SHORT-TERM LOAD DEMAND FORECASTING FOR TRANSNET PORT TERMINAL (TPT) IN EAST LONDON USING ARTIFICIAL NEURAL NETWORK

By

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Declaration

I, Mncedisi S Figlan (ID. No. _______ Student Number ______, hereby state that this study thesis submitted for the Master of Engineering to the Central University of Technology, Free State is my own creative project. It conforms with the Academic Integrity Code as well as with other related rules, practices, guidelines, and provisions of the Central University of Technology, Free State.

Signature of Student

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Acknowledgements

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ABSTRACT

The daily and weekly energy consumption patterns at the Transnet Port Terminal (TPT) in East London varies stochastically. This is as a result of the transient weather patterns that exist at the harbor. It has therefore become imperative to wisely manage this load in order to save electricity costs and for future infrastructure development. Hence the ongoing supply of electricity to port consumers requires an accurate and adequate short-term load forecast (STLF) for quality, quantity, and efficient management.

Many researchers have recently proposed Artificial Neural Networks for short-term load prediction. However, most of the studies have not considered the quickly changing weather patterns that exist at the port. Therefore, the objective of this study is to establish a supervised short-term load prediction using ANN models, and to verify the effectiveness of such predictions by using the real load data from the TPT. The suggested system architecture uses open- loop training with real load and weather information, and then a closed-loop network is used to produce a prediction with the predicted load as its feedback data.

Data collection points were set up in the ring network of the port by installing new power measuring meters, and weather data obtained from local meteorology offices in order to build a suitable alternative of localised data management (data base) for saving all data gathered. Hence, profiling of the load in the TPT was done and load forecasting was carried out, leading to improved load management strategies for the

harbor terminal. ANN short-term load prediction (STLP) models were developed utilising its own performance to improve precision by essentially implementing a load feedback loop that is less reliant on external data. To ensure that the timeseries data recorded at the port were well modeled, the Nonlinear autoregressive exogenous model (NARX) for load prediction were developed using mean squared error (MSE) as a performance metric.

Furthermore, to show the efficacy of the proposed model for STLP, the adaptive neuro-fuzzy inference system (ANFIS) was used with the same data for short-term predictions. The minimum mean squared errors obtained for both NARX and ANFIS models were 0.0010939 and 0.0032 respectively, indicating that the NARX model is more accurate during the forecast of departmental loads. The results of the predictions using the hourly timeseries indicated a close match between the forecasted and actual load demand at the port terminal. The effects of the load forecast could be used as a guide for implementing management plans for internal load, such as the generation of urgent electricity and the programme of implementation for demand-side management policies.

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Nomenclature

$\hat{L}$	total estimated load
B	backshift operator
L	Actual load value
Ln	normal part of the load
Lw	weather sensitive part of the load
L_S	special event component of the load
Lr	random term, the noise
Fw	current weather
F_S	special events
Fr	random fluctuation
t	standard load at time
a_i	varying coefficients
x_i	weather effect
ε	error term
N	number of observations
β_i	regression parameters

$S(t)$	seasonal term
$R(t)$	irregular component
$\in$	equivalent Euclidean norm
L_t	hourly load
L_t^P	hourly load on historical days
ΔL_t	load deviation
x_t	current load value
x_{t-1}	previous load values
σ_1	a tan sigmoid transfer function in the hidden layer
σ_2	a pure linear transfer function in the output layer
Φ	activation function for the output
Ψ	activation function for the hidden neurons
z_i	the weighted sums of the i^{th} hidden layer neuron
$\emptyset_1$	parameter for forecast
γ_{ij}	weights of the input layer

Abbreviations

ABCD	Audience, Behaviour, Conditions, and Degree
ANFIS	Adaptive Network-based Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Auto Regression Integrated Moving Average
ARMA	Auto Regression Moving Average
BCMM	Buffalo City Metro Municipality
CDD	Cooling degree of the day
DDR3	Double Data Rate 3
DSM	Demand Side Management
ES	Expert Systems
FCM	Fuzzy Cognitive Map
FFFB –MCANN	Feed Forward and Feedback Multi-Context Artificial Neural Network
FIS	Fuzzy Inference System
FNN	Feedforward Neural Network
GA	Genetic Algorithm
HD	High Definition
HDD	Heating Degree of the Day

IBM	International Business Machine
JDBC	Java Database Connectivity
LM	Levenberg-Marquardt
MAE	Mean Absolute Error
MAPE	Moving Average Percentage Error
MATLAB	Maths Laboratory
MDT	Maximum Demand Threshold
MLE	Maximum Likelihood Estimation
MLP	Multilayer Perceptron
MSE	Mean Squared Error
NG	Natural Gas
MW	Mega Watts
NARX	Nonlinear Autoregressive Exogenous Inputs
NMD	Notified Maximum Demand
ODBC	Open Database Connectivity
OLS	Ordinary Least Squares
PC	Personal Computer

RCGA	Real Coded Genetic Algorithm
SARIMAX	Seasonal Autoregressive Integrated Moving Average Model with Exogenous Inputs
SOGA	Structure Optimization Genetic Algorithm
SQL	Structured Query Language
STLF	Short-Term Load Forecast
STLP	Short-Term Load Prediction
TPT	Transnet Port Terminal
USB	Universal Serial Bus
W/S	Workshop

CHAPTER 1

INTRODUCTION

1.1 Background

As electrical system networks grow steadily and their complexity increases, many elements have played a vital role in the generation, demand, and administration of electrical energy [1]. Load prediction is one of the critical factors for economic operation of electrical systems.

Hence, for network planning and infrastructural development, the future prediction of loads is critical. However, the forecasts of power loads are two-dimensional: customer and utility forecasting. Thus, the importance of each prediction may be treated in a disjointed manner. Consumer-based predictions are used to provide inputs on improving network scheduling and expenditure, improved risk management and lower cost of operation.

For simple power plant operations, forecasting is aimed to assist planners make informed decisions on unit involvement, hydrothermal coordination, interchange reviews and safety assessments, etc.

Nevertheless, load forecasts for electrical systems can be classified as short-term, medium-term and long-term forecasts in three categories. In a variety of literary documents, the periods for these categories are also not clearly specified. Different studies therefore use different timelines to describe these categories. Short-term load forecasts mostly cover weekly predictions to every hour. Often these predictions are important for daily power plant economic activities.

Forecast for medium-term loads runs from weeks to a year. In such predictions the preparation and maintenance of plants and networks are also covered.

On the other hand, a long-term forecast deals with predictions for more than one year. It is intended primarily for the advancement of capacity planning, equity and corporate budgeting. Such predictions are intricate in nature because of potential uncertainties such as policy trends, conditions of the economy, growth of capital, etc. New planning and extensions for both utilities and customers to existing power system networks include forecasts in the long-term.

The precision of predictions is a key function in the forecasting of electrical system load. A bad load prediction deludes planners and typically leads to incorrect and costly construction plans. Accurate forecasting of loads is critical for investments in the distribution system, for the management of electric load. This is also one of the topics for load rationing, such as load shedding, DSM (demand side management) strategies, etc. The short-term load forecasts are an important function in everyday operations, especially for utility sectors, without replicating them. An error that is negative in the forecast could seriously influence the production levels of consumers, particularly for larger power users. For power system protection and their overall reliability, therefore, accurate forecasts are required.

One compelling way to predict loads on a short-term basis which vary constantly is to restrict to several minutes or hours load sampling point. This method is regarded in this work as a short-term load prediction.

There is no question that it is difficult for both utilities and customers to correctly predict their own loads. For decades this was a challenge, so different methods of load prediction strategies have been created and illustrated in a range of studies from classical to intelligent systems. The final difference between these methods can be drawn from the prediction accuracy.

A significant number of forecast models are using statistical methods or artificial intelligence algorithms, such as expert system, Fuzzy Logic, neural networks, and regression [2-5].

In generalisation and mastery of non-linear relationships between variables, ANNs (Artificial Neural Network) have proven to be successful, and therefore ANN-based strategies are frequently preferred for Short-terminal Load Forecast (STLF) problems [6].

The other significant characteristic of ANNs is their potential to adjust synoptic weights between layers iteratively. Traditional methods require, on the other side, static, complex mathematical equations and still do not work well as intelligent methods.

Another leading method of forecasting the load is Fuzzy Logic. Its load forecast application is formed on periodic correlation of electricity demand where the input variables, the output variables and the rules of governing are the main elements. The focus of this research incorporates these modern technologies and will be discussed in the following chapters.

1.2 Problem statement

The load demand patterns for the Transnet Port Terminal (TPT) power system network are very cumbersome and stochastic in nature. This may be attributed to the lack of available data due to some areas in the ring network not having properly functioning meters, weather variations caused by changing temperatures, humidity, high windy conditions around the harbour and finally, varying human behaviour towards electrical load utilisation. This daily affects short-term planning and provisioning of electricity at the port.

1.3 Objective of the study

The purpose of the research is to design ANN-based STLP models for end users at the TPT in order to improve monitoring of their load to enhance or strengthen the power generation efforts at the harbor.

The aim is to design ANN models for short-term load prediction (STLP) that is supervised to assess the results of these models by using the real load data from the Transnet Port Terminal to predict the load up to one week ahead.

The following goals were set in order to achieve this objective:

- The load forecasting method requires a time series of historical data; thus, historical load data needed to be collected on the Transnet Port Terminal reticulation network.
- Climatic conditions, particularly in areas around the port, can greatly affect the load. This work thus, considers the weather effects on the load. To implement this function, it is necessary to collect and monitor climate data such as humidity, low and high temperatures, wind speed, which must be provided as inputs to the network.
- A convenient local database system for the storage of all collected data is to be developed and set up.
- To design various Artificial Neural Networks models that are using short-term prediction approaches, and to test them using the mean squared error (MSE) as a performance metric.
- To evaluate some other strategies of prediction by descriptive mechanisms.
- Training of advanced models in the MATLAB software and forecasting of total loads for Transnet Port Terminal and loads of selected departments within the short term.

1.4 Research methodology

The following methodology will apply to this research:

- **Literature analysis:** Currently several load forecasting methods have been proposed. Therefore, the evaluation of various documented predictive approaches and associated disadvantages will require a detailed literature review. There are several literature reports that intelligent model systems, and particularly ANN-based models, are more advanced and attractive than traditional approaches to dynamic systems. In addition, the proposed prediction techniques will be thoroughly analysed.

- **Data collection:** The process of collecting the data is an exercise that is convoluted, whilst identifying a combination of research methodologies. In this research project, a quantitative method of research is used to collect the necessary data. Among other research methods, some data are obtained through questionnaires, personal interviews and numerical data measurement equipment (power meters).

  Modelling – The input data used for selection were interpreted carefully and standardised to prevent overfitting and input duplication before being displayed as model inputs.

- **Data preprocessing:** Historic load data of the port terminal have been acquired by measurements (i.e. using Landis+gyr E 650 meters). Weather data from a local weather office have been collected. For the model, weather-related data are relevant. The collected data were then, interpreted, analyzed, standardised, and in a simpler way, applied to the model. Other variables have also been considered such as seasonal change.

- **Forecasting of load:** Data were collected over a period of two years (both historical and current). 70% of data were used for training the network, 30% for testing and validation.

1.5 Hypothesis

Short-term load forecasting at the port terminal is made possible by developing prediction methods with multi-variable exogenous input and a local data management system in order to curb the stochastic and cumbersome nature of patterns in load demand. A custom-designed ANN technique based on the regular algorithm of error back propagation using a suitable learning approach will further better the average forecast error.

1.6 Limitation of the study

The work is focused solely on the ANN and Fuzzy Logic techniques and the results of performance comparisons are only carried out using ANN and models based on ANFIS. Nonetheless, some traditional common methods of load prediction are discussed and analysed with descriptive methods. The measure of performance for these methods are restricted to the real/actual load data of Transnet Port Terminal East London, but the same models with minor adjustments can be universalised to be used by utility companies. This research work only models and analyses short-term load forecasts. While the differences in seasonal loads (winter and summer) are taken into consideration, the models do not easily detect significant sudden load changes. Prediction of load for special days or holidays is not part of this project. The training data used for the work have been limited to nine months a year for historical load formats. In this study, both medium- and long-term load forecasts are not included.

1.7 Scope of the thesis

This thesis focuses on a particular area of short-term load forecasting. The predictions are accomplished by using Artificial Neural Network (ANN) and Fuzzy Logic-based models, i.e. NARX and ANFIS developed in MATLAB and Simulink environments. The models are then used to predict what is also known as "consumer own forecasting," using real load data from the Transnet Port Terminal in East London. The models will only be used as a case study for validating the method of application to actual data. Figure 1.1 below attempts to clarify the focus of this research.

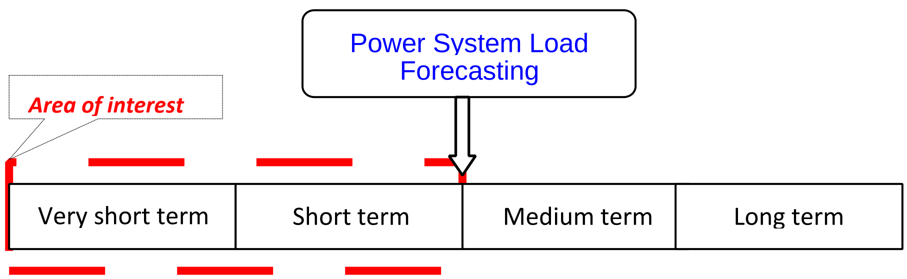

Figure 1.1: Types of load forecasting and focus of the research

1.8 Research outputs

The following outputs emanated from this research:

1. Figlan, Mncedisi, and Markus, Elisha. "Short-term Load Demand Forecasting for Transnet Port Terminal (TPT) in East London Using Artificial Neural Network." 2020. *International Journal of Simulation Systems Science & Technology* doi:10.5013/ijssst.a.21.02.26.
2. Figlan, Mncedisi, and Markus, Elisha "An overview of load classification and prediction methods: Case study of South Africa" Accepted at *5th International Conference on ICT for Intelligent Systems (ICTIS – 2021)* to be held at Ahmedabad, India, April 23-24 2021.

1.9 Dissertation outline

Chapter 1 discusses the background; intention of the work and context of the work breakdown.

Chapter 2 presents the literature review of the study. This includes an overview of the techniques that are used for predicting the load, comparisons of different articles, results and comments. In this chapter, deficiencies of various prediction methods are also highlighted. The use of genetic algorithms to STLF are also addressed exclusively in this chapter.

Chapter 3 covers data definition, methods of data gathering and pre-processing. This section also explains how the chosen data were compiled into the database system and then into the workspace of MATLAB. The definition of the data collected is also clearly explained in this chapter.

Chapter 4 discusses the results of the simulations performed in the study. Some detailed discussions on various STLP models are also addressed. Thus, this part of the document includes actual project implementation, i.e. transfer of dual models of short-term load prediction using the real load data of the East London Transnet Port Terminal as a study case.

Chapter 5 The final thesis chapter summarizes the end of the project and future perspectives.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

For decades, the topic of load prediction existed, and various approaches were created. Such techniques are based on a traditional or contemporary method. In order to determine the statistical relevance of the proposed research project, this section of the research is important for purposes of defining the general research question, to analyse current methods and to assess fields of potential advancements. Included also in this chapter is the review of different current load prediction methods, and a relative examination of the updated articles, results and observations.

2.2 Background knowledge of load prediction

Load predictions have been one of the most critical aspects of electricity planning. Enhanced load forecasting methods have had an economic effect and contributed to the development of alternative and more reliable electricity analysis algorithms [7]. Many researchers have therefore drawn alarming attention to the relevance of the topic in power systems, and so far several approaches for load prediction have been developed. Moghaddam et al. [8] applied pre-processing to improve noisy and missing data, then considered the time of day, the day of the week, the heating degree of the day (HDD) and cooling degree of the day (CDD) as ANFIS inputs, whereas historical electricity load was the target, and output was the forecasted load to predict STLF. Boudjema et al. [9] forecasted STL using half-hour weekly load data rearranged in multi-input single output by ANFIS. Their ANFIS input and output structures are shown in Figure 2.1 below:

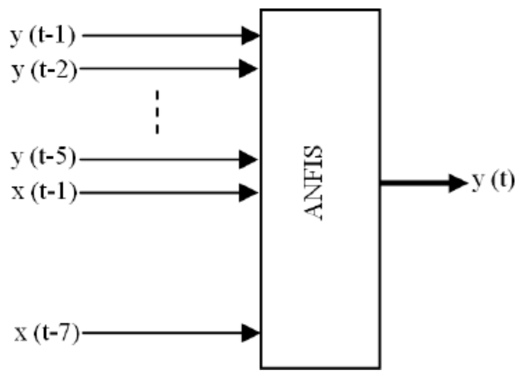

Figure 2.1: Input and output vectors to ANFIS [10]

However, it is not clearly indicated what their variable $x(t)$ is. Li et al. [11] forecasted electric load and price using input variables such as date, time, humidity and previous data sets taken from the various power corporations and obtained an overall accuracy of 76.8%. Ebteha et al. [12] employed population, GDP, export and import data to predict the annual energy consumption in Iran using three patterns of a hybrid ARIMA–ANFIS model. Tan et al. [13] suggested a different form of FNN (Feedforward Neural Network), taking as inputs to the neural network the fuzzy membership values of the load and other weather variables, and the membership values of the forecasted load as outputs.

Multi-layer perceptron ANN (ANN-MLP), ANN with radial base functions (ANN-RBF) and multivariate ordinary least squares (OLS), seasonal autoregressive integrated moving average model with exogenous inputs (SARIMAX) were analysed through various methods to forecast regular gas consumption [14]. A preliminary research project on the implementation of Fuzzy Cognitive Maps (FCMs) with ANNs for Natural Gas (NG) forecasting was conducted by [15], demonstrating the skills of evolving FCMs in this field for the first time. Poczeta and Papageorgiou [16] recently conducted a time series analysis study dedicated to the prediction of NG demand in three cities of Greek, applying an ancient entity prediction method by integrating ANN, real coded genetic algorithm (RCGA)-FCM, SOGA-FCM, and hybrid FCM-ANN.

This chapter addresses some of the more common techniques. Typical models of load prediction can be divided into two main groups: dynamic and time-of-day models. A non-dynamic approach is the time-of-day model, expressing the load as a specific time series which consists of the predicted value for each hour of the forecast period. The second category is the dynamic model that acknowledges that the load does not only depend on the time of day, but also on the load's recent actions.

The load forecast by the conceptual approach includes weighted inputs that are transmitted by nonlinear transfers. Thus, a combination of additive and multiplicative methodologies is somehow used by the proposed method to forecast the needed load values.

2.3 Classification of prediction methods

The approaches used for load prediction are the same day approach, models of regression, time series, neural networks, expert systems, Fuzzy Logic, and statistical learning algorithms [17]. Such approaches can be categorised according to their statistical analytical levels in the forecast models.

While historical data is in most cases inadequate or not at all usable, planners are still required to accurately predict and thus typically use qualitative forecasting methods. Such methods include, among other things:- Delphi method [18], curve fitting and technological comparisons [19]. Other forecasting techniques such as decomposition methods [20], regression analysis [21], exponential smoothing [22], and the Box Jenkins approach [23] are quantitative methods. These techniques are considered in the dissertation.

The next load prediction approaches are analysed and are compared in the document:

- Regression methods
- Series of time
- Day time techniques
- Similar day method
- Stochastic time series structures
- Intelligent network-based systems (using GA and ANN)

2.3.1 Regression methods

This is one of the mostly used techniques for electrical load forecasting. By defining a mathematical equation, regression methods attempt to model the connection between the influencing factors such as changes in climate, day form, etc. and electricity load frequency. Regression is one of the most popular statistical methods and is generally easy to implement. Regression is usually used to model the connection between electricity usage and other influences, such as climatic conditions, day types and customer categories. This approach assumes that a standard pattern based on loads and a design can be divided linearly depending on such load-influencing factors [24]. The regression-based algorithms, with a high computational load and lengthy computational time, are of high complexity [25]. A regression analysis is used by [26] to forecast a day ahead hourly electricity loads using real building and Campus data obtained from the Kensington Campus and Tyree Energy Technologies Building (TETB) at the University of New South Wales (UNSW).

2.3.1.1 Regression based on linearity

The most popular technique is linear regression, mostly used in the prediction of load affected by a number of factors such as weather, per capital growth, energy prices, economic growth and so on. Recognisable strategies like linear regression and ordinary least square regression are parametric in that the function of regression is described as a finite number of unknown data-estimated parameters [27]. Manca et al. [28] used a linear regression design to investigate the electrical consumption behaviour of a supermarket situated 100 miles north-northwest of Houston, Texas, on hourly and daily basis. Claridge et al. [29] compared Gaussian Processes' multiple linear regression on energy usage of data from 2008 to 2010 to forecast values in Norway over the next 24 hours.

Al-Hawani et al. [30] proposed a high-precision approach that involved multiple linear regression and simple regression models, along with other strategies, to forecast India's total energy consumption.

2.3.2 Series of time

Electric load forecasting has in recent times received great and increasing attention, as it is seen as a vital component of power generation and management systems, in cities and countries with a fast growing rate of infrastructural development [31].

Accurate load forecasting will aid both the electricity generation companies and the distribution companies to make unit commitment decisions with regards to energy, load switching, voltage control, network reconfiguration, and infrastructure development [32]. The time series strategy can be described as a successive collection of data, such as hourly, or weekly loads, calculated over time. The fundamental principle of forecasting is to first establish as accurately as possible a format recognition of available data, and to then obtain the forecast value using the approved model [33] with respect to time. Box et al. [34] provides a pragmatic approach which can be used to build models for electric power load forecasting as a reference. This approach is primarily focused on the time series of load decomposition and segmentation.

A consolidated fuzzy structure, data extraction and the framework of time series were proposed in the work of [35] to evaluate and forecast electricity demand for seasonal and monthly changes in electricity use, especially in developing countries such as China and Iran, using non-stationary data. In [36], the Auto Regressive Integrated Moving Average (ARIMA) approach was used to predict greenhouse gas emissions and energy consumption in a pig iron manufacturing organisation in India.

In the case of [37], who studied household electrical consumption, the Autoregressive Moving Average (ARMA) and ARIMA models were used. Methods of time series assume that the data have an internal structure like autocorrelation, pattern or seasonal change [38].

2.3.3 Day time techniques

The simplest type of load prediction is this method. The model uses the real load pattern of the previous week to forecast the load of the current week. Additionally, a sequence of load patterns with various weather conditions is stored for typical weeks. To establish the prediction, they are then integrated computationally [39,40]. The duration of daylight as a variable is also presented in [41,42] as part of a thorough analysis of the modeling of France and Germany's load. The French research dismisses the use of daylight variables due to its high correlation with temperature. Nevertheless, the German study does find the variable significant. However, as both of them use duration of daylight as variables.

2.3.4 Similar days method

Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA) [43], Autoregressive Moving Average Model with Exogenous Inputs [44], Time Series Analysis, Exponential Smoothing, Adaptive Filtering, Similar Day Lookup Approach, Regression Method and Probabilistic Approaches, as illustrated in [45], can be used to achieve statistical-based LF. The evaluation defined by the Euclidean norm is useful to utilise. It allows us to comprehend the similarities by using a norm-based expression definition. The reduced Euclidean norm leads to an effective assessment of similar days [46]. Rae-Jun et al. [47] used similar days approach to forecast historical total load of Korean power systems and the weather information for the Korean peninsula. The historical total load was provided by the Korea Power Exchange, which is the national service of the Republic of Korea. It controls the operation of Korea's electricity market and power systems, the execution of real-time dispatch, and the establishment of the basic plan for supply and demand.

The "similar day" method takes into account a "similar" day in the historical data to the one predicted. It is routinely implemented in industrial applications due to its simplicity. The similarities are typically based on the patterns of calendars and weather. A linear combination or regression method that involves many similar days can be the forecast. The creation of this concept was implemented in [48] in a climatic-based prediction approach defined by [49] .

2.3.5 Stochastic time series structures

The methods of stochastic time series assume that data have an internal structure such as trends or autocorrelation [50-51]. The methodology for time series techniques is created on the basis of the past load data. The future load is then forecast based on the developed model [51]. Tao et al. [52] stated that one of the very popular LF models is the stochastic time series method. Page et al. [53] assessed the weaknesses of stochastic integer multi-stage programming and suggested an improved method based on stochastic dual dynamic integer programming. The writers modified the problem and combined Lagrangian cuts with decomposition algorithms. Narayan et al. [54] suggested a small successive stochastic convex approximation technique for solving non-convex problems. Nijhuis et al. [55] developed a method to face problems with stochastic composition optimisation with two expected value functions. An inner goal function was incorporated into an outer one by the approach [56]. Ayob and Amat [57] used Stochastic Forecasting Discharge Level Time Series Data to analyse the Water Use Trend at Universiti Tekologi Malaysia.

In relation to its previous value, the method of the stochastic time series presents the existing load linearly, and the zero mean and variance white noise sequence, contrasting with the classic forecasting techniques.

The backshift operator is introduced by this representation and enables the technique to partially control the difficulty of complex load prediction.

2.3.6 Intelligent network- based systems

"The thread that unifies so many different concepts are woven from the interpretation of the intelligent system. Practically speaking, an intelligent system is one which employs Artificial Intelligence (AI) to fulfil some or all of its computation requirements" [58] . Many studies have shown that intelligent system methods are superior to load forecast models. Some of the widely used artificial intelligence strategies are now discussed briefly in the following section.

2.3.6.1 Artificial Neural Networks

A computer model inspired by the biological nervous system is an artificial neural network (ANN). The network comprises interconnected memories and arranges data using a generative computing technique. Neuron-distributed simulation results in intelligent outcomes. The ANN structure learns to complete the required function using specialised training principles directly from examples. Figure 2.2 illustrates the basic structure of an ANN process. This technique is mostly seen as an integrated approach that adjusts its design on the basis of external or internal network data during training.

