NEURAL NETWORK MODELING AND CONTROL OF DATA CENTER

by

NACHIKET RAJENDRA KANSARA

Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science in Mechanical Engieering

THE UNIVERSITY OF TEXAS AT ARLINGTON

December 2015

To my mother Nutan Kansara and my father Rajendra Kansara

who made me who I am.

ACKNOWLEDGEMENTS

I would like to thank my supervising professor Dr. Alan Bowling for motivating and encouraging me consistently. His advice was valuable throughout the course of my graduate studies. I want to thank Dr.Dereje Agonafer and Dr. Ratan Kumar for showing interest in my research and for taking time out to be a part of the panel for my thesis defense. I would like to thank the National Science Foundation and it's IUCRC program for providing me with such a wonderful research opportunity. I would like to extend my deep gratitude to Dr.Bahgat Sammakia and his team at SUNY, Binghamton,Dr. Alfonso Ortega and his team at Villanova University and team at Georgia Tech University for their support and knowledge transfer. I would specially like to thank Kouroush Nemati,a graduate student at SUNY Binghamton for providing me with CFD simulation results of Data Center setup available at SUNY Binghamton.

I am grateful to all the professor who taught me during the years I spent in University of Texas at Arlington.I would like to thank all my friends and colleagues from The Robotics, Biomechanics and Dynamic System Lab. Rohit Katti, Ashley Chase Guy, Abhishek Chatterjee and Pranav Parikh for all their support and valuable feedback regarding my work and for also being good companion in my lab.I would also like to thank my undergraduate professor Dr.Abhaykumar Bagawade who mentored me through my undergraduate years for recognizing my potential and nurturing sense of belief in me.

I would like to extend my deepest gratitude to my grandpa Shri.Dattabhai Shankarbhai Kansara and my grandma Sau.Nandini Dattabhai Kansara who's blessings and support made me what I am today. Also to maternal grandma Late.Usha Lakuchandbhai Tambat who's last few words taught me one of the best lesson's of my life. To my mother Nutan Kansara who have taught me everything whatsoever I have known till the day, I wouldn't have been in position where I am today without her.My father Rajendra Kansara whose dreams I am living today, I want to thank him for supporting me throughout of my life and for being my backbone.I am also grateful to my brother Aniket Kansara for his love and encouragement.

Lastly I would like to thank my friends here at UTA Sayalee Sabne, Vishal Sarode, Amit Kumbhar, Nikhil Chate, Prasad Kulkarni,Darpan Pol,Nikit Lonari and Akshay Kulkarni whose support helped me to sail through easily.

November 20, 2015

ABSTRACT

NEURAL NETWORK MODELING AND CONTROL OF DATA CENTER

NACHIKET RAJENDRA KANSARA, M.S.

The University of Texas at Arlington, 2015

Supervising Professor: Dr.Alan Bowling

Data Center has become a definitive element of Modern IT infrastructure. With the development of high performance computing architectures and equipment, data centers consume large amount of electricity. Due to low Demand/Supply ratio of electricity production there is need to develop ways to reduce power footprint.

Many researchers are working on approaches to resolve problems related to energy usage of Data Center. One of these approaches is to develop a model-based control system that would control data centers in efficient way to reduce power footprint. Computational Fluid Dynamic (CFD) has been used to model the dynamic and complex environment of the data center. However, the drawback of this approach is its computational inefficiency. The effects of changing a single input may take an entire day to compute. Thus the CFD model is not well suited for model-based control. Instead we propose to use an Artificial Neural Network (ANN) model which predicts and control server temperatures in significantly less time.The Artificial Neural Network will be trained by using CFD data where first we will show that ANN can be used to predict temperature of data center servers.Both the steady state as

well as transient data will be tested and then Neural Network model based controller will be used to control the temperature of data center

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

CHAPTER 1

INTRODUCTION

The Data Centers are large group of networked computer servers typically used by organizations for the remote storage, processing or distribution of large amount of data.They serves has house for backup power supplies, data communication connections, environmental controls(e.g., air conditioning, fire suppression) and security system. According to statistics received during the year 2013 there were about 3 million data centers in US., amounting to be one center per 100 people in U.S.,and the number is still climbing.According to report submitted to U.S. congress, in the year 2006 about $61 billion kilo-watt hours of energy was consumed by the data center; which amounted to be 1.3% of total energy consumed in year 2006[1].According to data available with Natural Resources Defense Council (NRDC).In the year 2013 U.S. data centers consumed an estimated 91 billion kilowatt-hours of electricity equivalent to the annual output of 34 large (500-megawatt) coal-fired power plants and it amounted to be 1.9% of total U.S., electricity consumption for the year 2013. Data center electricity consumption is projected to increase to roughly 140 billion kilowatt-hours annually by 2020, the equivalent annual output of power plants, costing American businesses $13 billion annually in electricity bills and emitting nearly 100 million metric tons of carbon pollution per year.Due to the environmental concerns and higher power cost has led the manufacturers to find better ways to improve energy efficiency of the system.[2].

1.1 Power Usage Effectiveness

Power usage effectiveness (PUE^{TM}) has become the preferred metric for measuring infrastructure energy efficiency for data centers.It is an excellent metric for understanding how well a data center is delivering energy to its information technology equipment.It is globally adopted by industry since 2007.

PUE is defined as the ratio of total facilities energy to IT equipment energy, as shown in equation 1 below.

$$PUE = \frac{TotalFacilityEnergy}{ITEquipmentEnergy} \tag{1.1}$$

Total facility energy is defined as the energy dedicated solely to data center (e.g.the energy measured at the utility meter of dedicated data center facility or at the meter for a data center or data room in a mixed-use facility).The IT equipment energy is defined as the energy consumed by equipment that is used to manage, process,store, or route data within the computer space.[3]

According to the survey conducted by Uptime Institute in year 2012 says that average PUE of all U.S. data center is in the range of 2.0-2.5. The ideal PUE the data center setup should have is 1.0. One of the Google data center setup has the PUE value of 1.06[4].It has been the highest PUE recorded till date by any data center around the world.

The data center industry is continuously in search of energy efficient practices to reduce their PUE value.Hot, cold asile 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 field in which a lot of studies and experiments and testing is being done to

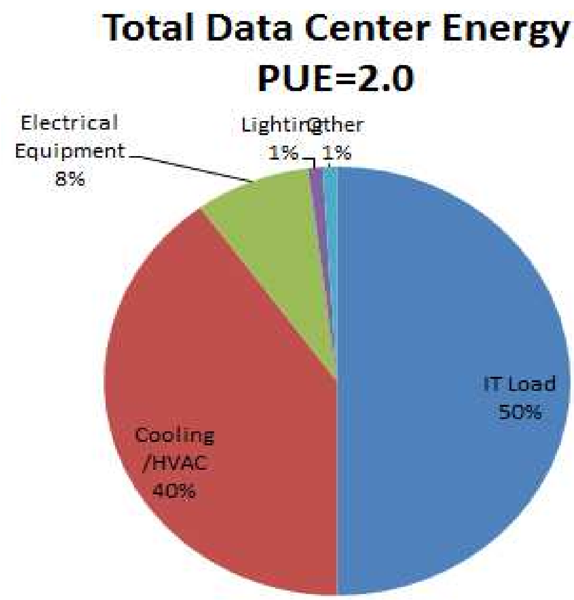


Figure 1.1. Power Usage Effectiveness.

improve efficiency of modern data centers. Development of control systems to control such data centers in efficient way can be one of the technique to reduce power footprints.There is a need to develop a control algorithm that has to be adaptive and dynamic for highly nonlinear system like data center.The controller should also be efficient with respect to cost and time.

Computational Fluid Dynamics is currently used to model data centers and to simulate behavior and response according to certain conditions.CFD is a technique that is expensive, consumes time and also requires and experienced user. The model developed in CFD lacks the complete accuracy of actual facility. The Control theories being developed today uses CFD as reference data in development and verification stages.However, due to increasing complexity of the data centers model based simulation takes long time to achieve steady state. This further leads to increase in time

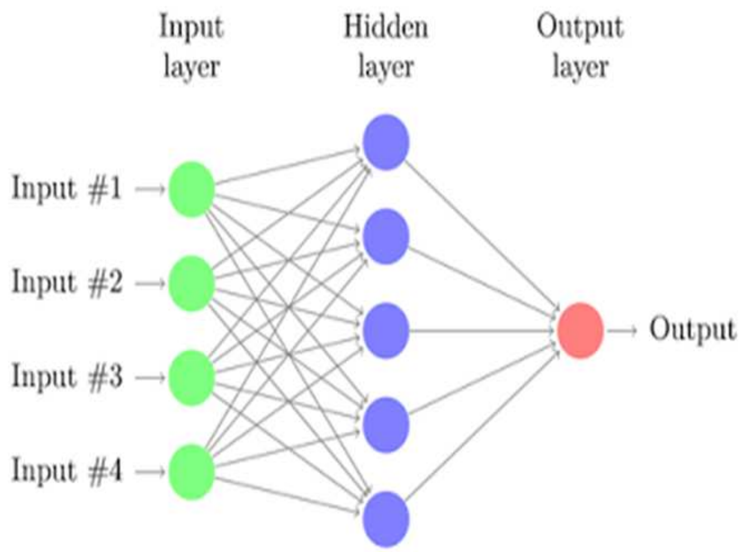


Figure 1.2. A Simple MLP Neural Network.

to develop and study the controller.Moreover,even a small amount of change in the input parameter make take long time to simulate. Therefore, we will have to spend a lot of time on verification studies and still may get highly unpredictable response if the system goes out of control. Hence, there is a need to develop a predictive type of control for such a highly nonlinear and complex systems.

Artificial Neural Networks have been use since long time for pattern recognition and data manipulation.We aim to use this pattern recognition technique to our advantages.The Data Centers are highly nonlinear system which has the complex combination of heat and mass transfer.Varying atmosphere temperature, source temperature and cooling temperature can become observable due to its highly complex nature.Therefore,a control system with a good feed forward and feedback algorithm will be best suitable for such kind of applications.

Neural Networks as a concept is derived from human brain. The typical human brains contains 100 billions miniscule cells called neurons. These neurons receives information through dendrites, they process information and gives and output. These concept when applied with Artificial Neural Network can be used to learn things, recognize patterns and make decision.The typical neural network has small miniscule cells called node.These nodes are arranged in layers.The network has input layer that receives information from outside world that the network will attempt to learn about,recognize or process. Other set a layer are on opposite side and respond to information that it is learned are called as output layer. In between the input and output layer, one or more layers of hidden units, which together form the majority of the artificial brain. Most of the neural network is fully connected, which means each hidden unit and each output unit is connected to every unit in the layers either side. The connection between one unit and another are represented by a number called a weight, which can be either positive or negative. The higher the weight, the more influence of one unit has on another. This is how we receive the output from the process output layer.The flow of information from input layer to output layer through hidden layer is called as feedforward system.Before output layer gives the final output it verifies whether it has reached the target value, or else error is sent to the input and hidden layer and the weights are varied before the final output is processed. This phenomenon of Neural Network is called as backpropagation. the Data Centers are highly complex and non-linear system.It is highly impossible to find the transfer function of such a non-linear system. Artificial Neural Network(ANN) has a great potential to map unknown functions between a set of input and output vectors.Hence, we can use ANN as a function approximation system which is also referred as Black box modeling can be used to predict the behavior of Data Center.

CHAPTER 2

Data Center Layout and Background

The Data Center setup that we have consider for our experimental study is available at SUNY Binghmaton University.The Data Center setup taken into consideration is hybrid data center. By hybrid we mean that cooling is done both by water and air. The experimental study is performed on Knurr CoolTherm^{TM} ® cabinet. The Fig 2.1[5] shows the closed loop cabinet.The cooling is done with the combination of a CDU and chilled water supply.The warm water from the heat exchanger is supplied to chilling system. The chilled water is supplied at about 8-15 degree celcius.The setup has CDU i.e coolant distribution unit and cabinet is located inside the equipment center.The chiller is situated outside the the equipment center.The Cooling tower is located outside the building.The CDU unit,chiller,cooling tower and racks unit are very well connected to each other.Hybrid cooling system is advantageous in terms of efficiency,operation cost and energy recovery capability.

2.1 Data Center Cabinet

A schematic of the Knurr CoolTherm^{TM} ® server cabinet [5, 6] characterized in this study is shown in Fig. 2.2. The Cabinet is of size 1.2m x 0.8m x 2.33m.It has 16 1U severs and 9U load banks are used for generating heat load[5].The cabinet has capability of 25 kW.There are 3 nos. of radial fans connected at the back end of the cabinet. Each fan has capacity of around 1800rpm. There is the heat water/air heat exchanger located at the bottom of the cabinet.The IBM heat exchanger is of 35 kW capacity [6].

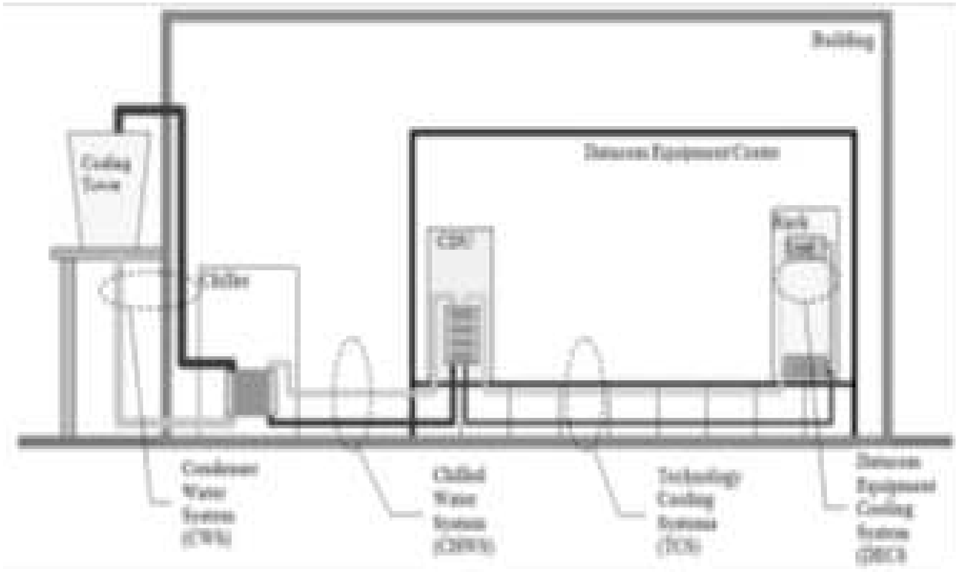


Figure 2.1. Liquid Cooling Systems-Loops within Data Center.

2.2 Working of the Server Cabinet

Fig 2.3 shows the top and side view of the server cabinet.The hot air that is exiting the server is directed towards the heat exchanger through fans. The heat is being removed in the exchanger. After it leaves the heat exchanger the cooled air moves upwards in the front of the cabinet and is drawn by the server fans.The cabinet is designed in such a manner that hot air travels through the rear end of the cabinet[5].

2.3 Experiment Study

For the experimental studys the cabinet has 16 DELL PowerEdge 1950 1U servers[5]. Each servers has two Quad-Cores processors operating at 2.66 GHz an have a maximum power capacity of about 450 W.Fig.2.4 shows the view of the server.Empty parts of cabinet are covered by a fiber glass to prevent recirculation of cold air.It act as a partition between the two sections of the cabinets.

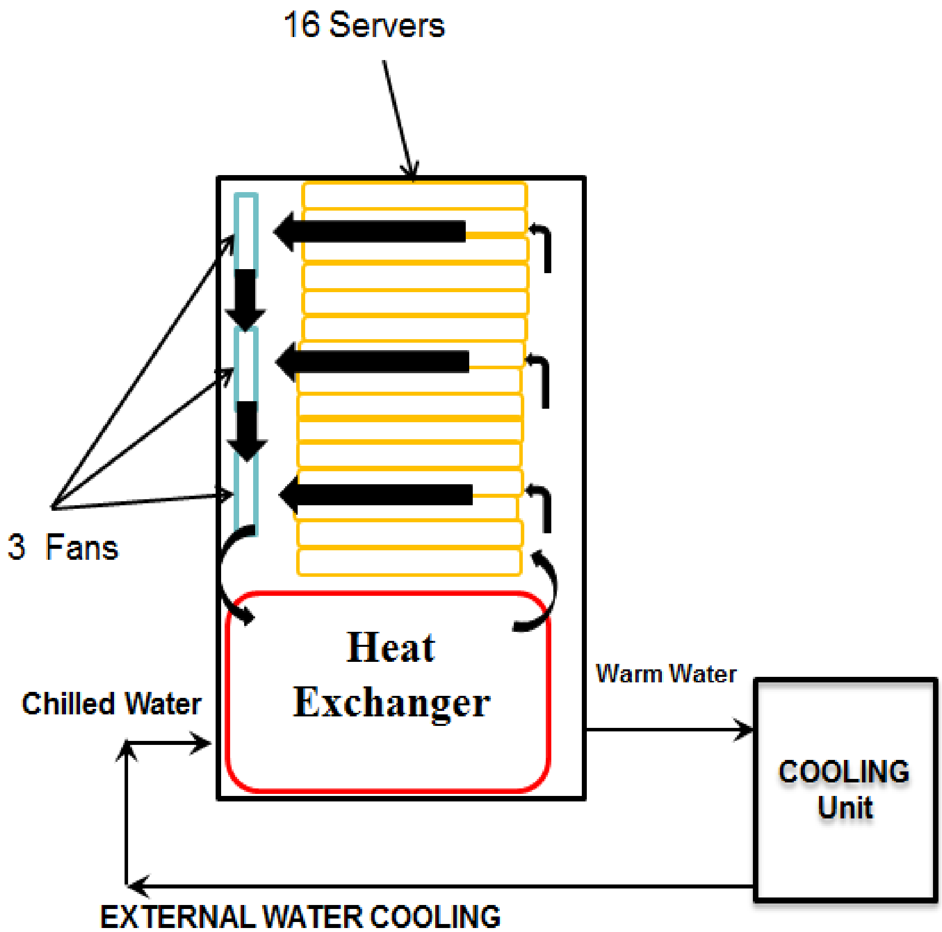


Figure 2.2. Schematic diagram of Data Center Cabinet.

