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Predictive Modelling of Load Dynamics in Smart Grids Using ECO-GRU Architecture and Exploratory Temporal Feature Engineering

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ABSTRACT: Load Forecasting (LF) is essential in order to operate and plan the electricity system. Therefore, predicting future energy demands is crucial for controlling consumption by matching utility offers with consumer demand. To statement these problems, this paper proposed an ECO-Gated Recurrent Unit (ECO-GRU) to designed for time series load forecasting in smart grid. The raw data such as voltage, current, Photovoltaic (PV)/wind power, power etc. are as an input to pre-processing stage. Four techniques are utilized in the pre-processing stage time/lap alignment, re-sampling, handling missing values, and exploratory analysis. The time lap alignment and re-sampling utilized for standardizing timestamps and re-estimates the data. Also, handling missing values and Exploratory Data Analysis (EDA) utilized for finding missing values in the input data and analyse the presence of multiple hidden features. Feature engineering, a log feature and rolling statistics computes the statistical measures over rolling period of data for further analysis. A proposed classifier ECO-GRU utilized for reducing the training parameter and ensures the prediction accuracy. Implementing Python software, the proposed ECO-GRU accommodate the actual generation pattern better than existing methods and produce the Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) , R2 value of 0.13, 1.8 and 99% respectively.

Keywords: Gated Recurrent Unit, Time/lap alignment, Re-sampling, Handling missing values, EDA, Log feature, Rolling statistics, Smart grid, Load forecasting.

1. Introduction

A smart grid is a sophisticated electrical transmission and distribution network that utilizes the use of control, communication, and information technologies to increase the grid's security, dependability, and economics [1]. Consequently, LF is helpful to the power system industry to produce electrical transmission. High LF accuracy is a crucial component of the smart grid since it provides precise information about power generation and purchase in the electrical market [2]. Whereas, seasonal variations, climatic shifts, weekends and holidays, natural disasters and political factors, power plant operating situations, and network faults all affect load demand and generation [3]. The power supply and delivery system is calculated using long-term forecasts, the fuel purchases is calculated using medium-term forecasts [4]. Whereas, electric LF is categories into two methods: the common standard approaches and the innovative artificial intelligence-based soft computing techniques [5]. The primary issue of the deregulation of energy markets, the demand pattern have become nearly extremely complex .Consequently, it is challenging to identify a suitable forecasting model for a particular electrical network [6].Additionally, LF is getting harder these days for two reasons: First, consumers are free to choose electricity supplier from available options, as many countries have deregulated and privatized their power distribution sectors [7-8]. Further increasing forecasting accuracy and decreasing forecasting time is the primary goal of forecasting model development. Precise plans result in significant operational and maintenance cost reductions, enhanced power supply and delivery system dependability, and wise choices for future advancement.

For smart grid LF, some of the following techniques are utilized as follows to classify the model training. Random forest-based LF algorithm to increase the accuracy of LF burdens and reduce the LF model's reliance on power-consuming activities. However, it is computational complexity and lack of interpretability [9]. Consequently, AdaBoost model is utilized to forecast the load by smart grid with increasing forecasting performance. AbaBoost is simplicity of use, and ability to manage both categorical and numerical data. Nevertheless, computational cost, over fitting potential, and susceptibility to data [10]. For smart grid LF used Light Gradient Boosting Machine (LGBM), eXtreme Gradient Boosting (XGB), and Multi-Layer Perceptron (MLP) is utilized for the stochastic variations in load demand. LGBM-XGB-MLP effectively handles large datasets, faster training and effectively manages structured data. Nonetheless, over fitting and difficult on interpreting the mode from complicated tree structure, particularly in complex models [11].

Whereas, Radial Bias Function (RBF) neural network is utilized to forecast the load for smart grid. RBF have faster training, efficient handling of non-linear problems, and localized learning network. Nonetheless, its computationally demanding when working with large datasets and it need more data for training [12]. To predict the sustainability of the smart grid Multi-Layer Perceptron (MLP) is used. MLP is flexible, managing complex nonlinear interactions and adjusting to different tasks. However, its black box character, are computationally costly, and prone to over fitting [13]. Moreover, Long Short Term Memory (LSTM) is utilized to forecast the load for smart grid. LSTM is well suited for processing data sequences with long-range dependencies, retrieve data across lengthy durations. However, computationally complexity, over fitting, hyper parameter tuning, it takes long training time [14-15]. To overcome this problem a proposed ECO-GRU is utilized with high performance for smart grid LF. ECO-GRU effectively handles sequential data for smart grid LF.

