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SUPPLY AIR TEMPERATURE PREDICTION IN AN AIR-HANDLING UNIT USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Continuous provision of quality supply air to data center's IT pod room is a key parameter in ensuring effective data center operation without any down time. Due to number of possible operating conditions and non-linear relations between operating parameters make the working mechanism of data center difficult to optimize energy use. At present industries are using computational fluid dynamics (CFD) to simulate thermal behaviour for all types of operating conditions. The focus of this study is to predict Supply Air Temperature using Artificial Neural Network (ANN) which can overcome limitations of CFD such as high cost, need of an expertise and large computation time.

For developing ANN, input parameters, number of neurons and hidden layers, activation function and the period of training data set were studied. A commercial CFD software package 6sigma room is used to develop a modular data center consisting of an IT pod room and an air-handling unit. CFD analysis is carried out for different outside air conditions. Historical weather data of 1 year was considered as an input for CFD analysis. The ANN model is "trained" using data generated from these CFD results. The predictions of ANN model and the results of CFD analysis for a set of example scenarios were compared to measure the agreement between the two.

The results show that the prediction of ANN model is much faster than full computational fluid dynamics simulations with good prediction accuracy. This demonstrates that ANN is an effective way for predicting the performance of an air handling unit.

INTRODUCTION

In the year 2006, 1.3% of total energy consumed in the United States namely 61 billion kilowatts of energy was consumed by data centers [1]. According to the national resources defense council (NRDC) report for the year 2013 data centers consumed approximately 91 billion kilowatt-hours of electricity [2]. This shows that energy consumption of data centers is 1.9% of the total electricity consumption in the United States. The NRDC also reported that electricity consumption of data centers could be 140 billion kilowatt-hours by 2020 which could cost thirteen billion dollars annually. Hence it is important to improve the data center energy consumption.

Previously individual systems were used to store the data in digital format. Due to the need of data sharing, data centers were created and internet is used to access this data whenever required. New technologies such as Internet of Things (IOT), Big Data, cloud computing has increased the dependency on internet and data centers. On the other hand, computation power has increased rapidly making speed of data transfer as the limitation. Hence easy and quick access to database is important which requires continuous working of data center with minimal downtime.

IT equipment, which stores and provides access to dynamic data, uses electrical power, also called IT load, which varies with time according to consumer's demand. Electrical energy provided to this IT equipment transforms into heat energy resulting in heating up of the device. IT equipment fails when the temperature of the device exceeds the maximum allowable temperature [3]. Removal of this excess heat can be done by air cooling or liquid cooling techniques. In air cooling technique, Air Handling Unit (AHU) cools the incoming air and supplies it to the cold aisle of the data center which reduce the temperature of IT equipment by convection mode of heat transfer. Hence accurate prediction of supply air temperature of AHU is a crucial parameter for continuous working of data center.

Currently, Computational Fluid Dynamics (CFD) method is used for estimation of different parameters such as temperature, pressure, humidity in data centers. If physical properties of the data center are known, CFD or white-box modeling provides accurate estimation since it is based on the fundamental equations of mass and energy balance for fluids. But, high cost of the CFD tool, requirement of large computation power, time-consuming simulations and need of an expertise are major drawbacks of this method.

This study provides an alternative approach of Artificial Neural Network (ANN) which can overcome drawbacks of CFD approach while retaining a useful degree of accuracy. ANN learning is similar to the human brain. It takes available data as input and captures nonlinear relationships between inputs and outputs of the system in order to predict output with useful accuracy. The quality and quantity of dataset is crucial in ANN training. Provided the sensors are not faulty large, historical sensor (real-time) data can be used if it captures all the possible working scenarios. In the absence of sensor data, synthetic data set can be obtained using CFD simulations. In this study, the purpose of CFD modeling is only to generate synthetic dataset for ANN training.

The objectives of this paper are: 1. Provide a summary of the domain knowledge required for building such CFD model and preparing the synthetic dataset. 2. using synthetic dataset, develop ANN models to predict supply air temperature. These ANN predictions can be used for pro-active control of energy efficient data center.

The paper is organized as follows: section 2 describes the CFD model of data center. Section 3 explains generation of dataset. Section 4 focuses on development of ANN model. Section 5 presents results and discussion; Finally, section 8 concludes this research work.

NOMENCLATURE ALPHABETICAL

ACU	Air Cooling Unit
AHU	Air Handling Unit
ANN	Artificial Neural Network
ASE	Air Side Economization
CA	Cold Aisle
CAP	Cold Aisle Pressure (in/ H2O)
CAT	Cold Aisle Temperature (F)
CFD	Computational Fluid Dynamics
CFM	Cubic Feet per Minute
DEC	Direct Evaporative Cooling
HA	Hot Aisle
HAP	Hot Aisle Pressure (in/ H2O)
HAT	Hot Aisle Temperature (F)
HX	Heat Exchanger
IDEC	Indirect Evaporative Cooling
MAE	Mean Absolute Error (F)
MAT	Mixed Air Temperature (F)
MDC	Modular Data Center
OAH	Outside Air Relative Humidity (%)
OAT	Outside Air Temperature (F)
OAH	Outside Air relative Humidity (%)
RMSE	Root Mean Squared Error (F)
SAT	Supply Air Temperature (F)
% OA	Vent opening for outside air (%)
% RA	Vent opening for return air (%)

CFD MODEL OF DATA CENTER

The real time model chosen for this study shown in Figure 1 and 2 approximately represents a modular data center (MDC) of MESTEX Inc, located at Dallas, Texas, USA. This reduced order model consist of IT pod room, Air Handling Unit (AHU), overhead cold air supply and hot air return duct which connects the AHU and IT pod. Figure 3 shows isometric view of K-ε turbulence CFD model which is developed in 6Sigmaroom CFD software. IT pod is shown on the left side while AHU is on the right side. Figure 4 and 5 shows front and top view of MDC respectively. The IT pod room which is 3.2 m in length 3.2 m in width and 2.8 m of height consists of four racks in single row which separates cold and hot aisles and each rack consists of five 7U servers each of 1500 W with maximum total IT load of 30 KW. Empty server slots are blanked. In 6SigmaRoom software, each 7U server is modeled as black box with heat power factor of 90% and 100% heat convected to air without internal air circulation in server. Maximum allowable temperature of server is 90 F with thermal effectiveness of 0.8. Weight of each server is 70 Kg with effective specific heat of 500 J/Kg K.

