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MINIMIZATION OF AT&C LOSSES ON DISTRIBUTION SIDE USING AI TECHNIQUES

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ABSTRACT:

Non-Technical Losses (NTL) in electrical distribution systems can have serious repercussions on energy suppliers and national economies, mainly involving the theft of electricity. Consumer fraud, illegal tapping of power lines, meter bypassing, and manipulation of energy meters are some common examples of non-technical losses. One of the important factors that determines the effectiveness of smart meters is the ability of all stakeholders to collect, transmit, analyze, and interpret data. Meter tampering or energy theft can be found and detected using artificial neural networks. The findings can potentially be used to improve bigger real systems. Over the past decades, AT&C has suffered heavy losses in the Indian energy sector. Combined loss, i.e., AT&C [AT&C stands for Aggregated Technical and Commercial Loss], including technical and commercial loss. Technical losses are unavoidable power flow losses due to network design in transmission and distribution systems. These losses represent a significant portion of India's overall loss of productivity and economic power. An in-depth study shows that these technical and Non-technical losses are a serious problem in India, accounting for 4% of the annual total. The main interest of researchers lies in this concept. It also recommends monitoring, analyzing and highlighting signs of non-technical damage, especially in these areas. Further, a MATLAB/Simulink Simulation has been carried out on a grid to examine power or energy theft by the different loads using data collected from the same grid and using Long Short-Term Memory (LSTM) Neural Network training in Python.

Key Phrases- Neural Networks, Non-Technical Loss, Smart Meters, Long-Short Term Memory, Advanced Metering Infrastructure, Python, Automatic Meter Reading, Databases, Intelligent Systems, Communication Systems, and Electricity Theft.

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1. INTRODUCTION

In India, the power sector is defined as the appropriate balancing power sector for both parties in the event of power shortages or unreliable generation and demand supply chains leading to power shortages. electricity, blackouts and system losses that frustrate on-site electricity investors. Over the past decade, remote power supply in rural India has been undersupplied by around Rs 24 crore.[1] Although the main challenge is to accurately identify cases of NTL in the Indian power sector. In order to identify these loss issues and keep them as low as possible, a proper and reliable technique must first be developed which will be implemented including appropriate preventive and corrective measures. Here, the technical losses are assumed to be constant, but the main constraints are also taken into account. First, local utilities must provide uninterrupted power. These unavoidable frequent losses appear to be a task for the distribution industry to minimize, and the government also has concerns. Loss is the difference between energy output and energy loss. The aforementioned loss accounts for a large part of India's 2-3% loss, as it leads to an overall productivity loss in the Indian economy. The above losses result in overall productivity loss, economic loss and hence a large part of India's 2-3% loss[2].

2. NTL DETECTION:

Causes of Non-Technical Losses:

- Power Theft
- Under keying of meter reading
- Illegal Connection
  - Pure
  - Self-Line Construction
  - Administrative
- Premises connected but a/cs not set up in system.
- Meter related problems
  - Meter bypass/ tamper
  - Wrong readings
  - Over aged meters
  - High Meter Position
  - Meter ratings
  - Faulty meter
  - Meter Transfers
- Unpaid bills
- Overlooked meter readings

The most frequent and serious issues with the non-technical losses techniques outlined above are those that are hard to trace, such as meter manipulation, bypassing, and other issues connected to meters. Meter tampering has been shown to be the largest threat to utility businesses, and for the grid to operate more efficiently and healthily, stringent measures must be taken against the dishonest customers. Unpaid bills result in significant financial losses for utility providers, who must make up the difference by raising the unit's price, which eventually causes discomfort for all grid-connected users. All of the techniques result in significant non-technical losses that are recorded on the grid.

Smart meters and smart security systems that can continually monitor all the data from the customers on the grid can be used to identify such fraudulent users. The company may contact suspected fraudulent customers personally and penalize them if they were caught in the act if the system had warned it about potential power theft via consumer data. Errors in the metering process may also be caused by dishonest employees who encourage and enable such thefts in exchange for money.[3] Poor vision makes it possible for utility workers to manually measure meters incorrectly, and meters mounted high on walls add to the pain and risk of false readings. In addition, inaccurate and outdated meters may result in inaccuracies in meter reading. Poor meter protection or a weak seal on the meters can potentially result in a breach since users can easily access the meter and tamper with it to record less units, which would eventually result in a lower amount when billed.

