Mindanao Journal of Science and Technology Vol. 21 (2) (2023) 95-115

Day-Ahead Electricity Load Forecasting with Multivariate Time Series

Lorenz Jan C. Crujido*, Clark Darwin M. Gozon and
Reuel C. Pallugna
Department of Electrical Engineering
University of Science and Technology of Southern Philippines – Cagayan de Oro
Cagayan de Oro City, 9000, Philippines
**lorenzjan.crujido@ustp.edu.ph*

Date received: November 2, 2022
Revision accepted: September 18, 2023

Abstract

The importance of day-ahead load forecasting cannot be overstated. Electricity load forecasting is highly important because it allows electric distribution utilities to increase their transmission efficiency and their revenues, increase the reliability of power supply, and correct decisions for future developments. In this paper, day-ahead load forecasting was studied using multivariate time series analysis. Traditional forecasting method such as seasonal autoregressive integrated moving average (SARIMA) was used. Machine learning algorithms such as Feed Forward Neural Network (FFNN) and Long Short Term Memory (LSTM) were also utilized to determine their applicability to short-term load forecasting. For SARIMA, only historical hourly load was needed while FFNN and LSTM required the addition of temperature data, hour of the day and day of the week, special events and previous hour load. In the prediction, FFNN and LSTM performed better with mean absolute percentage error (MAPE) of 1.80 and 1.75%, respectively, compared with SARIMA with a MAPE of 4.48%. The study demonstrated that machine learning like FFNN and LSTM outperformed the traditional SARIMA models, highlighting their effectiveness in applications such as short-term load forecasting in time series prediction.

***Keywords**:* ARIMA, feed-forward neural network, load forecasting, LSTM, multivariate time series

1. Introduction

Because of the important role the electric power system plays in a country's economy, both long-term and short-term reliability and improvement are given significant emphasis. Thus, electricity demand forecasting is of crucial importance for the proper operation, maintenance and planning of the electric power system (Dedinec *et al.*, 2016; Hong *et al.*, 2016; Guo *et al.*, 2018). Electricity suppliers encounter various obstacles while providing electricity to their clients daily (Clements *et al.*, 2015). Anticipating electricity usage can lower the initial expenses of constructing power-generating stations and minimize the risks of unstable operations, fluctuating demand and equipment failures. Accurately predicting electricity demand is of utmost importance for ensuring reliable power delivery, strategic planning and efficient energy management. However, the dynamic nature of power generation and consumption has made the task of forecasting electricity demand increasingly intricate. Precise energy forecasts are essential for effective planning and decision-making within the energy system. Nevertheless, the challenge lies in predicting energy consumption accurately due to the presence of complex patterns (Baliyan *et al.*, 2015; Nichiforov *et al*., 2017; Chodakowska *et al.*, 2021; Sankalpa *et al.*, 2022). Various methods, including linear regression, exponential smoothing, Kalman filtering and neural networks have been developed to deal with forecasting issues for complex demand patterns. The active power generation of the system needs to keep pace with its active power load, and load forecasting during hourly changes is crucial (El-Hawary, 2017; Yukseltan *et al.*, 2020; Chen *et al.*, 2022).

Load forecasting is divided into short-term, medium-term and long-term. Short-term load forecasting ranges from an hour to a week while medium-term ranges from a week to a year. Long-term forecasting is for over a year and is used by electric utilities for network expansion. Short-term load forecasting is crucial to power system operations such as unit commitment and power generation coordination. It is challenging due to deregulation and the penetration of renewable energy sources which makes predicting the load more complex (Gonen, 2007; Almeshaiei and Soltan, 2011). Many studies were conducted for short-term electricity demand forecasting. Shilpa and Sheshadri (2017) used an autoregressive integrated moving average (ARIMA) model with stochastic time series analysis and achieved a mean absolute percentage error (MAPE) of 4.46%, while Nie *et al.* (2012) used a hybrid ARIMA and support vector machine (SVM) model to correct deviations from the former forecasting with an estimated MAPE of 2.6%. Tarsitano and Amerise (2017) used SARIMAX with backward stepwise regression to predict the next day's load and achieved a root mean squared percent error of 1.32-2.80% for one-day ahead and 2.27-3.54% for nine-day ahead predictions. All studies found that past loads and calendar effects greatly affect forecasting performance. In the study conducted by Hong *et al.* (2016), a hierarchical load forecasting approach was proposed for the Global Energy Forecasting Competition 2012. The authors used multivariate time series analysis and a hierarchical clustering algorithm to model the electricity demand for 370 regions. In contrast, traditional methods such as ARIMA and ARMA may not be suitable for short-term forecasting because they cannot adapt to environmental factors such as weather temperatures and holidays.

In electricity demand forecasting, machine learning models have been recently used as they offer advantages from their ability to capture complex patterns in data, adapt to changing conditions and provide accurate and timely predictions (Briones *et al.*, 2019; Shapi *et al.*, 2021; Weeraddana *et al.*, 2021; Zhu *et al.*, 2021). Machine learning models have been applied to short-term load forecasting, with comparative studies showing that artificial neural network (ANN) and model based on support vector machine (SVM) performed well (Oğcu *et al.*, 2012). The ANN model learns the relationship between input and output criteria using training data and has the advantage of being able to learn non-linearities in the data. Muzaffar and Afshari (2019) concluded that a long short-term memory (LSTM) model performed better than ARMA, SARIMA and ARMAX models in predicting electrical load using hourly observations and exogenous variables such as temperature, humidity and wind speed. The LSTM achieved a MAPE of 1.522% for a 24-hour prediction horizon. Alden *et al.* (2020) explored the use of LSTM neural networks for forecasting electricity usage in smart homes. Their paper suggested a two-stage forecasting approach where the LSTM model first predicted the next 24-hour electricity usage based on historical data, and then adjusted the forecast using real-time weather and occupancy data. The proposed approach was evaluated using a dataset of smart home electricity usage and compared with other commonly used methods. The results showed that the LSTM model outperformed other methods in terms of accuracy making it a promising method for smart home electricity usage forecasting. The paper also discussed the potential applications of the proposed approach in demand response and energy management systems.

