]. One of the primary advantages of VAR models is their flexibility and ability to capture the dynamic interrelationships between multiple time series variables [37]. This flexibility is particularly beneficial in the context of electricity forecasting.

A study by Kumar employed a VAR model to predict the peak load in order to manage peak demand control in the smart grid [38]. The study by [39] use multivariate variables such as temperature, solar radiation, and wind speed to improve forecast accuracy. VAR models are relatively less time-consuming and cost-effective to develop and apply compared to more complex machine learning models [40]. However, VAR models also have limitations. One significant challenge is the high dimensionality that arises when incorporating multiple time series and lag orders. This condition can lead to noisy estimates and unstable predictions if not properly managed [41]. VAR models are commonly applied for forecasting multivariate time series, especially when the underlying variables are related to each other. The value of each variable in a system is formulated as a linear function of its past value along with the past values of all other variables in the system in a VAR framework. The period of forecast, or the time-length of the forecast, is a characteristic of the model itself. This is indicated, for instance, by a VAR(p) model, where p is the number of lags entered. A VAR(1) model captures dependencies only from the previous time step, whereas a VAR(2) model captures dependencies from the two previous time steps. Choosing the right lag order is crucial because, if the order is too low, then it would fail to capture some of the complex temporal dependencies. On the other hand, if the order is too high, then the model may get overfitted and, also, the complexity of the model would increase, especially in situations with limited amount of data.

Moreover, in dynamic environments where the inter-variable relationships evolve, various methods and criteria have been proposed to identify the appropriate lag length, each with its strengths and weaknesses [42]. Different methods have been proposed, including the use of information criteria such as Akaike Information Criterion (AIC), Schwarz-Bayesian Criterion (SBC), and Hannan-Quinn Criterion. Overall, the selection of lag order and model specification must strike a balance between predictive accuracy, model interpretability, and computational feasibility, particularly in the context of long-term forecasting and real-world applications [43]. Even with a small dataset, VAR models have many additional advantages. The implementation and interpretation of VARs is quite simple and this condition makes them practical for small datasets where complex models might overfit the data. Hence, using VAR models to forecast electricity with a small dataset can benefit from capturing the dynamic interrelationships of the variable series and reveal how various determinants influence the demand for electricity.

3. Research methodology

The procedure for constructing and implementing a machine-learning model for forecasting electricity is illustrated in Figure 1. Clearly, there are several phases of Business and Data Understanding, Data Preparation, Modelling, and Evaluation. In this case, the study uses a VAR model for forecasting electricity consumption in Lampung Province, Indonesia. This model takes historical population with GRDP data as predictors.

The initial stage called Business and Data Understanding allows for the alignment of the machine learning project with a specific goal or objective. VAR model used in this study which useful to predict electricity consumption. Population and GRDP growth are variables which impact electricity consumption. The research identifies the need for accurate electricity consumption forecasts to support energy planning in Lampung Province during the requirement analysis phase. Historical data on population, GRDP, and electricity consumption from 2010 to 2023 are examined in this phase. This requirement analysis helps uncover trends and relationships between the predictor variables and electricity consumption. In the data collection step, the required historical data are GRDP, population statistics, and energy reports sourced from the Central Agency of Statistics of Indonesia at Lampung Region. The data can be accessed at the official website in [44]. The data exploration step is conducted to verify the quality of raw data collected in previous phase.

In the Data Preparation stage, the raw data is prepared to ensure it is clean and fit for use in the VAR model. The first step is the data integration process. This stage consists of a combination of the population, GRDP, and energy consumption data. Next, the data is cleaned to remove any missing values, as well as flagging inconsistencies or errors in the data due to outliers, this fixes the data errors to prevent skewed forecasting results. Feature extraction is then used for selecting multiple columns of

