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EDGE-ENABLED LOAD FORECASTING IN SMART GRIDS

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Abstract: As a result of the smart grid's rapid development, the volume of user-side data has increased dramatically. Load forecasting is vital in order to control the smart grid. But traditional load forecasting methodologies now confront the difficulty of maintaining the accuracy of dynamic forecasting. Due to concerns with latency, security, and other factors, processing all of the data in a centralized data center is not ideal, so we need an effective technique. A potential computing ,edge computing performs calculations locally and overcomes the above challenges. The objective of the project is to meet the requirement of demand analysis using Long Short-Term Memory (LSTM) network based on a short-term load forecasting approach for more accurate load forecasting results.

***Index Terms* - Smart grids,Load forecasting,Long Short Term Memory(LSTM),Edge computing.**

I. INTRODUCTION

In principle, the grid is an electricity supply network for electric power produced by producers to consumers. The network is composed of a distributed transmission and distribution system consisting of many high voltage lines and local distribution networks, which are also commonly called the 'electric grid' or an "electrical grid." Smart grids are, however, a modern electrical system using communications, automation and information technology systems to monitor electricity flows from production sites to consumption points. Electricity is used by an average family for a number of household tasks, such as cooking, lighting, refrigeration, and electric vehicle charging. However, in order to monitor electricity consumption or measure it, a conventional power network does not have an advanced metering infrastructure AMI. In addition, in the case of electricity outages and power network problems, tardy and unreliable energy management processes are not perfect.

A smart energy network links all the components of the electricity grid from generation through transmission, storage and distribution till consumption. An integrated network of data and energy is created when all devices are connected on a plug & play basis. A smart grid can automatically reroute power if there is an outage or failure in equipment due to its two way interactivity. Large Scale and prolonged blackouts are prevented, for example, by the identification and isolating of an outage. When compared to the traditional grid, a smart grid makes consumers participate and receives a quicker response about how much demand is required by collecting the electric load from various infrastructures and processing it using information services to forecast future power consumption.

The electric load forecasting (ELF) is an important procedure for the planning of the power system industry, which helps in scheduling the electricity and to manage the power system (PSM). Therefore, the ELF at a preliminary stage is great at managing energy production capacity, scheduling, monitoring, peak reductions, market evaluation and so on. As a result, energy load forecasts promote the planning of power generation and development for an electricity system. The precise forecasting of electricity demand is crucial to the operation of electrical power systems economically, safely and reliably. Electric load forecasting can be classified into the following - long-term load forecasting, medium-term load forecasting, short-term load forecasting and ultra-short-term load forecasting, corresponding to annual, monthly, single-day, and hourly load forecasting. Few methods have been applied in the estimation of electrical load, e.g. regression analysis, exponential smoothing and weighted iteration, etc. Other improved algorithms like Adaptive Prediction and Stochastic Time Series are also implemented. In electric load forecasting, neural networks and genetic analysis are also widely used.

The proposed model, LSTM, is a type of neural network that operates in deep learning. Long term dependencies, primarily in sequence prediction problems, can be learned through a variety of recurrent neural networkRNNs. The LSTM contains feedback connections which enable it to process a complete range of data, except for the single information points like images. In this way, it is applicable to speech recognition, machine translation and so on.

For numerous benefits like important technical and economic impacts, it is important to know earlier about the electrical load. It's not just enough to only forecast the load for shorter periods but also for long term like hours, days, weeks, months, years, decades, given the growing load requirements and the sophistication of power plants. For many decades, conventional methods have been applied such as ARMA, ARMAX and SARIMA. Artificial intelligence, such as deep learning techniques and neural networks , has been developing for the past few years to analyze time series. In this context, artificial neural networks(ANN) and recurrent neural networks(RNN) are explored and that has ensured to predict much better results than traditional methods. A unique type of RNN, which has the ability to understand intermediate dependencies, is the proposed LSTM model. Here the electrical load data with corresponding hourly time is obtained.The information is used for the training of the LSTM network. The data can also be used in conventional methods for calculating the series of loading time, so that an accurate comparison is made.In this case, forecasts for 1 day, 2 days, 7 days and 30 days shall be based on trained LSTM networks and developed models. For any forecast horizon, the results of conventional methods using MSE are analyzed in comparison with forecasts made by LSTM.The problem now lies with the enormous volume of data which needs to be processed for future forecasts.Traditional techniques use centralized approach to store the massive volumes of data, and this takes a lot more time,with increased complexity in computing.To solve this problem we need an enhanced approach forecast the future load.

A new computer paradigm known as edge computing describes a number of networks and gadgets that are placed at or close to the user. The idea of processing data at the edge is to do it near to the point of origin. This allows for higher processing volumes and rates, which produces more immediately actionable results. Compared to conventional models where processing power is centralized at an on-premise data center, it provides a few key advantages. Businesses may improve how they manage and use physical assets while also producing new interactive, human experiences by moving computation to the edge. Examples of edge use cases include automated shopping, autonomous robots, smart equipment data, and self-driving cars.

Edge components that might exist include the Edge devices. Smart speakers, wearables, and phones are just a few examples of edge computing devices that we presently use on a regular basis. These gadgets collect and process data close to where they are being used. IoT edge devices, POS systems, robots, cars, and sensors that compute locally and interact with the cloud are just a few examples of edge devices.Edge computing, on the other hand, does not require the existence of a specific "edge network"; instead, it might be installed on a router or a single edge device, for example. It is just another point on the continuum between users and the cloud where a new network is employed, and this is where 5G could be useful. 5G opens up very potent wireless edge computing access with low latency and high cellular speed.

II. Proposed Work

2.1Proposed Architecture Diagram

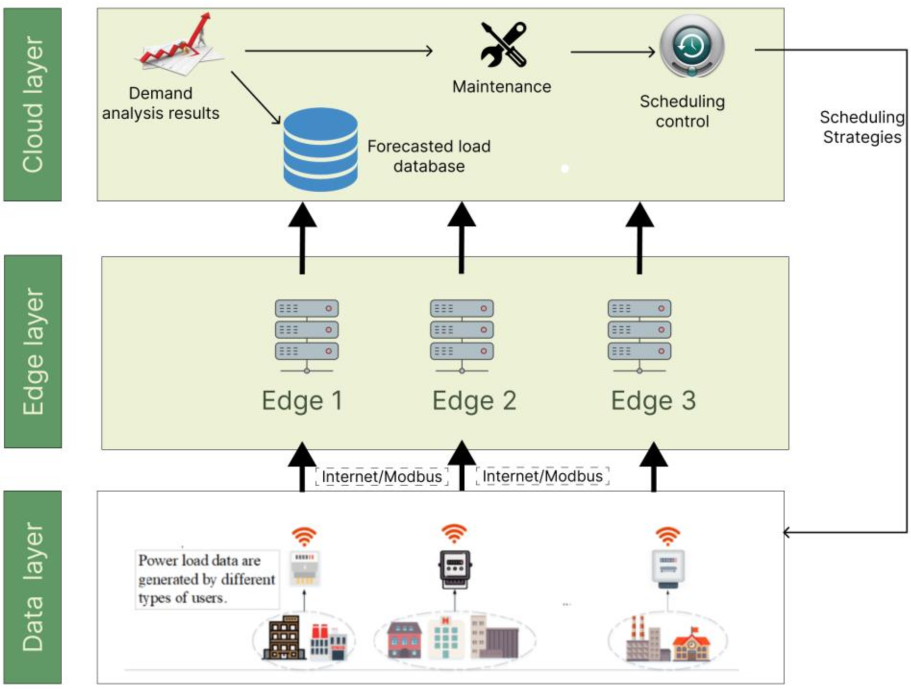


Figure 3.1 Three Tier Architecture

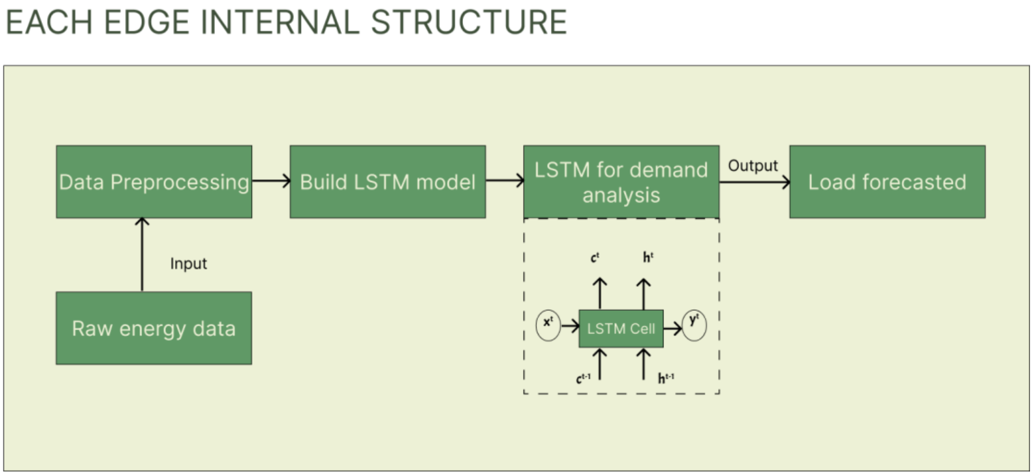


Figure 2.2 Internal structure in each edge

2.2 Project Description

The main objective of this project is to develop an application for load forecasting.This application allows the users to develop a model which predicts the electric load consumption of smart grids in the edge node.The main motive of this proposed system is to extend the capabilities of the smart grids and increase the economic benefits of the customers and the prediction of electric load consumption is done with Long Short Term Memory(LSTM) Algorithm.