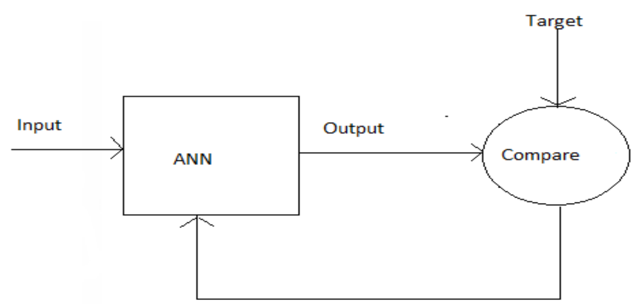

Figure 2.2: A simple structure of ANN

2.3.6.1.1 Approximation tool for neural network modelling

Neuronic networks are basically non-linear circuits that have shown ability to match non-linear curve. The method is also reliable to analyse complex structures. Any numerical mechanism that are linear or non-linear with their inputs are the outputs of an artificial neural network.

Inputs may be the output of other elements of the network and the real inputs of the network. In reality, parts of the network are grouped between network inputs and outputs into a relatively small number of connected element layers. By adjusting the weights of neurons in a perceptron multilayer, the target output is achieved.

2.3.6.1.2 Proposed ANN-based models

There have been many ANN-based architectures developed [59,60,61]. Radial based, recurrent and feed-forward forms of ANN are the three main ANN family models. The proposed research project analyses efficiency and precision directly of a recurrent and a feed-forward model using ANN [62].

2.3.6.1.3 A Multilayer perceptron

A network set up of a three-layered feed-forward network is shown in Figure 2.3. The inputs are fed and multiplied by interconnection weights into the input layer, before moving to the next layer, and then passed through an activation function.

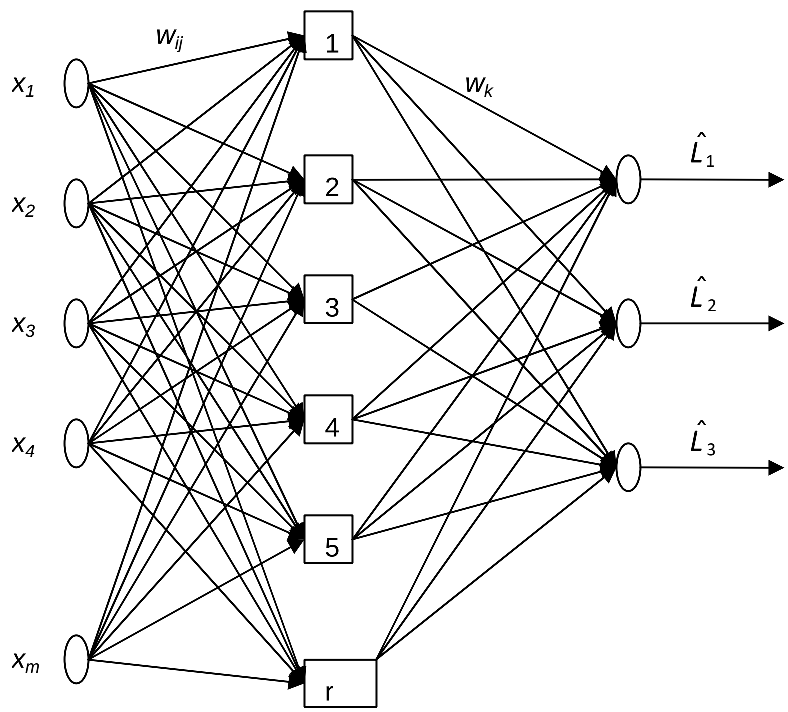

Figure 2.3: A single hidden layer and multi-output Feedforward neural network [63]

2.3.6.2 Expert (Methods) Systems

This approach is using high-level machine learning. It is built by computer programmers and specialists by means of close interactions and experience [64]. The scientific objective of AI is to grasp intelligence by designing software applications that show inventive behaviour. The ideas and techniques for computer reasoning or symbolic inference are addressed and how the information used to generate these results is depicted inside the machine.

The basic principle here is the manipulation and encapsulation of high-level information to emulate an expert's behaviour [65].

Expert Systems or Knowledge-Based Expert Systems (KBES) as pointed out by [66] are recent heuristic techniques resulting from progress in the artificial intelligence (AI) field. No specific technique structure or historic pattern is needed for the expert system.

The prediction operation is more or less embedded in rules from professional interviews. When these regulations are explicitly and accurately established, the inconsistencies that could have an impact on the load will hopefully be resolved, so that this technique could be effective. Christodoulou et al. [67] used as a knowledge-based load-forecasting approach that combines existing system knowledge, load growth patterns, and horizon year data to develop multiple load growth scenarios. Weron et al. [68] led to the establishment of expert systems on the basis that once the load and the factors influencing it are identified and extracted, a parameter-based rule can be applied. This rule is of the form "if-then", plus some mathematical expressions. This rule can be used on a daily basis to generate the forecasts.

2.3.6.3 Fuzzy approach

In the growth of the fuzzy set theory that Dr. L.A. Zadeh championed in the mid-1960s, the word "Fuzzy Logic" emerged. A Fuzzy Logic model is a logical-mathematical mechanism that imitates the human viewpoint in the simple machine form based on an "if-then" rule structure. There are typically four modules in a fuzzy rule structure [69]:

a. Input fuzzification – which converts the "crisp" into a fuzzy input method.

b. Fuzzy rules – logic if-then statement that links the input to the output variables.

c. Fuzzy inference – a system that illustrates and incorporates the effects of rules.

d. Output defuzzification – the tool that converts the fuzzification into a fuzzy output number.

Since its introduction, such approach has received broad acceptance, and a number of articles have been produced in this regard, though there was an initial perception of pessimism in the Western World. The goods range from air conditioners, washing machines, medical instrumentation, cameras to industrial process control, signal processing and speech recognition.

Particularly, fuzzy rules based on demand forecasts need to be formed in load prediction to supply domain-specific data to improve non-linear models. Using linguistic descriptions, the technical expertise created in the model can easily be integrated into high-quality data for load forecasting [70].

2.3.6.4 Developmental computing

Recent STLF literature indicates that one of the appropriate methods is the Genetic Algorithm (GA), particularly for optimising the network model of load prediction [71]. The dependency on earliest conditions, lengthy preparation, routing protocol configuration, etc. are most of the disadvantages associated with conventional experts computing and can be easily solved using this method [72].

It was deemed appropriate to provide a brief introduction to the theory behind the method due to the expected dominance of GAs in STLF.

2.3.6.5 Optimization based on genetics

A number of straightforward optimisation problems can be solved using the basic regulations based on back propagation rules. Nonetheless, their efficiency falls quickly as problem complexity increases. Other disadvantages include problems such as lengthy instruction time, one-point quest, weighing, reliance on earliest conditions, etc. The genetic algorithm (GA) is, however, seen as a back-up solution.

The first discovery of this method was by John Holland at Michigan University in the mid-1970s. The key concept was to develop artificial systems that maintain natural systems' robustness and adoption properties. Since the beginning, other researchers have enhanced these methodologies, and in various fields (business, research, engineering, etc.) they are now commonly used to resolve a spectrum of problem maximisation outside the reach of conventional Toolbox multiplication.

In a given N-dimensional potential number of solutions, GA emulates physiological mechanisms to run a selection of mechanisms. Through a given search space for an optimisation problem, one must try to determine the right answer. Darwin's evolutionary theory (survival of the fittest) inspires the idea behind the GA concept.

2.3.6.5.1 How does a GA operate?

The quest for space that contains a number of solutions (or chromosomes) called populace is started with the algorithm. Chromatids from one group are selected based on strength and then merged to create a new grouping, like their counterpart in nature. In the next generation, it is more likely that the best fit people will be found and ultimately be reproduced. This strategy is supported by the wish that the young populace would be stronger compared to the old population. These processes are repeated until certain pre-defined conditions to stop (e.g. time limits, generation) are fulfilled. This method, similar to its biological co-partner, requires certain genetic operators such as recombination, crossover, and mutation [73].

The objective function to be optimised must be specified in order to implement a genetic-based search. The objective function, strictly speaking, can be interpreted as the input to the equation. This role's intention is to supply an estimate on how people do in the trouble spot. Most fit elements will preferably have the highest integer data in the event of optimisation problems, depending on the maximisation target.

2.3.6.5.2 Standard simulation versus GA

GA varies greatly from regular methods of simulation exploring. The four key differences discussed previously and established in the work of [74] are:

1. GA does not need derivative data or other supporting information but uses an analytical function.
2. In a population, GAs perform a search that is parallel, not a singular point.
3. Probable transitional rules are used by GA, not deterministic ones.
4. GAs work on encoding the parameter set instead of the parameters themselves, except in real-value representations.

Even though GA-based rules would not be used to train the proposed models, this brief background to GA may be useful for general knowledge. Therefore, the next part provides a performance comparison of several prediction models using ANN.

2.3.6.6 Relative review of current existing prediction models using ANN

Different papers had to be compared in order to ascertain the shortcomings and to assess the efficiency of current approaches.

The comparisons were made on the basis of the following:

- Problem statement
- Objective of the project
- Proposed or used method
- Results or findings
- Drawbacks and possibilities for improvement

2.3.6.6.1 Comparison of literature

The papers that are viewed show a number of solutions that are based on load prediction problems related to different approaches, specifically for short-term load predictions. Therefore, a global boundary has been made between the limitations of different techniques, and the approach proposed may be an ideal attempt.

TABLE 2.1 RELATIVE REVIEW OF SOME CURRENT PREDICTION MODELS USING ANN

PAPER	PROBLEM STATEMENT	OBJECTIVE	MODEL	CONSTRAINTS
Sharif and Taylor, 2005 *"Short-term load forecasting by Feed forward neural networks"* [75]	Having the Average Feed-forward neural network -based error prediction and a typical time series kit.	Using both methods to forecast a one-day hourly load ahead and measure the resulting performance index and error of forecast.	For STLP purposes, a built neural network of multi-layer feed-forward was used.	The accuracy of load forecasting depends primarily on the training and the selected forecast time period.
Feifei, et al. 2019 "A Hybrid Short-Term Load Forecasting Model Based on Variational Mode Decomposition and Long Short-Term Memory Networks Considering Relevant Factors with Bayesian Optimization Algorithm." [76]	The effect of electricity pricing in a short-term load prediction model.	To incorporate the pricing of electricity into the model and create influences.	The popular ANN-based multi-layer feed forward model was recognised.	The relation between load and price is highly nonlinear and difficult to model.
Adepoju, Ogunjuyigbe, and Alowode, 2007 *"Application of Neural Network to load forecasting in Nigerian Power System"* [77]	A power utility company's operation and planning require a precise model for electric power load forecasting.	Incorporate and submit to the Nigerian electric energy grid a forecast for short-term load using neural networks that are artificial.	To obtain the forecasts, a supervised artificial neural network model was used.	It is important to carefully select the number of neurons in the hidden layer, as too many neurons can lead to overspecialisation and eventual loss of generalising capability.

Lauret,Fock,Randrianarivony,Manicom-Ramsamy,2007 *"Bayesian neural network approach to short-term load forecasting"* [78]	Optimal structure of the Neural Network for load prediction.	Usage of the ANN-based model to optimise the accuracy of Bayesian methodology.	A probabilistic model was presented using the Bayesian Neural Network technique.	It is important to establish uncertainty in model inputs.
Rashid and Kechadi, 2005 *"A practical approach for electricity load forecasting"* [79]	The impact on prediction accuracy of the values of absolute and changes in climate components and past load.	Instead of absolute values, using the change in meteorological elements and/or previous load data.	The paper presented a model using exogenous and endogenous variables called feed forward and feedback multi-context artificial neural network (FFFB-MCANN).	Recurrent ANN models are difficult and often need excellent training.
Al-Saba, and El- Amin, 1999 *"Artificial neural networks as applied to long-term forecasting"* [80]	Forecasting of the yearly peak demand for the Middle East utility.	To search different prediction methods and match the predictions with the method suggested.	The paper presented various models of time-series load forecasting and the approach focused on ANN.	The uncertainty of the future allows long-term load forecasting and forecasting exceptionally complex computational problems.
Sun, Chao, et al. 2016 "Nonlinear Predictive Energy Management of Residential Buildings with Photovoltaics & Batteries." [81]	Prediction of energy consumption in buildings.	To present an approach with high precision for load forecasting.	A model for feedback based on ANN was introduced. The ANN training was carried out using hybrid algorithms.	Only limited load variables were considered.
Li, Junfang, et al. 2015 "Forecasting Method for Urban Rail Transit Ridership at the Station-Level Using a Weighted Population Variable and Genetic Algorithm Back Propagation Neural Network." [82]	Shortcomings of commonly used back propagation ANN-based models.	To improve the BP-based ANN model, eliminate the drawbacks, and establish an optimal network structure for better forecast.	A three-layered feedback propagation network trained by genetic algorithm (GA) was developed.	The model did not have the ability to detect sudden load changes.
Madal, Senjyu, Urasaki, and Funabashi, 2006 *"A neural network based on several-hour-ahead electric load forecasting using similar days approach"* [83]	Linking traditional load forecasting techniques with an intelligent ANN-based network.	To unite similar days approach load forecasting methods with an ANN-based network.	In order to predict one to six hours ahead of the forecast, a variation of a model based on ANN and a classical approach has been used. The model used a basic algorithm with the Euclidean norm and weighted factors.	A great variation in weather conditions may influence the forecast accuracy.

Topalli, Erkme, and Topalli, 2006 *"Intelligent short-term load forecasting in Turkey"* [84]	Inaccuracy in load forecasting and numerical volatility in forecasting methods for time series.	To present a new technique of intelligent prediction.	They used an Elman recurrent neural network model with embedded dynamic testing to enable the framework to incorporate actual load forecasting and actual current training.	The potential of the proposed method to create an efficient network structure and suitable learning algorithms.
Kandil, Wamkeue, Saad, and Georges, 2006 *"An efficient approach for short-term load forecasting using neural networks"* [85]	The effect on load forecasting of expected values (historical load data).	The potential with small input data to predict the load to demonstrate neural networks (i.e. just the temperature)	The common multi-layered feed forward ANN-based model was utilised for a localised prediction. The design of the algorithms of Levenberg Marguardt were used in training.	The study addressed only preliminary outcomes.
Xiao, Ye, Zhong and Sun, 2007 *"BP neural network with rough set for short-term load forecasting"* [86]	Disadvantages of ANN-based models for load forecasting.	Assessing the relationship for both outputs and inputs in a complex setting.	A neural network technique of rough back propagation and a moment approach were used to enhance training.	The development of an optimum attribute deduction threshold was never achieved. Further historical data is necessary.

2.4 Discussion of findings

Different academics show that the literature use various techniques to respond to a load forecast. Taylor et al. [75] introduced a feed-forward, multilayer neural network model to compare the accuracy of prediction of ANN using a time series model. The model based on ANN gave fair results. The accuracy of load forecasting depends primarily on the training and the chosen forecast time period.

In [76], in a load forecasting model, the authors evaluated the influence of electricity prices. For areas with sudden adjustments in the energy tariff, this evaluation would typically be ideal because it greatly affects the predictive accuracy. The relation between load and price is highly nonlinear and difficult to model. And more so, a supervised model based on the neurotic network was used to predict the load in the Nigerian national grid in [77]. However, due to environmental conditions, the analysis did not consider the impact of climate, so the accuracy could be enhanced. It is important to carefully select the number of neurons in the hidden layer, as too many neurons can lead to overspecialisation and consequently loss of generalising ability. However, in [78] a model was built with regard to the weight-space probability distribution (pdf) function. This formation solves a few of the modelling instabilities, so further progress could thus improve forecast model efficiency. It is important to establish inconsistency in model inputs.

In addition a multi-context artificial neural network feed forward and feedback (FFFB-MCANN) as a realistic load forecasting approach was proposed in [79]. In order to achieve improved accuracy, they suggested using the rate values rather than the absolute. Recurrent ANN models are difficult and often need excellent training. However, in [80] the application of ANN to the forecast of long-term loads was highlighted. The model forecasted a Middle Eastern utility 's annual peak demand using a time-series form and doing it all over again. The research showed that the model based on ANN generates better prediction than traditional approaches (ARMA, etc.). Long-term load forecasting is an exceedingly difficult computational problem because of future uncertainty.

The authors used an ANN-based feedback model in [81] to forecast energy consumption in high-precision buildings. A hybrid algorithm was used to train the model. Evidently, the optimal network structure was not achieved. Only small variables of load were considered. In an attempt to establish the optimal neural network model, authors used the structure of ANN and the genetic algorithm to dominate back propagation in [82]. Aside from the fact that sudden load changes cannot be identified by the approach, this technique is strong, but the method still needs further development. The model did not have the ability to detect sudden load changes, whereas, in [83] a comparative analysis of the modern load prediction approach using actual load data, was provided using artificial neural networks. The models have been used to predict loads of 1-6 hours. The Moving Average Percentage Error (MAPE) has shown that the ANN model produces precise outcomes. Once more the optimum network architecture was never achieved for a good forecasting. A great variation in weather conditions may influence the forecast accuracy. Meanwhile the authors in [84] used a recurrent neural network technique to forecast Turkey's total load one day in advance using combination training methods to offline real-time training. The study revealed that a mean deviation of 1.6% was recorded. Good network implementation can be used to obtain accurate prediction, which is the ability to create an efficient networking structure with appropriate learning algorithmic rules. Also, the authors in [85] examined the ability of ANN to forecast load, but only temperature without the use of the background load pattern. The finding notes that the use of projected values of the load can result in a high level of forecast inaccuracy, so only the temperature was used as an input. This method may be successful because of the input-output mapping power of the ANN. However, other important input variables and better network training parameters may be selected to produce better performance. The study addressed only preliminary outcomes.

The authors eventually implemented the rough array and their ability to investigate and to remember the input-output relationship in [86]. A multilayer back network for neural transfer was used in the analysis to reduce the selectivity of local sections of the deviation curve surface by a pulsed approach. This method needs to be upgraded in order to allocate the baseline for deduction. The development of an optimal threshold for attribute omission has never been rendered. Furthermore, historical load data are needed.

The major goal of this study is believed to enrich the current electric load forecasting literature for non-domestic customers, in this case the Port Terminal, with the main focus on complementing the explanation provided in field review papers already written. The study shows that despite the relative simplicity of all models examined, regression analysis is still commonly used and effective for long-term forecasting. As for short-term predictions, machine learning or artificial intelligence-based models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Fuzzy Logic are favoured.

2.5 Conclusion

A comprehensive literature review was conducted on current load prediction methods. In addition to this chapter there has been a comparative analysis of some specific models. Research reports on comparisons of intelligent system-based structures with traditional methods of load forecasting were compared. Ideally, such evaluations are meant to show the strengths of classical ANN-based models and pay less interest to the limitations of modern devices. A majority of papers analysed have not specifically highlighted the emphasis on network model optimisation, therefore it is immense that similar model network groups are evaluated and network optimisation for load prediction is explored. Research also stated that intelligent system-based models outperform classical methods, so an ANN method is used for this project proposal.

In comparison, a number of artificial neural network models have some disadvantages. Long training times, reliance on input values and the design of an optimised system architecture for better load prediction are the three main problems encountered. The use of good network training using suitable training algorithmic rules (customised back propagation algorithms, rough set theory, genetic algorithm, etc.) will definitely enhance ANN-based load forecasting models, and therefore this subject needs to be explored.

Because this study concentrated on predicting the load of an electricity grid, general criteria for a good system of forecasting and factors influencing the load at various time spheres need to be addressed. The next chapter of this manuscript therefore shortly addresses the above-mentioned problems.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter's main objective is to discuss the design of the Nonlinear Autoregressive Exogenous Inputs (NARX) neural network and the Adaptive Network-based Fuzzy Inference System (ANFIS) model, its structures and outputs for the suggested prediction models and methods of collecting data used in the analysis. The chapter also deals with the significance of data analysis, load profiling and, in particular, data pre-processing prior to forecasting.

3.2 Data description

The collection of data is an essential feature of any form of research study. Inaccurate or inadequate data may have an effect on the results of the analysis and eventually lead to invalid or distorted results [87]. In this section, various methods of data collection were used to ensure adequate historical load samples. A variety of variables, including exogenous and endogenous variables, influence the load of the power system. Variables that have a strong correlation with the load need a good forecasting method. The following inputs are therefore presented to the developed models: weather and load data to predict the load at various timeframes. The picking of initial parameters is done randomly, on the basis of quantitative variables, and often on the basis of suggestions made in recent tasks and encounters. Literature states that temperature, among all climatic condition factors, has the most important dependence on load variance [88].

To test the efficacy of the model, the actual load data for the Transnet Port Terminal (TPT) was used. Eight substations and five mini-substations, primarily feeding elevators, workshops, poles, mast lights, offices, the car terminal, clinic and a fuel depot from the terminal 11kV ring linked reticulation network were studied. The network has 2 x

1.25MVA,11kV/420V and 1 x 1.6MVA,11kV/3.3kV distribution transformers. In Figure 3.1, Appendix A, this network's single line layout is shown. There were two types of loads measured: departmental and total loads. At different points in the network, the departmental loads' measurements were taken using Landis & Gyre meters. Data at the main intake of the substation (*labelled 'B' supply from Municipality in Fig.3.1*) were measured for the total load. Figure 3.1, Appendix A, also demonstrates the spatial layout of these substations, as well as some measuring points. Power meters were installed at specified substations during the data collection process to measure out energy consumption at various installation times, i.e. sub-hourly, hourly and on a quarterly basis during the measurement process. A local meteorological office collected weather data on our behalf.

3.3 Data collection methods

Different quantitative data collection methods have been used. Some of them include gathering of relevant information as presented below:

Measuring: (departmental loads and real load for the entire port); well-defined observation and documentation of load patterns (special events, abnormal days, recess break times, etc.)

Management information systems (maximum demand threshold-2 MW announced by Buffalo City Metro Municipality (BCMM) were used to obtain true data.

Daily interaction (questionnaires, face-to-face and telephone interviews) with network operators, Electrical Technicians and Electricians took place.

Several initiative meetings with communities or partners were held on the basis of the measurable (CARS) rule of community, attitude, requirements and standard goals. Inter alia, a commonly used approach, namely interactions, were initiated one-on-one with stakeholders, network technicians, TPT managerial staff and service providers, with a view of developing a partnership and likely obtaining their support. Compared to the aforementioned technique, phone calls have also been used, not just to allow enough use of services, but mostly because lesser time was needed for this interaction approach. The collection of data is an exercise that is demanding and sometimes devours many resources and time. Table 3.1 shows a sequential data collection plan for this document. Data on historical load can be observed, in particular total load and different departments loads. The total load reflects the combined actual load recorded by the statistical or power meter at the main intake substation for the entire port. This instrument was designed to measure the load using an interface time of thirty minutes, as per the Eskom maximum demand metering requirements. As a result, the research on this topic was expanded to document energy usage for various departments and buildings inside the port terminal premises at a lower integrating test cycle for departmental loads. Landis & Gyre power meters recorded this data for a duration of two weeks per location.

Table 3.1 A standard combined timetable – for data collection model

Data type	**Data source**	**Recording integration period**	**Parameter**	**Location/building**	**Mobility**	**Duration**
Total load	Main substation	30 mins	MW	Main Intake substation	Stationary	7 months
Departmental loads	Landis & Gyre meters	30 mins	kW	Admin. BLD, Elec. workshop, lifts, Millwright Workshop, car terminal, Saddle Carrier Workshop and fuel depot	Stationary	7 months
Weather	SA weather	30 mins	Min, max temp (°C), wind speed, humidity, and cloud rate	Nearest weather service point (East London)	Stationary	March – September 2018. Daily records

Table 3.2 An example of load data obtained from building offices

GRAIN ELEVATOR 11 kV SUBSTATION

FEEDING CONVEYER BELTS, LIFTS AND OFFICES

Recorder	Date	Time	kW	KVAR
LGZ97816730	2/3/2018	030	5,4	16,1
LGZ97816730	2/3/2018	100	11,9	3,5
LGZ97816730	2/3/2018	130	14,9	2,4
LGZ97816730	2/3/2018	200	5,9	15,3
LGZ97816730	2/3/2018	230	5,3	18,4
LGZ97816730	2/3/2018	300	4,8	16,9
LGZ97816730	2/3/2018	330	12,7	4,6
LGZ97816730	2/3/2018	400	18,9	0,5
LGZ97816730	2/3/2018	430	25,3	0,0
LGZ97816730	2/3/2018	500	25,6	0,0
LGZ97816730	2/3/2018	530	21,4	0,0
LGZ97816730	2/3/2018	600	20,5	0,0
LGZ97816730	2/3/2018	630	17,1	0,0
LGZ97816730	2/3/2018	700	17,2	0,0
LGZ97816730	2/3/2018	730	0,1	14,9
LGZ97816730	2/3/2018	800	2,0	8,0
LGZ97816730	2/3/2018	830	4,9	0,6
LGZ97816730	2/3/2018	900	7,4	1,1

3.4 Data analysis of the load profile for the lifts

3.4.1 Load curve characteristic, departmental load – Lifts, conveyer belts and offices

Individual loads for various departments were also measured according to the measurement schedule shown in Table 3.1. A typical daily load profile for the conveyer belts, lifts and offices (for a non-holiday period) is shown in Figure 3.2.

Departmental load demand data for the second day of March 2018 is shown in Table 3.2. The reliability and credibility of the March data were initially graphically analysed, comparing each hour of the same day of each week with the data collected from the second day of June 2018 and the second day of July 2018, etc.