Categorization of NTL Detection methods:

A review of the research literature at NTL revealed that there is no accepted method for fraud detection. Researchers from various disciplines are working, including distributed network analysis, machine learning, vulnerability detection and cybersecurity. There are three types of NTL calls: data-driven, network-driven, and hybrid. Information sharing techniques differ from network-oriented ones in their use of network information such as network information, network topology, or network measurement. Only customer-related information will be used for strategic information purposes (e.g. energy consumption, type of customer, etc.). Data from both groups were used in a mixed process. The main categories are as mentioned in the figure below:

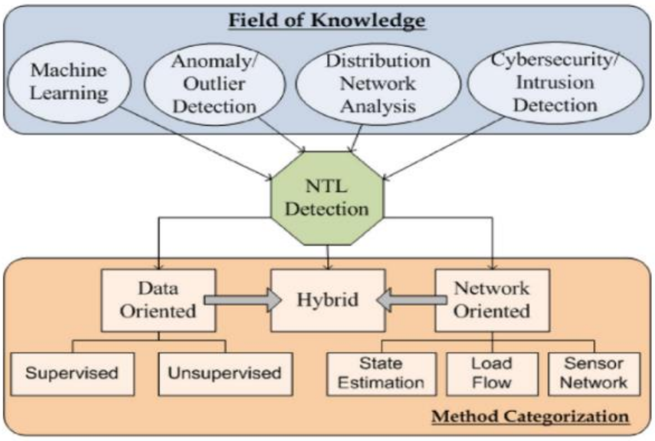

Figure 1: Categorization of NTL detection methods

In the electrical sector, the term "Non-Technical Loss" (NTL) is used to identify faulty meters or improper use of electrical equipment. As the units detected by the malfunctioning meter are little in comparison to the amount of electricity used, the electricity provider is responsible for the loss. The fact that the datasets in question are associated with the class imbalance issue is a significant feature of them. This is an issue where the dataset is biased towards one class due to the large amount of representation and is misrepresented by another class. Surprisingly, the issue gets more challenging when the real representation of disadvantaged classes is the goal. Of course, power outages in communities are far more common than attempted robberies.

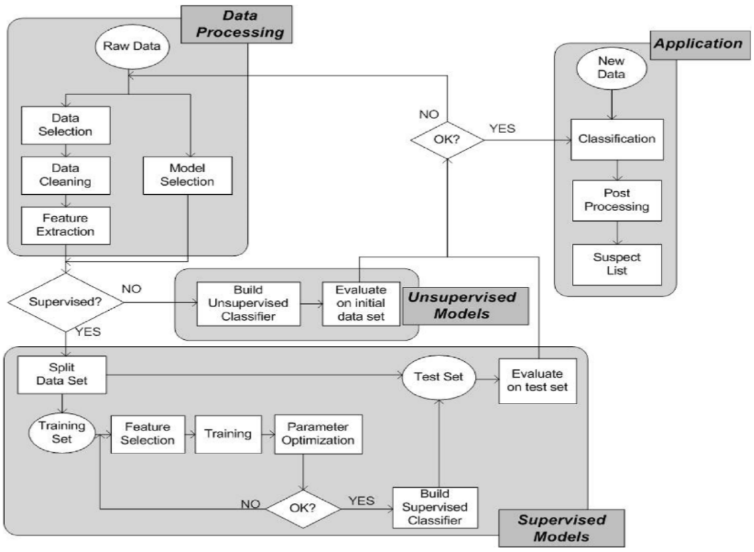

Figure 2: Data-oriented methods for NTL Detection

There is a problem with class imbalance in the real electrical data set, which is evident from the fact that there are more negative class samples than positive class samples. Before machine learning algorithms employ the data set, an NTL detection approach must be capable of balancing positive and negative samples. Using conventional machine learning methods to the power usage dataset is one method for locating the NTL.

Data Processing and Selection of Model: Raw data should be used to select samples for NTL detection. The decision to use supervised or unsupervised methods depends on the availability (or absence) of recorded data, while the algorithms used depend on the quality and diversity of the data. The algorithm may remember some raw data (level selection data). After that, the data should be cleaned (usually during information search) and features extracted (if necessary).

Modeling: This process differs depending on whether the model is supervised or unsupervised. Unsupervised models use the recorded data only for evaluation, not for training. Data are divided into training and testing using supervised techniques. Depending on the context of the training process (sometimes beyond validation), custom selection is usually used to train the model, while the optimization process uses metrics from the tag.

Application: New data (not part of the "raw data" layer) is used to complete the model's tasks and functions. The classification results are then used to create a grievance list with all potential customers. This phase may include NTL model testing or simulation. If there is a recommendation (related to manual measurement), field research is required.