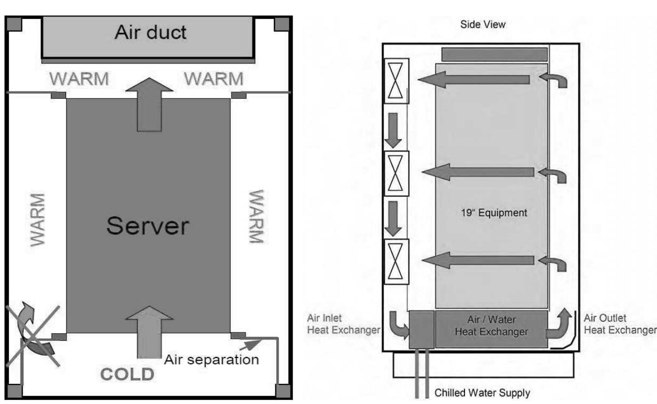


Figure 2.3. Top and Side View of the Server Cabinet.

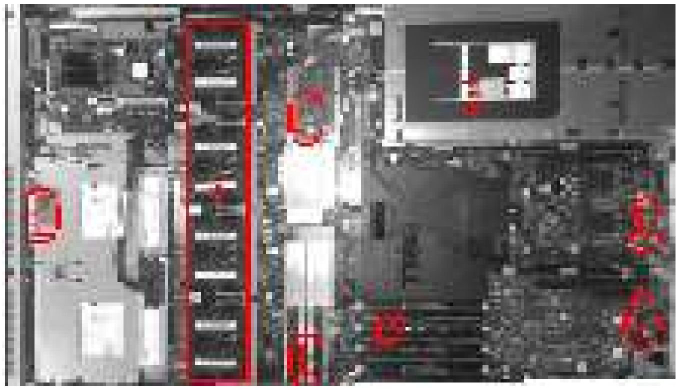


Figure 2.4. Top view of DELL PowerEdge 1950 server.

There are about 5 thermocouples installed inside each server, to monitor air temperature distribution.[5].Fig.2.3 shows the location of the thermocouples 1) air inlet, 2) right CPU heat sink, 3) left CPU heat sink, 4) right outlet and 5) left outlet. The servers has 8 fans marked as (i) in Fig.2.3. (ii) is the location of the power supply and (iii) the array of memory cards[5] . The power dissipation of each server is 6-W in idle condition,250 W at the time of normal computation and 450W at complete loading.A maximum of 14.7 kW of power can be generated inside the cabinet[5]. There are about 7 thermocouples that measure the air temperature at the inlet and 9 thermocouples at the outlet of the heat exchanger.Fig.2.4 shows the rear view of the heat exchanger[5].

Fig.2.5 shows the front and rear view of the heat of the cabinet[5].The three radial fans located at the rear end of the cabinet can be seen.We can also see the ducts from where the air flows into the heat exchanger. The air flow rate into the cabinet can be controlled by thermostat.The flow rate of air is around 75% below 16 degree celcius and it is 100% around 19 degree celcius.

In order to measure the flow rate and the temperature of the water vortex flowmeter with the temperature sensors is installed on supply pipes of heat ex-

Figure 2.5. Rear view of Heat Exchanger.

Figure 2.6. FRONT AND REAR VIEW OF FULLY ENCLOSED CABINET.

Figure 2.7. Location of vortex flow meter on the supply pipe of heat exchanger.

changer.the water at the inlet is at the constant temperature of 16.7 degree celcius.Fig.2.6 shows the flow meter location.

CHAPTER 3

Neural Network and Learning Algorithm

Neural Network has a same concept as human brain. The human brian has small unit called neurons which receives inputs through dendrites, it processes the information and in turn gives an output signal. If same concept applied with Artificial Neural Network can be used to learn things, recognize patterns and make decisions.

3.1 NEURAL NETWORK MODEL

Simple Neuron

Similar to human brain, Neural Network has single unit called as Neurons. The neurons are nothing but the transfer function. These transfer function would predictive the output on basis of relative input. The Artificial Neural Network Model consist of these simple Neurons, whose transfer function can be varied based on our requirements. A simple neuron is also termed as a *Perceptron.*

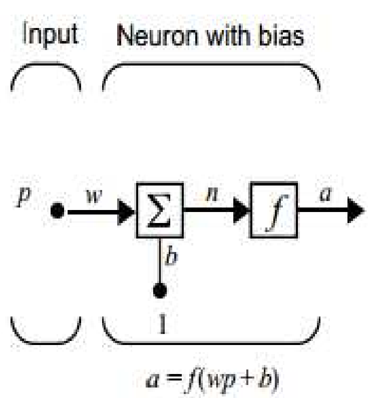


Figure 3.1. Perceptron.

Fig 3.1.1 shows the structure of perceptron. The ANN model will have hundreds of perceptrons connected to each other. These layer in which the perceptrons are located is called as the hidden layer and the connection between the perceptron are called as weights and biases.

The neuron output for a Perceptron is computed with the following equation

$$a = f(wp + b) \tag{3.1}$$

Where p is the input value that neurons receives and its multiplied by weight (w) and the reference input b is added to the function which in turn produces a as a output.

3.1.1 Weights and Biases of a Neural Network

The performance of Neural Network depends on weights and biases. These variables are adjusted on basis of the data used to train the neural network. The weight of a Neuron helps to train the model while the biases are used to shift the activation function. On basis of the value of weight whether it is negative of positive triggers the corresponding neuron in the hidden layer which in turn will trigger the neuron in the output layer. The initial value of weight and biases can be given in some cases but after we train the neural network will itself adjust the values of weights and biases.

3.2 Working of Neural Network

As mentioned earlier neural network has unit neurons arranged in layers. It has bunch of input layer where we input the information or data to be processed. It has the output layer which gives the output of the processed data. In between it has bunch of Neurons which are called as hidden neurons and the layer is called as hidden layer. All these neurons are densely connected to each. The input layer receives the information hidden layer process it and output layer gives an output.This type of working of Neural Network system is termed as feed forward system.When the output layer receives the information it sends signals to input layer to check whether it has matched with the target set of value or not this type of working of the neural network system is termed as back propagation.

3.3 Training a Neural Network

Training Neural Network means altering weights and biases. When a Neural Network is trained on basis of sufficient amount of data a steady state transfer function which govern the system is obtain.The data used to train a Neural Network is termed as a training set. In order to see how training process exactly works lets consider the functionality one of the simple training algorithm namely gradient descent . The weights and biases of the function are adjusted in such a way that error is reduced in performance function. The following equation shows how the single iteration of performance function looks like.

$$x_{k+1} = x_k - a_k g_k \tag{3.2}$$

where x_k is the vector with current weights and biases, g_k is the current gradient, and a_k is the learning rate

The training of Neural Network is divided into three parts :

1)Selecting the Learning Algorithm

2)Selecting number of neurons in hidden layers

3)Validating our Network

3.3.1 Selecting Learning Algorithm

On the basis of type of data we have there are two possible learning algorithm which can be used for training our network.

1) Levenberg-Marquardt Algorithm (LM). 2) Gradient Descent Back Propagation Algorithm (GD).

The LM function and GD are mostly widely accepted algorithms for function approximation.The Gradient Descent is a training function which update values of weight and bias[7].The GD backpropagation algorithm updates weight and biases along negative gradient[7].The LM algorithm is also one of the fastest back propagation algorithm. While selecting one of the algorithm speed and time are two important factors to be consider. As we need our ANN to be trained fast and with higher amount of accuracy.Therefore, both algorithms were compared on basis of time and accuracy. Both the algorithm were used for training of a same example data set.

In Fig.3.3.1[7] and Fig 3.3.2[7] shows us the comparison of both LM and GD algorithm for time and accuracy for different number of neurons.The LM algorithm is faster and accurate than GD back propagation algorithm.As the number of neurons of neurons increases our algorithm attains good accuracy.Hence,Levenberg-Marquardt algorithm will be best suitable for training our Artificial Neural Network.

3.3.1.1 Levenberg-Marquardt Algorithm

On the basis of the results obtained in the above section *Levenberg-Marquardt* algorithm will be used to train our Neural Network model. This algorithm is designed to attain the second order training speed.It is one of the fastest back propagation

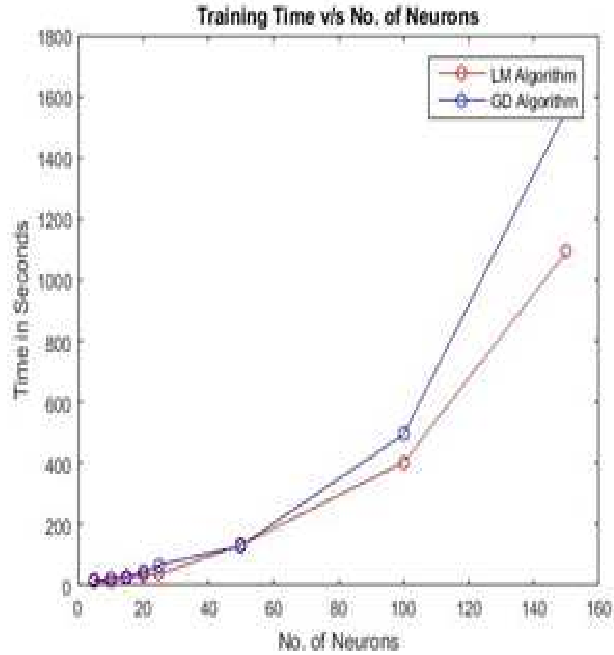


Figure 3.2. Time comparison for LM and GD algorithm for different no. of neurons .

algorithm available. This algorithm is termed as *trainlm*, in MATLAB.It can be expressed as follows

$$x_{k+1} = x_k - [J^T J + \mu \, I]^{-1} \, J^T e \tag{3.3}$$

where $J^T J$ is the *Hessian Matrix* , $J^T e$ is the *gradient*
and e is the vector of the network errors thus obtained by training.

The J consist of first derivative of network errors to the weights and bias. This is much faster for finding Jacobian than Hessian matrix.This is one of the vital things that makes LM algorithm faster than GD back propagation algorithm.Unlike in GD algorithm weights in LM algorithm are updated using Newtonian method according to the above equation.[8]

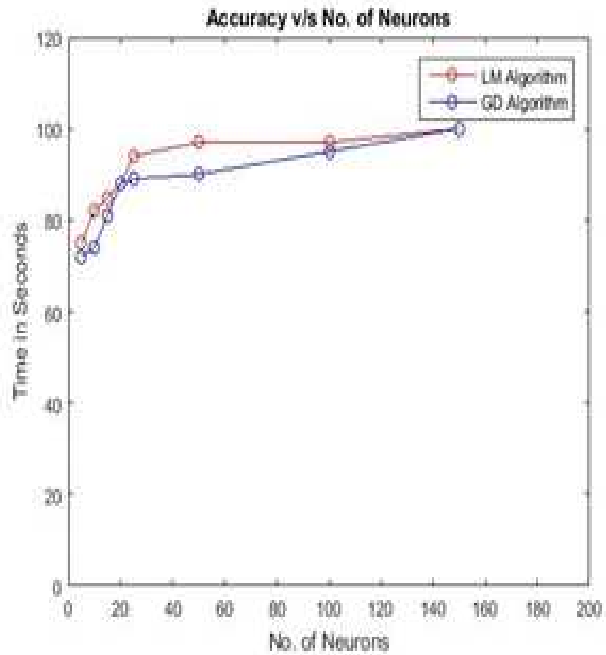


Figure 3.3. Accuracy comparison for LM and GD algorithm for different no. of neurons .

Due to its regression model, fast convergence, and accurate training the Levenberg-Marquardt algorithm is a sound choice for our Neural Network model.

3.3.2 Number of Neurons

The Artificial Neural Network has to be trained several times before the best state is achieved.The Network should have sufficient number of neurons in its hidden layers to be properly tuned.There are many rule-of-thumb to decide number of neurons.However, we don't have any empirical formula to determine no. of neurons and hidden layers.Some of them are as follows[7] 1)Number of neurons should be between size of input layer added to size of the output layer.
2)The number can be 2/3 the size of the input layer,plus the size of the output layer.

3)The number should be less than twice the size of input layer.

3.3.3 Validating the Network

3.3.3.1 Regression Plot

We used regression plot for validating our Neural Network.Its is one of the check to show that our regression plot is sufficiently trained. The plot is generated after training the data set.When neural network trains our data its is divided into three section 70% for training,15% for validating and 15% for testing.The regression plot shown below has four section training,validation ,testing and the fourth plot is the combination of all[8].The regression plot draws the mean line for the target value to achieve and the black dots are the values attain after training the neural network.The more closer the dots to the line better are our predictions.The following regression plot is for 13923 watts, 57 % Fan Efficiency , 1,2& 3 Fan Active data set .The value R=0.9843 signifies that the optimum training was obtained from the data-set

3.4 Fitting Tool

There are some ready made tools available in MATLAB Neural Network toolbox.The Fitting tool is one of them.It is used for data-fitting,pattern recognition and clustering.As one of our data is steady state which doesnot depend on time we can use this fitting for training our network.After we use the fitting tool Fig.3.6 shows the transfer function that is obtained.The diagram shows one set of data given as an input to network in turn we are receiving one set as an output.It has 10 number of neuron the corresponding block shows the sigmoid transfer function and the next block which has 1 number neuron shows linear transfer function.

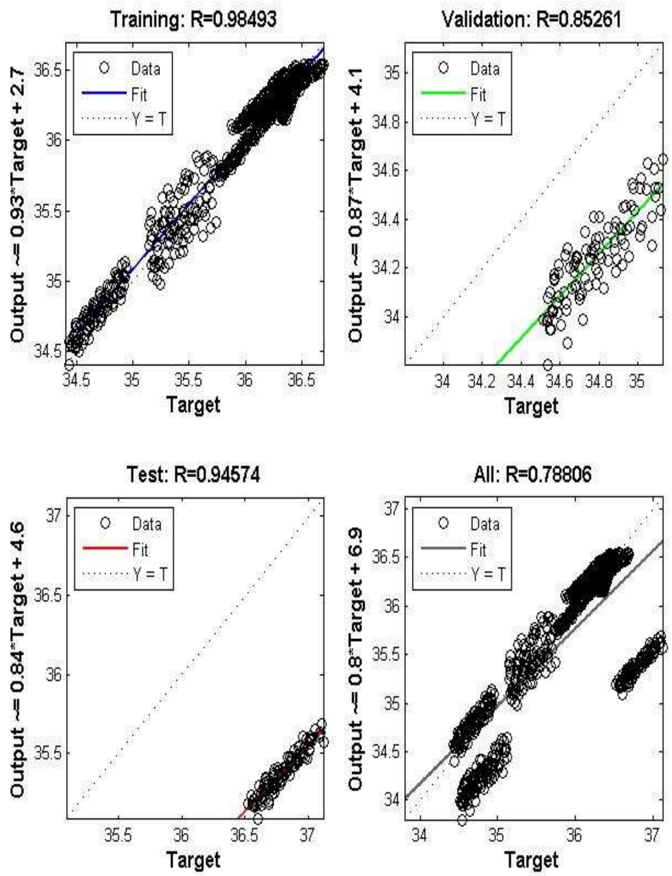


Figure 3.4. Regression plot for 13923 watts, 57 % Fan Efficiency , 1,2& 3 Fan Active.

3.5 Dynamic Time Series Tool

A Dynamic time series tool in the neural network toolbox for time-series prediction, non-linear dynamic system modeling and control systems application.We can train our transient data using this tool.It also has the feedback system to check whether target value is reached.Fig 3.9 shows the transfer function generated after we train our data. The function shows that it has one set of input data and one set of target data to reach.There are 10 neurons in hidden layers which has sigmoid transfer function and 1 neuron in hidden layer which has a linear transfer function.

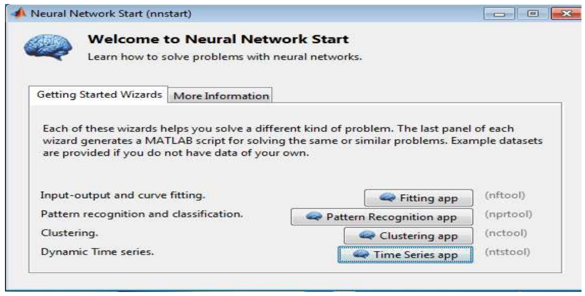


Figure 3.5. NN Fitting Tool selection box.

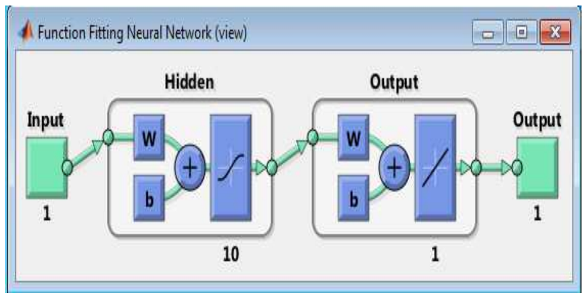


Figure 3.6. Fitting Tool Neural Network transfer Function.

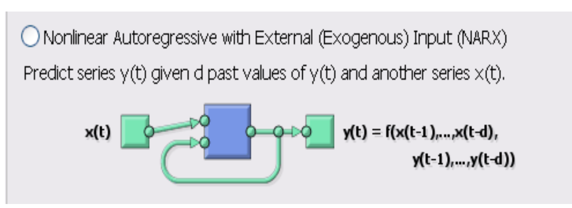


Figure 3.7. NN- NARX Symbol.

