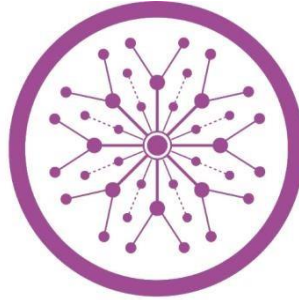


# AI-BASED ENERGY MANAGEMENT OF A SMART CITY



## SUPERIOR UNIVERSITY

### **B.Sc. ELECTRICAL ENGINEERING**

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Session: [2019 – 2023]

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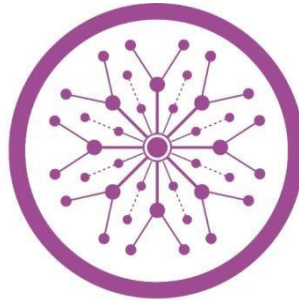
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**DEPARTMENT OF ELECTRICAL ENGINEERING**

## **SUPERIOR UNIVERSITY**

**Lahore, Pakistan**

# AI-BASED ENERGY MANAGEMENT OF A SMART CITY



## SUPERIOR UNIVERSITY

A thesis submitted in partial fulfillment of the requirements for the  
Degree of Bachelor of Science in

Electrical Engineering

Ahmed Saeed

Mazhar Abbas

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Lahore, Pakistan

## DECLARATION

This thesis is a presentation of my original research work. Every attempt is taken to explicitly state where other people's contributions are involved, with appropriate citations to the literature and acknowledgment of teamwork in research and discussions. Additionally, I certify that this work is original to the extent that it is not plagiarized and that all references are included.

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Thank you,

Ahmed Saeed

Hamza Aziz Khan

Mazhar Abbas

## **DEDICATION**

I want to dedicate my thesis to my cherished friends, family, and teachers.

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## **ABSTRACT**

Interest in the idea of smart cities has grown dramatically over the past several years as a result of the growing desire for efficient and sustainable urban environments. With an emphasis on the use of Long Short-Term Memory (LSTM) for forecasting and the creation of a software program with a graphical user interface (GUI), this thesis offers comprehensive investigation into load forecasting within the framework of a smart city. The goals and difficulties Smart City have with regard to managing its energy are highlighted. An essential part of a smart city is efficient energy management, which necessitates precise load forecasting in order to optimize energy distribution, lower peak loads, and facilitate informed decision-making. In the thesis, the use of LSTM for load forecasting in a smart city setting is covered. For precise load forecasts, LSTM, a deep learning technique, is well suited since it can model complicated temporal patterns and capture long-term dependencies. The benefits of LSTM over conventional statistical approaches and other machine learning algorithms are highlighted, with an emphasis on its capacity to manage non-linear and dynamic load patterns frequently found in smart city energy systems. The study also looks at how a GUI software for load forecasting might be created in a smart city setting. The GUI software offers a user-friendly interface that allows participants, such as city administrators, energy managers, and residents, to enter pertinent data and acquire precise load estimates catered to their particular needs. The GUI app's straightforward design and features streamline the load forecasting process and give stakeholders the information they need to make wise choices about energy use, resource allocation, and demand response programmed. The output of the GUI app and the LSTM programmed for load forecasting is shown and analysed. 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 smart city context. User comments and case studies are used to evaluate the GUI app's effects on decision-making and energy optimizations, emphasizing the role that it plays in promoting informed and effective energy management. While the GUI interface improves accessibility and decision-making for stakeholders, the use of LSTM for load prediction meets the particular issues of smart city energy systems. Building effective and sustainable urban environments is a goal that is advanced by the study, which promotes energy management practices in smart cities.. In order to further increase the precision and efficacy of load forecasting models and GUI apps, future research may concentrate on combining real-time data streams, sophisticated optimizations algorithms, and demand-side management tactics.

# **CHAPTER 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 as a result 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. According to statistics 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 day. 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. In order to exploit these predictions, live for efficient energy management, this proposal tackles the fundamental concept of load forecasting utilizing Deep Learning algorithms in an IOT context.

### **1.1 Concept of Smart Cities**

In the 1990s, every city was traditional because the Internet hadn't yet been created. The concept of a "Smart City" has gained increasing traction in recent years thanks to the Internet's growth, and it now affects both small and large cities. The only answers in the current situation for the challenges that metropolitan areas face, such as the use of outdated technological appliances that use a lot of power, are Smart Cities. The adjective "smart," which refers to a digital, intelligent, and sustainable city, is key to understanding what smart cities are.

With a population of over 22.5 crore, Pakistan has severe issues with transportation, pollution, energy, poverty, and other factors. From an economic and social standpoint, scaling up urban architecture is scarcely a viable strategy. Despite the fact that the concept of a "smart city" a futuristic metropolis managed by intelligent automata was coined in 2009.

### 1.1.1 Factors to Identify Smart Cities:

Three factors are used to identify smart cities which are as follows:

- The Technology
- The People
- And the Institutions

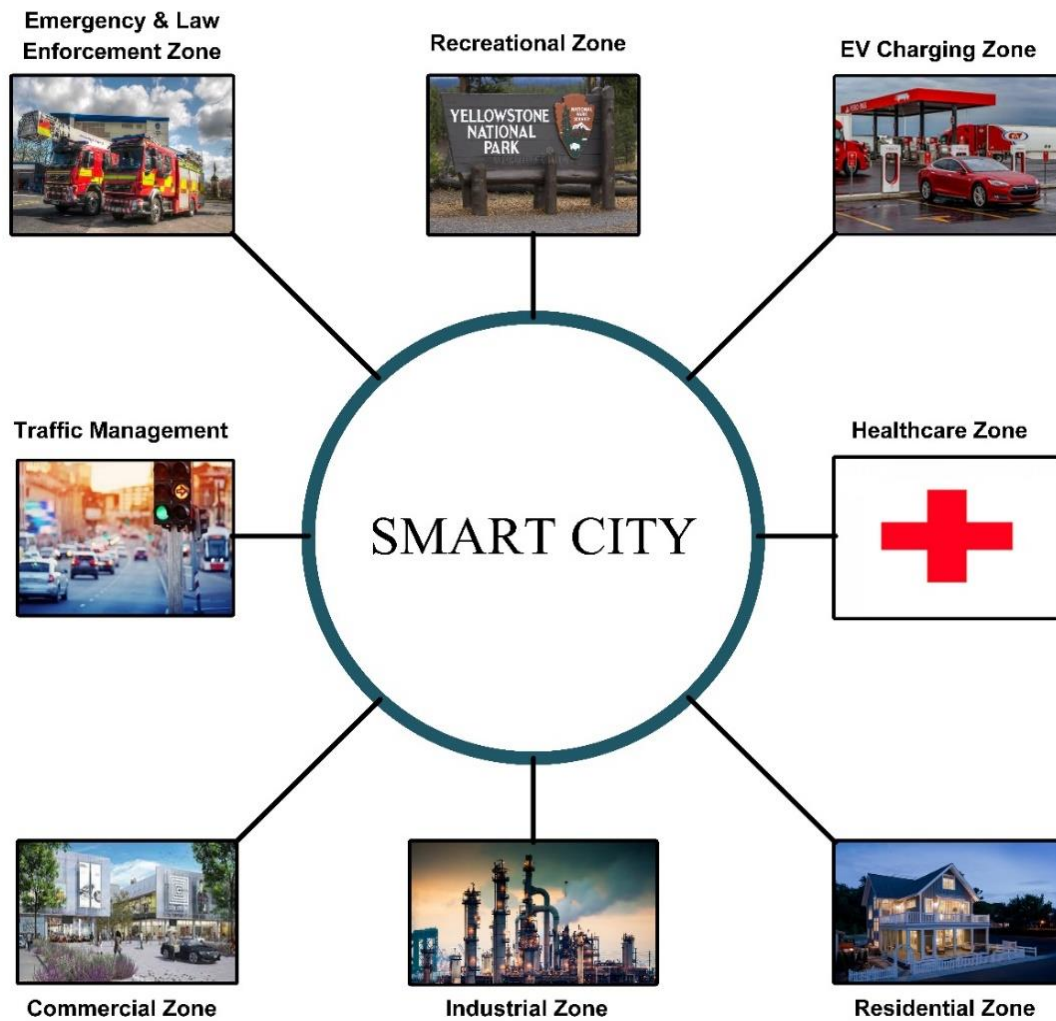


Figure 1.1: Smart City Zones

In order to solve urban concerns and contribute to the development of a more sustainable and living environment for people, the goal of a smart city should be to integrate these three components. From this vantage point, a smart city may be defined as an endeavor to link physical, social, technical, and commercial infrastructures to boost operational effectiveness and general quality of life. This partnership should result in a framework with four generations of each of the four key elements: smart communities, smart energy, smart transport, and smart healthcare. The establishment of smart cities is only influenced by the gathering and analysis of data.

### **1.1.2 Layers of Smart Cities Identification:**

As a result, smart cities have discovered a four-layer architecture.:

- Sensing Layer
- Transmission Layer
- Data Management Layer
- Application Layer

#### **1.1.1.1 Sensing Layer**

A sensor network that collects data from numerous physical devices makes up the sensing layer, which is required to acquire the data.

#### **1.1.1.2 Transmission Layer:**

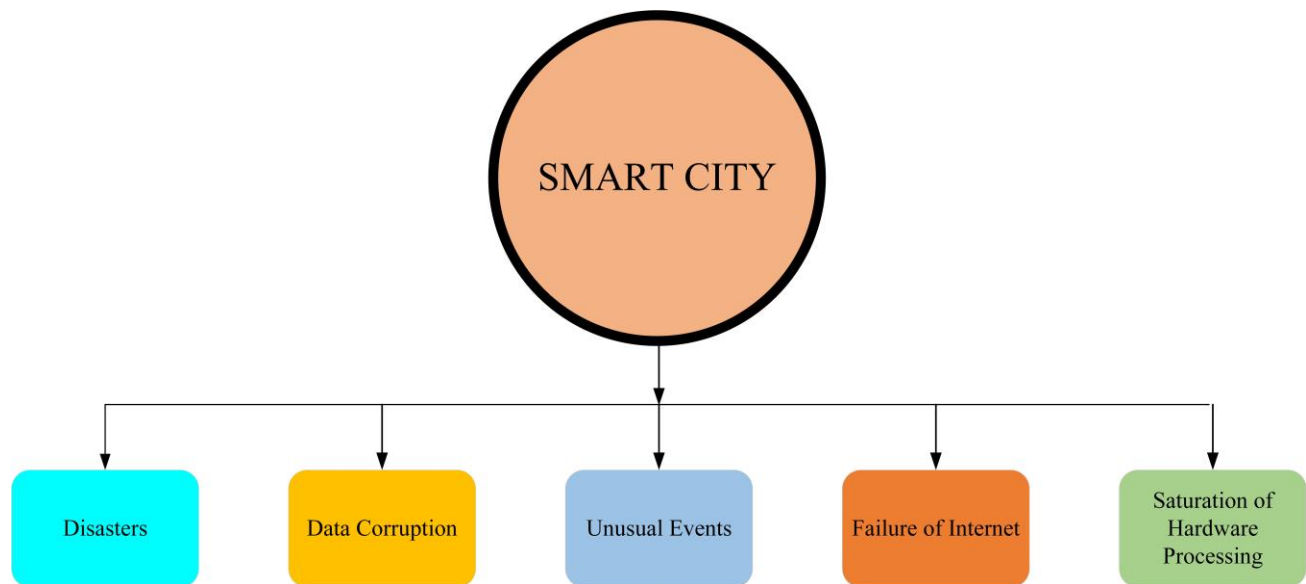
All data sources and communication networks are brought together via the transmission layer.

#### **1.1.1.3 Data Management Layer:**

The data management layer collects, stores, and analyzes data to support decision-making processes.

#### **1.1.1.4 Application Layer**

Residents and the information management layer, that's an illustration of all the services supplied in the smart city, communicate through the application layer. Recently, it has been thought that AI is a potent instrument for the development of smart cities [1]. Applications powered by AI are still being developed, and as such, their full potential is not yet realized. However, the introduction of AI has already revealed a potential double-edged sword, according to which negative impacts can go unnoticed because of a propensity towards technology.



**Figure 1.2:** Factors Affecting the Smart City

A technologically advanced urban setting known as a "Smart City" makes use of various electrical devices and sensors to gather certain data. The data's information is utilized to enhance daily operations and more effectively manage the city's resources, services, and assets [2]. To monitor and regulate transportation and traffic systems, hospitals rescue stations, charging stations for electric vehicles, and parks, data is collected from people, devices, structures, and assets. Cities are referred to as "smart cities" [3] if they successfully employ technology in their organizing, tracking, evaluation, and management of the city. An idea known as a "smart city" integrates information and communication technology among a wide range of physical objects linked to the Internet of Things (IoT) network to communicate with locals and improve operations and services. Municipal officials can communicate directly with both community and municipal infrastructure thanks to smart city technology. They can so keep tabs on the city's activities and overall development. ICT boosts citizen-government interaction, lowers costs and resource usage, and improves the efficacy, efficiency, and interaction of urban services [4]. Applications are created for "smart cities" to control traffic in metropolitan areas and enable quick responses. A Smart City might therefore be better able to address problems than one that just has a "transactional" connection with its residents. Smart city technology have already been applied in a number of cities [5]. It is difficult to give a specific definition of a "smart city," given the diverse spectrum of technology that it encompasses. Deakin and Al [6] outline four elements that go into the concept of a smart city:

- The spread of various electrical and digital technologies in cities.
- Using ICT to enhance local livability and employment opportunities.
- Governmental systems incorporating such information and communications technology.
- ICT and humans come together via the territorialities of practices to improve the innovation and knowledge they provide.

## **1.2 Problem Statement**

Load forecasting (LF) will be crucial to the power grid in the near future. In addition to the technological and financial difficulties that the smart grid is facing, as mentioned above, 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 model we propose 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 aforementioned techniques also 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 20 years based on various inputs for the smart city have been included in our 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.

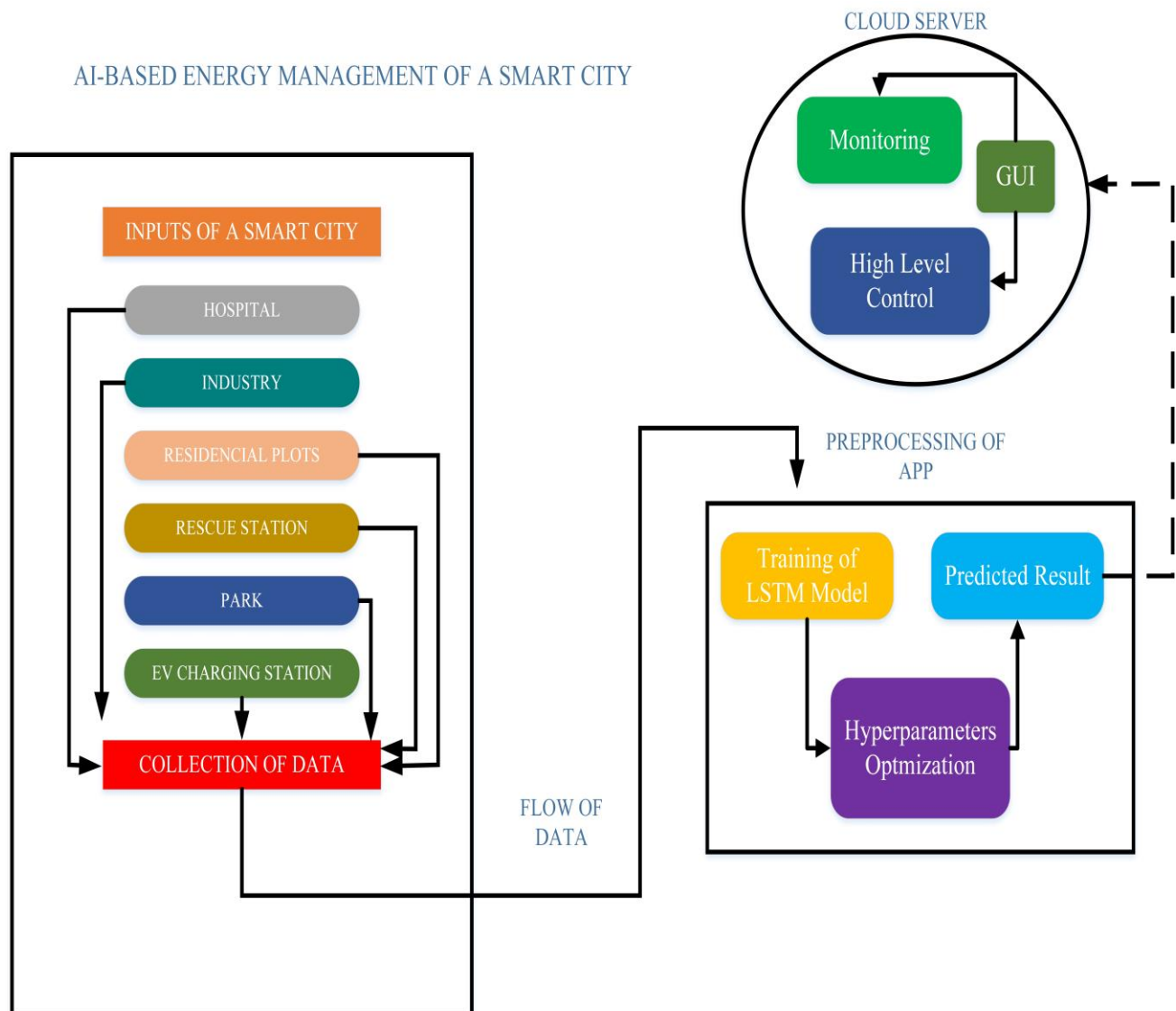
When various loads at various times are connected to the system, a load of each input varies. This study's system is built on inputs that have two distinct conditions: heavy instruments and low instruments. To achieve this, the suggested system's Root Mean Square Error (RMSE) is reduced by optimizing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

## **1.3 Objectives**

This thesis has the following four objectives:

- Development of the Smart City by using the latest technology
- Data acquisition of the Smart City through IoT
- Optimize the Smart City through ANN
- Data analytics and effective data processing are needed in cities.

