VoltCast: A Medium-term Multivariate Forecasting Web App for Electricity Demand, Price, and Supply Using Deep Learning

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Abstract. Forecasts of electricity are crucial for providers and beneficial for consumers, aiding in the planning and management of electric use and grid operations. Time series forecasting has been a vital tool in this field, with various methods and architectures emerging over the decades. With the availability of large data, deep learning approaches have become more plausible and preferable for forecasting tasks. This study developed a web application utilizing deep learning to forecast electricity demand, price, and supply up to 180 days ahead using data from the Philippines. It compared GRU, LSTM, and TCN algorithms using MSE, RMSE, MAE, and MAPE as error metrics, with ARIMA models as benchmarks. The results showed that deep learning models outperformed ARIMA models. Moreover, LSTM performed best for Visayas supply, while GRU performed best in forecasting demand, price, and Luzon supply. The best models were integrated into the web application.

Keywords: electricity forecasting, medium-term, multivariate, demand, load, price, supply, deep learning, GRU, LSTM, TCN

1 INTRODUCTION

Forecasts of electricity demand, price, and supply (especially the demand or load) are crucial for the electric sector as they utilize these forecasts for better planning (including allocation and distribution of electricity), efficient management, and cost-effective operations of the electric power system [4, 17, 8, 11, 10]. One significant factor in time-series forecasting is the forecasting horizon, which defines the number of steps ahead to be predicted [3]. These forecasting horizons, each having their own use-cases, can be categorized into short-term, medium-term, and long-term [11, 7, 23, 22]. Short-term load forecasting (STLF) usually ranges from hours to a week ahead, which could help in the day-ahead planning of the electricity market, demand management, and security of supply from the market. Long-term load forecasting (LTLF) extends from years up to decades ahead, which could help in management of assets, construction of new generations, and planning and development of power systems expansions.

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Medium-term load forecasting (MTLF) typically ranges from weeks up to a year ahead, which could help in the management and maintenance of product units, scheduling of inspection and repair, management of consumption peaks especially in special seasons, planning of fuel purchases, and provision of stable service to the customers. Among these forecasting horizons, MTLF seems to be less often studied [11].

With the availability of large datasets, machine learning techniques (e.g., deep learning) are becoming more preferable [9]. Various deep learning methodologies have been utilized in forecasting electricity load, demand, supply, and price, such as fully-connected neural networks, recurrent neural networks (RNN), and convolutional neural networks (CNN) [6]. Among these, RNNs (e.g., LSTM and GRU) are more frequently studied with great performance yields, but CNNs are also gaining popularity especially with the development of temporal convolutional network (TCN). These algorithms tend to be used by previous studies to forecast electric load or demand alone and not for multivariate demand, price, and supply.

In the context of the Philippines, a number of studies were already conducted in light of forecasting electricity demand, price, and supply. Some of these made use of ARIMA models in obtaining forecasts [19, 2, 15], machine learning models like support vector regression and random forests [1], and neural networks like artificial neural network (ANN) [21, 20, 15]. Most of them focused on forecasting the electric load, consumption, or demand alone, some of them only using the historical load, consumption, or demand data. Moreover, these studies tend to focus on the short-term forecasting horizon, with some of them dealing with long-term forecasting as well.

There seem to be limited studies that tackled medium-term (up to 6 months or 180 days ahead) multivariate forecasting of electricity demand, price, and supply. Moreover, the use of state-of-the-art algorithms like GRU, LSTM, and TCN have not been explored much yet for the same task using electricity data from the Philippines. Thus, this study aimed to utilize the deep learning algorithms GRU, LSTM, and TCN for medium-term multivariate forecasting of electricity demand, price, and supply up to 180 days ahead in the Philippine context.

2 RELATED WORKS

In 2020, Mir et al. analyzed studies on electricity load forecasting in low- and middle-income countries across different time horizons [11]. They characterized short-term load forecasting (STLF) as ranging from hours to weeks, medium-term load forecasting (MTLF) from months to years, and long-term load forecasting (LTLF) from five years to decades. The review found that while few studies address short- and medium-term horizons, time-series models are extensively used for forecasting in these periods.