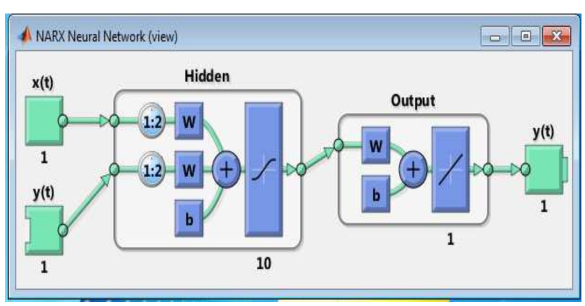


Figure 3.8. Dynamic Time series Tool Transfer Function.

CHAPTER 4

Training Data and Results

4.1 Training Data

Training CFD data was generated at SUNY Binghamton under the setup explained in Figure 2 and 3.Each set of data consist of input and output matrix. The input matrix has Power, Fan Efficiency and Server Position as an input parameters and the output matrix has temperature generated due to corresponding power supply in each server.A Neural Network model was generated to record for the prediction for temperature similar to the variable defined for the CFD data. These prediction were compared with their CFD counter parts for the same settings.

4.2 Results

4.2.1 Steady State Results

Following graph shows comparison of steady state CFD server temperature with respect to NN output server temperature at single time step.Comparison of CFD and NN Output data is being plotted and the second graph shows the comparison of the absolute and percentage error for same sets of data.

4.2.2 Transient State Results

Following graph shows comparison of transient data of CFD server temperature with respect to NN output temperature for one server at variable time step.

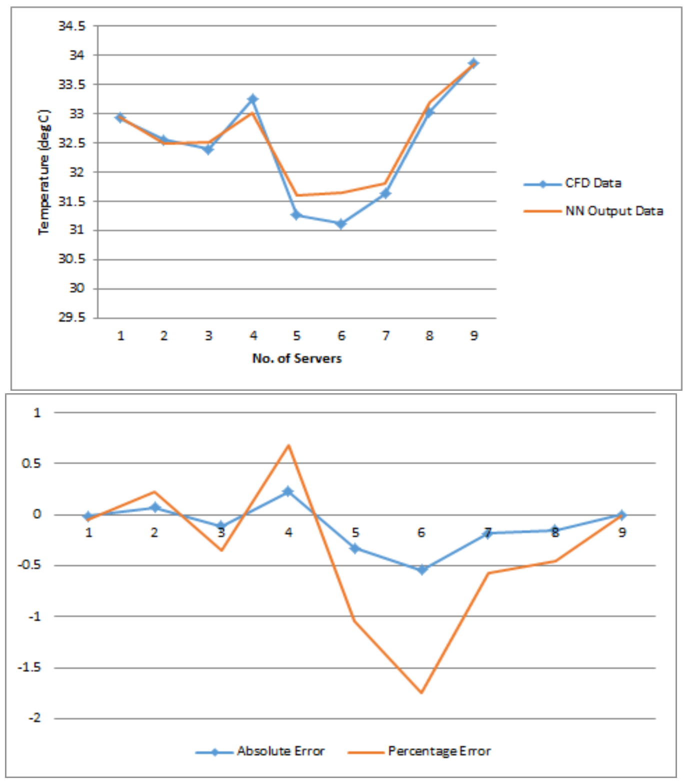


Figure 4.1. Results and Error for 11529 watts, 57 % Fan Efficiency ,Vent 1, out.

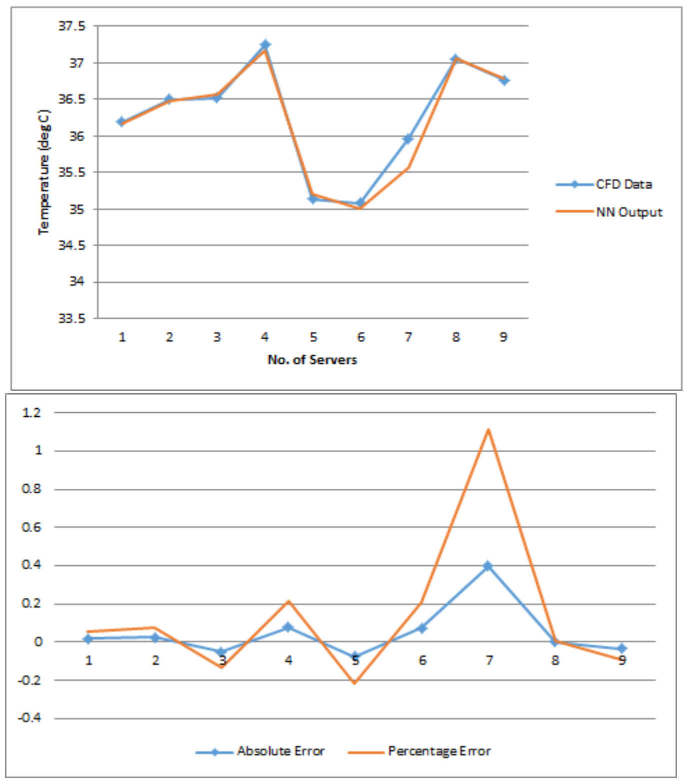


Figure 4.2. Results and Error for 6783 watts, 21 % Fan Efficiency ,Fan Active 1 and 2, Vent 1.

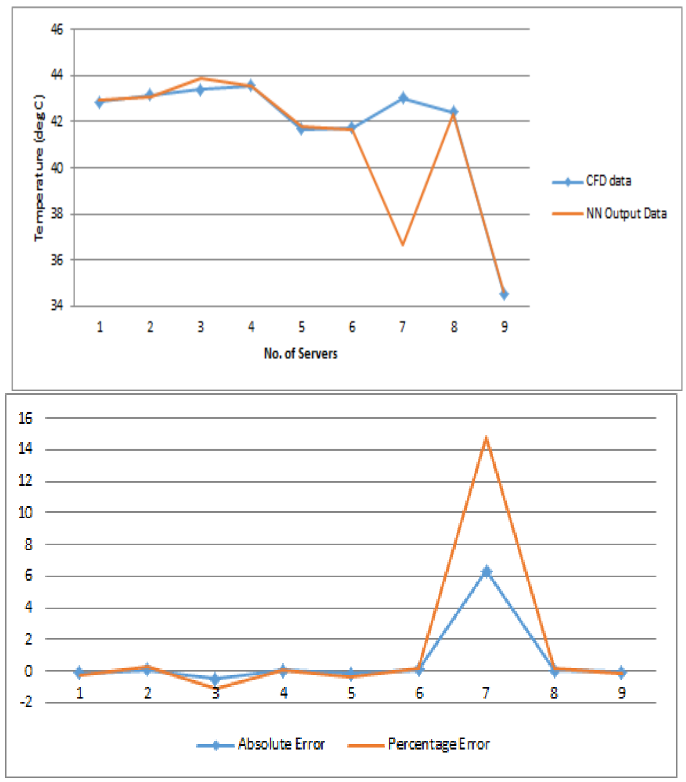


Figure 4.3. Results and Error for 14112 watts, 41 % Fan Efficiency ,Vent 1, outlet.

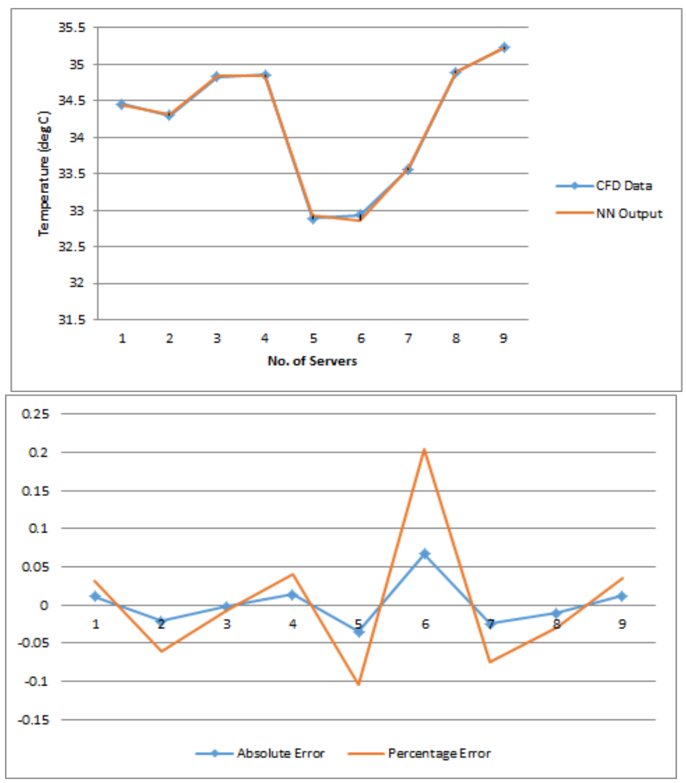


Figure 4.4. Results and Error for 8295 watts, 41 % Fan Efficiency ,Fan Active 1 and 2,outlet.

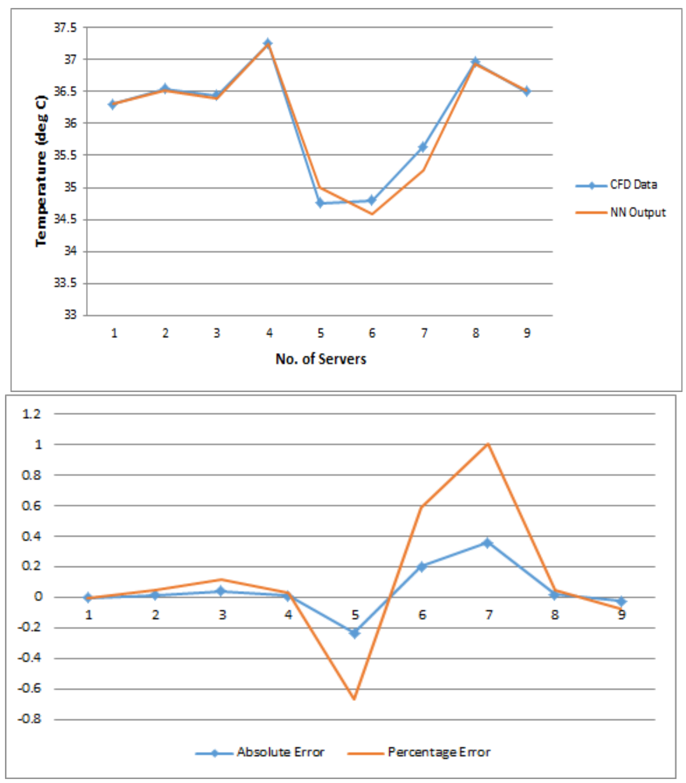


Figure 4.5. Results and Error for 8295 watts, 41 % Fan Efficiency ,Fan Active 1 and 2,Vent 2,outlet.

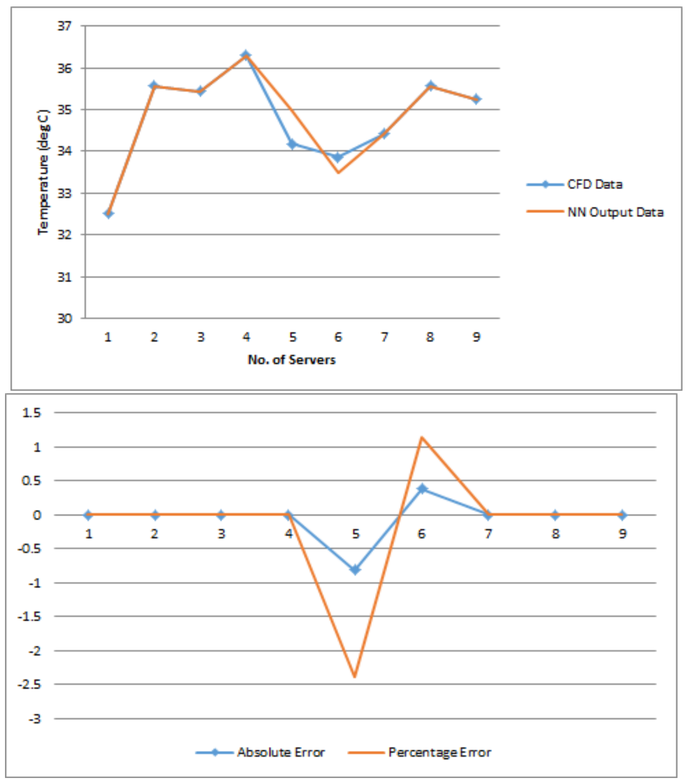


Figure 4.6. Results and Error for 9954 watts, 79 % Fan Efficiency ,Fan Active 1 and 2,Vent 1,inlet.

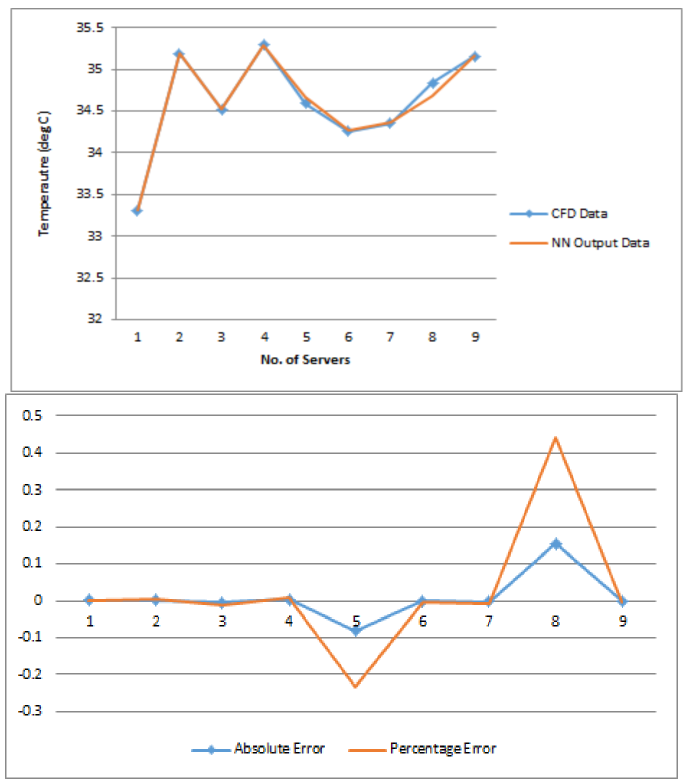
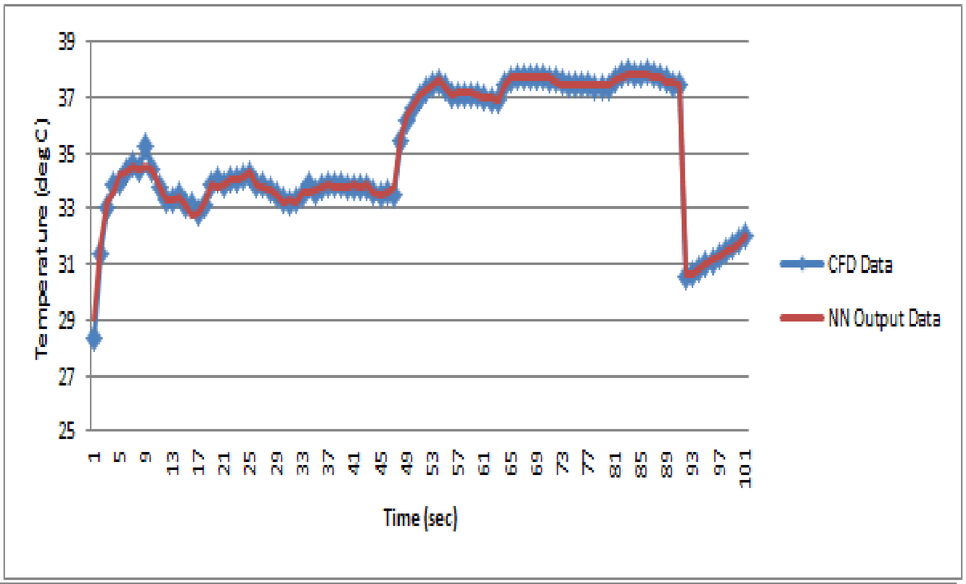


Figure 4.7. Results and Error for 11523 watts, 31 % Fan Efficiency ,Fan Active 1 and 2,Vent 1,inlet.



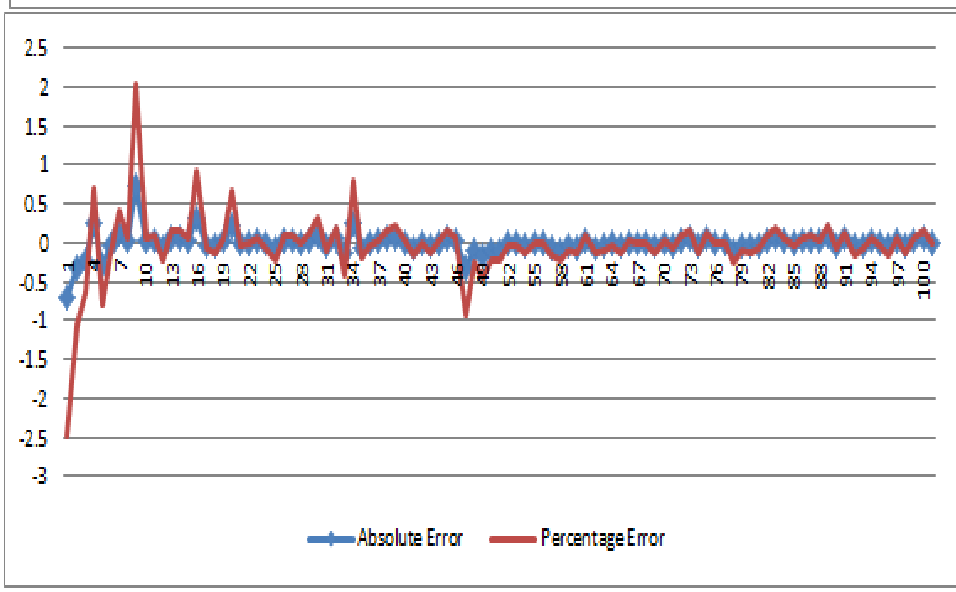


Figure 4.8. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 1st Server.