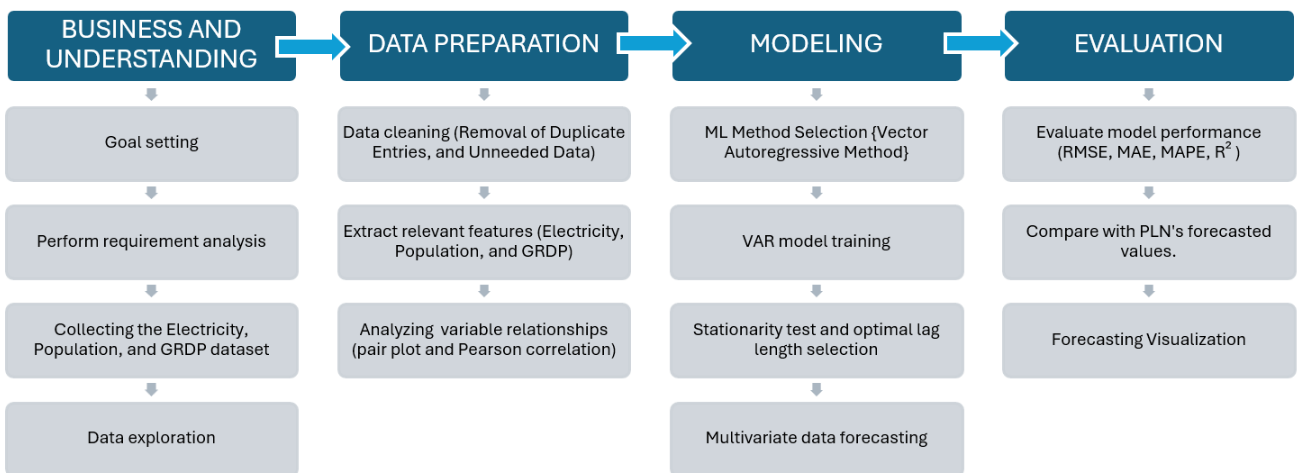

Figure 1: Research methodology.

the relevant feature. The variables used for multivariate analysis were population, GRDP, and electricity. The next step involves applying Pearson's correlation to examine the relationship of the variables under study. The correlation heatmap is used to visualize the results.

A pair plot analysis was performed as an initial exploratory analysis for the variables Electricity (GWh), Population and GRDP (billion). With this visualization, one can quickly judge whether there are any potential linear or non-linear associations, how strong these correlations were or other patterns in the data, such as clustering or outliers. In the Modelling phase, machine learning focuses on building and training the model. The first step involves selecting the machine learning algorithm, which in this case is the VAR model. The VAR is chosen because it can capture the interdependencies between multiple time series variables [45,46]. Before applying the VAR model, all time-series variables were tested for stationarity using the Augmented Dickey-Fuller (ADF) test.

Initial run showed that all series were non-stationary at the level, thus required first-order differencing to achieve stationarity. The transformed data were then used to estimate the VAR model. Following this, the optimal lag length for the VAR model was determined using the Akaike Information Criterion (AIC). This step is important in ensuring that the VAR model can capture how past values of the predictors (population and GRDP) affect future electricity consumption.

The next step is splitting data to divide the historic data into training and testing dataset. The data used in this study is for the years 2010 to 2023, namely electricity consumption, population and GRDP Lampung Province. Each data set has a total of 14 rows of yearly data. For model development, training was done using 70% of the data (10 rows) and the testing and validation were done using 30% (4 rows).

The last step is model training. It was done with the sample spanning the period from 2010 to 2023. Testing showed that based on the AIC, the final model was assigned a lag length of three. The model incorporated a constant trend component that accounts for structural breaks in the data. The model forecasted electricity consumption for the next seven years after estimation.

The forecast information is made by transforming the differed forecast results again to the actual values by applying cumulative summation and adding the last levels observed. The model learns the relationship between electricity consumption and time, population and time, and GRDP and time. Consequently, the VAR model forecasts the electricity demand for future years 2024 to 2030.The last stage is Evaluation. Evaluation stage assesses how well the VAR model performs. This step was carried out to test the accuracy of the forecasting electricity consumption. During model testing, the fitted VAR model is applied to the validation data used for forecasting the future electricity consumption based on the historical trends in population and economic growth. Model performance is evaluated using error metrics such as Mean Absolute Error (MAE), R-squared (R^2), Mean Absolute Percentage Error (MAPE), or Root Mean Square Error (RMSE).

This performance is attributed to gauging the accuracy of the forecasts [47,48]. We also make a comparison of our forecasting results with the PLN (National Electricity Company) forecast. Finally, a visualization presents the forecasting results. The graphs the years 2023 to 2030, illustrating the predicted electricity consumption trends. This visualization provides valuable insights for energy planners and policymakers.

