Domestic and Commercial Load forecasting of LESCO using Machine Learning

SUPERIOR UNIVERSITY

MS ELECTRICAL ENGINEERING

BY

Hafiz Arslan Manzoor

Roll No: MSEE-F21-003

SESSION: 2021-2023

DEPARTMENT OF ELECTRICAL ENGINEERING

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SUPERVISOR **Dr. Manzoor Ellahi**

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Abstract

The LESCO is the largest power distribution company in Punjab, Pakistan and handle both domestic and commercial loads. The main problem with LESCO is its manual system to handle the load record which shows poor management with forced load shedding. In this thesis, the proposed model solves the load management problem in LESCO using load forecasting with the help of Machine Learning (ML) algorithm. The domestic and commercial load data will be collected from grid stations in real time scenario and then machine learning algorithm will be applied on real time data for Long Short-Term Memory (LSTM) forecasting. ANACONDA was used as a simulation platform. In the proposed model the electrical load data is trained through ML and optimal solutions can be achieved through training the specific data multiple times. Forecasting will be more sophisticated and effective because of its ability to use recent data for training and gives predictions for the next load. The best-suited ML algorithm is suggested for the proposed forecasting with supporting results. The examination of the accuracy and performance of the LSTM-based load forecasting model using acceptable criteria demonstrates its efficacy in gathering and forecasting complex load patterns in a LESCO context. The use of LSTM for load prediction meets the issues of LESCO energy systems which promotes energy management practices. To further increase the precision and efficacy of load forecasting models future research may concentrate on combining real-time data streams, sophisticated optimizations algorithms, and demand-side management tactics.

HAFIZ ARSLAN MANZOOR

Dated:

DEDICATION

I want to dedicate my thesis

To ALLAH the Almighty

&

To My Parents Teachers & Family

RESEARCH COMPLETION CERTIFICATE

The undersigned hereby certify that they have read and recommend the thesis entitled "**Domestic and Commercial Load forecasting of LESCO using Machine Learning**" by Hafiz Arslan Manzoor for the degree of Master of Science in Electrical Engineering.

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AUTHOR'S DECLARATION

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I would like to express my gratefulness to Almighty **ALLAH** and the Holy Prophet **MUHAMMAD P.B.U.H.** for giving me strength and helping me achieve my goal of life about which I just imagined.

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HAFIZ ARSLAN MANZOOR

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List of Abbreviation

LESCO	LAHORE ELECTRIC SUPPLY COMPANY
LF	Load Forecasting
ML	Machine Learning
ICT	Information and Communication Technology
DSM	Demand Side Management
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Square Error
ANN	Artificial Neural Network
MLR	Multi Linear Regression
STLF	Short Term Long Forecasting

CHAPTER 1

1.1 Introduction:

The history of electricity has seen several modifications and advancements since it first emerged during the time of the ancient Egyptians. As of right now, the Rankine cycle, a key component of power production with a poor efficiency nature is the largest source of pollution. However, there have been major advancements in the field of renewable energy in recent years. Information and communication technology (ICT) has enhanced the effectiveness of green energy and made it feasible to accurately monitor power a consumption and production at each node. The main grid may be used more effectively and at a reduced cost to service providers and customers because of ICT-enabled coordination between the main grid and the grid for renewable energy sources. The worldwide carbon production is dramatically decreased as a result [1], [2], [3]. According to statistical data, the need for electricity is growing every year, and practically every industry depends on it to do its job. Also keep in mind that research into alternate energy sources has started because fossil fuels will eventually become obsolete. Despite appearing to be promising energy sources, nuclear, solar, and wind power cannot currently provide the world's demand for electricity, either now or in the future. Numerous studies, including load forecasting, are being conducted to fulfill the necessary electricity demand throughout the year. It is an essential technique for accurately forecasting demand ahead of time. For various load kinds, there are many projections available. Forecasting demand for a brief period of a period of time such as a few days or hours is the first form of prediction. While the second form of forecast estimates desires from just a few weeks to a few months, the third kind of projects need from a few months to several years. To exploit these predictions, live for efficient energy management, this proposal tackles the fundamental concept of load forecasting utilizing Machine Learning algorithms in a power distribution company context. The traditional mechanisms of electric power dispatch have been upgraded to intelligent systems to consider the substantial progress in ICT [4]. These smart mechanisms are commonly known as smart grids, and they are implemented to compensate for limitations attributed to the traditional power systems with the incorporation of digital communication in the power dispatch networks. Demand-Side Management (DSM) is one of the important modern mechanisms designed for the Home Energy Management Systems (HEMS). In DSM, various incentives are offered to the consumers to encourage the change their power usage patterns to lower the power requirement and prevent the load peak. Efficient implementation of DSM programs requires precise estimation of conumer's load [5]. The forecasted demand, along with other factors measured using intelligent devices to optimize the electric power usage through decisions made in the real-time [6]. Nonetheless, the vagueness attributed with various load parameters, impacting the routine usage can hinder acquiring effective DSM process. This emphasizes the development of advanced models for the precise load prediction to avoid over and under estimation of the forecasted power demand [7]. The efficiency of the load prediction system is significant to provide the exact details of the power demand as any inaccuracy may result in power outages or unwanted increase in the power generation, resulting in an enhancement of power production cost.

The authors in reference [8], presented a technique for the energy optimization planning to improve the efficiency and profit amongst multi-home micro grids. The presented paper highlighted the significance of using micro grids instead of the traditional mechanisms that work only on efficient connectivity between the consumers and the power suppliers. This mechanism can also increase the profitability for both the consumers and suppliers. In reference [9], the authors present their work with the aim of lowering the cost of energy for the electricity consumers while maintaining the profits of the power producers. The authors concluded through their work that by using the presented hierarchical energy optimizing mechanism for multi-home energy hubs, both sides supplier and consumer can benefit.

Developing forecasting algorithms for power consumers depend on fitting according to the non-linear load patterns. The ever-increasing load demand also results in enhancement of datasets, and these large datasets required advanced techniques to perform the necessary forecasting calculations at much faster speed to assist the system in making real-time decisions. To handle the issue of continuously varying loads, data-driven techniques are more suitable as they work on identifying the nature of available data through historical patterns [10]. Long Short-Term Memory (LSTM) is such an approach that is finding widespread prominence in the field of resource estimation. But in the case of power demand estimation the fundamental LSTM may not be suitable due to some inherent limitations like parameter optimization and setting the layers. The modified LSTM presented by the authors, is used for the load estimation of certain regions to efficiently implement DSM. Besides, it can also be employed by the power network planners to achieve a precise estimation for future electricity consumption.

1.2 Problem Statement

In summer, force load shedding is done by LESCO because of sudden increase in load. The sudden increase in load is not predicted which causes unpredicted load shedding and increases burden on the system. In order to minimize the issues such a system is required that can predict the trend of load increase with the passing time and which timelines are more prone to sudden load increase. Such predictions can help the service providers like LESCO to plan beforehand that how to cater such issues. In this thesis develop a system which will predict about the load based upon the historical data. The ML techniques will be used to predict that load and the problem of sudden load on the system may be decreased. Load forecasting (LF) will be crucial to the power grid for now a days. In addition to the technological and financial difficulties that the LESCO is facing, LF also needs to provide more precise forecasts with the lowest MAPE. There are two distinct types of problems with the present LF model, and the proposed model is better than other models for the following reasons.

The fact that the feature selection technique has not been used for the analysis is the first issue with the current models. The forecasting techniques without using machine learning algorithms have issues with long calculation times, complicated data, repeating data, and the extraction of pertinent facts from a vast volume of data. The historical data of four seasons over a period of 5 years based on various inputs for LESCO have been included in suggested model, LSTM, while the redundant, irrelevant, and insignificant data have been eliminated without damaging the information. Comparatively to other current models that do not use the feature selection technique, our addition shortens the computing time and makes it less difficult.

The second difficulty is that several models that have been researched in the literature each have defects that can change depending on the circumstance. The goal is to increase the success rate by combining a time series forecasting method that uses the LSTM model with our suggested integration technique.

When various loads at various times are connected to the system, the load of each input varies. This study's system is built on inputs that have two distinct conditions: heavy instruments and low instruments. To achieve this, the suggested system's Root Mean Square Error (RMSE) is reduced by optimizing LF.

1.3 Objectives

This thesis has the following four objectives:

- Development of the Machine Learning Algorithm for Load Forecasting.
- Real time data acquisition
- Data analytics and effective data processing
- Optimize the LESCO data through ANN

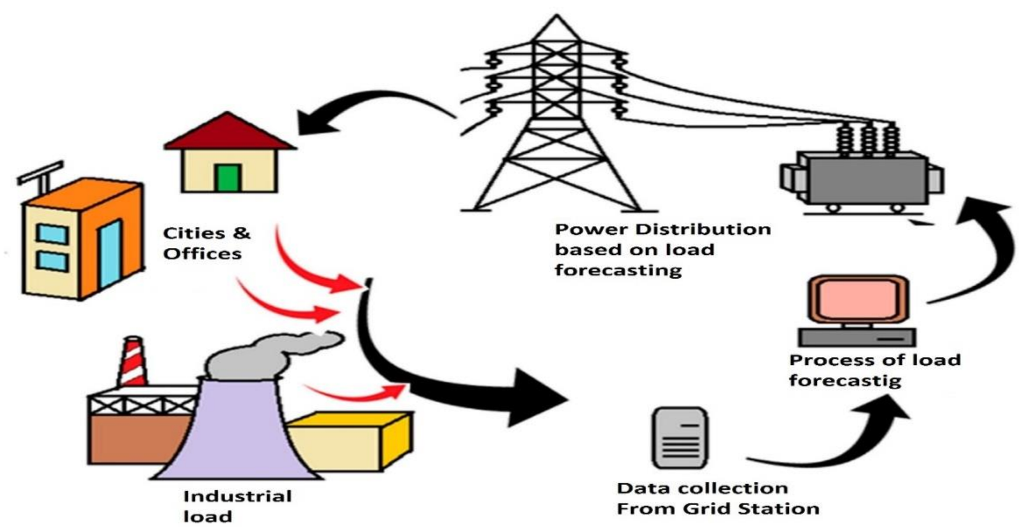

Figure 1.1**:** Load Forecasting

1.4 Project Methodology

The fundamental components of the LF methodology include the time series, suggested feature selection approach, and ANN method. In this step, the forecast was further optimized by lowering the root mean square error (RMSE). The area where data collection along with time-series model modelling is considered includes all methods in this regard. The integration approach doesn't consider twenty-year data containing four seasons, per-month data transformation, ANN, or choosing features as a final option. It concentrates on the best method of the pertinent week of each season. Additionally, we modified the RMSE computations to consider the integration method that we created as follows for each specific building.

- Collect the real time data from LESCO grids.
- Redundant, irrelevant, and insignificant data have been eliminated without damaging the information.
- Data analytics.
- Data processing through machine learning.
- Optimize the LESCO data.
- Results and analysis

1.5 Structure of the Dissertation

Earlier bibliometric studies are examined in Chapter 2 to look at trends in scientific research. Chapter 3 discusses the procedures for data collection. Chapter 4 covers the findings and the debate. The business concept is described in Chapter 5. The final chapter, chapter 6, offers recommendations for additional research and conclusions.

CHAPTER 2

LITERATURE REVIEW

2.1 Literature Study

The STLF didn't start until the latter part of the 1990s. One of the earliest approaches to forecasting that was taken into account was the Time Series Approach [7], which took the effect of temperature on loads into account. The system's non-linear nature is compromised by routinely altering the settings through external means because there was no online mechanism available at the time. Later, as AI developed, STLF started utilizing Artificial Neural Networks (ANN), which—unlike Regression models—create their own correlations based on inputs and outputs rather than requiring the linkages between parameters. When the ANN is fully trained, the operator provides actual value inputs for anticipated outcomes. The first STLF simulations constructed using a three-layer neural network were created by authors in [11] to forecast the coming hour, peak, and total day load. The fact that these models learn on their own, without human input, has increased the demand for this technology throughout time. One of several studies that enhanced this technique was one by authors in [12] worked to lessen prediction mistakes. An overview and assessment of the neural networks in STLF to soothe the worries of contemporary academics because the ANN was just starting to gain traction at the time [13]. All of the aforementioned offline models use regular and obvious data input. Furthermore, once the model was trained, its algorithm was unchangeable. Online STLF is made possible by improvements in communications technology and digital sensor development. From this point, the master unit receives the current data and stores it there for analysis and forecasting. Autoregressive models are used in online models. For instance, using climate predictions as inputs, Peder Bacher suggested an autoregressive framework with a 35% Root Mean Square Error [14]. Even though there has been a lot of improvement over the years, here are still a number of problems, including robustness and a lack of adequate sensors. IOT and ICT developments have improved the systems' dependability and accuracy. The optimal regression model for STLF is evaluated and proven in this study to be Multi Linear Regression (MLR), which June Tae Kim recommended in his thesis and highlighted is best suited for more accuracy [15]. A novel approach for online prediction that is based on IOT has been investigated in an area that many scholars as presented in [16].

For controlling and decreasing the workload and reducing power consumption, proposed the two stages deep dilation multi-kernel convolution network (DDMKC)-modified elephants herd optimization algorithm (MEHOA) model [17]. The suggested method utilized demand reaction (DR) price information to precisely estimate the subsequent pricing signal, allowing customers to make the best decisions and reduce suffering.

In [18], the authors suggested model's first stage mostly entailed preparing and normalizing the data. The CNN-ABLSTM model for calculating energy was also included in the AJODL-DSSEM model. Finally, using the AJO approach, the CNN-ABLSTM model's hyper parameters were adjusted. The IHEPC and ISO-NE datasets were used to assess the experimental dependability of the proposed AJODL-DSSEM model. The comparison study revealed the fact that the AJODL-DSSEM model produced better results than more modern approaches.

The authors in [19], created an hour-ahead DR method for HEMS in order to lower the user's electric bills and level of discomfort. To address the uncertainty surrounding future pricing, a price-stability forecasting approach based on ANN is offered. The optimum course of action to take for specific appliances is determined using multi-agent RL and forecasted pricing. According on simulation results, the proposed DR algorithm may regulate energy management and lower user utility expenses and dissatisfaction costs. Additionally, the DR approach in this study may significantly reduce the user's energy costs, as shown by the contrast of the two different scenarios' power prices.

The overall effect of AC on construction electricity demand is very significant, as discussed in [20]. Therefore, controlling its energy use is essential for DR programs. Numerous pieces of data that point to a rise in AC load have been investigated globally. Numerous big data analytical applications have also been investigated in the areas of power systems and load forecasting. In addition, an LMA-based ANN method for estimating residential AC load is presented in this study. Additionally, other evaluation markers have been researched [21]. The LMA-based ANN technique beats both the SCG-based ANN and the traditional multi linear regression method for estimating residential AC load, according to error formulations. It has been found that LMA-based ANNs have the fastest computation speeds for large input data sample numbers and increase error performance. Additionally, due to improved LMA-based ANN forecast accuracy, data on AC load is most precisely available for various periods on a daily, hourly, and monthly basis. In comparison with SCG-based ANN or traditional regression-based techniques, it can forecast appliance-level loads like AC more correctly [22].