## 1.4 Project Methodology



**Figure 1.3:** Proposed Block Diagram of the System

## 1.5 Work Division

**Table 1.1:** Work Division Between Group Members

<b>Sr. No</b>	<b>Name</b>	<b>Allocated Task</b>
1.	Ahmed Saeed	Software Design
2.	Mazhar Abbas	Hardware Integration
3.	Hamza Aziz Khan	Documentation

## 1.6 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 Park et al. [8] 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 S.J. Kiartzis, who published a model in [9] to lessen prediction mistakes. Henrique Steinherz Hippert performed 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 [10]. 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. [11]. Despite the fact that 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 [12]. A novel approach for online prediction that is based on IOT has been investigated by Ahmed Yousuf Sabre [13], an area that many scholars are presently interested in.

In this part, the author gives a comprehensive overview of energy administration software developed for smart cities. For controlling and decreasing the workload and reducing power consumption, Shreenidhi et al. [14] proposed the two stages deep dilation multi-kernel convolution network (DDMKC)-modified elephants herd optimization algorithm (MEHOA) model. The suggested method utilised demand reaction (DR) price information to precisely estimate the subsequent pricing signal, allowing customers to make the best decisions and reduce suffering.

The AJODL-DSSEM model was presented by the author for estimating energy consumption in a setting of smart cities in [15]. The suggested AJODL-DSSEM 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 hyperparameters 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 AJODL-DSSEM model can therefore be used for making energy management decisions in the context of a real-time smart city.

The author of [16] 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, based on G. Hafeez et al. [17]. 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. 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.

The WBFA algorithm, that integrates the WDO and BFO approaches, was first forth by the author in [18]. In the IoT-enabled environment of the SG, the EMC set with our suggested WBFA algorithms rapidly reacts to DR programs to participate in the energy management of the homes. Our suggested WBFA-based technique proposes a schedule for the electricity consumption of households and other smart equipment under the DAPS, RTPS, or Toups price-based DR programs, which we approved. Use our WBFA-based approach to reduce electricity costs, reduce PAR, and increase UC. When comparing to the DAPS or RTPS DR programs, simulation results show that using the ToUPS DR designed for energy management results in the cheapest price of electricity, the most dependable utilization timetable for smart appliances in households, and the lowest PAR. Additionally, when compared to not using price-based DR programs, our suggested WBFA-based strategy reduced the cost of both electricity and PAR by 27.6% and 58% when using the DAPS DR regulated, by 40% and 54% if using the RTPS DR regulated and by 52.1% and 62% if using the ToUPS DR controlled. As a result, employing a ToUPS DR created to control energy benefits both customers and DSOs.

According to the author of [19], obtaining useful insights from unprocessed IoT data is a very challenging process that falls outside the purview of traditional analytical paradigms. Since DL can learn structure models using the input data, it is the greatest answer for a variety of categorization and prediction problems in the IoT. Modeling complex behaviors of diverse datasets is another application of DL. It contains a wide variety of structures and applications. CNN excels at using audio and visual data. The RNN and LSTM are used in time series forecasting. In high-dimensional data, AEs are used to minimize the number of dimensions. GANs perform effectively in noisy settings. The RBM and DBN both capture complicated representations of data in an unsupervised manner. Due to their extensive range of applications, DL models are excellent for IoT contexts. In order to accomplish this, our study presented a thorough review of the research activities on DL-driven IoT application scenarios. The paper also built an LSTM-based algorithm for HAR and evaluated the suggested framework against other machine learning approaches to show the superiority of the DL model over existing approaches. Although DL models outperform traditional machine learning techniques, their

computational complexity makes them risky to use in time-limited IoT applications. Therefore, it is crucial to look for techniques to reduce the computing needs for these models without compromising accuracy. A last point to make is that the proliferation of services catered to specific applications and industries will result from the addition of DL into IoT systems.

The author in [20] recommended ways to enhance the IoT smart home system, including the creation of microcontrollers, sensors, as well actuators as well as the integration of cameras, LCD touchscreen displays, as well minicomputers. The Internet of Things outlets and fittings were successful in enabling remote web-based control and monitoring of electrical equipment. The Internet of Things cameras, meanwhile, were successful in publishing photos, analyzing image data, and remotely presenting video via a web interface. Additionally, it was successful to carry out forecast computations, device control, and monitoring via a private intranet network in conjunction with the local workstation (as a backup for cloud computing). A fairly precise short-term estimate for the residential electric load is provided by the PCA and ARIMA, however. Additionally, the IoT smart home system performance offers high data package delivery and transfer speed.

In this research, we suggest the multitasking attention-LSTM (MTAL) model for forecasting reactive as well as active load based on hard sharing of parameters. To train the suggested model to predict multitasking load, we created a combined-task-wise function of loss. Cross-validation and a grid search approach are used to adaptively optimize the loss function's hyperparameters. In order to increase the data dimensionality and boost forecasting accuracy, we additionally take into account the influence of external elements, such as calendar considerations and weather conditions, in addition to the past reactive and proactive load data. Experimental results show that our MTAL model performs well in terms of prediction performance or dependability for both subdivisions, namely active load forecasting and reactive load forecasting, on a range of data sets. This shows that our model might provide a workable answer for power system use. Future research will concentrate on speeding up the learning or inference stages while also reducing the model's complexity to make it more straightforward. To increase the model's total prediction capacity, we will further tune the parameters for anticipating demand during peaks and dips.

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. 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. [21].

Numerous prediction methods have been examined. One of the most popular techniques among them involves foreseeing using artificial neural networks, or ANN [22]. 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[23].

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, the majority 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 [24]. This technology may help satellite and space stations that are in Earth orbit.

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 as a result 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. 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 [25]. 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. The goal of experts is to create some automated devices with excellent energy distribution capabilities. Monitoring and maintaining enhanced power distribution networks, and in particular, improving load forecasts, are essential responsibilities of smart grids. Creating secure networks and enhancing the efficiency of the power supply are required for this. 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.

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 systems. 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. 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. A number of factors, among others, have an impact on the STLF:

- 1) As some patterns, such as daily patterns, exist within a set of data, time is the most crucial factor for STLF.
- 2) The weather, which includes the temperature and humidity.
- 3) The demand for electricity might alter significantly during 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. Even However, the majority of 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 [26]. 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 estimate for the long term make up the modified time frames. These scales use various extracted features and methodologies. 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.

This essay is divided into the following sections. The information and associated feature extraction processing are described in Section II. The text's third section contains an explanation of the algorithm, followed by a summary of the changes and findings[27].

constructing prediction models utilizing two different techniques. The first approach uses parametric estimating to produce distinct models for every day of the week. Through the use of many data points that correspond to the same time period over the corresponding days, the quantity of energy used is estimated as a total for a given time period. There is a pattern that emerges for every day. 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.

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 [27].

After the tolerance was reached, a number of strategies for precise electric load forecasting were developed. Three main forecasting loads can be created using the approaches examined: short-term forecasts, medium-term projections, and future forecasting. Short-term forecasts are used to provide the information required to provide oversight of routine operations and unit commitment. They typically cover the period from one hour to a full week. The use of medium forecasting, which commonly spans from one week to a year, is made to give executives at electric utility firms an estimate of forthcoming demands for growth, equipment purchases, or human employment. Long-term forecasting is used for durations longer than a year to plan fuel delivery and equipment maintenance. Forecasts for various time periods are necessary for the varied operations of a utility

company. These projections also come in a variety of forms. For example, with an accuracy of around, it is possible to predict the load for the following day for a certain area.

However, since accurate long-range climate predictions are not accessible, it is challenging to anticipate the load at the highest point of the next year without the same accuracy. Using past weather observations, it is possible to calculate the distribution of probability for the workload for the peak forecast for the following year. According to standard industrial practice, it is also possible to estimate what is known as climate normalized load, which occurs during typical yearly peak weather conditions or worse than typical peak weather for a certain area. The load that has been "weather-normalized" is the load that has been calculated in "normal" weather circumstances, which are the typical weather circumstances for the highest historic loads for a certain time period.

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. [28].

In the study, the phrases "energy prediction" and "error," "load forecast" with "error," as well as "demand 0722-2 3 forecast" and "error" were searched. The majority of the papers that were discovered discussed forecasts for demand, electric load, and electrical energy consumption. Articles and conference papers that only addressed the production of renewable energy were ignored.

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 [29].

The authors propose an RNN model for load forecasting with periods of 24 hours, 48 hours, 7, and 30 days. The authors of the research [30] developed an ANN model for district-level forecasting load based on three different approaches. The authors of [31] concentrated on perceptual DNN for extraction of features and showed that using deep learning's unsupervised learning capabilities significantly improved prediction accuracy. For load forecasting, the inventors of [32] devised a recurring inception CNN. In order to determine home load, a deep RNN with a pooled foundation was

examined in [33]. Provided a description of the LSTM-based multi-input multi-output windows technique [34].

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. A collection of sequential information called a "open-ended stream" is one that can only be read once (or twice) in a given 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.

Following and/or predicting appliance-by-appliance consumption, according to another studies, will help consumers alter their habit to use less energy [35]. Building occupancy has also been calculated using predictions and estimates of electricity use [36]. These techniques are used to regulate active equipment, such as lighting or HVAC (Heating, Ventilation, and Air-Conditioning) systems. 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. Kleiminger et al. [37] recommended integrating the setting up of PIR sensors with an analysis of the electricity consumption of 5 residences over a period of eight months in order 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%. Muhammad et al.'s [35] 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. In order 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 [37]. 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 (Long Short-Term Memory) 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.	[14]	Deep Learning-Based Decision Support System for Energy Management in Smart Cities	(MEHOA) based deep dilated multi-kernel convolutional network	DR Model Exploited cannot predict the suitable future pricing
2.	[14]	Utilizing Deep Learning to Drive a Decision Support System for Energy Management in Smart Cities	Convolutional Neural Network	There should be a lot of training data, but avoid encoding the object's orientation and position.
3.	[15]	Utilizing Artificial Neural Networks and Reinforcement Learning for Demand Response in the Management of Home Energy	Artificial Neural Network and Multi-Agent Reinforcement Learning	Not Reduced the irrelevant data
4.	[16]	Smart Monitoring, Artificial Intelligence, and Energy Consumption Optimization for Energy Sustainability in Smart Cities	Support Vector Machine	Computational time is very high
5.	[17]	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

6.	[18]	Price-Based Demand Response on the Smart Grid is Scheduled for Effective Energy Management of IoT-Enabled Smart Homes	Intelligent Forecaster and Internet of Things (IoT)	Increased privacy concerns
7.	[19]	Deep learning's advantages and applications for the internet of things	Deep Learning driven Internet of Things (IoT)	The incoming data can be used by IoT to learn hierarchical representations.
8.	[20]	Electric forecasting of loads for Internet of Things smart homes using a hybrid PCA and ARIMA algorithm	(PCA) and (ARIMA) using the Internet of Things (IoT)	IoT Highly dependent on the internet
10	[21]	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.
11	[26]	Online adaptive recurrent neural networks are able to 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.
12	[27]	Machine learning-based short- and long-term electric load forecasting	Machine Learning	Complexity of the used models' computations
13	[28]	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.
14	[37]	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.
15	Proposed Model	AI-Based Energy Management of a Smart City	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 project, a novel approach for residential LF was presented using our 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
$\sigma_g$	Sigmoid Function
$\tanh$	Hyperbolic Tangent Function
$C_t^{\sim}$	Input Modulation Gate

## 3.2 Proposed Framework

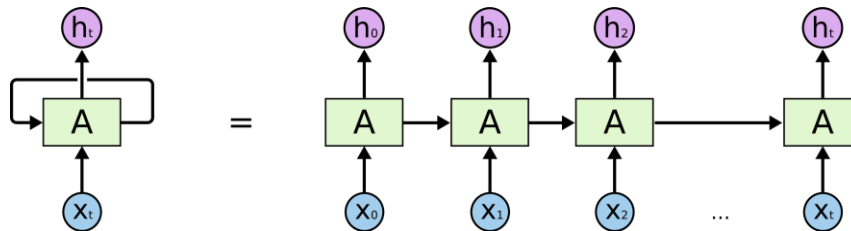
Based on the suggested LF methodologies and structure, this section includes:

### 3.2.1 Neural Networks required background

As indicated in Section 2, the focus of this project is on neural network techniques, namely deep 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 acquire them. Hochreiter and Schmidhuber [1997] 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 (shown in Figure 4 by the top horizontal arrow). 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:

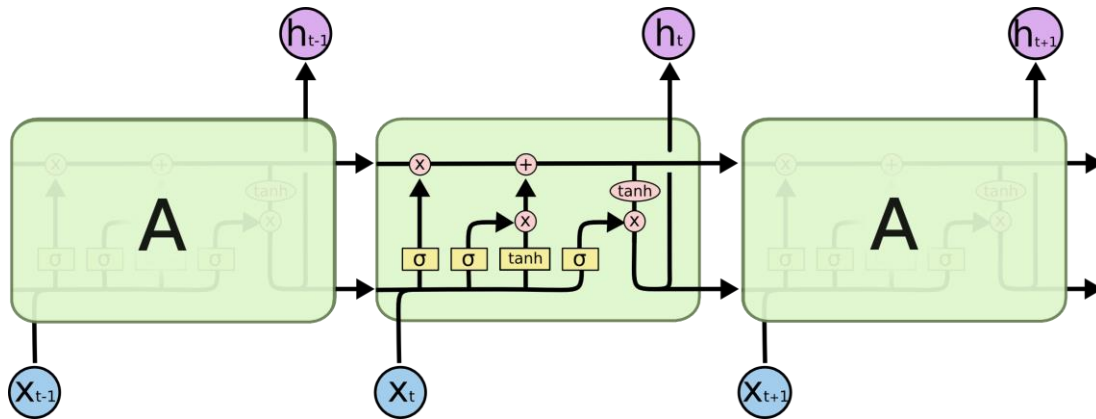


Figure 3.2 Long Short-Term Memory Layers

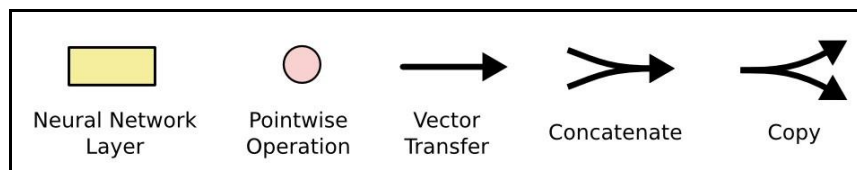


Figure 3.3: Notations of LSTM Layers

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:

- 1) **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.

