Comparison of Approaches for Calculating Annualized Data Center Energy Metrics

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ABSTRACT

Calculation of the annualized Mechanical Load Component (MLC) and Power Usage Effectiveness (PUE) of a data center requires determining the annual facility energy consumption in kWh. For this purpose, ASHRAE Standard 90.4 recommends running an annual simulation for 8760 hours using an hourly timestep. The Standard also allows an annualized metric calculation by running a simulation with external temperature values placed into bins with a 1°C (2°F) increment. However, the influence of bin size in the latter approach on the calculated annualized MLC and PUE is unknown. Therefore, this paper examines the influence of bin size on these energy metrics for four commonly-encountered climate conditions in the US. The results of this work show that the calculated metrics are essentially independent of bin size. A minimum bin width limit of 0.5-0.75°C (0.9-1.35°F) is seen for all four locations where non-continugous bins occur due to the hourly discretization of annual weather data. A maximum bin width limit also exists that results in nonphysical psychrometric conditions for the chosen binning method, and this limit is location-dependent since these nonphysical conditions occur near saturation conditions.

INTRODUCTION

ASHRAE standard 90.4 dictates that there are two acceptable methods for calculating annualized mechanical load component (MLC) values for a data center (ASHRAE 2016). The first approach requires temperature data to be categorized into bins with a maximum 2°F (1°C) increment. A temperature bin specifies a temperature range and bin width or bin increment, which is defined as the difference between the upper and lower limits of that range. The dry-bulb temperature is used as the primary parameter. The bin frequency represents the number of hours that external dry-bulb temperatures fall into that bin within a year. Each dry-bulb temperature is accompanied by a corresponding wet-bulb temperature, and the average of these set of values for each bin represents the mean corresponding wet-bulb (MCWB) temperature of that bin. This parameter is required to capture humidity effects for performing psychrometric calculations for annual energy simulations.

This consolidation of weather data assumes that all hours containing similar temperatures throughout the year can be grouped together and used in a single load calculation to avoid repetition of load calculations. Such data is used in steady-state calculations to compute data center annual design and performance metrics. Since these temperature bin data are based on hourly weather data as opposed to daily averages, they are more accurate than degree-day

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calculations (Al-Homoud 2001) and able to perform latent load calculations in addition to sensible load calculations due to the availability of wet-bulb temperature data (Papakostas and Sotiropoulos 1997).

The National Renewable Energy Laboratory (NREL) already used a value of 2°F (1.2°C) in their report back in September 2014 (NREL Report 2014). They also mention bin sizes of 5°F (2.8°C) and 8°F (6.7°C) occurring in the literature. Davidson (2009) examined the potential of using airside economization for a data center located in Los Angeles, CA using annual data grouped into bins with a 2°F (1.2°C) bin size representing external dry-bulb and wet-bulb temperatures. He alludes to the data being available in this form from ASHRAE's Weather Data Viewer (ASHRAE 2005). However, study does not reports the use of different bin sizes, so the impact of bin size on the annual energy consumption cannot be assessed. Hassan et. al. (2015) investigated the potential of free-air cooling in Islamabad, Pakistan using weather data over the past sixteen years classified into monthly bins. They conclude that free air cooling has the potential of saving US$ 4000 in utility bills over the course of three months (December - February) when airside economization is possible. However, the influence of bin width was not mentioned.

Similarly, a lack of available temperature bin data for Greek cities caused Papakostas and Sotiropoulos (1997) to publish the first ever bin data for Greece using 10 year climate data collected for the city of Thessaloniki. They used six periods of four hours each and a bin width of 2.8°C (5°F) to sort temperature into bins on monthly and annual bases. They noted that monthly data is better for energy analysis; however, bin width was not a focus of their pioneering study. Papakostas (1999) used the same approach to collect and publish temperature bin data for Athens, Greece, and Papakostas et. al. (2008) further tabulated dry-bulb temperature bin data for 38 other Greek cities using a bin width of 2°C (3.6°F).

Bulut, Buyukalaca and Yilmaz (2001) compiled dry-bulb temperature bin data for 78 different cities in Turkey using the same approach introduced by Papakostas and Sotiropoulos (1997) but with a 3°C (5.4°F) temperature increment. Bulut and Aktacir (2011) further used that data to study the airside economization potential of a typical HVAC system in Istanbul, Turkey, and found the technique to be favorable during the transition months of Fall and Spring. However, they only used one temperature increment and did not investigate the impact of varying bin size on the annual energy savings realized through using airside economization. Lastly, Peng et. al. (2009) used the same approach of Papakostas and Sotiropoulos (1997) to categorize outdoor dry-bulb weather data into bins for 26 cities in China. They also employed a bin width of 2°C (3.6°F) and categorized their data on a monthly and annual basis.