2. Related work

Khan *et al* [16] (2021) have proposed a LSTM and Kalman Filter (KF) to forecast the load for smart grid. LSTM-KF is used to improve the performance and error for smart grid LF. Also, It is an effective method, which is enhances the filtering and model training for smart grid LF. LSTM-KF have longer training time and higher computational properties when the process is going on. However, LSTM-KF is struggle with capturing complex patterns and handling large dataset.

Chen *et al* [17] (2023) have presented a Residual Neural Network (ResNet) and LSTM to improve the accuracy of smart grid LF. ResNet-LSTM effectively utilizes load data's time series features, suitable for sequential data processing and time series forecasting, on LF for smart grid. LSTM is well suited for processing data sequences with long-range dependencies. Nonetheless, ResNet-LSTM is computationally complexity when dealing with large dataset, if greater accuracy required it takes more time.

Ali *et al* [18] (2023) have developed a Levenberg–Marquardt (LM) based Artificial Neural Network (ANN) to more accurately, precisely, and better predict the short-term electrical load for smart grids. ANN interconnects the nodes and it is well suited for the prediction and classification. LM-ANN handle high-dimensional, complex data, adjust to new information, and find patterns that are hidden from the data. Nevertheless, necessity for large datasets, problems with interpretability, and a high processing cost

Nirmal *et al* [19] (2024) have proposed a CNN-AdaBoost to perform LF in smart grid. CNN effectively handles high-dimensional data and class imbalance issues, while AdaBoost is a strong and accurate ensemble method. In the context of smart grid LF systems, CNN captures complex data patterns, and AdaBoost enhances model performance. The combined CNN-AdaBoost approach improves forecasting accuracy, particularly when the base classifier is weak. However, it tries to fit every point precisely, making it liable to outliers and noisy data, over fitting for outliers.

Wan *et al* [20] (2023) have presented a CNN-LSTM model to forecast the load for smart grid. This model forecast an information loss in long input time series for smart grid LF. When employing CNN-LSTM, both the spatial and temporal dimensions present throughout the time step. It is better in computer vision and time series analysis forecasting the load in smart grid. Nonetheless, requirement for large datasets and significant processing demands for LF.

The contribution of this work is follows

- Data pre-processing involves time/lap alignment, re-sampling, handling missing values, and exploratory analysis. These steps are used to standardize timestamps, re-estimate data, identify and handle missing values, and uncover multiple hidden features within the dataset
- Feature engineering a log feature and rolling statistics used to computes the statistical measures over rolling period of data.
- An ECO-GRU is employed, to enhance the model prediction for smart grid LF.

3. Proposed work

The proposed block diagram shown in figure 1 for smart grid LF using Neural Network with Smart Grid Real-time Load Monitoring Analysis datasets. The input data is taken from the Smart Grid Real-time Load Monitoring Analysis datasets to find the load generated. Initially data pre-processing stages involves time/lap alignment, re-sampling, handling missing values and exploratory data analysis. Time/lap alignment is to it adjusts and standardize timestamps across multiple time series, re-sampling technique it re-estimates the selected samples from the datasets. Using handling missing values the missing values in the input data is collected for smart grid LF. And exploratory data analysis analyse the presence of multiple hidden features from the input datasets. Next using feature engineering a log feature and rolling statistics computes the statistical measures over rolling period of data for further analysis. Finally featured value is given as input to the model prediction technique as ECO-GRU to reduce the training parameter and ensure the prediction accuracy for smart grid LF.

