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EVALUATING AND OPTIMIZING UTILITY PLANT OPERATION USING TREND DATA

A Thesis

by

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ABSTRACT

Trend data have been the main source for utility plant evaluation and optimization. However, the current practice of trend data processing has not been well addressed in previous research as an important part of the workflow. As a consequence, the evaluation and optimization process can fail due to unreliable data, as the performance indicators are improperly estimated.

The chilled water systems in the Texas A&M University utility plant have been investigated in this thesis. The hourly average timeseries data of chilled water systems are categorized with various methods in order to validate the reliability of meter records and performance benchmarking. After-processing, data are input for characteristic performance mappings and anomaly detection, which will help the plant operator in fault diagnosis and improving the performance of the chilled water systems.

The outputs of this data-only–based validation process have been aligned with an on-site commissioning report, which requires an investment of labor and resources. It can be applied in other utility plants with similar configuration.

DEDICATION

To my family, my mentors, and my colleagues.

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Contributors

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All other work for the thesis was completed independently by the student.

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I. INTRODUCTION

I.1 RESEARCH MOTIVATION

The campus-level utility plant often consists of an enormous number of different systems with specific characteristics in both load demands and production capacities. This natural heterogeneous character of these systems has made it nearly impossible to standardize best practices on evaluating and optimizing their performance and acquiring useful “know-how” at reasonable cost in terms of time, material, and human resources.

Campus-level utility plants are often equipped with sophisticated industrial-grade control and monitoring systems at plant and equipment level (sometimes at the user level), which have been designed, installed, and maintained by dedicated engineering teams with hundreds of years of total professional and practice experience. Nevertheless, characterizations of useful performance benchmarking and efficient analysis of utility plant performance have remained questions that do not have comprehensive and widely recognized answers. While the adoption of a direct digital controller (DDC) and building management systems (BMS) have made trend data from utility plants more available than ever, the usable knowledge, collected from trend data, has still been very limited to a case-by-case basis. Sometimes the trend data overloads operators and becomes useless. One of the limiting factors might be simply the conflicting constraints of different energy demands (e.g., electricity and heat production of a heat recovery generator in a cogeneration heating plant [CHP] or condenser flow rate and lift of chillers). However, the most frequent issues are often raised from: the reliability of data values (i.e., meters), the sensitivity of benchmark methods, and the performance mapping (e.g., load demands vs. productivity capacities vs. resources consumption relationships).

Due to the inherent characteristics of utility plant operation, the optimization process always has been a continuous process in which trend data is the most important input. However, there are several distinct disparities of data usage between the plant level, which mostly focuses on total productivity and efficiency rates, and the component level where most operating indicators are focused on the component performance and stability. This work attempts to filter out the less useable parts and form useful indicators of trend data for (semi-)automatic fault diagnostics and plant evaluation workflow mapping, which could be applied in different situations (i.e., plant configurations, equipment).

This work also classifies and compares various methods of plant performance review and their relationships with input values in a dashboard form to assist operators.

I.2 PURPOSE AND OBJECTIVES

The purpose of this research is to develop a procedure to better use building automation system (BAS) trend data to evaluate and improve chilled water plant performance. This procedure will be developed in the following four steps:

- Develop a procedure to prescreen data from chiller plant sensors and meters to identify obvious problems with the specific sensors/meters.
- Develop a procedure to use data that passes the prescreening process to conduct an energy balance on the plant performance to detect other possible sensor errors.
- Develop a procedure to use the cleaned data to compare actual chiller performance with models developed from the manufacturer's performance data.

- Develop a procedure for optimizing chiller operation based on use of repetitive diurnal cycles of chiller loads, ambient weather data, and operational schedules.

II. LITERATURE REVIEW

There are two key topics related to the optimization process based on use of data analysis: data analysis (includes statistical learning and system modeling) and visualization analytics. The building management and automation systems of a typical plant seem to have both of those aspects: the database of metered values constitutes the data, and the graphical user interfaces help operators visualize the data to monitor and review both real-time values and trend data. So, the BMS system is the core component in data collection, data mining, and evaluation of results for use in the optimization process. Although the amount of research on optimization using data analysis is extensive, my research will focus on chiller systems in district chiller plants.