Sequential and continuous time sequences correspond to a result value in forecasting techniques. The methods used to estimate the need for loads can be broadly categorized into two groups: extrapolation and correlation, depending on the sort of forecasting being done. Using time series algorithms, extrapolation forecasts future load demands based on historical and current demand. Econometric forecasting and the search for underlying factors that could affect load demand are the two techniques based on correlation [23]. While accurate load prediction includes underlying factors that could impact the demand for load, like temperature, weather, holidays, events, etc., econometric forecasting uses economic variables that affect the demand profile, such as price. Depending on how much time is involved, we can divide predicting into three categories: short-term predictions, short- or forecasts for the future, and long-term forecasts [24].

Numerous prediction methods have been examined. One of the most popular techniques among them involves foreseeing using artificial neural networks, or ANN [25]. Demand-side load forecasting can be carried out utilizing historical load data and further methods, including Support Vector Machine, Random Forest, Support Vector Machine Classifier, k-Nearest Neighbor, and logistical regression modeling. A communication infrastructure is also required for applications that are urgently required, such as smart meters, electrical grid status, and power plant status. The system's parts included base stations, networks of sensor communications nodes, and wireless, lightweight, portable devices that can forecast and assess power use [26].

A situation like this allows for the examination of many forms of network infrastructure. Wireless communication is one of these that is most frequently employed. In such a grid environment, wireless technologies are more advantageous when connecting over extended distances between power-producing facilities that have been separated by significant geographic distances. Additionally, most of the grid is constructed in outlying areas. The budget and upkeep costs rise when a wired system of communication is installed for these circumstances. Due to the considerable distance between Smart and micro-grids, the grids usually line up and out of sight, which creates a communication challenge. Long-distance transmission of electricity in space was the subject of recent research and analysis by Japan Aerospace Exploration, which also provided a chronology. This technology may help satellite and space stations that are in Earth orbit [27].

Additionally, a survey reveals that a variety of sources of clean energy supply electricity to microgrids. In some cases, household green energy resources like photovoltaic cells on rooftops may even help the grid meet its energy needs. The establishment of the electrical grid is now a certain prospect because of this circumstance. The most current simulation also implies that areas with regular passing traffic, such as roadside charging stations, may get grid electricity directly. It is commonly assumed that there are too few grid installations to allow communication over the air to be possible without high power antenna because the grids are typically placed far apart [28]. It is conceivable in this situation to link and expand the grid network on a pricey basis. If users or clients are traveling or in adjacent cities, they might not be informed of electricity usage or real-time information. The wired network facilities (Local Area Network or The Metropolitan Area Network) are the primary alternative solution to establish the network link between a smart meter and household devices via the Ethernet interface, but such a network frequently experiences high costs, signal attenuation, and cable errors, especially in situations of disaster or emergency. An effective wireless design that enables sparse grid networks that are dispersed geographically to interact may be the answer to this problem. By exploiting and connecting the social framework of the Grid, adjacent towns, and transportation modes like buses and other vehicles, we have developed an ecosystem for the network of grids based around the Internet of Drones Things (IoDT), helped by Delay Tolerant Networks [29]. According to this theory, information transfer between grids, clients, houses, and charging stations can be used to create a social grid design.

Demand-side management, which assists in controlling electricity use while prioritizing the needs of the consumer, is one of the fundamental elements of smart grids. It is far more important to comprehend the need for and consumption of energy in residential or non-residential structures. Reducing load utilization could have numerous financial and environmental benefits. As an alternative to expanding the electrical network, experts suggested load forecasting techniques since they can help control the demand for electricity and increase energy efficiency [30]. The goal of experts is to create some automated devices with excellent energy distribution capabilities. Monitoring and maintaining enhanced power distribution networks, and improving load forecasts, are essential responsibilities of smart grids. Creating secure networks and enhancing the efficiency of the power supply are required. They can be seen as ways to close the gap between supply and client usage because demand in the future can be predicted. However, a mistake could result in significant financial loss [31].

For example, in 1985, it was estimated that just a small increase in error in forecasting would cause a loss of over ten million pounds per year to the entire UK power system. Because of this, a lot of big businesses have prioritized accurate demand forecasting as well as load control, which has led to expenditures such as the 80% of grid improvements done by the Electricity Supply Organization of Australia. The terms STLF, MTLF, and LTLF, respectively, stand for short-, medium-, and long-term forecasting of load. Load methods for forecasting are categorized into three classes based on their functions for diverse uses [32]. The MTLF estimates the demand for the upcoming few months, the LTLF predicts the consumption of load for the upcoming year, and the STLF predicts the on hourly basis load for the upcoming week. The forecast for every one of these tactics is influenced by numerous factors. The success of STLF methods indicates how important a part they play in energy management. They are regarded as a crucial component of systems for energy management due to their function of offering adequate oversight for electrical equipment. Electrical equipment may see an instant impact from an STLF issue [33]. Several factors, among others, have an impact on the STLF:

- As some patterns, such as daily patterns, exist within a set of data, time is the most crucial factor for STLF.
- The weather, which includes the temperature and humidity.
- The demand for electricity might alter significantly during the holidays.

However, this article concentrates on duration as a factor that impacts the use of electricity and can help with accurate estimations. Timeseries data can be used in conjunction with other methods to perform precise short-term forecasting. Models based on deep learning, time-series models, as well as statistical regression models, are a few of these techniques. Along with the previously mentioned factors, the dimension of the residence, the age of appliances and machinery, and international problems like epidemics can all affect the load estimate for short- and long-term predictions. Nevertheless, most techniques have the same features despite a few slight changes. Time series can be used to visualize data sets regarding load usage. A later section will describe specific time-series features including Trend, Seasonality, and Noise. Due to the numerous challenges associated with working with time-series information, investigators utilized Artificial Neural Networks (ANN), which have an architecture resembling that of the human brain [34]. They used previous information for the predicted variable and the outside temperature to develop and test an electrical load forecasting system. A one-hour prediction for the near future and a one-week estimates for the long term make up the modified time frames. The amount of electricity that will be consumed during a particular week will be predicted using the energy load forecasting. To achieve this, we will employ a comparison statistic known as accumulated error for a week (CEPW), that is derived by dividing the total quantity of energy spent during the analyzed week by the sum of residuals. The average absolute percentage error (MAPE) and the value of the coefficient of Variability of Root-mean-square Error (CV-RMSD) are the final two criteria for assessing forecasting models [35].

Using many data points that correspond to the same period over the corresponding days, the quantity of energy used is estimated as a total for a given period. It is vital to note that the relative consumption at each point in time is more significant in this case since we are more interested in the consumption pattern than the actual quantity of power used. Afterward, the total consumption for the day is determined based on the climate, precipitation, amount of sunlight, and wind speed. Meteorological data is used to input future variables and calculate total consumption when a prediction for a certain day is needed. The days of the week are then used to divide up this total consumption [36].

With an average prediction error of 12%, this approach of energy forecasting has generally proven reliable. The second method argues against the idea that every single day of the week is special and unique. For instance, one week Wednesday can behave like Monday. The first day of the month in January will also be distinct compared to the Monday of February. The creation of models has so been given priority each day of the workweek. There are three parts to this strategy. How to select a certain model, how to create a distinctive model, along with how to anticipate actual usage [37].

The duration of this interval differs between utilities. The forecasting of short-term loads is the main emphasis of this work. In this paper, a precise load forecasting system based on artificial neural networks is provided. It is applied to many historical data sets to show how accurate the suggested approach is, and the outcomes are contrasted with those from publicly available sources [38].

The terms proportional error (RE), median percentage error in absolute terms (MAPE), mean relative scaled errors (MASE), root-mean-square error (RMSE), MSE, which is MBE, as well as MAPE were mentioned in the review. The research investigations that were reviewed are listed with their reference numbers and relevant performance measures [39].

The authors propose an RNN model for load forecasting with periods of 24 hours, 48 hours, 7, and 30 days. They developed an ANN model for district-level forecasting load based on three different approaches. They concentrated on perceptual DNN for extraction of features and showed that using deep learning's unsupervised learning capabilities significantly improved prediction accuracy [40]. For load forecasting, the inventors of devised a recurring inception CNN. To determine home load, a deep RNN with a pooled foundation was examined in. Provided a description of the LSTM-based multi-input multi-output windows technique [41].

Large volumes of information are now available for the real-time analysis of power demand and load thanks to the development of smart grids. Data processing switches from batches to stream mode. In settings with continuously arriving data, traditional forecasting techniques that build static models from a training set are becoming useless. To overcome the limitations of stream processing and generate accurate and timely forecasts, continuous or online processing techniques are needed [42]. A collection of sequential information called an "open-ended stream" is one that can only be read once (or twice) in each amount of time or memory. The non-stationary distributions that provide the data cause it to frequently change quickly. A continuous sample is discarded or kept after processing. Online approaches, as compared to incremental methods, process each item sequentially and lack any data in the memory, especially in the form of a sliding window. The ability to adjust to changes that naturally take place in knowledge over time—often referred to as idea drift, non-stationarity, or a changing environment—is a critical component of stream mining methodologies [43].

Following and/or predicting appliance-by-appliance consumption, according to another studies, will help consumers alter their habit of using less energy. Building occupancy has also been calculated using predictions and estimates of electricity usage. These techniques are used to regulate active equipment, such as lighting or HVAC (Heating, Ventilation, and Air-Conditioning) systems [44]. For instance, researchers looked at reliable occupancy identification using measurements of power use as well as showed that they could predict values accurately to around 80% of the actual value. The authors in [45] recommended integrating the setting up of PIR sensors with an analysis of the electricity consumption of 5 residences over a period of eight months to determine if a building is occupied. The supporting vector machine (SVM), the k-nearest-neighbor algorithm (KNN), threshold holding (TH), and the hidden Markov model (HMM) are among the classifiers used in their proposed methodology. This method made it possible to estimate the building occupancy with an accuracy of 80% [46].

In [47] non-intrusive technique for creating a smart office was presented within a similar framework and is based on energy usage analysis. By combining worker behaviors with different equipment qualities, this method is made better. To avoid annoying circumstances like turning off the lighting and air conditioning, it considers the standby state (a situation in which the employee leaves the office for a brief amount of time). For establishing an office occupancy profile, they used KNN and SVM clustering techniques.

An artificial neural network called a recurrent neural network (RNN) is made to handle input in succession, such as the kind used for load estimation or language translation [48]. RNNs' mental state (memory) as well as constant connections to the identical neurons from the previous time step make them particularly well-suited for mimicking temporal behavior. RNNs are normally trained through backpropagation throughout time; nevertheless, this may produce the problem of vanishing gradients, which causes the NN to disregard older data, especially for long runs. This issue was resolved using LSTM networks because of their enhanced information storage and prediction precision.

Table 2.1**:** Comparison of Latest Research

Sr. No	References	Key contribution	Techniques	Limitations
1.	[19]	Data-driven load forecasting of air conditioners using an ANN based on the Levenberg-Marquardt algorithm for demand response	(LMA)-based Artificial Neural Network (ANN)	Quite complicated because no strategy was utilized to remove unnecessary data
2.	[24]	Using data from smart meters, online adaptable recurrent neural networks can forecast loads.	Adaptive Recurrent Neural Network	The buffering module's goal is to locate and temporarily hold batches where the model failed to deliver.
3.	[34]	Online adaptive recurrent neural networks can forecast loads using input from smart meters.	Parallel Deep LSTM-CNN and ML Techniques	The findings may vary depending on the weather. The load one was predicted using the previous consumption as a parameter.
4.	[37]	Machine learning-based short- and long-term electric load forecasting	Machine Learning	Complexity of the used models' computations

5.	[38]	Understanding error calculation techniques in the context of energy forecasting	A Novel related to Errors	Underestimating the situation and failing to make sufficient preparations. using multiple dimensions to forecast performance.
6.	[48]	Smart meter data and deep learning for load forecasting: Online Adaptive Recurrent Neural Network	Deep Learning	The buffering module's goal is to locate batches for which the model could not effectively perform and temporarily store them.
7	Proposed Model	AI-based load management of LESCO	LSTM (Long Short-Term Memory)	

2.2 Conclusion

Both forecasting load and language translation make use of recurrent neuronal networks (RNNs), a category of neural network designed for sequential input. This was the general resolution of the chapter. RNNs are highly suited for simulating temporal behavior because of their internal configuration (memory) as well as ongoing connections to the equivalent neurons in the preceding time step. RNNs are usually taught through time; however, this method might result in a problem called vanishing gradients, which causes the NN to forget prior knowledge, especially for lengthy sequences. This problem has been solved by the development of LSTM networks, which are able to retain knowledge for a greater amount of time and produce forecasts that are more precise.

CHAPTER 3

DATA COLLECTION AND METHODOLOGY

3.1 Introduction:

In this thesis, proposed a model for LESCO LF using LSTM-based choice of features approach and recommended integration strategy. The bulk of publications in the scientific literature has used AI methods to boost MAPE accuracy rates, including SVM, ANFIS, evolution computing, trained systems, fuzzy logic, LF-related problems, etc. Due to their sluggish processing times and complexity from the amount of data they use, these solutions are limited. Removal of redundant and irrelevant information without affecting the most important data is hence an essential step in LF.

Table 3.1: Symbolic representations of LSTM.

Symbols	**Description**
h_t	Hidden Gate
o_t	Output Gate
x_t	Input Vector
i_t	Input Gate
σ_g	Sigmoid Function
$tanh$	Hyperbolic Tangent Function
$C_t^{\sim}$	Input Modulation Gate

3.2 Proposed Framework

Based on the suggested LF methodologies and structure, this section includes:

3.2.1 Networks required background

As indicated in Section 2, the focus of this thesis is on neural network techniques, namely machine learning techniques. The most important family of neural networks, recurrent neural networks, are covered in this chapter. Finally, the variables that are essential to them are presented.

3.2.1.1 Recurrent Neural Networks

For networks whose directed graph does not contain cycles, the typical neural network methodology known as feed-forward is used. Recurrent neural networks (RNN), on the other hand, are networks containing cycles in their graph. Even while the RNN seems to have a completely unique structure, if the cycle is unrolled, it may be regarded as a collection of identical networks that are all copies of one another and deliver messages to their respective successors. Figure 3 depicts an unrolled RNN diagram, where A denotes the repeating section of the NN and x_t is an input that yields the output h_t.