In 2022, Pavićević and Popović forecasted electricity load and price using artificial neural networks (ANN), including traditional neural networks, LSTM, and temporal convolutional networks (TCN) [16]. The price dataset consisted of hourly records from July 10, 2010, to December 31, 2019, while the load dataset spanned June 1, 2015, to June 19, 2021. Data preprocessing included handling missing values, omitting duplicates, and one-hot encoding categorical data. Models used 14 days of hourly values to predict the next 24 hours. Evaluation metrics were MAPE, MAE, and MSE. TCN and LSTM provided the best predictions. Recommendations included expanding the dataset with additional variables and exploring Gated Recurrent Units (GRU) for potential accuracy improvements.

In 2019, Muzaffar and Afshari tested LSTM performance in short-term load forecasting using exogenous variables such as temperature, humidity, and wind speed [12]. They evaluated models with different forecasting horizons (24 hours, 48 hours, 7 days, 30 days) using RMSE and MAPE. LSTM models had 60 units, used the Adam optimizer, 400 epochs, and a 0.005 learning rate. Compared to benchmark models (ARMA, SARIMA, ARMAX), LSTM outperformed them, with narrower forecasting horizons showing better performance. For a 24-hour horizon, LSTM had an RMSE of 89.40 and MAPE of 1.52; for 30 days, the RMSE was 554.90 and MAPE was 9.75%.

In 2022, Rezaei et al. proposed a framework using Gated Recurrent Units (GRU) for electricity price forecasting [18]. To address noise in time-series data, they employed the CEEMDAN method for decomposition and noise reduction, and a Stacked Auto Encoder (SAE) for feature extraction. GRU was chosen as the predictor due to its faster computation and lower training weight requirements compared to LSTM. The framework, tested on 1,186 days of hourly price data for training and 209 days for testing, was evaluated using RMSE and MAE. Results showed the GRU-based method outperformed the LSTM-based method. The authors recommended incorporating additional factors such as weather and temperature in future studies.

In 2020, Lara-Benítez et al. applied Temporal Convolutional Networks (TCN) for forecasting Spain's national electric demand and power demand at charging stations [5]. Data preprocessing involved min-max normalization and a multi-input multi-output strategy. TCN and LSTM underwent hyperparameter tuning, using the Adam optimizer and mean absolute error (MAE) as the loss function. Models were evaluated using weighted absolute percentage error (WAPE). TCN achieved the best WAPE of 0.0093 with 288 time-steps (48 hours) of past data, surpassing LSTM. TCN was deemed superior in accuracy and reliability due to its reduced sensitivity to parameter selection.

3 METHODOLOGY

3.1 Dataset

The raw dataset used in this study were obtained from the electricity markets and from the [14] National Grid Corporation of the Philippines (NGCP). It comprises mainly of hourly records of electricity demand, price, and supply. It records the electricity data of the three major grids of the Philippines (Luzon, Visayas, and Mindanao grids) from January 9, 2015 to December 25, 2022.

After preprocessing, the resulting list of features of the cleaned data is shown below:

1. **Date** as the index in the format MM/DD/YYYY, including the hour in 24-hour format
2. **Block** indicating whether the day is a weekday, weekend, or holiday, with values "Weekday", "Sat", and "Sun / Hol"
3. **LuzVis GWAP, PHP/kWh** measuring the grid weighted average price of Luzon and Visayas grids in PHP per kilowatt-hour
4. **Luzon RTD Demand, MW** measuring the total electricity demand of Luzon grid in megawatts
5. **Visayas RTD Demand, MW** measuring the total electricity demand of Visayas grid in megawatts
6. **Luzon Supply, MW** measuring the total electricity supply of Luzon grid in megawatts
7. **Visayas Supply, MW** measuring the total electricity supply of Visayas grid in megawatts

Moreover, table 1 lists the descriptive statistics of the numerical features.

	Luzon Demand (MW)	Visayas Demand (MW)	LuzVis Price (PHP per kWh)	Luzon Supply (MW)	Visayas Supply (MW)
count	2,549	2,549	2,549	2,549	2,549
mean	182,779.25	36,068.82	3.49	245,761.01	49,066.92
std	22,496.21	4,433.96	2.18	27,668.78	7,943.74
min	100,627.00	12,415.00	-7.45	149,739.00	25,801.67
max	240,737.00	45,538.00	16.83	315,484.30	63,897.70

Table 1. Descriptive Statistics of the Numerical Features

3.2 Data Preprocessing

1. The feature selection process was done manually and with the aid of a domain expert. First, **Temp** was dropped because it could only represent the temperature from Metro Manila. Then, redundant features were dropped as well. These include the features representing the supply from specific sources, as well as the system-wide features since they are just the sum of the values from its subgrids.
2. Missing values were addressed by dropping the features whose majority of values are missing. **HVDC**, all **Mindanao** features, and **Luzon and Visayas prices** were dropped since these records were only available from December 26, 2021 onwards.

