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Comparative evaluation of multiple linear regression, ARIMA, and artificial neural network models for electricity price forecasting in energy planning and cost optimization

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ABSTRACT

Accurately predicting electricity prices may facilitate better planning of energy expenditures and enable utilities to make informed decisions regarding resource utilization and budget allocation. This paper examines forecasting models for electricity power rate prediction to support future energy cost optimization and management. Monthly energy consumption data were collected from January 2020 to June 2025, including average power rates (APR), average generation charge (AGC), average electricity consumption (AEC), and total demand (TD). Three forecasting models were compared: multiple linear regression (MLR), autoregressive integrated moving average (ARIMA), and artificial neural networks (ANN). Model performance was evaluated using mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) using validation data from July 2024 to June 2025. The ANN model achieved the most accurate forecast, with an MAE of 0.5922 PHP/kWh, RMSE of 0.7685 PHP/kWh, and MAPE of 6.81%. MLR yielded MAE, RMSE, and MAPE values of 0.9232 PHP/kWh, 1.1488 PHP/kWh, and 11.31%, respectively, while ARIMA (0,1,3) yielded 2.8820 PHP/kWh, 3.9610 PHP/kWh, and 25.78%, respectively. The findings indicate that ANN can accurately forecast electricity rates and support energy cost optimization, planning, budgeting, and decision-making process.

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1. INTRODUCTION

The cost of energy plays a large part in organization's operating expenses. Recent changes in electricity pricing due to market volatility can complicate energy usage by an organization through both production and consumption; therefore, it is critical to know what the current electricity price will be for proper budgeting/procurement strategies and energy work plans [1], [2]. It should be noted that there are several variables influencing electricity market prices; these include but are not limited to: market relationships, government regulations, supply/demand, transmission constraints, and fuel sources. Accurately predicting the average power rate (APR) price is vital for making correct forecast assumptions for future expenditures [3].

Statistical regression and time-series analysis are standard forecasting techniques used extensively in the energy sector [4]–[6]. Multiple linear regression (MLR) provides an interpretable means of modeling relationships between different types of energy variables [7]. Autoregressive integrated moving average (ARIMA) models are often used to create forecasts from historical data [8]. However, because electricity prices are often influenced by complex nonlinear relationships between several different factors, the ability of traditional forecasting methods to predict electricity pricing accurately may be limited.

Advancements in the field of machine learning have led to the creation of artificial neural network (ANN) which can be used to forecast complicated systems [9]. Their ability to identify hidden patterns and learn non-linear correlations from past data allows for accurate energy forecasting applications to be developed [10], [11]. Multiple studies have pointed to the capabilities of machine learning approaches being greater than traditional forecasting methods for predicting energy demand and prices for electricity [12], [13].

The recent research has indicated that statistical and machine learning approaches are successful in electricity forecasting, but there has been limited work done comparing MLR, ARIMA, and ANN models with the same dataset and metrics for forecasting power rates. This means that there is a need for a complete comparative study aimed at identifying the best forecasting model for making decisions related to energy. The contribution of the current study is in the fact that it carries out the comparative evaluation of MLR, ARIMA, and ANN models through a unified forecasting system for forecasting periods and accuracy measures.

While there have been many studies on forecasting electricity prices utilizing either statistical or machine learning methods, most have aimed at assessing a certain prediction model or comparing a few models just on a limited dataset and selecting evaluation methods. Therefore, practically, there exist few cases of MLR, ARIMA, and ANN approaches being thoroughly compared with each other while all of them are using uniformly developed dataset, inputs as well as evaluation methods especially when it comes to electric distribution companies of the Philippines. The originality of the current research is predetermined by the establishment of the comparative forecasting framework where MLR, ARIMA and ANN techniques are examined while always relying on similar historical sources, testing period and methods of forecasting performance assessment (mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE)).

The research used a simulation-based evaluation structure to examine methods of prediction and to produce output in forecasting usable as input for subsequent mathematical optimization methods of energy costs. It made use of MLR, ANN and ARIMA models to obtain APR and their performance was evaluated according to identical historical data, evaluation criteria and time period. The most efficient method of forecasting was considered the best for input generation for future energy cost optimization methods. The comparative research opens the way for objective evaluation of various approaches to electricity price forecasting.

In addition to comparisons of the different models used, the results of this research can have practical implications in the field of energy planning and management. Accurate estimates of average electricity prices can help electric companies, other organizations, and energy managers in forecasting change in electricity price trends, developing their budgets, and implementing their energy purchasing and usage plans. Forecasts can also serve as an input in the design of future optimization models which make use of energy consumption and supply limitations as well as cost goals. As a result, the research serves as a basis for development of data-driven decision-making systems which unite electricity price forecasting and energy cost efficiency methodologies.

2. METHOD

2.1. Research design

The study used a simulation-based comparative framework to evaluate how well MLR, ARIMA, and ANN predict power rates. The chosen comparative research design based on simulation is therefore appropriate as it enables the researchers to perform an unbiased comparison of different forecasting techniques under the same conditions. The use of one and the same dataset, set of independent variables, and validation procedure for all presented forecasting techniques guarantees that accurate efficiency assessment and a suitable decision on which forecasting method to use in electricity pricing is conducted.

The overall framework utilized in the research is shown in Figure 1, which indicates that the framework has the structure allowing for a flow consisting of the stages of data preparation, model development, forecasting, and performance evaluation. This means that the historical data on power rates and the chosen predictors were processed, used, and reused in MLR, ARIMA, and ANN models in a similar way. Hence, each model produced and calculated predicted power rates and actual power rates that were compared based on the evaluation metrics (MAE, RMSE, and MAPE). This means that Figure 1 shows that all three models used the same dataset and evaluation methods which allowed to compare their performance.

