APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR EVAPORATIVE COOLING IN DATA CENTRES

by

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To my mother Omolara Adejokun and my father Adesegun Adejokun.

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Abstract

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A data center is a facility that may be used to house telecommunication or storage devices. Because of the 24/7 required operation of a data center, large segments of a data center are geared towards evacuating heat generated from operating one. Data centers entail multiple operating configurations, great amount of constraints and nonlinear correlations. The need to effectively optimize a data center operation presents a daunting challenge. The data center considered in this research is a test bed modular data center (MDC). Comprising of an Information Technology (IT), DEC and IEC module. Typical MDC are dynamic and complex in nature with various mechanical and electrical control systems aimed at continuous operation of the MDC. To achieve the aim of optimizing a data center, we propose the use of an Artificial Neural Network. A typical Artificial Neural Network architecture is dynamic in nature and able to perform adaptive learning in minimal computation time. An Artificial Neural Network model of the data center was created using its operating historical data. The Neural Network model allows for the ability to predict and control our MDC at optimum configuration.

The MDC considered in this study is the MESTEX unit located in the Dallas Texas area. Using various parameters related to the operation of the unit. Such as Outside Air Temp, IT load, Cold Aisle Temp, Cold Aisle Humidity etc. We intend to give the Artificial Neural Network model some of these parameters as input and some as targets. In order to analysis and achieve real world results. The operational data used, are available from time periods logged on the MESTEK unit. More specific, the Neural Network model built in this study will be used to study weather impact analysis and prediction of future data (Step-ahead & Multi-Step ahead) that may be desired.

Table of Contents

List of Illustrations

Chapter 1

Introduction

1.1 Data Centers

Data Centers are a collection of equipment that are used to for remote data storage, transmission and processing large amount of data. A typical data center can be sub-divided into two categories: IT equipment and Support Infrastructure. The IT equipment is basically used for storing, transmitting and processing data. Storage servers, network equipment and computer servers achieve this respectively. The Support Infrastructure allows for the maintenance preservation for the IT equipment. Specifically, equipment found can range from power modules to cooling module

Continual increases of Internet enable devices. Also, the recent push for the Internet of things (IOT). The need to scale Data Centers have been on the rise. According to findings, in the year 2006, 1.3% of total energy was consumed. Which translates to sixty-one-billion-dollar kilo-watts of energy was consumed by data centers [1]. Relatively, in the year 2013, the NRDC reported that Data Centers situated in the United States amassed approximately ninety-one billion kilowatt-hours of electricity. This is energy consumed is directly proportional to 1.9% of the total electricity consumption for the year 2013 in the United States. It is projected that data center electricity consumption will be on the rise, towards the 140 billion kilowatt-hours mark. Which in turn will cost the America small and large business thirteen billion dollars annually due to electricity consumption. For this reason, and the further disadvantageous consequences. It is important innovate around cutting energy consumption by data centers. Essentially improving energy efficiency of data centers.

1.2 Energy Consumption in Data Center

Given, the rate of high-energy consumption of a typical data center expected to increase. It is important we take into consideration equipment found in the data center. The goal is improving data center efficacy and minimize the overall energy/power consumption. In order to achieve this goal, employed in this research is the use of Artificial Neural Network.

1.2 Power Usage Effectiveness

A preferred metric for measuring infrastructure energy efficiency for data center is the power usage effectiveness (PUE). With the PUE, industries are able to understand how energy is being used in data center operations. Thereby, making it possible to increase efficiency as required.

PUE is defined as the ratio of total facility energy to IT equipment energy. Total facility energy is defined by energy dedicated to the operation of a data center. IT equipment energy is defined by energy used by devices for processing, sorting and transmitting data within a center [2]. Various internet companies have made numerous effort in improving data center efficiency by lowering the PUE metric. Some examples include, using techniques sure as employing robust heat exchanger builds, hot/cold air containment, active load scheduling, waste heat recovery. Due to limitations, and an already exhaustive use of these methods. The quest for an innovative way of reducing PUE value is in need.

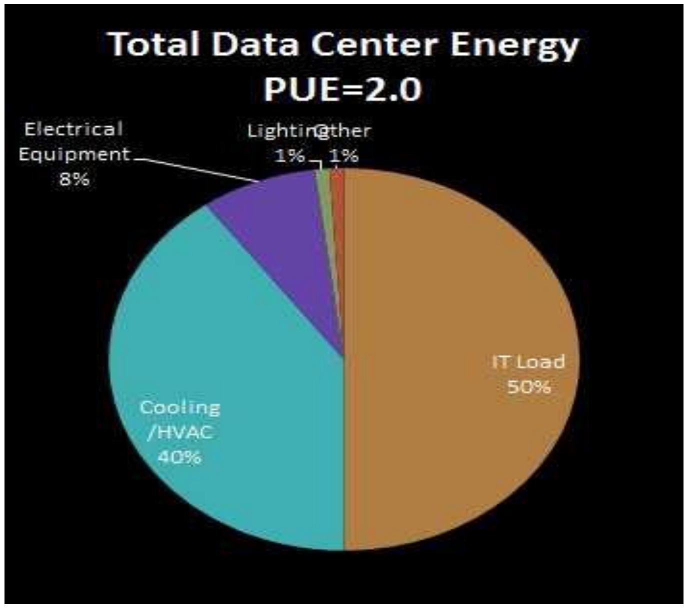

Figure 1.1 Power Usage Effectiveness

In order to achieve a more efficiency and an innovative approach towards reducing the PUE metric, employed in this research is Artificial Neural Network(ANN). ANN gives us the opportunity to model, simulate behavior and response of a typical data center. Industries currently use Computation Fluid Dynamics (CFD) to model, simulate behavior and response of a data center a. But, this method consume time, lacks great accuracy and is expensive. A data center is a highly dynamic environment, changes in input parameters results in significant amount of changes in system response. Within this research we find that using ANN in comparison to CFD helps tackle the disadvantages of CFD.

ANN algorithms are used to recognize patterns and make logical decisions based on patterns recognized. The use of ANN has been in existences for quite a while. Currently, used for data manipulation, driverless cars and so much more applications. Using the computation power of ANN, we intend to take existing logged data, used in monitoring data center operation. Create an ANN architecture that makes meaningful correlations between this data. Essentially modeling a typical data center operation with artificial neurons. ANN capability of making meaningful correlations, ensures that these correlations are used create best fit models. In turn, we use this model generated by the ANN algorithm to perform various test and optimize the data center in consideration.

1.4 Artificial Neural Network

ANN is a concept derived from the biological composition of the human brain. Just like the human brain, neurons processing information, ANN is able to replicate this process. Neurons are generally synaptic interconnected, they are able to receive information through dendrites, process this information and give an output. Based on what problem is required to be solved. An ANN model can also be used to solve specific problems by adjusting the values of weights between elements of the artificial neuron. Given it operates similarly like interconnected biological neurons.

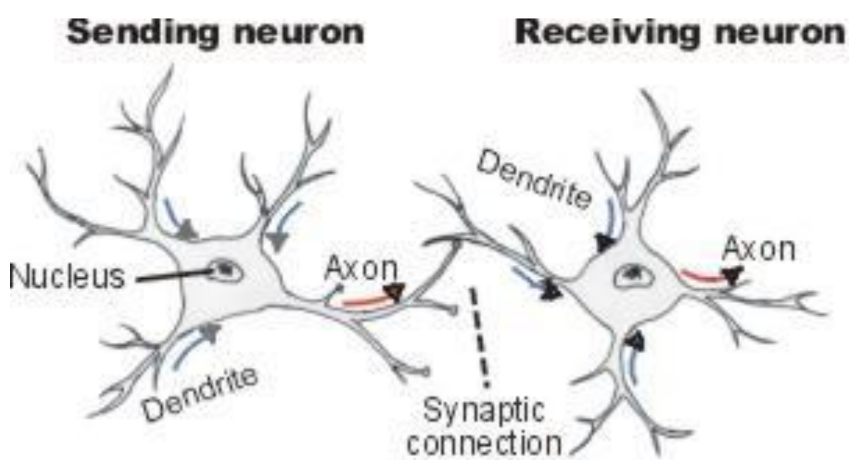

Figure 1.2 Schematic of a biological neuron

Artificial Neural Network can be used to learn new concepts based on training (recognizing patterns) and making informed decisions. Neural network contains cells called nodes. A node is a point at lines or pathways connect to each other. In a neural network nodes are arranged in various layers. An input layer receives information from the outside world, a processing or recognizing layer, a layer at the opposite end which responds by making decision from what it has learnt. The processing or recognizing layer, which forms the artificial network brain are usually hidden units.

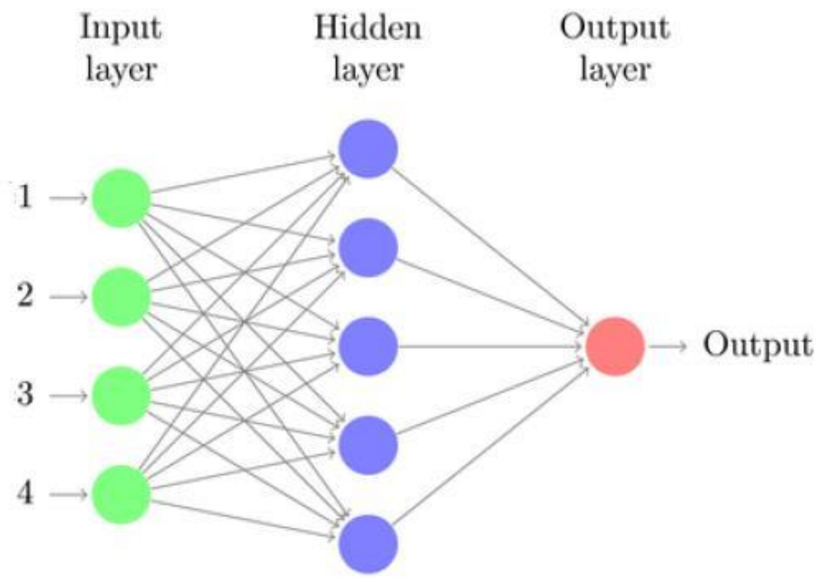

Figure 1.3 Feedforward Neural Network

Neural network is generally interconnected, making it possible for each hidden layer to be connected to its output unit. As shown in the diagram above. In ANN a connection between these entities are represented by value called weight, which may be positive or negative. Given weights, if a particle layer unit in the network architecture has a higher value than another unit. The unit with the higher value has more influence in decision making process. Information can flow from input layer to output layer in a static feedforward manner. A case where the output of a neural network depends both on the current or past inputs is called a Dynamic neural network. A Dynamic neural network is more advantageous compared to the Static feed-forward network. Because it has the ability to take previous states into consideration while making decisions The Dynamic neural network can be used for recognizing time vary patterns. Which is perfectly suitable for the nonlinear environment of a data center. Predicting the behavior of a data center past and current state using the Dynamic neural network enables for the possibility for developing control systems.

