CONTROL STRATEGIES FOR AIR-SIDE ECONOMIZATION, DIRECT AND INDIRECT EVAPORATIVE COOLING AND ARTIFICIAL NEURAL NETWORKS APPLICATIONS FOR ENERGY EFFICIENT DATA CENTERS

by

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Abstract

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The skyrocketing growth in data centers, facilities that house information technology (IT) equipment for storage, management and distribution of data while striving for 24/7/365 operation with 100% up-time, has accounted for 1.3% of global energy use. A significant portion of data center energy is dedicated to removing the heat generated by IT equipment to maintain safe operating conditions and optimum computing performance. Energy efficient cooling of data center is of vital importance. One of the options for significantly cutting the cooling cost is the use of air side economization (ASE), Indirect evaporative cooling (IEC) and Direct evaporative cooling (DEC) without using expensive chilled-water systems or air-cooled CRAC units.

The topology of a test bed modular data center (MDC) under consideration consists of an Information Technology (IT) module supported with a DEC and IEC module. MDC is a dynamic and complex environment with multiple mechanical and electrical control systems aimed at maintaining continuous operation of the data center. Highly nonlinear correlations, large number of constraints and multiple operating

configurations make data center control a challenging research problem. In this study, a neural network model that adapts to the actual data center conditions using historical operating data and predicts the optimum configuration to reduce energy consumption is evaluated. In addition, the neural network model has the ability to learn from real time data collected from various data center sensors. When combined with a cooling unit, a predictive model that is fast and accurate in finding an optimal operating point for the modular data center unit can be implemented.

In 2011, the Technical Committee (TC) 9.9 under American Society of Heating Refrigeration and Air-Conditioning Engineers (ASHRAE) expanded the operating envelope for data center thermal management in its Thermal guidelines for Data Processing environments, thus making it possible to operate IT equipment at higher server inlet temperatures and humidity and also switch to Indirect/Direct evaporative (I/DEC) and free cooling mode for increased number of hours per year. This study includes control strategies for operating I/DEC in tandem and also individually to achieve the target conditions for data center environment with minimum fluctuations in temperature and humidity. Staging of DEC for segmented cooling will provide flexibility in efficiently controlling temperature and humidity with significant water saving capability. Predictive cooling using weather forecast will counteract the start time delay of cooling modules avoiding ramping of unit due to unexpected weather conditions. The results show potential energy savings achievable through the proper implementation of control strategies and artificial neural network in operation of ASE, DEC and IEC of data center.

Table of Contents

List of Illustrations

List of Tables

Chapter 1

Introduction

Importance of Data Centers

A data center is a dedicated space that centralizes an organization’s IT equipment for digital data processing, storage and transmission. Data centers have become the backbone of modern society with the widespread availability of internet and use of internet-enabled devices. Services that involve emails, online purchases, video streaming, digital bank transactions et cetera rely on presence of data centers for saving, accessing, protecting and sharing data. Advancement in computational and informational technology, improvements in hardware affordability and growth in Big Data have resulted in the accelerated rise of large scale data centers. Within the last two decades the amount of digital data generated, stored and transmitted has greatly increased. In 2011, IDC [2] reported that the zettabyte barrier was surpassed in 2010 and estimated that the amount of information created and replicated will surpass 1.8 zettabytes in 2011 – a 9 fold increase in just five years.

The primary contents of a data center can be broken down as follows:

1. IT equipment: actual equipment responsible for processing of data. This includes compute servers that process the information, storage servers that store the information and networking equipment that serve to enable communication across servers within facility.
2. Support Infrastructure: system responsible for maintaining reliable operation of IT equipment. Two primary components are power module that maintains uninterrupted operation of IT equipment, and cooling module that controls data center environment for reliable operation.

Data Center Energy Consumption Breakdown

Data centers house equipment such as servers, switches, power distribution units et cetera and the cooling infrastructure that consumes a tremendous amount of electricity. In 2010, electricity used by global data centers was estimated to be 1.1% to 1.5% of total electricity use and this number for US was 1.7% to 2.2% [1]. The high energy consumption of data centers and the increasing trends in the growth of data centers has positioned data center industries to improve data center efficiency and lower the overall power consumption. Efforts are being made in both IT equipment (demand) side and the cooling infrastructure (supply) side to improve efficiency. Focus of this study is on the efficiency improvement by using alternate cooling strategies.

Typical cooling infrastructure in a traditional data center facility consumes about 38% of total power consumption as in Figure 1-1, categorized as a parasitic load.

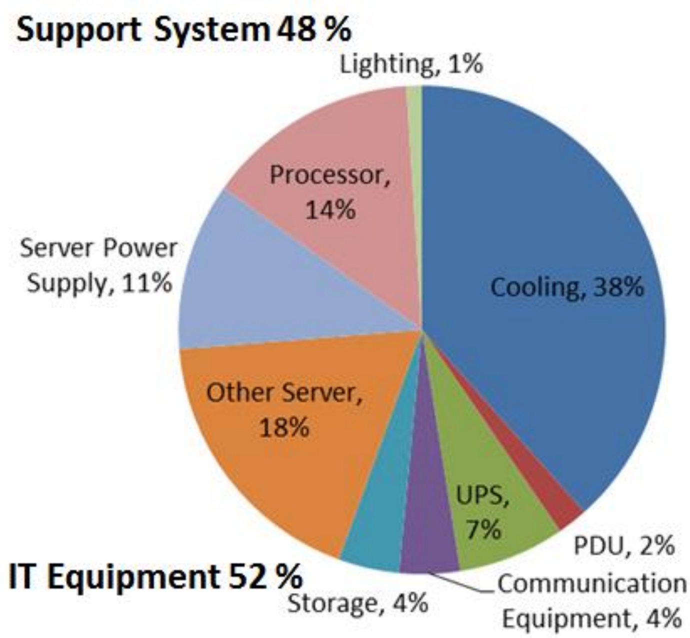


Figure 1-1 Energy Breakdown for Cooling Infrastructure [20]

Figure 1-2 shows the breakdown of cooling infrastructure power in to the individual equipment consumption. A typical data center cooling module consists of chiller compressors, CRAC fans, cooling tower building chilled water pumps et cetera. A sizeable portion of total cooling module power is attributed to chiller compressor. Significant energy savings can be achieved by cutting down this component of cooling module. Use of alternative cooling strategies such as air-side economization and water-side economization and their applicability to modular data centers are discussed in this study.

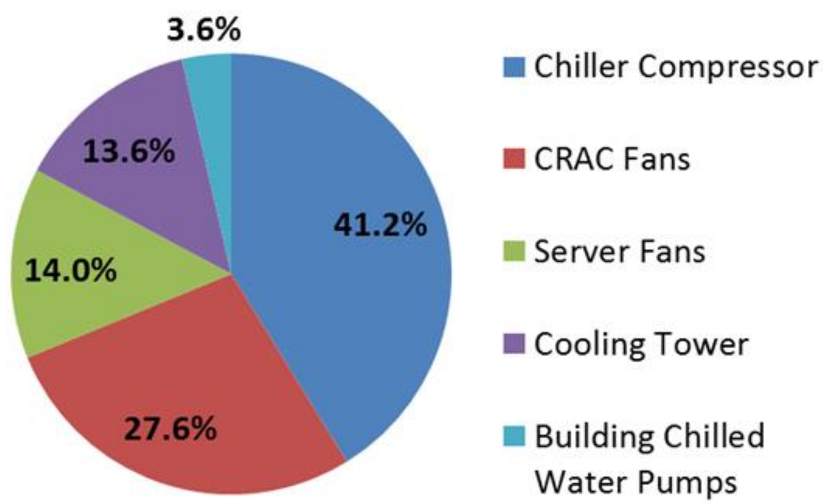


Figure 1-2 Energy breakdown of cooling infrastructure [18]

ASHRAE Thermal Guidelines for Data Processing Environment

ASHRAE Technical Committee 9.9, Mission Critical Facilities, Technology Spaces and Electronic Equipment along with data center companies, government agencies, research institutions have brought together the interests in efficiency improvements in data center cooling technologies. Thermal Guidelines for Data

Processing Environment have helped in understanding the implications of ITE cooling on the data center operational efficiency. In 2004, ASHRAE provided Thermal Guidelines for environmental specification of IT equipment with emphasis on performance and availability, instead of compute efficiency, of the ITE [2]. Since data centers house ITE from different vendors, a common ITE environmental condition that allows all equipment housed in the data center to reliably operate is needed.

The growing concerns about skyrocketing energy consumption by data center, particularly the cooling infrastructure have mandated TC 9.9 to update the Thermal Guidelines considering wider temperature and humidity ranges. The 2008 update focused on maintaining high reliability of the IT equipment and also operating data centers in the most energy efficient manner. The 2011 update widened the temperature and humidity envelopes compared to the 2004 or 2008 Thermal Guidelines. This update also defined additional two data center classes increasing the number of data center classes to four. Table 1-1 and Figure 1-2 show the 2011 Thermal Guidelines for Data Processing Environments – Expanded Data Center Classes and Usage. The Thermal Guidelines apply to the inlet air conditions to the IT equipment.

Since 2008, the recommended range for temperature and humidity of inlet air conditions were expanded, enabling increased number of economizer hours and reduced mechanical cooling. The industry now recognizes that outside air can be used with economizers to vastly decrease mechanical cooling in data center implementations, that there is room to exploit alternate renewable and sustainable cooling technologies like air-side and water-side economization.

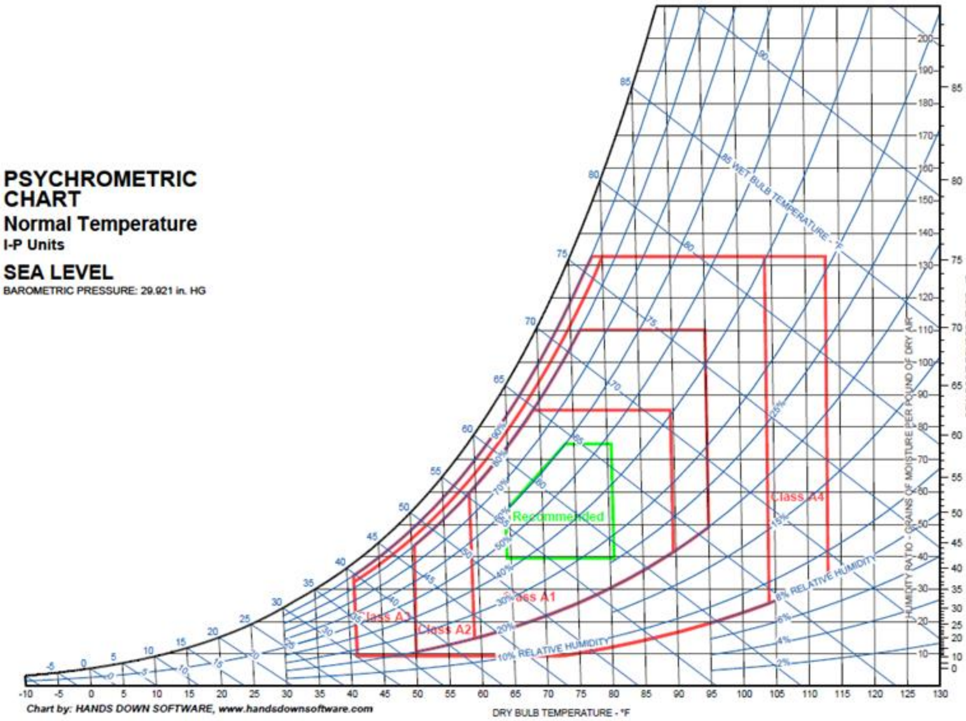


Figure 1-3 ASHRAE Environmental Classes for Data Centers

Table 1-1 ASHRAE 2011 Thermal Guideline Classes [2]

Classes (a)	Equipment Environmental Specifications							
	Product Operations (b)(c)					Product Power Off (c) (d)		
	Dry-Bulb Temperature (˚F) (e) (g)	Humidity Range, non-Condensing (h) (i)	Maximum Dew Point (˚F)	Maximum Elevation (f)	Maximum Rate of Change(˚F/hr) (f)	Dry-Bulb Temperature (˚F)	Relative Humidity (%)	Maximum Dew Point (˚F)
Recommended (Applies to all A classes; individual data centers can choose to expand this range based upon the analysis described in this document)								
A1 to A4	64.4 to 80.6	41.9°F DP to 60% RH and 59°F DP						
Allowable								
A1	59 to 89.6	20 to 80% RH	62.6	10,000	9/36	41 to 113	8 to 80	80.6
A2	50 to 95	20 to 80% RH	69.8	10,000	9/36	41 to 113	8 to 80	80.6
A3	41 to 104	10.4˚F DP & 8% RH to 85% RH	75.2	10,000	9/36	41 to 113	8 to 85	80.6
A4	41 to 113	10.4˚F DP & 8% RH to 90% RH	75.2	10,000	9/36	41 to 113	8 to 90	80.6
B	41 to 95	8% RH to 80% RH	82.4	10,000	NA	41 to 113	8 to 80	84.2
C	41 to 104	8% RH to 80% RH	82.4	10,000	NA	41 to 113	8 to 80	84.2

Air-Side Economization

ASHRAE recommendations to use air-side economization (ASE) partially or completely when ambient air conditions are favorable to reduce data center energy consumption. ASHRAE [3] defines air economizer as “a duct and damper arrangement and automatic control system that together allow a cooling system to supply outdoor air to reduce or eliminate the need for mechanical cooling during mild or cold weather.” In this method of cooling, outside air is drawn from the ambient air using fans or blowers and filtered for particulate contaminants as it passes through air filters before being introduced into cold aisle of a data center.

Use of ASE can significantly reduce the energy consumption of data center associated with cooling infrastructure. The main limitations of using this method of cooling data centers are that outside air needs to be within a specified temperature and humidity range and air contaminants, both particulate and gaseous, should be within manageable and acceptable ranges. These limitations result in ASE to be used for only few number of hours in a year. To increase the number of hours outside air can be used to cool data centers using compressor-less cooling system, direct evaporative cooling (DEC), indirect evaporative cooling (IEC), or two-stage indirect/direct evaporative cooling (I/DEC) system could be used.

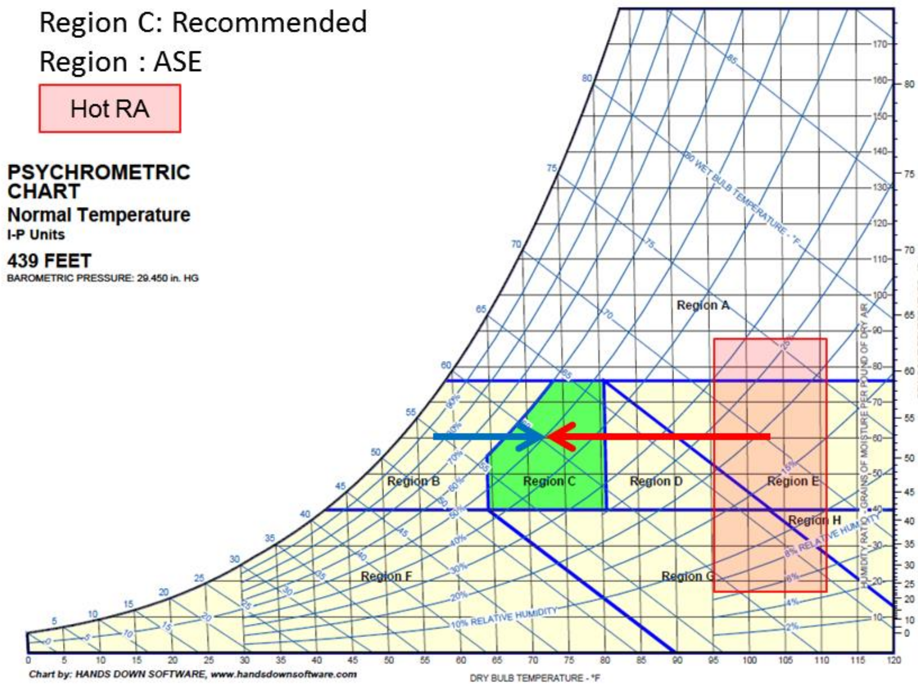


Figure 1-4 Air-side economization thermodynamic process

Modular Data Center

Modular data centers are containerized data centers or portable self-contained environment designed for rapid deployment, energy efficiency and better computing density. They are portable and can be deployed faster compared to a traditional one, at any given location in the world. They are self-sufficient modules consisting of thousands of systems built within a shipping container which houses all the necessary equipment, configured and shipped as a fully operational unit ready to be powered up. It requires power supply, internet access and chilled water supply upon delivery [7].