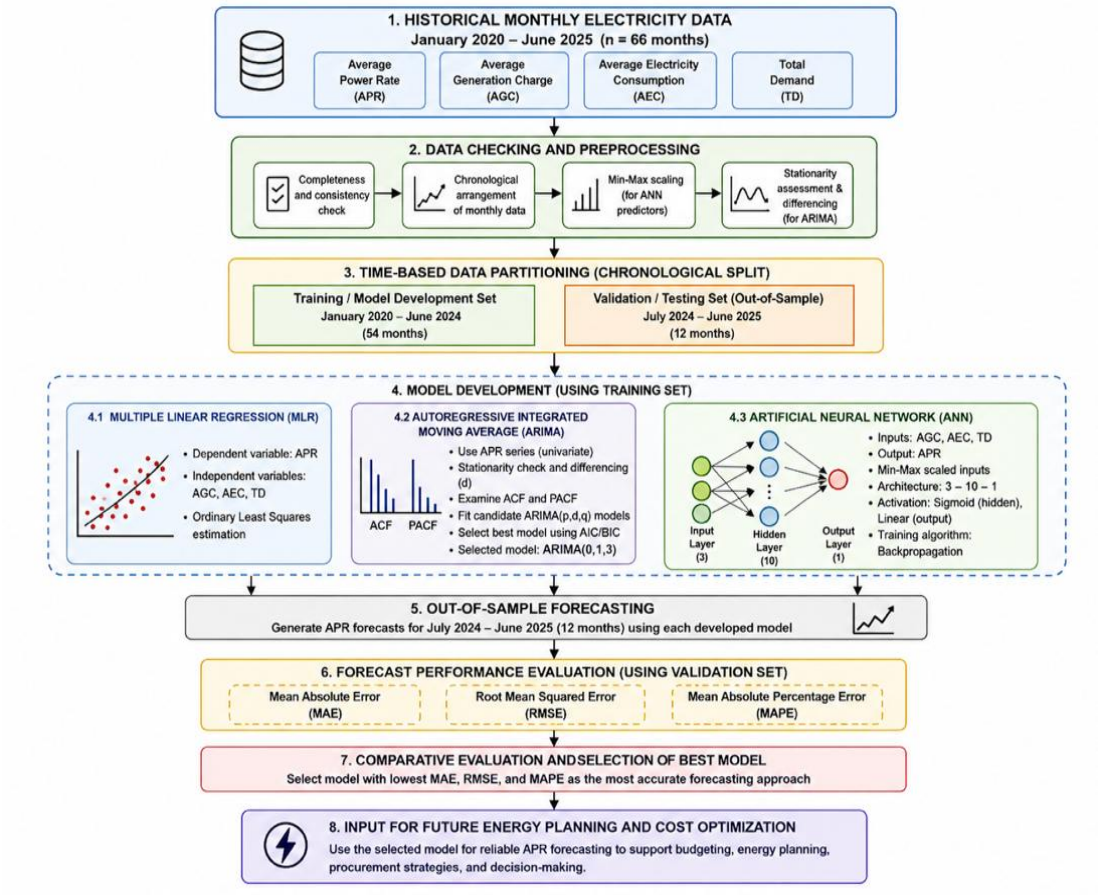

Figure 1. Simulation-based framework for evaluating the forecasting performance of MLR, ARIMA and ANN models

2.2. Data collection

The datasets utilized in this analysis were secondary monthly datasets that were provided from January 2020 to June 2025, yielding essential historical data needed in developing and testing the forecasting models. The datasets used included electricity variables such as the APR, average generation charge (AGC), average electricity consumption (AEC), and total demand (TD). These indicators were selected to give an insight on the historical price and demand characteristics of electricity for the years considered. The APR was taken as the main variable to forecast.

The dataset has been used to collect complete historical monthly data related to electricity in the specified period, which is shown in Table 1. It was requested and obtained from the Camarines Sur Electric Cooperative III (CASURECO III) located in the 5th District in Camarines Sur province, Philippines. Use of this electric cooperative gave assurance of the accuracy of the analysis conducted based on recorded actual price rates, consumption and demand levels of electricity in the study area.

2.3. Forecasting models

In this research, three separate forecasting models were created, including both MLR, ARIMA, and ANN forecasting models. The MLR and ANN forecasting models employed the AGC, AEC, and TD as predictor variables whereas the ARIMA model relied on previously recorded APRs as the inputs. Three predictor variables were selected: AGC, AEC and TD. All three have effect on the electricity power rate: AGC reflects the cost of electricity generation, AEC shows how much electricity customers ordinarily use, and TD shows what is the system load. Together, these features capture most of the economic and operational variables which affect the variation in the electricity price.

There were 66 months' worth of data available to develop these models, and they went from January 2020 through June 2025. The dataset available includes a total of 66 monthly observations, yet this analysis used an out-of-sample validation approach of an 80:20 time-based split in order to maintain the temporal characteristics of the data and gauge the performance of the models on data that has never been seen before. To

train each of the forecasting models, the data was split into a training and testing dataset, based on time order. The first 54 months' worth of data (January 2020 through June 2024) was used to train the models, while the next 12 months' worth of data (July 2024 through June 2025) was used to verify the accuracy of the model's predictions. This timeframe of 54 months used for training models and 12 months for validating model accuracy is representative of the widely recognized training/testing data split of 80 - 20 percent. The 12 months of data not used to train the models was chosen to give a true picture of the model's accuracy when used with data that was not part of the model development process, while maintaining the integrity of the sequential nature of the data and providing no future-looking information during the development of the models.

Table 1. Historical monthly electric data of CASURECO III from January 2020 through June 2025