Synthesized vs. Real Dataset[4]

Two types of data sets are used in NTL detection. A category belongs to the complete dataset, which is randomly generated taking into account the NTL detection requirements. Synthetic datasets have the benefit of being readily available, but they also run the risk of omitting important data that would otherwise aid in the detection of illegal consumer conduct. Another type is an actual dataset obtained from a distribution company. One of the main advantages of using these datasets is the ability to analyze real, unique patterns of energy consumption that may be missed in synthetic datasets.

Class Imbalance: An aspect of NTL Detection[5]

Class imbalance issues are a fascinating characteristic of distributed community datasets. Consider the categories of normal consumption and abnormal consumption; there will be a problem of class imbalance when the majority of consumption records fall into the normal consumption category and just a small number of records fall into the abnormal consumption category. If the classifier's success rate is not appropriately maintained when the objective is to forecast atypical consumption classes that are infrequently found in a dataset, the success rate may be reduced. To balance the number of records representing the two classes, the majority class in the sample can be used in a preprocessing step of the data preparation. This is called the Synthetic Minority Oversampling (SMOTE) technique. Another approach is to cross-check the minority class, that is, to randomly copy or create new synthetic records from the minority samples. Both techniques are used in different problem areas that belong to class imbalance.

Beneficial areas of NTL Detection

To significantly improve NTL identification, general patterns are followed when pre-processing datasets and using classifiers. Raw data containing consumption records is provided by distribution companies. Consumption data might be recorded on a half-hourly, hourly, daily, fortnightly, or monthly basis depending on the type of metering system used. Although the manual metering infrastructure employs monthly measurements manually acquired by meter readers, the automatic metering infrastructure (AMI) tracks consumption on an hourly or daily basis.[6] For NTL trace analysis, not all consumption profile records are accessible. Moreover, not all traits are crucial for identifying NTL. Records and qualities must be chosen in order to do this. The dataset will be scaled to standardize the numbers after it is complete. The classifier must next be trained and tested. There are many different classifiers in use. Performance evaluation measures are then used to gauge the classifier's effectiveness.

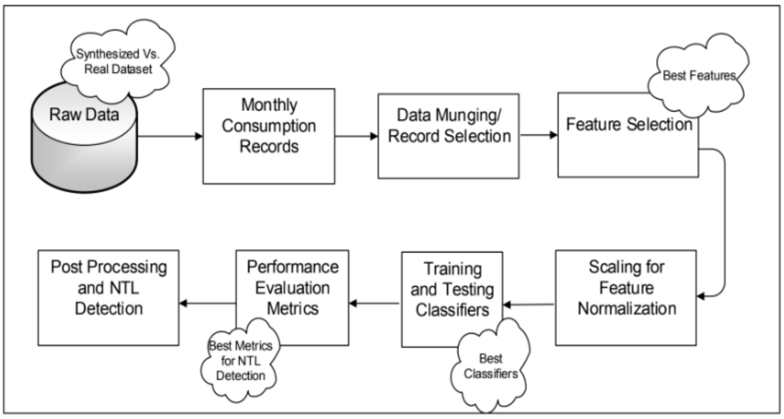

Figure 3: Pre-processing pattern for NTL Detection

Data analytics and machine learning techniques are at the heart of data-driven strategy. These methods are divided into two categories, supervised and unsupervised, and will be discussed in the next sections. However, it uses similar techniques, both supervised and unsupervised.

3. LONG SHORT-TERM MEMORY FOR ELECTRICITY THEFT DETECTION:

In contrast to ordinary RNNs, LSTMs are an RNN architecture that is intended to more precisely depict physical systems and their long-term interactions. certain of its key characteristics include the internal structure of LSTM cells, several LSTM model alterations, and certain well-liked LSTM implementations. This study looked into LSTM and GRU. The course ends with a summary of the drawbacks of LSTM networks and an explanation of the new observation models that are swiftly taking the place of LSTMs in real-world applications. LSTM networks are now utilized to assess neural networks (RNNs) and are created for circumstances when RNNs fail. When we discuss RNNs, we are referring to an algorithm that assesses inputs as they are fed, takes feedback from prior occurrences into account, and then temporarily stores this knowledge for the user. The most often used domains for numerous applications are non-Markovian volume control and music creation. RNNs do, however, have several drawbacks. The primary issue is inappropriate long-term data processing.