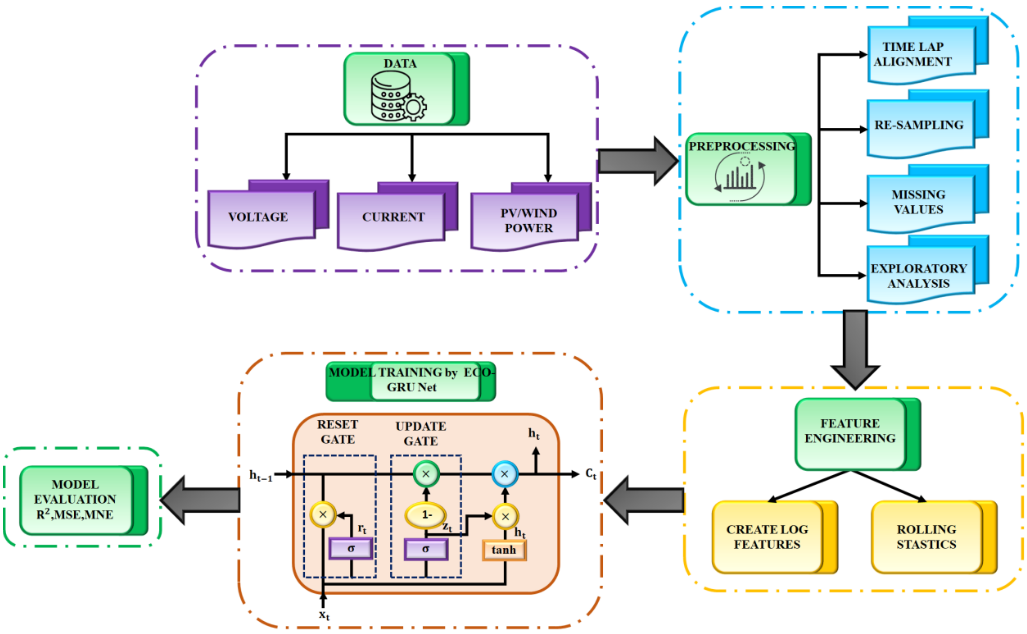

Figure 1: *Block diagram of the proposed work*

3.1 Data pre-processing for smart grid LF

In data pre-processing for smart grid LF it have four methods time/lap alignment, re-sampling, handling missing values, and exploratory analysis.

3.1.1 Time/lap alignment

In smart grid LF, time/lap alignment is the process of coordinating forecasting intervals (laps), time steps, and historical load data to guarantee that the input data and anticipated outputs are appropriately aligned in time. This alignment is essential for the model to acquire consistent temporal patterns and manage different forecasting horizons, which helps to make accurate prediction.

3.1.2 Resampling

In smart grid load forecasting, the term resampling refers to changing the time resolution of data either by decreasing or increasing the number of observations. This gives the data some consistency, fills in missing values, and fits the input needs for the forecasting model. This stage is essential for integrating data gathered at various points in time and enhancing the precision and effectiveness of load prediction models.

3.1.3 Handling missing values

Handling missing values in smart grid LF involves detecting, managing, and imputing incomplete or unavailable data points within time series datasets to maintain data integrity and improve forecasting accuracy. Handling of missing values is essential to ensure the robustness and reliability of predictive models.

3.1.4 Exploratory Data Analysis

In smart grid LF, EDA is the precise process of viewing and displaying historical load data from the Smart Grid Real-time Load Monitoring Analysis datasets. Plotting the load across time makes it easier to spot patterns, seasonality, and unexpected increases or decreases. Following to time/lap alignment, re-sampling, handling missing values, exploratory analysis the data's are set to feature engineering for smart grid LF.

3.2 Feature Engineering for smart grid LF

For feature engineering the processed data is given as an input data and is utilized by using log feature and rolling statistics for smart grid LF.

3.2.1 Log feature

Log features are frequently employed to modify data with a skewed distribution or exponential growth to sort the data more appropriate for statistical analysis. Log transformation increase the precision and dependability of forecasting models by stabilizing variance, reducing the impact of outliers, and making data more regularly distributed.

3.2.2 Rolling statistics

In smart grid LF the rolling statistics, also called moving statistics. The rolling statistics are used to compute statistical measures over a rolling window or rolling period of data, which moves step by step through the dataset and recalculates statistics at each step. The rolling statistics offer a more dynamic view of data, which is especially helpful for identifying trends and anomalies over time. The most popular rolling statistics for outlier detection are as follows:

- **Rolling mean:** Data points inside a specified timeframe are averaged using the rolling mean, commonly known as the moving average. It makes the data's trend more obvious and helps to even out fluctuations.
- **Rolling Standard Deviation:** This statistic quantifies the variability or dispersion of data within the rolling window. More variety in the data is indicated by a large standard deviation.
- **Rolling Median:** The rolling median determines the median value inside the rolling frame, like the rolling mean. Median is less and susceptible to extreme values for smart grid LF.