The above literature search suggests that bin data is not readily available for locations outside North America, so most researchers have focused on generating bin data from weather data available from their local or national meteorological departments. However, no work in the published literature searched so far has accounted for the influence of bin size on the nature of the data generated and its influence, if any, on the resulting annual energy analysis performed for modern data centers. Hence, this study aims to fulfill this gap by investigating the impact of bin size on the annual power usage effectiveness (PUE) and annualized mechanical load component (MLC) of a simulated data center using the in-house software tool Villanova Thermodynamic Analysis of Systems (VTAS).

LEARNING OBJECTIVES

This study aims to understand the feasibility of the bin approach and the influence of bin size on accuracy and robustness. The intended goal is to come up with the sensitivity of bin size on calculated annualized PUE and MLC as well as to uncover issues that arise in the limits of small or large bin sizes.

MODELING

Data center cooling system

The cooling system modeled for this study is shown in Figure 1. It consists of airside economization aided by an evaporative cooler. Outside air is drawn in to cool the IT equipment when ambient conditions are conducive, such as low external temperatures and low to moderate relative humidity. These conditions are commonly prevalent in the winter months. However, ambient conditions occasionally prohibit the use of free air cooling, so data center operators must rely on mechanical cooling to cool the IT equipment. Such cooling systems commonly consist of standalone direct expansion (DX)-based computer room air conditioner (CRAC) or computer room air handler (CRAH) units using air-cooled or water-cooled chillers, which further utilize cooling towers. Since both chillers and DX-based CRAC units are power intensive, this study uses the latter to reduce the number of cooling components to minimize the complexity of the cooling system model.

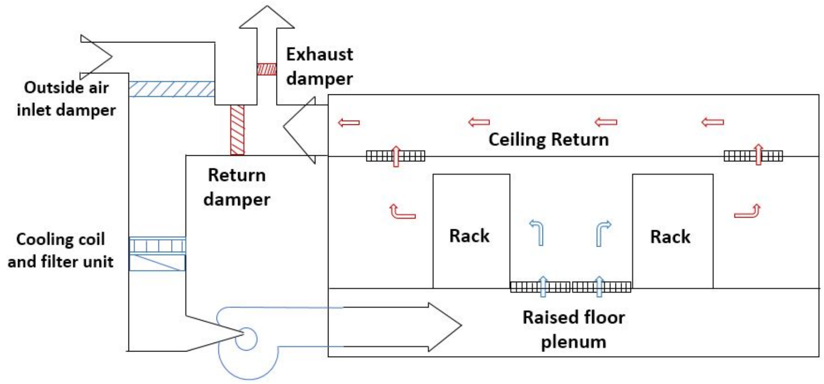

Figure 1 Data center airside economizer system.

Villanova Thermodynamic Analysis of Systems (VTAS)

VTAS is a holistic thermodynamic modeling tool based on flow network modeling (FNM) (Wemhoff et. al., 2013). It is used to rapidly model data center IT equipment and cooling systems. Each equipment item is described by a component model. VTAS is divided theoretically into (i) flow network calculations, (ii) framework calculations and (iii) component calculations. In a steady-state simulation, the flow network calculations determine the values of fluid pressure drop and flowrate between components, the framework calculations provide the energy balances in the system to dictate the required flow states and energy transfer, and the component calculations dictate the exergy destruction in various portions of the system and provide the minimal design requirements to achieve the energy transfer specified in the framework calculations. VTAS also contains a controls modeling capability to model cooling systems operating below their maximum loads.

VIRTUAL TESTBED USED FOR STUDY

The virtual testbed shown in Figure 2 has been developed using VTAS to model the chosen data center cooling system to test out the bin approach for data center annualized metrics. The testbed contains an airside economizer with an evaporative cooler to simulate free air cooling, and a DX-based CRAC unit for mechanical cooling. The CRAC unit's supply air (S/A) fan cools the data center using a mixture of outdoor and return air, which gets mixed in junction J2. Equal amounts of outside air are drawn in and exhausted to ensure a mass balance using damper d1 and junction J2 respectively. The condenser fan cools the CRAC unit using outside air to complete the cooling system.