Example of electrical expenditure in March 2018 in Fig. 3.2

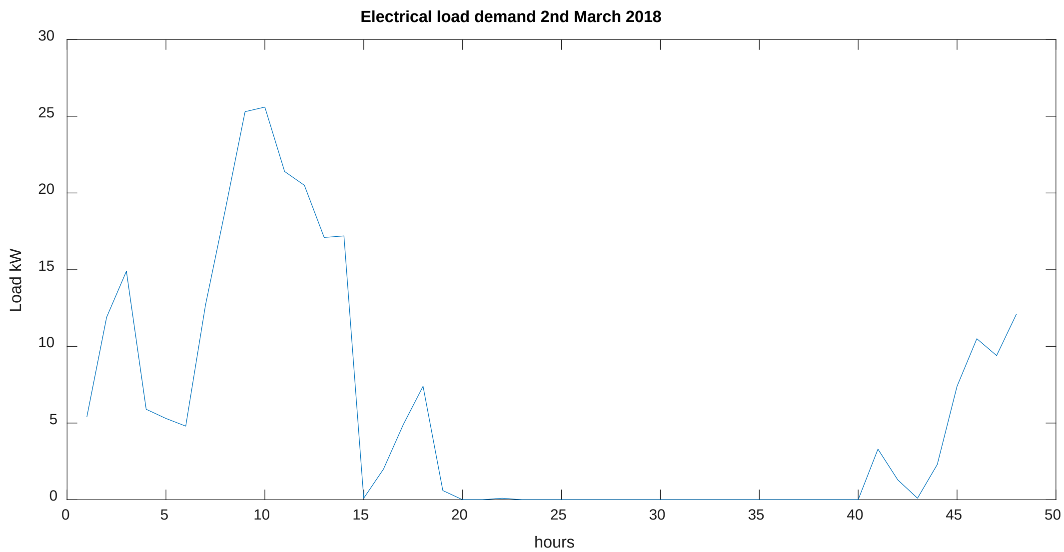

Figure 3.2: Departmental load profile for March 2nd 2018

The load starts to pick up to 25 kW at about 10 hours on Friday, which indicates many activities at the port terminal. A large drop in the curve is seen during 20 to 40 hours indicating no electricity consumption in this period to 0kW. Energy demand reaches minimum levels during this time. This shows the end of the shift on Friday and the start of the weekend, which indicates little or no activity at the port terminal. An increase is shown in the curve again during 40 to 48 hours, indicating an increase to above 10 kW of electricity consumption. This is as a result of a late shift for the receiving department starting on Saturday, with a limited number of staff.

From this load profile, the following hourly variance can be seen:

- A maximal consumption of 25 kW around 10 hours.
- A consumption of 15 kW during 15 and 48 hours.
- A consumption above 5kW and below 5kW during 18 and 42 hours.
- A minimum or no consumption of 0 kW during 20 to 40 hours.

Electric load data time series plots were generated and visually examined for common patterns, such as averages, hourly elements, and sudden shifts in peak and valley magnitudes.

3.4.2 ***Load curve characteristic, departmental load –*** *Admin Blog*

The first measurement was taken on Friday, 1st June for a duration of seven days. Figure 3.3 indicates that the load reaches its height (approx. 12.5 kW) at around 09:30 on Friday, and drops to 1.3 kW - a reduction of about 90% at 17:30 the same day. Usually, these offices are occupied on weekdays from about 08:30 to 16:30. Therefore, beginning from Monday to Thursday, a peak average of 18 kW and a drop average of 1.3 kW is observed. As for weekend load profiles, an average of 1.3 kW has been recorded and, technically speaking, since the building will presumably be unoccupied on weekends, this substantial reduction in power usage seems to be valid.

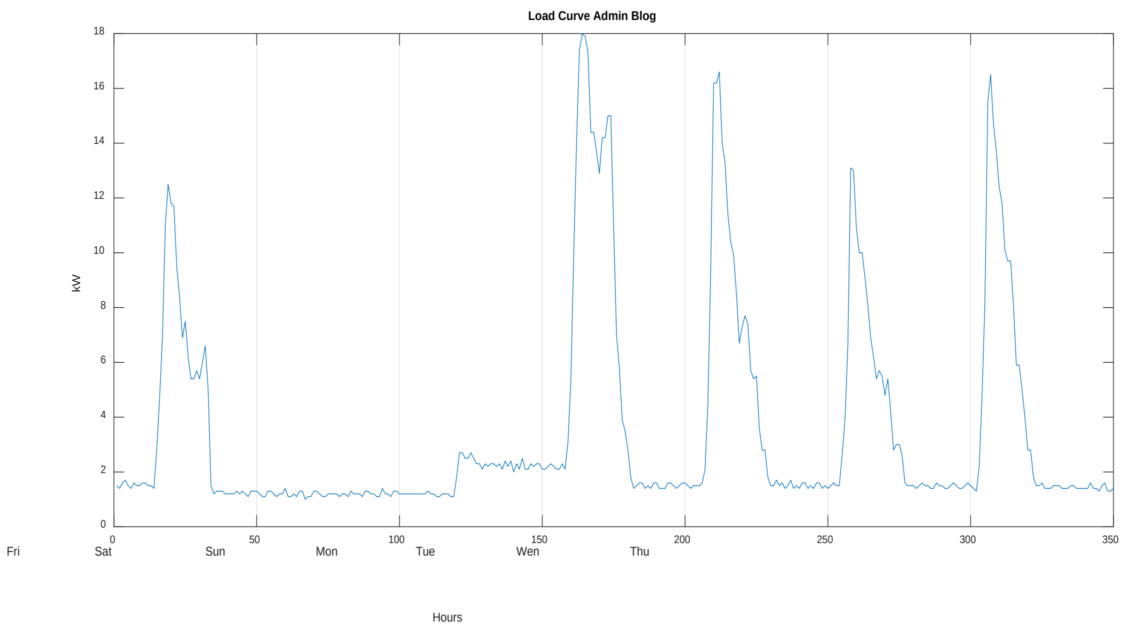

Figure 3.3: The load for the Administration Building over the period June 01 - 14, 2018

One can clearly distinguish two different load formats during the daylight and after hours, as seen in Figure 3.3 above. During the day the load reaches its height and then decreases steadily immediately after hours.

3.4.3 Load characteristic, departmental load – *Electrical Workshop*

The highest peak of more than 85 kW was observed from Friday to Saturday at the workshop. The lowest peak was recorded on Sunday to below 2.5 kW, indicating no work being carried out on this day.

3.4.4 Load characteristic, departmental load – *Millwright Workshop*

The load profile for the Millwright workshop was recorded for almost a month, period (12th till 31st August 2018). Electricity consumption reaches low levels of 0.1 kW at the end of week 1, Saturday at 11:00, and reaches high levels of 3.1 kW at the beginning of week 2, Monday at 11:00.

3.4.5 Load characteristic, departmental load – *car terminal*

The highest recording of electricity consumption for April is observed on Friday the 13th about 10:00 AM. The highest recording of energy consumption is about 381 kW for the departmental load. This is attributed to the fact that this is one of the busiest car terminals in the southern hemisphere, which carries out export and import duties for Mercedes Benz South Africa (MBSA), big revenue for the port. Pictures of a car terminal at Transnet Port Terminal (TPT) in East London are shown in Figure A3.4 and Figure A3.5 in Appendix A.

3.4.6 Load consumption, departmental load – *fuel depot*

The lowest levels of electricity consumption of about 0.1 kW was recorded starting from Monday around 2:30 AM, and it continued throughout the week on days like Tuesday, Saturday and Sunday. If the fuel depot in this harbour is compared to other departmental loads, this one records the lowest electricity consumption in the port, indicating less activity in terms of energy usage.

3.4.7 Load consumption, departmental load – *Saddle Carrier Workshop*

The load for the Saddle Carrier Workshop was recorded for almost a two-week period (3rd till 16th September 2018). The data were generated and visually checked in time series for common patterns, e.g. averages, hourly components and sudden shifts in peak and valley scale.

This load presented an hourly energy demand variation which can be observed as:

- An average consumption of about (8.9-18.8) kW of power mostly a week.
- A maximum consumption of 22.5 kW of electricity at 12:00 PM Saturday.
- A minimum consumption of 3.1 kW of energy at 11:00 AM on Sunday.

3.5 Data analysis of the load profile for total consumption

3.5.1 Load curve characteristic of the total load

As described before, the accumulated load data were recorded for the duration of four months per season at the main intake substation of the TPT. Since seasonal variations significantly affect the load, the set of data were divided into two groups (seasons) for the total load used: winter and summer. The subsequent seasons were then defined: summer-February to May window season, and winter- June to September window season.

The highest and lowest load curves recorded in the summer are shown in Figure 3.6.

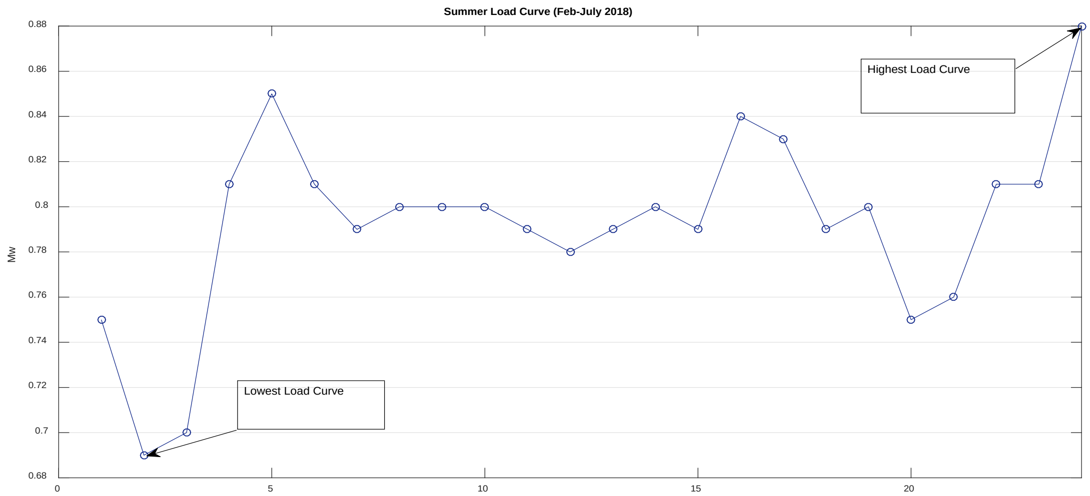

Figure 3.6: Load profiles – for combined load in summer 2018

The complete load depiction, excluding outages due to load shedding by ESKOM, for the total load is illustrated in Figure 3.7 for the chosen winter period. Figure 3.7 displays the peaks and valleys as normal electricity usage during days of the week and weekends. It also shows the load profile of the Port for different seasons of the year specifically for summer and winter periods. It is extremely important to evaluate the load data of the past to assess the input-output data structure.

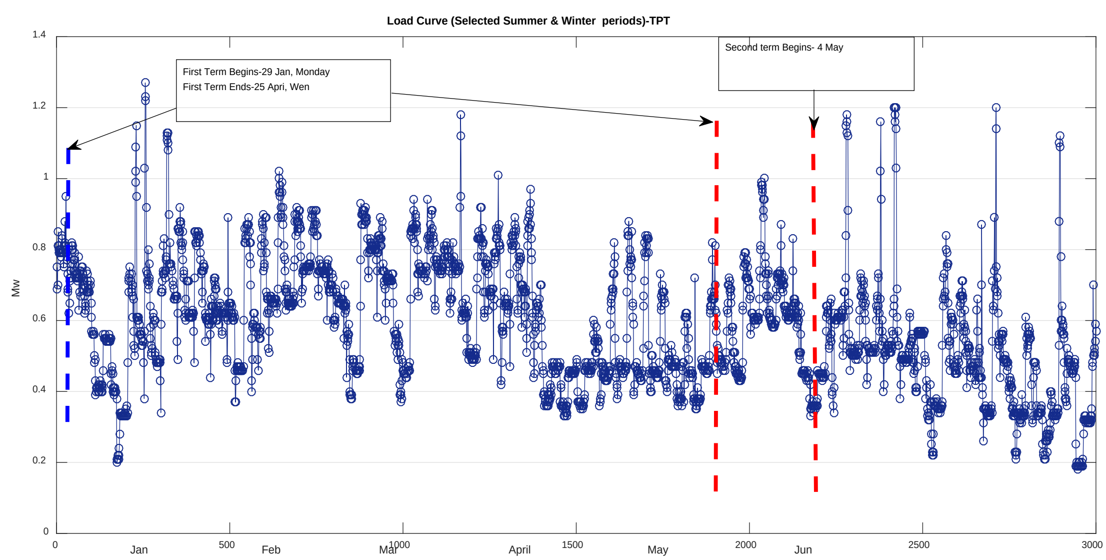

Figure 3.7: Time series for the chosen summer and winter period load pattern

A load profile typical for the chosen winter period (June – August), which bears resemblance to the one in Figure 3.7, shows high levels of electricity usage on the 16th June 2018 which is the mid-term period.

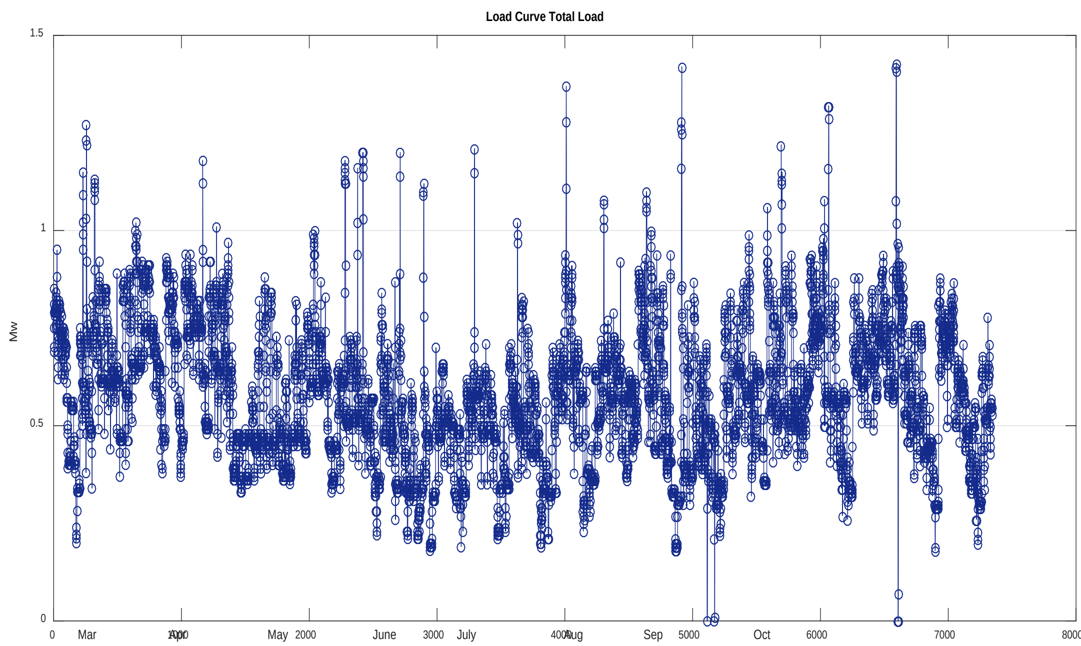

Figure 3.8: Annual load profile used from January 2018 to December 2018

In the winter, electricity demand increases. Based on the winter season, it may be May, June or July during the specific year under observation. As time shifts around October, the load falls in the spring as observed, which is quickly down to below 1 MW.

From this load profile, the following seasonal variation is observed:

- Maximum consumption during the summer and autumn seasons of less than 1.42 MW.
- Maximum consumption of over 1.42 MW in winter and early spring.
- The base load level is just marginally lower than 0.5 MW throughout the year.

Anomalous data sets or deviations were verified and removed where possible. The purpose of the initial analysis of data were to give the data a " feel ". The seasonal months meet the sequence of Eastern Cape in South Africa shown in Figure 3.9.

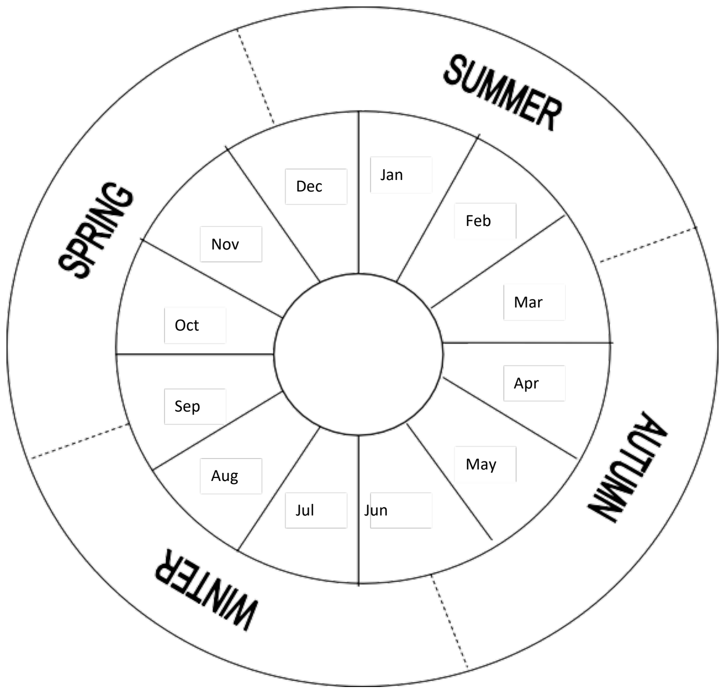

Figure 3.9: Months segment in the various seasons of the year

Table 3.3 A standard presentation of created tables for different seasons

d	time (Hr)	temp (deg)	wind (m/s)	rain(mm)	humidity(%)
18	00:00	12,5	58	0,0	79
18	00:30	12,5	58	0,0	79
18	01:00	12,2	46	0,0	73
18	01:30	12,2	46	0,0	73
18	02:00	14,2	65	0,0	69
18	02:30	14,2	65	0,0	69
18	03:00	14,0	70	0,0	68
18	03:30	14,0	70	0,0	68
18	04:00	14,1	74	0,0	69
18	04:30	14,1	74	0,0	69
18	05:00	13,4	75	0,0	68
18	05:30	13,4	75	0,0	68
18	06:00	13,5	69	0,0	67
18	06:30	13,5	69	0,0	67
18	07:00	14,0	65	0,0	68
18	07:30	14,0	65	0,0	68
18	08:00	15,8	61	0,0	64
18	08:30	15,8	61	0,0	64
18	09:00	17,5	81	0,0	57
18	09:30	17,5	81	0,0	57
18	10:00	19,1	92	0,0	47
18	10:30	19,1	92	0,0	47
18	11:00	20,6	92	0,0	43

The annual peak during the winter season is usually maximum because of the high use of electricity. In addition, widespread load shedding is applied in the months of May, June and July to save the substantial penalties caused when exceeding the notified maximum demand (NMD). Weather data for temperature, wind, rain, and humidity supplied by SA Weather offices in East London is shown in Table 3.3 above.

3.6 Data storage for the entire port terminal

Utilising previous load data and climate prediction, stored data in a central database, the suggested ANN using forecasting models will be taught offline. The standard procedure for a good prediction application is that the applicable data source is automatically obtained by the design structure.

For this setup, the necessary database must be established and then installed properly on a localised desktop (PC).

There are plenty of free software base systems available for storage of data, including: Microsoft Access, Microsoft SQL Server, DB2, IBM, Microsoft Excel, Informix, MySQL, Oracle, PostgreSQL, etc. If one wants to use the MATLAB Database Toolbox though, it is important to pick an appropriate data management application, since this toolbox mainly supports systems compatible with the ODBC/JDBC protocol.

In this work as in Figure 3.10, all historical data are stored in the Landis+Gyr.MAP110 Service Tool, and then imported into MS Excel for data standardisation and for enhanced diagnostic functions. Once the data is standardised, it can be imported into MATLAB via ODBC communication protocol. This is primarily designed for research purposes.

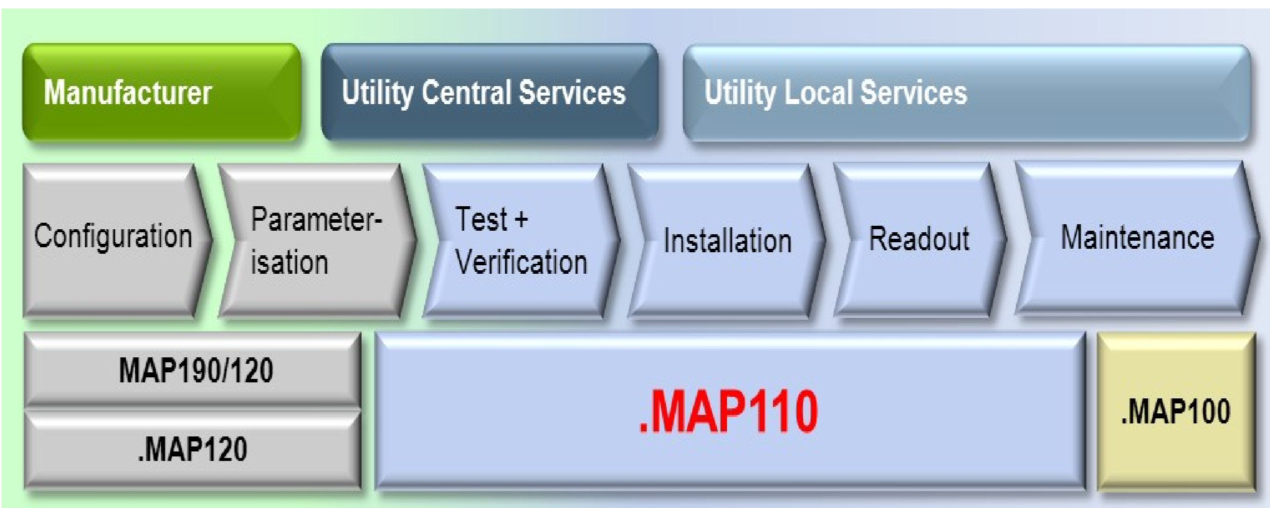

Figure 3.10: The Landis+Gyr.MAP110 Service Tool supports services

Figure 3.11 gives a general layout of Landis+Gyr.MAP110 Service Tool. Landis+Gyr.MAP110 Service Tool Software permits one or more databases and tables to be generated by a user. One database *('combined load data')* on the grounds of this research, was developed, and then calibrated. Inside this database, different record storage tables were developed for various models. Figure 3.12 displays some of the tables set up in the Database. Using Standard Query Language (SQL) MATLAB functions, the required data were then extracted from these tables into the MATLAB workspace.

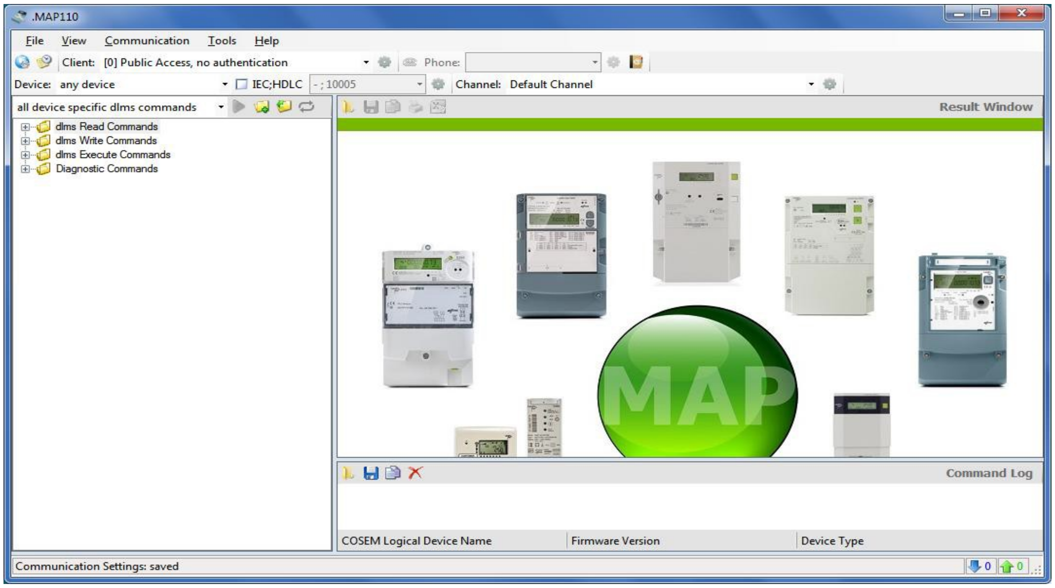

Figure 3.11: A general overview of MAPE 110 Service Tool for the load

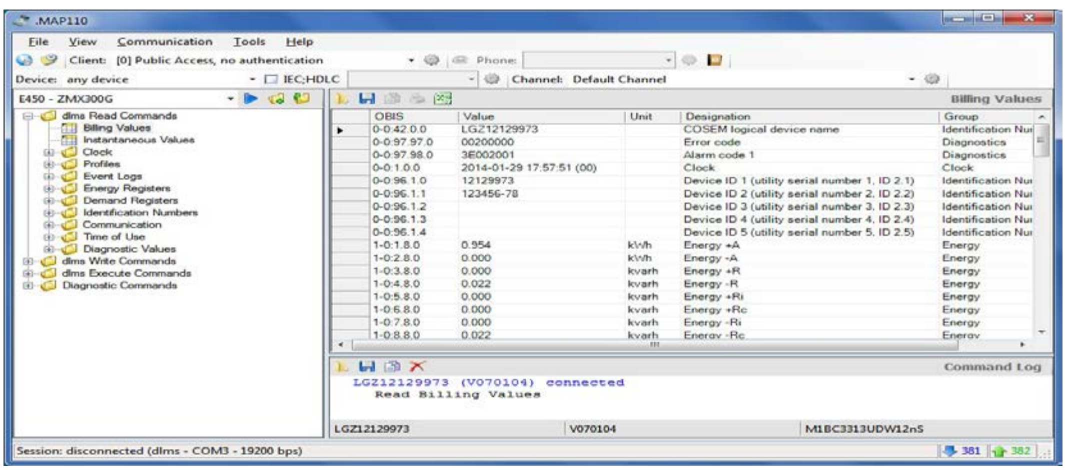

Figure 3.12: A standard format of some of the tables created

3.6.1 *Importing data into MS Excel*

The Landis+Gyr.MAP110 Service Tool can upload, make structured data exportation to and from the recognised data warehouse, as shown in Figure 3.13. Depending on the pattern and layout of the information needed, the importing wizard for the MAP 110 Service Software Tool can be used to upload a file from Landis+Gyr devices (meters and USB or COM port) into PC with MS Excel Database.