Month, Year	APR	AGC	AEC	TD	Month, Year	APR	AGC	AEC	TD
Jan. 2020	9.3235	6.069	7,560.17	21.828	Oct. 2022	14.0334	9.9734	10,880.72	24.519
Feb. 2020	8.9671	6.1911	8,389.26	20.529	Nov. 2022	9.6563	6.0178	10,281.05	22.870
Mar. 2020	9.3374	6.2065	8,151.78	22.317	Dec. 2022	9.1264	5.5285	10,753.76	23.206
Apr. 2020	9.5532	6.2430	9,603.06	23.013	Jan. 2023	10.0228	6.4515	9,780.56	24.475
May 2020	9.3418	6.0644	10,553.88	23.214	Feb. 2023	8.9307	5.2454	9,516.47	21.583
June 2020	9.2938	5.9982	10,251.74	24.127	Mar. 2023	9.3575	5.8321	9,732.28	25.763
July 2020	9.2415	5.9614	9,922.57	23.372	Apr. 2023	8.9737	5.6689	11,731.00	26.506
Aug. 2020	8.3513	5.4150	10,529.72	25.161	May 2023	8.3333	5.5220	12,151.45	27.916
Sep. 2020	8.0947	5.5397	10,303.95	24.909	June 2023	9.5811	6.6980	12,054.75	26.789
Oct. 2020	8.0803	5.3621	7,464.12	22.904	July 2023	8.3183	5.7128	10,674.11	25.833
Nov. 2020	8.0129	5.0965	5,084.74	13.989	Aug. 2023	7.7801	5.1935	12,442.60	26.883
Dec. 2020	9.3090	5.8277	9,108.64	20.493	Sep. 2023	7.6982	5.2350	13,114.18	26.821
Jan. 2021	8.9306	5.4173	7,489.93	20.603	Oct. 2023	7.4068	4.9194	12,041.20	26.788
Feb. 2021	8.8099	6.0839	8,283.55	18.959	Nov. 2023	6.9022	4.7788	11,778.43	27.020
Mar. 2021	9.0461	6.3473	9,360.23	21.659	Dec. 2023	7.1845	4.5862	12,515.33	27.794
Apr. 2021	8.9630	6.3319	9,939.53	22.260	Jan. 2024	7.2881	4.7362	10,875.94	26.880
May 2021	8.2634	5.7060	10,560.25	23.842	Feb. 2024	7.5541	4.9322	11,670.16	24.600
June 2021	8.7432	6.1736	10,213.93	25.245	Mar. 2024	7.9163	4.8420	12,168.43	25.647
July 2021	8.8528	6.2559	10,710.74	24.116	Apr. 2024	8.1280	5.4567	13,476.59	32.104
Aug. 2021	10.0553	7.1190	10,441.59	23.999	May 2024	10.1010	7.2133	14,530.59	33.532
Sep. 2021	9.5659	6.7978	10,542.25	23.227	June 2024	5.3929	2.4737	13,989.13	32.457
Oct. 2021	10.2424	7.5783	9,521.07	22.775	July 2024	11.7976	8.6513	12,587.96	29.530
Nov. 2021	10.3480	7.5034	9,860.41	22.219	Aug. 2024	12.2576	8.9558	13,555.49	30.923
Dec. 2021	11.1895	8.0223	9,953.94	22.738	Sep. 2024	15.9007	11.5591	13,269.93	30.210
Jan. 2022	10.6717	7.1505	8,781.83	21.553	Oct. 2024	10.0278	6.6229	11,668.08	29.699
Feb. 2022	12.0489	8.7132	9,149.02	23.472	Nov. 2024	7.8485	4.6697	10,392.80	25.870
Mar. 2022	12.1042	8.5558	10,151.94	23.440	Dec. 2024	8.2452	5.2002	13,474.41	26.123
Apr. 2022	12.1840	8.5550	10,021.28	23.632	Jan. 2025	7.6632	3.9488	13,322.00	26.796
May 2022	12.2524	8.4510	10,382.76	25.078	Feb. 2025	6.8511	3.1983	13,059.42	26.245
June 2022	9.9540	6.5438	10,274.06	24.990	Mar. 2025	6.5181	2.6256	13,316.18	28.027
July 2022	12.5844	8.6472	10,986.31	23.999	Apr. 2025	8.5039	3.7463	17,067.85	34.630
Aug. 2022	14.9850	10.6878	10,424.74	23.919	May 2025	9.1113	5.1541	17,529.76	33.001
Sep. 2022	14.3670	10.5555	11,136.76	25.928	June 2025	8.9948	5.1133	17,161.43	34.183

Note—APR = average power rate (PHP/kWh), AGC = average generation charge (PHP/kWh), AEC = average electricity consumption (MWh), and TD = total demand (MW).

The entire process involved four main phases: i) gathering and preprocessing historical data related to energy consumption, ii) building MLR, ARIMA, and ANN forecasting models, iii) testing all forecasts using the hold-back test dataset, and iv) comparative analysis. This sequence of actions guarantees replication of acquired models by means of the same dataset and methods. Before model development, the dataset that was collected was checked for completeness and consistency. The data were organized in chronological order, and it was determined that there were no missing data throughout the study period. Afterward, the input variables were prepared for analysis using MLR and ANN, while the historical APR series was used for developing ARIMA models.

The first step in conducting ARIMA analysis was to transform the APR series using the method of differencing, resulting in a stationary series. Then the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots were checked to find combinations of autoregressive and moving average terms that can be used in our candidate models. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) were used to evaluate the candidate models, with lower scores being more reliable. Thus, ARIMA (0,1,3) proved to be the best choice based on the AIC and BIC values received while being designed in the simplest way. For the ANN, before building the ANN model, all predictor variables underwent Min-Max scaling to enhance the stability of training and convergence. The model design included feedforward multilayer perceptrons, comprised of three input neurons for AGC, AEC, and TD, ten hidden-layer neurons, and one output neuron for APR. The hidden layer was operated through a sigmoid

function, while the output layer operated through a linear activation function. The weights of the network were obtained by means of an optimization procedure employing the backpropagation method. The same training data set (January 2020 to June 2024) and validation set (July 2024 to June 2025) were continuously used in the forecasting models to guarantee fair comparison.

The prediction techniques are built on various theoretical concepts. While MLR presumes linear connections amid the dependent and independent variables, ARIMA presumes a time series being constant and autocorrelation of past values, ANN does not set limitations on linearity and assumes learning nonlinear correlations. These specifications influenced the choice and use of forecasting techniques in this research project. The MLR method is selected on account of its role as a model for the assessment of linear relationships between electricity prices and various other parameters. The ARIMA model is employed to derive temporal dependencies from previous electricity prices, and the ANN model is applied to discover complex non-linear dependencies among predictive parameters. Thus, these various techniques help in evaluating different forecasting techniques for predicting electricity tariffs.

