A STUDY ON EVAPORATIVE COOLING FOR DATA CENTERS & ARTIFICIAL NEURAL NETWORKS MODELING

by

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I would like to thank my family and friends for always being so supportive and graceful towards me.

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Abstract

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This study mainly aims at exploring how, one of the best “Green” solutions for IT equipment cooling aka Evaporative Cooling, can be optimized for better future deployment. Also, this study focuses on ways to deploy Artificial Neural Network models to Dynamic Systems.

Today, SERVERS are one of most important devices that our technology driven world cannot do without. Efficiently cooling these delicate yet highly power dense beasts, while being environment friendly is one of our prime concerns. This study is a combination of two deceptively divergent works. First, on exploring the workings of this technique by investigating one such Evaporative Cooling unit for optimization purposes; and second, an exhaustive study and analysis on Artificial Neural Networks Modeling.

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Chapter 1

The Issue

Data Centers across the globe are buildings and/or constructions that house several IT equipments (Servers). Today's technology driven world would be non-functional without them. Servers are usually expensive, compact, Temperature & RH fragile IT equipments. Considering the tiny spaces they are crammed into and the amount of heat generated by them, it makes them highly power-dense devices. According to 2013 survey on Data centers on an average, a rack held power densities of about 5.94kW. 35% of them held 2-4kW of power while 37% held 4-8kW of power density per rack. Heat in such intensity can easily damage the equipment if not cooled properly all the time.

Conventional methods have involved using several methods to cool servers. However, cooling or maintaining ambient environment along with being eco-friendly and resource efficient is a major challenge. As engineers it becomes our responsibility to do thorough studies in order to come up with effective and efficient solutions and/or insights pertaining to this issue.

This study addresses such insights on viable solutions upon doing studies and/or simulations on three different approaches to tackle the issue at hand.

Chapter 2

Evaporative Cooling

Evaporative Cooling is a process of removing heat from an object by evaporation of a liquid coolant. Also, it may be a process wherein an airstream is pre-cooled before passing it through a controlled space. The most familiar day to day example would be perspiration.

Evaporative Cooling is very promising solution for our problem since it is comparatively very easy to deploy and implement. Also, it is very cost effective and environment friendly. These benefits majorly incorporate due to the fact that the only chemicals we use using this solution are water and air. Hence, this is a potential “Green” solution for IT equipment cooling in future.

There are two kinds of Evaporative Cooling.

Direct Evaporative Cooling

Most of us have experienced direct evaporative cooling first hand regardless of the realization. Whenever we hold a soaked cloth in the way of the air flowing from a fan towards us we feel cooler air. This essentially is exactly direct evaporative cooling in action. For industrial purposes we find a more efficient mechanism, however the concept is the same. In industrial evaporative units we use wet media to enhance efficiency. Fig 2-1 depicts a graphic model rendition of the direct evaporative cooling mechanism in an Aztec Evap Cooling unit. The closely packed wavy structure is the “medium” which is maintained wet for direct evaporative cooling purposes.

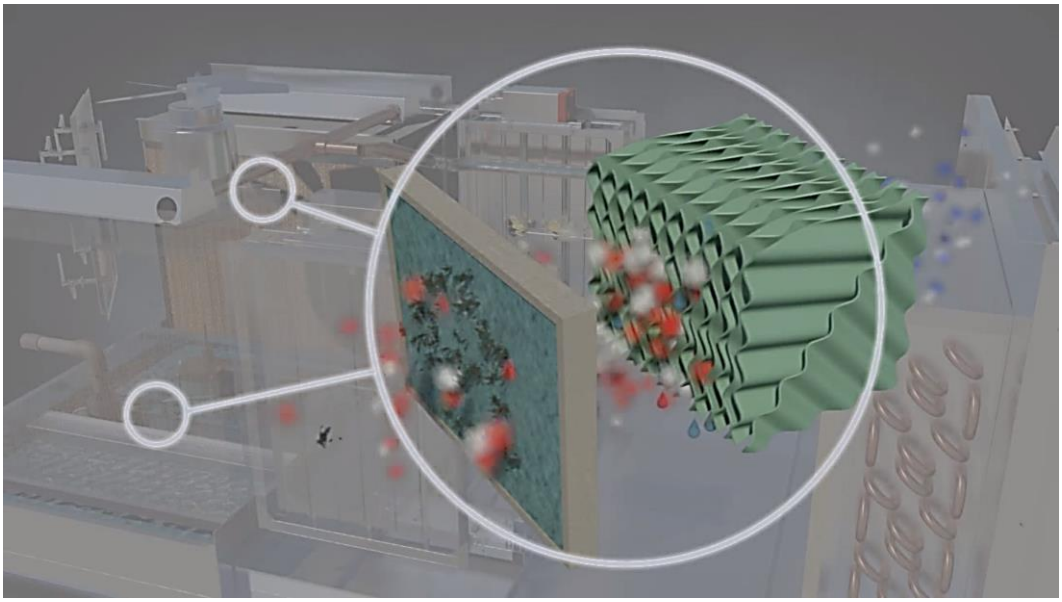


Figure 2-1 Direct Evaporative Cooling (Source: Youtube.com)

We pass an airstream through a wet media and obtain cooler air downstream. Here the airstream comes in direct contact with water. Hence, the humidity ratio of the airstream increases while the Dry bulb temperature decreases. The Wet bulb temperature of the airstream stays constant. These changes correspond to moving up and to the left on the Psychrometric Chart.

Indirect Evaporative Cooling

We have all tried to cool our hot beverages by blowing over the surface at some point in our lives. While we did that knowingly or unknowingly we employed forced advection where, as long as the air velocity is high enough we will succeed in cooling the liquid surface practically regardless of temperature of the air. Sometimes, for better cooling of the fluid we pour it onto a saucer or plate which increases the surface area and thereby enhancing the cooling efficiency. In industries wet media are used to increase

area efficiently. For indirect evaporative cooling this idea is used to cool the water which is later pumped though cooper coils. Fig 2-2 depicts a graphic rendition of the indirect evaporative cooling mechanism employed in an Aztec cooling unit.

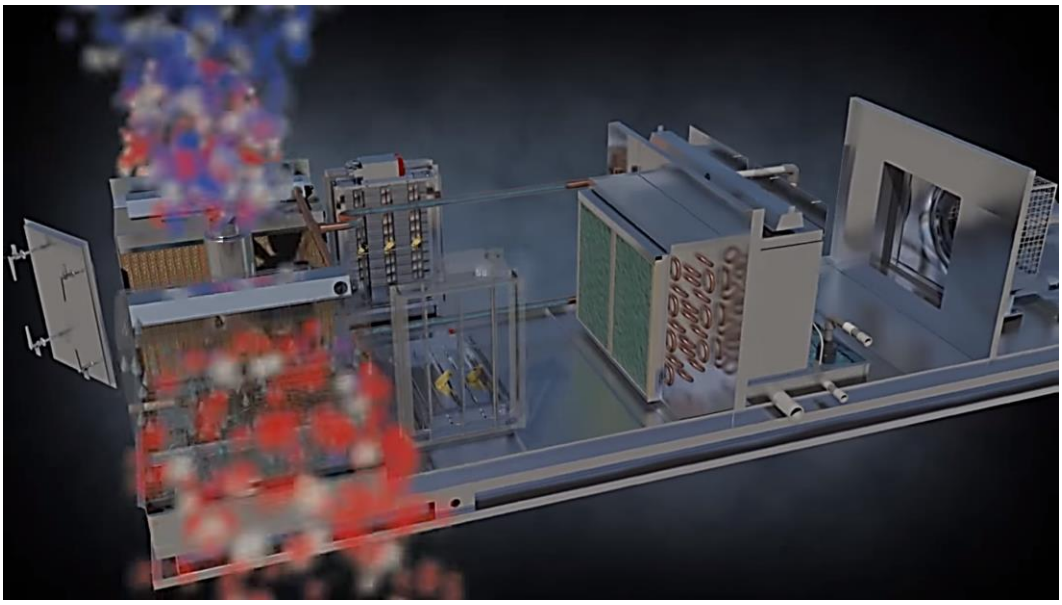


Figure 2-2 Indirect Evaporative Cooling (Source: Youtube.com)

In this technique we have a secondary airstream passing over a wet media which cools down the water that is running through the wet media. This water is then run through copper coils as the primary airstream then passes through it hence sensibly cooling the airstream. Here the Primary airstream never comes in direct contact with water. Hence, its Dry bulb temperature is reduced sensibly while the humidity stays constant. These changes correspond to moving to the left on the Psychrometric Chart.

Chapter 3

Psychrometric Chart

Psychrometry is a field of engineering, concerned with the determination of physical and Thermodynamic properties of Gas-Vapor mixtures. Since we are concerned with Cooling and Air-conditioning industries here the mixture we deal with is going to be moist air, which is a mixture of dry air and water vapor at 1atm barometric pressure.

Using equations in [1] depicting the thermodynamic properties of moist air we can obtain relations between Dry bulb temperature and Humidity Ratio at various constant properties like RH, dew point temperature, wet bulb temperature, specific enthalpy and specific volumes, to plot the Psychrometric Chart. For example, the relation for various constant RH and specific volumes can be formulated as

$$w = 621.98\,\varphi\,\frac{e^{\sum_{i=0}^{5} c_i T^{i-1} + c_6 \ln T}}{p - e^{\sum_{i=0}^{5} c_i T^{i-1} + c_6 \ln T}} \tag{3.1}$$

$$w = 621.98\frac{pV}{R_a T} - 1 \tag{3.2}$$

where, the coefficients for different temperature ranges [1] are as follows,

$173.16 \le T \le 273.15\,K$:	$273.16 \le T \le 473.15\,K$:
$c_0 = -5.6745359 \times 10^3$;	$c_0 = -5.8002206 \times 10^3$;
$c_1 = 6.3925247$;	$c_1 = 1.3914993$;
$c_2 = -9.6778430 \times 10^{-3}$;	$c_2 = -4.8640239 \times 10^{-2}$;
$c_3 = 6.2215701 \times 10^{-7}$;	$c_3 = -4.1764768 \times 10^{-5}$;
$c_4 = 2.0747825 \times 10^{-9}$;	$c_4 = -1.4452093 \times 10^{-8}$;
$c_5 = -9.4840240 \times 10^{-13}$;	$c_5 = 0$;
$c_6 = 4.1630159$;	$c_6 = 6.5459673$;

Using above formulations [16] we can plot the Psychrometric chart like in Fig 3-1 below