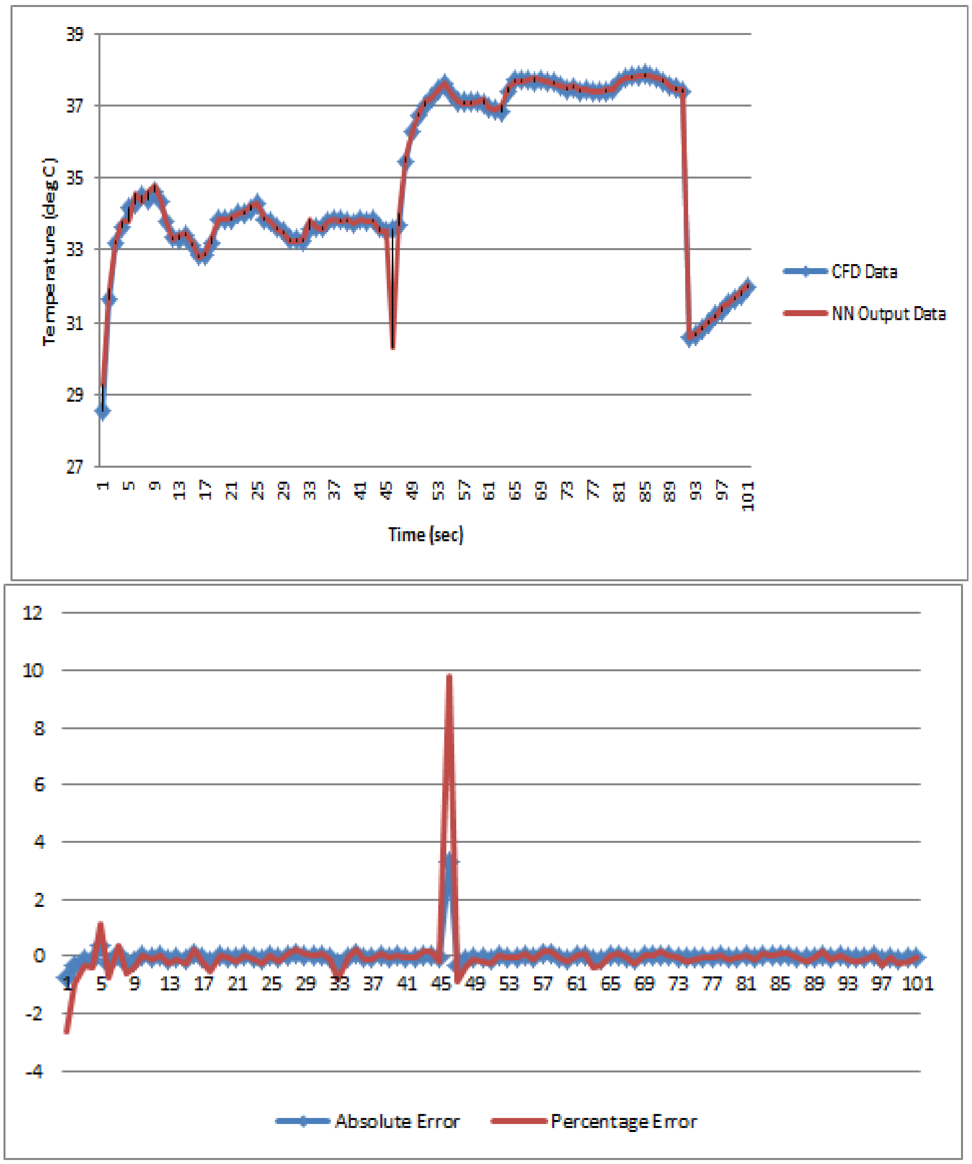


Figure 4.9. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 2nd Server.

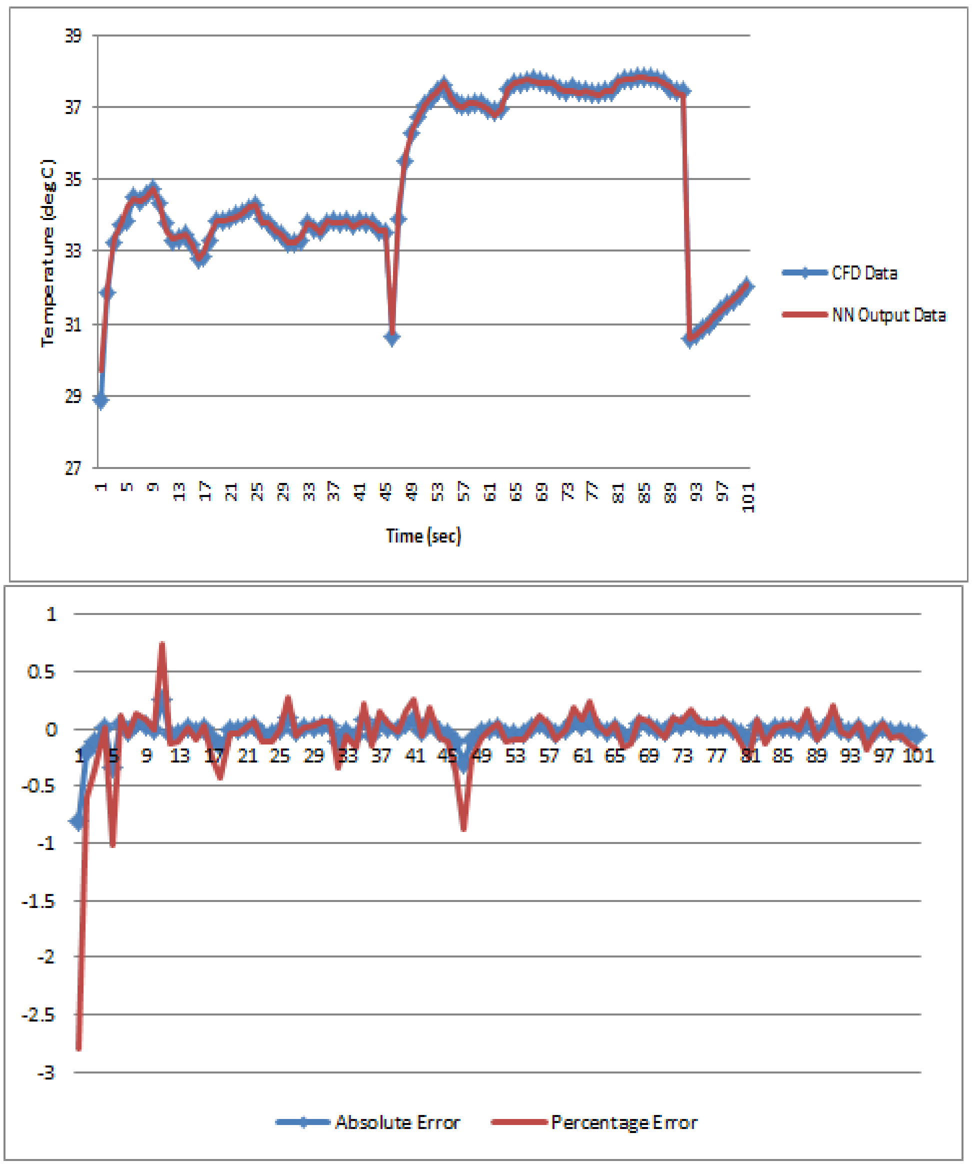


Figure 4.10. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 3rd Server.

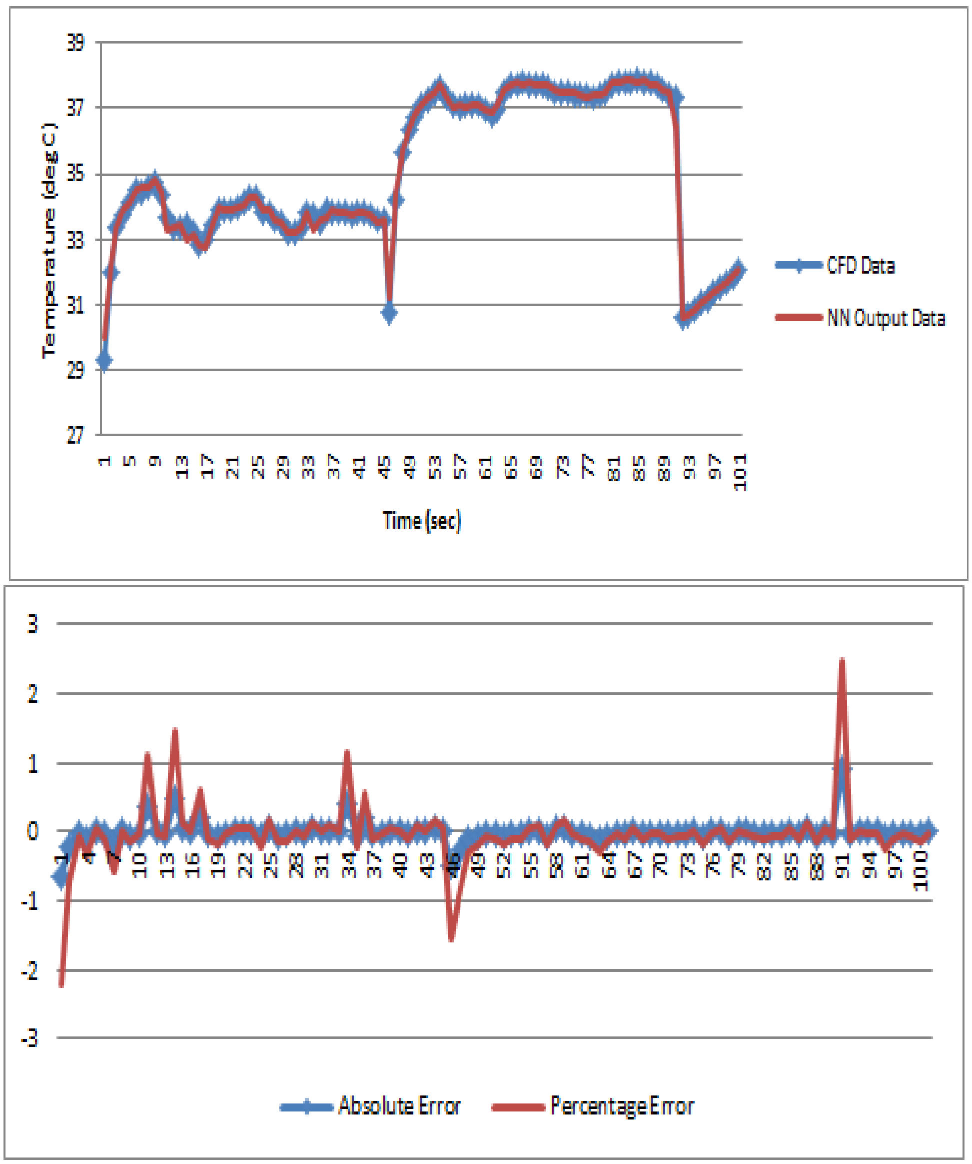
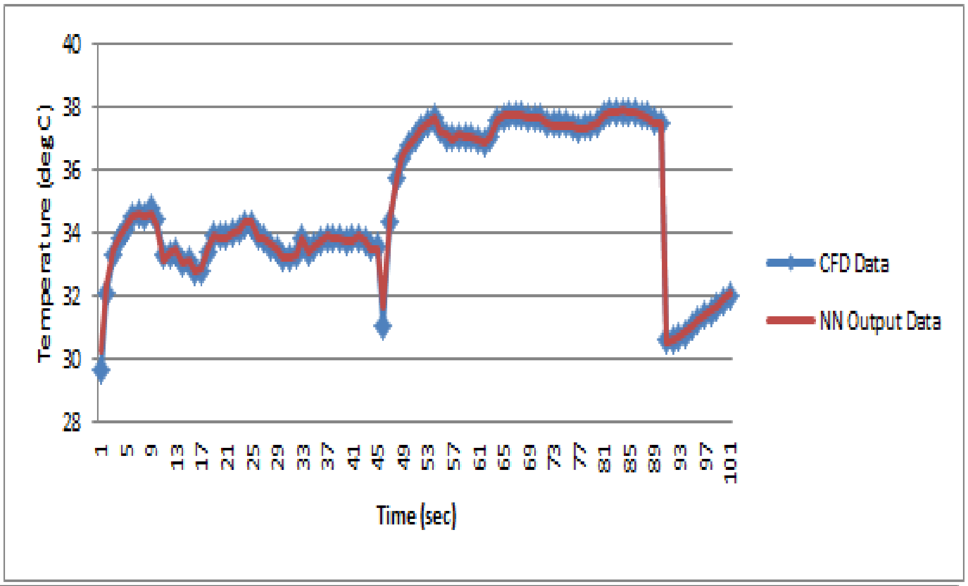


Figure 4.11. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 4th Server.



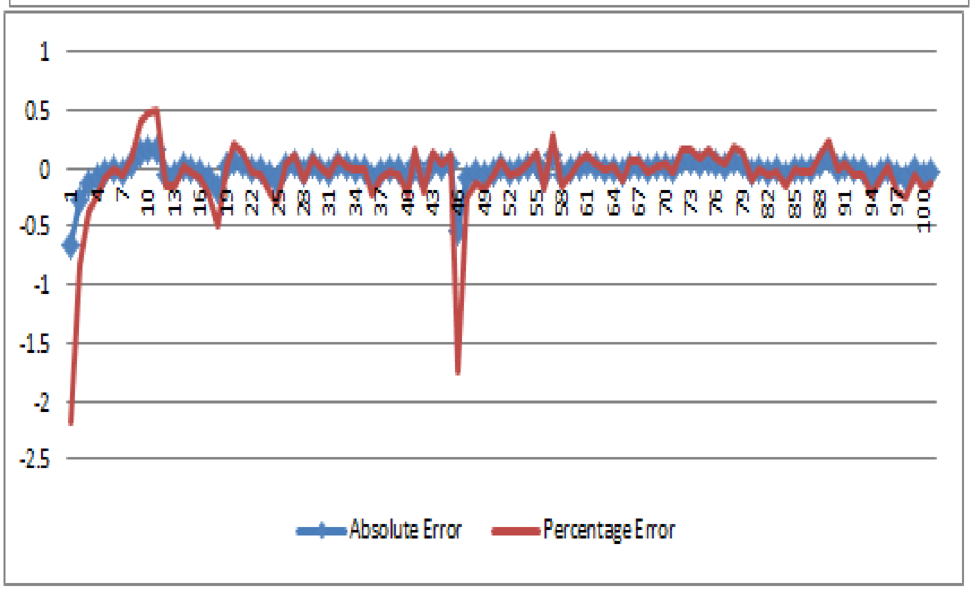


Figure 4.12. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 5th Server.

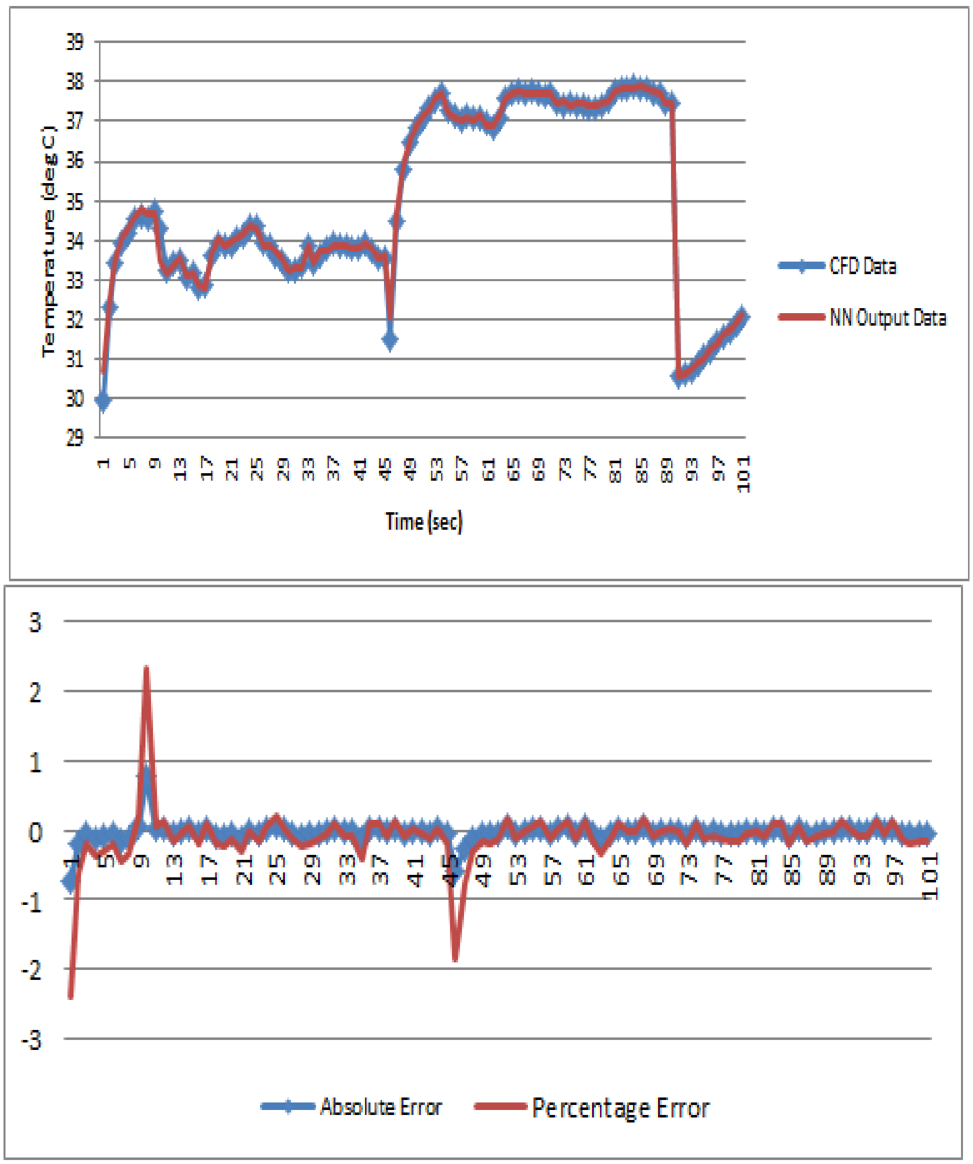


Figure 4.13. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 6th Server.