To ascertain current findings, it is occasionally essential to consult pre-recorded ancestors' records. But RNNs are unable to manage these "long-term dependencies". The inability to manage which previous information should be preserved and which should be forgotten is the second issue. RNNs also have the issue of rapid peak emergence and disappearance when trained via backtracking. Long Term Memory (LTM) was added as a result. The gradient fading issue is nearly entirely solved because the training samples are unnecessary. LSTMs can be used to address issues with long delays, such as those brought on by noise, scattering factors, or infinite numbers. When using LSTMs, they are unable to maintain the same number of states for as long as the hidden Markov model (HMM) requires. We have access to a large number of LSTM parameters, such as learning rates and input and output biases. Small modifications are thus not required.[7] The work to update each weight is lowered to O(1) by employing LSTMs, which is analogous to how they are used in Back Propagation Through Time (BPTT), which is a substantial advantage.

Data processing and deep learning models built on LSTMs are used to explain a strategy for early detection of power theft. Methods for selecting data based on data processing, data normalization, and weight adjustment. The obtained data was also used to train and analyze LSTM-based deep learning models. With only 9% of the total data, this technique aims to balance the NTL data. For the last stage of the data classification procedure, an LSTM model is created. To examine the reliability of this test, a model based on long-term memory (LSTM) was created[8]. Being a significant RNN with a memory cell, the LSTM model performs better than the deep neural network in classifying messages and data signals. Analyzing input memory cells is necessary to verify the input. To confirm that the output flow to the LSTM block is validated, output memory data is also examined. The probability of the preceding node might be affected by certain levels in the LSTM architecture that are maintained in memory. The backward gates of LSTM memory blocks are managed by layered neural networks.

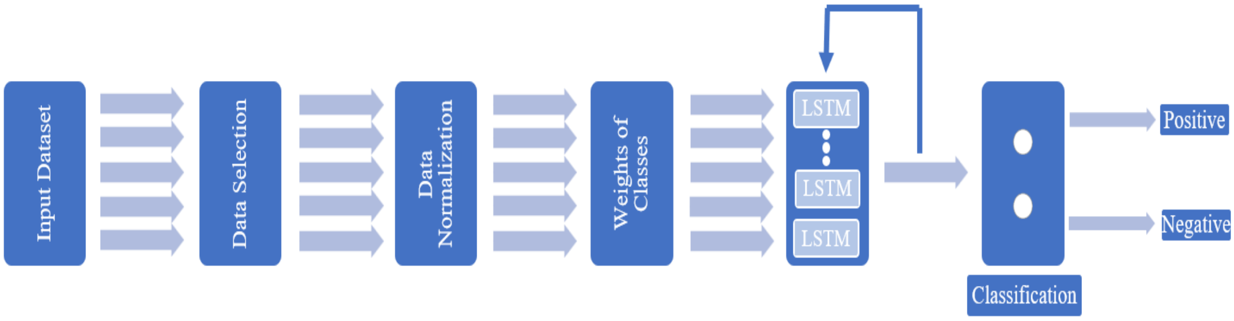

Figure 4: Block Diagram of LSTM

To address the short-term memory difficulty that RNNs have, long short-term memory (LSTM) networks, a special type of RNN, was established. From the start of the network until its end, LSTMs may remember and send significant information. The fundamental structure of an LSTM is utilized. An LSTM and an RNN both have repeating structures, but the fundamental structure of the modules differs. An essential part of an LSTM is the cell state, which transfers information down the chain. A number of parts together referred to as gates delete or alter the data in the cell state. An LSTM module is made up of three gates: an output gate, an input gate, and a forget gate.

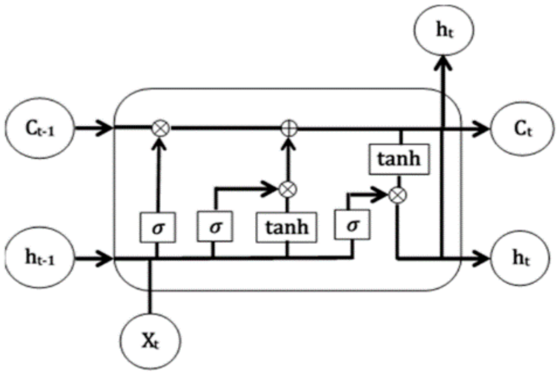

Figure 5: LSTM Architecture, Source: Internet

3.1 LSTM Architecture:

The main difference between LSTMs and RNNs may be seen in the fact that the hidden layer in LSTMs is the gated unit or cell. It has four layers, which work together to create the output and state of the cell. They both go on to the subsequent tier. LSTMs include three logistic sigmoid gates in addition to a Tanh layer, in contrast to RNNs, which only comprise a single Tanh-based neural network layer. Gates were used to limit the quantity of information that passed between cells. They decide which data should be eliminated from the previous cell and which should be added to the one after it. The result will normally vary from 0 to 1, with "0" standing for "Reject all" and "1" for "Include all."