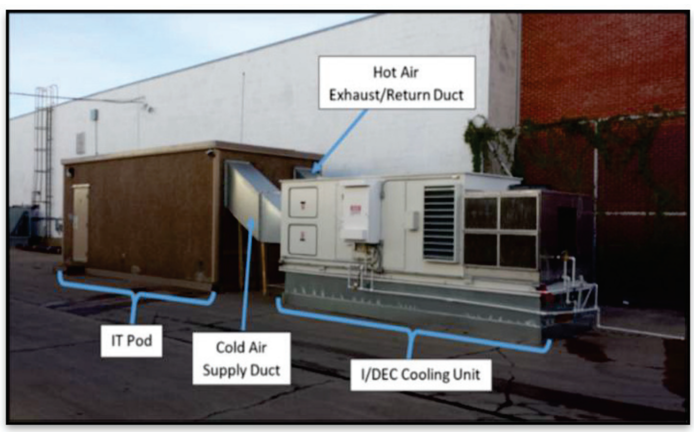

Figure 1: *Front view of MDC shows cold air supply duct*

AHU is 4.5 m long by 1.8 m wide and 1.7 m high and consist of heat exchanger (HX), direct evaporative cooling pad and four supply fans. Four circuits, six rows heat exchanger has effectiveness of 0.75 with tube diameter of 0.013 m and fin spacing 0.2 m. The nominal cooling capacity of heat exchanger (HX) is 30 KW. Maximum allowable flow rate is 2 CFM with water temperature 70 F and condensation coefficient of 1. The evaporative efficiency of direct evaporative cooling (DEC) pad is 90% with viscous resistance coefficient of 3 and inertial resistance coefficient of 30. The maximum water flow rate on the top surface area of DEC pad is 0.8 CFM with water temperature 70 F. On the fan wall, total four fans are installed with diameter 18.2 in and hub diameter 6 in and thickness of 4 in. Each fan has uniform flow rate of 1500 CFM and rated speed of 3300 rpm. Total CFM of cold air demanded by all server fans is equal to CFM of air supplied by AHU. For the CFD calculations, a finite-volume approximation of the Reynolds-averaged Navier-Stokes and energy equations with the standard k-ε turbulence model is solved using the commercial CFD software package 6SigmaRoomDC. Constant air properties and buoyancy effects are considered. Grid independent study was carried out using AHU's Supply air temperature to evaluate accuracy of simulation which concludes 1.64 million grid cells from Figure 6 with maximum aspect ratio of 2.53. Note that solar radiation, wind speed and contaminations are not incorporated in CFD modeling. 5% air leakage is considered across the aisle.