Figure 3.13: Importing data from Landis+Gyr metre into an Excel spread sheet

Table 3.4 A typical layout of load profile 1

Load Profile 1

	0-0:1.0.0	0-0:96.10.1 [hex]	1-0:1.8.0 [kWh]	1-0:2.8.0 [kWh]	1-0:3.8.0 [kvarh]
1	2014-01-27 01:00:00 (01)	36	0.954	0.000	0.000
2	2014-01-27 02:00:00 (01)	36	0.954	0.000	0.000
3	2014-01-27 03:00:00 (01)	36	0.954	0.000	0.000
4	2014-01-27 04:00:00 (01)		0.954	0.000	0.000
5	2014-01-27 05:00:00 (01)		0.954	0.000	0.000
6	2014-01-27 06:00:00 (01)	36	0.954	0.000	0.000
7	2014-01-27 07:00:00 (01)	36	0.954	0.000	0.000
8	2014-01-27 08:00:00 (01)	36	0.954	0.000	0.000
9	2014-01-27 09:00:00 (01)	3	.954	0.000	0.000
10	2014-01-27 10:00:00 (01)	3	.954	0.000	0.000
11	2014-01-27 11:00:00 (01)	3	.954	0.000	0.000

Profile state 1

Invalid time [0]
Daylight savings inactive [7]

Clock invalid [1]
Data not valid [2]
No data [4]
Clock adjusted [5]

3.7 Pre-processing of data

As shown in Table 3.5, the database stores load data and climate data that are pre-processed or raw. Therefore, before the presentation of data to a training model or other predictive method, the data should be standardised.

Data scaling is important, because neural networks are also prone to data that are raw. To prevent convergence issues, it is extremely important that data are scaled (typically values between 0 and 1, or -1 and 1). There are many techniques that can be used as described in Equation (3.1) to (3.4) for data standardisation.

Table 3.5 Raw load and weather data stored in MS Excel

d	time (Hr)	temp (deg)	wind (m/s)	rain(mm)	humidity(%)	M1 (kW)	M2 (kW)	M4 (kW)	M6 (kW)	M7 (kW)	M8 (kW)	M9 (kW)
18	00:00	12,5	58	0,0	79	29,9	0,50	2,60	0,00	2,55	324,60	11,37
18	00:30	12,5	58	0,0	79	25,2	0,40	2,80	0,10	2,56	323,90	8,65
18	01:00	12,2	46	0,0	73	26,5	0,40	2,60	0,00	2,57	326,20	8,60
18	01:30	12,2	46	0,0	73	25,9	0,40	2,70	0,00	2,57	327,30	8,60
18	02:00	14,2	47	0,0	69	26,8	0,40	2,60	0,00	2,56	326,30	8,58
18	02:30	14,2	48	0,0	69	25,7	0,50	2,60	0,10	2,56	328,00	8,58
18	03:00	14,0	49	0,0	68	26,5	0,40	2,60	0,00	2,56	327,20	8,60
18	03:30	14,0	50	0,0	68	23,6	0,40	2,70	0,00	2,57	325,40	8,60
18	04:00	14,1	51	0,0	69	25,7	0,40	2,60	0,10	2,55	323,20	8,58
18	04:30	14,1	52	0,0	69	31,0	0,40	2,60	0,00	2,54	323,20	8,56
18	05:00	13,4	53	0,0	68	37,2	0,40	2,70	0,00	2,59	330,00	8,63
18	05:30	13,4	54	0,0	68	23,7	0,40	2,60	0,00	2,58	328,20	8,62
18	06:00	13,5	55	0,0	67	20,9	0,50	2,60	0,10	2,55	327,00	8,59
18	06:30	13,5	56	0,0	67	18,9	0,40	2,80	0,00	2,54	264,60	8,52
18	07:00	14,0	57	0,0	68	4,2	0,40	54,40	0,00	2,56	387,80	4,51
18	07:30	14,0	58	0,0	68	0,0	0,40	86,10	0,00	0,23	223,10	0,00
18	08:00	15,8	59	0,0	64	0,0	0,40	85,30	0,10	0,00	303,40	0,00
18	08:30	15,8	60	0,0	64	16,5	0,40	83,20	0,00	0,00	326,50	0,00
18	09:00	17,5	61	0,0	57	35,4	0,40	83,20	0,00	0,00	326,40	0,00
18	09:30	17,5	62	0,0	57	36,9	0,40	83,20	0,10	0,00	302,60	0,00
18	10:00	19,1	63	0,0	47	30,9	0,40	84,20	0,00	0,00	281,50	0,00
18	10:30	19,1	64	0,0	47	10,7	0,40	83,70	0,00	0,00	281,20	0,00
18	11:00	20,6	65	0,0	43	0,0	0,40	84,60	0,00	0,00	281,80	0,00

3.7.1 *Methods of scaling the data*

Using one of the following equations in [89], data can be standardised:

$$\textit{Standardised value} = \frac{\text{true value} - \text{minimal value}}{\text{maximal value} - \text{minimal value}} \tag{3.1}$$

$$\textit{Standardised value} = \frac{\text{true value}}{\text{total of each day}} \tag{3.2}$$

$$\textit{Standardised value} = \frac{\text{true value}}{\text{maximal value}} \tag{3.3}$$

$$\textit{Standardised value} = \frac{\text{true value} - \text{medium value}}{\text{maximal value} - \text{medium value}} \tag{3.4}$$

3.8 Proposed framework description

This section describes the solution proposed: a design of the NARX neural network which uses exogenous inputs, such as weather and time variables and endogenous input (electricity) to generate a 168-hour forecast. The study also involves the application of

Adaptive Neuro Fuzzy Inference System (ANFIS) to predict the electrical load for 24 hours to a week in advance. This forms the part of comparative analysis for the models to establish a better performing one in terms of load forecasting. Firstly, time is dedicated to explaining how to arrive to the proposed networks, which will facilitate the implementation explained later on.

3.8.1 NARX Model

Its input-output relationship can describe the dynamics of ANN using NARX. [90-91].

$$y(t) = F[x(t), x(t-\Delta t), \ldots, x(t-n\Delta t), y(t), y(t-\Delta t), \ldots, y(t-m\Delta t)] \qquad (3.5)$$

where n is the number of steps to delay input time, m is the number of time delays to feedback(output), and F is usually a nonlinear function. Note that the delayed y output is included in equation (3.5) alongside the exogenous x variables. The weather and time variables are exogenous x-t input, with load yt being the input of the endogenous. Using the actual load, y_i values, the network was trained and used at a closed loop to provide the next 168-hour prediction for every one-hour phase of the loady_i. Using a Levenberg–Marquardt backpropagation technique, the network is developed utilising 365 previous consecutive days of open-loop data.

The design of the proposed neural network starts with the structure of a feedforward perceptron network, in order to learn the behaviour of the output (target) y at time t (yt), by using inputs yt and modelled as a nonlinear functional type of a regression model for y (output layer):

$$y_t = \Phi[\beta_o + \textstyle\sum_{i=1}^{q} \beta_i \, h_{it}] \qquad (3.6)$$

where (hidden layer)

$$h_{it}= \Psi[\gamma_{i0} + \sum_{j=1}^{n} \gamma_{ij}\, x_{jt}] \qquad (3.7)$$

Φ is the output activation function, where $\Phi(x) = x$ is the linear function; Ψ are the hidden neurons activation function - in our case, the form's logistic function which is:

$$\Psi(t) = \frac{1}{1+ e^{-t}} \qquad (3.8)$$

that is used to flatten the neural weights or restrict them; the output bias is β_o; the output layer weights are β_i, γ_{i0} is the input bias; and γ_{ij} are the weights for the input layer. The sub-index of the q neurons is i, and the sub-index of the n inputs is j. A combination of equations (3.5) and (3.7), (3.9) was generated:

$$y_t= \Phi\{\beta_{\text{o}} + \sum_{i=1}^{q} \beta_i\, \Psi[\gamma_{i0} + \sum_{j=1}^{n} \gamma_{ij}\, x_{jt}]\} \qquad (3.9)$$

The dynamic term, an autoregression on the output, was then added to describe a recurring network in which the hidden layers are represented by:

$$h_{it} = \Psi[\gamma_{i0} + \sum_{j=1}^{n} \gamma_{ij}\, x_{jt} + \sum_{r=1}^{q} \delta_{ir}\, h_{r,t-1}] \qquad (3.10)$$

where, δ_{ir} is the delayed weight, $h_{r,t-1}$ is the term for the feedback. By substituting (3.11) for (3.7), we get:

$$y_t = \Phi\{\beta_{\text{O}}+\sum_{i=1}^{q} \beta_i\, \Psi[\gamma_{i0}+\sum_{j=1}^{n} \gamma_{ij}\, x_{jt}+ \sum_{r=1}^{q} \delta_{ir}\, h_{r,t-1}]\} \qquad (3.11)$$

Equation (3.11) represents network dynamics: past output values and multiple inputs. However, our structure is responsible for only one hidden neural layer to date. By adding index l and the multi-dimensional existence of the t outputs, we must expand the definition to N layers by adding index k to produce:

$$y_t^k = \Phi\{\beta_O^k + \sum_{l=1}^{N} \sum_{i=1}^{q} \beta_0^k \, \Psi[\gamma_{i0}^l + \sum_{j=1}^{n} \gamma_{ij}^l \, x_{jt} + \sum_{r=1}^{q} \delta_{ir} \, h_{r,t-1}]\} \quad (3.12)$$

$$k = 1 \cdots \tau$$

The NARX Neural Network implemented in this research is described in equation (3.8). Open- and closed-loop networks are the same, with the exception of the delayed output value. The open-loop network gets the y value from the previous known output values and is thus a regular network input; and the closed-loop model obtains the value from the forecasted output value. For an example of the implementation of NARX, see [92].

3.8.2 ANFIS Model

Adaptive neuro fuzzy inference system (ANFIS) is a hybrid system from adaptive neural network and fuzzy logic. The adaptive neural network method provides the capability of learning and adapting the parameters of the fuzzy rule base. Adaptive neural network can eliminate the deficiency of a conventional fuzzy system, where the researcher must set up a membership function value for both input and output membership function.

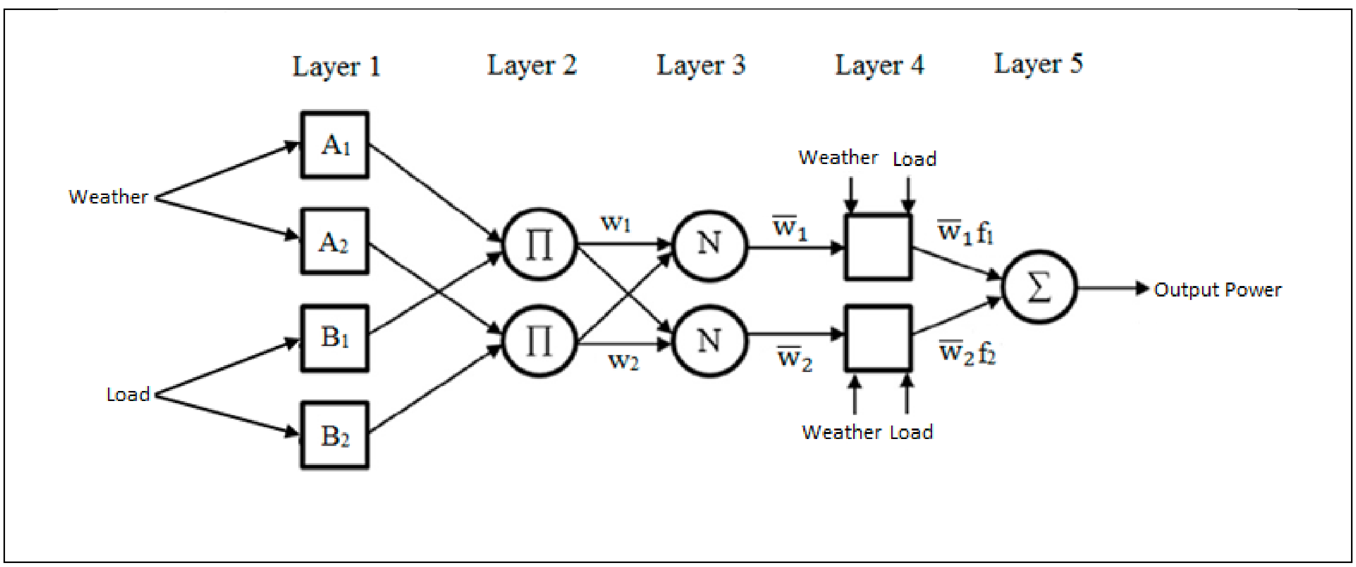

Figure 3.14: ANFIS structure

Figure 3.14 shows an ANFIS structure as adapted from [93], composed of five layers with two inputs weather and load, and one output power. Each layer contains several nodes which describe the node function. Square node indicates an adaptive network, while circle node indicates a fixed node. In layer 1, all the nodes are adaptive network. There are two fuzzy parameters A1-A2, and B1-B2. The output of layer 1, which is called the fuzzification layer, is given by:

$$O_{1.i}= \mu Ai\ (weather), i=1,2 \quad (3.13)$$

$$O_{1.i}= \mu Bi-2\ (load), i=3,4 \quad (3.14)$$

whilst weather and load values are the input for each node. The membership function for A and B describes by type of membership function.

In layer 2, each node is a fixed node which computes the strengths of the rules. Output of layer 2 is given by:

$$O_{2,i}=w_i=\mu_{Ai}(weather)\Delta\mu_{Bi}(load),\ i=1,2 \quad (3.15)$$

or,

$$w_1=\mu_{A1}(weather)AND\mu_{B1}(load) \quad (3.16)$$

$$w_2=\mu_{A2}(weather)AND\mu_{B2}(load) \quad (3.17)$$

In layer 3, each node labelled N is also a fixed node. The output of this layer is called a normalised firing level. The outputs are given by:

$$O_{3,i}=\overline{wi}=\frac{wi}{w1+w2}, i=1,2 \quad (3.18)$$

In layer 4, each node is an adaptive network which computes the contribution of each rule. The outputs of this layer are given by:

$$o_{4,i}= wi\ output\ power\ i = wi(pi\ weather + qi\ load + ri) \quad (3.19)$$

In layer 5, which is the last layer, is the summation of all incoming signals from the previous layer, the output is given by:

$$o_{5,i} = \sum_i \bar{w}_i \; output\, power\, I = \frac{\sum_i w_i \; output\; power_i}{\sum_i w_i} \qquad (3.20)$$

In this study, ANFIS is trained by a hybrid learning algorithm, which combined the least squares method and the gradient descent method [94]. Each membership functions type in this study is compared to find the best type of membership function that generates the better MSE.

3.9 Membership function

Different types of membership function were used to find the best forecasting result. The membership function types used in this section are trimf, trapmf, gbellmf, gaussmf, gauss2mf, and dsigmf.

Each membership function has a different equation that is used in the fuzzification process at layer 1. The equation for each membership function is defined as follows:

1. Triangular-shaped membership function (trimf)

$$f(x;a,b,c) = \begin{Bmatrix} 0, & x \ll a \\ \frac{x-a}{b-a}, & a \ll x \ll b \\ \frac{c-x}{c-b}, & b \ll x \ll c \\ 0, & c \ll x \end{Bmatrix} \qquad (3.21)$$

2. Trapezoidal-shaped membership function (Trapmf)

$$f(x;a,b,c,d) = \begin{Bmatrix} 0, & x \ll a \\ \frac{x-a}{b-a}, & a \ll x \ll b \\ 1, & b \ll x \ll c \\ \frac{d-x}{d-c}, & c \ll x \ll d \\ 0, & d \ll x \end{Bmatrix} \qquad (3.22)$$

3. Generalised bell-shaped membership function (Gbellmf)

$$f(x;a,b,c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \tag{3.23}$$

4. Gaussian curve membership function (Gaussmf)

$$f(x;a,c) = e^{\frac{-(x-c)^2}{2a^2}} \tag{3.24}$$

5. Difference between two sigmoidal function membership functions (Dsigmf)

$$f(x;a,c) = \frac{1}{1+e^{-a(x-c)}} \tag{3.25}$$

3.10 Model accuracy

There are other accuracy measuring methods in terms of errors that obtain good prediction results of the load. Examples are Mean Absolute Percentage Error (MAPE),Mean Absolute Error (MAE) and Root Mean Squares Error (RSME), but MSE is the best preferred accuracy measuring method, as it presents the smallest error between the actual data and the forecasting data.

The accuracy of short-term electrical load forecasting results computed with mean squared error (MSE) is defined as follows:

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}\left(a_{e,i} - a_{p,i}\right)^2 \tag{3.26}$$

where n is the number of experimental data, $a_{p,i}$ is the predicted values, $a_{e,i}$ is the experimental values, and i is the number of input variables. The smallest value of MSE indicates the best forecasting method.

3.11 Conclusion

The methods used to collect the required data and the reasons for such data are listed in this chapter, and the chapter also provides some information on the storage of input data and results. Moreover, the mathematical modelling of the selected neural network and the other model have also been presented in this chapter.

The next chapter discusses results obtained by using neural networks to generate a 168-hour ahead forecast. As will be seen in Chapter 4, NARX ANNs and ANFIS forecasting outcomes are explained.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the simulation results of NARX and ANFIS forecasting models discussed in the previous chapter. The first section of this chapter discusses departmental load forecasts, and the second part encapsulates the combined/total load forecast. Many discussions related to specific forecasting error results were also included in the form of mean squared error (MSE) as a performance measure function to evaluate the performance of the models.

4.2 Results of load forecasting for Transnet Port Terminal

In the development, testing and use of the ANN forecasting solution based on Nonlinear Autoregressive with External Exogenous Input (NARX) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models, an Intel i3-5005u central processing unit with 4 GB of 850 MHz running at 2.0 GHz, DDR3 dual channel, and a 5500 HD graphics card were used as a hardware configuration. The software architecture used includes the operating system of Educational Edition 1903 of Windows 10 and the application program of MATLAB R2016a.

4.3 Forecasting the departmental loads

Consequently, the preceding topic specifically addresses forecasts obtained from the predictive model created.

The evolved NARX model was gradually trained in both seasons (winter and summer) to forecast the load. Exogenous and endogenous inputs were added to the networks in all cases to predict the load with a forecast period of 168 hours.

4.3.1 Predicting the load for the Lift Department

The Lift Department's load measurements at Transnet Port Terminal in East London were taken from 12th March – 25th March 2018. The data set were therefore described as training data (18th March – 24th March) and target data (11th – 17th March) respectively.

4.3.1.1 Results with respect to the ANN prediction solution developed based on the NARX Model, climate and time used as exogenous variables

In keeping with the method mentioned above and using the exogenous variables meteorological and time dataset, the forecasting approach was integrated on the basis of the NARX artificial neural networks that synthesised the collected findings, the MSE values and the coefficient of correlation (R), i.e. between targets of the network and the outputs of the network, for the entire dataset per database contained (see Table 4.1).

While testing the results, it was noticed that the architectural LM training algorithm consists of the delay parameter 3, which ensures the optimal hourly forecast accuracy of the hidden layer with 5 neurons, since it has the lowest mean squared error value, (0.0014156) and the measured correlation coefficient for the entire dataset quite close to 1 (0.9452). In comparison, the network developed using 20 neurons in the hidden layer and the delay parameter 40 has the worst hourly predictability, as it provides the highest value of the mean squared error (0.0052285) and the correlation coefficient calculated from 1 (0.95691) for the entire dataset. This network provides the highest hourly forecast accuracy of the 15 LM-based algorithms network trained, as simulation results show good hourly predictive accuracy for March 2018.

Table 4.1 Results developed using the weather and time stamp for lift

		The Levenberg-Marquardt Training Algorithm				
n	*d*	3	5	10	20	40
5	MSE	0.0014156	0.0017939	0.0025668	0.0026711	0.0026441
	R	0.9452	0.95494	0.94224	0.96657	0.96461
10	MSE	0.002562	0.0025346	0.0024407	0.0035346	0.004226
	R	0.9535	0.96052	0.95989	0.96446	0.94427
20	MSE	0.0029508	0.0032255	0.0026358	0.0040899	0.0052285
	R	0.9635	0.96512	0.94781	0.9572	0.95691

The results indicated that the best hourly forecasting accuracy is generated when the LM delay parameter is at 3. It has been seen that ANN, developed using the NARX model LM Algorithm, uses the exogenous variables weather and time stamp data has the best hourly forecast accuracy, with n = 5 neurons in the hidden layer and a delay parameter of d = 3 entitled NARX_ANN_LM_ALL (see Figure 4.1).

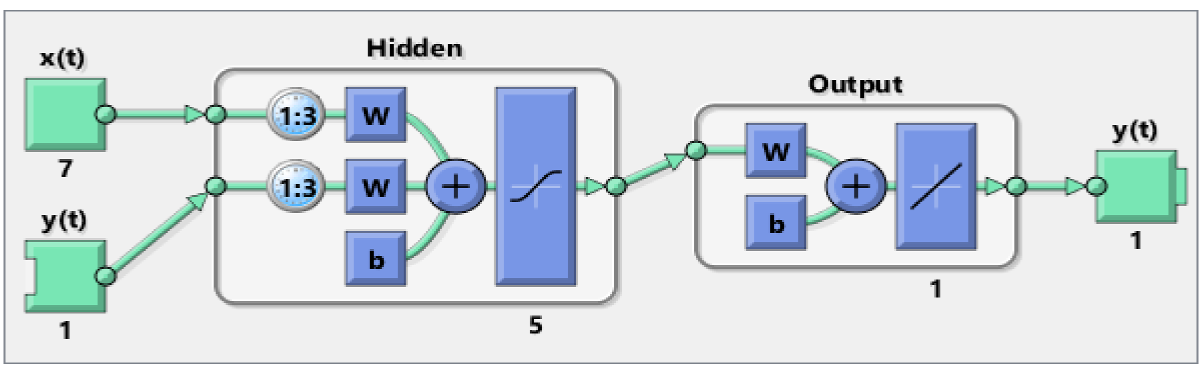

Figure 4.1: The structure of NARX_ANN_LM_ALL

To evaluate the training efficiency of electricity forecast for a week in March 2018 on an hourly basis, and using the ANN developed on the basis of the LM algorithm and the NARX model, using climate and time stamp data as exogenous variables, the training, validation, and testing curves were plotted first. In this case, the best validation performance at the fourth epoch was registered when the mean squared error had the value of 0.0014156. By analysis, the devised prediction solution remains stable, no overfit process is occurring, and the neural network NARX_ANN_LM_ALL offers a high level of performance and accuracy (see Figure 4.2).

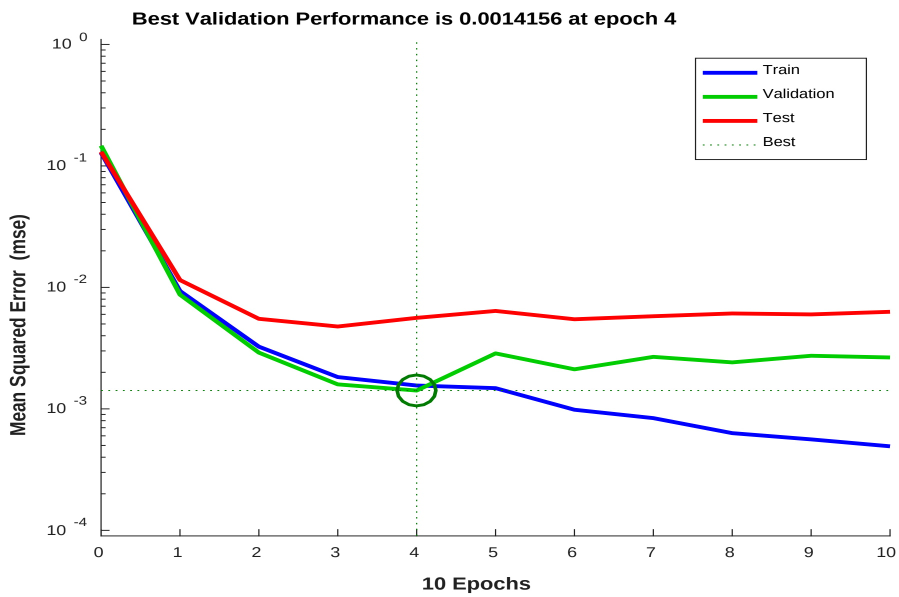

Figure 4.2: The best validation results for NARX_ANN_LM_ALL

After that, in predicting electricity usage for the week of March, the error histogram using the above-mentioned forecasting ANN was presented (see Figure 4.3).

