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Injection Substation Feeder Load Modelling Using Recurrent Neural Network With Enhanced Model Parameters Modification Technique

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***Abstract*— In this work, injection substation feeder load modelling using recurrent neural network with enhanced model parameters modification technique. The evaluation of loss function for the RNN model is done using enhanced model parameters modification technique. The detail mathematical expressions associated with the RNN model, the gradient drop optimization the enhanced model parameters modification technique and accommodative learning rate of the RNN model are presented. A four months hourly feeder load profile dataset from a substation in Akwa Ibom State Nigeria is employed as case study dataset for the RNN model training and validation. Performance metric used is root mean square error and a Python program is developed and used for the simulation. The loud profile training data stet was segmented into batches of 24. This means that the model needs 24 data points to predict the 25^{th} data point. Essentially, hourly data for one day is used to predict the beginning data point for the following day. Consequently, the number of hours to be predicted into the future was set to1. The prediction outputs for the case study Secretariat feeder load profile results shows that the mean square error value obtained from the model predictions is 1.21. With is MSE value, it is evident that the RNN approach is good in the modelling of the case study Secretariat feeder load profile. Hence, the RNN model was used to forecast the case study Secretariat feeder load profile for one month period.**

Keywords— Injection Substation, Machine Learning Algorithms, Feeder Load Modelling, Power Distribution System, Recurrent Neural Network

1. Introduction

Across the globe, effective and adequate power supply has been identified as essential for sustainable development of any nation [1,2,3]. As such, developed nations are known to have invested heavily in their national power system which includes such subsystems as power generation, power transmission and power distribution system [4,5,6]. Each of these subsystems in the power industry requires careful planning to achieve effective service delivery.

Accordingly, the focus in this work is to provide technological tool that can assist in power distribution system management by providing machine learning-based model that can be used to characterize the injection substation feeder load and also provide load forecasting for each of the feeder [7,8,9]. This tool is essential as it will provide the requisite insight into the feeder load variation pattern and enable accurate estimation of the load demand, the time series variations in the load demand and the possible variation of the load profile in the feature. These information are essential for appropriate sizing of the distribution system components to avoid over sizing which can cause equipment damage due to over loading. On the other hand oversizing of equipment may occur if the accurate load estimation information is not available. This again will lead to waste of funds through oversized transformers and other key distribution system equipment.

Specifically, in this work, Recurrent Neural Network (RNN) with enhanced model parameters modification technique is considered for the feeder load modelling [10,11,12]. Although there has been different machine learning models, as well as time series models and other models used in the distribution system load prediction and forecasting, however, this work is focused on using the RNN with enhanced model parameters modification technique which give more accurate load prediction and forecasting for the case study feeder loads. The RNN model and details of the mathematical expressions associated with the enhanced model parameters modification technique are presented. Finally, simulation with the case study feeder dataset is conducted and the results are presented and discussed.

2. Methodology

In this work, the focus is on substation feeder load modelling based on recurrent neural network (RNN) approach. The evaluation of loss function for the RNN model is done using enhanced model parameters modification technique. The detail mathematical expressions associated with the model and the enhanced model parameters modification technique are presented in this section.

2.1 Substation feeder load modelling based on recurrent neural network (RNN) approach

The recurrent neural network (RNN) model expresses new machine states by making use of certain transfer function based on the input vectors and previous states [13,14,15]. This work leverages on the universal approximation behavior of RNN to approximate the considered nonlinear system based on certain precision factors and to obtain some complex routing from input series to output series. For prediction purpose, the RNN model learns from time-related data input denoted as $x(t)$ to yield a corresponding output $y(t)$ being the predicted value. In some cases, the combination of $x(t)$ and $x(t-n)$ is made to obtain $y(t)$, where n is a time shift quantity. The model must be composed such that the loss function is minimized. The error $e(t)$ in this case is the difference between the expected output $\hat{y}(t)$ and the actual output $y(t)$, and can be represented mathematically as:

$$e(t) = \hat{y}(t) - y(t) \qquad (1)$$

Due to the retentive nature of RNN, they can recreate time based signatures which resembles those they have learned. The RNN model is presented in Figure 1.

