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NEURAL NETWORK BASED BIN ANALYSIS FOR INDIRECT/DIRECT EVAPORATIVE COOLING OF MODULAR DATA CENTERS

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ABSTRACT

With an increase in the need for energy efficient data centers, a lot of research is being done to maximize the use of Air Side Economizers (ASEs), Direct Evaporative Cooling (DEC), Indirect Evaporative Cooling (IEC) and multistage Indirect/Direct Evaporative Cooling (I/DEC). The selection of cooling configurations installed in modular cooling units is based on empirical/analytical studies and domain knowledge that fail to account for the nonlinearities present in an operational data center. In addition to the ambient conditions, the attainable cold aisle temperature and humidity is also a function of the control strategy and the cooling setpoints in the data center.

The primary objective of this study is to use Artificial Neural Network (ANN) modelling and Psychrometric bin analysis to assess the applicability of various cooling modes to a climatic condition. Training dataset for the ANN model is logged from the monitoring sensor array of a modular data center laboratory with an I/DEC module. The data-driven ANN model is utilized for predicting the cold aisle humidity and temperatures for different modes of cooling. Based on the predicted cold aisle temperature and humidity, cold aisle envelopes are represented on a psychrometric chart to evaluate the applicability of each cooling mode to the territorial climatic condition. Subsequently, outside air conditions favorable to each cooling mode in achieving cold aisle conditions, within the ASHRAE recommended environmental envelope, is also visualized on a psychrometric chart. Control strategies and opportunities to optimize the cooling system are discussed.

NOMENCLATURE

ACU	Air Cooling Unit
AHU	Air Handling Unit
ANN	Artificial Neural Network
ASE	Air Side Economization
CA	Cold Aisle
DEC	Direct Evaporative Cooling
DC	Data Center
DP	Dew Point Temperature
IEC	Indirect Evaporative Cooling
MSE	Mean Square Error
OAH	Outside Air Relative Humidity (%)
OAT	Outside Air Temperature (F)
RH	Relative Humidity

INTRODUCTION

Data centers need to be maintained within a certain range of temperature and humidity for equipment reliability and energy efficiency. Evaporative cooling can be used in many guises to make data center cooling more efficient and enables elimination of chiller-based cooling entirely. In addition to that, evaporative cooling units along with air-side economization provides the data center industry a sure pathway to gain cooling efficiency. While disruptive cooling technologies such as liquid cooling [1] and immersion cooling [2] present energy saving benefits, the capital expenses in implementing evaporative cooling for an existing air-cooled data center is comparatively less.

Many studies show that majority of the energy used for data center cooling is utilized for direct expansion air conditioners (DX). Thus, to reduce the use of DX, other modes of cooling are being used. This includes air side economization

(ASE), direct evaporative cooling (DEC), indirect evaporative cooling (IEC) and multi-stage cooling (I/DEC). Use of these alternative modes of cooling reduces the power consumption of an ACU by over 70% as compared to the DX [3]. But the use of ASE is limited by the ambient air conditions such as temperature, humidity, and pollutants. The added savings potential represented by airside economization for favorable ambient conditions based on psychrometric-based modeling approach coupled with Typical Meteorological Year data for various climate zones is well documented. In this study, we set to investigate the applicability of ASE, IEC and IDEC cooling modes for a hot and humid climatic condition. More importantly, this study tests the feasibility of developing ANN models to account for the non-linearities inherent in data center cooling.

PSYCHROMETRIC BIN ANALYSIS

A psychrometric chart represents the thermodynamic properties of moist air, i.e. its graphical equation of state. The territorial weather data is readily available as typical meteorological year (TMY3) data for a specific location [4]. The hourly-bin TMY3 weather data for the Dallas-Love field weather station is shown in Figure 1a, visualized on a psychrometric chart. The ASHRAE recommended environmental envelope for ITE (Information Technology equipment) is considered in this study as a desired target envelope for data center cold aisle conditions. The recommended range is the guidance from ITE manufacturers for high reliability, minimal power consumption (of ITE) and maximum performance [5]. Figure 1b shows the ASHRAE recommended envelope on the psychrometric chart along with regions defined for categorization of territorial outside air conditions. The regions A to H are defined by considering all possible thermodynamic processes for each cooling mode. The region C in Figure 1b is the targeted envelope for cold aisle conditions whereas the regions A to H are defined to categorize the outside air conditions over a typical year.

Table 1: ASHRAE Recommended Range for ITE

Recommended Envelope	
Low End Temperature	64^{o}F (18°C)
High End Temperature	81^{o}F (27°C)
Low End Moisture	41.9^{o}F DP (5.5°C)
High End Moisture	60% RH; 60^{o}F DP (15°C)

Previous studies have been able to use the regional weather data and estimate either the total number of hours available for air-side economization based on similar regions defined on a psychrometric chart or estimate the applicability of available modes of cooling by analyzing the underlying thermodynamic processes accompanying the various cooling modes [6,7]. As shown in Figure 1c, the 46% of outside air in region A depicts the percentage of outside air that requires dehumidification over a typical year to satisfy the targeted recommended range for cold aisle conditions. Similarly, the combined 50% of outside air from regions B, C and F can be considered as the total air-side economizer hours available.

