Short Term Load Forecasting

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For the partial fulfilment of the requirements
for
The Degree of Bachelor of Science
in
Electrical Engineering

by

Fahad Iftikhar (F2017019030)
Hafiz Faizan Butt (F2017019025)
Hamza Tahir (F2017019028)

Dated
26-May-2021

CERTIFICATE OF APPROVAL

The research work presented in this thesis, entitled **"Short Term Load Forecasting"** was conducted by **Fahad Iftikhar (F2017019030), Hafiz Faizan Butt (F2017019025), Hamza Tahir (F2017019028)** under the supervision of Prof. **Zawar Hussain**

The thesis is submitted to the Department of Electrical Engineering at the University of Management and Technology, Lahore in partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical Engineering.

RESEARCH SUPERVISOR:

Prof. Dr. ……. **Signature: _______________**

EXTERNAL EXAMINER:

Prof. Dr. ……. **Signature: _______________**

Date of Approval: **Day/Month/Year**

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I declare that this research work titled "**Short Term Load Forecasting**" has not been submitted elsewhere for any other degree and has been properly acknowledged/referred. In case, any of the information provided is found plagiarized or copied from any source, I am aware that I will be held liable and serious actions can be taken against me.

Fahad Iftikhar (F2017019030)

Hafiz Faizan Butt (F2017019025)

Hamza Tahir (F2017019028)

Signature: __________________

Dated: 26-May-2021

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In the name of ALLAH, the most gracious, the most Merciful. All praise to ALLAH Almighty who is the most beneficent and merciful who has given me the strength and courage to complete my research project.

I acknowledged that the data I have taken is from journal articles and I did not take data from any illegal sources.

Dedicated to our Parents and Teachers

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SYMBOLS /ABBREVIATIONS

Abbreviation	Meaning	Page
ANN	Artificial neural networks	1
MTLF	Medium term load forecasting	2
STLF	Short-term load forecasting	3
WT	Wavelet transformation	3
BNN	Bayesian neural network	7
DNN	Deep neural networks	7
BPNN	Back propagation neural network	8
SNNs	Simulated neural networks	11

Abstract

This project is focused on the method of short-term load forecasting using the new approaches of artificial neural networks and other methodologies. A model has been proposed in the research to overcome the problems that are faced during short-term load forecasting. It is a very effective model for calculating accurate timespan and efficacy of load forecasting of activities in a utility. At the end of the report, motivation of the work has been discussed, and the conclusions of the conducted research have been provided. Based on those conclusions, it has been proposed that further research is also needed in the field.

Chapter 1

Introduction

The objective of short-term load forecasting models is to predict the load during the next specified time period may it be an hour or the next two or three weeks. Numerous different approaches for calculating aggregated household demand have been suggested and evaluated. Accumulating the data smooth things out, making forecasting smoother. Request forecasting at the person level is much more difficult and has a greater failure rate. Load forecasting assists in the preparation of potential generating plants in terms of capacity, position, and size. The facilities would most likely produce electricity near the load whether they identify areas or territories of strong or increasing demand. This reduces the size of the generation & distribution technologies, and the damages that come with them.

1.1 Motivation for Work

There are several methodologies that have been used up till now for load forecasting, each method devis

ed for a certain amount of time. However, I believe that there are major drawbacks in the methodologies. The motivation of conducting this research was to introduce and implement a new approach using the combination of Neural Network, ANN approaches such as back propagation methodology and integration of these approaches. It will help in solving major challenges in the short-term load forecasting faced by multiple organizations and utilities in the present environment. It had always been my goal that I will research about the implementation of appropriate AI and Machine Learning approach in the Load forecasting method to make it more effective and less time-consuming. Based on this perspective, the presented model has covered the important part of the innovative Short-term load forecasting approach. There are multiple problems that are associated with the short-term load casting such as lack of efficacy of the measured forecast for a certain condition such as the response time calculation and instantaneous machine operations. These factors are very crucial for a utility since there can be numerous risks and losses associated with them including the failure of the ongoing operation. Therefore, the research was developed so that a major breakthrough can be made and these challenges can be overcome.

The objective of short-term load forecasting models is to predict the load during the next specified time period may it be an hour or the next two or three weeks. Numerous different approaches for calculating aggregated household demand have been suggested and evaluated. Accumulating the data smooth things out, making forecasting smoother. Request forecasting at the person level is much more difficult and has a greater failure rate. Load forecasting assists in the preparation of potential generating plants in terms of capacity, position, and size. The facilities would most likely produce electricity near the load whether they identify areas or territories of strong or increasing demand. This reduces the size of the generation & distribution technologies, and the damages that come with them.

1.2 Four Types of Load Forecasting

There are four type of Load forecasting which is discussed below: -

1.2.1 Very-Short Term Forecasting

Very short-term forecasts for loads in the near future in 5 minutes, on the basis of real-time data gathered, in a spatial dimension. Efficient forecasting is essential for management of area development and dispatch of resources. These forecasting predictions are usually used by companies and grid managers for the real-time programming of load frequency management and responding recommendations in the electricity sector. The rather short load predictions are often critical to manufacturers, electricity marketers and trading companies' business activities.

1.2.2 Short Term Forecasting

Short time forecasting is made for day-to-day operations in order for a week to be generated and the necessary deposit to be maintained. It is normally conducted 24 hours before the next day's weather outlook so it is accessible from of the atmospheric department.

1.2.3 Medium Term Forecasting

This prediction is being made for 5 - 7 years and will play an important part in preparing the scale of a power station and in building and installing power station facilities. MTLF projects for moderate electricity & fuel use that are planned monthly in the upcoming year.

1.2.4 Long Term Forecasting

In order to promote different plans, including the long-term load forecasting methods and timeline of generators, play a vital role as a program for further extension of the power generation capacities can be extended over 20 or perhaps more than decades in advance to negotiations deals on electricity interchange with neighboring utilities.

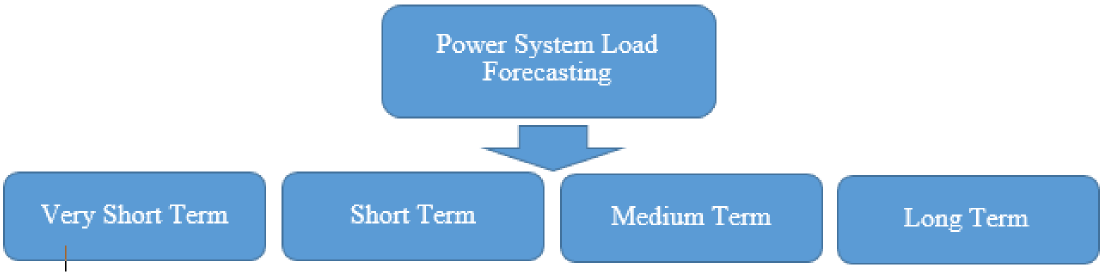

Figure 1 Load Forecasting Block Diagram

The utilities will use short-term load forecasting methods and tools to determine when to do repairs to guarantee that it has the least amount of effect on customers. They can also decide how to maintain residential areas during the daytime when the majority of the people are working and consumption is minimal. The functioning of both managed power grids and energy markets is affected by short-term load forecasting (STLF).