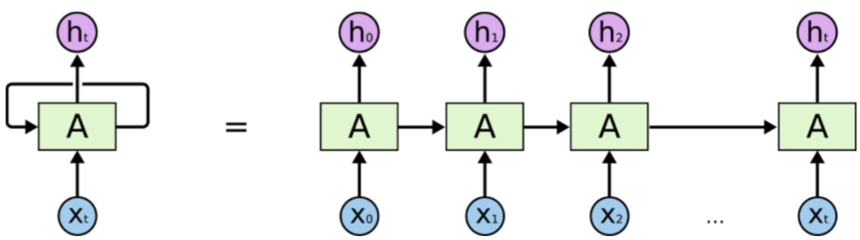

Figure 3.1: Unrolled Recurrent Neural Network

In contrast to what people think, feed-forward neural networks begin each activity from the beginning. The results of many sequence and list-related problems can be improved by making use of the prior states. By allowing information to be transferred from one network phase to the next, RNN accomplishes information persistence between instances. These models include specific application examples that utilize temporal series issues, and the recurring feedback in these instances takes advantage of the temporal relationship between the data.

3.2.1.2 Long Short-Term Memory Neural Networks

Although simple RNNs can theoretically handle "long-term dependencies," it appears that in actuality they are unable to suggest Long Short-Term Memory Neural Networks (LSTM), a type of RNN that can memorize information for extended periods of time, as a solution to this issue. The LSTM differs from a standard RNN in its repeating module construction. For instance, in typical RNNs, this repeating module will consist of simply one hyperbolic tangent layer. As shown in Figure 3.2, LSTMs feature four neural network layers as opposed to just one. The syntax in Figure 3.2 is meant to make it simpler to understand the schemas.

The main distinctiveness of the LSTMs is the two recurrent connections in the repeating module. The LSTMs use the output of the prior prediction in addition to the typical recurrent connection present in RNNs. The storage of cumulative data is made possible by this cell state, which allows for a small number of linear interactions to change the data throughout each execution. To understand the internal behavior of the LSTM, there are four steps:

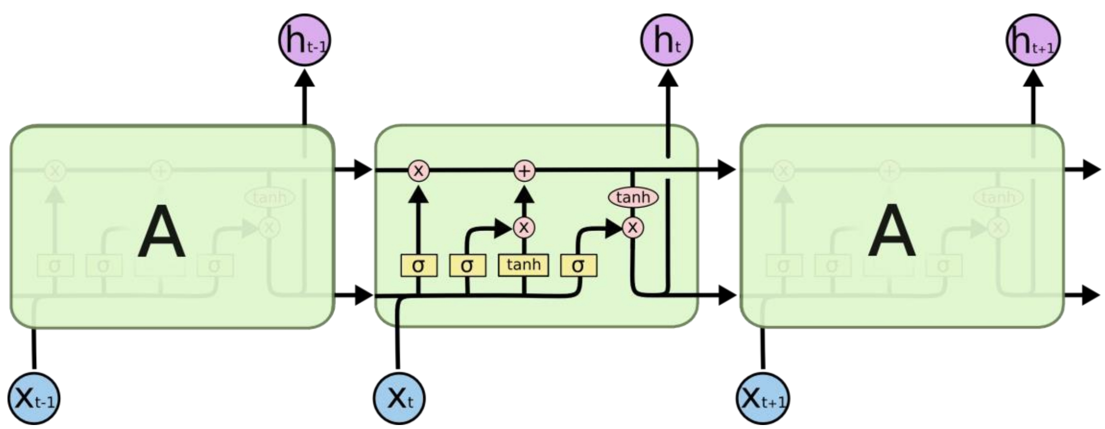

Figure 3.2: Long Short-Term Memory Layers

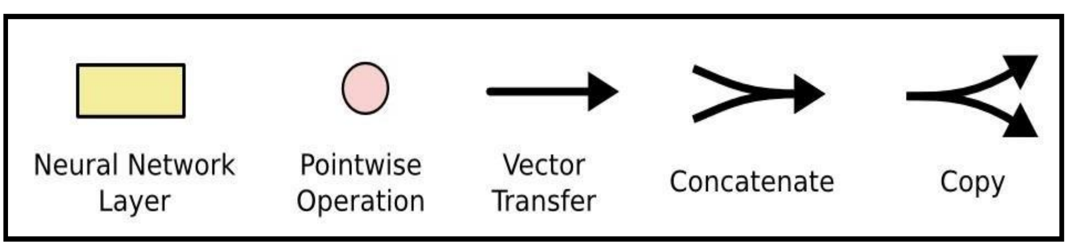

Figure 3.3: Notations of LSTM Layers

LSTMs are nothing more than a stack of neural networks with linear layers composed of weights and biases, just like any other traditional neural network. The weights are updated continuously using backpropagation. Here, we go over a few crucial terms specific to LSTM:

3.2.1.3 Cell

Each LSTM network element is referred to as a "cell" in this sentence. There have three input and two outputs for each cell.

x_t—current input at time step t

h_{t-1}—previous hidden state

C_{t-1}—previous cell state

h_t—the update of hidden state is used for prediction of output

C_t—current cell state.

3.2.1.4 Gates:

LSTM makes use of a unique theory to manage the memorization process. The LSTM's gates, sometimes referred to as the gating mechanism, multiply analogue memory elements point-wise with a sigmoid activation function and store the outputs in the 0 to 1 range to create probabilistic scores. Gates regulate the flow of information into and out of LSTM cells.

In essence, an LSTM cell consists of 4 distinct parts.

Forget gate

Input gate

Output gate

Cell state

The proposed model has four phases, each of which includes an LSTM. The training procedure is as follows:

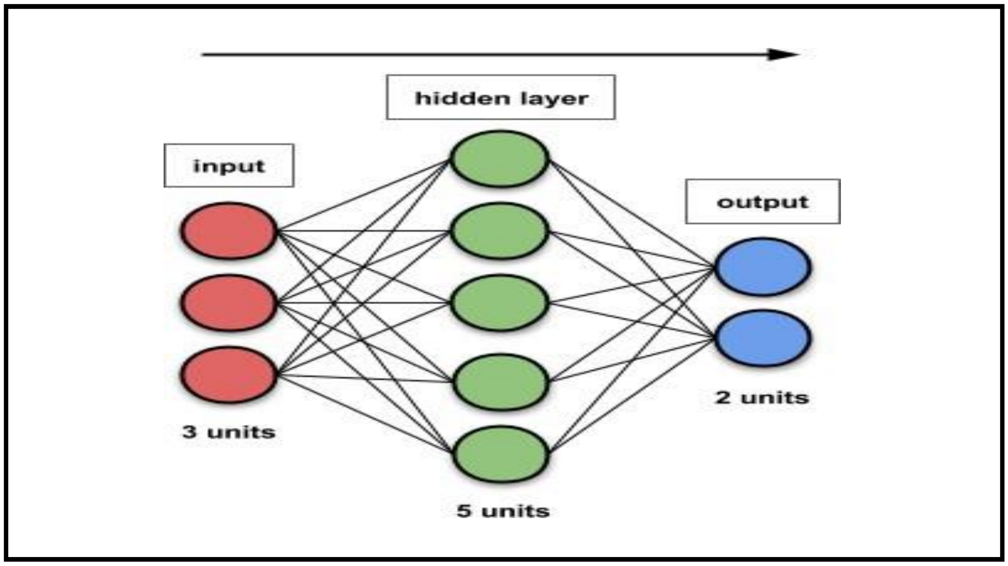

Figure 3.4: Different Layers of LSTM

3.2.1.5 Forget Gate

The data to be deleted from the cell state is chosen by the forget gate, the first part of an LSTM (Figure 3.5). Using a sigmoid layer that combines the input (x_t) and the hidden state (h_t), Equation 3.1 states that for each number in the cell state C_(t-1) it outputs a number between 0 (destroy it altogether) and 1 (keep it completely).

$$f_t = \sigma\left(W_f . [h_{t-1}, x_t] + b_f\right) \quad \textbf{(3.1)}$$

3.2.1.6 Input Gate

The second one, referred to as an input gate (Figure 3.6), chooses what data needs to be included in the cell state. It is made up of two components. A sigmoid layer first uses h_{t-1} and x_t to produce a

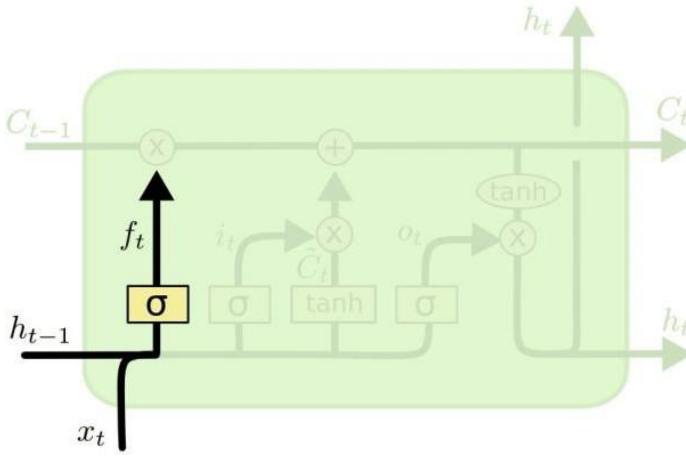

Figure 3.5: First Step of LSTM

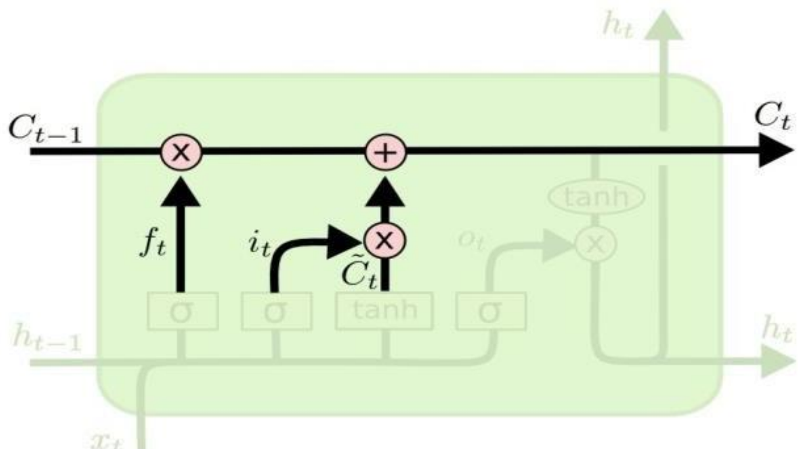

Figure 3.6: Second Step of LSTM

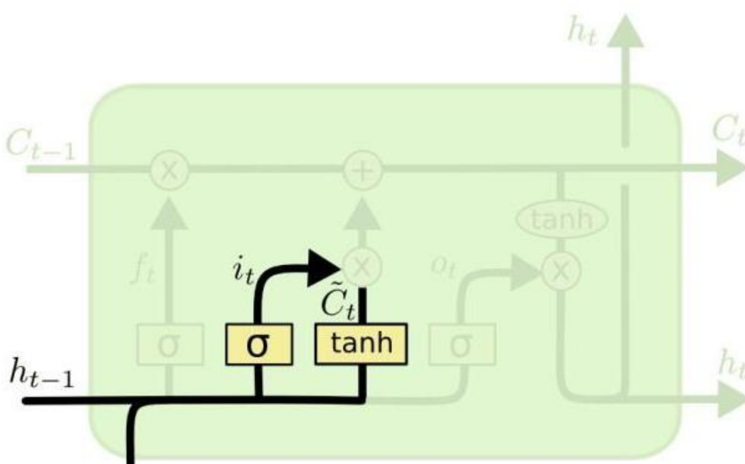

Figure 3.7: Third Step of LSTM

The vector $i_t$contains values between 0 and 1. These numbers indicate the percentage of the state values that will be modified. Then, using a tanh layer, h_{t-1} and x_t are combined to produce a vector of fresh candidate values $C_{t-1}^{\sim}$ (Equation 3.3).

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \quad \textbf{(3.2)}$$

$$C^{\sim}{}_t = tanh(W_c . [h_{t-1}, x_t] + b_c) \quad \textbf{(3.3)}$$

3.2.1.7 Cell State

An essential element that allows a system with LSTM (Long Short-Term Memory) system to store and update data across lengthy sequences is the cell state. It serves as a unit of memory, storing pertinent data and passing it on selectively to subsequent time steps so that the network can identify long-term dependencies. They fail to see that input and output gates keep the state of the cell stable by controlling the flow of data and ensuring effective information storage and usage. The cell state can be updated using the outcomes of the previous processes (Figure 3.7). The new cell state forgets the data chosen in the first step after multiplying the previous state by f_t,. As a result, the new state is updated with the new information from step two. The modified values i_t and the new candidates' values $C_t^{\sim}$ are multiplied to get this new information. Equation 3.4 contains all of the operations.

$$C_t = f_t * C_{t-1} + i_t * C_t^{\sim} \quad \textbf{(3.4)}$$

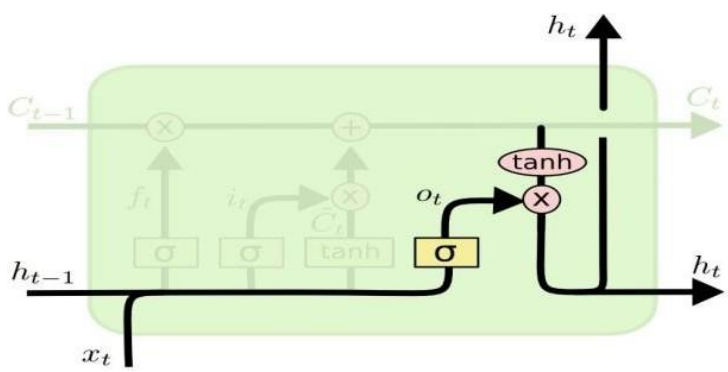

Figure 3.8: Fourth Step of LSTM

3.2.1.8 Output Gate

The output is generated as the last step (Figure 3.8), and it is a filtering description of the modified cell state. Based on h_(t-1) and x_t, a sigmoid layer first decides which elements of the cell state are crucial for the output (Equation 3.5). After that, a tan h is used to multiply the sigmoid layer results such that the cell state is translated into values between 0 and 1 (Equation 3.6).

$$O_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad \textbf{(3.5)}$$

$$h_t = O_t * \tanh(C_t) \quad \textbf{(3.6)}$$

There are other somewhat different LSTM schemas even though the one presented is one of the most used. Some of them go by their own names and are regarded in different ways because of their literary effect.

3.2.2 Proposed Integration Strategy

The LF methodology's fundamental components include time series, the suggested feature selection approach, and the ANN method. In this step, the forecast is further optimized by lowering RMSE. The area where data collecting along with time series model modeling are considered includes all methods in this regard. The integration approach doesn't consider twenty-year data containing four seasons, per-month data transformation, ANN, or choosing features as a final option; instead, it concentrates on the best method of the pertinent week of each season. Additionally, we modified the RMSE computations to consider the integration method that we created as fellows for each specific building.