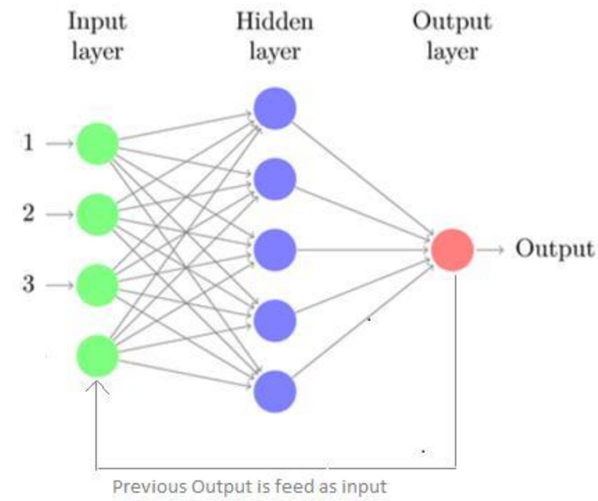

Figure 1.4 Dynamic Recurrent Neural Network

Chapter 2

Data Center Layout

For our research study we consider a modular data center located in Dallas, Texas. Below are diagrams of the data center in Fig 2.1 and Fig 2.2. Also, shown is the IT pod and schematic diagram of the IT pod Fig 2.3. The schematic diagram is divided into two sections; the first section entails a workstation computer, used for gaining access to servers stored in the second section. The second section of the schematic diagram is configured in a hot/cold aisle configuration and contains four 42U Panduit P/N S6212BP cabinets. The cabinets contain a total of 120 HP SE1102 servers. Aztec Sensible Cooling Model is the supply air-cooling unit, which is delivered to the cold aisle through a supply duct. From the hot aisle, hot air is conveyed and returned to the cooling unit. The conveyor is equipped with relief pressure dampers. Shown in Fig 2.2

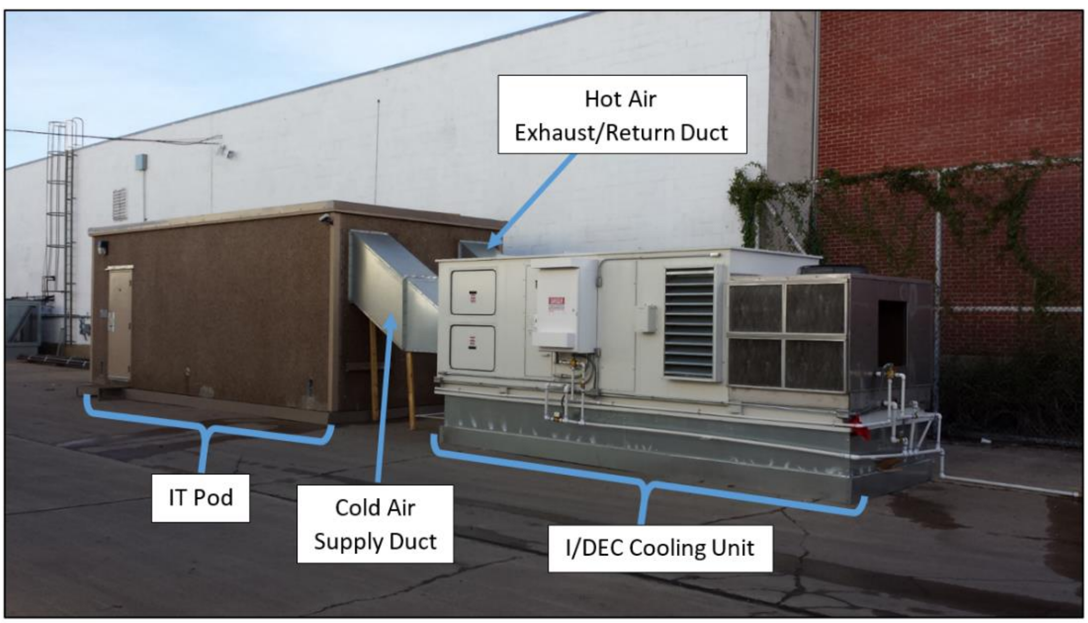

Figure 2.1 Modular Data Center: Cold Air Supply Duct

Figure 2.2 Modular Data Center: Hot Air Data Center Return Duct

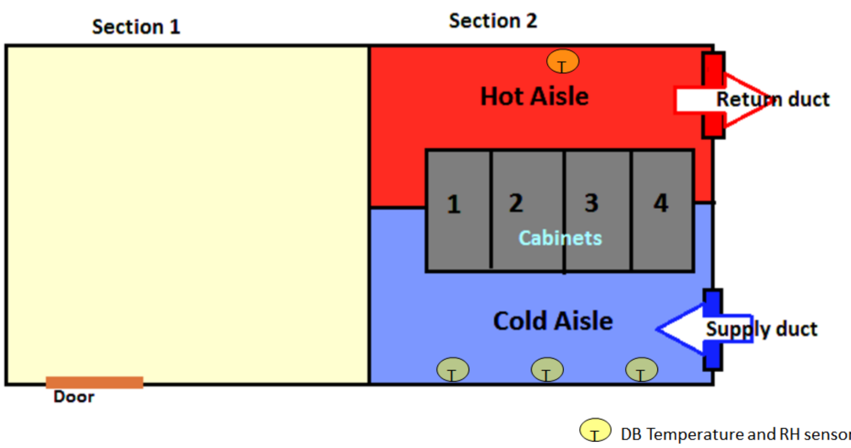

Figure 2.3 Schematic of IT Pod and Sensor Location

Below is a detail diagram of the cooling unit Fig 2.4. Through a motorized chamber, outside air goes into a mixing chamber. The motorized air damper dedicates the amount of return air to outside air mixing chamber base on its position. The air mixture passes through a wall of filters, in this case MERV 11 filters. The IEC, which is the first contact mixed air experiences, absorbed sensible heat from air. Furthermore the mixed air experiences secondary cooling through the DEC. The DEC also provides adequate humidification as required. Present, are the cooling tower providing cold water to the IEC coils. Amount of water leaving these coils is distributed on the DEC media. Furthermore, the cooling tower causes cooling and evaporation of water of water flowing down the media by collecting outside air across the DEC media.

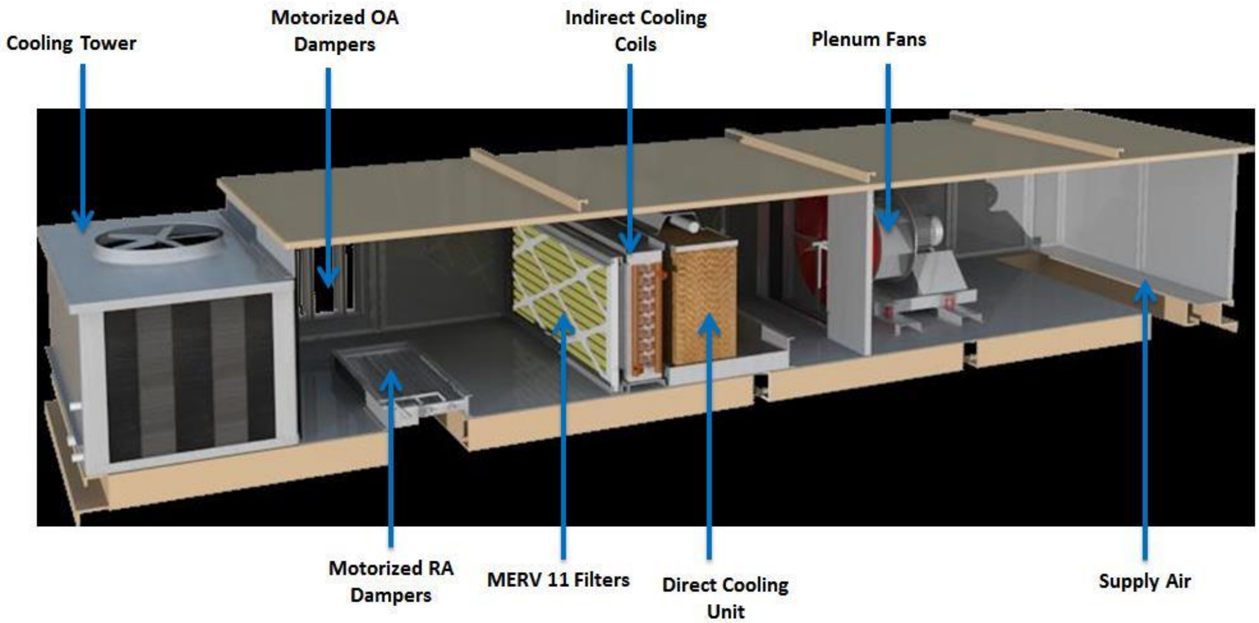

Figure 2.4 Internal Configuration of Cooling Unit for Modular Data Center

Ensuring controlling cooling in the modular data test bed. The modular center is equipped with various sensors such as humidity, static pressure, temperature etc. These sensors ensure a directing and informed control of entities such as DEC water pump, unit blower fan speed etc. The modular data center is also equipped with WebCTRL Building Automation System, in order to ensure all sensor data are available to be read easily. A sample of data that can be obtained from the WebCTRL is shown below Fig 2-5. The unit is monitored 24/7 for performance analysis. In order to use ANN to model the modular data center, these values read off the WebCTRL, which have been gotten over a period of operation, are vital.

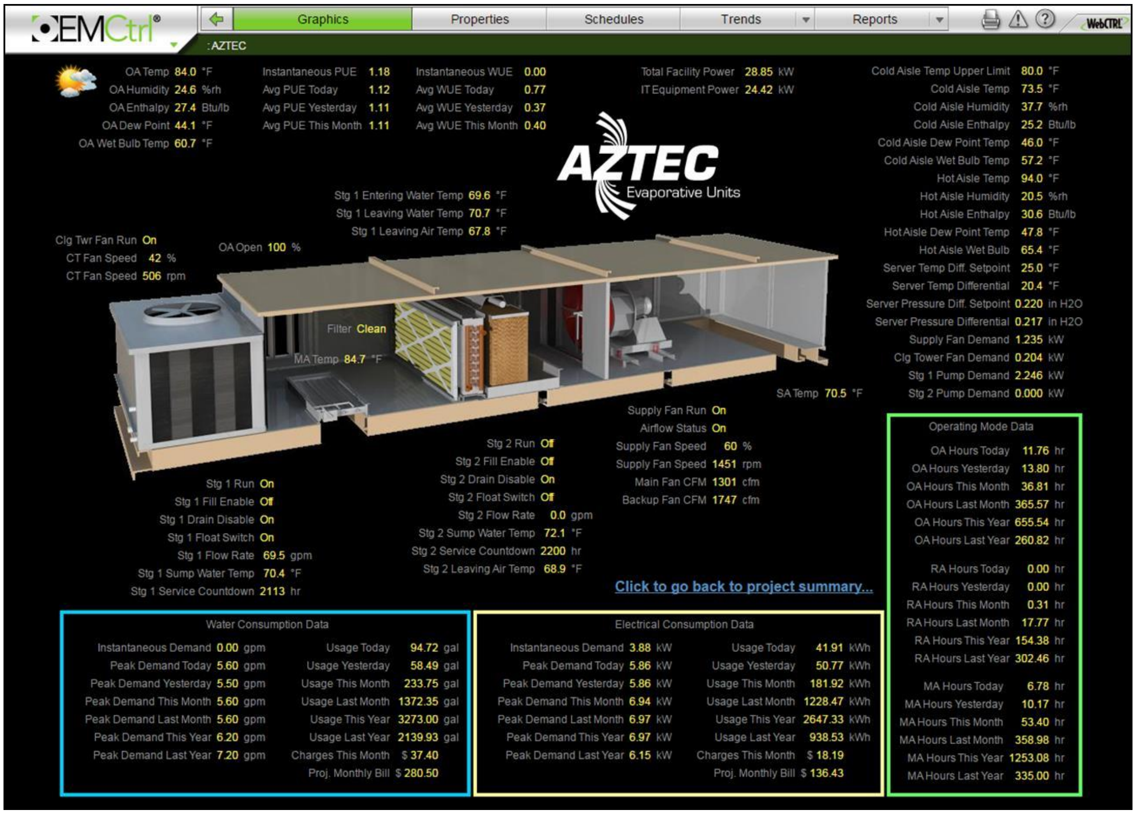

Figure 2.5 Webpage of BAS showing real time data for Research MDC

Typical Meteorological Year Weather

In order to perform weather analysis on the Modular Data Center. It is important to discuss the Typical Meteorological Year Weather (TMY) Data. This data gives us the ability to analyze outside air conditions for the MDC with relation to operation parameters in the MDC. Considered is the TMY data for Dallas-Love field for a typical year. In the figure below, we are able to show, plotted on a psychometric chart, the hourly weather data for Dallas-Love Field region. Weather condition for an hour is represented by points on the psychometric chart.

Recommended environmental envelops for ITE published by ASHRAE and capability of cooling technologies used in the test bed MDC are used to categories the psychometric chart into different regions. ASHRAE recommended region is represented by region C. This recommended environment is also the target supply air condition that is need to be gotten by the I/DEC. With the range of ITE load variation and supply air condition in scope. The range of hot air/return air(RA) in hot aisle is indicated by a red block in the psychometric chart below (Fig 2.6).

