Comparative Analysis of Deep Learning Techniques Based COVID-19 Impact Assessment on Electricity Consumption in Distribution Network

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ABSTRACT: Energy is a fundamental human need for several activities. Energy can be impacted by several factors ranging from technical to social and environmental. The impact of COVID-19 outbreak on the energy sector is enormous with serious global socioeconomic disruptions affecting all economic sectors, including tourism, industry, higher education, and the electricity industry. Based on the unstructured data obtained from Eko Electricity Distribution Company this paper proposes three deep learning (DL) models namely: Long Short-Term Memory (LSTM), Simple Recurrent Neural Network (SimpleRNN), and Gated Recurrent Unit (GRU) were used to analyse the effect of COVID-19 pandemic on energy consumption and predict future energy consumption in various district in Lagos, Nigeria. The models were evaluated using the following performance metrics namely: Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). On overall, the lowest MAPE, MAE, RMSE, and MSE of 0.120, 71.073, 93.981, and 8832.466 were obtained for LSTM in Orile, SRNN in Ijora, and GRU in Ijora, respectively. Generally, the GRU performed better in predicting energy consumption in most of the districts of the case study than the LSTM and SimpleRNN. Hence, GRU model can be considered the optimal model for energy consumption prediction in the case study. The importance of having this model is that it can help the government and other stakeholders in economic planning of electricity distribution networks.

KEYWORDS: COVID-19, Energy Consumption, Deep Learning, Distribution Networks

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I. INTRODUCTION

Energy is one of the most essential commodities for running day-to-day activities of different sectors like industries, commercial, residential, educational, and sports (Makinde *et al*., 2021; Haq *et al*., 2021). The efficiency and growth of these sectors largely depend on the availability of quality and affordable electricity. The availability of electricity needed for the effective running of these sectors also depends on a number of factors among which include the technical, economic, and consumption patterns of the consumers (Jangali Satish & Nagesha, 2015; Amole *et al*., 2020). Energy consumption has been defined as the amount of energy an individual, household (De Araujo, 2019), industry, or organization requires to carry out their basic activities (Shah *et al*., 2020). The consumption of energy is generally a point of attention for energy planners as it helps to understand energy production, management, and sales (Fezzi & Fanghella, 2020). The SDG's goal 7: clean, reliable, and affordable energy for all will not be realistic without a clear understanding of the energy consumption patterns of the consumers (Khan *et al*., 2021). Energy deficit and poverty limits economic growth of a nation hence, it is important to embrace energy consumption prediction prevent it. The outbreak of coronavirus disease 2019 (COVID-19) came as a rude shock to the entire human race in late 2019 with its origin in Wuhan, a city of 11 million inhabitants in China's Hubei region (Nour *et al*., 2020). The outbreak of COVID-19 has left an indelible mark on almost every aspect of human endeavours like health, transport, sport, agriculture, education, and energy (Musumeci, 2022; Ahshan *et al*., 2020). The coronavirus pandemic has arguably exposed deficient socioeconomic systems' resilience to economic shocks in several nations and areas around the world sports (Soava *et al*., 2021). The first confirmed case of COVID-19 in Nigeria was reported in February, 2020 and spread to the 36 states in Nigeria like wildfire resulting in about 3,143 deaths in May 18, 2022 according to the Nigeria Centre for Disease Control (NCDC). The outbreak of COVID-19 greatly impacted the Nigerian Electricity Supply Industry (NESI) negatively during the lockdown, with Generation Companies (GenCos) and Distribution Companies (DisCos) experiencing

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the more pronounced effect due to gas shortage (Ojosu & Akolo, 2020).

The impact of COVID-19 on the electricity industries can be predicted with the help of forecasting models. Deep learning (DL) is one of the recent forecasting models that has gained significant visibility in a variety of fields, including computer gaming, natural language processing, pattern identification, and medical diagnosis, to mention a few (Ungureanu *et al*., 2021). It utilizes algorithms to analyze data and mimic the cognitive process, as well as to build abstractions. It has capability to process data, understands human speech, and visually recognizes things (Nour *et al*., 2020). Architecturally, DL has layers namely: input layer, output layer, and the hidden layer with only one type of activation function for each layer, which makes them all simple, homogenous algorithms. There are several models of DL which have been used for different purposes like prediction and classification. However, the neural network models have been mostly used for most of prediction purpose (Zhou *et al*., 2020).

Though it has been argued that DL models have complicated structures and over-fitted performances (Lee *et al*., 2021), there are several models of DL that have been deployed by researchers to depict and analyze different scenarios. Though, use of DL models for event forecasting (Hernandez-Matamoros *et al*., 2020; Ibrahim & Rabelo, 2021; Azeem *et al*., 2021; Ullah *et al*., 2021) seems to be prevalent. However, the use of DL models transcends forecasting to find applications in scientific and industrial fields (Moradzadeh *et al*., 2021), data classification and feature extraction (Nour *et al*., 2020), fault detection (Wlodarczak, 2019), renewable power plant potential measurement and image processing (Abraham & Nair, 2020), object detection (Melanthota *et al*., 2022; Slart *et al*., 2021), vehicle energy monitoring (Ko *et al*., 2021), and cyber security (Mahdavifar & Ghorbani, 2019).

One of the recent variants of DL is extreme learning machine (ELM) that has capability to overcome the non-linear and non-stationary aspect of the electricity price. ELM have been used to predict short-term electricity price in Australia (Khan *et al*., 2021). The long short-term memory (LSTM) model appears to be one of the popular DL models that have been used in different fields of energy study like solar irradiation prediction (Ozdemir *et al*., 2022), wind speed prediction (Elsaraiti & Merabet, 2021), state of charge estimation (Vellingiri *et al*., 2022), and load forecasting (Masood *et al*., 2022; Ungureanu *et al*., 2021). The popularity of LSTM may be attributed to its ability to effectively handle very huge amount of data which is crucial model accuracy. A modified LSTM is the Bi-LSTM which has also aided short-term load forecasting to ensure sustainable energy management in microgrid (Moradzadeh *et al*., 2021). Similarly, gated recurrent unit (GRU) is another DL model that gained popularity in prediction and forecasting problems (Bahij *et al*., 2022; Sehovac *et al*., 2019; Ji *et al*., 2021). The recurrent neural networks (RNN) and its various variants can be said to have played a significant role in the field of prediction and forecasting as it is evident in (Ahn & Park, 2021; Liang *et al*., 2018; Mocanu *et al*., 2016). The convolutional neural networks (CNN) is another versatile DL model that has been applied to solve emerging problems both in the medical and energy fields (Jogunola *et al*., 2022; Pereira *et al*., 2020). The CNN model has been modified to the multi-CNN and Faster Regions with CNN (Faster R-CNN) with applications mainly in the diagnosis of COVID-19 diseases (Abraham & Nair, 2020; Shibly *et al*., 2020).

The energy consumption during the COVID-19 outbreak is highly dynamical thereby making it difficult to forecast. Energy consumption is difficult to forecast due to a variety of issues, including a lack of data, finding the optimal forecasting model, and unpredictable forces that could disrupt projections, such as weather disasters, COVID, and the outbreak of war. The goal of this article is to find an optimal energy consumption forecast model through a comparative analysis using some districts in Lagos, Nigeria as case study. To achieve this, a concise review of the various methods currently in use for energy consumption forecast was carried out. Consequently, three DL models namely: LSTM, SimpleRNN, and GRU were employed to accurately forecast the energy consumption. This work is motivated by the need to create an accurate forecasting model that can be adopted by governments and policymakers to make future economic decisions on energy planning and management. To that effect, the following research issues are attempted to be addressed in this study: (1) DL techniques capable of forecasting energy consumption, (2) Optimal model for forecasting future energy consumption, (3) Effect of COVID-19 lockdown on the energy consumption in the distribution network.

II. MATERIALS AND METHODS

The energy consumption data for three years was obtained from Eko Electricity Distribution Company. The following operations namely: data acquisition and preparation, data exploration and visualization; model training, model testing, performance evaluation and comparison. Three Deep Learning models namely; GRU, LSTM, and Simple Recurrent Neural Network (SimpleRNN) were used for the analysis while the performance of the models was evaluated and compared using MAE, MAPE, MSE, and RMSE.

A. Case study description and data acquisition

The case study in this work, Eko Electricity Distribution Company (EKEDC) located within Lagos State, Nigeria. EKEDC has three circles namely: east, west, and central. The distribution network of the company is made up of ten districts with seventy-six 33kV feeders as presented in Table 1. The daily energy consumption dataset was collected from Eko Electricity Distribution Plc over a three-year period from the 1st of January 2019 until the 30th of November 2021. This period spans the pre-COVID, COVID, and post-COVID periods to reflect the impact of COVID-19 on the energy consumption of the study area. It contains the daily consumption of each District, Circle, and 33kV feeder as shown in Plate 1. Every month had a different sheet in each dataset for each year. For analysis purpose, one master sheet showing the feeders, circle, district, and consumption in Plate 2 was generated from the dataset in Plate 1.

The consumption per circle of the distribution company is presented in Figure 1 which revealed the data distribution and behaviour. Figure 1 showed that more energy is generally consumed within the east circle while the least energy consumption is experienced within the west circle. It can also be observed from Figure 1 that the consumption variability of the east circle is generally high compared to that of the west and central.

ut[3]:

	S/N	CIRCLE	DISTRICT	Injection S/S	33KV FEEDER	Colour Code	DAY 1	DAY 2	DAY 3	DAY 4	...	DAY 24	DAY 25	DAY 26	DAY 27	DAY 28	DAY 29	DAY 30	DAY 31	MONTHLY	DAILY AVG
0	1.0	CENTRAL	APAPA	NaN	AMUWO LOCAL T3	NaN	191.0	162.0	122.0	170.0	...	153.0	84.0	188.0	183.0	168.0	145.0	167.0	165.0	5123.0	165.258065
1	2.0	CENTRAL	APAPA	NaN	APAPA MAINS 1	NaN	75.0	123.0	87.0	126.0	...	107.0	68.0	19.0	49.0	97.0	98.0	69.0	92.5	3132.5	101.048387
2	3.0	CENTRAL	APAPA	NaN	APAPA MAINS 2	NaN	22.0	56.0	45.0	95.0	...	49.0	45.5	67.5	88.0	81.0	106.0	46.0	68.5	2098.0	67.677419
3	4.0	CENTRAL	APAPA	NaN	APAPA ROAD LOCAL T1	NaN	135.3	113.8	85.7	114.5	...	110.3	79.4	100.3	106.1	90.2	114.3	112.4	121.6	3257.0	105.064516
4	5.0	CENTRAL	APAPA	NaN	APAPA ROAD LOCAL T2	NaN	192.3	111.3	83.4	97.6	...	100.4	93.8	125.2	123.6	126.4	118.9	105.7	114.2	3300.8	106.477419

Plate 1: Sample dataset

In [8]:

```
#Show the last months
datacombined.head()
```

Out[8]:

DATE	CIRCLE	DISTRICT	33KV FEEDER	Consumption
2019-01-01	CENTRAL	APAPA	AMUWO LOCAL T3	191.0
2019-01-01	CENTRAL	APAPA	APAPA MAINS 1	75.0
2019-01-01	CENTRAL	APAPA	APAPA MAINS 2	22.0
2019-01-01	CENTRAL	APAPA	APAPA ROAD LOCAL T1	135.3
2019-01-01	CENTRAL	APAPA	APAPA ROAD LOCAL T2	192.3

Plate 2: The transformed dataset

B. *Data pre-processing*

The consumption data for each circle and district obtained in sub-section *A* contain a wide range of values not suitable for deep learning models. Consequently, scaling of the dataset was performed to improve the performance of the models. Data normalization was performed to avoid bias during the training of data using Eqn. (1) and result of the normalization is shown in Plate 3.