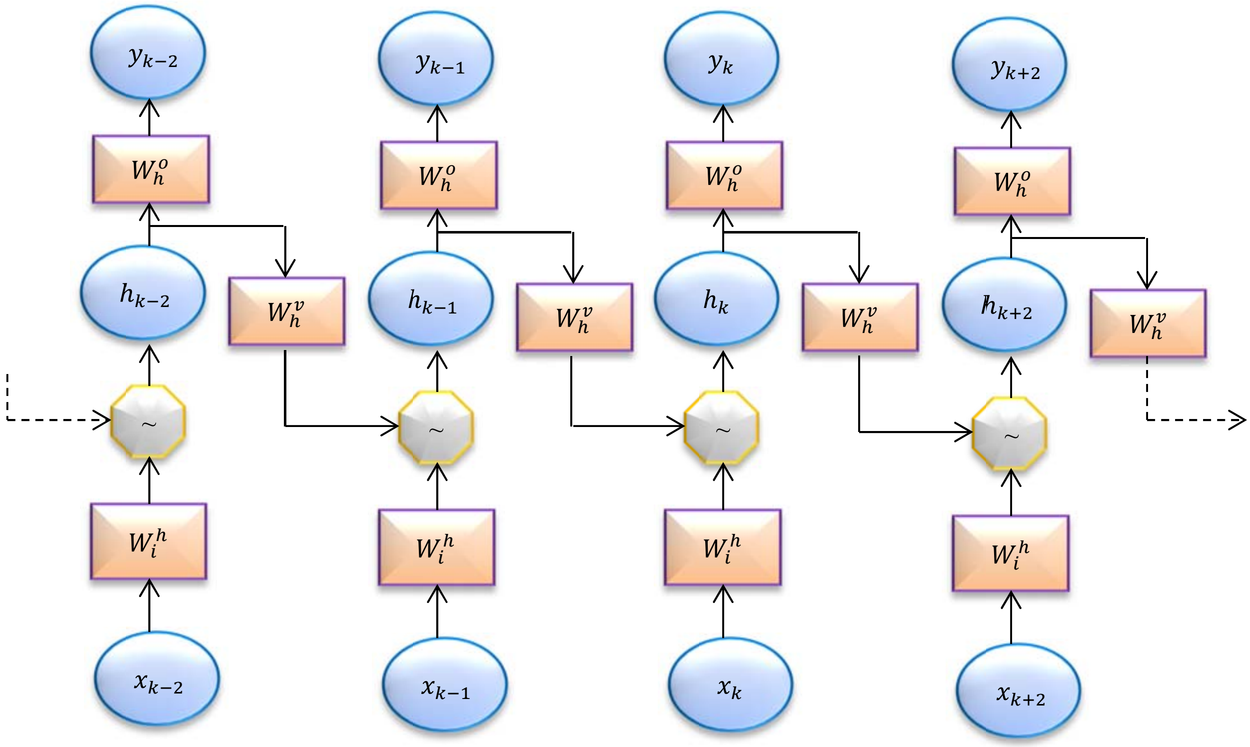

Figure 1: The schematic diagram of the recurrent neural network (RNN) model.

The model is designed such that three nodes are formed which are the input nodes x_k, the virtual node h_k and the output node y_k. These nodes are weighted and organized in recursive pattern. The virtual nodes are designed to have both input and output links.

In Figure 1, x_k and y_k represents input and output respectively. Each of these variables relates to various times. W_h^o denotes the weight matrix for the output, W_i^h denotes the weight matrix for the input, and W_h^v denotes the virtual weight matrix.