4. Results and discussion

Lampung Province is located at the tip of Sumatra Island, Indonesia, it is the gateway island of Sumatra. Recent manufacturing construction activities have led to the construction of several big infrastructure projects including toll roads, electric power transmission and distribution lines. As a result of these developments, electricity consumption in Lampung Province has surged.

Figure 2 shows historical data on electricity consumption in Lampung Province from 2010 to 2023. This data is collected from Electricity Supply Business Plan (RUPTL) 2021-2030 MEMR Indonesia [11]. Figure 2 illustrates energy consumption trends across various sectors over several years. Electricity consumption is divided into several categories: Household, Industry, Business, Social Agency, Government, and Public.

In Lampung Province, the Household sector is the largest consumer of electricity and is consistently increasing. The trend may reflect a rising population or growing energy consumption through the more widely use of electrical home appliances.

An insight in sector-wise energy consumption can help in future energy infrastructure planning and policymaking priorities. The electricity increases sustainability and reliability of electricity supply according to demand for every sector [2]. According to Figure 2, the energy

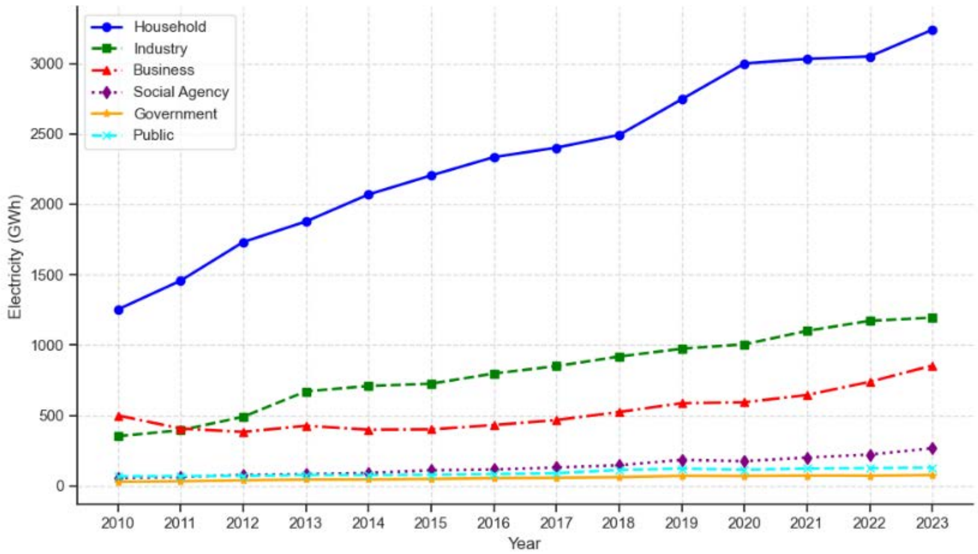

Figure 2: Electricity consumption by category in Lampung Province [11].

consumption in the Household sector has increased by approximately 158.58% from the first year of the data to 2023. Total consumption in Lampung Province in 2023 was 5761.91 GWh.

The Household sector alone consumes 3230.05 GWh, which is around 56.2% of total consumption. The other sectors including Industry, Business, Social Agency, Government, Public consumes 2522.86 GWh (43.8 % remaining). The Government of Indonesia's Rural Electrification Program has corresponded with this significant growth [1]. The objective of the scheme was to provide electricity in all over the country. The increase in energy use in households is most likely because the households that used to consume electricity have started using it.

The result was a heightened use of electrical appliances and an increase in demand for energy. The effectiveness of the program in uplifting living standards and achieving economic development is undeniable. However, it has also led to a considerable surge in household energy use.

Although other sectors show less electricity consumption than households, both industry and business sectors experienced an increase. For example, a slight increase in electricity consumption can be observed from industry sector. Notably, after the COVID-19 pandemic relief in 2022, the business sector started to grow significantly, shown by steeper gradient in electricity consumption. This business sector covers tourism businesses, including hotels, tourist sites, and restaurants. This development indicates that the business sector's recovery is underway. The sector of Social Agency seems to be maintaining a steady trend. Some slight increase indicates a continued level. Government energy consumption shows minor growth. The consumption increase could be limited due to efficiency measures or budget constraints. There are noticeable upward trends in most sectors which suggests that there may be an increase in energy demand. This may have some implications for the energy policy as well as resource management in the future.