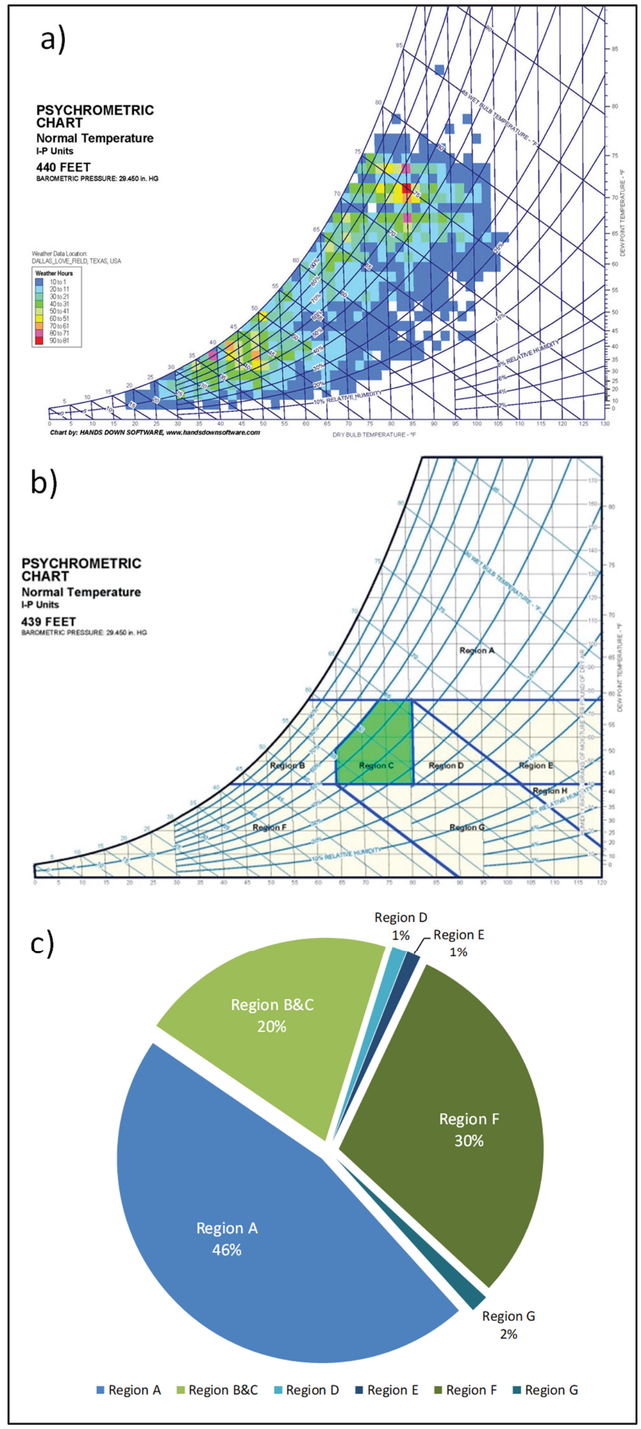

Figure 1: a) Dallas-Love Field TMY3 hourly weather bin-data plot; **b)** ASHRAE recommended envelope for ITE along with regions A to H defined for categorization of territorial outside air conditions; **c)** Pie chart showing the percentage of weather bin-data distributed in terms of the outside air regions A to H