Every LSTM cell has three inputs and two outputs, ht and Ct. At a certain point in time, t, where ht is the hidden state and Ct is the cell state or memory. It xt is the input or current information point. Two inputs are present in the first sigmoid layer: ht-1 and xt, where ht-1 is the state that is hidden in the cell before it. Since its output is a selection of the quantity of data from the last cell that should be included, it is also known by its name and the forget gate[9]. It will produce a number [0, 1] multiplied (pointwise) by the state of the cell before it.

3.2 LSTM Applications:

LSTM networks find useful applications in the following areas:

- Language modelling
- Machine translation
- Handwriting recognition
- Image captioning
- Image generation using attention models
- Question answering
- Video-to-text conversion
- Polymorphic music modelling
- Speech synthesis
- Protein secondary structure prediction

Cells and gates both play a role in memory modification and information retention. Three gates are present:

1. **Forget Gate:** The forget gate purges information that is no longer relevant in the cell state. The gate receives two inputs, x_t (input at the current time) and h_t-1 (prior cell output), which are multiplied with weight matrices before bias is added. The output of the activation function, which receives the outcome, is binary. If a cell state's output is 0, the piece of information is

lost, however if it is 1, the information is saved for use in the future.

2. **Input gate:** The input gate modifies the cell state by adding pertinent information. To start, the inputs h_t-1 and x_t are used to control the information using the sigmoid function and filter the values that need to be remembered similarly to the forget gate. Then, a vector containing every possible value between h_t-1 and x_t is produced using the tanh function, which produces an output ranging from -1 to +1. In order to extract the valuable information, the vector's values and the controlled values are finally multiplied.

3. **Output gate:** The task of extracting useful information from the current cell state to be presented as output is done by the output gate. First, a vector is generated by applying tanh function on the cell. Then, the information is regulated using the sigmoid function and filter by the values to be remembered using inputs *h_t-1* and *x_t*. At last, the values of the vector and the regulated values are multiplied to be sent as an output and input to the next cell.

3.3 LSTM Drawbacks[10]:

1. They gained popularity as a result of their ability to address the disappearance of gradients. However, they are unable to solve the issue. The problem is that moving data across cells is necessary for its processing. Furthermore, with the inclusion of new functions (like the forget gate) into the picture, the cell is becoming incredibly complicated.
2. They need a lot of time and money to train them and get them ready for practical use. Technically speaking, they need a lot of memory bandwidth because each cell has linear layers, which the system frequently cannot provide. Therefore, LSTMs become rather ineffective in terms of hardware.
3. Scientists working in data mining are looking for a system that can retain historical data for longer periods of time than LSTMs in light of the field's developing technologies. The inclination of humans to break up large amounts of information into smaller chunks to aid in memory served as the inspiration for the creation of such a model.
4. LSTMs operate like neural networks that feed forward and are influenced by different random weights. They choose light weights over heavy initialization.
5. Dropout can be difficult to implement, and LSTMs frequently overfit, making it difficult to address this issue. When building a network, dropout is a regularisation technique that makes sure inputs and recurrent connectivity with LSTM units are systematically exempted from weight updates and activation.