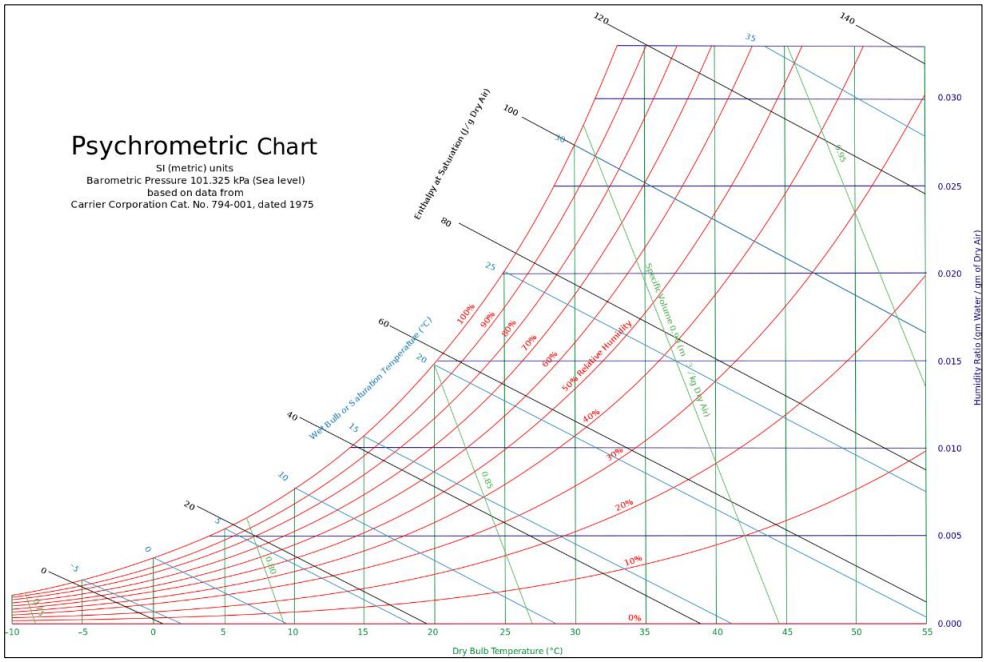


Figure 3-1 The Psychrometric Chart (Source: Wikimedia.org, ArthurOgawa, 2009)

Sensibly cooling corresponds to moving left along a process line on the chart, while sensibly heating moves right. Humidifying corresponds to moving up while Dehumidifying moves down. Fig 3-2 is an image outlining few process lines on the psychrometric chart.

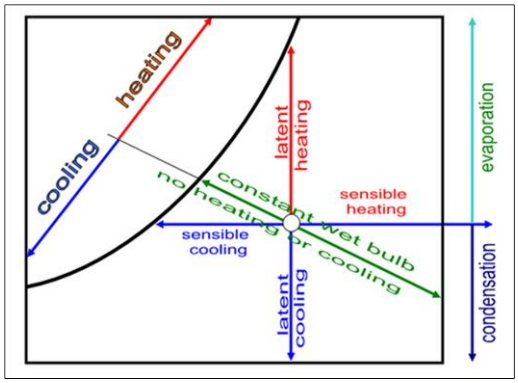


Figure 3-2 Process lines (Source: minewiki.org, Venteditor,2011)

For our purposes we also need to be aware of consequences of mixing two airstreams. Fig3-3 shows an image of process lines on the psychrometric chart concerned with adiabatic mixing of two airstreams.

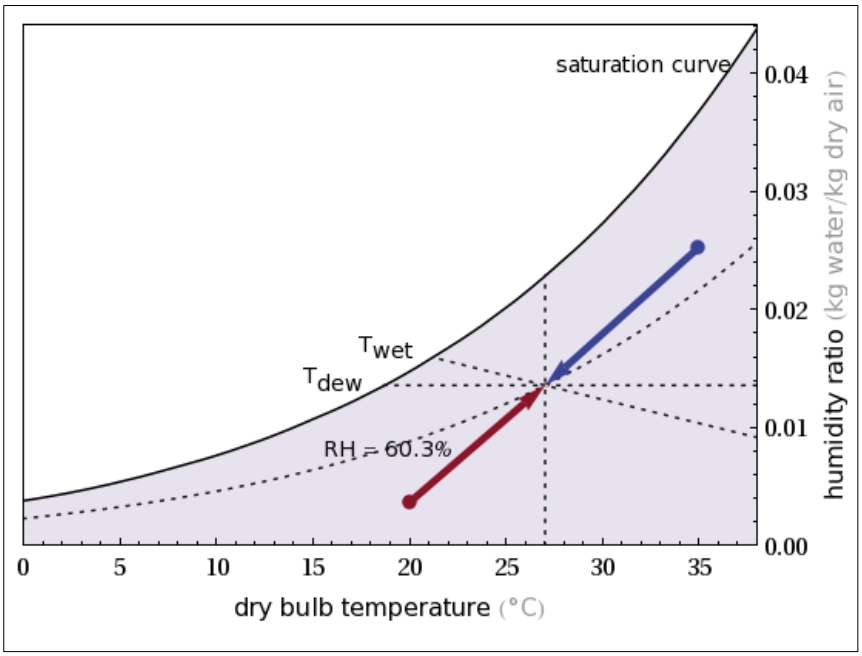


Figure 3-3 Adiabatic mixing process lines. (Source: [Generated] wolframalpha.com)

Mixing involves a mass and energy balance (mass flow and enthalpy balance in our case) corresponding to two points on the chart moving in a straight line towards each other.

It is very important to keep track of where we move to on the psychrometric chart since we are going to use this airstream over our expensive IT equipments and there are recommended envelopes on the chart that we do not want to fall out of, in order to not violate the ASHRAE TC9.9 recommendations.

Chapter 4

The Evaporative Cooling Unit

Mestex Inc., Dallas has one working mechanical equipment that uses evaporative cooling, providing cooling solutions for an IT Pod that houses several data server racks.

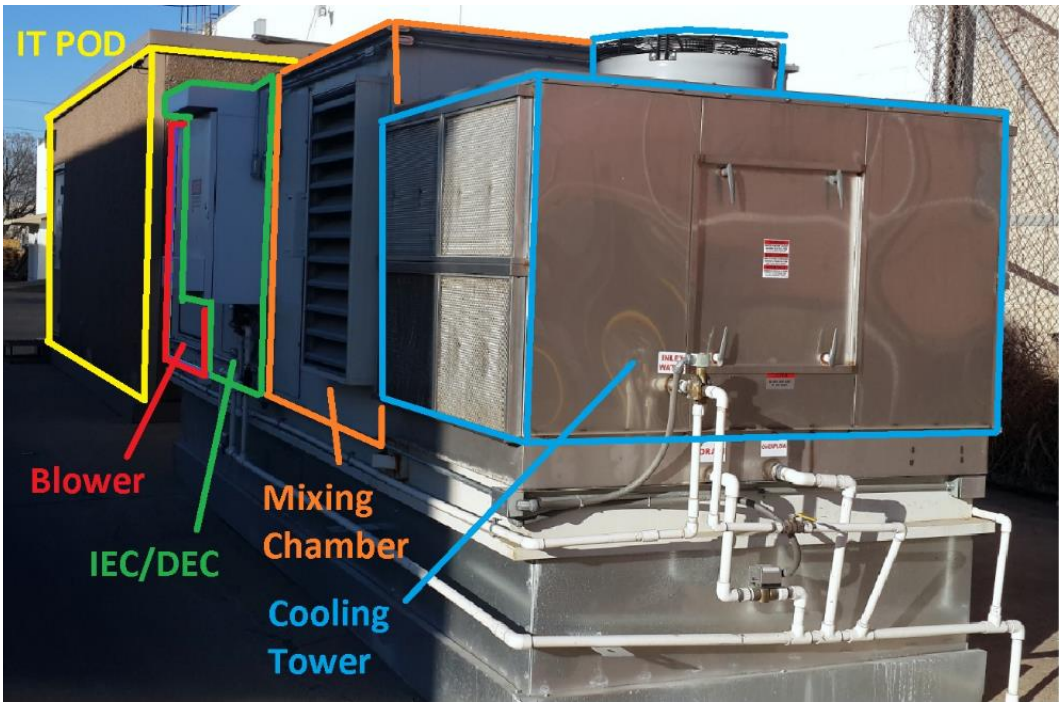


Figure 4-1 Aztec Evaporative Cooling Unit

The unit uses only evaporative techniques to cool, condition and treat an airstream in order to provide cool air for the servers in the IT pod. It has few distinctively identifiable parts as labeled in Fig 4-1. Blower fan, Cooling Tower Fan and pump are power consuming devices. Supply fan consumes 10hp power is 5 times more than the second highest power consumer aka the cooling tower fan. Hence, in this study supply fan will have our attention the entire while.

The Mechanical Design

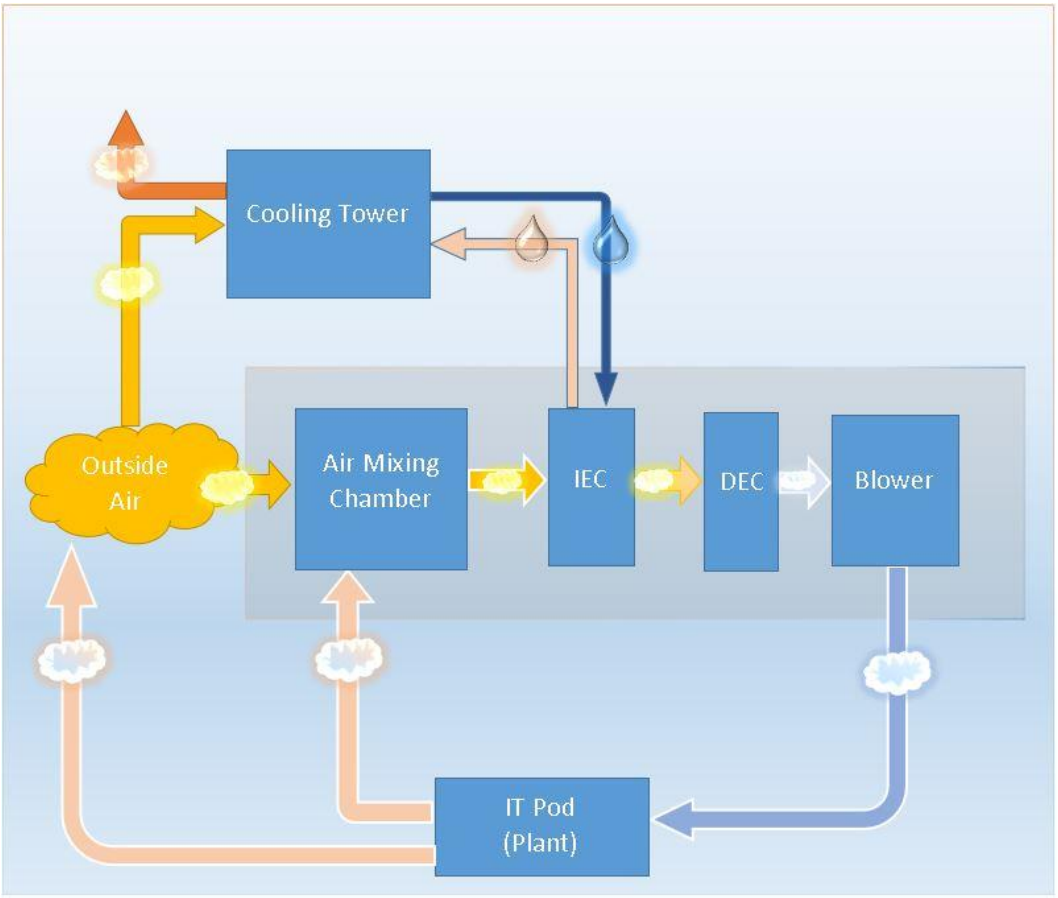


Figure 4-2 Block scheme of an Aztec evaporative cooling unit.