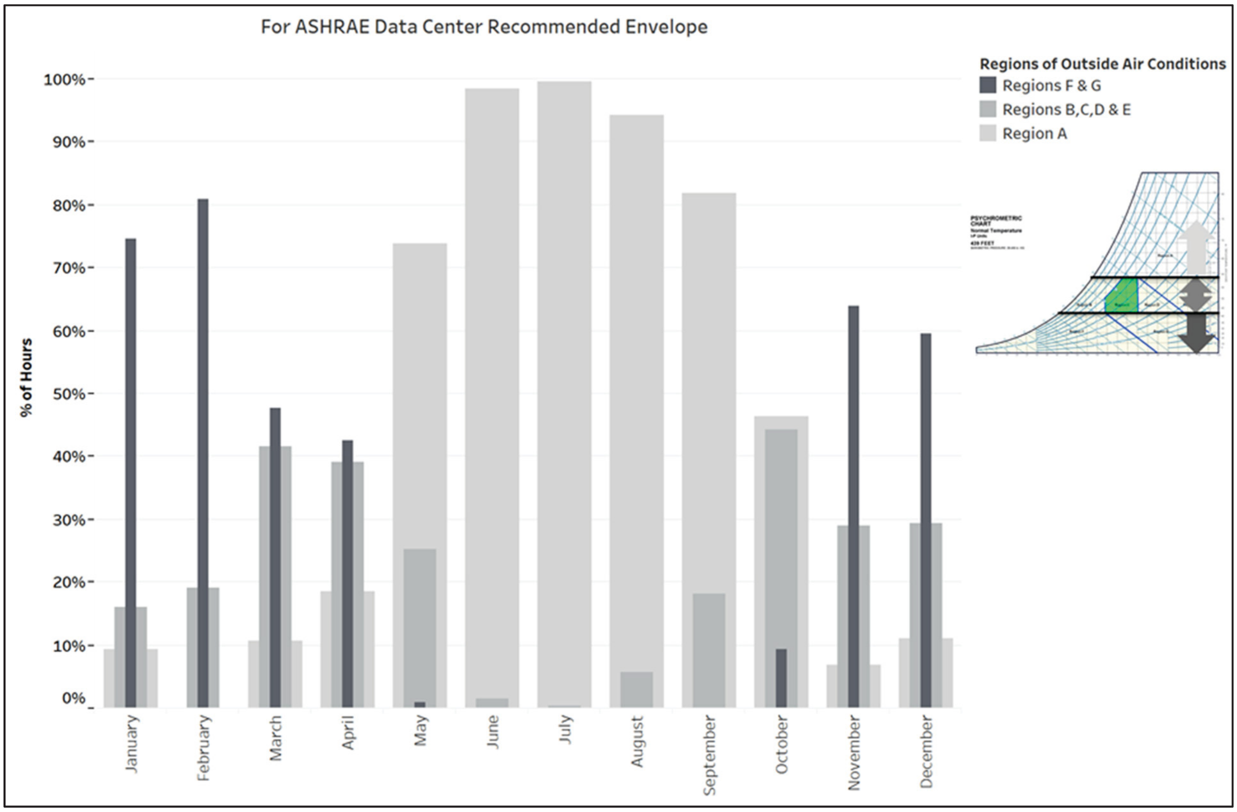

Figure 2: Monthly weather bins and percentage of total hours based on dew point temperature bounds

Furthermore, the upper and lower dew point temperature bounds, as per the ASHRAE recommended envelope, can be used as a reference for categorizing outside air conditions when evaporative cooling is to be implemented in addition to air-side economization. Figure 2 shows the percentage of total hours each month for Dallas-Love Field TMY3 data categorized based on the dew point temperature bounds. When the percentage of outside air for region A is considered month-wise in Figure 2, one can infer that the need for dehumidification is predominantly during the summer months. And the applicability of the direct and indirect evaporative cooling is evident for the rest of the months. However, such estimates of hours of applicability for air-side economization and evaporative cooling based on weather data and thermodynamic processes fail to account for the limitations due to operational control strategy and cooling system design.

In this study, a test bed modular data center (MDC) with a cooling module consisting of three types of cooling configurations has been considered. These include the Air Side Economizer (ASE), Direct Evaporative cooling (DEC) and Indirect Evaporative Cooling (IEC). The MDC also consists of an IT module and ductwork for supply to the CA and return from the hot aisle. This MDC laboratory has been operating for several years and the cooling module is an Indirect/Direct evaporative cooling unit wherein air-side economization is also implemented.

An ANN model has been developed using the Levenberg-Marquardt algorithm function in MATLAB neural network toolbox. This model was trained using the logged data from a map of monitoring sensors for over a year from an operational data center [8,9]. Tableau software and a Python code was used for data pre-processing and cleaning. The trained network was then used to predict the PUE and cold aisle conditions for different modes of cooling. Using these predicted results, different bounds for cold aisle conditions for the cooling mode can be obtained. Further, the outside air conditions for which the predicted cold aisle conditions were within the ASHRAE recommended envelope were filtered out and new outside air regions for each cooling mode are defined. These results can be used to test the applicability of a cooling configuration for different weather zones while designing new data centers and for setting up control strategies in an existing data center implementing various cooling modes.

ANN Modeling and Training

ANN is a machine learning tool that can predict the results based on the learning data set. It uses the Levenberg-Marquardt algorithm to establish a relation between the input parameters with the outputs by assigning a set of values called as weights. These weights are updated with each iteration thus increasing the accuracy of the model. In this study, the curve fitting ANN tool in MATLAB has been used for defining, training, and testing of the model. The ANN model uses the Levenberg-Marquardt algorithm with 20 hidden neuros and a non-linear activation function for the hidden layers and a linear activation function for the output layer. The network uses seven input parameters and 3 output parameters. These include outside air temperature, humidity, IT load, temperature difference across the servers and the three types of cooling as the inputs and Power Usage Effectiveness (PUE) and the cold aisle temperature and relative humidity as the output. The network model is shown in Figure 3. The real time sensor data from the MDC laboratory in Dallas has been used for training and validation of the network. TMY 3 data for the Dallas Love-Field weather station has been used for testing and prediction.

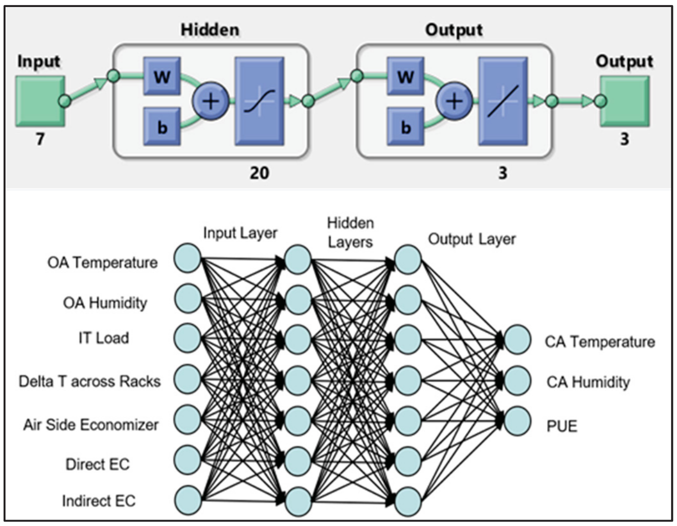

Figure 3: ANN model (top) and the network topology depicting input and output parameters (Bottom)

Figure 4 shows the variation of the error with each iteration. It can be seen from the graph that the error starts at around 5000 and then decreases with each iteration. The training and validation stop when the MSE is stable at 11.035. This value represents the maximum MSE among all the validation errors and is called the best validation performance.