2.3 Load Forecasting

By projecting future consumption of commodities transmitted or delivered by the utility, load forecasting reduces utility risk. Price elasticity, weather and demand response/load analysis, and renewable generation forecast modeling are some of the techniques used. Forecasts must use regional customer load data as well as time series customer load profiles. Seasonality modifications are required for accurate forecasting. As part of the distribution circuit load measurements, distribution load forecasts must be matched with distribution network configuration.Because LSTMs can learn long-term connections between data time steps, they are commonly employed to learn, analyze, and classify sequential data. Sentiment analysis, language modeling, speech recognition, and video analysis are all common LSTM applications.Most forecasting methodologies use numerical methods or artificial intelligence algorithms such as neural networks, fuzzy logic, and recession. Load forecasting is classified into three types:

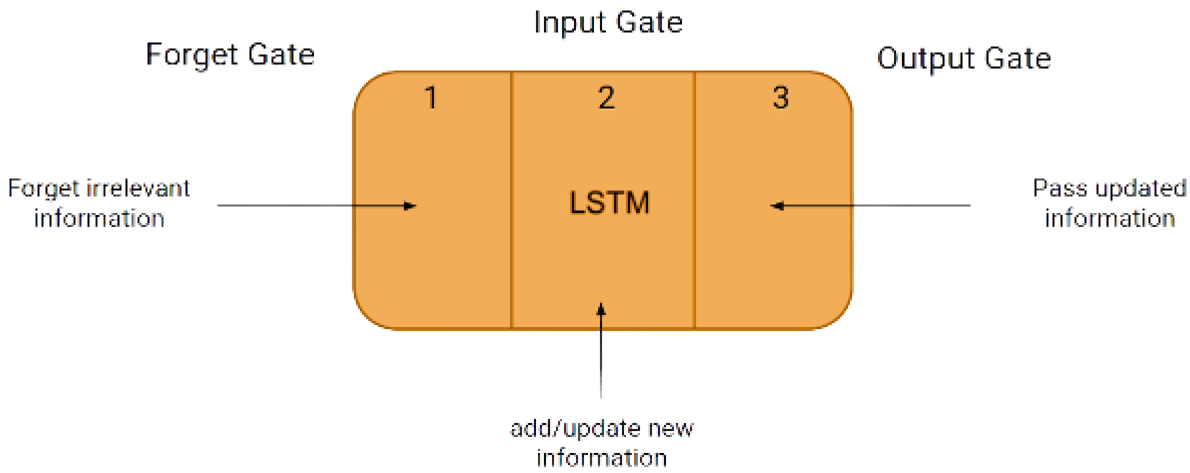
- short-term (a few hours)
- medium-term (a few weeks to a year)
- long-term (over a year).

The end-use and econometric approach is used for medium- and long-term forecasting, as opposed to the similar-day approach, multiple regression models, time series, neural networks, statistical learning algorithms, and fuzzy logic, which have all been developed for short-term forecasting. The outcomes can be characterized based on the time-series forecasting as follows:

- Seasonal: Dependson the season, the use of some utilities changes.
- Trend : on some occasions.
- Random : without a known reason

2.3 LSTM Model

This is a very special kind of Repeated Neural Network that can learn lifelong dependencies on data. This is achieved by having a combination of four layers interact with one another in the recurrent model module. A memory cell, which is called a 'cell state' and retains its structure over time, has the central role of an LSTM model. The cell state is the horizontal axis, which ends at the bottom of this diagram.It can be pictured as a conveyor belt through which information goes unaltered. In LSTM, information can be added to or withdrawn from the cell state, which is controlled by gates. These gates allow information to flow into and out of the cell. It includes a pointwise multiplication operation as well as a sigmoid neural net layer to help the mechanis



2.3.1 Forget Gate

The amount of data from the previous time step is kept in the current time step is determined by the forget gate. The type of data that must be remembered and what information can be lost is determined by the forget gate.

2.3.2 Input Gate

The extent to which fresh data from the most recent time step is contributed to the cell state is determined by the input gate.

2.3.3 Output Gate

The output gate regulates how much data from the current time step's cell state is used to generate an output. The value of the following hidden state is decided by the output gate. The information on earlier inputs is contained in this state.

2.3.4 Advantages of LSTM

- They excel at managing long-term dependencies, to start. This is a result of their propensity for long-term memory retention.
- Secondly, the vanishing gradient problem is significantly less likely to affect LSTMs. This is due to the fact that they employ an LSTM cell, a new type of activation function that aids in information retention across lengthy periods.
- Finally, modeling complex sequential data with LSTMs is quite effective. This is so that they can acquire high-level representations of the data's structure.
- This improves demand forecasters' accuracy, which helps the ne make better decisions.
- Long-term dependencies are handled by them far more effectively. This is a result of their propensity for long-term memory retention.

2.3.5 Disadvantages of LSTM

- Primarily they are more intricate than conventional RNNs and need more training data to function properly.

- Furthermore, they are not suitable for online learning tasks when the input data is not a sequence, such as prediction or classification tasks. Third, training LSTMs on sizable datasets can be time-consuming. This is because they have to learn the LSTM cell parameters, which can be computationally taxing.

- Finally, not all forms of data may be suitable for LSTMs. For instance, they might not perform well when dealing with noisy or extremely nonlinear data.

III. Implementation Modules

3.1 Module 1:Data Preprocessing

Data Preprocessing includes raw data collection. Here the raw data is collected from each edge node like shown below:

- Node1:"C:\Users\sneha\Desktop\PROJECT\location 1\Dataset1.csv".
- Node2:"C:\Users\sneha\Desktop\PROJECT\location 2\Dataset2.csv".
- Node3:"C:\Users\sneha\Desktop\PROJECT\location 3\Dataset3.csv".

Then the dataset has been cleaned, which can require removal of duplicates, correct errors, correcting missing values and converting data types. The cleaned dataset then undergoes data transformation to convert the data into usable format to visualize and normalize the data. Subsequently, training and testing sets will be divided up in the resulting dataset.

3.2 Module 2:Build LSTM Model

A few modules from Keras must be imported in order to construct the LSTM.These modules are LSTM, DENSE, and Sequential. Initialising the neural network is done by the sequential module, adding a layer of densely linked neural networks is done by the dense module, and adding a layer of long short-term memory is done by the LSTM module. Here, 256 neurons are used by the model to create a deep neural network.

3.3 Module 3:Prediction and Results

The LSTM model takes the preprocessed dataset as input.The input dataset proceeds into the input layer. Then into the deeply connected neural network to produce an output.The output will be a forecast of load in the next day,week and month.The prediction is presented using various visualization techniques.

3.4 Module 4:Deployment in Cloud

The forecasted data will then be deployed to the cloud where it can be stored in a centralized way.The forecasted data deployed can be used for managing the electricity demands.

3.5 Module 5:User Interface

The forecasted output data will be displayed in the user interface.This user interface can be accessed and used by the managing operators of the power grid from anywhere in the world.