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

The normalized data is then partitioned into train and test data. This allows for the training of the models prior to test while test permits the performance evaluation of the models using the specified metrics.

The training data are the observations used to build the algorithm to learn from. For this work, the train data ranged from 01/01/2019 - 10/03/2021 which captured the pre-COVID and COVID periods. The test data which must be exclusive to the train set is used to test the performance of the deep learning model based on different metrics.

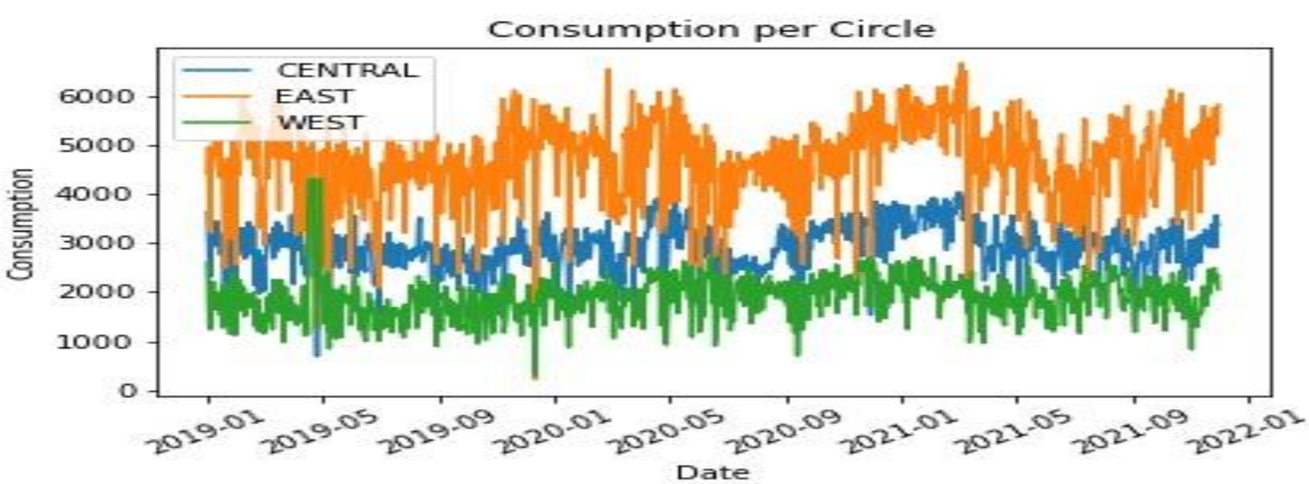
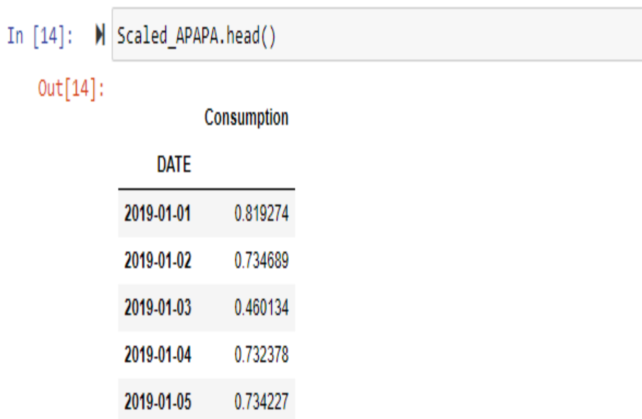


Figure 1: Consumption per circle

Table 1: Districts and its associated 33kV Feeders

DISTRICT	33KV FEEDER
APAPA	Amuwo Local T3, Apapa Mains 1, Apapa Mains 2, Apapa Road Local T1, Apapa Road Local T2, Badia 33, Flour Mills, Naval Base
IJORA	NRC (AKOKA), Akoka Local T3a, Causeway 1 33, Causeway 2 33, Nrc (Akangba), Sabo 33, UNILAG
MUSHIN	Idi Araba 33, Ijesha, Isolo Local, LUTH, New Yaba (Akangba), New Yaba (Akoka), NITEL 33, PTC
ORILE	Adelabu 1, Adelabu 2, Amuwo, Iganmu 1, Iganmu 2, Sanya 33
IBEJU	Ajah Local T1, Eleko, Elemoro, Ibeju, Main One, Oke-Ira, Royal Garden City, Urban Prime
ISLAND	Berkley Express, Ademola 2, Ademola 1, Ajele 1, Ajele 2, Alagbon Local T1, Alagbon Local T2, Anifowoshe 1, Anifowoshe 2, Banana Island 1, Banana Island 2, Custom 1, Custom 2, Federal Secretariat 33, Fowler 1, Fowler 2, Fowler 3, Maroko, New Idumagbo, UBA/UBN, Ademola 3, Anifowoshe 3, 21st Century
LEKKI	Agungi, Chevron 33, Elegushi, Igbo Efon, Ikate Express, Lasan, Lekki, Oniru 33, Twinlake, Water Front, 21st Century
AGBARA	Agbara 33, Agbara Local T4, Agbara Local T5, Agbara Local T6, Badagry 33, Badagry Express, Guinea (Beta) Glass, Oko Afo, Ryder Glass
FESTAC	FESTAC 1 (Amuwo), FESTAC 2, Kirikiri Express, Satellite 1 33, Satellite 2 33, Snake Island, TINCAN,
OJO	FESTAC 1 (Ojo), Ojo Local T1, Ojo Local T2, Ojo Local T3, Volkswagen


In [14]: Scaled_APAPA.head()

Out[14]:

DATE	Consumption
2019-01-01	0.819274
2019-01-02	0.734689
2019-01-03	0.460134
2019-01-04	0.732378
2019-01-05	0.734227

Plate 3: The normalized data

For this work, the test data was taken from 11/03/2021 – 30/11/2021 that represent the post-COVID period.

C. Deep learning models

Deep learning provides a cutting-edge technique that mimics how neurons in the human brain function. Deep learning takes a lot of memory and time to train the model because due to several layers and millions of weights from which it must learned makes it exceptionally accurate. Three models namely: Long-term short-term memory (LSTM), simple recurrent neural network (SimpleRNN), and gated recurrent unit (GRU) subsequently presented were used for the prediction of energy consumption across the case study distribution.

1) Long short-term memory (LSTM)

The LSTM has become a popular and scalable method for solving learning challenges using sequential data. It's a type of recurrent network that has excelled at various task because it can distinguish between recent and old samples by giving each a different weight while forgetting memories that aren't crucial for forecasting future results. It can handle lengthy input sequences better than other RNNs in this regard. The LSTM architecture presented in Figure 2 has three gates namely: the input, forget, and output gates that regulate the information flow between cells inspired by RNNs. The input and forget gate structures has the capability to alter the information moving along the cell state and the final output is a filtered version of the cell state depending on the context of the inputs. The sigmoid activation function was adopted for the recurrent layers while the network was trained for 100 epochs, a batch size of 1 and verbose of 2 is used with an added dense layer.

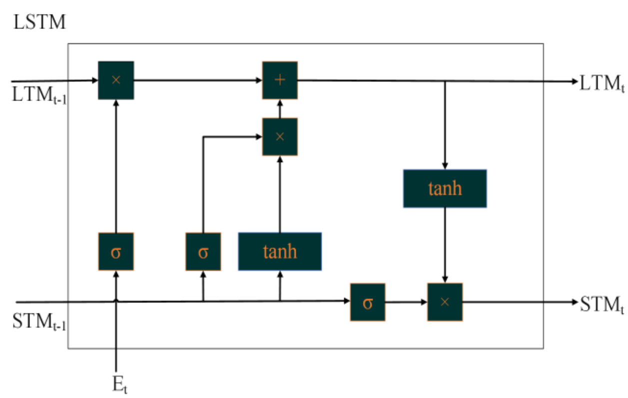


Figure 2: The architecture of LSTM Unit

The adam optimizer and mean squared error was used for optimization and the loss function, respectively. The gates and the cells states can be described by the following equations given the input time-series X_t and the number of hidden units h:

Input Gate: $I_t = \sigma(X_t W_{xi} + H_{t-1} W_{hi} + b_i)$ (2)

Forget Gate: $F_t = \sigma(X_t W_{xf} + H_{t-1} W_{hf} + b_f)$ (3)

Output Gate: $O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o)$ (4)

Intermediate Cell State: $\tilde{C}_t = \tanh(X_t W_{xo} + H_{t-1} W_{ho} + b_c)$ (5)

Cell State (next memory input): $C_t = F_t \circ C_{t-1} \tilde{C}_t$ (6)

New State: $H_t = O_t \circ \tanh(C_t)$ (7)

Here, $W_{hi}, W_{xc}, W_{xf}, W_{xo}, and\ W_{hc}, W_{hf}, W_{ho}$ are the weight parameters while b_i, b_f, b_c, b_o symbolise bias parameters, ° represents the element-wise multiplication. It should be noted that the estimation of C_t depends on the output information's from memory cells (C_{t-1}) and the current time step $\tilde{C}_t$.

2) Simple Recurrent Neural Network (SimpleRNN)

The RNNs fundamentally considers the impact of previous knowledge when generating the output. The architecture of SimpleRNN used in this work is presented in Figure 3. Consider, an RNN is a neural network with a hidden state h and an optional output y which works on a sequence $X = (x_1, \ldots, x_t)$ of variable length, at each time step t, the hidden state $h_{(t)}$ of the RNN is updated by Eqn. (8):

$$h_{(t)} = f\left(h_{(t-1)}, x_t\right) \quad (8)$$

Where f represents a non-linear activation function which is an element-wise logistic sigmoid function and complex as LSTM unit. However, one visible layer with 1 input, a hidden layer with 100 neurons, and an output layer was used to create the Simple RNN model for this work. Consequently, the sigmoid activation function is used for the recurrent layers while the network was trained for 100 epochs, a batch size of 1, and verbose of 2 is used with an added dense layer. The adam optimizer and mean squared error was used for optimization and the loss function, respectively.

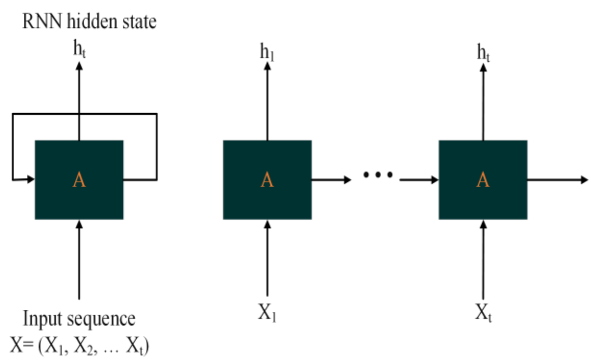


Figure 3: The architecture of SimpleRNN Unit

3) Gated Recurrent Unit (GRU)

GRU is an alternate LSTM with enhanced performance, decreased number parameters, and streamlined design process. As a result, GRU is straightforward to compute and use. GRU has two gates namely; update and reset gates as opposed to LSTM's three as shown in its architecture presented in Figure 4. The input and forget gates of the LSTM model have been integrated into a single gate known as the update gate in GRU. Therefore, the GRU components were modelled using Eqns. (9) to (12):

Update gate: $Z_t = \sigma(X_t W_{xz} + H_{t-1} W_{hz} + b_z)$ (9)

Reset gate: $R_t = \sigma(X_t W_{xr} + H_{t-1} W_{hr} + b_r)$ (10)

Cell State: $\widetilde{H}_t = \tanh\left(X_t W_{xh} + (R_t \circ H_{t-1}) W_{hh} + b_h\right)$ (11)

New state : $H_t = Z_t \circ H_{t-1} + (1 - Z_t) \circ \widetilde{H}_t$ (12)

The recurrent layer had one visible layer with 1 input, a hidden layer with 100 recurrent layer blocks or neurons, and an output layer that makes a single value prediction. The default sigmoid activation function is used for the recurrent layers. The network is trained for 100 epochs, a batch size of 1 and verbose of 2 is used. The adam optimizer was used and the loss function was mean squared error.