Despite all of the research conducted in this field, there is indeed a critical need for more precise and reliable load forecasting methods. Low and elevated factors are mainly seen in daily load periodicity, as well as global smooth patterns and sharp local variations. WT (wavelet transformation) can disintegrate a time - series data into its constituents quickly. Each portion is estimated using a variation of NN and EA, and the total power prediction is estimated using inverse WT (wavelet transformation). In the energy sector, various numerical intelligence approaches and research methods are being used for short-term forecasting models, but there is little information regarding their effectiveness when evaluating the type of information and other possible considerations.

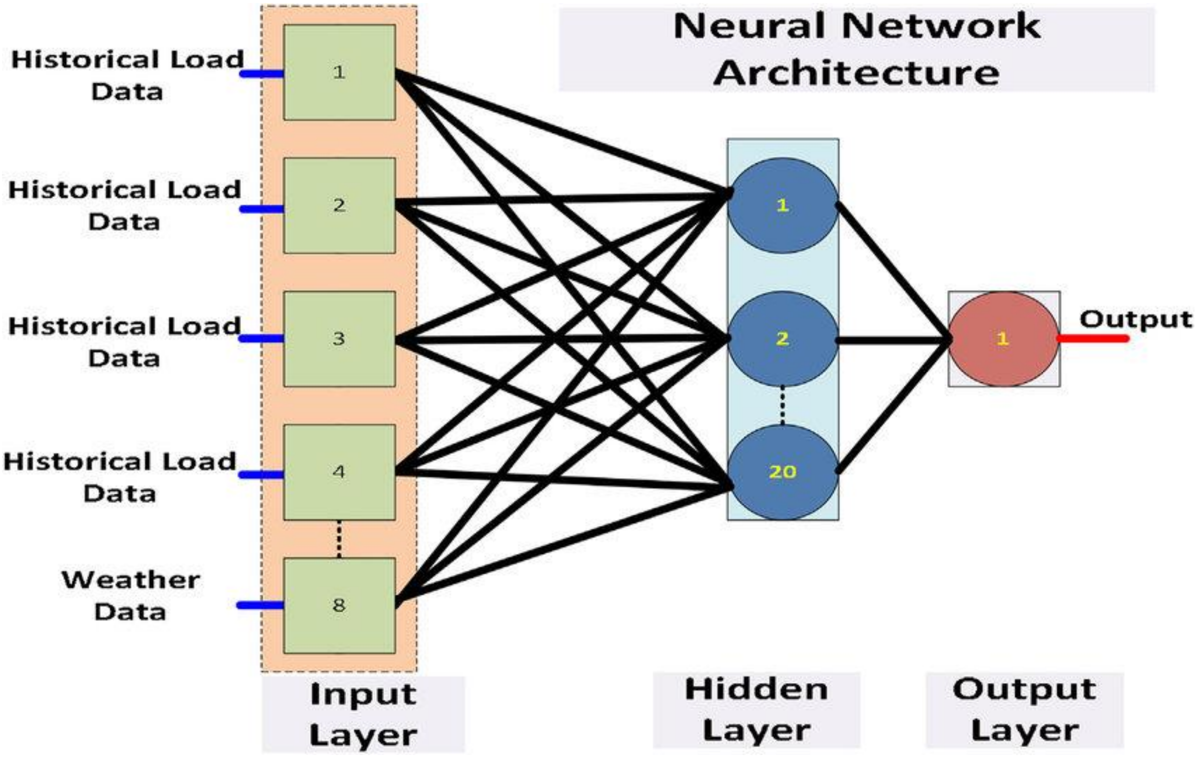

Figure 2: A proposed model for load forecasting using neural networks [2]

However, the majority of seasoned utility forecasters focus on traditional methodologies that include a deep knowledge of a broad variety of key contributors' dependency on upcoming events or a specific dataset. Owing to the growing level and complexities of forecasts, depending on manual forecasts is no longer viable. As a consequence, companies must search for innovations that will have consistent outcomes and mitigate complications that could arise if seasoned forecasters either fail to do their tasks appropriately or lose their jobs. As a result, consumption patterns vary between customers that use specific varieties of metrics, especially among intelligent and conventional metrics, and also between multiple tariffs. Therefore, the utility must acknowledge this and create different forecast models for each of the calibration schemes, which must then be added together to arrive at the final predicted value. In this dissertation, the short-term load forecasting methods will be discussed in details including their shortcomings and current issues. The data will be collected from various sources to identify the problems that occur during the process and analysis will be drawn out of it so that the problems can be solved. After the analysis has been done, we will discuss them and find out ways to overcome those problems and recommendations will be provided accordingly. A conclusion will be provided at the end of dissertation and future research recommendations will be given to further investigate the issues associated with it.

1.3 Neural Network

Neural networks, also known as artificial neural networks (ANNs) or simulated neural networks (SNNs), are a subset of machine_learning and are at the heart of deep_learning algorithms. Their name and structure are inspired by the human brain, mimicking the way that biological neurons signal to one another.

Artificial neural networks (ANNs) are constructed from node layers, containing an enter layer, one or greater hidden layers, and an output layer. Each node, or artificial neuron, connects to every other and has a related weight and threshold. If the output of any person node is above the desired threshold value, that node is activated, sending statistics to the following layer of the network. Otherwise, no statistics are surpassed alongside the next layer of the network.

Neural networks depend on education statistics to examine and enhance their accuracy over time. However, as soon as these mastering algorithms are fine-tuned for precision, they're effective gear in laptop technology and synthetic intelligence, permitting us to categorize and cluster statistics at an excessive velocity. Tasks in speech reputation or photograph reputation can take mins instead of hours while in comparison to the guide identity with the aid of using human experts. One of the maximum famous neural networks is Google's **seek** algorithm.

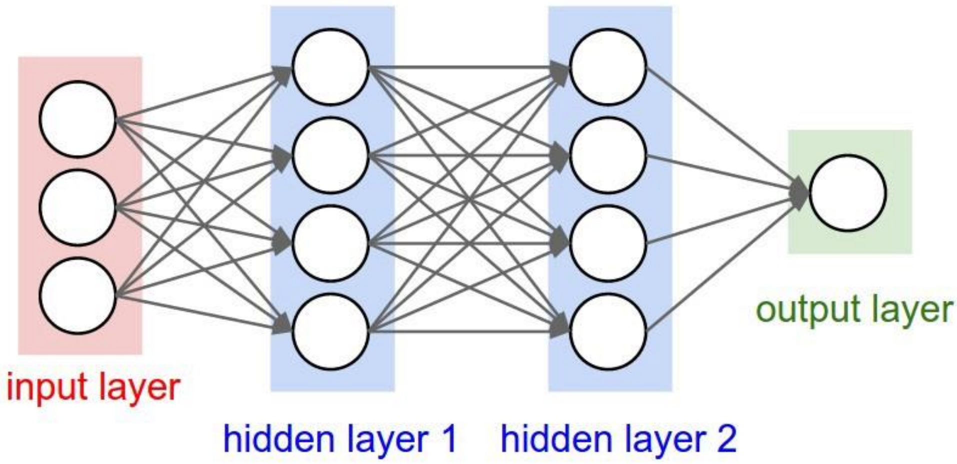

Figure 3 : Deep Neural Network

Chapter 2

Literature Review

We have studied some research papers and on the bases of that we have extract some data related tour work.