Following to log feature and rolling statistics the data's are set to model training for smart grid LF.

3.3 Model training for smart grid LF

In the proposed work ECO-GRU is to enhance the model prediction for smart grid LF.

3.3.1 ECO-GRU

ECO-GRU for smart grid LF reduces the training parameters and maintaining the precision of the predictions. The ECO-GRU, have structural parameters and more quick convergence, it is composed of the update gate and reset gate. The update gate controls the status information from the previous moment is retained in the present state. Greater value means that more of the status information from the previous moment is retained. The reset gate controls the extent to which the present state is combined with previous data. Greater disdain for the information is indicated by a lower score. Figure 2 depicts the GRU's architecture for LF. The direction of data flow is indicated by the arrow in the illustration below.

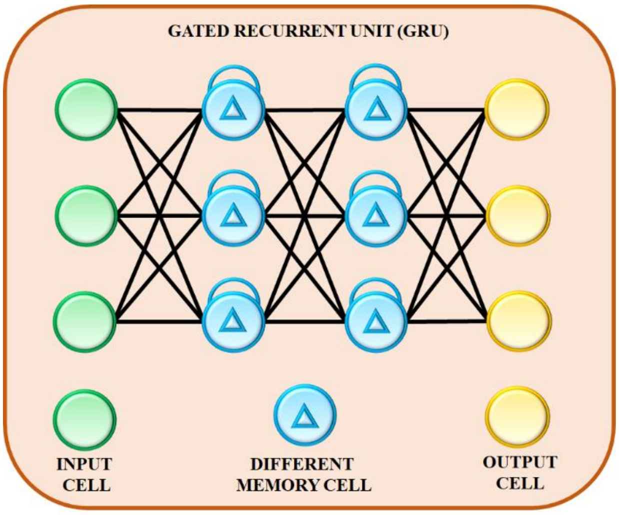

Figure 2: *Basic GRU architecture*

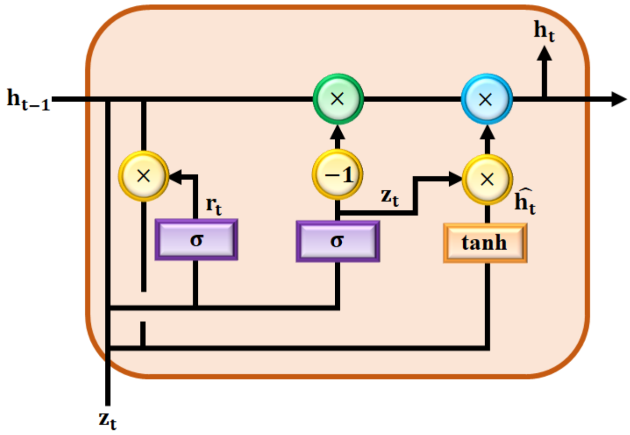

Figure 3: *Data flow for GRU*

The update and reset gates are denoted by $z_t$and $r_t$respectively, in Figure 3. $x_t$represents the input, and $h_t$represents the hidden layer's output. The data flow is shown by the arrows, where x stands for matrix multiplication. Sigmoid, represented by σ, and $tanh$, for the $tanh$ activation function, functions that are employed. The forward-propagating data in the link $1 - z_t$as shown by the notation as $1 - z$. The proposed model fully absorbs and collects the data to the construction of the GRU structure in a single layer. The output in the GRU layer is denoted byh_t, and the output at step t is denoted by

$$h_t = GRU\left(h_{c,t-1}h_{c,t}\right), t \in [1, i] \quad (1)$$

$z_t$denotes the update door, whereas $r_t$stands for the reset door. These two gates are used to regulate the amount of information. The hidden stateh_t at the prior time and the input $x_t$at the present moment serve as the inputs of both gates. The following is the formula used to calculate the two doors:

$$z_t = \sigma(W_z \cdot [h_{t-1,}x_t]) \quad (2)$$

$$r_t = \sigma(W_r \cdot [h_{t-1,}x_t]) \quad (3)$$

Where the input at time t is represented byx_t, the hidden state at the previous time by$h_{t-1,}$, the weight matrix is represented by$W_z and$ W_r, and the sigmoid function is represented by $\sigma(\cdot)$.GRU computes the candidate hidden state value $\widehat{h_t}$ after discarding and memorizing the input data using two gate structures.

$$\widehat{h_t} = \tanh(W_{\hat{h}}[r_t \odot h_{t-1,}x_t] \quad (4)$$

In order to provide the optimal output value, equation 4 states that ECO-GRU uses two gates to store and filter data. ECO-GRU takes less time to train when the same result is obtained.