Scope of the work

The objectives of this work are as follows:

- Control Strategies for ASE, DEC, IEC and I/DEC on Test Bed Modular Data Center
    - Importance of designing control strategies and sequence of operations for DEC, IEC and I/DEC
    - Control optimization of I/DEC for test bed MDC
    - Maximize the use of DEC, IEC and I/DEC by using weather bin analysis ,DEC staging and predictive cooling
- Artificial Neural Network Approach for Energy Efficient Data Centers
    - ANN background and motivation
    - ANN models and their application

Layout

This thesis discusses the work carried out to accomplish the above-mentioned objectives in next two chapters. Importance of the control strategies for using I/DEC and its implementation on test bed modular data center located in Dallas, Texas is presented in chapter 2. This chapter also includes the applicability of staging of DEC, predictive cooling and weather bin analysis to maximize the use of ASE, DEC & I/DEC. Chapter 3 provides insight on the application of Artificial Neural Networks (ANN) in improving the performance of data centers. It details the various techniques used to model and predict the data center efficiency.

Chapter 2

Control Strategies for ASE, DEC, IEC and I/DEC on Test Bed Modular Data Center

Background and Motivation

As energy cost rise and the need to address climate change grows, energy efficiency becomes the a top criterion when designing the data center and cooling infrastructure . Looking at ways to increase the operational efficiency in data centers, energy efficient strategies for maintaining IT equipment within acceptable ranges for temperature and humidity is essential for efficient data center operation. Some of these strategies include use economizers depending on weather condition and system cooling capacity.

Water and air-side economization is prominent strategy for reducing energy consumption but its precise implementation is not generally known. Facebook's data center uses chiller-less air conditioning system that uses 100% outside air economization and evaporative cooling to maintain the operating envelop and have resulted in most energy efficient data center facilities [4] [5] [6]. However, dependability on ambient conditions has presented challenges to control the air handing system to work in tandem. Also, not having robust sequence of operation to account for rapid changes in ambient conditions can lead to humidity events such as condensation on power supply units and servers in data center.

This study discusses the importance and design of robust sequence of operation and recommendations for maximizing the use of DEC, IEC and I/DEC for test bed modular data center located in Dallas,Texas.

Thermodynamic Process for DEC, IEC and I/DEC

Psychrometric charts are used to simplify calculations dealing with air state changes. The following state changes are involved when conditioning air in heating, ventilation and cooling systems in air cooled data center.

- Mixing two volumes of air having different states
- Sensible heating/pre-heating
- Sensible cooling
- Adiabatic cooling/Humidifying air
- Dehumidifying/drying air

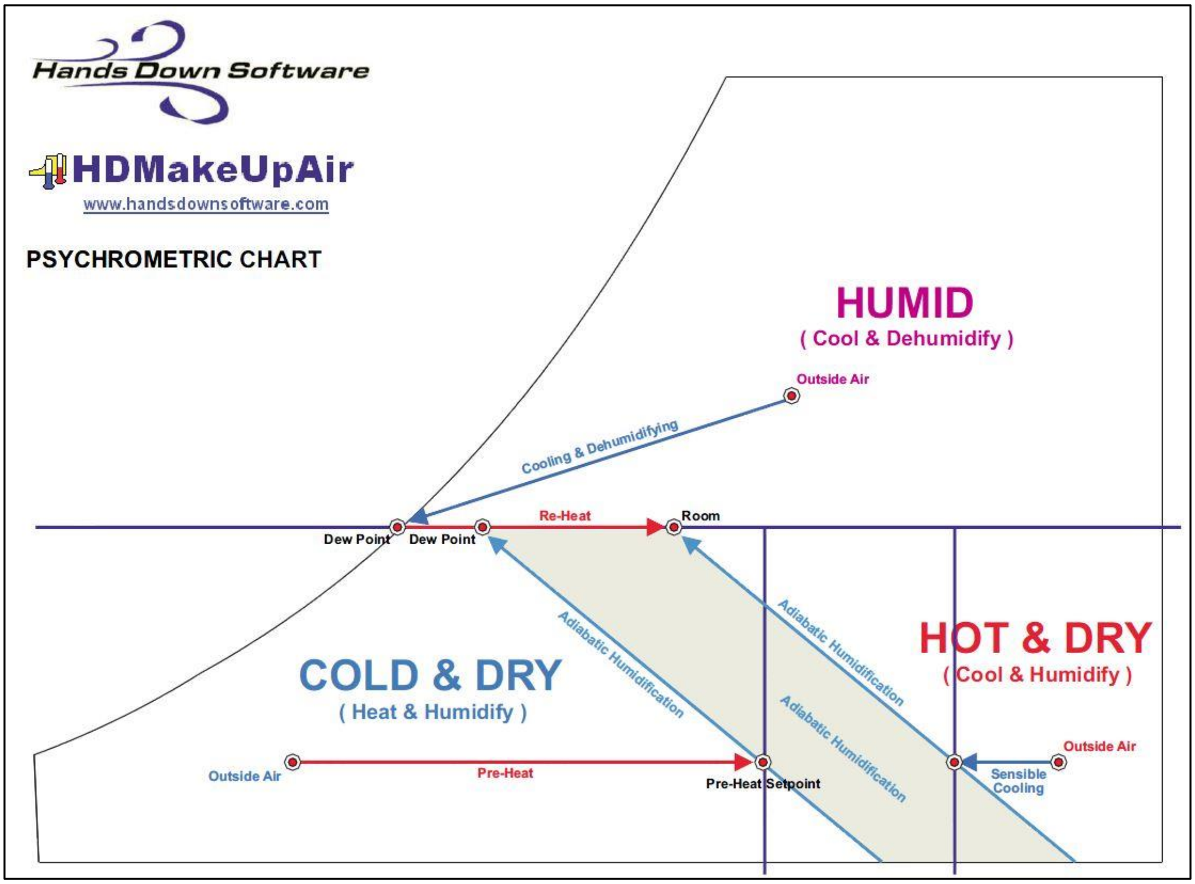


Figure 2-1 Thermodynamic Processes for DEC, IEC & I/DEC [17]

These thermodynamic processes are explained and shown in Figure 2-1. Psychrometric charts are either enthalpy (KJ/kg)-humidity ratio (g/kg) (or) temperature (K)-humidity ratio (g/kg). For temperature-humidity ratio graph, x-axis represent dry-bulb temperature and y-axis represents water content. Pre-heating (or) sensible heating of air is increasing the temperature of air without adding or removing moisture content. There are two possibilities for cooling the air. First, bring air in contact with a colder surface the temperature of air will drop depending on the heat exchanger property and dehumidification will take place if the temperature of cooling surface lies below the dew point temperature of air. Second, cooling air by adding moisture in the airflow. Mixing of two air streams with different properties will lie on the line connecting two states on psychrometric chart and the position of mixing point lies closer to the air state of the larger of the two mixed quantities [7].

DEC is a method of cooling warm air through direct contact of air and water. As warm air comes in contact with water, the warm air gives up its energy to evaporate the water in the form of latent heat of vaporization thereby decreasing the air temperature and increasing its humidity content. This method of cooling is also referred to as adiabatic cooling since the total energy content of the cooling system remains constant. In other words, wet bulb temperature of the conditioned air remains same as the warm. This process is shown on the psychrometric chart in Figure 2-2.

In IEC, there is no direct contact between data center supply air and water. This can be achieved by many possible configurations. One way of accomplishing IEC is to to blow data center supply air across a water-to-air cooling coil that has cold water flowing through it. The water leaving the coil, which is warmer than the inlet water temperature, is ducted to a cooling tower and dispersed on top of a DEC media. Cooling tower fan draws outside air across the DEC media thereby cooling the water flowing down the media. The cold water is collected at the bottom of the cooling tower and is pumped back into the cooling coil. Since there is no addition of water into the supply air, the specific humidity of the inlet air remains constant while the dry-bulb temperature decreases and the relative humidity increases as in Figure 2-3.

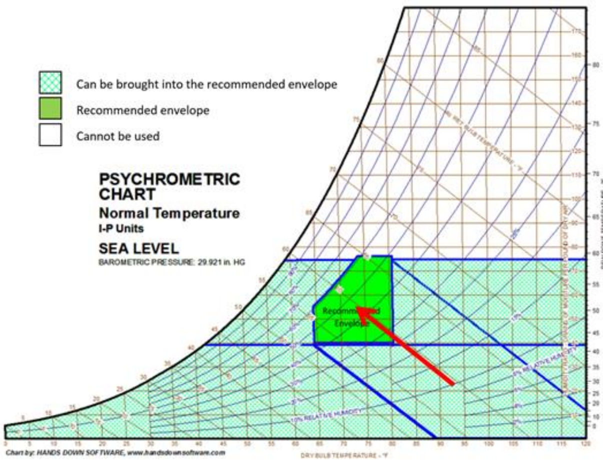


Figure 2-3 DEC Thermodynamic Process

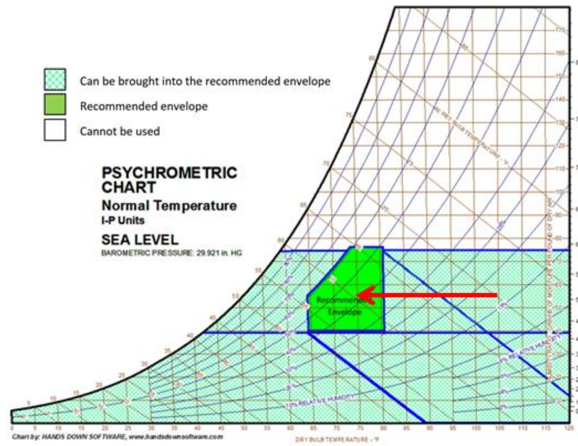


Figure 2-2 ICE Thermodynamic Process

Multi-stage I/DEC process allows for a wider range of ambient air conditions to be used for cooling data centers. In first step, IEC is used to decrease the dry bulb temperature of air stream by sensible cooling. In second step, this air stream is further adiabatically cooled by adding moisture. Multi-stage I/DEC is usefully in providing controlled conditioned air, where cooling is assisted by increase in moisture content as shown in Figure 2-4. This is important for data processing environments where air inlet condition is within specific range for reliable operation of ITE.

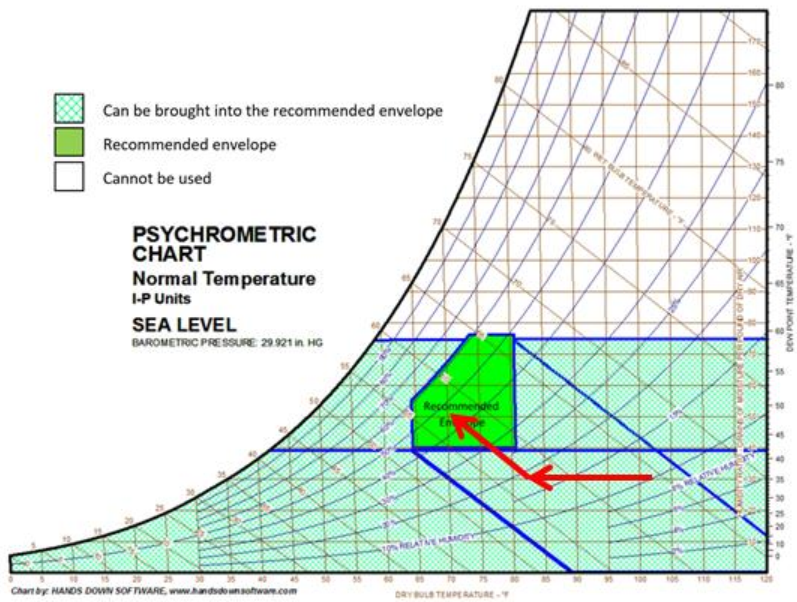


Figure 2-4 Multi Stage I/DEC Thermodynamic Process

To study use of ASE, DEC, and IEC for data center cooling applications, a modular data center has been built in Dallas, Texas. This data center is shown in Figure 2-5 and Figure 2-6. The IT pod, the schematic of which is shown in Figure 2-7, has two sections. Section 1 contains a workstation computer that is used for accessing servers stored in Section 2. Section 2 of the IT pod is configured in a hot/cold aisle configuration and contains four 42U Panduit P/N S6212BP cabinets. The cabinets contain a total of 120 HP SE1102 servers. Supply air from a cooling unit, Aztec Sensible Cooling Model ASC-15, is delivered to the cold aisle through a supply duct. Hot air from the hot aisle is ducted to be returned to the cooling unit or to be exhausted to the ambient as in Figure 2-6. The return duct has pressure relief dampers for pressure control.