2.1 Multiple methodologies being used for Load Forecasting

The concept of forecasting relates to expected load needs which can be calculated in adequate quantitative detail by a comprehensive method of identifying potential loads to allow a utility to decide about certain situations for critical systems expansion.

Load forecasts are indeed a method used by power firms to estimate the power or resources required to match production and consumption at all times. It is essential in order for the electrical industries to work properly. It may be categorized as short-term, moderate (some weeks to one year) or long-term (multiple years of time). There are several macroeconomic approaches used for short and long-term forecasts. Different methods are being used for short-term forecasting, such as predictor variables, time - series data, neural networks, mathematical calculations and fuzzy logic [3].

2.2 The Need for Load Forecasting

There is an increasing tendency to unbundle the energy infrastructure. This constantly tackles the growing need for the preparation management and activities of the network in the various industries. The management and preparation of a power service corporation involves an appropriate model for predicting electrical loads.

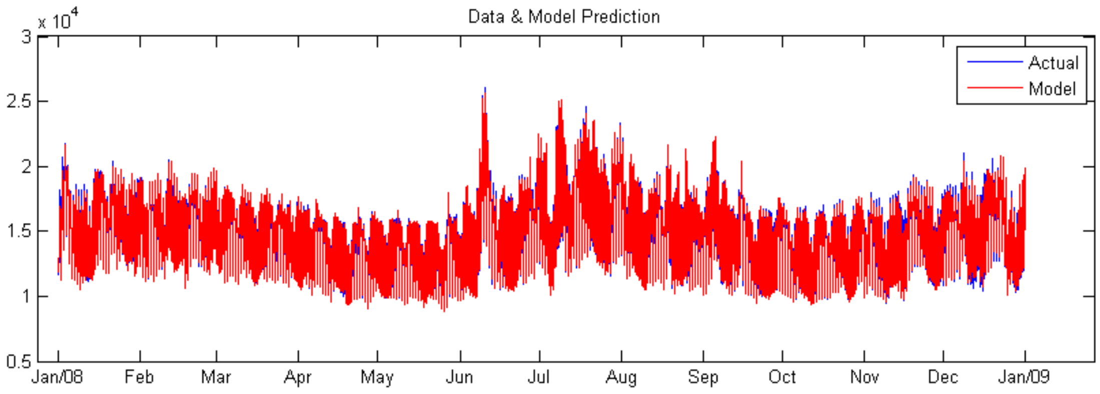

Figure 4: example of electric load forecasting [5]

Load forecasting subsidies for the electricity industry to conclude decisions on power generation and acquisition, loading shifting, voltage management, frequency regulation and infrastructure growth. Electric load prediction is the method used for predicting potential electricity load, considering historical load and environment and actual and predicted weather. Several studies have been performed in recent decades to predict electricity consumption more precisely. With the advent of deregulation of the power sector, the energy business members faced several new obstacles. Wind power, electricity and oil costs have been a big problem in electricity schemes. Different methods are used to predict wind power, electricity prices and power demand following industry requirements. The business danger associated with trade is substantial owing to extreme energy price fluctuations. Given the uncertainty of potential pricing in dynamic energy markets, price projections are utilized by operational planning operators. In addition, the safe functioning of the electrical system involves the analysis of its actions under various postulated hazard circumstances at some stage in the future [4].

2.3 Short Term Load Forecasting- Artificial Intelligence Approach and Fuzzy Time Series

The popularity of STLF among investigators in various macro and micro sectors of organizations, the convergence of alternative energy sources closer to customers, as well as the degree of complexity that this field of forecasting research involves, have grown in recent years. Additional modern approaches such as machine learning and AI and probabilistic reasoning have been used in recent times for load forecasting. Smart applications built on AI technology are being increasingly popular for solving STLF. In several implementations, AI-based systems are created and implemented worldwide, largely due to their symbolic simplicity and explanations.

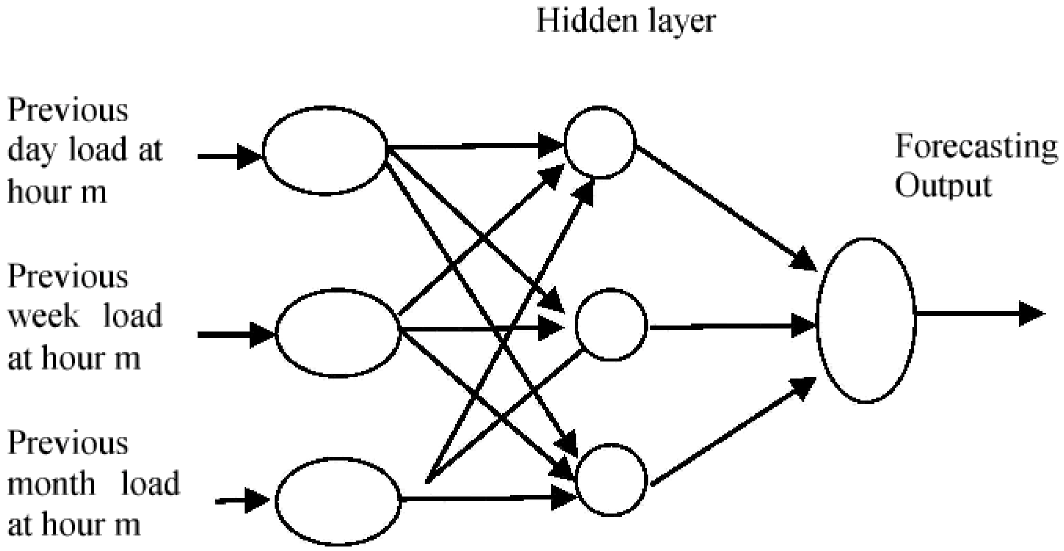

Figure 5: Hidden and visible layers of transformation in neural networks [6]

Ghofrani implemented a Bayesian neural network (BNN) configuration and a WT (wavelet transformation) to generate the comprehensive frequency response for BNN training. A weighted average of the BNN outputs was used for predicting the load for a particular day. Any aspects need to be considered into account to include a strong STLF model (Sadaei & Lima e Silva, 2018). A short-term load is generally thought to be a vector that depends on many variables, such as past demand details, weather information, including wind velocity, precipitation, barometric pressure, temperature and moisture. A precise forecast can hardly be made from utilizing a single model.

2.3.1 Usage of Artificial Neural Networks in Load Forecasting

The forecast is among the most exciting applications for the deep neural networks (DNN) and artificial neural networks (ANN). Various scholars have tried to use the back - propagation optimization algorithms to prepare ANNs for predicting time - series data. This concept can be generalized to the real-world issue in Werbos's research, where the back propagating algorithm is generalized to the recurring energy market model. It was indeed detrimental that perhaps the forecast capacity of the under-consideration algorithm was lower than simple predictor variables in regression analysis. (Lee, 1992).