Figure 5 represents the regression graph, in which the circles are the actual data points and the line represents the best between the outputs and the targets. The average value for R is 0.9954 which is very close to 1 and it can be stated that the trained network predictions are acceptable. The training and validation errors is represented by the error histogram shown in Figure 6. It can be observed from the graph that the majority instances of the error lie between -3.5 and 2.8. The maximum validation error is 11.035 which is considered as the best performance achieved for the model.

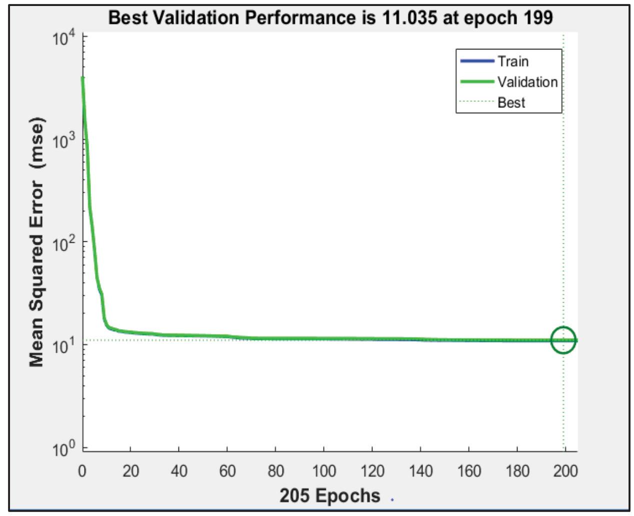

Figure 4: Performance Plot

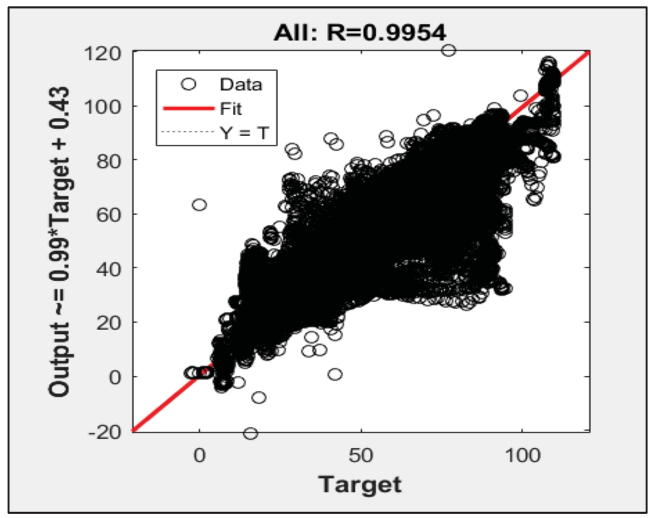

Figure 5: Regression Plot

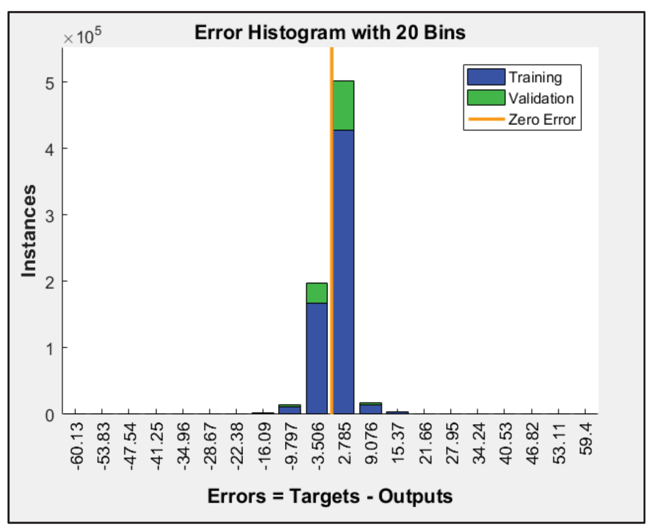

Figure 6: Error Histogram

RESULT AND DISCUSSION

The TMY3 data from Dallas Love Field weather station was used as inputs to test the network. The IT load was kept constant at 15W and the rise in temperature across the servers was set to be 20. The type of cooling mode was parameterized for every run and the results were stored separately for each type of cooling mode. The predicted results were then analyzed to see how the cold aisle conditions varied over a typical year when the model was run on only one type of cooling. The output results from this ANN model are the predicted PUE, cold aisle temperature and relative humidity. The ANN model is used to predict the PUE of the data center for each type of stand-alone cooling mode when the data center is operated over a typical year. All the results are presented in this results and discussion section. Our findings are not generalizable beyond the subset of weather data examined and beyond the control logic and cooling mode settings considered in this study. However, the analysis framework and the results yielded in this study provide preliminary evidence to suggest that ANN models can be successfully used in place of traditional analysis methods.