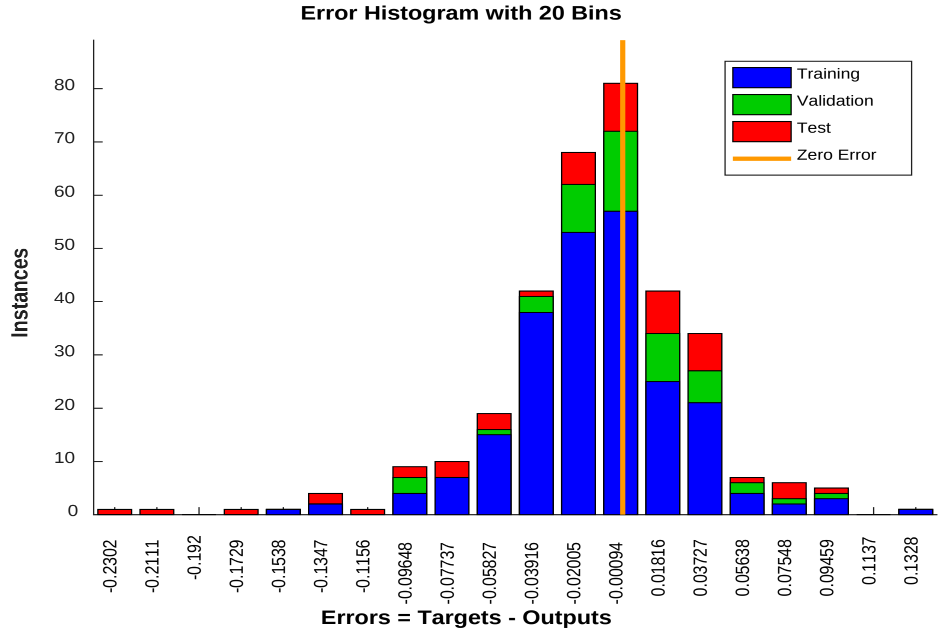

Figure 4.3: The error histogram in the week of March, using the NARX

Analysing the plot, it has been noticed that most of the errors fall between −0.02005 and 0.01816, a short range. There are only a few training points on observation that fall outside the range of errors. In this case, the error histogram shows good results.

Eventually the system represented another important plot, the regressions between network targets and outputs, in order to analyse the predictive accuracy. The values indicating correlation coefficient R are close to 1, all of them being equal to 0.9452. Therefore, a conclusion was reached that a good fit was obtained (see Figure 4.4).

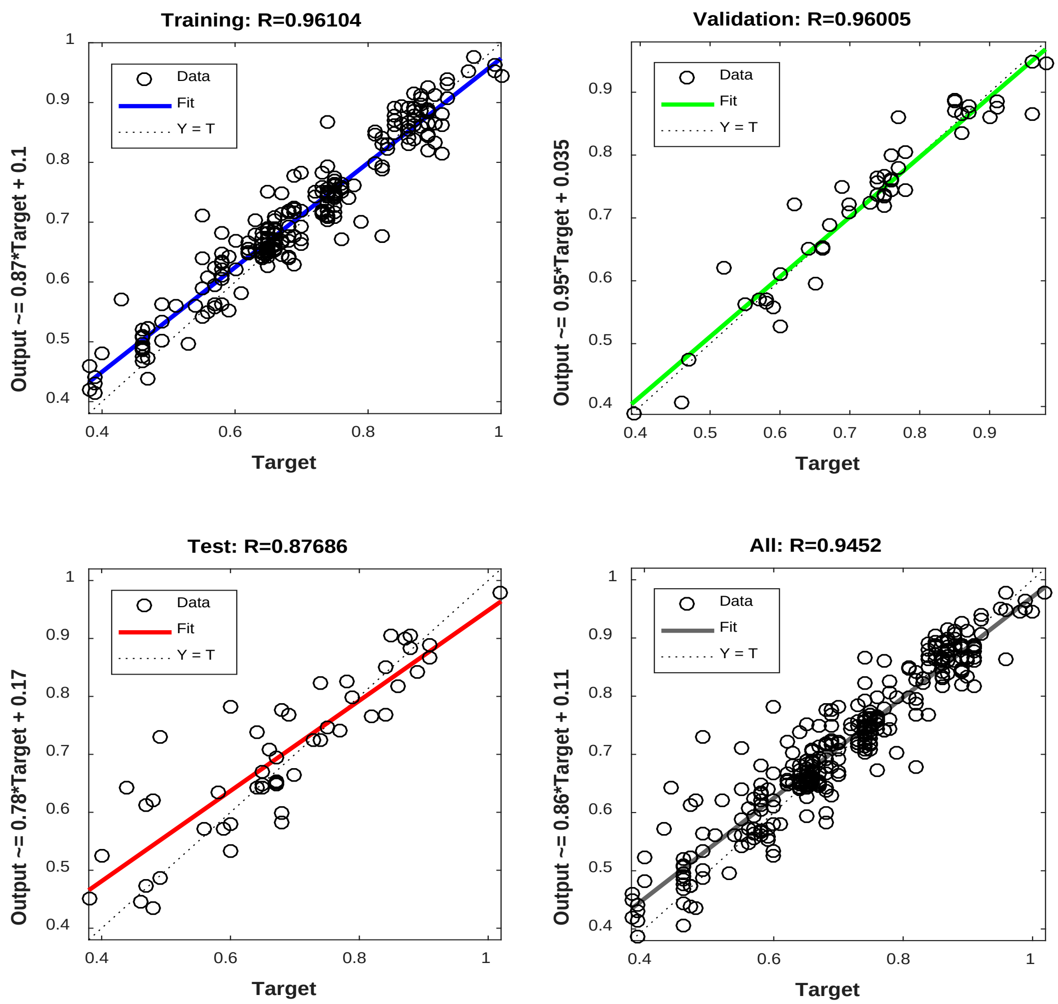

Figure 4.4: The regression plots using the NARX_ANN

To validate the output of the network, the way in which the prediction errors are related in time through the autocorrelation function was also analysed. In this situation the rest fall in the 95 % confidence limit above zero, except for a few including zero-lag correlation, and the relevance of the forecasting method is thus verified (see Figure 4.5). Figure 4.6 shows two graphs of actual and forecast load for 48 hours ahead for the Lift Department which emerged from the NARX weather sensitive model.

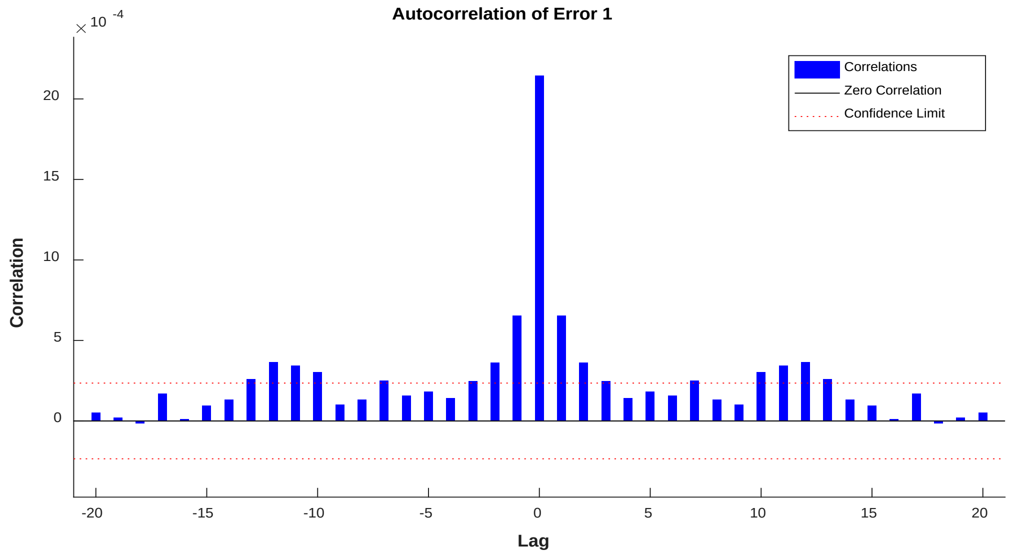

Figure 4.5: The error autocorrelation function, using the NARX_ANN

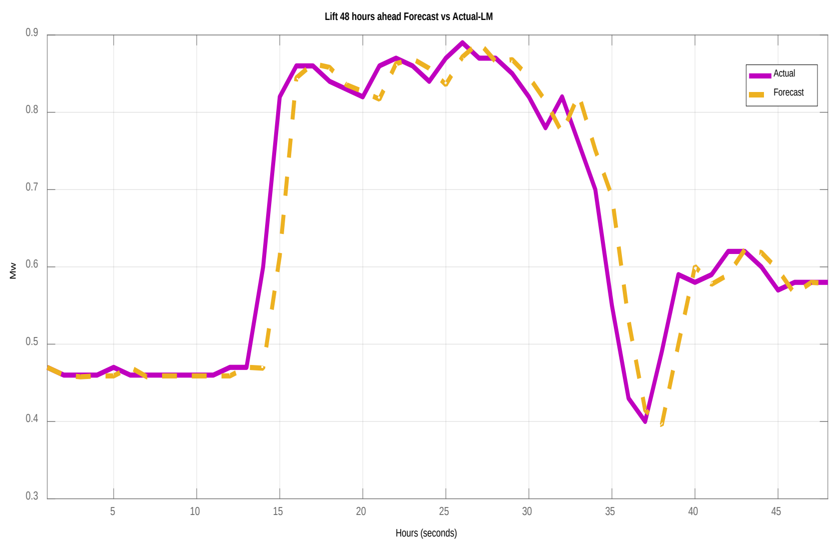

Figure 4.6: Forecast using Levenberg-Marquardt for lift

4.3.2 *Forecasting the load for the Administrative Building*

The Administrative Building's load measurements at Transnet Port Terminal in East London were taken from 1st June – 14th June 2018. The data set were therefore described as training data (7th June – 13th June) and target data (31st May – 6th June) respectively.

4.3.2.1 Results with respect to the ANN prediction solution developed based on the NARX Model, climate and time used as exogenous variables, contained in Table 4.2

Table 4.2 Results developed using the weather and time stamp for Admin Building

The Levenberg-Marquardt Training Algorithm						
n	***d***	**3**	**5**	**10**	**20**	**40**
5	**MSE**	0.0058598	0.0040027	0.0041171	0.0043699	0.0057633
	R	0.95204	0.87445	0.93506	0.96062	0.96614
10	**MSE**	0.0021875	0.0030078	0.0052888	0.0057832	0.0048998
	R	0.94365	0.93247	0.93242	0.97203	0.95592
20	**MSE**	0.0041747	0.0031809	0.0050763	0.0053925	0.0085429
	R	0.939	0.92816	0.92183	0.96799	0.94783

Lowest MSE is 0.0021875 and R value is 0.94365. Figure 4.7 shows two graphs of actual and forecast load for one week ahead forecast for the Administrative Building which emerged from the NARX Weather Sensitive Model.

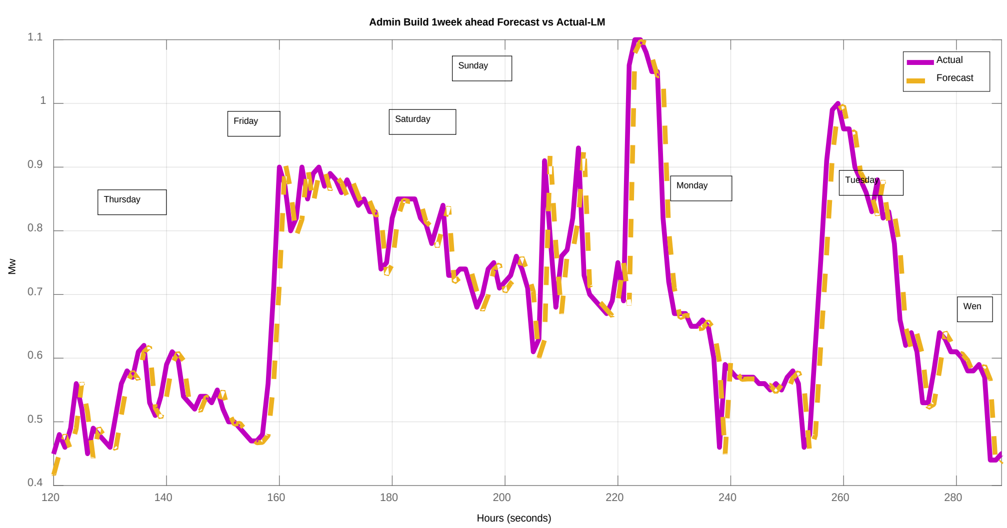

Figure 4.7: Forecast using the Levenberg-Marquardt for Admin Building

4.3.3 *Forecasting the load for the Electrical W/s*

The Electrical Workshop's load measurements at Transnet Port Terminal in East London were taken from the 15th June – 28th June 2018. The data set were therefore described as training data (21st June – 27th June) and target data (14th – 20th June) respectively.

4.3.3.1 Results with respect to the ANN prediction solution developed based on the NARX Model, with climate and time used as exogenous variables, as contained in Table 4.3

Table 4.3 Results developed using the weather and time stamp for Electrical W/s

The Levenberg-Marquardt Training Algorithm						
n	***d***	**3**	**5**	**10**	**20**	**40**
5	**MSE**	0.0046049	0.0049389	0.0040172	0.0034581	0.0043945
	R	0.93455	0.89279	0.94593	0.88623	0.97786
10	**MSE**	0.0069446	0.0036845	0.0066709	0.0042037	0.003925
	R	0.93167	0.96286	0.9047	0.95716	0.97358
20	**MSE**	0.00369	0.0052294	0.0065786	0.0036141	0.0064274
	R	0.92622	0.9308	0.89997	0.95506	0.96064

Lowest MSE is 0.0034581 and R value is 0.88623. Figure 4.8 shows two graphs of actual and forecast load for one week ahead for the Electrical W/s which emerged from the NARX Weather Sensitive Model.

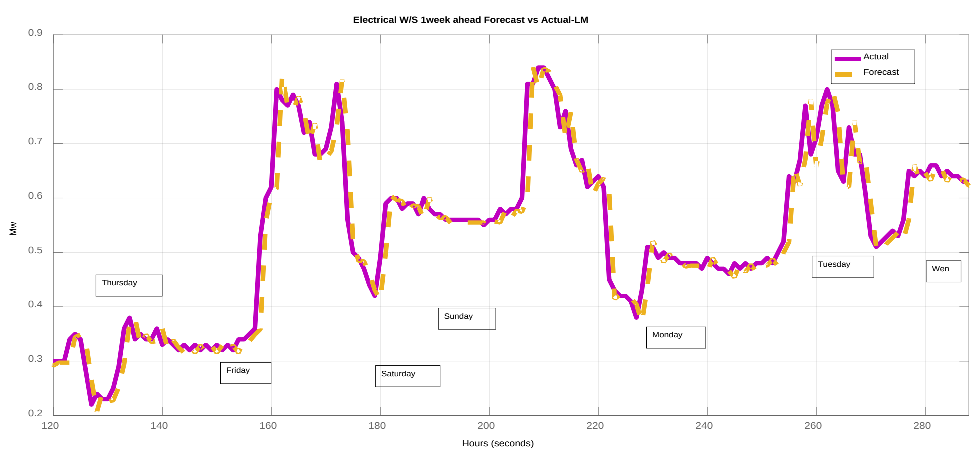

Figure 4.8: Forecast using Levenberg-Marquardt for electrical W/s

4.3.4 Forecasting the load for the Millwright W/S Department

The Millwright W/S Department's load measurements at Transnet Port Terminal in East London were taken from 12th August – 31st August 2018. The data set were therefore described as training data (24th August – 30th August) and target data (16th – 22nd August) respectively.

4.3.4.1 Results with respect to the ANN prediction solution developed based on the NARX Model, with climate and time used as exogenous variables, as indicated in Table 4.4

Table 4.4 Results developed using the weather and time stamp for Millwright W/s

The Levenberg-Marquardt Training Algorithm						
n	***d***	**3**	**5**	**10**	**20**	**40**
5	**MSE**	0.0037685	0.0016794	0.0035046	0.0047702	0.0021919
	R	0.94566	0.93693	0.94892	0.89219	0.98186
10	**MSE**	0.0020914	0.002507	0.0016728	0.0038385	0.0018174
	R	0.94074	0.93853	0.95559	0.96774	0.96785
20	**MSE**	0.0022072	0.0035929	0.0022821	0.0033704	0.0040651
	R	0.94018	0.95642	0.94501	0.96854	0.96142

Lowest MSE is 0.0016728 and R value is 0.95559. Figure 4.9 shows two graphs of actual and forecast load for one week ahead forecast for the Millwright W/s which emerged from the NARX Weather Sensitive Model.

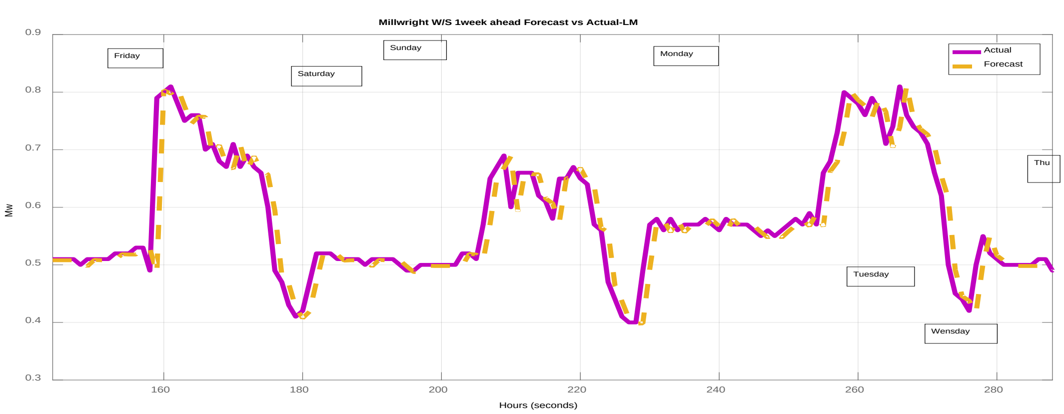

Figure 4.9: Forecast using Levenberg-Marquardt for Millwright W/s

4.3.5 Forecasting the load for Car Terminal Department

The load measurements of the Car Terminal Department at Transnet Port Terminal in East London were taken from the 2nd April – 15th April 2018. The data set were therefore described as training data (8th April – 14th April) and target data (1st – 7th April) respectively.

4.3.5.1 Results with climate and time used as exogenous variables, as contained in Table 4.5

Table 4.5 Results developed using the weather and time stamp for car terminal

The Levenberg-Marquardt Training Algorithm						
n	***d***	**3**	**5**	**10**	**20**	**40**
5	**MSE**	0.0017243	0.0041164	0.0020794	0.0043838	0.0014852
	R	0.91424	0.93034	0.95188	0.94992	0.97296
10	**MSE**	0.00233	0.004583	0.0014868	0.0025163	0.0063421
	R	0.91394	0.93713	0.93431	0.97227	0.94389
20	**MSE**	0.0061674	0.0021524	0.0058691	0.0050561	0.0035644
	R	0.9325	0.93887	0.93478	0.95471	0.96081

Lowest MSE is 0.0014852 and R value is 0.97296. Figure 4.10 shows two graphs of actual and forecast load for one week ahead forecast for the Car Terminal Department which emerged from the NARX Weather Sensitive Model.

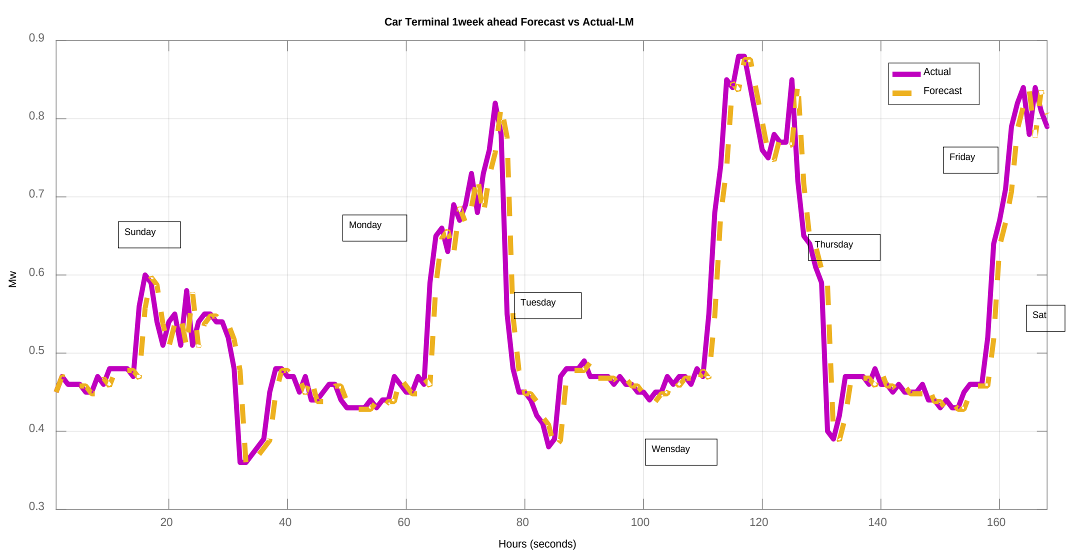

Figure 4.10: Forecast using Levenberg-Marquardt for car terminal

4.3.6 *Forecasting the load for the Fuel Depot Department*

The load measurements of the Fuel Depot Department at Transnet Port Terminal in East London were taken from 15th May – 28th May 2018. The data set were therefore described as training data (22nd May – 28th May) and target data (15th – 21st May) respectively.

4.3.6.1 Results with respect to the ANN prediction solution developed based on the NARX Model, climate and time used as exogenous variables, as contained in Table 4.6

Table 4.6 Results developed using the weather and time stamp for fuel depot

The Levenberg-Marquardt Training Algorithm						
n	***d***	**3**	**5**	**10**	**20**	**40**
5	**MSE**	0.0024623	0.0048173	0.004182	0.0068079	0.0023822
	R	0.93228	0.93653	0.9293	0.94921	0.98173
10	**MSE**	0.0025314	0.0071958	0.0092482	0.0061181	0.0043989
	R	0.93037	0.93839	0.9182	0.93574	0.96972
20	**MSE**	0.0051813	0.00413	0.012275	0.0066628	0.0046532
	R	0.93087	0.92182	0.89447	0.94368	0.9597

Lowest MSE is 0.0023822 and R value is 0.98173. Figure 4.11 shows two graphs of actual and forecast load for one week ahead forecast for the Fuel Depot Department which emerged from the NARX Weather Sensitive Model.

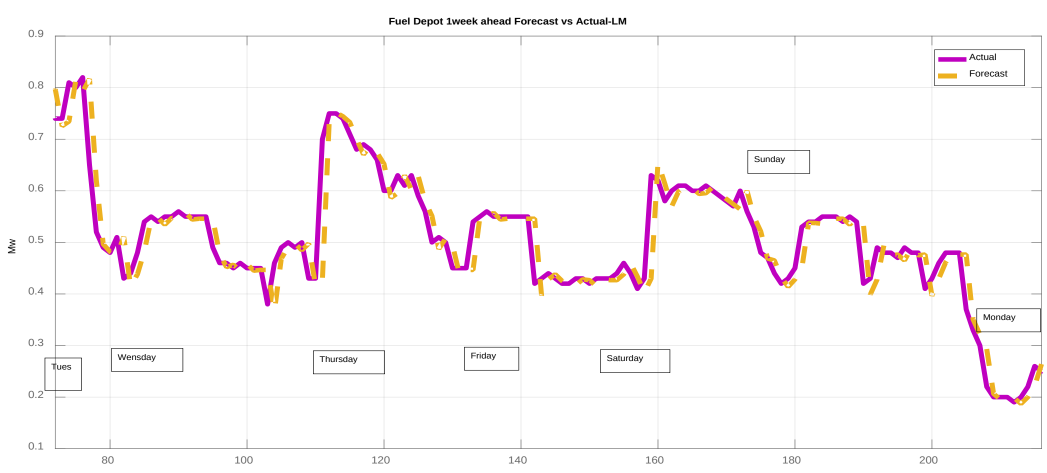

Figure 4.11: Forecast using Levenberg-Marquardt for fuel depot

4.3.7 *Forecasting the load for Saddle Carrier W/s*

The load measurements of the Saddle Carrier W/s at Transnet Port Terminal in East London were taken from the 3rd September – 16th September 2018. The data set were therefore described as training data (9th September – 15th September) and target data (2nd – 8th September) respectively.

4.3.7.1 Results with respect to the ANN prediction solution developed based on the NARX Model, with climate and time used as exogenous variables, as contained in Table 4.7

Table 4.7 Results developed using the weather and time stamp for Saddle Carrier W/s

		The Levenberg-Marquardt Training Algorithm				
n	***d***	**3**	**5**	**10**	**20**	**40**
5	**MSE**	0.0026051	0.0010939	0.0013999	0.0018192	0.0022018
	R	0.96643	0.97299	0.97035	0.97484	0.98477
10	**MSE**	0.0024205	0.0014813	0.0013784	0.0026876	0.0026122
	R	0.97259	0.9545	0.97606	0.98001	0.97474
20	**MSE**	0.0018696	0.0021341	0.0015637	0.0014362	0.0051963
	R	0.97556	0.97906	0.97765	0.98075	0.96491

Lowest MSE is 0.0010939 and R value is 0.97299. Figure 4.12 shows two graphs of actual and forecast load for one week ahead forecast for the Saddle Carrier W/S which emerged from the NARX Weather Sensitive Model.