Algorithm 1 Standard Gated Recurrent Unit

1. **Step 1: GRU initialization**
2. **while** i in mini-batches **do**
3. $d_0 \leftarrow 0$ (Initialize 1st moment)
4. $z_0 \leftarrow 0$ (Initialize 2st moment)
5. $i_0 \leftarrow 0$ (Initialize timestep)
6. **Step 2:Create GRU model**
7. Add the 1st GRU layer of L_1 units with sigmoid activation (Sigm) and dropout is d_1 and recurrent dropout isr_1.
8. Add the 2nd GRU layer of L_2 units with sigmoid activation (Sigm) and dropout is d_2 and recurrent dropout isr_2.
9. **Step 3: Train and validate model**
10. Compute the update gate z_t, and reset gate r_t, using equations (2),(3)
11. Compute the candidate state h_t,using equation (4)
12. **while** stopping candidate did not met **do**
13. **while** training for all instances **do**
14. Prepared a mini—batch feature set as model input.
15. Calculate categorical cross entropy loss function.
16. Update weights and bias applying back propagation optimization algorithm.
17. **end while**
18. **end while**
19. **Step 4:Test model**
20. Test fine-tuned hyper-parameters with test dataset.
21. **return** Evaluate result in test dataset.

Using ECO- GRU for training and prediction yields superior results and protects a lot of effort, especially when dealing with large training sets. In order to accomplish the goals of fast training time and good forecasting effect, this paper chooses a GRU neural network model for smart grid LF.

4. Result and Discussion

In the result and discussion the smart grid LF is predicted using the proposed ECO-GRU. For identifying and forecasting load the Smart Grid Real-time Load Monitoring Analysis dataset is taken from the kaggle.com, which is implemented using Python software.

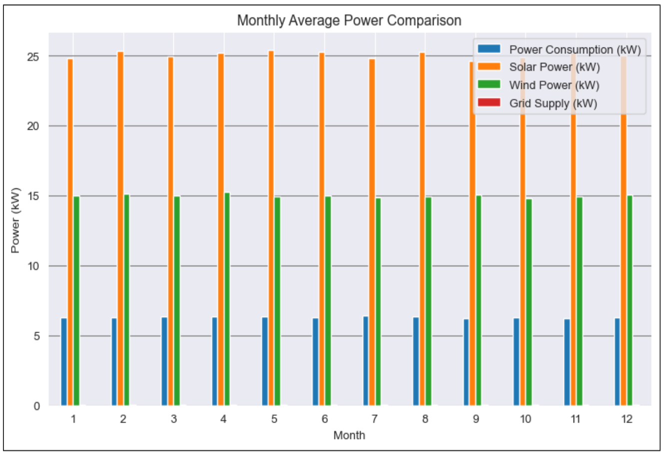

Figure 4: *Monthly average power comparison*

Figure 4 shows the monthly average power comparison for smart grid LF. The X-axis indicates the month and Y-axis indicates power (kW) for smart grid LF. Blue color indicates the power consumption (kW), orange color indicates the solar power (kW), green color indicates the wind power (kW) and red color indicates the grid supply (kW). Solar power is high in all the months compared to wind power and power consumption. Solar power is peak in the fifth month which is above 25 kW. Power consumption is low in all the months which is up to 6kW.