Figure 2: *Rear view of MDC shows hot air return duct*

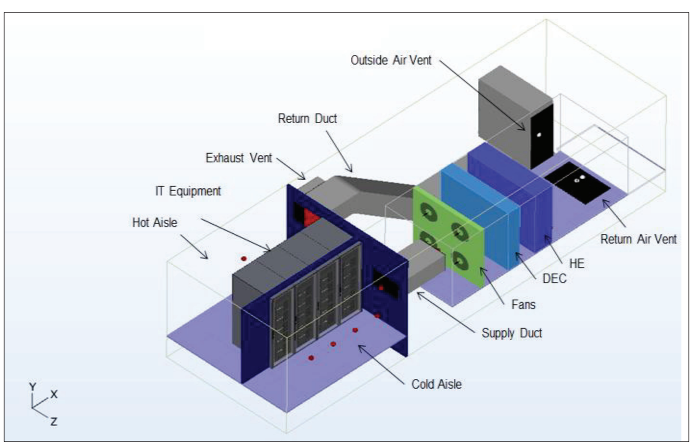

Figure 3: *Isometric view of CFD model*

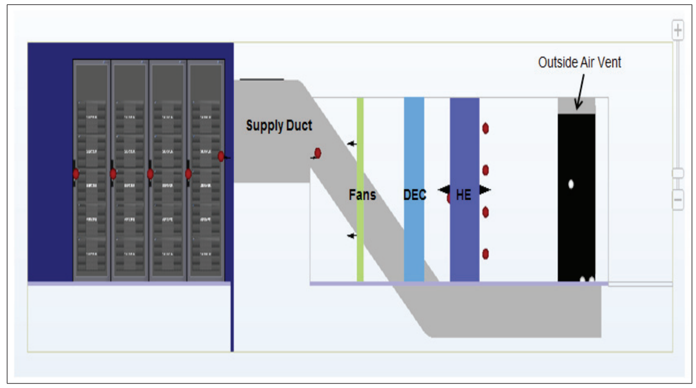

Figure 4: *Front view (x-y)*

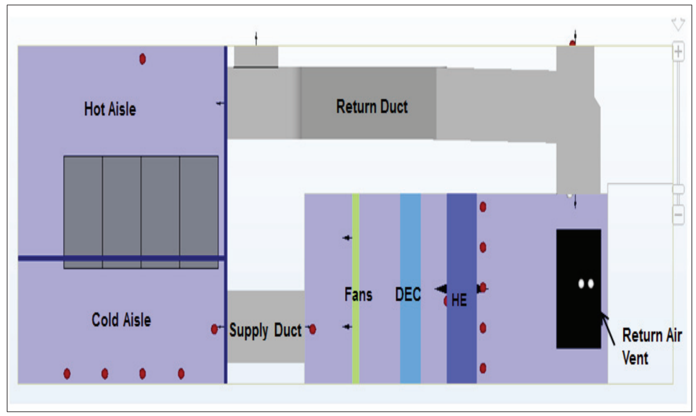

Figure 5: *Top view (x-z)*

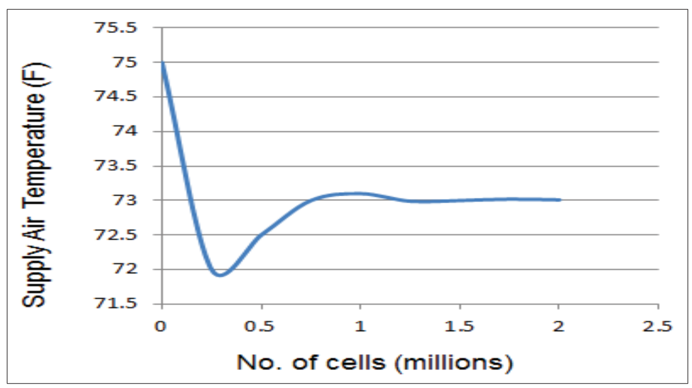

Figure 6: *Grid Independent Study*

Air-flow Path in Data Center

The ambient air entering through outside air vent opening blends with air from hot aisle entering through return air vent. This mixed air further passes through heat exchanger (HX) first, which provides sensible cooling and then through direct evaporative cooling (DEC) pad which further cools the air adiabatically. Since direct evaporative cooling increases humidity it is leveraged as second stage of cooling while sensible cooling using heat exchanger is the first stage. Four fans placed after DEC pad pulls the volume of cold air and deliver it to the cold aisle of IT pod room through the supply duct. Server fan of each IT equipment withdraws cold air from cold aisle, which cools the server by convection mode of heat transfer and raises its own temperature. This high temperature air accumulated in hot aisle is then either exhausted from the IT pod room or passes through the return duct towards mixing chamber to blend with outside ambient air. This completes the air flow loop.

Control Strategies of Air Handling Unit

AHU provides following three types of cooling:

1. Free cooling (Air-side economization)
2. Indirect Evaporative Cooling (IDEC) or Sensible cooling
3. Direct Evaporative Cooling (DEC) or Adiabatic cooling

Following control strategies are designed to incorporate above mentioned cooling types and to ensure that supply air temperature (SAT) of an AHU will always lie within "Recommended" innermost envelope of ASHRAE as shown in Figure 7.

Strategy 1: The percentage opening of outside air vent and return air vent is controlled to maintain mixed air temperature at least 65 F (lowest limit of ASHRAE's "Recommended" envelop) by attaching equal weighted 20 temperature sensors (red circles shown in Figure 4 and Figure 5), placed before heat exchanger which measures mixed air temperatures. Figure 8 shows the validation of this control strategy for random consecutive 5 days of month of April when outside air temperature (OAT) was less than hot aisle temperature (HAT), and percentage opening of outside air vent (%OA) was more than percentage opening of return air (% RA) in order to maintain mixed air temperature (MAT) at around 65 F.

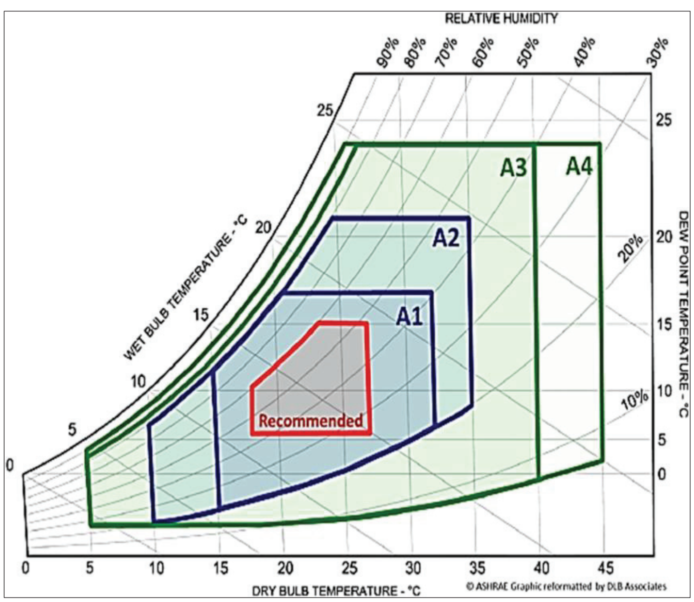

Figure 7: *ASHRAE's envelopes*

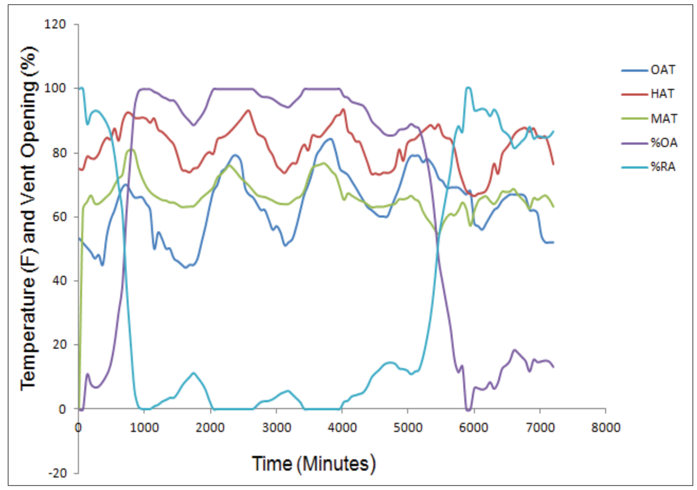

Figure 8: Validation of Outside and Return Air Vent Control

Strategy 2: Water flow in heat exchanger tubes will turn ON when four temperature sensors (red circles shown in Figure 3,4 and 5) placed equidistantly in cold aisle read above 70 F. Also water flow on top surface area of direct evaporative cooling pad will turn ON when cold aisle temperature sensors read above 74 F. This demonstrates that sensible cooling or IDEC provided by heat exchanger (HX) is first stage of cooling and adiabatic cooling or DEC provided by direct evaporative cooling pad is second stage of cooling. Figure 9 shows random consecutive 5 days of July when outside air temperature is in the range of 70 to 90 F, water flow in tubes of heat exchanger (HX) is turned ON (heat exchanger is providing IDEC which is measured in KW) and water flow on top surface area of direct evaporative cooling pad is turned ON (cooling pad is providing DEC measured in KW). It is clear from Figure 9 that heat exchanger provides first stage of cooling (IDEC) since heat removed by HX has continuous non zero value while Direct evaporative cooling pad provides second stage of cooling (DEC) since heat removed by DEC has both zero and non-zero value. It can be observed in Figure 9 that cold aisle temperature (CAT) is successfully maintained in the range of 70 to 74 F. Figure 10 shows random consecutive 5 days of month of January when outside air temperature (OAT) is below 60 F. Since the cold aisle temperature for 5 random consecutive days in January month is always below 70 F as shown in Figure 10, heat removed by both heat exchanger (HX) and direct evaporative cooling pad (DEC) has the value of zero KW since they are never turned ON. Note that cold aisle temperature (CAT) is varying around 65 F since previous controller attached to outside air vent and return air vent are maintaining mixed air temperature to 65 F. This mixed air with temperature 65 F is being delivered in cold aisle without providing IDEC cooling by HX and DEC cooling by evaporative pad.