2.2 Gradient Drop Optimization

The loss function characterizes the performance precision of the neural network; as such the model parameters must be modified during the neural network training to optimize the gradient drop. This optimization involves two iterative processes which include the loss function L_k evaluation when certain input x_k with distributed weight W_k is parsed, and back propagation of the gradient $\frac{\partial L_k}{\partial W_k}$ on the network to modify the model parameters. Mathematically, the loss function is given as:

$$L_k = \mathfrak{I}_e(x_k, \tilde{y}_k, W_k) + \mathbb{R}_\hbar(W_k) \qquad (2)$$

Where, $\mathfrak{I}_e$ denotes the function which operates on the network estimated error, x_k denotes the input, and $\tilde{y}_k$ denotes the predicted output, $\mathbb{R}_\hbar$ denotes an hyper-parameter $\hbar$ dependent regularization function. The role of $\mathbb{R}_\hbar$ in the loss function presented in Equation 3 is to measure the benefaction of the regularization in the integrated deprivation. In this work, the mean square error, denoted as MSE is used to compute the error. Considering the input x_k, the actual output y_k, and the predicted output $\tilde{y}_k$, MSE can be computed as:

$$MSE(y_k, \tilde{y}_k) = \frac{1}{|x_k|}\sum_{x \in x_k}(y_x - \tilde{y}_x)^2 \qquad (3)$$

Where, $y_x \in y_k$ denotes the result yielded by the recurrent neural network.

The regularization object $\mathbb{R}_\hbar$ injects some bias to enhance the performance of RNN. The bias minimized excess fitting on the trained dataset. This work adopts the dropout regularization approach. This approach ensures that the neurons are properly engaged during data training using some probabilistic distribution measures. At the virtual stage, arbitrarily formulated gauze is located on the neuron outputs while the hyper parameter computes the probability of the gauze still at that stage. At the end of data training, the activation function is shifted by the probabilistic output such that the target output is sustained.

2.3 Model Parameters Modification Technique

Other methods fancy the evaluation of loss function on the whole dataset and modifying the model parameters once, based on the evaluation results. However, this work applies such modifications on small chunks of the input. The modification function is given as:

$$W_{k+1} = W_k + \eta \nabla L_k(W_k) \quad (4)$$

Where, η denotes the learning rate which must be optimally selected to achieve reasonable training on the dataset. A step decay approach can slow down the learning rate by α if the learning rate fails to be minimized after some time. The exponential decay can be computed as:

$$\eta = \eta_0 e^{-\alpha k} \quad (5)$$

Where, α denotes hyper-parameter and k is the present optimization time. The distributed weight W_k is modified based on the blend of the gradient $\nabla L_k(W_k)$ at the present instance and earlier modifications V_{k-1} which can be shifted by hyper-parameter μ.

$$V_k = \mu V_{k-1} - \eta \nabla L_k(W_k) \quad (6)$$

$$W_{k+1} = W_k + V_k \quad (7)$$

Equation 6 and Equation 7 ensure that the modification steadily increment the velocity to achieve a stable gradient.

2.4 Accommodative Learning Rate

The learning method of the model must be selected to accommodate various conditions. The learning rate is selected in this work to vary for each model parameter. If the modified data is provided from past iterations as $\nabla L_k(W_j)$, where $j \in (0,1,2,\dots,k)$, then a different modification must be selected for all parameters i contained in W.

$$W_{k+1}^{(i)} = W_k^{(i)} - \eta \frac{\nabla L_k\left(W_k^{(i)}\right)}{\sqrt{\sum_{j=0}^{k} \nabla L_k\left(W_j^{(i)}\right)^2 + \epsilon}} \quad (8)$$

Where, ϵ denotes a minute positive integer applied to prevent dividing the numerator by zero. An exponential dying average of the gradient can prevent the drastic decrease in learning rate. This can be expressed as:

$$v_k^{(i)} = \begin{cases} (1-\delta)\cdot v_{k-1}^{(i)} + \delta \nabla L_k\left(W_k^{(i)}\right)^2, & if\ \nabla L_k\left(W_k^{(i)}\right) > 0 \\ (1-\delta)\cdot v_{k-1}^{(i)}, & otherwise \end{cases} \quad (9)$$