2.4. Forecast validation

The forecast accuracy of the created models was validated with the testing datasets that contained the actual recorded APR from July 2024 to June 2025 and analyzed based on three error metrics, namely: MAE, RMSE, and MAPE. Error metrics allowed measuring the discrepancy between the expected result and the actual APR, thus providing grounds for comparison of the applied forecasting methods. In this respect, the model with the smallest errors was acknowledged to be the most effective of the applied forecasting methods and therefore became the best option to be used in future optimization-based energy management solutions.

In order to achieve fairness and consistency when assessing the models' forecast accuracy, all models were evaluated based on the same validation data and measurement methods. The model with the least forecast errors was deemed the most appropriate for future use in predicting costs of electricity and optimizing loads. No human subjects or sensitive data were involved in this study, thus exempting it from any institutional ethics review approval.

3. RESULTS AND DISCUSSION

3.1. Multiple linear regression model

The forecasting models were created from 66 monthly energy datasets that occurred between January 2020 - June 2025 and included the APR, AGC, AEC, and TD. The first 54 observations would help with model building and training with January 2020 - June 2024 being used to build and train the forecasting models. The remaining 12 observations, from July 2024 - June 2025, would be used for model testing. The primary purpose of creating the models was to identify the relationships between the four variables and provide reliable forecasting tools that may allow for optimization of energy costs in the future. Forecasting and regression methods are commonly used for energy economics and analysis of electricity markets because they quantify the relationships between many of the variables that impact the energy market, while providing interpretable results that can aid decision-making [14], [15].

To assess how AGC, AEC, and TD impact the APR, an MLR model was created. MLR is one of the more common methods of statistical analysis that examines how one dependent variable relates to multiple explanatory variables or predictors by estimating how much each individual predictor contributes to the dependent variable when holding all others constant; i.e., it allows for determining the effect of each individual predictor on the dependent variable while using the other predictors simultaneously as control variables (unlike simple linear regression, where one individual predictor was used at a time to determine its effect) [16], [17]. This MLR model has been presented in (1).

$$\hat{Y} = 2.2547 + 1.1875X_1 - 0.000046X_2 + 0.0045X_3 \quad (1)$$

Where: $\hat{Y}$ = average power rate, X_1 = average generation charge, X_2 = average electricity consumption, and X_3 = total demand.

Based on the derived regression coefficients, we can conclude that AGC is the strongest predictor of APR. Holding all other variables constant, a one-unit increase in AGC is expected to yield an average increase of 1.1875 PHP/kWh in APR. This high degree of correlation between AGC and APR shows that there is indeed a significant impact from changes in generation costs to total rates for electricity. The findings are also consistent with pricing theories for electricity, where generation costs are viewed as one of the most important components driving retail electricity prices and rate fluctuations [2], [18].

The TD shows a positive relationship with APR, its impact is still less significant when compared with other variables taken into consideration. In particular, an increase of 1 unit in TD would result in an

increase in APR of 0.0045 PhP/kWh (keeping the rest of the variables unchanged). This aligns well with the established economic concepts explaining how electricity markets work, whereby higher demands result in higher generation demands, eventually leading to upward pressures on pricing [19], [20].

The AEC has a weak negative correlation with the APR, indicated by its coefficient of −0.000046. Therefore, it can be concluded that AEC has a negligible effect on APR compared to that of the AGC and the TD. In multiple regression analyses such as this one, coefficients with low magnitude typically suggest little practical influence on the dependent variable relative to stronger predictor variables in the model [21], [22]. The regression outputs verify the significance of AGC as the major contributor to APR, indicating that generation costs significantly affect the prices of electricity. The model's high explanatory quality adds to the strength of AGC as a significant variable in the prediction of APR, substantiating other conclusions in the energy forecasting literature that demonstrate the overriding influence of generation-based costs on the price behavior of electricity [20], [23].

Table 2 summarizes some statistics for the MLR model. The MLR model's R^2 was 0.9596, which indicates that 95.96% of the variability in APR can be attributed to the AGC, AEC, and TD. The coefficient of determination (R^2) reflects how much variance in a dependent variable is explained by independent variables, so if you use a higher R^2 value, your model will have a better fit [24]. The MLR model's adjusted R^2 was 0.9572. Therefore, we can conclude that the MLR model has a high degree of explanatory ability after considering the number of predictors used. The use of adjusted R^2 allows for a more reliable assessment of the overall performance of your model because it imposes penalties for using extraneous predictors and gives a less biased estimate of the explanatory ability of your model [25].

The F-test results showed an F-value of 395.72 with a significant value ($p < 0.001$), which indicates that the regression model used is significant and gives a good representation of the relationships between the variables. The F-test evaluates if the set of predictors, as a group, explains a significant proportion of the variance in the response variable and thus is widely used to indicate the overall significance of the regression model [26]. The results indicate that the selected predictors have a substantial effect on electricity power rates and support the utility of the developed model for forecasting applications [21].

The results of the MLR model forecast validate the prediction model was able to recreate the actual APR during the data collection period (July 2024 to Jun 2025), as shown in Table 3. In addition, the directions (in increasing/decreasing order of APR) of the model's prediction on the actual APR value followed the same trend or pattern over the periods of validation. Therefore, it can be said that the MLR model was able to represent the patterns of APR variation. The average prediction error, as measured by absolute percentage error (APE), ranged between 1.24% and 28.50%, with the lowest being for August 2024 and the highest being for April 2025. Predictive error was measured in APE, which is an easy-to-understand way of measuring the accuracy of a forecast because APE expresses the predicted errors in terms of actual values [27]. Shown also in Figure 2 is the graphical comparison between the actual and forecasted APR values. The figure illustrates the ability of the model to closely track the observed APR trends over the study period, highlighting the accuracy of the forecasting approach.