The LSTM, SimpleRNN, and GRU models were extracted and stored in a JSON serialized file. The plots of learning rate for the actual consumption, train prediction, and test prediction were obtained for each of the models.

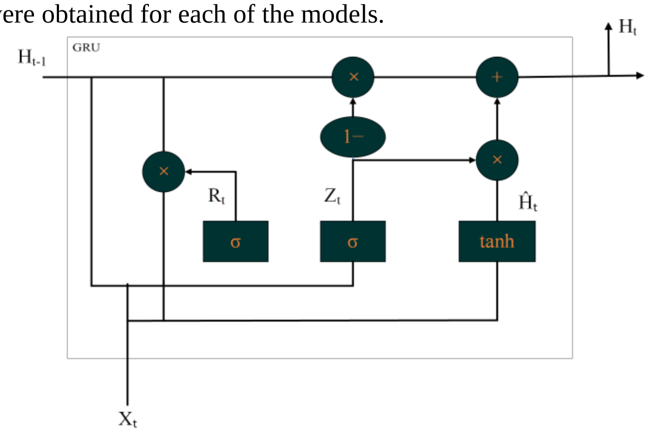


Figure 4: The architecture of GRU Unit

D. Performance Evaluation of the Forecasting Models

It is important to evaluate the performance of the forecasting models to select the best model using specified metrics. In this study, the forecasting models are evaluated using the Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE) presented in Eqns. (13) to (16), respectively:

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(Y_t - \widehat{Y}_t)^2 \quad (13)$$

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \widehat{Y}_t\right| \quad (14)$$

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \widehat{Y}_t}{Y_t}\right| \quad (15)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \widehat{Y}_t\right)} \quad (16)$$

where Y_t and $\widehat{Y}_t$ are the actual and estimated values, respectively, and n represents the number of observations. It should be noted that the lower the values of RMSE, MAE, or MAPE the more accurate forecasting models. The models were finally used to predict the consumption of the feeders for a year ahead and the performance of the models were evaluated using the listed metrics.

III. RESULTS AND DISCUSSION

This section present model's consumption forecasting results and discussion for all the feeders under consideration. The LSTM, GRU, and SimpleRNN predictions for Central, East, and West circles are shown in Figures 5, 6, and 7, respectively. It can be generally observed from the Figures that the trends of both the training and test closely followed the trend of the actual consumption for all the prediction models. This implied that the models were able to predict the energy consumption during the post-COVID era based on the pre-COVID and COVID era energy consumption data. It was observed that there was a drop in the energy consumption of all the circles during the COVID period specifically from April to August, 2020, which might result from inactivity of some of