Then,

$$W_{k+1}^{(i)} = W_k^{(i)} - \eta v_k^{(i)} \quad (10)$$

Following the modification concept, if there exist some swings in the gradient modification, then the learning rate will be damped by $(1-\delta)$, but in other cases, it appreciates by δ. Typically, the rate of decay is initialized as 0.01

3. Results and Discussion

3.1 The model simulation

The case study substation is located in Uyo, Akwa Ibom State Nigeria. The case substation has some other feeders however, the study is based on the historical load profile of one specific feeder identified as the Secretariat feeder. Specifically, hourly feeder load data from the case study feeder were obtained from May 2022 to August 2022. The data set has 2802 row count. A python simulation program was written using Pycharm for the simulation of the model. The model performance parameter used is Mean Squared Error (MSE).

Furthermore, one of the objectives of this research is to transform the given data using the standard scaler in order to minimize error. A cross-section of the raw dataset for Secretariat feeder is presented in Figure 2 and a cross section of the scaled dataset for Secretariat feeder is presented in Figure 3.

	SEC	FDR_SEC
TIME		
2022-05-01 01:00:00	3.5	2.4
2022-05-01 02:00:00	3.5	2.4
2022-05-01 03:00:00	3.5	2.4
2022-05-01 04:00:00	4.2	2.4
2022-05-01 05:00:00	4.2	2.4
...	...	...
2022-08-25 20:00:00	20.0	0.3
2022-08-25 21:00:00	20.0	0.3
2022-08-25 22:00:00	20.0	0.3
2022-08-25 23:00:00	12.0	0.2
2022-08-26 00:00:00	12.0	0.2

2808 rows × 2 columns

Figure 2: A section of the un-scaled (raw0 Secretariat feeder dataset

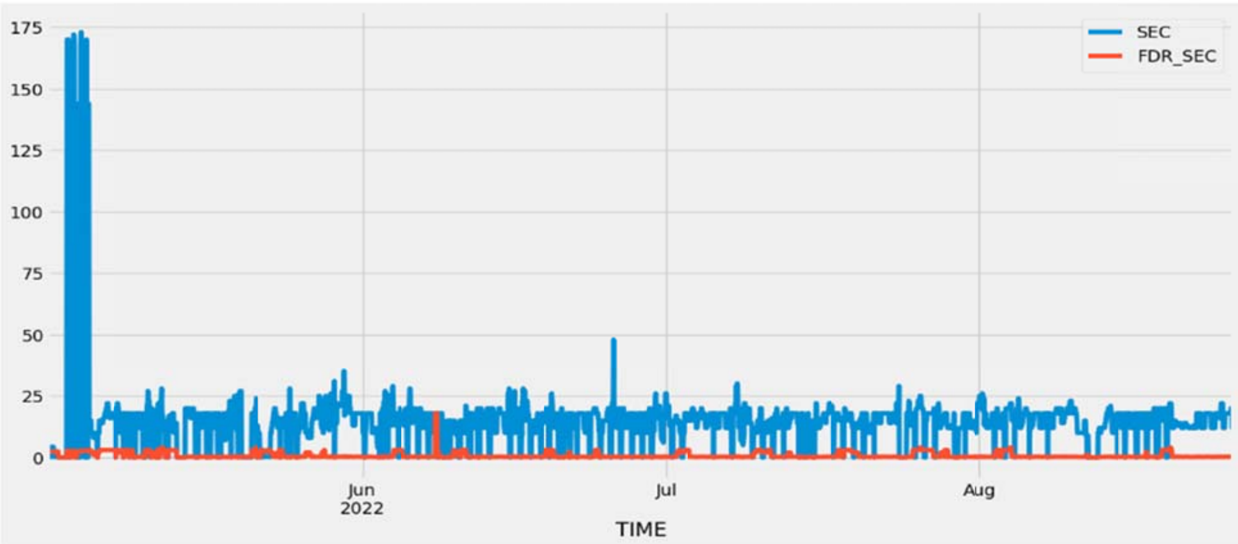

Figure 3: Raw data visualization for the Secretariat feeder historical load profile