Table 2. Multiple linear regression model summary

Statistic	Value
R^2	0.9596
Adjusted R^2	0.9572
F-statistic	395.72
Significance	$p < 0.001$

Table 3. MLR forecast validation results

Year	Month	Actual APR	Forecasted APR	Error	APE
2024	July	11.7976	12.0861	-0.2885	2.45%
	August	12.2576	12.4098	-0.1522	1.24%
	September	15.9007	15.5110	0.3897	2.45%
	October	10.0278	9.7201	0.3077	3.07%
	November	7.8485	7.4417	0.4068	5.18%
	December	8.2452	7.9322	0.3130	3.80%
2025	January	7.6632	6.4562	1.2070	15.75%
	February	6.8511	5.5745	1.2766	18.63%
	March	6.5181	4.8907	1.6274	24.97%
	April	8.5039	6.0799	2.4240	28.50%
	May	9.1113	7.7233	1.3880	15.23%
	June	8.9948	7.6970	1.2978	14.43%

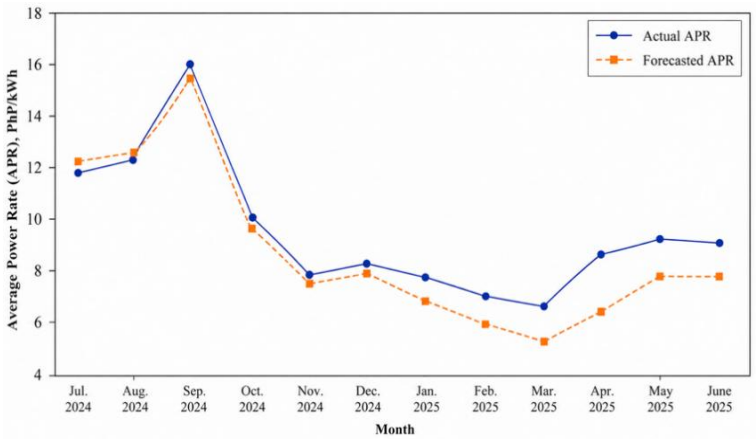

Figure 2. Actual and forecasted APR values from July 2024 to June 2025 using the MLR model

Throughout the latter part of 2024, the model performed remarkably well, as all APE values remained below 6% and there was a notable correlation between the expected APR figures and the actual APR figures. However, for the first six months of 2025, the model tended to underestimate the actual power rates for the period (January-May 2025), with greater forecasting errors registered in this period. One of the reasons for the discrepancies is the changes in production costs and electricity market conditions, fuel prices, and demand patterns that were not sufficiently reflected in the historical data that the model was based on. Similar problems were recorded in research on electricity price forecasting since whenever there are quick changes in the market and/or demand, it's not rare that predictive accuracy decreases if those changes were not properly reflected in the historical dataset used for the model's creation [20].

Even with these discrepancies, the MAPE that the model created is equal to 11.31%, which shows that the forecasts are accurate to a certain degree and that the multiple linear regression can be used for producing fairly useful short-term predictions regarding the average power costs. Lewis [28] states that a MAPE of between 10% and 20% is considered a good forecast, while a MAPE of less than 10% is considered to be a high-quality forecast. Because MAPE is easy to interpret and independent of scale, they are widely viewed as one of the most used metrics in evaluating the performance of forecast models [29]. These validation results suggest that the model is an effective tool for predicting electricity rates and therefore can be used to assist in the planning and decision-making processes that are involved with energy management and forecasting [26].

In Table 4, the accuracy metrics associated with forecasting by the MLR Model during the twelve-month validation period (July 2024-June 2025) are summarized. The MLR Model produced an MAE of 0.9232 PHP/kWh and was able to maintain reasonable proximity of the predicted values of APR to the actual values throughout the validation period. The RMSE for MLR was 1.1488 PHP/kWh, meaning that the predicted APR had a generally close relationship to the actual values observed during this period. The MAPE value for this model demonstrated an 11.31% forecast accuracy level for electricity rate forecasting. While the MAE and RMSE values are regarded as the two most commonly used (standard) measures of forecasting accuracy of models, because both MAE and RMSE provide a measure of the absolute value of the predicted error in the same measurement units as the original data, the MAPE measure has the benefit that it does not require a defined "unit of measurement; therefore, it provides a way of comparing the performance of models on a common scale that is not dependent on a specific unit of measurement [29]–[31].

Table 4. MLR forecast accuracy

Metric	Value
MAE	0.9232 PHP/kWh
RMSE	1.1488 PHP/kWh
MAPE	11.31 %

3.2. ARIMA forecasting model

From January 2020 through June 2024, data from a total of 54 months of the APR were analyzed for all available months to develop and evaluate multiple ARIMA models. The best-fit model is ARIMA model (0,1,3). The model was selected using the Akaike Information Criterion provided in Table 5 (with the lowest value of the 7 models evaluated).

Locations are shown in Table 5, and statistics based on an ARIMA (0, 1, 3) were found to give good results. The ARIMA (0, 1, 3) was chosen based on its information criteria values, which provided an appropriate balance of fit to the data with the simplicity of the model. An AIC value of 175.399 and a BIC value of 183.280 indicate that the ARIMA (0, 1, 3) reasonably captures the underlying APR time series behavior while being as simple as possible. The Log Likelihood of −83.700 also indicates that the ARIMA (0, 1, 3) fits the data reasonably well [32].

Based on analysis of three MA terms within an ARIMA (0,1,3) model, significant results were obtained for both the first lagged and third lagged MA error terms. Statistically significant MA parameter estimates in ARIMA models indicate that previous forecast error carries useful information for explaining future observations [33]. Therefore, those two MA parameters are evidence that lagged forecast errors help to explain current changes in electric power rates. As a result, ARIMA (0,1,3) was able to model the time series dynamics of the APR Series well and may serve as a valid base forecasting model for the forecasting of monthly electric power rates. The fitted ARIMA model may be expressed as seen in (2).

$$\Delta Y_t = e_t - 0.2970e_{t-1} + 0.2808e_{t-2} - 0.4415e_{t-3} \quad (2)$$

Where ΔY_t is the APR and e_t is the forecast error term. This formulation indicates that the differenced APR series is modeled as a function of the current error and the weighted effects of the previous three error terms, which is characteristic of a moving-average process of order three [32]. Table 6 presents the forecast validation results of the ARIMA (0,1,3) model using actual data from July 2024 to June 2025.

Forecasts produced by the ARIMA (0,1,3) model for the validation period ranged from ~4.94 PHP to ~6.98 PHP per kilowatt-hour (kWh). Shown also in Figure 3 is the representation of the relationship between the actual and forecasted APR values. The figure illustrates the general trend captured by the model, although substantial deviations were observed during periods of rapid APR increase.