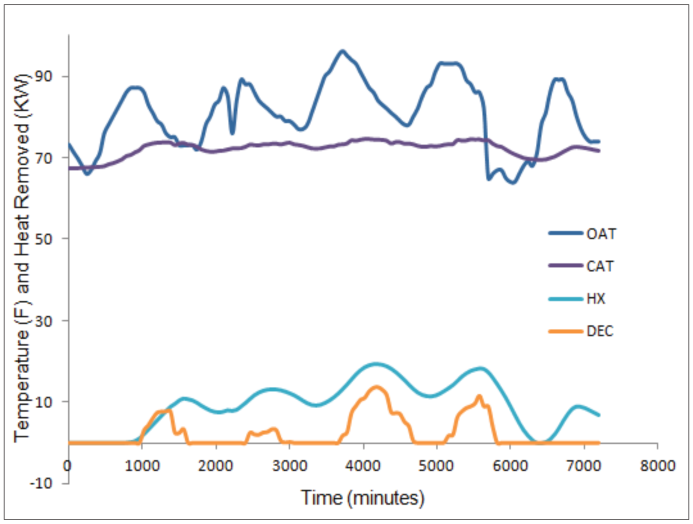

Figure 9: *Validation of IDEC and DEC turn ON for in July*

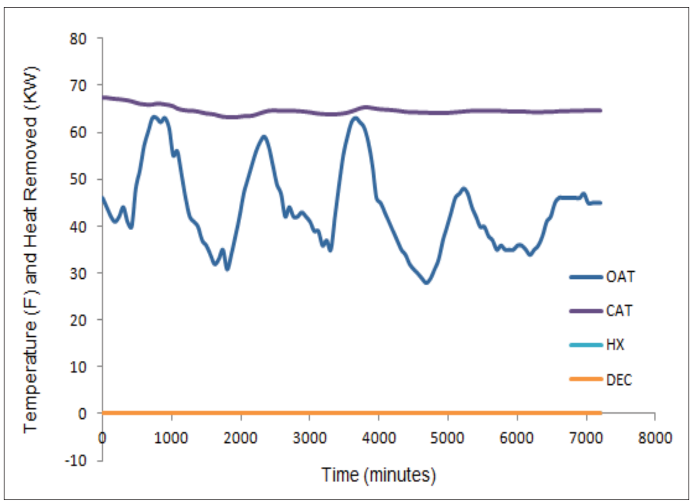

Figure 10: *Validation of IDEC and DEC turn OFF for in Jan*

Strategy 3: Increase in IT load increases server temperature and hence the hot aisle air temperature increases. To maintain server temperature within safe limits (Maximum allowable server temperature 90 F), the increased demand of CFM of cold air from the server has to be provided by increasing speed of supply fan of AHU. Hence hot aisle temperature (HAT) sensor shown as red circle in hot aisle in Figure 3 and Figure 5 is attached to supply fan speed control. The supply fan speed increases to 3300 rpm when HAT sensor reads a value above 90 F, otherwise 2119 rpm. For five random consecutive days, Figure 11 shows that as the IT load increases hot aisle temperature (HAT) increases and hence supply fan speed increases respectively. Note that supply fan speed values in rpm are normalized in order to represent them on same graph.

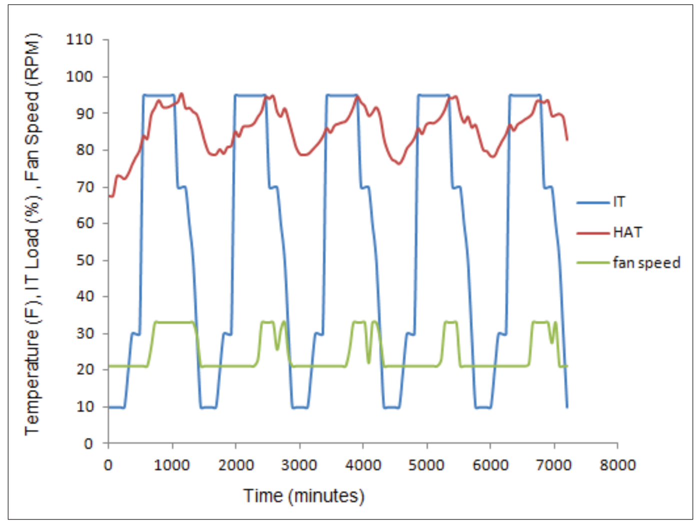

Figure 11: *Validation of Supply Fan Speed Control*

Strategy 4: Effective cooling is achieved when cold aisle pressure is more than hot aisle pressure, which assures that there will be no recirculation of hot air from hot aisle to cold aisle which otherwise increases server temperature and decreases cooling efficiency. To avoid the recirculation, four equidistant cold aisle pressure sensors with positive weights and one pressure sensor in hot aisle with negative weight are attached to this controller, which tries to keep a minimum positive pressure difference of 0.04 inch of water (10 Pa) across cold and hot aisle as shown in Figure 12. Note that since pressure sensors are point sensors, which are at same location as temperature sensors (red circles), they are not separately displayed in model Figure 3, 4 and 5. For random five consecutive days, Figure 12 shows that cold aisle pressure (CAP) is always more than hot aisle pressure (HAP).