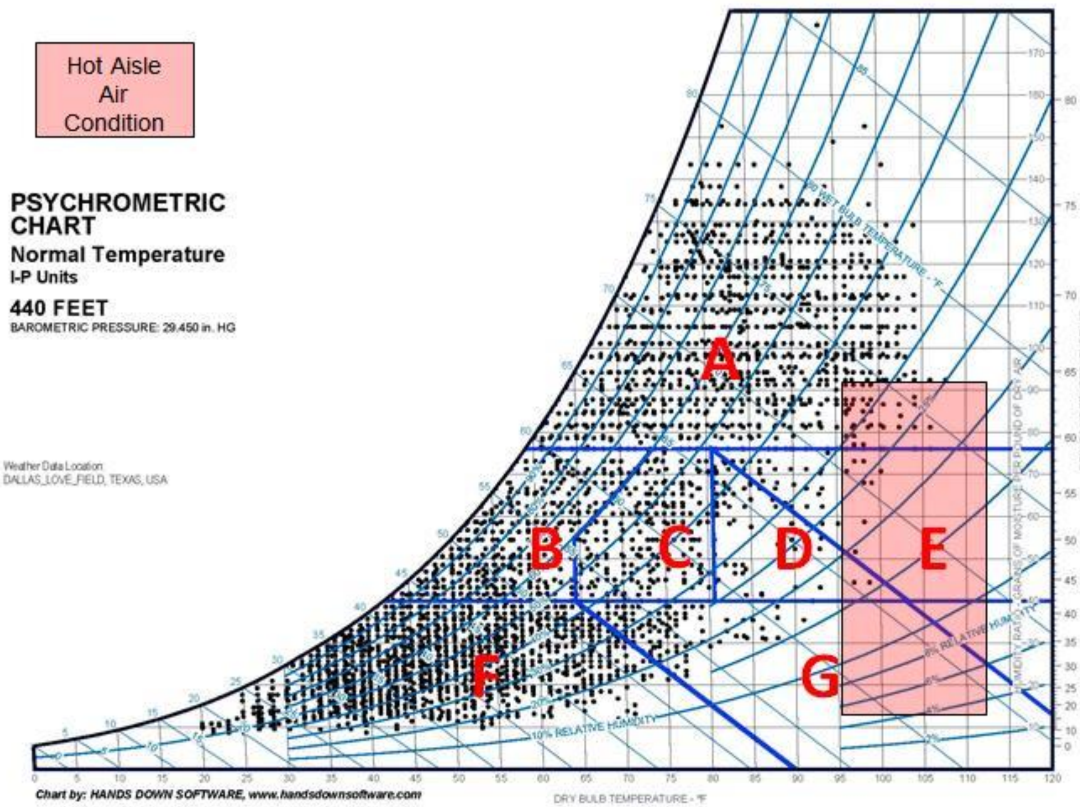

Figure 2.6 TMY for Dallas Love Field

2.1 Operational Sequence

Typical yearly weather conditions psychometric chart can be divided into seven distinct operation regions. The sequence in which this I/DEC unit responds to the ambient condition while in these regions is as follows.:

- Zone F (<41.9^{0}F DP <52^{0}F WB): When OA conditions lie within this region, economizer mixes OA/RA to control MA to 65^{0}F minimum and relative humidity (RH) is maintained above 20% . Humidification is not provided in this region due to risk of excessive drop in DB temperature and increase in RH, resulting in condensation. Cold aisle is maintained at 65^{0}F and above 20% RH as show in Fig 2.7

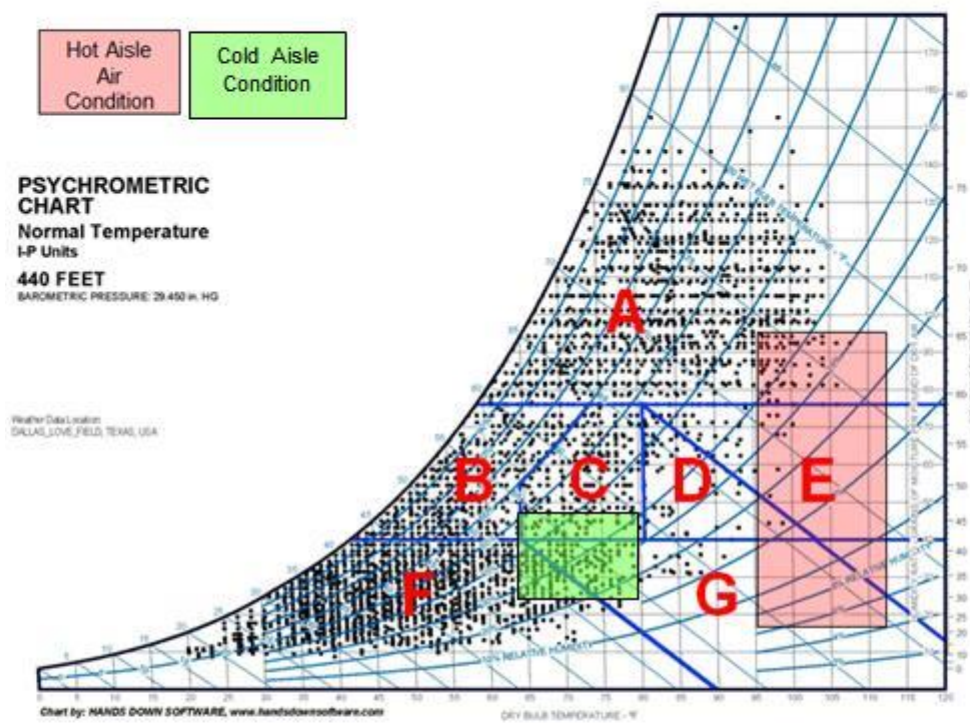

Figure 2.7 Cold Aisle Condition for Zone F & G

- Zone G (<41.9^0F DP >52^0F WB): In this region, economizer is at 100% OA. Supply air maximum 80^0F DB and RH above 20% is maintained. When RH falls below 20% and DB temperature is above 75^0F, humidification is enabled. When temperatureis above 80^0F, IEC is enable. Cold aisle is maintained between 65^0F and 80^0F with RH above 20% operating ITE in ASHRAE allowable A1 envelop.
- Zone C (>65^0F DB &<41.9^0F DP and <80^0F WB & <59^0F DP & <70%RH). This region calls for economizer at 100% OA. DEC and IEC are turned off and cold aisle maintained with the ASHRAE recommended envelop.
- Zone B (<65^0F DB & > 41.9^0F DP & <59^0F DP &>70% RH): Economizers mixes OA/RA to maintain mixed air temperatures at 65^0DB. DEC and IEC are turned off. RA condition is critical in this case and is monitored to keep it below 59^0DP. Cold aisle is maintained with the ASHRAE recommended envelop.
- Zone D (>80^0F DB &>41.9^0F DP & <65.76^0WB): nit will run in 100% OA economizer mode and IEC provides required sensible cooling to maintain SA temperature between $75^0$and 80^0F DB. Dew point temperature is maintained within 41.9^0 and 59^0F

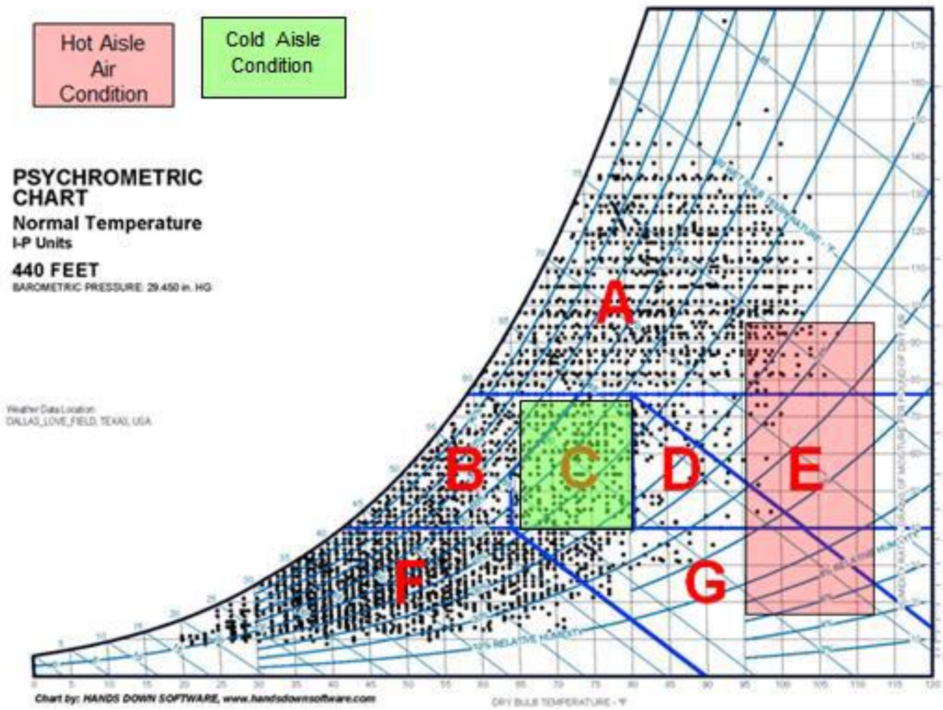

Figure 2.8 Cold Aisle Condition for Zone D, B, C & E

- Zone D (>80^0F DB &>41.9^0F DP & >65.76^0WB): This region demands 100% OA till dry bulb temperature of OA less than 95^0F. Unit will switch to either 100% OA or 100% RA depending on the DB whichever is lower. Indirect evaporative cooling provides required sensible cooling to maintain SA temperature between 75^0 & 80^0F Db. Dew point temperature is maintained within 41.9^0 and 59^0F
- Zone A (>59^0F DP): Economizer mixes OA/RA to decrease Mixed Air RH to 70% and maximum cold aisle temperature to 80^0F DB. Unit will switch to 100% RA when Cold Aisle RH shoots above 70%. Dew point temperature is higher

than 59^0F DP for maximum number of hours. Unit will function to maintain the cold aisle is allowable A1 zone as shown in Figure 2.9

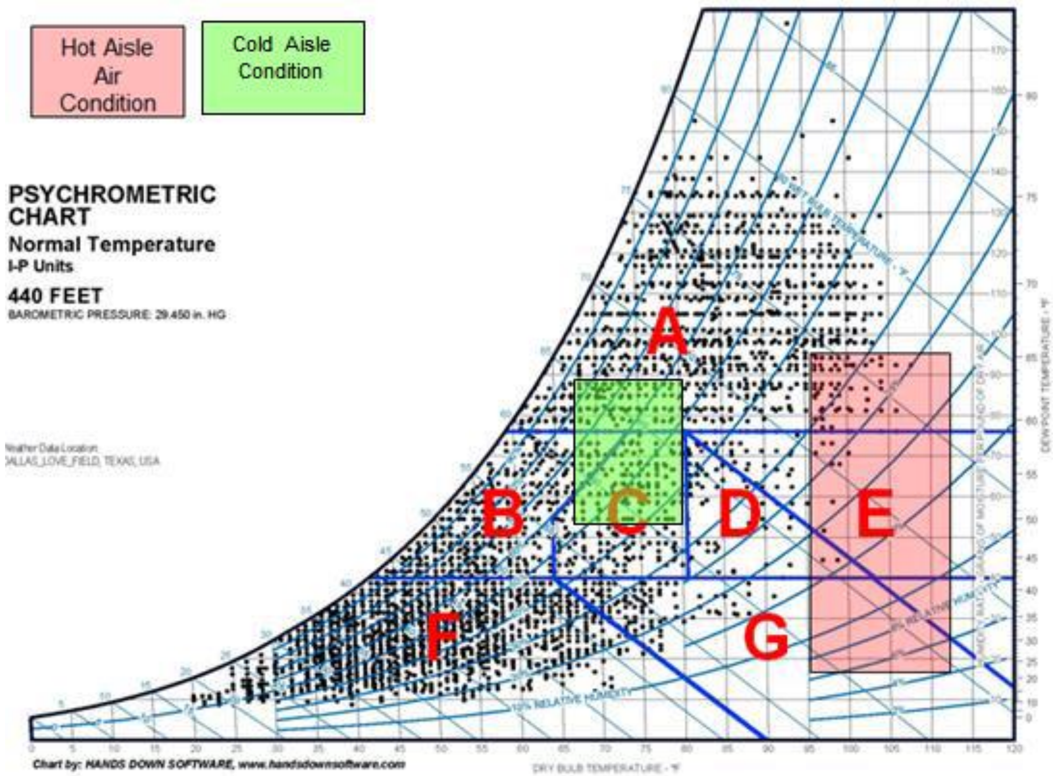

Figure 2.9 Cold Aisle Condition for Zone A

Chapter 3

Neural Network and Learning Algorithm

As mentioned above, artificial neural network is a concept derived from the way the human brain works. The dynamics of the brain ensures processing information, acting on this information and making decisions. Neurons in the brain receives input through dendrites and ensures an output signal is derived.

3.1 Neural Network Model

A neural network contains a single input unit know as Neurons. These neurons are transfer functions with the ability to predict the output on basis of relative input. A typical Neural Network model entails having this transfer functions varied based on required goals. This neuron is also knowing Perceptron. Below is diagram of perceptron. A model ANN will be containing numerous perceptron connected together. The layer where these perceptions are connected is called a hidden layer and the connection made are called weights and biases. A scalar input p is multiplied by a scalar weight w to form a product wp. This weighted input wp is then added to a scalar bias b to form the net input n. The net input is then passed through a transfer function f, which produces an output a

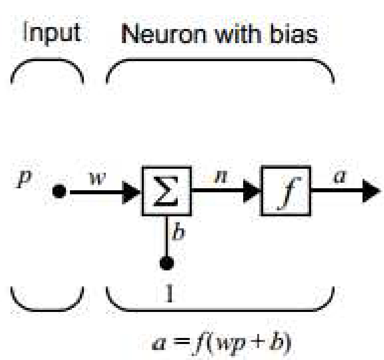

Figure 3.1 Simple Neuron Model [3]

3.2 Weighs and Biases of a Neural Network

Neural Network overall performance is reliant on its weights and biases. Depending on the data intended for use, the weights and basis are adjusted to train the neural network. Specifically, weights are used for training a mode and the biases are used to shift the activation function. The value of weight, be it negative or positive triggers the corresponding neuron in the hidden layer. Thereby triggering the neuron in the output layer. Generally, weight and biases initial values are assigned. But as we train the neural network, these values are adjusted accordingly.