Like any AI models, LSTM networks have flaws, and several variables, including the caliber of the input information, the selected hyper parameters and the network's size, can influence how effectively they function. A further challenge when developing LSTM networks is the potential for overfitting, which can significantly reduce accuracy.

In general, LSTM networks have been demonstrated to be an extremely potent and effective tool for a range of machine learning applications, particularly for natural language processing. Even if there are some issues that still need to be resolved, continuous research is anticipated to further improve the precision and effectiveness of these models.

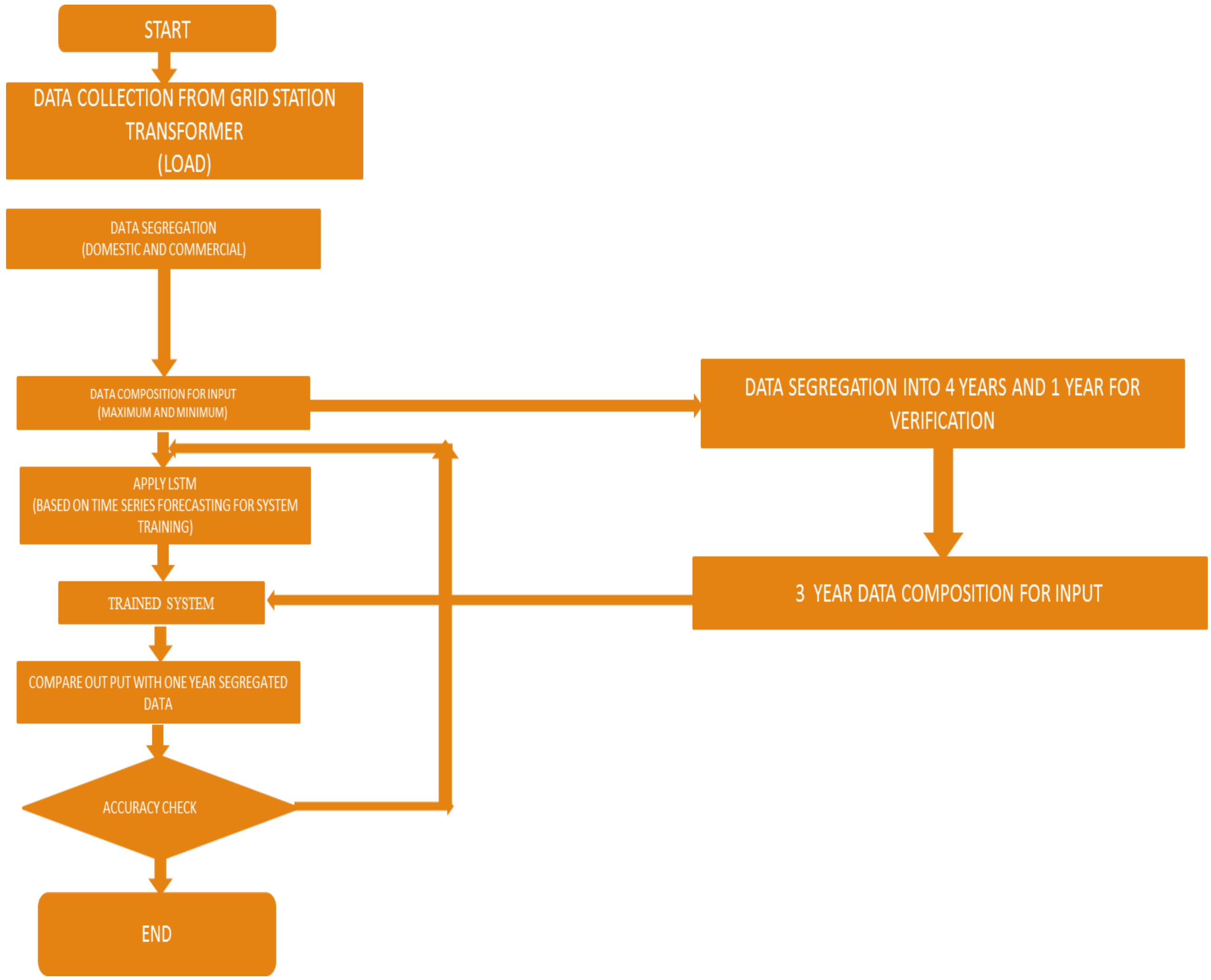

Figure 3.9: Sequence of Flow Chart of Simulation

Table 3.2 provides a more thorough description of the algorithm, which is validated using a 5-year LF artificial neural network. This integration's goal is to identify which data points are falser. Once the root average square error for each set of data has been determined, a workable solution should be developed. The more exact data should then be sent to the hardware. The simulation outcomes show that the suggested five-stage LSTM model, which incorporates current data as the input for the error-correcting function, has an acceptable root mean square error (RMSE) of less than one.

Table 3.2: Sequence of Simulations

Proposed Algorithm	
Step 1:	Set the hidden state and cell state to 0.
Step 2:	According to the input sequence, at each time step t: Calculate the signal to the gate using the present input vectors and the previous hidden state i_t. Calculate the forget gate using the present input vector and the previous hidden state f_t. Calculate the candidate memory cell vector using the current input vector and the previous concealed state. C_t. Update the current memory cell vector using the input gate i_t, the forget gate f_t, and the prospective memory cell vector C_t.
Step 3:	Calculate the output gate using the current input vector and the previous hidden state o_t. Apply the output gate o_t to the current memory cell vector $C_t$using a hyperbolic tangent activation function to determine the current hidden state h_t.
Step 4:	As the output, give the hidden state sequence $h_1, h_2, h_3 \dots \dots \dots . . h_t$.
Step 5:	Plot the Figures of LSTM Prediction
Step 6:	Plot the Figures of Future Values

In summary, the LSTM cell receives an input vector and the previously hidden state at each time step, and then modifies the memory cell and concealed state based on the input, forget, and outputs gates. The hidden state functions as a short-term memory that selectively accesses information from the memory cell, while the memory cell serves as a long-term store for pertinent data.

Evaluation of the LSTM for Load model Measuring the model's precision in forecasting a LESCO Data's LF based on input features like power involves forecasting prediction.

The effectiveness of the LSTM model can be evaluated using a variety of measures, including MAE, MSE, RMSE, R-squared, accuracy, and F1 score. The evaluation metrics to be utilized are determined by the specific situation and the type of data being used. The equation for RMSE are [23-25]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{n}\left(C_n - \hat{C}_n\right)^2} \quad \textbf{(3.7)}$$

When N is the total amount of cycles, C_n is the predicted capacity, and C_n is the ground truth capacity.

We divided the data from the Smart Cities dataset into testing, confirmation, and training datasets to assess the utility of the LSTM model as a load prediction tool. The desired variables and input attributes are used in a training dataset to train the LSTM model. The LSTM model's hyperparameters are adjusted using the validation dataset, and the model's training effectiveness is evaluated. The training LSTM model's final performance is assessed using the testing dataset.

Preparing the data is the initial stage in assessing an LSTM model. In order to achieve this, the data must be cleansed, divided into sets for training and testing, and arranged so that the LSTM algorithm can use it. To help the model better identify trends in the data, the data should be standardized.

The LSTM model must then be trained. The model's predictions and the actual output can be more closely matched by giving it training data and altering the neural network's parameters. Depending on the amount of information and the level of complexity in the model, training may take quite a while.

We utilize the test data to predict the information from the load after training the LSTM model, and we then compare the values that were predicted with the actual values. The effectiveness of the LSTM model is then assessed using a variety of indicators, including RMSE.A successful LSTM model for data prediction should have low RMSE values and high R-squared and accuracy values. If the LSTM model's performance is unsatisfactory, we can change its hyperparameters or test out several LSTM architectures to make it perform better. The overall Model is depicted as follows, with examples of the various LESCO Data inputs:

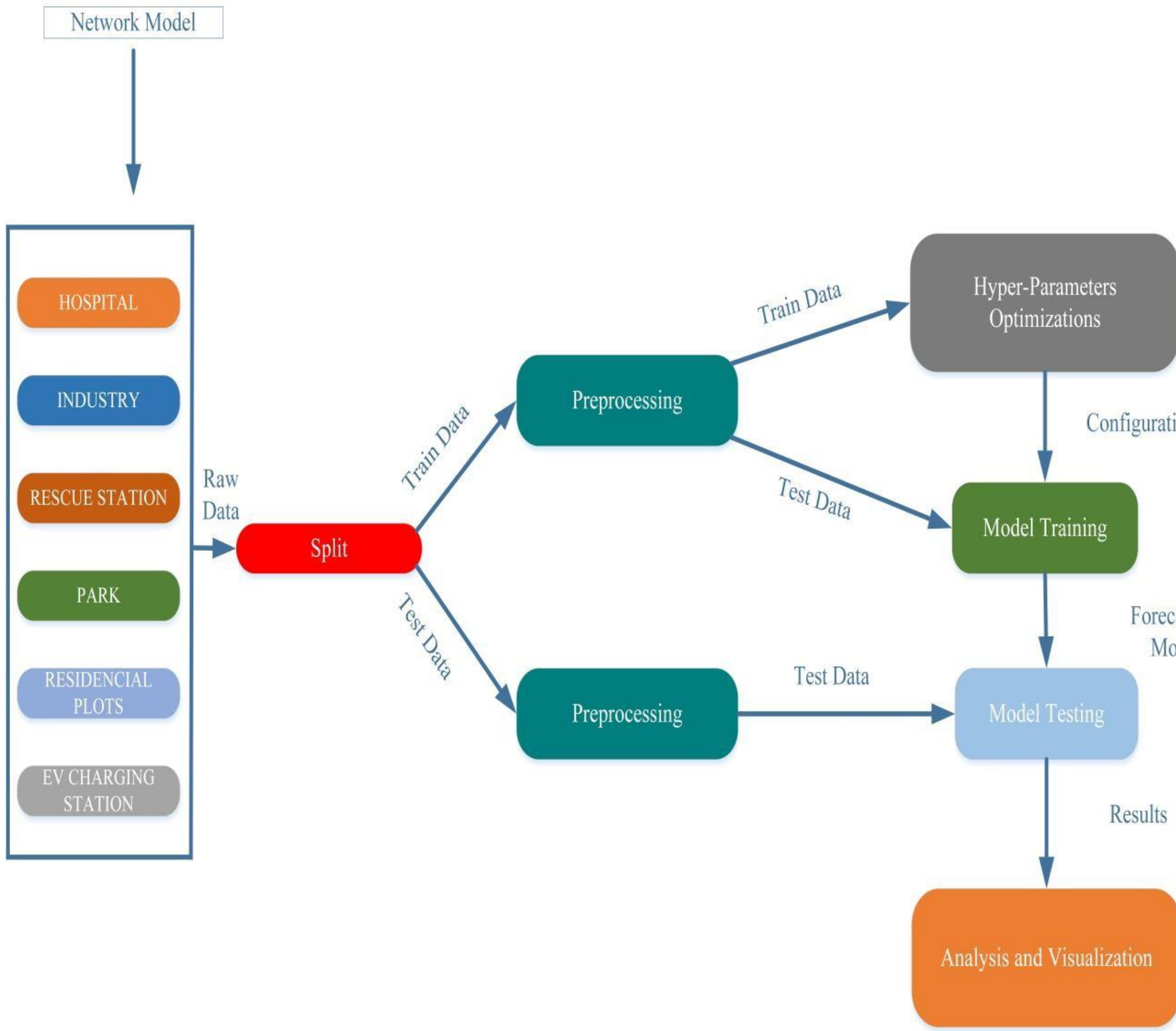

Figure 3.10: Data Flow Between Different Parts of the Developed Project

An essential part of evaluating an LSTM model is choosing the loss function. The difference between the anticipated and actual output of the model is computed using loss functions. Three types of loss functions that can be used to LSTM models include cross-entropy loss, mean squared error, and mean absolute error. Between expected and actual output, MSE calculates the average squared difference, whereas MAE calculates the average absolute difference. Our model operates in this manner, after which we can preprocess our data. At the conclusion, we receive the various behavior visualizations provided by the LSTM. Figure 3.13 depicts the overall procedure.

3.3 Mathematical Modeling of Proposed Model

Mathematically, each LSTM layer is a collection of interconnected cells that perform various operations involving input, output, and memory states. Here's a simplified mathematical representation of an LSTM cell:

Given:

Xt is the input at time step t.

ht is the hidden state at time step t.

Ct is the cell state at time step t.

ft , it , ot are the forget, input, and output gates, respectively.

W, U, b are weights and bias terms for the gates and transformations.

sigmoid is the sigmoid activation function

tanh is the hyperbolic tangent activation function

$$f_t = \sigma(W_f * [h_{t-1}, X_t] + b_f) \quad \textbf{(3.8)}$$

$$i_t = \sigma(W_i * [h_{t-1}, X_t] + b_i) \quad \textbf{(3.9)}$$

$$C'_t = \tanh(W_c * [h_{t-1}, X_t] + b_c) \quad \textbf{(3.10)}$$

$$C_t = f_t * C_{t-1} + i_t * C'_t \quad \textbf{(3.11)}$$

$$O_t = \sigma(W_o * [h_{t-1}, X_t] + b_o) \quad \textbf{(3.12)}$$

$$h_t = O_t * \tanh(C_t) \quad \textbf{(3.13)}$$

Where:

W are the weights for the gates.

B are the bias.

h_{t-1}, X_t represents the concatenation of the previous hidden state. The epoch size is 1000 and batch size is 10.

3.4 Data Collection and Analysis

In which various load data are gathered to show how differently the load in a LESCO Data operates in order to validate short-term load forecasts. The quantity of load that is monitored and sent alongside the system varies depending on the day. Detailed data has been included in the appendix section of the thesis. First, we take 21 Years data in which the 16.5 years data should be trained and the remaining should be tested data.

CHAPTER 4

Result Analysis

4.1 Introduction

In which the different load data is collected to demonstrate the difference of LESCO load is operating in way to check the short-term load forecasting. The different day have the different load amount on which the data is monitor and send next to the system. The different figures and data graphs are given below.

Table 4.1**:** Load Forecasting Data of LESO Starting from 2002

Sr No	Date	Residential Plot(W)	Industry(W)
0	01/01/2002	5715	62452.32
1	02/01/2002	5641	6245.43
2	03/01/2002	5113	5211.41
3	04/01/2002	5258	3236.12
4	05/01/2002	5456	3778.47
5	06/01/2002	5651	3897.7

Now first we discuss the data of Residential Plots as shown Figures 4.1,4.2 and 4.3 also discuss its Yearly Consumption Data, LSTM Predicted Data, and Forecasted Data.