Table 5. ARIMA (0,1,3) model performance statistics

Statistic	Value
AIC	175.399
BIC	183.280
Log Likelihood	-83.700

Table 6. ARIMA forecast validation results

Year	Month	Actual APR	Forecasted APR	Error	APE
2024	July	11.7976	6.9797	4.8179	40.84
	August	12.2576	4.9409	7.3167	59.69
	September	15.9007	6.7729	9.1278	57.41
	October	10.0278	6.7729	3.2549	32.46
	November	7.8485	6.7729	1.0756	13.71
	December	8.2452	6.7729	1.4723	17.86
2025	January	7.6632	6.7729	0.8903	11.62
	February	6.8511	6.7729	0.0782	1.14
	March	6.5181	6.7729	0.2548	3.91
	April	8.5039	6.7729	1.7310	20.35
	May	9.1113	6.7729	2.3384	25.66
	June	8.9948	6.7729	2.2219	24.70

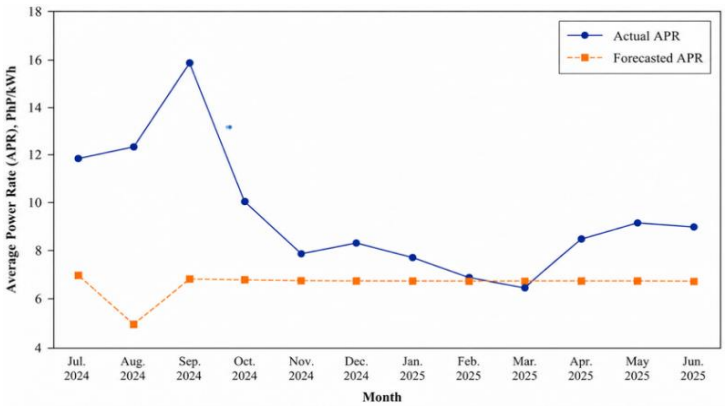

Figure 3. Actual and forecasted APR values from July 2024 to June 2025 using the ARIMA model

When compared to real APR rates, however, the forecasts were found to have generally fallen below the actual observed rates. This was especially true in the third quarter of 2024 when power prices increased significantly. The largest deviation from observed to forecasted occurred in August 2024 (absolute percentage error of 59.69%), followed closely by September 2024 (57.41% APE). Conversely, the smallest deviation APE for the ARIMA model was recorded in February 2025 with an APE of 1.14%. While the model was able to identify the declining trend in APR after the late 2024 period, it was poor at capturing the sudden rise in electricity rates from July to September 2024, resulting in high forecast error amounts during these months. Typical of all ARIMA models, they are reliant upon the use of historic relationships between time periods and are often unable to accurately forecast abrupt systemic changes or large unanticipated volatility in a time series data set [32], [33]. The model performed moderately when measured against the MAPE of 25.78%. As per Lewis [28], MAPE values of between 20% and 50% are indicative of reasonable or acceptably accurate forecasts; therefore, while not effective in capturing abrupt rises in electricity power rates, ARIMA (0,1,3) provides a valuable reference point for developing future forecasts for this market. Shown in Table 7 is the overall forecasting accuracy of the ARIMA model.

According to the validation results, the ARIMA (0,1,3) forecasting model had an MAE of 2.882 PHP/kWh, an RMSE of 3.961 PHP/kWh, and a MAPE of 25.78%. The large forecast errors can be attributed to the large increase in the price of energy from July to September 2024, and the model did not provide a good prediction for that period. However, the model performed well on the long-term downward trend in the price of energy starting in late 2024. This suggests that while there were a number of deviations from the actual figures, the ARIMA (0,1,3) model was moderately accurate for forecasting purposes and may be beneficial for near-term forecasting of electricity prices [34].

Table 7. ARIMA forecast accuracy

Metric	Value
MAE	2.882 PHP/kWh
RMSE	3.961 PHP/kWh
MAPE	25.78 %

3.3. Artificial neural network

Based on monthly data collected between January 2020 and June 2024, an ANN model was created using 54 observations to predict APR based on three predictor variables: AGC, AEC, and TD. The main reason for using an ANN was its ability to model complex, nonlinear relationships among predictor variables, which is particularly important for forecasting electricity prices influenced by multiple interacting factors [35]. The ANN model consisted of three input neurons representing the predictor variables, a single hidden layer containing 10 neurons, and one output neuron for predicting the APR. A sigmoid activation function was applied in the hidden layer, while the network parameters were trained using the backpropagation algorithm. The mathematical ANN model is shown in (3).

$$\hat{Y} = f\left(\sum_{j=1}^{10} \omega_i f\left(\sum_{i=1}^{3} \omega_{ij} X_i + b_j\right) + b_o\right) \quad (3)$$

Where: $\hat{Y}$ = predicted average power rate, X_1 = average generation charge, X_2 = electricity consumption, X_3 = total demand, ω_{ij} = connection weights, and b_j, b_o = bias values.

Through iterative adjustment of the weights and biases, an ANN model learns expressively (and satisfactorily) the connections amongst all independent variables and the target variable [36]. The first 54 months of data (from January 2020 up to and including June 2024) were used to develop and train the model; the last 12 months (from July 2024 to June 2025) were set aside for external validation of the model (out of sample). The majority of predictive modelling uses a training/test division in the dataset to produce an unbiased test of the model's ability to generalize on new, previously tested data [37]. By reserving a portion of the original dataset for testing with the ANN model, the model's forecasting performance can be evaluated with new, previously untested data. The architecture and parameters of the ANN model are shown in Table 8.

An effective balance of model complexity and forecasting accuracy was achieved with the chosen ANN configuration. The model's ability to utilize a hidden layer meant that it also had a means for capturing the nonlinear interactions of the predictor variables, and the backpropagation method afforded an efficient way of learning from the historical dataset. Table 9 presents the estimated APR resulting from the use of the ANN model from January through June 2025. Figure 4 presents the graphical comparison between the actual and forecasted APR values. The figure illustrates the ability of the model to closely track the observed APR trends over the study period, highlighting the accuracy of the forecasting approach.