In Fig 4-2 we can see a block schematic diagram of the workings of the evaporative cooling unit. The systems includes various blocks as labeled but four of them involve occurrences of psychrometric events in them; namely the Mixing Chamber, IEC, DEC and the IT Pod.

The Mixing Chamber involves Adiabatic Mixing of two airstreams. The IEC involves sensible cooling. The DEC involves Humidification and Cooling, while the IT Pod (plant) involves Sensible Heating.

The Control Design

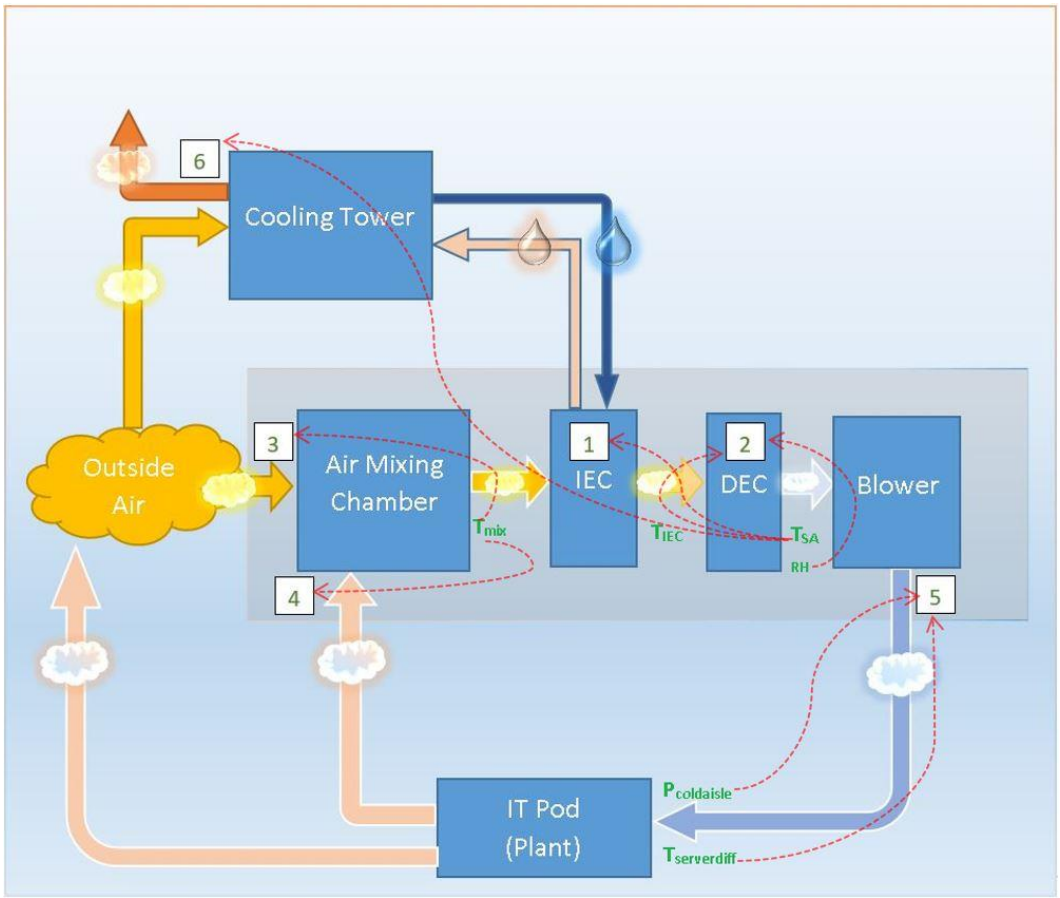


Figure 4-3 Block scheme and Control dependency lines.

The real heart of the system though are the controls. Fig 4-3 gives a view of the underlying control scheme. The numbers on the figure refer to various following control signals.

1. IEC Pump
2. DEC Pump
3. OA Dampers
4. RA Dampers
5. Supply/Blower Fan Speed

6. Cooling Tower Fan Speed

The arrow tails indicate the controlled variable while arrow heads point at their corresponding control signals.

Table 4-1 Control Scheme Table

MANIPULATED VARIABLES (CONTROL SIGNALS)	**CONTROL SECTIONS**	**CONTROLLED VARIABLES**
Supply Fan Speed	Section B: *Supply Fan Control*	*Cold Aisle Pressure* *Server Temperature Differential*
OA Dampers *RA Dampers*	Section C: *Damper Control*	T_{mix}
Cooling Tower Fan Speed *IEC Pump enable*	Section D: *IEC Control*	$T_{supplyair}$
Cooling Tower Fan Speed *DEC Pump enable*	Section E: *DEC Control*	$T_{supplyair}$ $RH_{supplyair}$

The above table 4-1 tabulates the important control sections of the current control scheme. The current control system is DDC controller based and various interfacing options like WebCTRL, BACview etc.

Chapter 5

Artificial Neural Network Modeling

Our modern technology driven world is getting ever obscuring with the advent of more and more complex systems whose dynamics are becoming practically impossible to model. Few decades ago, a quest to build and control such systems led us to probing into the human neurobiology itself for inspiration to re-create seminal intelligence. Although we are far from achieving goals of that magnitude yet, we are on the verge of mastering 'Learning' techniques. Machine learning is a gamut of techniques which embellish us with the power to leverage computing technologies to learn complex input-output mappings especially for "Recognition" problems like Pattern recognition, Face recognition, Hand-writing recognition etc. Mathematical models are essentially complicated mappings between sets of inputs and outputs in space and time. If we have data about these inputs and their corresponding outputs, though we may not find it easy to come up with closed mathematical models, we sure can still build models that can learn the mappings and in time start to behave approximately like the closed mathematical model we were looking for. In simple words, we can make machines look at big data and learn its mappings.

Artificial Neural Network modeling is one of the numerous modeling techniques in machine learning tool created mainly to tackle two very broad kinds of problems; namely Regression and Classification, which otherwise are extremely difficult to solve. As far as our application is concerned we will primarily focus on the regression part since our problem falls into the regression kind. The data we have are time series [14].

Artificial Neuron Model

A network of artificially modeled ‘Neurons’ is referred to as an Artificial Neural Network. Neurons are the fundamental cellular structures that all Neurobiological brains (CNS) are mostly made of. We first model the artificial neuron based on the neurobiological neuron as follows.

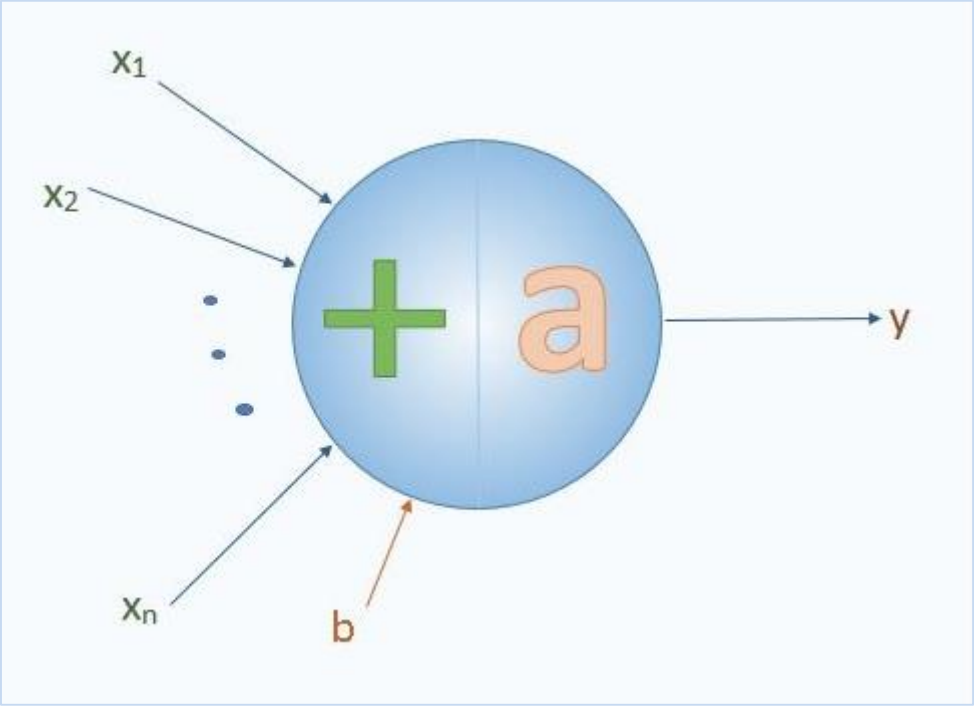


Figure 5-1 An artificial Neuron model.

As shown in fig 5-1, an artificial neuron is inspired by the neurobiological neuron.

Here we model [12] dendrites that carry input signals to the neuron by simple directed connections. Similarly, the Axon is modeled by another such simple directed connections directing away from the neuron. The cell body is symbolized by one structure with two distinctive parts and functions, which are as follows.

Adder

The adder receives all input signals into it and sums them all up to produce an intermediate output say ‘z’.