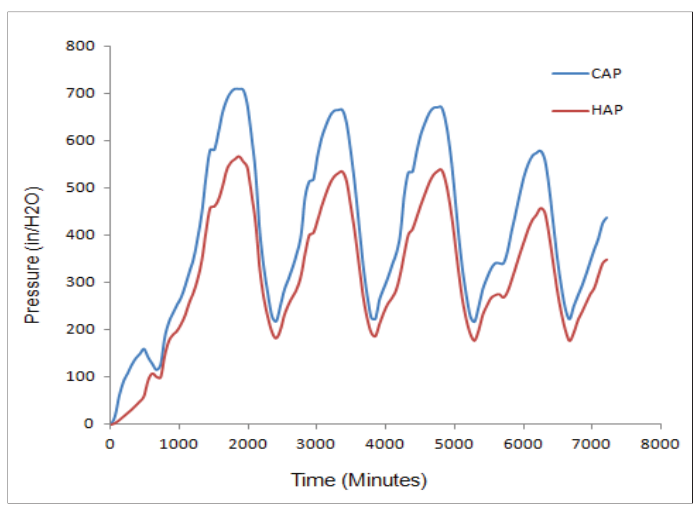

Figure 12: *Validation of positive pressure difference between cold and hot aisle*

GENERATION OF DATA SET

In this study, hourly weather data of year 1981 for the location Fort worth, Texas, USA available at National Solar Radiation Data Base website is used. Since transient CFD simulations are time consuming, we chose 4 months of data out of complete one year weather data. These four months are: January (winter), April (spring), July (summer), and October (fall), which represents every season. Since one season is made up of approximately 3 months, mid-month of every season is selected assuming that it will truly capture weather pattern of the respective season while other months contain transition days. For above mentioned four months (total 123 days), hourly data points generated from CFD simulations are 2952.Data normalization is not necessary step in this case since both input and output variables are in the range of 0 to 100.

Out of various parameters available Outside Air Temperature (OAT) (F) and Outside Air Relative Humidity (OAH) (%) are determined as the boundary conditions for CFD model. Also variation of IT Load is internal independent variable of the model. Figure 13 shows the assumed variation in IT load for sample consecutive five days. The assumption is based on the general observation that IT load starts to increase from 10 % at dawn, reaches to a peak value of 95% during working hours of the day and again decreases to 10% at dusk.

ANN MODEL

ANN is data driven modeling technique which is well suited when nonlinear inter-relations between parameters of complex system exist. This approach has been used in applications such as classification, pattern recognition and adaptive control. Examples applications of ANN are prediction of prices of houses, weather conditions, stock market, etc. Performance mechanism of ANN is similar with the functioning of human brain [4] & [5]. ANNs are black-box model which captures the non-linear relations between the variables of the domain [6].

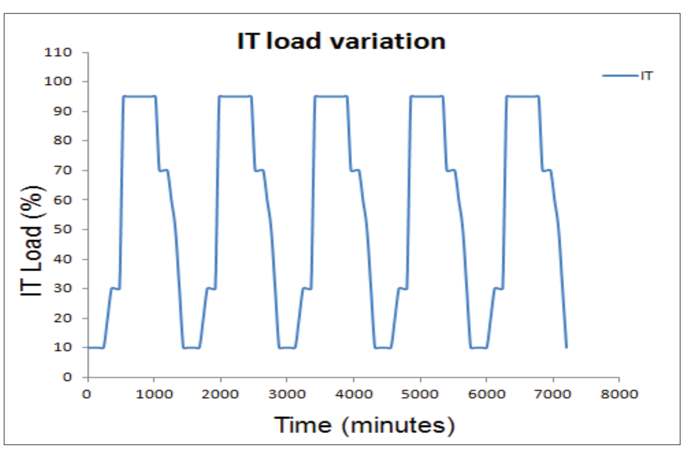

Figure 13: *Assumed IT load Variation*

The structure of ANN consist of three layers: Input layer, hidden layer, output layer. There could be multiple hidden layers depending on the complexity of working system. More the complexity working system, more will be the number of hidden layers. But there will be always one layer dedicated for input and output layer. A graphical representation of ANN model with three layers is shown in Figure 14. Every layer is made up of neurons (shown as circles in Figure 14) which perform the computation. Each neuron in hidden and output layer is connected to each neuron in its previous layer. The progression of signals or output generated in one layer, after computation, passes through these connections. Each connection has 'weight' associated with it. More the weight more impact on output will be made by respective neuron.

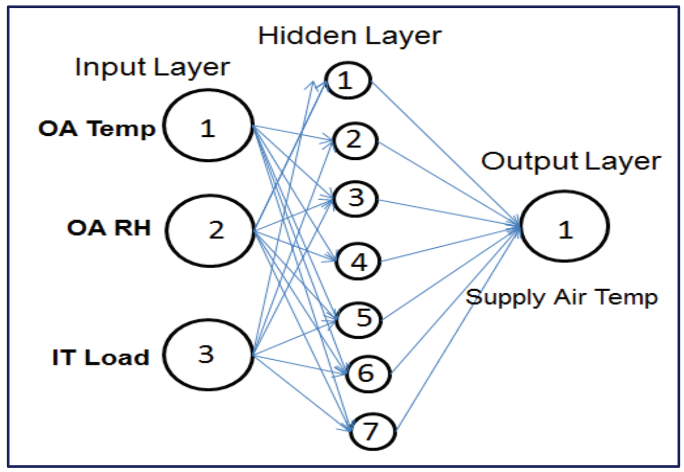

Figure 14: *Structure of ANN*

Selection of Model

ANNs are broadly classified in two categories: static and dynamic. Curve fitting, pattern recognition and clustering are examples of static ANN while time series problem is example of dynamic ANN. In static ANN the data feeding is done in random fashion. Data has been shuffled before feeding to the network. But in the case of dynamic ANN, data has to be provided in time series format. The output of dynamic ANN is depended on the past values provided to network hence availability of sequential input data is crucial for the dynamic case. Dynamic ANN is also called time series which is a vector sequence and a function of time.

In the case of data center, the future values of parameters or cooling strategies depend on past thermal conditions of data center hence a dynamic neural network also called time series is required to capture all transient non-linear relations among several parameters of data center. The dynamic neural network recognizes transient variation of inputs and outputs which captures nonlinear dynamic environment of data center.