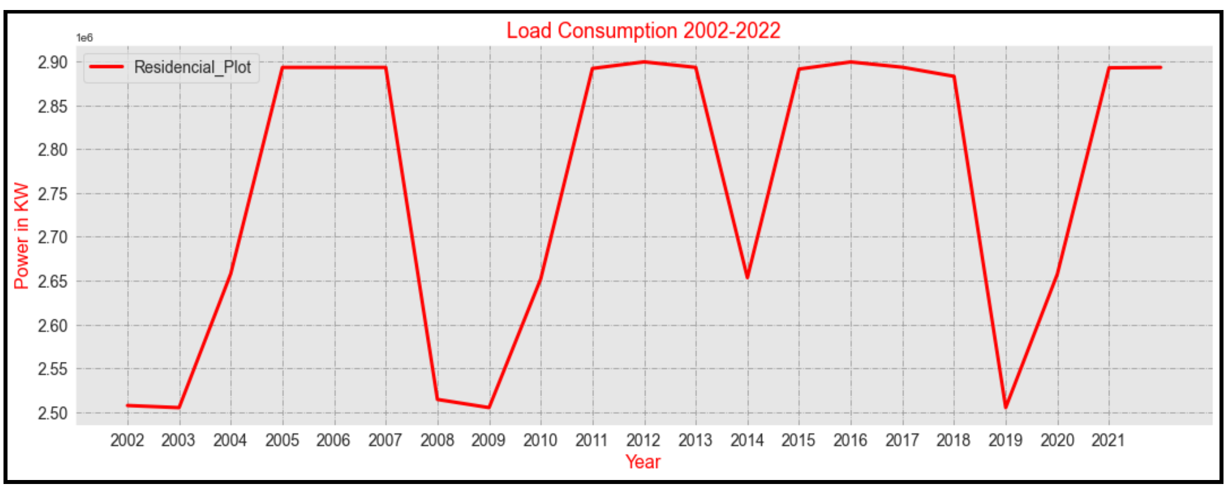

Figure 11: Yearly Consumption Data of Residential Plots

First, we take 21 Years data in which the 16.5 years data should be trained and the remaining should be tested data. Figure 4.2 depicts that the prediction should be based on 5.5 years for the next 10 Years. The overlapping shows the predicted data.

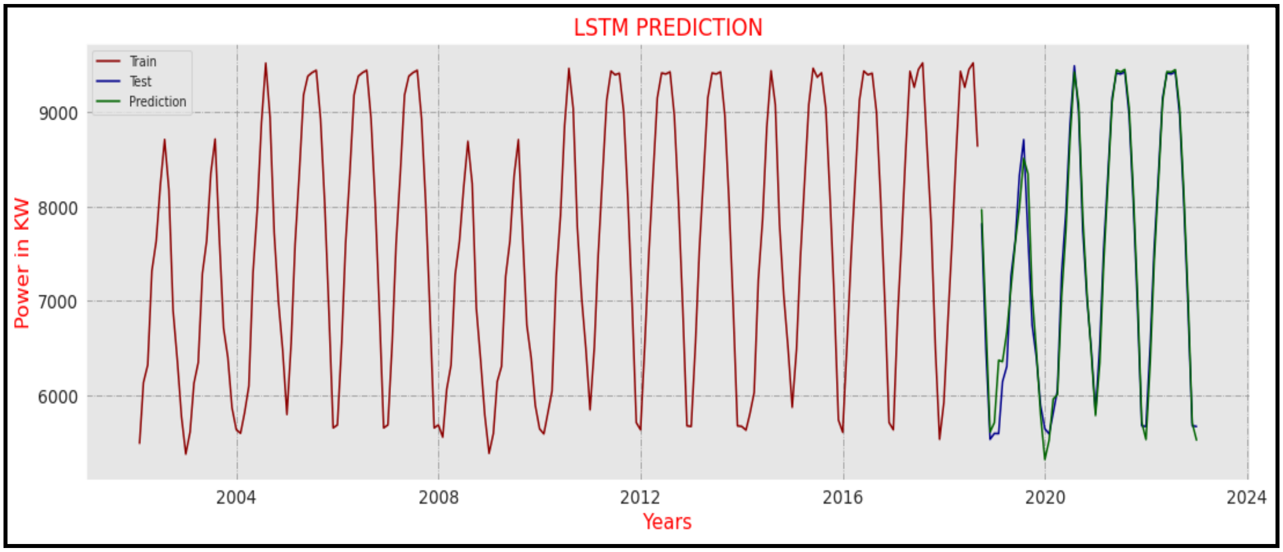

Figure 12: LSTM Predicted Data

Figure 4.3 shows the forecasted values of the 10 Years the dotted represents the Future Values and the simple line shows the Original Data. This is how an LSTM predicts the data,

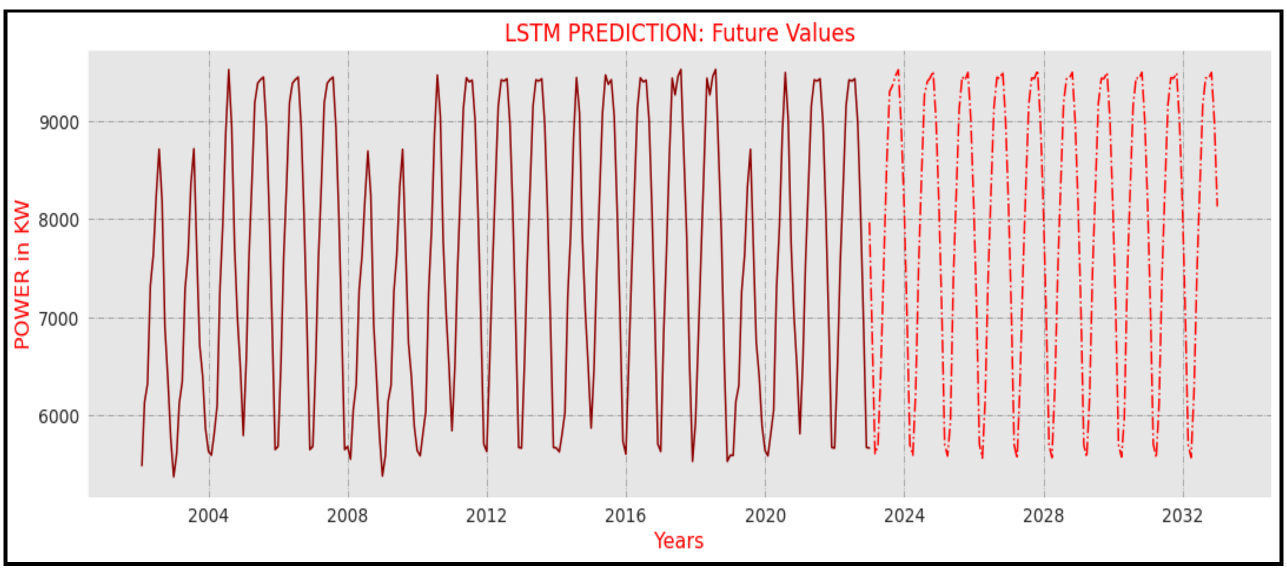

Figure 13: Original Data Vs Forecasted Data

Now we discuss the data Industry as shown in Figures 4.4, 4.5 and 4.6 also discuss its Yearly Consumption Data, LSTM Predicted Data, and Forecasted Data.

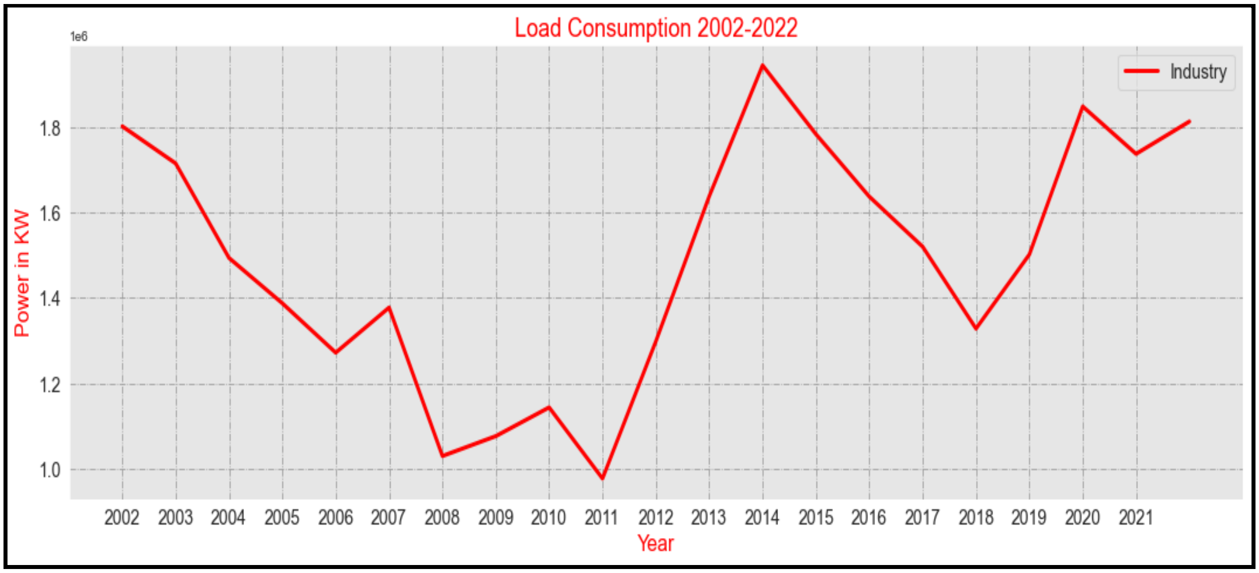

Figure 14: Yearly Consumption Data of Industry

First, we take 21 Years data in which the 16.5 years data should be trained and the remaining should be tested data. Figure 4.5 depicts that the prediction should be based on the 5.5 years for the next 10 Years. The overlapping shows the predicted data.

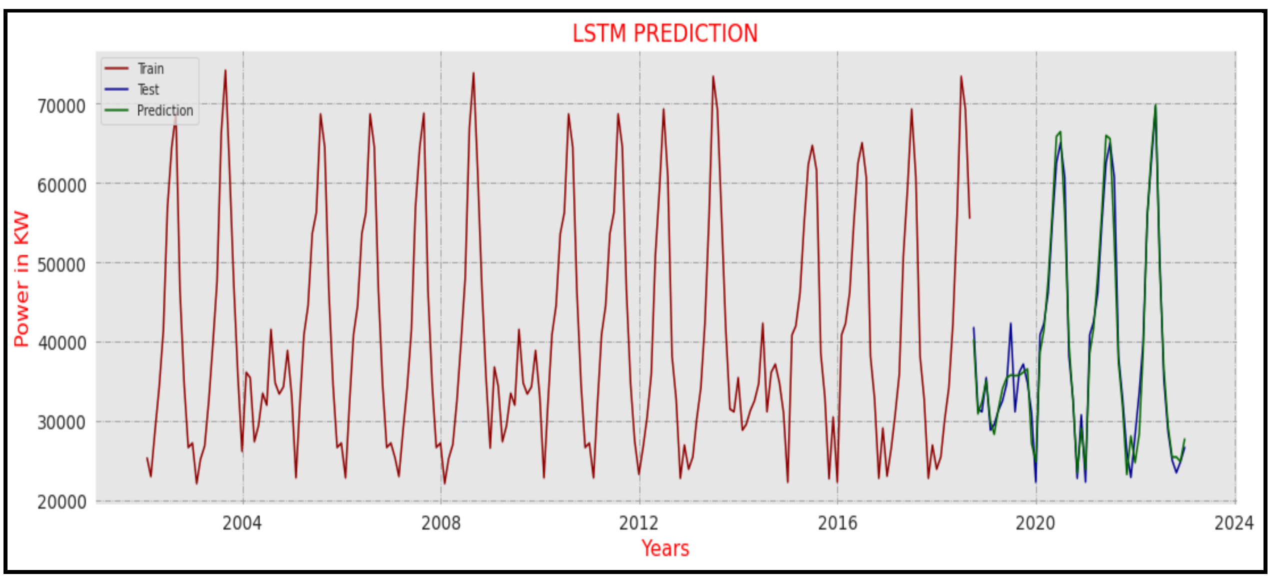

Figure 15: LSTM Predicted Data

Figure 4.6 shows the forecasted values of the 10 Years the dotted represents the Future Values and the simple line shows the Original Data. This is how an LSTM predicts the Data.

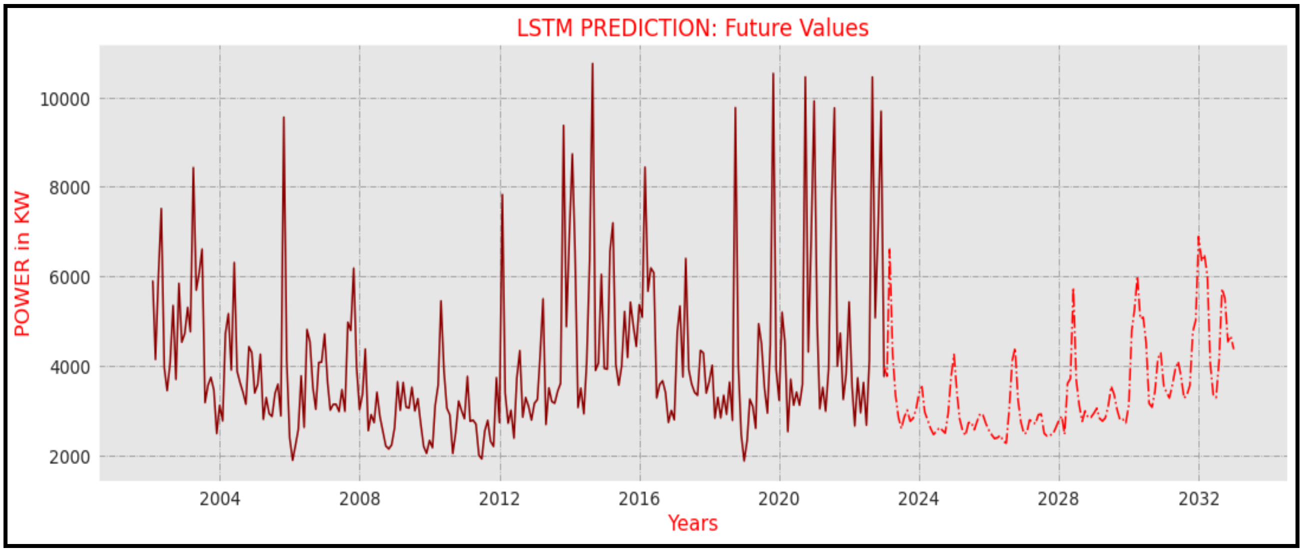

Figure 16: Original Data Vs Forecasted Data

The table shows the accuracy for the prediction of LESCO Data with Root Mean Square Error (RMSE) and loss in the Model.