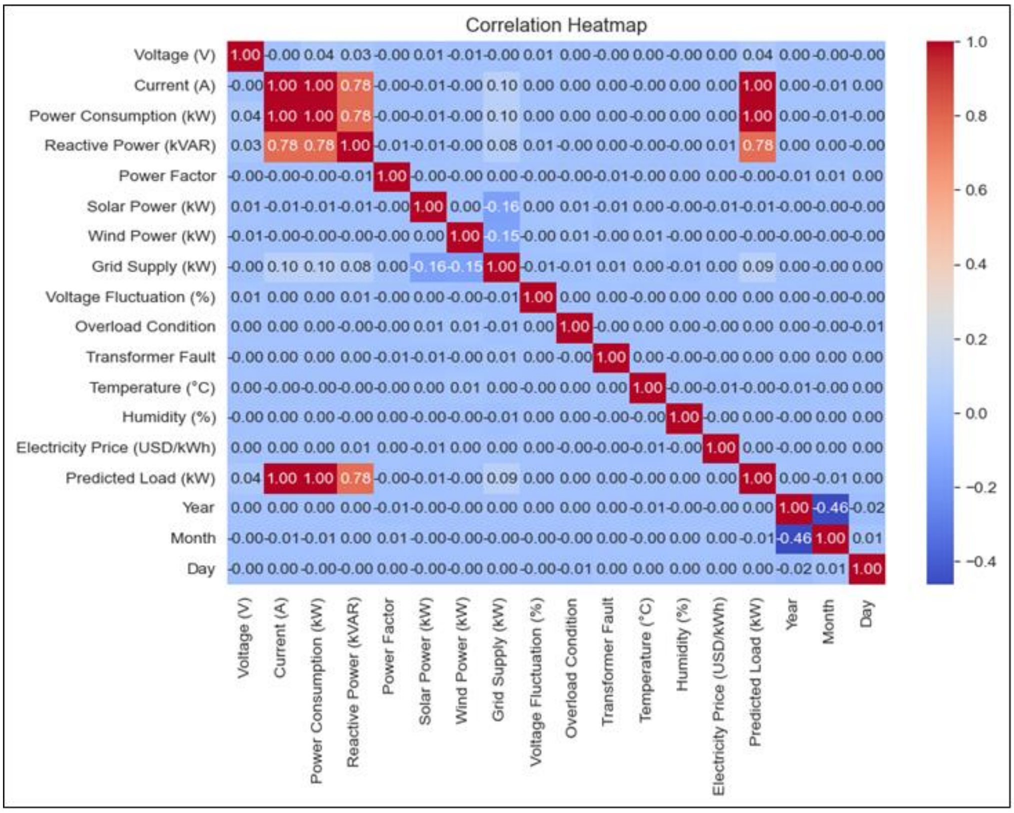

Figure 5: *Correlation heat map for smart grid LF*

Figure 5 shows the correlation heat map for smart grid LF. It displays the Pearson correlation coefficients between the Smart Grid Real-time Load Monitoring Analysis dataset. The correlation's direction and strength are shown by the color scale: Red (nearer +1) indicates a high degree of positive association, blue indicates strongly negative correlation (nearer to -1), and white (0) indicates the no association that is linear. High correlations that are positive correlation between Current (A) and Power Consumption (kW) = 0.78.

Low or no correlation indicates that the impact of some factors, such as humidity, temperature, solar power, wind power, transformer failure, are insignificant to the expected load. This represent very weak linear effects, as both models monitor nonlinear impacts. Additionally, lower to negative correlations in the month against predicted load show the likely correlation with seasonal impacts in electricity usage.

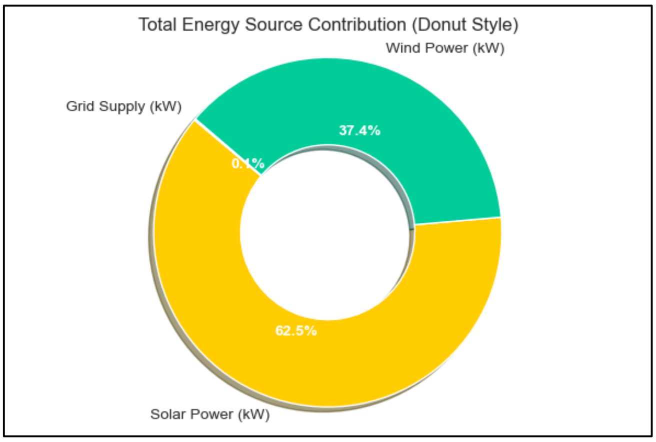

Figure 6: *Total energy source contribution*

Figure 6 shows the total energy source contribution for smart grid LF. Donut style plot shows the total energy source of solar power (kW), grid supply (kW) and wind power (kW).Total energy power for solar power is 62.5%, wind power is 37.4% and grid power is 0.1%. Here the solar power is high compared to the wind and grid power for smart grid LF.