4. SIMULATION & RESULTS:

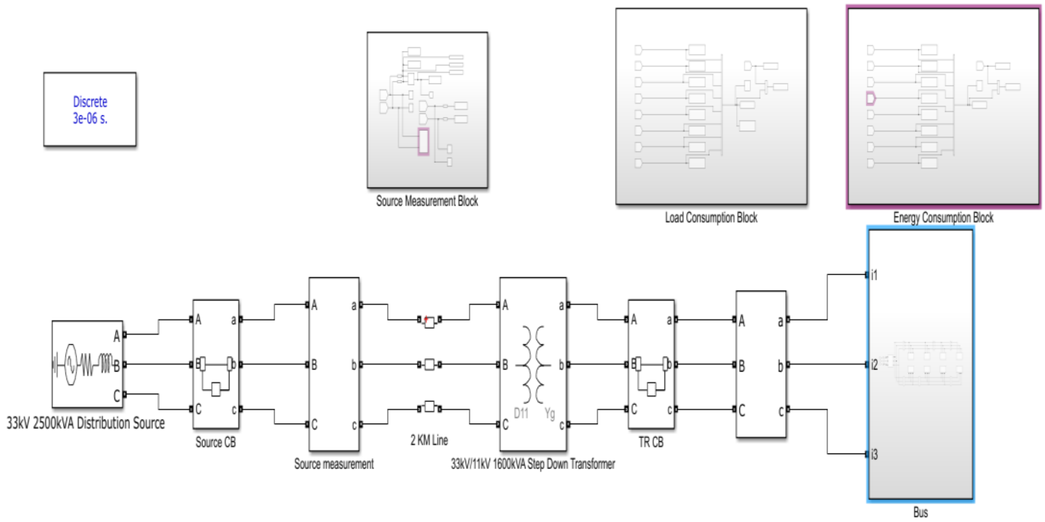

Figure 6: The main system with a distributive three phase source of 33kV

The figure above shows the 33kV distribution system that has the bus connected across it. It also has the source measurement block, along with the Load consumption block that is assumed to be at the utility side. The utility continuously monitors all the load data being transmitted from the meter that are present at the consumers premises and keeps sending the data to the utility at certain pre-decided intervals. Here, measurements have been taken using simple logical calculation using various Simulink mathematical block and data for voltage, current, power and energy have been taken into consideration and the data is sent to the MATLAB Workspace where all of the data is accumulated.

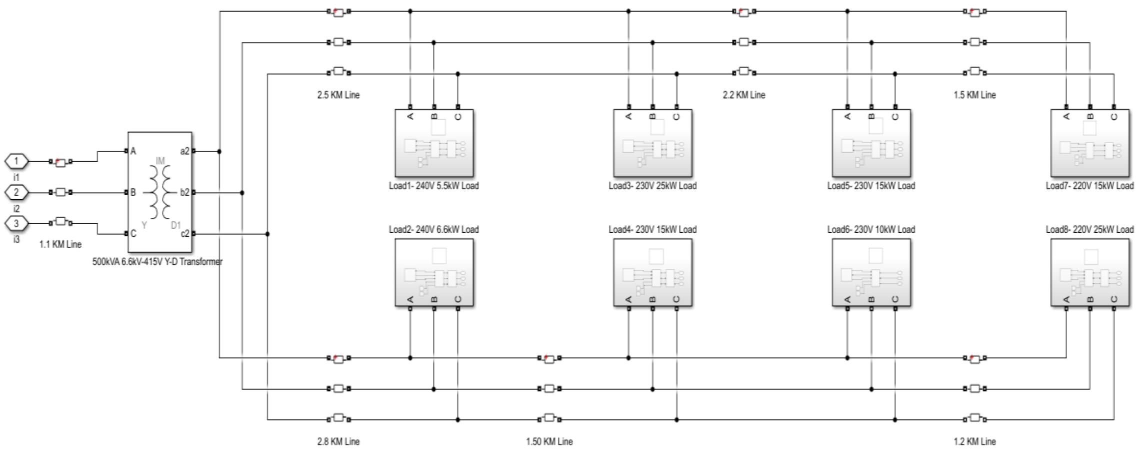

Figure 7: The Bus Subsystem

This system shows load subsystem and various loads that are connected across the grid. The parameters of every load are as labelled above and distribution line have also been added to show the distances between the loads as labelled.

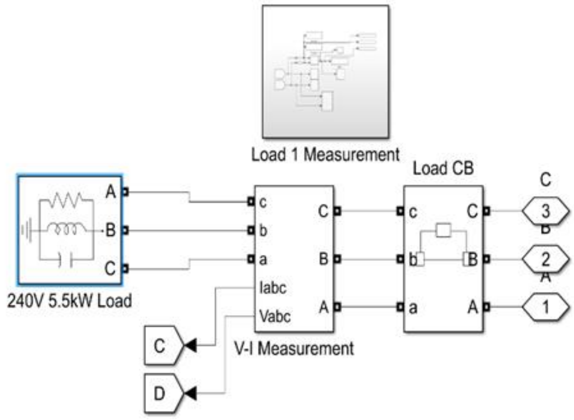

Figure 8: Load Subsystem

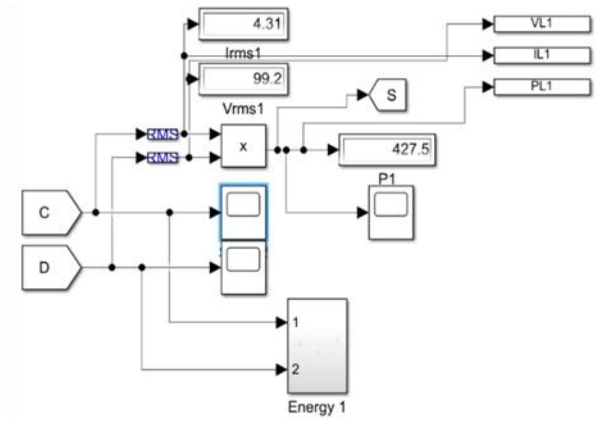

Figure 9: Load Consumption Subsystem

The load subsystem shows the loads connected to the grid and the measurement block acts as meter that calculates the various parameters such as voltage, current, power, and energy as shown below and sends the data to MATLAB workspace and to the load and energy calculation subsystem as mentioned earlier which acts as utility monitoring the loads.