Table 4.2: RMSE, Loss and Accuracy of Inputs

Sr No	Inputs	Root Mean Square Error (RMSE)	Loss	Accuracy (%)
0	**Residential Plots**	0.040939193257074055	0.0001	74
1	**Industry**	0.09736663127160096	0.0014	77

Forecasting the load of a LESCO Data is a critical task as it helps in efficient planning and utilization of resources. With the increasing population and the adoption of new technologies, the load on a city's power grid can fluctuate significantly. A LESCO Data's power system should be able to handle this variation in demand while maintaining reliability and stability. To forecast the load, data from various sources such as weather patterns, population growth, industry and commercial development, and energy consumption trends need to be analyzed. Machine learning models and algorithms can be applied to this data to predict the load for different timescales, from minutes to months. With accurate load forecasting, LESCO Data can optimize its power distribution and management systems, reduce energy costs, and enhance the overall efficiency of the power grid. It is an essential aspect of building a sustainable and LESCO Data that can provide a high quality of life to its residents.

4.2 Limitations

The proposed model has following limitations,

- Like any AI model, LSTM networks have flaws, and several variables, including
    - the Caliber of the input information,
    - selected hyperparameters, and
    - network size, can influence their effectiveness.
- A further challenge when developing LSTM networks is the potential for overfitting, which can significantly reduce accuracy.
- Although some issues still need to be resolved, continuous research is anticipated to further improve the precision and effectiveness of these models.

CHAPTER 5

Conclusion and Future Work

5.1 Conclusion

There is an AI-based energy management system for LESCO is presented in this thesis, with a particular emphasis on load forecasting. The outcomes show how well LSTM performs in precisely forecasting energy loads in the setting of LESCO.

The importance of load forecasting in the context of LESCO energy management was the first thing we looked at. Accurate load forecasting is crucial for cost reduction and the optimization of energy generation, distribution, and consumption. It is usually the case that traditional forecasting methodologies fall short of accurately capturing the complex and dynamic nature of energy loads LESCO. As a result, we made use of the LSTM deep learning algorithm, which is renowned for its capacity to recognize temporal correlations and patterns in sequential data.

We saw encouraging results in load forecasting through the use and assessment of the LSTM model. The LSTM model successfully learned the historical load patterns and produced precise forecasts for upcoming load requirements. The algorithm showed enhanced accuracy compared to traditional forecasting methods by including elements including weather data, time of day, and historical load statistics. The values for the RMSE for residential and industrial loads are 0.040939193257074055 and 0.09736663127160096 respectively.

5.2 Future Work

There are several opportunities for further research and development, even though this study shows a strong AI-based energy management system using LSTM for load forecasting:

5.3 Integration of real-time data

By combining real-time data sources, such as weather updates, traffic patterns, and data on energy usage from smart meters, load forecasting models can become more accurate and responsive. A more thorough picture of the dynamics of energy demand in a LESCO Data can be obtained by combining data from numerous IoT (Internet of Things) devices and sensors.

5.4 Hybrid models

By exploring the potential for hybrid models that integrate LSTM with different machine learning approaches like ARIMA (Autoregressive Integrated Moving Average), SVM (Support Vector Machines), or ensemble methods, the accuracy of load forecasting may be improved. To capture diverse features of load patterns, hybrid models can make use of the advantages of several techniques.

5.5 Optimization strategies

LESCO Data's energy management system can benefit considerably by investigating optimization options to reduce energy expenditures and maximize energy efficiency based on load estimates. This may require developing algorithms that maximize energy generation, storage, and distribution while taking demand response programs and the incorporation of renewable energy sources into account, depending on the load projections.

5.6 Demand-side management

By looking into demand-side management tactics and financial incentives to support energy efficiency and load shifting, demand for energy and supply in a LESCO Data can be balanced. Utilizing demand-side management strategies that take load forecasting into account can lead to more efficient use of power sources and reduced peak demand.

5.7 Scalability and scalability considerations

It is critical to think about scalability and resource allocation for AI-based energy management systems as smart cities continue to grow and expand. To ensure the scalability and sustainability of such systems, it will be crucial to create effective algorithms and architectures that can manage massive amounts of data processing and analysis.

In conclusion, the use of AI, in particular LSTM, for load forecasting in the context of smart cities demonstrates promising outcomes in the improvement of energy management. The creation of GUI software improves the accessibility and usability of load forecasting models even more. Future research is needed in a number of areas, including the incorporation of real-time data, hybrid model exploration, energy strategy optimization, demand-side management promotion, and scaling issues.

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APPENDIX

Table A-1: KWH (Units) April 2018

KWH READING T-1								KWH READING T-2							
Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF	M.F		TOTAL UNITS	Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF.	M.F		TOTAL UNITS
1	INCOMING T-1	87032240	83060165	3972075	01	____	3972075	1	INCOMING T-2	382790	81924	300866	01	____	300866
2	DEFENCE ROAD	51129724	49443542	1686182	01	____	1686182	2	JUBILEE TOWN-1	15044	0	15044	01	____	15044
3	BUBTIAN CHOWK	20552049	19604335	947714	01	____	947714	3	JUBILEE TOWN-2	0	0	0	01	____	0
4	MONOO TEXTILE	10869783	9831011	1038772	01	____	1038772	4	JUBILEE TOWN-3	167872	0	167872	01	____	167872
5	SHAMAS BIN IKRAM	7111201	6597325	513876	0.5	____	256938	5	JUBILEE TOWN-4	104074	0	104074	01	____	104074
6								6							
7								7							
8															
9	AUXILIARY	106569	103371	3198	1	____	3198								

T-1			T-2		
Received Units	3972075		Received Units	300866	
Sent Out Units	3932804		Sent Out Units	286990	
Difference	39271		Difference	13876	
% Age	0.99		% Age	4.61	

Table A-2: Maximum Load (Ampere) April 2018

T-1												
1		INCOMING T-1	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 75 = 675	465	15:00	25-04-2018	396
2	112701	DEFENCE ROAD	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	250	11:00	04-04-2018	212
3	112703	BUBTIAN CHOWK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	130	20:00	01-04-2018	110
4	112702	MONOO TEXTILE	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	110	20:00	09-04-2018	93
5	112704	SHAMAS BIN IKRAM	SCHNEIDER	FICO	200/400/5	200/5	3 x 500MCM (single core)	3 x 115 = 345	40	17:00	01-04-2018	34
T-2												
1		INCOMING T-2	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 95 = 855	45	17:00	14-04-2018	29
2		JUBILEE TOWN-1	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 110 = 330	5	01:00	27-04-2018	5
3		JUBILEE TOWN-2	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	ON	ON	ON	ON
4		JUBILEE TOWN-3	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	40	20:00	09-04-2018	25
5		JUBILEE TOWN-4	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	20	17:00	14-04-2018	14

Table A-3: KWH (Units) May 2018

KWH READING T-1								KWH READING T-2							
Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF	M.F		TOTAL UNITS	Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF.	M.F		TOTAL UNITS
1	INCOMING T-1	91436492	87032240	4404252	01	_____	4404252	1	INCOMING T-2	877774	382790	494984	01	_____	494984
2	DEFENCE ROAD	53068700	51129724	1938976	01	_____	1938976	2	JUBILEE TOWN-1 MOHLANWAL	94092	15044	79048	01	_____	79048
3	BUBTIAN CHOWK	21859350	20552049	1307301	01	_____	1307301	3	JUBILEE TOWN-2 AB	0	0	0	01	_____	0
4	MONOO TEXTILE	11736714	10869783	866931	01	_____	866931	4	JUBILEE TOWN-3	343026	167872	175154	01	_____	175154
5	SHAMAS BIN IKRAM	7624844	7111201	513643	0.5	_____	256821.5	5	JUBILEE TOWN-4	313809	104074	209735	01	_____	209735
6								6							
7								7							
8															
9	AUXILIARY	111401	106569	4832	1	_____	4832								

T-1			T-2		
Received Units	4404252		Received Units	494984	
Sent Out Units	4374862		Sent Out Units	463937	
Difference	29391		Difference	31047	
% Age	0.67		% Age	6.27	

Table A-4: Maximum Load (Ampere) May 2018

T-1												
1		INCOMING T-1	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 75 = 675	530	10:00	23-05-2018	453
2	112701	DEFENCE ROAD	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	260	11:00	24-05-2018	226
3	112703	BUBTIAN CHOWK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	150	20:00	16-05-2018	131
4	112702	MONOO TEXTILE	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	120	10:00	23-05-2018	102
5	112704	SHAMAS BIN IKRAM	SCHNEIDER	FICO	200/400/5	200/5	3 x 500MCM (single core)	3 x 115 = 345	40	10:00	23-05-2018	31
T-2												
1		INCOMING T-2	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 95 = 855	60	21:00	16-05-218	46
2		JUBILEE TOWN-1	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 110 = 330	10	01:00	01-05-2018	9
3		JUBILEE TOWN-2	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	ON	ON	ON	ON
4		JUBILEE TOWN-3	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	25	21:00	16-05-2018	19
5		JUBILEE TOWN-4	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	25	22:00	11-05-2018	21

Table A-5: KWH (Units) June 2018

KWH READING T-1								KWH READING T-2							
Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF	M.F		TOTAL UNITS	Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF.	M.F		TOTAL UNITS
1	INCOMING T-1	95412873	91436492	3976381	01	_____	3976381	1	INCOMING T-2	1414672	877774	536898	01	_____	536898
2	DEFENCE ROAD	54713120	53068700	1644420	01	_____	1644420	2	(A&B) BLOCK	179701	94092	85609	01	_____	85609
3	BUBTIAN CHOWK	23209786	21859350	1350436	01	_____	1350436	3	MOHALANWAL SCHEME	0	0	0	01	_____	0
4	MONOO TEXTILE	12599754	11736714	863040	01	_____	863040	4	(F&D) BLOCK	540272	343026	197246	01	_____	197246
5	SHAMAS BIN IKRAM	7798128	7624844	173284	0.5	_____	86642	5	(C&E) BLOCK	521979	313809	208170	01	_____	208170
6								6							
7								7							
8															
9	AUXILIARY	116352	111401	4951	1	_____	4951								

T-1			T-2		
Received Units	3976381		Received Units	536898	
Sent Out Units	3949489		Sent Out Units	491025	
Difference	26892		Difference	45873	
% Age	0.68		% Age	8.54	

Table A-6: Maximum Load (Ampere) June 2018

T-1												
1		INCOMING T-1	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 75 = 675	560	15:00	04-06-2018	430
2	112701	DEFENCE ROAD	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	270	11:00	01-06-2018	201
3	112703	BUBTIAN CHOWK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	175	19:00	08-06-2018	139
4	112702	MONOO TEXTILE	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	120	09:00	16-06-2018	102
5	112704	SHAMAS BIN IKRAM	SCHNEIDER	FICO	200/400/5	200/5	3 x 500MCM (single core)	3 x 115 = 345	40	15:00	04-06-2018	18
T-2												
1		INCOMING T-2	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 95 = 855	65	15:00	04-06-2018	54
2	112705	(A&B) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 110 = 330	10	01:00	01-06-2018	9
3	112708	MOHALANWAL SCHEME	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	ON	ON	ON	ON
4	112706	(F&D) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	30	21:00	08-06-2018	22
5	112707	(C&E) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	30	15:00	04-06-2018	23

Table A-7: KWH (Units) July 2018

KWH READING T-1								KWH READING T-2							
Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF	M.F		TOTAL UNITS	Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF.	M.F		TOTAL UNITS
1	INCOMING T-1	5047301	198504	4848797	01	_____	4848797 - 3024 - 1225 = 4844548	1	INCOMING T-2	2653324	2001430	651894	01	_____	651894 + 3024 + 1225 = 656143
2	DEFENCE ROAD	58566889	56723775	1843114	01	_____	1843114	2	(A&B) BLOCK	256878	256878	0	01	_____	0
3	BUBTIAN CHOWK	26247727	24653688	1594039	01	_____	1594039	3	MOHALANWAL SCHEME	137090	23720	113370	01	_____	113370
4	MONOO TEXTILE	14801600	13631510	1170090	01	_____	1170090	4	(F&D) BLOCK	984986	748852	236134	01	_____	236134
5	SHAMAS BIN IKRAM	8632927	8279505	353422	0.5	_____	176711	5	(C&E) BLOCK	987528	739036	248492	01	_____	248492
6								6							
7								7							
8															
9	AUXILIARY	127257	121551	5706	1	_____	5706								
T-1								T-2							
Received Units		4844548						Received Units			656143				
Sent Out Units		4789660						Sent Out Units			597996				
Difference		54888						Difference			58147				
% Age		1.13						% Age			8.86				

Table A-8: Maximum Load (Ampere) July 2018

T-1												
1		INCOMING T-1	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 75 = 675	530	15:00	03-08-2018	444
2	112701	DEFENCE ROAD	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	260	10:00	03-08-2018	200
3	112703	BUBTIAN CHOWK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	170	22:00	03-08-2018	140
4	112702	MONOO TEXTILE	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	120	11:00	14-08-2018	105
5	112704	SHAMAS BIN IKRAM	SCHNEIDER	FICO	200/400/5	200/5	3 x 500MCM (single core)	3 x 115 = 345	35	13:00	08-08-2018	25
T-2												
1		INCOMING T-2	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 95 = 855	85	23:00	05-08-2018	65
2	112705	(A&B) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 110 = 330	on	on	on	on
3	112708	MOHALANWAL SCHEME	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	15	01:00	01-08-2018	10
4	112706	(F&D) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	35	22:00	05-08-2018	26
5	112707	(C&E) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	35	23:00	05-08-2018	26

Table A-9: KWH (Units) August 2018

KWH READING T-1								KWH READING T-2							
Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF	M.F		TOTAL UNITS	Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF.	M.F		TOTAL UNITS
1	INCOMING T-1	198504	95412873	4785631	01	_____	4785631	1	INCOMING T-2	2001430	1414672	586758	01	_____	586758
2	DEFENCE ROAD	56723775	54713120	2010655	01	_____	2010655	2	(A&B) BLOCK	256878	179701	77177	01	_____	77177
3	BUBTIAN CHOWK	24653688	23209786	1443902	01	_____	1443902	3	MOHALANWAL SCHEME	23720	0	23720	01	_____	23720
4	MONOO TEXTILE	13631510	12599754	1031756	01	_____	1031756	4	(F&D) BLOCK	748852	540272	208580	01	_____	208580
5	SHAMAS BIN IKRAM	8279505	7798128	481377	0.5	_____	240688.5	5	(C&E) BLOCK	739036	521979	217057	01	_____	217057
6								6							
7								7							
8															
9	AUXILIARY	121551	116352	5199	1	_____	5199								

T-1			T-2		
Received Units	4785631		Received Units	586758	
Sent Out Units	4732201		Sent Out Units	526534	
Difference	53431		Difference	60224	
% Age	1.12		% Age	10.26	