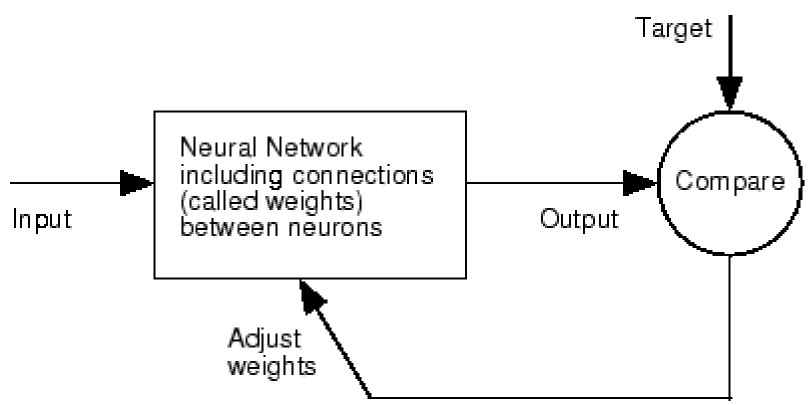

Figure 3-2 Neural Network Schematic

3.3 Training a Neural Network

In order to train a Neural Network, we need to adjust weights and biases. Training a Network with sufficient amount of data, achieving a steady state transfer function reigning over the system is possible. This training data is known as the training set. The training of a Neural Network works by taking a functionality e.g. gradient descent function. The weights and biases of the function are adjusted in order error is reduce to a minimum during performance of the function. The equation (3.1) shows the single iteration of performance function.

$$X_{k+1} = X_k - a_k g_k \quad (3.1)$$

X_k is the vector with current weights and biases, g_k is the current gradient and a_k is the learning rate.

Training of a Neural Network is segmented into three parts:

1. Selecting Learning Algorithm
2. Selecting Number of Neurons in the hidden Layer
3. Validating trained Network.

3.3.1 Selecting Learning Algorithm

Selecting a learning algorithm for training our network is based on the type of data at hand. Base on the data, there are two types of learning algorithm to choose from. A) Levenberg-Marquardt Algorithm (LM) B) Gradient Descent Back Propagation Algorithm (GD).

For approximating functions these are the widely used functions. The GD Descent is a training function which update values of weight and bias [3]. The GD backpropagation algorithm updates weight and bias along negative gradient [7]. The Lm algorithm is rapid back propagation algorithm. In selecting on of both algorithms for training it is important we factor in speed and time. We also need our ANN to be trained in the quickest time possible and with high degree of accuracy. To choose the best algorithm for our research, we considered a comparison between both algorithms on the bases of time and accuracy.

Figure (3.3)(3) and Figure (3.4)(3) demonstrates this comparison between LM and GD algorithm for time and accuracy for different number of neurons. As seen in both figures, Lm algorithm is faster and accurate than the GD back propagation algorithm. Therefore, the bases for using LM algorithm in this research.

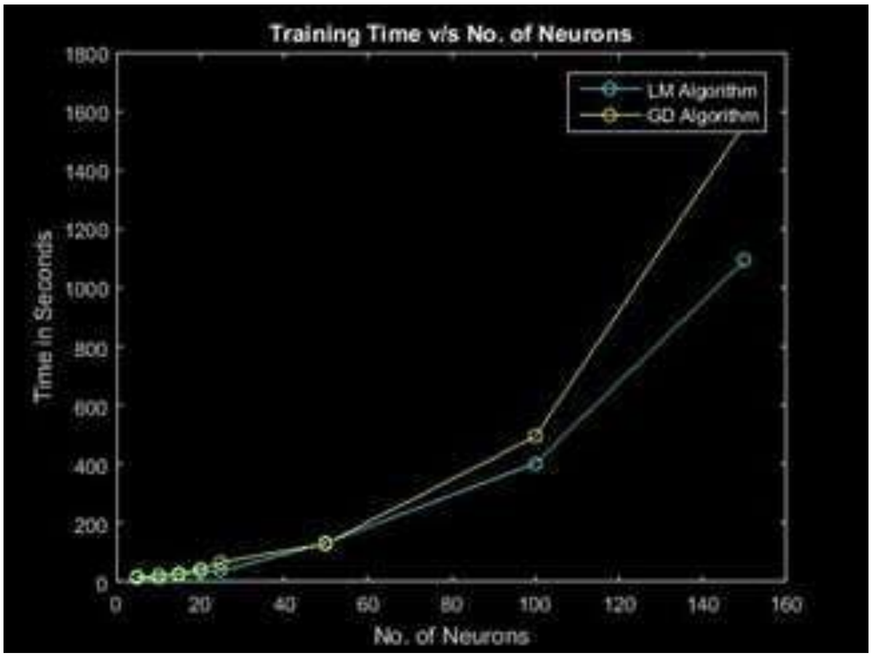

Figure 3.3 Training time comparison between LM and GM against no of neurons

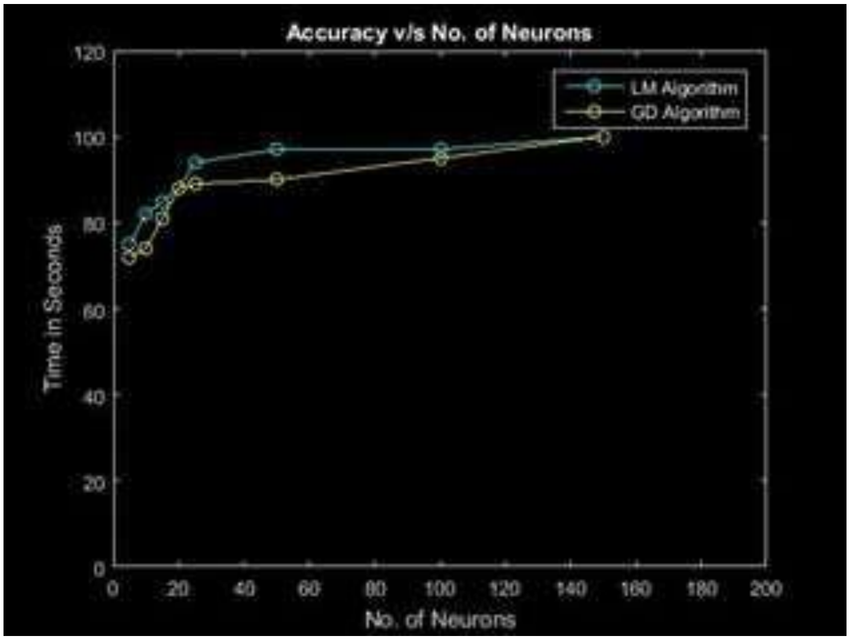

Figure 3.4 Accuracy comparison between LM and GM against no of neurons

3.3.2 Selecting Number of Neurons in the hidden layer

There are no specific rules in choosing the number of neurons needed to train a network. Keeping the goal of training the ANN to achieve optimum state, sufficient number of neurons are to be choosing. Some rules in determining the number of neurons to be chosen are as follow. 1) Number of neurons should be between size of input layer added to size of output layer. 2) The number can be 2/3 the six of the input layer plus the size of the output layer. 3) This number should be less than twice the size of input layer.

3.3.3 Validating trained Network

To validate our trained Neural Network, we use the regression plot. This plot generated after training has been done. Using the recommended division of data; the GUI takes a certain percentage of available data in order to show target value are close to a mean line target value. The more the overall data after training is closer to the mean value, confidence is given to our results. Figure 3-5 shows regression plot for a weather analysis, with three inputs and five outputs using the fitting tool app found on MATLAB.

The value R= 0.99802 indicates that optimum training was obtained from the data set

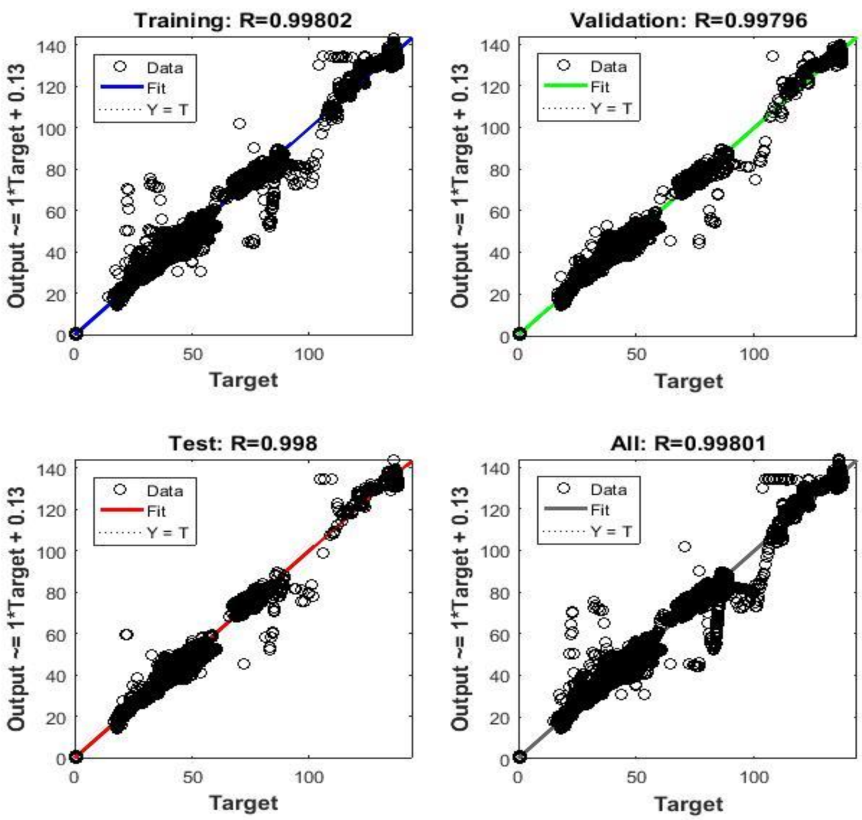

Figure 3.5 Regression plot for three inputs and five outputs using the fitting tool app

3.4 Fitting Tool

The fitting tool is a ready-made tool available in the Neural Network GUI on MATLAB. This tool is useful for data fitting, pattern recognition and clustering. Because the weather analysis experiment carried out in this research is not dependent on time, the fitting tool works perfectly in training out data. The diagram above shows the regression plot after training our ANN with data gotten from the operation of our model data center. Three parameters such as outside air temperature, IT load are chosen as our input to the network. Five parameters such as cold aisle temperature and blower fan speed are chosen as output to the same network. Figure 3-6 shows the transfer function that is obtained. The sigmoid transfer function contains fifteen number of neurons in the first block and the next block, the linear transfer function contains five neurons.

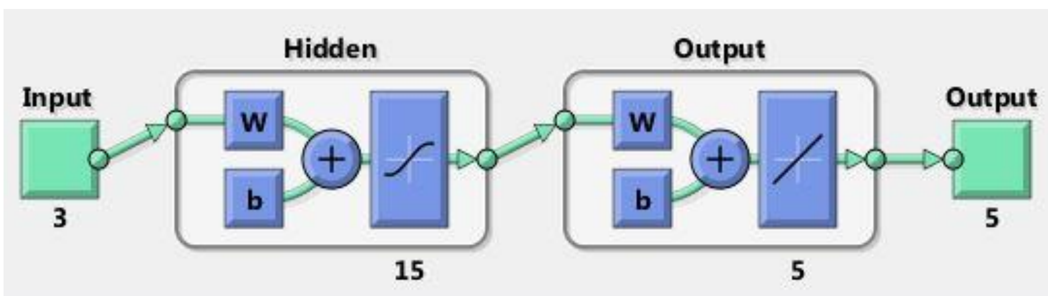

Figure 3.6 Fitting Tool Neural Network Transfer Function

3.5 Dynamic Time Series Tool

The Dynamic time series tool, a feedback loop system is also a ready made tool available in the Neural Network GUI on Matlab. It is generally used for time-series prediction, non-linear dynamic systems modeling and control systems application. We would be using this tool to predict certain transient parameters on our data center model. The dynamic time series tool has the ability to continuously perform checks on when target values are achieved. Figure 3.7 shows the transfer that is obtained generated after data center model training is done. As seen below, there are three input data and five set of target data that needs to be achieved. Found in the sigmoid transfer function are twenty neurons in the hidden layers and five neurons in the linear transfer function hidden layer.