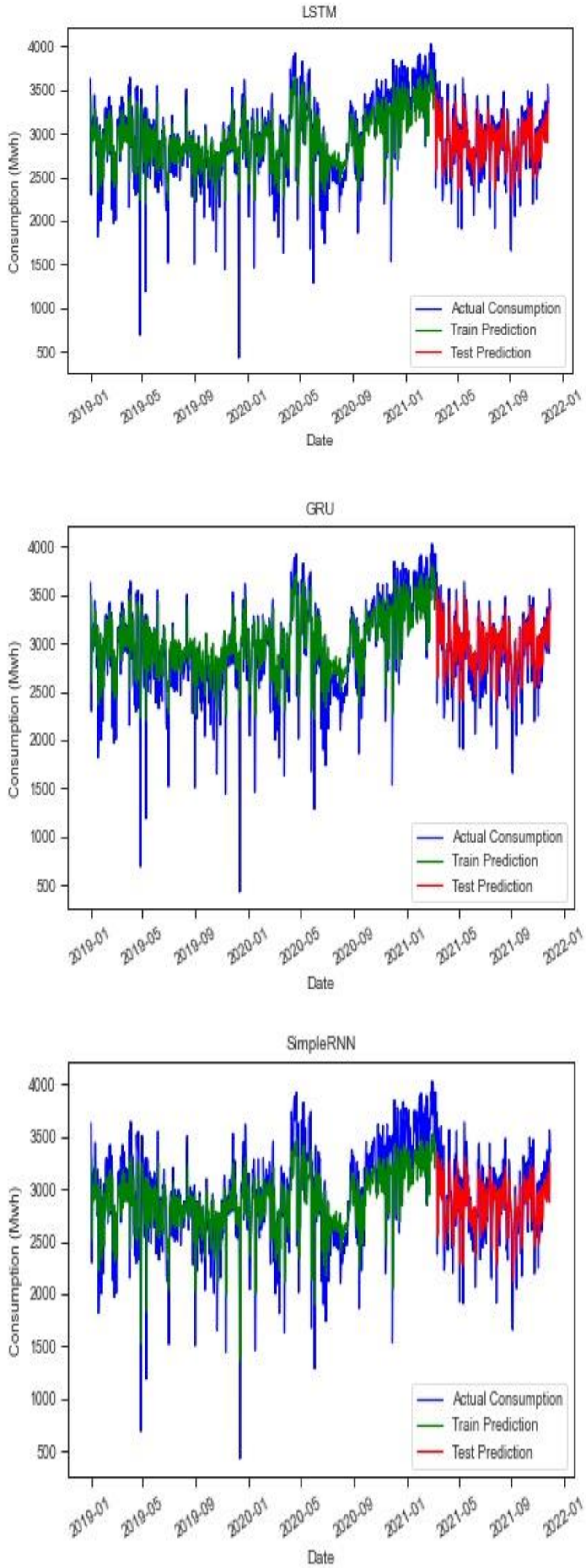


Figure 5: Central Circle prediction for LSTM, GRU, simpleRNN

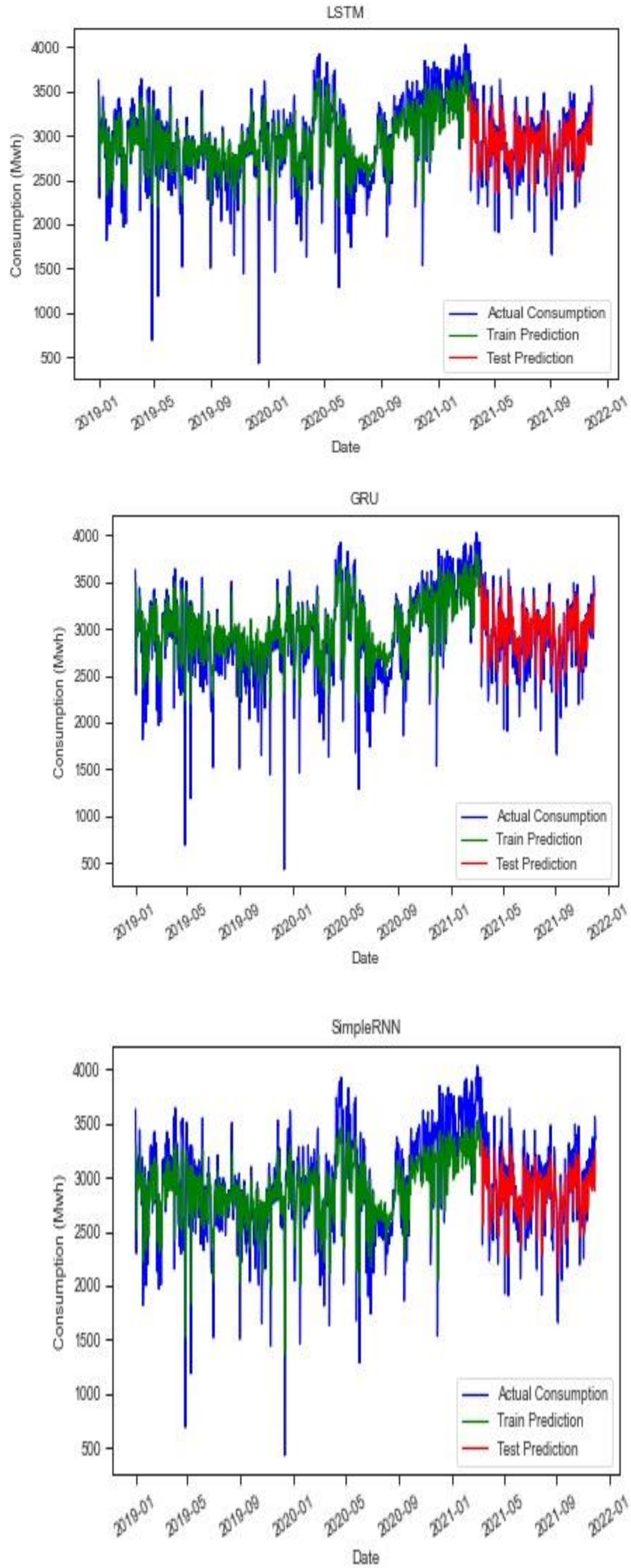


Figure 6: East Circle prediction for LSTM, GRU, SimpleRNN

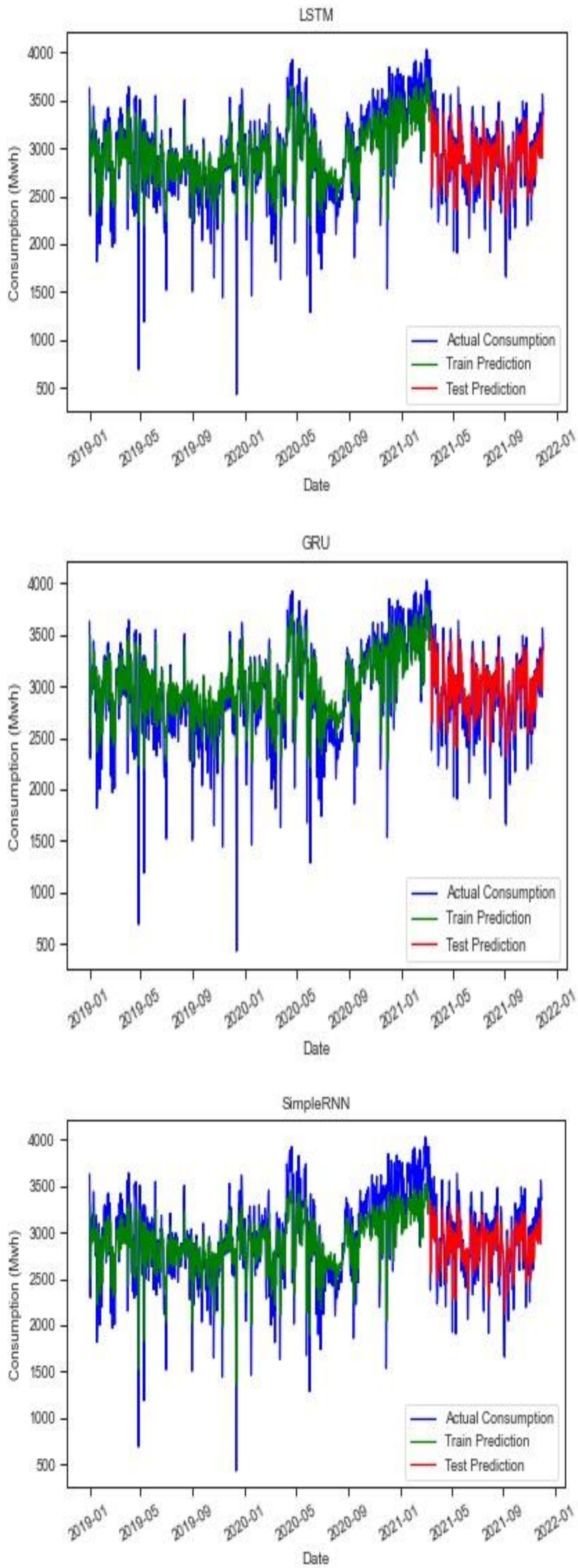


Figure 7: West Circle prediction for LSTM, GRU, SimpleRNN

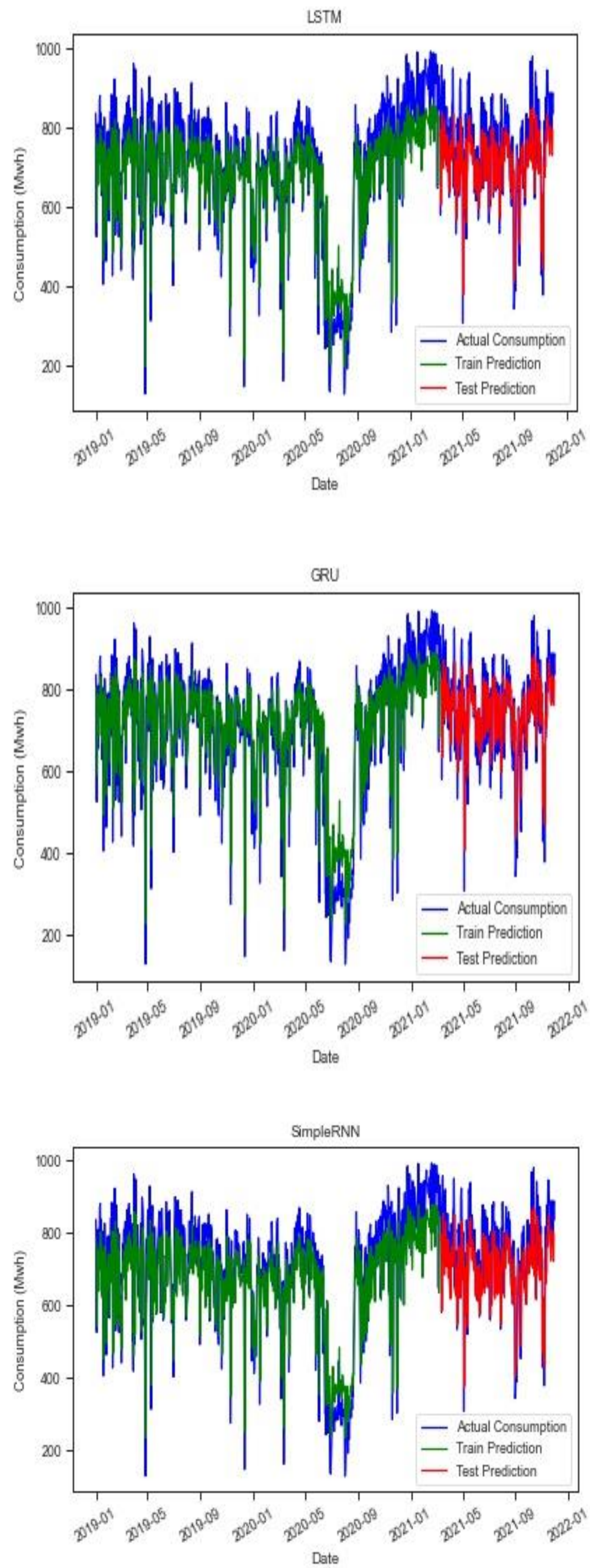


Figure 8: Apapa District prediction for LSTM, GRU, SimpleRNN

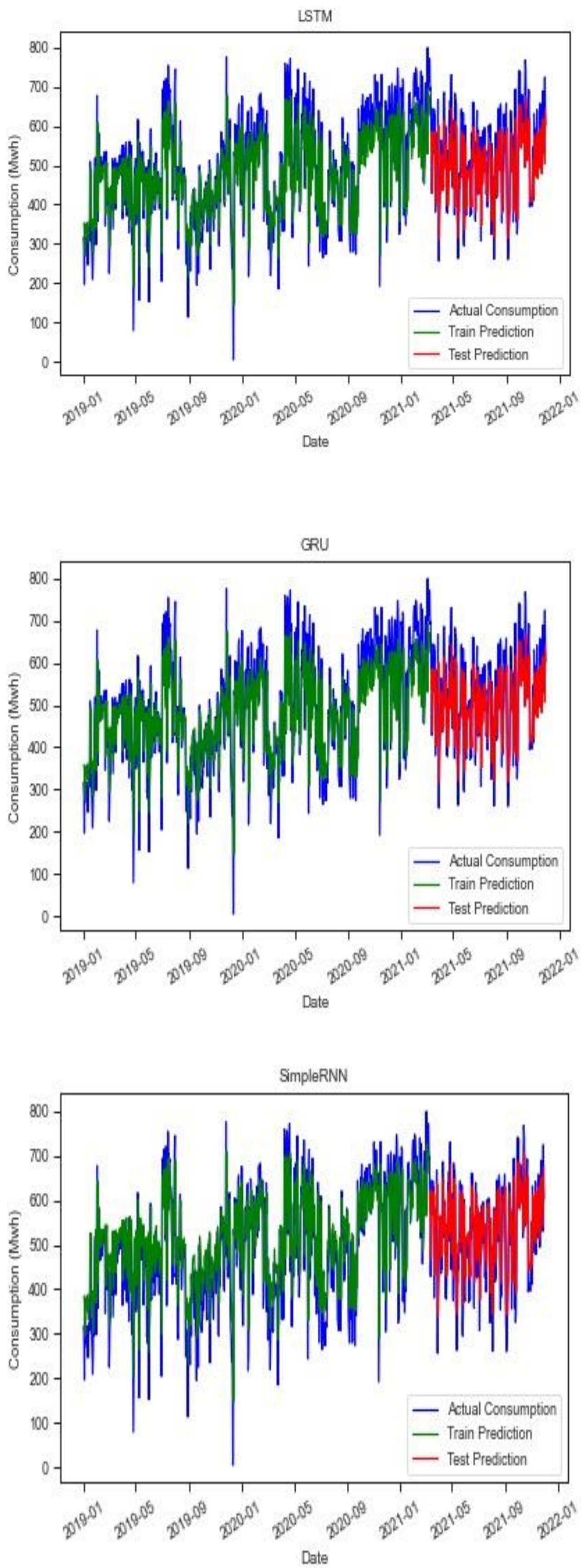


Figure 9: Ijora District prediction for LSTM, GRU, SimpleRNN

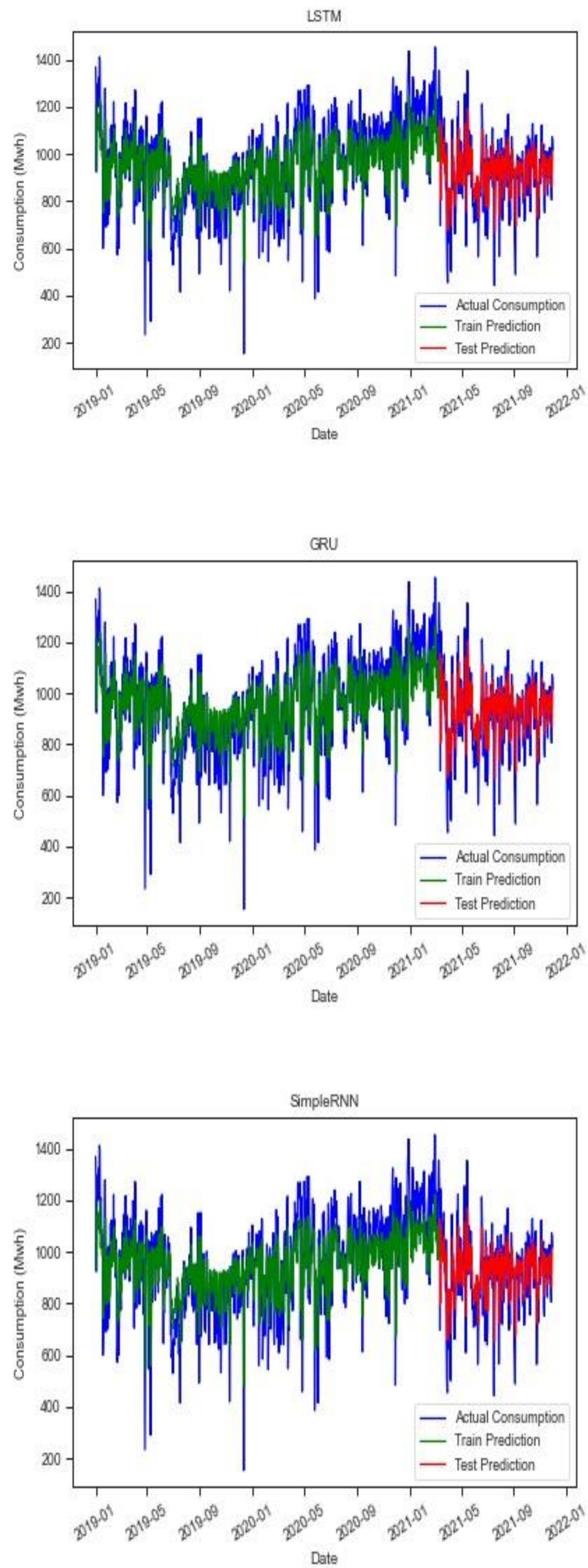


Figure 10: Mushin District prediction for LSTM, GRU, SimpleRNN

the energy-consuming industries due to lockdown which is consistent with the assertion of (Edomah & Ndulue, 2020). Furthermore, the LSTM, GRU, and SimpleRNN predictions for the ten feeders are presented in Figures 8 to 17. Figure 8 shows the energy consumption prediction of the LSTM, GRU, and SimpleRNN models for Apapa feeder. It was observed that there was a sharp drop in the energy consumption of Apapa feeder during the COVID period; May to September, 2020, due to the lockdown of energy-consuming industries in Apapa (Ghiani *et al*., 2020). It can be inferred from the energy consumption prediction of the LSTM, GRU, and SimpleRNN models for Ijora feeder in Figure 9 that there was a slight drop in the energy consumption during the COVID period because is a mixed area of both residences and industries which is consistent with the result of (Alavi *et al*., 2022).

