DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK BASED BLACK BOX MODEL OF A DATA CENTER AS A TEMPERATURE PREDICTING TOOL AS A FUNCTION OF SERVER LOCATION, DISSIPATING SERVER HEAT AND CRAC FAN SPEED

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To my dearest parents, Tanuja and Niranjan Date– for the love, support, opportunities and motivation.

And to my family- whom I miss so dearly.

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ABSTRACT

DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK BASED BLACK BOX MODEL OF A DATA CENTER AS A TEMPERATURE PREDICTING TOOL AS A FUNCTION OF SERVER LOCATION, DISSIPATING SERVER HEAT AND CRAC FAN SPEED

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Modern data centers consume an astonishing 1.3% power all around the world. As the number of data centers continue to grow, there is an increasing need and demand to develop new ways to reduce the power footprint. Several approaches are being made to achieve this. One of such several approaches is to develop control systems that would keep the data centers running energy efficiently. Various control theories have been developed throughout the world to achieve the optimal energy efficient state. However, during the synthesis of such control schemes, the CFD simulations take up excessive time for plotting the thermal map of such complex, dynamic and highly nonlinear data center systems. In this paper, we aim to develop and train artificial neural networks for a typical scaled setup of modern data center like a Black Box Model which would predict the temperature at points in the state space throughout the room as a function of the dissipating heat at those points and CRAC fan speeds at the time. Due to significantly low analysis time than computational fluid dynamics, the Black Box is able to predict the temperatures in real time at different points in the setup thereby enabling faster optimization analysis. The Neural model is trained on a huge set of data generated by CFD simulations from hypothetical arrangements in a data center. Discussion about neural network training functions, its training parameters and comparisons of accuracy and computational time and the reason for the same is also done in this paper. Various suggestions to train such highly non linear and dynamic systems are summarized. To prove the accuracy of the neural network, the data generated is compared to the output of the CFD model. The robustness of the Black Box within the training data limits has been verified for changing CRAC fan speed and server heat. The Black Box tool developed is not only accurate but also very fast which enables its use in a feed forward adaptive control setup or the dynamic learning setup or both. Such a Black Box tool mimicking the CFD proves very useful in development of control systems for data centers.

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CHAPTER 1

Introduction

Modern data centers are growing in size and scale as we are moving forward in technology. As the data centers continue to grow in size, their footprint on power usage is becoming more significant by the day. As per the US Environmental Protection Agency, EPA estimations, the data centers and servers throughout the US has consumed an astonishing 1.5 % of total power in 2006 which is the peakload equivalent to the output of 15 baseload power plants. These were predicted to almost double by 2011. This amounts to a major chunk of the global power. The high power usage results in higher energy costs. Environmental concerns and more importantly higher power costs have led the manufacturers and users of such systems to explore newer and better ways to improve their energy efficiency.

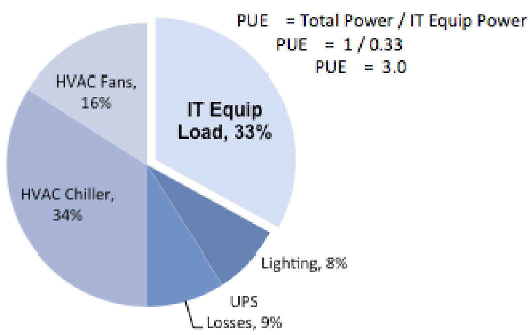

Figure 1.1. Power Usage Effectiveness.

The term PUE is a metric used to determine the efficiency of a data center industry.

It is the ratio of the total power used for the facility to the IT load catered. According to the Uptime Institute, most data centers had an average PUE of 2.5. Using the most energy efficient methods available, some of the data centers could achieve 1.6. When put in perspective, this means for every 2.5 Watts of power, only 1 Watt is used for the IT load. This is highly inefficient as we want the PUE to be near 1.

Therefore, attempts to improve the energy efficiency of such power guzzling data centers are being made in various aspects of the facility. Recent results published by Google Inc. shows them to have a PUE of 1.14. But this has been the most efficient data recorded by any data center known. The data center industry is continually in search of other energy efficient practices to reduce their PUE. Hot, cold aisle containment, better heat exchanger designs, application of evaporative cooling, changes in layout, load scheduling, Waste Heat Recovery and application of absorption cooling, contamination studies, etc. are various fields in which a lot of studies, experiments and testing is being done to improve the efficiency of modern data centers.

Development of control systems to control such data centers is an efficient way to reduce power footprint. The need for such control algorithms to be scalable and effective is huge. These controllers need to be smart, fast, adaptive and dynamic in nature to control a highly non linear environment like that in a data center. The need for a predictive and fast controller is huge as the repercussions of ineffective or failed control are huge both in terms of cost and time.

Computational Fluid Dynamics is used currently to model data centers in computer software and simulate their behavior or response to certain present conditions. CFD is not only expensive to model but also requires an experienced user. moreover, the CFD still lacks complete accuracy to the actual facility. All the control theories being developed today use CFD as reference data in the development stage and later for the verification studies. However, as the complexity of the data centers is increasing, the

model based simulations take very long hours to achieve steady state for a preset condition. This lengthens the parametric studies and thereby development of controllers. Moreover, every minute change in the input parameters of a complex system has a high effect response from a system. So a control engineer has to spend a lot of time on verification studies and still faces the problem of highly unpredictable response if the system goes out of control. Hence there is a very urgent need to develop predictive type of control for such highly non linear and complex systems.
Artificial Neural Networks have been around for a long time and have been effectively used for pattern recognition and data manipulation. We aim to use this pattern recognition and duplicating effects of the neural network to our advantage in this approach. The Data Center is a complex system wherein the thermal characteristics have a very complex combination of heat and mass transfer. These systems form parallel interconnections of dynamic elements that are highly coupled energy sources, energy sinks and energy storage units. The primary challenge of the thermal management system is to maintain the peak temperature for any server within some preset zone of temperature band. These systems form parallel interconnections of dynamic elements that are highly coupled energy sources, energy sinks and energy storage units. The highly varying local temperatures, point source temperature measurements and cooling together create an under actuated system which can be called unobservable due to its sheer complex nature. This is a challenging scenario for any successful feed-forward or feedback control system design.

The main reason behind the application of neural network for data prediction is its fast computational rates over the regular CFD techniques. Neural Networks as a concept has been derived from the biological human brain which gives it the capacity to learn from the training data and model relationships between the inputs

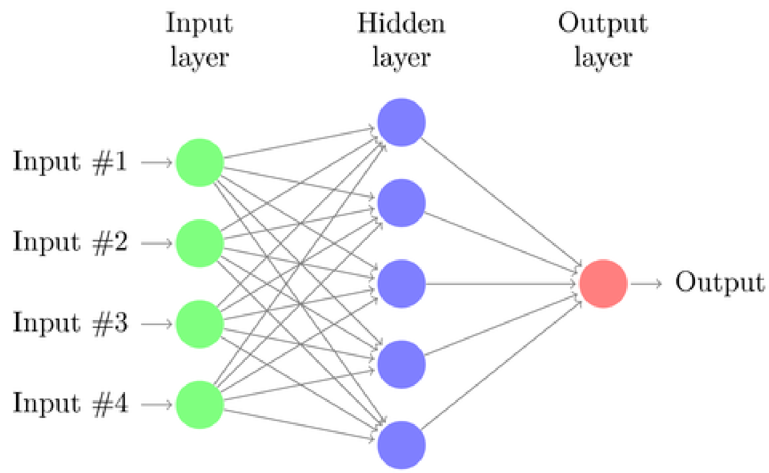

Figure 1.2. A Simple MLP Neural Network.

and outputs of any level of complexity. They have an increasing application by the day to accomplish complex tasks such as modeling, approximations, classification and optimization. Neural networks have been proven to be very efficient in approximation of nonlinear mapping with a high degree of accuracy. When such a system is analyzed by the conventional CFD techniques, the analysis time is too large which hinders the approaches to improve the system. To reduce this analysis time we use the Multi Layered Perceptron(MLP) technique which is a feed-forward artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back-propagation for training the network. MLP is a modified form of the standard perceptron and has the ability to effectively distinguish given data which is not linearly separable. If there would be a neural network based tool which would predict the behavior of the data center when given a preset input, would prove very useful. Such a tool could be used for proof of concept as well as direct use in a feed forward controller. Hence, the development of such a Black Box Model of a data center mimicking the CFD was thought of and developed.

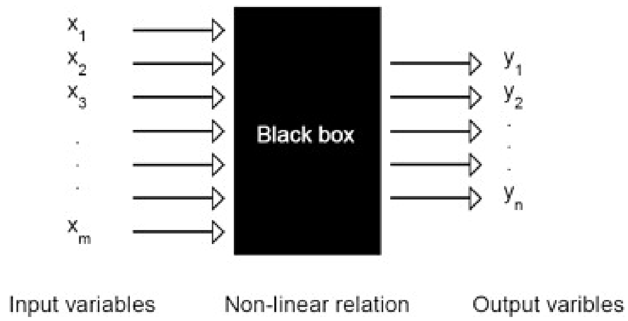

Figure 1.3. Black Box Model.

CHAPTER 2

Background

2.1 Data Center Room Air Flow

A Data Center is a facility which houses servers, storage devices, computers and other such IT equipment. Such rooms need conditioned air at precise temperatures for predictable performance. ASHRAE Thermal Guidelines for Data Centers recommends inlet temperatures in the range of 10 to 35°C (50-95°F) for Class A1 (high-end enterprise servers and storage products) equipment. The cold air distribution is typically done through a raised floor plenum throughout the data center. Computer Room Air Conditioners(CRACs) continuously pump cold air into the plenum at a set temperature like 18. The air exits the plenum through perforated floor tiles and other openings. The cold air rises through the 'hot' IT equipment be it servers or storage devices thereby cooling it. Hot air which has cooled the IT equipment is usually recirculated and returned to the CRACs though either duct-work, raised plenums or through the room CRAC openings. Standard best practice employed today in most data canters is to arrange the perforated floor tiles in rows forming either cold or hot aisles . IT equipment racks are then placed in rows along and facing each long side of the cold aisle. Alternating hot and cold aisles are formed as this configuration is repeated across the data center. The temperature of the cooling air actually available for IT equipment depends on the airflow dynamics between the perforated tile and the equipment inlet. Equipment will draw air as needed and, if sufficient cooling air is unavailable, warm exhaust air will be recirculated over the racks or around the row ends. It is, therefore, essential that perforated tiles located near the equipment provide sufficient cooling air.

2.2 ASHRAE Guidelines for Server rooms and IT Equipment

The ASHRAE thermal guidelines for IT Equipment housing or data centers were updated in 2011. The previously known classes of 1,2,3,4 are now renamed A1, A2, A3, A4. We are concerned with these as these contain all the ITE we might encounter in a data center.

ASHRAE Thermal Guidelines for Data Centers recommends inlet temperatures

Table 2.1. ASHRAE Server Classification- 2008 and 2011

2011 Classes	**2008 Classes**	**Applications**	**IT Equipment**	**Environmental Control**
A1	1	Data Center	Enterprise Servers, Storage Products	Tightly Controlled
A2	2	Data Center	Volume Servers, Storage Products, Personal Computers, Workstations.	Some Control
A3	NA	Data Center	Volume Servers, Storage Products, Personal Computers, Workstations.	Some Control
A4	NA	Data Center	Volume Servers, Storage Products, Personal Computers, Workstations.	Some Control
B	3	Office, Home, Transportable Environment, etc.	Personal Computers, Workstations, Laptops and Printers.	Minimal Control
C	4	Point-of-Sale, Industrial, Factory, etc	Point-of-Sale Equipment, ruggedized controllers or computers and PDAs	No Control

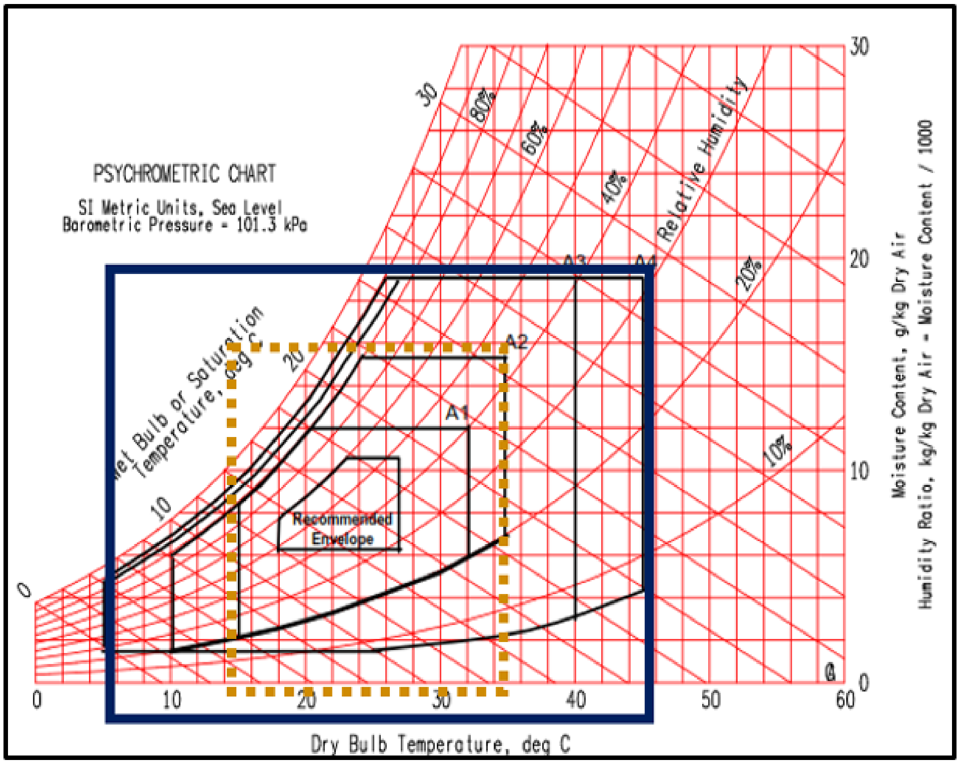

Figure 2.1. ASHRAE Server Classes Psychrometric Chart.

Classes (a)	Equipment Environmental Specifications							
	Product Operations (b) (c)					Product Power Off (c)(d)		
	Dry-Bulb Temperature (°C) (e) (g)	Humidity Range, non-Condensing (h) (i)	Maximum Dew Point (°C)	Maximum Elevation (m)	Maximum Rate of Change (°C/hr) (f)	Dry-Bulb Temperature (°C)	Relative Humidity (%)	Maximum Dew Point (°C)
Recommended (Applies to all A classes; individual data centers can chose to expand this range based upon the analysis described in this document)								
A1 to A4	18 to 27	5.5 °C DP to 60% PH and 15°C DP						
Allowable								
A1	15 TO 32	20% RH to 80% RH	17	3050	5/20	5 TO 45	8 TO 80	27
A2	10 TO 35	20% RH to 80% RH	21	3050	5/20	5 TO 45	8 TO 80	27
A3	5 TO 40	-12°C DP & 8%RH to 85% RH	24	3050	5/20	5 TO 45	8 TO 90	27
A4	5 TO 45	-12°C DP & 8%RH to 90% RH	24	3050	5/20	5 TO 45	8 TO 90	27
B	5 TO 35	8% RH to 80% RH	28	3050	NA	5 TO 45	8 TO 80	29
C	5 TO 40	8% RH to 80% RH	28	3050	NA	5 TO 45	8 TO 80	29

Figure 2.2. ASHRAE Thermal Guidelines for Data Centers.

in the range of 10 to 35°C for Class A1-A4 (high-end enterprise servers and storage products) equipment. e.g. 18 °C. Maintaining these temperatures within that zone is vital for high performance of the servers. Heating of servers results in decrease of computing performance and repercussions of such under performing systems in a data center are huge. From the controller development stand point of view, we need to ensure that the servers are maintained in this range for best operation efficiency.

2.3 Control Problem

The control problem in such a dynamic and non linear system is to not only maintain the servers under the desired temperature range but also to maintain the whole system stability. Such complex systems have a significant response when their input parameters are changed. Also, the thermal map of a data center is dependent on a lot of parameters and hence predictive type of control is required. For predictive type of control we need a fast and accurate type of predicting tool. A nicely trained Black Box tool would be perfect for such application. Also, the conventional PID type of control is not effective in such systems because, we cant have too many shifts in input parameters. Constant change in inputs makes the system fluctuate and the whole system can go out of control. Hence, ANN based control that would be fast, accurate, robust and adaptive is the ideal control system for such data center system.

2.4 Use of Artificial Neural Networks

Due to the large amount of power usage by data centers, a lot of different approaches have been made to optimize the system. The sheer complexity of the system as a whole makes the optimization much more complex. Artificial Neural Networks have been used to predict certain parameters like temperature and hence control the CRAC fan speeds for maintaining server temperatures. The temperatures predicted are in real time which can be easily used to predict and make the necessary changes in the fan speeds. The Neural network has been used in conjunction with a genetic algorithm and a "cooling performance engine" can be formulated. However, it becomes a bit more tricky when one tries to control the server temperatures by shifting the loads around the servers. If we can train a network as a function of the heat at the point, it will be much more effective in real sense of controlling the temperature. Due to the ever increasing system performance demands the system is expected to be able to scale i.e. Scalability has become one of the important parameters in the design process. Hence, we thought of using the neural model in conjunction with a Power Controller to change more than one parameters for the optimized system. As the Server Power and Fan Speed are controlled, the system can be maintained at the "Optimized Point" in real time. With this theory in mind, the neural network is trained in such a way that it has the freedom and robustness to map the temperature at points it hasn't been trained on.

2.5 The Plant

The system or The Data Center layout is an IBM data center. The room has 4 CRACs in the layout. The cold air is supplied from the CRACs through the perforated tiles from below. The cold air enters the Racks, cools them and returns from the elevated plenums. The cold air movement can be seen in the fig. The server aisles are named A,B,C and D. The Aisles A and B have 6 racks whereas the aisles C and D have 4 racks. The Layout is along a line of Symmetry i.e. its scaled to half. The space between the aisles A-B and C-D are the hot aisles and the others are cold aisles. The modeling of the racks in aisles is done so that the heat dissipation is per load bank. And there are 4 load banks on a rack. The dimensions and details of the system is as follows.