The growing business sector trend should be emphasized even more. The tourism of Lampung Province will be able to attract tourists from neighboring provinces such as South Sumatra, Bengkulu, Banten, and Jakarta. Thanks to a toll road network that connects the major cities in Sumatra, Lampung's tourism sector seems to be attracting an increasing number of visitors. In recent times, numerous hotels were built in Lampung to accommodate more tourists with several tourist attractions developed along the coast of Lampung.

After looking at the trend of electricity consumption in the period 2010-2023, the next step is to make sure electricity consumption has relationship with population and GRDP. Pearson's correlation coefficient, r, is a measure of the strength of the linear relation between two variables. The correlation is calculated using equation 1. The correlation coefficients range from -1 to 1, with values closer to 1 indicating a strong positive relationship. The values closer to -1 indicate a strong negative relationship, and values near 0 indicate no linear correlation.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})2\sum(y_i - \bar{y})^2}} \tag{1}$$

Where:

- r_{xy}: Pearson correlation coefficient
- x_i,y_i: Individual data points for variables X and Y
- $\bar{x}, \bar{y}$: Mean (average) of variables X and Y
- n: Number of paired observations

The results show strong positive correlations between these variables. There is a very high relationship with a coefficient of 0.99 between electricity consumption with GRDP. This means that economic growth is closely related with energy use. Electricity usage rises along with GRDP in nearly proportional terms. To examine the relationships concerning that feature, a correlation heatmap in Figure 3 was generated. Likewise, electricity consumption and growth in population have a high correlation of 0.98 which means with a greater population there will be greater electricity consumption. Moreover, there's a strong interdependence between the population and GRDP as indicated by a correlation coefficient of 0.95. Thus, population and GRDP have a close relationship. The studies reveal that the financial growth, increase in population and energy consumption related to each other.

Figure 4 shows the relationship among electricity consumption, population, and GRDP. This plot confirms the findings from the correlation analysis. The graph representing electricity consumption versus population shows an upward trend. The graph also shows that as the number of people increases, energy consumption also increases steadily. The strong positive correlation of these variables is consistent with this.

Moreover, the graph between electricity consumption and GRDP indicates an almost linear relationship. This indicates that electricity plays a very important role in economic growth. As GRDP rises, energy consumption