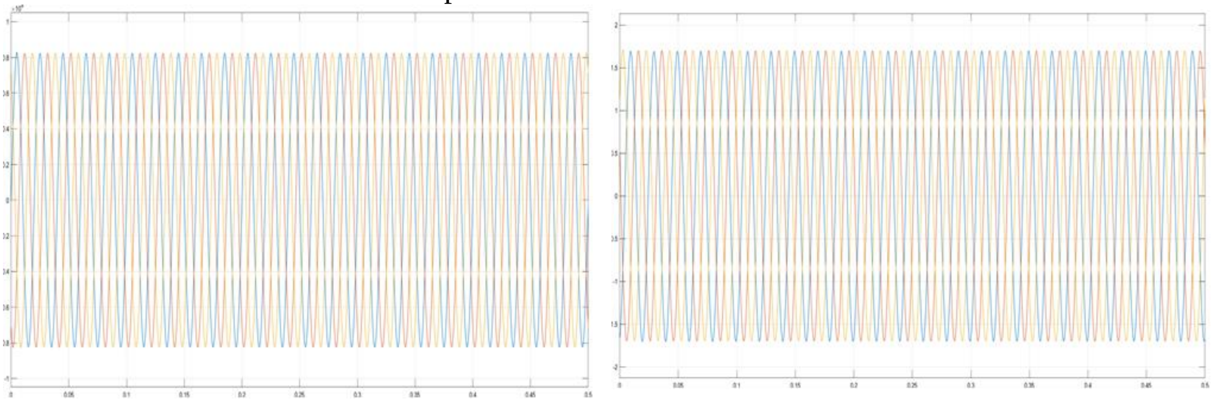

Figure 10: Current and Voltage Scope

The plots for voltage and current scope is as shown above. The plot for Mean Absolute Error for the input data is as shown below,