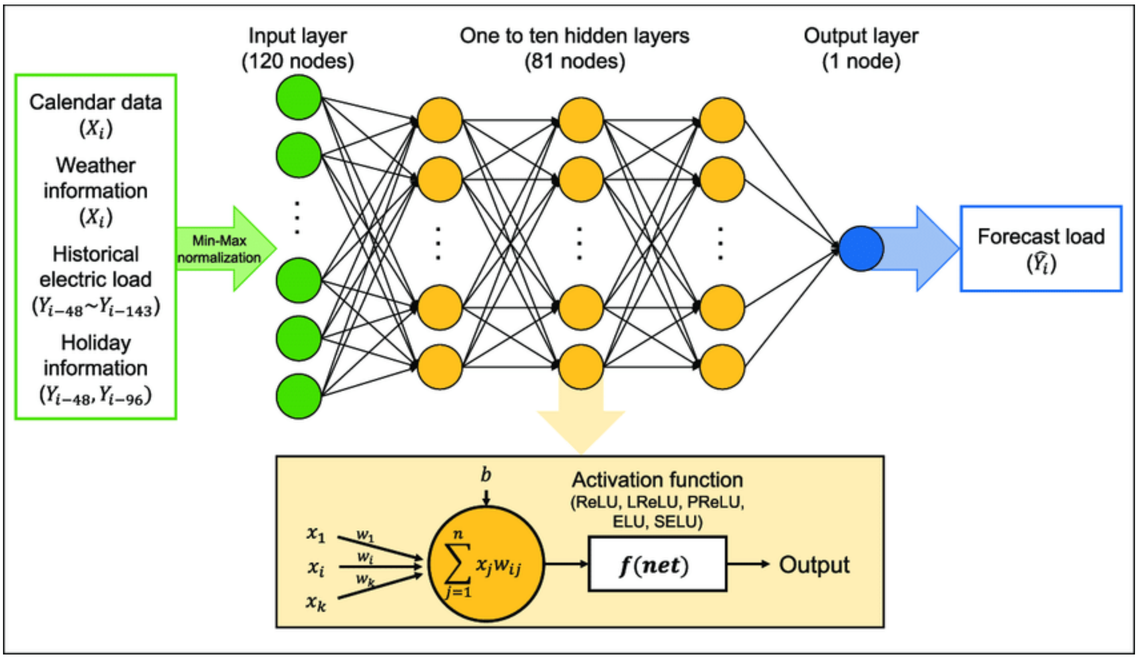

Figure 6: ANN short term load forecasting [1]

Nevertheless, the National Science Foundation has currently held a seminar on the role of ANNs (Artificial Neural Networks) in power distribution infrastructure and researchers have shown that ANN can be utilized with acceptable precision in a considerable short-term load forecasting method. The backpropagation algorithm is introduced in several studies as a technique to predict electrical loads. A non-linear loading model is proposed and non-linear loading model parameters are calculated with the background propagation algorithm. Findings from the underlying study suggest that the ANN is used satisfactorily, with a standard deviation of approximately 2 percent.

2.4 Short Term Load Forecasting Using Back Propagation Approach

By revealing the strategy of neural networks to new innovations, we can adapt the ANNs. Its ability to exceed conventional methods and its time taken for growth, particularly in quickly shifting weather, have rendered ANN's contingency analysis based on prediction modeling a very enticing alternative for online deployment in optimal power flow organizations. The learning mechanism of the backpropagation neural network (BPNN) involves two stages, one of which is the transmission of input knowledge in the forward orientation and the second is deviation in the reverse direction.

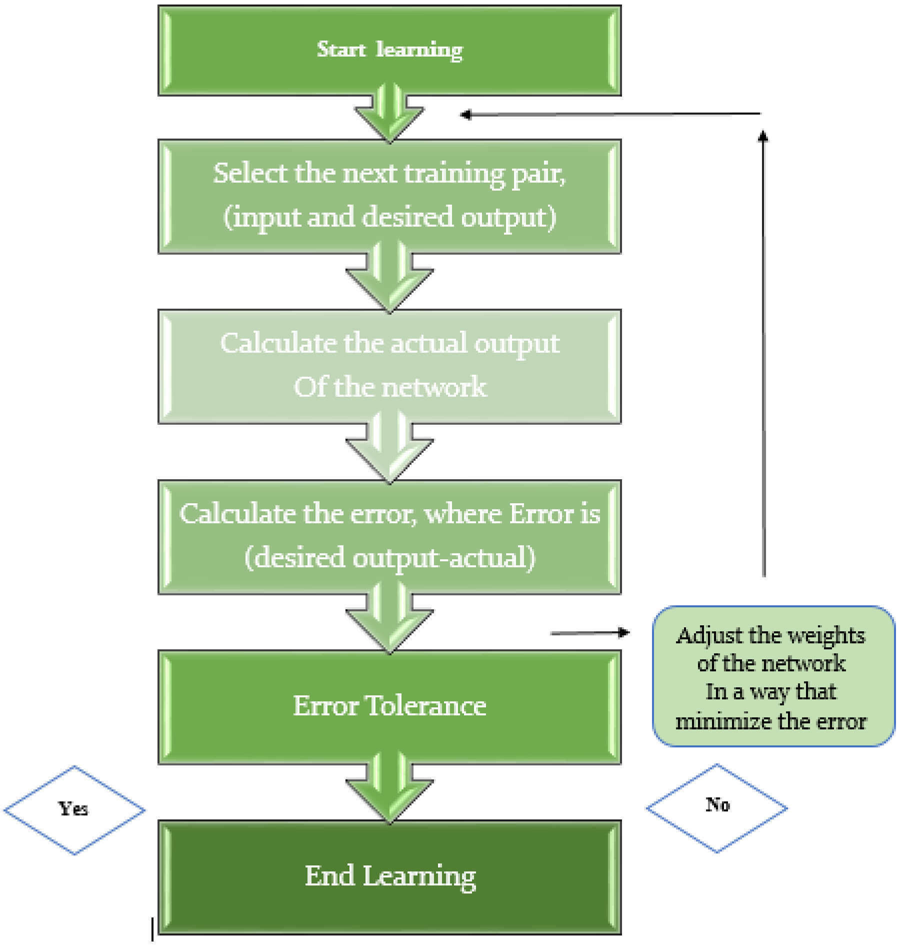

Figure 7: back propagation training approach

The data knowledge goes to the unseen layers in the forward operation. When the output unit value differs from the intended output outcome, so the output error is measured, a reverse path is communicated and the weights of each layer are changed in order to minimize the error. The framework is then assumed to be equipped for the information or operation in question. The error value is then chosen depending on the discrepancy between the real answer and the goal. Eventually, the error signal produced is redirected via the secret framework to the appropriate path.