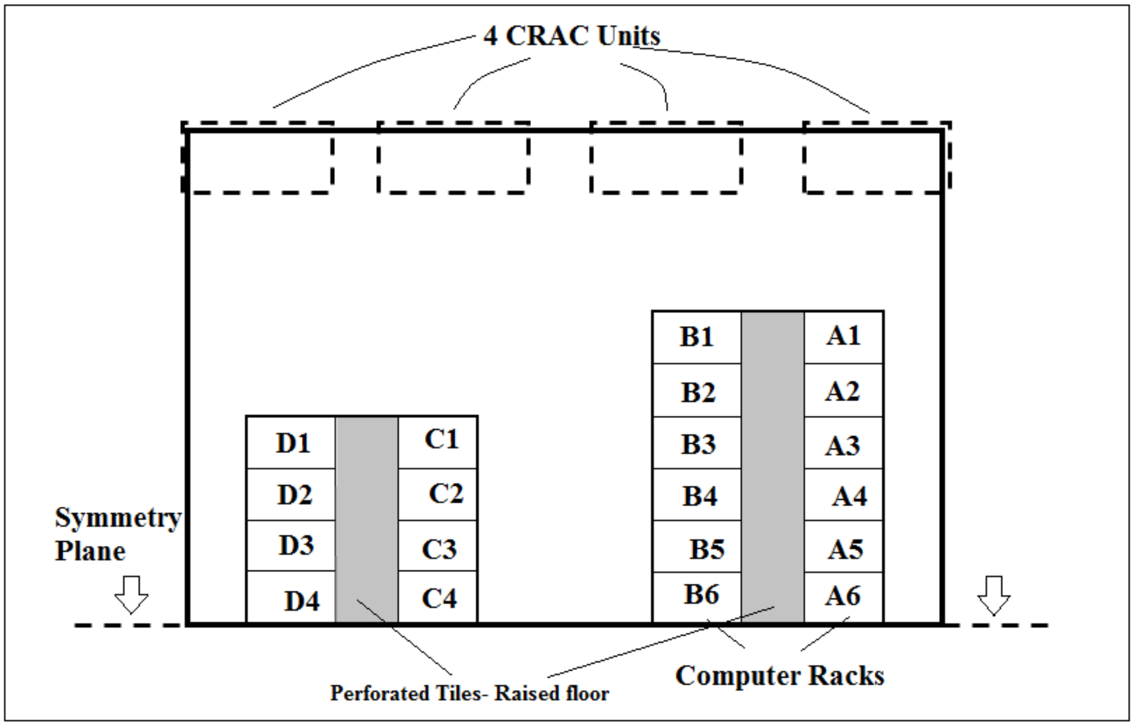

Figure 2.3. System Layout.

Table 2.2. Server Room Details

Room Size	6.05 m * 13.42 m * 3.648 m
Plenum Depth	0.3 m
Server Rated Air Flow	1460 cfm
Tile Open Area	50%
Perforated Tile Area	0.61 m * 0.61 m
CRAC Air Flow (100 %)	7300 cfm
Chilled Air Supply Temperature	15°C
Ambient Air Temperature	30°C

2.6 Past Work on the topic

In the past several similar approaches have been made to bypass the CFD to save time as well as deal with the high non-linearity of the data center. ANNs have been used to predict the air flow required to cool the room which enters through perforated tiles. Successful attempts to predict whether the room is sufficiently cooled have been made. Combined with a cooling system model, control algorithms to find the optimal operating point for CRACs have been tested.The performance of such Genetic Algorithms has been accurately demonstrated. Such studies have shown upto 30% reduction on energy usage. Rack level cooling performance and development of an optimization algorithm has been proved. Hard floor room studies that conclude the effectiveness of the Neural Network can be found. Such studies have been extended to raised floor, overhead supply types also. Combination of ANNs with a cost function based Multi-Objective Genetic Algorithm using Latin Hypercube method which predict the operating conditions inversely for the desired outputs are very useful in control scheme synthesis. ANNs as Cooling prediction engine using genetic algorithms to find the optimized cluster layout enhance the chances to find the Best Arrangement for a fixed inventory of racks, Best rack location, etc. However, neural network trained which is highly accurate to map both change in CRAC fan speed and Server heat with a high degree of robustness will prove to be very useful.

CHAPTER 3

Artificial Neural Networks for Function Approximation

The ANN has a great potential to map unknown functions between a set of input and output vectors. We use this ability to our advantage especially since the system we are dealing with is highly nonlinear and complex. We use the ANN as a function approximation system also referred to as *Black Box Modeling*. Lets assume x as the input vector and d is the output vector. If there is a set of N different points in a y dimensional input space such that $x^k \in R^y, k = 1, 2, 3, ..., N$ and another N points in a z dimensional output space such that $d^k \in R^z, k = 1, 2, 3, ..., N$, we want to find a mapping function $F : R^y \longrightarrow R^z$ which will satisfy the equation

$$T(x^k) = d^k, \qquad k = 1, 2, 3, ..., N.$$

Then the actual unknown function $f(*)$ which maps the input-output relationship is denoted by

$$f(x^k) = d^k$$

Then the approximation should be such that the error between desired and actual outputs, ε should be as small as possible. The approxiamtion function will be,

$$\parallel T(x^k) - f(x^k) \parallel < \varepsilon.$$

As long as we make sure that the training data sets are large enough and the network is given sufficient number of free parameters or *neurons* , then the approximation error ε can be made very small thereby increasing the accuracy of the predictions.

The challenges with main stream control systems such as PID and Fuzzy systems is that there are no system energy transfer equations which are easily found for such complex systems. The transfer function in our model is also deeply buried in many different parameters and variables. Black Box Modeling can approximate such systems using the system identification. The structure of system identification is as shown below, We trained the ANN to map 5 inputs to 1 output of such an un-

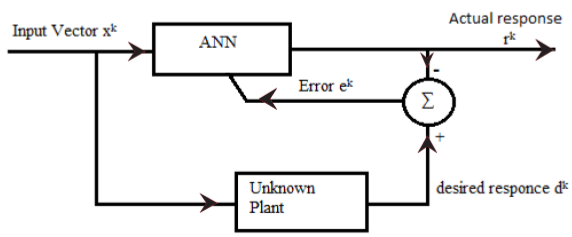

Figure 3.1. System identification.

known system. The inputs were mainly location coordinates in 3-d space, heat load and CRAC fan speed. We tested our ANN on a control algorithm which would read through the temperatures at all the points and thereby make changes to the heat load there bu shifting it to some point which was at a lesser temperature. We did this just to test the speed and robustness of the ANN. A verification study with CFD was also conducted after a few iterations of load shift to check if such a designed ANN could maintain the accuracy at points it wasn't trained on. Due to its high VLSI implement-ability the ANN is able to predict the temperatures in almost real time. The total simulation time for 50 iterations was less that 10 seconds which compared to the CFD is negligible. The control algorithm was based on the Power Reservoir concept. The server temperature is assumed to be proportional to the heat load at the server.

CHAPTER 4

Training Algorithms and Comparison

We know from the adaptive control or dynamic learning control studies that the ANNs that can effectively run with those setups not only need to be accurate but need to be fast. They need to train fast i.e. update of weight matrices should be fast and predict accurately.For the ANN training, there are several algorithms which could be used viz.

i Levenberg-Marquardt algorithm

ii Gradient Descent method

iii Bayesian Regularization

iv Scaled Conjugate Gradient method

v Resilient Back Propagation method

vi One Step Secant method, etc.

The LM function and Gradient Descent are widely used as function approximation tools and hence we look at the speed and accuracy of these two algorithms for comparison. The Gradient Descent is a training function which works by updating the weight and bias values according to the gradient descent. There are 2 ways in which the Gradient Descent is implemented viz.

a. Gradient Descent Back propagation method

b. Gradient Descent with Momentum Back Propagation

Both of the above operate on similar lines with some addition. These methods update the weight and bias. The GD Back Propagation updates the wights and biases in the negative gradient direction of the performance function. The Learning rate lr is multiplied by the negative gradient to evaluate the update on weight and biases. Size of the lr directly affects the size of the step towards convergence. Small lr takes a lot of analysis time whereas a huge lr value will make the network unstable.

The variables are updated using the Back Propagation which in turn is used to calculate the derivative of the performance function as follows

$$dX = lr * \frac{dPerf}{dX}$$

The Gradient Descent with Momentum allows a network to respond to the local gradient as well as the trend in the error surface. It works like a low pass filter, where the momentum allows the network to ignore small features in the error surface. Without momentum a network can get stuck in a shallow local minimum. With momentum a network can slide through such a minimum. This algorithm depends on two training parameters. The parameter lr indicates the learning rate, similar to the simple gradient descent. The parameter mc is the momentum constant that defines the amount of momentum. The weights and biases are updated as follows.

$$dX = mc * dXprev + lr * (1 - mc) * \frac{dPerf}{dX}$$

where dXprev is the previous change to the weight or bias.

Gradient Descent with momentum turns out faster but less accurate as compared to gradient descent back propagation. Shown below is an example of their behavior when trained on different settings of neurons.

On comparison, GD Back Propagation algorithm fares greater accuracy as compared to the other. The difference in time of training is too insignificant as the difference in accuracy is high.

Then there is *Levenberg-Marquardt* training algorithm which is one of the fastest back

Table 4.1. Comparison of Training time and Number of Neurons for GD Back Propagation and GD with Momentum

Neurons	5	10	15	20	25	50	100	150
GD Backpropogation algorithm	17	22	31	43	67	130	494	1557
GD with momentum algorithm	13	17	25	37	60	118	452	1387

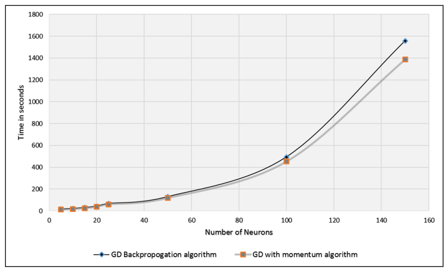

Figure 4.1. Comparison of Training time and Number of Neurons for GD Back Propagation and GD with Momentum.

Table 4.2. Comparison of Training accuracy and Number of Neurons for GD Back Propagation and GD with Momentum

Neurons	5	10	15	20	25	50	100	150
Accuracy for GD Backpropogation algorithm	72	74	81	88	89	90	95	100
Accuracy for GD with momentum algorithm	62	67	73	73	78	79	81	83

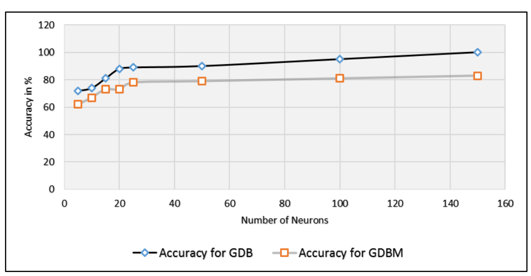

Figure 4.2. Comparison of Training accuracy and Number of Neurons for GD Back Propagation and GD with Momentum.

propagation algorithms present. This algorithm is designed to attain second order training speed bypassing the computation of the hessian matrices. Its performance function attains the sum of squares form hence the Hessian, H can be approximated as,

$$H = J^T J$$

And the gradient, g can be computed as,

$$g = J^T e$$

where, J consists of the first derivative of network errors w.r.t the bias and weights & e is the vector of network errors. This is useful as computing the Jacobian is much easier than computing Hessian. This also plays a major role for the LM algorithm to be fast. The wights are updated using the standard Newtonian method. The equation is as follows

$$w_{k+1} = w_k - [J^T J + \mu I]^- 1 J^T e$$

where w is the current network weights and μ is zero, following the Newtonian mothеod using the approximate Hessian matrix. And the Jocobian is calculated as,

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial w_1} & ... & \frac{\partial e_1}{\partial w_n} & \frac{\partial e_1}{\partial w_0} \\ . & & . & . \\ . & & . & . \\ . & & . & . \\ \frac{\partial e_p}{\partial w_1} & ... & \frac{\partial e_p}{\partial w_n} & \frac{\partial e_p}{\partial w_0} \end{bmatrix} = \begin{bmatrix} x_{1_1} & . & x_{n_1} & 1 \\ . & & . & . \\ . & & . & . \\ . & & . & . \\ x_{1_p} & . & x_{n_p} & 1 \end{bmatrix}$$

where w is the vector of weights, w_0 is the bias of neuron and e is the error vector.

The figures below shows the comparison between LM and GD with Back Propagation when trained on different neurons and the graphs depict the time and accuracy of both the algorithms.

Table 4.3. Comparison of Training time and Number of Neurons for GD Back Propagation and LM Algorithm

Neurons	5	10	15	20	25	50	100	150
LM algorithm	11	13	22	35	37	132	403	1092
GD algorithm	17	22	31	43	67	130	494	1557

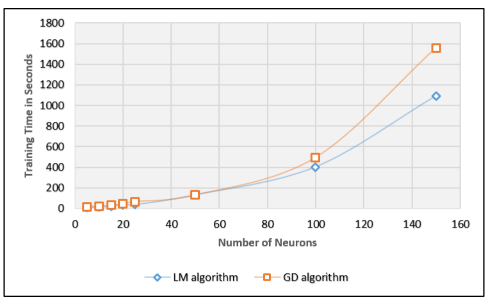

Figure 4.3. Comparison of Training time and Number of Neurons for GD Back Propagation and LM Algorithm.

Table 4.4. Comparison of Accuracy and Number of Neurons for GD Back Propagation and LM Algorithm

Neurons	5	10	15	20	25	50	100	150
Accuracy for GD Back Propagation Algorithm	72	74	81	88	89	90	95	100
Accuracy for LM Algorithm	75	82	85	88	94	97	97	100

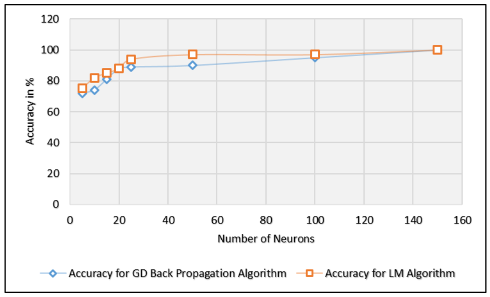

Figure 4.4. Comparison of Accuracy and Number of Neurons for GD Back Propagation and LM Algorithm.

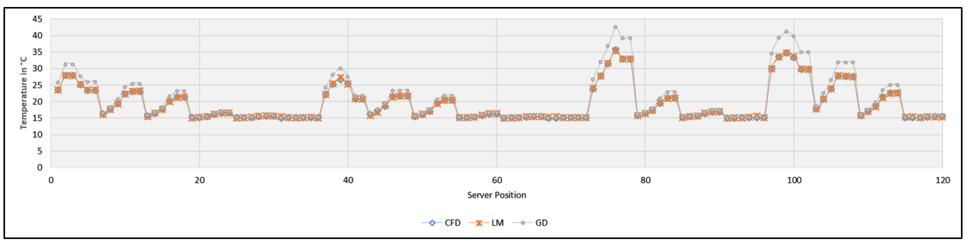

Figure 4.5. Comparison of Predicted Temperature Results from CFD, GD and LM Algorithms.

As can be seen from the graphs above, the LM algorithm is much faster than GD Back propagation when tested. Since, speed is a vital feature required for the ANN for it to be useful across platforms, LM algorithm looks best to train our ANN on. The Fig.9 shows a comparison of prediction results of a test case for CFD, LM and GD algorithms. It can be clearly seen that LM is better suited since the difference in predictions between CFD and LM is least. So, for our ANN based Black Box we will use the LM Algorithm for training. The Black Box shows fine tuning with LM Algorithm which in turn means that there are no disconnections in the internal structure of the ANN.

CHAPTER 5

Training of the ANN achieved

The ANN was trained on LM algorithm several times before the best state was achieved.The tables and figures below show a few different attempts made to finely tune the Black Box. The number of neurons need to be adjusted in the hidden layer. A trial and error method needs to be implemented to achieve the optimum training parameters.

The tables below show case of tuning the network for 80% CRAC Fan Speeds. The number of Neurons in hidden layers are changed as per the behavior of the ANN.

Table 5.1. Comparison of Best Performance Points during Training and Validation for different Number of Neurons

Neurons	5	10	25	50	100	150	500	120	130	140	160	600	720
Best Validation Performance	4.21	2.4	0.2924	0.2522	0.1146	0.0768	0.1606	0.15138	0.167	0.14165	0.163	0.25212	0.42466
Best Training Performance	4.64	2.71	0.23	0.163	0.049	0.0185	0.0007	0.0479	0.062	0.0225	0.04	4.13E-11	9.21E-09

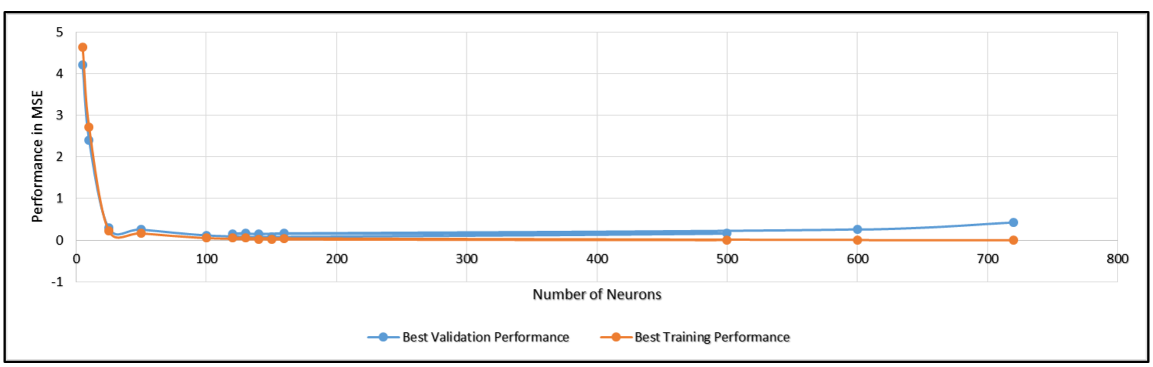

Figure 5.1. Comparison of Best Performance Points during Training and Validation for different Number of Neurons.