Table 8. Architecture and parameters of the ANN model

Parameter	Specification
Input variables	Average generation charge, electricity consumption, total demand
Output variable	Average power rate
Input layer	3 Neurons
Hidden layer	10 Neurons
Output layer	1 Neuron
Activation function	Sigmoid
Training algorithm	Backpropagation
Training dataset	January 2020 – June 2024 (54 months)
Validation dataset	July 2024 – June 2025 (12 months)

Table 9. ANN forecast validation results

Year	Month	Actual APR	Forecasted APR	Error	APE (%)
2024	July	11.7976	12.1617	-0.3641	3.09
	August	12.2576	12.6114	-0.3538	2.89
	September	15.9007	15.9827	-0.082	0.52
	October	10.0278	9.6299	0.3979	3.97
	November	7.8485	7.6575	0.191	2.43
	December	8.2452	8.1129	0.1323	1.60
2025	January	7.6632	7.0700	0.5932	7.74
	February	6.8511	6.6454	0.2057	3.00
	March	6.5181	5.8730	0.6451	9.90
	April	8.5039	9.6902	-1.1863	13.95
	May	9.1113	10.7018	-1.5905	17.46
	June	8.9948	10.3598	-1.365	15.18

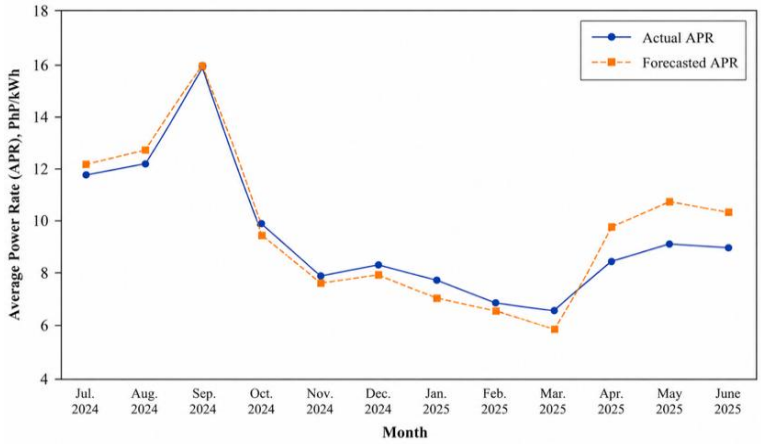

Figure 4. Actual and forecasted APR values from July 2024 to June 2025 using the ANN forecasting model

From July 2024 until June 2025, the ANN predictions tracked the changes experienced by actual APRs well over the full 12-month validation period. In general, the forecasted values matched the observed values, with larger deviations occurring during April–June 2025; therefore, the ANN was able to successfully capture the nonlinear relationships of both independent variables and electricity pricing behavior. The ANN has long been known to model complex nonlinear patterns and interactions that are frequently found in electricity and energy markets [38]. During the first nine months of this validation period, the forecasting ability of the ANN was particularly strong, as there were only minor differences between actual and predicted APR values.

The maximum APE that has been reported throughout monthly validation observations has occurred in May with 17.46% as the value. The minimum occurred in September when the APE appeared to be 0.52%. A considerable number of the months show tiny percentage errors, thereby indicating that the model has been able to generate fairly accurate predictions under different electricity prices. There has also been an increase in errors observed in the last quarter of the validation period (from April to June 2025); however, the ANN model demonstrates that the overall existing trend is still present in the actual APR values. This result indicates that the model has been able to maintain a proper level of prediction skill despite the presence of certain episodes of volatility in the market [37].

The ANN model's forecasting accuracy is illustrated in Table 10, which summarizes the results of all accuracy metrics calculated over a twelve-month validation process (July 2024 – June 2025). The MAE was computed to be 0.5922 PHP/kWh, and the RMSE was found to be 0.7685 PHP/kWh, with indications suggesting that it would not have been far from the actual APR for each month during the validation period. Nonetheless, RMSE is greater than MAE because RMSE gives greater weight to larger forecasting errors.

The ANN model achieved a MAPE of 6.81%, which is low enough to place it within the range required to consider it highly accurate as a forecasting tool (< 10% standard range) [28]. This result confirms the strong predictive power of the ANN model's ability to forecast APR. The low MAPE value also indicates that the ANN model accurately captured the underlying relationships and patterns driving electricity prices.

The ANN model's ability to model relationships that are complex and non-linear is responsible for its excellent performance in forecasting. The ANN model can capture non-linear interactions and hidden structures in data that are not captured well by typical statistical approaches; ANN has been shown to work quite well for capturing these types of phenomena [39]. Traditional statistical techniques such as MLR assume a linear relationship between the predictor variables and the dependent variable, whereas ANN can capture complex nonlinear interactions and underlying patterns within the dataset [39], [40]. Also, unlike the ARIMA model, which is primarily considered a historical APR model, ANN takes into consideration explanatory variables that influence the price of electricity, which allows it to explain additional sources of variation in the price of power.

While forecasting errors showed a slight rise between April and June 2025, the ANN model tracked the overall trend and changes in APR during the entire period of testing successfully. The ability of ANN to use historical data for generalization and good forecasting performance with different conditions has been well documented in the forecasting literature [41]. From these results, it is clear that ANN provides reliable and accurate forecasts and can be effectively utilized by electric cooperatives, energy planners, and policymakers as a decision support tool in forecasting future electricity prices, supporting budgeting activities, and optimizing operational planning and resource utilization.

Table 11 shows how well the three models performed when forecasting APR, with MAE, RMSE, and MAPE used to evaluate their performance. The ANN model produced the most accurate estimates overall, as it had a lower MAE (0.5922) than both of the other two models (RMSE: 0.7685, MAPE: 6.81%). Based on forecasting conventions, MAPE should be below 10%, which means that the ANN model has superior accuracy.