2.4.1 Elite Load Methodology

ELITE load prediction technique builds several machine-learning, high-quality, language models and optimal architectures for STLF agents. The implementation of these various models may have different prediction precision, but the same load prediction samples are applied. It can be noted that various STLF analysts have different aspects of ability prediction, such as various times of certain circumstances or climates. ELITE uses an ideal mix of neural networked various prediction models to identify the most suitable one for improved widespread capability (Zhang & Chiang , 2020).

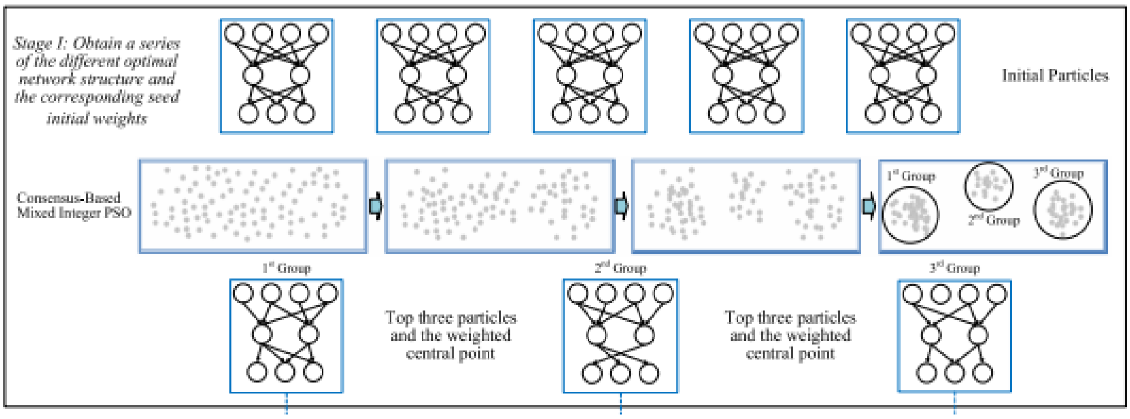

Figure 8: stages of ELITE model approach [Zhang, Y.-F.][3]

The CMPSOATT (PSO and Trust Technology Integration Methodology) is a new and strongly theoretically testable optimization tool. It is carried out by local optimization process, in order to calculate quickly a series of high-quality specific optimum solution capable of containing the global optimum solution, and hence is a more composable method for adjusting the model parameters.

As great work is completed by term load forecasting AN, it's essential to current sensible energy management systems. Each day, there are different and more uses for load forecasting. Usually, a short-run Load statement (STLF) with lead times within the scope of AN hour to 1 day is necessary to regulate programming and energy transfer planning and cargo dispatching. Thus, any improvement within the accuracy of STLF will improve the performance of power management and a decrease in the expenses of the facility system. Important work a correct STLF could be the key to success for electricity offer corporations. It actuated the researchers of our study to develop accurate and sensible strategies for this end. STLF is done victimization numerous methods, that embody the supposed similar day approach, numerous regression models, time series, neural networks, knowledgeable systems, fuzzy logic, and applied mathematics learning algorithms, are used for short-term forecasting.

Chapter 3

Proposed Methodology

This is our proposed method in which we have divided our work in three section Per Processing, Train test split and Prediction. In our proposed method each step is defined in the form of flow chart. In this flow chart first is defined as Pre Processing. Train test split is consisting of second and third step. And the last three steps are from prediction.

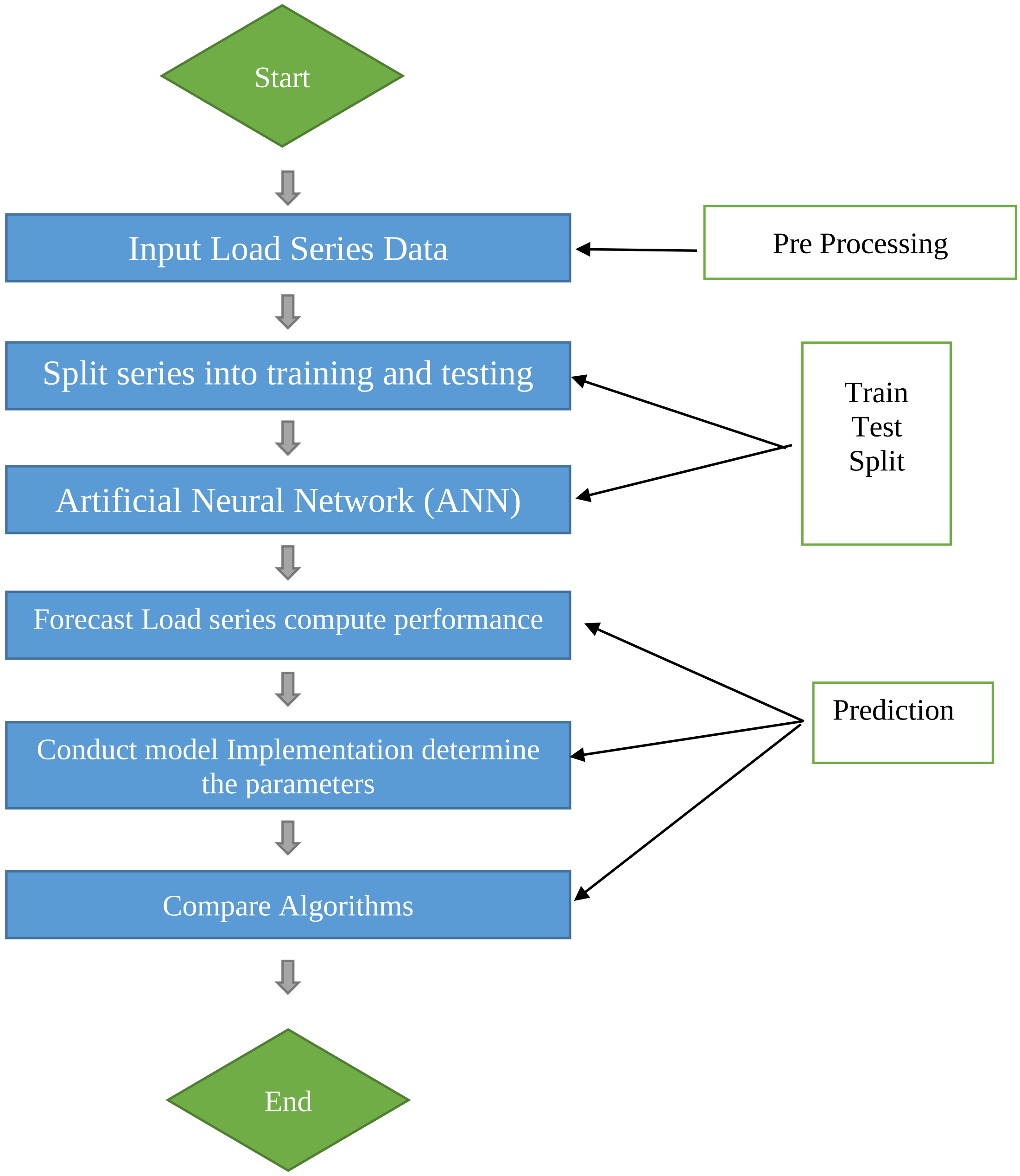

Figure 9: Proposed Methodology

3.1 Pre Processing

Using the Ann technique for Short term load forecasting, we collect the data of Malaysia for two years (2009-2010). Having data of load and temperature of every hour, we refined our data by adding humidity and public holidays. We collect the humidity data from (www.worldweatheronline.com), and we collect the holiday data from (www.time-anddate.com). But there is a hurdle that they collect data every three hours. We represent public holidays with 0 and working days with 1. Once we collect and set the data into an excel file, we start with pre-processing using Jupyter notebook.