3. The originally hourly time series data were converted to daily. The conversion made use of the daily total demand, daily average price, and daily total supply. The features **Day** and **Hour** were merged with the **Date** feature and were dropped. Likewise, the **Peak/Off-Peak** feature was dropped since it represents the peak hours. The **Block** feature were filled based on the day's weekday category and the list of regular holidays in the Philippines obtained from [13].
4. The categorical feature **Block** was one-hot encoded. This increased the number of features from 6 to 8 (excluding the index).
5. All numerical features were normalized using Min-Max Normalization.
6. The time series was sequenced into windows where each window contains 180 days of records. This step was also necessary for converting the time series into a supervised learning task by generating input and label sequences using the training set.
7. The dataset was split into 6 years training set (2015-2020, with 1 year allotted for validation) and 1 year for testing set (2021). The remaining year (2022) was set aside for running tests during the web app development stage.

3.3 Model Building

1. Initial models for the three deep learning algorithms (GRU, LSTM, and TCN) were built and trained using the training set. The GRU models were defined to have an input layer followed by GRU layers and a dense (output) layer as the last layer. Likewise, the LSTM models were defined to have an input layer followed by LSTM layers and a dense (output) layer as the last layer. Meanwhile, the TCN models were defined to have an input layer, then pairs of a TCN and a Conv1D layers, and a dense (output) layer as the last layer. The Adam optimizer and MSE loss function were used for all the models. Table 2 lists the parameters that were set to define the initial models.
2. The initial models were tuned using the random search algorithm to obtain the models' parameters that yield better performance. Three additional models (tuned models) were obtained after hyperparameter tuning. The number of trials for the random search function was set to 100 for GRU and LSTM, and 200 for TCN. Tables 3, 4, and 5 list the hyperparameters tested and the optimal parameter values found after tuning.

4 RESULTS AND DISCUSSION

4.1 Deep Learning Models

All the models (initial and tuned) were used to forecast the last 180 days of the testing set. The error metrics were obtained by comparing the obtained forecasts with the actual values from the testing set. Tables 6, 7, 8, and 9 compile the error metrics of each model, including a benchmark statistical model ARIMA. The lowest metric values for each target feature are highlighted on each table.

Parameter	Value	Parameter	Value
no. of layers	1	dropout rate	0.2
no. of units (GRU and LSTM)	32	regularization coefficient	0.0005
no. of filters (TCN)	32	no. of epochs	50
kernel size (TCN)	6	batch size	64
dilations (TCN)	[1, 2, 4, 8, 16]	optimizer	Adam
activation (TCN)	linear	loss function	MSE
learning rate	0.001	early stopping patience	5

Table 2. Parameter Values of the Initial Models

Parameter	Grid	Best Value
no. of layers	1, 2, 3, 4, 5	1
no. of units	32, 64, 128	64
dropout rate	0.0, 0.1, 0.2, 0.3, 0.4, 0.5	0.4
regularization coefficient	0.0001, 0.0005, 0.001, 0.01, 0.1	0.0001
learning rate	0.0001, 0.001, 0.01, 0.1	0.01

Table 3. GRU Hyperparameter Tuning using Random Search

Parameter	Grid	Best Value
no. of layers	1, 2, 3, 4, 5	1
no. of units	32, 64, 128	64
dropout rate	0.0, 0.1, 0.2, 0.3, 0.4, 0.5	0.4
regularization coefficient	0.0001, 0.0005, 0.001, 0.01, 0.1	0.0001
learning rate	0.0001, 0.001, 0.01, 0.1	0.01

Table 4. LSTM Hyperparameter Tuning using Random Search

Parameter	Grid	Best Value
no. of layers	1, 2, 3, 4, 5	2
no. of filters (TCN layers)	3, 8, 16, 32, 64, 128	16 (layer 1) 32 (layer 2)
kernel size (TCN layers)	1, 2, 3, 4, 5, 6	2 (layer 1) 4 (layer 2)
no. of filters (Conv1D layers)	3, 8, 16, 32, 64, 128	16 (layer 1) 64 (layer 2)
kernel size (Conv1D layers)	1, 2, 3, 4, 5, 6	5 (layer 1) 2 (layer 2)
dropout rate	0.0, 0.1, 0.2, 0.3, 0.4, 0.5	0.1 (layer 1) 0.4 (layer 2)
regularization coefficient (Conv1D layers)	0.0001, 0.0005, 0.001, 0.01, 0.1	0.01 (layer 1) 0.01 (layer 2)
activation function (TCN layers)	linear, tanh, relu	linear (layer 1) tanh (layer 2)
learning rate	0.0001, 0.001, 0.01, 0.1	0.01