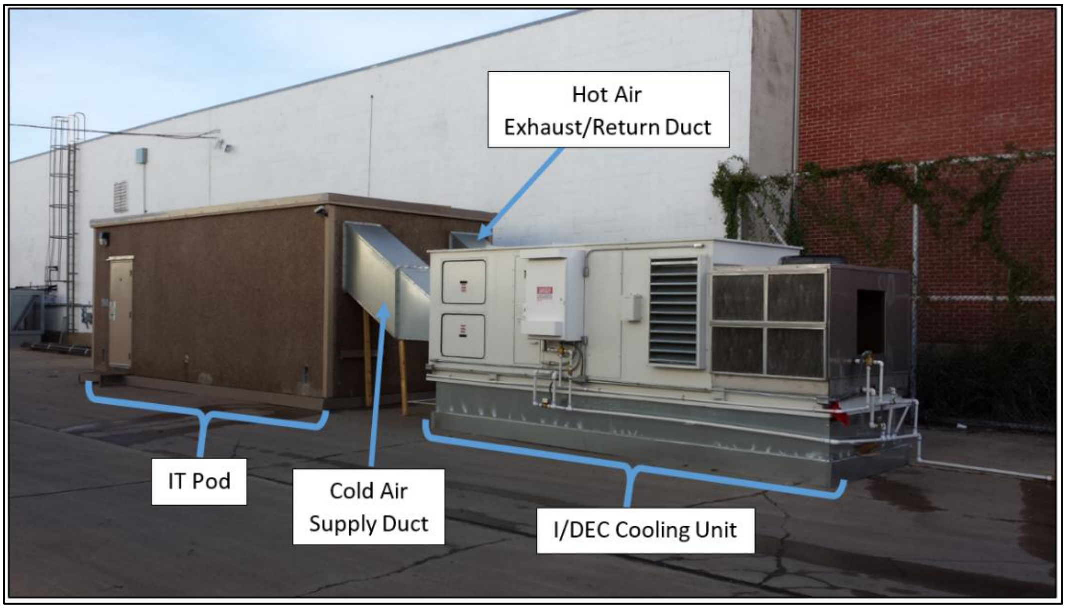


Figure 2-5 Modular Data Center: Shows Cold Air Supply Duct

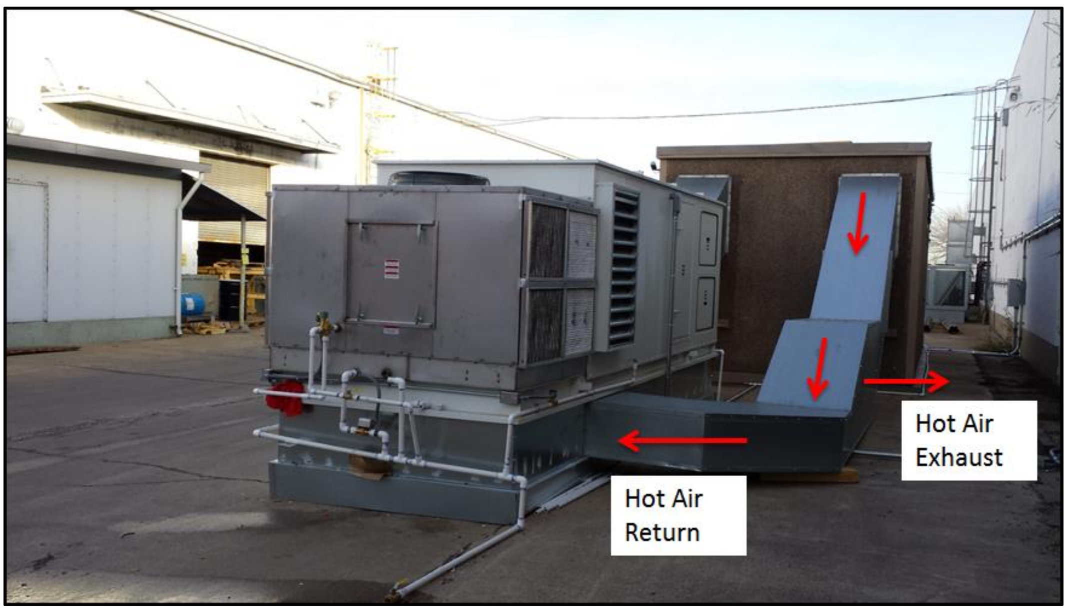


Figure 2-6 Modular Data Center: Shows Hot Data Center Return Duct

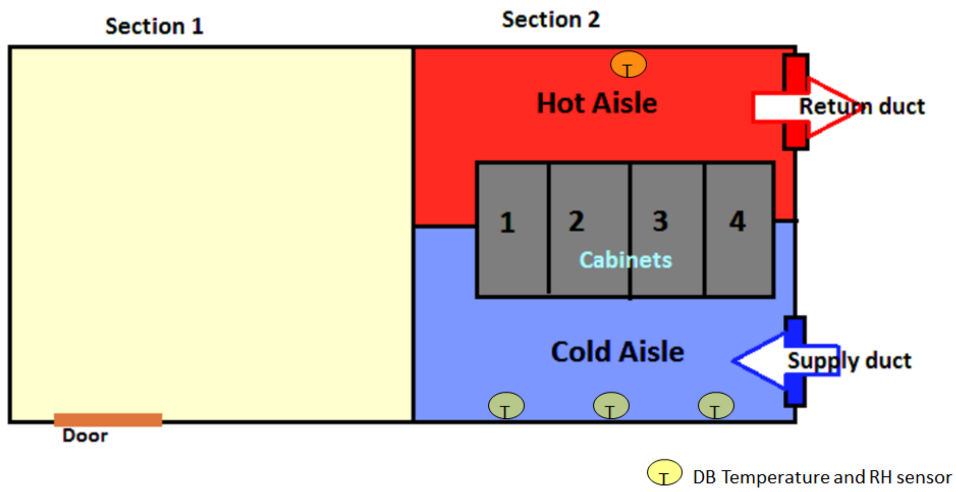


Figure 2-7Schematic of IT Pod and Sensor Location

The design of this cooling unit is shown in Figure 2-8. Outside air enters the mixing chamber through the motorized out air dampers. Position of return air motorized damper decides the proportion of return air to outside air in mixing chamber. The mixed air passes through the filter wall consist of MERV 11 filters. Mixed air first encounters the IEC coils which absorb sensible heat from air. DEC provides secondary cooling and humidification to the conditioned air when required as second stage. Multiple cooling stages are modulated based on the temperature and humidity of the supply air. Cooling tower facilities the cold water supply to IEC coils. Water leaving from coils is distributed on the DEC media and cooling tower fan draws outside air across the DEC media resulting in evaporation and cooling of water flowing down the media.

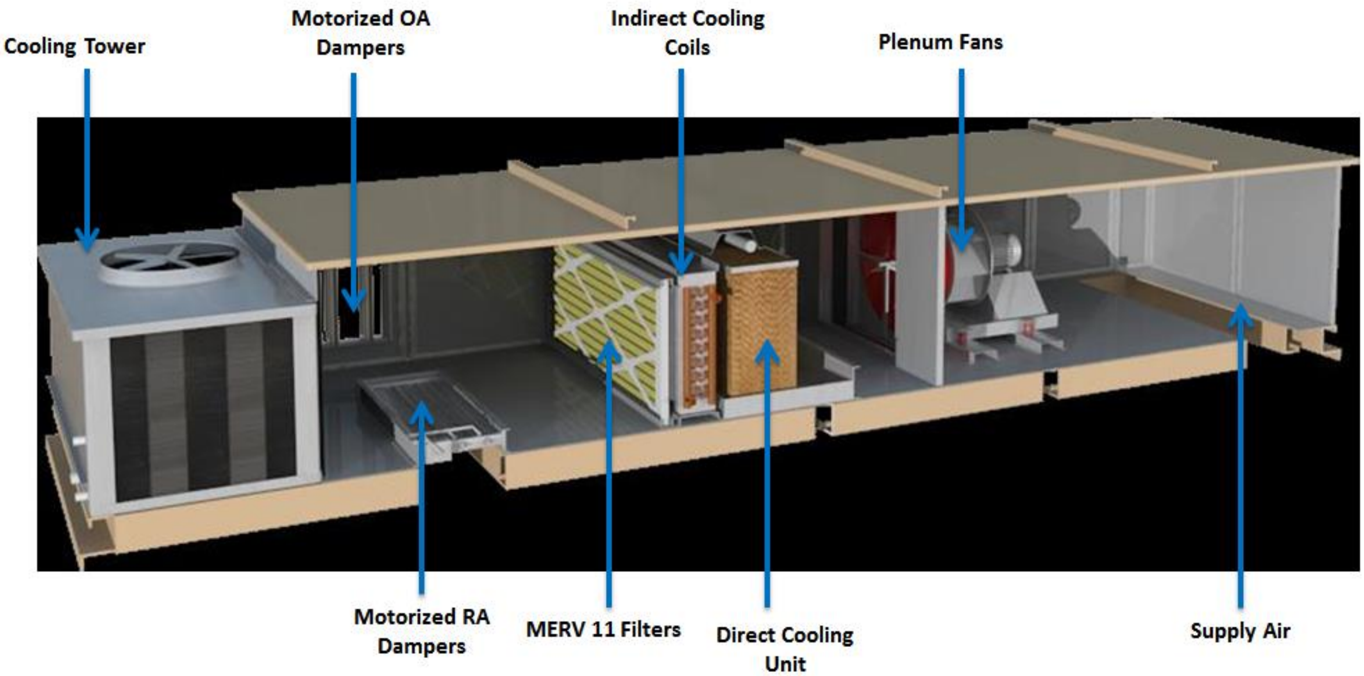


Figure 2-8 Internal Configuration of Cooling Unit

The test bed modular data center is equipped with various sensors such as temperature, humidity, static pressure, et cetera which are used for controlling the cooling unit's blower speed, DEC water pump on/off state, et cetera. This modular data center is equipped with WebCTRL Building Automation System and all the sensor data is available through a webpage dedicated to this test bed modular data center. Figure 2-9 shows a sample of the data that can be obtained from the webpage. This test unit is monitored for the water and power performance 24x7 and performance data is recorded for analysis. Control program is designed for measuring the power consumed by each equipment and also the state of operation of unit showing economizer hours for each month.

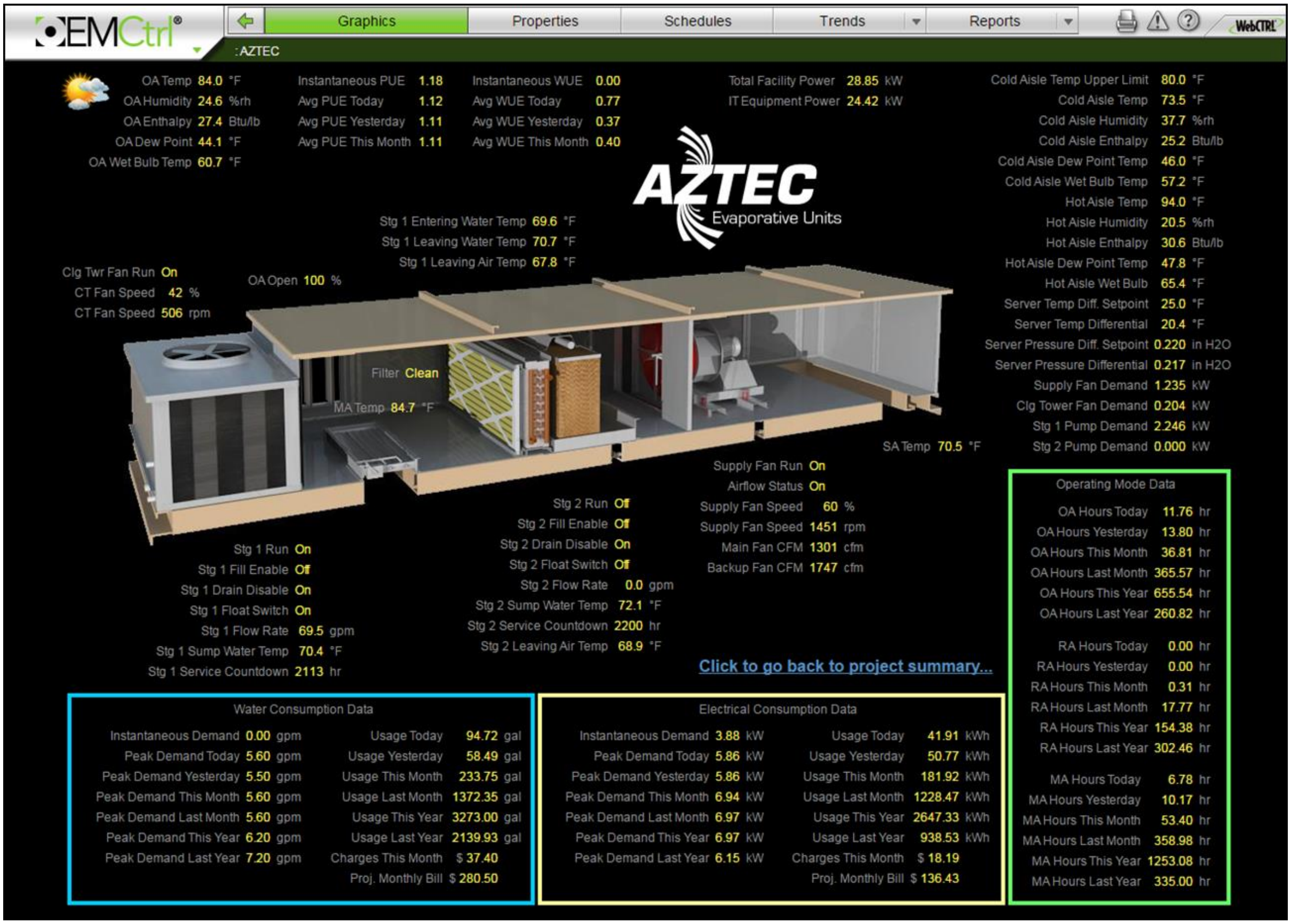


Figure 2-9 Webpage of BAS showing real time data for Research MDC

Control Strategies for Test Bed Modular Data Center

The total IT load in the test bed modular data center fluctuates between 15KW to 25KW depending on the server utilization workload. The primary objective of the test bed MDC is to study the applicability of evaporative cooling, including ASE, for a location such as Dallas, TX. The cooling unit installed has enough cooling capacity to maintain cold aisle at a targeted envelope of temperature and humidity set points. The cooling unit shall utilize outside air when favorable and activate DEC or I/DEC when further cooling is necessary to always maintain the CA at required operating set points. The outside air conditions play an important role in determining the economizer mode of the cooling unit. Typical Meteorological Year weather data for Dallas-Love field weather station is considered to further understand the regional outside air conditions the MDC will operate in for a typical year. Figure shows the hourly weather data for Dallas-Love Field region is plotted on psychrometric chart. Each point represents the weather condition of an hour in a year.

Recommended environmental envelopes for ITE published by ASHRAE and capability of the cooling technologies installed in test bed MDC are used to divide the psychrometric chart into different regions. Region C represents the ASHRAE recommended environmental envelop which is also the target supply air condition to be achieved by I/DEC. Considering the range of ITE load variation and supply air condition, the range of hot air/return air (RA) in hot aisle is indicated by red block in Figure 2-10 . Thermodynamic processes involved in efficiently achieving the target state from the ambient air condition in different regions are discussed in detail in this study. Ambient air

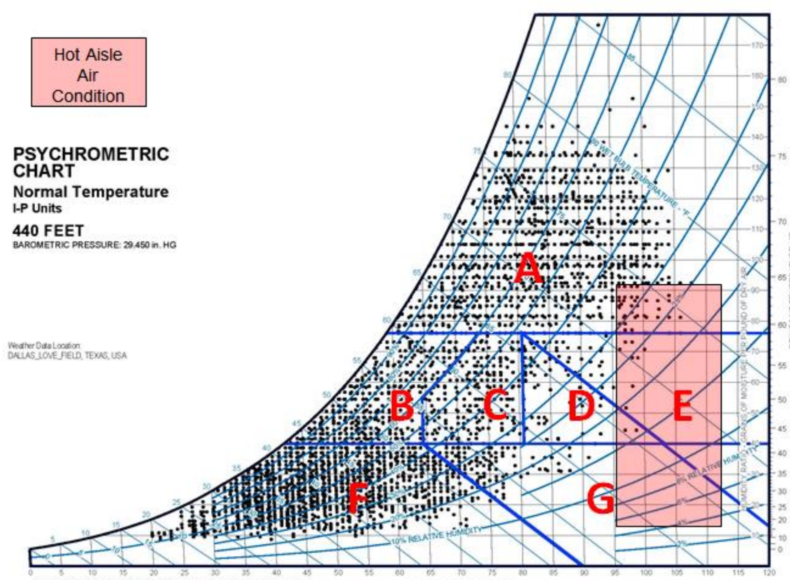


Figure 2-10 Dallas Love Field

condition directly affects the response of cooling unit to the ITE load. So it is required to have control strategies and sequence of operation that will smartly switch between the available cooling methods maximizing the economizer hours to reduce the overall operational cost while maintaining the stable ITE environment.

Sequence of Operation

The psychrometric chart is divided into seven distinct operational regions as in Figure which covers typical yearly weather conditions. The sequence in which this I/DEC unit responds to the ambient condition while in these regions is as follows:

- Zone F (< 41.9^0 F DP and < 52^0 F WB): When OA conditions lie within this region, economizer mixes OA/RA to control MA to 65^0 F minimum and relative humidity (RH) is maintained above 20%. Humidification is not provided in this region due to risk of excessive drop in DB temperature and increase in RH, resulting in condensation. Cold aisle is maintained at 65^0 F and above 20% RH as in Figure 2-11

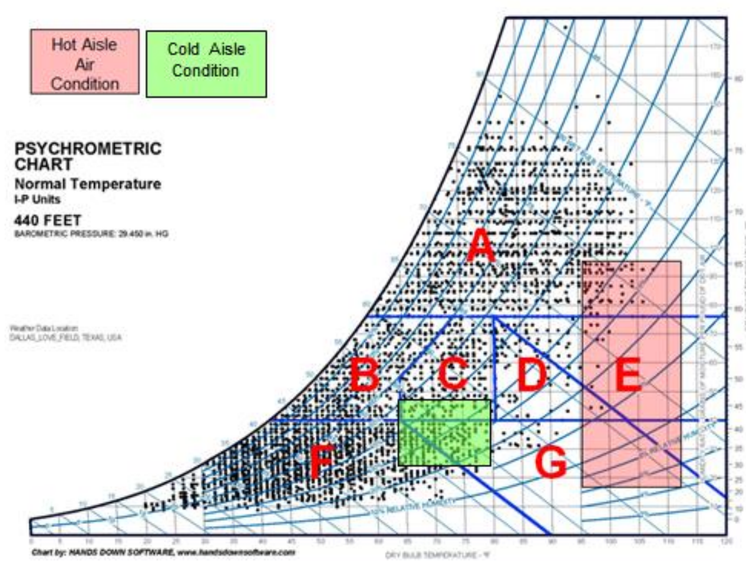


Figure 2-11 Cold Aisle Condition for Zone F & G

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

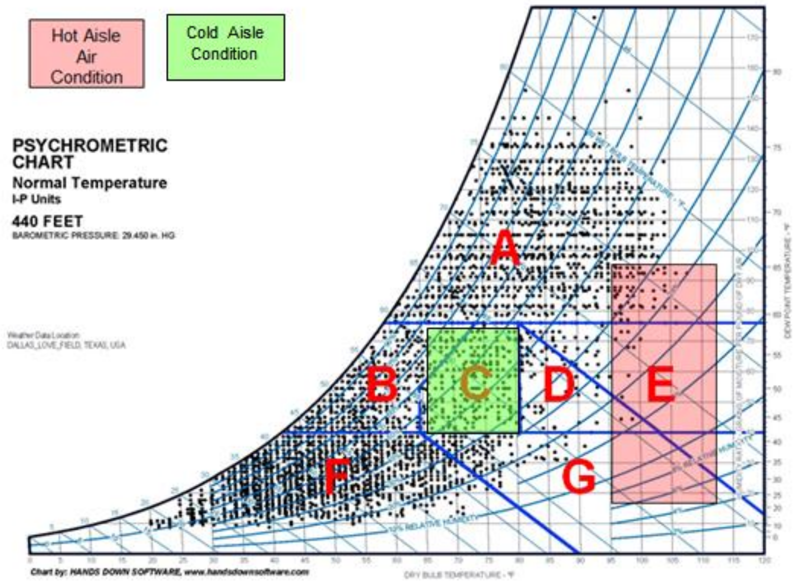


Figure 2-12 Cold Aisle Condition for Zone D, B, C and E

- Zone E(> 80^0 F DB & > 41.9^0 F DP & < 59^0 F DP & > 65.76^0 WB): This region demands 100% OA till dry bulb temperature of OA less than 95^0 F. Unit will switch to either 100% OA or 100% RA depending on the DB whichever is lower. Indirect evaporative cooling provides required sensible cooling to maintain SA temperature between 75^0 & 80^0 F DB. Dew point temperature is maintained within 41.9^0 and 59^0 F.
- Zone A (> 59^0 F DP): Economizer mixes OA/RA to decrease Mixed Air RH to 70 % and maximum cold aisle temperature to 80^o F DB. Unit will switch to 100% RA when Cold Aisle RH shoots above 70 %. Dew point temperature is higher than 59^o F DP for maximum number of hours. Unit will function to maintain the cold aisle is allowable A1 zone as in Figure 2-13