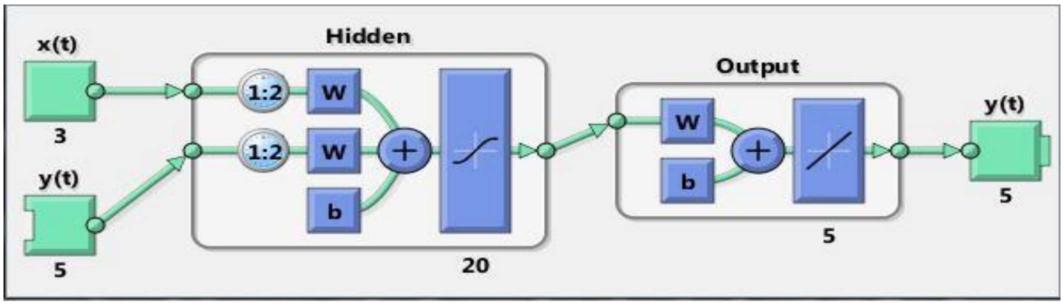

Figure 3.7 Dynamic Time series Tool Transfer Function

Chapter 4

Weather Analysis for Modular Data Center

The goal of performing weather analysis on our modular data center unit (MDC) is to be able to determine the suitability of evaporative cooling for data centers in different climate conditions. The MDC under consideration for this research is located in Dallas, Texas. We have used the ASHRAE thermal guidelines for data processing environment has our benchmark. Taking parameters, based on climate conditions, such as Outside Air temperature, Outside Relative Humidity and IT load for a Data center. We determine how these parameters affect the overall operation of our model data center. As mentioned earlier data pre-processing, such as data analysis and filtration, model training and post processing are done using the Neural Network $Toolbox^{TM}$ R2015b on MATLBAL. We are able to model complex nonlinear systems with this toolbox.

For our ANN model, we have three input variables and five target set point (output variables). All data used are available from logged sensor readings from our MDC (Aztec I/DEC unit.

Input Variables:

1. Outside dry bulb temperature(f)
2. Outside air relative humidity (RH) (%)
3. IT load.

Output Variables:

1. Cold aisle air temperature (f)
2. Cold aisle air relative humidity (RH)
3. Blower fan speed
4. IEC water pump enable
5. DEC water pump enable

For our weather analysis we will be using the ‘Fitting tool app” discussed in 3.4 to train our Neural Network model.

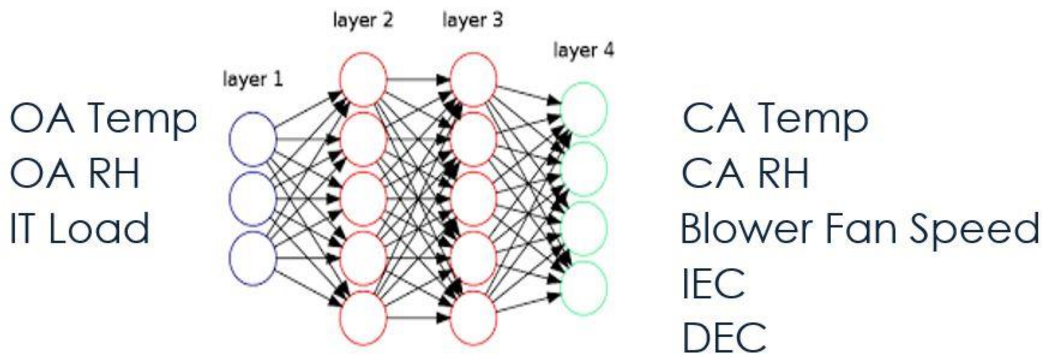

Figure 4.1 Data Center Efficiency Model

4.1 Results and Discussion

After training and validating our ANN model is done, using the training “Levenberg-Marquardt” referred as ‘trainlm’ in MATLAB. We evaluate the performance of the I/DEC unit based on Typical Meteorological Year (TMY3) data for Dallas- Lovefield. To show that our ANN model has been trained sufficiently and is ready for use. We take one of the output variable (a target) and make a comparison with our ANN version of the same output target. Figure 4.2 shows the plot for blower fan speed against a time step in blue, and the plot for ANN output for blower fan speed in red. Also include is the regression plot. The regression plots provide more insights on relationship between outputs of the network and the targets. The value of R is indicating the degree of relationship between output and target. A value of R directly proportional to 1 indicates a perfect linear relationship. A value of R directly proportional to 0 indicates there is no relationship between outputs and targets. In our experiment, the value of R is greater than 0. 9, for the training, validation, testing and a combination of all three. This indicates a good fit neural network model as shown in Figure 4.3

Training Function: 'trainlm' (Levenberg-Marquardt)

Delay: 1

Hidden Layer: 15 and 5

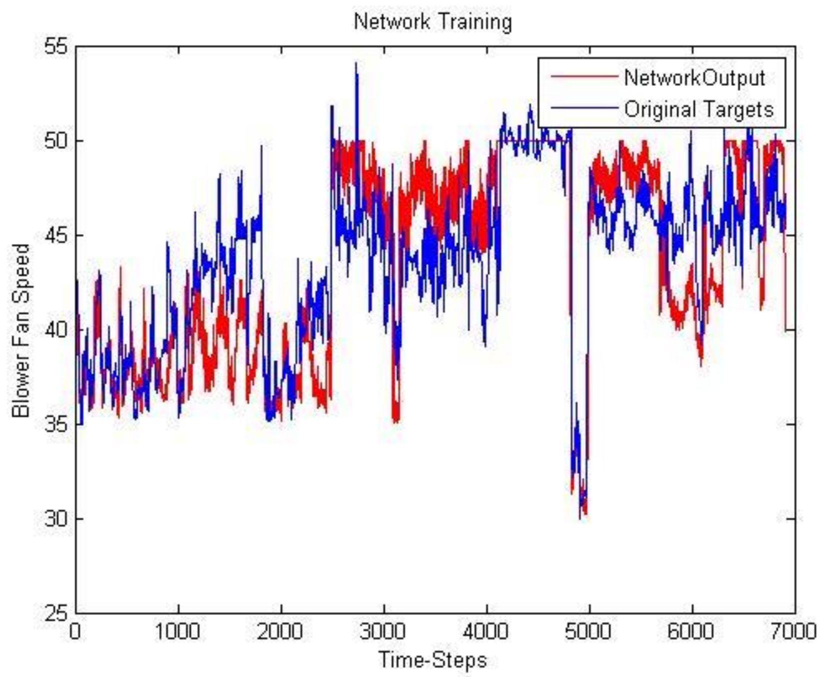

Figure 4.2 Blower Fan Speed; Original target vs. Network output

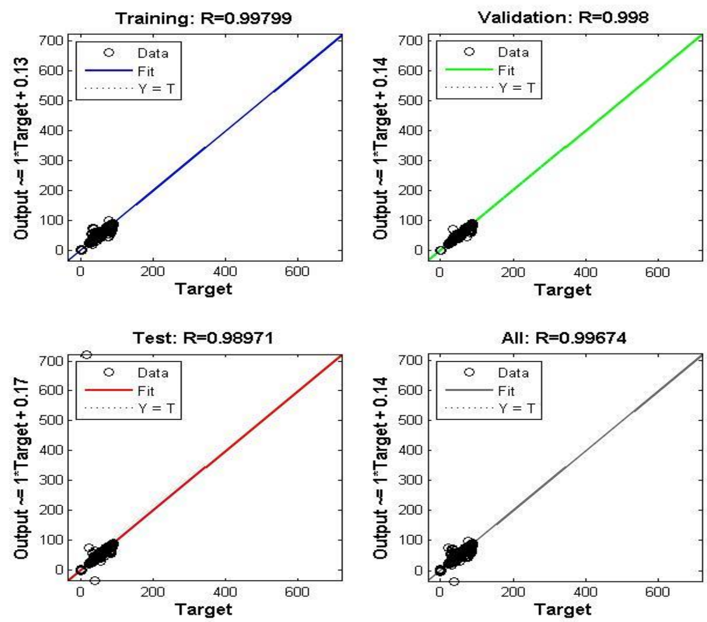

Figure 4.3 Regression plots for weather analysis

Discussed in chapter 2, following the operational sequence of a Typical Meteorological Year Weather as recommended by the ASHRAE thermal guidelines for data processing environments. We use the ANN trained model to generate new outputs, and compare this ANN output with our original target. By plotting our results on a psychometric chart.

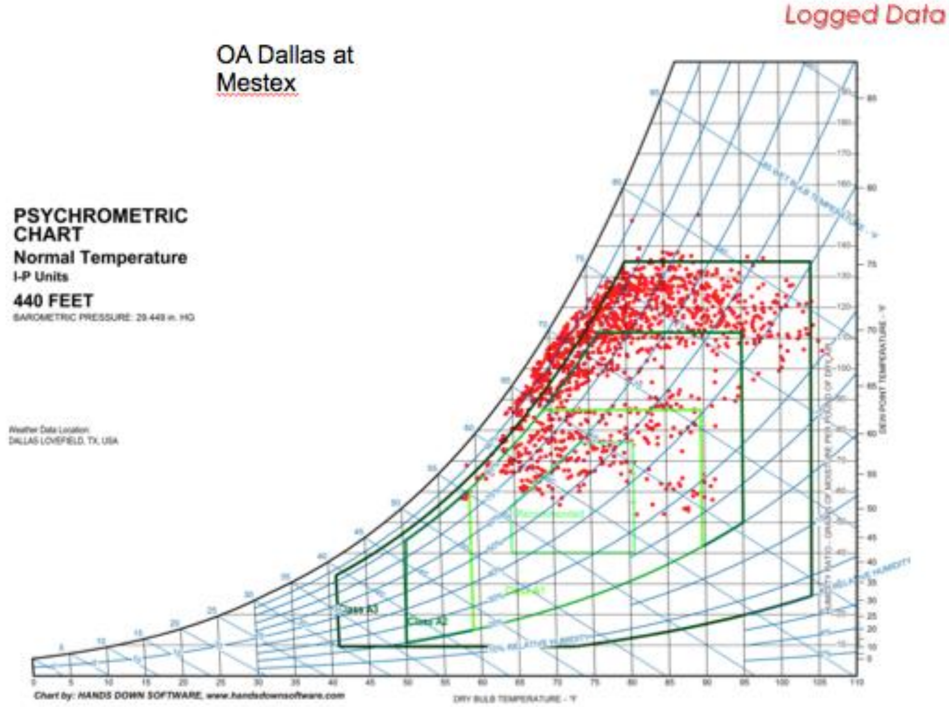

Figure 4.4 Outside air logged data for Dallas Mestex

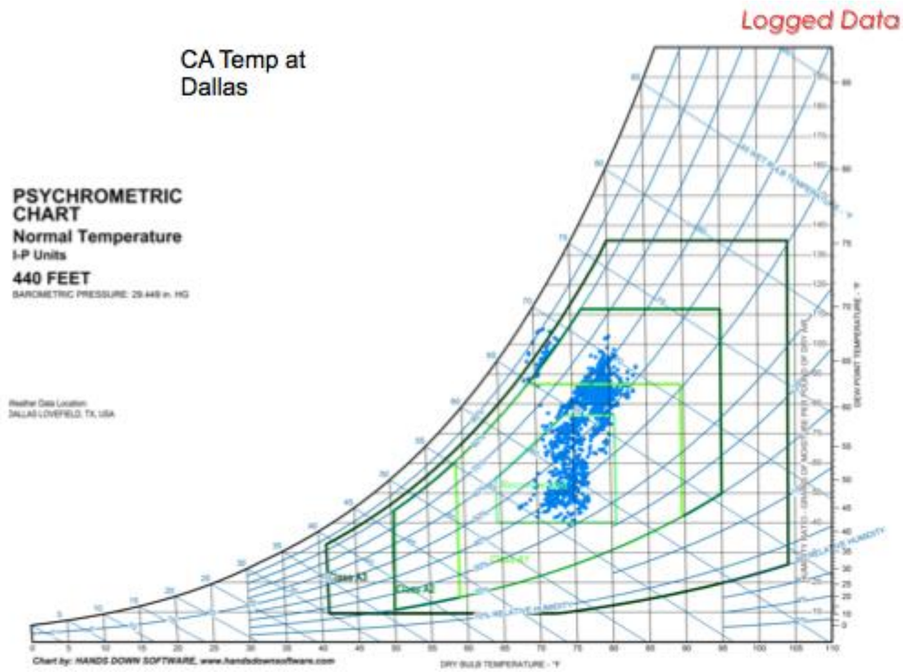

Figure 4.5 Cold aisle Air logged data for Dallas Mestex

Figure 4.4 Shows logged data for where the outside air temperature is for our modular data center and Figure 4.5 shows where the cold aisle temperature resides for our modular data center. To train our ANN we will be using this logged data, after training is done. We derive as output cold aisle temperature from the ANN model as shown in Figure 4.5. After, this procedure is complete, we attain weather data for outside air temperature in form of Typical Meteorological Year 3(TMY3). TMY3 represents weather in form of bins. Putting these data into bins, which is an average estimate, will ensure more robustness in our analysis. Moving forward in our experiment, we use outside air data in form of TMY3 to further test our ANN model and derive cold air temperature for our modular data center as outputs.