Table 5.2. Max Difference and Max %Error between ANN and CFD results

Neurons	5	10	25	50	100	150	500	120	130	140	160	600	720
Max Error	42.71168	20.66355	7.559624	6.601913	3.87639	4.540827	3.798227	5.913775	6.054006	3.806505	4.318931	9.226235	8.743773
Max Difference	8.093864	5.168147	1.893656	1.835244	1.479199	0.918543	0.830523	1.570114	1.609745	0.907286	1.127568	2.92418	1.815706

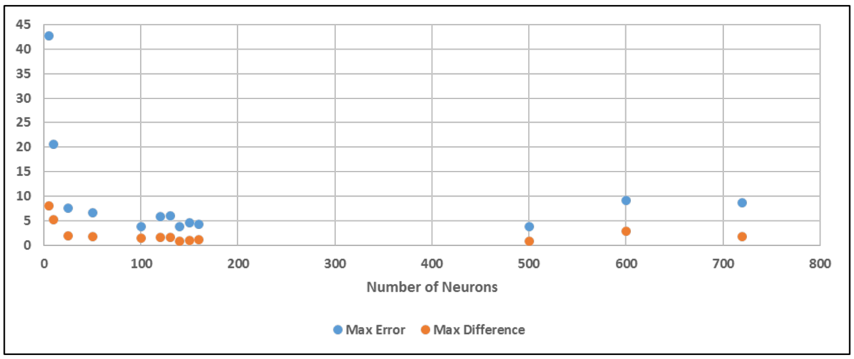

Figure 5.2. Max % Error and Max Difference for number of Neurons.

The 2 best operating points are found to be 150 and 500 Neuron Models. These 2 Networks are tested for accuracy to a 120% CRAC Fan Speed Model. The Table and Fig. below show the test results.

Clearly, 150 Neuron Model is better tuned that 500 Neuron Model. To verify this, we

Table 5.3. Max % Error and Difference between ANN and CFD for 120% CRAC fan speed Test Case.

Neurons	500	150
Max Error	4.554417	3.437699
Max Difference	1.292665	0.6725

again test this for another 80% CRAC Fan Speed case. The results are shown below.

The difference is $< 1°C$ which is quite accurate and passes the test.

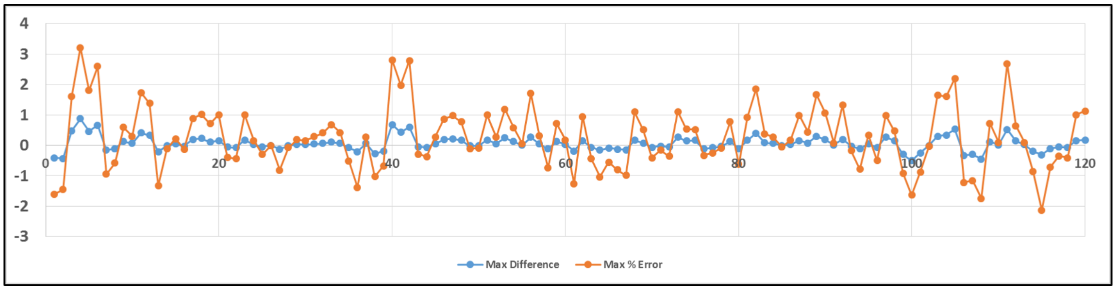

Figure 5.3. Testing on 80 % CRAC fan speed case; % Error and Difference in CFD and ANN predictions.

The Network needs to be given sufficient number of neurons in its hidden layer for the ANN to be finely tuned. The number of hidden neurons can be decided on several factors. Higher the complexity of the system, greater the number of neurons required.There are many rule-of-thumb methods to approximately determine the correct number of neurons to use in the hidden layers. Some of them are as follows

[1] Number should be between the size of the input layer and the size of the output layer.

[2] Number should be 2/3 the size of the input layer, plus the size of the output layer.

[3] Number should be less than twice the size of the input layer.

However, there is no empirical formula since the variety of systems that can be dealt with using ANN is huge. This ANN was trained with 150 neurons in it s hidden layer. The goal value for e was set at $1e^{-6}$ which was suitable due to the insignificance of Temperature after the fourth decimal.

The ANN block diagram and internal structure is shown above.The Gradient, G tells us how a small change in the weight will affect the overall error E. In ANN,

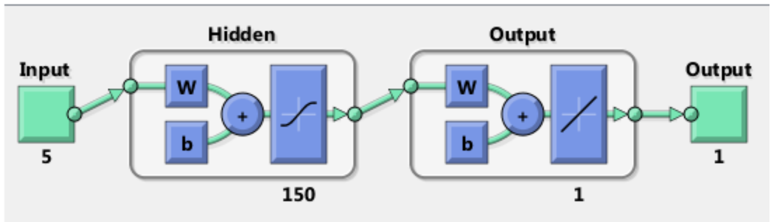

Figure 5.4. Artificial Neural Network.

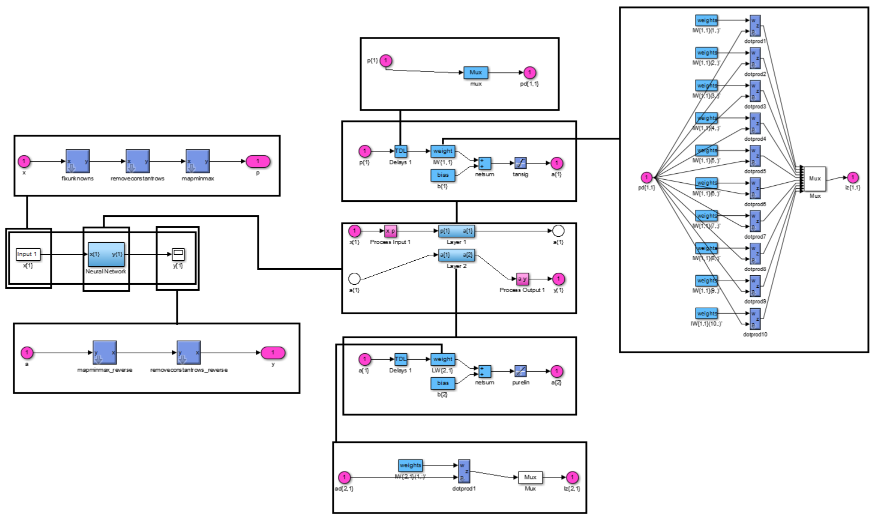

Figure 5.5. Internal Structure of a neural network.

μ controls how much the weights are changed on each iteration. The value can be anything from $1e^{-6}$ to as high as 0.1. A small value will cause the network to converge too slowly whereas too large of a value will cause the convergence to be abnormal and unstable during the final solution stage. It is difficult to understand or predict how an ANN will react to any value of μ. This however forces us to monitor the network behaviour during the training. The graph below shows the value of μ through out the training. The number of validation checks until the training would go on was set to 6. The training state is shown below The regression plot of the training, validation and testing state is shown below. The values of R $\approx$ 1 shows the proper tuning of the network. The performance of the function is measured in MSE. The

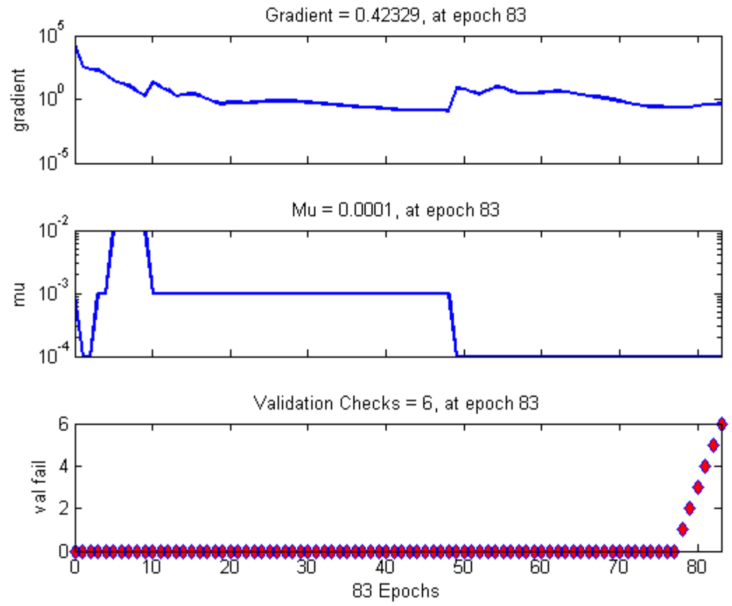

Figure 5.6. Training state of ANN.

best validation performance is 0.0676 at epoch 77. The MSE graph is shown below

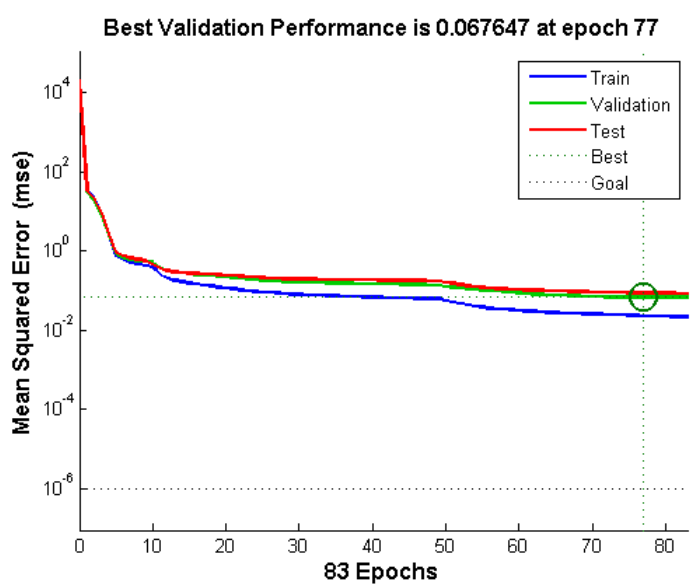

Figure 5.7. Performance of ANN while training in MSE.

The figure below is a comparison of results of CFD simulations and ANN predictions.

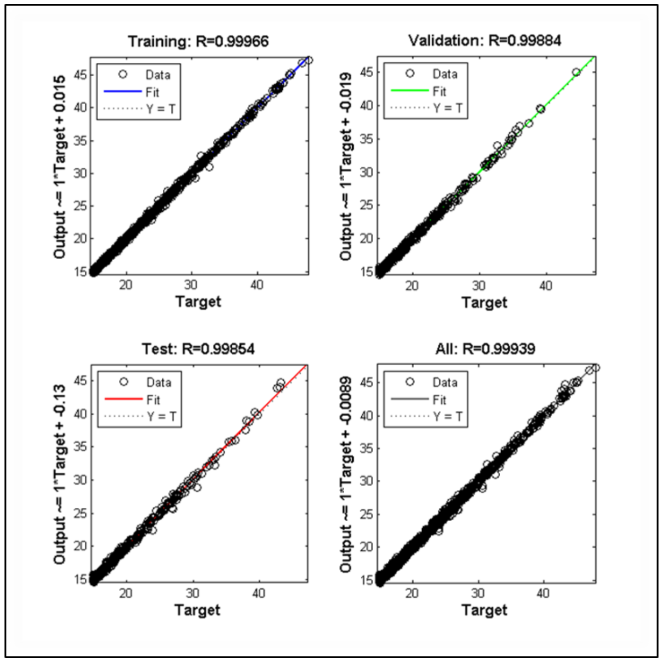

Figure 5.8. Root MSE Values during Training, Testing and Validation.

The fine tuning of the ANN is evident by the accuracy of the ANN predictions. The errors are very low and points of inaccuracy are minimal if not zero. This network can be deemed fit to be further tested on other loading conditions and other robustness study. However, the training parameters at the end of training, the testing of accuracy and gradient values suggest that the ANN is very well trained.

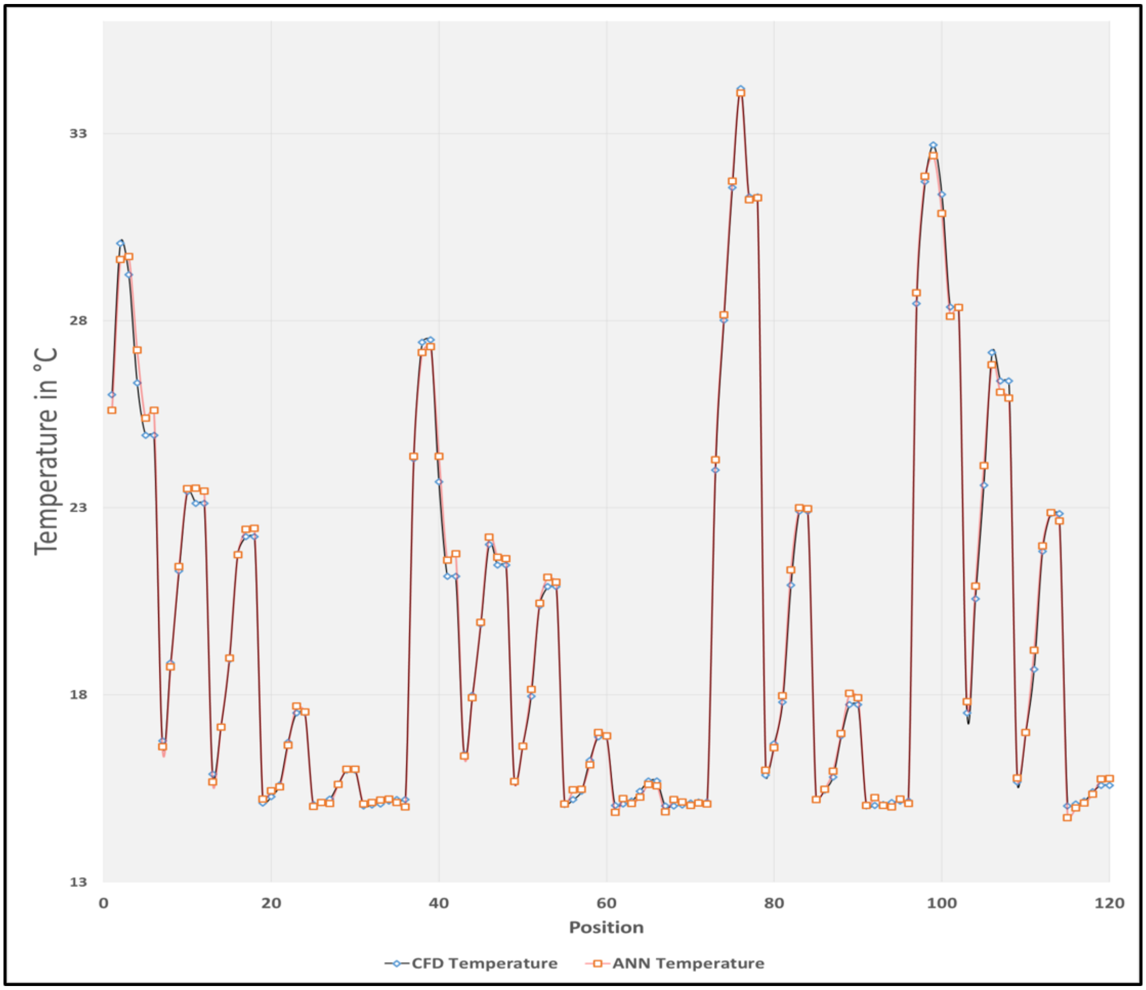

Figure 5.9. Temperature Plot comparing CFD and ANN for 20 kW , 80 % CRAC fan speed.

CHAPTER 6

Verification by comparison to CFD data

When the Black Box model is fully trained and tuned, the predicted outputs were tested for accuracy. This is a very important as inaccurate model might prove useless in a controller. The verification testing was done for different cases of server heat loading conditions. The Black Box was tested for its robustness to changing server location, CRAC fan speed and Server Heat load. During the verification, the testing data was removed from the training data for the Black box model. The Black Box was verified for 2 different tests viz.

1 Sever Heat Loading Pattern.
  - a Uniform server heat loading.
  - b Non uniform server heat loading.

2 Robustness tests for varying-
  - a CRAC fan speed.
  - b Server heat loading.

The Black Box model can be considered fairly accurate and verified when the difference in predictions from ANN and CFD would fall below 1°C.

6.1 Verification for Sever Heat Loading Pattern

The CFD model of the data center was modeled like a 4 load bank model. Considering steady state loading patterns on all 80 load banks, the temperature patterns were compared to that of the CFD simulation outputs. However, there are two types

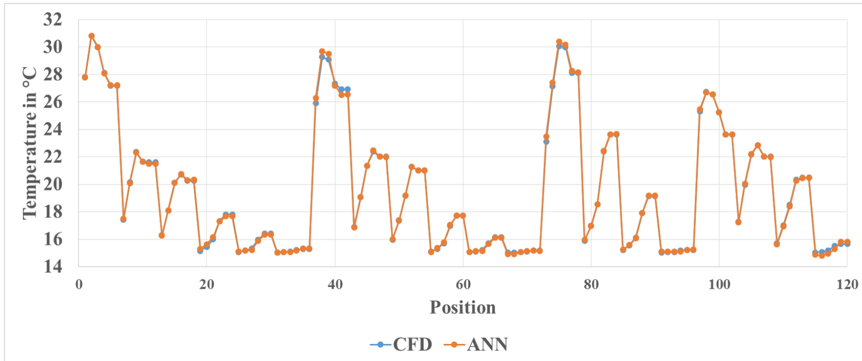

Figure 6.1. 5 KW per Load Bank and 60 % CRAC Fan Speed.

of loading patterns viz. Uniform and Non Uniform loading. A uniform loading is when all the load banks are at the same heat load e.g. all 80 load banks are loaded with 5 kW of heat and the CRAC units are running at 100 % fan speed.