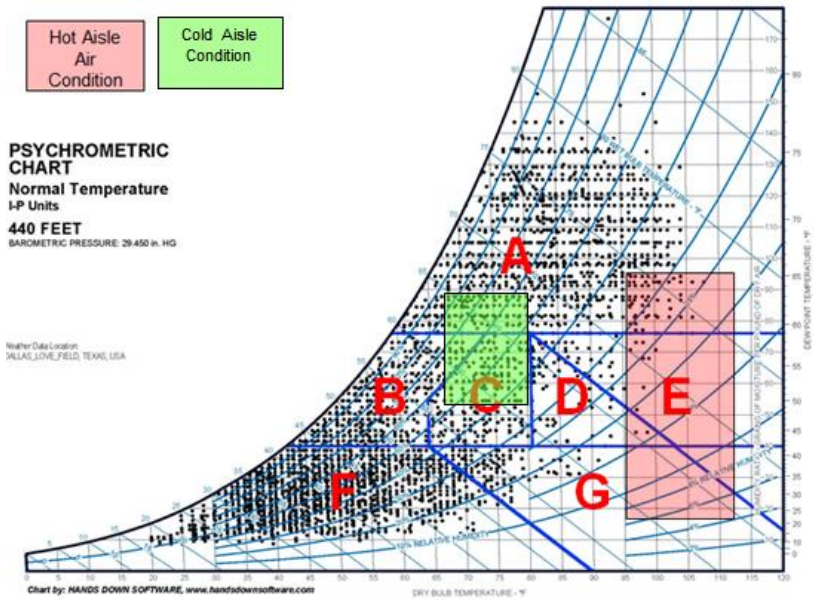


Figure 2-13 Cold Aisle Condition for Zone A

Results and Discussions

Implications of Current Control Strategies

The control strategies and sequence of operation discussed in previous chapter maintains the best possible cold aisle conditions either in ASHRAE recommended or allowable A1 zone. Current set up of cooling unit gives control on IEC but not DEC. DEC cannot provided controlled cooling in this configuration and only runs on 100% outside air to avoid the risk of sudden increase in RH.

Limitations of this cooling configuration will risk ITE operation in zone A and zone G for extended period of time. Operating in Zone A i.e. at higher relative humidity will increase the chances of condensation on the ITE and power supply components leading to failure. In zone G further humidification control would be necessary to alleviate concerns regarding Electrostatic discharge at lower humidity levels.

Recommendations in design and analysis are proposed that can maximize the use of ASE, DEC and IEC and overcome the above mentioned issues.

Staging and Control of DEC

The amount of moisture added to a system can be controlled by frequently modulating the water supply to the media. However, this method results in scale and mineral build up on the media. Segmented cooling or staged cooling can be a potential solution. These systems allow some section of the media to be wetted while other sections remain dry. Figure 2-14, Figure 2-15, and Figure 2-16 show three ways to have staged DEC system [8].

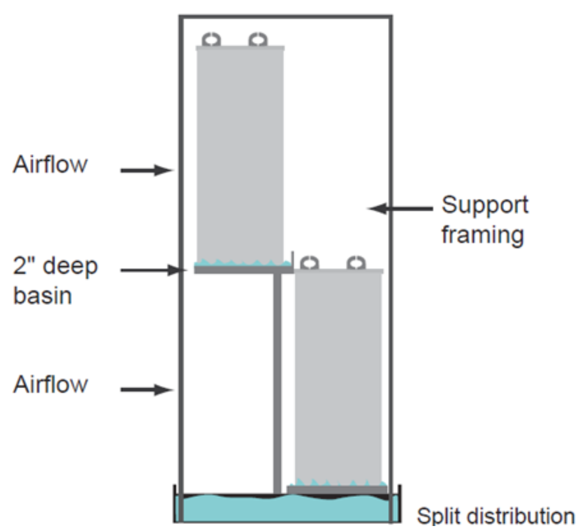


Figure 2-14 Horizontally split distribution [8]

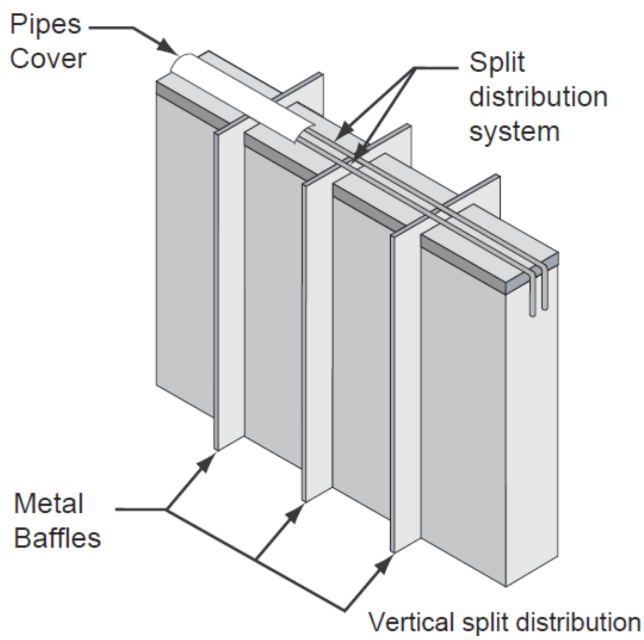


Figure 2-15 Vertically Split distribution CITE

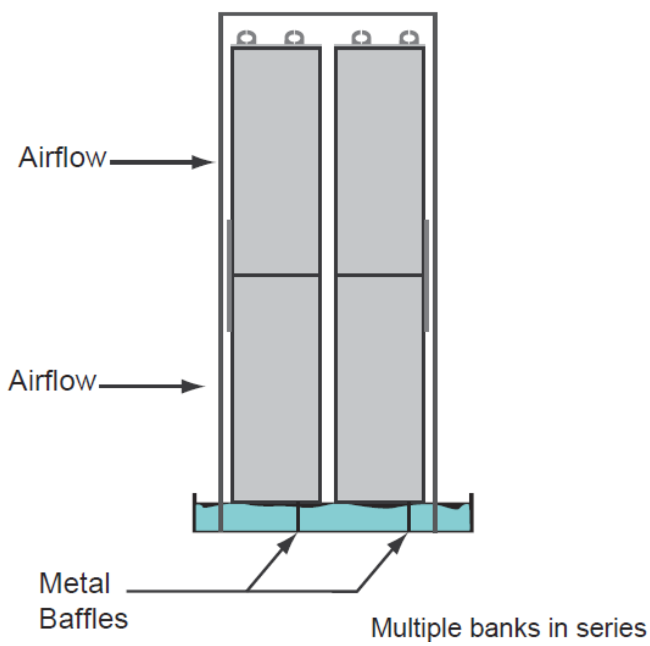


Figure 2-16 Multiple banks in series

Comparison of single and four stage DEC

Consider a 12” deep GlassDek rigid media with face area 16 square feet having 94% saturation efficiency at 4000 cfm. Inlet air conditions are 83^0 F DB and 58^0 F WB and leaving air conditions are 59.9^0 F DB and 58^0 F WB calculated by saturation effectiveness equation expressed as:

$$\epsilon_e = 100\ \frac{t_1 - t_2}{t_1 - t'}$$

where

ϵ_e = saturation effectiveness,%

t_1 = dry-bulb temperature of entering air, °F

t_2 = dry-bulb temperature of leaving air, °F

t' = thermodynamic wet-bulb temperature of entering air, °F

Figure 2-17 shows this process on psychrometric chart with leaving air condition outside ASHRAE recommended envelop.

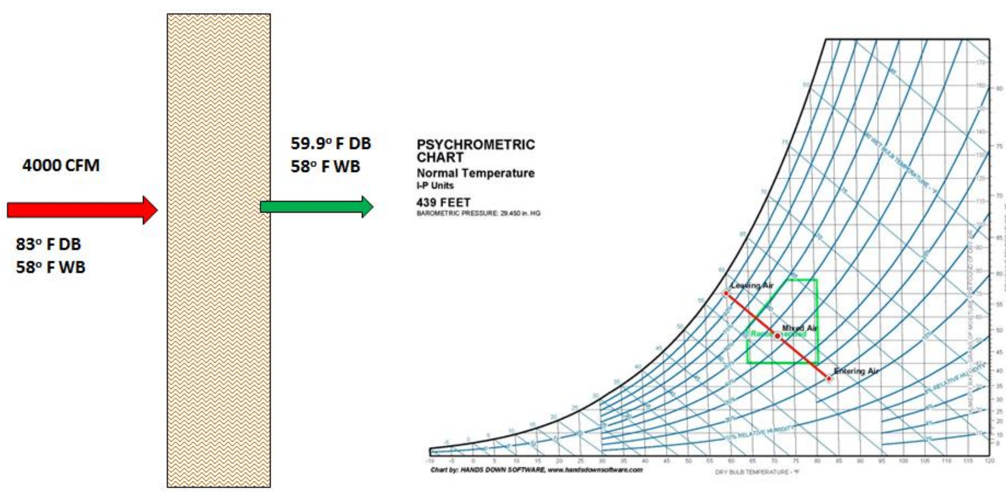


Figure 2-17 Thermodynamic Process for Single Stage DEC

Similar conditions are assumed for four stage DEC system with equal section. These four stages can be turned on /off and fan mixes both the streams of air as in Figure 2-18. Results for one stage on and two stages on are shown in Figure 2-20 and Figure 2-19 on psychrometric chart respectively.

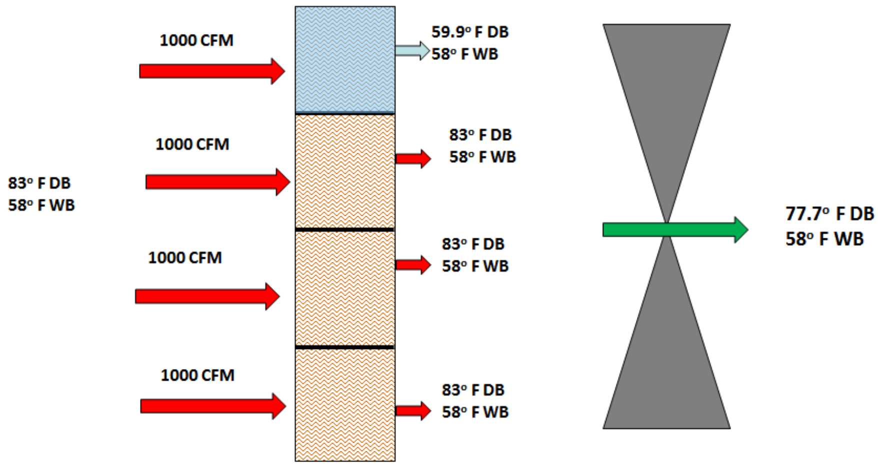


Figure 2-18 Four stage DEC

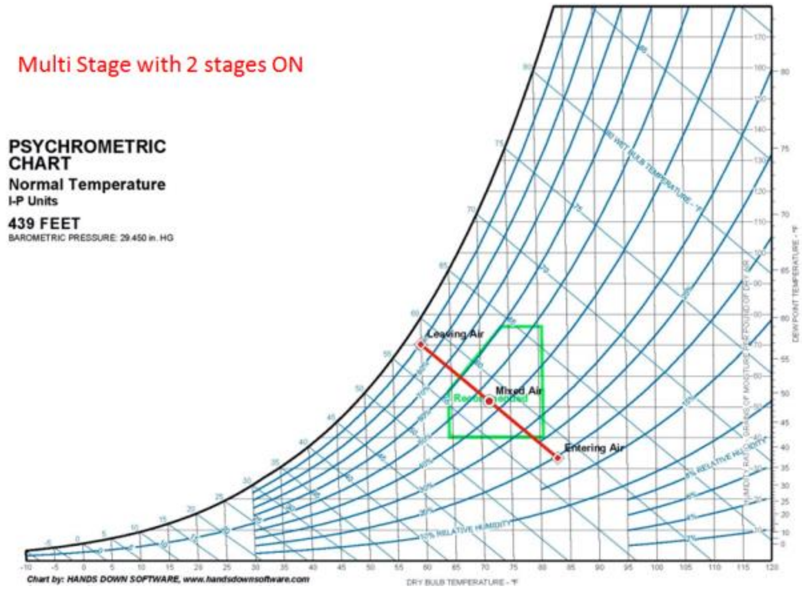


Figure 2-19 Thermodynamic Process: Multi Stage with 2 Stages ON

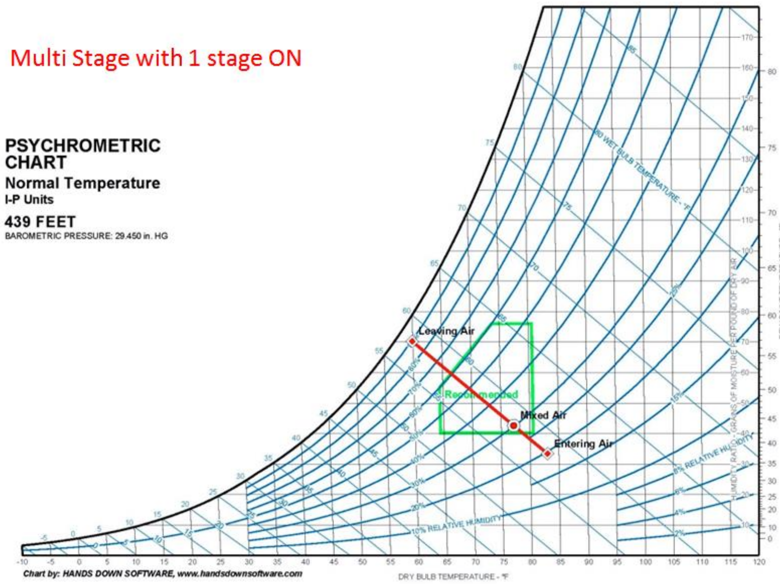


Figure 2-20 Thermodynamic Process: Multi Stage with 1 Stage ON

Predictive cooling

Predictive cooling is a control strategy with constant monitoring of weather forecast and the state of data center operation to proactively facilitate the cooling infrastructure in maintaining stable data center environment. Weather Station with accurate forecast and control logic to check the DC state will facilitate predictive cooling.

Case Study: Importance of predictive cooling for IEC

When there is sudden increase in outside air temperature, which cooling module cannot anticipate and continue operating in normal sequence turning ON IEC when set point is reached. IEC will deliver cooling when Cooling Tower (CT) water is charged. It takes approximately 25 minutes for CT to charge water when OA temp is 89^0 F as in Figure 2-21. Predictive Cooling can avoid this shift in CA temp with proactively turning ON Cooling Tower when weather forecasts increase in temperature.

Similarly, when OA temp and RH is above 75^0 F & 70% respectively, 100% RA is used and IEC mode is switched ON. With change in outside air humidity i.e. raining for extended period of time, unit can no longer takes advantage of fresh outside air as relative humidity is high. Unit will end up running at higher dew point temp (A1 or A2

Allowable Zone). If this condition prevails for extended duration, may result in condensation in cold aisle. Predictive cooling can anticipate any such abnormal behavior in ambient conditions and alert the normal sequence of operation.