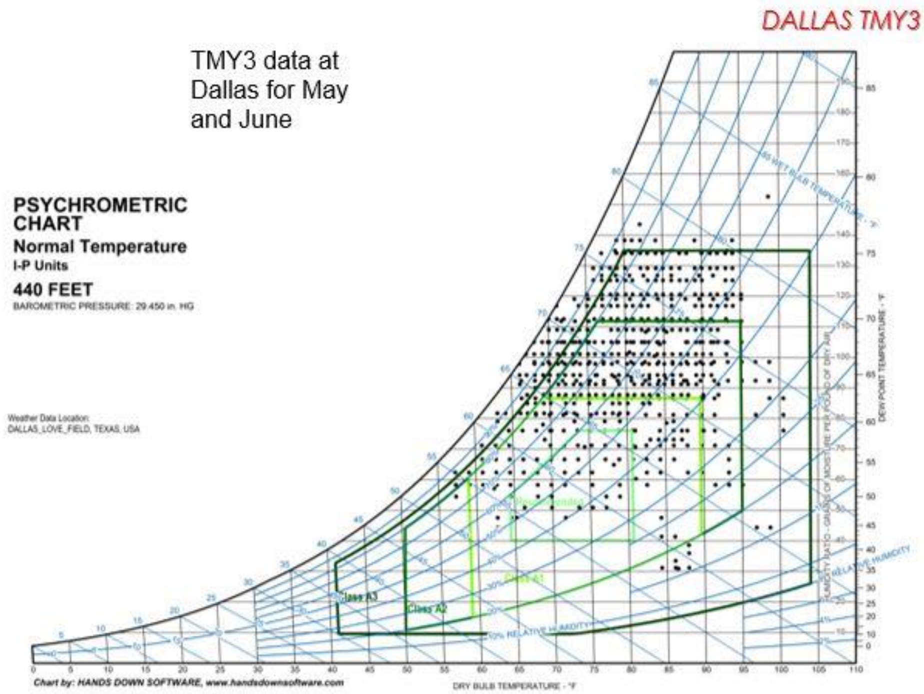

Figure 4.6 TMY3 data for Outside air temperature Dallas.

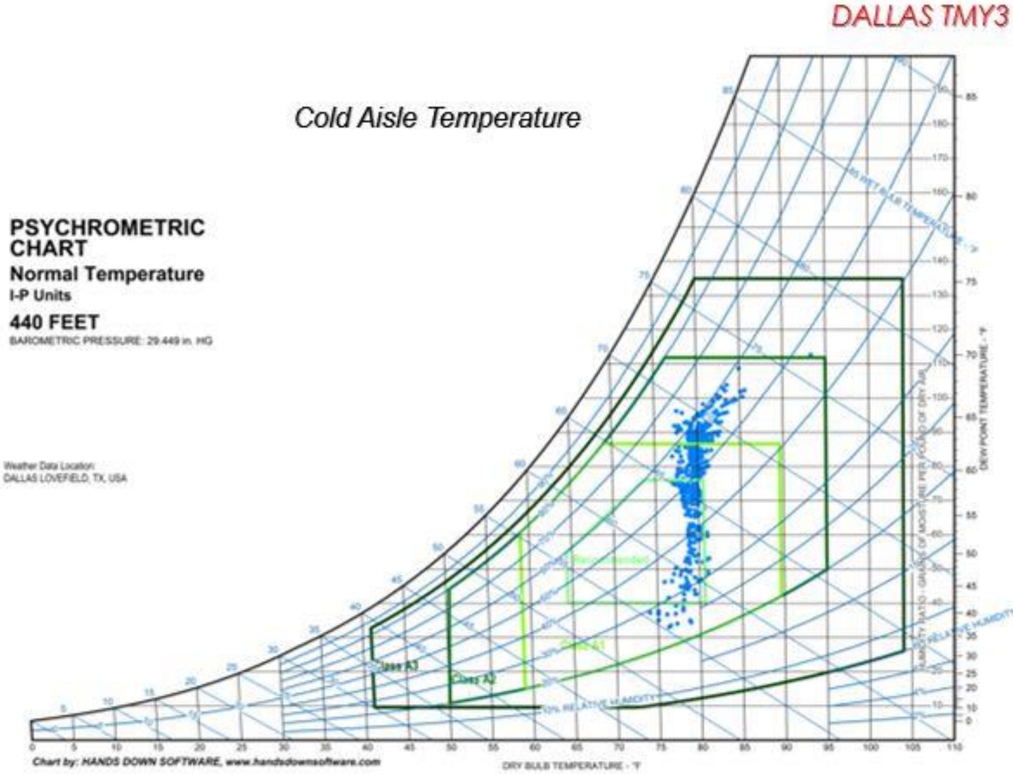

Figure 4.7 ANN output; Cold aisle at Dallas.

Figure 4.6 Shows the Outside Air Temperature TMY3 data at Dallas for MAY and June, for our modular data center. Figure 4.7 is the output gotten from the ANN model as Cold aisle temperature for MDC in Dallas. When Outside Air Temperature is fed into the ANN model as input.

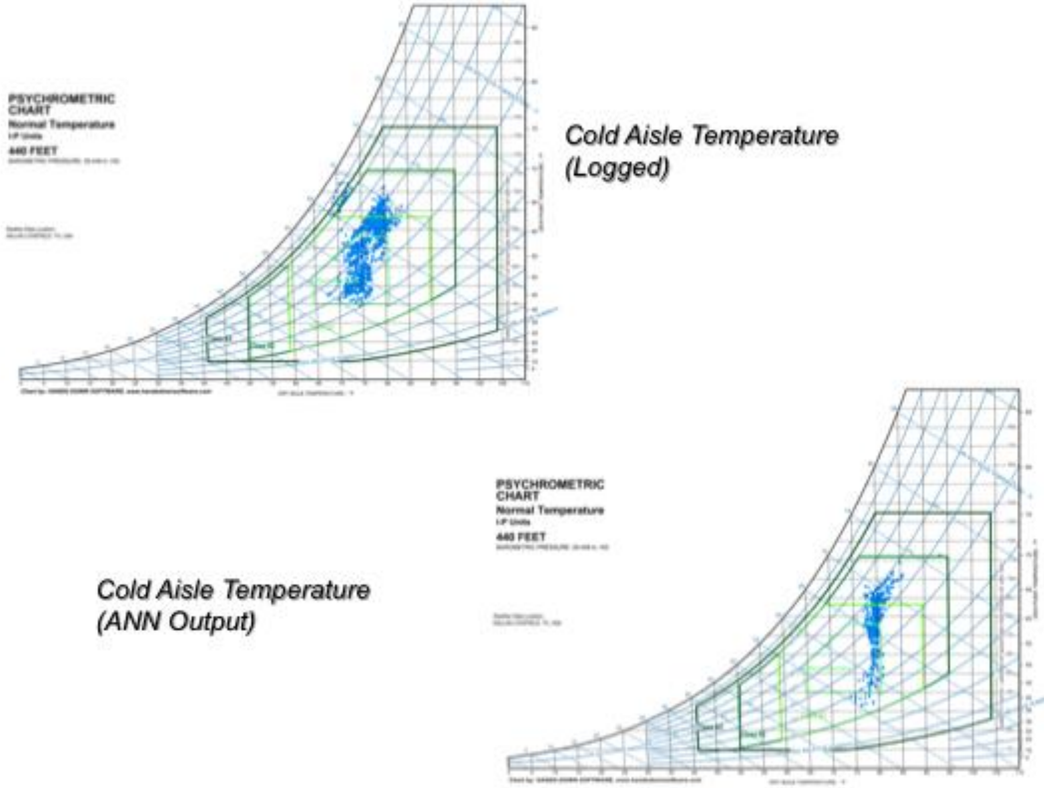

Figure 4.8 Comparison between cold aisle temperature(target) and cold aisle temperature (ANN output)

Figure 4.8 Shows the comparison between cold aisle temperature logged data, and cold aisle temperature gotten from our ANN model (output). This output data from the ANN is gotten after training is done. Evidently, the plot for cold aisle temperature on the psychometric chart for both logged data and ANN output shows a very clear correlation. They both fall in the same region of operation. Given this confidence in our result, we are able to further use the ANN model to get various other numerous outputs (cold aisle temperature in this case) for different cities. We take our trained model, give it, as input, outside air temperature and derive what the cold air temperature will be for our MDC in different cities or regions.

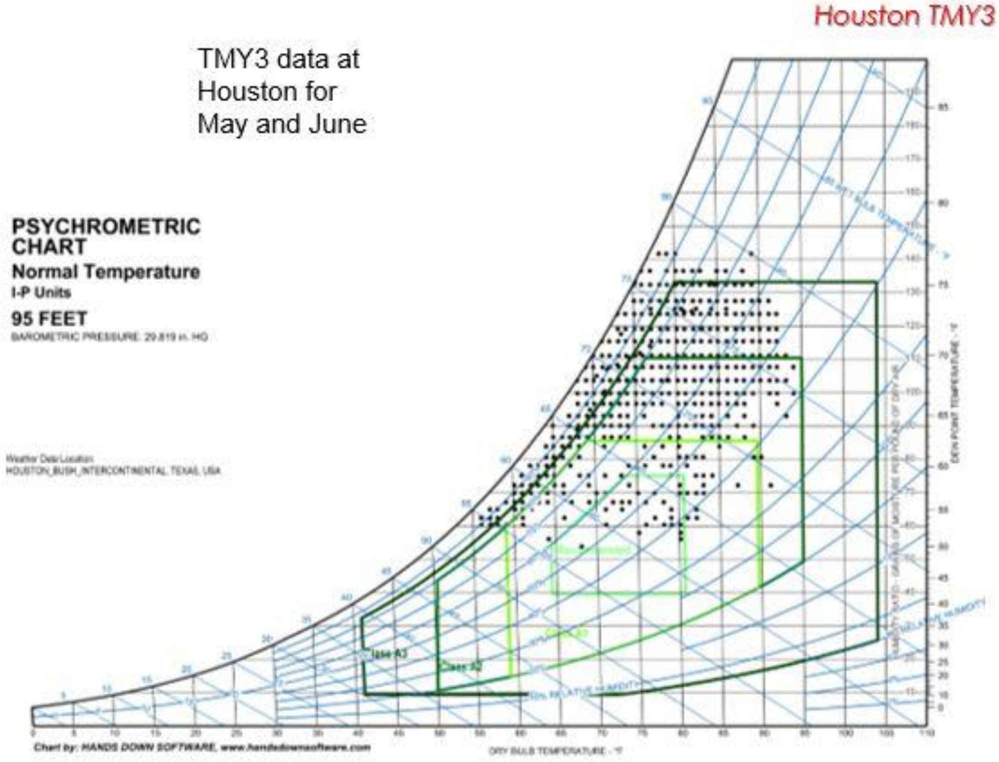

Figure 4.9 TMY3 data for Outside air temperature for MDC at Houston.

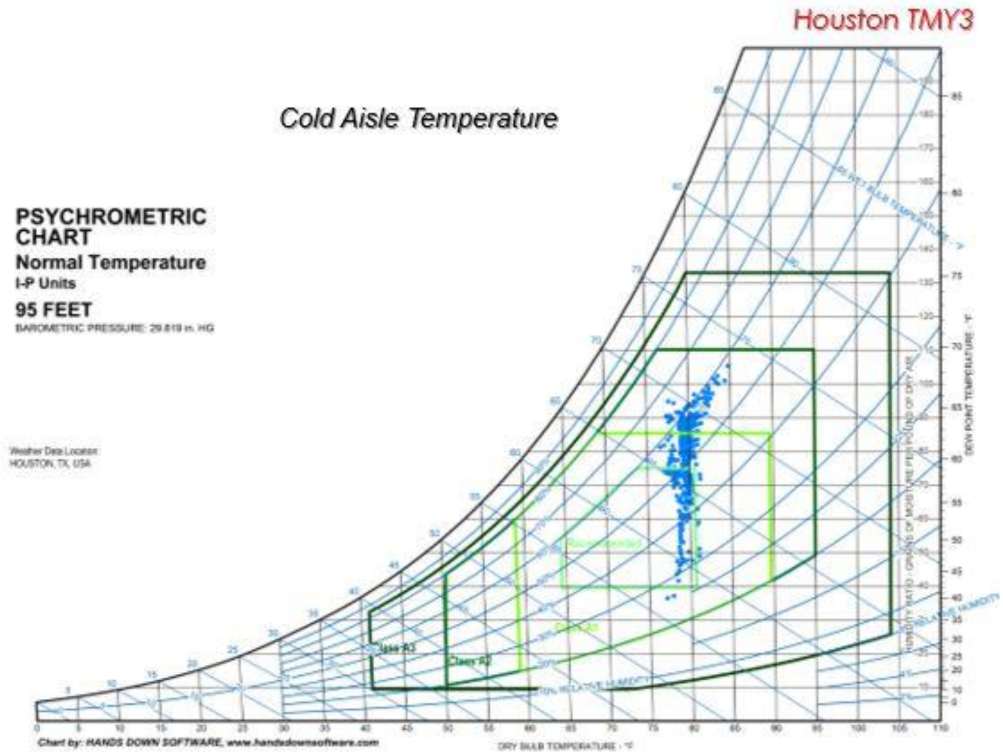

Figure 4.10 ANN output; Cold aisle temperature for MDC at Houston

Figure 4.9 Shows the Outside Air Temperature TMY3 data at Houston for MAY and June for our modular data center. Figure 4.10 is the output gotten from the ANN model as Cold aisle temperature for Houston, when Outside Air Temperature is fed into the ANN model as input.