Cold Aisle Envelopes Based on the Different Cooling Modes:

For ASE, the process of mixing OA and return air from the hot aisle is primarily dependent on the placement of the mixed air temperature sensor and the control algorithm of the damper system installed on OA and return air vents. Therefore, the training data obtained from the MDC laboratory must adequately capture this phenomenon when developing the ANN model and the predicted CA conditions will be representative of the control setpoints in the MDC laboratory. Figure 7 shows the predicted CA conditions plotted on the psychrometric chart if the DC operated on ASE for the whole year. We can see from Figure 7 that the dry bulb temperature is maintained between 64°F and 81°F for majority of time. The effectiveness of the mixing process, of recirculating air with the OA, determines how efficiently the extreme cold and extreme hot outside conditions can be conditioned to the desired cooling setpoints in the CA. Therefore, the CA envelope obtained for ASE can be further improved by optimizing the mixing chamber of the cooling unit.

Figure 8 shows the predicted CA conditions plotted on the psychrometric chart if the DC operated in IEC mode. Here the air is cooled sensibly and hence there is not much rise in the humidity content of the cooled air. Hence, we can see that the relative humidity remains under 70%. Similarly, Figure 9 shows the predicted CA conditions plotted on the psychrometric chart if the DC operated on IDEC over a typical year.

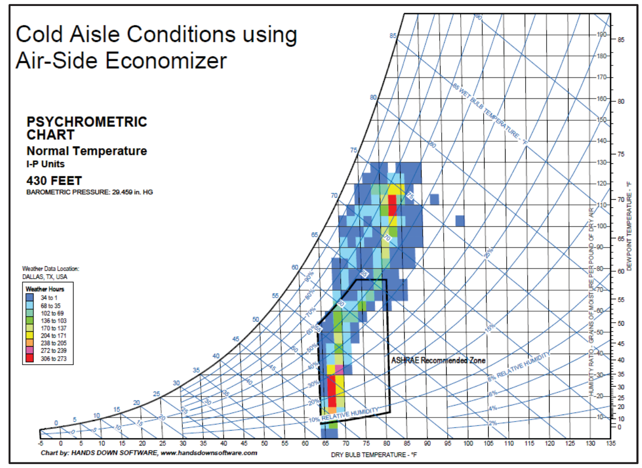

Figure 7: Predicted CA condition when operating the data center in ASE cooling mode throughout a typical year

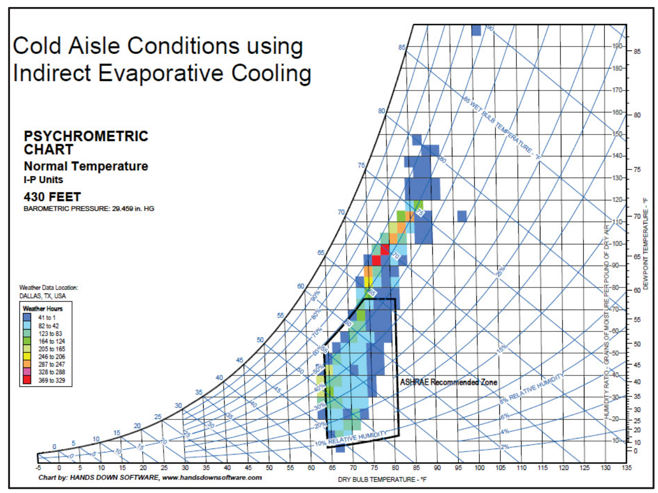

Figure 8: Predicted CA condition when operating the data center in IEC mode throughout a typical year

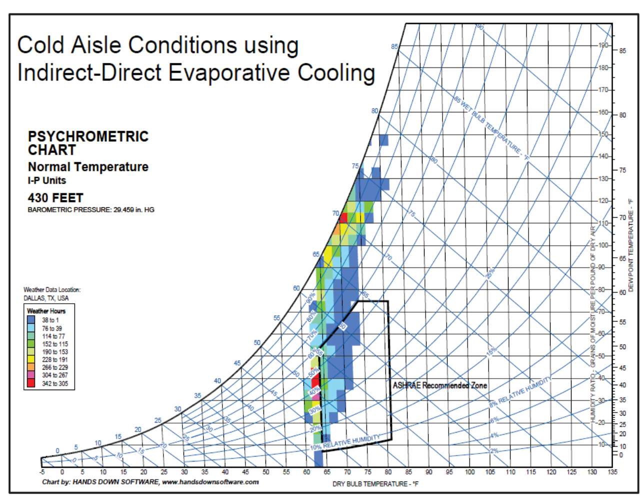

Figure 9: Predicted CA condition when operating the data center in I/DEC mode throughout a typical year

From Figure 9, we can see that the dew point temperature increases compared to the previous chart as there is humidification of the supply air due to DEC. The combined effect of both the direct and indirect evaporative coolers deliver an increased overall cooling effect. This can be easily inferred by comparing the lower dry bulb temperature bound of the CA envelopes plotted in Figure 7, 8 and 9. These Figures also suggest that humidity excursions are prevalent in the cold aisle regardless of the cooling configuration. The extent of humidification is a clear function of the operational saturation efficiency of the wet cooling media wall and the OAT. The validity of the data collection approach in the CA contributes to lower cooling setpoints [10] and thereby can also lead to in excessive humidification. Rapid changes in the OAT and stratification of inlet air can result in scenarios of excessive humidification [11]. Erroneous control strategy can lead to such high humidity (95% RH) conditions in the cold aisle and this can be catastrophic due to condensation related ITE failures in the data center [12].