3.2 The recurrent neural network model load prediction results

In the model development phase, the dataset was partitioned into 70% to 30% for training and testing respectively. For the training set, the dataset were segmented into batches of 24. This means that the model needs 24 data points to predict the 25^{th} data point. In other words, hourly data for one day is used to predict the beginning data point for the following day. Consequently, the number of hours to be predicted into the future was set to1. The prediction outputs for the Secretariat feeder load profile are presented in Figure 4. It should be noted that the load predictions are done on the scaled data to enhance accuracy. The training of the dataset was done for 50 epochs and Figure 5 shows both training and validation loss for the Secretariat feeder load data training after 50 epochs.

The graphical visualization of the raw load profile dataset for the Secretariat feeder is presented in Figure 6. The graphical visualization of the 70% training dataset, 30% test dataset as well as the load forecast for the next 30 days for the Secretariat feeder are presented in Figure 7. In all, the results shows that the MSE obtained from the model predictions is 1.21.

	TrainX	TrainY
0	[[-0.7015321584970157, 1.3063430373453015], [-...	[-0.9176453156831321]
1	[[-0.7015321584970157, 1.3063430373453015], [-...	[-0.9176453156831321]
2	[[-0.7015321584970157, 1.3063430373453015], [-...	[-0.9176453156831321]
3	[[-0.6583095270597924, 1.3063430373453015], [-...	[-0.9176453156831321]
4	[[-0.6583095270597924, 1.3063430373453015], [-...	[-0.9176453156831321]
...	...	...
2779	[[0.3172870110946758, -0.40628810665918375], [...	[0.3172870110946758]
2780	[[0.44078024377245656, -0.40628810665918375], ...	[0.3172870110946758]
2781	[[0.44078024377245656, -0.40628810665918375], ...	[0.3172870110946758]
2782	[[0.44078024377245656, -0.40628810665918375], ...	[-0.1766859196164474]
2783	[[0.44078024377245656, -0.40628810665918375], ...	[-0.1766859196164474]