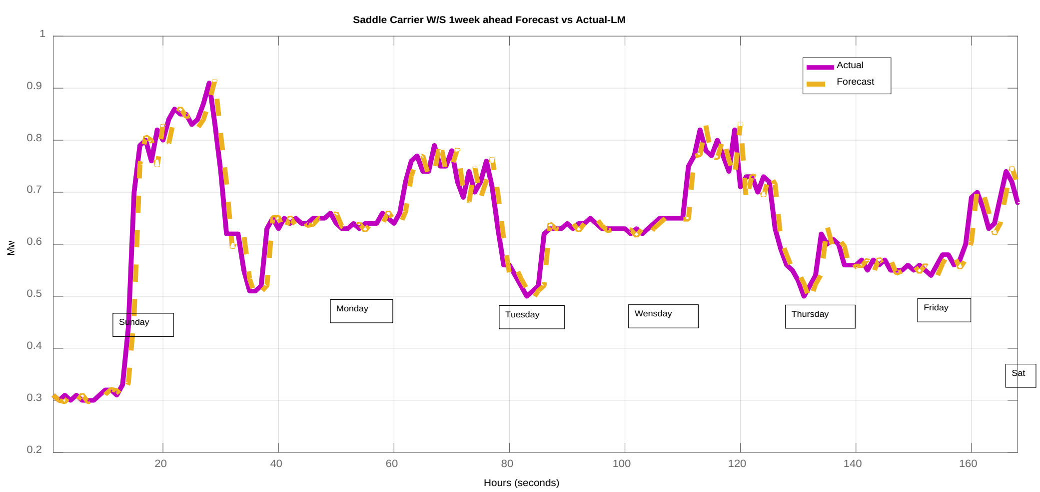

Figure 4.12: Forecast using Levenberg-Marquardt for Saddle Carrier W/s

4.4 Forecasting the total/combined loads

4.4.1 Forecasting the total/combined load for summer

The load measurements of the total/combined load for summer at Transnet Port Terminal in East London were taken from the 12th March – 25th March 2018. The data set were therefore described as training data (18th March – 24th March) and target data (11th – 17th March) respectively.

Lowest MSE is 0.0023122 and R value is 0.97549. Figure 4.13 shows two graphs of actual and forecast load for one week ahead prediction for the summer load which emerged from the NARX Weather Sensitive Model.

4.4.1.1 Results with respect to the ANN prediction solution developed based on the NARX Model, climate and time used as exogenous variables, as contained in Table 4.8

Table 4.8 Results developed using the weather and time stamp for summer

The Levenberg-Marquardt Training Algorithm						
n	***d***	**3**	**5**	**10**	**20**	**40**
5	**MSE**	0.0033876	0.0035343	0.0030013	0.0027362	0.0044843
	R	0.89001	0.95293	0.96464	0.96199	0.96961
10	**MSE**	0.0030221	0.0023122	0.0045779	0.0035201	0.0057965
	R	0.96433	0.97549	0.96314	0.9699	0.95937
20	**MSE**	0.0025454	0.0028651	0.0015637	0.0087932	0.0054254
	R	0.96048	0.96501	0.95695	0.94156	0.9426

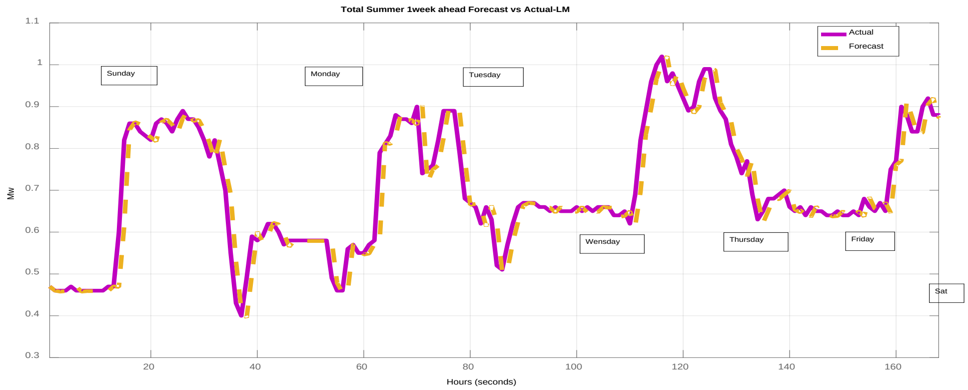

Figure 4.13: Forecast using Levenberg-Marquardt for total load summer

4.4.2 *Forecasting the total/combined load for winter*

The load measurements of the total/combined load for winter at Transnet Port Terminal in East London were taken from the 15th June – 28th June 2018. The data set were therefore described as training data (21st June – 27th June) and target data (14th – 20th June) respectively.

4.4.2.1 Results with respect to the ANN prediction solution developed based on the NARX Model, with climate and time used as exogenous variables, contained in Table 4.9

Table 4.9 Results developed using the weather and time stamp for winter

The Levenberg-Marquardt Training Algorithm						
n	***d***	**3**	**5**	**10**	**20**	**40**
5	**MSE**	0.0015996	0.0016605	0.0030271	0.0014461	0.00117
	R	0.96995	0.98127	0.97561	0.98712	0.97279
10	**MSE**	0.0020415	0.0017202	0.0035917	0.00267	0.0027768
	R	0.97895	0.96489	0.95655	0.98194	0.96998
20	**MSE**	0.0017988	0.0032385	0.0057617	0.0053734	0.0035842
	R	0.97301	0.97536	0.95881	0.96937	0.98014

Lowest MSE is 0.00117 and R value is 0.97279. Figure 4.14 shows two graphs of actual and forecast load for one week ahead prediction for the winter load which emerged from the NARX Weather Sensitive Model.

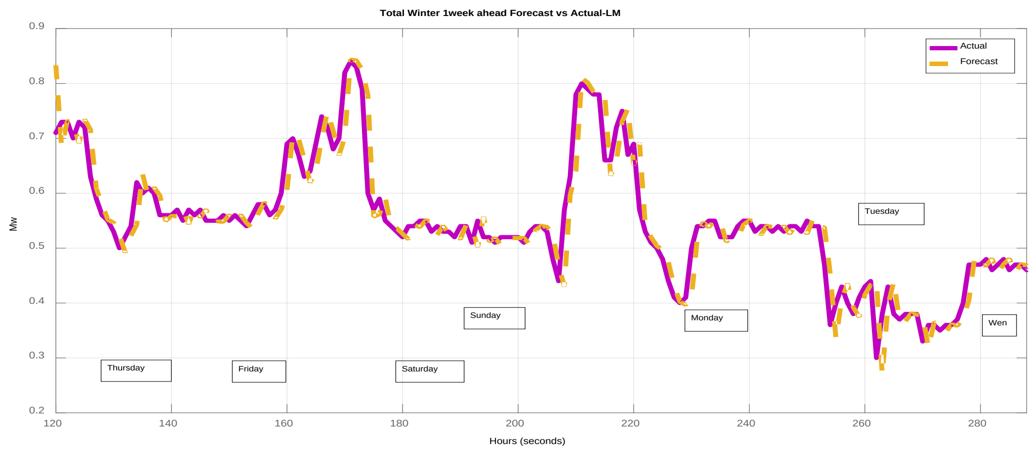

Figure 4.14: Forecast using Levenberg-Marquardt for total load winter

4.5 ANFIS prediction

The research data used in this section are the daily electrical load from Transnet Port Terminal East London for the period March 2018 - September 2018. The daily electrical load is composed from data collected every 30 minutes. So, in one day it consists of 48 data collections. Total data collections conducted for purposes of this research is 337 collections. The data were collected in two parts. The first group consisted of 70% of the data used for training, and the second group consisted of 30% data used for controlling purposes (15% for testing and 15% for validation).

4.5.1 Results with respect to the ANFIS Forecasting Solution for the Lift Department

The ANFIS approach is applied to forecasting next week electrical load for the Lift Department at the terminal. Load forecasting is computed using historical data from the 18^{th} to the 24^{th} of March, specifically on the 18^{th} Sunday of that week. Different types of membership functions were used to find the best forecasting result. Table 4.10 presents the MSE for each membership function in this section.

TABLE 4.10
Comparative MSE results

Day	MSE					
	trimf	trapmf	gbellmf	gaussmf	gauss2f	dsigmf
Sunday	0.0497	6.2645	0.2100	0.1659	0.5906	0.4770
Monday	0.1659	8.6914	0.5681	0.4141	1.2314	0.9497
Tuesday	0.0128	7.0265	0.1838	0.1156	1.7218	1.1067
Wednesday	0.0062	5.4196	0.1913	0.0832	1.2537	1.0305
Thursday	0.0367	5.0711	0.3811	0.2530	1.865	1.2688
Friday	0.0126	9.2435	0.1713	0.1203	1.6614	0.6449
Saturday	0.1417	5.4911	0.2874	0.1132	1.9730	0.9228
Average	0.4256	47.2077	1.993	1.2653	10.2969	6.3998

From Table 4.10 it can be seen that triangular-shaped membership function (trimf) has the smallest average error value 0.4256, while trapezoidal-shaped membership function (trapmf) has the largest average error value 47.2077. From this data it can be stated that trimf is the best type of membership function for electrical load forecasting in this research. Triangular-shaped membership function (trimf) was considered for input and constant membership function was considered for output parameters. Hybrid algorithm was used to define the optimum number of parameters to describe the FIS.

Training data for the 18th of March 2018 consisted of 75% of the data, while 25% of the data were assigned for testing in ANFIS. MSE was found as 0.0497 for both training and testing with 3 epochs (see Figure 4.15 below).

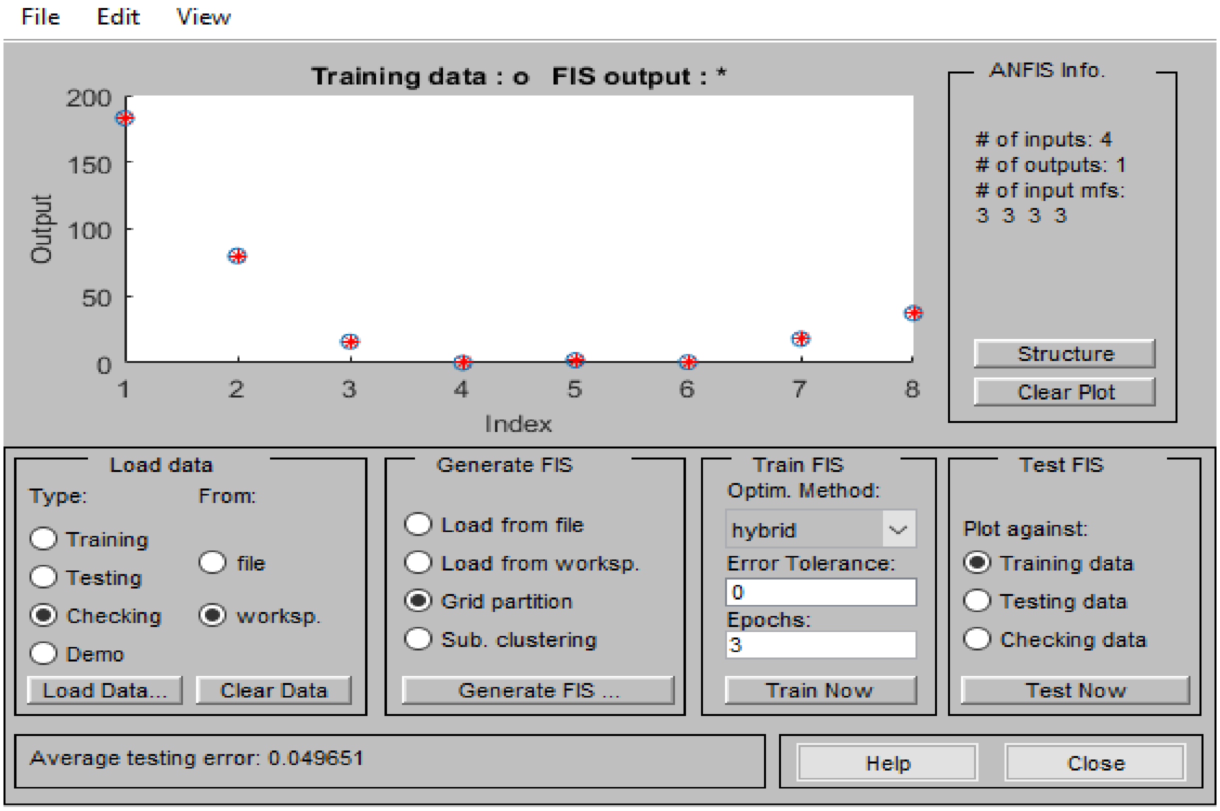

Figure 4.15: Plot for FIS output with 3 epochs on Sunday

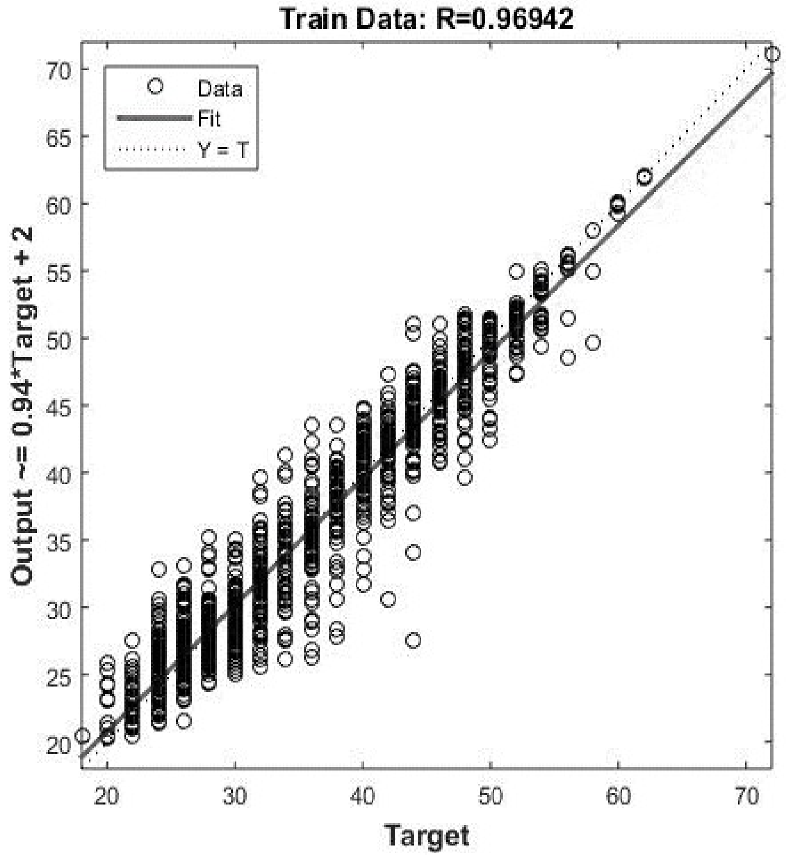

Figure 4.16: The regression plot using ANFIS on Sunday

The values indicating correlation coefficient *R* is 0.96942 away from 1, as shown in the figure above. This shows that there is almost an exact relationship between the output obtained from the network and the targets, and a good fit of the data points being used. Figure 4.17 below explains the relationship between the actual load and the predicted load graphically using the NARX and ANFIS models.

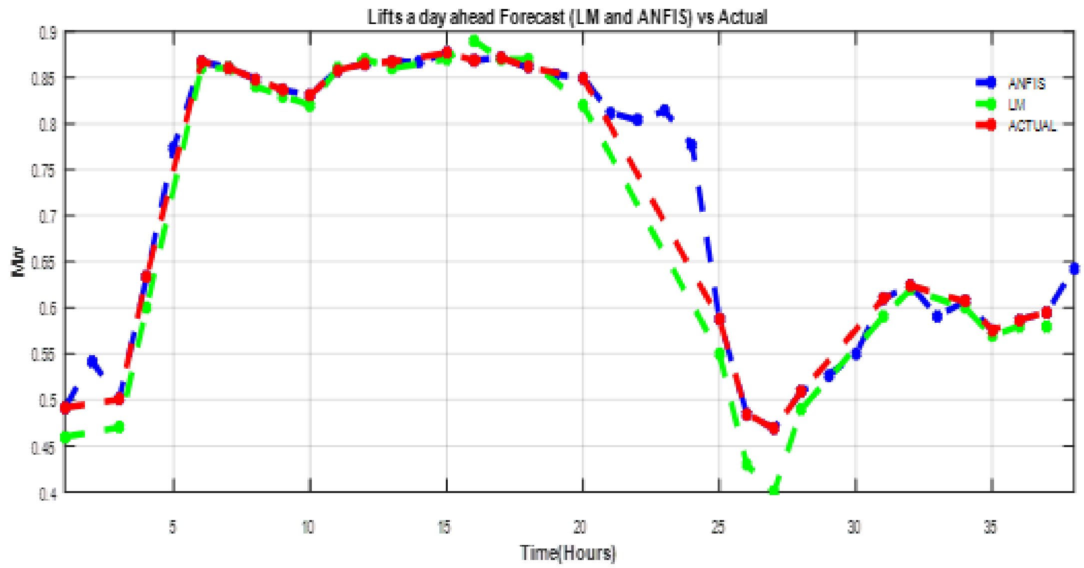

Figure 4.17: Forecast using LM and ANFIS for the 18th March 2018

TABLE 4.11 Error comparison for Sunday

Day	**Department**	Model	MSE	R
18th March 2018	**Lifts**	NARX	0.0014156	0.9452
		ANFIS	0.0497	0.96942

- The results demonstrate the optimal structure of both the NARX and ANFIS methods achieved with minimum forecasting error. The parameters of models were finalised after several trials and error efforts to give the optimum performance.

- The NARX Model has less MSE than the ANFIS Model. This represents a high degree of accuracy in the ability of neural networks to forecast electric load.

- It was observed during the case study that NARX is fast in comparison to ANFIS. NARX does not require the optimisation of numbers of neurons and layers in the network.

4.5.2 *Results for Administration Building*

TABLE 4.12
MSE results for Admin. Building on Monday

Day	MSE					
	trimf	trapmf	gbellmf	gaussmf	gauss2mf	dsigmf
Thursday	0.0124	0.5467	0.0210	0.0128	0.5245	0.4906
Friday	0.0028	0.5434	0.0234	0.0095	0.5258	0.4932
Saturday	5.3891	7.4264	5.7233	5.5695	6.3406	6.3176
Sunday	0.0215	4.4153	0.0560	0.0328	0.5107	0.4503
Monday	0.0032	3.1391	0.0820	0.0555	0.4909	0.4501
Tuesday	0.0624	4.1878	0.1365	0.1237	0.5010	0.4575
Wednesday	0.0012	5.8328	0.0824	0.0331	0.4745	0.4431
Average	5.4926	26.0915	6.3352	5.8369	9.368	9.1324

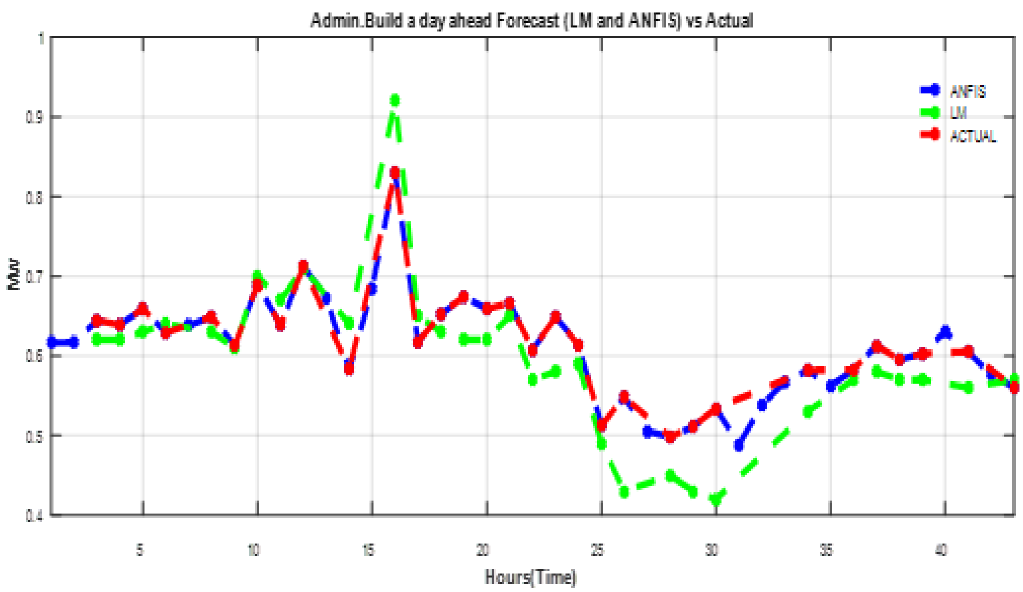

Figure 4.18: Forecast using LM and ANFIS for the 11th June 2018

TABLE 4.13 Error comparison for Monday

Day	**Department**	Model	MSE	R
11th June 2018	**Administration Building**	NARX	0.0021875	0.94365
		ANFIS	0.0032	0.7558

4.5.3 *Results for Electrical W/s*

TABLE 4.14
MSE results for Electrical W/s on Tuesday

Day	MSE					
	trimf	trapmf	gbellmf	gaussmf	gauss2f	dsigmf
Thursday	0.0301	9.5773	0.1118	0.0738	2.0116	0.8542
Friday	0.1016	7.2058	0.3350	0.3189	1.9054	1.1056
Saturday	0.0084	3.6197	0.2764	0.1513	0.7878	0.5906
Sunday	0.0364	3.6197	0.1730	01118	0.9205	0.6467
Monday	0.0177	12.6078	0.1947	0.1233	1.4841	0.6265
Tuesday	0.0578	10.2775	0.2175	0.1421	2.5344	1.3970
Wednesday	6.3622	22.1385	8.0377	6.8707	5.4523	5.9457
Average	6.6142	69.0401	9.3461	7.7919	15.0961	11.166

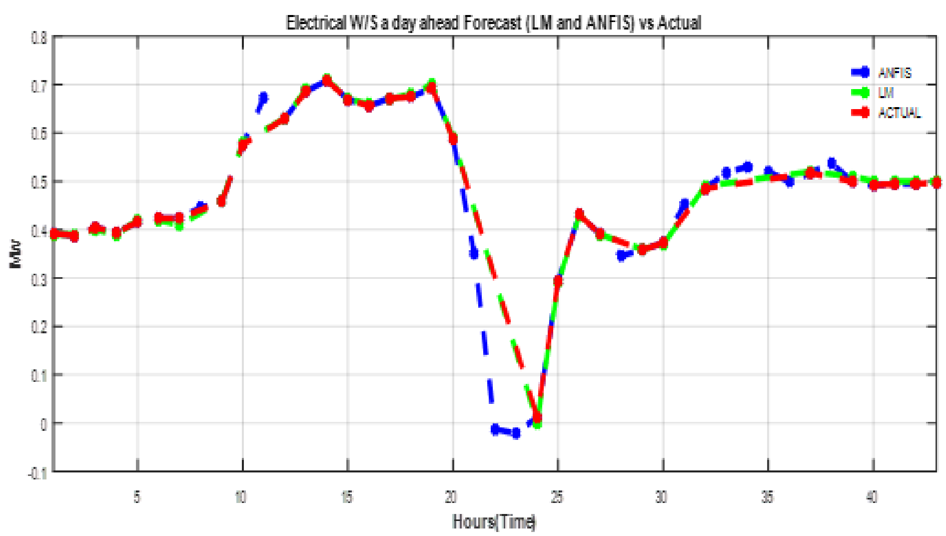

Figure 4.19: Forecast using LM and ANFIS for the 26th June 2018

TABLE 4.15 Error comparison for Tuesday

Day	**Department**	Model	MSE	R
26th June 2018	**Electrical W/S**	NARX	0.0034581	0.88623
		ANFIS	0.0578	0.99166

4.5.4 *Results for Millwright W/s*

TABLE 4.16
MSE results for Millwright W/s on Wednesday

	MSE					
Day	trimf	trapmf	gbellmf	gaussmf	gauss2f	dsigmf
Friday	0.0997	20.3642	0.5633	0.5444	3.5478	1.1688
Saturday	0.1243	25.7268	0.9278	0.8422	3.8433	1.7368
Sunday	1.1967	16.6266	1.3903	0.8316	4.4426	2.8761
Monday	0.0600	11.822	0.6777	0.3888	5.6346	1.6624
Tuesday	0.4536	12.5244	0.7897	0.7238	10.1033	0.5188
Wednesday	0.1549	23.8314	0.4386	0.4619	5.9330	0.7061
Thursday	0.1321	22.5955	0.4480	0.3775	5.6563	0.4944
Average	1.2213	133.40	5.2354	4.1702	39.1609	8.164

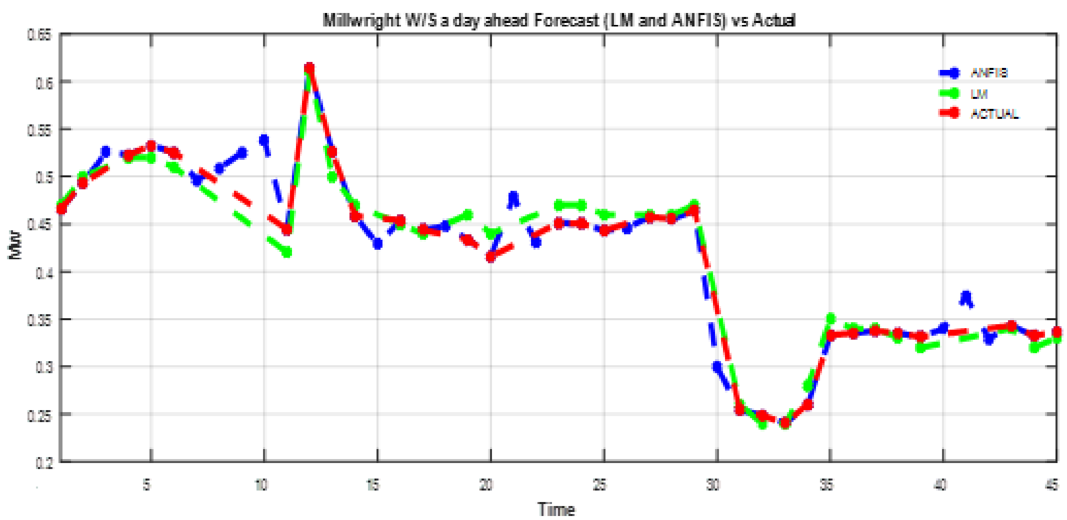

Figure 4.20: Forecast using LM and ANFIS for the 29th August 2018

TABLE 4.17 Error comparison for Wednesday

Day	**Department**	Model	MSE	R
29th August 2018	**Millwright W/S**	NARX	0.0016728	0.95559
		ANFIS	0.1549	0.99219