The Philippines' electric power industry became competitive with the establishment of the Wholesale Electricity Spot Market (WESM). Accurate electricity demand forecasting is crucial to avoid wasting energy or incurring additional costs. This study aimed to develop a short-term forecasting model using historical data, weather data and other variables through exploratory data analysis, built and compared statistical and machine learning models, and tested and evaluated the developed models for day-ahead forecasts.

2. Methodology

2.1 Data Gathering

Figure 1 illustrates the flowchart methodology used in this research. The historical hourly electricity demand was collected from an electrical substation that serves four feeders, with the hourly demand of each feeder summed to represent the substation's total hourly load. The historical weather data was obtained from a weather station in the same area as the substation ensuring that the temperature data is reflective of the region.

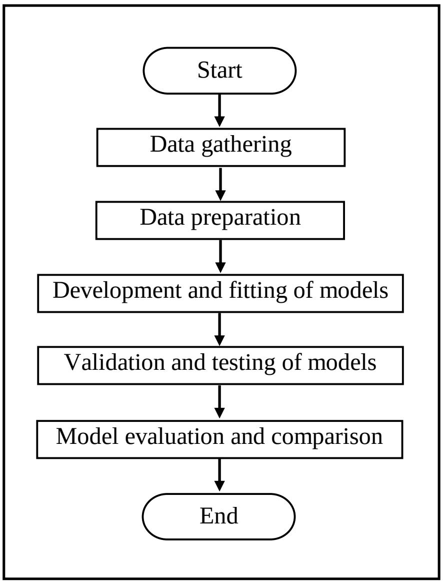


Figure 1. Methodology flowchart

The researcher employed a web scraping script in Python to extract the necessary weather data from a public website (Weather Underground, n.d.).

2.2 Exploratory Data Analysis

The dataset was then analyzed visually, searching for significant patterns such as correlated features, treatment of missing data and outliers, if any. Exploratory data analysis (EDA) was conducted using the Pandas package in Python to seek insights from the data through in-depth analysis. Using the historical hourly load demand and weather data, predictors were generated and then subjected to correlation analysis to determine their significance. This analysis considers the impact of special days and events such as holidays and Christmas Day. The correlation analysis quantifies the relationship between two variables using the correlation coefficient, which ranges from -1 to 1. A correlation coefficient of “0” indicates no relationship between the variables. The Pearson correlation coefficient, the most common measure of correlation (Schober and Schwarte, 2018), was used in this study, which is defined by Equation 1 where r is the correlation coefficient, x_i is the observations of variable x, y_i is the observations of variable y, $\bar{x}$ is the mean of observations of x, and $\bar{y}$ is the mean of observations of y. Only variables with a strong correlation (r > 0.70) with the hourly electrical load were considered in this study.

$$r=\frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}} \tag{1}$$

2.3 Forecasting Model Building and Fitting

For the statistical models, the study used the SARIMA model while for the machine learning models, the FFNN and LSTM were utilized.

2.3.1 Seasonal ARIMA Time Series Forecasting

A seasonal autoregressive integrated moving average model of the form SARIMA(p, d, q) × (P, D, Q)m is a statistical analysis approach that employs time series data to forecast future trends or to better comprehend the current data collection. This method is used for univariate time series forecasting. This is an extension of the ARIMA model that incorporates seasonal effects. The formula for the seasonal ARIMA model (Chang *et al.*, 2012) is shown in Equation 2.

$$\left(1-\phi_1B-\ldots-\phi_PB^p\right)\left(1-\Phi_1B^S-\ldots-\Phi_PB^{PS}\right)(1-B)^d\left(1-B^S\right)^Dy_t=\left(1+\theta_1B+\ldots+\theta_qB^q\right)\left(1+\Theta_1B^S+\ldots+\Theta_QB^{QS}\right)\epsilon_t \tag{2}$$

where p is the number of autoregressive terms, d is the number of non-seasonal differences, q is the number of moving average terms, P is the number of seasonal autoregressive terms, D is the number of seasonal differences, Q is the number of seasonal moving average terms, S is the number of time periods in a season and B is the backshift operator. For SARIMA, the first step is to determine if the time series is stationary. To do this, the researcher used the Augmented Dickey-Fuller Test and Kwiatkowski-Phillips-Schmidt-Shin

(KPSS) test to check the stationarity of the time series. Once the stationarity is met, the next step is to fit a SARIMA(p,d,q) × (P,D,Q)m. In determining the best parameters, the Akaike Information Criterion (AIC) is the basis. The combination of the parameters with the lowest AIC value is chosen. The model was used to predict 24 h, and forecasting accuracy was measured.

2.3.2 Feed Forward Neural Network

The dataset that is fed to the feed-forward neural network (FFNN) is determined from the correlation analysis. Once the data is ready, it will first undergo normalization. Normalization is needed since machine learning models like FFNN are sensitive to the magnitude of the input data. For example, the temperature column is in the range of 18.6-36 °C while other exogenous variables like holidays are 0 or 1. This will significantly affect the forecasting ability of the model as larger weights will be assigned to large numbers. Once the normalization is done, the data will be split into training, validation and testing. The data split is 80, 10 and 10% for training, validation, and testing, respectively (Chi *et al.*, 2022). This is to ensure that the model is doing good in forecasting and there is no over-fitting.