2784 rows × 2 columns

Figure 4: Prediction output for Secretariat dataset

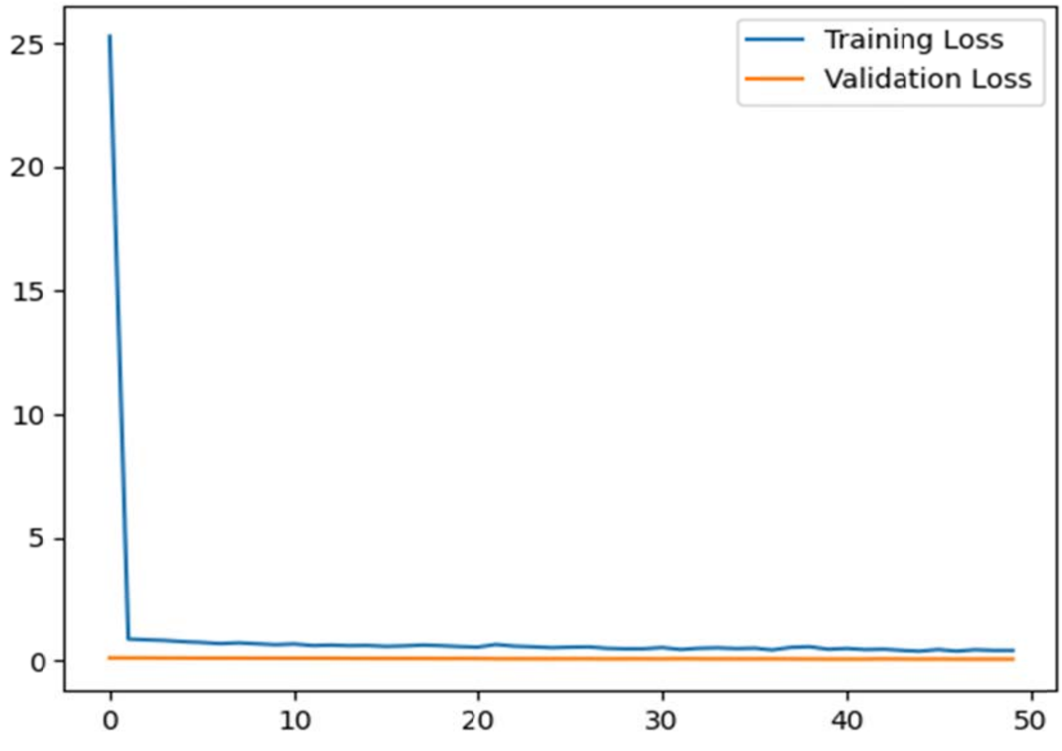

Figure 5: Training loss versus validation loss for the Secretariat data after 50 epochs

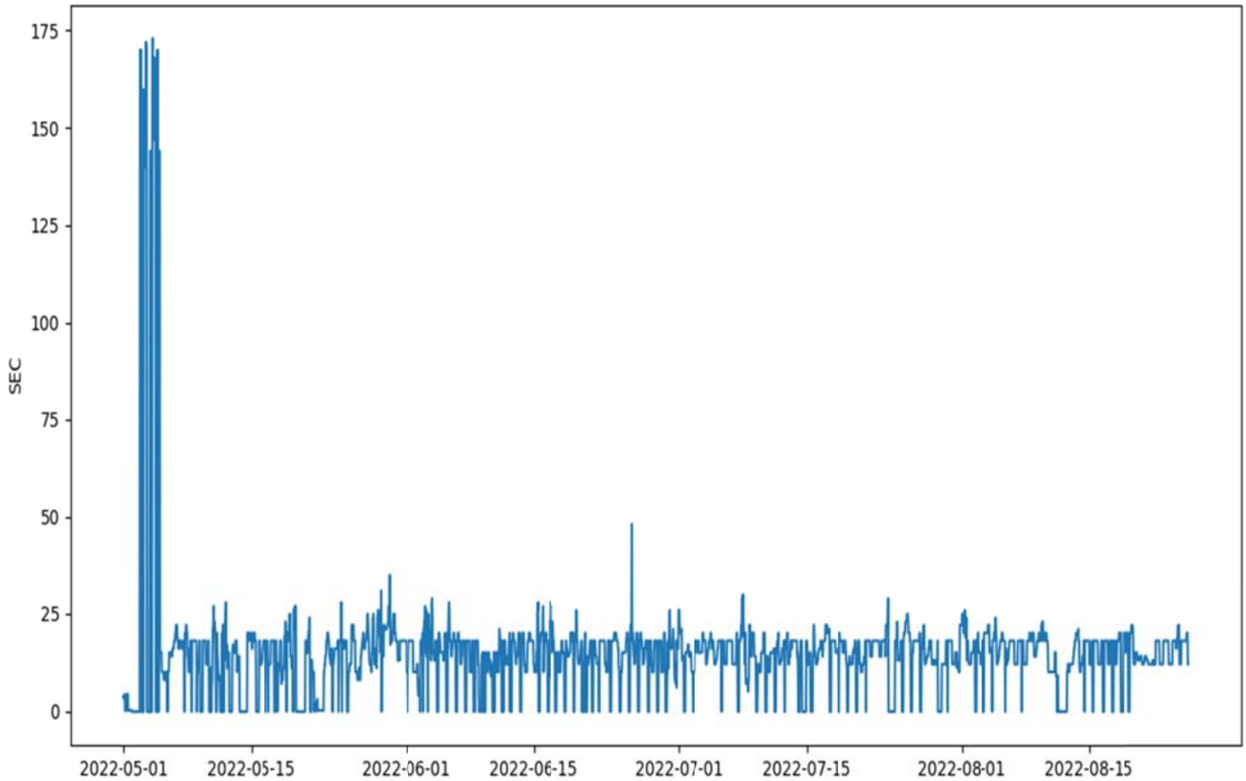

Figure 6: Graphical visualization of the raw load profile dataset for the Secretariat feeder