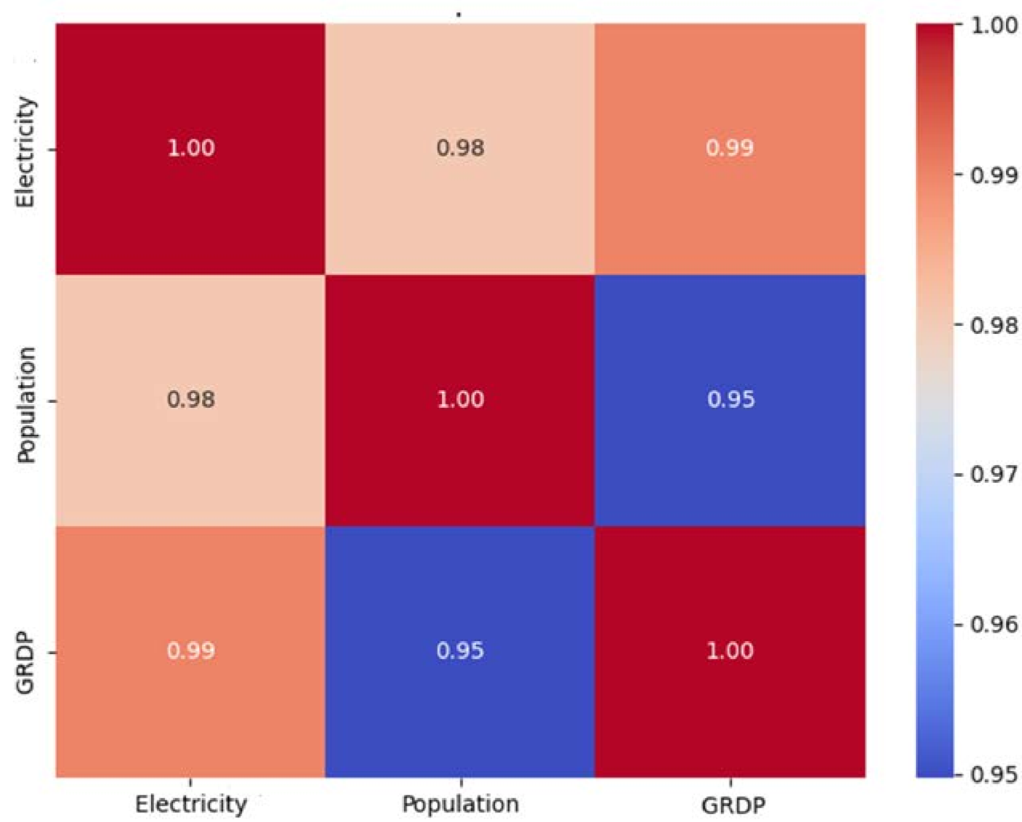

Figure 3. Correlation heatmap between variables in Lampung Province within the period of 2010-2023.

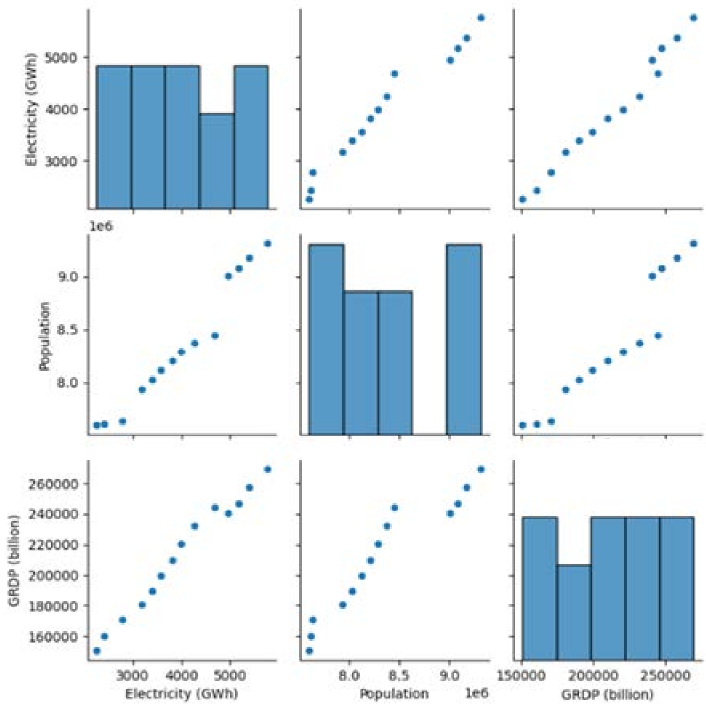

Figure 4. Pairplot analysis for variables in Lampung Province within period of 2010-2023.

rises. The graph of population and GRDP indicates a positive relationship. The distribution is slightly more scattered, suggesting that population growth causes expansion but is not the only reason for GRDP. The pair of visual illustrations provide a clear idea of the relationship of these necessary variables.

After a strong correlation is confirmed, all features can be used in forecasting using multivariate analysis. The data used in this study were sourced from the Lampung regional dataset and cover the years 2010 to 2023. The variables include electricity consumption (in GWh), population, and GRDP (in billion Indonesian Rupiah). This data was extracted from an Excel file and structured into a multivariate time-series format.

The VAR model is used to describe the dynamic relationships among variables over time. Each variable in a multivariate setting depends not only on its past values but also on the past values of the other variables in the system. The general form of the VAR model with p lags is shown in Equation 2:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \epsilon_t \tag{2}$$

Yt is a vector containing the variables (Electricity Consumption, Population, and GRDP) at time t. The variables A_1, A_2, …, and A_p are coefficient matrices, and ϵ_t is a vector of error terms (white noise). In this study, A VAR model with a three-year lag was employed. This lag was chosen using the Bayesian Information Criterion (BIC), as the dataset is small, which helps avoid overfitting.

The selected lag produces the best working model overall. The setup captures the impact of money aspects and people aspects after some years. The model does not include the vector of intercepts because the data were mean-differenced in order to focus on the dynamic relationships of the variables, and to ensure stationarity. This is a key assumption of VAR models. This formulation makes it possible to analyze how consumption of electricity, population and GRDP interacts with each other over time as well as to predict what would happen in the future based on their interaction in the past.