4.5.5 Car Terminal Department

TABLE 4.18
MSE results for Car Terminal on Thursday

Day	MSE					
	trimf	trapmf	gbellmf	gaussmf	gauss2f	dsigmf
Sunday	0.0036	0.5237	0.0404	0.0128	0.5106	0.4861
Monday	0.0030	0.5264	0.0250	0.0123	0.5110	0.4780
Tuesday	0.0038	2.9718	0.0359	0.0130	0.5117	0.4813
Wednesday	0.0084	5.0941	0.0418	0.0157	0.5295	0.5151
Thursday	0.0270	9.8084	0.2073	0.1087	0.6356	0.5243
Friday	0.0757	13.0594	0.4151	0.2894	0.5040	0.4988
Saturday	0.0597	17.8124	0.1500	0.0748	2.5206	1.0365
Average	0.1812	49.7962	0.9155	0.5267	5.723	4.0201

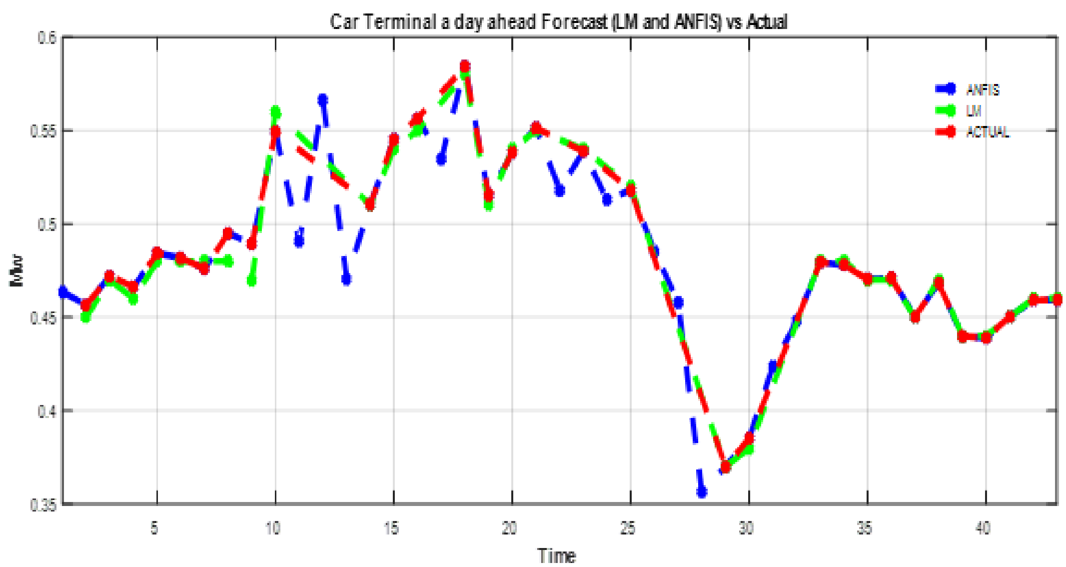

Figure 4.21 Forecast using LM and ANFIS for the 12th April 2018

TABLE 4.19 Error comparison for Thursday

Day	**Department**	Model	MSE	R
12th April 2018	**Car Terminal**	NARX	0.0014852	0.97295
		ANFIS	0.0270	0.5611

4.5.6 *Fuel Depot*

TABLE 4.20
MSE results for Fuel Depot on Friday

	MSE					
Day	trimf	trapmf	gbellmf	gaussmf	gauss2f	dsigmf
Tuesday	0.0084	5.4189	0.1490	0.0872	0.5498	0.4493
Wednesday	0.0476	11.6758	0.2254	0.1065	0.7912	0.5814
Thursday	0.0060	5.2369	0.1470	0.0868	0.7327	0.4399
Friday	0.0112	10.6812	0.1405	0.0842	1.8092	0.6264
Saturday	0.0195	11.1724	0.1665	0.1046	1.7628	0.6307
Sunday	0.0292	6.3783	0.2243	0.1577	1.5430	0.7357
Monday	0.0620	12.06	0.0918	0.0555	0.9283	0.5062
Average	0.1839	62.6235	1.1445	0.6825	8.117	3.9696

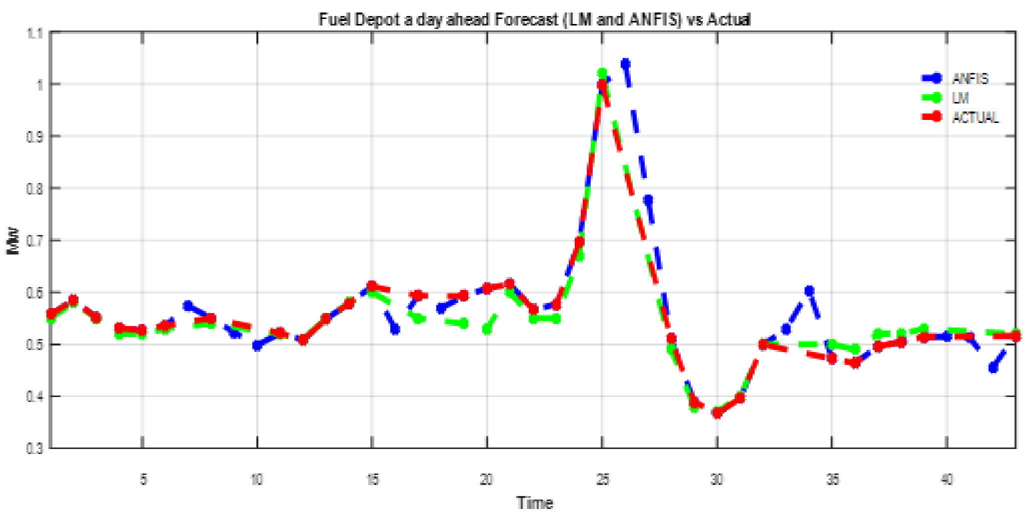

Figure 4.22: Forecast using LM and ANFIS for the 25th May 2018

TABLE 4.21 Error comparison for Friday

Day	**Department**	Model	MSE	R
25th May 2018	**Fuel Depot**	NARX	0.0023822	0.98173
		ANFIS	0.0112	0.92506

4.5.7 Saddle Carrier W/s

TABLE 4.22
MSE results for Saddle Carrier W/s on Saturday

	MSE					
Day	trimf	trapmf	gbellmf	gaussmf	gauss2f	dsigmf
Sunday	0.3686	31.9659	1.2178	0.7221	8.4387	0.7963
Monday	0.2378	36.7322	0.8043	0.4908	9.1556	0.5208
Tuesday	0.4258	40.0709	0.4349	0.4394	8.9270	0.6853
Wednesday	0.5331	40.8288	0.5634	0.5190	9.0431	0.5719
Thursday	0.1390	44.5995	0.8690	0.6198	10.9788	0.9268
Friday	0.1958	47.9835	0.6220	0.4433	8.3274	0.9355
Saturday	0.1982	50.8006	1.0571	0.4986	13.103	0.5260
Average	2.0989	292.984	5.5685	3.733	67.9736	4.9626

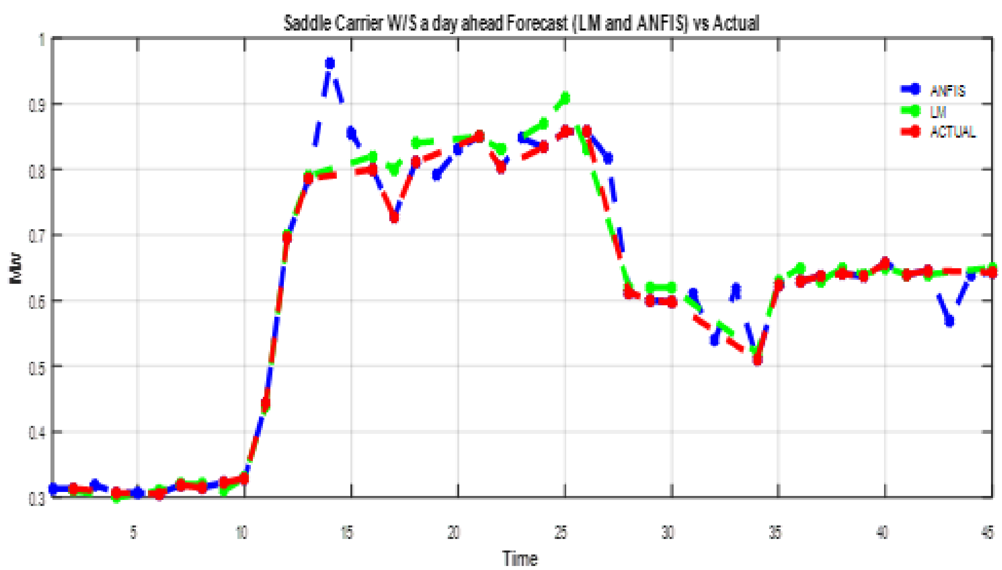

Figure 4.23: Forecast using LM and ANFIS for the 15th September 2018

TABLE 4.23 Error comparison for Saturday

Day	**Department**	Model	MSE	R
15th September 2018	**Saddle Carrier W/S**	NARX	0.0010939	0.97299
		ANFIS	0.01982	0.93792

4.5.8 Total summer

TABLE 4.24
MSE results for total summer on Sunday

	MSE					
Day	trimf	trapmf	gbellmf	gaussmf	gaussmf	dsigmf
Sunday	0.1513	5.3526	0.2328	0.2223	1.1535	0.6593
Monday	0.1481	7.8020	0.4667	0.3973	1.6135	1.2287
Tuesday	0.2143	6.1399	0.7503	0.7028	2.9032	1.5845
Wednesday	0.3380	4.7682	0.6492	0.6333	3.0615	1.1506
Thursday	0.0741	4.9879	0.3333	0.2270	1.8861	1.2320
Friday	0.0945	7.9879	0.1878	0.1831	2.8461	1.0221
Saturday	0.5445	5.1934	1.4267	1.0986	4.0089	1.7476
Average	1.5648	42.2272	4.0468	3.4644	17.4728	8.6248

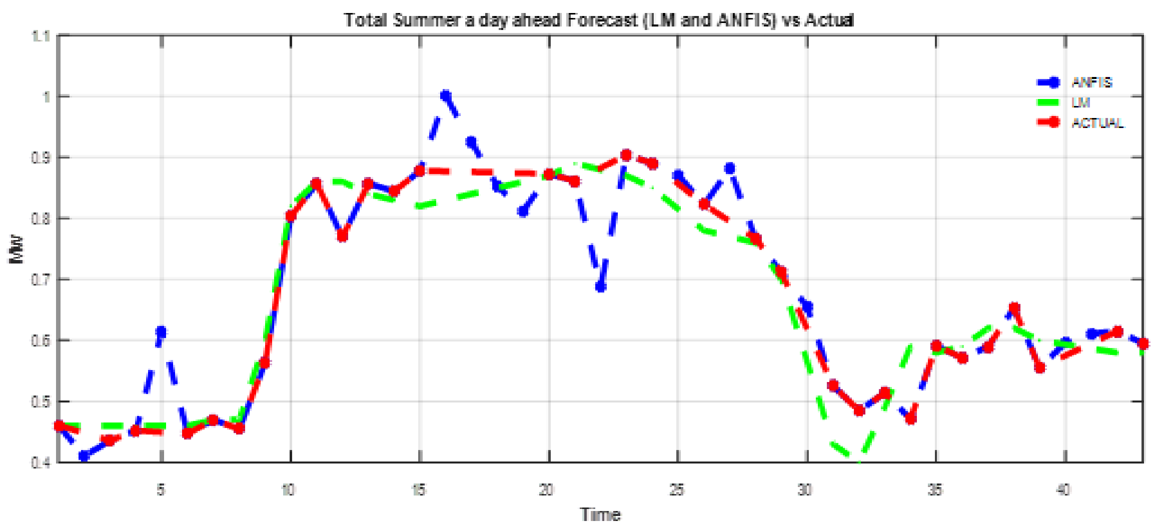

Figure 4.24: Forecast using LM and ANFIS for the summer

TABLE 4.25 Error comparison for a summer day Sunday

Day	**Department**	Model	MSE	R
18th March 2018	**Total Summer**	NARX	0.0023122	0.97549
		ANFIS	0.1513	0.96942

4.5.9 *Total winter period*

TABLE 4.26
MSE results for total winter on Monday

Day	MSE					
	trimf	trapmf	gbellmf	gaussmf	gauss2mf	dsigmf
Thursday	0.0565	8.5605	0.1816	0.1535	3.3271	2.0783
Friday	0.3296	6.8328	0.6616	0.6146	2.3233	1.1923
Saturday	0.1108	5.8813	0.2702	0.2431	1.7655	0.7511
Sunday	0.1927	6.3367	0.4390	0.1790	4.5845	1.6194
Monday	0.0652	10.7233	0.2034	0.1120	2.0138	1.1659
Tuesday	0.5924	9.2321	0.5588	0.5423	2.5605	1.3665
Wednesday	5.5419	18.2162	6.0887	5.3253	4.2035	4.5964
Average	6.8887	65.7829	8.4033	7.1698	20.7782	12.769

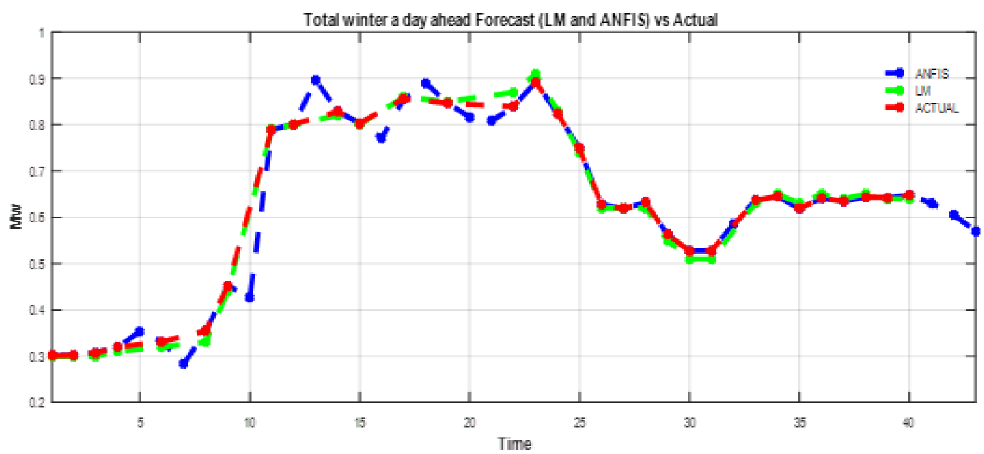

Figure 4.25: Forecast using LM and ANFIS for winter

TABLE 4.27 Error comparison for a winter day Monday

Day	**Department**	Model	MSE	R
25th June 2018	**Total Winter**	NARX	0.00117	0.97279
		ANFIS	0.0652	0.95774

TABLE 4.28 NARX and ANFIS prediction models using different types of departments in the port

Day	Department	Model	MSE	R
18th March 2018	Lifts	NARX	0.0014156	0.9452
		ANFIS	0.0497	0.96942
11th June 2018	Administration Building	NARX	0.0021875	0.94365
		ANFIS	0.0032	0.7558
26th June 2018	Electrical W/s	NARX	0.0034581	0.88623
		ANFIS	0.0578	0.99166
29th August 2018	Millwright W/s	NARX	0.0016728	0.95559
		ANFIS	0.1549	0.99219
12th April 2018	Car Terminal	NARX	0.0014852	0.97295
		ANFIS	0.0270	0.5611
25th May 2018	Fuel Depot	NARX	0.0023822	0.98173
		ANFIS	0.0112	0.92506
15th September 2018	Saddle Carrier W/s	NARX	0.0010939	0.97299
		ANFIS	0.01982	0.93792
18th March 2018	Total summer	NARX	0.0023122	0.97549
		ANFIS	0.1513	0.96942
25th June 2018	Total winter	NARX	0.00117	0.97279
		ANFIS	0.0652	0.95774

4.6 Significance of the results and discussions

The forecasts achieved can also be used as reference for the formulation of internal management policies of the Transnet Port Terminal loads, such as the generation of electricity and the application of demand-side management initiatives. The fluctuating load curves, seasonal variations, weather drifts, and operational standards of the Transnet Port Terminal have resulted in stochastic energy demands. The forecasting results have assisted to develop a port terminal load demand pattern to be modelled as a stochastically timedependent process with various data samples d, such as d = 3, d = 5, and d = 10. Every time-varying event in the harbour is stochastic, such as load demand and utility perturbation revenues. These prediction models' results will estimate present and future utilities revenue outcomes from the random load demand patterns of the Transnet Port Terminal. The findings also have helped to establish an accurate prediction solution that uses comprehensive data on consumption of energy obtained from the following departmental list of equipment in the harbour: air conditioners, lifts and conveyer belts, pumps, grinding and cutting machines, drill press, welding machines and office machines, making it possible for the port terminal to develop a tailored, productive consumption plan that better fits their needs, achieving substantial savings in electricity costs. This will guarantee the provision of stable electricity throughout the port on a yearly basis, and a smooth running of export and import operations of cargo at the terminal.

The development of hourly and weekly consumption forecasting solutions will also help to enhance energy management, which benefits both the port terminal (in order to choose the right billing plan that corresponds to their actual consumption trends and to formulate an appropriate business strategy), and the electricity suppliers (in order to implement the best possible market strategies suited to the needs of the customer). The optimal operation can be planned by applying these techniques, depending on the versatility of the consumer. As a further step, the port can submit the day-ahead consumption schedule to the supplier (his forecast) and obtain the optimal schedule (considering a certain objective function) based on its versatility that would improve energy efficiency.

A precise forecast for grid operations such as ESKOM, with its continuous economic growth and the company facing power deficiencies would assist it to deal more effectively with the problem of load shedding. The accuracy of the forecast would help ESKOM to save money by not committing costly, independently operated coal generation units. This can ease the government's burden by regulating the subsidised amount on the current energy tariff.

4.7 Conclusion

Applying Artificial Neural Networks to a problem of short-term load prediction is clearly seen in this chapter, as well as being able to discover and classify a faster algorithm such as Levenberg-Marquardt. The results of the simulation obtained from the NARX-LM and ANFIS models are self-explanatory.

All in all, for both NARX and ANFIS cases, the error analysis comparison results (MSE) show that the built hour-by-hour models are accurate, effective and also have high accuracy levels, as these models adapted very well unconditionally to the test data provided.

Table 4.28 shown above presents the best performance for both NARX and ANFIS models in terms of Mean Squared Error (MSE), which recorded the smallest errors between the actual and forecasting data in their respective departments, namely the Saddle Carrier W/s and the Administration Building, which read 0.0010939 for NARX and 0.0032 for ANFIS on the 15th September 2018 and 11th June 2018 respectively.

In contrast to the ANFIS Model, the results obtained using the NARX Model indicate a clear relationship between exogenous variables and electricity consumption, making the proposed forecasting approach a feasible alternative to other models.

CHAPTER 5

CONCLUSION AND FUTURE STUDIES

5.1 Application of the model

During the time of training with customer load data, such models can be slightly changed so that the total load of an energy utility business can be accurately predicted. As is the case with South Africa, the first step in making certain that there is steady consistent availability of electricity in this region is to get a good forecasting structure that can provide accurate, effective predictions that are reliable in an environment with predominant power shortages.

This will allow the economic operation of complex power system networks by power system planners and operators by taking good strategic decisions to perform key engineering duties such as power distribution planning, effective sharing and risk evaluation of electrical systems. A company is well aware that a basic thermoelectric synchronisation decision or an energy import / export schedule could cost millions of dollars if miscalculated. Most of these policy choices rely upon good forecasts, so undoubtedly, accurate forecasting techniques are critical.

As for power consumers, in particular LPUs, it is of the utmost importance to control their load in order to improve customer demand management strategies implemented by utility organisations in the South African region. This means that the estimation of load specifically helps to accelerate the process of power demand management. This practice also eliminates the risk of penalties that are charged for going above the maximum reported demand payable by customers. In particular, the forecasts obtained for the Port Terminal can basically be used to guide the parastatal on issues pertaining the development of internal load management schemes, such as urgent electrical distribution and the creation of a plan for the demand-side management policies.

These models that have been built could be applied in soft computing and further research into ANN, forecasting and control as part of the postgraduate course materials.

5.2 Conclusion

In order to predict the departmental loads and the total load of the Transnet Port Terminal in East London on an hourly to daily basis, various forecasting models (NARX and ANFIS) have been created.

A nonlinear autoregressive neural network with exogenous input (NARX) implementation has been presented. The method shows that by using all available endogenous and exogenous inputs, an ANN can be trained in an open loop. As the endogenous variable, electric load was used, and time and weather were used as exogenous inputs. The network is a recursive ANN, connecting the output, hidden and input layers. A Levenberg–Marquardt backpropagation algorithm was used to train the network.

The load input is disconnected, and the forecast (predicted) value of the output is fed back to the input after the neural weights have been calculated. It isolates the network and decreases the necessity for retraining to generate each instance of performance (predicted load) and increases the accuracy of the traditional ANN network to a forecast MSE of 0.0010939 for NARX, as compared to 0.0032 for ANFIS. The accuracy in the forecast is particularly important because the reduced forecasting error could save the port millions of dollars a year, from energy cost savings.

5.3 Suggestion for further studies

In particular, the focus of the project was limited to off-line training. However, certain problems need to be dealt with during the model creation process for real-time applications. The fact that the historical load curve and the weather data have bad data (outliers) can adversely influence the accuracy of the prediction.

A manually based approach was used to detect and replace bad data. However, this method is inadequate for applying the input variable curve in real time, and must therefore be automated with a mechanism to detect and replace irregular data. Building a genetic model for a detailed model structure performance analysis would be a smart idea, as well as comparing the following errors and network performance indices for further evaluation or for benchmarking purposes.