Several model architectures will be made and tested until a forecasting error has a MAPE of less than 5%. Once the best model is determined, it will then be tested to forecast 24 h and will be evaluated. The neural network that will be used is similar to Figure 2. Y_t is the load time series, and x_t is the input layer that is a vector consisting of other time series and exogenous variables that influence the target time series which is the load. The number of inputs depends on the output of the correlation analysis. The number of neurons in each layer of the hidden layers will be updated depending on the MAPE until a final network structure is achieved. Since this is a regression problem, the training of the neural network will be structured as a supervised learning problem where the target variable is the hourly load, and the input variables are the temperature data and the exogenous variables. One way to ensure that the training model achieves the same level of accuracy is to use a fixed random seed when initializing the weights of the neural network. This ensures that the same initial weights are used for each training process and thus the same training process is repeated every time. Additionally, using early stopping techniques and monitoring the validation loss can help prevent overfitting and ensure that the model generalizes well to unseen data.

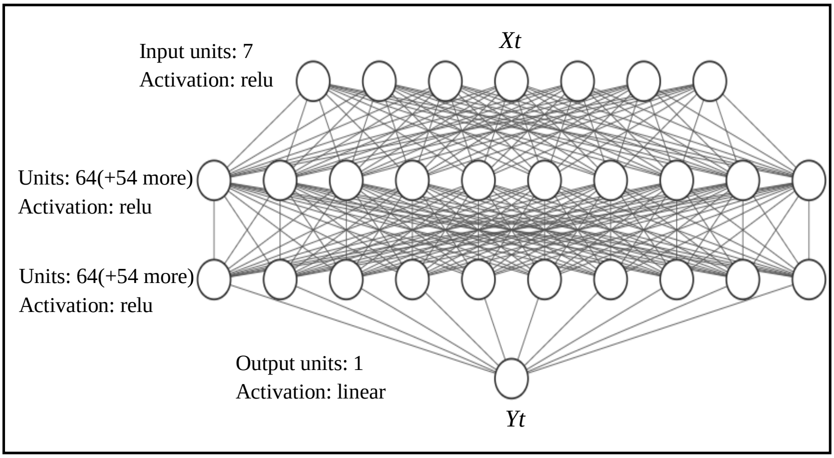


Figure 2. Feed forward neural network

2.3.3 Long Short Term Memory

The input to the Long Short Term Memory (LSTM) model is 3-dimensional which includes a number of samples, time steps and a number of features. The time steps are the number of previous observations that will be used to predict a single time step into the future and the number of features refers to the hourly load, temperature and all exogenous variables including the target variable. Data will undergo normalization since machine learning models are sensitive to the magnitude of inputs. Splitting the dataset into training, validation, and testing comes next to normalization. The training dataset is then used to train the LSTM model, along with the validation data set to see if the model is performing well. A dropout layer is added to the model to prevent overfitting. Lastly, when the model is done with the training and validation, the model is then used to forecast 24 h using the test data set. The forecast will be compared with the actual value of the target variable and forecast error will be evaluated.

2.3.4 Determination of Hyperparameters

The selection of hyperparameters such as learning rate, training technique, and momentum is a crucial aspect of developing an accurate and effective model. In this study, a systematic approach was used to choose these hyperparameters based on established best practices and prior research. For the learning rate, a range of values is typically explored to determine the optimal value that results in the lowest training error and avoids overfitting. This study used a grid search approach to tune the learning rate hyperparameter. A range of values is selected, and the model is trained with each learning rate value. The performance of each model is then evaluated, and the learning rate that produces the best results is chosen. In this study, a learning rate of 0.001 gave the best result. For the training technique, different techniques can be used depending on the nature of the data and the desired outcome. This study used the Adam optimizer (Hassan *et al.*, 2023).

2.4 Validation and Testing of Models

In this phase, the performance of the fitted models was evaluated by testing them on a validation dataset. This phase ensured that the models were not overfitting the data and that they were capable of generalizing to new data.

2.5 Measure of Forecasting Accuracy

The accuracy of a model is measured by how such a model performs with a new set of data that was not used in building the forecasting model. In this case, the data will be split into training data (used to build the model) and test data (used to test the model). The training data is utilized to estimate the parameters of the forecasting models while the test data will be used to measure the performance of the model. Forecasting models used in the study were compared through forecast performance. The measure that will be used is the Mean Absolute Percentage Error (MAPE). The MAPE is given by Equation 3.

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \quad (3)$$

where A_t is the actual value of the load, F_t is the forecasted value of the load, and n is the number of times the summation iteration happens.

3. Results and Discussion

3.1 Dataset

The dataset used in this study consisted of 17,472 hourly observations from October 3, 2017 to September 9, 2019. This included information on hourly temperature and dew point in degrees Celsius, solar irradiance in W/m^2, and electrical load in megawatts (MW).

The historical hourly load observations used in this study are plotted in Figure 3. The load was lower on weekends. Holidays also influenced the daily load profile as can be seen in the plot (red line). August 27, 2018, is a regular holiday (National Heroes' Day), which is Monday, and August 28, 2018 (Tuesday) is a special (non-working) public holiday. It can also be seen that it exhibited daily and weekly seasonality. The average daily load profile in this data set is shown in Figure 4. The peak load occurred at 2 PM which was about 22.5 MW, and the lowest was at 4 AM, which was about 4 MW. It can be seen that the time of the day influenced the daily load profile.