The VAR model projects the electricity demand for the next seven years, namely the years 2024 to 2030. The population and the GRDP variables are forecasted simultaneously as they are paramount in formulating how much energy will be needed in years to come. To compare the historical data that was collected from 2010 to 2023 with the help of a plot of the forecasted values from 2024 to 2030. As depicted in Figure 5, the forecasted electricity consumption resulting from the VAR model (indicated by the dotted yellow dashed line) shows a steady upward trend in energy demand from 2024 to the end of 2030. The projected growth follows the pattern of the historical data, as increased electricity consumption has steadily risen due to population and economic growth.

The MEMR also published the electricity consumption projection by PLN in the National Electricity Supply Business Plan 2021-2030 [11]. Figure 5 shows the forecast results by PLN (indicated by the dotted green line) and compares them with those of the multivariate VAR study indicated by the dotted yellow line. The steady increase shown by PLN forecast implies an almost constant economic growth assumption.

Electricity consumption in Lampung Province is growing steadily from about 2000 GWh in 2010 to over 6000 GWh in 2023 (dotted blue line). This increase has been consistent with demand driven by population growth, urbanization, business expansion, and industrial growth. Figure 5 also shows that the forecasts diverge significantly. According to the VAR model, consumption is expected to continue increasing moderately, reaching approximately 8,000 GWh by 2030. The projection assumes a more conservative growth rate. It is attributed to realistic factors, such as a slowing pace in population growth, fluctuations in the economy, or an improved energy efficiency index. The VAR model is a potent tool for forecasting, as it considers all the influencing variables of population and economic variables, providing a more balanced projection based on historical trends.

By contrast, the PLN forecasting, a green dotted line, assumes a much more significant increase to more than 10,000 GWh by 2030. Optimistic assumptions on steep industrial growth, ambitious infrastructure projects, or further electrification initiatives may underpin such a projection. Although such assumptions are plausible, they may result in overestimation if economic and industrial expansion does not occur as quickly as assumed. Hence, this creates a scenario in which the power plants installed capacity exceeds the actual technical minimum load.

Considering the methodologies behind these forecasts, as mentioned earlier, the most reliable forecast for this level of demand in the future is likely to be that provided by the VAR model. Historical trends have been factored into this model, and several influences may alter the historical trend. Therefore, it is more recognizable as a tool for effectively predicting long-term planning. On the other hand, the PLN projection may be overly optimistic, so future demand is expected to be less than initially anticipated, particularly for industrial and economic development.

The forecasted total energy consumption and peak load from 2024 to 2030 are given in Table 1. Accordingly, the gross energy consumption in 2024 is estimated

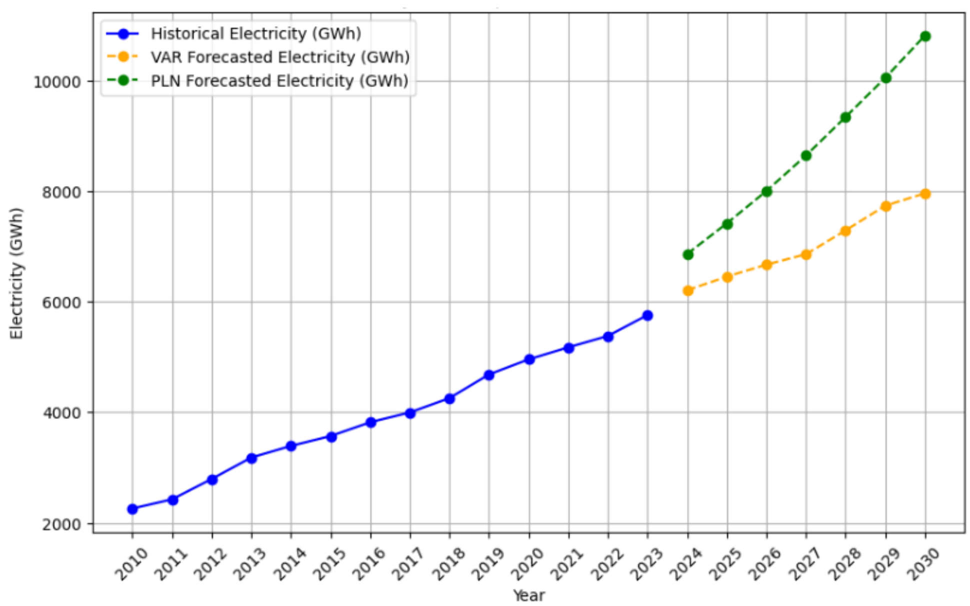

Figure 5. Combined plot of historical and forecasted electricity consumption in Lampung Province.