6.1.1 Uniformly Loaded Server Heat Pattern

Uniformly loaded server heat means that all the load banks are loaded with same values of heat load. Though this type of loading pattern is not very realistic in a real data center, the use of controller might turn the non uniform loading to uniform for which the ANN has to be tested prior to application. Shown below are the tests for 3 uniformly loaded banks of different values and different CRAC fan speeds. The first figure is a comparison of CFD and ANN predicted temperatures and since the accuracy is not evident the figure that follows shows the difference and % Error as compared to CFD. The table following each set of test results are the Maximum Difference and Maximum % Error associated with the tests. A Consolidated Accuracy diagram follows the 3 test results.

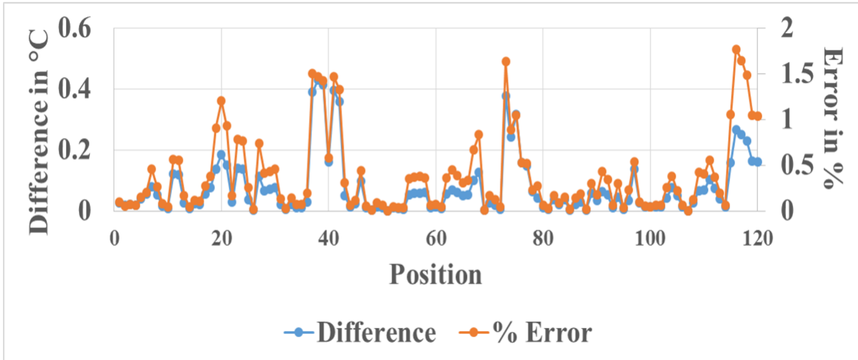

Figure 6.2. Comparison of CFD and ANN in Difference and % Error.

Table 6.1. 5 kW and 60% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.4285**
Max % Error	**1.7699**

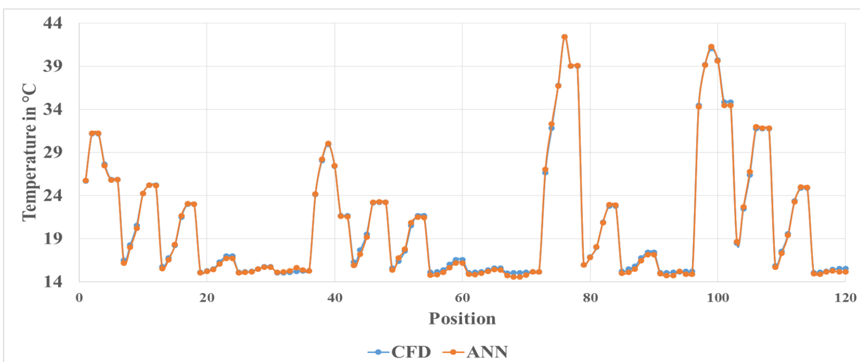

Figure 6.3. 7.5 KW per Load Bank and 100 % CRAC Fan Speed.

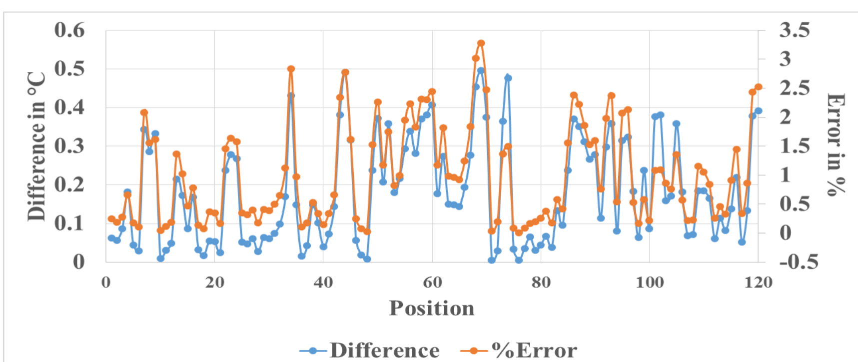

Figure 6.4. Comparison of CFD and ANN in Difference and % Error.

Table 6.2. 7.5 kW and 100% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.4953**
Max % Error	**3.2822**

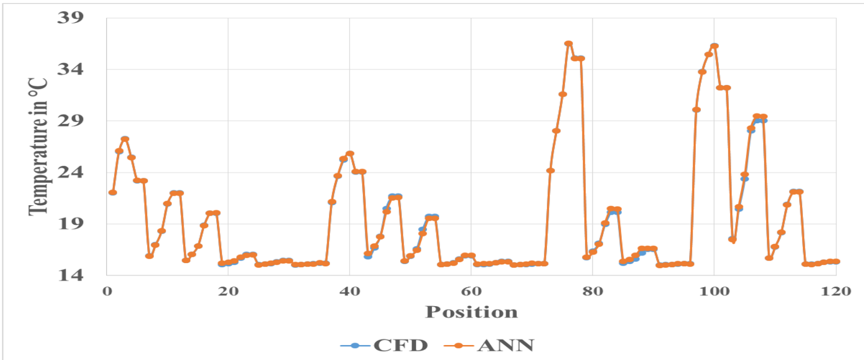

Figure 6.5. 6.25 KW per Load Bank and 120% CRAC Fan Speed.

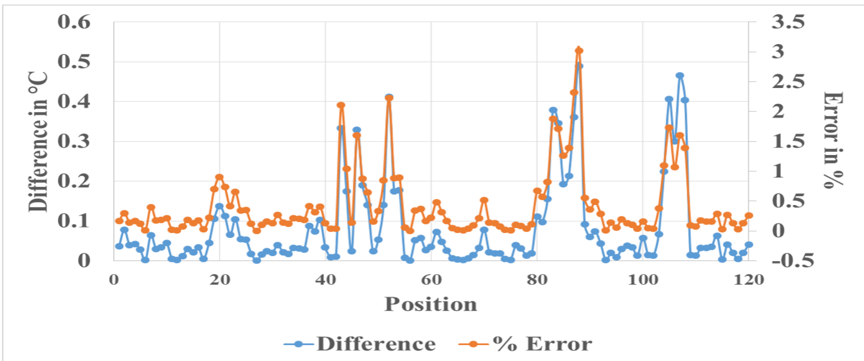

Figure 6.6. Comparison of CFD and ANN in Difference and % Error.

Table 6.3. 6.25 kW and 120% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.4889**
Max % Error	**3.0238**

Table 6.4. Average % Accuracy

Average % Accuracy	**99.3985**

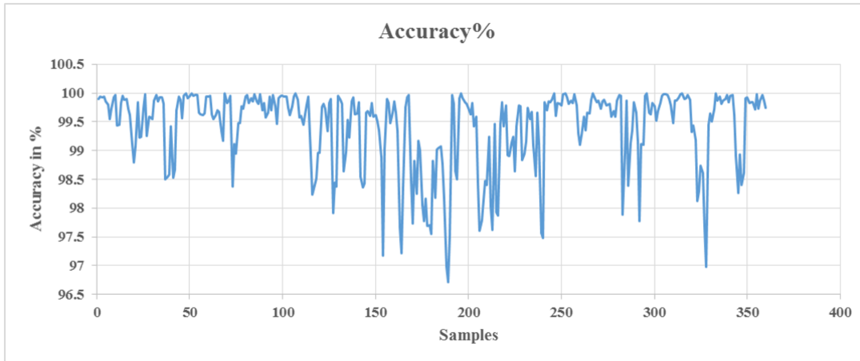

Figure 6.7. % Accuracy.

6.1.2 Non Uniformly Loaded Server Heat Pattern

Non Uniformly loaded server heat means that all the load banks are loaded with different values of heat load. This type of loading pattern is more realistic in a real data center, as the real load banks will be non uniformly loaded.

Shown below are the tests for 3 non uniformly loaded banks of different values and different CRAC fan speeds. The variable loading is shown in the table. The first figure is a comparison of CFD and ANN predicted temperatures and since the accuracy is not evident the figure that follows shows the difference and % Error as compared to CFD. The table following each set of test results are the Maximum Difference and Maximum % Error associated with the tests. A Consolidated Accuracy diagram follows the 3 test results.

6.2 Verification for Robustness tests for varying input parameters

The 3 tests for checking the robustness of the Black Box are shown in the subsections below. Since this Black Box was designed with the premise of being able to use with a controller, the accuracy check for its robustness is vital. In these tests we check the accuracy of the Black Box for varying or unknown input parameters

Table 6.5. 60% CRAC Fan Speed; Variable Loading

Rack	LB1	LB2	LB3	LB4
1	5	5	5	5
2	5	5	5	5
3	5	5	5	5
4	6.25	6.25	6.25	6.25
5	6.25	6.25	6.25	6.25
6	5	5	5	5
7	3.75	3.75	3.75	3.75
8	3.75	3.75	3.75	3.75
9	5	5	5	5
10	5	5	5	5
11	3.75	3.75	3.75	3.75
12	3.75	3.75	3.75	3.75
13	5	5	5	5
14	5	5	5	5
15	5	5	5	5
16	6.25	6.25	6.25	6.25
17	6.25	5	6.25	5
18	5	6.25	5	6.25
19	5	5	5	5
20	5	5	5	5

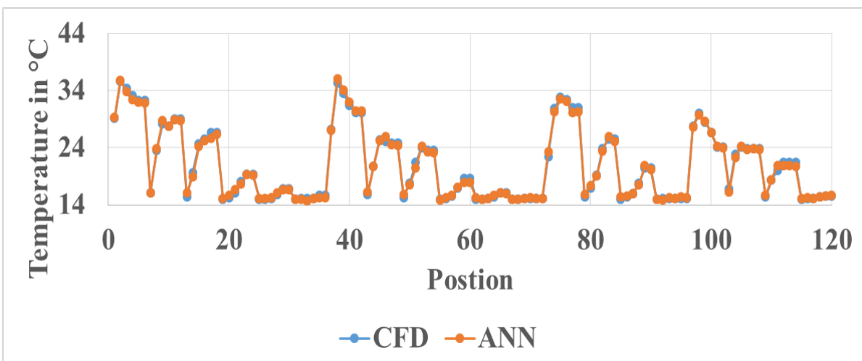

Figure 6.8. 60% CRAC Fan Speed.

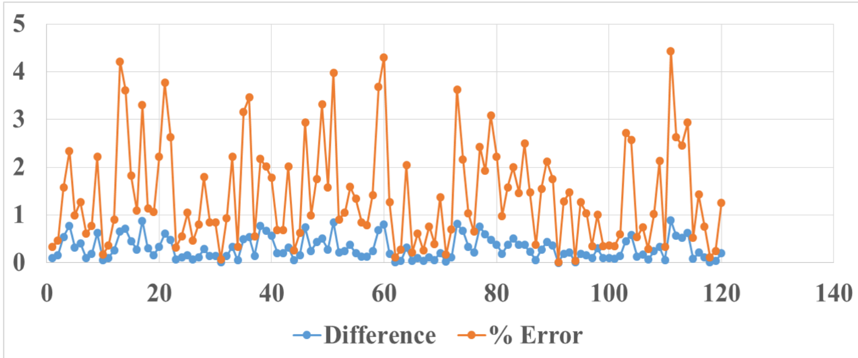

Figure 6.9. Comparison of CFD and ANN in Difference and % Error.

Table 6.6. 60% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.8888**
Max % Error	**4.4329**

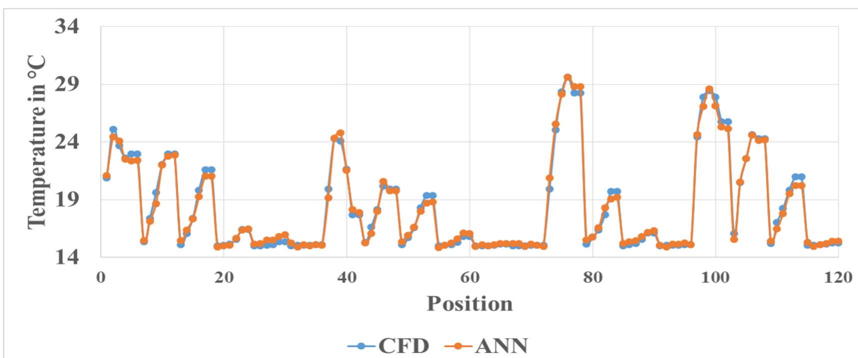

Figure 6.10. 100% CRAC Fan Speed.

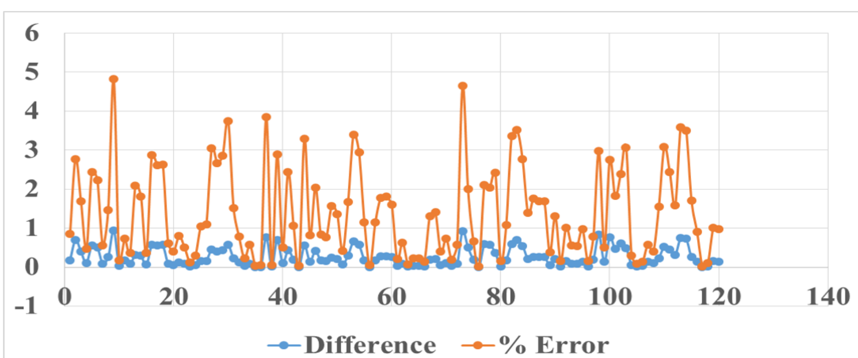

Figure 6.11. Comparison of CFD and ANN in Difference and % Error.

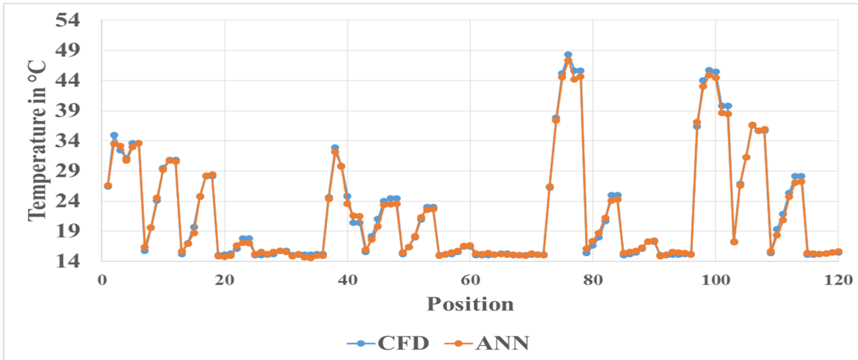

Figure 6.12. 100 % CRAC Fan Speed.

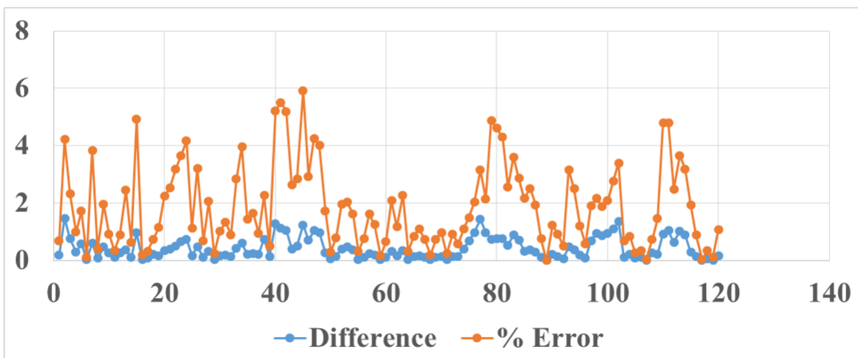

Figure 6.13. Comparison of CFD and ANN in Difference and % Error.

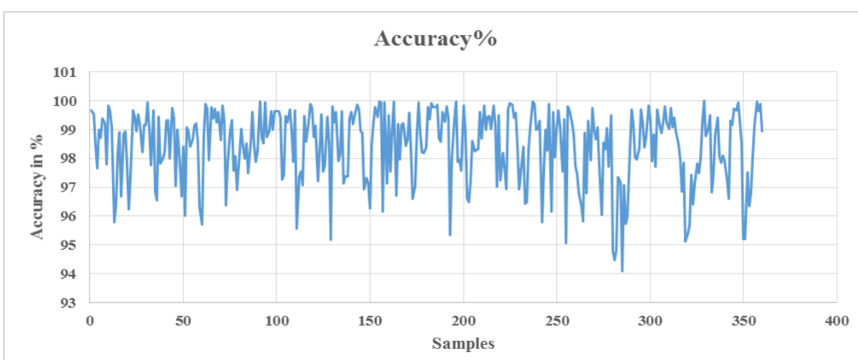

Figure 6.14. Average % Accuracy.

Table 6.7. 100% CRAC Fan Speed; Variable Loading

Rack	LB1	LB2	LB3	LB4
1	3.75	3.75	3.75	3.75
2	3.75	3.75	3.75	3.75
3	3.75	3.75	3.75	3.75
4	5	5	5	5
5	5	5	5	5
6	3.75	3.75	3.75	3.75
7	2.5	2.5	2.5	2.5
8	2.5	2.5	2.5	2.5
9	3.75	3.75	3.75	3.75
10	3.75	3.75	3.75	3.75
11	2.5	2.5	2.5	2.5
12	2.5	2.5	2.5	2.5
13	3.75	3.75	3.75	3.75
14	3.75	3.75	3.75	3.75
15	3.75	3.75	3.75	3.75
16	5	5	5	5
17	3.75	5	3.75	5
18	5	3.75	5	3.75
19	3.75	3.75	3.75	3.75
20	3.75	3.75	3.75	3.75

set within and outside the training data range. The Black Box needs to be able to predict fairly accurately for points it is not trained for. This would give the controller a predictive ability for different input scenarios. With the understanding, that these are limitations to this as the ANN cannot predict beyond a certain limit, the tests below check the accuracy for varying CRAC fan speed and modeled Server Heat Load.