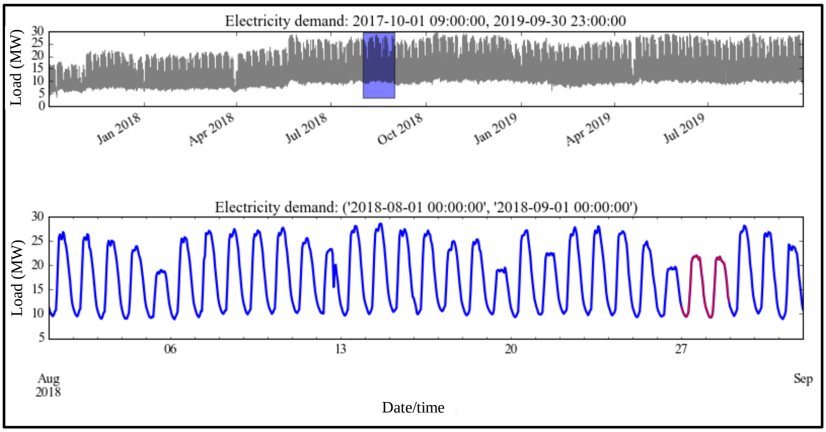


Figure 3. Historical hourly load profile showing daily seasonality

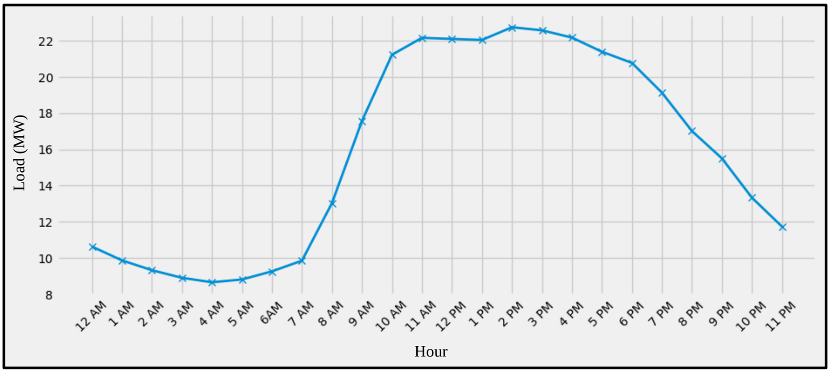


Figure 4. Average daily load profile showing peak demand in the afternoon

The hourly temperature data is plotted in Figure 5. The minimum temperature was 18.6 °C, and the maximum temperature was 36.6 °C. The average temperature was 27.42 °C.

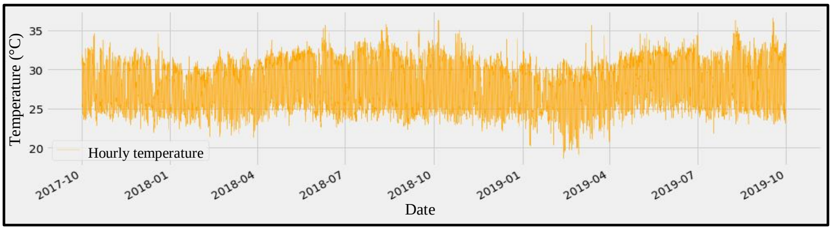


Figure 5. Hourly temperature data from October 2017 to October 2019

3.2 Correlation Analysis, Stationarity and Grainger Causality Test

The correlation analysis conducted resulted in a high correlation of the temperature to the load demand with 0.79 (Table 1). The other variables (dew point, humidity, wind direction, speed, gust, pressure, precip.rate, precip.accum, UV and solar) in the dataset were discarded since the correlation coefficient was less than 0.5. The temperature column, as well as the load demand column, underwent a stationarity test, and these time series were stationary which is a requirement for classical time series forecasting algorithms such as seasonal ARIMA. Table 2 shows the result of the stationarity test, and both time series had a P-value of 0.05 making both time series stationary. The result of the Grainger Causality test in Figure 6 showed that the P-value for TemperatuteC_x and TotalLoad_y was 0.0, the null hypothesis was rejected; it can be concluded that temperature influenced the load demand.

Table 1. Correlation coefficients of the other variables with respect to the load demand

Variables	Load demand
TemperatureC	0.78
Dew point	0.69
Humidity	-0.10
Wind Direction	-0.04
Speed	0.49
Gust	0.52
Pressure	-0.10
Precip.Rate	0.02
Precip.Accum	0.01
UV	0.51
Solar	0.53

Table 2. Stationarity test result for the temperature and the total load time series

Variables	Augmented Dickey-Fuller (ADF) test P-value
Temperature	0.0000
Load demand	0.0000

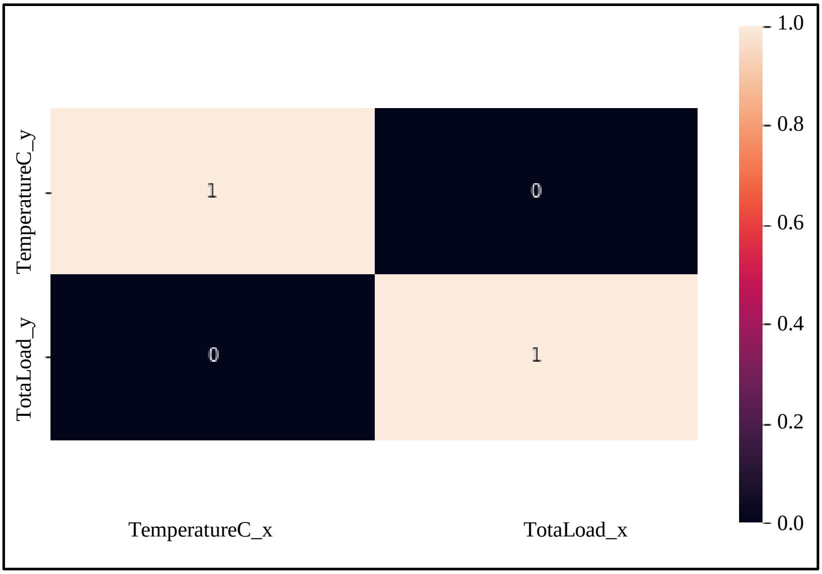


Figure 6. Grainger Causality matrix of the temperature and the total load demand

3.3 Determination of Exogenous Inputs

The daily electricity load profile was influenced by factors that include the temperature of the day, the hour of the day, the day of the week, whether it was a weekend or weekday, the month of the year, whether it was a holiday or not, special events, etc. It was important to determine how these factors influenced the electricity load to develop a forecasting model with high accuracy. The results of feature engineering conducted in this study are discussed in this section.