The box and whisker plot in Figure 10, 11 and 12 show variability of the CA temperature and humidity over each month for different but stand-alone cooling modes. For ASE and IEC modes, the monitoring sensor location and the CA cooling setpoint is generally temperature-based and the variability in CA humidity is a function of OAT. By optimizing the mixing process of outside air and return air, there is a possibility of reducing the variability in CA conditions. Control strategies to achieve incremental humidification in DEC is further explored in [11].

Outside Air Envelopes Based on Different Cooling Modes

The applicability of a cooling mode, for a specified location, is often reported in terms of the total OA hourly bins available for adequate cooling provisioning [6,7]. However, thermodynamic and analytical models in previous studies assume an idealized airflow distribution and cooling control mechanism. In this study, such nonlinearities are inherent in the training data used for developing the ANN model. The predicted CA conditions from the ANN model yielded some interesting findings. By extracting the OA input conditions for which the predicted CA conditions satisfy the ASHRAE recommended envelope, OA envelopes can be visualized on a psychrometric chart. Using these results, the total effective hours of operation for a cooling mode over a typical year, as well as for each month, was obtained for all the cooling modes considered in this study. Figure 13 shows the OA plots for which ASE can be used to maintain the CA conditions within the ASHRAE recommended region. It can be observed that the high humidity and low temperature air was conditioned to be within the recommended bounds by mixing it with the hot and dry air from the hot aisle using ASE. But there are no points in the high humidity region once the temperature goes above 60°F.

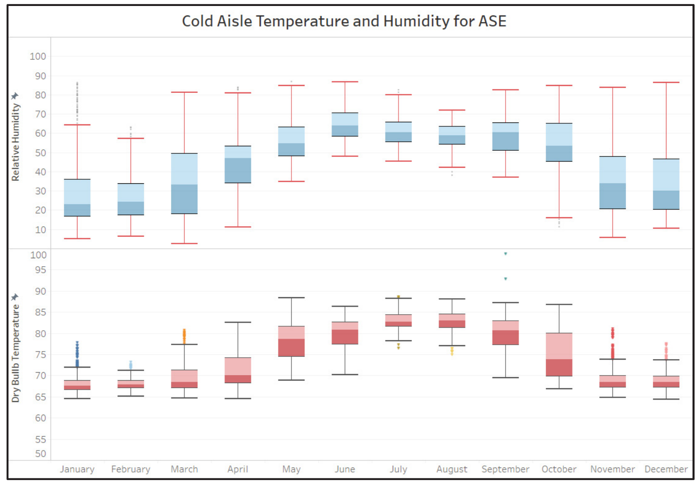

Figure 10: Variability of the CA condition when operating the data center in ASE mode throughout a typical year

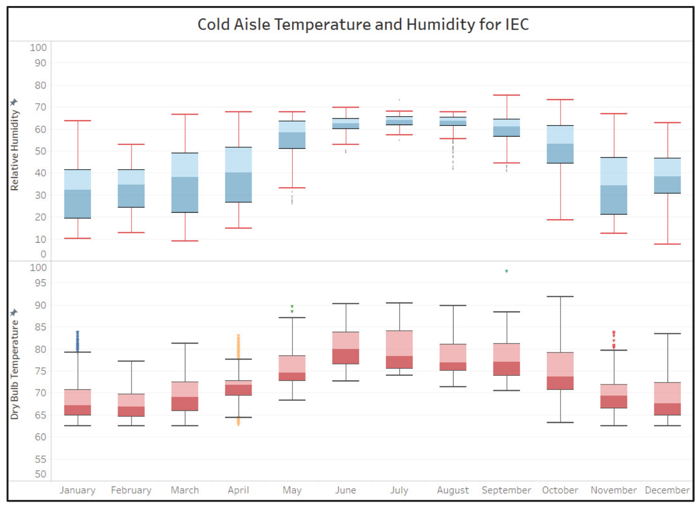

Figure 11: Variability of the CA condition when operating the data center in IEC mode throughout a typical year

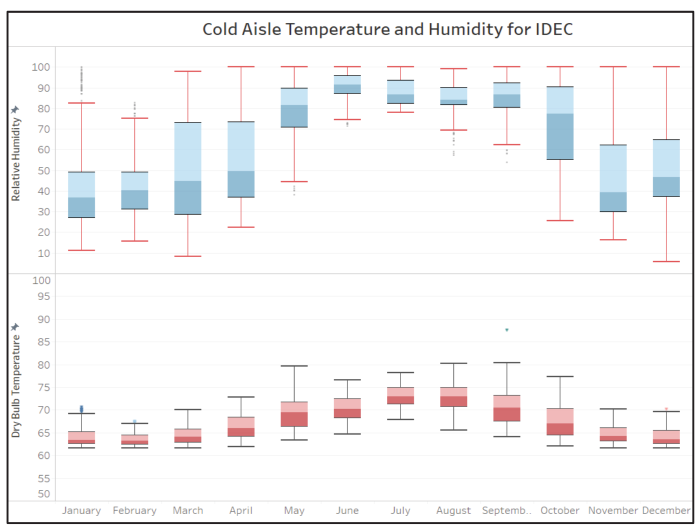

Figure 12: Variability of the CA condition when operating the data center in IDEC mode throughout a typical year