The result for Mushin feeder presented in Figure 10 from which it can be inferred that the energy consumption prediction of the LSTM, GRU, and SimpleRNN models for the feeder depicted a rise in the energy consumption during the COVID period because the feeder supplies residential areas. This result is in accordance with the work of (Soava *et al.*, 2021) which claimed that household global electricity consumption has increased by 40%, resulting from lockdown to stop the spread of COVID-19.

Figure 11 shows the result for Orile feeder, and it is evident from Figure 11 that the energy consumption prediction based on LSTM, GRU, and SimpleRNN models showed an average rise in the dynamics of the energy consumption during the COVID period because Orile is predominantly residential areas. A similar result to that of Figure 10 is obtained in Figure 12 for Ibeju district feeder. Consequently, the rise in the energy consumption during the COVID period can be attributed to the fact that Ibeju is a residential area. This result is also corroborated by the work of (Soava *et al*., 2021). The result presented in Figure 13 for Island district feeder is similar to that presented in Figure 11 that showed an average rise but highly dynamic energy consumption in LSTM, GRU, and SimpleRNN models which is supported by (Alavi *et al*., 2022).

Figure 14 shows the result of energy consumption of Lekki district feeder using LSTM, GRU, and SimpleRNN. This result demonstrates that the energy consumption generally rose during COVID-19 lockdown. This can be attributed the fact that Lekki is strictly residential area, the residents were forced to stay at home during the lockdown (Alavi *et al*., 2022). There was increase in the energy consumption of Agbara district feeder during COVID as shown in Figure 15. The result is a contradiction to the assertion that there was a drop in the energy consumption of the industrial hub during COVID-19 lockdown. The result of FESTAC and Ojo districts feeders presented in Figures 16 and 17 respectively, exhibited the same trends as that of Figure 15. Arising from these results presented so far, it can be summarized that there was an increase in the energy consumption of the following districts: Ijora, Mushin, Orile, Ibeju, Agbara, Ojo, Lekki, Festac, and Island during COVID-19 while in Apapa district a decrease in the energy consumption occurred during COVID-19. Also, it was generally observed that after COVID-19, an increase in energy