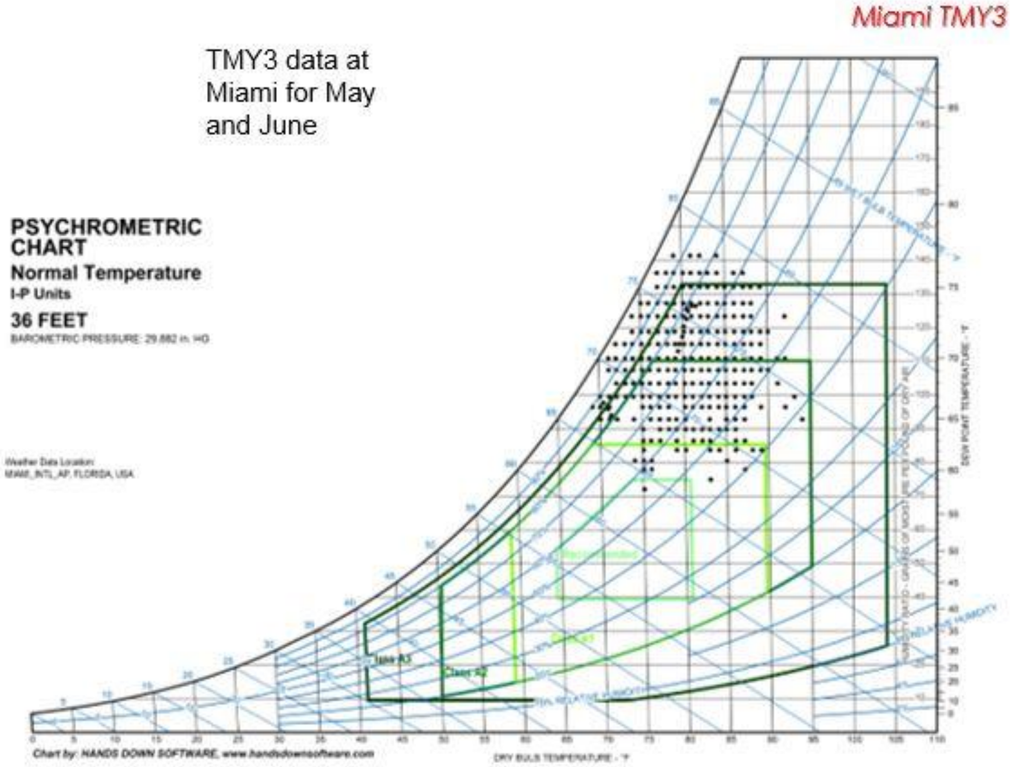

Figure 4.11 ANN output; Cold aisle temperature for MDC at Miami

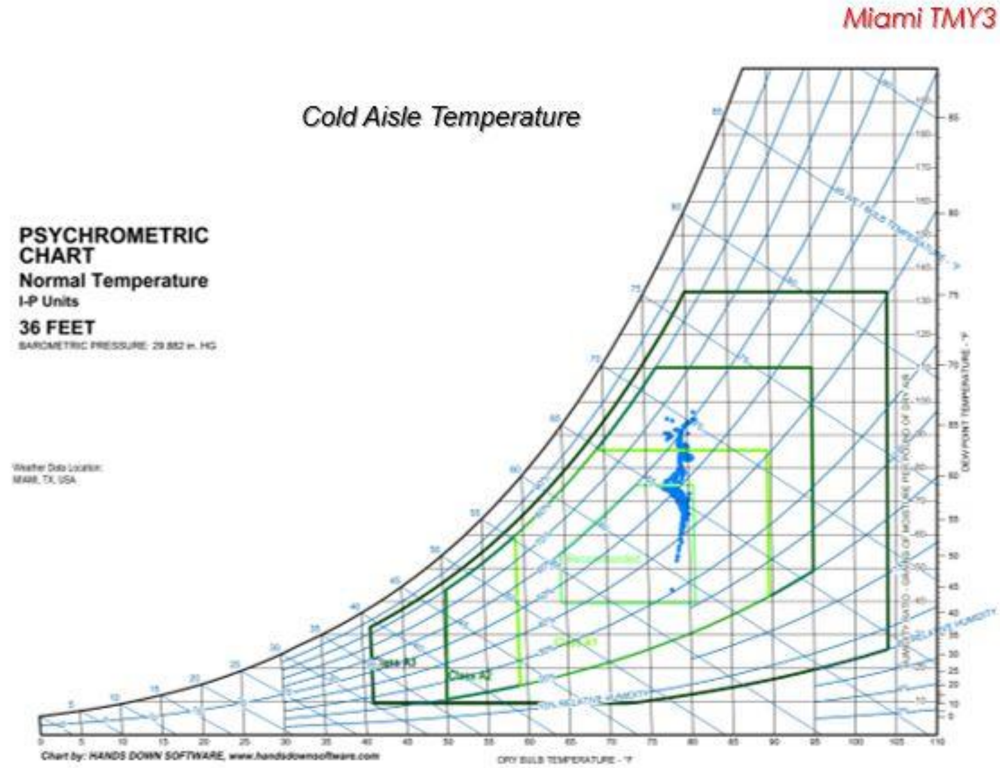

Figure 4.12 ANN output; Cold aisle temperature for MDC at Miami

Figure 4.11 Shows the Outside Air Temperature TMY3 data at Miami for MAY and June for our modular data center. Figure 4.12 is the output gotten from the ANN model as Cold aisle temperature for Miami, when Outside Air Temperature is fed into the ANN model as input.

4.3 Data Center Efficiency Model

Making further analysis on the work done by [4]. We intend to improve prediction results in our MDC. The dynamic neural network is employed, in order to learn time varying patterns associated with our MDC data. The dynamic neural network ensures that using past and current state we are able to predict system behavior. For prediction we will be using the Nonlinear Autoregressive Network with Exogenous Inputs (NARX) which is a recurrent dynamic network, with feedback connections enclosing several layers of the network. y(t) = f(y(t-1), y(t-2), …., y(t-ny), u(t-1), u(t-2), …, u(t-nu)) defines the NARX model. The consequent value of the dependent output y(t) is regressed on the previous values of the output signal and previous values of an independent (exogenous) input signal [5].

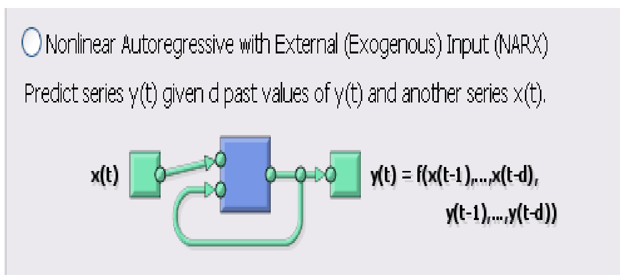

Figure 4.13 Nonlinear Autoregressive with External Input (NARX)

For our ANN model for prediction, we have three normalized input variables and five normalized target set point (output variables). All data used are available from logged sensor readings from our MDC (Aztec I/DEC unit. Similar with the weather analysis experiment. The neural network model contains 20 neurons in its hidden layer and 0.001 regularization parameter. Our dataset is divided into three segments. 70% for training, 15% for testing and 15% for cross-validation. This is also the cases in our weather analysis model.

4.4 Results and Discussion

The models are used to derive one step ahead and multi-step ahead prediction performance. Using the training “Levenberg-Marquardt” referred as ‘trainlm’ in MATLAB we set numbers of hidden neurons and delay time to 20 and 2 respectively. We carry out training in this model in a series-parallel format and then convert this ANN model into a closed loop system. Thereby, making current neural network output as input at the next time step as shown in Figure 4.15. In order to predict one time step ahead we remove one input delay is removed from the input layer. Given values y(t) and x(t) our model goes on to predict y(t+1) shown in Figure 4.16

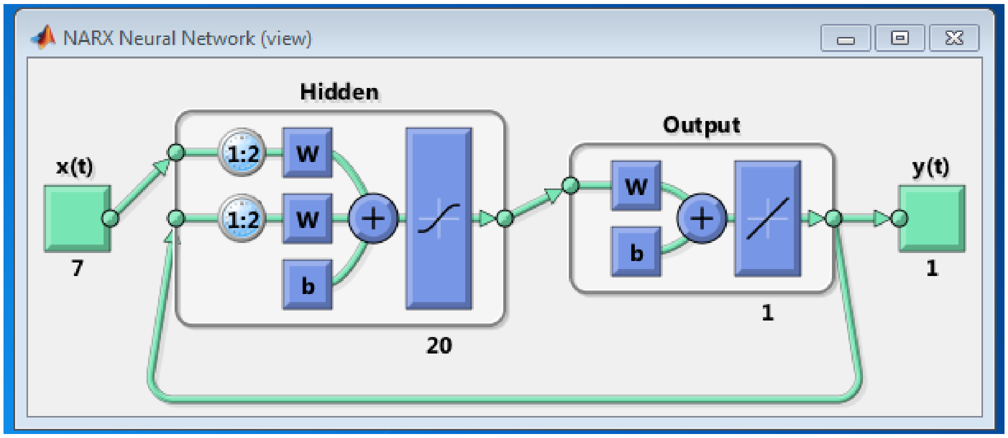

Figure 4.15 Multistep Ahead Prediction Neural Network Architecture

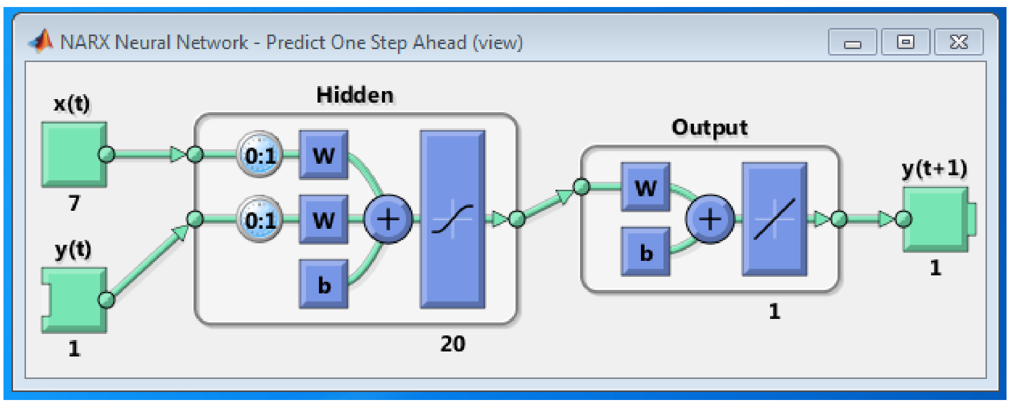

Figure 4.16 One Step Ahead Prediction Neural Network Architecture

We evaluate neural network performance after training by looking at the performance plot and the regression plot. The performance plot below, in Figure 4.17 shows when valid performance from iterations reached a minimum. As mentioned earlier, the regression plots provide more insights on relationship between outputs of the network and the targets. In this case, the value of R is greater than 0. 9, almost 1. Indicates a good fit neural network model as shown in Figure 4.18