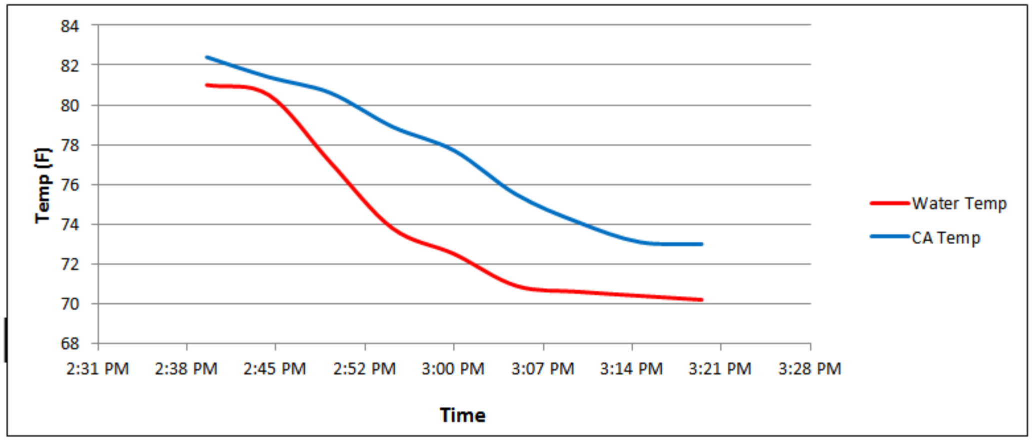


Figure 2-21 Cooling Tower Water Charging Time

Yearly Vs Monthly Weather Bin Data Analysis

To estimate number of hours a given data center could use ASE, DEC, and IEC, weather data of the data center’s location needs to be analyzed. This analysis is further used in selecting the cooling technologies that could best with in that weather condition in providing continues and required performance.Two sets of regions are prepared based on the recommended and Class A1 allowable envelopes as defined in 2011 ASHRAE Thermal Guidelines [9]. Figure 2-22 and Figure 2-23 show the Typical Meteorological Year 3 (TMY3) data for Dallas Love Field plotted on with percentage of TMY3 data hours in each defined region.

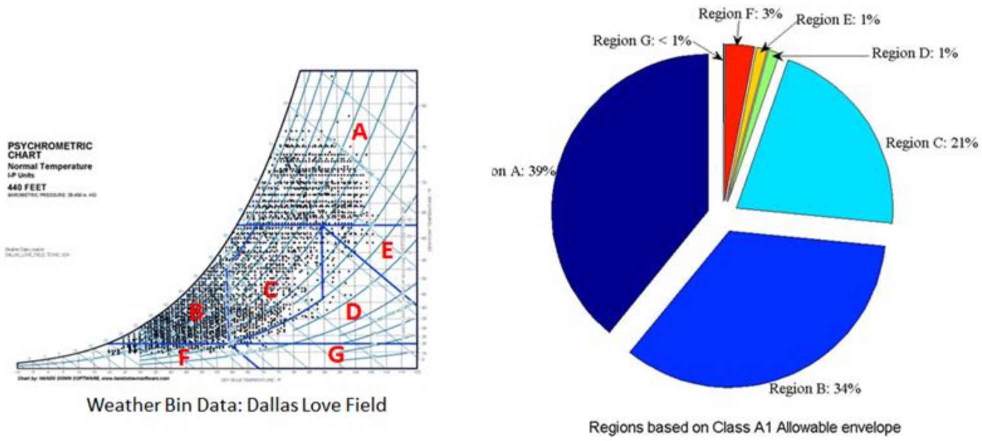


Figure 2-22 Percentages of TMY3 hourly weather data in each region for ASHRAE Allowable A1

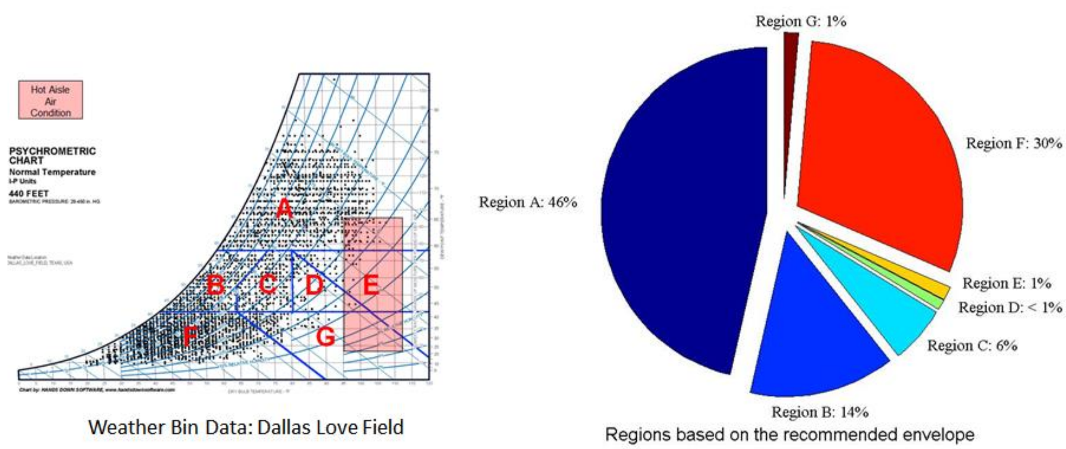
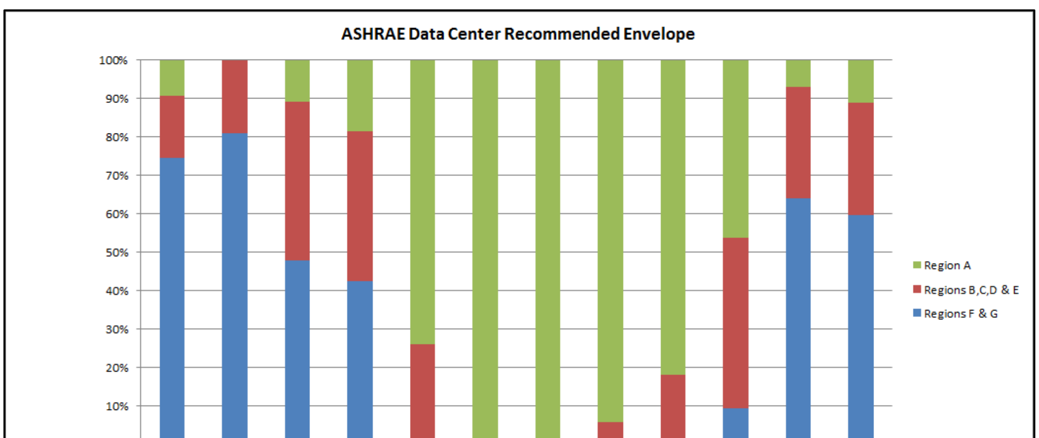


Figure 2-23 Percentages of TMY3 hourly weather data in each region for ASHRAE Recommended Envelope

Estimated percentage of hours that fall in region A for both ASHRAE recommended and allowable A1 envelop for which data center cannot use ASE are 46% and 39% respectively. These percentages when divided in each month gives a clear picture of exact duration where ITE operates outside defined operating envelops. Such analysis is presented in Figure 2-24 & Figure 2-25. Region A above the dew point of operating envelop where ASE, DEC and IEC cannot be used. Regions B, C, D and E which lie between the dew point bounds of operating envelop and Regions F and G which lie below the minimum operating dew point.

Detailed analysis of weather data for the regions where data centers are located will assist in application of the best practices and recommendations for lower the operational costs by maximizing the use of air and water-side economizers



	January	February	March	April	May	June	July	August	September	October	November	December
Region A	9.4%	0.0%	10.8%	17.9%	73.9%	95.3%	99.6%	94.2%	79.2%	46.4%	6.7%	11.0%
Regions B,C,D & E	16.0%	17.2%	41.5%	37.8%	25.1%	1.5%	0.4%	5.8%	17.6%	44.2%	28.1%	29.4%
Regions F & G	74.6%	73.1%	47.7%	41.1%	0.9%	0.0%	0.0%	0.0%	0.0%	9.4%	61.8%	59.7%

Figure 2-24 Percentages of TMY3 hourly weather data sorted into regions for ASHRAE recommended envelop for each month based on dew point bounds

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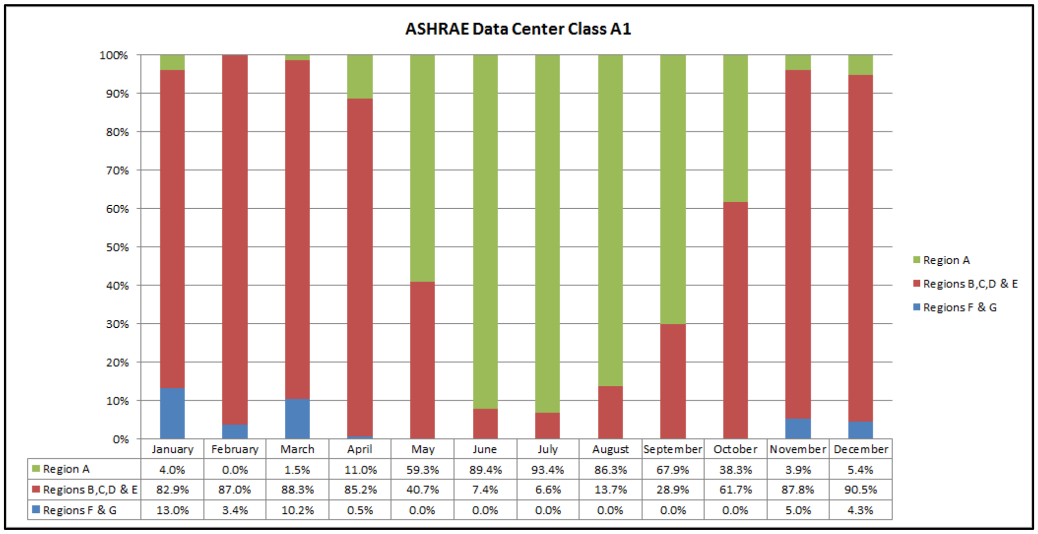

	January	February	March	April	May	June	July	August	September	October	November	December
Region A	4.0%	0.0%	1.5%	11.0%	59.3%	89.4%	93.4%	86.3%	67.9%	38.3%	3.9%	5.4%
Regions B,C,D & E	82.9%	87.0%	88.3%	85.2%	40.7%	7.4%	6.6%	13.7%	28.9%	61.7%	87.8%	90.5%
Regions F & G	13.0%	3.4%	10.2%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.0%	4.3%

Figure 2-25 Percentages of TMY3 hourly weather data sorted into regions for ASHRAE Allowable A1 envelop for each month based on dew point bounds

Chapter 3

Artificial Neural Network Applications for Energy Efficient Data Centers

Introduction

Data centers have become the backbone of modern society with the widespread availability of internet and use of internet-enabled devices. Services that involve emails, online purchases, video streaming, digital bank transactions et cetera rely on presence of data centers for saving, accessing, protecting and sharing data. Advancement in computational and informational technology, improvements in hardware affordability and growth in Big Data have resulted in the accelerated rise of large scale data centers as well as modular data centers and their corresponding operational challenges.

Data centers strive for 24/7/365 operation with 100% up-time. Electricity used in 2010 by global data centers was estimated to be between 1.1% and 1.5% of total electricity use and for the US this number was between 1.7% and 2.2% [9]. Due to low demand/supply ratio of electricity production, growing energy costs and environmental responsibility have put the DC industry under pressure of increasing its operational efficiency. One of the most difficult challenges is power management. At this scale, even small efficiency improvements yield significant cost savings and avoid tons of carbon emissions.

Power usage effectiveness (PUE™) has become the industry-preferred metric for measuring infrastructure energy efficiency for data centers [10]. The PUE metric is an end-user tool that helps boost energy efficiency in data center operations. PUE is defined as the ratio of total facility energy to IT equipment energy. Google Inc. and other major internet companies have made noteworthy efforts towards improving their data center efficiency but due to the limitations of existing cooling technology, pace of PUE reduction has reached a plateau[11]. Furthermore, best practices techniques such as hot/cold air containment, better heat exchanger designs, application of evaporative cooling, active load scheduling, Waste Heat Recovery, extensive monitoring et cetera are now commonplace in large data centers to improve efficiency. Figure 3-1 demonstrates the PUE performance of Google Inc. large scale data centers from 2008 to 2013 showing continues improvements due to adaptation of best practices and cooling technology. But the asymptotic decline of the trailing twelve-month PUE graph indicates the need to dig deep into new methods to further improve data center performance.

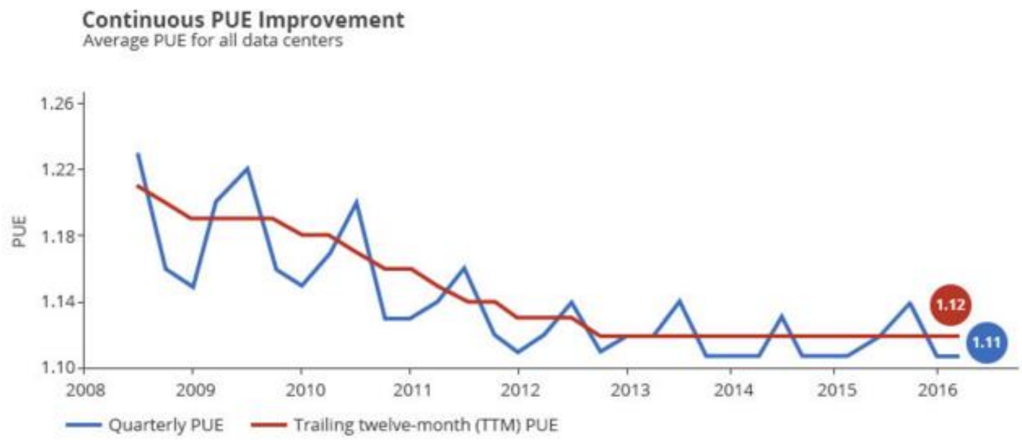

Figure 3-1 PUE data for all large scale Google data center [19]

Methodology

General background

Large and modular data centers are a dynamic and complex environment with multiple mechanical and electrical control systems aimed at maintaining operation of data center. Highly nonlinear correlations and multiple operating configurations create challenges to optimize the operation of the data center and accurately predict efficiency using standard formulas. A simple change in one set point will result in load variations in the cooling infrastructure which in turn causes nonlinear changes in overall efficiency. The sheer number of possible equipment combinations and their set points makes it difficult to determine where the optimal efficiency lies. It is possible to meet the target set points through multiple combinations. Parametric testing of different possible combination to improve efficiency would be unfeasible given time constraints, fluctuations in IT load and ambient conditions while maintaining a stable data center environment.

Development of efficient control system can significantly reduce data center power footprint. Control algorithms and controllers need to be smart, fast, adaptive and dynamic to control highly non-linear data center environment. Computational Fluid Dynamics (CFD) is used currently to model data centers and simulate their response to certain operating conditions. CFD is not only expensive to model but also requires expertise and takes considerably long time to converge to a steady state causing loss of productive time and resources. As stated earlier, data center environment is highly intricate and dynamic and even a minute change in the input parameters will result in significant system response. Hence performing continuous parametric CFD simulation to mimic data center behavior is not a realistic solution.

Machine learning algorithms have been around for a long time and haven been effectively used for pattern recognition and data manipulation. Artificial neural networks (ANN) are essentially a class of machine learning computer algorithms that can recognize patterns and then make decisions based on those patterns. We aim to use ANN with existing monitoring data to mimic the data center behavior via interactions between artificial neurons. ANN can learn from actual operation of DC to model the plant performance by searching for patterns and interaction between features to generate best fit model. This data driven model of data center can learn by crunching the data over and over again during real time operation to create a robust model which provides opportunity to significantly improve operational performance.

Artificial Neural Network

An Artificial Neural Network (ANN) is an information processing system that is inspired by the way biological nervous systems, such as the brain. Just as in biological nervous system, it is composed of a large number of highly interconnected processing elements called neurons. These neurons work in unison to solve a specific problem and its function is highly dependent on the connections between these elements. In the nervous system, learning is achieved through precise tunings to the synaptic connections between neurons. Similarly in the artificial neural networks, we train ANN to perform a particular function by adjusting the values of weights between the elements [12], [13].