II.1 RAW DATA PREPROCESSING

The raw data are often not sufficient for evaluation, as they contain errors from the following:

- BMS hardware, software, and communication issues
- Sensor bias due to installation and drift issues

While the BMS-related issues could be simply filtered by a simple spreadsheet, the sensor bias problem is much more problematic and takes significant time and effort to identify and correct. The most basic validation methods are heat balance and pressure–flow rate balance. In most cases, the normal (good) data, which could be used in chiller performance analysis, should satisfy the energy and flow rate balances. AHRI

Standard 550/590 (Air Conditioning Heating and Refrigeration Institute 2015) provides a good reference method for chiller performance validation and verification and is widely recognized by chiller manufacturers based on energy balance. Many researchers have used the experimental data set from the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Research Project (RP) 1043 (Braun and Comstock 1999), which tested a 90-ton capacity centrifugal chiller under laboratory conditions. However, that data may not be appropriate for modern big capacity chillers. The list of faults imposed to the lab chiller in ASHRAE Project 1043 is shown below:

- Reduced condenser water flow
- Reduced evaporator water flow
- Refrigerant leak
- Refrigerant overcharge
- Condenser fouling
- Non-condensable in refrigerant
- Defective pilot valve
- Multiple faults

In order to identify sensor bias, principle component analysis (PCA) was preferred by many authors. Wang and colleagues applied principle component analysis to sensor fault detection for air handling units (AHUs) (S. Wang and Xiao 2004) and centrifugal chillers (S. Wang and Cui 2005, 2006) based on sensors that could be verified by energy balance rules. Du & Jin (2007) used energy balance, and water-side and air-side flow pressure balances with PCA to rule out sensor-based anomalies. Wang & Wang (2002) implemented sensor bias estimators based on all concerned energy balances for water-side systems. The typical PCA method flowchart in sensor fault detection diagnostics investigated for centrifugal chiller is described in Figure II.1.

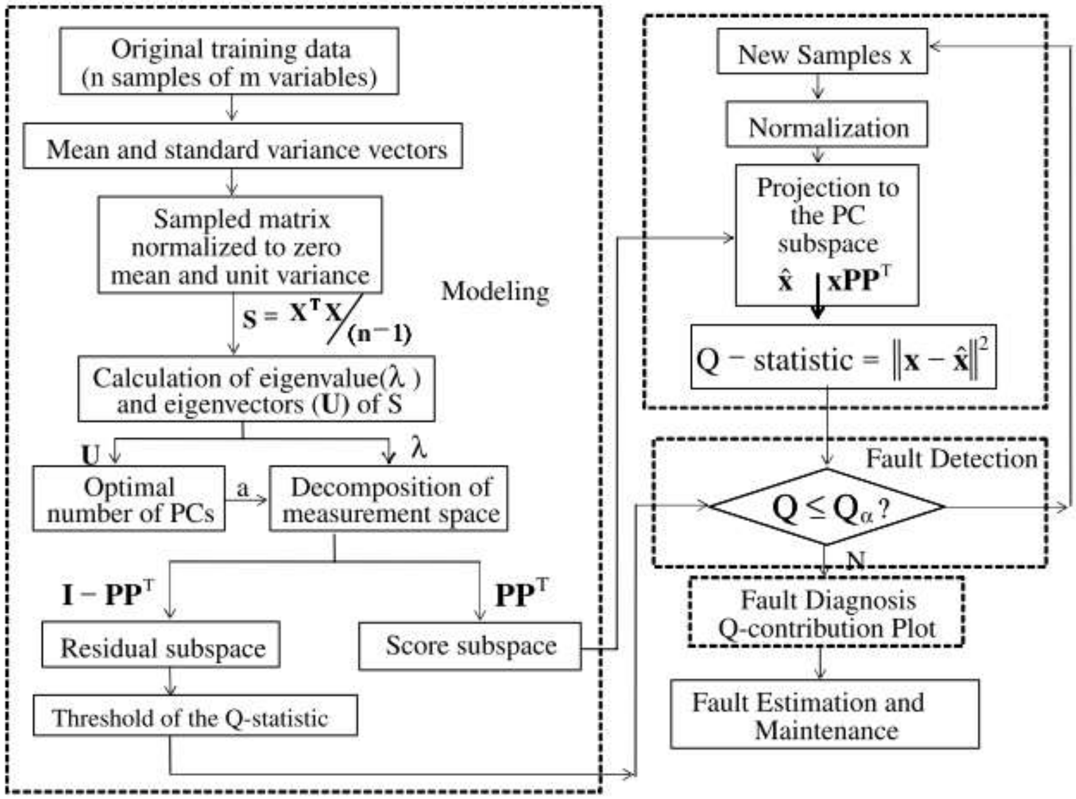

Figure II.1. PCA method flowchart. **Reprinted from S. Wang and Cui (2005).**

II.2 CHILLER PLANT AND COMPONENT MODELING

System and component modeling describe a system or component in terms of three different types of variables: input variables, system structure, and output variables. System structure is usually a mathematical relationship or mathematical model between a (sub)set of input variables with one or several output variables. Typically, mathematical models are classified in two categories (see Figure II.2): forward-models (simulation-based) and/or inverse models (based on performance data). Forward models are often used in system design as white-box models, while inverse models typically focus on understanding, predicting, and controlling existing systems.