In this, we have load our data into Jupiter notebook. After that, we have used timestamp distribution to distribute date-time data into the year, month, week, day, hour, minute, second. As we know that our humidity is for every three hours, but we need it for every single hour. We use the interpolation () function to fill NA values in the data frame or series to find this missing data. But, this is a very powerful function to fill the missing values. It uses various interpolation techniques to fill the missing values rather than hard-coding the value.) After achieving the unknown data, we move towards the data visualization. In data visualization, we plot the load against Date time, humidity against Date time, and temperature against date time. Once we were done with preprocessing, we had created a CSV file having named book 1. Now we move towards train test split

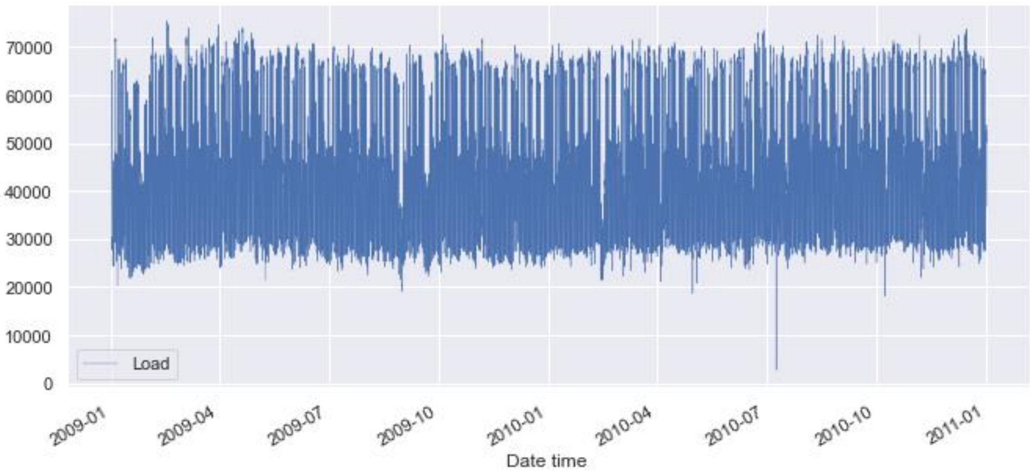

Figure 10: Load against Date time

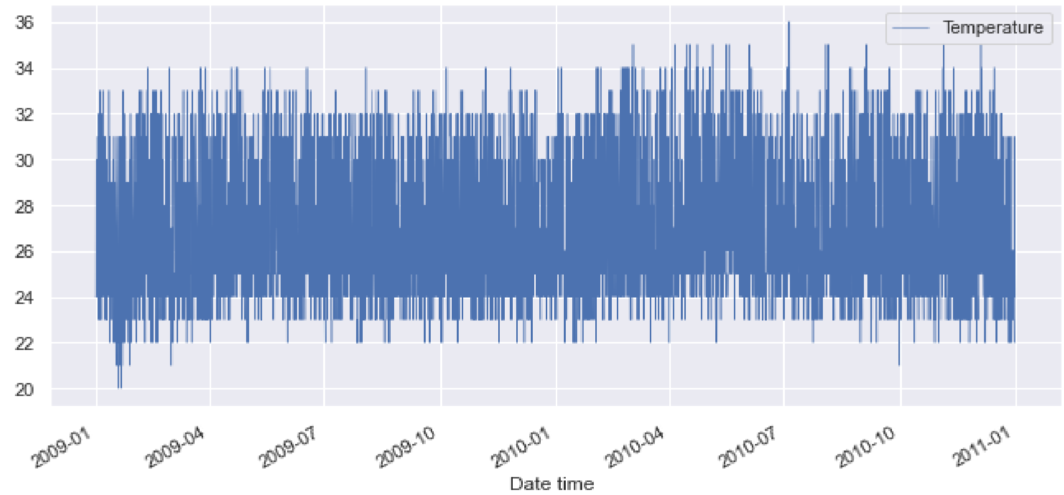

Figure 11: Temperature against Date time

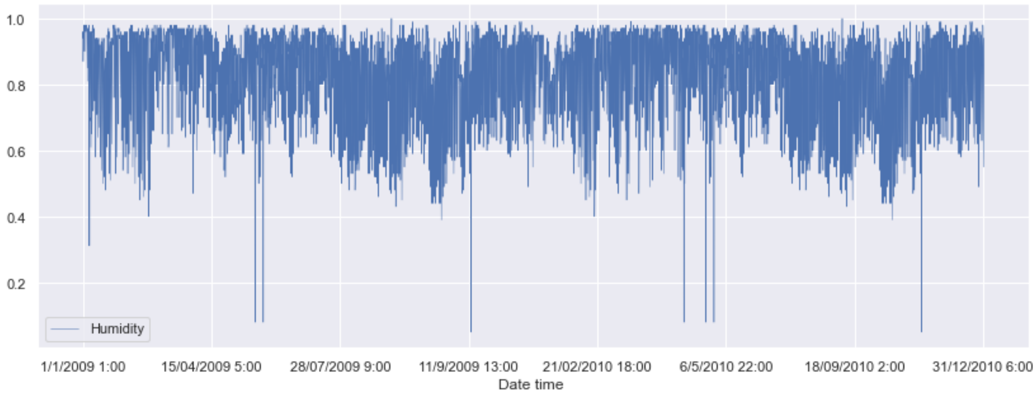

Figure 12: Humidity against Date time

3.2 Train Test Split

In our file our data has a datatype int64.so we need to change into datatype float64 and for that we have use a command astype (np. float64) np is use for the library numpy after that we move towards to train our data. In training we use first **MinMaxScalar** for each value in a feature (MinMaxScalar subtracts the minimum value in the feature and then divides by the range. The range is the difference between the original maximum and original minimum. MinMaxScalar preserves the shape of the original distribution.) in this we took our data into **scalar.fit_transform** (fit_transform() is used on the training data so that we can scale the training data and also learn the scaling parameters of that data) after using MinMaxScalar we train our data for one step ahead. Then we have stored our data into x and y for **train_test_split** (train_test_split is a function in Sklearn model selection for splitting data arrays into two subsets: for training data and for testing data. With this function, you don't need to divide the dataset manually.). In **X** we have stored (Temperature, Humidity, Holidays 0 for close 1 for open, year, month, day, hour, minute, second, weekday, Original Load). And in **Y** we stored (y_t+1). Now by using train_test_split we have split our data into X_train, X_test, Y_train, Y_test.