2) **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

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

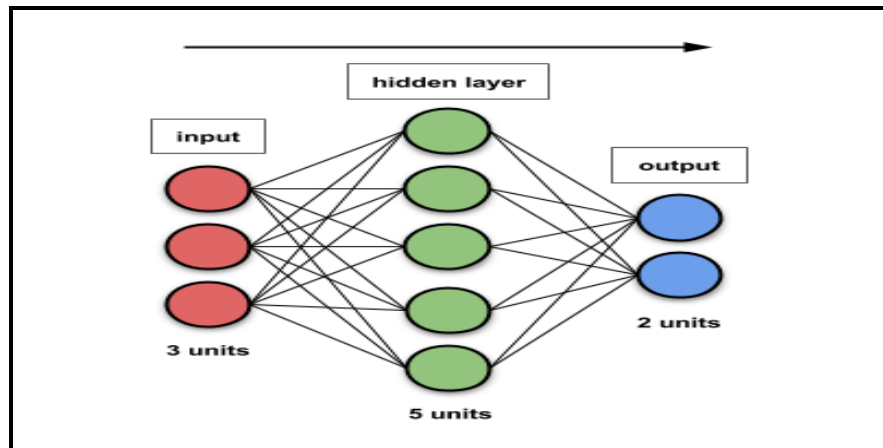


Figure 3.4: Different Layers of LSTM

## 1. 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).

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

## 2. 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

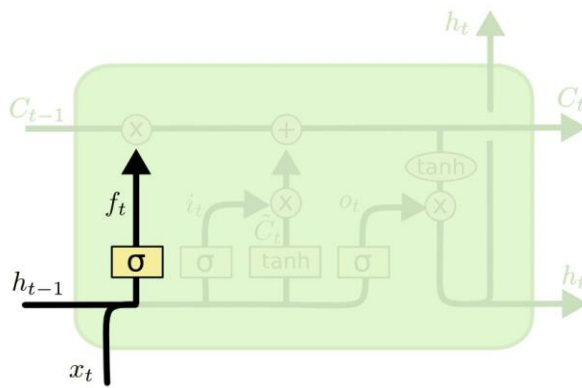


Figure 3.5: First Step of LSTM

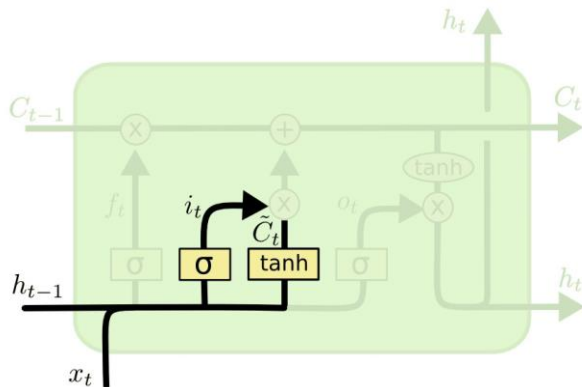
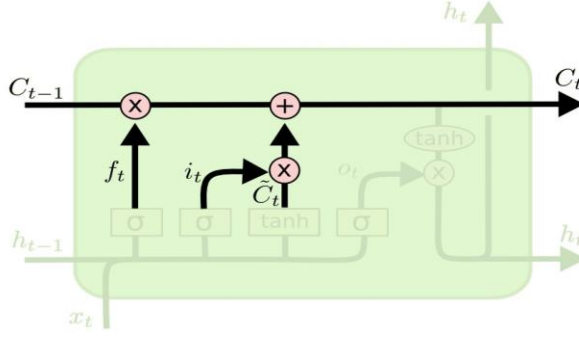


Figure 3.6: Second Step of LSTM



**Figure 3.7:** Third Step of LSTM

(Equation 2) 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).

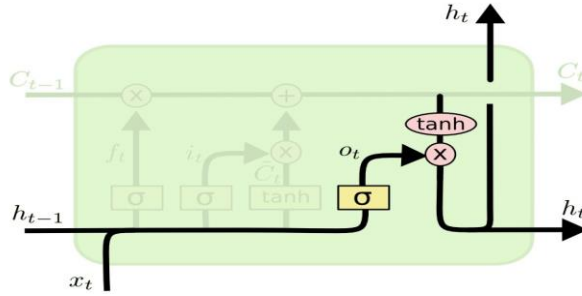
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3.2)$$

$$C_t^{\sim} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3.3)$$

### 3. 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.

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



**Figure 3.8:** Fourth Step of LSTM

#### 4. Output Gate

The output is generated as the last step (Figure 3.8), and it is a filtering description of the modified cell state. On the basis of  $h_{(t-1)}$  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 tanh is used to multiply the sigmoid layer results such that the cell state is translated into values between 1 and 1 (Equation 3.6).

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

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

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 as different ways as a result of their literary effect.

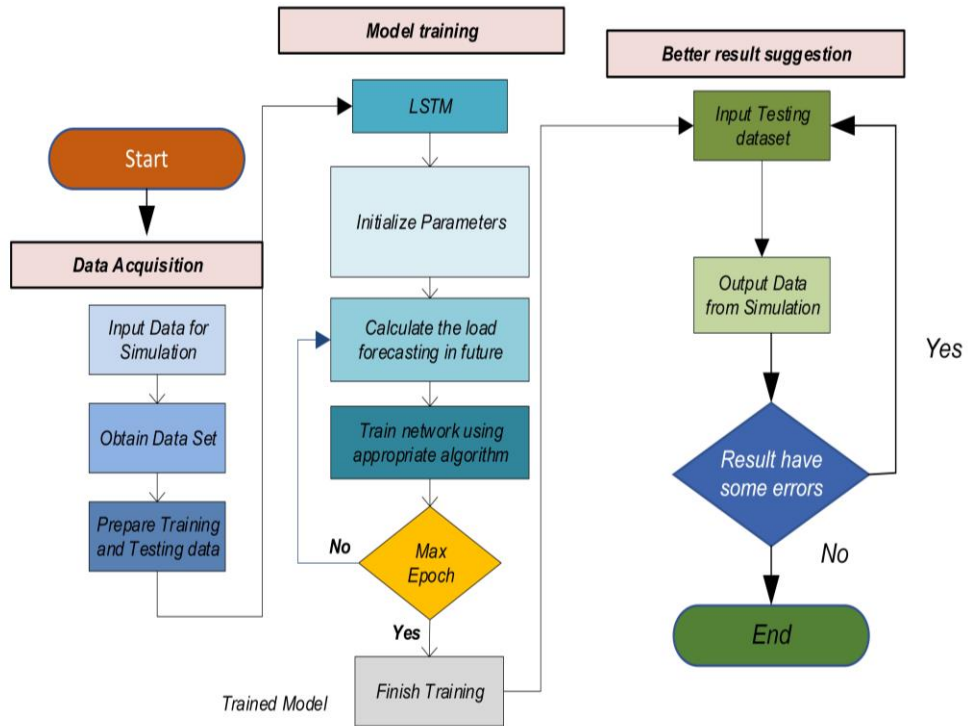
#### 3.2.2 Proposed Integration Strategy

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 taken into account 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 take into account the integration method that we created as fellows for each specific building.

Like any AI models, LSTM networks have flaws, and a number of variables, including as the caliber of the input information, the selected hyperparameters that 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 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 provides a more thorough description of the algorithm, which is validated using a 20-year LF artificial neural network. This integration's goal is to identify which data points are more false. 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

<b>Proposed Algorithm</b>	
<b>Step 1:</b>	1. Set the hidden state and cell state to 0.
<b>Step 2:</b>	2. According to the input sequence, at each time step t: <ul style="list-style-type: none"><li>▪ Calculate the signal to the gate using the present input vectors and the previous hidden state <math>i_t</math>.</li><li>▪ Calculate the forget gate using the present input vector and the previous hidden state <math>f_t</math>.</li><li>▪ Calculate the candidate memory cell vector using the current input vector and the previous concealed state. <math>C_t</math>.</li><li>▪ Update the current memory cell vector using the input gate <math>i_t</math>, the forget gate <math>f_t</math>, and the prospective memory cell vector <math>C_t</math>.</li><li>▪ Calculate the output gate using the current input vector and the previous hidden state <math>o_t</math>.</li><li>▪ Apply the output gate <math>o_t</math> to the current memory cell vector <math>C_t</math> using a hyperbolic tangent activation function to determine the current hidden state <math>h_t</math>.</li></ul>
<b>Step 5:</b>	3. As the output, give the hidden state sequence $h_1, h_2, h_3 \dots \dots \dots h_t$ .
<b>Step 6:</b>	Plot the Figures of LSTM Prediction
<b>Step 7:</b>	Plot the Figures of Future Values

In summary, the LSTM cell receives an input vector and the previous 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.

### 3.2.3 Model Evaluation

Evaluation of the LSTM for Load model Measuring the model's precision in forecasting a Smart City'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:

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

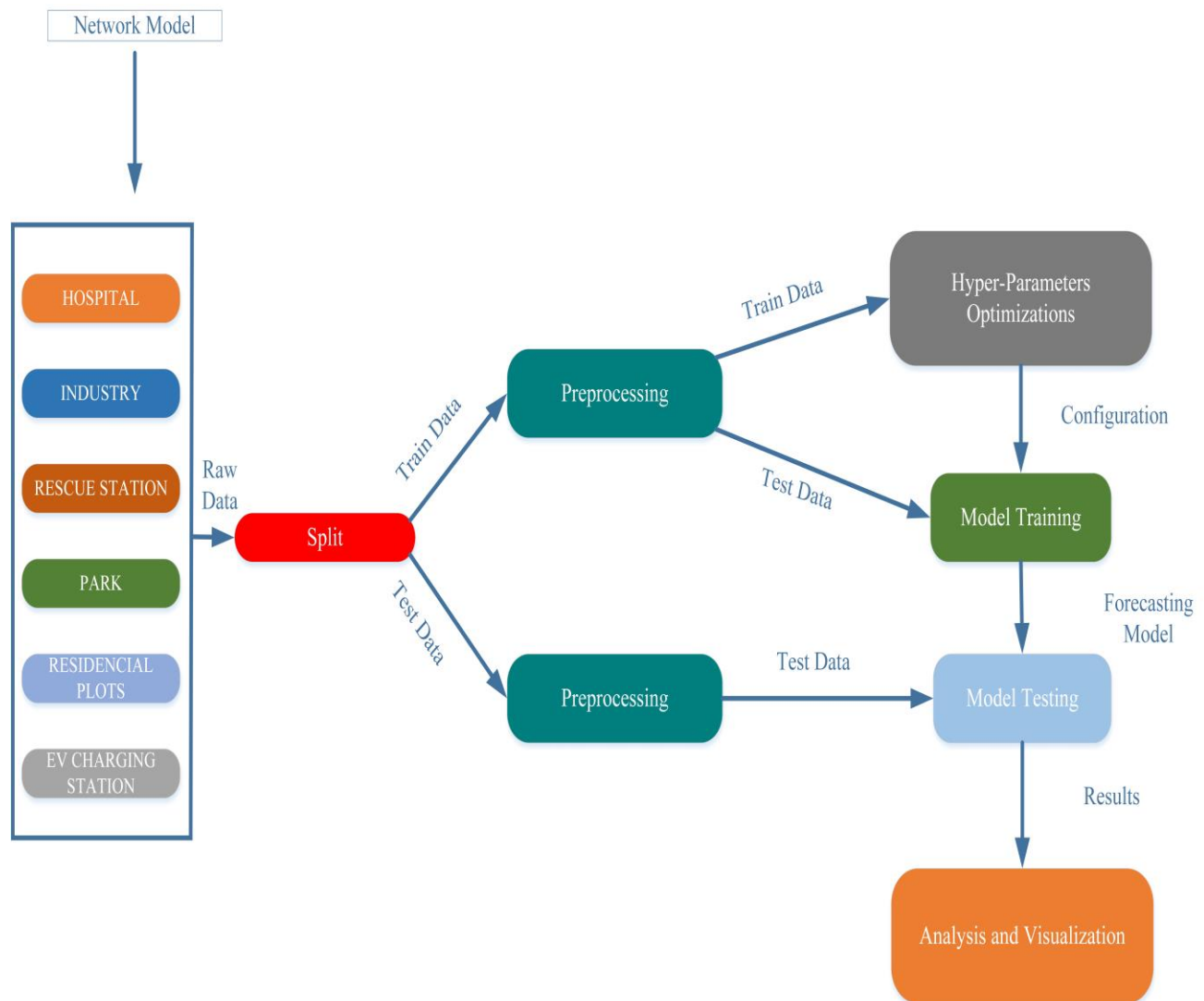
When N is the total amount of cycles,  $C_n$  is the predicted capacity, and  $\hat{C}_n$  is the ground truth capacity.

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 smart city 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.

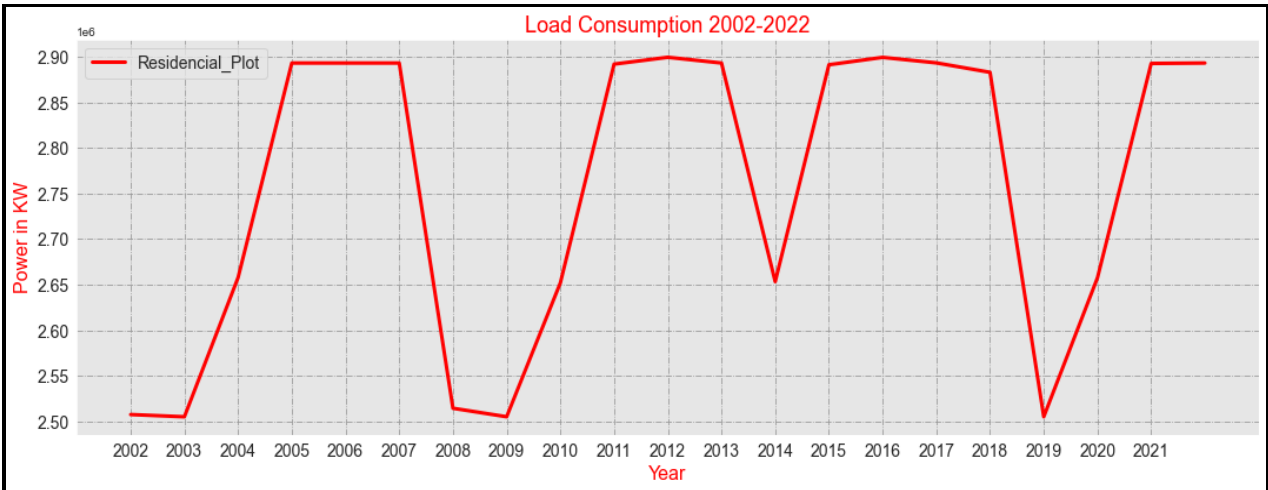
### 3.3 Data Collection and Analysis

In which various load data are gathered to show how differently the load in a smart city 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. The different figures and data graphs are given below.

**Table 3.3:** Load Forecasting Data of Smart City Starting from 2002

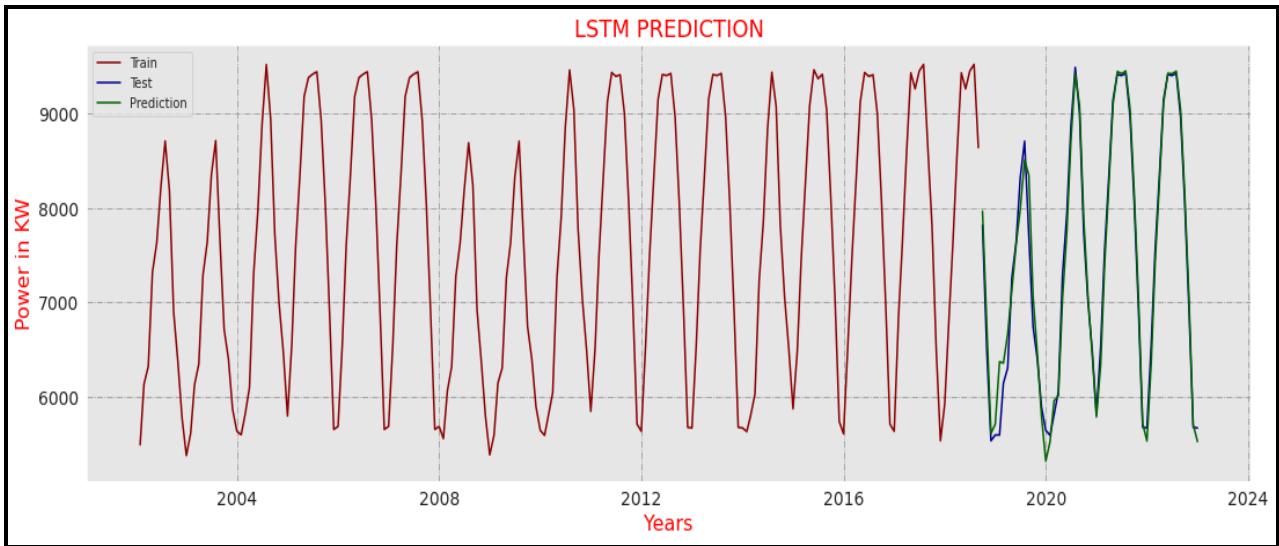
Sr No	Date	Residential Plot(W)	Industry(W)	Hospital(W)	Park(W)	Rescue(W)
0	01/01/2002	5715	62452.32	15128	2170	1754
1	02/01/2002	5641	6245.43	14526	2012	1845
2	03/01/2002	5113	5211.41	13832	1845	1945
3	04/01/2002	5258	3236.12	12456	2015	1245
4	05/01/2002	5456	3778.47	11256	2312	1452
5	06/01/2002	5651	3897.7	14556	2415	1654

Now first we discuss the data of Residential Plots as shown Figure 3.11,3.12 and 3.13 also discuss its Yearly Consumption Data, LSTM Predicted Data, and Forecasted Data.