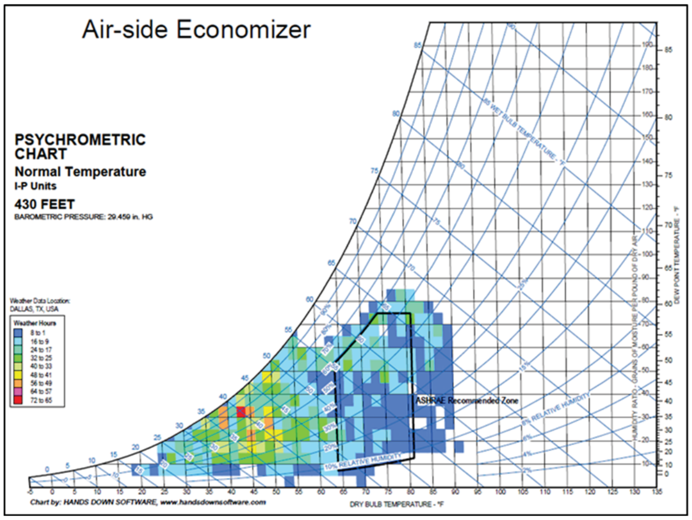

Figure 13: OA conditions when using ASE for achieving CA operating conditions in the ASHRAE Recommended Envelope

Also, depending on the effectiveness of the control algorithm, a large part the IEC utilizes return air for sensible cooling and adds no moisture to the supply air. This is evident in Figure 14, as the dataset used for training the ANN model was obtained from the MDC wherein the IEC operated by recirculating the return air when the outside air is hot and humid or just too humid. Thus, OA envelope for IEC in Figure 14 spans the high humidity region although in reality the majority of the return air is recirculated for cooling purposes.

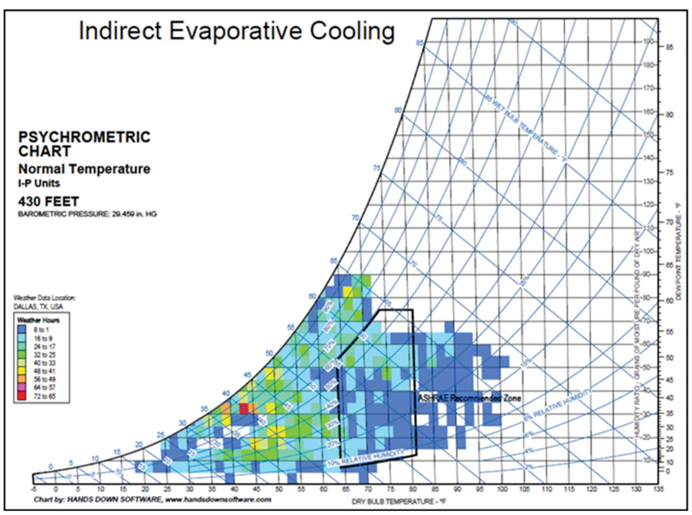

Figure 14: OA Envelope using IEC for achieving CA operating conditions in the ASHRAE Recommended Envelope

In the MDC laboratory, the control algorithm was setup in such a way as to always initiate IEC first and switch to IDEC only when additional cooling was required. During IDEC, the OA first undergoes sensible cooling with no moisture added. In the second stage, the pre-cooled air is then passed through the direct evaporative cooling pads further reducing its temperature. Also, a significant increase in seen in the humidity of the air during this second stage. As a result, the final supply air is cool and humid. Thus, I/DEC is mostly used for dry and very hot OA conditions. Again, erroneous control can lead to over-humidification of the pre-cooled air.

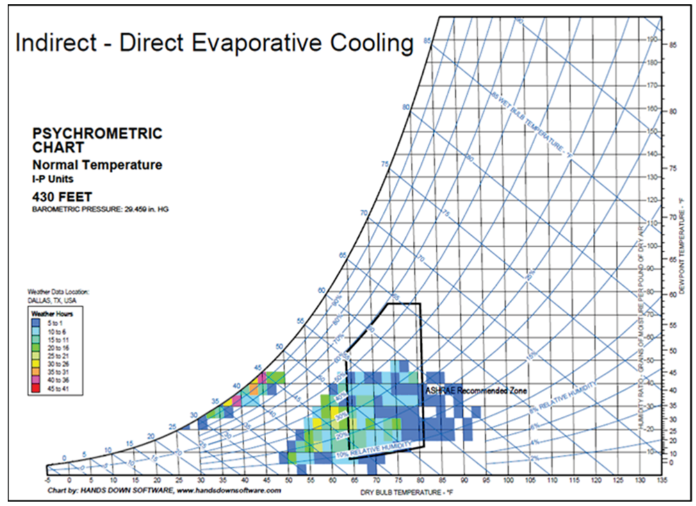

Figure 15: OA Envelope using IDEC for achieving CA operating conditions in the ASHRAE Recommended Envelope

Figure 16 shows the predicted month-wise usage of different type of cooling modes. It can be seen from the graph that the trend is similar for all types of cooling. The utilization is higher expect during the summer months. This is mainly because of the rise in the outside air temperature and humidity during the summer. It should be noted that the lack of utilization of any mode of cooling during the summer resulting in CA conditions within the ASHRAE recommended envelope is primarily due to the large fluctuations in humidity.