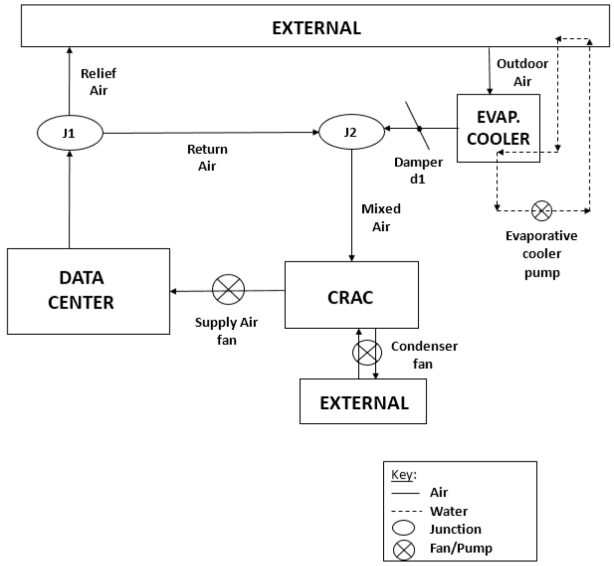

Figure 2 Data center airside economizer system modeled as a virtual testbed using VTAS.

SORTING WEATHER DATA INTO BINS

Typical metrological year weather data for 1020 cities across the US is available from NREL (NREL 2009) and used in VTAS. Four different locations across the US, shown in Table 1 below, have been selected to represent different ASHARE climate zones (ASHRAE 2016) with significant data center activity.

Table 1. US Locations Chosen for This Study

Location	Climate Zone	Climate Description	Data Collection Site
Chicago, IL	5A	Cool Humid	O' Hare Intl. Airport
Denver, CO	5B	Cold Dry	Centennial/Golden NREL
Seattle, WA	4C	Mixed Marine	Seattle-Tacoma Intl. Airport
San Diego, CA	3B	Warm Dry	San Diego Lindbergh Field

Weather data from NREL is available in an hourly format featuring external dry-bulb temperature and relative humidity. Dry-bulb temperature is the primary parameter for each bin. Since ASHRAE standard 90.4 lists wet-bulb temperature as the secondary parameter for the calculation of MLC when no waterside economization is present in the system, the wet-bulb temperatures were calculated using available data with VTAS's built-in psychrometric calculator. The calculator was developed using ASHRAE's Handbook (ASHRAE 2002) and has been verified for a dry bulb temperature range of -30°C to 50°C using two online psychrometric calculators (UIGI and SugarTech). The hourly dry-bulb and corresponding wet-bulb temperatures were then sorted into bins with a constant bin width using a self-developed algorithm different from the technique developed by Papakostas and Sotiropoulos (1997). The details of the algorithm, hereon called the RK algorithm, are shown in the flowchart of Figure 3.

The RK algorithm creates bins using the minimum and maximum values of the dry-bulb array. The mean value of each bin represents the bin dry-bulb temperature. All dry-bulb and their corresponding wet-bulb temperature values are sorted into bins using the following logic: a raw bin number for each value is determined by taking the difference between the maximum range maximum and that value, and dividing the result by the required bin width. If that number is zero, then that dry-bulb temperature and its corresponding wet-bulb temperature fall in the lowest bin; if the ratio is an integer, then they fall in the bin with the same index as the raw bin number; otherwise they are moved one bin above. All bins are therefore populated and the corresponding wet-bulb temperatures for each bin is summed and divided by the bin frequency.