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APPENDICES

APPENDIX A

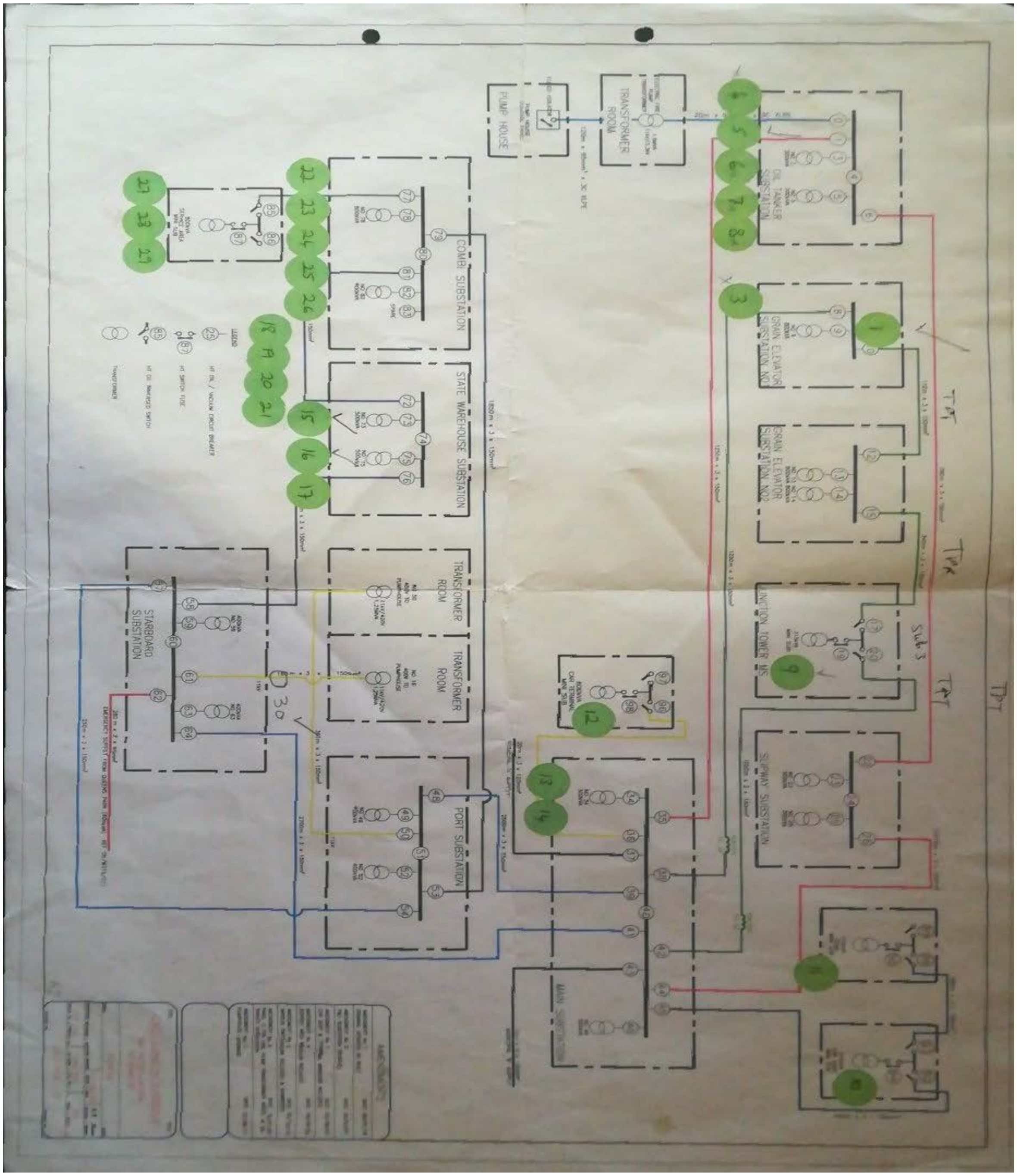


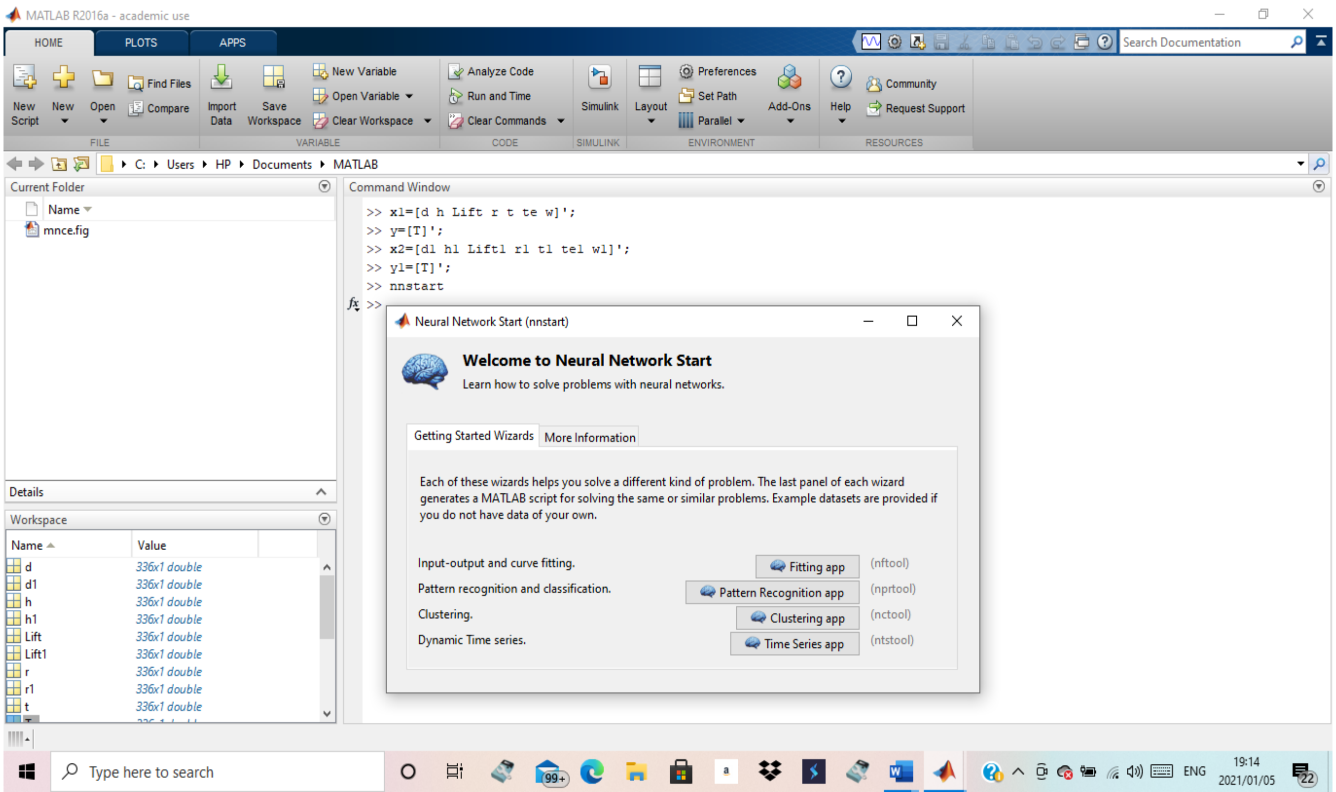
Figure A3.1: Transnet Port Terminal's single line diagram-11kV network reticulation

Figure A3.4: Car Terminal

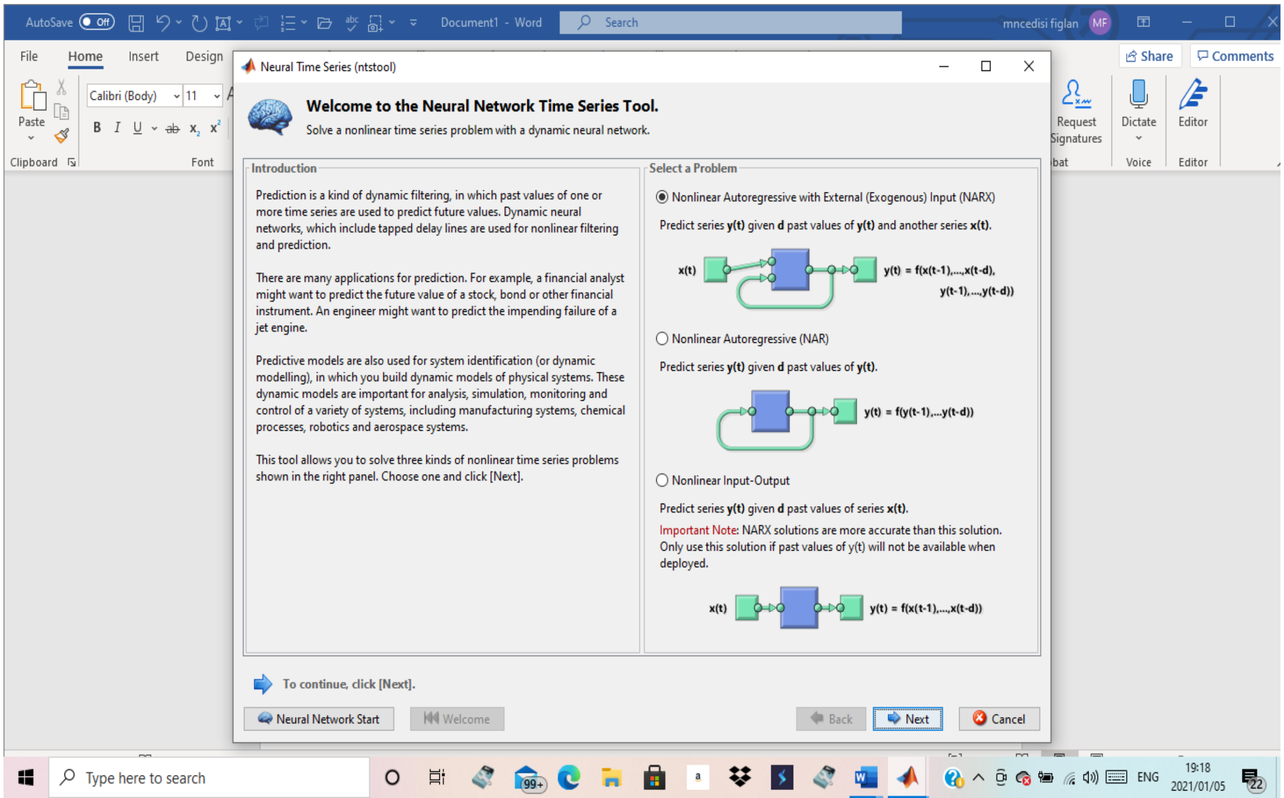
Figure A3.5: Transnet Port Terminal in East London

APPENDIX B

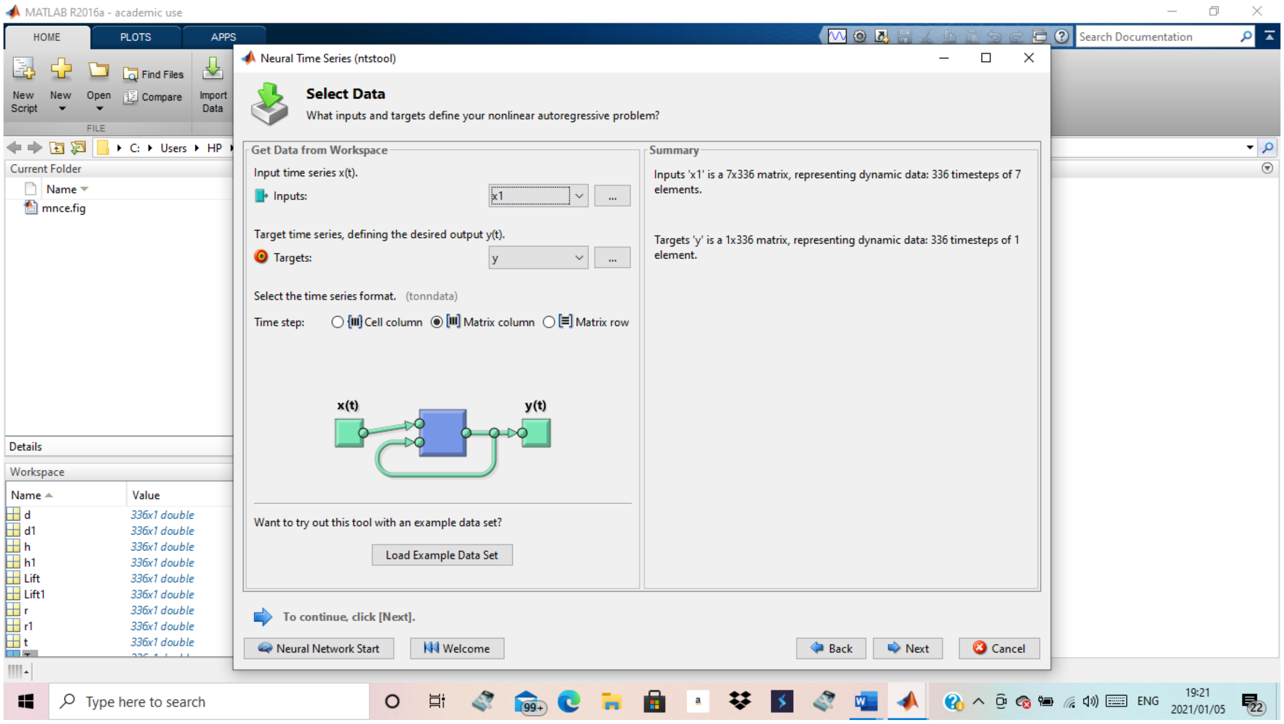
Screen shots of neural network design process using the NN TIME SERIES TOOL.



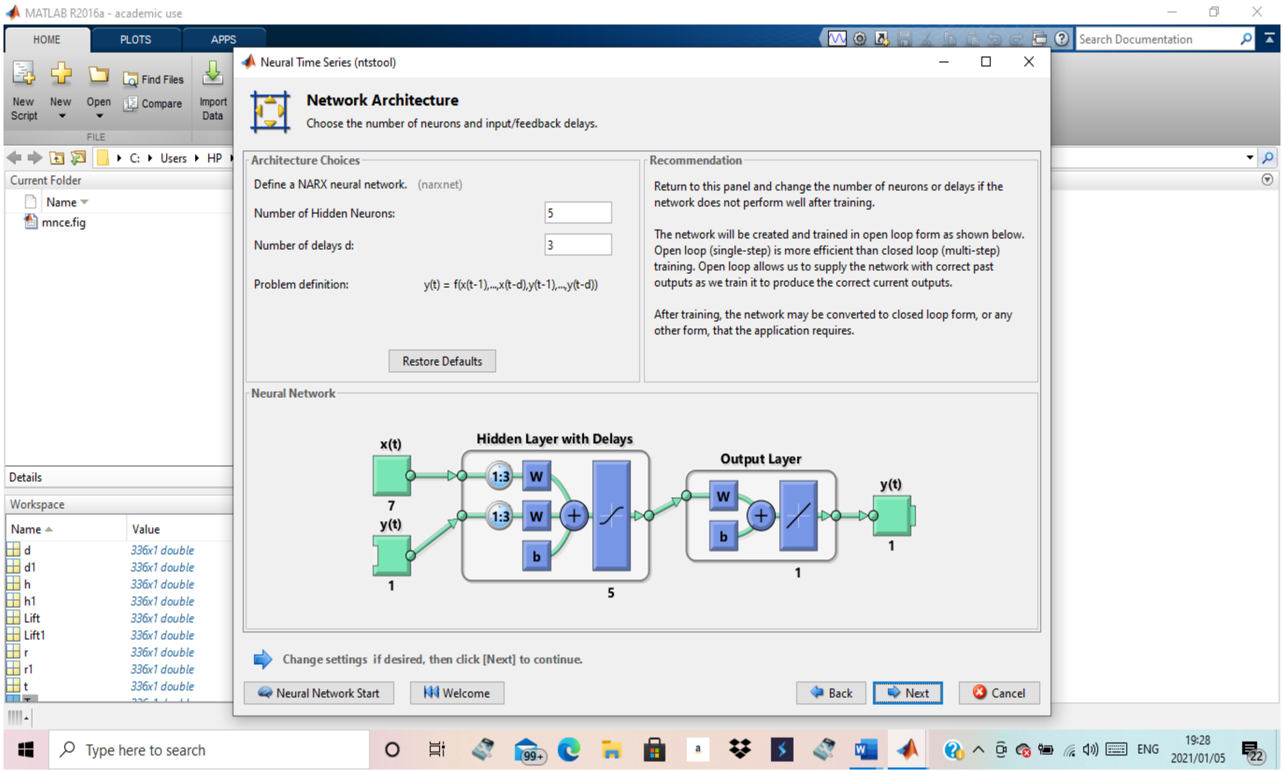
NNSTART



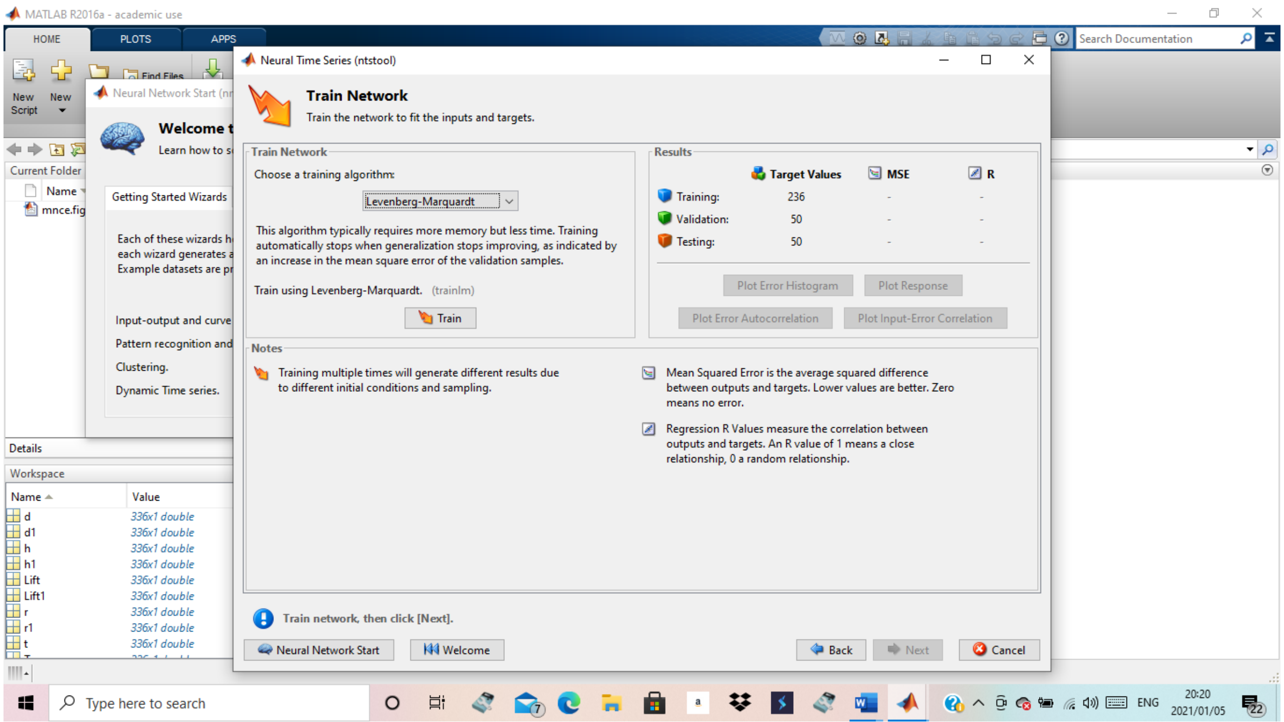
CREATING A NEW NARX NETWORK



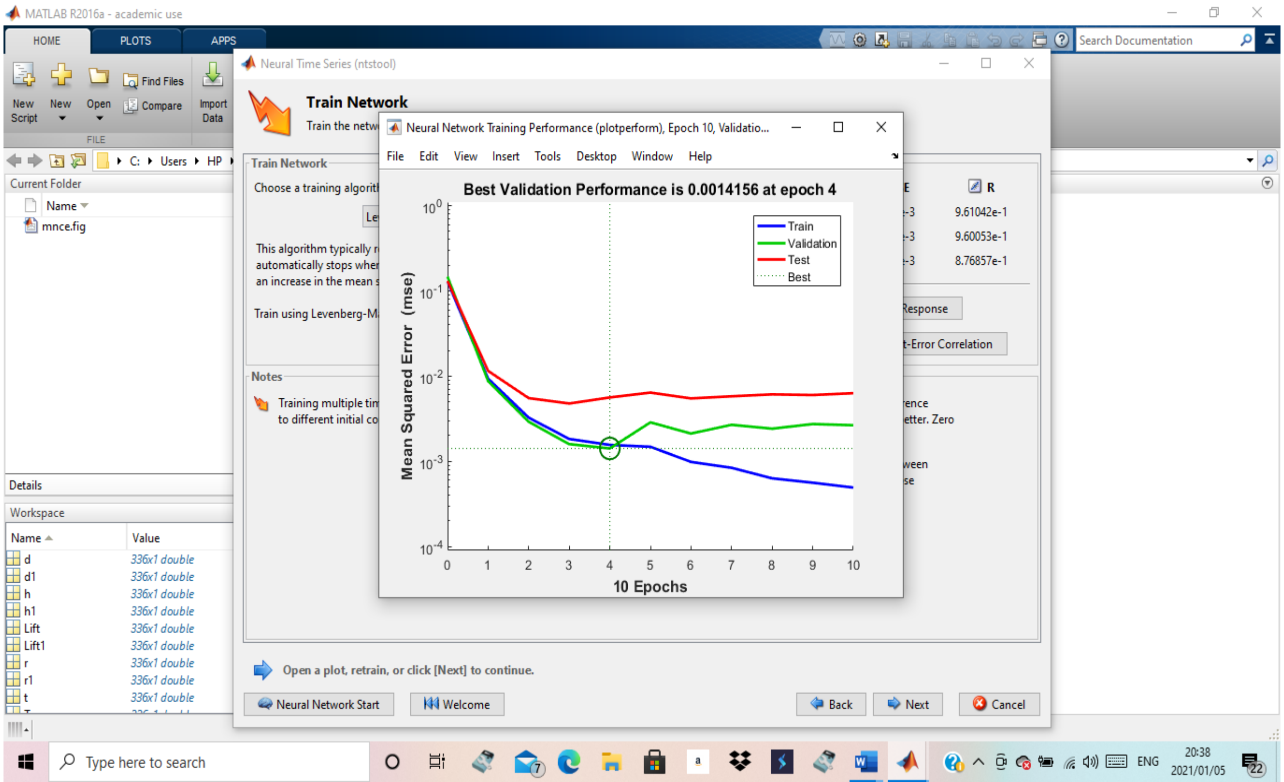
IMPORTING DATA INTO THE NETWORK



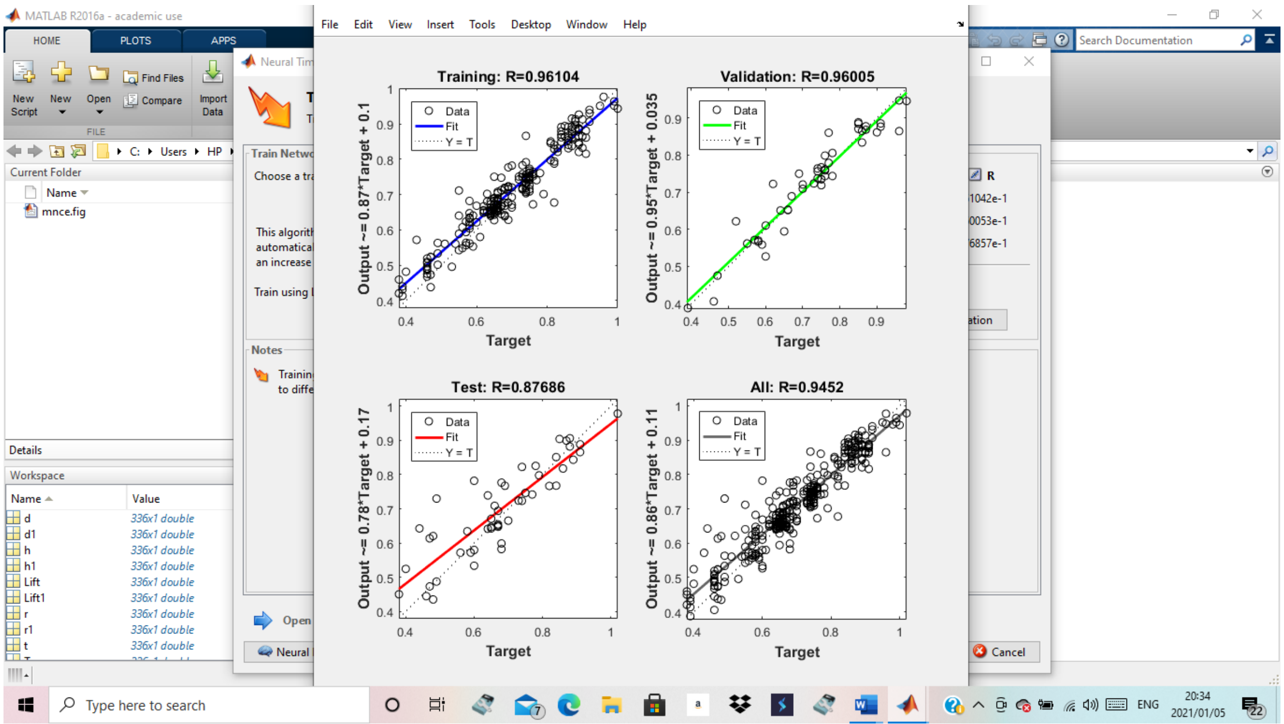
NETWORK ARCHITECTURE VIEW



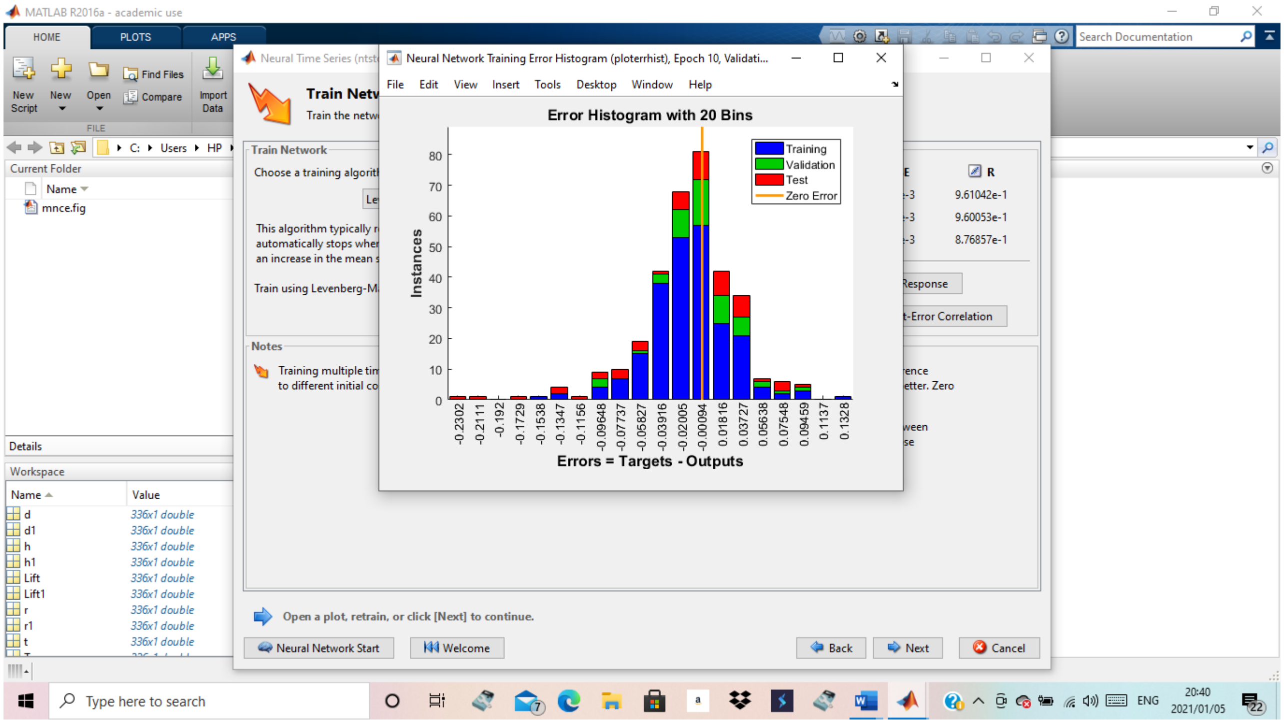
TRAINING THE NETWORK USING LEVENBERG-MARQUARDT



TRAINING SESSION



REGRESSION ANALYSIS



ERROR HISTOGRAM