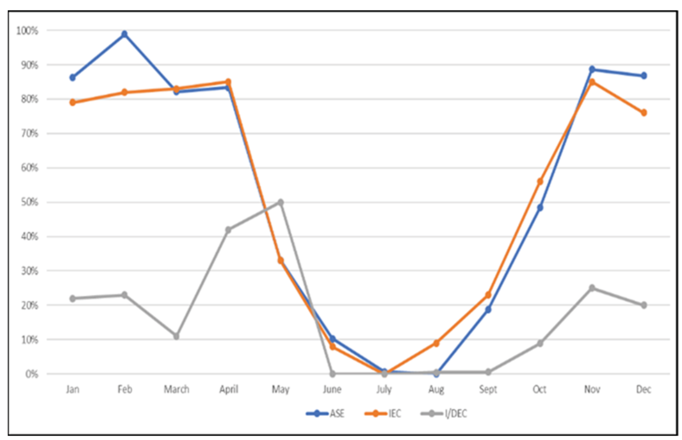

Figure 16: Month-wise %OA for different types of cooling satisfying ASHRAE Recommended Envelope

The cooling setpoints in data center cannot reliably consider humidity setpoints due to the lack of refined humidity control in evaporative cooled data centers without any dehumidification available. Even the humidification process due to the direct evaporative cooling lacks incremental humidification effect if the wet cooling media wall is not vertically staged with discrete pumps [11]. Therefore, alternative cooling such as direct expansion cooling or dehumidification of supply air must be used to maintain the server within the ASHRAE recommended zone during these months. Depending on the type of ITE populated in the data center, short humidity and temperature excursions can be safe and energy efficient. Taken altogether, the data presented here provide evidence that the three cooling modes i.e., ASE, IEC and IDEC can be used for cooling the outside air to the recommended envelope. From the OA envelopes, 53% of the outside air is compatible for ASE, 10% for IEC and 8% for IDEC when the targeted CA condition is the ASHRAE recommended envelope. Minimizing or accommodating the humidity excursions can further improve these figures. However, for total minimization of cooling power, controls must be set to first use ASE as it has the lowest PUE and thus minimizes the cost of cooling. Figure 17 represents the scenario when all the cooling modes are available, and the control algorithm mimics the controls set up on the MDC laboratory.

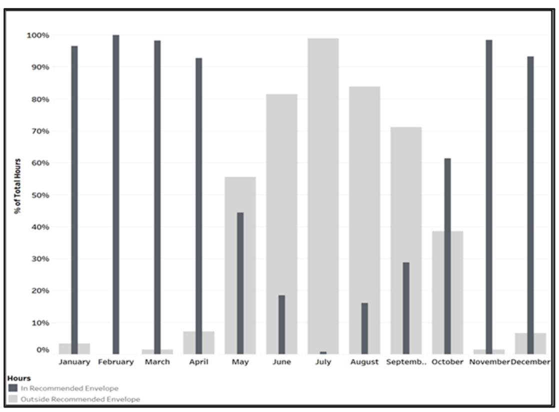

Figure 17: Month-wise Predicted Utilization for all cooling modes in tandem when targeting ASHRAE recommended CA conditions

There is a possibility of using data-driven ANN models to facilitate control strategies that can pro-actively minimize the operational cost. For the optimum sequence of operation and switching between cooling modes, further investigation is necessary. The transients involved in initiating a cooling mode and the temperature and humidity variations within the CA are all important operational features of the cooling system design that can be captured with an ANN model. The challenge in developing such models would primarily be in acquiring the right and enough training data set. Computational Fluid Dynamics models of data centers have been used to generate robust training data sets to predict the temperature and airflow distribution within a data center [13-15]. Future studies will have to continue to explore how the complex features of an operational data center can be extracted and adequately represented in a training dataset to develop better ANN models.

CONCLUSION

In this study, the logged field data from a modular data center was used to train the ANN model which was then used to predict the conditions inside the cold aisle. The results presented in this paper show that ANN can be utilized to predict the performance of the cooling systems which can be then used to set up control algorithms for the data centers. Firstly, the ANN model predicted the cold aisle conditions achieved when only one cooling mode is used over a typical year. For each cooling mode operated over a typical year, a CA envelope was visualized on a psychrometric chart. These results can be used to understand the variations in the cold aisle with respect to the cooling mode in different weather zones. Furthermore, OA envelopes were visualized on a psychrometric chart to determine the variability of the outside air conditions over which a cooling mode can be effectively used to attain ASHRAE recommended CA conditions. The ANN model accounts for the non-linearities developed in the data center due to the interdependence of mechanical, electrical and control systems and hence give a more realistic results compared to other analysis methods.

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