Table 1: Forecast using multivariate VAR.

Year	Total Energy Consumption (GWh)	Peak Load (MW)
2024	6210.04	1357.12
2025	6456.34	1440.56
2026	6673.61	1511.69
2027	6862.17	1585.03
2028	7294.79	1664.06
2029	7740.55	1744.85
2030	7964.08	1829.59

at 6,210 GWh, with an approximate peak load of 1,357 MW. With each passing year, both these dimensions increase at a slow growth rate. In 2025, energy consumption is projected to rise to 6,456 GWh, accompanied by a peak load of 1,440 MW. This upward trend culminates in approximately 7,740 GWh in 2029 and a peak load of 1,744 MW. Energy consumption is expected to increase to 7,964 GWh by 2030, creating an estimated gross peak load of 1,829 MW. Overall, this represents a significant growth in energy consumption from 2024 to 2030 of about 28%.

The performance results show that the VAR model in this analysis shows excellent predictive performance. This performance was corroborated by metrics such as MSE (1424.53), RMSE (37.74), and MAE (23.65). Thus, exact predictions result from this model. More importantly, the MAPE is only 0.57%, indicating that forecasted electricity consumption values are, on average, 0.57% away from accurate data.

Furthermore, the reported R-squared value of this model equals 0.998, which means that it can explain 99.8% of the variance in electricity consumption, resulting in an almost perfect fit to the data. These performance metrics confirm that the VAR model is robust in providing a correct forecast of the trend in electricity consumption based on past population and GRDP data and thus presents reliable insight for future energy planning.

PLN produces most electricity required by the demand, and additional supplies are sourced from independent power producers (IPPs) through power purchase agreements (PPAs) and leased power plants. As shown in Table 1, energy demand is projected to increase significantly from 2024 to 2030. The table shows that the peak load will rise from 1357 MW to 1829 MW. This increase will necessitate the establishment of more power plants in Lampung Province to secure its future electricity demand.

In 2023, PLN published that the peak load in Lampung Province reached 1274.3 MW, while the net capacity of power plants in Lampung is 890.3 MW, as shown in Table 2. This means around 380 MW of electric power is imported by Lampung from the Sumatra grid. As future electricity demand will increase as well

Table 2: Existing power plant capacities in Lampung Province in 2023 [11].

Power Plant	Units	Total Capacity (MW)	Net Capacity (MW)
Hydropower	4	118.6	117.6
Coal-fired	4	400.9	290.0
Diesel	8	59.3	26.9
Gas Turbine	1	21.4	14.8
Geothermal	2	110.0	103.8
Diesel (isolated in Sebesi Island)	5	0.5	0.4
Total PLN	24	710.7	553.5
Hydropower	2	55.0	55.0
Geothermal	2	90.9	90.9
Coal-fired	3	24.0	24.0
Total IPP	7	169.9	169.9
Gas Turbine	4	112.9	112.9
Gas Engine	2	54.0	54.0
Total Leased	6	166.9	166.9
Grand Total	37	1047.5	890.3

as the peak load, unless more power plants are constructed in Lampung, high dependency on the supply from the Sumatra Grid cannot be avoided. The current power transfer from the Sumatra Grid via 150 kV transmission lines will be sufficient to cover the power deficit in Lampung for the typical operating scenario, with necessity of expansion of 275 kV connection to Lampung Province from Sumatra Grid in the near future.

However, during a contingency, the electric power supply in Lampung Province is at risk of a blackout because any fault in the Sumatra Grid will lead to islanding operation of the Lampung network. Moreover, once cascading blackouts occur in the future, a black start mechanism will require energizing from the islanding grid. In order to provide a more reliable power supply to Lampung, additional power plants must be allocated in Lampung.