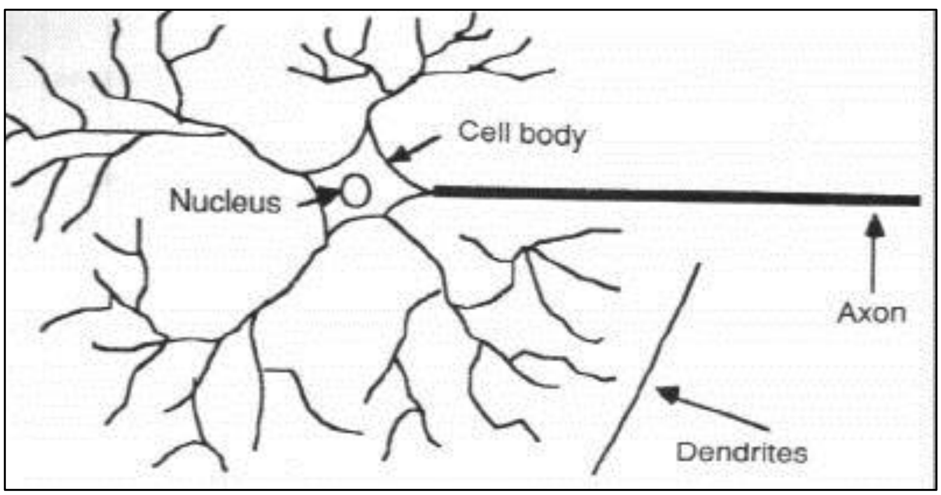

Figure 3-2 Components of Biological Neurons

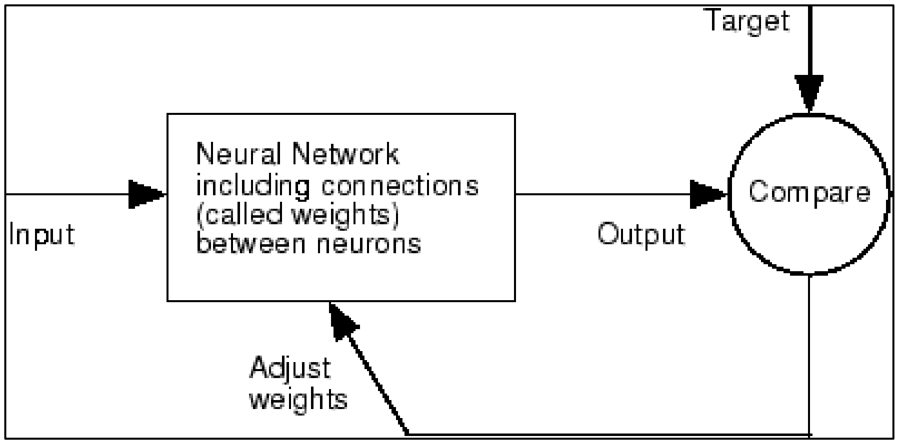

Figure 3-3 ANN working concept

Usually, neural networks are trained, so that a particular input leads to a particular target output. The Figure 3-3 illustrates such a situation. Here, the network is trained, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target pairs are needed to train a network. ANN has the capacity to learn from the training data and model relationships between the inputs and the outputs of any level of complexity. Complex tasks like modeling, approximations, classification and optimization can be accomplished by ANN application. They have been proven to be very efficient in approximation of nonlinear function with a high degree of accuracy.

Neuron Model

The fundamental building block for neural networks is the single-input neuron as in figure There are three separate functional operations that define the functioning of neural networks. First, the scalar input p is multiplied by the scalar weight w to form the product wp. Second, the weighted input wp is added to the scalar bias b to form the net input n. Finally, the net input is passed through the transfer function *f*, which produces the output *a*.

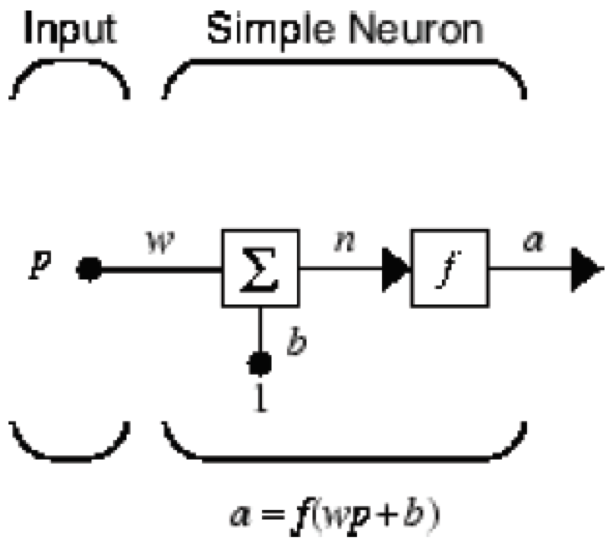

Figure 3-4 Simple Neuron Model [14]

Neural Network Design

The work flow for a general Artificial Neural Network design has been categorized into following steps. These steps cover the development of the ANN to its execution, validation and deployment [14]. The steps are:

1. Collect data
2. Create the network
3. Configure the network
4. Initialize the weights and biases
5. Train the network
6. Validate the network (post-training analysis)
7. Use the network

Dynamic Neural Networks

Artificial Neural Networks can be categorized into static and dynamic. Static feedforward network are the ones with no delays and feedback elements; feedforward connections gives the output from input directly.

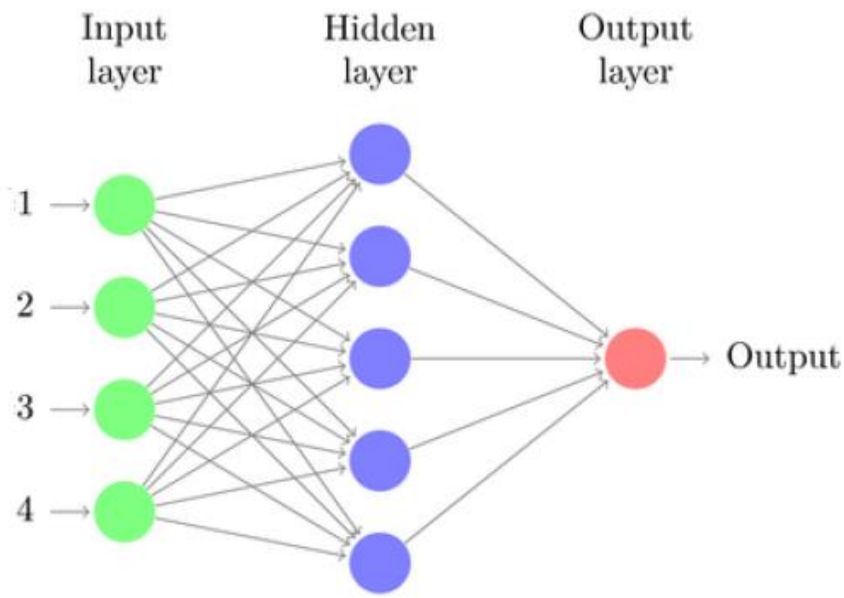

Figure 3-5 Feedforward Neural Network

In Dynamic neural networks, the output depends not only on the current input to the network, but also on the current or past inputs, outputs or the states of the network. Dynamic neural networks are more powerful than static networks due to their ability to store previous states. These networks can be trained to learn time varying patterns, suitable for data center dynamics. One principal application of dynamic networks is in control systems, where it can predict the behavior of system with past and current state.

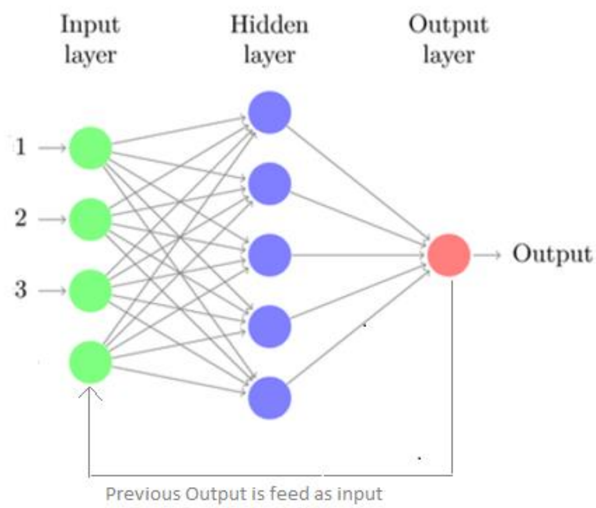

Figure 3-6 Dynamic Recurrent Neural Network

NARX Feedback Neural Networks

Most commonly used dynamic networks are focused networks with the dynamics only at the input layer or feedforward networks. The Nonlinear Autoregressive Network with Exogenous Inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The equation that defines the NARX model is $y(t) = f(y(t-1), y(t-2), \ldots, y(t-ny), u(t-1), u(t-2), \ldots, u(t-nu))$ where the next value of the dependent output y(t) is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal [14].

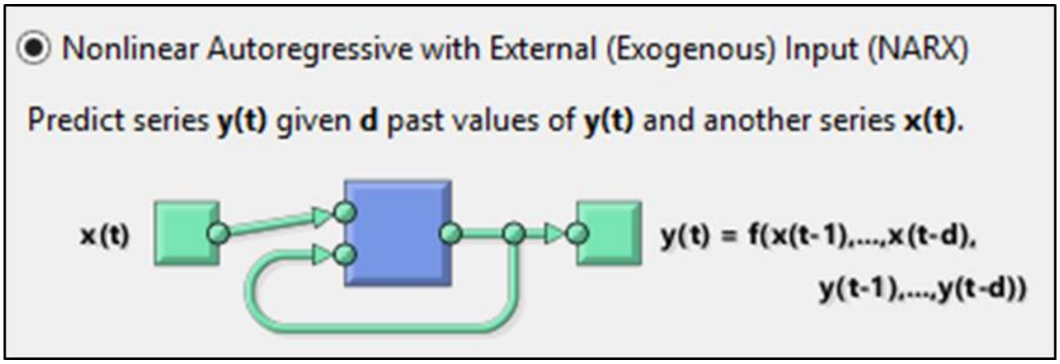

Figure 3-7 Nonlinear Autoregressive with External Input (NARX) [14]

NARX Network Architecture

There are two configurations of NARX network that are very useful in training are implemented in present study.

1. Series-Parallel Architecture
2. Parallel Architecture

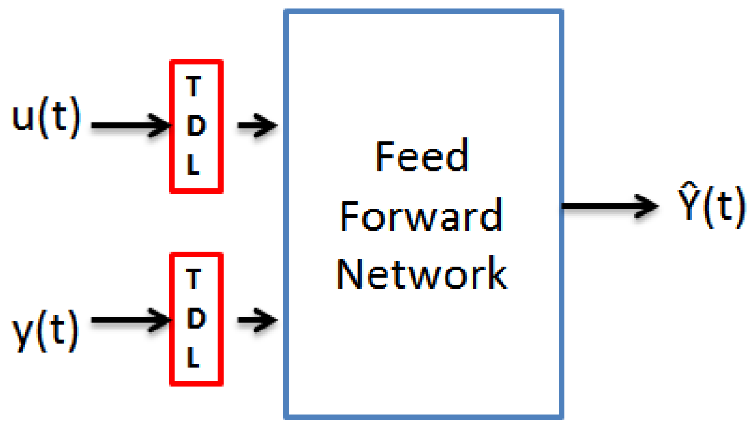

Figure 3-8 Series-Parallel Architecture

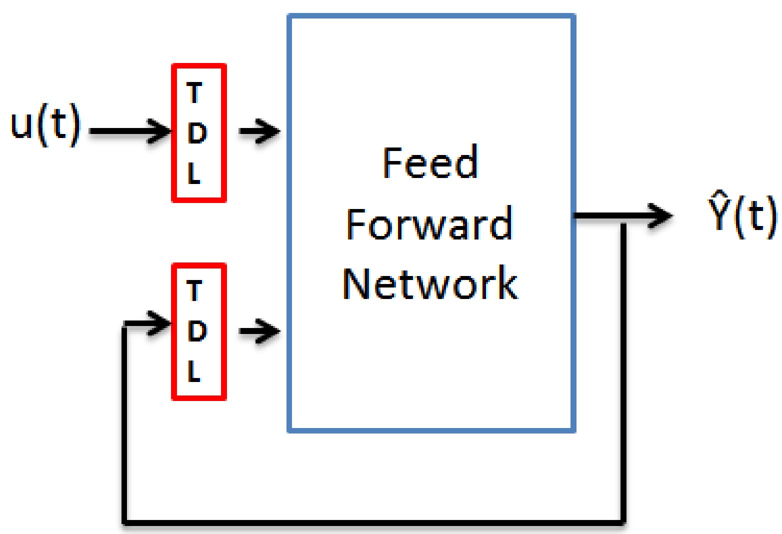

Figure 3-9 Parallel Architecture

The output of the NARX network is an estimate of the output of some nonlinear dynamic system that is being modeled. The output is fed back to the input of the feedforward neural network as a standard parallel NARX architecture, as shown in Figure 3-7. In this case, previous outputs are not available so this network architecture is used after training the model in Series-Parallel network. Initially, model is trained using the available previous input and the true outputs using Series-Parallel network as shown in Figure 3-8. True output is used instead of feeding back the estimated output from the model. Advantages of using these architectures in tandem are the inputs to the feedforward network are more accurate and the resulting network has standard feedforward architecture and static back propagation is used for training.

Model Implementation

A three-layered neural network is shown in Figure 3-9. In this study, the input matrix *u* is an (*m x n*) array where *m* is the number of training samples and *n* is the number of features. The input matrix *u* is then multiplied by the model parameters matrix θ^1 to produce the hidden layer state matrix *a* [15]. In practice, *a* acts as an intermediary state that interacts with the second parameters matrix θ^2 to calculate the output y(u) [15]. The size and number of hidden layers depends on the complexity of model.

Here, y(u) represents the output matrix of interest. PUE and operating set points of equipment are selected to represent DC efficiency. The neural network will develop the pattern between the input and out matrix to generate mathematical model that represents y(u) as a function of input matrix. It is important to check for the linear independence among the input features or predictors to simply model and avoid overshooting.

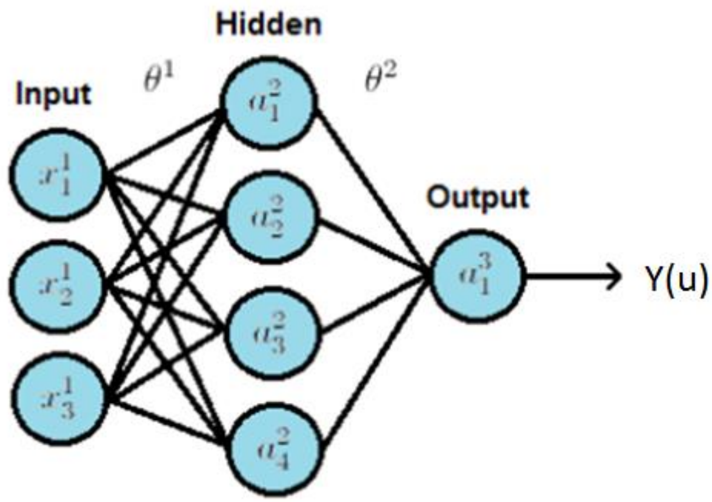

Figure 3-10 Three Layered Neural Network [11]

The process of training a neural network model goes through four steps as described below [16]:

1. Random initialize the model parameter θ
2. Feedforward Propagation
3. Compute cost function J(θ)
4. Back propagation algorithm
5. Repeat steps (2-4) until convergence.

Random initialization is the process of randomly assigning θ values between [-1, 1] before training model to avoid formation of unstable equilibriums. Failing to randomly initialize will result in identical inputs into each successive layers and error backward propagation will also be identical and model performance will not improve.

Feedforward Propagation refers to the calculation of successive layers, since the value of each layer depends upon the model parameter and layers before it. Hidden matrix state *a(i,j)* depends on the previous layers state θ *(i,j)* and input parameters *u(i,j)*. Similarly, output parameter *y(u)* depends on the all successive layer and its state as shown in below equations. *g(z)* is the activation function that mimics biological neuron firing within a network by mapping the nodal input values to an output within the range (0, 1).

$$a_1^2 = g(\theta_1^1 \ u_0^1 + \theta_2^1 \ u_1^1 + \theta_3^1 \ u_2^1 + \theta_4^1 \ u_3^1)$$

$$y(u) = a_1^3 = g(\theta_1^2 \ a_0^1 + \theta_2^2 \ a_1^1 + \theta_3^3 \ a_2^1 + \theta_4^3 \ a_3^1)$$

Cost function J(θ) serves as the quantity to be reduced with each iteration during model training. It is expressed as the square of the error between the predicted and actual outputs. Error is the difference between neural network output and actual available target output.