3.3 Prediction

Now For neural network we have import keras from tensorflow and from keras we import these libraries (layers Model, DenseNet121, Dense, Activation, optimizers, Earlystopping, modelcheckpoint) After importing the libraries we created a model using model.sequence. Then we have created a neural network in first layers we have used 11 neurons. We use 11 neurons because we have input data in 11 columns in **X** variable. For activation of neural network, we have **sigmoid** function. In next layers of neural network, we have used 10 neurons and sigmoid function. In last layer of artificial neural network, we have used only one neuron for output. In order to reduce the losses in neural network we have use optimizer Adam the goal of a training is to minimize the loss. With this, the metric to be monitored would be 'loss', and mode would be 'min'. A model.fit() training loop will check at end of every epoch whether the loss is no longer decreasing, considering the min_delta and patience if applicable. We have used 300 epochs because they provide us accurate figures and we have use batch_size 500 which is average. However, if we increase the batch_size it will generalize our data and if we set lower than 500 it will not capture the proper features. Once it's found no longer decreasing, model.stop_training is marked True and the training terminates. In model.fit() we have calculated train_loss and validation_loss. After that by using matplotlib we have plot our train_loss and validation_loss which nearly same with little difference. Then we have plotted predicted load and true load.after getting our predicted we get some errors means absolute error, mean absolute percentage error, mean square error and root mean square error.

Chapter 4

Experimentation & Results

We have reached to forth and second last chapter of experimentation and results which is the most important chapter of our report as it contains our prediction using Short term load forecasting with Neural Network and errors.

Before diving deep into the concept of RMSE, MAPE, MSE and MAE, let us first understand the error metrics in Python.

4.1 Error metrics

Error metrics enable us to track the efficiency and accuracy through various metrics.

4.1.1 Mean Absolute Error

Mean Absolute Error is the amount of error in your measurements. It is the difference between the measured value and “true” value.
Equation

$$\mathbf{MAE}=\frac{1}{n}\sum_{i=1}^{n}|x_i - x|$$

4.1.2 Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error (MAPE) is a measure of how accurate a forecast system is. It measures this accuracy as a percentage, and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values.
Equation

$$M = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

4.1.3 Mean Square Error

MSE is a risk function that helps us determine the average squared difference between the predicted and the actual value of a feature or variable.

Equation

$$\mathbf{MSE}=\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2$$

4.1.4 Root Mean Square Error

RMSE is an acronym for Root Mean Square Error, which is the square root of value obtained from Mean Square Error function.

Using RMSE, we can easily plot a difference between the estimated and actual values of a parameter of the model.

Equation

Errors	Loss
Mean Absolute Error	0.02880682046097274
Mean Absolute Percentage Error	0.050383559211373975
Mean Square Error	0.0014376397197986442
Root Mean Square Error	0.16972572127103405

$$\textbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}}$$

From above table we can say that the errors in our data are very low which means our prediction is very good. As we know in Mean Absolute error is the difference between target load and predicted load which is 0.02881. In Mean Absolute Percent-age Error it measures the average absolute percent error for each time period minus actual values di vided by actual values which is 0.05038. Mean Square Error is used to find variance in system which is 0.001437. In Root Mean Square Error use root is Mean Square Error w hich is 0.1697.

4.2 Simulation:

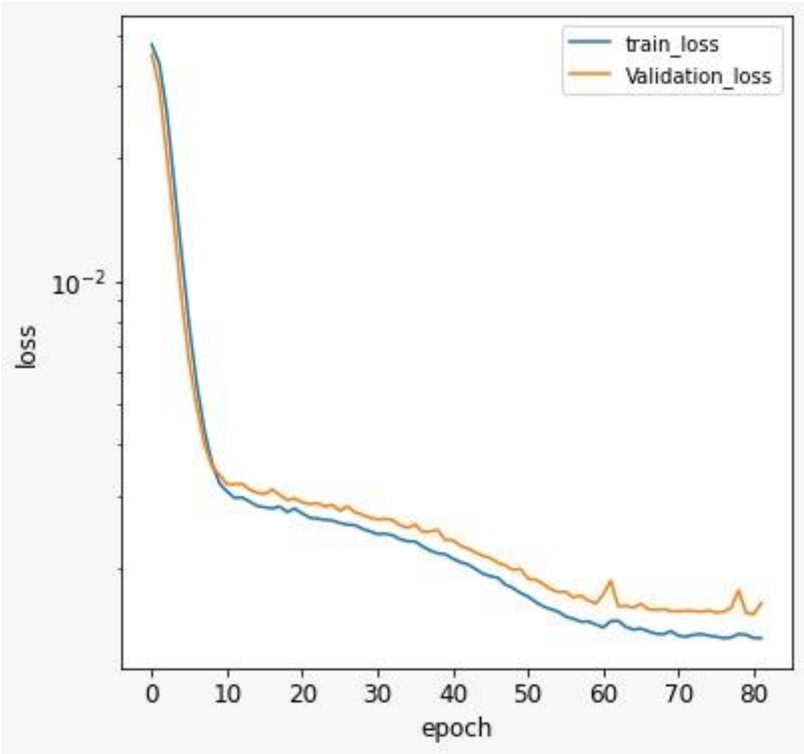

Figure 13: Graphical Representation of Train loss and validation loss

This graph shows the relation between Train loss and validation loss in terms of loss and epochs. By observing this graph, as we see with the increase of epoch our training and Validation loss decreasing which represents overfitting which occur when, the plot of training loss continues to decrease with experience and The plot of validation loss decreases to a point and begins increasing again. The train loss and validation loss is perfectly mapping because the shape of validation loss id same as train loss but there is a slight difference between them that why we can say it represent overfitting.

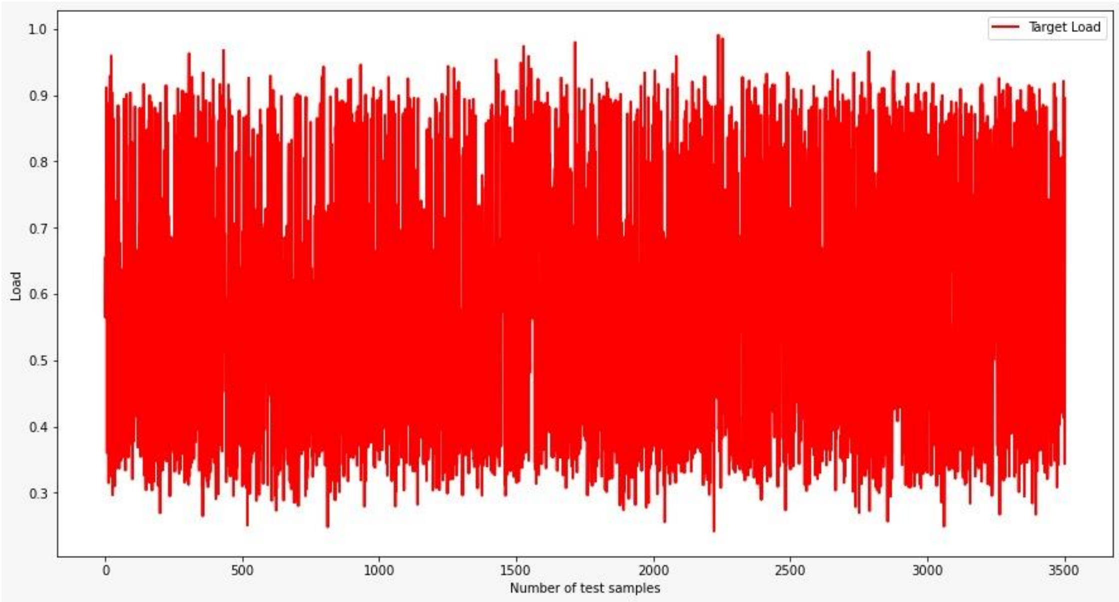

Figure 14: Graphical representation of Target Load

This graph shows the relation between Load (Target Load) and Number of samples.