Table 5. TCN Hyperparameter Tuning using Random Search

Model	Luzon Demand	Visayas Demand	LuzVis Price	Luzon Supply	Visayas Supply
$\mathrm{GRU_{Initial}}$	2.3146×10^8	3.0537×10^7	8.1962	3.1973×10^8	2.7815×10^7
$\mathrm{GRU_{Tuned}}$	3.3954×10^8	3.6153×10^7	10.0749	2.6516×10^8	4.0262×10^7
$\mathrm{LSTM_{Initial}}$	2.9649×10^8	3.4891×10^7	7.4691	3.2129×10^8	2.8976×10^7
$\mathrm{LSTM_{Tuned}}$	4.0030×10^8	4.0129×10^7	7.5603	3.8592×10^8	4.0222×10^7
$\mathrm{TCN_{Initial}}$	3.6197×10^9	1.6321×10^8	144.3646	4.0190×10^9	2.1450×10^8
$\mathrm{TCN_{Tuned}}$	4.9941×10^8	4.0471×10^7	10.1288	3.9607×10^8	8.5465×10^7
ARIMA	3.3578×10^9	4.6821×10^7	16.3766	3.1620×10^8	3.0250×10^7

Table 6. Mean Squared Error (MSE) of the Initial and Tuned Models

Model	Luzon Demand	Visayas Demand	LuzVis Price	Luzon Supply	Visayas Supply
$\text{GRU}_{\text{Initial}}$	1.5214×10^4	5.5260×10^3	2.8629	1.7881×10^4	5.2740×10^3
$\text{GRU}_{\text{Tuned}}$	1.8427×10^4	6.0128×10^3	3.1741	1.6284×10^4	6.3452×10^3
$\text{LSTM}_{\text{Initial}}$	1.7219×10^4	5.9068×10^3	2.733	1.7925×10^4	5.3829×10^3
$\text{LSTM}_{\text{Tuned}}$	2.0008×10^4	6.3347×10^3	2.7496	1.9645×10^4	6.3421×10^3
$\text{TCN}_{\text{Initial}}$	6.0164×10^4	1.2775×10^4	12.0152	6.3395×10^4	1.4646×10^4
$\text{TCN}_{\text{Tuned}}$	2.2347×10^4	6.3617×10^3	3.1826	1.9902×10^4	9.2447×10^3
ARIMA	5.7947×10^4	6.8426×10^3	4.0468	1.7782×10^4	5.5000×10^3

Table 7. Root Mean Squared Error (RMSE) of the Initial and Tuned Models

Model	Luzon Demand	Visayas Demand	LuzVis Price	Luzon Supply	Visayas Supply
$\text{GRU}_{\text{Initial}}$	1.2118×10^4	3.6781×10^3	1.9032	1.4588×10^4	2.8923×10^3
$\text{GRU}_{\text{Tuned}}$	1.5879×10^4	3.8362×10^3	2.0926	1.2993×10^4	5.1790×10^3
$\text{LSTM}_{\text{Initial}}$	1.3072×10^4	3.5566×10^3	1.8414	1.4475×10^4	2.6475×10^3
$\text{LSTM}_{\text{Tuned}}$	1.6436×10^4	4.4437×10^3	1.8736	1.5352×10^4	5.0487×10^3
$\text{TCN}_{\text{Initial}}$	4.6785×10^4	9.7685×10^3	8.9694	4.8663×10^4	1.1167×10^4
$\text{TCN}_{\text{Tuned}}$	1.9946×10^4	5.0887×10^3	2.104	1.5909×10^4	8.8321×10^3
ARIMA	5.6532×10^4	6.0889×10^3	3.1295	1.4014×10^4	3.3931×10^3