6.2.1 Varying CRAC Fan Speeds

In this test we will test the robustness of the Black Box for an unknown CRAC fan speed. For this test we will test the ANN for test cases of 80 % and 100% CRAC

Table 6.8. 100% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.94636**
Max % Error	**4.82592**

Table 6.9. 100% CRAC Fan Speed; Variable Loading

Rack	LB1	LB2	LB3	LB4
1	8.75	8.75	8.75	8.75
2	8.75	8.75	8.75	8.75
3	8.75	8.75	8.75	8.75
4	10	10	10	10
5	10	10	10	10
6	8.75	8.75	8.75	8.75
7	7.5	7.5	7.5	7.5
8	7.5	7.5	7.5	7.5
9	8.75	8.75	8.75	8.75
10	8.75	8.75	8.75	8.75
11	7.5	7.5	7.5	7.5
12	7.5	7.5	7.5	7.5
13	8.75	8.75	8.75	8.75
14	8.75	8.75	8.75	8.75
15	8.75	8.75	8.75	8.75
16	10	10	10	10
17	10	8.75	10	8.75
18	8.75	10	8.75	10
19	8.75	8.75	8.75	8.75
20	8.75	8.75	8.75	8.75

Table 6.10. 100% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**1.47487**
Max % Error	**5.92152**

Table 6.11. Accuracy % in CFD and ANN

Average % Accuracy	**98.4332**

fan speed. During these tests the data for the particular CRAC fan speed was removed for convenience of testing.

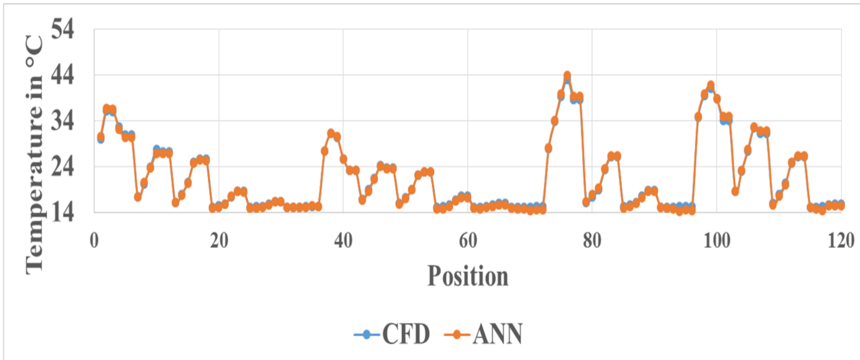

Figure 6.15. 7.5 KW per Load Bank and 80% CRAC Fan Speed.

Figure 6.16. Comparison of CFD and ANN in Difference and % Error.

6.2.2 Varying Server Heat Loading

Server heat load is one of the most important factors which influence the temperature at those points. Hence an accuracy check is presented in the test below. This is somewhat already established that the Black Box is predicting accurately for

Table 6.12. 7.5 kW per Load Bank and 80% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.96012**
Max % Error	**6.32073**

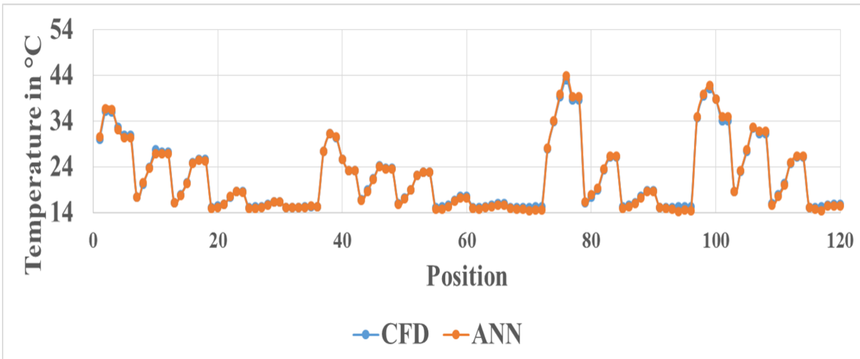

Figure 6.17. 8.75 KW per Load Bank and 100% CRAC Fan Speed.

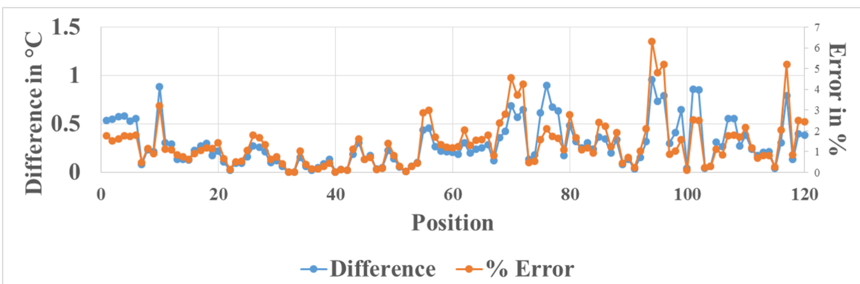

Figure 6.18. Comparison of CFD and ANN in Difference and % Error.

Table 6.13. 8.75 kW per Load Bank and 100% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.89919**
Max % Error	**5.60502**

Table 6.14. 3.125 kW per Load Bank and 100% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.56769**
Max % Error	**2.58983**

changing server heat load. In this test, we check for 2 cases of uniform server heat loading viz.

1. Inside the training range but for unknown heat load.
2. Outside the training range for unknown heat load.

6.2.2.1 Inside the training range but for unknown heat load.

In this sub section, we will test the Black Box for Test inputs which are inside our training range which is 5 to 35 kW range. Through this test we will verify whether the Black Box is ready for a robust use of a data center.

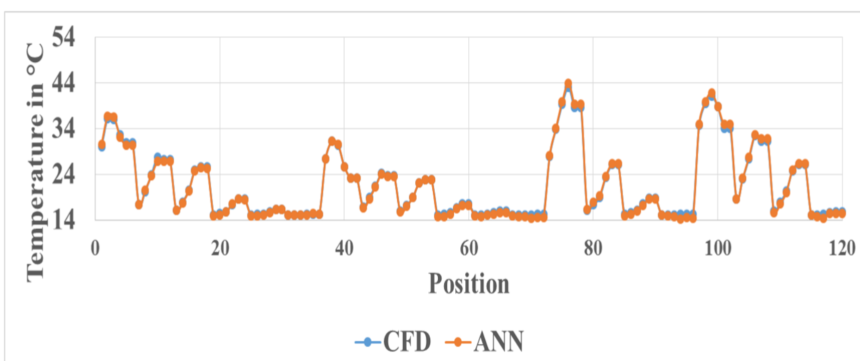

Figure 6.19. 3.125 KW per Load Bank and 100% CRAC Fan Speed.

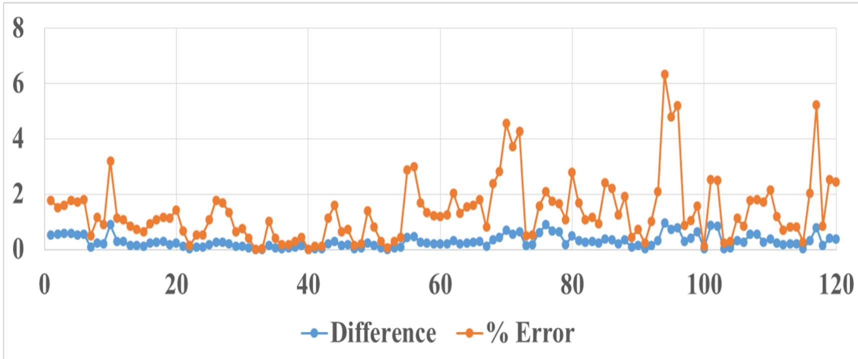

Figure 6.20. Comparison of CFD and ANN in Difference and % Error.

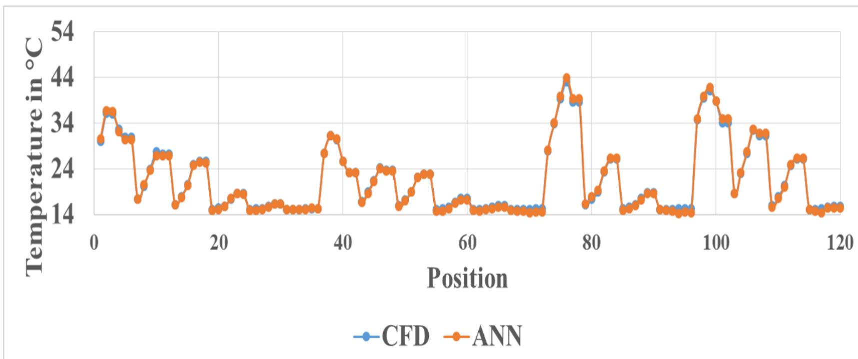

Figure 6.21. 4.435 KW per Load Bank and 100% CRAC Fan Speed.

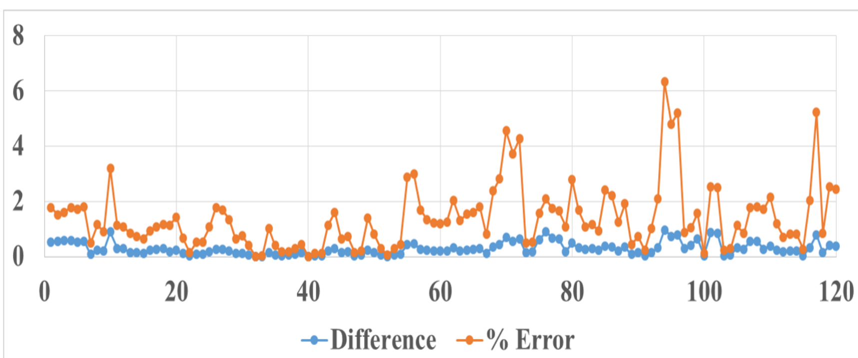

Figure 6.22. Comparison of CFD and ANN in Difference and % Error.

Table 6.15. 4.435 kW per Load Bank and 100% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.59573**
Max % Error	**2.43951**

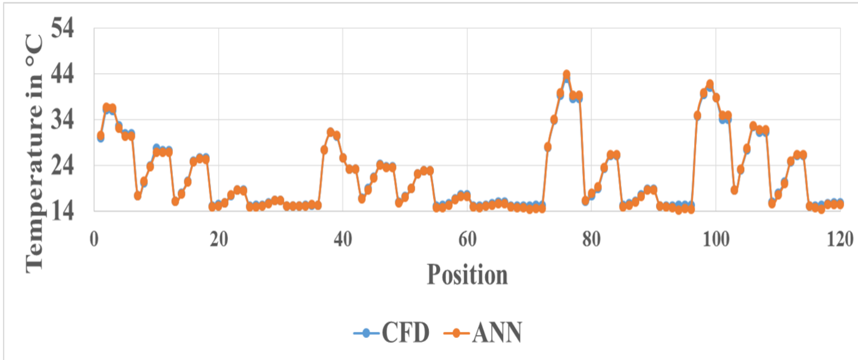

Figure 6.23. 5.625 KW per Load Bank and 100% CRAC Fan Speed.

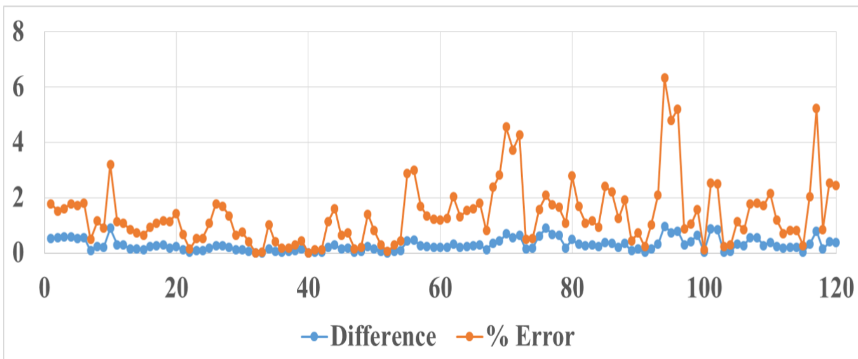

Figure 6.24. Comparison of CFD and ANN in Difference and % Error.

6.2.2.2 Outside the training range for unknown heat load.

In this sub section, we will test the Black Box for Test inputs which are out side our training range which is 5 to 35 kW range. Through this test we will verify whether the Black Box is ready for a robust use of a data center.

Table 6.16. 5.625 kW per Load Bank and 100% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**0.57733**
Max % Error	**2.97959**

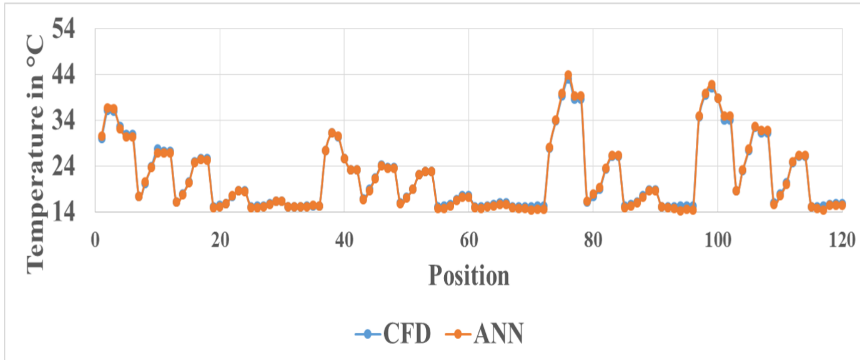

Figure 6.25. 9.375 KW per Load Bank and 100% CRAC Fan Speed.

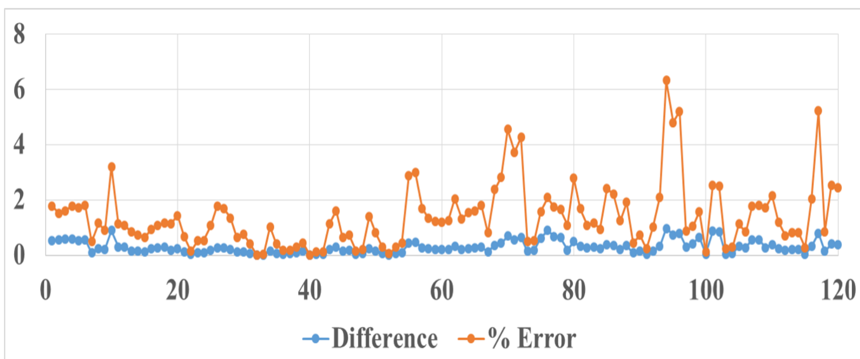

Figure 6.26. Comparison of CFD and ANN in Difference and % Error.

Table 6.17. 9.375 kW per Load Bank and 100% CRAC Fan Speed; Maximum Difference and Maximum % Error between CFD and ANN

Max Difference	**1.32837**
Max % Error	**3.94392**

CHAPTER 7

Conclusion

To check the accuracy of the Black Box in a broader sense, let us plot an error graph for all the tests on a server position axis. The figure below shows the consolidated graph followed by aisle wise graphs.

To conclude from the above we can summarize points as follows.

1. The Black Box developed has been so trained that it is not only accurate but very fast. Different algorithms for training and their effect has been demonstrated to find the best suited training conditions for the Black Box.
2. The ANN developed can be seen to accurately predict the temperatures in the data center room as a function of the server heat and CRAC fan speed at different points in state space.

Table 7.1. Point wise analysis for errors above 5 %

	Value	**Point**	**Rack**	**Case**	**Power**	**Fan**	**Location**	
a	5.22	40	B1-4	6	Transient	NA	C T CRAC	Return Air
b	5.51	41	B1-5	6	Transient	NA	C T CRAC	Return Air
c	5.2	42	B1-6	6	Transient	NA	C T CRAC	Return Air
d	5.92	45	B2-3	6	Transient	NA	NA	Highly varied LBs
e	5.01	51	B3-3	8	Unknown	Check	NA	Highly varied LBs
f	6.32	94	C4-4	7	Unknown	Check	Shown	NA
g	5.21	96	C4-6	7	Unknown	Check	Shown	NA
h	5.61	116	D4-2	8	Out of Range	NA	NA	More Data
i	5.22	117	D4-3	7	Out of Range	NA	NA	More Data

3. The Robustness check of this Black Box has been done for input conditions for which the ANN was not trained. Robustness check was important from a controller development point of view as the controller would want the freedom to change the CRAC fan speeds throughout the range and not in steps. So the Black Box should be ready for such robustness.
4. The Black Box was verified on 2 types of tests viz. Uniform loading and the more real Non-Uniform loading patterns. The ANN was found to be reliably accurate in the training range to be used in a model predictive type of controller setup.

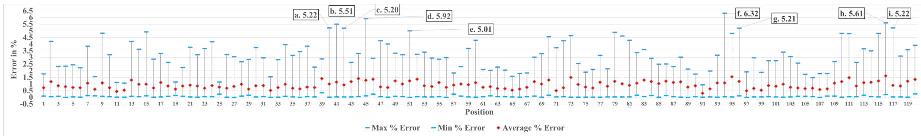

Figure 7.1. Error plot for server positions.

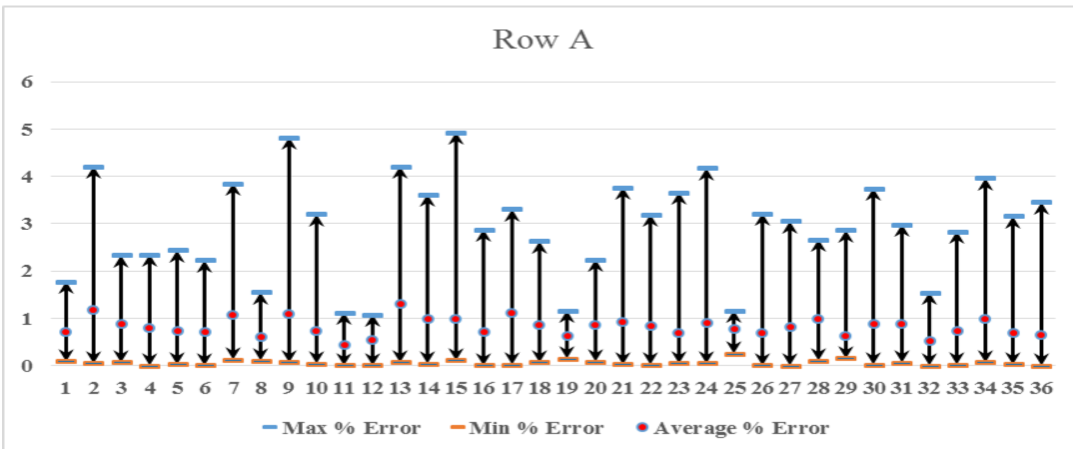

Figure 7.2. Aisle A.