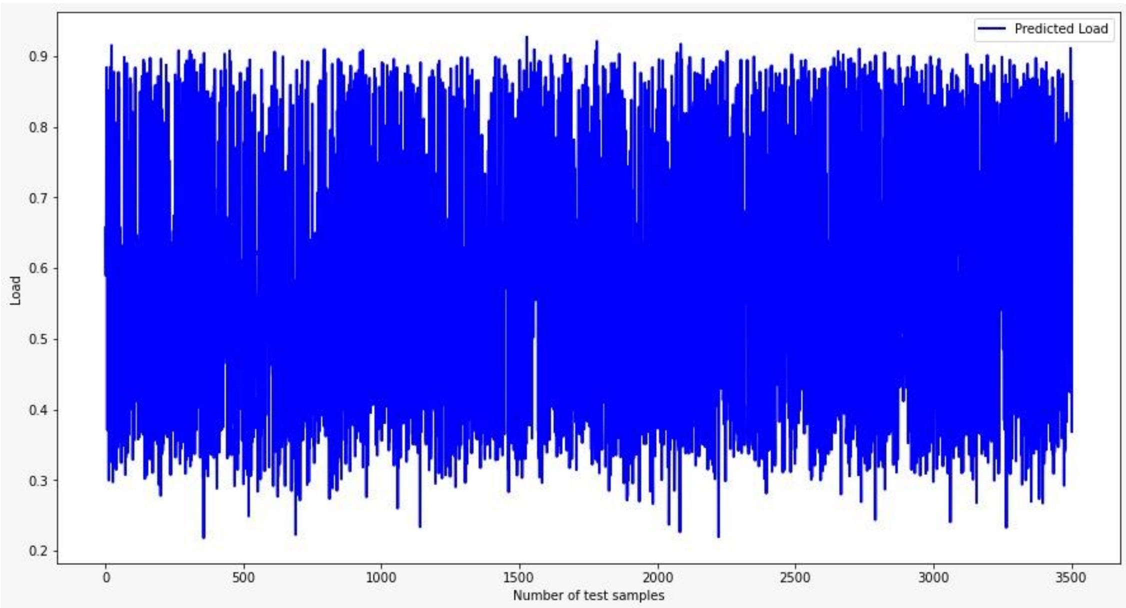

Figure 15: Graphical Representation of Predicted Load

This graph shows the relation between Load (Predicted Load) and Number of samples.

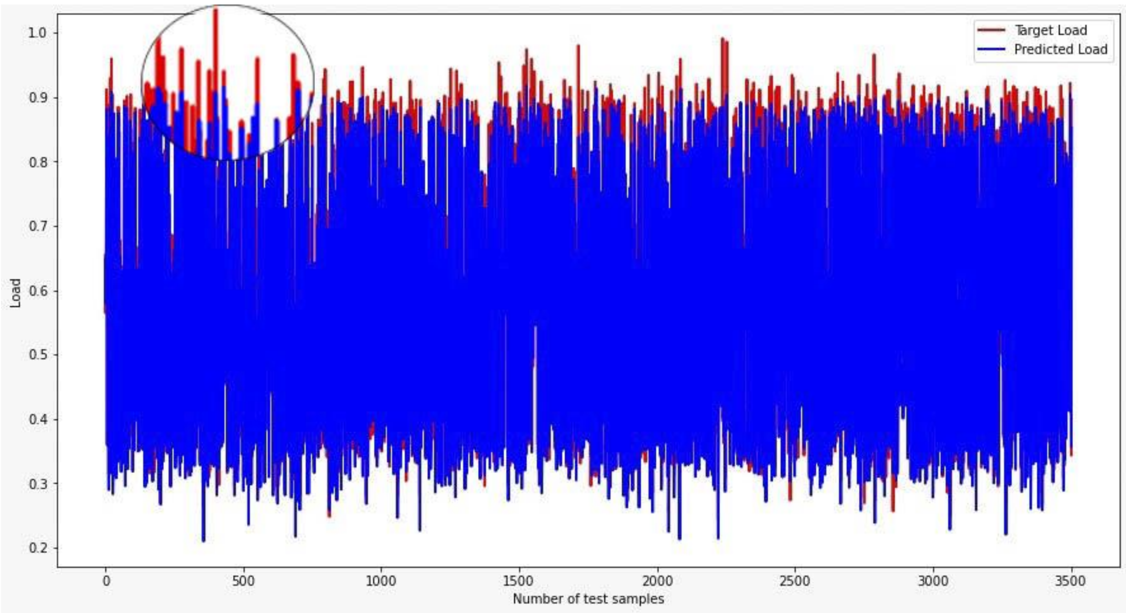

Figure 16: Graphical Mapping between Target Load and Predicted Load

As blue area shows the predicted load while red showing the target load. By observing the predicted load over targeted load we can see our results predicted very accurately except on edges as some of these edges not fully covered by predicted load which means our function needs further improvement. The proposed ANN model is assessed on RMSE, MAE, MAPE and MAE metrics where the mathematical equations are shown above. Basically, these metrics calculate the variance between predicted and actual values.

Chapter 5

5.1 Conclusion

In conclusion we can say that the proposed model of short-term load forecasting is commendable and cuts down various risks associated with the forecasting process such as extra time consumption. By utilizing images generated out of the sequential parameters of the multiple regression, the proposed short-term load forecasting combination model could implicitly and automatically evaluate and remove important elements without the requirement for human input and specialist experience, and all on its own. It was demonstrated how using the proposed approach is simpler than certain standard STLF models by implementing this technique. This may then be considered one of the best great disparities between the proposed approach and other significant STLF methodologies. Moreover, through utilizing fuzzy reasoning, the regulation of over fitting was greatly contributed by representing an element of a periodicity through a fuzzy area, a continuum, and a shadow, rather than by including an exact amount. The reliability of the suggested approach is supported by many studies on test data sets. Moreover, after performing certain calculations and demonstrating the analysis by using graphs has demonstrated the effectiveness of the proposed STLF model. However, future research and further implementation of neural network approaches need to be done in order to deal certain limitations of the study.

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