In this study, Nonlinear Autoregressive with Exogenous Input (NARX) has been chosen since it predicts one time series y (t) from past values of itself and another time series x (t). This distinguishes NARX from rest of the time series ANN models. Detailed explanation of Architecture and Learning of NARX is explained in [7].

The input-output relationship defined in NARX is described as y (t) = F[x (t), x (t − Δt)… x (t − nΔt), y(t), y(t − Δt), .. , y(t − mΔt)], where n is the number of time delay steps in the input, m is the number of time delays on the feedback (output) and F is nonlinear function. In addition to the exogenous variables x, NARX incorporate the lagged output y. The time and weather variables are exogenous inputs x − t, and the supply air temperature y_t is the endogenous input.

The goal of this study is to predict supply air temperature (SAT) one hour step ahead. The NARX model was simulated using MATLAB 2016 Neural Network Toolbox [8].ANN Toolbox model and its architecture for one step ahead prediction is shown in Figure 15.

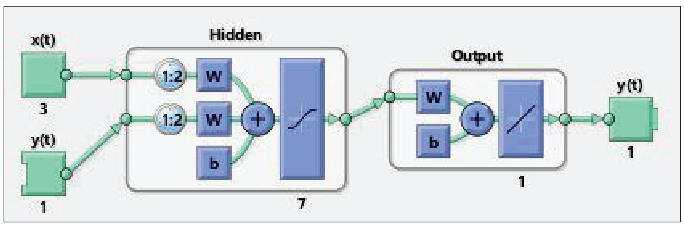

Figure 15: *ANN network Model*

Development of ANN

Step 1: Selection of inputs

The difficulty of selecting input variables arises due to:

1. The numerous numbers of available variables in CFD generated dataset or sensor (real-time) dataset
2. The complex correlations between potential input variables, which creates redundancy
3. Variables that have little or no predictive power [9].

Inclusion of all significant variables that has major impact on supply air temperature of AHU and to omit irrelevant or redundant variable having lower impact is important since irrelevant variables increases model complexity, learning difficulty and performance of developed network [9].

Out of all the available variables from CFD dataset, outside air temperature (OAT) (F), outside air relative humidity(OAH) (%) and IT load (%) are chosen as input variables because they are only function of time, independent and changing due to external factors which do not belong inside the datacenter domain. Hence x (t) = inputs variables (OAT, OAH, IT load) and y (t) = output variable (SAT) in Figure 15.

Step 2: Number of hidden layers and neurons in hidden layer

Only single hidden layer is chosen based on the fact that data complexity will be captured sufficiently if sufficient numbers of hidden neurons are provided in one hidden layer [10]. Hence number of hidden layer is one. The number of hidden neurons is not easy to determine since there is no systematic principle to guide. There are many thumb rules such as n/2, n + 1 and 2n + 1 where n is number of input parameters. But none of them works well for all the cases. [11] Also, from literature survey it has been observed that alternative way to determine number of neurons in hidden layer is trial and error approach (analyzing ANN predictions for different number of neurons in hidden layer)[12-13]. Since performance analysis of ANN for different number of neurons is out of scope of this paper the thumb rule 2n + 1 has been decided to implement in ANN development. For three input variables number of neurons in hidden layer become 7 as shown in Figure 15. The NARX model uses the Levenberg-Marquardt algorithm and a non-linear sigmoid activation function for the hidden layers and a linear activation function for the output layer as shown in Figure 15. Number of time delay steps in the input and output are two for one hour step ahead prediction. This is shown in Figure 15 as 1:2.

Step 3: Training, Testing and validation sample size

As per standard practice of ANN, 70% of the available data utilized for training, 15% for testing and 15% for validation purpose.

Step 4: Performance Analysis

To capture multiple types of variances following statistical indices were chosen for error evaluation:

1. Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - y_i|$$

2. Root Mean Squared Error

$$RMSE = \sqrt{1/n\sum_{i=1}^{n}(Y_{i-}y_i)^2}$$

Where,

Y = ANN Predicted supply air temperature

y= Actual supply air temperature from CFD data

n= Number of time interval

RESULT AND DISCUSSION

Four ANN models are developed for four months representing all four seasons. The one hour step ahead prediction of SAT provided by ANN is compared with CFD simulation value. To measure the performance of ANN two statistical indices have been measured namely, mean absolute error (MAE) and root mean squared error (RMSE).

One Hour Step Ahead Prediction

Figure 16 shows outside air temperature (OAT) (F) and outside air relative humidity (%) for the January month of 1981. Since the January month represents the winter season, it can be observed in Figure 16 that OAT mostly remained below 70 F. For this outside air condition, AHU will work on free cooling mode (Air Side Economization) in which outside air and return air from hot aisle is blended and delivered to cold aisle according to control strategy for outside air vent and return air vent opening which tries to maintain mixed air temperature to 65 F. From Figure 17 this can be validated as supply air temperature is varying around 65 F. Figure 17 shows the comparison of one hour step ahead prediction of ANN model with true values of CFD model for supply air temperature (SAT). The blue line indicates the ANN prediction whereas orange line predicts CFD value. MAE and RMSE values for ANN of January are 0.13 F and 0.19 F as shown in Table 1. This indicates that ANN provides useful accuracy.

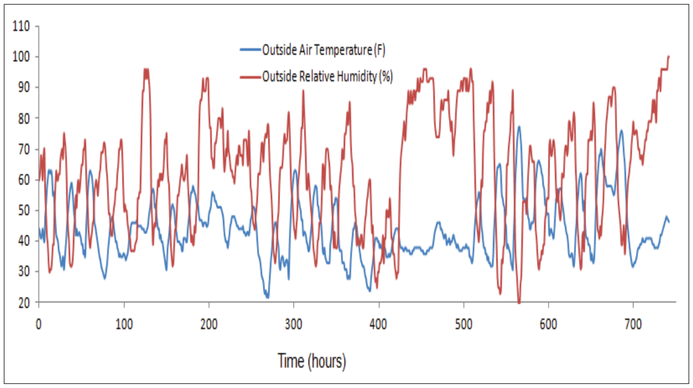

Figure 16: *OAT and OAH for January*

Figure 18 shows OAT and OAH for April month of 1981. Comparison of Figure 19 is compared with Figure 18 shows that though the maximum OAT is around 80 F, the AHU is providing supply air below 74 F. Also, Figure 19 shows one hour step ahead prediction of ANN and CFD values which are in good agreement with each other. MAE and RMSE values for ANN of April are 0.17 F and 0.23 F as shown in Table 1.