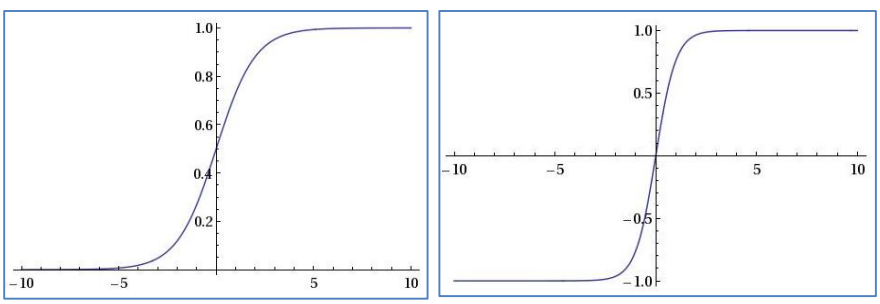
$$z = \sum_{i=1}^{n} x_i$$

Activation

This part applies an activation function on the intermediate output to give the final output say ‘a’.

$$a = f(z)$$

These activation functions could be any linear or non-linear functions like Sigmoid, Hyperbolic Tangent, softmax or Heaviside step function. The two most commonly used activation functions are Sigmoid and Hyperbolic Tangent.



(a) (b)

Figure 5-2 (a) Sigmoid plot. (b) Hyperbolic Tangent plot.

The two most commonly used activation functions are the Sigmoid and the Hyperbolic Tangent functions. Figures 5-2(above) and 5-3 (below) show the plots of both the functions, given by the equations $f(z) \equiv \frac{1}{1+e^{-z}}$ & $f(z) \equiv \tanh z$ respectively.

Synapses are modeled as ‘weights’ across each connections. Also, we introduce bias inputs for easier implementation purposes.

ANN model

A typical ANN model usually consists of an input, an output layer and multiple hidden layers of artificially modeled neurons. All connections are bidirectional. A typical ANN has approximately somewhere between 10-10000 neurons. The largest created ANN (until July, 2015) has approximately 160 billion connections. Figure 5-4 is an image where the author shows a diagram for a typical ANN model.

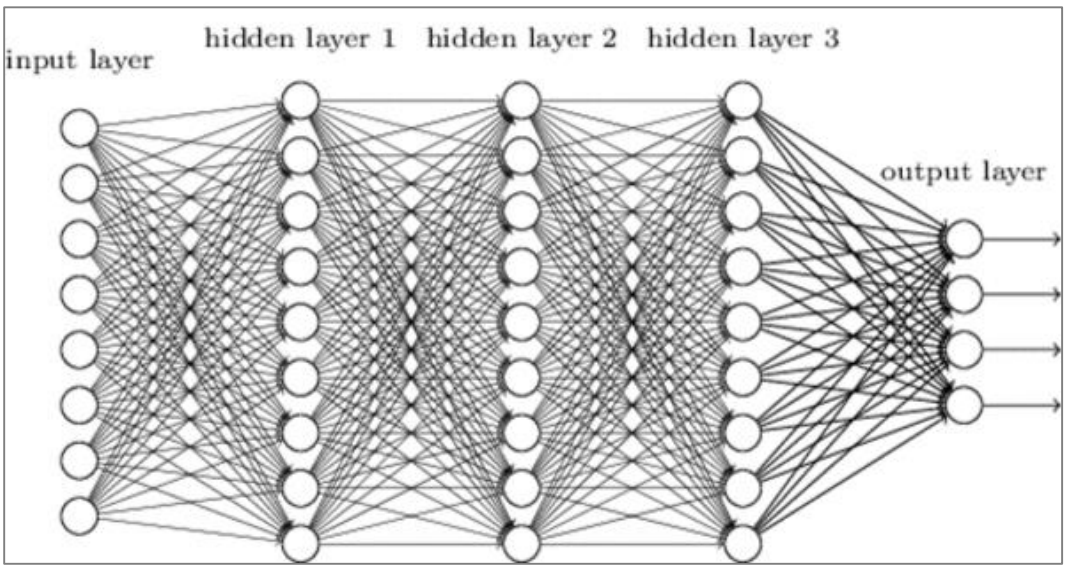


Figure 5-3 A Typical ANN model. (Source: google.com, Michael Nielsen, ”Neural Networks and Deep Learning”, Determination Press, 2015)

Forward Propagation

Once our model is ready we push the inputs to get an estimated or predicted output and this process is called [12] Forward Propagation. We start with some assumed (hyper-parameters) ‘L’ number of hidden layers and an initial $W^{(k)}$. For each layer the following calculations are to be done.

$$z^{(0)}(x) = x \tag{5.1}$$

$$z^{(k)}(x) = b^{(k)} + a^{(k-1)}(x)\, W^{(k)} \tag{5.2}$$

$$a^{(k)}(x) = f\left(z^{(k)}(x)\right) \tag{5.3}$$

$$\hat{y} = a^{(L+1)}(x) = o\left(z^{(L+1)}(x)\right) \tag{5.4}$$

The equations 5.1 – 5.4 depict the computation at each kth layer, given the input 'x' to predict the output $\hat{y}$.

Training using Back Propagation

The next step is to then train the network to learn the mapping and produce desired target outputs. This can be done by various techniques such as Genetic Algorithm, Particle Swarm Optimization or Back propagation. Back Propagation is the fastest among the lot and figure 5-4 shows a diagram of one of the intermediate processes in this technique.

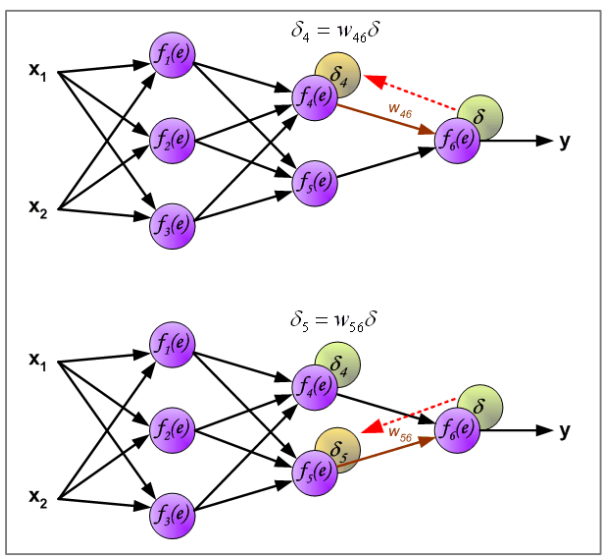


Figure 5-4 Error Propagation in Back Propagation. (Source: google.com Ryszard Tadeusiewcz "Sieci neuronowe", Kraków 1992)

Training a network refers to minimizing a cost function. For back propagation the cost function is of the form shown in equation 5.5.

$$J = \sum \frac{1}{2}\left(y - \hat{y}\right)^2 \tag{5.5}$$

Since this form makes the function convex it is of great advantage as our primary goal would be to minimize this function and the convex nature would imply a single global minima. Minimizing the cost function involves solving equation 5.6.

$$\frac{\partial J}{\partial W^{(k)}} = 0 \tag{5.6}$$

$$\sum -(y - \hat{y}) f'\left(z^{(k+1)}\right) \frac{\partial z^{(k+1)}}{\partial W^{(k)}} = 0 \tag{5.7}$$

$$\delta = -(y - \hat{y}) f'(z) \tag{5.8}$$

Equation 5.6 is short hand for k equations and k unknowns and therefore it yields a k dimensional point as a solution. Hence this point`s co-ordinates gives the correct weights (parameters) for the desired mapping. Equation 5.7 & 5.8 depict the error propagation as shown in Fig 5-4 while training the network. Few other training methods to get to these correct weights are Levenberg-Marquardt [5], Gauss-Newton approximation [3], Bayesian, [5] Scaled Conjugate Gradient.

Data Analysis

In an attempt to employ ANN for optimization purposes a data with over 650,000 data rows were taken and pruned. Using SQL and Excel the data was cleaned and made ready to be fed to an ANN model. After data analysis was done on the data that captured the fan speed and the cold aisle behavior only over 11,000 were chosen.

MATLAB NN Tool

An ANN model was created using the MATLAB Neural network tool. As shown in figure 5-5 the tool provides us with powerful options to build ANNs that caters our applications.

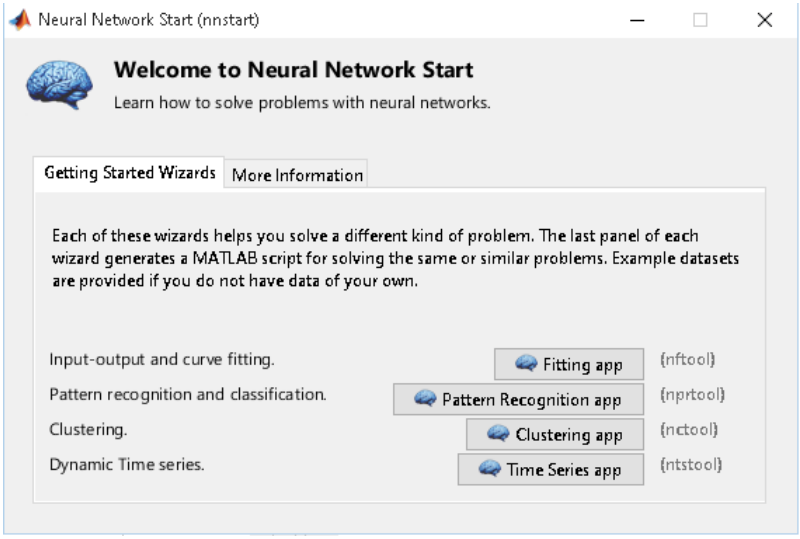


Figure 5-5 MATLAB NN Tool

The data we have is the data that was monitored and recorded through the sensors in the Evaporative Cooling unit over various intervals of time in minutes across a period of weeks. In other words it is a time series data. Ideally we would desire for our ANN model to capture the behavior and hence learn the mapping between the inputs and outputs and also at least the first and second order states of the input and output. And hence we will require the Time Series app. Figure 5-6 shows the GUI of the time series app that allows us to leverage the utilities provided to work with dynamic time series data. Among the various options seen in fig 5-6 NARX and the nonlinear input-output options are most suitable for our task