3.3.1 Temperature and Electricity Load

A plot of the temperature and the electrical load can be seen in Figure 7. The demand was lower at lower temperatures and significantly increased as the temperature increased. It can be noted that these were due to air-conditioning loads where the temperature inside commercial and residential buildings must be maintained at a cooler temperature throughout the day.

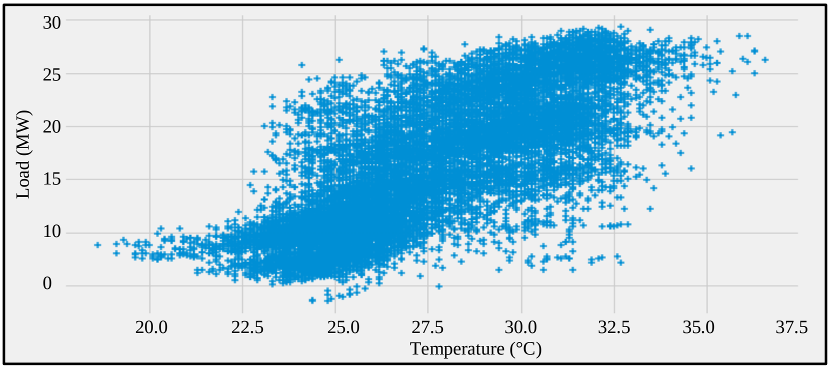
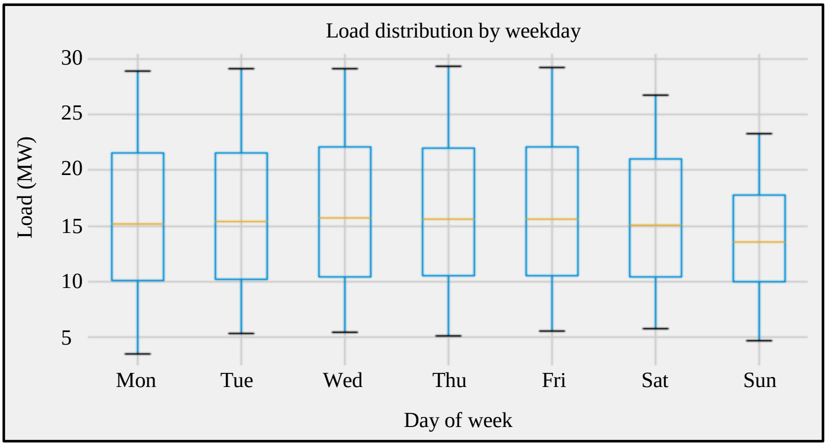


Figure 7. Relationship between temperature and electrical load indicating a positive correlation between the two variables

3.3.2 Load Profile with Respect to the Day

A box plot is shown in Figure 8 for the weekly load profile. It was important in 24-h ahead forecasting to know the day of the week that the load had to be predicted.



The boxes represent the interquartile range (IQR) of the data, with the central line representing the median value.

Figure 8. Distribution of hourly load data for each day of the week

In the plot, the load was higher starting from Monday (1) which peaked on Friday (2) and was lower on weekends. This feature was important since there was a significant difference in the load between the days of the week. As can be seen in Figure 9, there was a difference in the load profile during weekdays compared with weekends. Non-working days corresponding to holidays and special events also affected the load profile. As shown in Figure 10, there was a significant decrease in the load profile during holidays. It can also be noted that the load profile might be different from the other electrical substations. It might be that there is no decrease in load if the customers are industrial and manufacturing plants where there is operation even on holidays. All these features are considered in the building of the forecasting model since all of these features affect the behavior of the load profile.

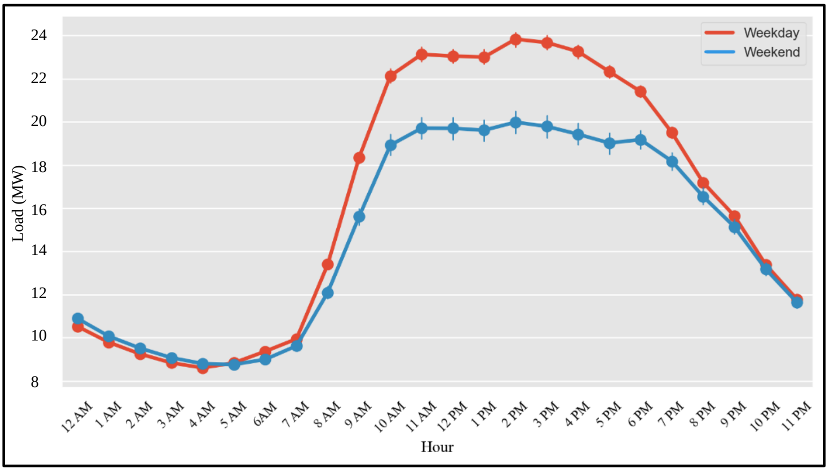


Figure 9. Comparison of average hourly load profile between weekdays and weekends

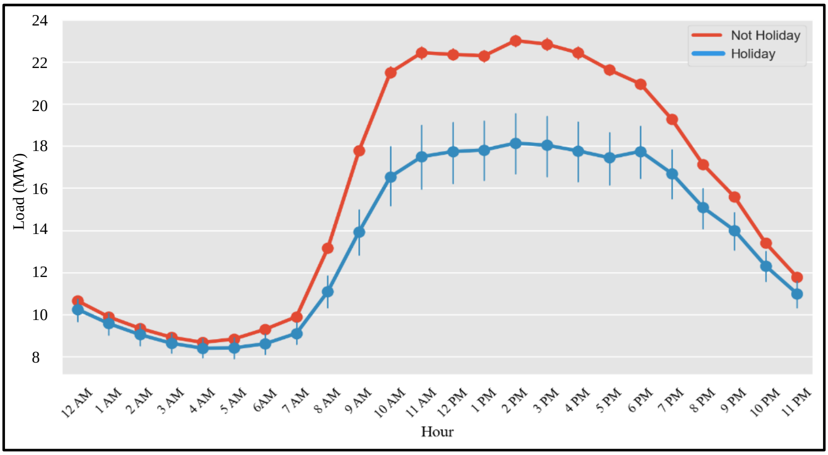


Figure 10. Comparison of average hourly load profile between holiday and non-holiday

3.4 Comparison of the Results

The hourly data from the first observation up to September 29 was used for the training of all the models. All the models were used to forecast 24 h, which are the 24-h observations of September 30. The result of the forecast of the three models is plotted in Figure 11.