Figure 20 shows OAT (F) and OAH (%) for July month of 1981. Though the maximum value OAT is around 90 F the SAT provided by AHU is well maintained around 74 F as shown in Figure 21. This proves that all the control strategies of AHU are working as designed. Also, Figure 21 shows one hour step ahead prediction of ANN with contrast to CFD which is again in a good agreement. MAE and RMSE values for ANN of July are 0.21 F and 0.36 F as shown in Table 1.

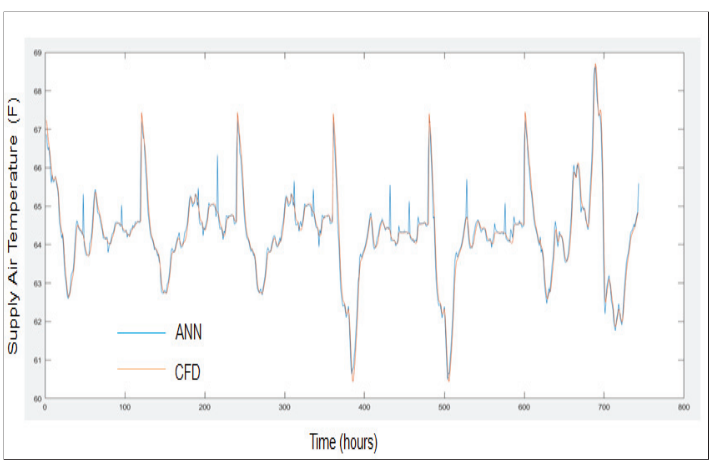

Figure 17: *One Hour Step Ahead Prediction of SAT for January*

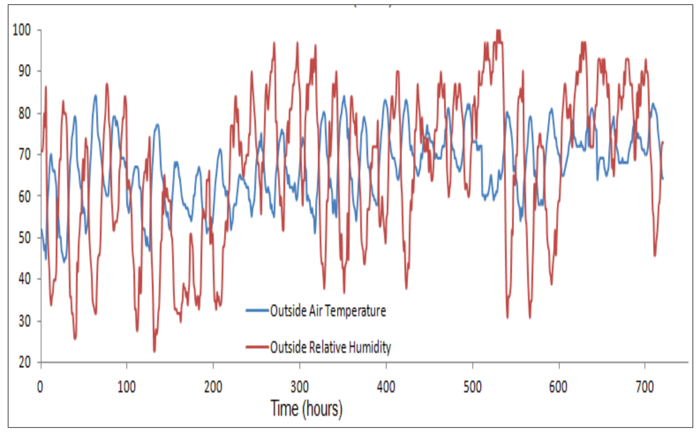

Figure 18: *OAT and OAH for April*

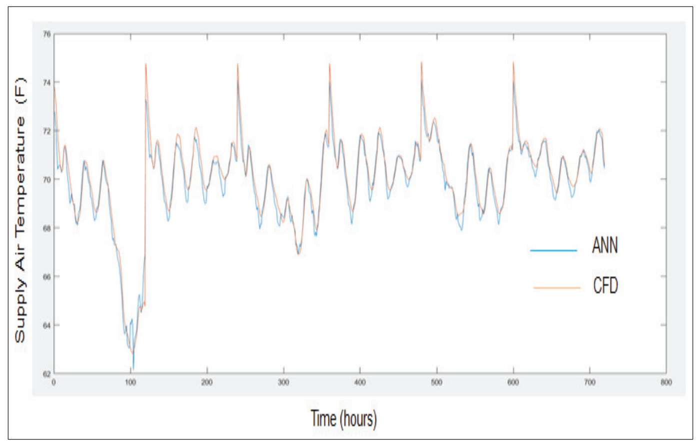

Figure 19: *One Hour Step Ahead Prediction of SAT for April*

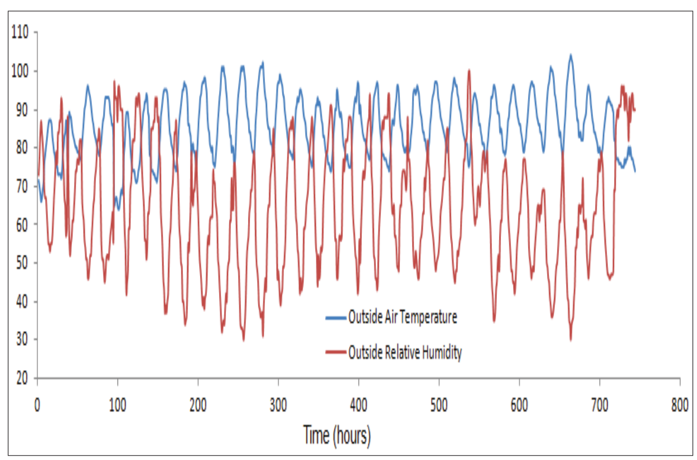

Figure 20: *OAT and OAH for July*

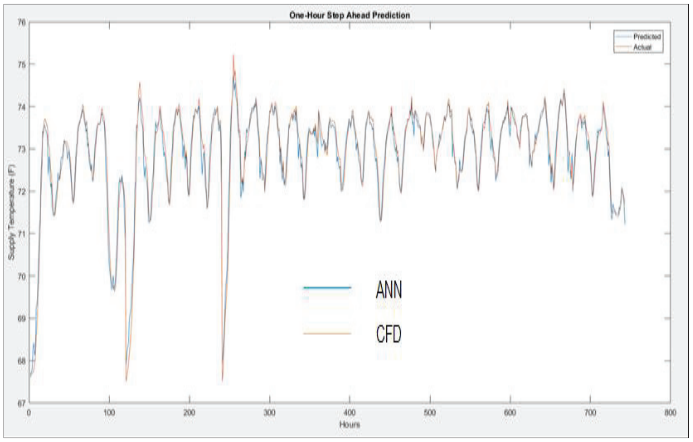

Figure 21: *One Hour Step Ahead Prediction of SAT for July*

Figure 22 shows OAT and OAH for October month of 1981. Comparison of Figure 22 is compared with Figure 23 shows that though the maximum OAT is around 80 F, the AHU is providing supply air below 74 F. Also, Figure 23 shows one hour step ahead prediction of ANN and CFD values which are in good agreement with each other. MAE and RMSE values for ANN of October are 0.23 F and 0.31 F as shown in Table 1.