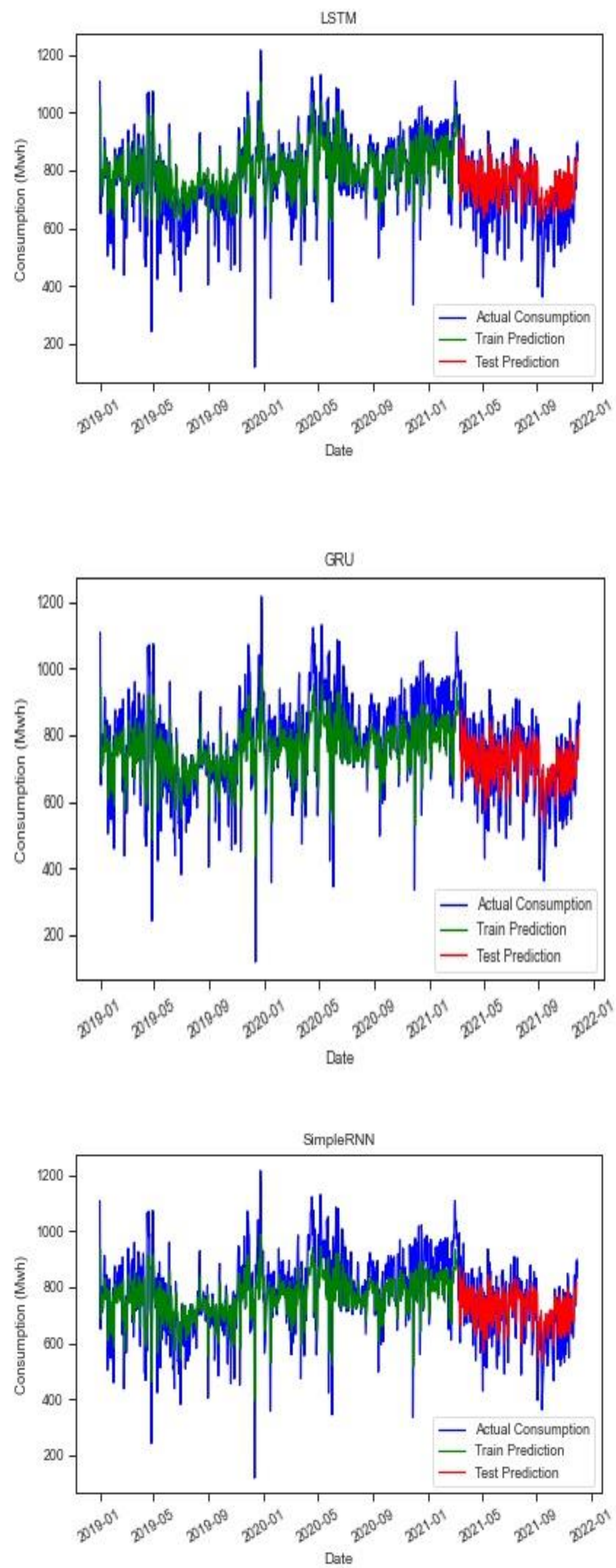


Figure 11: Orile District prediction for LSTM, GRU, SimpleRNN

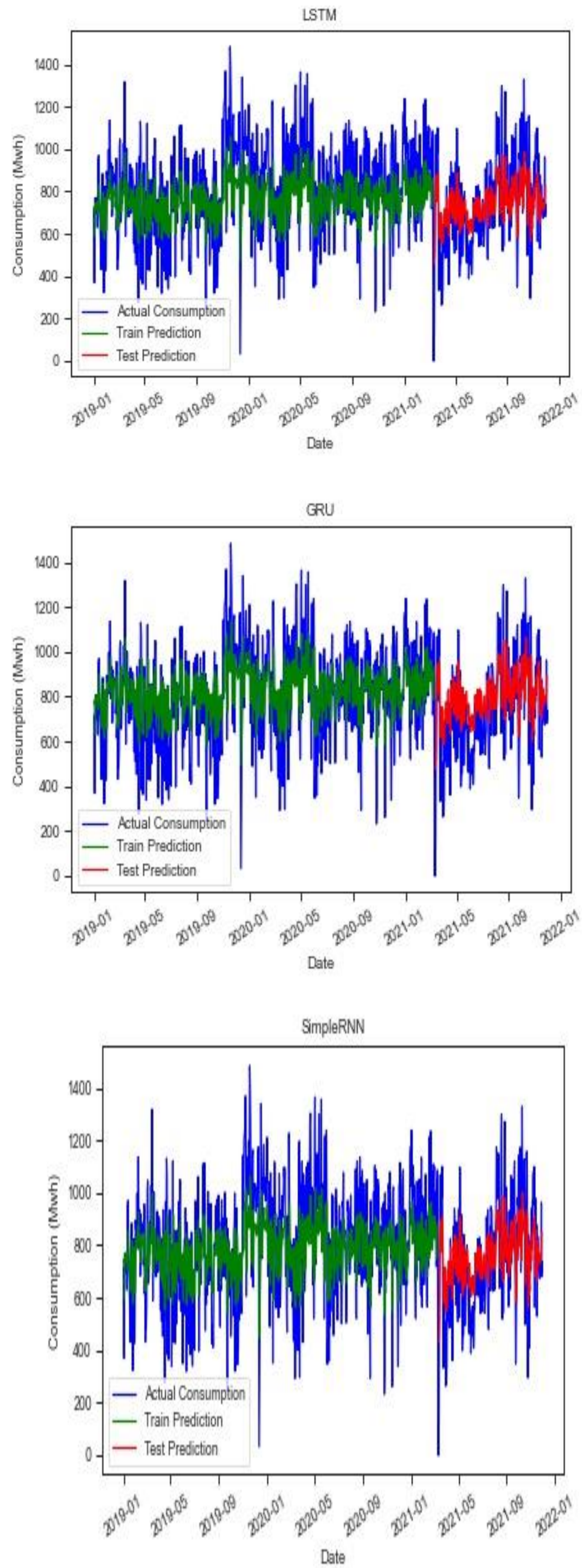


Figure 12: Ibeju District prediction for LSTM, GRU, SimpleRNN

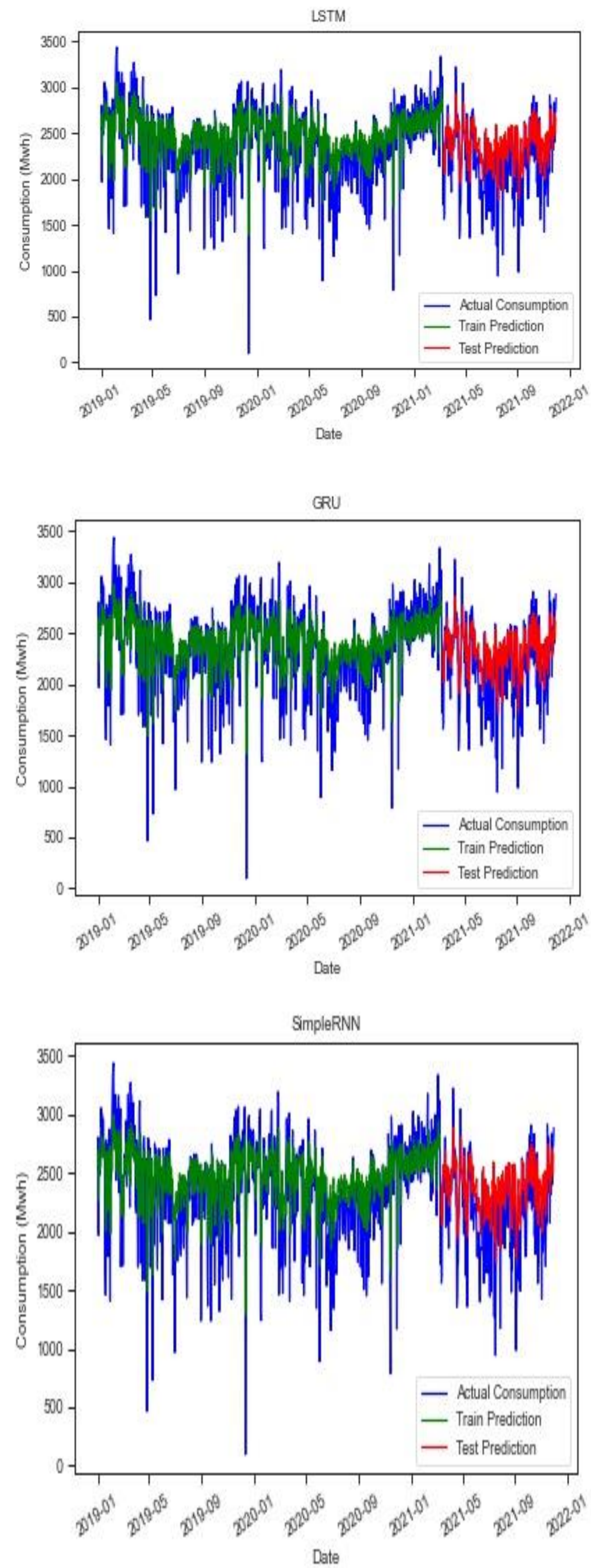


Figure 13: Island District prediction for LSTM, GRU, SimpleRNN

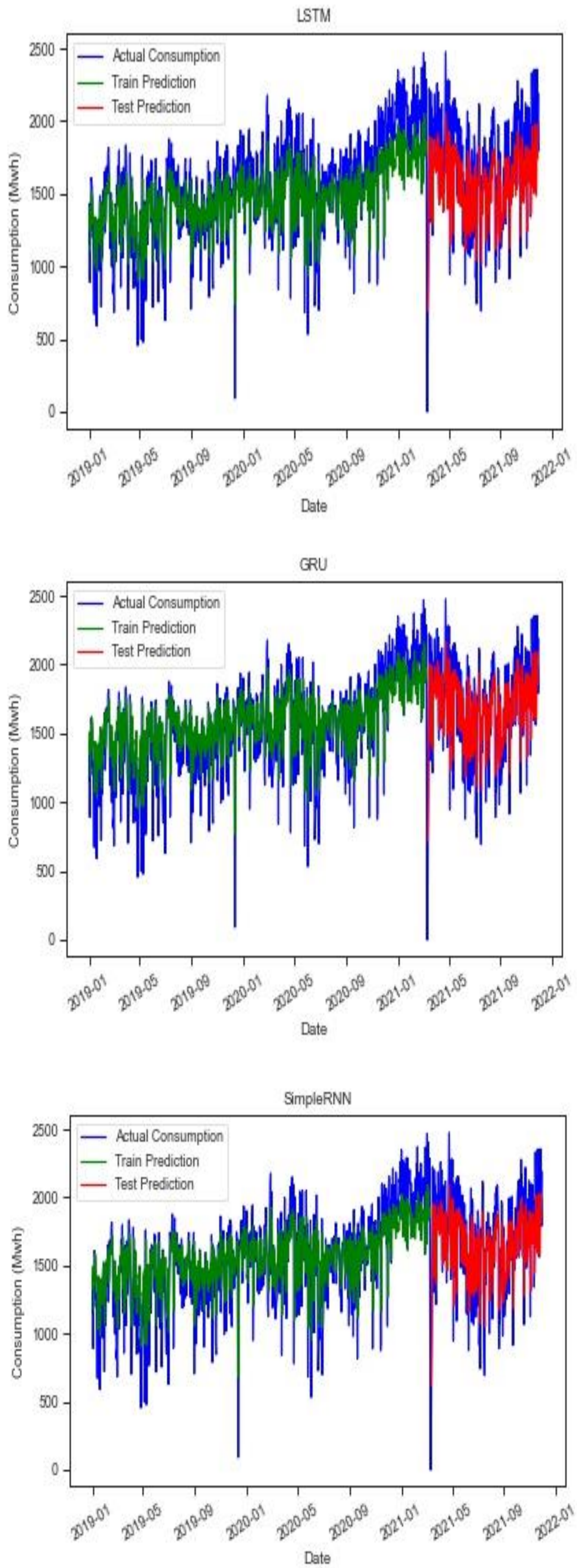


Figure 14: Lekki District prediction for LSTM, GRU, SimpleRNN

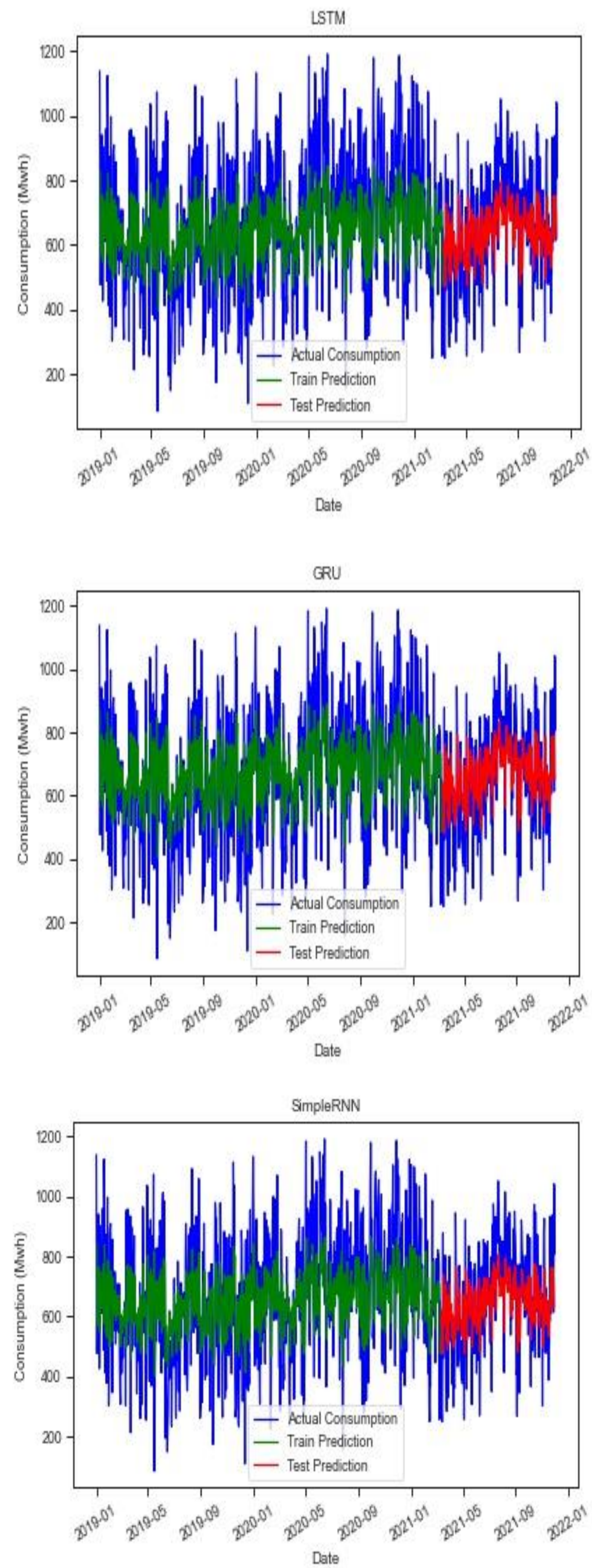


Figure 15: Agbara District prediction for LSTM, GRU, SimpleRNN

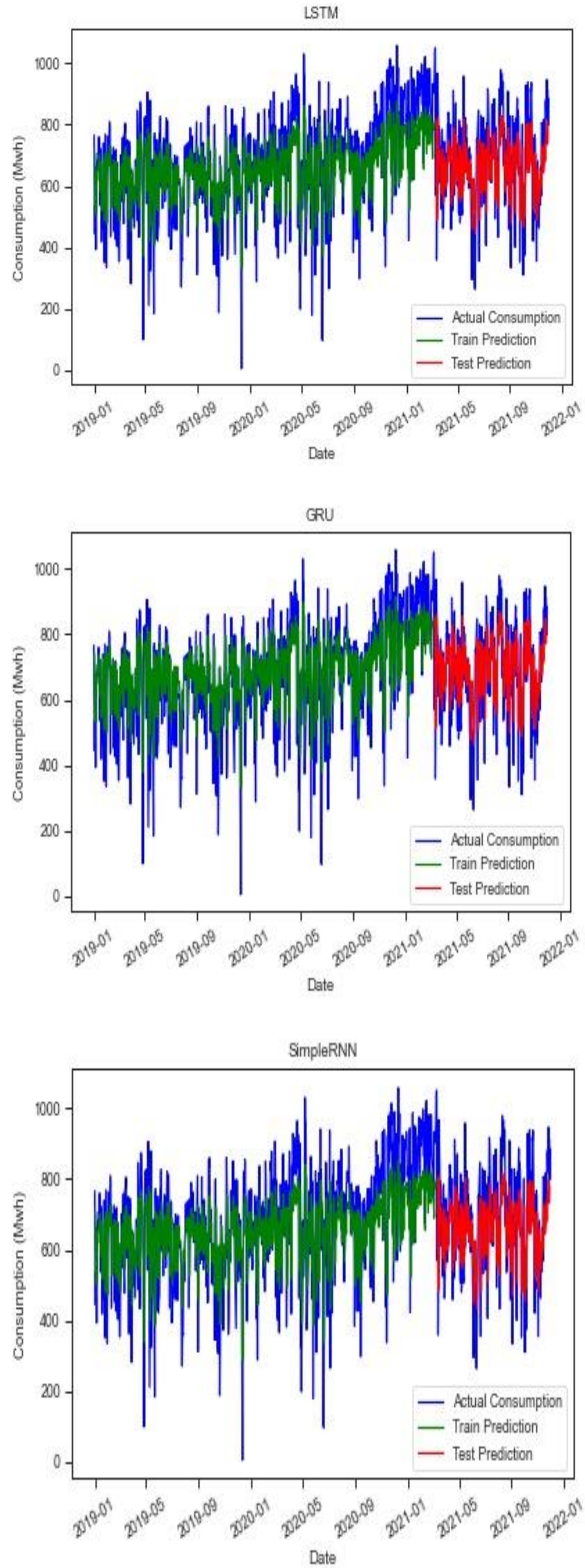


Figure 16: Festac District prediction for LSTM, GRU, SimpleRNN

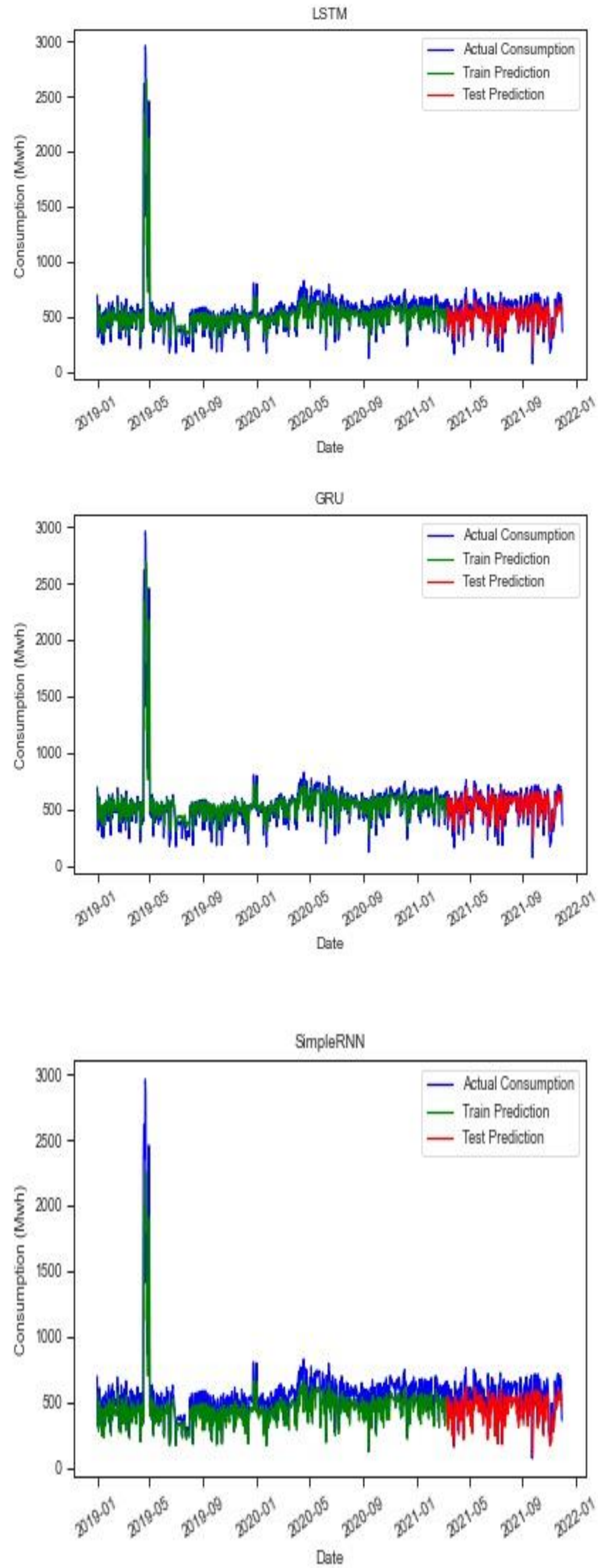


Figure 17: Ojo District prediction for LSTM, GRU, simpleRNN

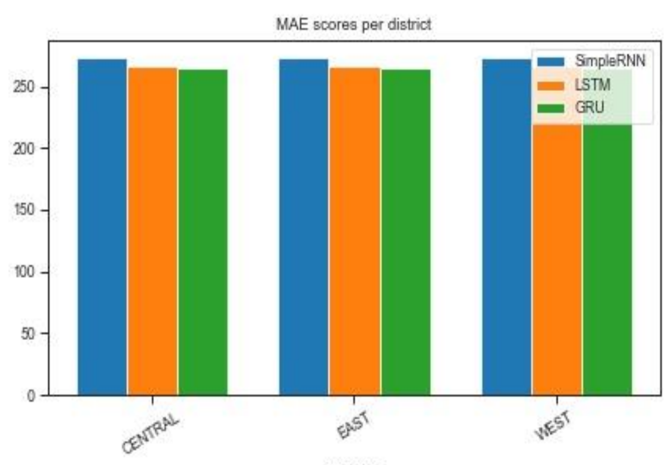
consumption occurred in Apapa, Ijora, Island, Lekki, Festac and a decrease occurred in Mushin, Orile, Ibeju, Agbara, Ojo.

The performance evaluation of the prediction models namely: SimpleRNN, LSTM, and GRU is presented in Table 3. It should be noted that the lower the value of MAPE, MAE, RMSE, and MSE values of a model, the better the model. It can be deduced fromthe table that GRU gave the best prediction result in terms of MAE, RMSE, and MSE of 82.265, 113.468, and 12874.893, respectively for Apapa district. Also, GRU gave the best prediction result in terms of RMSE and MSE of 93.981 and 8832.466, respectively for Ijora district. However, for Mushin district, the GRU model was seen to have the best result arising from the fact that it has the lowest values in terms of MAE and RMSE of 112.580 and 151.252, respectively. The LSTM model performed excellently well compared to SimpleRNN and GRU for Orile district in terms of MAPE, MAE, RMSE, and MSE of 0.120, 79.539, 110.202, and 12144.388 respectively. The Ibeju district has the best prediction from GRU model with a MAE, RMSE, and MSE of 149.605, 189.910, and 36065.918 respectively. The GRU model demonstrated an excellent performance for Island district in terms of MAPE, MAE, RMSE, and MSE of 0.164, 274.052, 378.234, and 143060.188 respectively. The SimpleRNN model exhibited the preferred result for Lekki district in terms of RMSE and MSE of 286.408 and 82029.320 respectively, while for Agbara district, the GRU model outperformed LSTM and SimpleRNN with a MAE, RMSE, and MSE of 156.880, 193.497, and 37441.194 respectively. Finally, it can be seen from the table that Festac and Ojo districts are characterized by the same metrics namely: MAE, RMSE, and MSE for GRU model with 104.179, 138.883, and 19288.491 respectively, for Festac district and 91.812, 153.519, and 