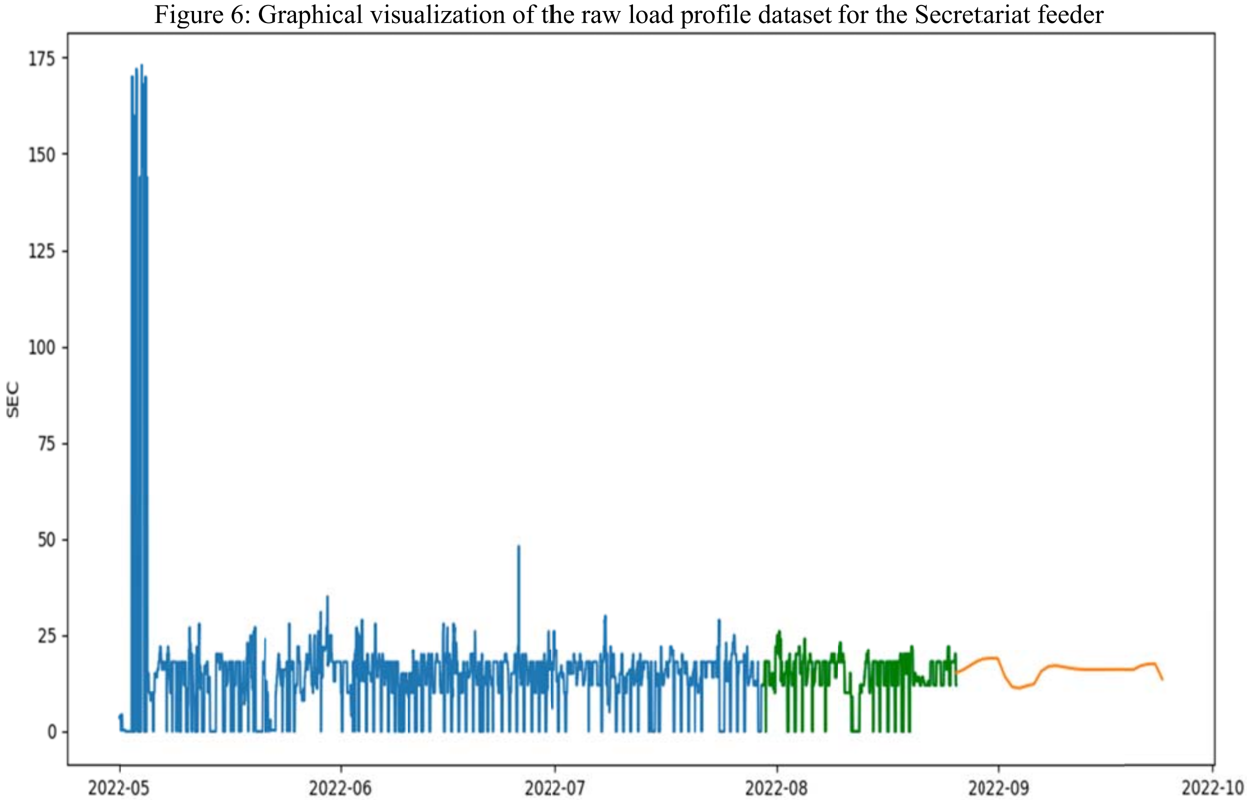

Figure 7: Graphical visualization of the of the 70% training dataset, 30% test dataset as well as the forecast for the next 30 days for the Secretariat feeder

4. CONCLUSION

An approach to characterize the feeder load of an injection substation in Uyo Akwa Ibom State, Nigeria is presented. The data driven model is based on the recurrent neural network with enhanced model parameters modification technique. The key analytical models associated with the various aspects of the recurrent neural network method are presented. The case study feeder dataset of a substation located in Uyo, Akwa Ibom State Nigeria is used for the model training and validation. The model was eventually used for the feeder load prediction and also for one moth forecasting of the feeder load profile. In all, the recurrent neural network with enhanced model parameters modification technique gave small mean square error value that showed that the model is suitable for characterizing the case study feeder load profile.

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