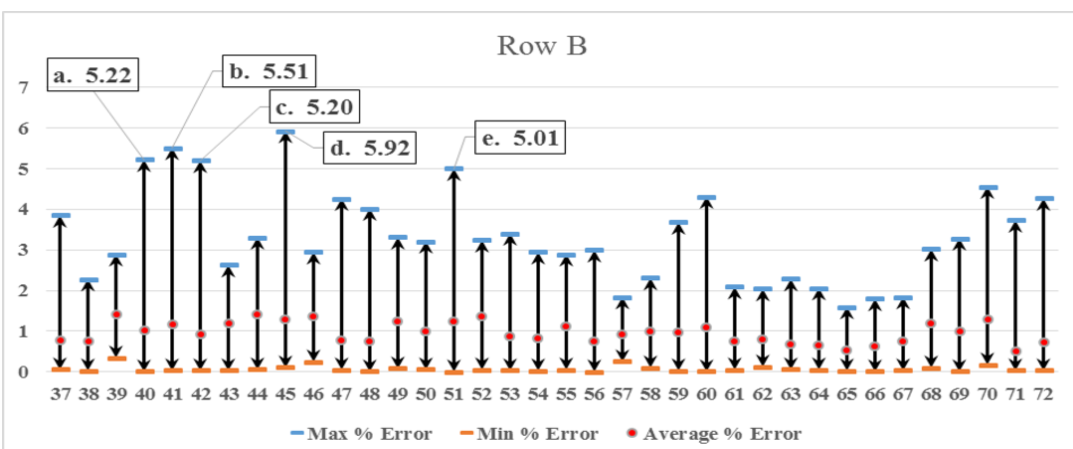

Figure 7.3. Aisle B.

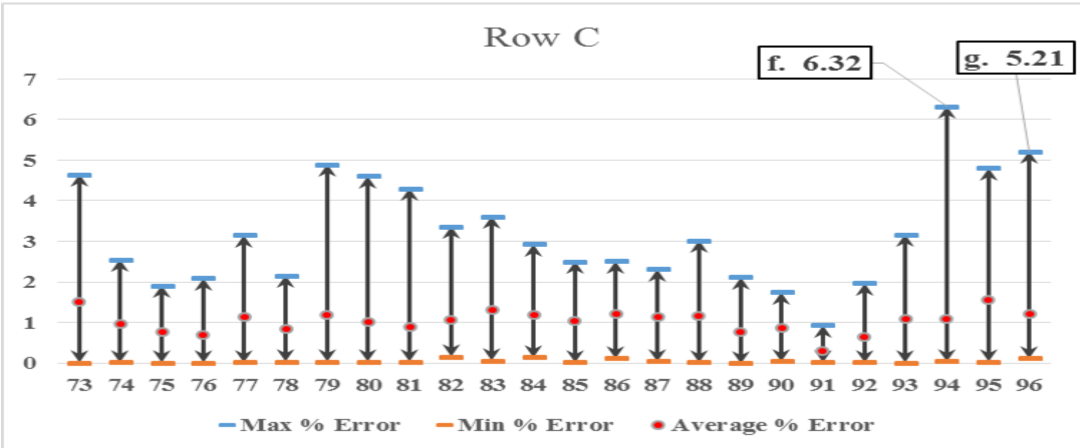

Figure 7.4. Aisle C.

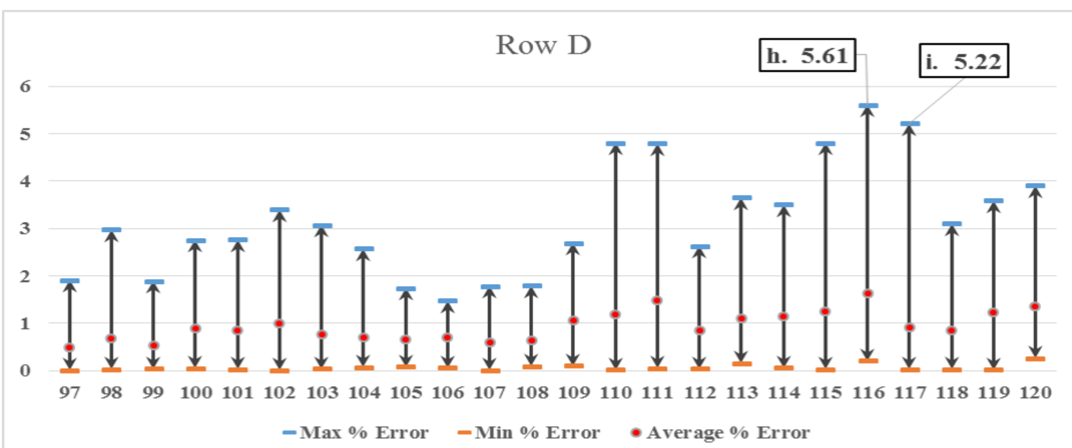

Figure 7.5. Aisle D.

CHAPTER 8

Future Scope

This tool is currently being used as a predicting tool only, but it has a greater potential to be used in a feed forward control system. A highly accurate ANN with a PID controller in a feed forward control scheme seems ideal in monitoring and control of the highly dynamic and nonlinear data center temperature. This system can be further extended to a reinforcement learning system or it can be made 'Adaptive' to the changing operating parameters. Introduction of this Black Box to *dynamic update of weight* matrix and training data to make the ANN dynamic learning would make it further reliable and reduce the CFD simulation time required right now for training and verification studies. Moreover, using this ANN tool developed as a black box model in an Adaptive Controller setting and application in a real data center for testing would be the ultimate test of this Black Box model.

APPENDIX A

Computaional Fluid Dynamics Data used for ANN Training.

The Data generated from CFD simulations was used for training of the Black Box. The Data was first generated for uniform loading conditions e.g. 5 kw to 35 kW for variable CRAC fan speed steps of 60,80,100 & 120 % in steps of 5 kW. This was used to train the Black Box initially. Steps of CRAC fan speed and Server Heat gave the Black Box a certain robustness within the range.

Table A.1. 5 KW, 60 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	17.96	15.59	15.31	15.04	15.02	15.01	17.65	15.49	15.25	15.03	15.01	15.01	17.63	15.3	15.08	15.01	18.76	15.85	15.26	15.01
T2	18.81	16.28	15.78	15.11	15.04	15.02	18.48	16.05	15.62	15.08	15.03	15.01	18.85	15.63	15.18	15.02	19.23	16.71	15.72	15.03
T3	18.64	16.96	16.36	15.27	15.09	15.03	18.57	16.7	16.12	15.2	15.06	15.02	19.64	16.12	15.36	15.02	19.01	17.38	16.23	15.08
T4	18.06	17.13	16.88	15.69	15.28	15.05	18.2	17.1	16.78	15.57	15.21	15.03	19.2	17.25	15.93	15.05	18.35	17.69	16.9	15.21
T5	17.69	17.09	16.97	15.89	15.43	15.08	17.99	16.98	16.78	15.79	15.34	15.04	18.59	17.58	16.3	15.07	17.93	17.61	16.98	15.29
T6	17.69	17.09	16.97	15.89	15.43	15.08	17.99	16.98	16.78	15.79	15.34	15.04	18.59	17.58	16.3	15.07	17.93	17.61	16.98	15.29

Table A.2. 5 KW, 80 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	18.27	15.54	15.27	15.03	15.02	15.01	17.83	15.44	15.22	15.02	15.01	15.01	17.29	15.22	15.06	15.01	18.77	15.74	15.2	15.01
T2	19.3	16.15	15.65	15.08	15.03	15.02	18.8	15.93	15.51	15.06	15.02	15.01	18.37	15.44	15.12	15.01	19.55	16.57	15.57	15.02
T3	18.97	16.82	16.15	15.18	15.06	15.02	19.02	16.55	15.94	15.13	15.04	15.02	19.34	15.74	15.21	15.02	19.56	17.3	16.03	15.05
T4	18.1	17.37	16.92	15.5	15.18	15.04	18.21	17.41	16.8	15.4	15.13	15.03	19.69	16.56	15.51	15.03	18.87	17.95	16.75	15.12
T5	17.62	17.3	17.06	15.72	15.28	15.05	17.42	17.33	17.03	15.61	15.22	15.03	18.98	17.04	15.73	15.04	18.23	17.74	16.95	15.16
T6	17.62	17.3	17.06	15.72	15.28	15.05	17.42	17.33	17.03	15.61	15.22	15.03	18.98	17.04	15.73	15.04	18.23	17.74	16.95	15.16

Table A.3. 5 KW, 100 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	17.29	15.33	15.16	15.02	15.02	15.01	16.9	15.27	15.13	15.02	15.01	15.01	17.02	15.18	15.04	15.01	18.48	15.64	15.17	15.02
T2	18.25	15.71	15.38	15.05	15.03	15.01	17.63	15.56	15.3	15.04	15.02	15.01	17.92	15.34	15.09	15.01	19.29	16.37	15.47	15.02
T3	18.11	16.15	15.68	15.1	15.04	15.02	17.92	15.93	15.54	15.07	15.03	15.01	18.77	15.55	15.15	15.02	19.52	17.06	15.84	15.04
T4	17.38	16.78	16.29	15.27	15.1	15.03	17.61	16.66	16.13	15.21	15.07	15.02	19.62	16.08	15.33	15.03	19.08	17.9	16.51	15.08
T5	16.94	16.92	16.54	15.4	15.15	15.04	16.57	16.72	16.38	15.33	15.11	15.03	18.97	16.42	15.46	15.04	18.31	17.84	16.75	15.1
T6	16.94	16.92	16.54	15.4	15.15	15.04	16.57	16.72	16.38	15.33	15.11	15.03	18.97	16.42	15.46	15.04	18.31	17.84	16.75	15.1

Table A.4. 5 KW, 120 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	16.54	15.21	15.1	15.02	15.02	15.01	16.3	15.18	15.09	15.01	15.01	15.01	16.85	15.16	15.04	15.01	18.18	15.56	15.15	15.02
T2	17.45	15.44	15.23	15.04	15.03	15.01	16.85	15.36	15.19	15.03	15.02	15.01	17.63	15.29	15.08	15.01	18.96	16.19	15.4	15.03
T3	17.81	15.74	15.42	15.06	15.04	15.02	17.21	15.61	15.34	15.05	15.03	15.01	18.36	15.44	15.12	15.02	19.26	16.82	15.7	15.04
T4	17.46	16.36	15.88	15.16	15.07	15.03	17.41	16.21	15.76	15.13	15.05	15.02	19.31	15.83	15.25	15.03	19.13	17.7	16.27	15.06
T5	16.95	16.58	16.14	15.24	15.1	15.04	17.24	16.52	16.06	15.2	15.08	15.03	18.91	16.07	15.33	15.03	18.24	17.79	16.51	15.08
T6	16.95	16.58	16.14	15.24	15.1	15.04	17.24	16.52	16.06	15.2	15.08	15.03	18.91	16.07	15.33	15.03	18.24	17.79	16.51	15.08

Table A.5. 10 KW, 60 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	21.24	16.22	15.65	15.08	15.04	15.02	20.48	15.99	15.51	15.06	15.03	15.01	20.15	15.59	15.15	15.02	21.78	16.54	15.47	15.02
T2	22.82	17.61	16.59	15.23	15.09	15.03	22.18	17.12	16.25	15.17	15.06	15.02	22.49	16.24	15.36	15.03	22.48	18.17	16.33	15.06
T3	22.39	18.77	17.64	15.53	15.18	15.05	22.27	18.39	17.23	15.39	15.12	15.03	24.08	17.18	15.7	15.05	22	19.45	17.3	15.14
T4	21.21	18.4	18.07	16.27	15.54	15.1	21.51	19.01	18.42	16.11	15.41	15.06	23.4	19.42	16.81	15.1	20.83	20.01	18.55	15.39
T5	20.57	18.22	17.82	16.58	15.8	15.15	21.13	18.76	18.28	16.53	15.67	15.09	22.08	20.09	17.55	15.14	20.05	19.75	18.71	15.53
T6	20.57	18.22	17.82	16.58	15.8	15.15	21.13	18.76	18.28	16.53	15.67	15.09	22.08	20.09	17.55	15.14	20.05	19.75	18.71	15.53

Table A.6. 10 KW, 80 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	21.21	16.01	15.51	15.06	15.04	15.02	20.34	15.83	15.41	15.05	15.03	15.01	19.52	15.44	15.11	15.02	22.43	16.45	15.38	15.02
T2	23.56	17.2	16.24	15.15	15.07	15.03	22.31	16.76	15.97	15.11	15.05	15.02	21.65	15.87	15.24	15.03	23.89	18.06	16.12	15.05
T3	23.21	18.61	17.26	15.34	15.12	15.04	22.84	17.96	16.78	15.25	15.08	15.03	23.56	16.47	15.43	15.04	23.83	19.51	17	15.09
T4	21.5	19.86	18.89	15.99	15.35	15.08	21.13	19.63	18.45	15.76	15.25	15.05	24.43	18.1	16.01	15.07	22.53	20.81	18.43	15.22
T5	20.51	19.69	19.18	16.45	15.56	15.1	19.77	19.57	18.93	16.17	15.41	15.07	22.97	19.07	16.46	15.09	21.34	20.41	18.82	15.31
T6	20.51	19.69	19.18	16.45	15.56	15.1	19.77	19.57	18.93	16.17	15.41	15.07	22.97	19.07	16.46	15.09	21.34	20.41	18.82	15.31

Table A.7. 10 KW, 100 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	19.28	15.62	15.31	15.05	15.03	15.02	18.59	15.51	15.25	15.03	15.02	15.01	19	15.35	15.09	15.02	21.82	16.26	15.32	15.03
T2	21.22	16.32	15.71	15.1	15.06	15.03	20.01	16.06	15.57	15.07	15.04	15.02	20.78	15.67	15.18	15.03	23.44	17.68	15.92	15.05
T3	20.98	17.17	16.28	15.19	15.09	15.04	20.62	16.77	16.02	15.14	15.06	15.03	22.47	16.07	15.3	15.03	23.96	19.05	16.65	15.08
T4	19.57	18.39	17.45	15.5	15.19	15.07	20.03	18.18	17.15	15.4	15.14	15.05	24.22	17.12	15.64	15.06	23.18	20.76	17.97	15.15
T5	18.71	18.68	17.94	15.76	15.29	15.09	18	18.3	17.63	15.62	15.22	15.06	22.96	17.79	15.89	15.07	21.62	20.67	18.46	15.2
T6	18.71	18.68	17.94	15.76	15.29	15.09	18	18.3	17.63	15.62	15.22	15.06	22.96	17.79	15.89	15.07	21.62	20.67	18.46	15.2

Table A.8. 10 KW, 120 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	18	15.4	15.2	15.04	15.03	15.02	17.55	15.35	15.17	15.03	15.02	15.01	18.69	15.31	15.08	15.02	21.28	16.1	15.29	15.04
T2	19.76	15.85	15.45	15.07	15.05	15.03	18.63	15.71	15.38	15.06	15.04	15.02	20.26	15.57	15.15	15.02	22.82	17.34	15.77	15.06
T3	20.44	16.43	15.8	15.12	15.07	15.04	19.33	16.19	15.67	15.1	15.05	15.03	21.7	15.88	15.24	15.03	23.43	18.57	16.38	15.07
T4	19.76	17.62	16.7	15.3	15.14	15.06	19.7	17.36	16.49	15.25	15.11	15.05	23.62	16.64	15.49	15.05	23.35	20.38	17.51	15.12
T5	18.76	18.05	17.21	15.46	15.19	15.08	19.31	17.96	17.06	15.39	15.15	15.06	22.89	17.12	15.66	15.07	21.57	20.61	17.99	15.15
T6	18.76	18.05	17.21	15.46	15.19	15.08	19.31	17.96	17.06	15.39	15.15	15.06	22.89	17.12	15.66	15.07	21.57	20.61	17.99	15.15

After initial training, the Black Box gave accurate predictions for uniform loading cases however, when it came to non uniform loading, there was a certain amount of inaccuracy present. To train the Black Box further, CFD data was generated for hypothetical non uniform loading cases. The data below has a few examples of non

Table A.9. 15 KW, 60 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	24.5	16.84	15.97	15.12	15.06	15.03	23.23	16.46	15.76	15.09	15.04	15.02	22.33	15.83	15.21	15.03	23.87	16.99	15.6	15.03
T2	26.79	18.89	17.36	15.34	15.13	15.05	25.78	18.12	16.83	15.24	15.09	15.04	25.64	16.76	15.51	15.04	25.07	19.3	16.77	15.08
T3	26.13	20.52	18.88	15.77	15.26	15.08	25.8	19.94	18.25	15.56	15.18	15.05	28.04	18.11	16	15.07	24.76	21.21	18.13	15.19
T4	24.52	19.85	19.27	16.81	15.76	15.15	24.6	20.77	19.92	16.58	15.58	15.09	27.34	21.35	17.57	15.14	23.29	21.88	19.85	15.5
T5	23.7	19.66	18.83	17.2	16.12	15.23	24.14	20.44	19.68	17.17	15.94	15.13	25.29	22.36	18.65	15.2	21.97	21.23	20.03	15.68
T6	23.7	19.66	18.83	17.2	16.12	15.23	24.14	20.44	19.68	17.17	15.94	15.13	25.29	22.36	18.65	15.2	21.97	21.23	20.03	15.68