Table 8. Mean Absolute Error (MAE) of the Initial and Tuned Models

Model	Luzon Demand	Visayas Demand	LuzVis Price	Luzon Supply	Visayas Supply
$\text{GRU}_{\text{Initial}}$	6.2128	12.5686	34.3855	5.7245	6.3527
$\text{GRU}_{\text{Tuned}}$	7.9458	13.4185	33.3433	5.0720	10.2794
$\text{LSTM}_{\text{Initial}}$	6.7614	12.6892	36.3862	5.6409	5.9123
$\text{LSTM}_{\text{Tuned}}$	8.2128	14.6357	37.0579	5.7402	10.0523
$\text{TCN}_{\text{Initial}}$	23.8934	27.8061	209.397	18.4941	20.7131
$\text{TCN}_{\text{Tuned}}$	9.7645	15.7545	33.5982	5.8910	16.2915
ARIMA	27.9762	17.9895	53.1153	5.2274	7.2774

Table 9. Mean Absolute Percentage Error (MAPE) of the Initial and Tuned Models

Based on all the error metrics, the deep learning models performed comparably well or even better than ARIMA, except for the initial TCN which had larger error metrics than ARIMA on all target features. This could imply that the deep learning models had satisfactory performance in forecasting electricity, except for LuzVis price whose lowest MAPE value is at 33.34%.

Between the initial and tuned models, only TCN found a decrease in its error metrics on the tuned model compared to the initial. This could be due to the hyperparameter tuning algorithm used not being able to search through the whole grid, unlike grid search. The chosen tuning algorithm was primarily due to computational limitations. Given the total number of parameter combinations in the search space, random search was a more cost-efficient choice.

Both GRU and LSTM had lower error metrics than the tuned TCN. For Luzon demand, the initial GRU model had the lowest error on all error metrics. Likewise, for Luzon supply, the tuned GRU model had the lowest error. For Visayas demand, the initial GRU model had the lowest MAPE value of approximately 12.57%. For Visayas supply, the initial LSTM model had the lowest MAPE value of approximately 5.91%. Lastly, for LuzVis price, the tuned GRU model had the lowest MAPE of approximately 33.34%.

Moreover, based on the results, $\text{GRU}_{\text{Initial}}$ had the lowest errors in forecasting Luzon demand, while $\text{GRU}_{\text{Tuned}}$ had the lowest errors in forecasting Luzon supply. Meanwhile, the other features had split results across the error metrics, but based on the MAPE (the main metric of this paper), $\text{GRU}_{\text{Initial}}$ had the lowest errors in forecasting Visayas demand, $\text{GRU}_{\text{Tuned}}$ for LuzVis price, and $\text{LSTM}_{\text{Initial}}$ for Visayas supply.

4.2 Web Application

The forecasting web app named VoltCast was developed integrating the best performing models. It contains two pages: the welcome page (landing page) and the results page. The sidebar is designated for the input form.

Figure 1 shows VoltCast's welcome page, which is also its landing page. The sidebar contains the input form where users may upload the input data in CSV format. It can accept both the historical data (required) and the actual data (optional). The historical data is used by the models to generate forecasts, while the actual data may be used to see how well the models forecasted the actual. Meanwhile, the left part of this page displays the about section which briefly describes the web app. Meanwhile, the right part displays the instructions and notes sections which guide the users on how to use the web app.