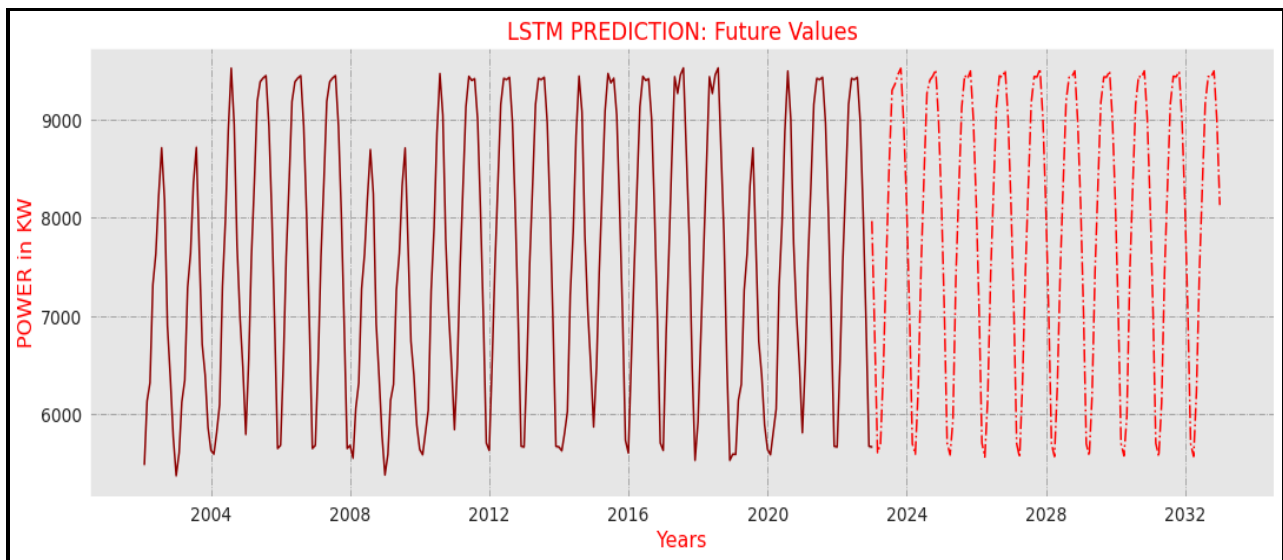
**Figure 3.11:** Yearly Consumption Data of Residential Plots

First, we take 21 Years data in which the 16.5 years data should be trained and the remaining should be tested data. Figure 3.12 depicts that the prediction should be based on the 5.5 years for the next 10 Years. The overlapping shows the predicted data.



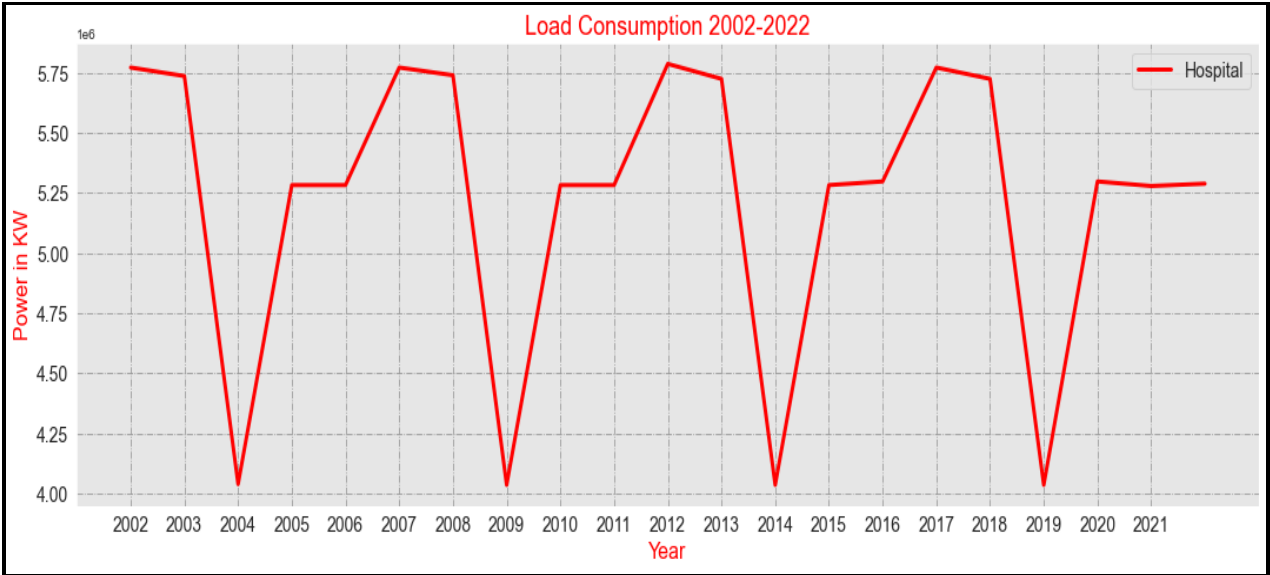
**Figure 3.12: LSTM Predicted Data**

Figure 3.13 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.



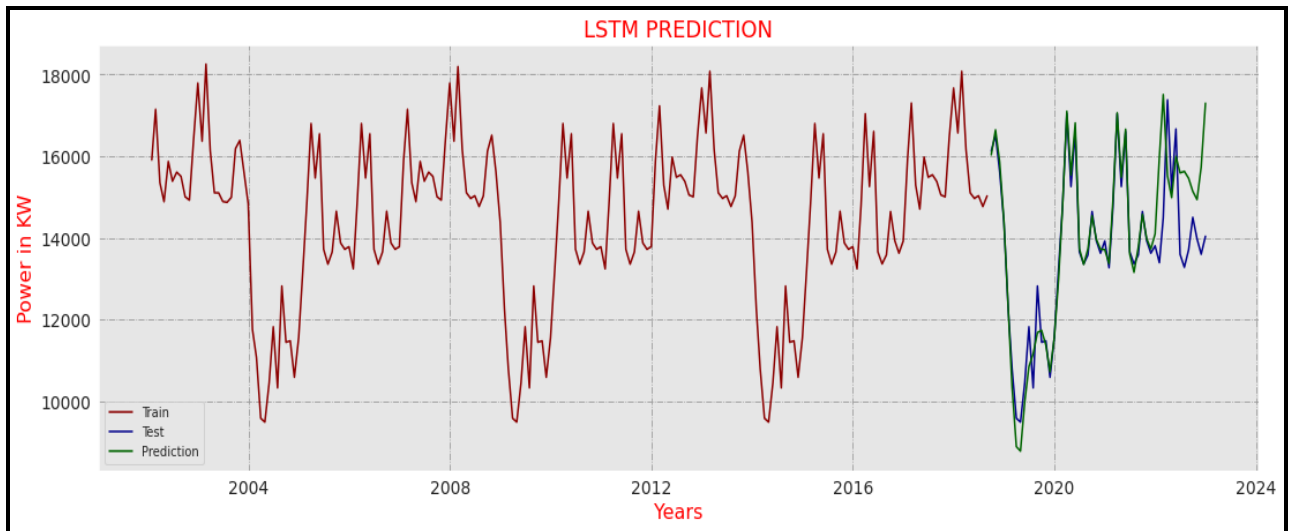
**Figure 3.13: Original Data Vs Forecasted Data**

Now we discuss the data Hospital as describe in Figure 3.14, 3.15 and 3.16 also discuss its Yearly Consumption Data, LSTM Predicted Data, and Forecasted Data.



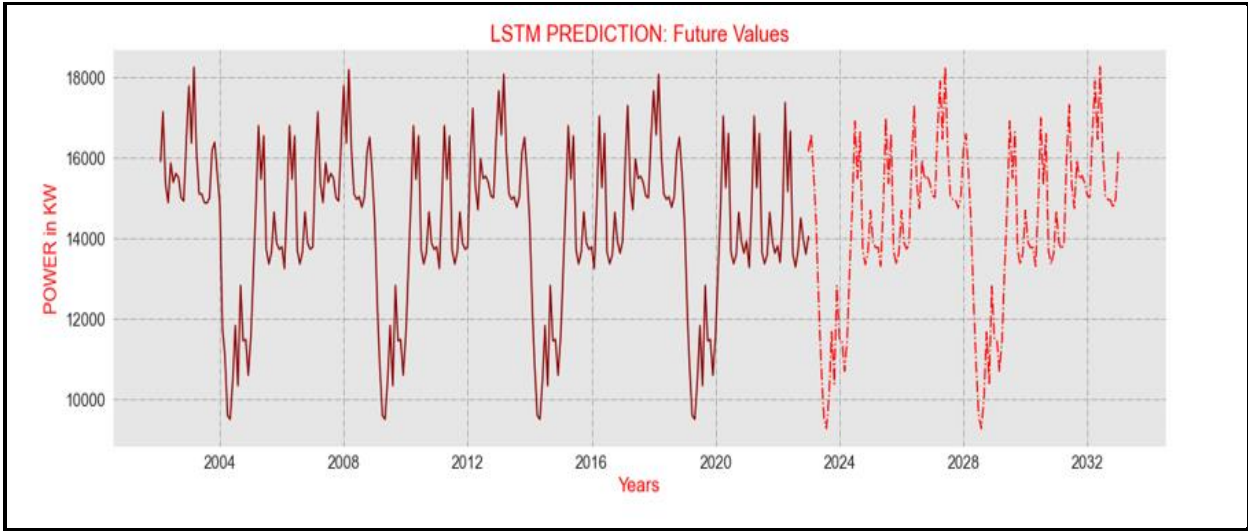
**Figure 3.14:** Yearly Consumption Data of Hospital

First, we take 21 Years data in which the 16.5 years data should be trained and the remaining should be tested data. Figure 3.15 depicts that the prediction should be based on the 5.5 years for the next 10 Years. The overlapping shows the predicted data.



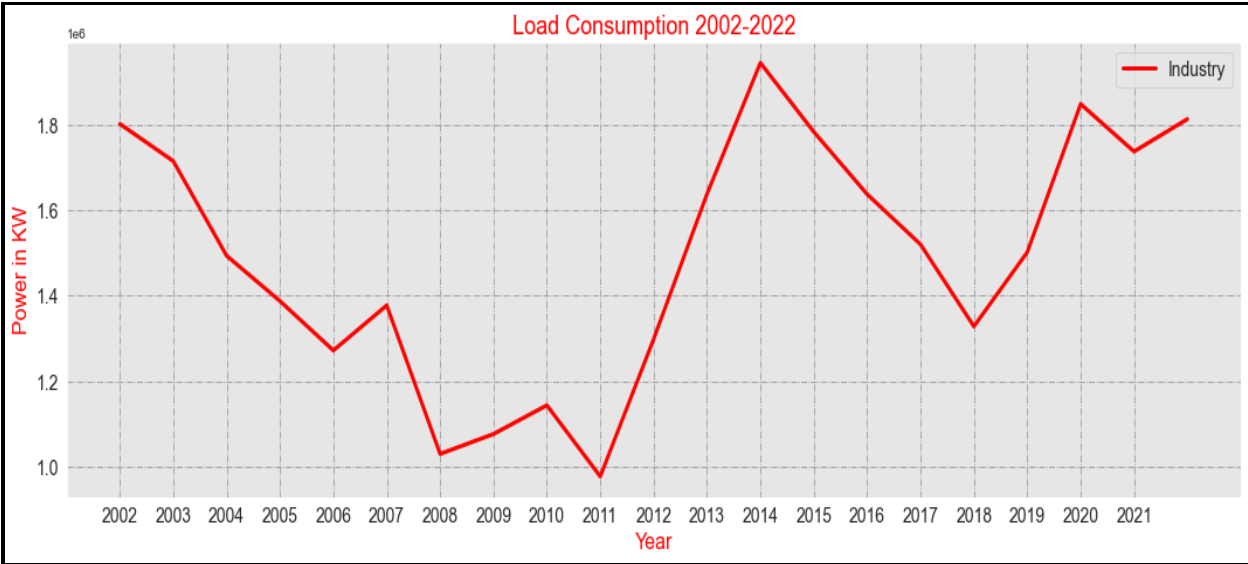
**Figure 3.15:** LSTM Predicted Data

The simple line in Figure 3.16 depicts the original data, while the dotted line indicates the anticipated values for the next 10 years. This is how an LSTM predicts the Data.



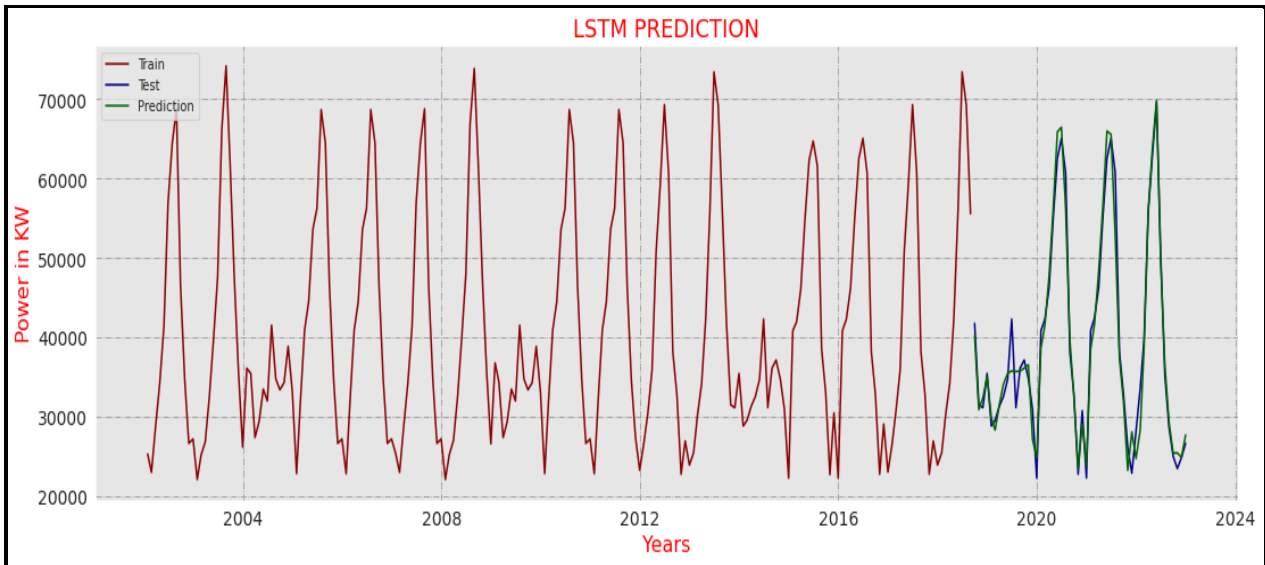
**Figure 3.16:** Original Data Vs Forecasted Data

Now we discuss the data Industry as shown in Figure 3.17, 3.18 and 3.19 also discuss its Yearly Consumption Data, LSTM Predicted Data, and Forecasted Data.



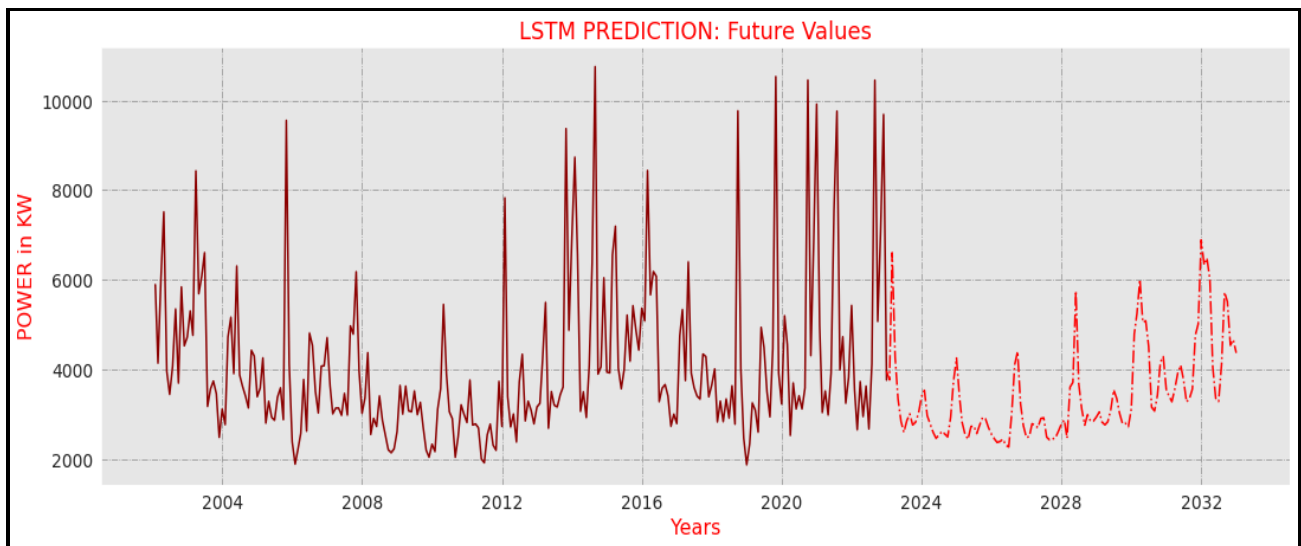
**Figure 3.17:** Yearly Consumption Data of Industry

First, we take 21 Years data in which the 16.5 years data should be trained and the remaining should be tested data. Figure 3.18 depicts that the prediction should be based on the 5.5 years for the next 10 Years. The overlapping shows the predicted data.