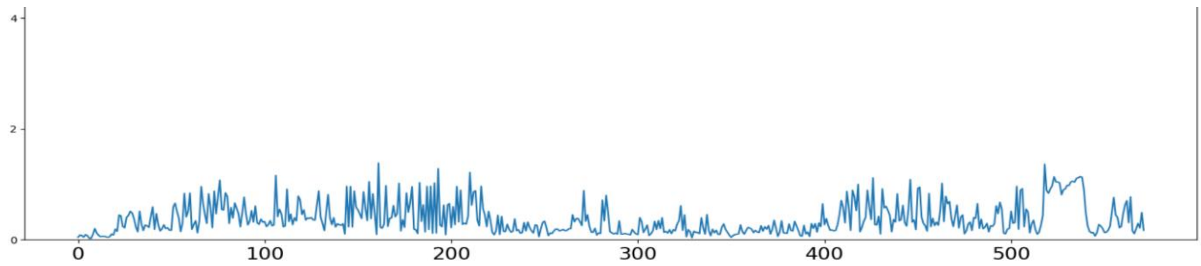

Figure 11: Mean Absolute Error

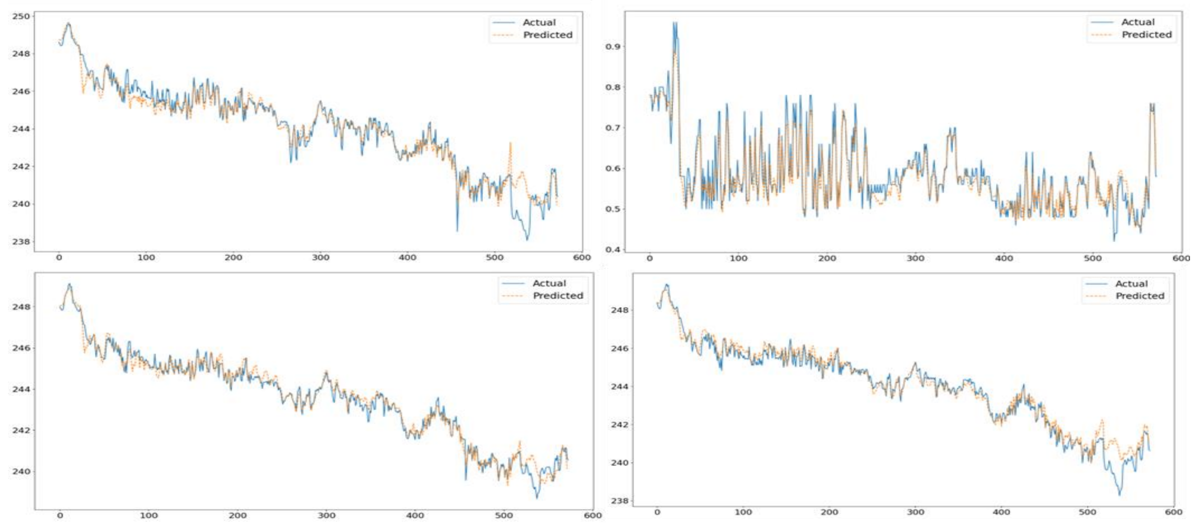

Figure 12: Voltage and Current Plots for various load

The above figure shows plots for voltage and current for various loads during the simulation time. The loads are expected to follow the predicted graph and is compared to the actual values. It is assumed that the parts where the actual and predicted data does not match, are the cycles where the electricity theft might have occurred.

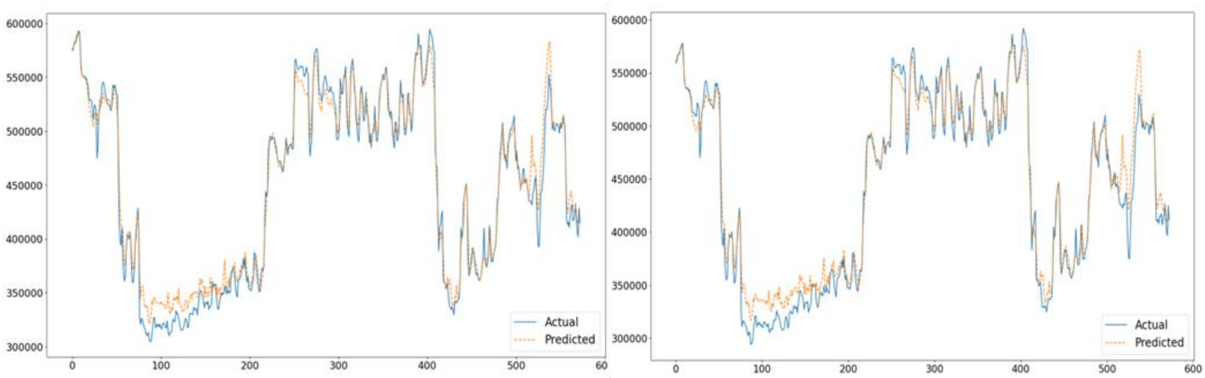

Figure 13: Active and Apparent Power Plots of the System

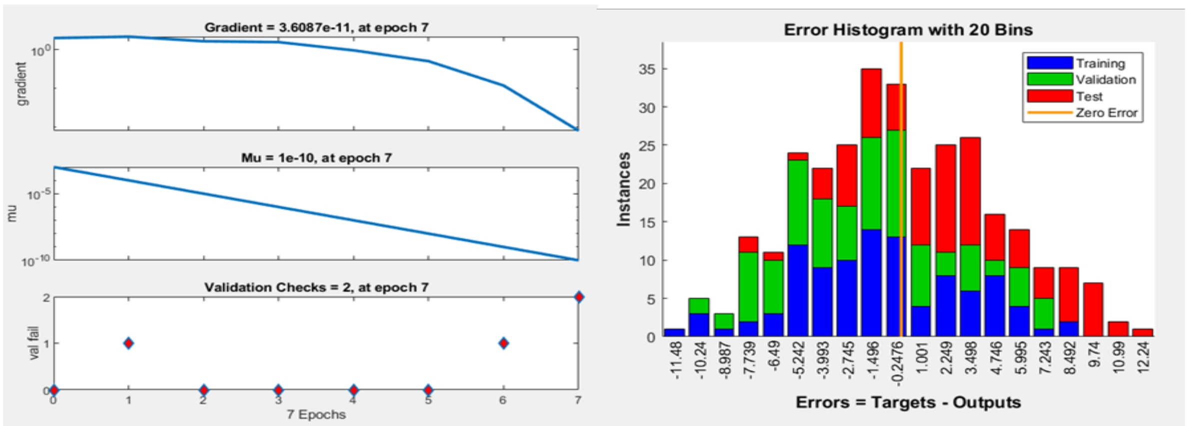

Figure 14: Neural Network Fitting Tool Training State and Error Histogram

The above figure shows the plot for training state at epoch 7 and error histogram with 20 bins.

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