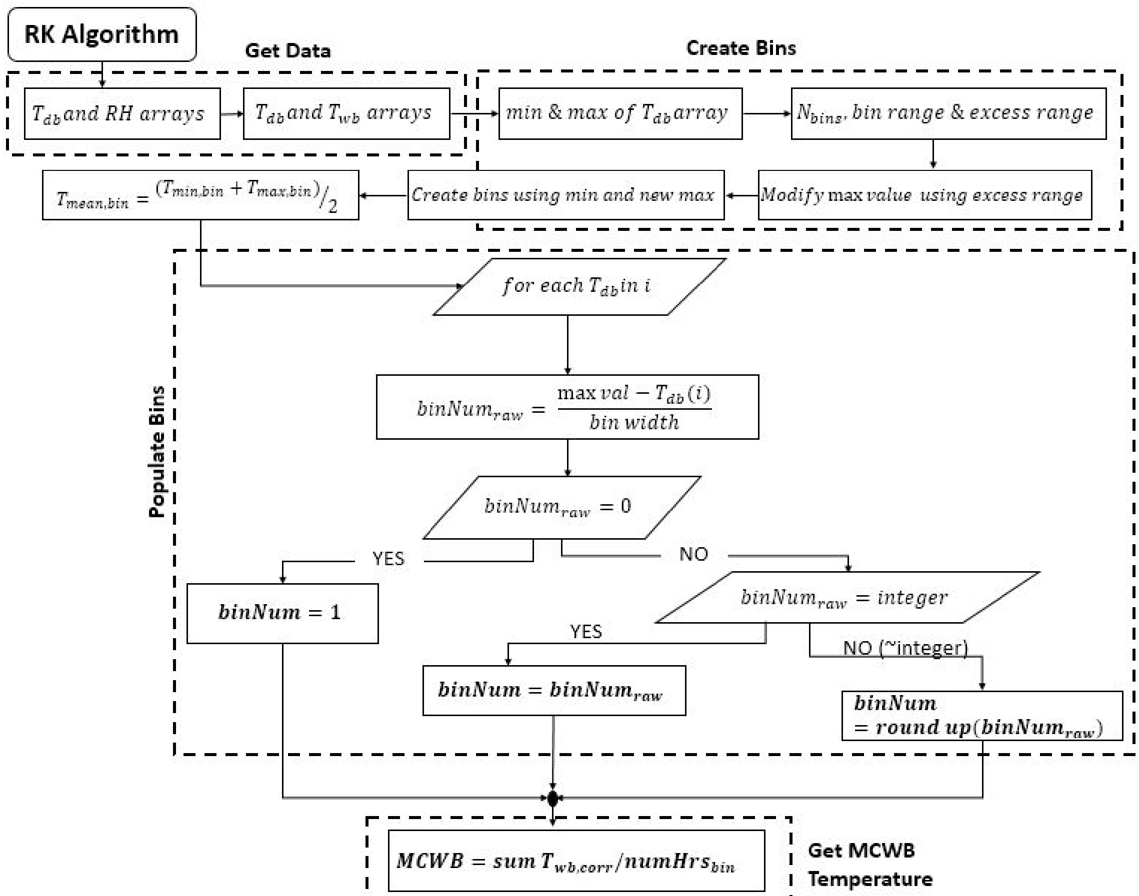

Figure 3 Flowchart for the RK algorithm for creating weather bin data of a specified bin width.

REPRESENTATION OF BIN DATA

Since these temperature bin data are intended to simulate annual metrics for data centers, they need to incorporate an additional parameter other than the dry-bulb temperature to fix the point on a psychrometric chart. This is contrary to what has been observed in the majority of the literature where bin data only featuring the dry-bulb temperature has been presented. Table 2 shows the general structure of a generated weather bin along with data for Chicago using the RK algorithm. Here, a large bin width of 8°C (14.4°F) has been used. Column 1 represents the dry-bulb bin range, Column 2 the mean temperature, T_{mean}, of the bin, while Columns 3 and 4 represent the number of hours in a year that external hourly dry-bulb temperatures lie in that range and the mean corresponding wet-bulb temperature (MCWB) for that range. From Table 2, it can be seen that the T_{db} bins are contiguous and the upper limit for each bin is not included as part of that bin. Another important thing to note is that the MCWB temperature for the last bin is higher than the mean dry-bulb temperature, so this bin width is not suitable for doing an annual energy analysis. This fact would be explored in detail in the results section.

Table 2. Weather Bin Data for Chicago using RK algorithm – Bin Width 8.0°C (14.4°F)

T_{db} range (°C)	T_{db} mean (°C)	Annual number of hours in bin	MCWB Temperature (°C)
30.1 ≤ T < 38.1	34.1	148	23.42
22.1 ≤ T < 30.1	26.1	1390	19.67
14.1 ≤ T < 22.1	18.1	2022	15.10
6.1 ≤ T < 14.1	10.1	1838	7.77
-1.9 ≤ T < 6.1	2.1	1969	0.03
-9.9 ≤ T < -1.9	-5.9	981	-6.59
-17.9 ≤ T < -9.9	-13.9	348	-14.14
-25.9 ≤ T < -17.9	-21.9	64	-20.66

METHODS OF ASSESSMENT

Steady-state simulations were performed using the generated bin data from the RK algorithm. Different bin sizes ranging from as small as 0.1°C (0.18°F) to as large as 10°C (18°F) (if feasible) were used to assess their influence on annualized PUE and MLC values and to uncover limitations that arise from small or large bin sizes.