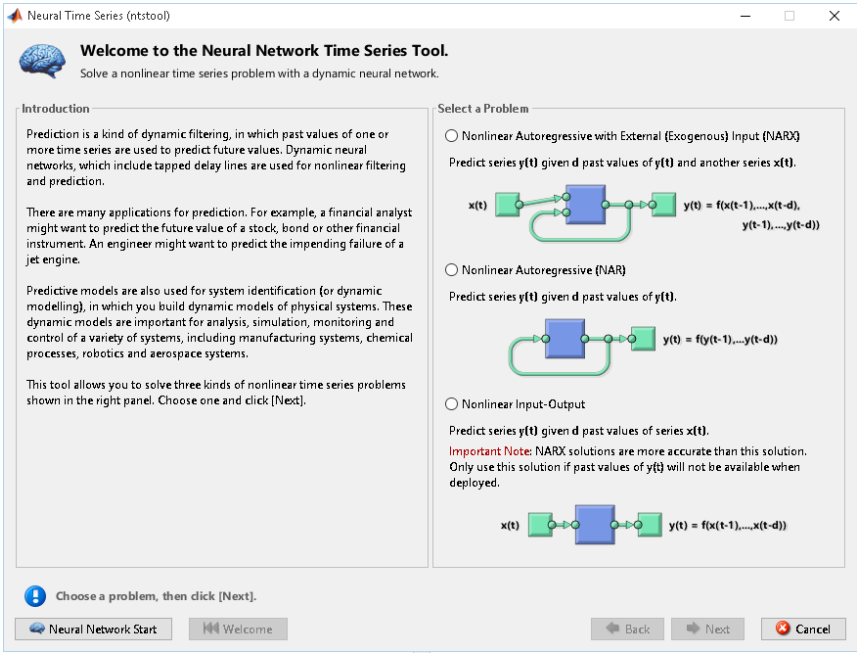
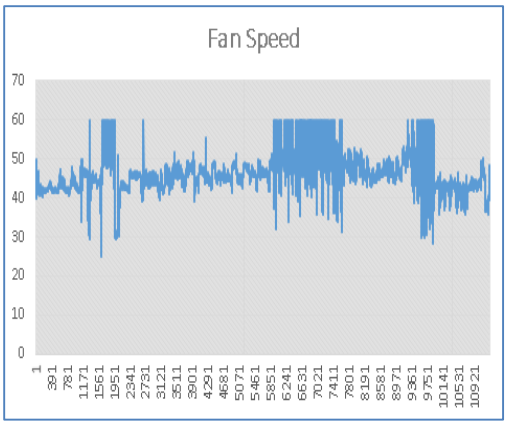
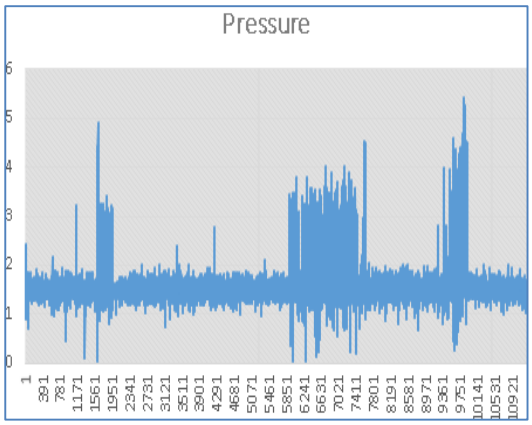


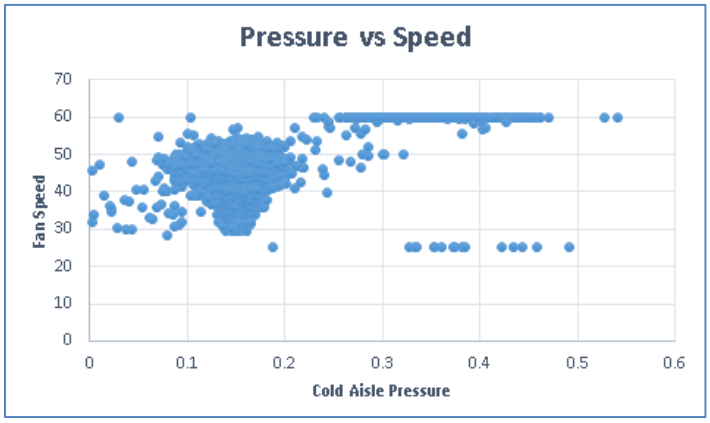
Figure 5-6 The Dynamic Time Series app window in MATLAB NN Toolbox

Using MATLAB and data from our equipment various ANN models were created with numerous different configuration. Figure 5-7 (a), (b) & (c) show how the pruned data looks and feels like.





(a) (b)



(c)

Figure 5-7 (a) Time series plot of Supply Fan Speed data. (b) Time series plot of Cold Aisle Pressure. (c) Scatter plot of the collected data of Cold Aisle Pressure vs Supply Fan Speed.

Feeding the data to the toolbox at different delays and different hidden units were tried but the best results came at 20 hidden units and a time delay of 2. The time delay factor seems to capture the non-linearity in the characteristic equation of the transfer function that might define the behavior of system. More number of delays seemed to

obscure the simplicity of the problem while more hidden units proved redundant. The best means squared error results are shown in figure 5-8.

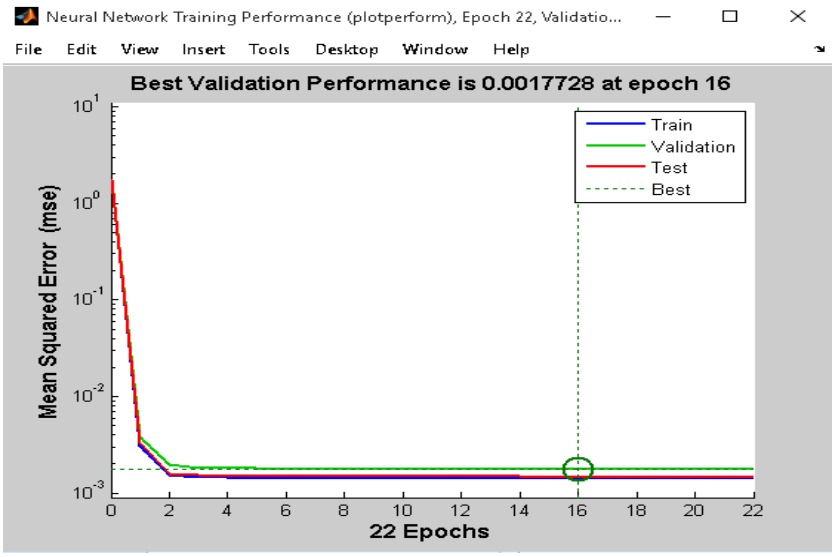
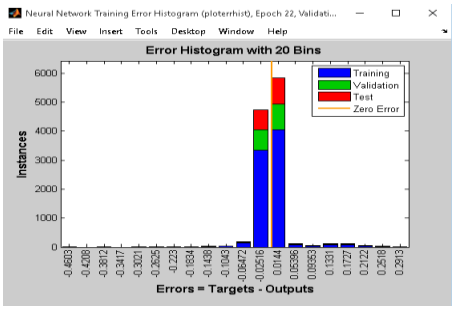
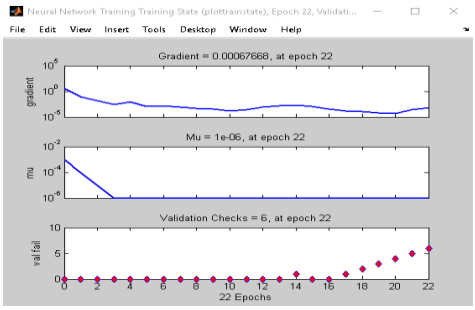


Figure 5-8 Neural Network Training Performance plot.

The figures 5.9 (a), (b), (c), (d) & (e) below show the plots of other performance specs of the this particular model with MSE 0.0017728



(a)



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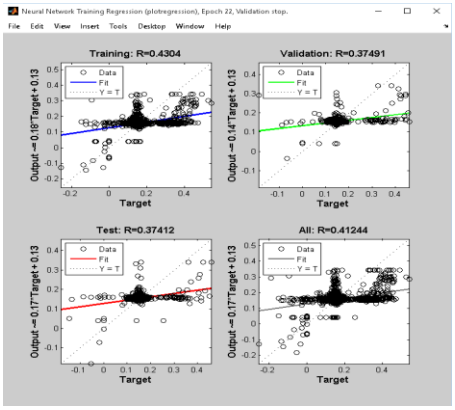

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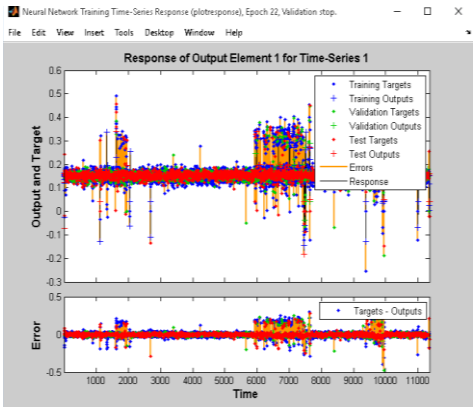
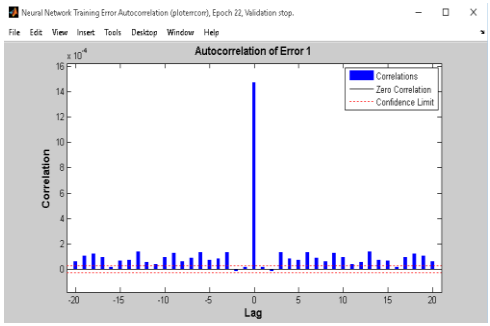


(d)



(e)

Figure 5-9 (a) Neural Network Error histogram (b) Neural Network Training State (c) Neural Network training Regression (d) Neural Network Time Series Response (e) Neural Network Error Autocorrelation

SIMULINK

The ANN model with the best mean squared error was chose for further experiments and simulations using Simulink. Since the data was a time series with approximately five minutes interval it was not very reliable. In an ideal case if the system were to be fully observable and we had synchronous time series with short intervals an attempt to identify the system transfer function for analysis purposes could have been tried using MATLAB System Identification tool. However, as that is not the case, it might be wise to use the model and check its steady behavior and validate it again with average independent data variables.