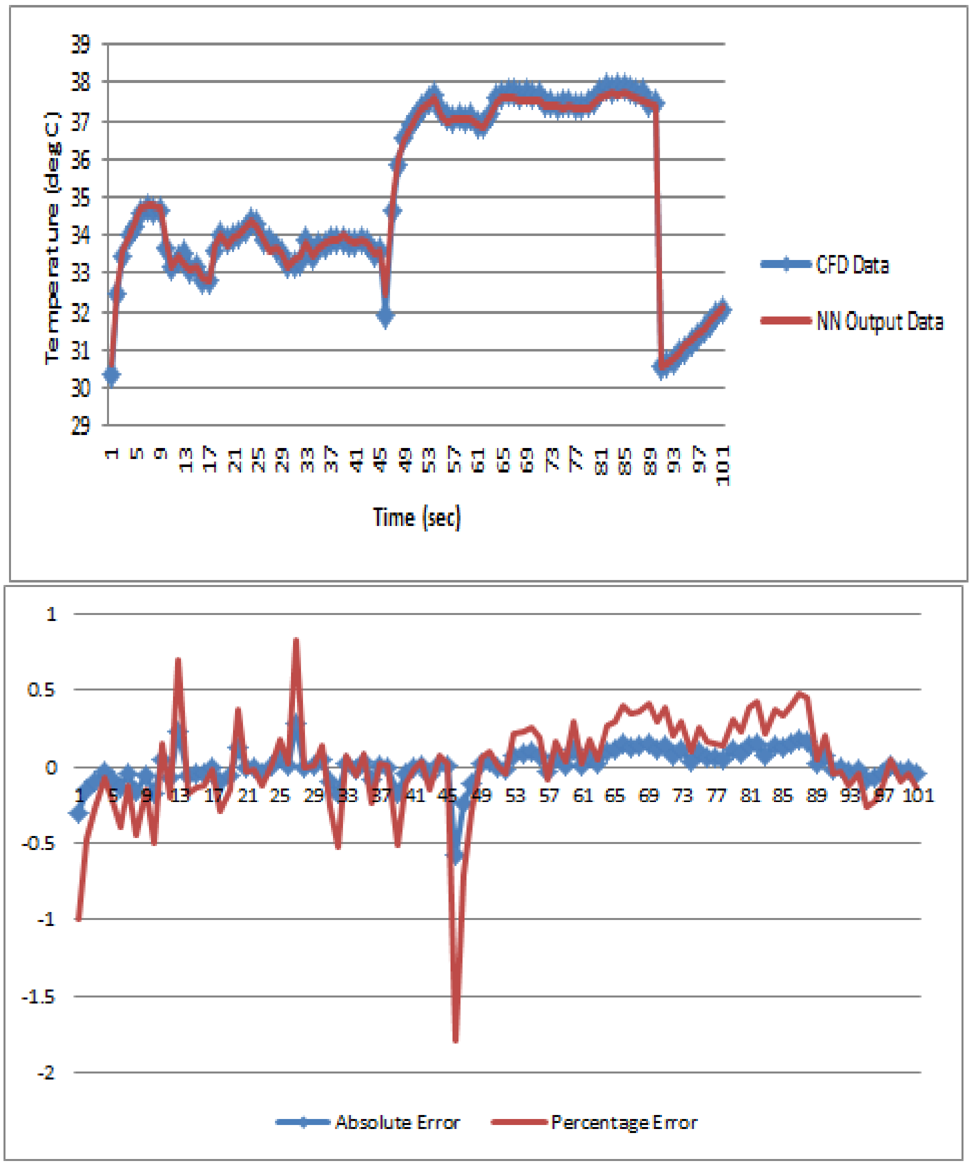


Figure 4.14. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 7th Server.

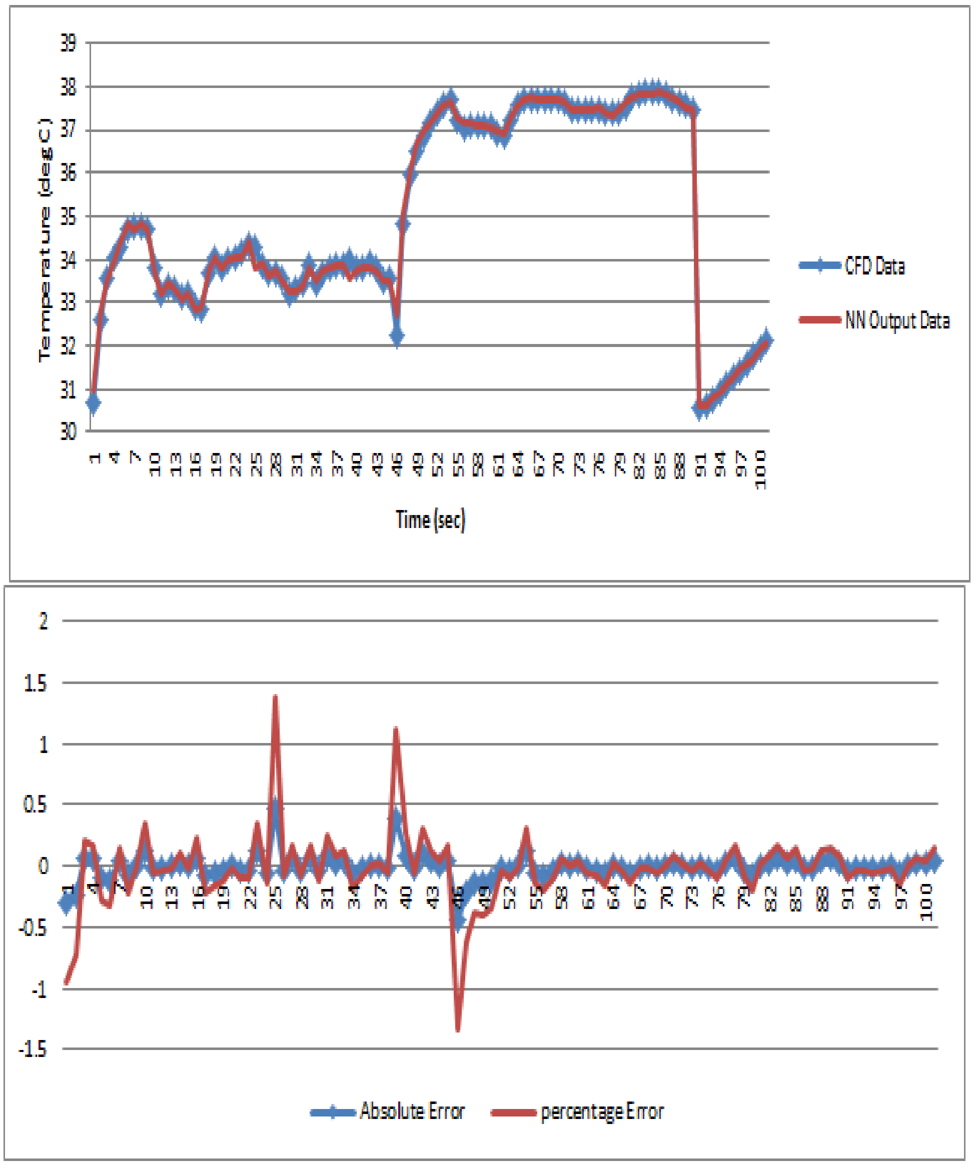


Figure 4.15. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 8th Server.

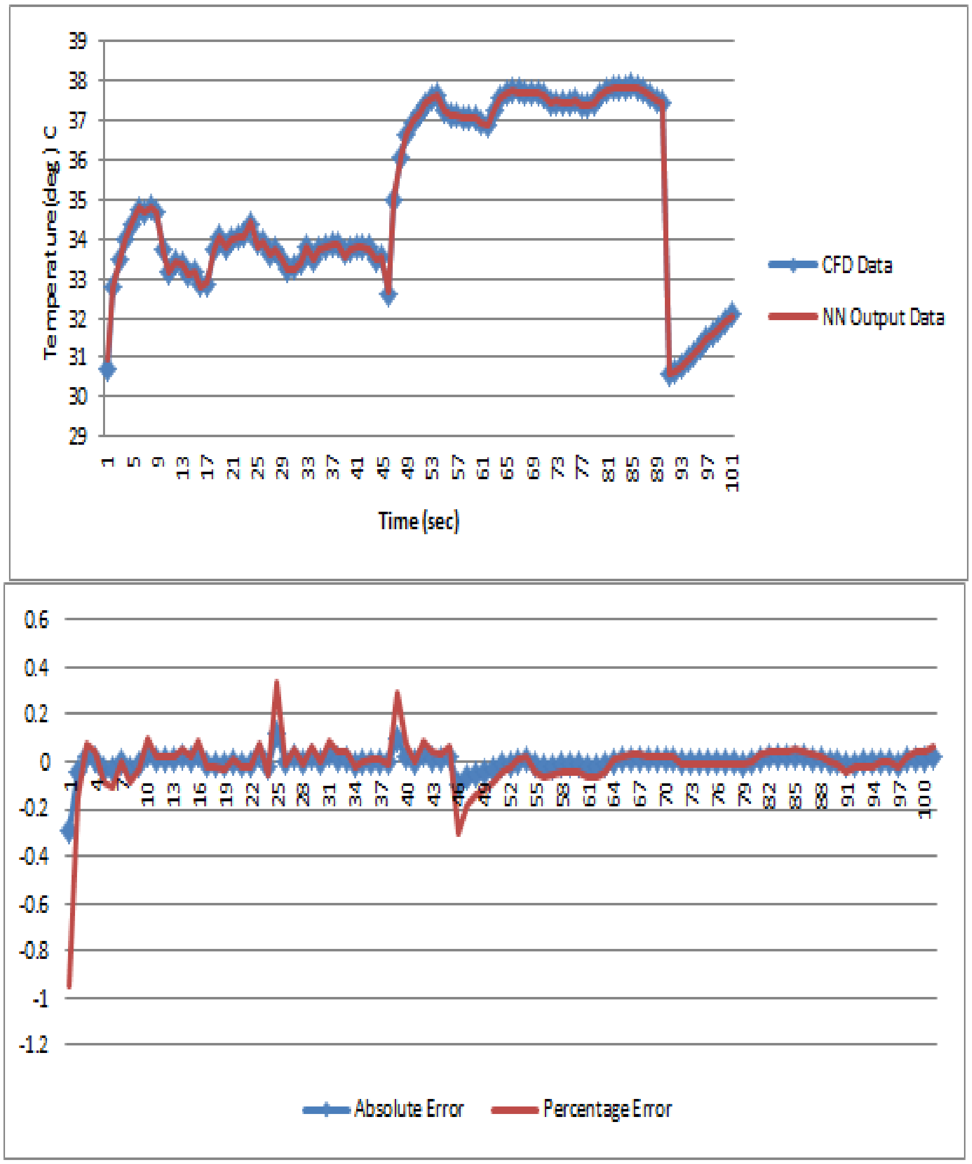


Figure 4.16. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 9th Server.

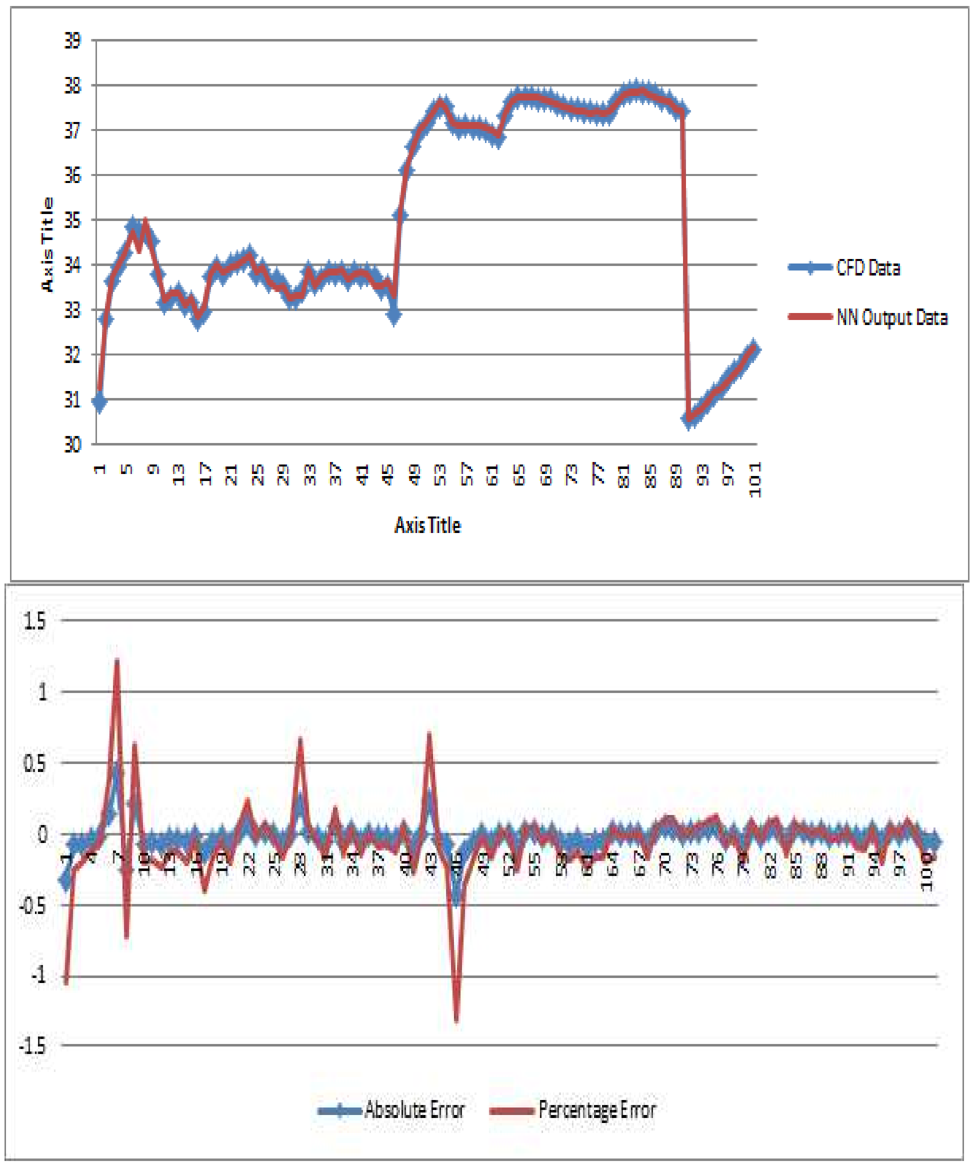


Figure 4.17. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 10th Server.

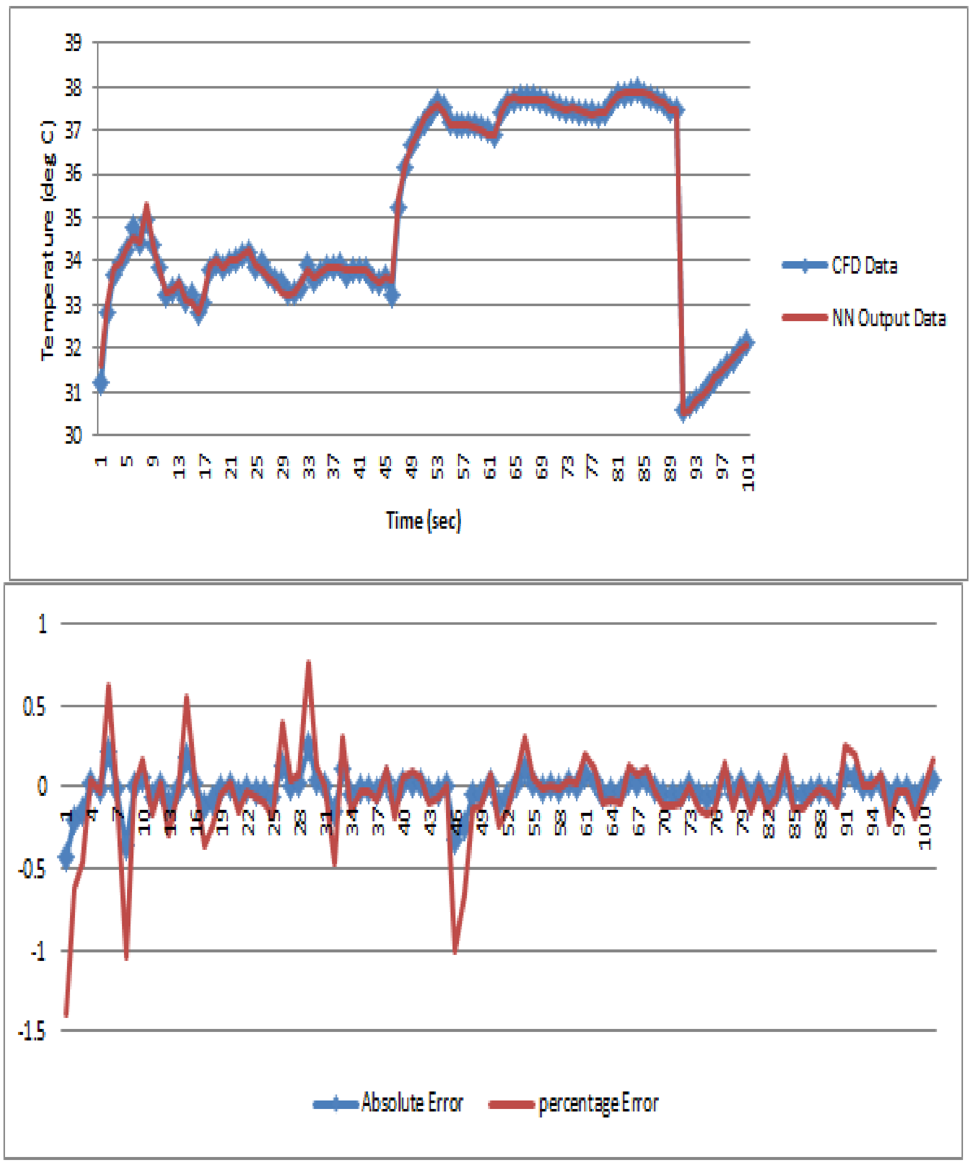


Figure 4.18. 210 to 320 WATTS, 51.667 % FAN EFFICIENCY , 1& 2 FAN ACTIVE, 11th Server.