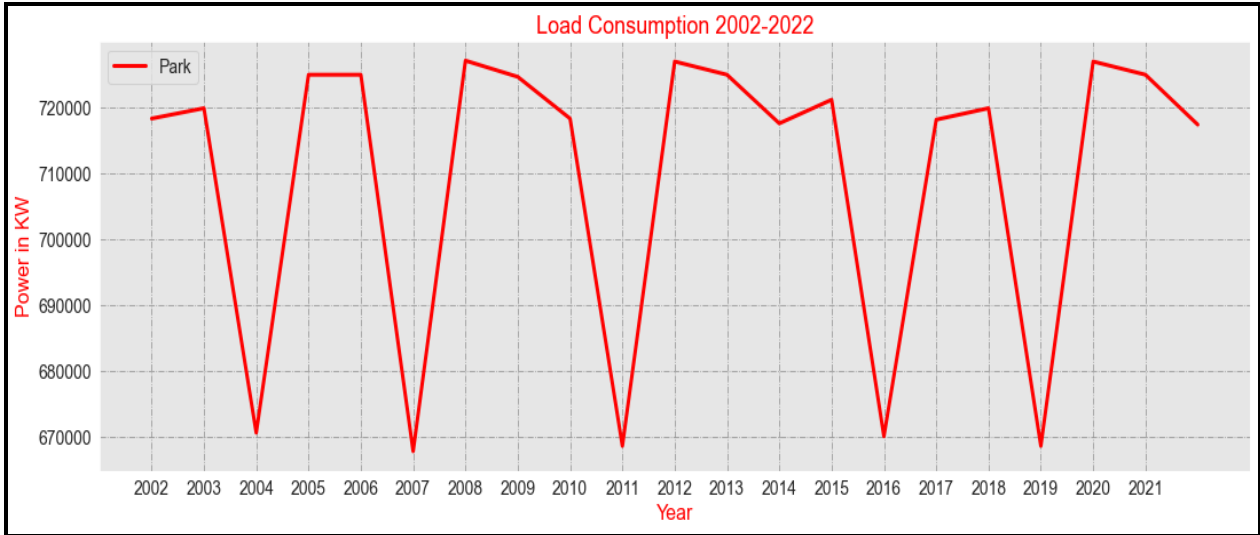
**Figure 3.18:** LSTM Predicted Data

The simple line in Figure 3.19 depicts the original data, while the dotted line indicates the anticipated values for the next 10 years. This is how an LSTM predicts the Data.



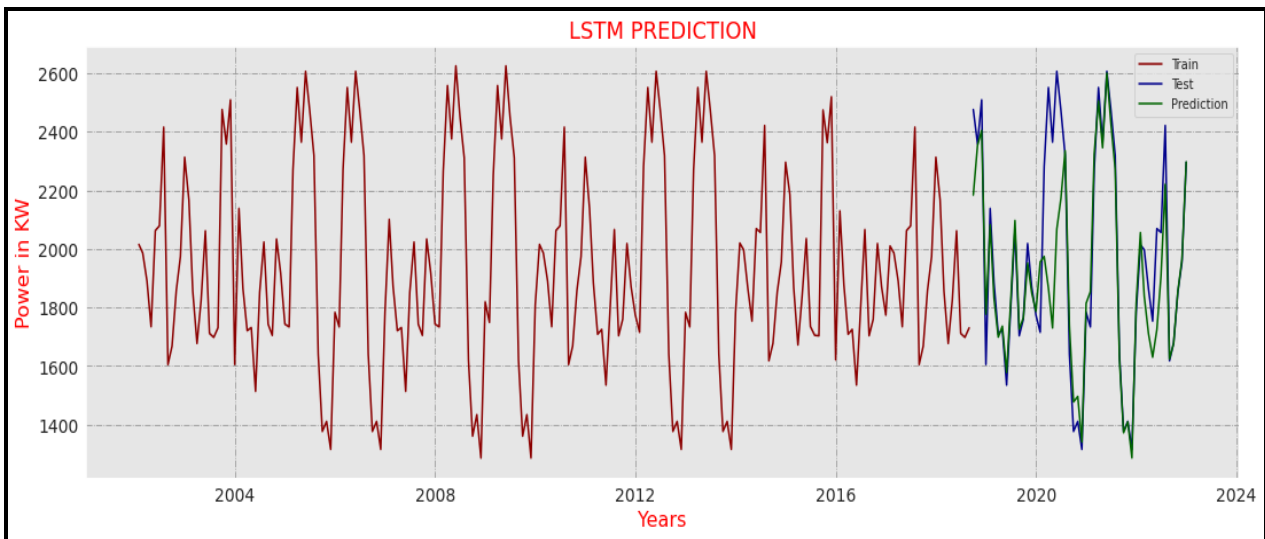
**Figure 3.19:** Original Data Vs Forecasted Data

Now we discuss the data Park as shown in Figure 3.20, 3.21 and 3.22 also discuss its Yearly Consumption Data, LSTM Predicted Data, and Forecasted Data.



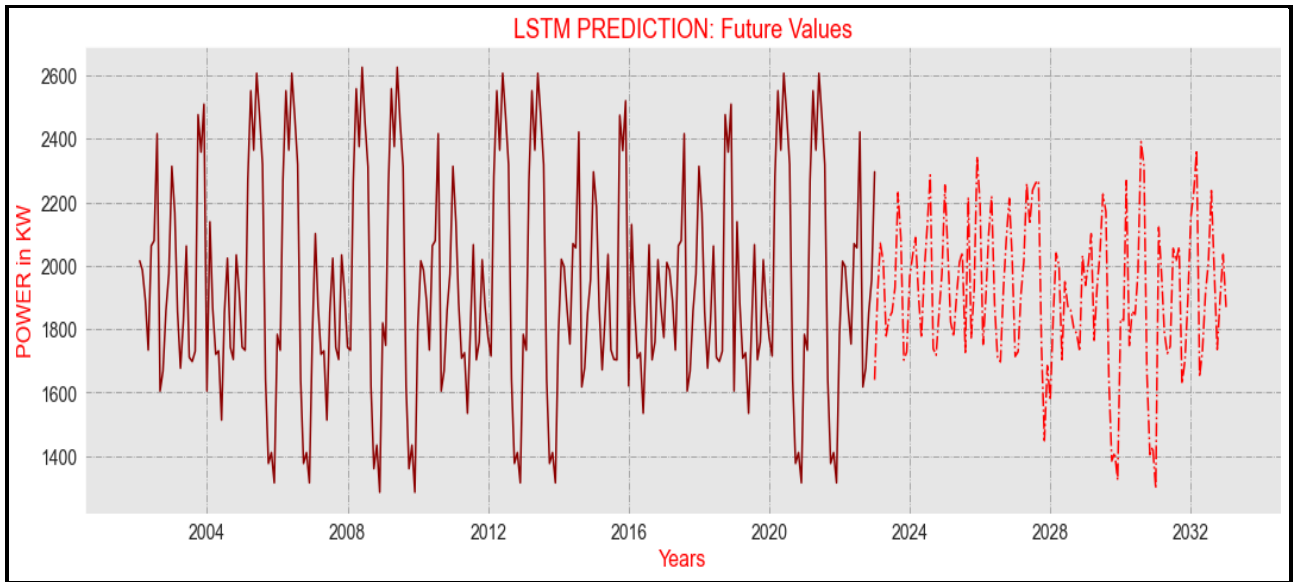
**Figure 3.20:** Yearly Consumption Data of Park

First, we take 21 Years data in which the 16.5 years data should be trained and the remaining should be tested data. Figure 3.21 depicts that the prediction should be based on the 5.5 years for the next 10 Years. The overlapping shows the predicted data.



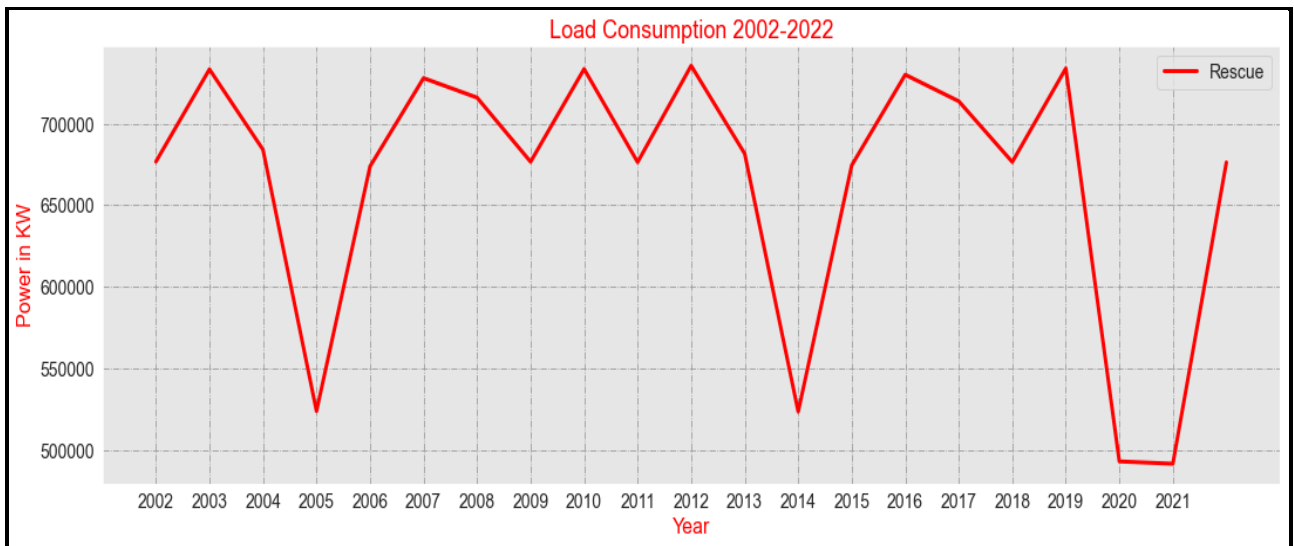
**Figure 3.21:** LSTM Predicted Data

Figure 3.22 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.



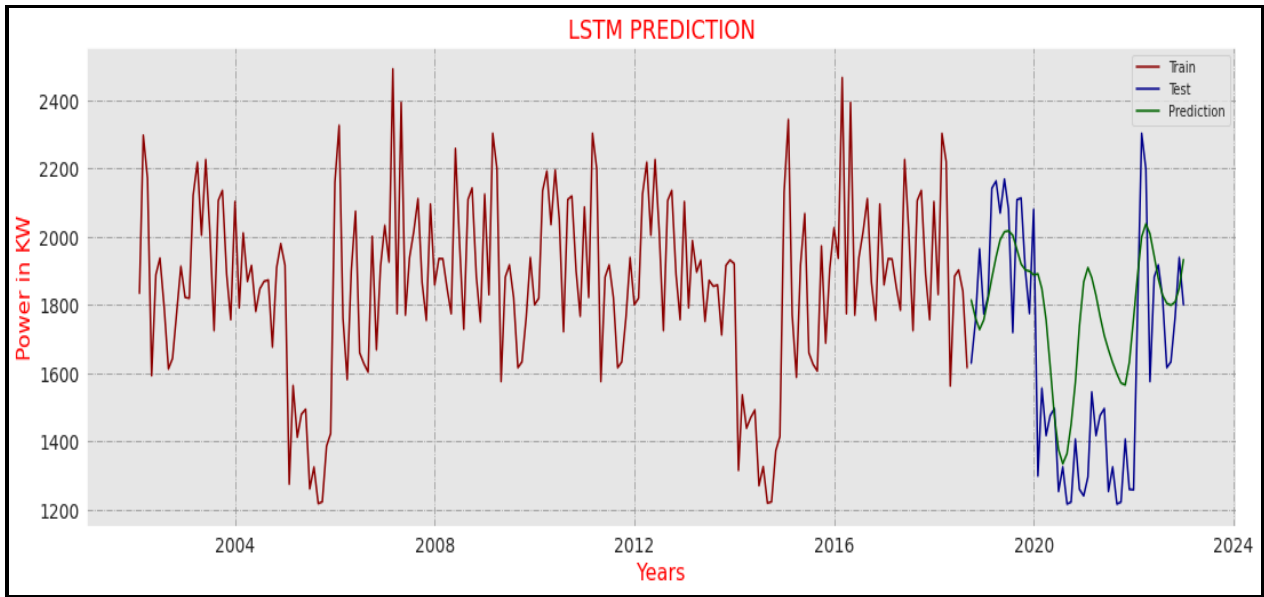
**Figure 3.22:** Original Data Vs Forecasted Data

Now we discuss the data Rescue as shown in Figure 3.23, 3.24 and 3.25 also discuss its Yearly Consumption Data, LSTM Predicted Data, and Forecasted Data.



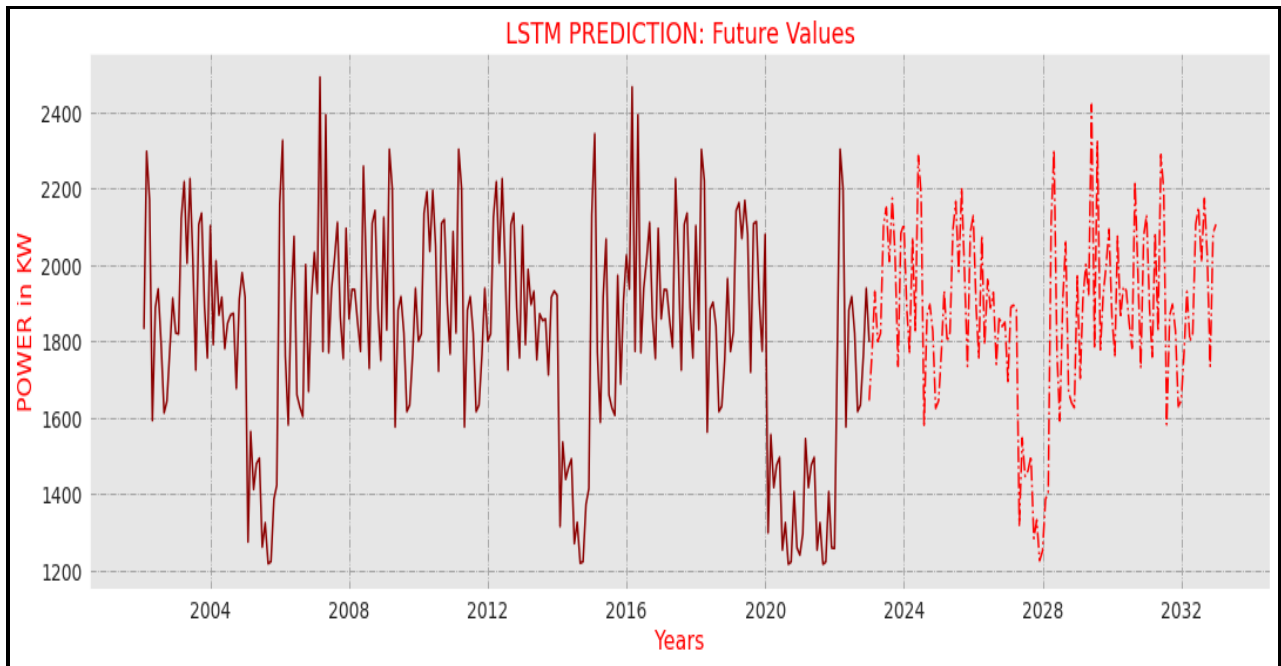
**Figure 3.23:** Yearly Consumption Data of Rescue

First, we take 21 Years data in which the 16.5 years data should be trained and the remaining should be tested data. Figure 3.24 depicts that the prediction should be based on the 5.5 years for the next 10 Years. The overlapping shows the predicted data.



**Figure 3.24: LSTM Predicted Data**

The plain line in Figure 3.25 depicts the original data, while the dotted line indicates the anticipated values for the next 10 years. This is how an LSTM predicts the Data.



**Figure 3.25: Original Data Vs Forecasted Data**

The accuracy for Smart City Data prediction is shown in the table along with Root Mean Square Error (RMSE) and loss in the model.

**Table 3.4:** RMSE, Loss and Accuracy of Inputs

<b>Sr No</b>	<b>Inputs</b>	<b>Root Mean Square Error (RMSE)</b>	<b>Loss</b>	<b>Accuracy (%)</b>
<b>0</b>	<b>Residential Plots</b>	0.040939193257074055	0.0001	4.0
<b>1</b>	<b>Hospital</b>	0.04350975468418003	0.0001	4.3
<b>2</b>	<b>Park</b>	0.051962410171365395	0.0001	5.1
<b>3</b>	<b>Rescue</b>	0.03746223564954682	0.0001	3.7
<b>4</b>	<b>Industry</b>	0.09736663127160096	0.0014	9.7

A crucial task for efficient resource planning and use in a smart city is load forecasting. The load on a city's electrical system can change considerably due to population growth and the adoption of new technology. The electricity system of a smart city should be able to manage this variance in demand while yet being dependable and stable. Data from a variety of sources, including weather patterns, population growth, commercial and industrial expansion, and energy consumption trends, must be analyzed in order to forecast the load. Machine learning models and algorithms are able to predict the load across a variety of timescales, from minutes to months, using this data. A smart city may optimize its power management and distribution systems, save energy costs, and raise the overall effectiveness of the power grid with accurate load predictions. It is crucial to creating a smart, sustainable city that can offer its citizens a high quality of life.