RESULTS

Annual PUE and MLC values are obtained by doing a weighted average of their respective individual bin values with the corresponding number of hours in each bin. The individual bin values are obtained using a series of steady-state simulations based on the dry and wet-bulb temperatures for that bin. Table 3 provides a comparison of varying bin size on the relative values of annualized PUE and MLC for the four different locations in this study using the system shown in Figure 2. The results clearly show that the annulalized energy efficiency metrics are essentially independent of bin size. In addition, two bin size limits are shown. In the limit of small bin sizes, the bins become non-contiguous since bins exist with ranges that do not capture any of the hourly data due to the hourly discretization of dry-bulb temperatures in the NREL database. In the limit of large bin sizes, an increased risk of nonphysical psycrhometric conditions occurs, especially at very low temperatures. The reason for this phenomenon is that at very low temperatures the dry and wet-bulb temperatures are nearly equivalent and the data are sparse. Therefore, if the bin contains most of the dry-bulb data points towards the maximum limit of the bin, then the calculated MCWB value will also be towards the maximum limit of the bin, which is larger than the mean dry-bulb temperature of the bin. The minimum bin width limit appears to be similar for all locations since it is primarily dependent on the hourly discretization of continuous annual dry-bulb temperature measurements, but the maximum bin width limit is heavily location dependent since the nonphysical psychrometric conditions occur near saturation conditions.

Table 3. Relative Change in PUE and MLC Values for Select Cities across the US – Featuring Airside Economization

Location	Bin Width (°C/°F)	Comment on Bin Width	Comment on annual metrics
Chicago, IL	≤ 0.50 (0.90)	Bins not contiguous	No change
	0.75 – **1.25** (1.35 – **2.25**)	Bins OK	No change
	≥ 1.50 (2.70)	MCWB > mean T_{db} for low-T bin	N/A
Denver, CO	≤ 0.75 (1.35)	Bins not contiguous	No change
	1.0 – **3.0** (1.80 – **5.40**)	Bins OK	No change
	≥ 4.0 (7.20)	MCWB > mean T_{db} for low-T bin	N/A
Seattle, WA	≤ 0.50 (0.90)	Bins not contiguous	No change
	0.75 – **3.0** (1.35 – **5.40**)	Bins OK	No change
	≥ 4.0 (7.20)	MCWB > mean T_{db} for low-T bin	N/A
San Diego, CA	≤ 0.75 (1.35)	Bins not contiguous	No change
	1.0 – **9.0** (1.80 – **16.2**)	Bins OK	No change
	10.0 (18.0)	MCWB > mean T_{db} for low-T bin	N/A

Note: bin widths shown in bold are recommended based on this study.

Similar work was performed for a data center cooled only by a CRAC unit with no airside economization. Such a system differs from that of Figure 2 in that the data center block is only linked to the CRAC unit, so the junctions and evaporative cooler components are not present. Two fans, namely the Supply Air Fan and Condenser Fan of Figure 2 are still be present. Table 4 shows the results for such a data center cooled using mechanical cooling only.

Table 4. Relative Change in PUE and MLC Values for Select Cities across the US – Mechanical Cooling Only

Location	Bin Width (°C/°F)	Comment on Bin Width	Comment on annual metrics
Chicago, IL	≤ 0.50 (0.90)	Bins not contiguous	No change
	0.75 – **1.25** (1.35 – **2.25**)	Bins OK	No change
	≥ 1.50 (2.70)	MCWB > mean T_{db} for low-T bin	N/A
Denver, CO	≤ 0.75 (1.35)	Bins not contiguous	No change
	1.0 – **3.0** (1.80 – **5.40**)	Bins OK	No change
	≥ 4.0 (7.20)	MCWB > mean T_{db} for low-T bin	N/A
Seattle, WA	≤ 0.50 (0.90)	Bins not contiguous	No change
	0.75 – **3.0** (1.35 – **5.40**)	Bins OK	No change
	≥ 4.0 (7.20)	MCWB > mean T_{db} for low-T bin	N/A
San Diego, CA	≤ 0.75 (1.35)	Bins not contiguous	No change
	1.0 – **9.0** (1.80 – **16.2**)	Bins OK	No change
	10.0 (18.0)	MCWB > mean T_{db} for low-T bin	N/A
Note: bin widths shown in bold are recommended based on this study.			