23568.073, respectively for Ojo districts. Generally, the GRU model gave the best result for most districts except for Orile district where LSTM showed better performance and Lekki district where SimpleRNN gave a preferred result. Hence, Figures 18 and 19 illustrates the MAPE, MAE, RMSE, and MSE for the East, West, and Central circles. It is obvious from Figures 18 and 19 that the GRU model generally performed better in terms of MAPE, MAE, RMSE, and MSE for all the circles.

Table 3: Performance evaluation of SimpleRNN, LSTM, and GRU for all the feeders

District	Model	MAPE	MAE	RMSE	MSE
APAPA	SRNN	0.157	89.108	116.927	13671.893
	LSTM	0.154	86.151	114.878	13196.921
	GRU	0.158	82.265	113.468	12874.893
IJORA	SRNN	0.254	71.073	95.310	9084.027
	LSTM	0.235	71.424	94.319	8896.122
	GRU	0.237	71.242	93.981	8832.466
MUSHIN	SRNN	0.139	114.321	151.996	23102.707
	LSTM	0.138	113.342	151.302	22892.416
	GRU	0.139	112.580	151.252	22877.019
ORILE	SRNN	0.123	86.616	113.987	12993.032
	LSTM	0.120	79.539	110.202	12144.388
	GRU	0.123	87.472	114.471	13103.691
IBEJU	SRNN	0.245	153.339	191.249	36576.339
	LSTM	0.244	157.340	194.731	37920.128
	GRU	0.253	149.605	189.910	36065.918
ISLAND	SRNN	0.169	278.975	388.520	150947.830
	LSTM	0.169	278.825	389.163	151447.621
	GRU	0.164	274.052	378.234	143060.881
LEKKI	SRNN	0.182	214.091	286.408	82029.320
	LSTM	0.181	226.617	290.914	84630.959
	GRU	0.185	213.451	288.326	83131.962
AGBARA	SRNN	0.291	157.622	194.395	37789.351
	LSTM	0.289	158.221	195.193	38100.278
	GRU	0.299	156.88	193.497	37441.194
FESTAC	SRNN	0.310	110.019	139.857	19560.050
	LSTM	0.313	108.919	139.135	19358.453
	GRU	0.320	104.179	138.883	19288.491
OJO	SRNN	0.233	121.904	178.005	31685.781
	LSTM	0.192	95.332	155.107	24058.051
	GRU	0.196	91.812	153.519	23568.073

The result of future energy consumption predicted by LSTM, SRNN, and GRU for the east, west, and central circles are presented in Figure 20 which shows a decrease in the future energy consumption for all the models except for SRNN which predicted a rise in the future energy consumption in the west circle. The future energy consumption predicted by LSTM, SimpleRNN, and GRU for all the feeders are presented in Figures in 21-25. It is observed that the future energy consumption for all the models decreased except for Agbara feeder in which a rise in the future energy consumption was predicted by the all the models. The predicted values became constant after some time because the model assumed perfect electricity consumption. This is due to the inability of the models to capture unexpected events like simple electrical faults that may occur.