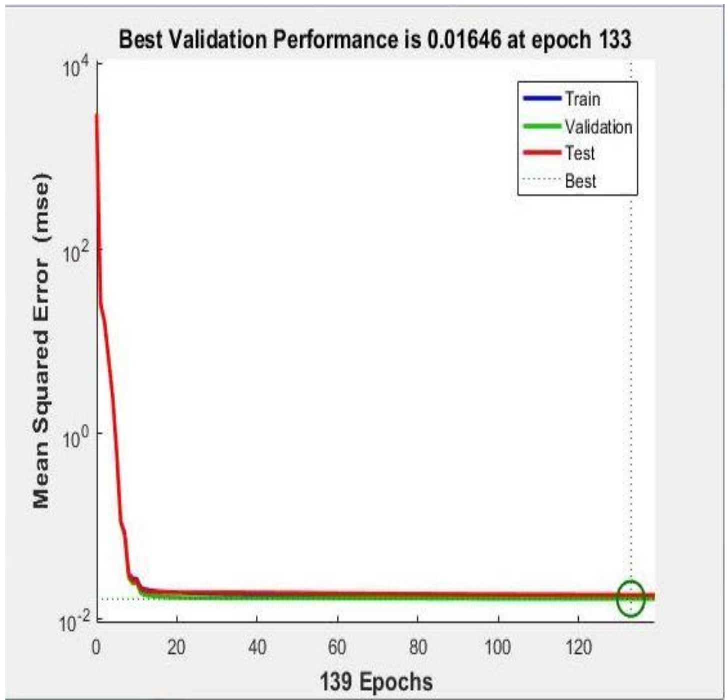

Figure 4.17 Training Performance Plot for Data Center Efficiency Model

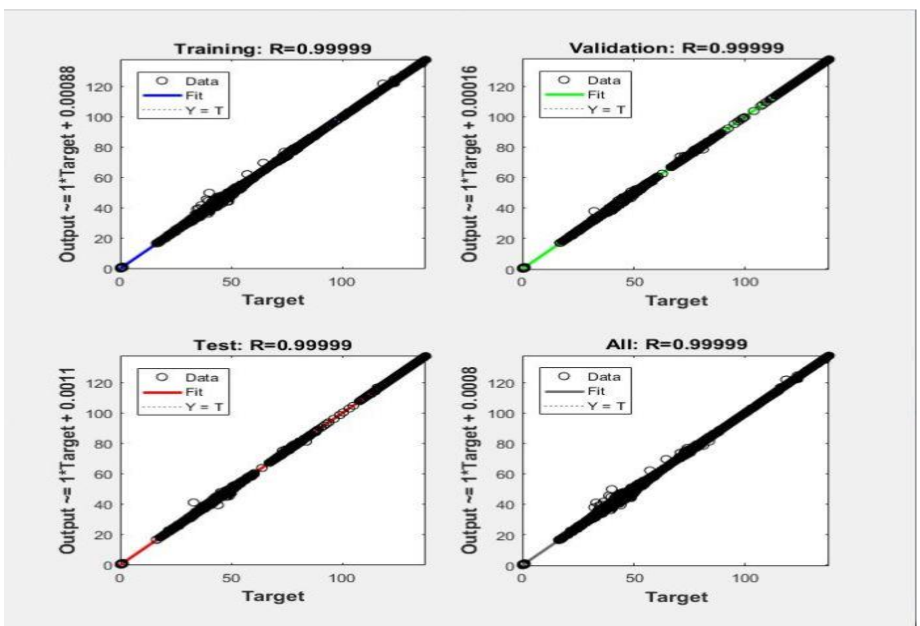

Figure 4.18 Regression Plot for Data Center Efficiency Model

4.4.1 One Step Ahead Prediction Results

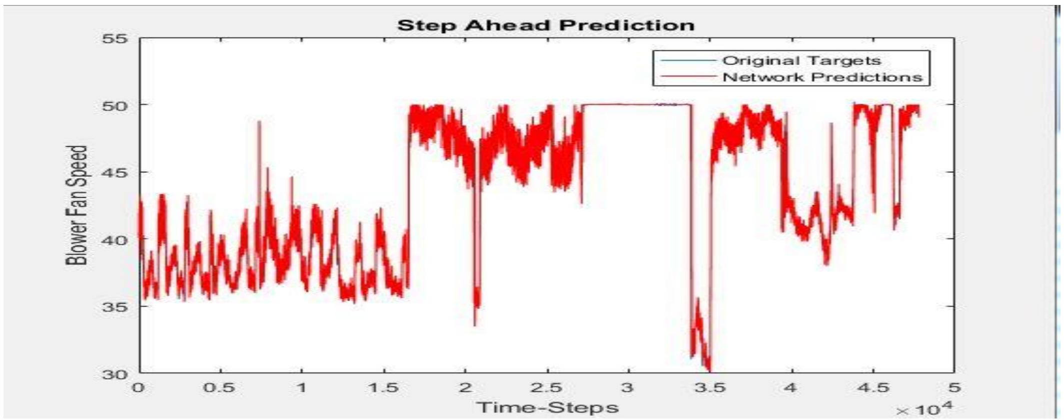

Figure 4.20 Data Center Efficiency Model: One step Ahead

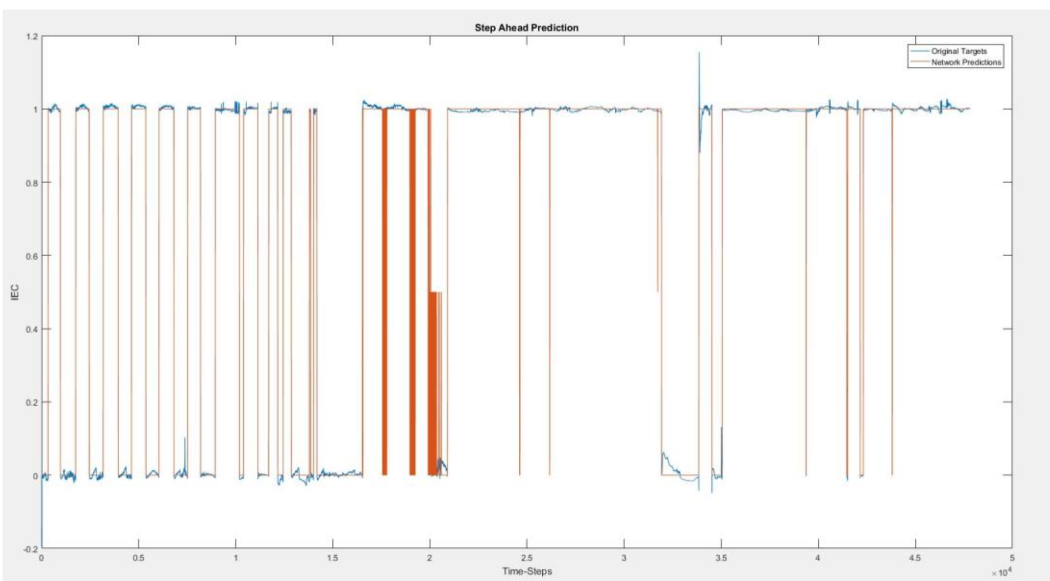

Figure 4.21 Data Center Efficiency Model: One step Ahead

The trained neural network model is tested for one step ahead prediction. Our model is able to predict targets one step ahead. In the above we predict blower fan speed in Figure 4.20 and IEC in Figure 4.21

4.4.2 Multi Step Ahead Prediction Results

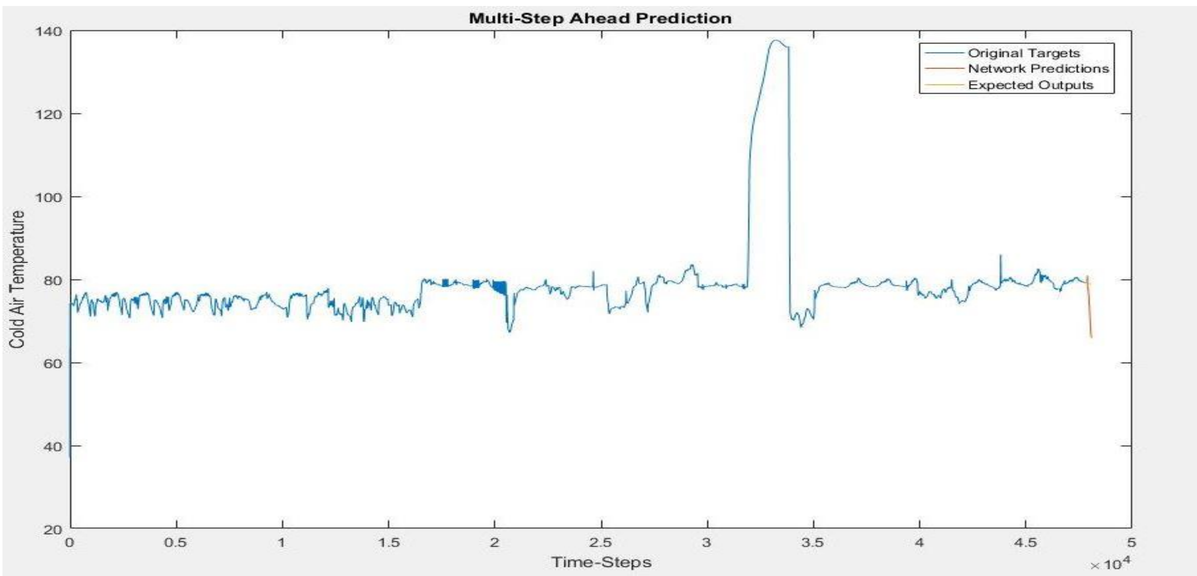

Figure 4.22 Data Center Efficiency Model: Multi Step Ahead

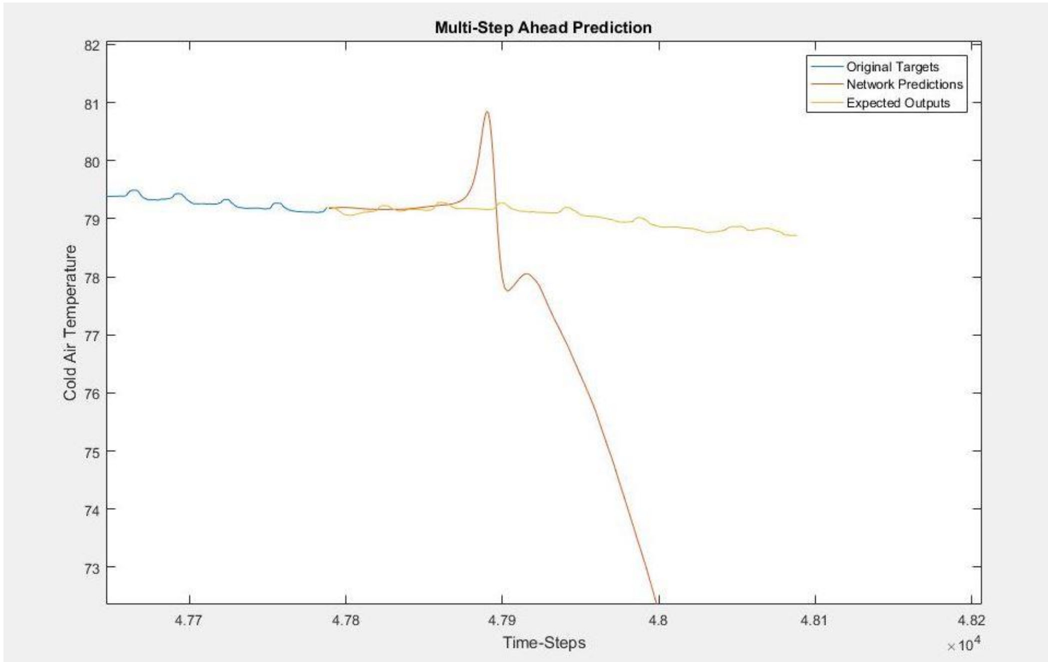

Figure 4.23 Data Center Efficiency Model: Multi Step Ahead (Zoomed)

The trained neural network model is tested for multi-step ahead prediction. In the above we predict cold aisle temperature in Figure 4.22 and 4.23

Chapter 5

Conclusion

In this research we are have been able to demonstrate the use of Artificial Neural Network to attain a significant degree in reduction of energy consumption in data centers and optimizing data center operations. Using the neural network tool box combined with monthly weather bin analysis, we were able to assist operators in weather bin data analysis of different regions and selection of cooling technologies. Furthermore, we tested the ability of neural network models in improving data center performance by optimizing data points generated from the actual performance of our model data center.

Chapter 6

Future Work

There is the opportunity to further improve weather bin analysis further. The Artificial Neural Network model gives the ability to optimize various parameters. There is an opportunity to train the Artificial Neural Network model with other operational parameters. In this research Artificial Neural Network analysis is done in a supervised method. We could further look at performing the same analysis in this research by exploring unsupervised training of our Artificial Neural Network.

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[5] M. H. Beale, M. T. Hagan, and H. B. Demuth, “Neural Network ToolboxTM User's Guide,” 2015.

Biographical Information

Feyisola Adejokun was born in Lagos, Nigeria in 1989. He received his Bachelor of Science degree in Physics with Electronics from Ajayi Crowther University, Oyo, Nigeria in 2010. He also, received a Postgraduate degree in Robotics from King's College London, United Kingdom in 2013. He started his Master of Science in Mechanical Engineering at the University of Texas at Arlington in January 2015. From January 2015 to December 2016. He is working on NSF I/UCRC projects for Energy Efficient Data Centers. His research interest includes Dynamic Systems Modelling, Robotic System Design and Machine Learning