Back propagation is propagation of error term backward through each layer to refine the values of model parameter θ, after computing the cost function J(θ).

Implementation on Test bed Modular Data Center

The modular data center (MDC) under consideration for research is located in Dallas, Texas. The topology of a modular data center (MDC) consists of an Information Technology (IT) module (IT POD) supported with a power module and a cooling module integrated for specific operational needs. This unit has four racks populated with 120 Hewlett-Packard servers in a cold/hot aisle (CA/HA) arrangement. The Aztec indirect/direct evaporative cooling unit is integrated with the IT POD for providing cooling required to maintain higher computing performance and reliability of IT equipment.

The MDC unit is equipped with multiple temperature, pressure, relative humidity (RH) and water flow sensors. The sensor data is collected 24/7/365, yet this data is rarely used for application other than monitoring purposes. This is the common scenario in typical large-scale and modular data centers.

Figure 3-11 Test Bed Modular Data Center

Baseline Model

Data pre-processing such as I/O, data analysis and filtration, model training and post processing was conducted using "Neural Network Toolbox™ R2015b" which provides functions and apps for modeling complex nonlinear systems that are not easily modeled with a closed-form equation. With the toolbox you can design, train, visualize, and simulate neural networks.

As all the sensor data are available in time series format, we have used the dynamic time series tool.

For the baseline model, only six input variables are considered that will predict three target set point values as described below.

Input Variables:

1. Outside air dry bulb temperature (F)
2. Outside air relative humidity (RH) (%)
3. Cold aisle air temperature (F)
4. Cold aisle air relative humidity (RH)
5. Hot aisle air temperature (F)
6. Hot aisle air relative humidity (RH)

Target set points:

1. Supply fan speed (RPM)
2. Cooling tower fan speed (RPM)
3. Outside air damper open percentage (%)

The training data is available from December 2014 till September 2015 for all the input and target variables. Test plan includes the following steps:

1. Data import and pre-processing
2. Input and target tags
3. ANN training
4. Testing the trained model
5. Optimizing the model for number of neurons and hidden layers

We adopted the “Levenberg-Marquardt” algorithm to train our baseline Neural Network model. This algorithm is designed to approach the second order training speed. This algorithm is termed as “trainlm”, in MATLAB.

Results and Discussion

Baseline model is tested for the accuracy and training time. These models need to train fast i.e. update weights and biases matrices fast and predict accurately. Results for two such cases are discussed below with different number of delay, hidden layer and training time.

1. Training Function: ‘trainlm’ (Levenberg-Marquardt)

   Delay: 1

   Hidden Layer: 10

   Retrained the Network: 3 times

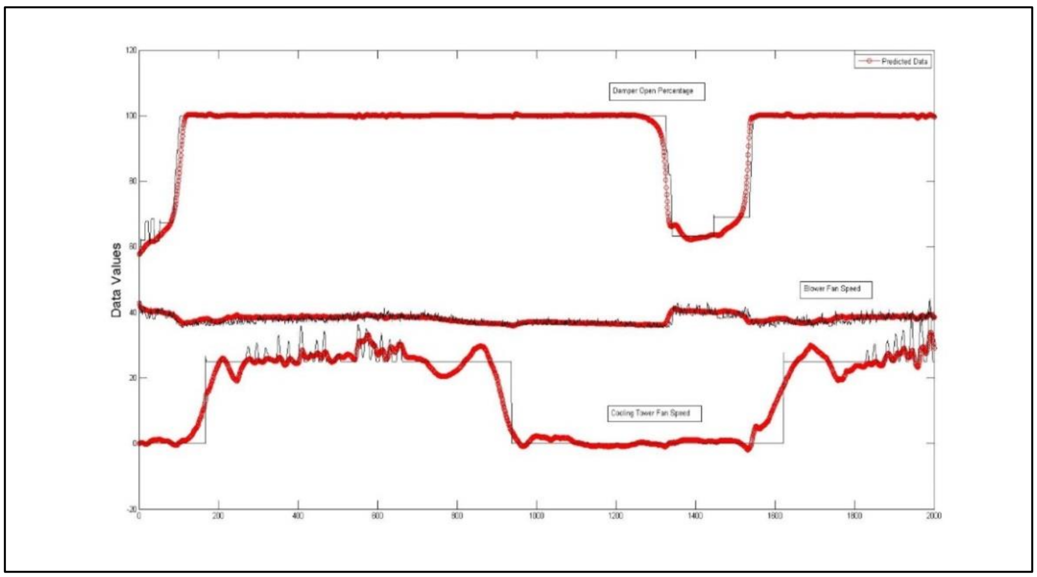

Figure 3-12 Multistep Prediction with Hidden Layer 10 and Delay 1

2. Training Function: ‘trainlm’ (Levenberg-Marquardt)

   Delay: 1

   Hidden Layer: 10 and 20

   Retrained the Network: 2 times with hidden layer 10 & 1 time with 20

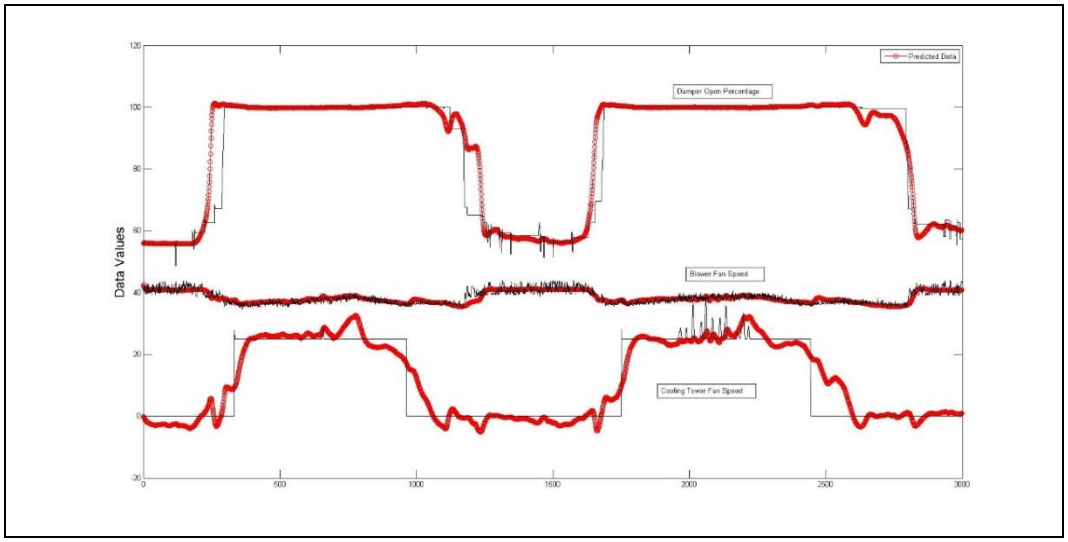

Figure 3-13 Multistep Prediction with Hidden Layer 10 & 20 and Delay 1

The results in Figure 3-12 and Figure 3-13 show the prediction (red) for all the three target values gives good match to the original sensor reading (black) for both the models. Having an accurate and robust predictive model will help DC operators to simulate the DC operation configuration without making physical changes.

Data Center Efficiency Model

PUE is selected here to represent data center efficiency as this metric is a ratio and not the symptomatic of total facility power consumption. The features of the test bed modular data center that directly affect the performance are listed in the figure

The neural network uses 20 neurons in the hidden layer and 0.001 as the regularization parameter. The training set contains 7 normalized input variables and one normalized output variable. These datasets are sampled at 1 minute time resolution. The dataset is dived into three segments of which 70% is used for training, 15% is used for testing and 15% is used for cross-validation. The chronological order of the datasets is shuffled before dividing to avoid biasing the training and testing sets on newer or older data.

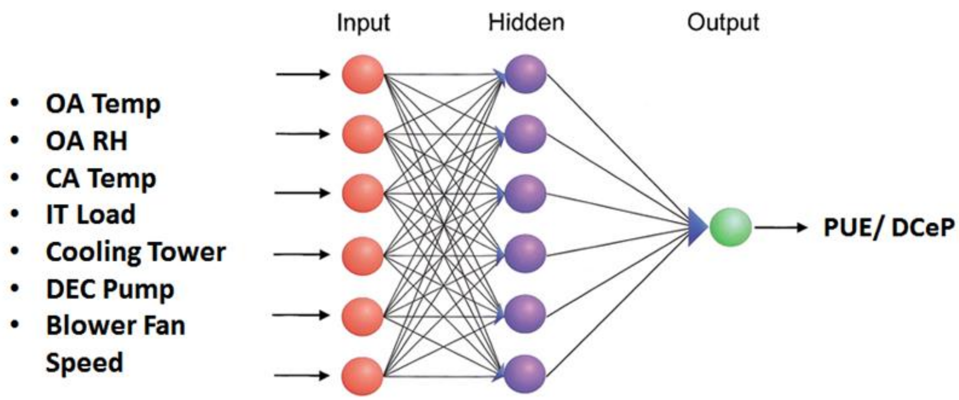

Figure 3-14 Data Center Efficiency Model

Results and Discussions

Data Center Efficiency Model A

Data center efficiency models are tested for one step ahead and multi-step ahead performance. Training algorithm “Levenberg-Marquardt” referred as ‘trainlm’ in MATLAB is used for both the models. Model A is configured for delay number of 2 and 20 hidden layers. Training is done Series-Parallel neural network architecture as shown in Figure 3-15, as both inputs and target outputs are available.

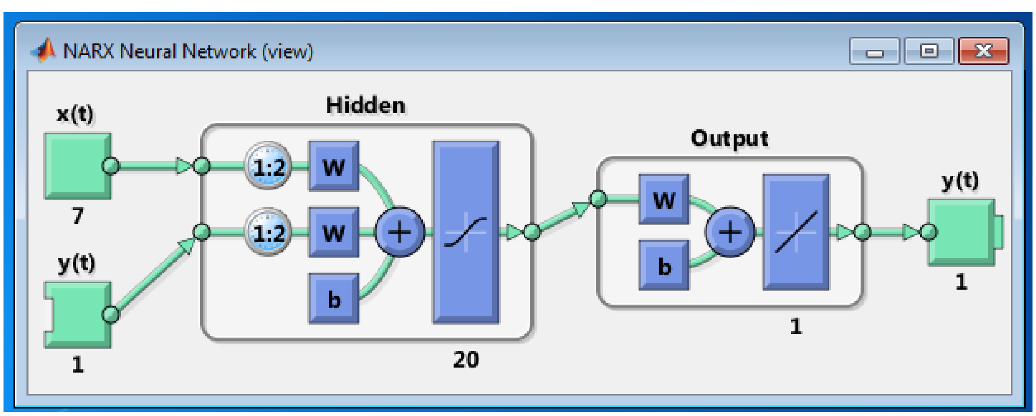

Figure 3-15 Model A: Neural Network Architecture

Once the network/model is trained it is converted into closed loop system where present neural network output is fed as input to predict the output at next time step as in Figure 3-16. To predict the output one time step ahead of the present condition which is advantageous in control system design, one input delay is removed from the input layer. The model will predict the output one time step ahead y(t+1) given y(t) and x(t) as shown in Figure 3-17.

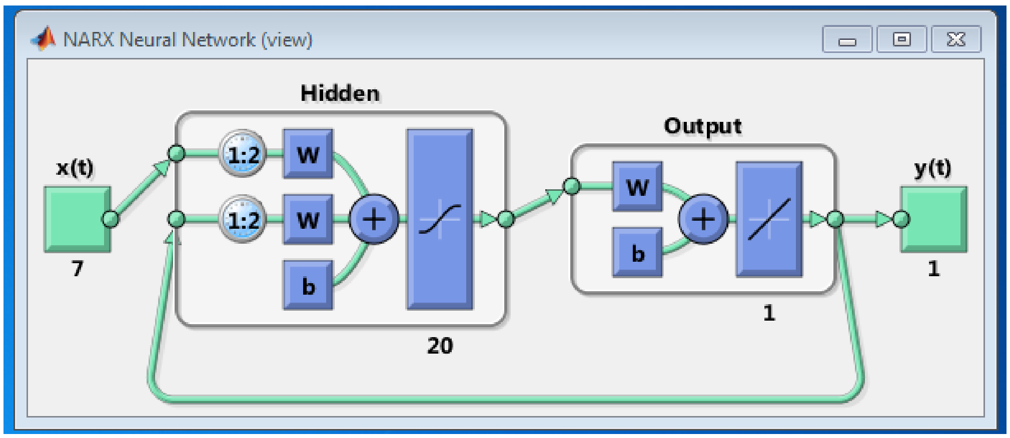

Figure 3-16 Multi Step Ahead Prediction Neural Network Architecture

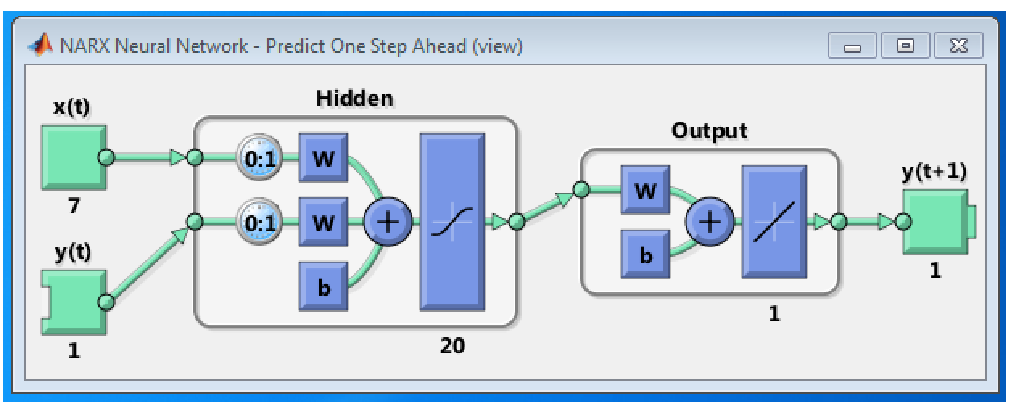

Figure 3-17 : One Step Ahead Prediction Neural Network Architecture

Neural Network Performance Analysis After Training

Performance Plot

Neural network model keeps track of several variables during training the model such as the performance function value, gradient, time series errors et cetera. The performance plot in figure indicates the iteration at which the validation performance reached a minimum. Training continues for some more iteration before stopping to check the validation performance does not shoot up. The performance figure indicates fair training with validation and test curves very similar as in Figure 3-18.

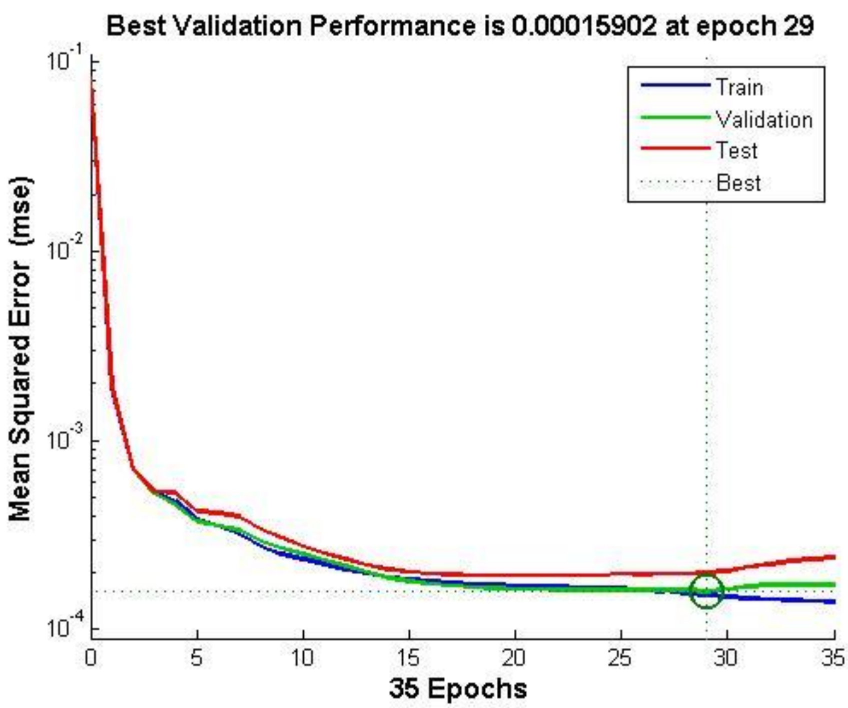

Figure 3-18 Training Performance Plot for Model A

Regression Plot

Regression plots give more insight in validating the network which shows the relationships between the outputs of the network and the targets. Network output and the targets would be exactly same if training was perfect, but in modelling nonlinear systems this relationship is not perfect in practice. The four regression plots represent the training, validation, testing and combination of three data. The dashed line in each plot represents the perfect result giving same outputs as targets. The solid line represents best fit linear regression line between outputs and targets. The value of R is an indication of relationship between output and target. Value of R =1 indicates exact linear relationship between outputs and targets while value of R=0 indicates there is no linear relationship between them. Training data is a good fit if validation and test results show R value greater than 0.9. Here the value of R is 0.98255 for the training, validation and testing combined, indicating a good fit neural network model as in Figure 3-19.