Table A-10: Maximum Load (Ampere) August 2018

T-1												
1		INCOMING T-1	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 75 = 675	515	11:00	10-07-2018	447
2	112701	DEFENCE ROAD	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	260	10:00	10-07-2018	212
3	112703	BUBTIAN CHOWK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	170	19:00	10-07-2018	138
4	112702	MONOO TEXTILE	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	120	19:00	17-07-2018	95
5	112704	SHAMAS BIN IKRAM	SCHNEIDER	FICO	200/400/5	200/5	3 x 500MCM (single core)	3 x 115 = 345	35	19:00	06-07-2018	26
T-2												
1		INCOMING T-2	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 95 = 855	70	03:00	10-07-2018	55
2	112705	(A&B) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 110 = 330	15	01:00	15-07-2018	8
3	112708	MOHALANWAL SCHEME	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	10	01:00	26-07-2018	3
4	112706	(F&D) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	30	03:00	10-07-2018	24
5	112707	(C&E) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	30	21:00	09-07-2018	23

Table A-11: KWH (Units) September 2018

KWH READING T-1								KWH READING T-2							
Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF	M.F		TOTAL UNITS	Sr NO	FEEDER NAME	PRESENT	PREVIOUS	DIFF.	M.F		TOTAL UNITS
1	INCOMING T-1	9640367	5047301	4593066	01	_____	4593066 - 4466 = 4588600	1	INCOMING T-2	3174740	2653324	521416	01	_____	521416 + 4466 = 525882
2	DEFENCE ROAD	60321557	58566889	1754668	01	_____	1754668	2	(A&B) BLOCK	256878	256878	0	01	_____	0
3	BUBTIAN CHOWK	27590921	26247727	1343194	01	_____	1343194	3	MOHALANWAL SCHEME	230085	137090	92995	01	_____	92995
4	MONOO TEXTILE	15969691	14801600	1168091	01	_____	1168091	4	(F&D) BLOCK	1172391	984986	187405	01	_____	187405
5	SHAMAS BIN IKRAM	9185285	8632927	552358	0.5	_____	276179	5	(C&E) BLOCK	1181891	987528	194363	01	_____	194363
6								6							
7								7							
8															
9	AUXILIARY	131770	127257	4513	1	_____	4513								

T-1			T-2		
Received Units	4588600		Received Units	525882	
Sent Out Units	4546645		Sent Out Units	474763	
Difference	41955		Difference	51119	
% Age	0.91		% Age	9.72	

Table A-12: Maximum Load (Ampere) September 2018

T-1												
1		INCOMING T-1	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 75 = 675	505	15:00	13-09-2018	420
2	112701	DEFENCE ROAD	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	260	10:00	11-09-2018	199
3	112703	BUBTIAN CHOWK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	155	20:00	07-09-2018	130
4	112702	MONOO TEXTILE	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 77 = 231	120	11:00	07-09-2018	103
5	112704	SHAMAS BIN IKRAM	SCHNEIDER	FICO	200/400/5	200/5	3 x 500MCM (single core)	3 x 115 = 345	40	22:00	07-09-2018	28
T-2												
1		INCOMING T-2	SCHNEIDER	FICO	800/1600/5	1600/5	9 x 1000 MCM	9 x 95 = 855	70	01:00	03-09-2018	56
2	112705	(A&B) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM (single core)	3 x 110 = 330	on	on	on	ON
3	112708	MOHALANWAL SCHEME	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	15	23:00	11-09-2018	9
4	112706	(F&D) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	35	02:00	07-09-2018	26
5	112707	(C&E) BLOCK	SCHNEIDER	FICO	200/400/5	400/5	3 x 500MCM	3 x 110 = 330	30	01:00	03-09-2018	27

Table A-13: KWH (Units) April 2022

	KWH READING T-1								
	INCOMING T-1	79577460	74494172	5083288	1		5083288	**Received units**	**5083288**
1	DEFENCE ROAD	35824333	33802091	2022242	1		2022242	**Sent out units**	**5092349**
2	BUBTIAN CHOWK	70012082	68597785	1414297	1		1414297	**Difference**	**-9061**
3	MONOO TEXTILE	60116171	58991551	1124620	1		1124620	**% Age**	**-0.18**
4	SHAMAS BIN IKRAM	19169524	19067648	101876	0.5		50938		
5	DAWOOD RESIDENCY	2012219	1880986	131233	0.5		65617		
6	INDUS HOSPITAL	858026	452402	405624	1		405624		
7	AUXILIARY	336351	327340	9011	1		9011		
	KWH READING T-2								
	INCOMING T-2	28795804	27598514	1197290	1		1197290	**Received units**	**1197290**
1	(A&B) BLOCK	274063	274063	0	0.5		0	**Sent out units**	**1205878**
2	MOHALANWAL SCHEME	8256571	7873721	382850	0.5		191425	**Difference**	**-8588**
3	(F&D) BLOCK	16406667	15542935	863732	0.5		431866	**% Age**	**-0.72**
4	(C&E) BLOCK	17336310	16468421	867889	0.5		433945		
5	ARMY WELFARE TRUST	1705585	1408300	297285	0.5		148643		
6									
7	AUXILIARY								

Table A-14: Maximum Load (Ampere) April 2022

T-1 & T-2												
Sr No:	FEEDER CODE	FEEDER CATEGORY	11 KV INCOMING/ FEEDERS NAME	PANEL MAKE	C.T. RATIO		CABLE		MAXIMUM LOAD			P.F
					AVAILABLE	CONNECT	SIZE	LENGTH	LOAD	DATE	TIME	
			INCOMING T-1	SCHNEIDER	800/1600/5	3	3 x 1000 MCM	9 x75 = 675	**580**	**09-04-2022**	**11:00**	**0.96**
1	112701	INDUSTRUAL DOMINATED	DEFENCE ROAD	SCHNEIDER	200/400/5	4	500MCM	3 x 77 = 231	**255**	**08-04-2022**	**12:00**	**0.89**
2	112703	DOMESTIC	BUBTIAN CHOWK	SCHNEIDER	200/400/5	400/5	500MCM	3 x 77 = 231	**160**	**27-04-2022**	**21:00**	**0.93**
3	112702	INDEPENDENT	MONOO TEXTILE	SCHNEIDER	200/400/5	1	500MCM	3 x 77 = 231	**150**	**10-04-2022**	**14:00**	**0.92**
4	112704	INDEPENDENT	SHAMAS BIN IKRAM	SCHNEIDER	200/400/5	200/5	500MCM	3 x 115 = 345	**30**	**12-04-2022**	**01:00**	**0.92**
5	112709	DOMESTIC	DAWOOD RESIDENCY	SCHNEIDER	200/400/5	200/5	500MCM	3 x 100 = 300	**15**	**12-04-2022**	**01:00**	**0.82**
6	STILL AWATED	INDEPENDENT HOSPITAL	INDUS HOSPITAL	SCHNEIDER	200/400/5	400/5	500MCM	3 x 100 = 300	**40**	**07-04-2022**	**16:00**	**0.99**
			INCOMING T-2	SCHNEIDER	800/1600/5	1600/5	3 x 1000 MCM	9 x 95 = 855	**135**	**12-04-2022**	**23:00**	**0.98**
1	112705	DOMESTIC	(A&B) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**ON**	**ON**	**ON**	**####**
2	112708	DOMESTIC	MOHALANWAL SCHEME	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**20**	**02-04-2022**	**17:00**	**0.90**
3	112706	DOMESTIC	(F&D) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**50**	**27-04-2022**	**16:00**	**0.91**
4	112707	DOMESTIC	(C&E) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**50**	**27-04-2022**	**10:00**	**0.90**
5	112710	DOMESTIC	ARMY WELFARE TRUST	PEL	200/400/5	200/5	500MCM	3 x 105 = 315	**20**	**12-04-2022**	**20:00**	**0.92**
6												
7												

Table A-15: KWH (Units) May 2022

				KWH READING T-1					
	INCOMING T-1	84590808	79577460	5013348	1		5013348	**Received units**	**5013348**
1	DEFENCE ROAD	37524152	35824333	1699819	1		1699819	**Sent out units**	**5016215**
2	BUBTIAN CHOWK	71524380	70012082	1512298	1		1512298	**Difference**	**-2867**
3	MONOO TEXTILE	61409333	60116171	1293162	1		1293162	**% Age**	**-0.06**
4	SHAMAS BIN IKRAM	19187437	19169524	17913	0.5		8957		
5	DAWOOD RESIDENCY	2152456	2012219	140237	0.5	**4100**	4100+70119= 74219		
6	INDUS HOSPITAL	1260675	858026	402649	1	**15900**	15900+402649= 418549		
7	AUXILIARY	345562	336351	9211	1		9211		
				KWH READING T-2					
	INCOMING T-2	30277527	28795804	1481723	1		1481723	**Received units**	**1481723**
1	(A&B) BLOCK	274063	274063	0	0.5		0	**Sent out units**	**1495234**
2	MOHALANWAL SCHEME	8715690	8256571	459119	0.5		229560	**Difference**	**-13511**
3	(F&D) BLOCK	17483159	16406667	1076492	0.5		538246	**% Age**	**-0.91**
4	(C&E) BLOCK	18427093	17336310	1090783	0.5		545392		
5	ARMY WELFARE TRUST	2069659	1705585	364074	0.5		182037		
6									
7	AUXILIARY								

Table A-16: Maximum Load (Ampere) May 2022

T-1 & T-2												
Sr No:	FEEDER CODE	FEEDER CATEGORY	11 KV INCOMING/ FEEDERS NAME	PANEL MAKE	C.T. RATIO		CABLE		MAXIMUM LOAD			P.F
					AVAILABLE	CONNECT	SIZE	LENGTH	LOAD	DATE	TIME	
			INCOMING T-1	SCHNEIDER	800/1600/5	3	3 x 1000 MCM	9 x75 = 675	**570**	**10-05-2022**	**14:00**	**0.96**
1	112701	INDUSTRUAL DOMINATED	DEFENCE ROAD	SCHNEIDER	200/400/5	4	500MCM	3 x 77 = 231	**280**	**16-05-2022**	**15:00**	**0.89**
2	112703	DOMESTIC	BUBTIAN CHOWK	SCHNEIDER	200/400/5	400/5	500MCM	3 x 77 = 231	**170**	**12-05-2022**	**16:00**	**0.93**
3	112702	INDEPENDENT	MONOO TEXTILE	SCHNEIDER	200/400/5	1	500MCM	3 x 77 = 231	**150**	**06-05-2022**	**19:00**	**0.91**
4	112704	INDEPENDENT	SHAMAS BIN IKRAM	SCHNEIDER	200/400/5	200/5	500MCM	3 x 115 = 345	**5**	**20-05-2022**	**15:00**	**0.68**
5	112709	DOMESTIC	DAWOOD RESIDENCY	SCHNEIDER	200/400/5	200/5	500MCM	3 x 100 = 300	**15**	**20-05-2022**	**14:00**	**0.87**
6	STILL AWATED	INDEPENDENT HOSPITAL	INDUS HOSPITAL	SCHNEIDER	200/400/5	400/5	500MCM	3 x 100 = 300	**40**	**03-05-2022**	**12:00**	**0.99**
			INCOMING T-2	SCHNEIDER	800/1600/5	1600/5	3 x 1000 MCM	9 x 95 = 855	**180**	**21-05-2022**	**01:00**	**1.00**
1	112705	DOMESTIC	(A&B) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**ON**	**ON**	**ON**	**1.00**
2	112708	DOMESTIC	MOHALANWAL SCHEME	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**30**	**12-05-2022**	**21:00**	**0.92**
3	112706	DOMESTIC	(F&D) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**80**	**09-05-2022**	**15:00**	**0.94**
4	112707	DOMESTIC	(C&E) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**70**	**21-05-2022**	**01:00**	**0.92**
5	112710	DOMESTIC	ARMY WELFARE TRUST	PEL	200/400/5	200/5	500MCM	3 x 105 = 315	**20**	**12-05-2022**	**20:00**	**0.94**
6												
7												

Table A-17: KWH (Units) June 2022

KWH READING T-1									
	INCOMING T-1	89738376	84590808	5147568	1		5147568	**Received units**	**5147568**
1	DEFENCE ROAD	39422260	37524152	1898108	1		1898108	**Sent out units**	**5148703**
2	BUBTIAN CHOWK	72910697	71524380	1386317	1		1386317	**Difference**	**-1135**
3	MONOO TEXTILE	62670600	61409333	1261267	1		1261267	**% Age**	**-0.02**
4	SHAMAS BIN IKRAM	19221686	19187437	34249	0.5		17125		
5	DAWOOD RESIDENCY	2308738	2152456	156282	0.5		78141		
6	INDUS HOSPITAL	1758891	1260675	498216	1		498216		
7	AUXILIARY	355091	345562	9529	1		9529		
KWH READING T-2									
	INCOMING T-2	31747740	30277527	1470213	1		1470213	**Received units**	**1470213**
1	(A&B) BLOCK	274063	274063	0	0.5		0	**Sent out units**	**1480711**
2	MOHALANWAL SCHEME	9184443	8715690	468753	0.5		234377	**Difference**	**-10498**
3	(F&D) BLOCK	18556471	17483159	1073312	0.5		536656	**% Age**	**-0.71**
4	(C&E) BLOCK	19499383	18427093	1072290	0.5		536145		
5	ARMY WELFARE TRUST	2416725	2069659	347066	0.5		173533		
6									
7	AUXILIARY								