IV. RESULTS AND DISCUSSION

Daily Load Consumption

NODE 1:

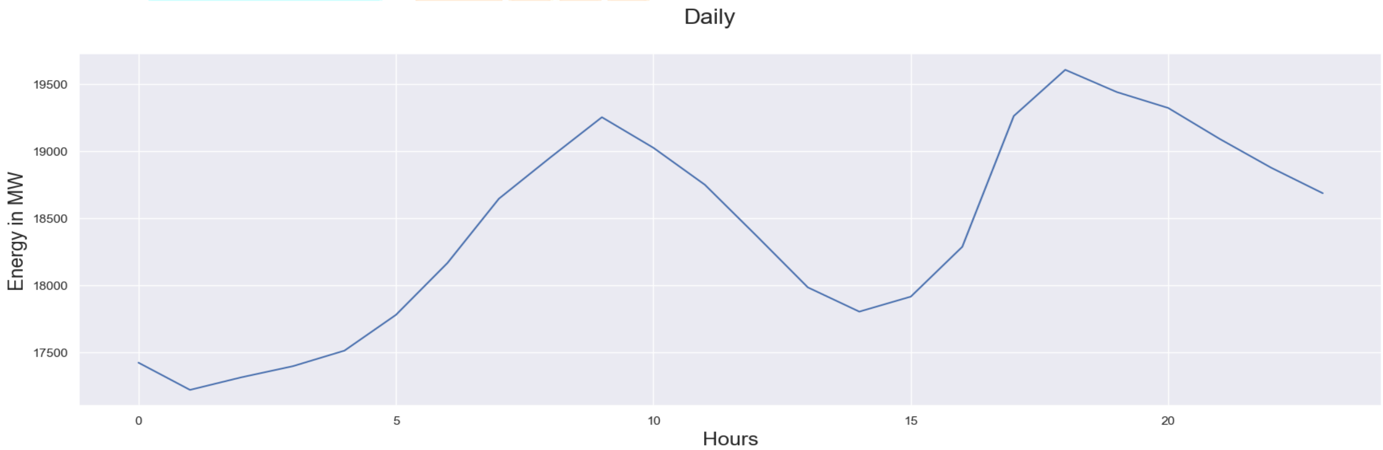


Figure 4.1 Graph that depicts the daily load consumption in node 1

NODE 2:

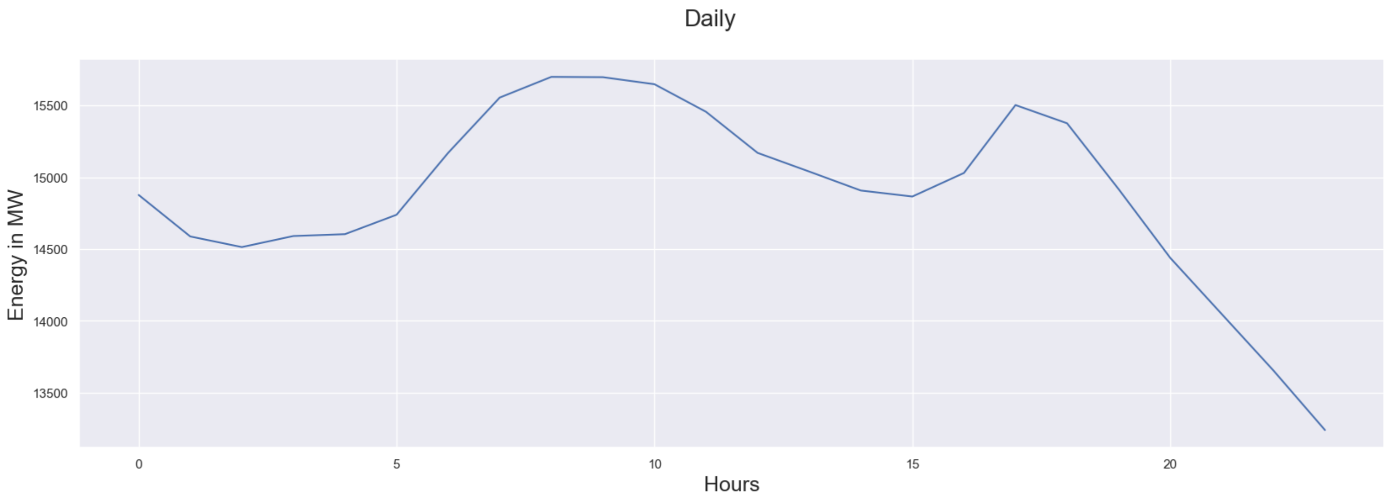


Figure 4.2 Graph that depicts the daily load consumption in node 2

NODE 3:

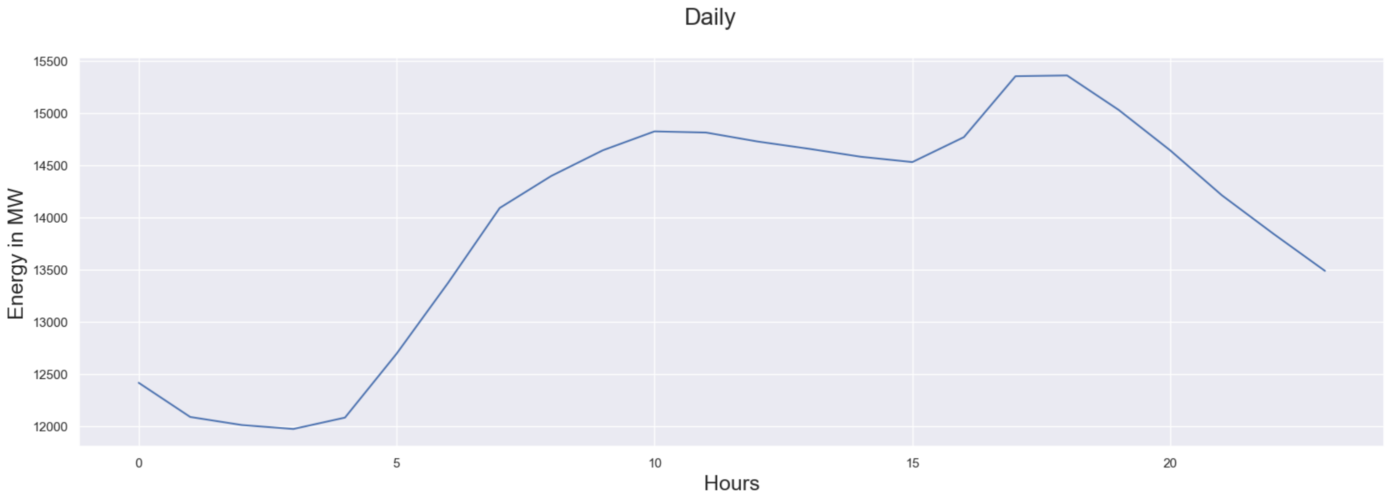


Figure 4.3 Graph that depicts the daily load consumption in node 3

Weekly Load Consumption

NODE 1:

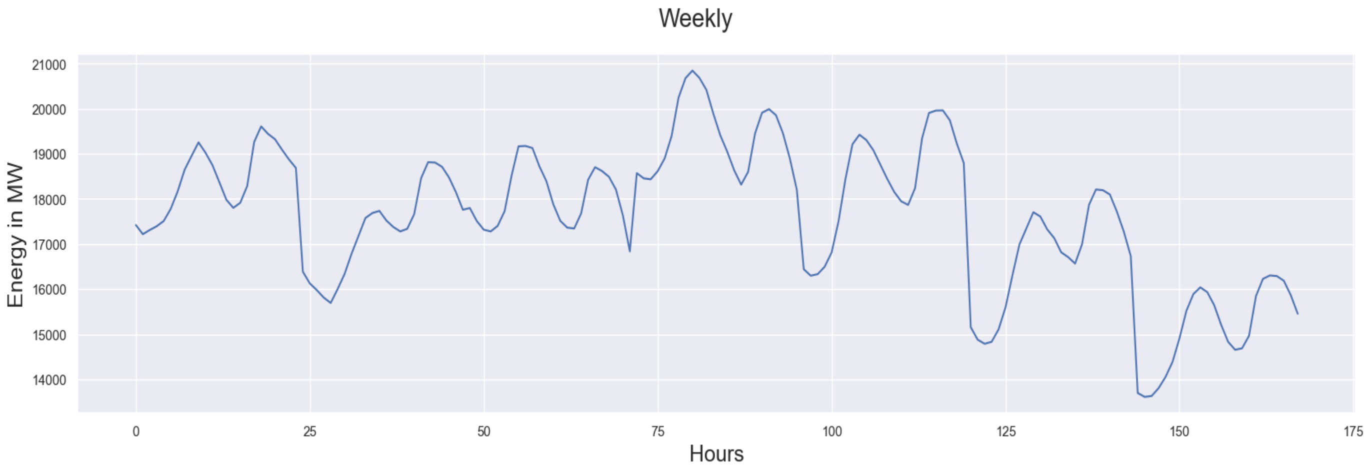


Figure 4.4 Graph that depicts the weekly load consumption in node 1

NODE 2:

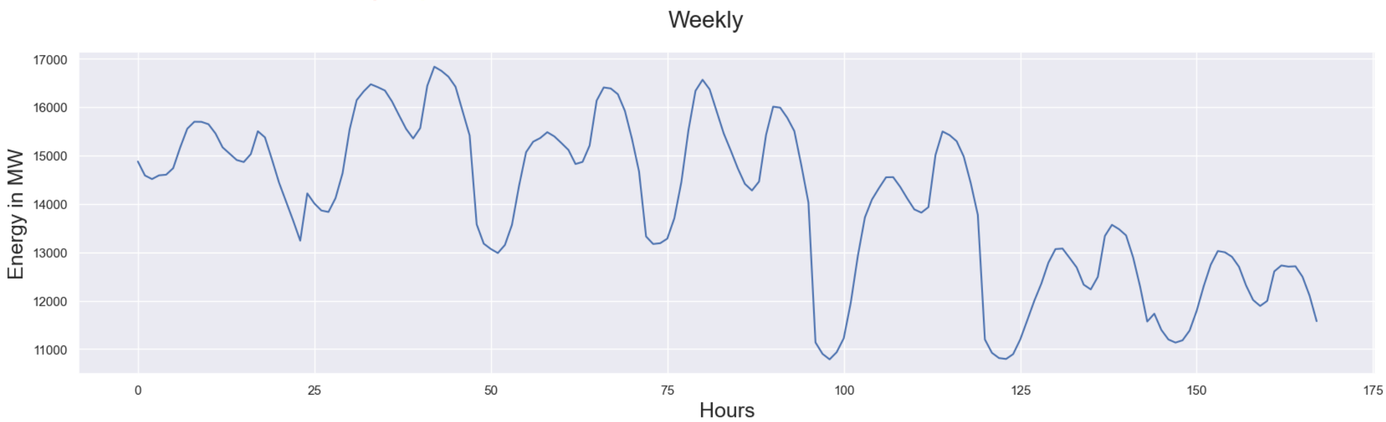


Figure 4.5 Graph that depicts the weekly load consumption in node 2

NODE 3:

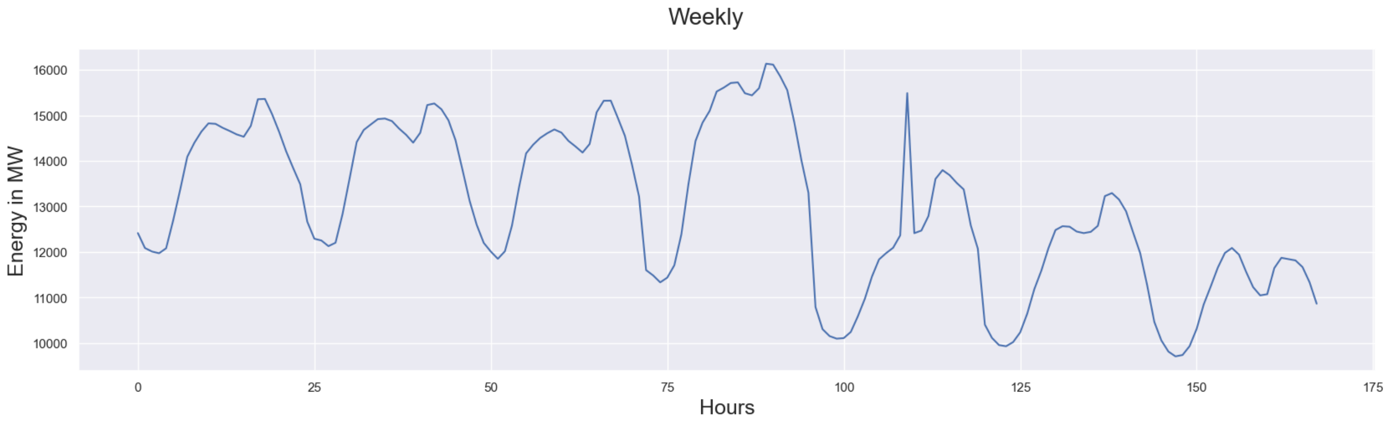


Figure 4.6 Graph that depicts the weekly load consumption in node 3

Monthly Load Consumption

NODE 1:

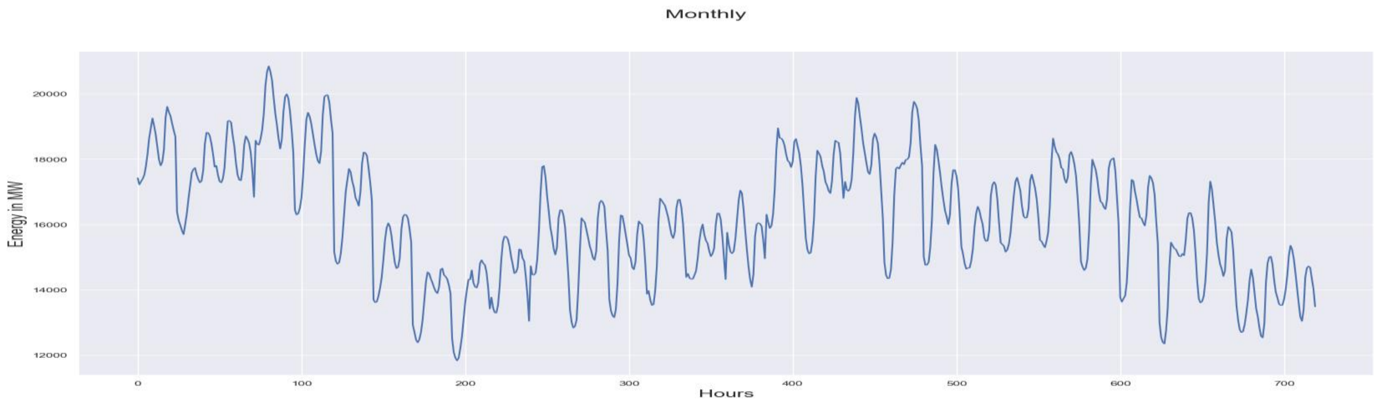


Figure 4.7 Graph that depicts the monthly load consumption in node 1

NODE 2:

Figure 4.8 Graph that depicts the monthly load consumption in node 2

NODE 3:

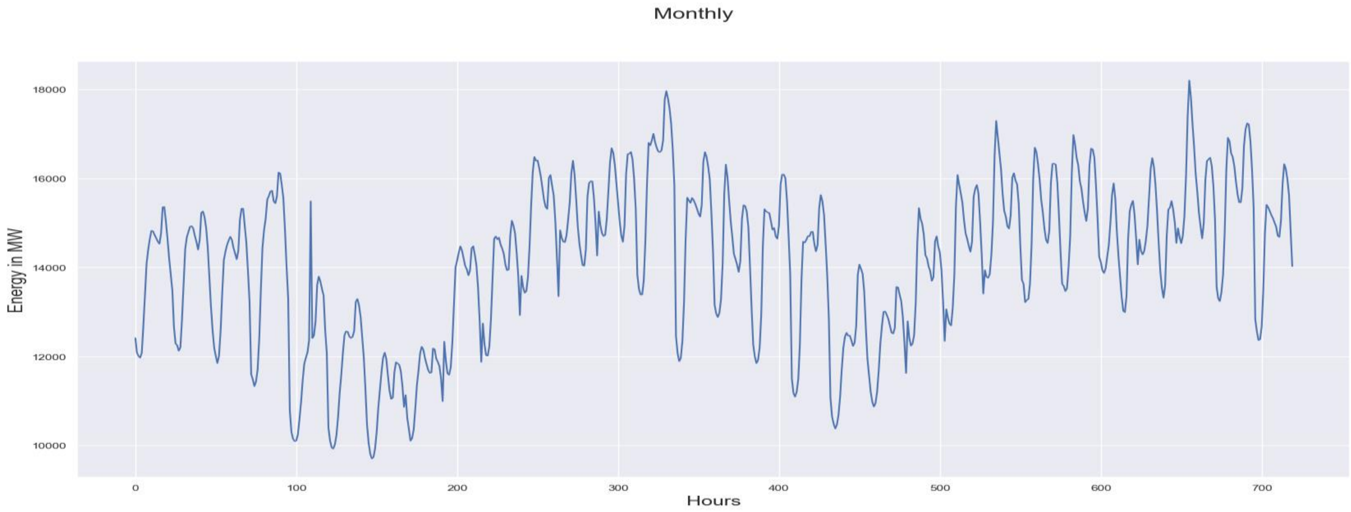


Figure 4.9 Graph that depicts the monthly load consumption in node 3

Prediction for Original ,Training and Test Data

NODE 1:

Figure 4.10 Graph that depicts the plot predictions for original, training and test data in node 1