Table A.10. 15 KW, 80 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	23.79	16.42	15.72	15.09	15.05	15.03	22.56	16.16	15.57	15.07	15.04	15.02	21.79	15.66	15.16	15.03	25.89	17.09	15.55	15.03
T2	26.84	18.07	16.73	15.22	15.1	15.05	25.19	17.45	16.35	15.16	15.07	15.03	24.9	16.29	15.34	15.04	28.27	19.51	16.62	15.07
T3	26.07	19.96	18.12	15.48	15.17	15.07	25.62	19.05	17.45	15.35	15.12	15.05	27.73	17.15	15.62	15.06	28.75	21.82	17.97	15.13
T4	23.68	21.51	20.25	16.36	15.49	15.12	22.89	21.06	19.59	16.03	15.34	15.08	29.42	19.55	16.46	15.1	27.07	24.14	20.29	15.33
T5	22.43	21.28	20.63	16.97	15.78	15.16	20.76	20.69	20.06	16.57	15.57	15.1	27.18	21.02	17.11	15.13	24.85	23.47	20.97	15.47
T6	22.43	21.28	20.63	16.97	15.78	15.16	20.76	20.69	20.06	16.57	15.57	15.1	27.18	21.02	17.11	15.13	24.85	23.47	20.97	15.47

Table A.11. 15 KW, 100 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	21.06	15.87	15.43	15.07	15.05	15.03	20.06	15.72	15.35	15.05	15.04	15.02	20.96	15.53	15.13	15.02	25.07	16.85	15.48	15.05
T2	24.1	16.87	16	15.14	15.08	15.04	22.15	16.5	15.8	15.11	15.06	15.03	23.6	15.99	15.26	15.04	27.5	18.94	16.34	15.07
T3	24.1	18.13	16.83	15.27	15.13	15.06	23.2	17.53	16.46	15.2	15.09	15.04	26.11	16.58	15.44	15.05	28.31	20.97	17.42	15.11
T4	22.07	20.11	18.64	15.73	15.28	15.1	22.58	19.68	18.15	15.58	15.21	15.07	28.8	18.13	15.95	15.09	27.25	23.58	19.38	15.22
T5	20.72	20.6	19.44	16.11	15.42	15.13	19.34	19.79	18.86	15.9	15.32	15.09	26.98	19.12	16.31	15.11	24.89	23.47	20.12	15.29
T6	20.72	20.6	19.44	16.11	15.42	15.13	19.34	19.79	18.86	15.9	15.32	15.09	26.98	19.12	16.31	15.11	24.89	23.47	20.12	15.29

Table A.12. 15 KW, 120 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	19.4	15.59	15.29	15.06	15.05	15.03	18.76	15.51	15.25	15.04	15.04	15.02	20.53	15.46	15.12	15.02	24.28	16.61	15.42	15.06
T2	21.94	16.24	15.65	15.11	15.08	15.04	20.35	16.05	15.55	15.08	15.06	15.03	22.88	15.85	15.22	15.04	26.57	18.43	16.13	15.08
T3	22.87	17.09	16.17	15.18	15.11	15.06	21.37	16.75	15.99	15.15	15.08	15.04	25.03	16.31	15.36	15.05	27.51	20.25	17.01	15.11
T4	21.81	18.79	17.45	15.45	15.2	15.1	21.84	18.46	17.18	15.37	15.16	15.07	27.93	17.44	15.72	15.08	27.65	23	18.69	15.17
T5	20.34	19.42	18.19	15.67	15.28	15.12	21.1	19.29	17.99	15.58	15.22	15.09	26.94	18.15	15.97	15.1	25.05	23.46	19.44	15.22
T6	20.34	19.42	18.19	15.67	15.28	15.12	21.1	19.29	17.99	15.58	15.22	15.09	26.94	18.15	15.97	15.1	25.05	23.46	19.44	15.22

Table A.13. 20 KW, 60 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	27.82	17.44	16.29	15.16	15.08	15.04	25.9	16.91	15.98	15.11	15.06	15.03	23.12	15.91	15.24	15.04	25.33	17.29	15.7	15.04
T2	30.81	20.15	18.12	15.45	15.17	15.07	29.27	19.06	17.37	15.31	15.11	15.05	27.16	16.98	15.57	15.06	26.73	19.98	17.01	15.09
T3	29.99	22.35	20.13	16	15.34	15.1	29.08	21.37	19.18	15.72	15.23	15.07	30.08	18.54	16.13	15.09	26.55	22.18	18.52	15.2
T4	28.11	21.66	20.73	17.33	15.97	15.21	27.35	22.39	21.29	16.99	15.72	15.12	30.01	22.39	17.93	15.17	25.23	22.84	20.34	15.51
T5	27.18	21.61	20.27	17.82	16.41	15.31	26.92	22.01	21	17.73	16.17	15.17	28.11	23.62	19.14	15.24	23.63	22.02	20.49	15.67
T6	27.18	21.61	20.27	17.82	16.41	15.31	26.92	22.01	21	17.73	16.17	15.17	28.11	23.62	19.14	15.24	23.63	22.02	20.49	15.67

uniform loading cases.

Table A.14. 20 KW, 80 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	26.02	16.77	15.89	15.11	15.07	15.04	24.31	16.42	15.7	15.08	15.05	15.03	24.01	15.86	15.21	15.03	28.46	17.52	15.67	15.04
T2	30.07	18.86	17.16	15.28	15.13	15.06	27.43	17.99	16.65	15.2	15.09	15.04	28.01	16.69	15.45	15.05	31.71	20.57	16.98	15.09
T3	29.23	21.31	18.94	15.6	15.22	15.09	27.49	19.89	17.97	15.43	15.16	15.06	31.56	17.81	15.8	15.07	32.7	23.6	18.68	15.16
T4	26.34	23.44	21.77	16.73	15.62	15.16	23.69	22.02	20.39	16.25	15.43	15.11	34.2	20.94	16.9	15.13	31.37	27.15	21.84	15.41
T5	24.94	23.12	22.23	17.52	15.99	15.21	21.17	21.47	20.89	16.88	15.7	15.14	31.31	22.91	17.74	15.17	28.36	26.39	22.85	15.59
T6	24.94	23.12	22.23	17.52	15.99	15.21	21.17	21.47	20.89	16.88	15.7	15.14	31.31	22.91	17.74	15.17	28.36	26.39	22.85	15.59

Table A.15. 20 KW, 100 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	22.69	16.09	15.54	15.09	15.07	15.03	21.47	15.92	15.45	15.07	15.05	15.03	22.87	15.69	15.17	15.03	28.26	17.43	15.62	15.06
T2	26.64	17.37	16.27	15.18	15.11	15.06	24.18	16.91	16.02	15.14	15.08	15.04	26.37	16.3	15.34	15.05	31.49	20.18	16.76	15.1
T3	26.76	18.99	17.33	15.34	15.17	15.08	25.58	18.24	16.86	15.26	15.12	15.06	29.7	17.07	15.58	15.07	32.61	22.85	18.17	15.15
T4	24.18	21.62	19.68	15.94	15.36	15.14	24.66	21	19.03	15.74	15.27	15.1	33.34	19.09	16.23	15.11	31.27	26.33	20.75	15.29
T5	22.52	22.28	20.74	16.43	15.54	15.17	20.38	21.11	19.93	16.16	15.41	15.12	30.95	20.4	16.71	15.14	28.11	26.21	21.73	15.38
T6	22.52	22.28	20.74	16.43	15.54	15.17	20.38	21.11	19.93	16.16	15.41	15.12	30.95	20.4	16.71	15.14	28.11	26.21	21.73	15.38

Table A.16. 20 KW, 120 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	20.75	15.77	15.38	15.08	15.06	15.03	19.94	15.67	15.33	15.06	15.05	15.02	22.37	15.61	15.15	15.03	27.19	17.09	15.55	15.08
T2	24.02	16.62	15.85	15.14	15.1	15.06	22.02	16.37	15.72	15.11	15.08	15.04	25.49	16.12	15.29	15.05	30.22	19.47	16.46	15.11
T3	25.14	17.71	16.52	15.24	15.14	15.08	23.34	17.29	16.29	15.19	15.11	15.06	28.34	16.74	15.48	15.07	31.5	21.85	17.61	15.14
T4	23.7	19.9	18.18	15.58	15.27	15.13	23.89	19.51	17.85	15.49	15.21	15.09	32.23	18.22	15.95	15.11	31.98	25.55	19.82	15.23
T5	21.81	20.73	19.13	15.87	15.37	15.16	22.67	20.54	18.88	15.75	15.29	15.11	31.01	19.16	16.28	15.13	28.62	26.27	20.83	15.28
T6	21.81	20.73	19.13	15.87	15.37	15.16	22.67	20.54	18.88	15.75	15.29	15.11	31.01	19.16	16.28	15.13	28.62	26.27	20.83	15.28

Table A.17. 25 KW, 60 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	31.06	17.99	16.58	15.19	15.1	15.05	28.37	17.29	16.18	15.14	15.07	15.04	24.5	16.05	15.28	15.04	28.28	17.9	15.87	15.05
T2	34.93	21.35	18.83	15.54	15.21	15.08	32.51	19.86	17.83	15.37	15.14	15.06	29.33	17.26	15.65	15.07	29.85	21.26	17.49	15.11
T3	34.1	24.21	21.37	16.22	15.41	15.13	32.03	22.59	19.97	15.85	15.27	15.09	33.02	19.04	16.28	15.11	29.65	23.76	19.26	15.24
T4	32.12	23.73	22.33	17.83	16.17	15.26	29.76	23.86	22.49	17.33	15.84	15.16	33.35	23.6	18.33	15.2	27.48	24.17	21.28	15.59
T5	31.15	23.93	21.98	18.43	16.69	15.39	29.5	23.51	22.19	18.19	16.35	15.21	30.74	25.02	19.72	15.29	25.2	23.35	21.39	15.77
T6	31.15	23.93	21.98	18.43	16.69	15.39	29.5	23.51	22.19	18.19	16.35	15.21	30.74	25.02	19.72	15.29	25.2	23.35	21.39	15.77

Table A.18. 25 KW, 80 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	26.97	16.91	15.95	15.13	15.09	15.05	24.78	16.41	15.68	15.09	15.07	15.03	26.41	16.2	15.32	15.04	32.58	18.72	16.03	15.06
T2	31.41	19.07	17.25	15.3	15.16	15.08	28.34	18.08	16.66	15.21	15.12	15.06	31.68	17.34	15.67	15.07	36.38	23.06	18.07	15.13
T3	33.86	22.03	19.27	15.64	15.26	15.12	28.73	20.23	18.11	15.43	15.18	15.08	36.42	18.89	16.2	15.1	36.92	26.95	20.49	15.24
T4	32.65	27.02	23.96	17.03	15.74	15.22	26.05	23.31	21.19	16.33	15.46	15.14	38.49	23.18	17.82	15.19	34.03	29.8	24.13	15.57
T5	30.6	26.82	25.16	18.19	16.23	15.3	23.93	22.74	21.99	17.08	15.75	15.18	34.92	25.64	19.04	15.25	30.72	27.86	24.83	15.77
T6	30.6	26.82	25.16	18.19	16.23	15.3	23.93	22.74	21.99	17.08	15.75	15.18	34.92	25.64	19.04	15.25	30.72	27.86	24.83	15.77

Table A.19. 25 KW, 100 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	24.24	16.31	15.65	15.11	15.08	15.04	22.85	16.11	15.54	15.08	15.06	15.03	24.77	15.85	15.21	15.04	31.41	17.99	15.77	15.07
T2	28.99	17.84	16.53	15.22	15.14	15.07	26.17	17.31	16.23	15.17	15.1	15.05	29.11	16.6	15.42	15.06	35.4	21.38	17.16	15.12
T3	29.03	19.8	17.8	15.42	15.21	15.1	27.83	18.91	17.25	15.32	15.15	15.07	33.26	17.55	15.71	15.09	36.88	24.68	18.9	15.18
T4	25.95	22.97	20.63	16.13	15.44	15.17	26.14	22.11	19.81	15.89	15.33	15.12	37.87	20.03	16.51	15.14	35.43	29.08	22.09	15.35
T5	24.21	23.8	21.91	16.71	15.66	15.22	21.03	22.22	20.85	16.39	15.5	15.15	34.94	21.64	17.09	15.18	31.41	28.97	23.33	15.47
T6	24.21	23.8	21.91	16.71	15.66	15.22	21.03	22.22	20.85	16.39	15.5	15.15	34.94	21.64	17.09	15.18	31.41	28.97	23.33	15.47

Table A.20. 25 KW, 120 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	22.04	15.94	15.46	15.09	15.08	15.04	21.07	15.82	15.4	15.07	15.06	15.03	24.19	15.76	15.19	15.04	30.06	17.57	15.68	15.1
T2	26.02	16.98	16.04	15.17	15.13	15.07	23.63	16.68	15.89	15.13	15.09	15.05	28.07	16.39	15.36	15.06	33.81	20.48	16.79	15.13
T3	27.29	18.31	16.86	15.3	15.18	15.1	25.24	17.81	16.58	15.24	15.13	15.07	31.61	17.15	15.59	15.08	35.44	23.4	18.18	15.17
T4	25.49	20.97	18.88	15.71	15.33	15.16	25.87	20.52	18.49	15.6	15.26	15.11	36.5	18.97	16.17	15.13	36.31	28.03	20.9	15.28
T5	23.21	22.01	20.05	16.06	15.45	15.2	24.07	21.72	19.73	15.92	15.36	15.14	35.09	20.13	16.57	15.16	32.22	29.04	22.17	15.35
T6	23.21	22.01	20.05	16.06	15.45	15.2	24.07	21.72	19.73	15.92	15.36	15.14	35.09	20.13	16.57	15.16	32.22	29.04	22.17	15.35

Table A.21. 30 KW, 60 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	34.18	18.48	16.83	15.22	15.12	15.06	30.61	17.62	16.34	15.16	15.09	15.04	25.9	16.19	15.32	15.05	30.62	18.42	16.03	15.06
T2	39.19	22.51	19.48	15.62	15.24	15.1	35.6	20.57	18.22	15.42	15.16	15.07	31.7	17.55	15.74	15.09	32.11	22.23	17.87	15.13
T3	38.48	26.18	22.61	16.4	15.48	15.16	34.84	23.72	20.67	15.95	15.31	15.1	36.23	19.58	16.45	15.13	31.65	24.88	19.82	15.27
T4	36.47	26.3	24.27	18.31	16.33	15.31	32.11	25.43	23.68	17.61	15.93	15.19	36.18	24.71	18.73	15.24	29.05	25.32	21.93	15.63
T5	35.46	26.87	24.2	19.03	16.93	15.47	31.99	25.12	23.49	18.59	16.49	15.25	33.41	26.24	20.25	15.33	26.47	24.87	22.1	15.82
T6	35.46	26.87	24.2	19.03	16.93	15.47	31.99	25.12	23.49	18.59	16.49	15.25	33.41	26.24	20.25	15.33	26.47	24.87	22.1	15.82

Table A.22. 30 KW, 80 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	30.07	17.38	16.2	15.16	15.11	15.05	27.4	16.9	15.94	15.12	15.08	15.04	28.01	16.22	15.3	15.05	34.7	18.69	15.97	15.07
T2	36.21	20.25	17.93	15.39	15.19	15.09	31.23	18.97	17.19	15.28	15.13	15.07	33.9	17.37	15.63	15.08	39.51	23.09	17.86	15.13
T3	35.98	23.9	20.48	15.83	15.32	15.13	30.39	21.39	18.9	15.58	15.22	15.09	39.28	18.93	16.12	15.11	41.09	27.47	20.3	15.23
T4	32.69	27.71	24.97	17.45	15.88	15.24	25.71	24.28	22.12	16.66	15.58	15.16	43.06	23.31	17.61	15.19	38.75	32.45	24.77	15.58
T5	30.92	27.14	25.67	18.62	16.41	15.31	23.23	23.62	22.87	17.49	15.94	15.2	38.67	26.08	18.77	15.25	34.1	31.18	26.17	15.83
T6	30.92	27.14	25.67	18.62	16.41	15.31	23.23	23.62	22.87	17.49	15.94	15.2	38.67	26.08	18.77	15.25	34.1	31.18	26.17	15.83

Table A.23. 30 KW, 100 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	25.72	16.52	15.76	15.13	15.1	15.05	24.18	16.29	15.63	15.1	15.07	15.04	26.69	16.01	15.25	15.05	34.48	18.52	15.9	15.09
T2	31.2	18.29	16.77	15.26	15.16	15.09	28.07	17.7	16.44	15.2	15.12	15.06	31.86	16.89	15.5	15.07	39.19	22.51	17.53	15.14
T3	31.17	20.56	18.24	15.49	15.24	15.12	29.96	19.55	17.61	15.38	15.18	15.09	36.78	18.01	15.84	15.1	41.06	26.41	19.57	15.21
T4	27.65	24.26	21.54	16.31	15.52	15.21	27.44	23.16	20.54	16.03	15.39	15.15	42.43	20.93	16.77	15.17	39.74	31.8	23.38	15.42
T5	25.89	25.24	23.03	16.99	15.77	15.26	21.7	23.26	21.7	16.6	15.59	15.18	39.02	22.83	17.45	15.21	34.83	31.77	24.88	15.55
T6	25.89	25.24	23.03	16.99	15.77	15.26	21.7	23.26	21.7	16.6	15.59	15.18	39.02	22.83	17.45	15.21	34.83	31.77	24.88	15.55