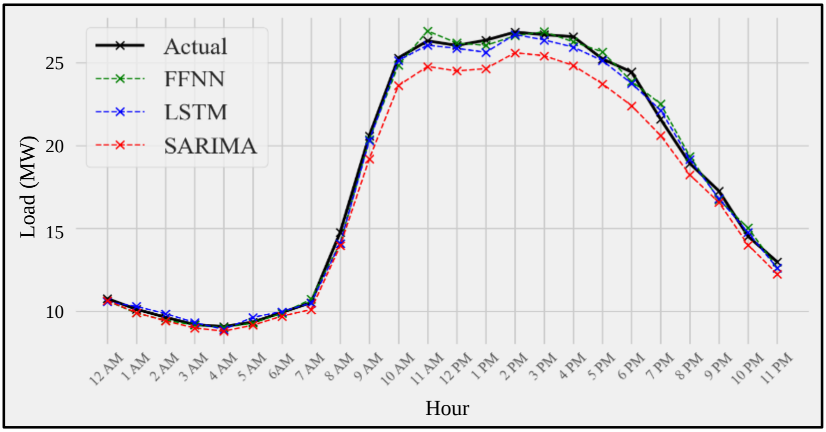


Figure 11. Comparison of the forecast results obtained from three models, namely SARIMA, FFNN, and LSTM

The 24-h ahead forecast is shown in Table 3, and the mean absolute percentage error of each model is shown in Table 4. The SARIMA model performed well with MAPE of 4.48% but unlike the machine learning models, it was not able to incorporate the effects of external factors such as weather and social events. On the other hand, FFNN and LSTM performed well with a MAPE of 1.80 and 1.75%, respectively.

Table 3. Comparison of forecasted values of the SARIMA, FFNN and LSTM models for a weekday

Sep-30	Actual	SARIMA	FFNN	LSTM
12:00 AM	10.76	10.64	10.62	10.56
1:00 AM	10.11	9.91	9.88	10.28
2:00 AM	9.63	9.40	9.45	9.85
3:00 AM	9.18	8.98	9.15	9.31
4:00 AM	9.06	8.79	9.01	8.89
5:00 AM	9.33	9.14	9.26	9.62

Table 3 continued.

6:00 AM	9.92	9.69	9.87	9.97
7:00 AM	10.51	10.09	10.71	10.49
8:00 AM	14.76	13.95	14.09	14.09
9:00 AM	20.59	19.20	20.37	20.31
10:00 AM	25.29	23.62	24.86	25.14
11:00 AM	26.32	24.77	26.92	26.06
12:00 PM	26.04	24.50	26.19	25.87
1:00 PM	26.36	24.64	26.05	25.63
2:00 PM	26.85	25.60	26.62	26.70
3:00 PM	26.69	25.42	26.87	26.37
4:00 PM	26.57	24.83	26.26	25.94
5:00 PM	25.23	23.73	25.65	25.12
6:00 PM	24.44	22.40	23.87	23.75
7:00 PM	21.58	20.60	22.50	22.12
8:00 PM	18.92	18.23	19.35	19.16
9:00 PM	17.25	16.56	16.73	16.79
10:00 PM	14.52	14.00	15.02	14.75
11:00 PM	12.97	12.24	12.61	12.59

Table 4. Mean absolute percent error of the three models forecasting a weekday

Model	MAPE (%)
Seasonal ARIMA (SARIMA)	4.48
Feed-Forward Neural Network (FFNN)	1.80
Long Short Term Memory (LSTM)	1.75

3.5 Models Forecasting Performance for Holiday

Models were tested to forecast the 24-h electrical load demand for a holiday. Specifically, the researchers chose August 28, 2019, which was a local holiday; it was a weekday (Thursday). The result is shown in Figure 12.