CHAPTER 5

Controller Algorithm and Results

5.1 Need of Control System

Data Center setup consist of CRAC unit, Cooling Distribution Unit (CDU), Server Cabinet, IT Equipment and other such units. Results thus presented in previous chapter shows that Neural Network has the capacity to learn any of these system. On the basis of data supplied Neural Network can be trained to learn the systems and further can be use to predict and control its behavior.Data centers are highly non-linear and complex system. Due continuous incoming and outgoing of information workloads,power consumption and temperatures vary to a greater extent throughout the day.We already have a system to monitor data center but there is an urgent need to control the few parameters of system upto certain prescribed limit.Even certain amount of change in the input parameters of system can result into significant change in response of the system. Constant change in inputs makes system fluctuate which can also result into system going out of control. For such a dynamic and non-linear system the problem is not only to maintain system parameters under prescribed limit but also to maintain whole system stability. Hence Artificial Neural Network based control which can be fast,accurate and adaptive is the best type of controller which will be suitable for such a data center system

5.2 Controller

The control problem on our system is to maintain server temperature under desired temperature range.The thermal properties of data center is dependent on lot of parameters and hence predictive type of control is required. The classical PID controller can't be used in this case because of too many changes in input parameters.Constant change and fluctuation in the system may cause huge amount error generated and supplied to the controller which may in turn result into unwanted response by the controller.

5.2.1 Structure of Controller

The figure given below shows the proposed Neural Network based model controller.The control parameter that we are considering is power.We have to control server temperature within prescribed limit.The blue block is our plant model.The plant which is also our neural network model is trained using the transient data set.The input parameters of the training data set for our plant model are power (Pp) which is time variant,fan efficiency (F) in percentage and server no.(I) which works as an identifier.The output parameters is the temperatures of the servers(Tp) in degree celcius. The plant model is trained using Levenberg-Marquardt algorithm. Its has 150 number of hidden neurons that process the information. The red block is the Inverse Neural Network(INN) model.As the name suggest its is an inverse model server temperature(Tm) act as an input parameter and power(Pp) is the output.The INN model is trained using Levenberg-Marquardt algorithm.It has 2 no. of hidden layers to process the trained dataset. The proportional gain block kp which has a gain of 0.01 added to error generated to the server temperature.The proportional gain kp is decidded on basis of trial and error method.A reference set of the target server temperature (Tref) is given to the controller.The above controller is trained for different servers.

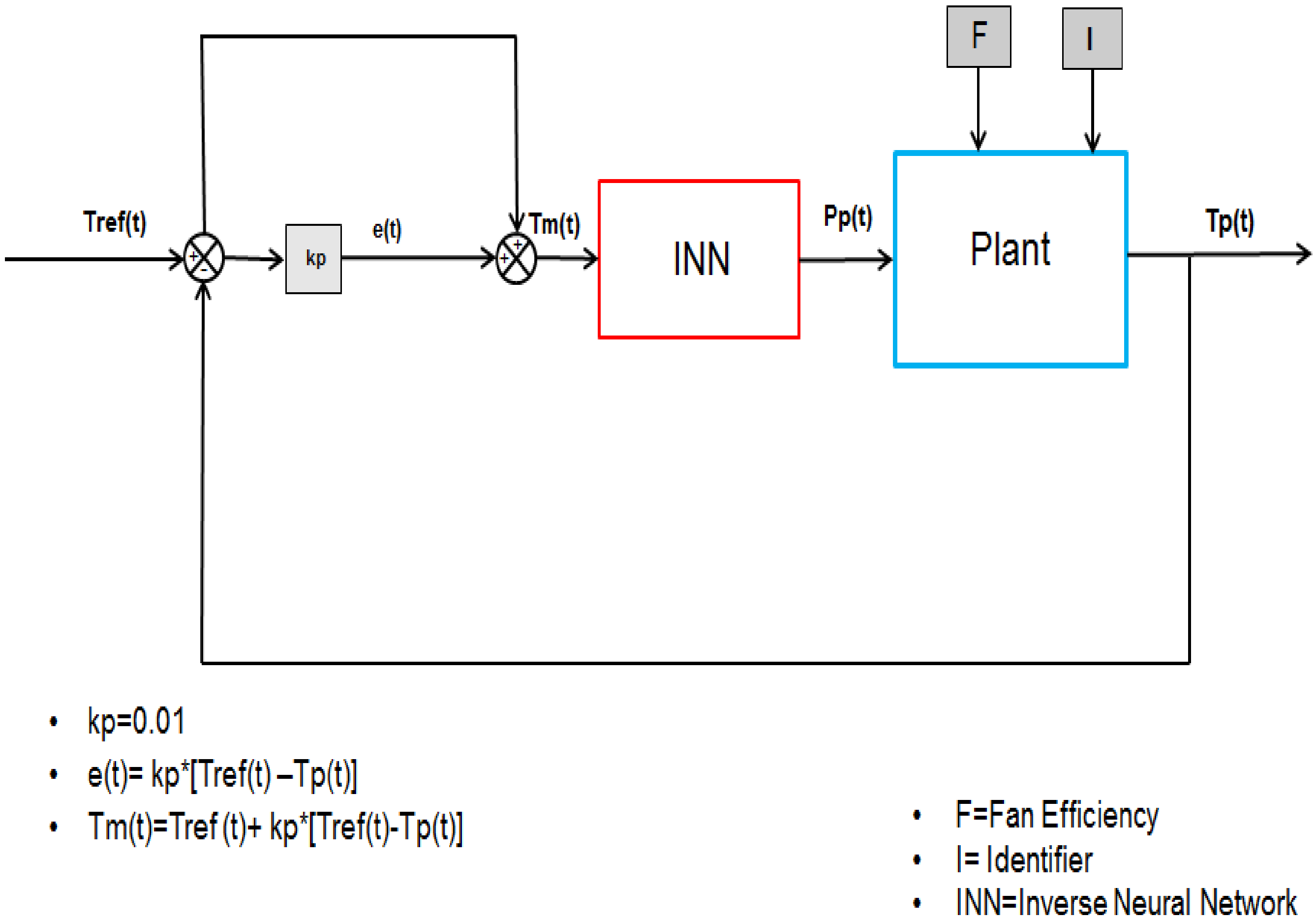


Figure 5.1. Model of Controller.

5.2.2 Working of Controller

The controller receives a reference set of temperature. For the first value of of reference temperature error added is zero. So the same reference value goes into the INN block where we get power as a output. The power thus received is added to set input matrix for the plant model and subsequent fan efficiency and identifier is added to each set of input power.And thus the plant output temperature (Tp) is obtained.If the plant output temperature does not match with our reference set of input and error signal is generated.The error is the difference between the reference temperature and plant temperature. The gain kp and error are added to next reference set of temperature value which is again passed through inverse model and subsequent value of power is adjusted o basis of the error thus generated.The loop thus stop when our error reduced to our prescribed limit.The final controlled plant temperature output is received.

5.3 Results of Controller

The following are the results thus obtained from the controller. These below given first graph are controller output,reference temperature and plant temperature for single server and second graph is the error obtained between the reference set of temperature and plant output temperature.

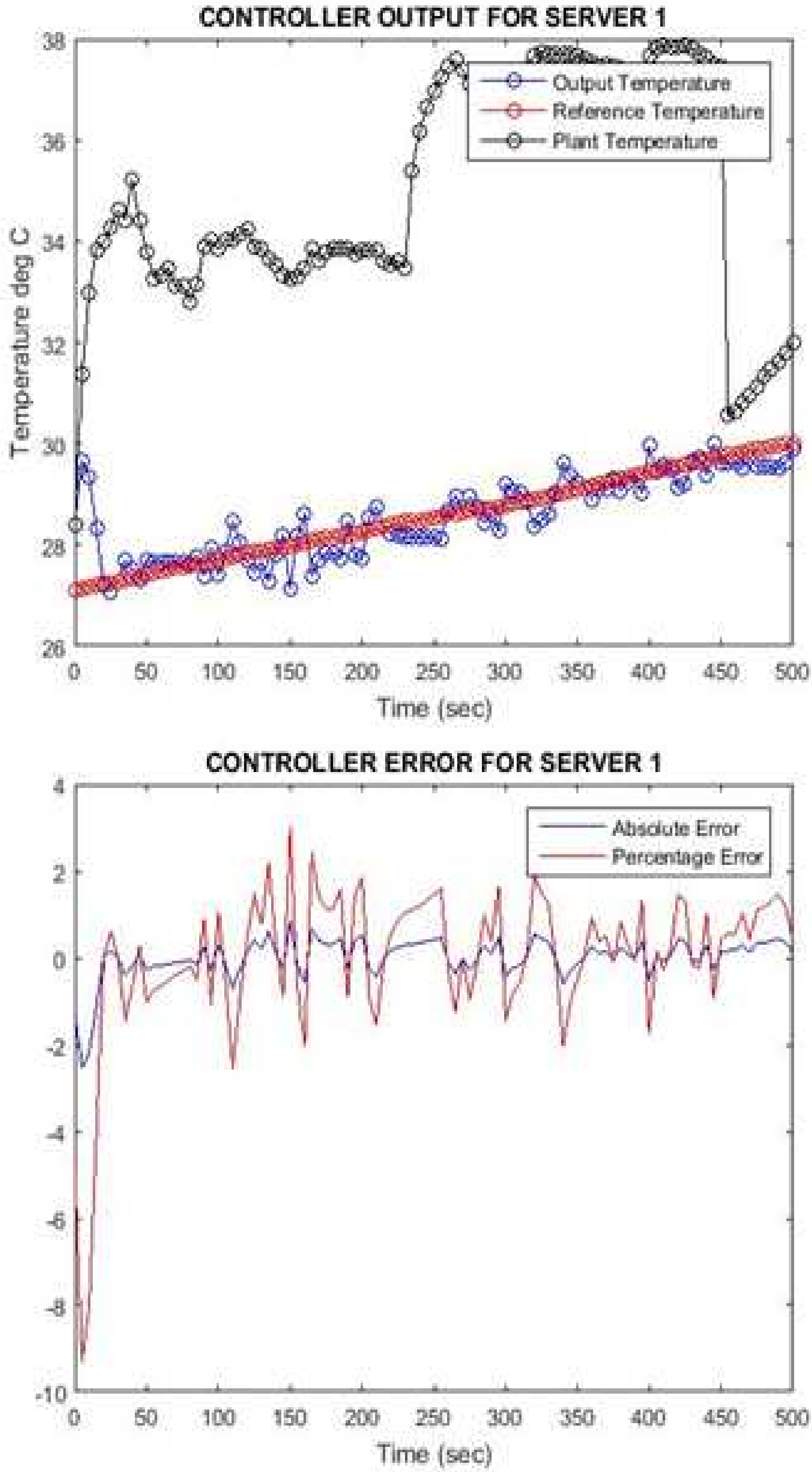


Figure 5.2. Controller and Error Output for Server No. 1.

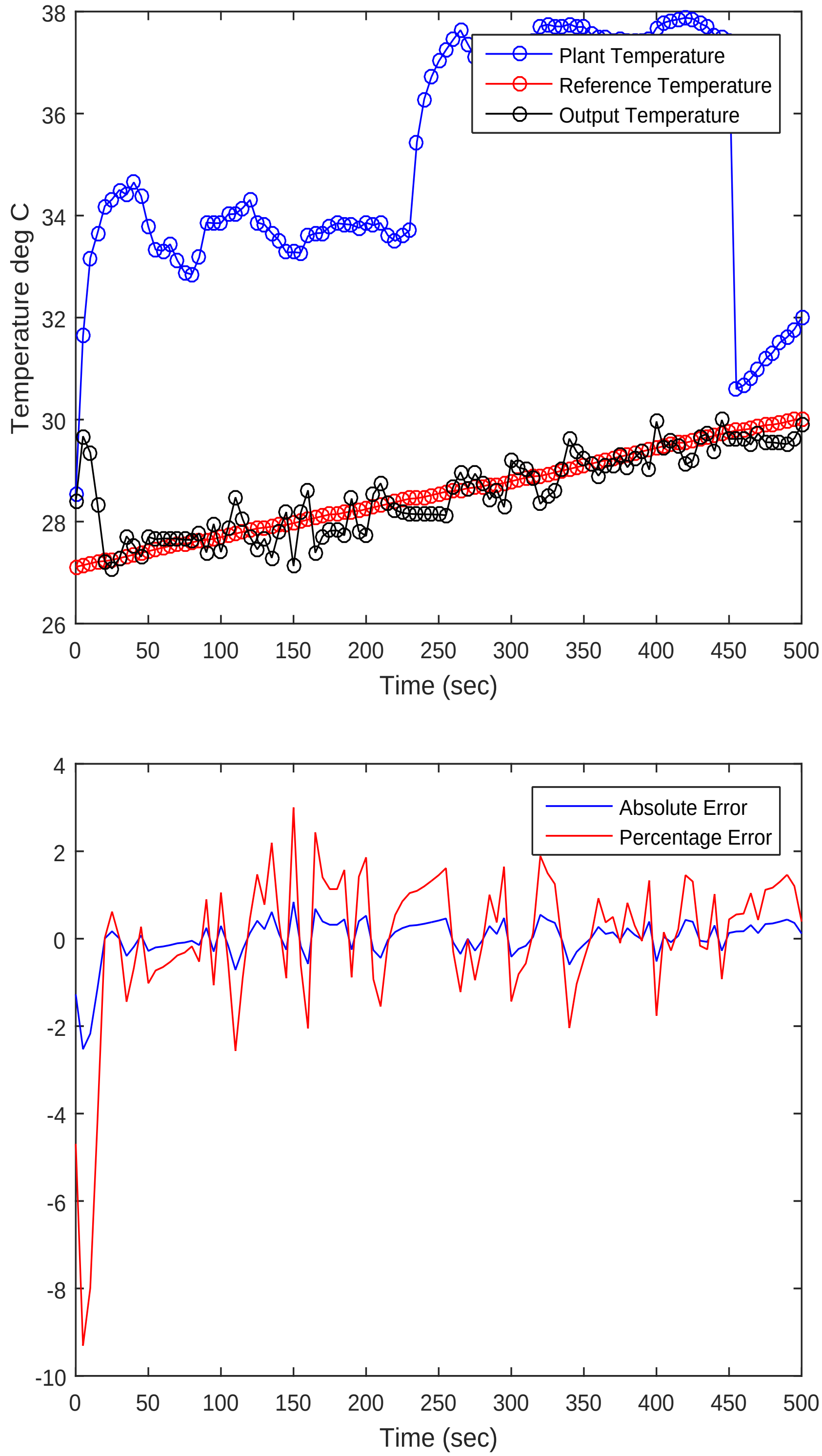


Figure 5.3. Controller and Error Output for Server No. 2.

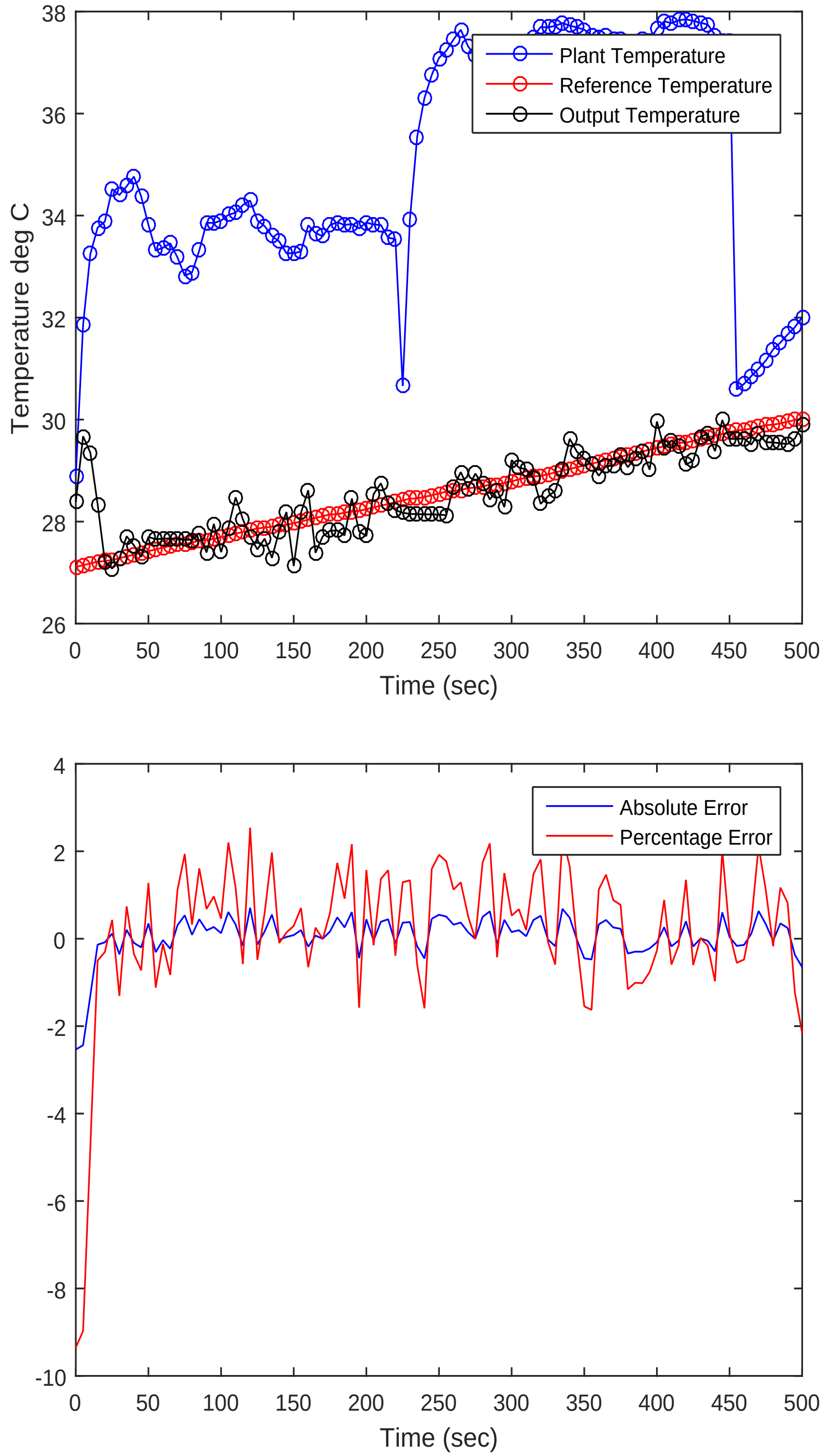


Figure 5.4. Controller and Error Output for Server No. 3.