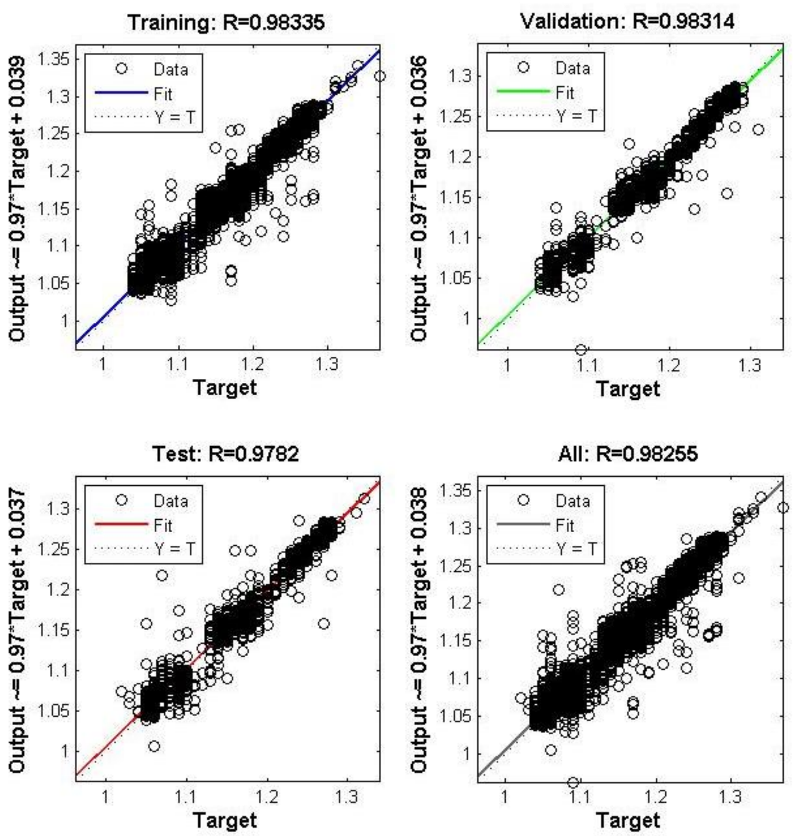

Figure 3-19 Regression Plots for Model A

Model A: One Step Ahead Prediction Results

Testing of one-step ahead prediction trained model as in Figure 3-20 is discussed. The trained model is tested for the new inputs and its performance is measured from the network generated output. Mean squared error (MSE) is calculated from the targets and network outputs and is used as the performance parameter. The predicted output is indicated by blue graph and know target in green. MSE of the network for given inputs is 0.000161 which is 0.0161%.This points towards the robustness and accuracy of the neural network model.

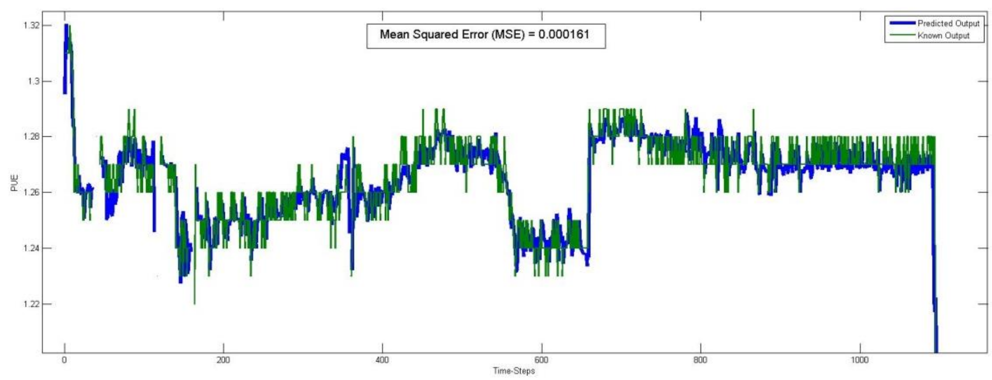

Figure 3-20 Model A: One Step Ahead Performance

Model A: Multi Step Ahead Prediction Results

Closed-loop networks make multistep prediction as in figure(). This network model continue to predict when external feedback is missing by using internal feedback, meaning using the network generated output as feedback when targets are not available. Model uses it's trained weights and biases to calculate the next value of output. In this case the error between target and network output will keep increasing with time steps. Output will keep diverging with increase in time steps and degree of divergence will indicate the robustness and accuracy of the model. Performance is measured in terms of mean squared error (MSE) which is equal to 0.00654.

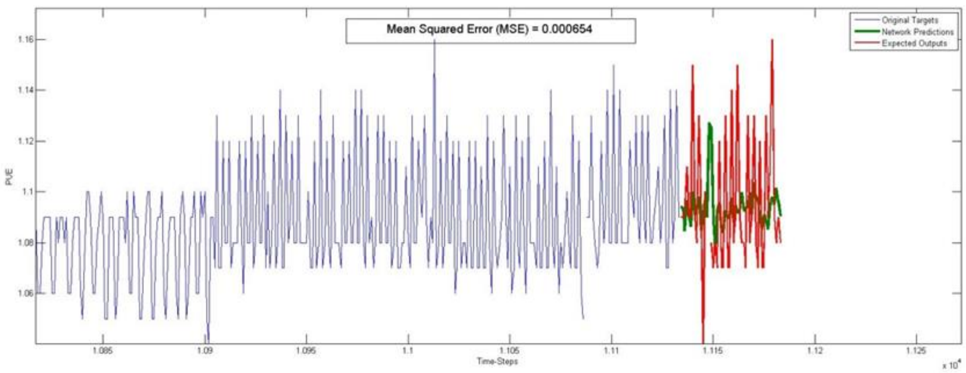

Figure 3-21 Model A: Multistep Ahead Performance

Data Center Efficiency Model B

Data center efficiency model B is tested for one step ahead and multi-step ahead performance. Training algorithm "Levenberg-Marquardt" referred as 'trainlm' in MATLAB is used for both the models. Model B is configured for delay number of 5 and 15 hidden layers. Training is done Series-Parallel neural network architecture as shown in figure as both inputs and target outputs are available.

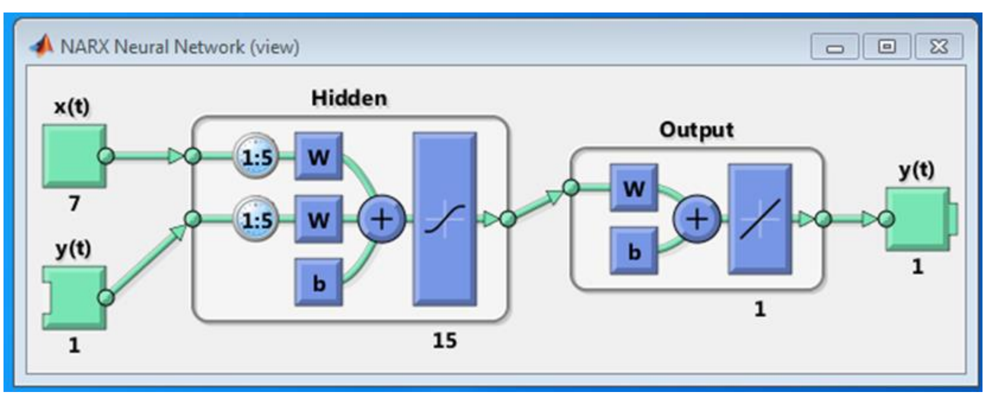

Figure 3-22 Model B: Neural Network Architecture

This model was specifically tested for lager number of missing data in time series and analyzing the performance for multi-step and one step prediction. Figure 3-23 and Figure 3-24 show one step ahead and multi-ahead prediction with some data randomly deleted respectively.

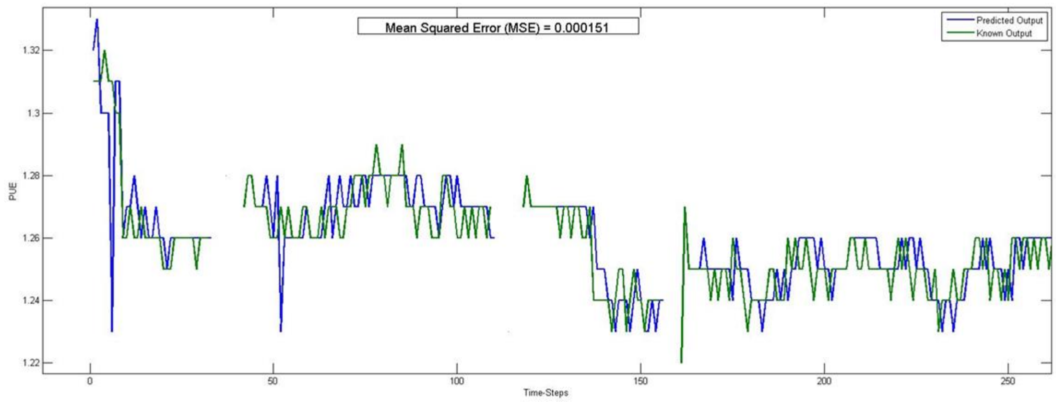

Figure 3-23 Model B: One-step Ahead Performance

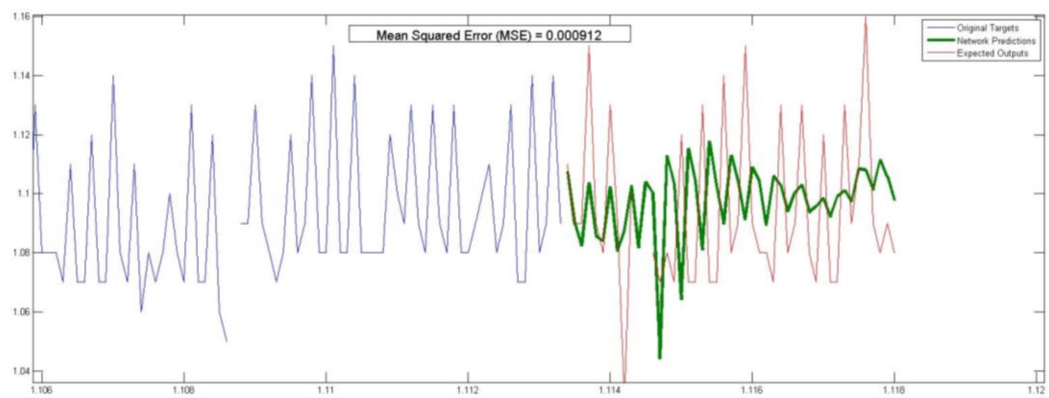

Figure 3-24 Model B: Multistep Ahead Performance

Chapter 4

Summary and Discussion

Data centers have become an important segment of modern infrastructure with advent of social media and personal mobile devices connected to internet. IT equipment that store, process and transmit digital data in data centers need to be properly cooled to maintain its reliable operation. Energy consumption of the cooling system in data centers contribute a significant portion of the overall data center energy consumption and reducing energy consumption of the cooling unit can significantly improve energy efficiency of data centers. The studies reported here discuss alternate cooling strategies and use of Artificial Neural Network for energy efficient data center. The principle contributions and findings of this study are outlined below.

Importance of control strategies for use of ASE along with DEC and IEC to use outside air for cooling data centers is discussed. The sequence of operation of test bed modular data center that uses a cooling unit ASE-15, which operates is ASE and I/DEC has been designed and implemented. To improve the performance of this system, recommendations in design and analysis are proposed and discussed. Monthly weather bin data analysis for precise selection of cooling technology and number of hours ITE will operate off designed envelop. Designing the operating envelop based on the ITE tolerance can reduce the cooling cost. Application of predictive/anticipated cooling can maximize the use of ASE, IEC and DEC while maintaining the controlled environment in cold aisle. Staging and incremental cooling of DEC can improve the precision of humidity and temperature control in cold aisle. Significant water and energy savings can be achieved.

Application of Artificial Neural Network in developing data center energy models with data points generated during its operation to improve performance by optimizing various parameters. These models mimic the actual behavior of data center and accurately respond to any changes to input parameters like actual data center would do. These models can be extended to perform sensitivity analysis revealing the impact of individual operating parameters [11].

References

[1] K. J, "Growth in data center electricity use 2005 to 2010. Analytical Press. Oakland, CA. 2011[Online]," 2011. [Online]. Available: http://www.analyticspress.com/datacenters.html.

[2] ASHRAE TC 9.9, "2011 Thermal Guidelines for Data Processing Environments – Expanded Data Center," pp. 1–45, 2011.

[3] ASHRAE, "2015 Supplement Energy Standard for Buildings Except Low-Rise Residential Buildings," vol. 8400, 2015.

[4] J. Park, "Open Compute Project, Data Center v1. 0," 2011. [Online]. Available: http://www.opencompute.org/assets/Uploads/DataCenter-Mechanical-Specifications.pdf.

[5] V. Mulay, "Humidity Excursions in Facebook Prineville Data Center," 2012. [Online]. Available: http://www.electronics-cooling.com/2012/12/humidity-excursions-in-facebook-prineville-data-center/.

[6] V. Mullay, "Learning Lessons at the Prineville Data Center," *opencompute.org*, 2011. [Online]. Available: http://www.opencompute.org/blog/learning-lessons-at-the-prineville-data-center/.

[7] SIEMENS, "Psychrometric Chart Structure and Application." [Online]. Available: https://www.downloads.siemens.com/download-center/Download.aspx?pos=download&fct=getasset&id1=8313.

[8] Energy Lab Inc., "Evaporative Cooling Systems." [Online]. Available: http://www.energylabs.com/web2/brochures/ELI_Evaporative.pdf.

[9] B. J. Gantz and D. Reinsel, "Extracting Value from Chaos State of the Universe : An Executive Summary," no. June, pp. 1–12, 2011.

[10] "PUE™: A comprehensive examination of the metric. The Green Grid. 2012

[Online]. Available: http://www.thegreengrid.org/~/media/WhitePapers/WP49-PUE%20A%20Comprehensive%20Examination%20of%20the%20Metric_v6.pdf?lang=en."

[11] J. Gao and R. Jamidar, "Machine Learning Applications for Data Center Optimization," 2014.

[12] D. Livingstone, *Artificial Neural Networks: methods and applications.* Humana, 2008.

[13] G. Dreyfus, *Neural Networks: methodology and applications.* Springer, 2005.

[14] M. H. Beale, M. T. Hagan, and H. B. Demuth, "Neural Network Toolbox^{TM} User's Guide," 2015.

[15] A. Ng, *"Neural Networks: Representation (Week 4)." Machine Learning. Retrived from www.coursera.org/learn/machine-learning/home/week/4*. .

[16] A. Ng, *"Neural Networks: Learning (Week 5)." Machine Learning. Retrived from www.coursera.org/learn/machine-learning/home/week/4*. .

[17] "Handsdown software/Makeup Air HD." .

[18] Emerson Network Power, "New Strategies for Cutting Data Center Energy Costs and Boosting Capacity."

[19] "Google Data Centers, Efficicency: How we do it." [Online]. Available: www.google.com/about/datacenters/efficiency/internal/.

[20] M. Iyengar, M. David, P. Parida, V. Kamath, B. Kochuparambil, D. Graybill, M. Schultz, M. Gaynes, R. Simons, R. Schmidt, and T. Chainer, "Server Liquid Cooling with Chiller-less Data Center Design to Enable Significant Energy Savings," vol. 1, 2012.

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