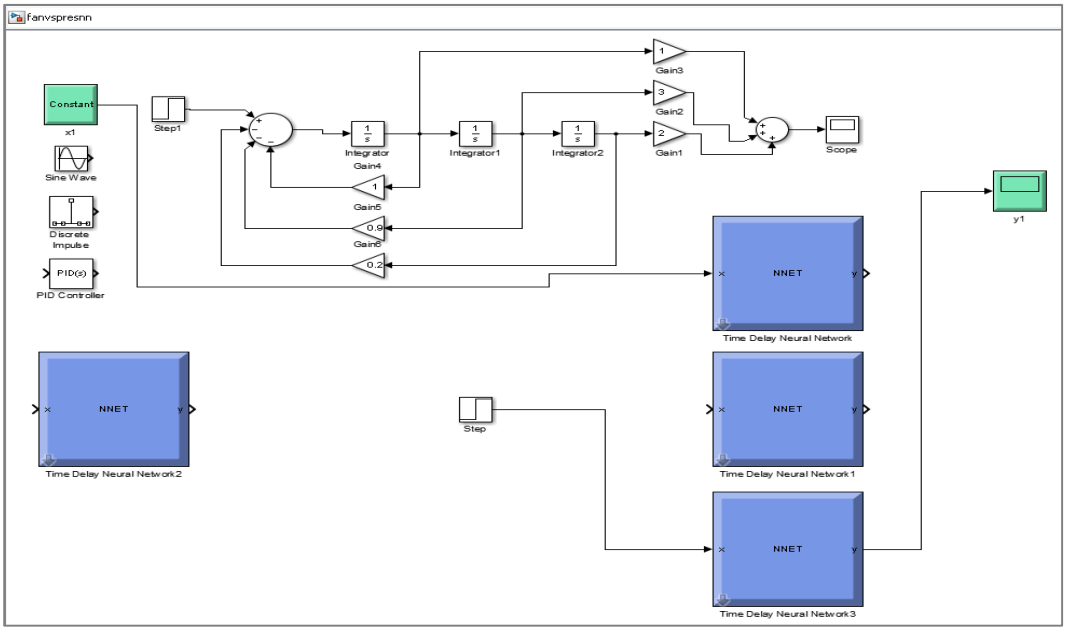


Figure 5-10 Simulink Workspace.

Figure 5-10 shows the workspace that can be used to produce the output of any block. The Neural Net blocks can be hooked up to scopes with various input signals for determining its steady state response.

Upon collecting the response data of the neural network model and cross validating with the actual time series we get varied percentages of agreement and errors at various fan speed. The below table shows the errors for chosen three ANN models and there percentage errors.

Table 5-1 Validation Error Percentages at various fan speeds

Speed\MSE	8.2262	0.04021	0.001773
30%	3.4	6.89	3.4
40%	21.62	17.3	2.03
50%	100	5.9	2.6
60%	150	25	16

The above results indicate that the model with the least mean squared error does agree with the systems time series data and implies its coherent capture of state information to agreeable degrees. However, this doesn't much help us with the optimization of the current control system much. We shall discuss about optimization in the Chapter 6, but for now we learnt from this that at best we can still use ANN to capture behaviors of various sections of the plant as long as we have good data with us post observing the system over prolonged periods of time.

Chapter 6

Optimization Solutions

Our main goal was perform studies in order to search for effective and efficient solutions and/or insights on the issue at hand. If we could learn how we could make the working of the equipment shown in fig 4-1 more efficient, it would be positive progress. Power Utilization Efficiency (PUE) & Water Utilization Efficiency (WUE) are metrics that indicate how efficiently the plant uses power and water for its working. Hence our goal indirectly targets PUE, WUE and control stability. There are three major ways which this study intends to explore to achieve that goal. They are as follows.

Tune PID controllers

As we saw in chapter 4, the study is based on experiment and analysis of the equipment shown in figure 4-1. The table 4-1 shows necessary details of the current control system designed with 12 universal inputs, 6 analog outputs, and 6 binary outputs. In order to tune PIDs we need to first be able to compute or formulate the appropriate transfer functions governing the state dynamics. The system at hand is too complicated and as most dynamic systems is chaotic [4]. Any system where the exact input can determine the exact output but approximate input cannot predict the approximate output can be deemed as chaotic [2]. Moreover, even if we could formulate its Retarded Time Delay Differential Equations or make it fully observable and use MATLAB to identify the transfer functions it may not seem to be a viable approach as heuristic research indicate that there practically exists no issue with stability, PM or GM. In very simple words the current control system scheme does well to regulate the set points. Therefore, tuning PIDs may not be our immediate priorities.

Artificial Neural Networks

Upon extensive study on ANN is a very power machine learning technique. However, that also acts as a drawback in our application. ANN models seem to at best mimic system behavior which can have its own use and implementations yet it again may not be a wise or viable approach to enhance the control system. ANNs may very well seem to solve any kind of problem thrown at it, but it may not be true since through studies and experience with the technique it becomes clearer that ANNs may not yet be ready to go head to head with modern control techniques. However, one may try to approach the problem while training the network using Evolutionary techniques like Genetic Algorithm since it has the non-deterministic elements, nevertheless it can provide solution to only specific systems while it has the longest disadvantageous learning curve too. How it may handle disturbance in the system transfer functions is to be known for the equipment in focus. Hence, the study would suggest that ANN may not be practically viable to attack the problem.

Mechanical or Control Design Tweaks

For the Evap cooling unit to have the best chances or attaining the best PUEs it should be able to use the Air-side Economizer configuration. Air-side economizer refers to using only the blower fan essentially to blow pure already conditioned air though the IT load. Figures 4-2 and 4-3 shows the mechanical and control design of the plant. One mechanical design change that may work out well would to be somehow bypass the airstream through the cooling stages while using Air-side economization. Figure 6-1 shows the Bypass Mechanism in the block scheme diagram of the Aztec evaporative cooling unit. This mechanism can have various advantages as far as power consumption is concerned.

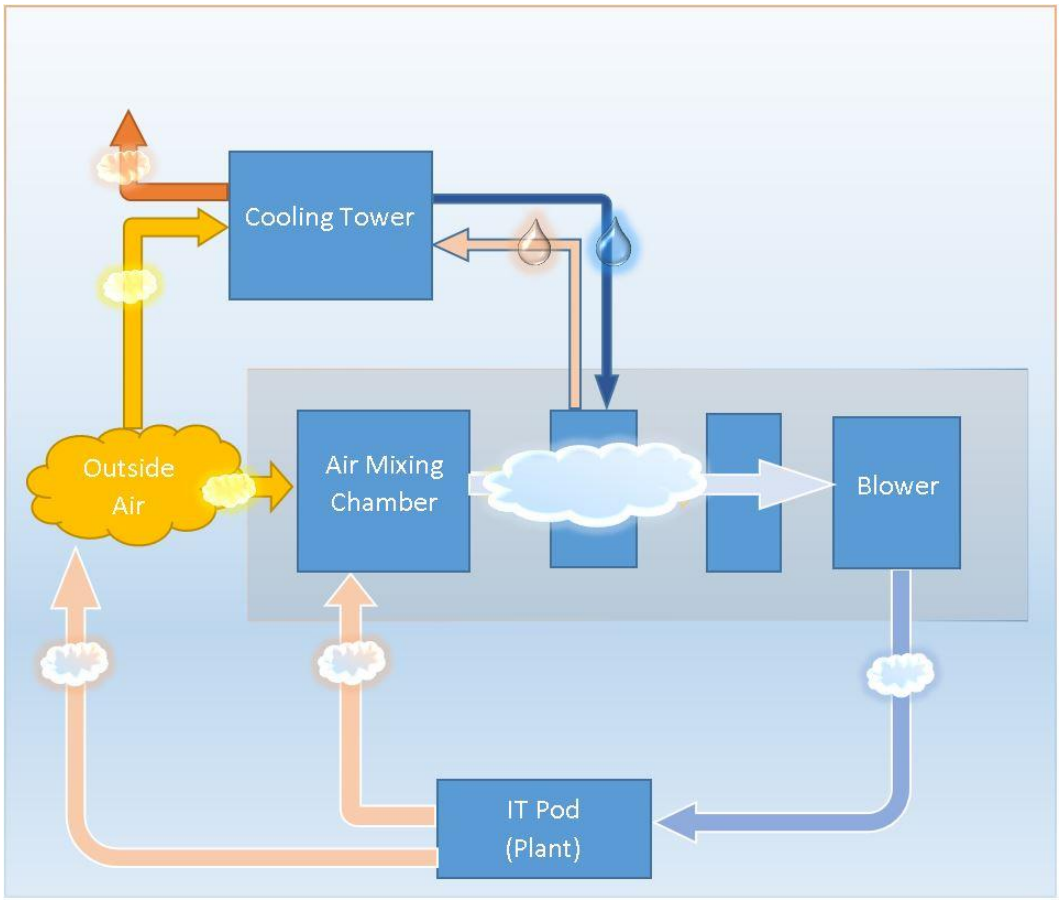


Figure 6-1 Evap Cooling Unit block diagram with By-pass Mechanism

Such a mechanism will result in lower pressure drops across the IEC/DEC blocks and hence the supply fan power utilization can be more efficient. This would result in higher PUE.

In order to come up with control design tweaks we first might want to identify modes of operation of the plant so the control system strategy can be formed with a better plan. The following modes are numbered and arranged in their ascending order of power usage.

Mode 1

This mode is essentially the Air-side economizer configuration and should made optimal use of. In this mode, the IEC & DEC pumps and the CT fan are all disabled.

The active controls here would be OA dampers, RA Dampers and Supply Fan Speed. The below figure 6-2 depicts the block scheme representation of mode 1.