The MLR forecast was ranked second in terms of accuracy with a MAPE of 11.31%, suggesting a fairly good level of accuracy. The MLR model exceeded the 10% threshold for highly accurate forecasts by a marginal amount. The MLR model provided a reliable level of predictive capability and exhibited reasonable performance in explaining the predominant trend of APRs over time, even with some limitations in doing so. Conversely, an ARIMA (0,1,3) model produced the highest level of forecasting error (MAPE = 25.78%), thus providing a moderate level of accuracy when forecasting. Higher forecasting error for an ARIMA model can be attributed to its reliance upon prior APR values to make forecasts, which restricted its ability to adequately capture unanticipated changes in electricity pricing conditions, as well as the influence of other outside explanatory factors on pricing conditions [20], [32].

The current results support previous research indicating that ANN is typically better than classical statistical methods for forecasting electricity prices because of its capability to model complex nonlinear patterns. Unlike prior studies, which concentrated on a specific forecasting technique, the current research provides an integrated comparison of MLR, ARIMA, and ANN based on the same database and validation scheme. The results found in this study show that the proposed ANN model can be used as a valid tool for aiding decision-making with respect to cost estimation of electricity, budgeting, and energy planning. Additionally, enhanced forecasting accuracy provides reliable inputs for future optimization models and intelligent energy management systems.

Table 10. ANN forecast accuracy

Metric	Value
MAE	0.5922 PHP/kWh
RMSE	0.7685 PHP/kWh
MAPE	6.81 %

Table 11. Summary of the comparison of the three forecast models

Model	MAE	RMSE	MAPE
ARIMA (0,1,3)	2.8820	3.9610	25.78%
Multiple linear regression	0.9232	1.1488	11.31%
Artificial neural network	0.5922	0.7685	6.81%

The reason for the superior performance of the ANN model compared to MLR and ARIMA methods is the ANN model's capacity to learn complex and nonlinear relationships between the explanatory variables: AGC, AEC, and TD. While MLR assumes that there are linear relationships between the explanatory variables, and ARIMA models rely on historical observations alone, the ANN model was able to detect the presence of hidden patterns and interactions between variables in the dataset, which led to more accurate forecasting of values than either of the other two methods used in this study [42].

The successful ability of the ANN model has been attributed to the fact that ANN excels at estimating complex non-linear relationships between variables involved in electricity pricing. Whereas the MLR method relies on the assumption of linear correlations between the dependent and independent variables, ANN can account for hidden relationships between generation costs, electricity consumption, and overall demand. Likewise, even though ARIMA is also good at understanding time-related dependencies of historical data, it depends solely on the values of the past data and is thus unable to model multiple independent factors affecting electricity prices.

Furthermore, the comparative results indicate that electricity power tariffs are influenced by numerous interrelated technical and economic aspects whose interactions cannot always be modeled properly by means of linear or pure time series models. The changes in the patterns of generation costs, system needs, and electricity consumption exhibit non-linear trends. Therefore, machine learning techniques such as ANN allow to capture these interactions better.

The present study was confined to historical data from one electric cooperative and a limited number of predictor variables. Future studies should use more factors related to the market, climate, and fuel prices, and apply hybrid forecasting methods to arrive at more reliable conclusions. While there is reason to be optimistic about the prediction capabilities of the ANN model, there are still a number of drawbacks to consider. In the first instance, only 66 monthly data points from a single electric cooperative were used for the research; this may hinder the ability to use the models in contexts involving other electricity providers or electricity markets. In the second instance, the research examined only three explanatory variables, which are AGC, AEC and TD. The input variables had very few lower-quality factors like fuel prices, weather conditions, inflation, share of renewable energy used, bottlenecks in transmission and indicators of the electricity market were not taken into account. In the future, it is necessary to work with bigger multi-utility datasets and take into account more variables in order to improve the accuracy of predictions and robustness of the model.

In addition to the accuracy of prediction, the developed ANN framework has practical consequences in terms of intelligent energy management systems. Accurate short-term forecasting of electricity prices could help optimize the scheduling of loads, implementation of demand-side management, operation of battery energy storage systems, smart grid applications, and planning for operations in electric power systems. Therefore, the forecasting model developed here can be considered as a tool for further optimization and intelligent control techniques in modern power systems.

4. CONCLUSION

Forecasting methods such as MLR, ARIMA, and ANN were compared and evaluated based on how well they predicted future power rate prices in this study. Of the three models used in this study, the ANN had better accuracy than both the MLR and the ARIMA (0,1,3) model; the ANN's MAPE was only 6.81% compared to 11.31% for the MLR and 25.78% for the ARIMA (0,1,3) model. In addition, the ANN had lower MAE and RMSE. This indicates that ANN-based models provided better predictions than the MLR or ARIMA (0,1,3) Models. These findings suggest that the APR could be affected by many complicated relationships between AGC, AEC, and TD and that these relationships can best be captured through non-linear machine learning models. In particular, the ANN's high performance supports the notion that when forecasting future prices for electricity, it is important to use advanced forecasting methods, as well as all relevant explanatory variables.

Although the forecasting framework designed produced excellent prediction results, research was confined to the historical data from one electricity cooperative and took into account only AGC, AEC, and TD as inputs. Because of that, the results may not be applicable to other types of electricity markets. Future studies are expected to widen the range of input variables and data and include a mixed methodology in order to increase the overall forecasting quality.

The developed ANN forecasting model should be regarded not only as a statistical prediction method but also as an important tool for intelligent energy management. The accurate forecast of electricity prices serves as an input for optimization models related to load management, demand-side management, distributed energy resources, and smart grid support systems utilized in making decisions. Further research can be performed in order to integrate the proposed ANN model with mathematical optimization techniques.

In light of the outcomes achieved, it is recommended that electric cooperatives, organizations, and energy managers should apply ANN models in forecasting short-term power prices because of their accuracy. In the future, research should include further explanatory variables, examine the robustness of models with a significant dataset, several utilities, multiple market conditions, and scenarios of demand variability, and analyze the importance of factors via sensitivity and feature importance analyses. The accuracy of model performance should be analyzed during times of market instability, seasonal variation, and unusual working conditions. Future studies may aim to discover combined forecasting mechanisms and include the offered model into smart grid management systems, renewable energy forecasting systems, tools for electricity market analyses, and methods of electricity price optimization.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the Camarines Sur Electric Cooperative III, Philippines.

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