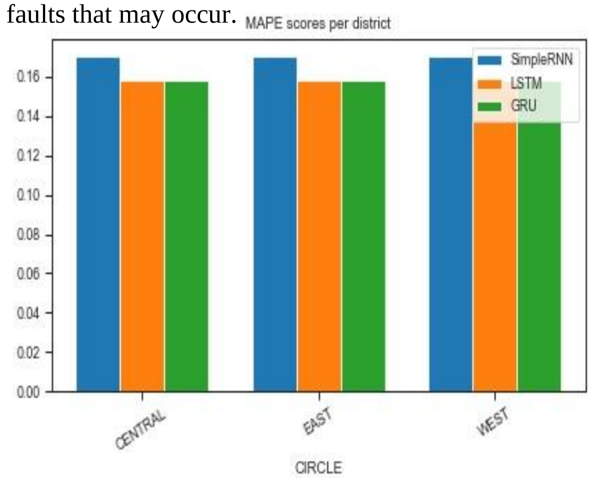


Figure 18: MAPE & MAE scores per circle

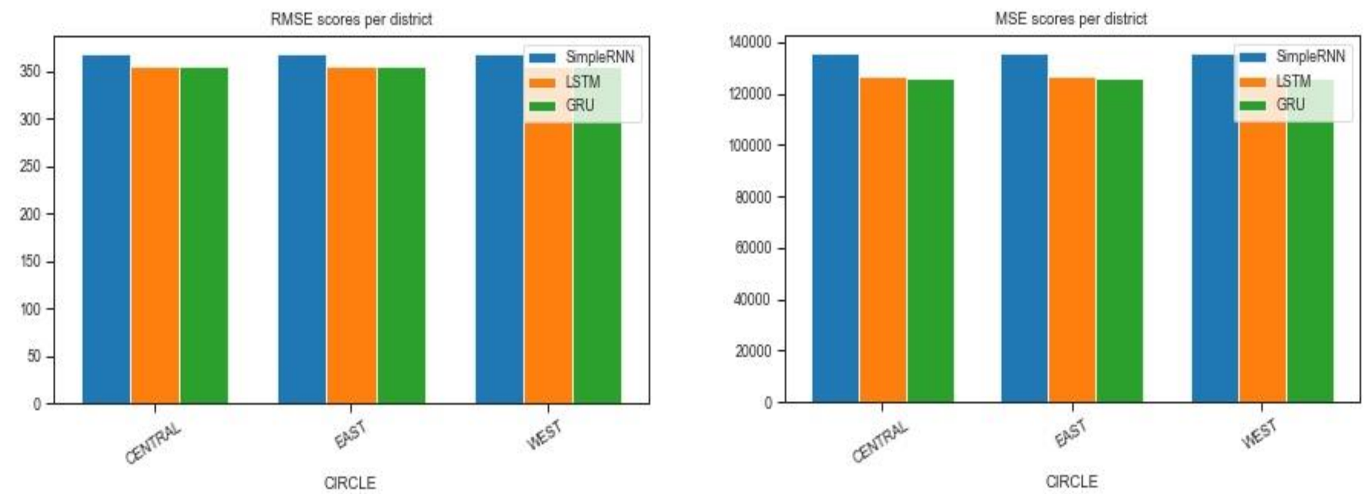


Figure 19. RMSE & MSE scores per circle

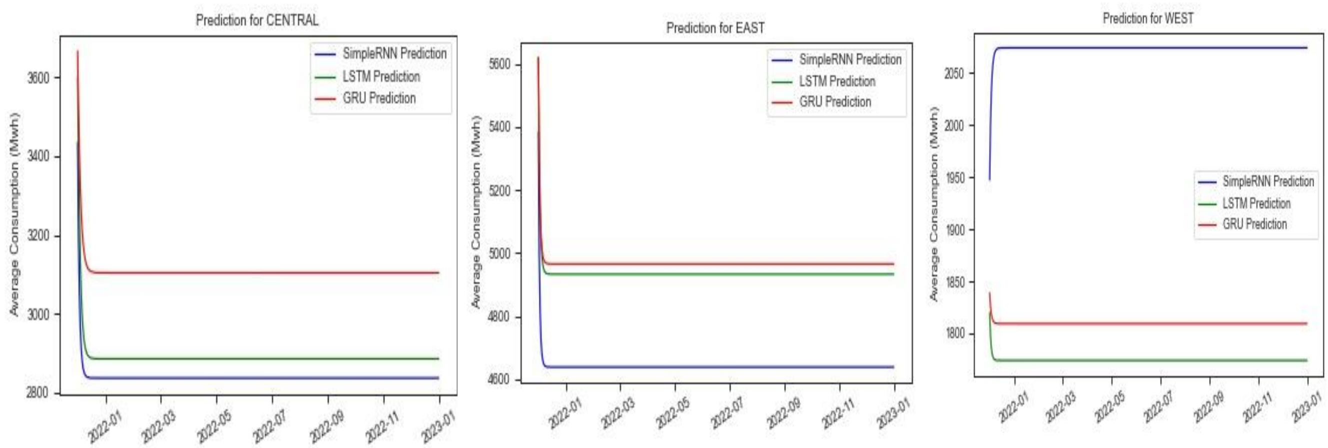


Figure 20: Consumption prediction in CENTRAL, EAST & WEST for 2022

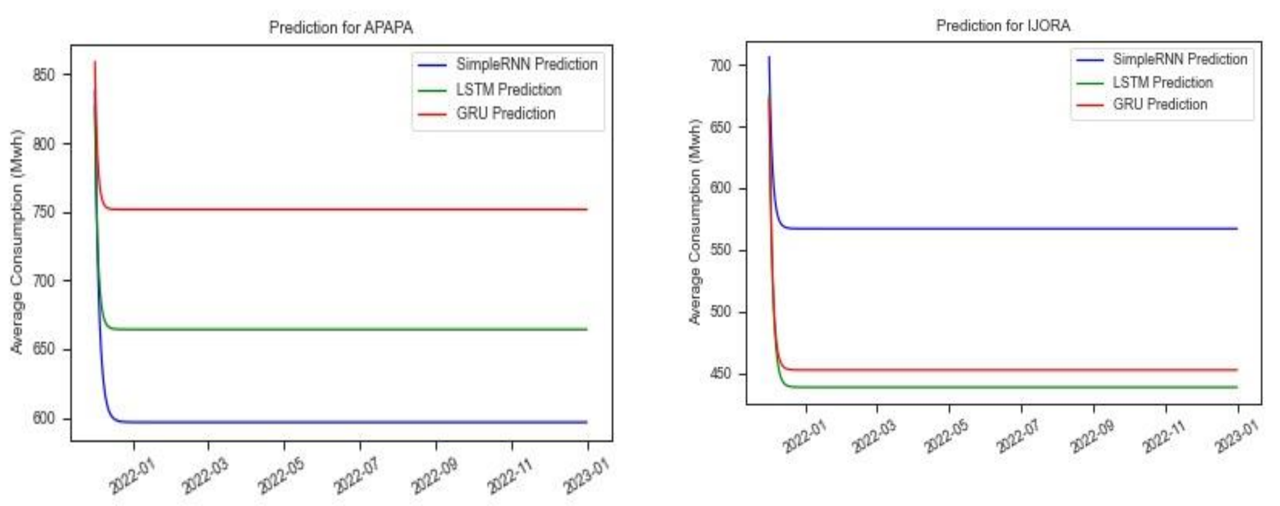


Figure 21: Consumption prediction in APAPA & IJORA for 2022

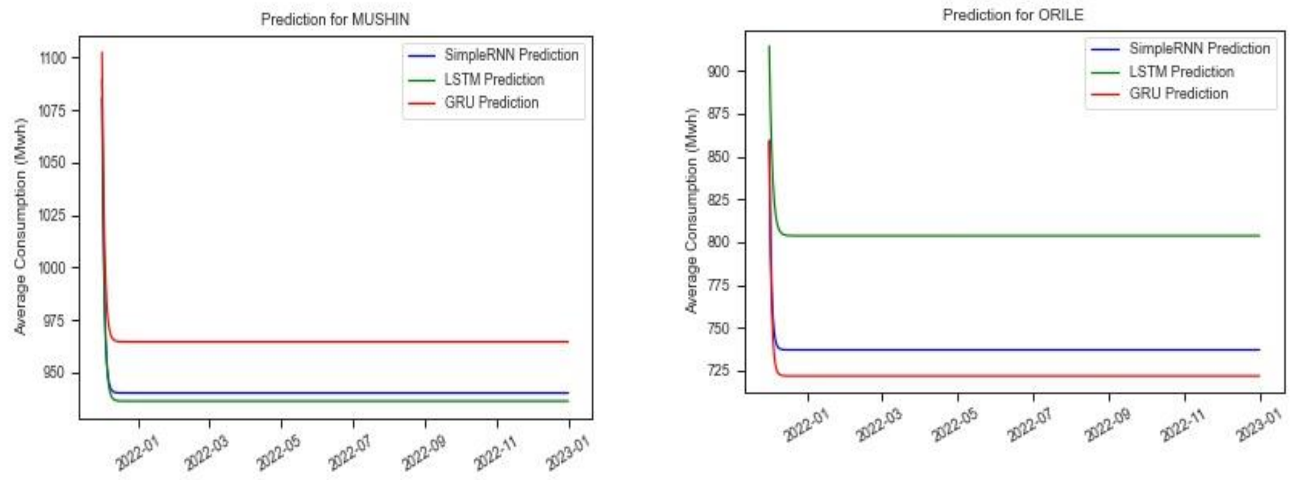


Figure 22: Consumption prediction in MUSHIN & ORILE for 2022

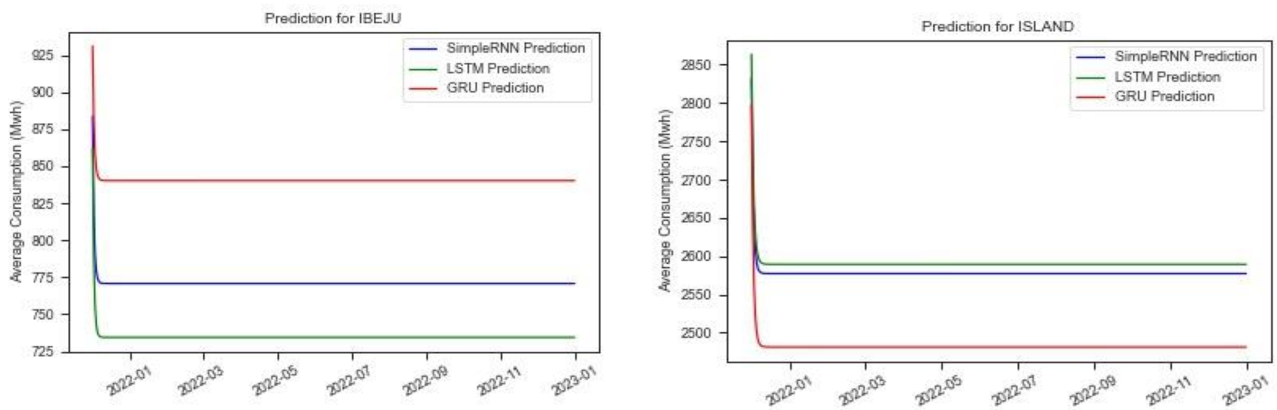


Figure 23: consumption prediction in IBEJU & ISLAND for 2022

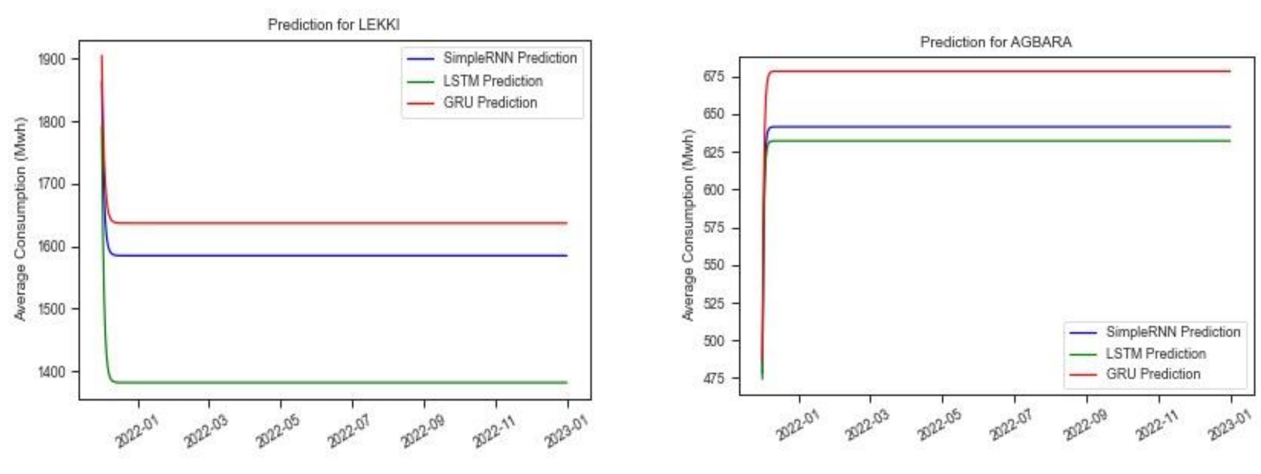
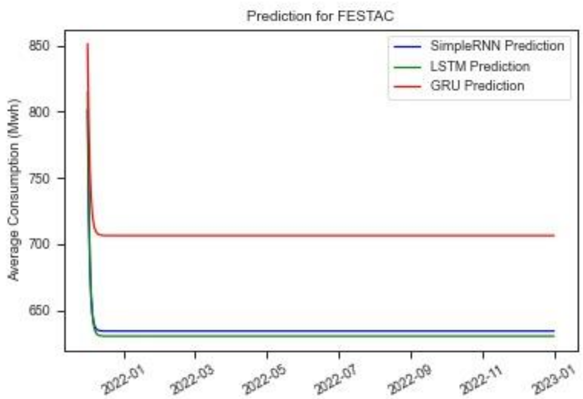


Figure 24: Consumption prediction in LEKKI & AGBARA for 2022



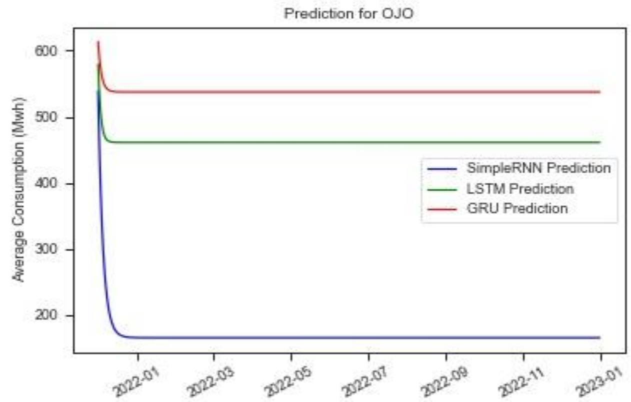


Figure 25: Consumption prediction in FESTAC & OJO for 2022

IV. CONCLUSION

Energy consumption in a distribution network was the focus of this study. An attempt was made to assess the impact of COVID-19 outbreak on the energy consumption within the case study using LSTM, SimpleRNN, and GRU for energy consumption prediction. The case study has three (3) circles namely: east, west, and central with ten (10) feeders namely: Apapa, Ijora, Mushin, Orile, Ibeju, Island, Lekki, Agbara, Festac, and Ojo from which daily energy consumption data were obtained. The results of the models based on the MAPE, MAE, RMSE, and MSE demonstrated that GRU is optimal for energy consumption prediction in the case study when compared to the LSTM and SimpleRNN. The results of the analysis showed that there was a drop in the energy consumption in the industrial areas within the case study while the residential areas in the case study witnessed a rise in energy consumption during COVID-19 outbreak due to lockdown. Consequently, it can be concluded that GRU model is optimal for energy consumption prediction in the case study. This work serves as a reference model for the case study network operator, government, and other stakeholders in future energy planning towards building a resilient energy system.

AUTHOR CONTRIBUTIONS

A. O. Amole: Conceptualization, Methodology, **S. Oladipo:** Writing – original draft. **D. Ighravwe:** Supervision, Writing – review & editing, **K. A. Makinde:** Writing – review & editing, **J. Ajibola:** Software, Validation

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