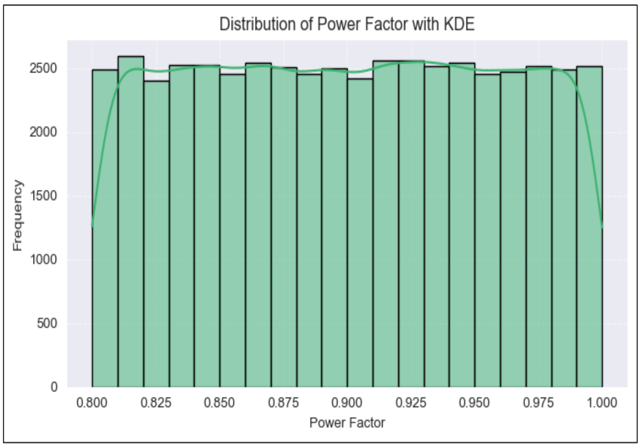

Figure 7: *Distribution of power factor with KDE*

Figure 7 shows the distribution of power factor with KDE for solar power LF. The X-axis indicates the power factor and Y-axis indicates the frequency. The frequency is high up to 2500 Hz and power factor is up to 1 for smart grid LF.

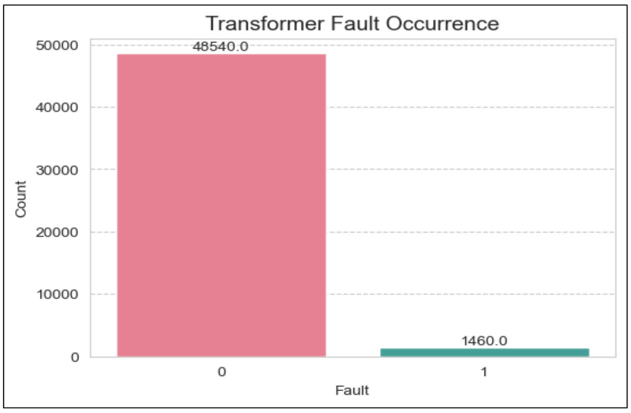

Figure 8: *Transformer fault occurrence*

Figure 8 shows the transformer fault occurrence for smart grid LF. The X-axis indicates the fault and Y-axis indicates the count for calculating the transformer fault occurrence. For fault 0 the transformer count is up to 48540 and for fault 1 the transformer count is 1460. Fault 0 is high compared to fault 1in the transformer fault occurrence for smart grid LF.

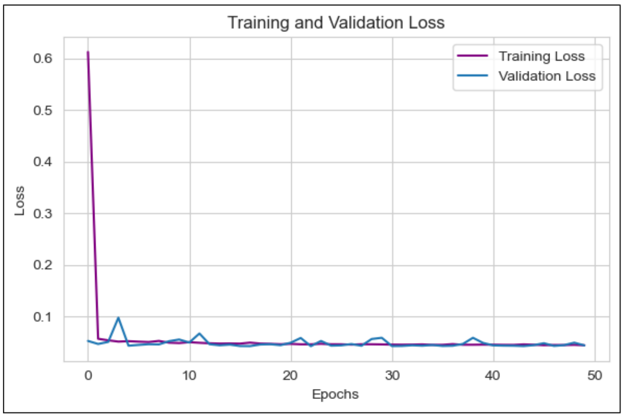

Figure 9: *Training and validation loss*

Figure 9 shows the training and validation loss for smart grid LF. The X-axis indicates the epochs and Y-axis indicates the loss for smart grid LF. The training loss is high up to 0.6 in the epochs 1 and the validation loss is high and low, there is a vibration up to 48 epochs.

4.1 Performance Criteria

The model performance is measured using a statistical evaluation for smart grid LF, including coefficient of determination (R^2), RMSE, MAE, and MSE. The smart grid LF criterion formulas are shown below.

$$MSE = \frac{\sum_{i=1}^{m}[x_i - \widehat{x_i}]}{m} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}[x_i - \widehat{x_i}]2}{m}} \tag{6}$$

$$R^2 = [\frac{1}{M}\frac{\sum_{j=1}^{M}[(Y_j - \bar{Y})(X_j - \overline{X})]}{\sigma_y \sigma_x}]^2 \tag{7}$$