### **3.4 Conclusion**

One of the crucial components for better organizing and managing power generation systems is load management (LF), which is a component of the Smart City. In this study, a brand-new time series-based forecasting model is employed. a suggested feature selection technique, a long short-term memory, and an integration strategy. For the analysis of the more intricate and substantial historical data, we presented a new time series and autoregression algorithm. The ANN-based feedback model, which computes five phases, is used to further validate the time series LSTM model. The method for selecting the best features is assessed in order to produce better optimized results. A proposed integration technique, which provides an annual rising increase as compared to earlier ones, has proven successful in achieving an impressive improvement in outcome that accurately predicts load and

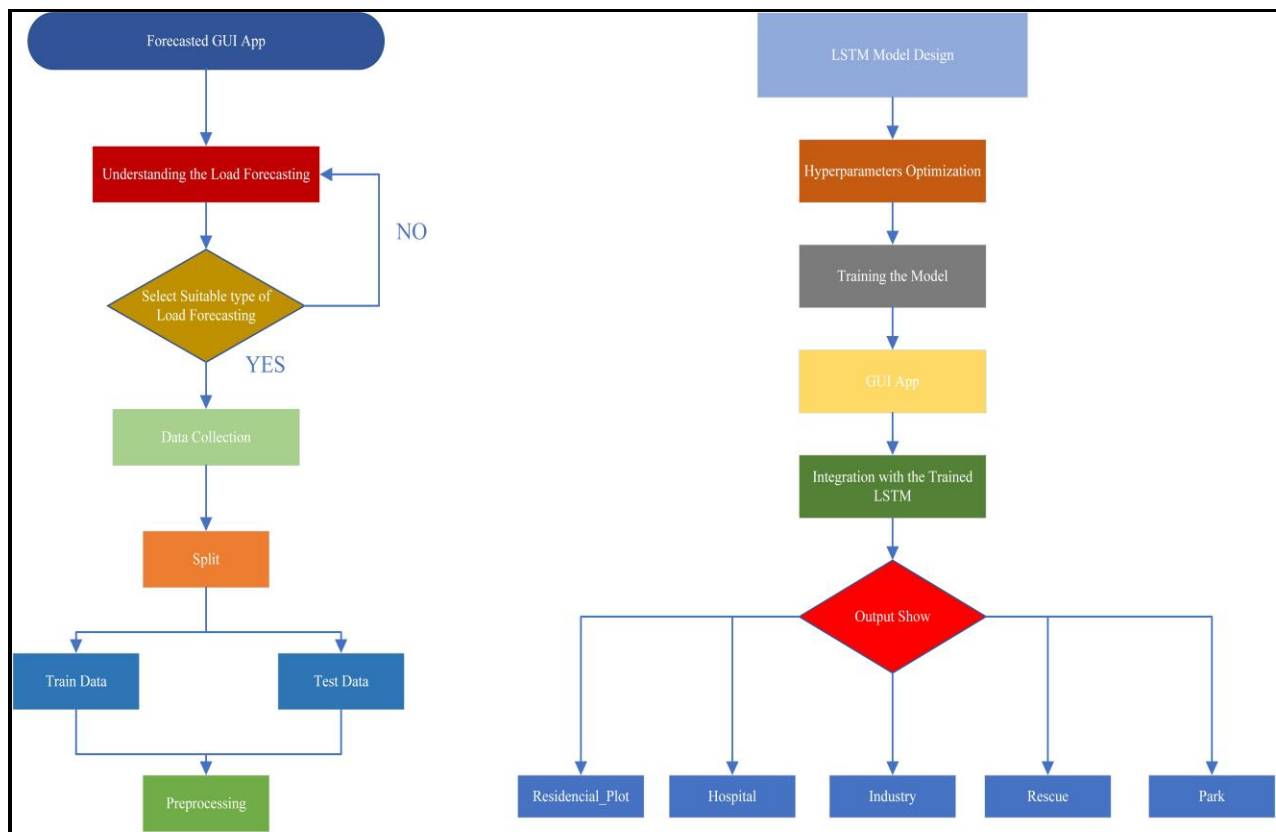
minimizes RMSE. respectively are highly desirable and promising. By forecasting the optimized STLF, this model can improve the functionality of Smart Cities and solve issues with load management and planning.

# CHAPTER 4

## SOFTWARE DEVELOPMENT

### 4.1 Introduction

In this age of rapid innovation, the concept of intelligent cities has generated a great deal of interest. A smart city attempts to raise the standard of living for its residents by effectively managing resources including infrastructure, transportation, and energy. Load forecasting is crucial to the efficient management of electricity distribution in a smart city. Accurate load forecasting paves the way for operational cost reduction, resource allocation optimization, and proactive decision-making. In this post, we'll go into great detail and give a detailed explanation of how an LSTM (long and short-term memory) artificial neural network-based graphical user interface is created for forecasting load in smart cities. A visual representation like the one in Figure 4.1 can be used to further clarify the structure and purpose of the GUI program.



**Figure 4.1:** Structure and Working of a GUI APP

#### **4.1.1 Step 1: Understanding Load Forecasting**

In load forecasting, the demand for electricity is projected for a future period of time, such as an hour, a day, or a week. Utility firms and city managers can effectively plan and distribute resources thanks to accurate load forecasts. Load forecasting is influenced by a number of variables, such as past load trends, weather patterns, unique events, and economic indicators. It has been demonstrated that machine learning methods, in particular LSTM neural networks, are efficient in capturing complicated temporal patterns and accurately forecasting future load demand.

#### **4.1.2 Step 2: Data Collection and Preprocessing**

Collecting pertinent data is a vital initial step in creating a load forecasting program. This contains past load statistics, weather information, and any other pertinent data that can affect electricity consumption. While weather information aids in capturing the influence of temperature, humidity, and other meteorological conditions on load demand, historical load data offers insights into previous consumption trends. To ensure the data's quality and compliance with the LSTM model, it must be preprocessed after it has been gathered. Handling missing values, normalizing the data, and constructing suitable input-output sequences for training the model are examples of data preparation activities.

#### **4.1.3 Step 3: LSTM Model Design**

The LSTM neural network, a kind of recurrent neural network (RNN), may successfully capture dependence over time in sequential data. The number of hidden layers, the number of LSTM components per layer, and the activation functions are some of the parameters that are set during the design of the LSTM model. The model architecture should also take into account input variables like historical load data and weather data. The LSTM model integrates historical load trends and weather information for accurate load estimates. The ideal optimization method and loss function must be picked in order to train the model successfully.

#### **4.1.4 Step 4: Training the LSTM Model**

By feeding the neural network with the provided data and changing model parameters to reduce prediction errors, the LSTM model is trained. A set for training and a set for validation are created from the data. The set for validation is used to assess the model's performance, while the set for training is used to enhance it. During training, the LSTM model develops the capacity to identify temporal correlations and produce accurate load projections. The training procedure is repetitive unless the

model performs successfully on the validation set. Reduce overfitting and enhance the generality of the model by using regularization approaches like dropout and early halting.

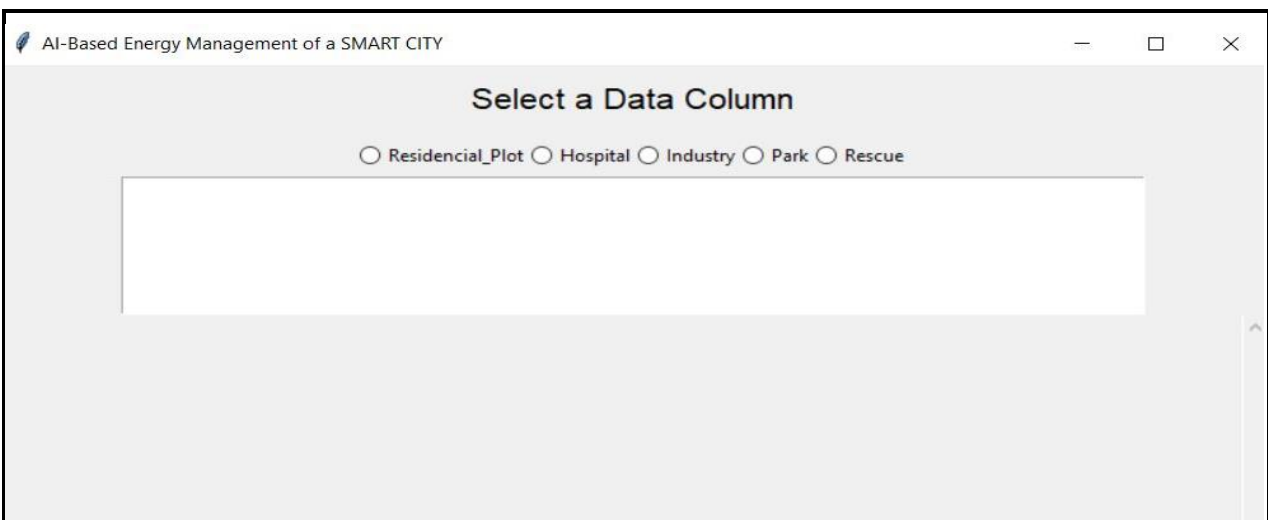
#### 4.1.5 Step 5: GUI App Development

The creation of a Graphical User Interface (GUI) application that offers an easy-to-use platform for load forecasting comes after the LSTM model has been trained. By entering the appropriate information, such as the date, time, and weather conditions, the GUI software enables users, such as city managers or utility operators, to generate load forecasts for the specified time period. Different computer languages and frameworks, including Python and Tkinter, can be used to create the GUI. The application should offer a user-friendly, interactive interface with clear load forecast visualizations.

#### 4.1.6 Step 6: Integration and Deployment

To enable real-time load forecasting, the GUI application must be connected with the trained LSTM model after it has been created. The integration process entails connecting the GUI and forecasting engine seamlessly and importing the trained model parameters into the application. The installation of the program could be done on local servers or cloud platforms, depending on the size and requirements of the smart city project. The deployed application's security, scalability, and dependability should be carefully considered.

Now we are going to discuss the GUI App configuration and their results.



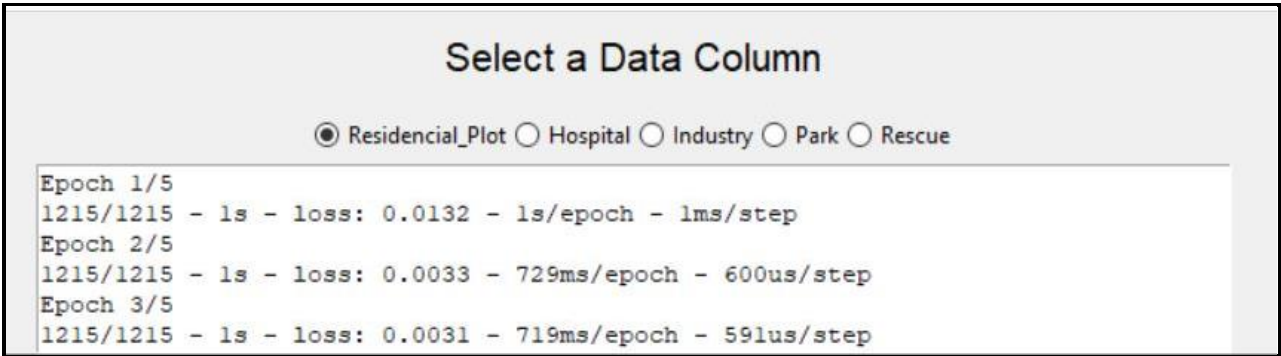
**Figure 4.2:** App Interface

See figure 4.3 in which a GUI interface is open first of all, we select a Data Column in which 5 inputs are used as shown below in fig.



**Figure 4.3:** Selection of Data Column

In the next step, there is an LCD attached with the App Interface its dimensions are 80 \*6. The purpose of the LCD interfacing is that to show the model training and the total loss which the LSTM removed from the raw data which we are providing to the App. Here is the running mode as shown in fig 4.4.

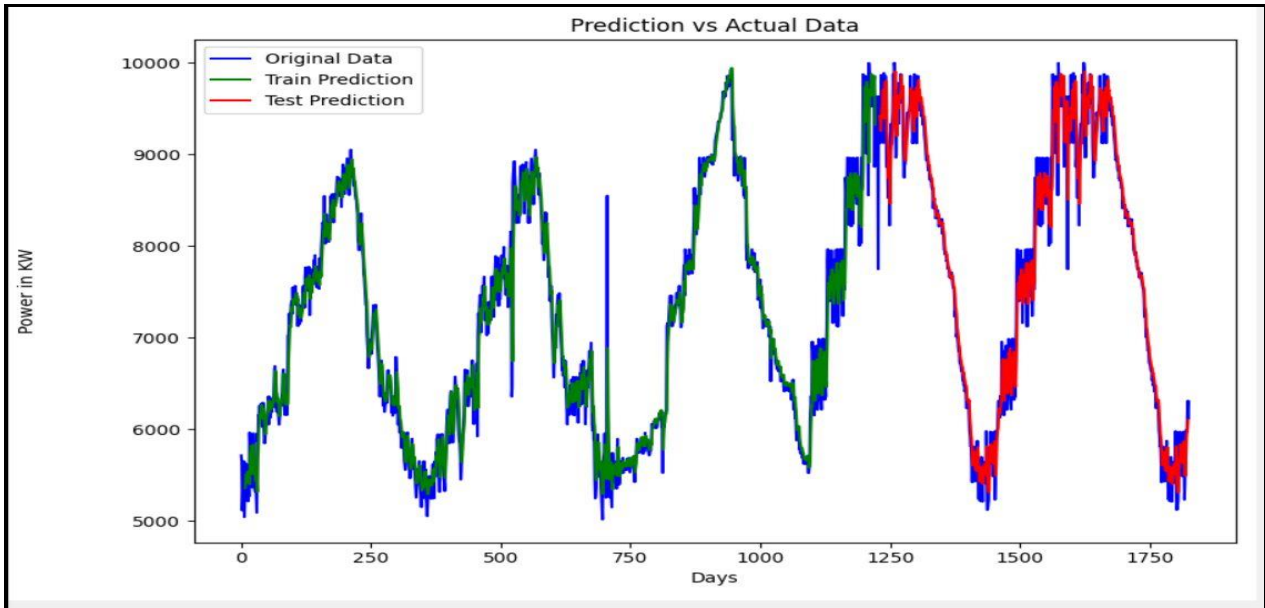


**Figure 4.4:** Integration of LCD with LSTM Model

Positive outcomes were obtained from the GUI app created for load forecasting in the AI-based energy management system. The software gave customers a simple way to enter pertinent information and rapidly get load forecasts. Energy managers, utility firms, and city administrators were able to plan energy generation and distribution effectively because to the LSTM model's incorporation into the app. The app's outcomes showed that accurate load forecasting is possible, allowing users to foresee future energy needs and allocate resources wisely. Energy manager may optimize energy management techniques, cut expenses, and improve overall efficiency in a smart city setting by utilizing the power of the GUI interface.

Now we are going to discuss the results of our Inputs.