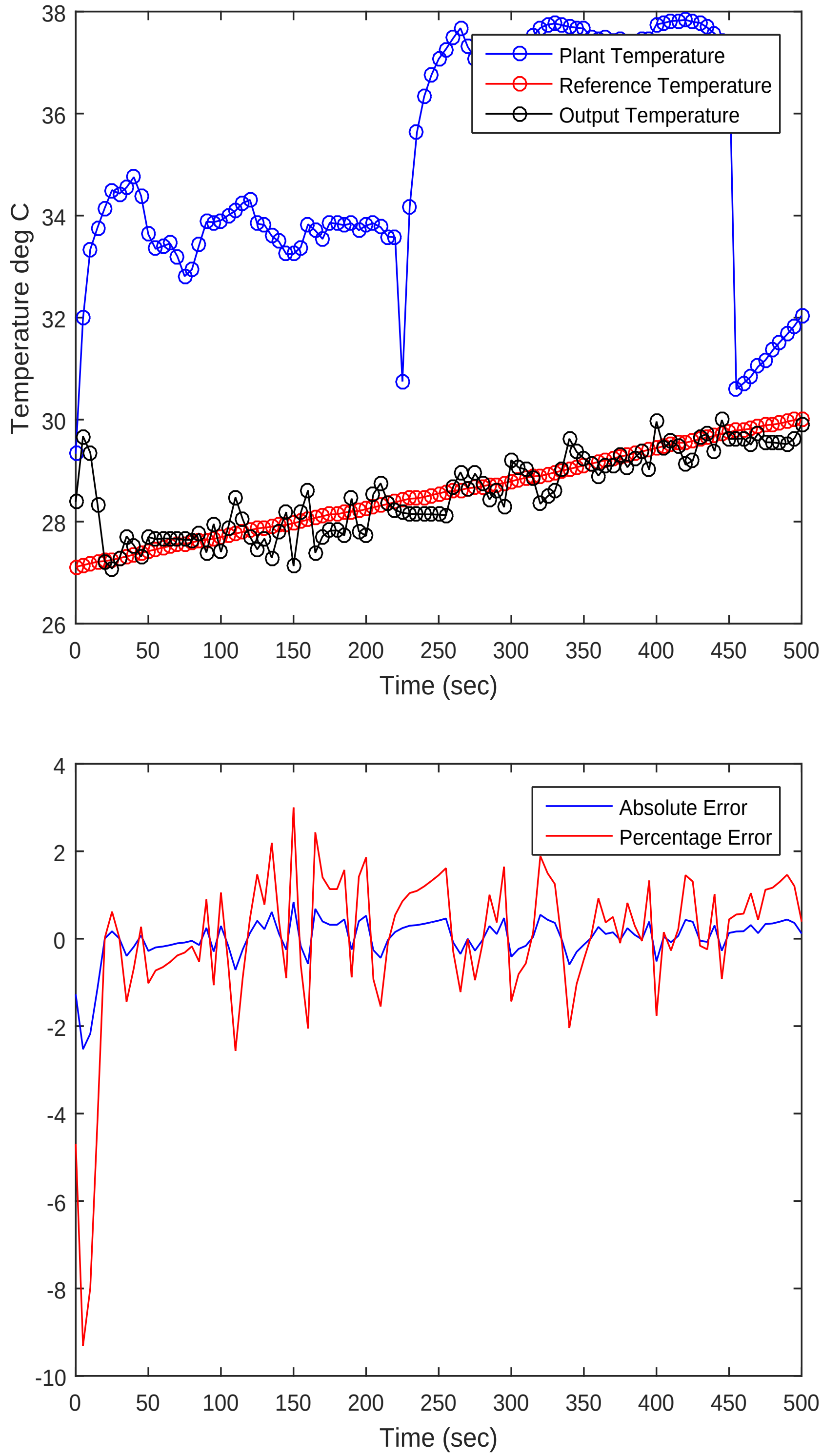


Figure 5.5. Controller and Error Output for Server No. 4.

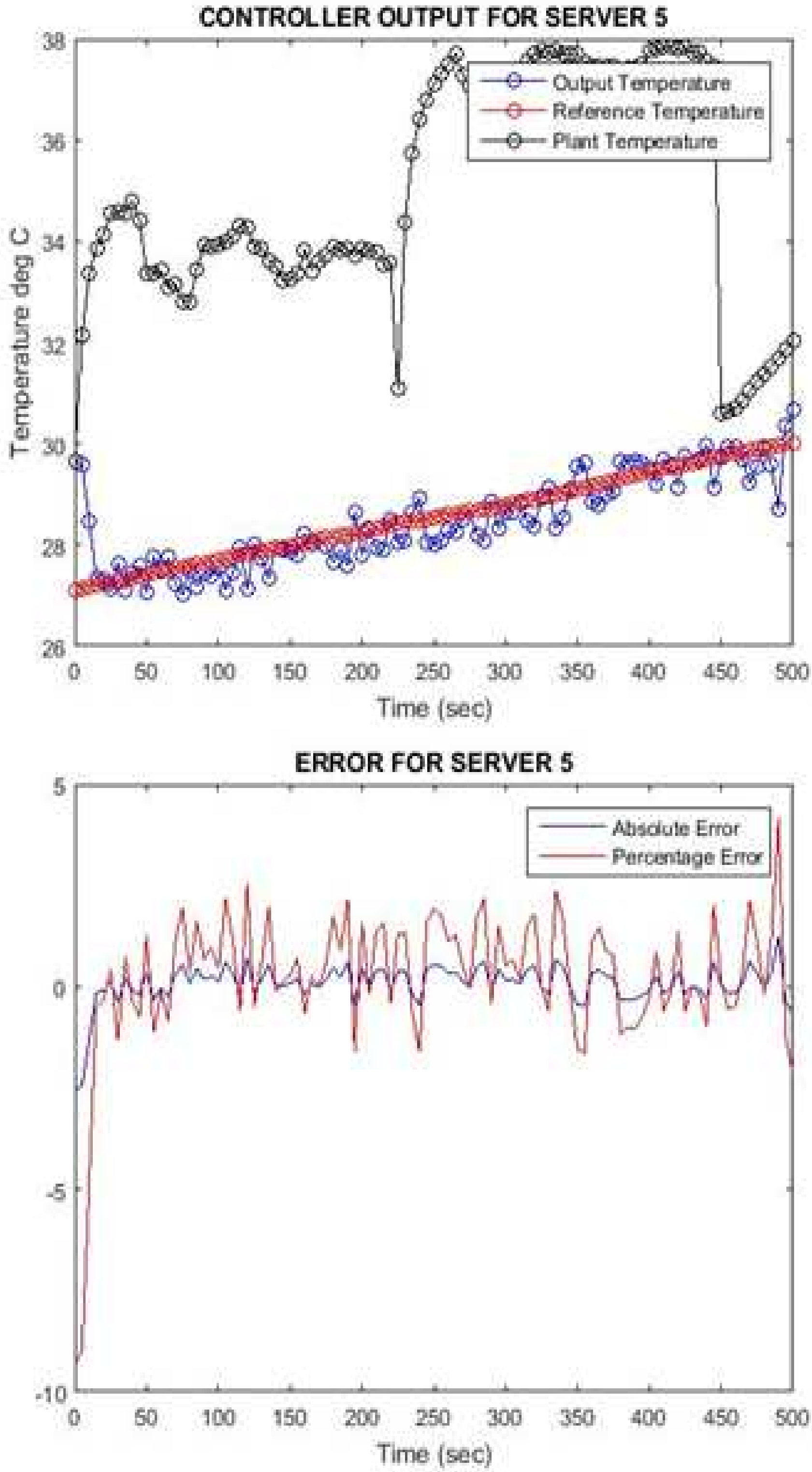


Figure 5.6. Controller and Error Output for Server No. 5.

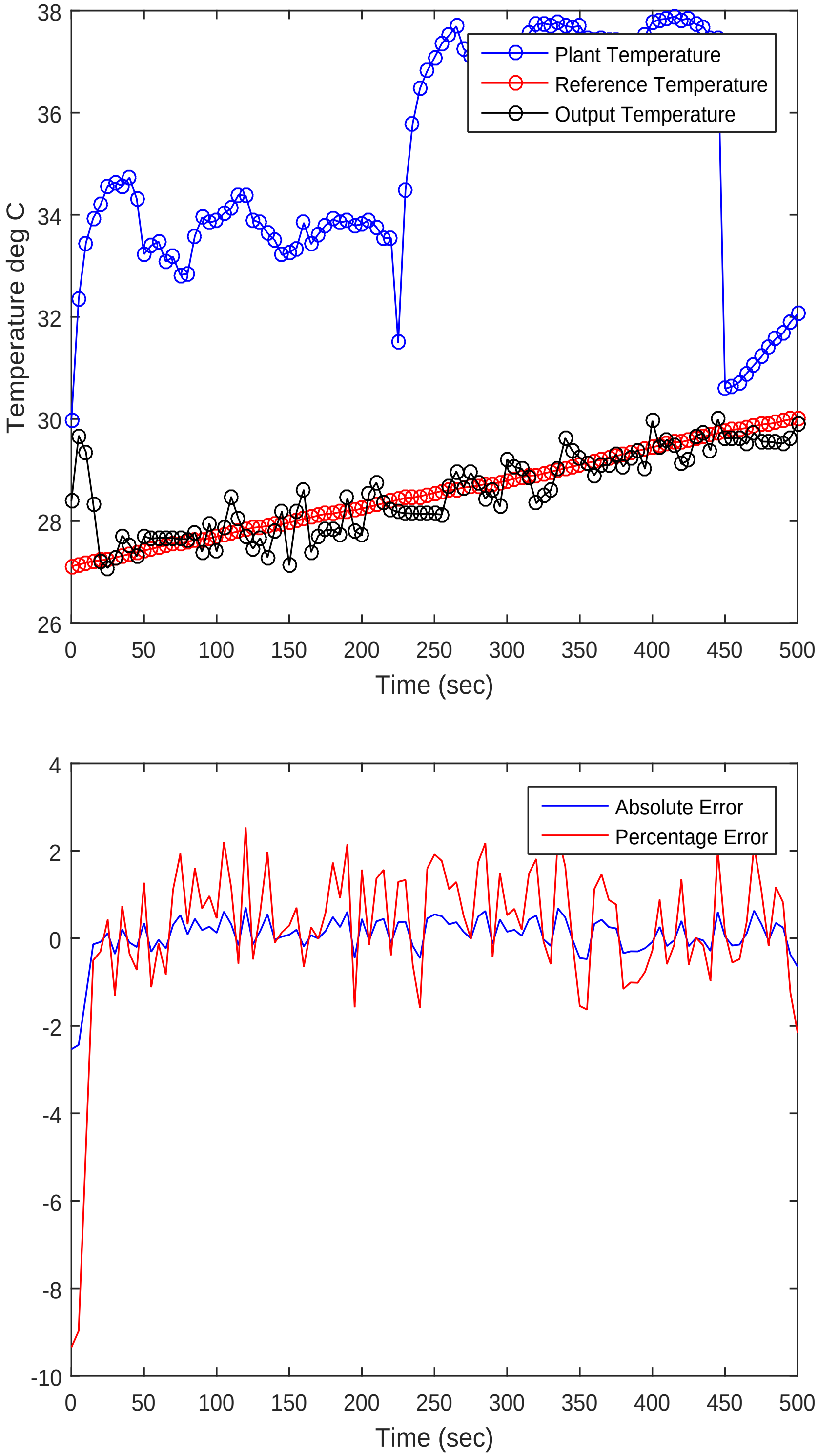


Figure 5.7. Controller and Error Output for Server No. 6.

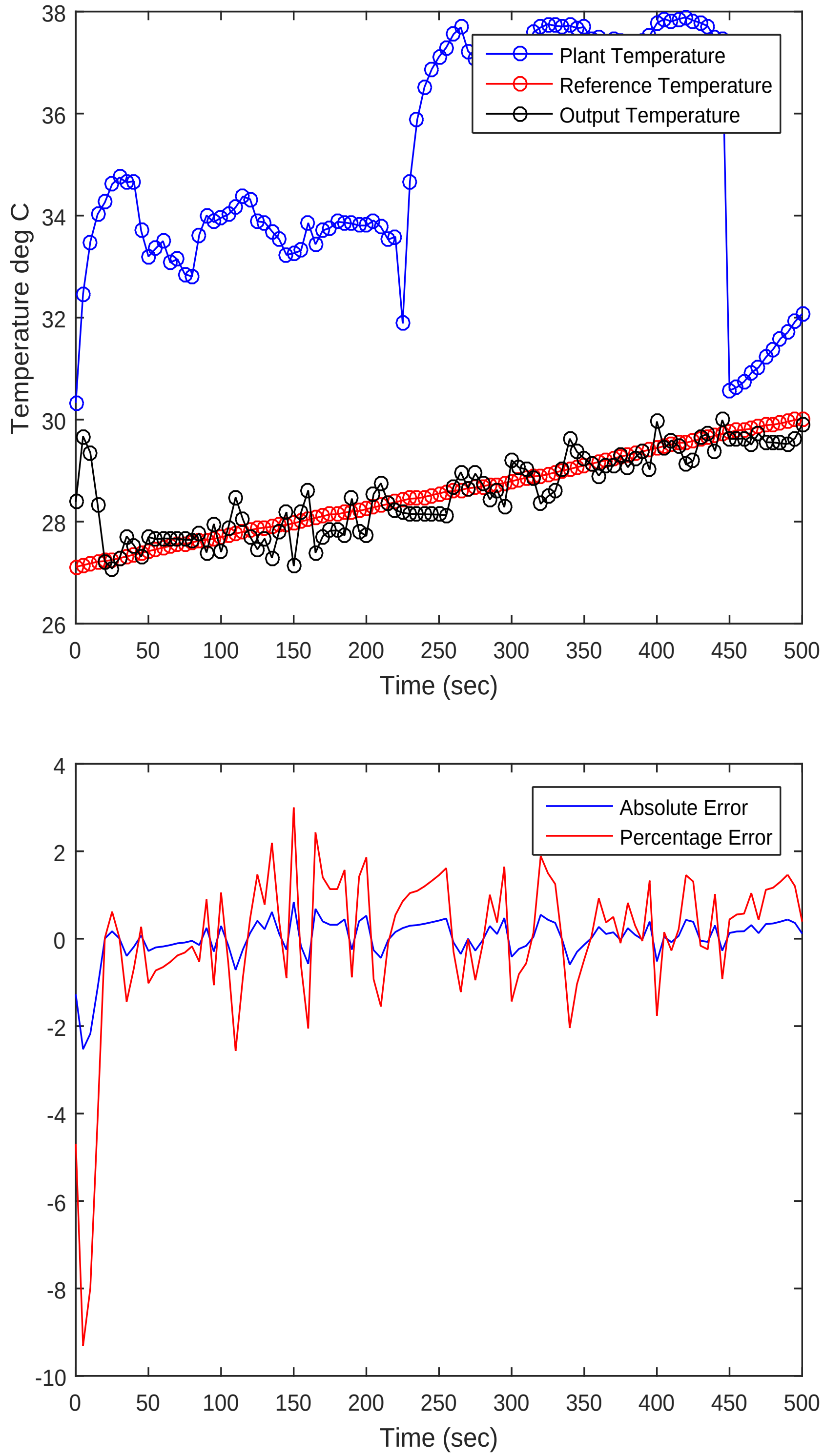


Figure 5.8. Controller and Error Output for Server No. 7.