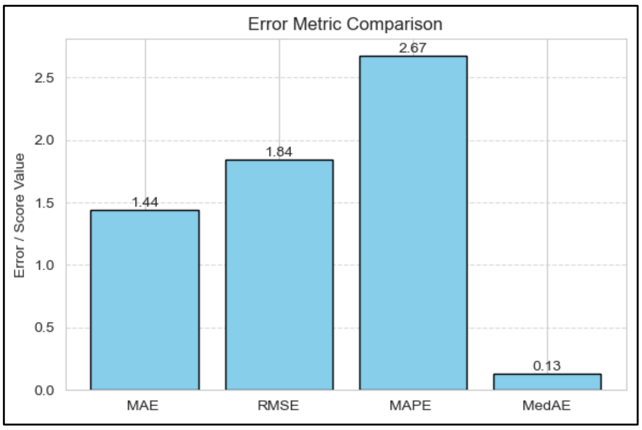

Figure 10: *Error metric comparison*

Figure 10 shows the error metric comparison for smart grid LF. The X-axis indicates the MAE, RMSE, MAPE and MedAE, Y-axis indicates the error/score value. The MAE value is 1.44, RMSE value is 1.83, MAPE value is 2.67 and MedAE value is 0.13 for smart grid LF. MAPE error value is high compared to MAE, RMSE and MedAE for smart grid LF.

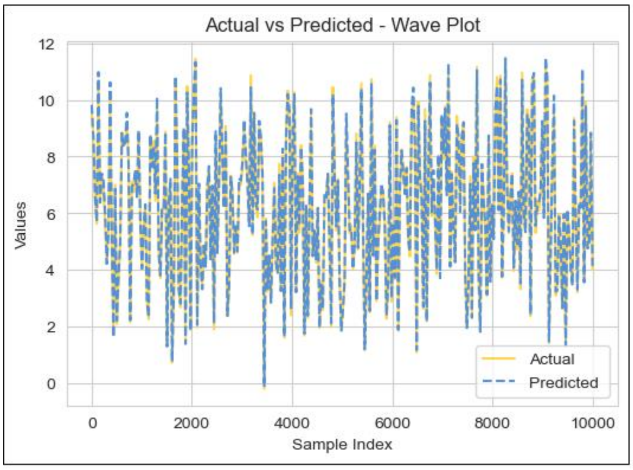

Figure 11: *Actual vs predicted- wave plot*

Figure 11 shows the actual vs predicted wave plot for smart grid LF. The X-axis indicates the sample index it is up to 10000 and Y-axis indicates the values up to 12. The blue dotted line shows the predicted value and orange color line indicates the actual value for the smart grid LF.

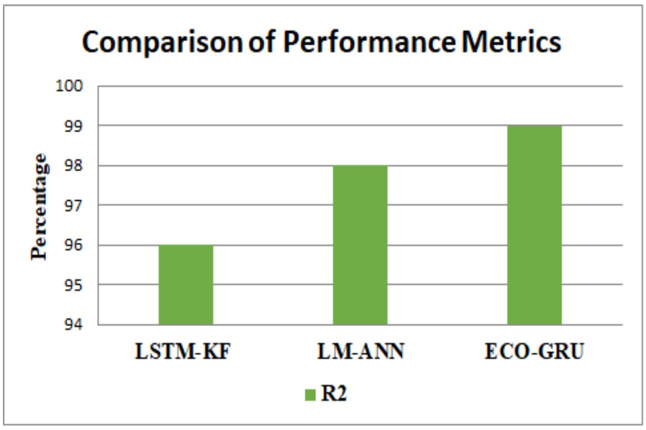

Figure 12: *Comparison of performance metrics for smart grid LF.*

Figure 12 shows the comparison of performance metrics for R2. The proposed ECO-GRU have the higher value of 99%, the LM-ANN [18] have the value of 98% and LSTM-KF have the value of 96% [16]. LM-ANN and LSTM-KF R2 value is low compared to the proposed ECO-GRU method.

5. Conclusion

In this paper, smart grid LF strategy is introduced ECO-GRU classifier to provide a faster and more accurate forecasting. The data pre-processing stage effectively standardize timestamps across multiple time series and re-estimated data by using time/lap alignment, and re-sampling technique. Additionally, with the aid of finding missing values and multiple hidden features are analysed handling missing values and exploratory data analysis. A log feature and rolling statistics feature engineering methods effectively computes the statistical measures over rolling period of data. A proposed ECO-GRU reduces the training parameter and ensures the prediction accuracy. The improved RMSE of 1.83, MAE value of 1.44 and R2 value of 99% is achieved as a greater performance in contrast to the surviving methods.

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