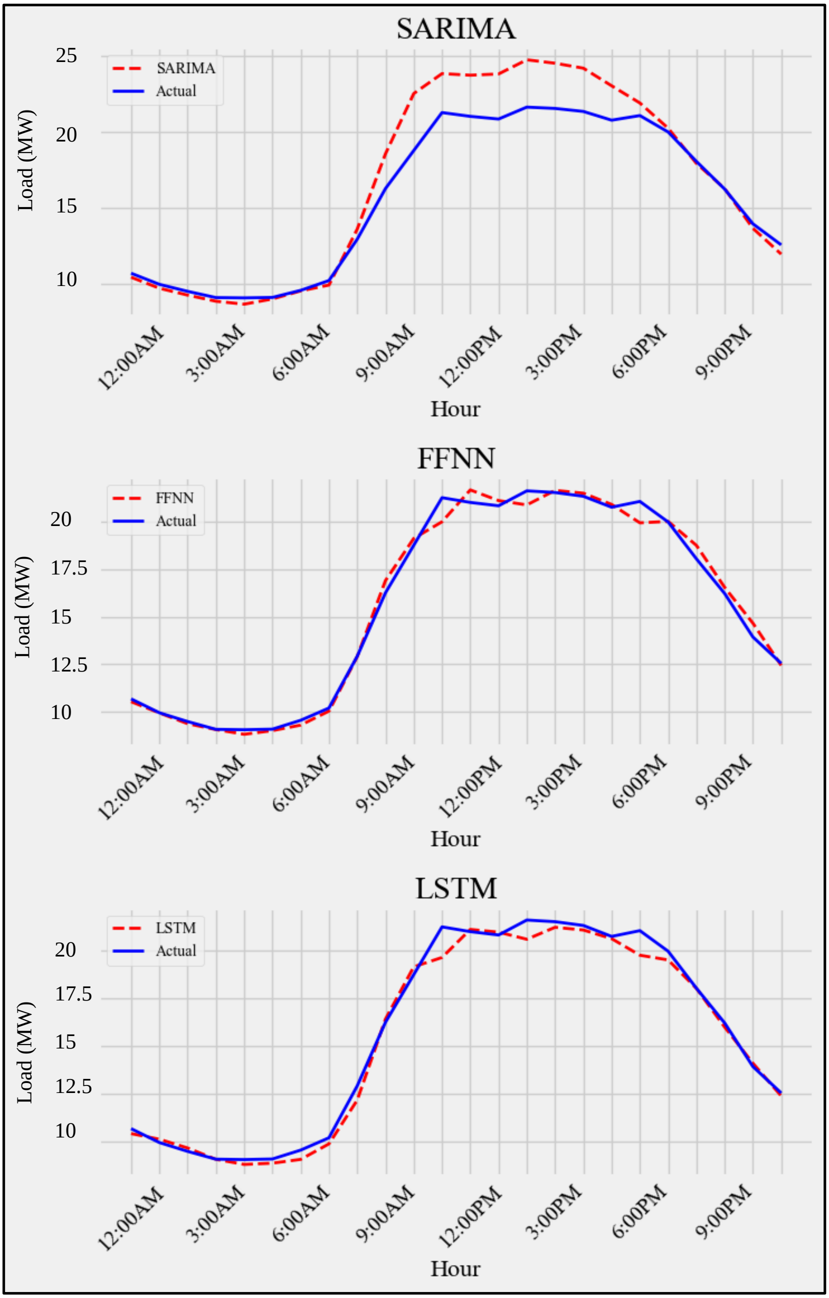


Figure 12. Performance of the three models for a holiday

It can be seen that the SARIMA model and VAR model were not able to forecast the load for the holiday because these models only used their past values to predict their future values. For the machine learning models FFNN and LSTM, both models forecasted accurately the electrical load demand for a holiday. The hourly forecast is shown in Table 5, and the errors are in Table 6.

Table 5. Comparison of forecasted values of the SARIMA, FFNN and LSTM models for a holiday

Aug-29	Actual	SARIMA	FFNN	LSTM
12:00 AM	10.68	10.41	11.19	10.41
1:00 AM	9.95	9.69	10.98	10.12
2:00 AM	9.48	9.23	10.52	9.66
3:00 AM	9.07	8.83	10.30	9.06
4:00 AM	9.05	8.64	10.40	8.80
5:00 AM	9.08	8.98	10.73	8.86
6:00 AM	9.55	9.51	11.03	9.06
7:00 AM	10.20	9.90	11.73	9.88
8:00 AM	12.92	13.58	15.68	12.17
9:00 AM	16.26	18.55	21.51	16.43
10:00 AM	18.77	22.52	25.88	19.17
11:00 AM	21.27	23.84	27.11	19.66
12:00 PM	21.02	23.73	26.84	21.13
1:00 PM	20.84	23.81	26.94	20.99
2:00 PM	21.63	24.75	27.46	20.62
3:00 PM	21.54	24.52	27.00	21.25
4:00 PM	21.34	24.19	26.38	21.10
5:00 PM	20.77	23.03	24.99	20.65
6:00 PM	21.07	21.90	23.46	19.78
7:00 PM	19.99	20.24	21.76	19.53
8:00 PM	18.05	17.92	19.62	18.04
9:00 PM	16.22	16.25	17.63	16.01
10:00 PM	13.93	13.64	15.15	14.11
11:00 PM	12.55	11.94	13.13	12.39

Table 6. Mean absolute percent error of the three models forecasting for a holiday

Model	MAPE (%)
Seasonal ARIMA (SARIMA)	6.81
Feed-Forward Neural Network (FFNN)	2.08
Long Short Term Memory (LSTM)	2.39

4. Conclusion and Recommendation

The crucial role of day-ahead load forecasting is of great importance. The SARIMA model did not consider the effects of other factors such as temperature in the forecasting. Such is the case for univariate time series analysis. It was shown that there was a difference in forecasting error, and there was an improved accuracy when using multivariate time series analysis, which included temperature and exogenous variables such as time, weather conditions and special events in forecasting the load pattern 24 h ahead. FFNN and LSTM performed better in the prediction with a MAPE of 1.80 and 1.75%, respectively, compared with the SARIMA (MAPE: 4.48%) and was therefore applicable to short-term load forecasting. The SARIMA model still needs to be studied further given factors such as time, weather conditions, and special events will be used as predictors of the electrical load. Given the ability of machine learning algorithms to learn the non-linear behavior of the electrical load, several neural network structures can be tested to see if accuracy is improved. The effects of additional variables such as hourly electricity price must also be studied to determine the influence on the hourly electrical load for better foresting. The applicability of such a forecasting model in very short-term load forecasting which includes very short time horizons (5-min intervals) must also be investigated.

5. References

Alden, R.E., Gong, H., Ababei, C., & Ionel, D. M. (2020). LSTM forecasts for smart home electricity usage. Proceedings of the 9th International Conference on Renewable Energy Research and Applications, Glasgow, United Kingdom.

Almeshaiei, E., & Soltan, H. (2011). A methodology for electric power load forecasting. Alexandria Engineering Journal, 50, 137-144. https://doi.org/10.1016/j.aej.2011.01.015

Baliyan, A., Gaurav, K., & Kumar Mishra, S. (2015). A review of short term load forecasting using artificial neural network models. Procedia Computer Science, 48, 121-125. https://doi.org/10.1016/j.procs.2015.04.160

Briones, A.G., Hernández, G., Corchado, J., Omatu, S., & Mohamad, M.S. (2019). Machine learning models for electricity consumption forecasting: A Review. Proceedings of the 2019 2nd International Conference on Computer Applications & Information Security (ICCAIS), Riyadh, Saudi Arabia.