Table A-18: Maximum Load (Ampere) June 2022

T-1 & T-2													
Sr No:	FEEDER CODE	FEEDER CATEGORY	11 KV INCOMING/ FEEDERS NAME	PANEL MAKE	C.T. RATIO		CABLE		MAXIMUM LOAD			P.F
					AVAILABLE	CONNECT	SIZE	LENGTH	LOAD	DATE	TIME	
			INCOMING T-1	SCHNEIDER	800/1600/5	3	3 x 1000 MCM	9 x75 = 675	**625**	**07-06-2022**	**12:00**	**0.96**
1	112701	INDUSTRUAL DOMINATED	DEFENCE ROAD	SCHNEIDER	200/400/5	4	500MCM	3 x 77 = 231	**290**	**14-06-2022**	**11:00**	**0.90**
2	112703	DOMESTIC	BUBTIAN CHOWK	SCHNEIDER	200/400/5	400/5	500MCM	3 x 77 = 231	**170**	**14-06-2022**	**18:00**	**0.93**
3	112702	INDEPENDENT	MONOO TEXTILE	SCHNEIDER	200/400/5	1	500MCM	3 x 77 = 231	**160**	**07-06-2022**	**13:00**	**0.90**
4	112704	INDEPENDENT	SHAMAS BIN IKRAM	SCHNEIDER	200/400/5	200/5	500MCM	3 x 115 = 345	**10**	**01-06-2022**	**18:00**	**0.80**
5	112709	DOMESTIC	DAWOOD RESIDENCY	SCHNEIDER	200/400/5	200/5	500MCM	3 x 100 = 300	**15**	**04-06-2022**	**01:00**	**0.88**
6	STILL AWATED	INDEPENDENT HOSPITAL	INDUS HOSPITAL	SCHNEIDER	200/400/5	400/5	500MCM	3 x 100 = 300	**50**	**26-06-2022**	**22:00**	**0.98**
			INCOMING T-2	SCHNEIDER	800/1600/5	1600/5	3 x 1000 MCM	9 x 95 = 855	**190**	**10-06-2022**	**04:00**	**1.00**
1	112705	DOMESTIC	(A&B) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**ON**	**ON**	**ON**	**####**
2	112708	DOMESTIC	MOHALANWAL SCHEME	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**30**	**12-06-2022**	**01:00**	**0.93**
3	112706	DOMESTIC	(F&D) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**80**	**06-06-2022**	**02:00**	**0.95**
4	112707	DOMESTIC	(C&E) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**80**	**10-06-2022**	**03:00**	**0.93**
5	112710	DOMESTIC	ARMY WELFARE TRUST	PEL	200/400/5	200/5	500MCM	3 x 105 = 315	**20**	**01-06-2022**	**20:00**	**0.95**
6												
7												

Table A-19: KWH (Units) July 2022

KWH READING T-1									
	INCOMING T-1	94665038	89738376	4926662	1		4926662	**Received units**	**4926662**
1	DEFENCE ROAD	41083292	39422260	1661032	1		1661032	**Sent out units**	**4911626**
2	BUBTIAN CHOWK	74397021	72910697	1486324	1		1486324	**Difference**	**15036**
3	MONOO TEXTILE	63831095	62670600	1160495	1		1160495	**% Age**	**0.31**
4	SHAMAS BIN IKRAM	19279861	19221686	58175	0.5		29088		
5	DAWOOD RESIDENCY	2455615	2308738	146877	0.5		73439		
6	INDUS HOSPITAL	2251378	1758891	492487	1		492487		
7	AUXILIARY	363853	355091	8762	1		8762		
KWH READING T-2									
	INCOMING T-2	33221756	31747740	1474016	1		1474016	**Received units**	**1474016**
1	(A&B) BLOCK	274063	274063	0	0.5		0	**Sent out units**	**1484375**
2	MOHALANWAL SCHEME	9638323	9184443	453880	0.5		226940	**Difference**	**-10359**
3	(F&D) BLOCK	19633858	18556471	1077387	0.5		538694	**% Age**	**-0.70**
4	(C&E) BLOCK	20584521	19499383	1085138	0.5		542569		
5	SPRING APARTMENTS	244	0	244	1		244		
6	ARMY WELFARE TRUST	2768582	2416725	351857	0.5		175928.5		
7	AUXILIARY								

Table A-20: Maximum Load (Ampere) July 2022

T-1 & T-2												
Sr No:	**FEEDER CODE**	**FEEDER CATEGORY**	**11 KV INCOMING/ FEEDERS NAME**	**PANEL MAKE**	**C.T. RATIO**		**CABLE**		**MAXIMUM LOAD**			**P.F**
					AVAILABLE	**CONNECT**	**SIZE**	**LENGTH**	**LOAD**	**DATE**	**TIME**	
			INCOMING T-1	SCHNEIDER	800/1600/5	3	3 x 1000 MCM	9 x75 = 675	**650**	**05-07-2022**	**12:00**	**0.96**
1	112701	INDUSTRUAL DOMINATED	DEFENCE ROAD	SCHNEIDER	200/400/5	4	500MCM	3 x 77 = 231	**290**	**01-07-2022**	**11:00**	**0.90**
2	112703	DOMESTIC	BUBTIAN CHOWK	SCHNEIDER	200/400/5	400/5	500MCM	3 x 77 = 231	**170**	**05-07-2022**	**12:00**	**0.93**
3	112702	INDEPENDENT	MONOO TEXTILE	SCHNEIDER	200/400/5	1	500MCM	3 x 77 = 231	**160**	**02-07-2022**	**18:00**	**0.90**
4	112704	INDEPENDENT	SHAMAS BIN IKRAM	SCHNEIDER	200/400/5	200/5	500MCM	3 x 115 = 345	**30**	**05-07-2022**	**22:00**	**0.85**
5	112709	DOMESTIC	DAWOOD RESIDENCY	SCHNEIDER	200/400/5	200/5	500MCM	3 x 100 = 300	**10**	**01-07-2022**	**11:00**	**0.86**
6	STILL AWATED	INDEPENDENT HOSPITAL	INDUS HOSPITAL	SCHNEIDER	200/400/5	400/5	500MCM	3 x 100 = 300	**50**	**01-07-2022**	**17:00**	**0.98**
			INCOMING T-2	SCHNEIDER	800/1600/5	1600/5	3 x 1000 MCM	9 x 95 = 855	**205**	**19-07-2022**	**23:00**	**1.00**
1	112705	DOMESTIC	(A&B) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**ON**	**ON**	**ON**	**####**
2	112708	DOMESTIC	MOHALANWAL SCHEME	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**35**	**05-07-2022**	**01:00**	**0.91**
3	112706	DOMESTIC	(F&D) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**80**	**04-07-2022**	**14:00**	**0.94**
4	112707	DOMESTIC	(C&E) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**70**	**05-07-2022**	**11:00**	**0.93**
5	112712	DOMESTIC	SPRING APARTMENTS	SCHNEIDER	200/400/5	400/5	500MCM	3 x 100= 300	**1**	**30-07-2022**	**01:00**	**1.00**
6	112710	DOMESTIC	ARMY WELFARE TRUST	PEL	200/400/5	200/5	500MCM	3 x 105 = 315	**20**	**01-07-2022**	**09:00**	**0.95**
7												

Table A-21: KWH (Units) August 2022

				KWH READING T-1					
	INCOMING T-1	99725739	94665038	5060701	1		5060701	**Received units**	**5060701**
1	DEFENCE ROAD	42928325	41083292	1845033	1		1845033	**Sent out units**	**5060398**
2	BUBTIAN CHOWK	75945108	74397021	1548087	1		1548087	**Difference**	**303**
3	MONOO TEXTILE	64808969	63831095	977874	1		977874	**% Age**	**0.01**
4	SHAMAS BIN IKRAM	19399625	19279861	119764	0.5		59882		
5	DAWOOD RESIDENCY	2613335	2455615	157720	0.5		78860		
6	INDUS HOSPITAL	2792417	2251378	541039	1		541039		
7	AUXILIARY	373476	363853	9623	1		9623		
				KWH READING T-2					
	INCOMING T-2	34805106	33221756	1583350	1		1583350	**Received units**	**1583350**
1	(A&B) BLOCK	274063	274063	0	0.5		0	**Sent out units**	**1594560**
2	MOHALANWAL SCHEME	10135614	9638323	497291	0.5		248646	**Difference**	**-11210**
3	(F&D) BLOCK	20792897	19633858	1159039	0.5		579520	**% Age**	**-0.71**
4	(C&E) BLOCK	21729851	20584521	1145330	0.5		572665		
5	SPRING APARTMENTS	4438	244	4194	1		4194		
6	ARMY WELFARE TRUST	3147654	2768582	379072	0.5		189536		
7	AUXILIARY								

Table A-22: Maximum Load (Ampere) August 2022

Sr No:	FEEDER CODE	FEEDER CATEGORY	11 KV INCOMING/ FEEDERS NAME	PANEL MAKE	C.T. RATIO AVAILABLE	C.T. RATIO CONNECT	CABLE SIZE	CABLE LENGTH	MAXIMUM LOAD LOAD	MAXIMUM LOAD DATE	MAXIMUM LOAD TIME	P.F
						T-1 & T-2						
			INCOMING T-1	SCHNEIDER	800/1600/5	3	3 x 1000 MCM	9 x75 = 675	**570**	**23-08-2022**	**10:00**	**0.97**
1	112701	INDUSTRUAL DOMINATED	DEFENCE ROAD	SCHNEIDER	200/400/5	4	500MCM	3 x 77 = 231	**260**	**24-08-2022**	**15:00**	**0.90**
2	112703	DOMESTIC	BUBTIAN CHOWK	SCHNEIDER	200/400/5	400/5	500MCM	3 x 77 = 231	**170**	**02-08-2022**	**20:00**	**0.93**
3	112702	INDEPENDENT	MONOO TEXTILE	SCHNEIDER	200/400/5	1	500MCM	3 x 77 = 231	**160**	**23-08-2022**	**09:00**	**0.92**
4	112704	INDEPENDENT	SHAMAS BIN IKRAM	SCHNEIDER	200/400/5	200/5	500MCM	3 x 115 = 345	**25**	**17-08-2022**	**19:00**	**0.95**
5	112709	DOMESTIC	DAWOOD RESIDENCY	SCHNEIDER	200/400/5	200/5	500MCM	3 x 100 = 300	**10**	**02-08-2022**	**23:00**	**0.87**
6	STILL AWATED	INDEPENDENT HOSPITAL	INDUS HOSPITAL	SCHNEIDER	200/400/5	400/5	500MCM	3 x 100 = 300	**50**	**03-08-2022**	**16:00**	**0.98**
			INCOMING T-2	SCHNEIDER	800/1600/5	1600/5	3 x 1000 MCM	9 x 95 = 855	**195**	**02-08-2022**	**23:00**	**1.00**
1	112705	DOMESTIC	(A&B) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**ON**	**ON**	**ON**	**####**
2	112708	DOMESTIC	MOHALANWAL SCHEME	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**35**	**04-08-2022**	**23:00**	**0.91**
3	112706	DOMESTIC	(F&D) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**75**	**02-08-2022**	**23:00**	**0.94**
4	112707	DOMESTIC	(C&E) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**70**	**02-08-2022**	**23:00**	**0.93**
5	112712	DOMESTIC	SPRING APARTMENTS	SCHNEIDER	200/400/5	400/5	500MCM	3 x 100= 300	**ON**	**ON**	**ON**	**1.00**
6	112710	DOMESTIC	ARMY WELFARE TRUST	PEL	200/400/5	200/5	500MCM	3 x 105 = 315	**20**	**03-08-2022**	**01:00**	**0.94**
7												

Table A-23: KWH (Units) September 2022

KWH READING T-1										
	INCOMING T-1	103995192	99725739	4269453	1		4269453	**Received units**	**4269453**
1	DEFENCE ROAD	44624229	42928325	1695904	1		1695904	**Sent out units**	**4254946**
2	BUBTIAN CHOWK	77278833	75945108	1333725	1		1333725	**Difference**	**14507**
3	MONOO TEXTILE	65490834	64808969	681865	1		681865	**% Age**	**0.34**
4	SHAMAS BIN IKRAM	19434458	19399625	34833	0.5		17417		
5	DAWOOD RESIDENCY	2750806	2613335	137471	0.5		68736		
6	INDUS HOSPITAL	3241307	2792417	448890	1		448890		
7	AUXILIARY	381886	373476	8410	1		8410		
KWH READING T-2									
	INCOMING T-2	36156647	34805106	1351541	1		1351541	**Received units**	**1351541**
1	(A&B) BLOCK	274063	274063	0	0.5		0	**Sent out units**	**1361744**
2	MOHALANWAL SCHEME	10572096	10135614	436482	0.5		218241	**Difference**	**-10203**
3	(F&D) BLOCK	21751601	20792897	958704	0.5		479352	**% Age**	**-0.75**
4	(C&E) BLOCK	22712658	21729851	982807	0.5		491404		
5	SPRING APARTMENTS	9415	4438	4977	1		4977		
6	ARMY WELFARE TRUST	3483195	3147654	335541	0.5		167770.5		
7	AUXILIARY								

Table A-24: Maximum Load (Ampere) September 2022

T-1 & T-2												
Sr No:	FEEDER CODE	FEEDER CATEGORY	11 KV INCOMING/ FEEDERS NAME	PANEL MAKE	C.T. RATIO		CABLE		MAXIMUM LOAD			P.F
					AVAILABLE	CONNECT	SIZE	LENGTH	LOAD	DATE	TIME	
			INCOMING T-1	SCHNEIDER	800/1600/5	3	3 x 1000 MCM	9 x75 = 675	**545**	**07-09-2022**	**10:00**	**0.96**
1	112701	INDUSTRUAL DOMINATED	DEFENCE ROAD	SCHNEIDER	200/400/5	4	500MCM	3 x 77 = 231	**270**	**10-09-2022**	**16:00**	**0.90**
2	112703	DOMESTIC	BUBTIAN CHOWK	SCHNEIDER	200/400/5	400/5	500MCM	3 x 77 = 231	**160**	**07-09-2022**	**18:00**	**0.93**
3	112702	INDEPENDENT	MONOO TEXTILE	SCHNEIDER	200/400/5	1	500MCM	3 x 77 = 231	**120**	**06-09-2022**	**10:00**	**0.89**
4	112704	INDEPENDENT	SHAMAS BIN IKRAM	SCHNEIDER	200/400/5	200/5	500MCM	3 x 115 = 345	**15**	**22-09-2022**	**14:00**	**0.85**
5	112709	DOMESTIC	DAWOOD RESIDENCY	SCHNEIDER	200/400/5	200/5	500MCM	3 x 100 = 300	**10**	**07-09-2022**	**01:00**	**0.85**
6	STILL AWATED	INDEPENDENT HOSPITAL	INDUS HOSPITAL	SCHNEIDER	200/400/5	400/5	500MCM	3 x 100 = 300	**40**	**10-09-2022**	**12:00**	**0.98**
			INCOMING T-2	SCHNEIDER	800/1600/5	1600/5	3 x 1000 MCM	9 x 95 = 855	**170**	**20-09-2022**	**23:00**	**1.00**
1	112705	DOMESTIC	(A&B) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**ON**	**ON**	**ON**	**####**
2	112708	DOMESTIC	MOHALANWAL SCHEME	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**30**	**13-09-2022**	**23:00**	**0.90**
3	112706	DOMESTIC	(F&D) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**60**	**13-09-2022**	**24-00**	**0.93**
4	112707	DOMESTIC	(C&E) BLOCK	SCHNEIDER	200/400/5	200/5	500MCM	3 x 110 = 330	**60**	**14-09-2022**	**22:00**	**0.92**
5	112712	DOMESTIC	SPRING APARTMENTS	SCHNEIDER	200/400/5	400/5	500MCM	3 x 100= 300	**5**	**01-09-2022**	**01:00**	**1.00**
6	112710	DOMESTIC	ARMY WELFARE TRUST	PEL	200/400/5	200/5	500MCM	3 x 105 = 315	**20**	**10-09-2022**	**01:00**	**0.94**
7												