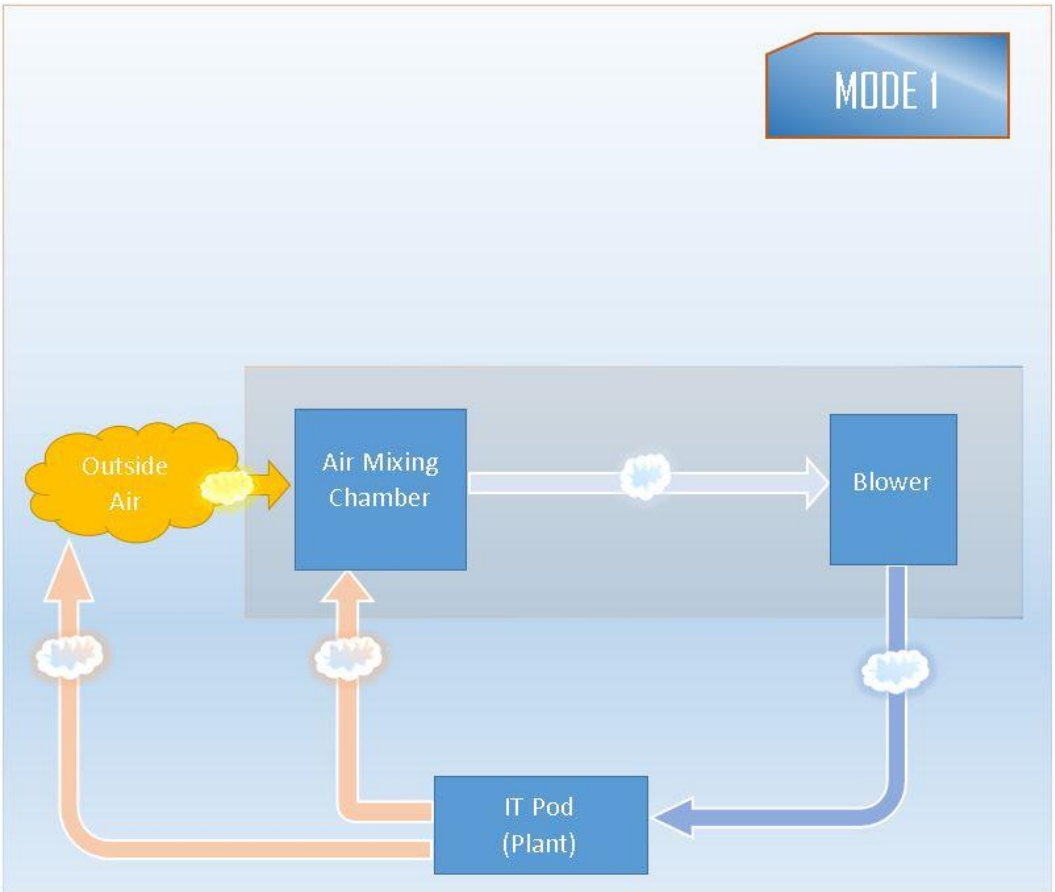


Figure 6-2 Mode 1 block scheme diagram

Mode 2

This mode is a humidifying configuration. Here the IEC pump, DEC pump and the CT fan are all disabled. The active controls for this mode are OA Dampers and the Supply fan Speed.

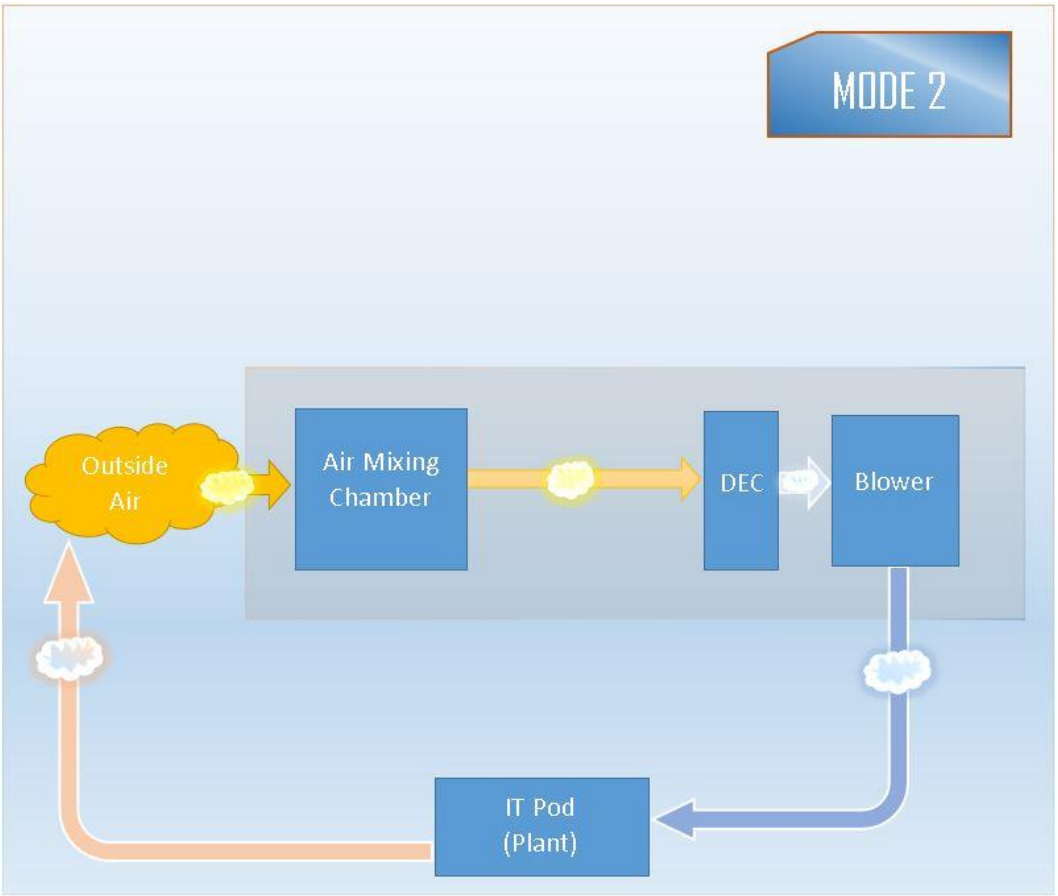


Figure 6-3 Mode 2 block scheme diagram

Mode 3

This mode humidifies and heats. Here the DEC Pump is enabled while the IEC pump and CT fan are disabled. The active controls would be OA Damper, RA Dampers and Supply Fan Speed. The figure 6-4 below depicts this configuration.

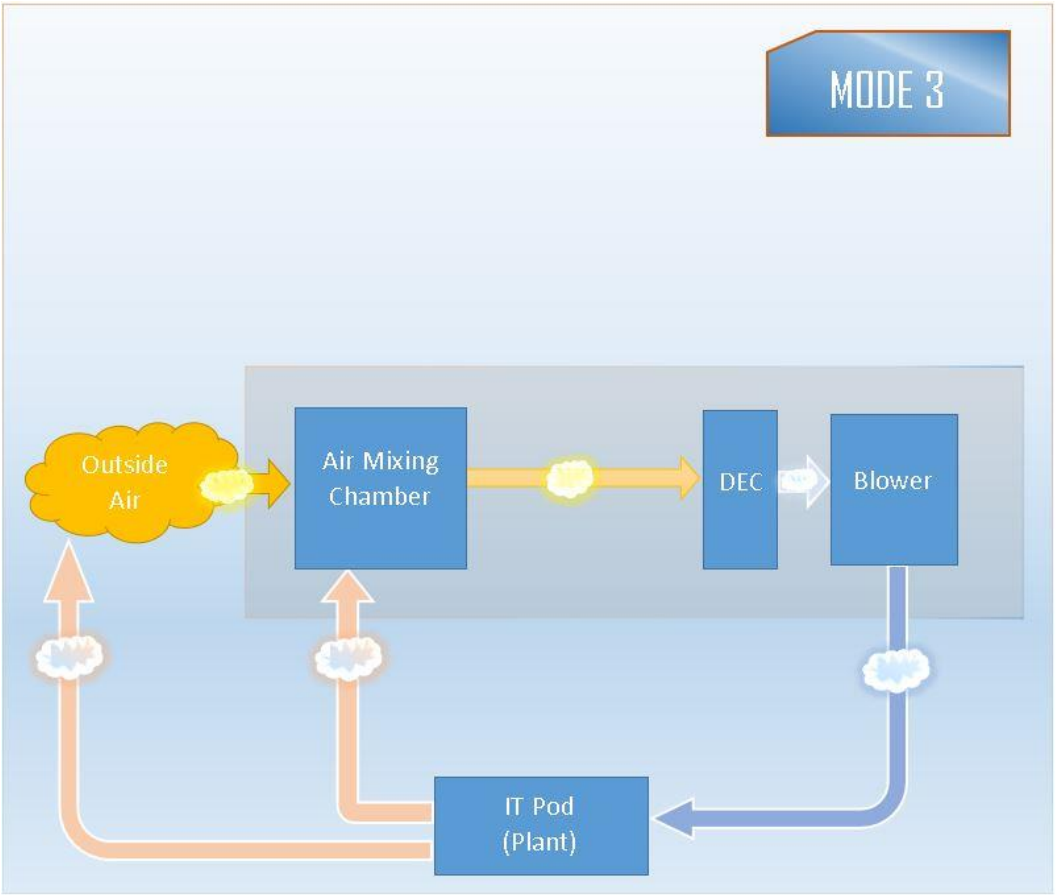


Figure 6-4 Mode 3 block scheme diagram

Mode 4

This mode does sensible cooling. Here the DEC Pump is disabled while the IEC pump and CT fan are enabled. The active controls for this mode would be OA Damper, RA Dampers, Supply Fan Speed and CT Fan Speed. The figure 6-5 below depicts this configuration.