For the mechanical cooling only case and with the CRAC unit model under consideration, no change in annual PUE or MLC value was noted either across different bin widths or various different locations. Furthermore, the bin size data experienced the same limiting behavior as in the system with airside economization. This behavior is seen because although indoor air dehumidification occurs beyond saturation in the CRAC model, the model neither accounts for reheat of the cold air nor its humidification. Further, the CRAC's condenser is not coupled to the outside air, so changes in ambient temperature do not affect its performance. However, this factor is insignificant to the underlying conclusion since the case with airside economization is also insensitive to change in bin size.

However, further work performed using an advanced CRAC model featuring humidity control determined the bin size to be slightly sensitive to annual PUE and MLC values. For example, a deviation of 7.6% was found for San Diego with the maximum investigated bin size of 9°C (16.2°F) vs. the maximum recommended bin size of 1°C (1.8°F) (as per ASHRAE Standard 90.4). A bin size of 5°C (9°C) yielded an error of just 1.1% as compared to the 1°C (1.8°F) case. Thus, although deviations in annual metrics values exist, they are small enough to be generally ignored.

To further understand the impact of bin size, a single bin approach is tried where all dry-bulb and cooresponding wet-bulb temperature values are intentionally lumped together to create one large bin, thus maximizing bin width. This approach results in the same nonphysical combination of dry-bulb and wet-bulb temperatures as seen for large bin sizes as shown in Tables 3 and 4. In San Diego, where the method yields a suitable single bin, a deviation of 8.67% was found compared to the 1°C (1.8°F) bin size. This result shows that an upper limit does exist for the bin size since a deviation in annual metrics does exist even if physical psychrometric conditions are achieved.

CONCLUSION & FUTURE WORK

Tables 3 and 4 show no variation in the calculated annual PUE and MLC values for a given location with respect to the bin width, which suggests that the bin width does not impact annual energy assessment results of a data center. However, a minimum bin width limit of approximately 0.5 to 0.75°C (0.9 to 1.35°F) exists for hourly annual weather data before non-contiguous binning occurs, which is generally a minor issue since the empty bin is simply bypassed when doing the energy metric calculations. More importantly, a maximum bin width limit exists where the risk of nonphysical psychrometric conditions makes calculations infeasible, and this limit depends on geographic location since the nonphysical conditions occur near saturation conditions. These limits are shown in the two tables.

The above work leads to the conclusion that the use of a bin width of 1°C (1.8°F) in most previous studies may be overly conservative for some locations, especially those in hot, dry conditions. The recommended method is therefore to use the maximum feasible bin width for each climate zone as the recommended bin size per Tables 3 and 4. This approach leads to the creation of the minimum number of bins and results in computational savings when running large numbers of data center simulations in order to achieve a roughly optimal system design. Typical errors of less than 10% would be encountered for these recommended bin widths as compared to the 1°C (1.8°F) bin width that ASHRAE Standard 90.4 recommends.

Lastly, by taking the mean of all the dry-bulb temperature values in a bin rather than taking the mean of the bin endpoints makes the binning algorithm more robust since it is impossible for the MCWB temperature to be higher than the dry-bulb temperature. This approach was found to yield single bins with viable psychrometric data that were previously unattainable using the RK method (e.g., Chicago and Dallas). Thus, this approach should be considered as a viable alternative for future binning algorithms.

Further work in performing annual transient simulations using TMY3 hourly weather data for a given location should be carried out to verify and validate the annualized PUE and MLC values obtained using the binning approach.

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NOMENCLATURE

CRAC	Computer Room Air Conditioner
DX	Direct Expansion
HVAC	Heating, Ventilation and Air Conditioning
IT	Information Technology
MCWB	Mean Corresponding Wet-Bulb
MLC	Mechanical Load Component
NREL	National Renewable Energy Laboratory
PUE	Power Usage Effectiveness (of Cooling System)
VTAS	Villanova Thermodynamic Analysis of Systems

Superscript

°	Degree

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