NODE 2:

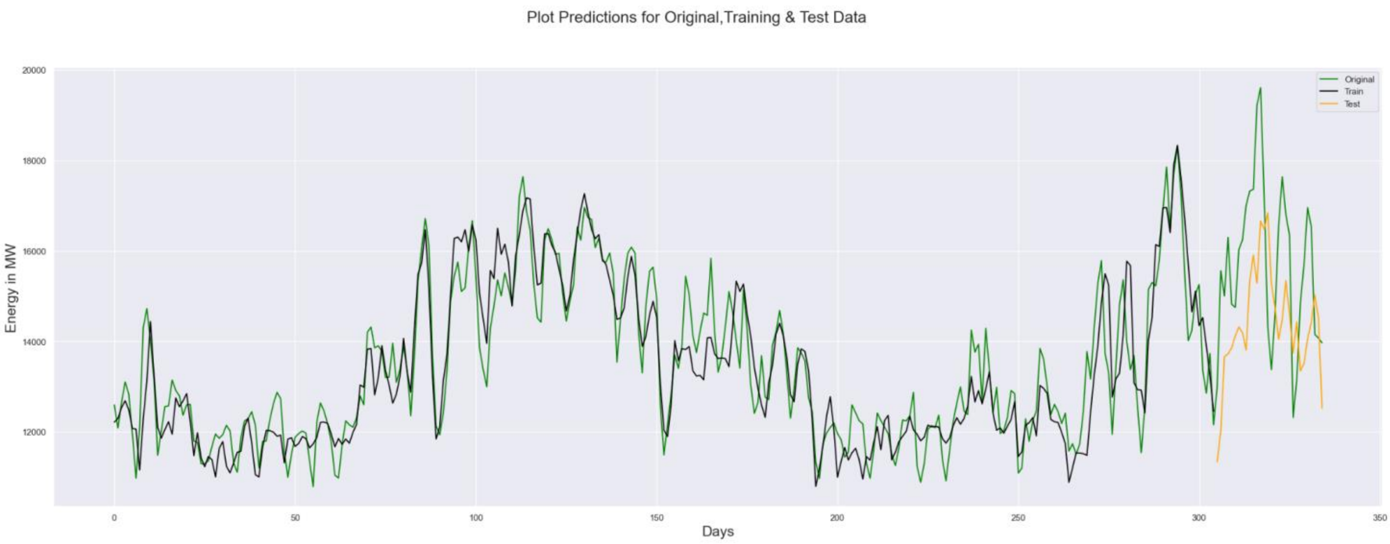


Figure 4.11 Graph that depicts the plot predictions for original, training and test data in node 2

NODE 3:

Figure 4.12 Graph that depicts the plot predictions for original, training and test data in node 3

Prediction for Training,Test and Forecast Data

NODE 1:

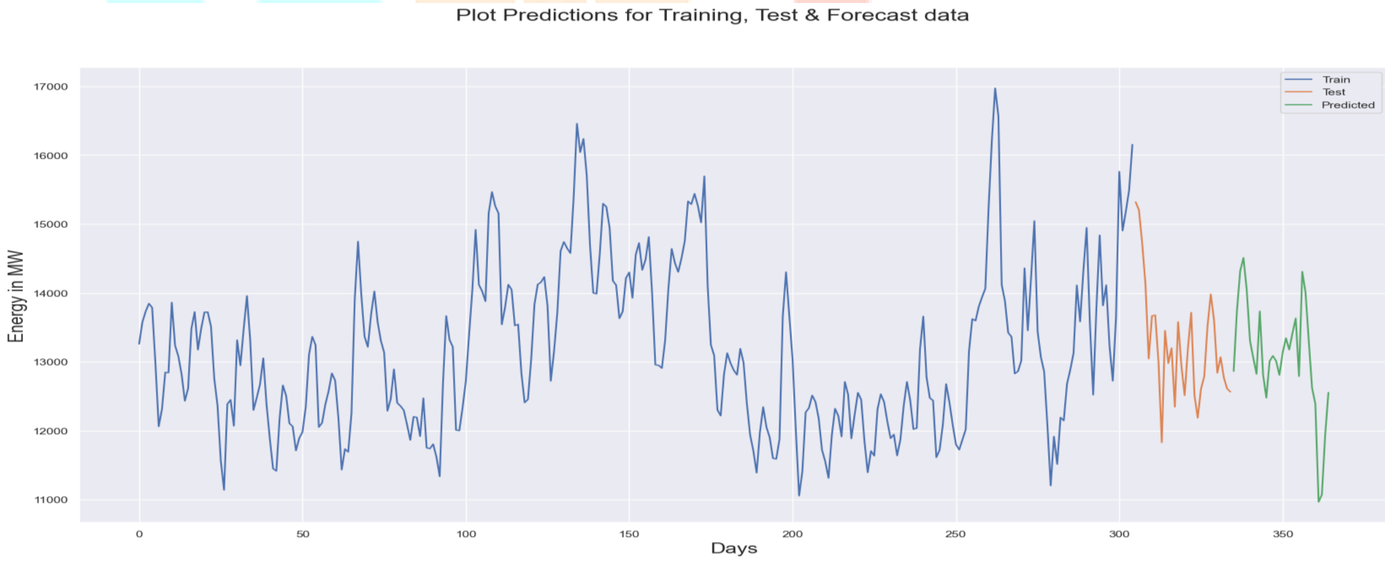


Figure 4.13 Graph that depicts the plot predictions for training, test and forecast data in node 1

NODE 2:

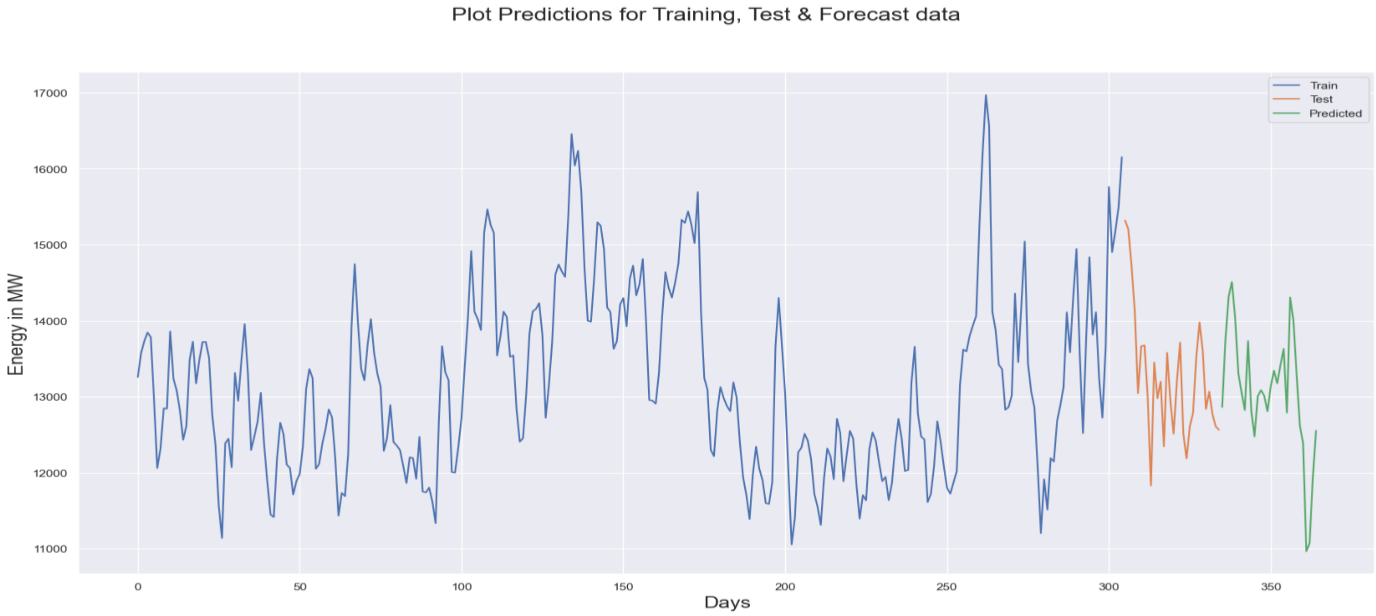


Figure 4.14 Graph that depicts the plot predictions for training, test and forecast data in node 2

NODE 3:

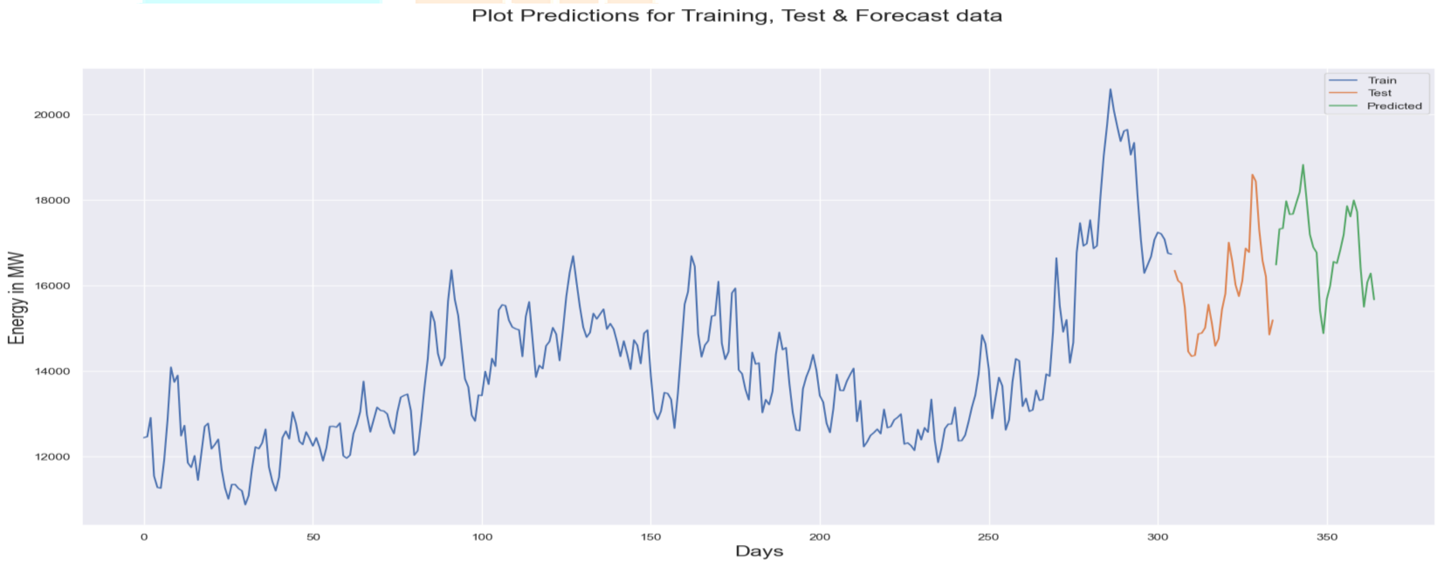


Figure 4.15 Graph that depicts the plot predictions for training, test and forecast data in node 3

Predicted Next Day Hourly Requests

NODE 1:

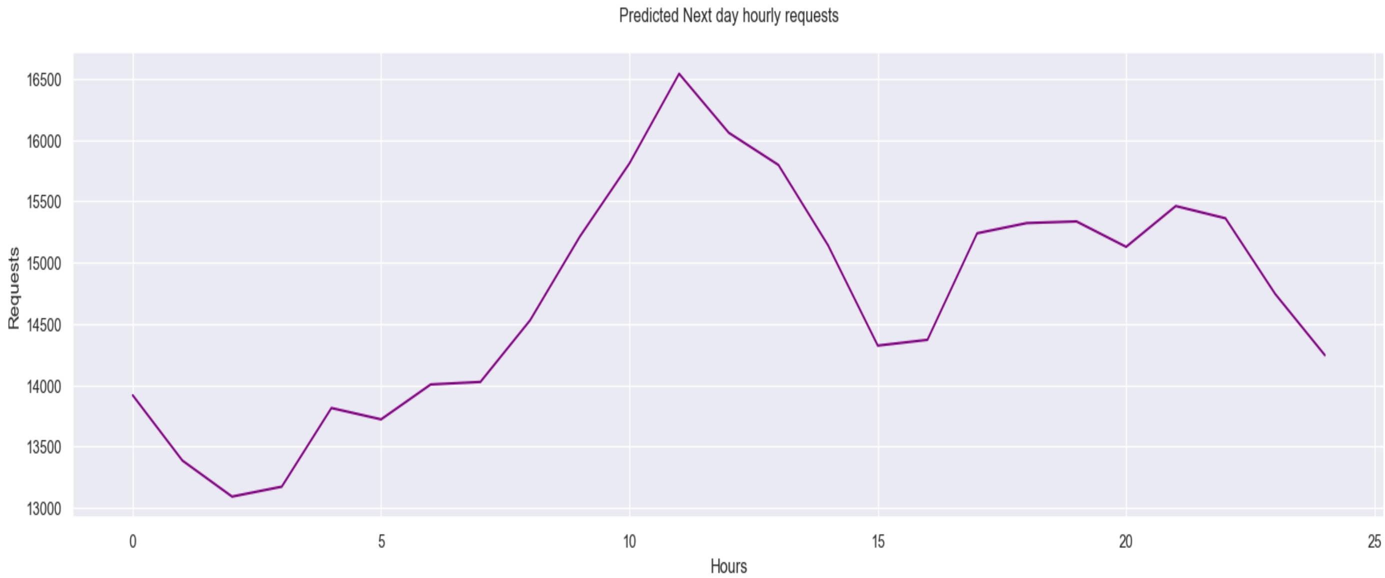


Figure 4.16 Graph that depicts the predicted next day hourly requests in node 1

NODE 2:

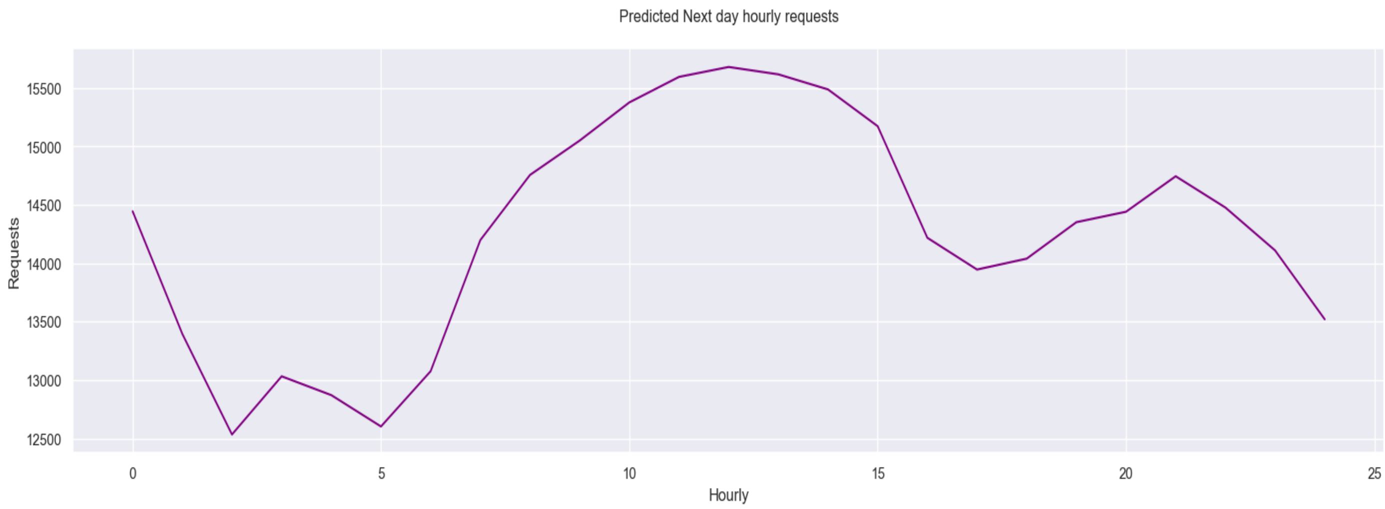


Figure 4.17 Graph that depicts the predicted next day hourly requests in node 2

NODE 3:

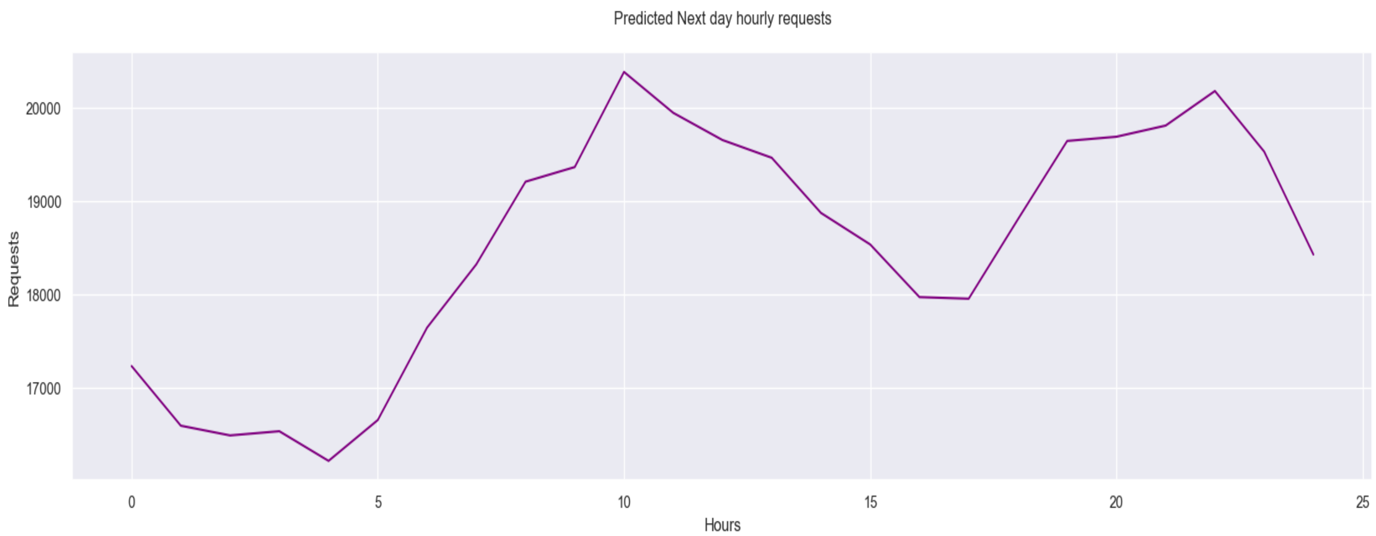


Figure 4.18 Graph that depicts the predicted next day hourly requests in node 3

Predicted Next Week Requests

NODE 1:

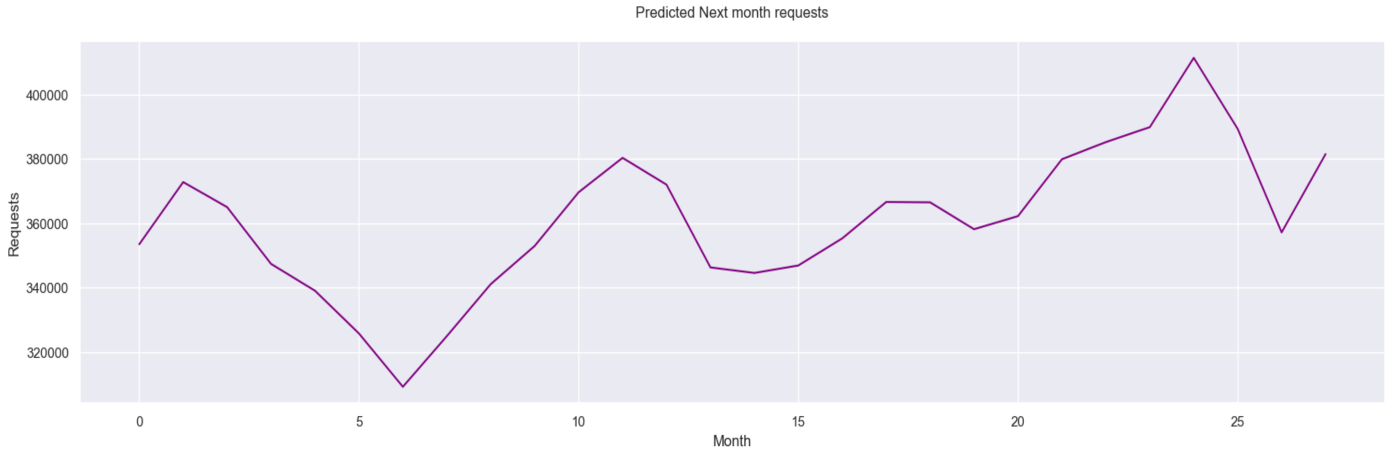


Figure 4.19 Graph that depicts the predicted next week hourly requests in node 1

NODE 2:

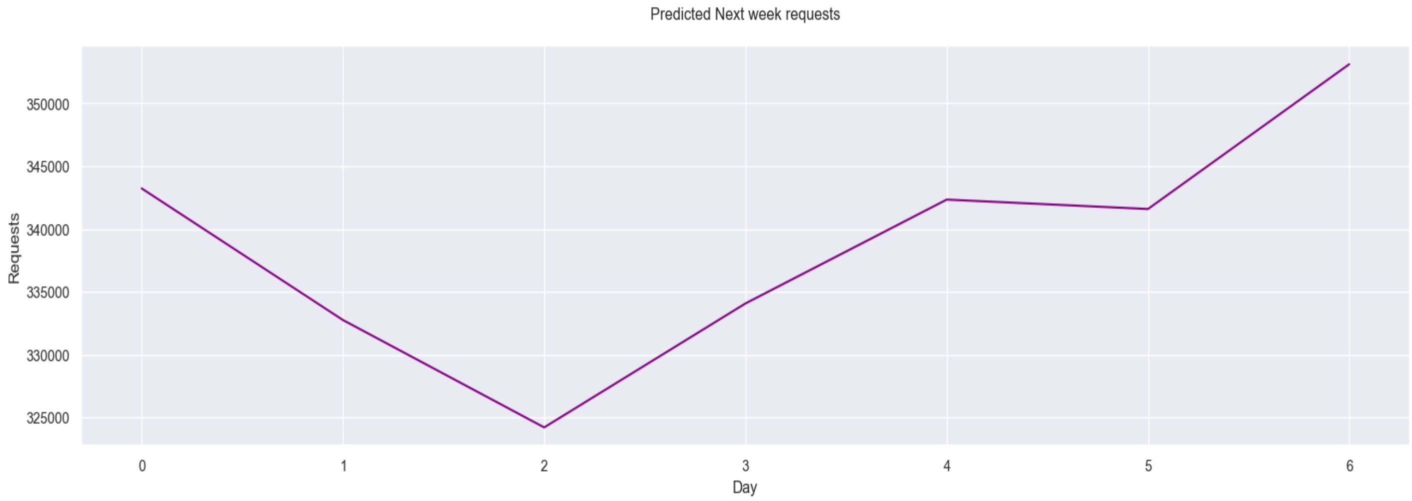


Figure 4.20 Graph that depicts the predicted next week hourly requests in node 2

NODE 3:

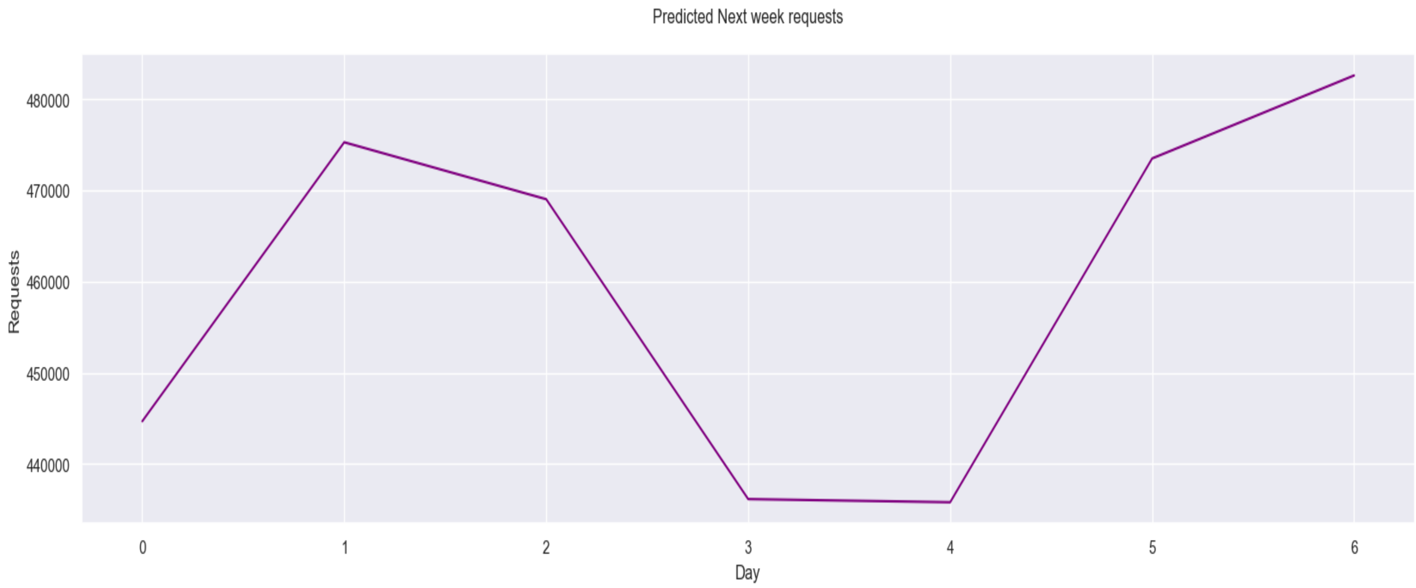


Figure 4.21 Graph that depicts the predicted next week hourly requests in node 3

Predicted Next Monthly Requests

NODE 1:

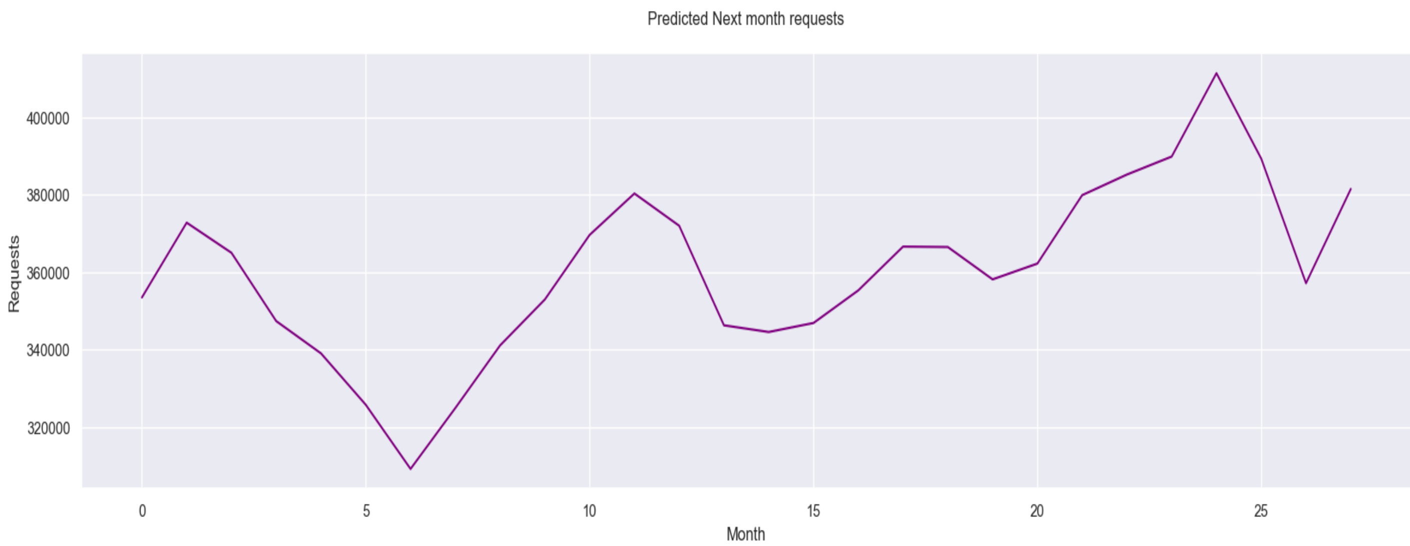


Figure 4.22 Graph that depicts the predicted next month hourly requests in node 1

NODE 2:

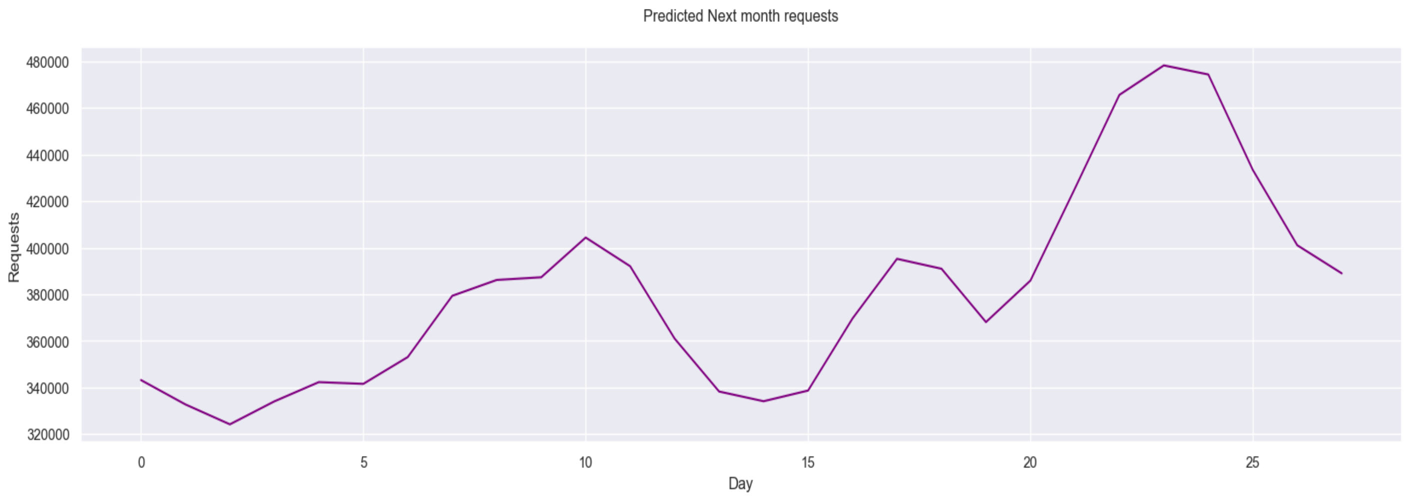


Figure 4.23 Graph that depicts the predicted next month hourly requests in node 2

NODE 3:

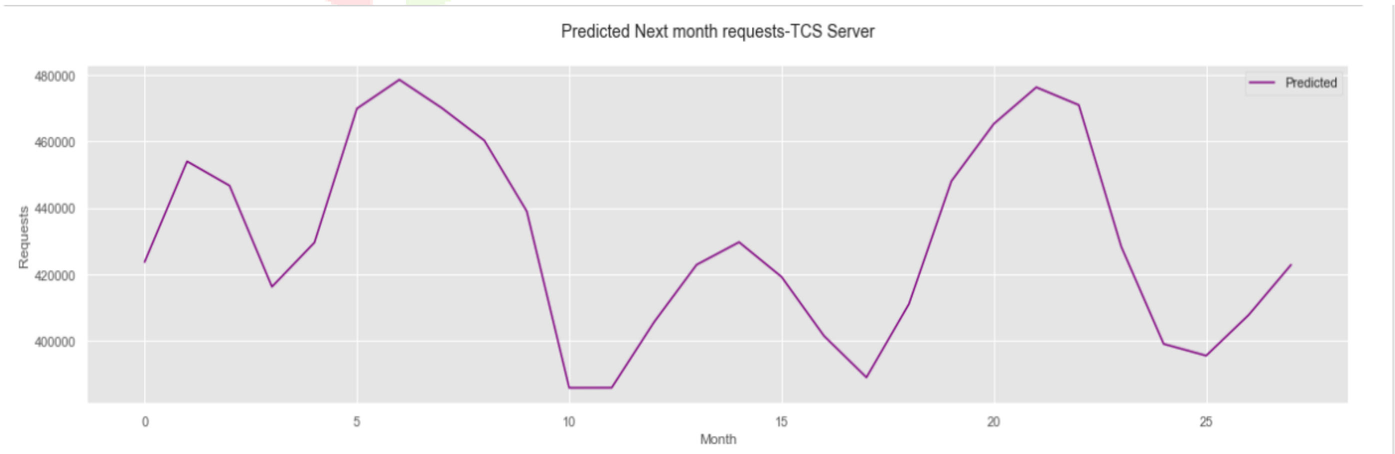


Figure 4.24 Graph that depicts the predicted next month hourly requests in node 3

V.CONCLUSION AND FUTURE WORK

In this work, the demand analysis is done by employing a Long Short-Term Memory (LSTM) network based on a short-term load forecasting technique to deliver more accurate load forecasting for the power consumption of various edges (nodes) connected on heterogeneous platforms. Here the study on three edges with the source connected to various network models including smart meters with wireless network, it is evident that the LSTM model builds on the inferred 'Predicting Future Energy Consumption Using Lstm' dataset.

Hence this work proposes Edge Nodes for faster,accurate and comprehensive computation.The findings are predictions of load for the next day,week and month. These findings will be deployed in a centralized platform for easy access to the service providers and efficiently manage the demands.

This algorithm can be applied over the real time data equipped for major industrial/ smart cities to utilize an efficient LSTM model for intelligent and accurate forecast of demand analysis to ensure Sustainable growth of the environment by optimal utilization of resources through efficient analysis.

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