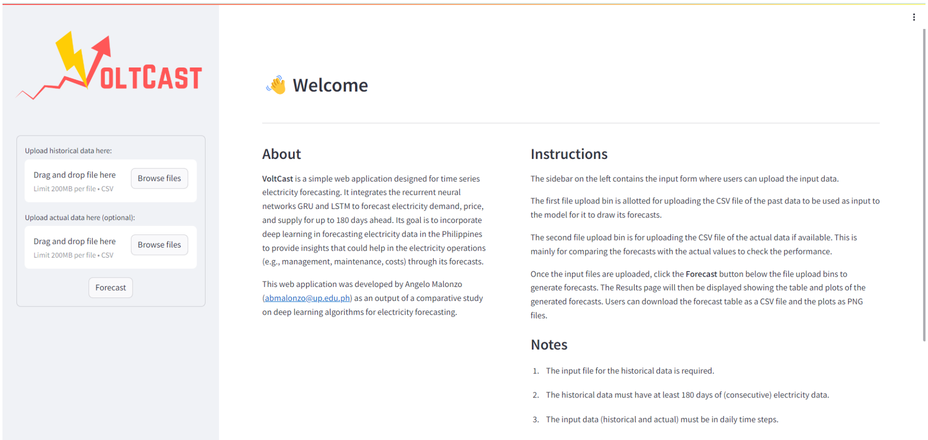


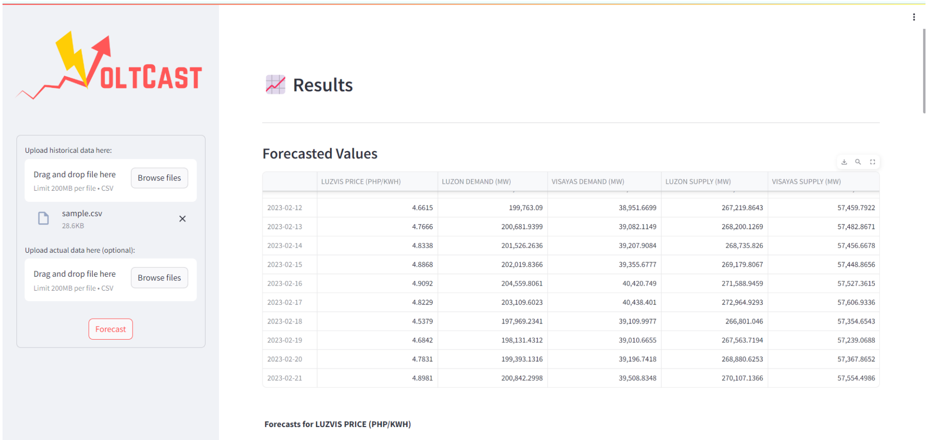
Fig. 1. VoltCast's Welcome (Landing) Page

Figures 2 and 3 show VoltCast's results page. It displays the forecasted values in table form. Users have the option to download this table in CSV format. On the lower portions, the time series plots of the actual vs forecasted values are displayed for each of the electricity features. Users have the option to download each of the plots as images in PNG format. Moreover, these plots are interactive plots, so users have controls like zooming and panning the plots.

5 CONCLUSION

In summary, this study aimed to utilize deep learning for medium-term multivariate electricity forecasting. It tested three deep learning algorithms (GRU, LSTM, and TCN) as forecasting models defined for 180-day ahead forecasting of multivariate electricity demand, price, and supply. After tuning, evaluation, and comparison via the error metrics (MSE, RMSE, MAE, and MAPE), the best models were identified for each of the target feature.

For Luzon demand, Visayas demand, and Luzon supply, the initial GRU model performed the best with a MAPE of 6.21%, 12.57%, and 5.07%, respectively. For LuzVis price, the tuned GRU model had the lowest MAPE of 33.34%.



	LUZVIS PRICE (PHP/KWH)	LUZON DEMAND (MW)	VISAYAS DEMAND (MW)	LUZON SUPPLY (MW)	VISAYAS SUPPLY (MW)
2023-02-12	4.6615	199,763.09	38,951.6699	267,219.8643	57,459.7922
2023-02-13	4.7666	200,681.9399	39,082.1149	268,200.1269	57,482.8671
2023-02-14	4.8338	201,526.2636	39,207.9084	268,735.826	57,456.6678
2023-02-15	4.8868	202,019.8366	39,355.6777	269,179.8067	57,448.8656
2023-02-16	4.9092	204,559.8061	40,420.749	271,588.9459	57,527.3615
2023-02-17	4.8229	203,109.6023	40,438.401	272,964.9293	57,606.9336
2023-02-18	4.5379	197,969.2341	39,109.9977	266,801.046	57,354.6543
2023-02-19	4.6842	198,131.4312	39,010.6655	267,563.7194	57,239.0688
2023-02-20	4.7831	199,393.1316	39,196.7418	268,880.6253	57,367.8652
2023-02-21	4.8981	200,842.2998	39,508.8348	270,107.1366	57,554.4986

Fig. 2. VoltCast's Results Page - Table

Fig. 3. VoltCast's Results Page - Plots

Lastly, for Visayas supply, the initial LSTM model had the lowest MAPE of 5.91%. These models were then integrated in the forecasting web app. The web app makes use of these models to generate the forecasts given the input historical data and present these forecasts to users using tables and plots.

Overall, the developed forecasting web app successfully provides medium-term (180 days ahead) forecasts of electricity. It is able to generate satisfactory forecasts that could serve as a foothold for electricity providers in terms of operations and maintenance, and even for consumers in terms of their daily electricity usage.

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