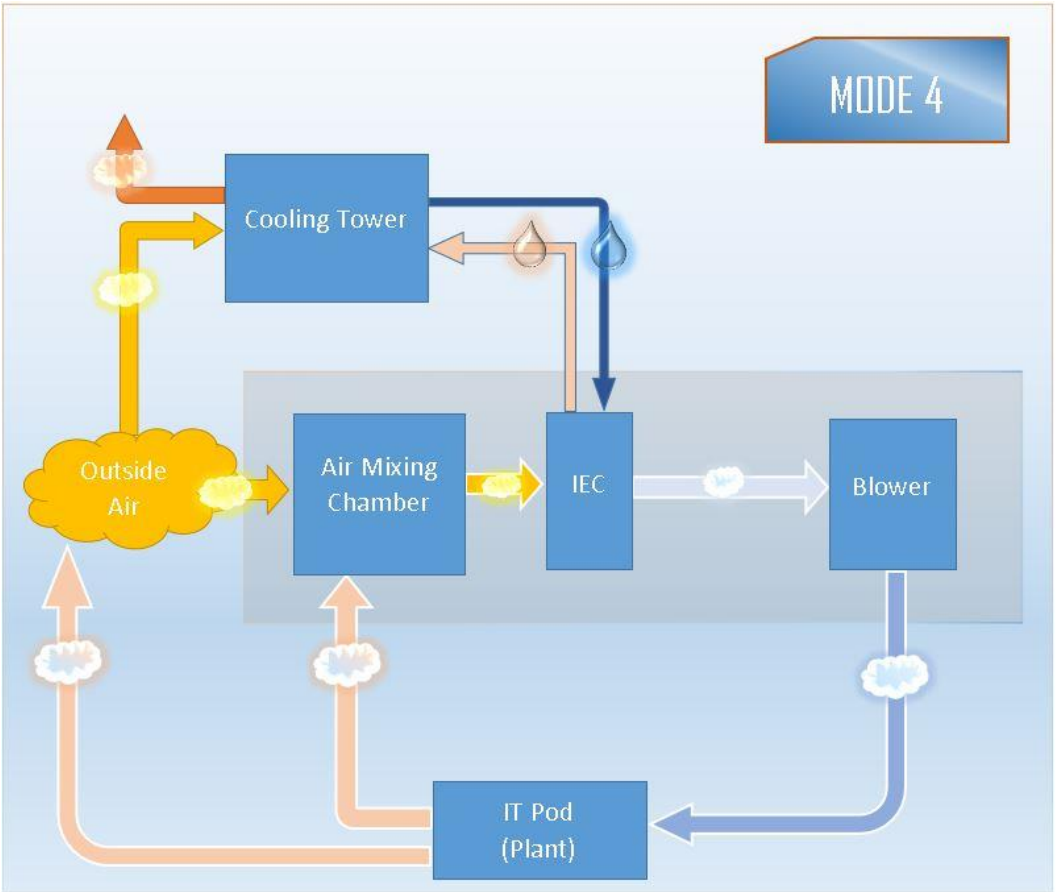


Figure 6-5 Mode 4 block scheme diagram

Mode 5

This mode has the best cooling capacity but at the same time will have the most power consumption. Here, the IEC & DEC pump and CT fan are enabled. The active controls for this mode would include OA Damper, RA Dampers, Supply Fan Speed and CT Fan Speed. The figure 6-6 below depicts this configuration.

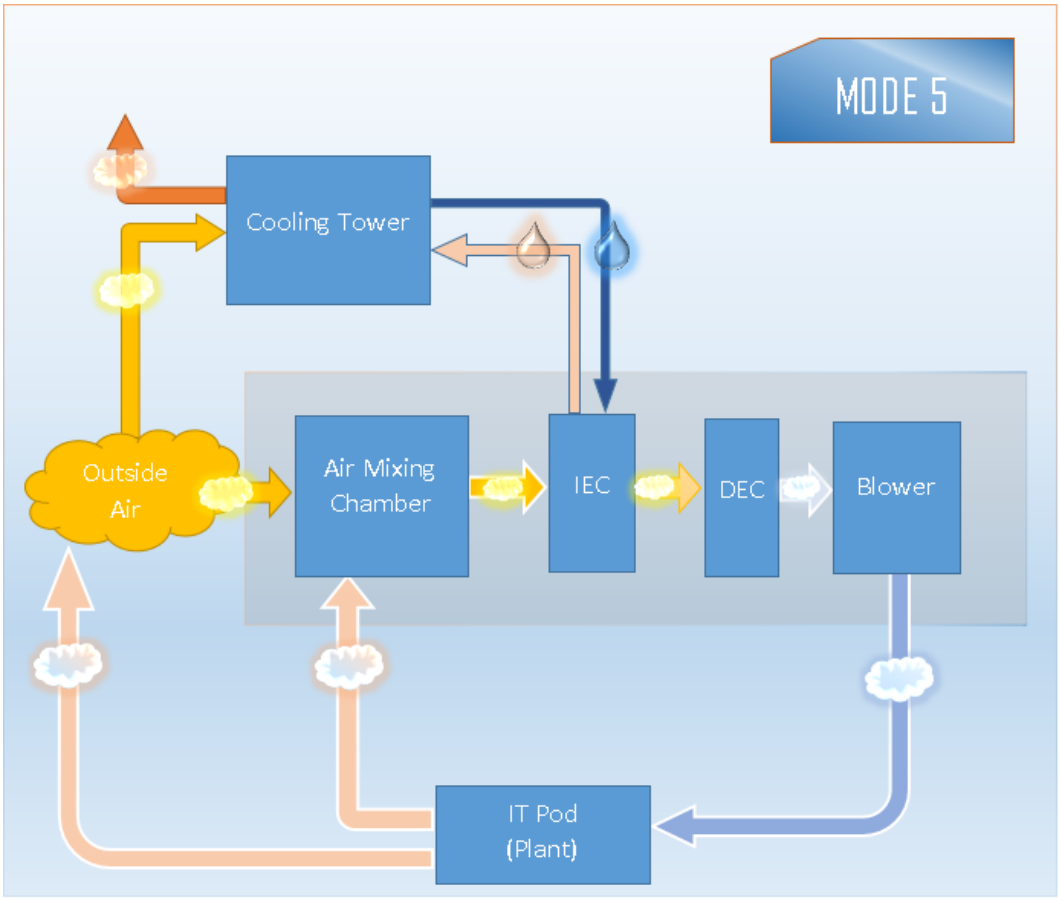


Figure 6-6 Mode 5 block scheme diagram

Chapter 7

Insights & Future Works

Following our extensive study over the issue we may take away from it the following insights.

Observing system to generate it's Dynamic Retarded Time Delay Differential Equations & Transfer Functions in order to tune PID may not be a viable approach since heuristics indicate no practical issues with stability with control system.

ANN models can at best mimic system behavior unless trained using Genetic Algorithm Approach, which is very slow and too problem specific to be practically viable.

However, efforts towards re-designing of Control Architecture Algorithms may be rewarding. And hence, there might be several future works still to be done.

Genetic Algorithm

Though ANN modeling didn't not seem promising to our problem we can still try different approaches that might attack our problem in a better way. Since Back propagation is very deterministic and could strictly reach supervised solution to learn and mimic any complex mapping, we can choose to take up other alternate methods to train the ANN model. Genetic Algorithm technique is inspired by biological evolutionary techniques. Though time consuming we can leverage the stochastic flavor of the GA based [17] evolutionary training techniques and may be able to model the behavior of the system better.

Design Control Architecture Algorithm

Using the modes we realized in chapter 6 we can now build better hierarchical control strategies in order to meet our eco-friendliness needs. A hierarchy can enable

better structure and order. For example, figure 7-1 depicts a possible hierarchical control architecture design.

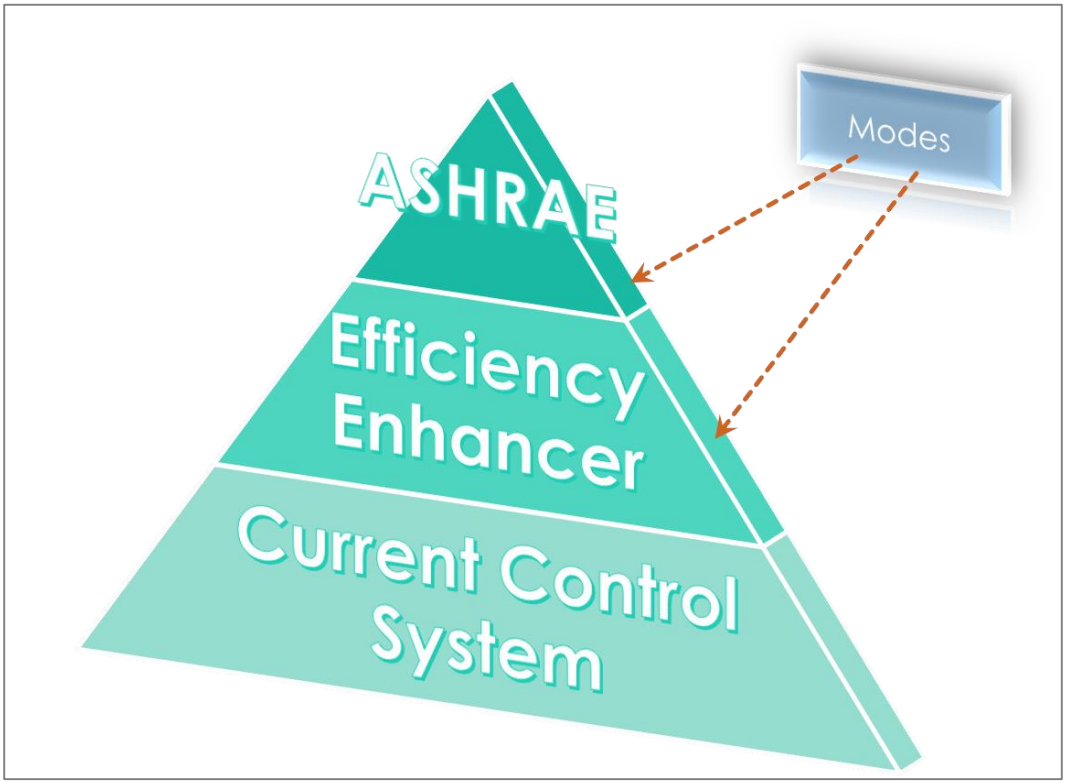


Figure 7-1 A Hierarchical Control Design Architecture

As shown in the above figure we can have an Efficiency enhancer block whose sole purpose can be making use of appropriate modes while being very efficiency minded. The efficiency enhancer block would be simple to perform only that task without really being bothered about ASHRAE recommendations and this is where the higher block comes in. The ASHRAE block should again be aware of the blocks and how it corresponds to moving on the Psychrometric Chart and it would monitor the Psychrometric properties and can override the lower blocks commands to the control system in order to stay within the ASHRAE TC9.9 recommended envelope

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Biographical Information

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The author, Pritam Karmokar was born and raised in Mumbai, Maharashtra, India and is currently residing in Arlington, TX, USA. He got his primary and secondary education done from Guru Nanak English High School where he consistently excelled in academics and extra-curricular activities and earned various awards, the most prestigious of which were the Best Boy Awards for all round performance. He got is Bachelor`s Degree in Information Technology from Terna Engineering College Mumbai University, India. He always got love & support from his family to go through any measures to quench his thirst for knowledge and education.

Fascinated by physics and mathematics, he decided to pursue Masters in Aerospace and Mechanical Engineering at UT at Arlington, USA. It took a lot of dedication, determination and hunger to learn after his 4 years of IT engineering and 2 years of brilliant IT job experience, to start from scratch, to begin from the basics to earn his Masters of Sciences Degree in Mechanical Engineering.

His current interests involve Robotics, Controls, CFD, Design, Theoretical physics, Mathematics, Cricket, Racquetball, Music, Driving, Eating and Travelling. Music, playing instruments prominently Guitar and singing on stage has been his cherished interests always and he has been fortunate to be able to do that time and again.

His future goals are to work on the most critical projects on the planet with a goal to make our planet a better habitable place and then go beyond.