Chang, X., Gao, M., Wang, Y., & Hou, X. (2012). Seasonal autoregressive integrated moving average model for precipitation time series. Journal of Mathematics and Statistics, 8(4), 500-505. https://doi.org/10.3844/jmssp.2012.500.505

Chen, Y., Ma, M., & Zou, Y. (2022). Forecasting hourly electricity demand with nonparametric functional data analysis. Procedia Computer Science, 214, 428-436. https://doi.org/10.1016/j.procs.2022.11.195

Chi, J., Liu, Y., Wang, V., & Yan, J. (2022). Performance analysis of three kinds of neural networks in the classification of mask images. Journal of Physics: Conference Series, 2181(1). https://doi.org/10.1088/1742-659 6/2181/1/012032

Chodakowska, E., Nazarko, J., & Nazarko, Ł. (2021). ARIMA models in electrical load forecasting and their robustness to noise. Energies, 14(23), 7952. https://doi.org/10.3390/en14237952

Clements, A.E., Hurn, A.S., Li, Z., & Li, Z. (2015). Forecasting day-ahead electricity load using a multiple equation time series approach. European Journal of Operational Research, 251(2), 522-530. https://doi.org/10.1016/j.ejor.2015.12.030

Dedinec, A., Filiposka, S., & Kocarev, L. (2016). Deep belief network based electricity load forecasting: An analysis of Macedonian case. Energy, 115(3), 1688-1700. https://doi.org/10.1016/j.energy.2016.07.090

El-Hawary, M.E. (2017). Advances in electrical power and energy systems load and price forecasting. New Jersey, United States: Wiley-IEEE Press

Gonen, T. (2007). Electric power distribution system engineering (2nd ed.) Florida, United States: CRC Press.

Guo, Z., Zhou, K., Zhang, X., & Yang, S. (2018). A deep learning model for short-term power load and probability density forecasting. Energy, 160, 1186-1200. https://doi.org/10.1016/j.energy.2018.07.090

Hassan, E., Shams, M. Y., Hikal, N. A., & Elmougy, S. (2023). The effect of choosing optimizer algorithms to improve computer vision tasks: A comparative study. Multimedia Tools and Applications, 82, 16591-16633. https://doi.org/10.1007/s11042-022-13820-0

Hong, T., Pinson, P., Fan, S., Zareipour, H., Troccoli, A., & Hyndman, R.J. (2016). Probabilistic energy forecasting: Global energy forecasting competition 2014 and beyond. International Journal of Forecasting, 32(3), 896-913. https://doi.org/10.1016/j.ijforecast.2016.02.001

Muzaffar, S., & Afshari, A. (2019). Short-term load forecasts using LSTM networks. Energy Procedia, 158, 2922-2927.

Nichiforov, C., Stamatescu, I., Făgărăşan, I., & Stamatescu, G. (2017). Energy consumption forecasting using ARIMA and neural network models. Proceedings of the International Symposium on Electrical and Electronics Engineering, Galati, Romania.

Nie, H., Liu, G., Liu, X., & Wang, Y. (2012). Hybrid of ARIMA and SVMs for short-term load forecasting. Energy Procedia, 16, 1455-1460. https://doi.org/10.1016/j.egypro.2012.01.229

Oğcu, G., Demirel, O.F., & Zaim, S. (2012). Forecasting electricity consumption with neural networks and support vector regression. Procedia - Social and Behavioral Sciences, 58, 1576-1585. https://doi.org/10.1016/j.sbspro.2012.09.1144

Sankalpa, C., Kittipiyakul, S., & Laitrakun, S. (2022). Forecasting short-term electricity load using validated ensemble learning. Energies, 15(22), 8567. https://doi.org/10.3390/en15228567

Schober, P., & Schwarte, L.A. (2018). Correlation coefficients: Appropriate use and interpretation. Anesthesia and Analgesia, 126(5), 1763-1768. https://doi.org/10.1213/ANE.0000000000002864

Shapi, M.K.M., Ramli, N.A., & Awalin, L.J. (2021). Energy consumption prediction by using machine learning for smart building: Case study in Malaysia. Developments in the Built Environment, 5, 100037. https://doi.org/10.1016/j.dibe.2020.100037

Shilpa, G.N., & Sheshadri, G.S. (2017). Short-term load forecasting using ARIMA model for Karnataka State electrical load. International Journal of Engineering Research and Development, 13(7), 75-79.

Tarsitano, A., & Amerise, I.L. (2017). Short-term load forecasting using a two-stage sarimax model. Energy, 133, 108-114. https://doi.org/10.1016/j.energy.2017.05.126

Weather Underground. (n.d.). Xavier University - IMISAMIS2: Forecast for Cagayan de Oro City, Ph. Retrieved from https://www.wunderground.com/dashboard/pws/IMISAMIS2

Weeraddana, D., Khoa, N.L.D., & Mahdavi, N. (2021). Machine learning based novel ensemble learning framework for electricity operational forecasting. Electric Power Systems Research, 201, 107477. https://doi.org/10.1016/j.epsr.2021.107477

Yukseltan, E., Yucekaya, A., & Bilge, A.H. (2020). Hourly electricity demand forecasting using Fourier analysis with feedback. Energy Strategy Reviews, 31, 100524. https://doi.org/10.1016/j.esr.2020.100524

Zhu, G., Peng, S., Lao, Y., Su, Q., & Sun, Q. (2021). Short-term electricity consumption forecasting based on the EMD-Fbprophet-LSTM method. Mathematical Problems in Engineering, 6613604. https://doi.org/10.1155/2021/6613604