Table A.24. 30 KW, 120 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	23.3	16.11	15.55	15.11	15.1	15.05	22.17	15.97	15.48	15.08	15.07	15.04	26	15.9	15.22	15.05	32.89	18.03	15.8	15.12
T2	27.93	17.33	16.23	15.21	15.15	15.08	25.2	16.98	16.05	15.16	15.11	15.06	30.64	16.65	15.43	15.07	37.36	21.47	17.1	15.16
T3	29.33	18.89	17.19	15.35	15.21	15.12	27.09	18.31	16.86	15.28	15.16	15.08	34.86	17.55	15.7	15.1	39.33	24.92	18.74	15.21
T4	27.17	22.02	19.56	15.84	15.39	15.19	27.75	21.49	19.1	15.71	15.31	15.14	40.75	19.71	16.39	15.16	40.63	30.46	21.95	15.33
T5	24.54	23.26	20.94	16.25	15.54	15.24	25.3	22.85	20.54	16.09	15.43	15.17	39.2	21.08	16.86	15.2	35.89	31.79	23.47	15.41
T6	24.54	23.26	20.94	16.25	15.54	15.24	25.3	22.85	20.54	16.09	15.43	15.17	39.2	21.08	16.86	15.2	35.89	31.79	23.47	15.41

Table A.25. 35 KW, 60 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	37.2	18.93	17.05	15.25	15.14	15.07	32.42	17.88	16.47	15.17	15.1	15.05	27.22	16.32	15.36	15.06	33.24	18.96	16.18	15.07
T2	43.91	23.63	20.1	15.69	15.27	15.12	38.38	21.12	18.52	15.46	15.18	15.08	33.94	17.83	15.82	15.1	34.4	23.12	18.23	15.15
T3	43.49	28.29	23.88	16.56	15.53	15.18	37.4	24.69	21.25	16.02	15.34	15.12	39.35	20.07	16.6	15.15	33.55	25.79	20.28	15.3
T4	41.54	29.25	26.44	18.78	16.48	15.37	34.49	27.12	24.85	17.82	16	15.22	38.81	25.61	19.07	15.27	30.37	26.13	22.38	15.67
T5	40.46	30.3	26.83	19.64	17.15	15.57	34.49	26.95	24.91	18.89	16.58	15.3	35.87	27.2	20.68	15.37	27.49	26.02	22.58	15.85
T6	40.46	30.3	26.83	19.64	17.15	15.57	34.49	26.95	24.91	18.89	16.58	15.3	35.87	27.2	20.68	15.37	27.49	26.02	22.58	15.85

Table A.26. 35 KW, 80 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	31.89	17.65	16.33	15.18	15.12	15.06	28.86	17.12	16.05	15.14	15.09	15.05	30.19	16.41	15.34	15.06	36.68	18.95	16.04	15.08
T2	38.93	20.85	18.25	15.43	15.22	15.11	33.09	19.42	17.44	15.32	15.16	15.08	36.86	17.74	15.72	15.09	42.36	23.8	18.07	15.14
T3	38.92	24.98	21.12	15.93	15.37	15.16	32.07	22.12	19.35	15.65	15.26	15.11	42.7	19.51	16.28	15.13	44.53	28.77	20.75	15.26
T4	35.48	29.37	26.22	17.72	15.98	15.27	27.03	25.49	23	16.84	15.65	15.18	47.79	24.5	17.98	15.22	43.31	35.27	26.01	15.64
T5	33.3	28.68	27	19.02	16.56	15.36	24.66	24.84	23.89	17.77	16.05	15.24	42.79	27.76	19.31	15.29	37.76	34.09	27.83	15.92
T6	33.3	28.68	27	19.02	16.56	15.36	24.66	24.84	23.89	17.77	16.05	15.24	42.79	27.76	19.31	15.29	37.76	34.09	27.83	15.92

Table A.27. 35 KW, 100 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	27.16	16.73	15.86	15.15	15.12	15.06	25.47	16.47	15.72	15.11	15.09	15.04	28.57	16.17	15.29	15.06	37.48	19.04	16.03	15.1
T2	33.3	18.73	17.01	15.3	15.19	15.1	29.91	18.06	16.63	15.23	15.14	15.07	34.55	17.18	15.57	15.09	42.9	23.6	17.89	15.16
T3	33.13	21.3	18.68	15.56	15.28	15.15	31.95	20.16	17.96	15.43	15.21	15.1	40.23	18.45	15.96	15.12	45.17	28.07	20.21	15.24
T4	29.21	25.49	22.42	16.49	15.6	15.24	28.38	24.07	21.2	16.17	15.45	15.17	46.93	21.77	17.02	15.2	44.05	34.44	24.6	15.47
T5	27.55	26.61	24.1	17.26	15.88	15.31	22.25	24.19	22.46	16.8	15.67	15.21	43.08	23.95	17.79	15.25	38.23	34.48	26.38	15.63
T6	27.55	26.61	24.1	17.26	15.88	15.31	22.25	24.19	22.46	16.8	15.67	15.21	43.08	23.95	17.79	15.25	38.23	34.48	26.38	15.63

Table A.28. 35 KW, 120 % CRAC Fan Speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	24.52	16.28	15.63	15.13	15.11	15.06	23.23	16.12	15.55	15.1	15.08	15.04	27.78	16.05	15.26	15.05	35.72	18.49	15.92	15.14
T2	29.79	17.67	16.41	15.24	15.18	15.1	26.72	17.28	16.2	15.18	15.13	15.07	33.18	16.91	15.49	15.08	40.91	22.45	17.41	15.19
T3	31.33	19.45	17.51	15.41	15.25	15.14	28.89	18.8	17.14	15.32	15.19	15.1	38.09	17.94	15.8	15.12	43.23	26.41	19.28	15.24
T4	28.84	23.06	20.24	15.97	15.46	15.23	29.61	22.44	19.7	15.81	15.35	15.16	44.98	20.42	16.59	15.18	44.93	32.84	22.97	15.38
T5	25.9	24.51	21.83	16.44	15.62	15.28	26.5	23.96	21.34	16.25	15.5	15.2	43.27	22	17.14	15.23	39.51	34.47	24.73	15.47
T6	25.9	24.51	21.83	16.44	15.62	15.28	26.5	23.96	21.34	16.25	15.5	15.2	43.27	22	17.14	15.23	39.51	34.47	24.73	15.47

Table A.29. Server Heat Loading on racks

	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
Load Bank 1	2.5	2.5	2.5	3.75	3.75	2.5	1.25	1.25	2.5	2.5	1.25	1.25	2.5	2.5	2.5	3.75	3.75	2.5	2.5	2.5
Load Bank 2	2.5	2.5	2.5	3.75	3.75	2.5	1.25	1.25	2.5	2.5	1.25	1.25	2.5	2.5	2.5	3.75	2.5	3.75	2.5	2.5
Load Bank 3	2.5	2.5	2.5	3.75	3.75	2.5	1.25	1.25	2.5	2.5	1.25	1.25	2.5	2.5	2.5	3.75	3.75	2.5	2.5	2.5
Load Bank 4	2.5	2.5	2.5	3.75	3.75	2.5	1.25	1.25	2.5	2.5	1.25	1.25	2.5	2.5	2.5	3.75	2.5	3.75	2.5	2.5

Table A.30. Temperatures for 60% CRAC fan speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	22.62	15.69	15.26	15.02	15.01	15.01	21.34	15.49	15.17	15.01	15	15.01	19.59	15.21	15.03	15.02	22.73	16.1	15.21	15.02
T2	24.98	19.47	17.51	15.18	15.04	15.03	24.32	18.03	16.54	15.09	15.01	15.01	25.2	16.25	15.22	15.03	23.85	19.89	17.08	15.06
T3	24.09	20.73	19.58	15.66	15.12	15.04	22.96	19.86	18.24	15.31	15.04	15.02	26.54	17.71	15.6	15.04	23.22	20.95	18.32	15.13
T4	23.37	20.46	19.46	16.74	15.52	15.07	21.92	19.01	18.99	16.07	15.22	15.03	25.94	20.76	16.79	15.06	22.3	20.56	19.31	15.28
T5	22.88	20.98	19.87	17.27	16.1	15.15	21.04	18.57	18.17	16.91	15.69	15.04	24.51	22.03	18.72	15.11	20.63	19.96	19.28	15.43
T6	22.88	20.98	19.87	17.27	16.1	15.15	21.04	18.57	18.17	16.91	15.69	15.04	24.51	22.03	18.72	15.11	20.63	19.96	19.28	15.43

Table A.31. Server Heat Loading on racks

	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
Load Bank 1	5	5	5	6.25	6.25	5	3.75	3.75	5	5	3.75	3.75	5	5	5	6.25	6.25	5	5	5
Load Bank 2	5	5	5	6.25	6.25	5	3.75	3.75	5	5	3.75	3.75	5	5	5	6.25	5	6.25	5	5
Load Bank 3	5	5	5	6.25	6.25	5	3.75	3.75	5	5	3.75	3.75	5	5	5	6.25	6.25	5	5	5
Load Bank 4	5	5	5	6.25	6.25	5	3.75	3.75	5	5	3.75	3.75	5	5	5	6.25	5	6.25	5	5

Table A.32. Temperatures for 60% CRAC fan speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	29.16	16.17	15.43	15.03	15.01	15.03	27.25	15.88	15.3	15.02	15.01	15.02	22.46	15.34	15.04	15.03	27.78	16.77	15.34	15.03
T2	35.67	23.62	19.56	15.28	15.05	15.06	35.34	20.75	17.8	15.14	15.03	15.05	30.92	17	15.34	15.06	30	22.84	18.32	15.09
T3	34.4	28.2	24.68	16.06	15.17	15.09	33.49	25.34	21.38	15.52	15.08	15.07	32.9	19.27	15.94	15.07	28.53	24.18	20.05	15.18
T4	33.17	27.78	25.49	18.13	15.77	15.15	31.42	25.16	24.03	16.9	15.34	15.1	32.35	23.86	17.75	15.1	26.62	23.83	21.4	15.36
T5	32.24	28.99	26.61	19.35	16.78	15.74	30.23	24.77	23.56	18.69	16.11	15.17	30.95	25.48	20.52	15.17	24.18	23.89	21.4	15.52
T6	32.24	28.99	26.61	19.35	16.78	15.74	30.23	24.77	23.56	18.69	16.11	15.17	30.95	25.48	20.52	15.17	24.18	23.89	21.4	15.52

Table A.33. Server Heat Loading on racks

	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
Load Bank 1	3.75	3.75	3.75	5	5	3.75	2.5	2.5	3.75	3.75	2.5	2.5	3.75	3.75	3.75	5	3.75	5	3.75	3.75
Load Bank 2	3.75	3.75	3.75	5	5	3.75	2.5	2.5	3.75	3.75	2.5	2.5	3.75	3.75	3.75	5	5	3.75	3.75	3.75
Load Bank 3	3.75	3.75	3.75	5	5	3.75	2.5	2.5	3.75	3.75	2.5	2.5	3.75	3.75	3.75	5	3.75	5	3.75	3.75
Load Bank 4	3.75	3.75	3.75	5	5	3.75	2.5	2.5	3.75	3.75	2.5	2.5	3.75	3.75	3.75	5	5	3.75	3.75	3.75

Table A.34. Temperatures for 100% CRAC fan speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	20.9	15.38	15.13	15.02	15.01	15.02	19.93	15.29	15.1	15.01	15	15.01	19.95	15.17	15.02	15.02	24.46	16.05	15.2	15.06
T2	25.12	17.38	16.07	15.07	15.03	15.04	24.31	16.64	15.71	15.04	15.01	15.02	25.05	15.75	15.1	15.04	27.9	20.47	17.02	15.08
T3	23.69	19.61	17.41	15.18	15.05	15.05	24.11	18.17	16.58	15.1	15.02	15.03	28.35	16.38	15.23	15.05	28.44	22.58	18.25	15.11
T4	22.63	22.05	19.84	15.58	15.13	15.07	21.64	20.2	18.29	15.32	15.06	15.04	29.63	17.72	15.55	15.07	27.92	24.65	19.85	15.17
T5	22.95	22.96	21.59	16.41	15.37	15.09	17.7	19.92	19.38	15.83	15.18	15.05	28.24	19.75	16.13	15.09	25.79	24.27	20.99	15.25
T6	22.95	22.96	21.59	16.41	15.37	15.09	17.7	19.92	19.38	15.83	15.18	15.05	28.24	19.75	16.13	15.09	25.79	24.27	20.99	15.25

Table A.35. Server Heat Loading on racks

	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
Load Bank 1	6.25	6.25	6.25	7.5	7.5	6.25	5	5	6.25	6.25	5	5	6.25	6.25	6.25	7.5	6.25	7.5	6.25	6.25
Load Bank 2	6.25	6.25	6.25	7.5	7.5	6.25	5	5	6.25	6.25	5	5	6.25	6.25	6.25	7.5	7.5	6.25	6.25	6.25
Load Bank 3	6.25	6.25	6.25	7.5	7.5	6.25	5	5	6.25	6.25	5	5	6.25	6.25	6.25	7.5	6.25	7.5	6.25	6.25
Load Bank 4	6.25	6.25	6.25	7.5	7.5	6.25	5	5	6.25	6.25	5	5	6.25	6.25	6.25	7.5	7.5	6.25	6.25	6.25

Table A.36. Temperatures for 100% CRAC fan speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	23.62	15.56	15.19	15.03	15.01	15.03	22.25	15.43	15.14	15.02	15.01	15.02	23.12	15.27	15.03	15.03	30.35	16.68	15.32	15.1
T2	29.77	18.49	16.56	15.1	15.04	15.06	28.71	17.4	16.04	15.06	15.02	15.04	31.45	16.2	15.17	15.06	35.77	23.63	18.15	15.12
T3	27.79	21.84	18.56	15.26	15.07	15.08	27.62	19.62	17.3	15.15	15.04	15.06	36.7	17.2	15.36	15.08	36.99	26.93	20.06	15.17
T4	26.61	25.57	22.22	15.85	15.18	15.11	23.43	22.23	19.67	15.46	15.09	15.08	38.87	19.26	15.85	15.1	36.81	30.75	22.65	15.26
T5	27.86	26.48	24.58	17.04	15.53	15.14	18.99	22.03	21.17	16.18	15.26	15.1	37	22.45	16.74	15.14	33.05	30.43	24.74	15.38
T6	27.86	26.48	24.58	17.04	15.53	15.14	18.99	22.03	21.17	16.18	15.26	15.1	37	22.45	16.74	15.14	33.05	30.43	24.74	15.38

Table A.37. Server Heat Loading on racks

	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
Load Bank 1	8.75	8.75	8.75	10	10	8.75	7.5	7.5	8.75	8.75	7.5	7.5	8.75	8.75	8.75	10	10	8.75	8.75	8.75
Load Bank 2	8.75	8.75	8.75	10	10	8.75	7.5	7.5	8.75	8.75	7.5	7.5	8.75	8.75	8.75	10	8.75	10	8.75	8.75
Load Bank 3	8.75	8.75	8.75	10	10	8.75	7.5	7.5	8.75	8.75	7.5	7.5	8.75	8.75	8.75	10	10	8.75	8.75	8.75
Load Bank 4	8.75	8.75	8.75	10	10	8.75	7.5	7.5	8.75	8.75	7.5	7.5	8.75	8.75	8.75	10	8.75	10	8.75	8.75

Table A.38. Temperatures for 100% CRAC fan speed

Rack	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	D1	D2	D3	D4
T1	26.41	15.74	15.26	15.04	15.02	15.04	24.65	15.57	15.19	15.03	15.01	15.03	26.28	15.37	15.04	15.04	36.4	17.31	15.44	15.14
T2	35	19.58	17.04	15.13	15.06	15.09	32.9	18.16	16.37	15.09	15.04	15.06	37.82	16.63	15.22	15.08	43.99	26.86	19.31	15.17
T3	32.45	24.09	19.69	15.34	15.1	15.12	29.72	21.02	18.01	15.2	15.06	15.08	45.24	17.96	15.48	15.11	45.78	31.33	21.89	15.23
T4	31.07	29.51	24.79	16.12	15.25	15.16	24.83	24.05	20.93	15.6	15.12	15.12	48.36	20.71	16.13	15.14	45.43	36.58	25.38	15.35
T5	33.6	30.86	28.18	17.78	15.72	15.2	20.44	24.51	23.07	16.51	15.34	15.15	45.68	24.97	17.29	15.18	39.78	35.7	28.14	15.5
T6	33.6	30.86	28.18	17.78	15.72	15.2	20.44	24.51	23.07	16.51	15.34	15.15	45.68	24.97	17.29	15.18	39.78	35.7	28.14	15.5

APPENDIX B

ANN code for Matlab using LM function

```
a= [ Power, CRAC fan speed, server position]

b= [ Temperature]

dataset= [a ; b ];

size(a)

size(b)

rand('seed', 491452)

net = fitnet(150);

net.trainParam.goal=1e-4;

[net, tr] = train(net, a, b);

nntraintool

plotperform(tr)

testA = a(:,tr.testInd);

testB = b(:,tr.testInd);

testC = net(testA);

perf = mse(net,testB,testC);
```

APPENDIX C

Nomenclature

EPA	Environmental Protection Agency
PUE	Power Usage Effectiveness
ANN	Artificial Neural Network
CFD	Computational Fluid Dynamics
CRAC	Computer Room Air Conditioner
MLP	Multi Layered Perceptron
MSE	Mean Square Error
RMSE	Root Mean Square Error
N	Number of training cases or data sets
PID	Proportional Integral Derivative
H	Hessian Matrix
J	Jacobian
LM	Levenberg-Marquardt training algorithm
GD	Gradient Descent

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BIOGRAPHICAL STATEMENT

Chinmay Niranjan Date was born in Mumbai, India, in 1989. He received his Bachelor of Engineering degree from Pune University, India, in 2011. He started his Master of Science in Mechanical Engineering at The University of Texas at Arlington in August 2011. From Feb. 2012 to Dec. 2013, he was working on an NSF IUCRC prject titled *Models and Metrics for Dynamic Air and Hybrid Liquid Cooled Data Centers Based on Computational and Experimental Approaches.* It was a collaborative project based out of three universities viz. The University of Texas at Arlington, SUNY at Binghamton and Villanova University. He has been working on Neural Network based control systems for thermal management systems for data centers. He is an active member of ASHRAE, SAE and other organizations. He has played leadership role in the Indian Students Association here at UT Arlington and been the President and Adviser of the student organization for the years 2011-2013.