Net-zero emissions are another issue to address while meeting the increasing demand. More than 60% of power is generated from non-renewable energy, i.e., coal, diesel, and gas, as indicated in Table 2. The Lampung government must carefully consider the types of power plants to build, either by PLN or IPP. A significant portion of electric power is generated from coal and diesel power plants, contributing heavily to carbon emissions. The Covid19 may impact the implementation in renewable energy implementation in Indonesia as presented by study in [49].

To mitigate environmental impact, the government should prioritize cleaner energy sources such as hydropower and geothermal power. Both of which are renewable and have minimal emissions. Expanding these plants, particularly in regions like Lampung, where the potential for hydropower and geothermal energy is high, will support future energy needs. This result is aligned with study by [50] that analyzed the optimization of power generation mix to achieve net zero emission pathway in indonesia.

In addition, natural gas power plants can serve as a lower-emission alternative to coal. This power plant provides a transitional energy source while more renewable capacities are developed. This enegy source transition is presented by study in [51]. This study provides strategic plan for renewable energy transition in a coal dependent region using participatory backcasting with study case of South Kalimantan Province in indonesia. While not entirely emission-free, gas plants emit significantly less carbon than coal and could help balance the energy mix. Moreover, although not currently prominent in the system, investing in solar and wind energy could further reduce reliance on fossil fuels and contribute to a cleaner energy portfolio.

As a result, the government and PLN are advised to focus on the addition of their capacity in Lampung Province to meet power needs with priority of renewable and low-emission energy. Investment should be made in hydropower, geothermal and other renewable energy technologies to cut carbon emissions and ensure power scarcity does not result from demand outstripping supply. This will enable PLN to suffice Lampung energy needs while also participating in global programs to curb greenhouse gas emissions. The recommendation is consistent with Ministerial Regulation Number 10 of 2025 of MEMR of Indonesia. This regulation serves as a roadmap in the energy transition of the electrical system. The objective of this regulation is to enhance the reduction of greenhouse gas emissions and achieve net zero 2060.

Important elements consist of strategies for the early retirement of coal-fired power plants, the execution of biomass co-firing, restrictions on the development of new coal-fired power plants until 2030 and acceleration of renewable energy. The regulation mandates that the transition roadmap be reviewed every six months to ensure effectiveness and alignment with the National Energy Goals.

The choice of independent variables was motivated by the assessment of data availability, completeness, and consistency at the regional level, as well as the positive correlation of these variables with electricity consumption, as determined by Pearson correlation and visualized in the heatmap. GRDP is an indicator of regional economic performance and arguably of industrial and commercial activity. Consequently, this study is subjected to this limitation by not taking electricity prices, tariff structures, technological advances, energy efficiency improvement, geo-political situations, and climate variables into account.

Another limitation is that the study is only conducted in the Lampung Province and may not be suitable to other regions with different economic structures, energy policies, and environment. It is acknowledged that the study excludes any other variables that might have an influence and also anything resulting from the study area. This opens possibility for future research to include more predictors and a larger geographical area for validation.

5. Conclusions

This research uses the VAR model to forecast the electrical consumption in Lampung Province. The result of forecasting electrical consumption in Lampung Province using the VAR model shows good results with MAPE of 0.57 and RSME of 37.74. The prediction shows that the electricity consumption will increase steadily in line with population growth and GRDP. Energy consumption is expected to rise by 30% in 2030 and this requires power plants and transmission line expansion.

It is advisable that attention should be made to focus on renewable energy sources of both hydropower plant and geothermal power plant in Lampung Province to sustainably cope with the demand as well as environmental issues. Findings in this work will equip policymakers with longer-term energy schemes, pointing out infrastructure investment and efficiency improvement requirements.

This research has notable results with acknowledgment of two key limitations. To start with, due to the limit and consistency of the data at the regional level, it only focuses on GRDP and population as the predictor of the energy consumption, ignoring other variable such as price, tariff, energy efficiency, climate, geo-politics, and detail technological advancement. The second limitation concerned with the study was that analysis only limited to Lampung Province. As a result, the findings is applicable to other regions with different economic and environmental conditions. It is recommended that future research should analyze the contribution of net-zero emission policies in addressing electricity planning needs as well as addressing more complex models with more variables considered.

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