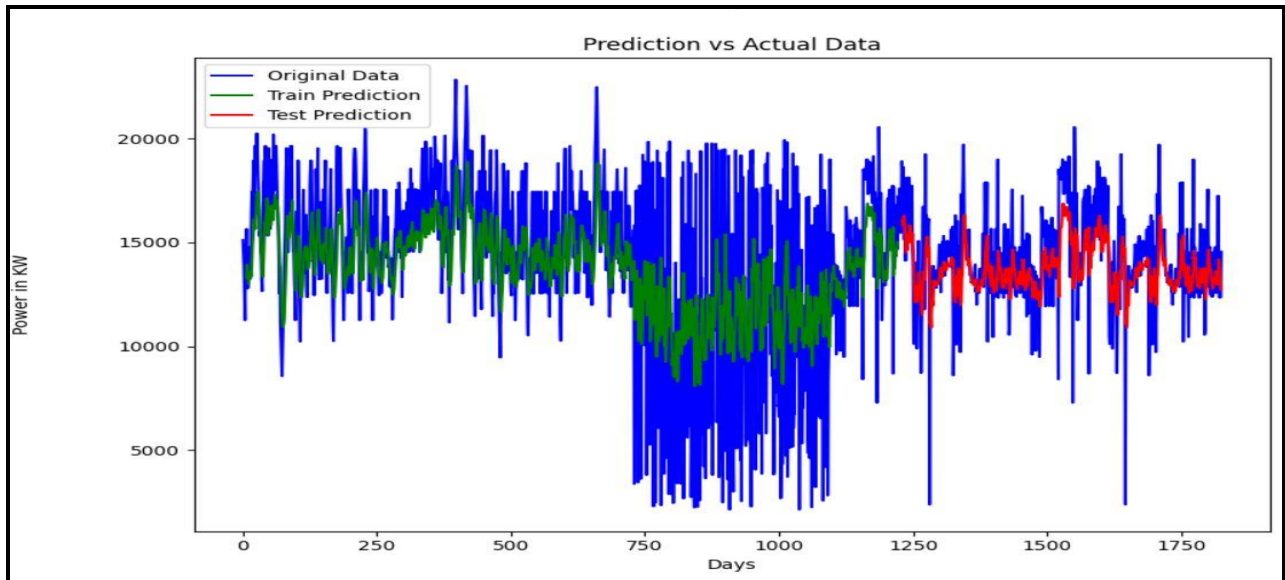
- **Residential Plots**



**Figure 4.5:** Residential Plot Result

Insightful findings came from the study of residential plot data in the AI-based energy management system. The technology produced precise projections of the energy demands in residential sections of the smart city by utilizing the obtained data and applying load forecasting algorithms. The outcomes showed how well the algorithm could detect and predict the intricate patterns of energy usage found in residential plots. Making informed choices about energy generation, distribution, and consumption strategies has shown to be extremely helpful for energy managers, utility companies, and city authorities. Stakeholders were able to maximize resource allocation, lower expenses, and eliminate energy waste by matching energy supply with anticipated demands. The information made it simpler to develop demand-side management programs, allowing for the detection of demand peaks and the implementation of strategies to promote load shedding and energy conservation amongst residential consumers. Overall, the findings showed that the AI-based energy management system is successful in boosting energy efficiency and encouraging sustainable behaviors in the smart city's residential zones..

- **Hospital**



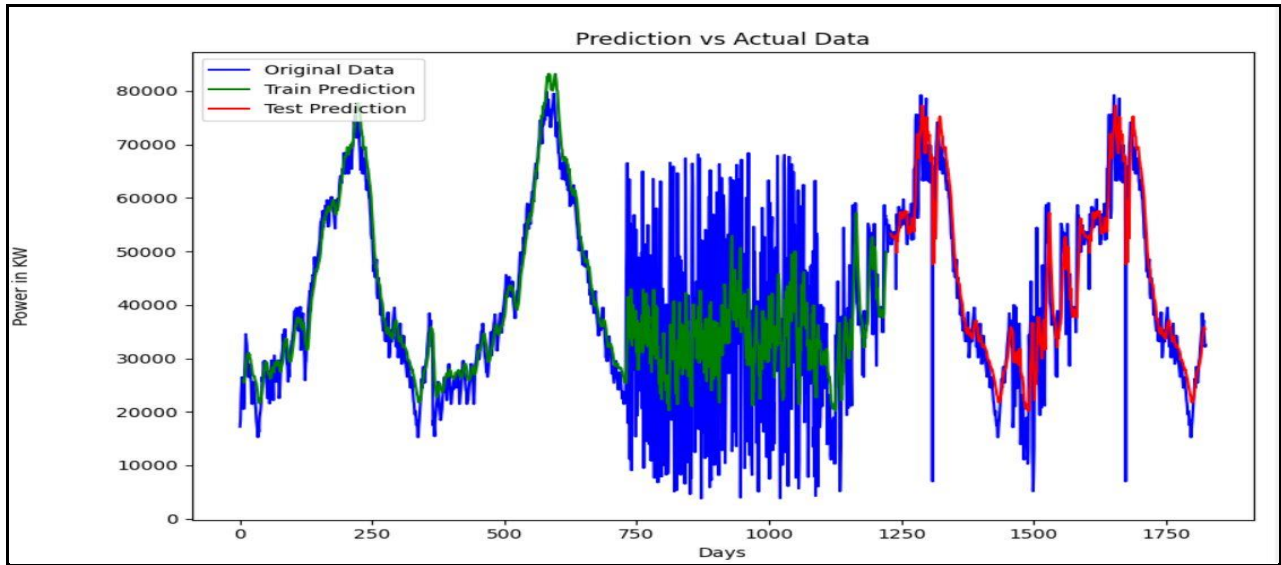
**Figure 4.6:** Hospital Result

In order to provide healthcare services to people in need, hospitals are essential. These specialized healthcare institutions offer a variety of services, state-of-the-art medical tools, and qualified medical staff to diagnose, treat, and care for patients. Hospitals are important centers for urgent care, surgery, specialised care, and long-term patient care. In addition to offering medical services, they also support healthcare industry innovation, training, and research. Hospitals frequently run around the clock to provide the population with access to healthcare every single day. In order to maintain operations, maintain patient comfort, and enable the use of cutting-edge medical equipment, hospitals must manage energy effectively. By implementing AI-based energy management systems, hospitals can successfully deliver high-quality healthcare services by optimizing energy use, reducing waste, and improving overall energy efficiency.

- **Industry**

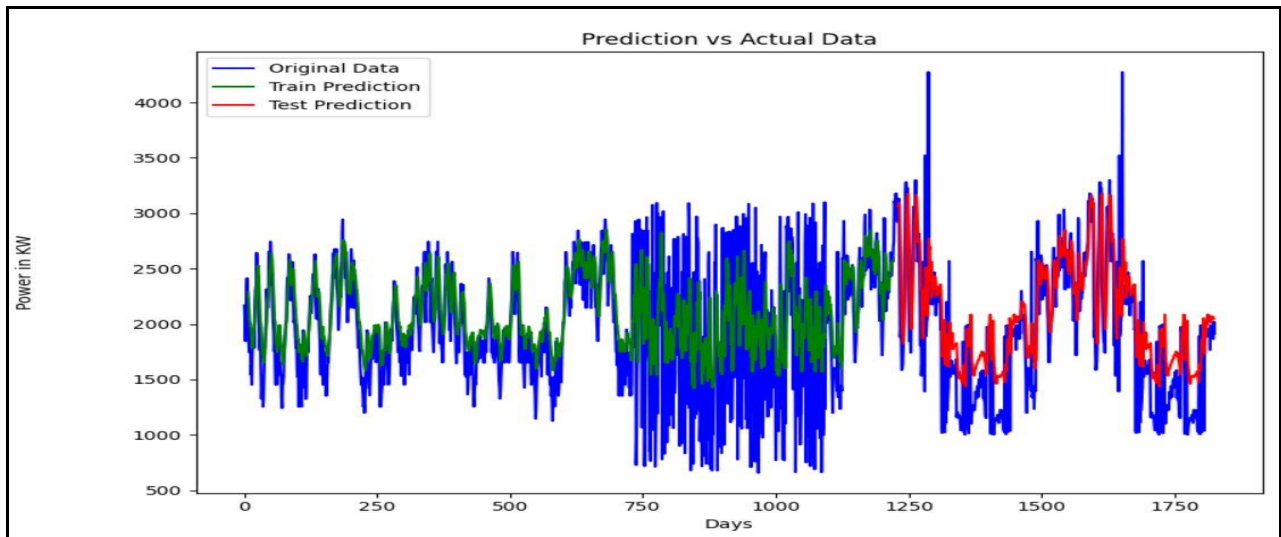
Industries, which include a wide range of industries like manufacturing, production, building, and more, are crucial parts of contemporary economies. AI-based energy management systems can be implemented in industries to optimise energy use, lower costs, and lessen environmental effect. Industries may increase productivity, sustainability, and competitiveness in the global market by

examining energy consumption trends, spotting inefficiencies, and putting energy-saving measures in place.



**Figure 4.7:** Industry Result

- **Park**

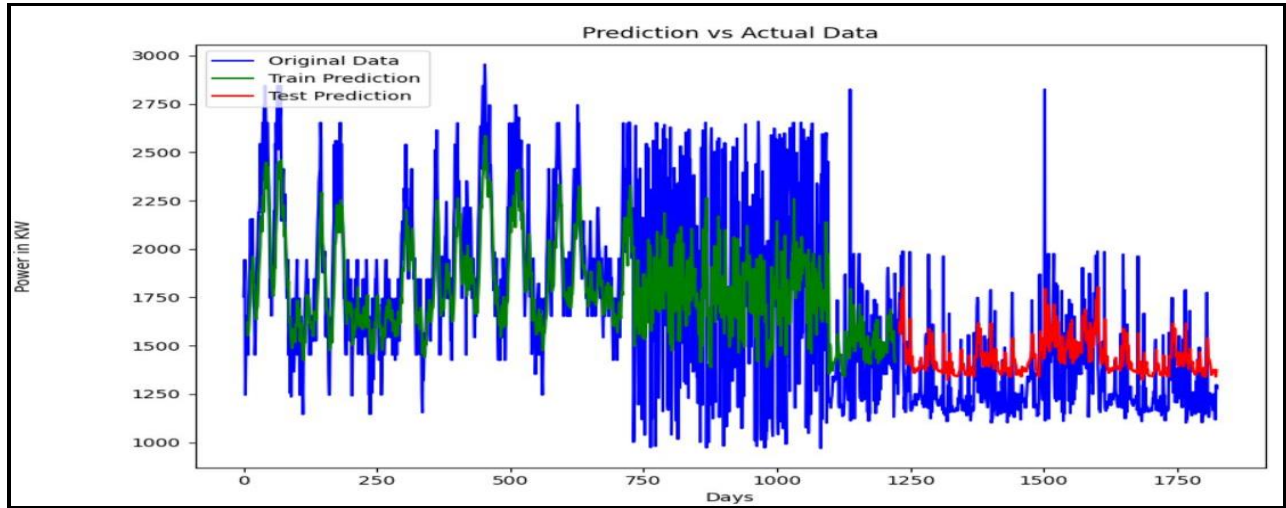


**Figure 4.8:** Park Result

The AI-based energy management system's analysis of Park data produced significant findings. Utilising the gathered data and applying load forecasting techniques, the system was able to produce precise projections of the energy requirements in the smart city's park areas. The outcomes

demonstrated the system's capacity to accurately record and forecast the intricate patterns of energy usage in Park.

- **Rescue**



**Figure 4.9:** Rescue Result

An extensive dataset of the energy consumption of residential plots, hospitals, industries, parks, and rescue services was gathered from a grid station during a five-year period and used in the AI-based energy management system. The load forecasting model was trained and tested using this dataset as the basis. The dataset was split into two independent periods—a training set with 3.5 years of historical data and a testing set with 1.5 years—to ensure an effective model. Stakeholders like energy managers, utility corporations, and city authorities might easily use the projections for wise decision-making by integrating the load forecasting model into a user-friendly GUI software. Users of the app could enter pertinent information, such as historical load data, weather information, and the time of day, to obtain load estimates that were especially suited to the residential plots inside the smart city. This user-friendly and accessible interface gave stakeholders the ability to improve energy management in the smart city by optimizing energy production, distribution, and consumption techniques. The GUI app for the AI-based energy management system showed good results in load forecasting for residential plots, hospitals, industries, parks, and rescue inside the smart city. It was trained on 3.5 years of data and tested on 1.5 years of data. Because of the model's precise forecasts and user-friendly interface, stakeholders were able to make wise choices and improve their energy management tactics. The system's effectiveness demonstrates its potential for raising energy efficiency, decreasing.

## **4.2 Conclusion**

In conclusion, the use of AI-based energy management systems in a variety of fields, such as business, healthcare, real estate, parks, and recreation places, has demonstrated promising outcomes in terms of maximizing energy consumption, lowering costs, and fostering sustainability. These systems have successfully analysed historical data and produced accurate load projections by utilizing cutting-edge technology like machine learning and load forecasting models. This has allowed stakeholders to make knowledgeable decisions and allocate resources effectively.

## **CHAPTER 5**

### **BUSINESS DESCRIPTION**

#### **5.1 Form of Business**

We shall operate as a sole proprietorship.

##### **5.1.1 Team/Organizational Structure**

Every firm begins on a small size and eventually begins to expand. Similar to that, we'll launch our company on a modest scale by creating a distinctive GUI App and attempting to market it globally. Our company will eventually start to expand and unquestionably turn a profit. The roles that will be given to the company's members are as follows:

The company's owner and director will be Ahmed Saeed.

The business will be run by Mazhar Abbas.

The marketing department will be overseen by Hamza Aziz Khan.

##### **5.1.2 Vision**

- Within the Windows ecosystem, it is our mission to promote and develop useful, user-centric programmes that improve connectivity, productivity, and overall user experience. Additionally, by developing a smart city load forecasting programme, a strong and precise tool for effective management of energy resources will be created. Our key values are:
- Accurate Load Forecasting of a Smart City;
- Real-time Monitoring from smart metres, IoT devices, and other sources to deliver current load estimates. As a result, proactive decision-making is made possible, and dynamic load balancing is made possible to maximise resource utilisation.
- To create a scalable and adaptable application that can respond to the evolving requirements and expansion of a smart city.
- The app should be able to communicate with smart grids, demand response systems, and energy management systems to share data.
- The app should analyse load forecasts, energy pricing, and other pertinent factors to suggest strategies for load shifting, demand response programmed, and energy

conservation measures. This integration enables a holistic approach to energy management and improves the overall efficiency of the smart city ecosystem. By doing this, operational costs are reduced and resource utilization is maximized.

- Supporting a smart city's sustainability objectives is a crucial goal. The integration of renewable energy, carbon emission reduction, and energy efficiency should all be given top priority in the app. The software enables proactive energy planning and makes it easier to integrate sustainable energy sources into the grid by offering precise load forecasting.

### 5.1.3 Mission

Our Mission is:

- Giving users more control over their digital experiences by creating applications that make work easier, are more productive, and empower users.
- Monitoring and analysis in real-time.
- Improved capacity to make decisions.
- Scalability and adaptability;
- Seamless Integration with Smart City Infrastructure;
- The goal is to continuously enhance the load forecasting app through user feedback and iterative development.

### 5.1.4 Goal and Objective

Our company's objective is to optimise energy management and resource allocation inside the smart city infrastructure by forecasting a smart city load. To ensure optimal energy usage, cost savings, and sustainability, the app seeks to deliver precise load estimates, enable real-time monitoring, and support data-driven decision-making.

- **Accurate Load Forecasting:** The main goal of the programme is to provide precise load estimates using historical data, weather patterns, and other pertinent variables. This goal makes sure that utility managers and city planners have accurate data to efficiently plan and distribute energy resources.
- **Real-time Monitoring and Analysis:** The goal is to make it possible to track energy demand and usage in real time within the smart city. The software delivers current insights into load

patterns by gathering and evaluating data in real-time, enabling preventive measures and dynamic load balancing.

- **Data Visualization and Insights:** The software seeks to display load forecasting data in a user-friendly and aesthetically pleasing manner. The goal is to deliver user-friendly visualisations, reports, and warnings that help users understand and draw valuable conclusions from the load forecasting data.
- **Integration with Smart City Infrastructure:** The goal is to seamlessly link the load forecasting software with other infrastructure elements of smart cities. This connection enables the deployment of demand response programmes and energy conservation measures, facilitates coordinated energy management, and optimises resource allocation.
- **User-Friendly Interface and Accessibility:** The goal is to create a user-friendly interface that is available to a variety of users, such as utility operators, city managers, and other stakeholders. In order to ensure that users can simply navigate and interact with the load forecasting capabilities, the app seeks to offer a fluid and intuitive user experience.
- **Scalability and Adaptability:** The goal is to create an app that is scalable and adaptable enough to meet changing requirements for a smart city. The software will be able to handle growing data quantities, interact with developing technologies, and adjust to future developments in energy management and load forecasting thanks to this goal.
- **Energy Efficiency and Sustainability:** The goal is to advance sustainability and energy efficiency in the smart city. The app's goal is to offer perceptions and suggestions for load optimisation, demand response schemes, and energy-saving solutions. This goal helps to achieve sustainability goals by minimising environmental effect, decreasing energy waste, and conserving energy.
- **Continuous Improvement and Innovation:** Iterative development, user testing, and feedback are being used to continuously enhance the app. To improve its accuracy, performance, and usability, the app will combine improvements in data analysis methods, machine learning algorithms, and user experience design.

## 5.2 Industry and Marketing Analysis

### 5.2.1 Industry Analysis

After the industrial visit, we learned about the firms and the demand for our software. Due to the fact that there aren't many users of this app in Pakistan, we sought assistance from various websites where we learned more about our product. We discovered that many industries are working on it, but they haven't had much success with their businesses, so we learned how to improve our app and what changes are necessary, as well as what kinds of features we can add to make it better. Here is some information about the various businesses in various nations. The companies' reports about our app cover the following topics, which we have found:

- **Collection of Suitable Data:** The system is totally based on the collection of suitable data.
- **Selecting the suitable Model:** The selection of a suitable model is very critical in this App.
- **Others:** There are other issues like security, monitoring handling and dealing with the emergency situation, etc. These are the critical flaws that we have to work hard to achieve our goals.