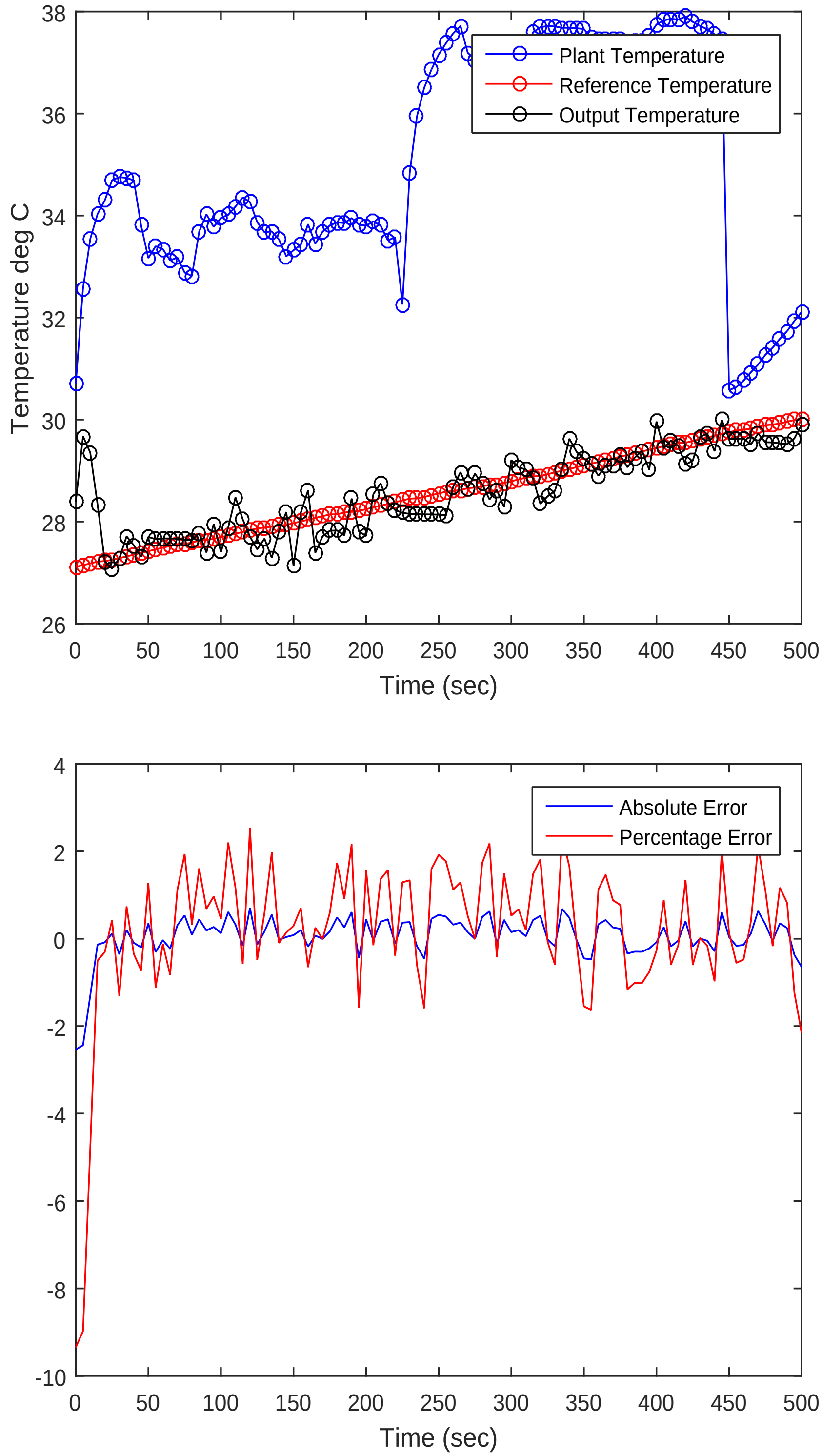


Figure 5.9. Controller and Error Output for Server No. 8.

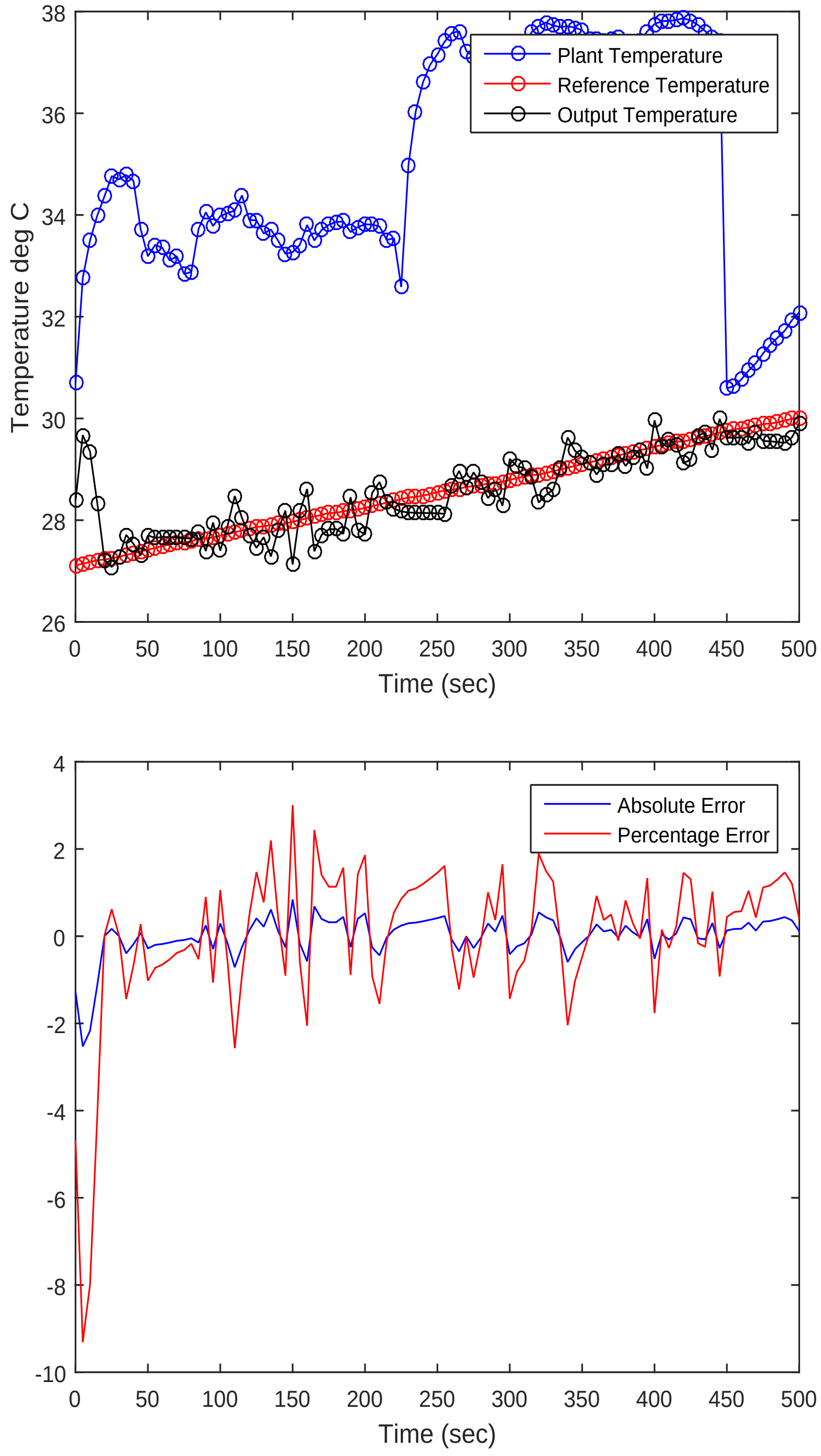


Figure 5.10. Controller and Error Output for Server No. 9.

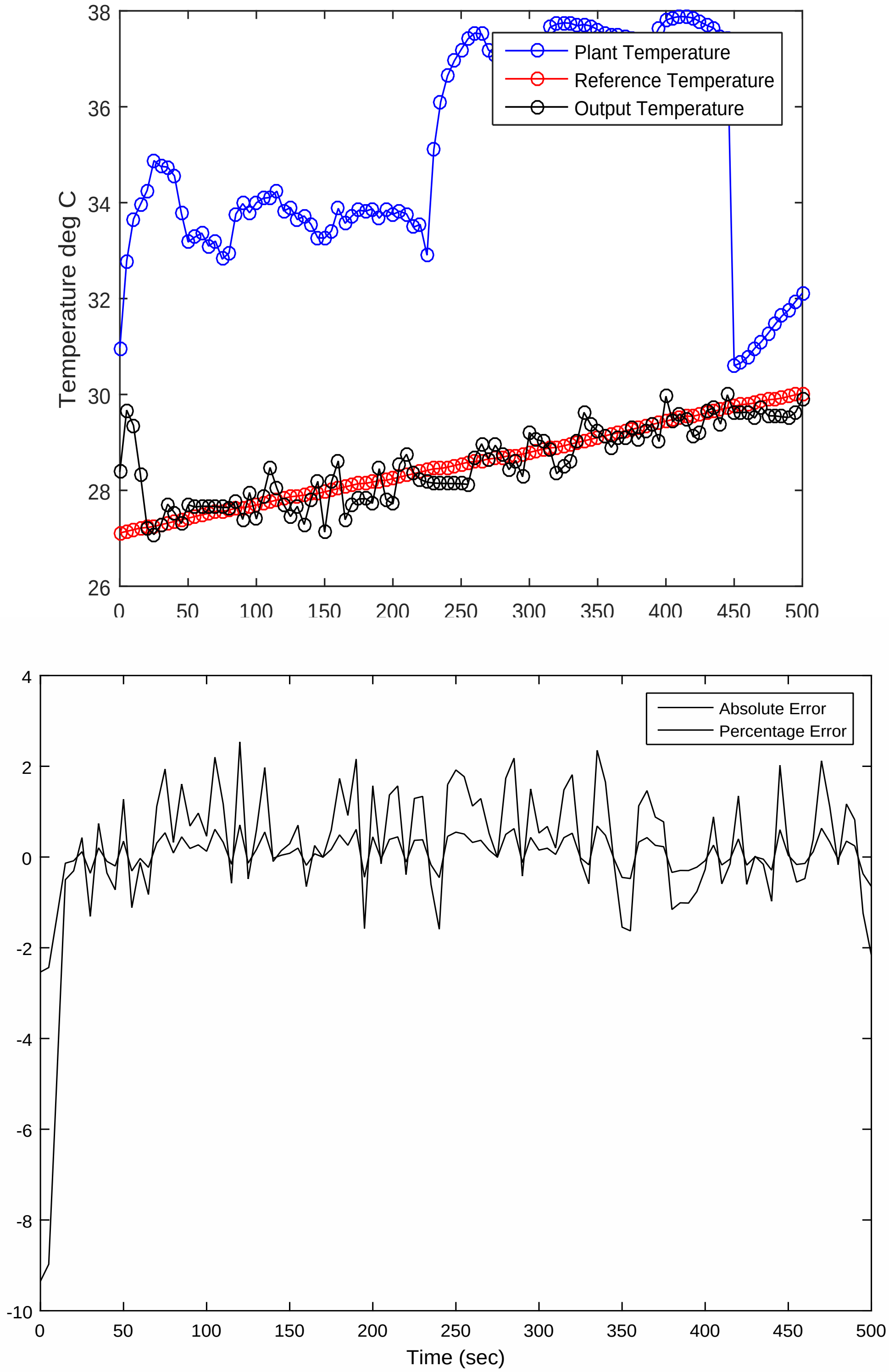


Figure 5.11. Controller and Error Output for Server No. 10.

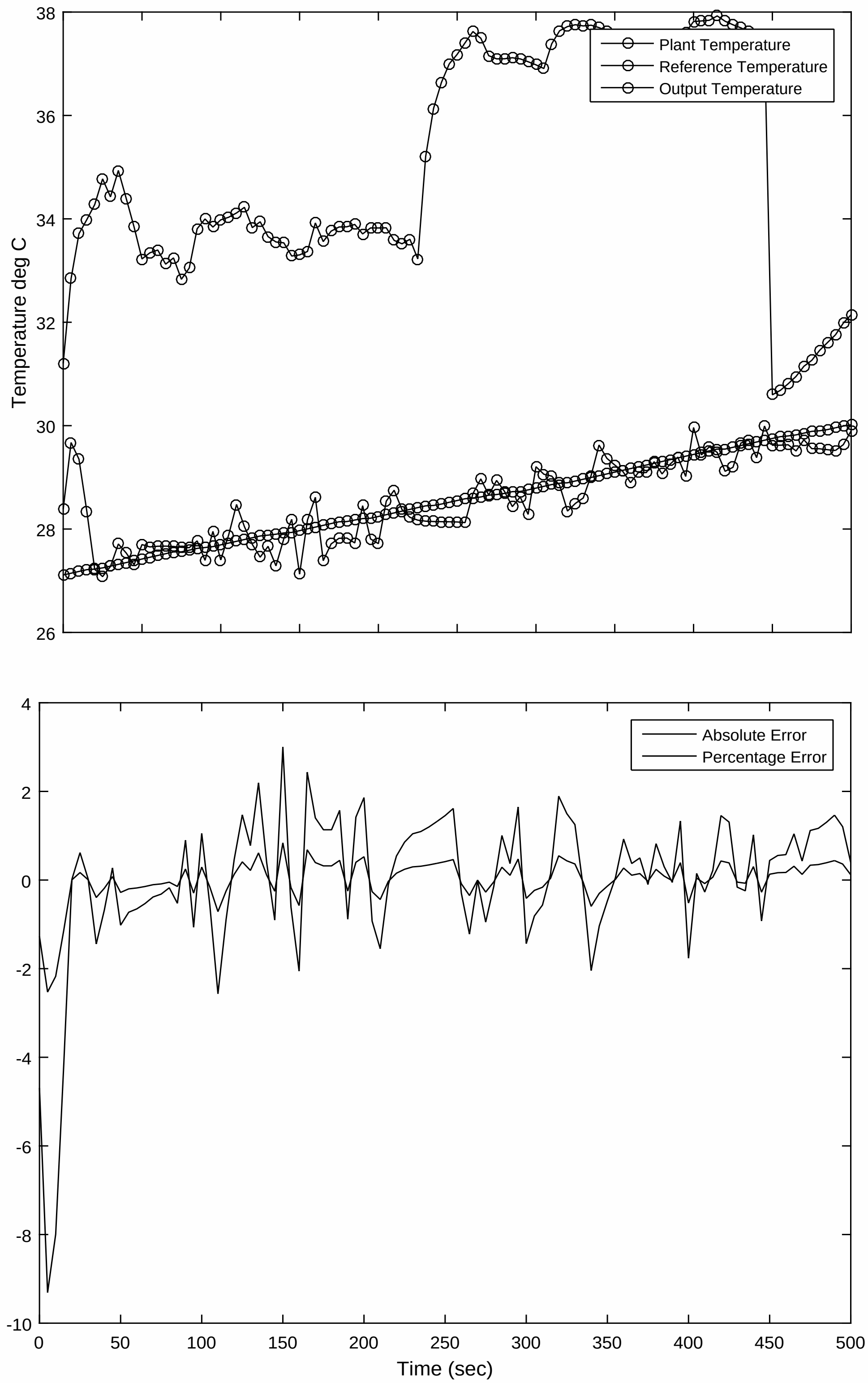


Figure 5.12. Controller and Error Output for Server No. 11.

CHAPTER 6

Conclusion

The Neural Network that was developed was successful in predicting the behavior of Data Center and shows a agreement with CFD model result with approx 95% accuracy for most of the cases.

The Artificial Neural Network technique proved to be successful predicting the output of the data center in both Steady State and Transient cases.Both the fitting tool and Dynamic time series tool worked well for predicting the behavior of Data Center.

The Controller designed using inverse model was successful in stabilizing the temperature of servers according to our reference set temperatures.There is a subsequent amount of error generated with controller results which can actually be reduced when we use more data to train the inverse as well as plant model

CHAPTER 7

Future Scope

Currently Neural Network was trained and compared with CFD, but the real time data can also be used to train and predict the behavior of our system. Lot of different parameters like cooling efficiency, humidity etc. that actually govern the system can be used to train the neural network.Neural Network controller can be tested with two or more control parameters.Implementing neural network learning and control algorithm on actual system using a controller chip. Then connecting it to actual system and tryin to apply our controller module to actual data center

REFERENCES

[1] "Report to congress on server and data center energy efficiency public law 109-431," U.S. Environmental Protection Agency ENERGY STAR Program, Tech. Rep., August 2007.

[2] N. R. D. Council. (2015) America's data centers consuming and wastig growing amounts of energy. [Online]. Available: http://www.nrdc.org/energy/data-center-efficiency-assessment.asp

[3] V.Avelar, K.Ramakrishnan, and D.Chiu, "Pue^{TM}: A comprehensive examination of the metric," the green grid, Tech. Rep., 2012.

[4] G. D. Centers. (2015) Google data centers efficiency: How we do it. [Online]. Available: https://www.google.com/about/datacenters/efficiency/internal/

[5] K.Nemati, B.T.Murray, and B.Sammakia, "Experimental characterization and modeling of a water-cooled server cabinet," in *ITHERM 2014*, ser. ITHERM.2014.6892352, 2014.

[6] K.Nemati, B.T.Murray, H.A.Alissa, B.Sammakia, and M.Seymour, "Experimental validated numerical model of a fully-enclosed hybrid cooled server cabinet," San Francisco,CA.

[7] C. Date, "Development of artificial neural network based black box model of a data center as a temperature prediciting tool as a function of server location,dissipating server heat and crac fan speed," Master of Science in Mechanical Engineering thesis, University of Texas at Arlington, Arlington,Texas,United States, 2013.

[8] N.Kansara, R.Katti, K.Nemati, A.Bowling, and B.Sammakia, "Neural network modeling in model-based control of a data center," in *InterPACK 2015*, ser. InterPACKICNMM2015-48684, San Francisco,CA.

BIOGRAPHICAL STATEMENT

Nachiket R. Kansara was born in Nasik, Maharshtra, India in 1990. He received his Bachelor of Engineering degree from University of Pune, Pune, India in 2012. He started his Master of Science in Mechanical Engineering at University of Texas at Arlington in August 2012. From May 2014 to December 2015, he was working on an NSF IUCRC project titled Models and Metrics for Dynamic and Hybrid Liquid Cooled Data Centers. It was a collaborative project by four universities viz. The University of Texas at Arlington, SUNY at Binghamton, Villanova University and Georgia Tech University. He was working on Neural Network Modeling and Control of Data Center project. He is an active member for ASME, Center of Energy System and Smart Electronics (ES2).