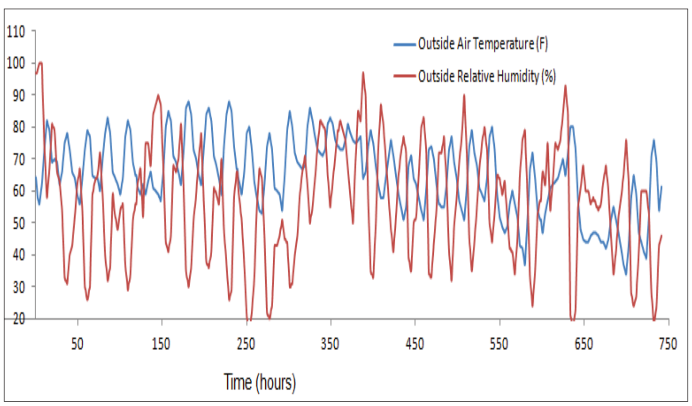

Figure 22: *OAT and OAH for October*

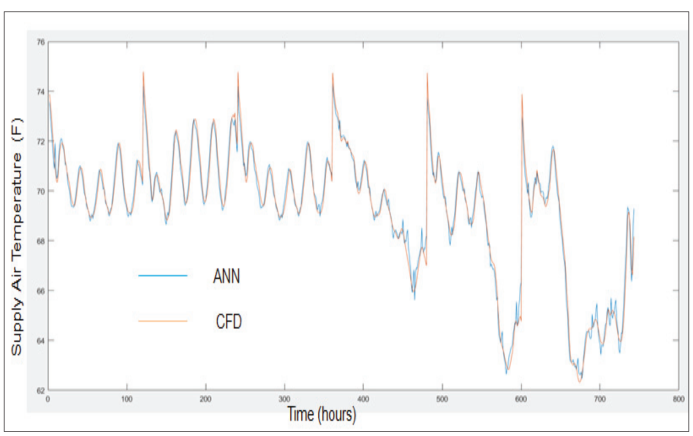

Figure 21: *One Hour Step Ahead Prediction of SAT for October*

Performance Analysis

Table 1 shows the performance analysis of all four ANN models. It demonstrates that MAE is in range of 0.1 to 0.2 (F) and RMSE has range of 0.2 to 0.4 (F), which is a good useful accuracy.It can be observed that magnitude of MAE values is less than RMSE for all four networks. This is because MAE calculates absolute difference between CFD value and ANN predicted value while RMSE squares the difference between the two. This makes RMSE values bigger than MAE values [14].

Table 1. Performance Analysis of ANN models

ANN model for the month of	MAE	RMSE
January	0.13 F	0.19 F
April	0.17 F	0.23 F
July	0.21 F	0.36 F
October	0.23 F	0.31 F

CONCLUSION

This study provides a summary of the domain knowledge required for building CFD model to prepare the synthetic dataset and development of ANN model trained using CFD simulations data to predict supply air temperature in an air handling unit. Predictions of ANN can be used for pro-active control to achieve energy efficient data center.

Training and hourly prediction of ANN model for supply air temperature for all four months which represents each of four weather season's working conditions of data center consumed approximately 30 minutes whereas development of CFD model and its simulations consumed around 30 days. For evaluating the accuracy of ANN prediction two statistical indices MAE and RMSE are used which has maximum value of 0.4 Fahrenheit. This implies that ANN predicts quickly with useful accuracy and hence ANN approach can be used as an alternative for traditional CFD approach.

REFERENCES

[1] J. G. Koomey, "Growth in Data Center Electricity Use 2005 to 2010," Analytics Press, 2011.

[2] National Resources Defense Council; Anthesis, "Data Center Efficiency Assesement," 2014.

[3]Unique Rahangdale, B Conjeevaram, Anirudhha Doiphode, Pavan Rajmane, Abel Misrak, Dereje Agonafer "Solder ball reliability assessment of WLCSP-Power cycling versus thermal cycling" IEEE International Thermal and Thermomechanical Phenomenon in Electronic Systems (ITherm), 2017

[4]Fausett, L, 1994. Fundamental of Neural Networks.

[5] Andrew Ng .Machine Learning. https://class.coursera.org .

[6] Yu, S.; Zhu, K.; Zhang, X. Energy demand projection of China using a path-coefficient analysis and PSO–GA approach. Energy Conver. Manag. 2012, 53, 142–153

[7] Eugen Diaconescu, “The use of NARX Neural Networks to predict Chaotic Time Series”

[8] https://www.mathworks.com/help/nnet/gs/neural-network-time-series-prediction-and-modeling.html

[9] Robert May , Graeme Dandy and Holger Maier,
“Review of Input Variable Selection Methods for Artificial Neural Networks”

[10] G. Mustafaraj, “Prediction of room temperature and relative humidity by autoregressive linear and nonlinear neural network models for an open office

[11] Tian Bo and Qin Zheng, “ Empirical Study of Financial Affairs Early Warning Model on Companies Based on Artificial Neural Network”

[12] Hecht-Nielsen, R. ,“Theory of the Back propagation Neural Network.” In International Joint Conference on Neural Networks; IEEE: Washington, DC, USA, 1989.

[13] Goopyo Hong, Byungseon Sean Kim, “Development of a Data-Driven Predictive Model of Supply Air Temperature in an Air-Handling Unit for Conserving Energy.

[14] Sukthankar Nikita, “Computational Fluid Dynamics Simulation-Based Artificial Neural Network Modelling For Data Center Cooling Prediction” MS Thesis, 2018