### 5.2.2 Competitive Analysis

As we have discussed that there are many companies that are working on different apps for forecasting. The Japanese and American industries are very much in this market but we use the scamper technique to complete this app so we are at the top of the list. This experiment is not much done by our industries so we should avail of this opportunity and have to fulfil the requirements of the market. With continued growth, to serve the people and Industries, the company will provide easy and cost-effective services to different companies in Pakistan and all others which are existing around the globe.

### 5.2.3 Purpose

Our purpose is to develop an app that addresses the following problems:

- To improve the efficiency
- Accurate load forecasting.
- Less Computational Time required for the Output

## **5.3 SWOT Analysis**

### **5.3.1 Strengths**

- It is very beneficial for the IT and Power Industry development of a country.
- It takes less time for giving accurate output.
- More efficient than any other app.

### **5.3.2 Weaknesses**

- The communication errors can occur with the passage of time.
- Constantly required the Wi-Fi Connection.

### **5.3.3 Opportunities**

- Introduction of a new app will attract the industries.
- The primary concern is to introduce modern ways in the field of the power sector.

### **5.3.4 Threats**

- People will have data breaching concerns.
- It is difficult to influence the conventional mindset.

### **5.3.5 Marketing Objectives Follow**

- Social media is a very much effective, powerful, and economical source of advertisement nowadays.
- Electronic media (News Channel) is also a very much attractive and convincing source to advertise our product.
- We will target Power Sector Industries for our project promotion.
- Letting the government know about its need and how it can fulfill its power sector requirements.

## **5.4 Marketing Communication**

In the next aspects of the public communications spectrum, the inherent strengths and shortcomings are taken into consideration and what they are incorporated, and how they are applied in this situation.

By using social and electronic media which are nowadays considered as the most powerful and effective source of promotion and advertisement.

#### **5.4.1 Advertising**

It is an informal and sponsored means of educating the consumers through, radio, news media, online portals, etc. about their goods and services. Advertising is one of the most commonly used marketing tactics in which the information about the goods and services of the business can be effectively conveyed to the vast target audience.

#### **5.4.2 Personal Selling**

Marketing involves the selling of our project through videos and portals. Telling our customers how our system can fulfil their needs and how this bus can help them in making their work more easy, convenient, and more economical.

#### **5.4.3 Direct Marketing**

The efficacy of direct marketing can be directly calculated. Through inventing the technology, businesses use emails, faxes, and cell phones to connect with potential clients directly without including someone else.

### **5.5 Financial Plan**

#### **5.5.1 Resources Required**

The following types of resources are needed:

- All the fundamental resources (such as tools, electronics, a suitable location, etc.) are needed to launch a firm.
- Additions.
- Personnel resources.
- Electrical (and other)

**Table 5.1:** Initial budget Expenses

<b>Sr. No</b>	<b>Capital Nature Expenses</b>	<b>Amount (PKR)</b>
<b>1</b>	Laptop (250,000 x 1)	250,000/-

2	Equipment (17,000 x 1)	17,000/-
	<b>Revenue Nature Expenses</b>	
3	Internet (4000 x 12)	48000/-
4	Misc. Expenses (1,500 x 12)	18,000/-
5	Electricity (10,000 x 12)	100,000/-
	<b>Total: Initial Expenses (Budgeted)</b>	433,000/-

**Table 5.2:** Statement of comprehensive income (budget)

Sr. No		1 <sup>st</sup> Year	2 <sup>nd</sup> Year	3 <sup>rd</sup> Year	4 <sup>th</sup> Year	5 <sup>th</sup> Year
1	<b>Revenue</b>	433,000/-	530,000/-	660,000/-	780,000/-	800,000/-
2	<b>Cost of Production</b>	(80,000)	(100,000)	(130,000)	(170,000)	(200,000)
3	<b>Other Operating Expenses</b>	(100,000)	(100,000)	(105,000)	(111,000)	(135,000)
4	<b>Depreciation</b>	(5,000)	(5,000)	(5,000)	(5,000)	(5,000)
5	<b>Misc.</b>	(4000)	4000	4000	4000	4000
6	<b>Marketing Expenses</b>	(8000)	(16000)	(16000)	(20000)	(20000)
7	<b>Profit before Commission</b>	30,000/-	40,000/-	60,200/-	89,800/-	110,400/-
8	<b>Commission</b>	(13,000)	(18,000)	(25,000)	(35,000)	(46000)

<b>9</b>	<b>Profit After Commission</b>	<b>20,000/-</b>	<b>23,000/-</b>	<b>38,000/-</b>	<b>53,000/-</b>	<b>69,000/-</b>
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## **5.6 Notes**

### **5.6.1 Note-1**

All expenses & revenue are estimated.

### **5.6.2 Note-2**

On all non-current assets, depreciation is provided using the straight-line approach at a rate of 10%.

### **5.6.3 Note-3**

On the basis of the annual profit, a 10% commission will be paid.

### **5.6.4 Note-4**

As the income is below the minimum prescribed level as per the "Income Tax Ordinance, 2001" in all years. Therefore, no tax provision is computed.

### **5.6.5 Note-5**

Sensors like Arduino, Relay, Wi-Fi controllers, and other necessary electrical equipment are included in raw material.

### **5.6.6 Note-6**

Depending on the number of units produced during the year, variable overhead varies with production.

### **5.6.7 Note-7**

All calculations are based on assumptions. So, there is a chance of imparity in these calculations.

## **5.7 Conclusion**

In this chapter, the total business strategy is portrayed exhaustively alongside the five-year monetary arrangement. The undertaking's qualities and different highlights are additionally portrayed exhaustively. The design is to make it simple for the peruse to comprehend the financial worth and social remaining of this venture.

## **CHAPTER 6**

### **CONCLUSION AND FUTURE WORK**

#### **6.1 Conclusion**

There is an AI-based energy management system for a smart city is presented in this thesis, with a particular emphasis on load forecasting using LSTM and creating a GUI (Graphical User Interface) app for forecasting. The outcomes show how well LSTM performs in precisely forecasting energy loads in the setting of smart cities.

The importance of load forecasting in the context of smart city 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 in a smart city. 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 include elements including weather data, time of day, and historical load statistics.

We created a user-friendly GUI software to make the usage of load forecasting in practical circumstances easier. Users can easily enter pertinent criteria into the app's user-friendly interface to immediately get load forecasts. Stakeholders, including energy managers, utility firms, and municipal officials, may plan the efficiency of energy generation and distribution thanks to the inclusion of the LSTM model into the GUI interface.

#### **6.2 Future Work**

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

##### **6.2.1 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 smart city can be obtained by combining data from numerous IoT (Internet of Things) devices and sensors.

### **6.2.2 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. In order to capture diverse features of load patterns, hybrid models can make use of the advantages of several techniques.

### **6.2.3 Optimization strategies:**

A smart city'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.

### **6.2.4 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 smart city 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.

### **6.2.5 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 a 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.

These lines of inquiry will advance the development and productivity of AI-based energy or power management systems in smart cities.

## REFERENCES

- [1] D. G. Costa *et al.*, “A Survey of Emergencies Management Systems in Smart Cities,” *IEEE Access*, vol. 10, pp. 61843–61872, 2022, doi: 10.1109/ACCESS.2022.3180033.
- [2] Goldsmith, Stephen (16 September 2021). “As the Chorus of Dumb City Advocates Increases, How Do We Define the Truly Smart City?”. [datasmart.ash.harvard.edu](https://datasmart.ash.harvard.edu). Retrieved 27 August 2022.
- [3] Mills, David; Pudney, Steven; Pevcin, Primož; Dvorak, Jaroslav (January 2022). “Evidence-Based Public Policy Decision-Making in Smart Cities: Does Extant Theory Support Achievement of City Sustainability Objectives?”. *Sustainability*. **14** (1): 3. doi:10.3390/su14010003. ISSN 2071-1050.
- [4] “Building a Smart City, Equitable City – NYC Forward”. Archived from the original on 4 December 2017. Retrieved 4 December 2015.
- [5] Deakin, Mark; Al Waer, Husam, eds. (2011). *“From Intelligent to Smart Cities”*. *Journal of Intelligent Buildings International: From Intelligent Cities to Smart Cities*. **3** (3): 140–152. doi:10.1080/17508975.2011.586671. S2CID 110580067.
- [6] A. Al-Qarafi *et al.*, “Artificial Jellyfish Optimization with Deep-Learning-Driven Decision Support System for Energy Management in Smart Cities,” *Applied Sciences*, vol. 12, no. 15, p. 7457, Jul. 2022, doi: 10.3390/app12157457.
- [7] Feinberg, E.A., Genethliou, D,” Load forecasting,” In: Chow, J.H., Wu, F.F., Momoh, J.J. (Eds.), *Applied Mathematics for Restructured Electric Power Systems: Optimization, Control and Computational Intelligence, Power Electronics and Power Systems*. Springer, US, pp. 269–285. 2020.
- [8] D.C. Park, M.A. El-Sharkawi, R.J. Marks 11, L.E. Atlas and M.J. Damborg, Electric load forecasting using an artificial neural network. *IEEE Trans. Power Syst.*, 6 (2020) 442-449.
- [9] S.J. Kiartzis, A.G. Bakirtzis and V. Petridis, “Short-term load forecasting using neural networks”, *Electric Power Systems Research* 33 (2020) 1-6.
- [10] Henrique Steinherz Hippert, Carlos Eduardo Pedreira, and Reinaldo Castro Souza, “Neural Networks for Short-Term Load Forecasting: A Review and Evaluation”, *IEEE Transactions On Power Systems*, VOL. 16, NO. 1, February 2020.

- [11] Peder Bacher, Henrik Madsen and Henrik Aalborg Nielsen, "Online short-term solar power forecasting", *Solar Energy* 83 (2020) 1772–1783.
- [12] Jun Tae Kim, "Short-Term Electric Load Prediction Using Multiple Linear Regression Method," A thesis submitted for the degree Master of Science in Electrical Engineering, University of California San Diego, 2020.
- [13] Ahmed Yousuf Saber, Senior Member, IEEE and Tanuj Khandelwal, Senior Member, IEEE, "IoT based Online Load Forecasting", 2020 Ninth Annual IEEE Green Technologies Conference.
- [14] R. Lu, S. H. Hong, and M. Yu, "Demand Response for Home Energy Management Using Reinforcement Learning and Artificial Neural Network," *IEEE Trans Smart Grid*, vol. 10, no. 6, pp. 6629–6639, Nov. 2019, doi: 10.1109/TSG.2019.2909266.
- [15] K. T. Chui, M. D. Lytras, and A. Visvizi, "Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption," *Energies (Basel)*, vol. 11, no. 11, Nov. 2018, doi: 10.3390/en11112869.
- [16] M. Waseem, Z. Lin, and L. Yang, "Data-driven load forecasting of air conditioners for demand response using levenberg–Marquardt algorithm-based ann," *Big Data and Cognitive Computing*, vol. 3, no. 3, pp. 1–17, Sep. 2019, doi: 10.3390/bdcc3030036.
- [17] G. Hafeez *et al.*, "Efficient energy management of IoT-enabled smart homes under price-based demand response program in smart grid," *Sensors (Switzerland)*, vol. 20, no. 11, Jun. 2020, doi: 10.3390/s20113155.
- [18] T. J. Saleem and M. A. Chishti, "Deep learning for the internet of things: Potential benefits and use-cases," *Digital Communications and Networks*, vol. 7, no. 4. Chongqing University of Posts and Telecommunications, pp. 526–542, Nov. 01, 2021. doi: 10.1016/j.dcan.2020.12.002.
- [19] H. W. Rotib, M. B. Nappu, Z. Tahir, A. Arief, and M. Y. A. Shiddiq, "Electric Load Forecasting for Internet of Things Smart Home Using Hybrid PCA and ARIMA Algorithm," *International Journal of Electrical and Electronic Engineering and Telecommunications*, vol. 10, no. 6, pp. 425–430, Nov. 2021, doi: 10.18178/ijeetc.10.6.425-430.
- [20] Okubo, Y., Dore, J.C., Ojasoo, T., & Miquel, J.F. (1998). A multivariate analysis of publication trends in the 1980s with special reference to south-east Asia. *Scientometrics*, 41 (3), 273-289.
- [21] Mubashar, Rida, M. Javed Awan, Muhammad Ahsan, Awais Yasin, and V. Partab Singh. "Efficient residential load forecasting using deep learning approach." *Int. J. Comput. Appl. Technol* (2021).

- [22] Muralitharan, K., Rathinasamy, S., Vishnuvarthan, R.: Neural network-based optimization approach for energy demand prediction in a smart grid. *Neurocomputing* 273, 199–208 (2018).
- [23] Mukherjee, A., Prateeti, M., Nilanjan, D., Debashis, D., Panigrahi, B.K.: Lightweight sustainable intelligent load forecasting platform for smart grid applications. *Sustain. Comput. Inform. Syst.* 25, 100356 (2020) 123 *International Journal of Parallel Programming*.
- [24] Mukherjee, A., Dey, N., De, D.: EdgeDrone: QoS aware MQTT middleware for mobile edge computing in opportunistic Internet of Drone Things. *Comput. Commun.* 152, 93– 108 (2020).
- [25] Vimal, S., Khari, M., Crespo, R.G., Kalaivani, L., Dey, N., Kaliappan, M.: Energy enhancement using Multiobjective Ant colony optimisation with Double Q learning algorithm for IoT based cognitive radio networks. *Comput. Commun.* 154, 481–490 (2020) .
- [26] Farsi, Behnam, Manar Amayri, Nizar Bouguila, and Ursula Eicker. "On short-term load forecasting using machine learning techniques and a novel parallel deep LSTM-CNN approach." *IEEE Access* 9 (2021): 31191-31212.
- [27] T. Vantuch, A. G. Vidal, A. P. Ramallo-González, A. F. Skarmeta and S. Misák, "Machine learning based electric load forecasting for short and long-term period," 2018 IEEE 4th World Forum on Internet of Things (WF-IoT), 2018, pp. 511-516, doi.
- [28] Kim J, Moon J, Hwang E, Kang P. Recurrent inception convolution neural network for multi short-term load forecasting. *Energy Build* 2019; 194:328–41.
- [29] Shi H, Xu M, Li R. Deep learning for household load forecasting—a novel pooling deep RNN. *IEEE Trans Smart Grid* 2018;9(5):5271–80.
- [30] Singh Mantinder Jit; Agarwal, Prakhar; Padmanabh, Kumar (2016). [IEEE 2016 2nd International Conference on Contemporary Computing and Informatics (IC3I) - Greater Noida, India (2016.12.14-2016.12.17)] 2016 2nd International Conference on Contemporary Computing and Informatics (IC3I) - Load forecasting at distribution transformer using IoT based smart meter data from 6000 Irish homes. (), 758–763.
- [31] Elgarhy, Shady Mahmoud; Othman, Mahmoud M.; Taha, Adel; Hasanien, Hany M. (2017). [IEEE 2017 Nineteenth International Middle East Power Systems Conference (MEPCON) - Cairo, Egypt (2017.12.19-2017.12.21)] 2017 Nineteenth International Middle East Power Systems Conference (MEPCON) - Short term load forecasting using ANN technique. (), 1385–1394. doi:10.1109/MEPCON.2017.8301364.
- [32] Kim J, Moon J, Hwang E, Kang P. Recurrent inception convolution neural network for multi short-term load forecasting. *Energy Build* 2019; 194:328–41.

- [33] Shi H, Xu M, Li R. Deep learning for household load forecasting—a novel pooling deep RNN. *IEEE Trans Smart Grid* 2018;9(5):5271–80.
- [34] Bedi J, Toshniwal D. Deep learning framework to forecast electricity demand. *Appl Energy* 2019; 238:1312–26.
- [35] Kelly, Jack, and William Knottenbelt. (2014) “The UK-DALE dataset, domestic appliances  
“Scientific Data volume2, Article number: 150007
- [36] Berouine, Anass, Fadwa Lachhab, Youssef Nait Malek, Mohamed Bakhouya, and Redouane Ouladsine, “A Smart Metering Platform using Big Data and IoT Technologies”, (2017). 3rd International Conference of Cloud Computing Technologies and Applications (CloudTech), IEEE: 1-6. 180 S. Hadri et al. / *Procedia Computer Science* 160 (2019) 173–180 8 S. Hadri / *Procedia Computer Science* 00 (2018) 00.
- [37] Labeodan, Timilehin, Zeiler, Wim Zeiler, Gert Boxem, and Yang Zhao. (2015).  
“Occupancy measurement in commercial office buildings for demand-driven control applications: a survey and detection system evaluation”. *Energy and Buildings*, 93, 303-314. DOI: 10.1016/j.enbuild.2015.02.028.
- [38] Fekri, Mohammad Navid, Harsh Patel, Katarina Grolinger, and Vinay Sharma. "Deep learning for load forecasting with smart meter data: Online adaptive recurrent neural network." *Applied Energy* 282 (2021): 116177.
- [39] [https://github.com/kmkarakaya/ML\\_tutorials/blob/master/images/LSTM\\_functions2.png?raw=true](https://github.com/kmkarakaya/ML_tutorials/blob/master/images/LSTM_functions2.png?raw=true).