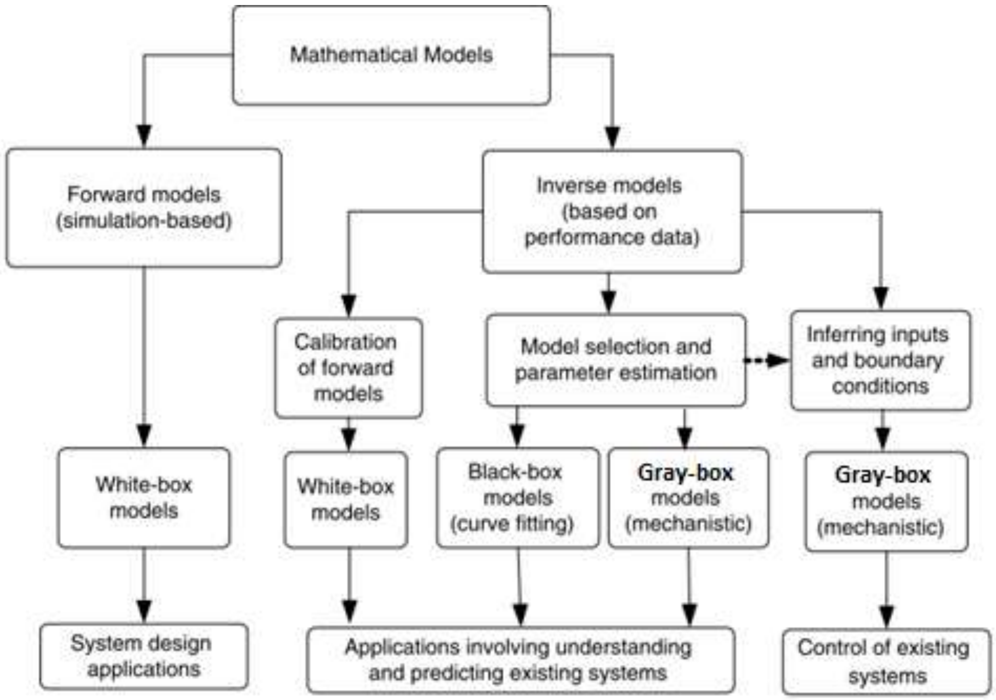

Figure II.2. Different types of mathematical models used in forward and inverse approaches.

Chiller system models are typically one of the following types: linear empirical models, artificial neural network (ANN) models, physical component models, or physical lumped parameter models. A summary of research performed for each category is shown in Table II.1. Research about chiller modeling often focuses on two applications: optimizing chiller performance (coefficient of performance [COP]) and fault detection and diagnosis (FDD).

Table II.1. Literature review about modeling methods.

Category	Research
Empirical model (black-box)	Yik and Lam 1998; Lawrence Berkeley National Laboratory 1980; Reddy and Andersen 2002; M Hydeman et al., n.d.; Y.-C. Chang et al. 2013; ASHRAE, n.d.; Y. Zhao, Xiao, and Wang 2013; Braun and Comstock 1999; Zmeureanu and Vandenbroucke 2015; Shan et al. 2016; Wei, Xu, and Kusiak 2014; Baillie and Bollas 2017;
Artificial neural network models	Y.-C. C. Chang 2007; Swider et al. 2001; L.-X. X. Zhao, Shao, and Zhang 2010;
Physical component models	Mclntosh, Mitchell, and Beckman 2000; Browne and Bansal 1998;
Physical lumped parameter models	Ng et al. 1997; Lee 2004;

Due to their simplicity, empirical models get a lot of attention and are widely used for both optimizing existing plants and predicting energy consumption of new plants at the conceptual design phase. However, because the empirical model coefficients are not based on the physical characteristics of a chiller, they are only reliable when historically measured data are available for a particular system. This characteristic makes their use in plants with multiple chillers very complex, especially when a new type of chiller is added, or new control sequences are proposed. Afroz et al. (2017) reviewed different modeling techniques and compared three basic modeling techniques based on the performance criteria shown in Table II.2.

Table II.2. Performance of different modeling techniques. Reprinted from Afroz et al. (2017)

Modeling Technique	Prediction Accuracy	Generalization Capability	Training Data Requirement	Complexity Level
Physics-based (white box/ mathematical/ forward) model	L	H	L	H
Data-driven (black box/ empirical/ inverse) model	H/ M/ L[1]	L/ M[2]	H	L
Gray-box (hybrid) model	H	M	M	M

Note: The letters H, M, and L stand for high, medium, and low, respectively.

[1] Prediction accuracy of data-driven models usually depends on model type, e.g., data mining algorithm, fuzzy logic, state-space, and stochastic models give high prediction accuracy; frequency domain with dead time, geometric, case reasoning, and instantaneous models give medium prediction accuracy; only statistical models provide low prediction accuracy.

[2] Generalization capability of data-driven models is commonly medium to low depending upon the model type. Frequency domain with dead time, data mining algorithm, state-space, stochastic, and instantaneous models possess high generalization capability, while fuzzy logic, statistical, geometric, and case-reasoning models possess medium generalization capability.

II.2.1 Empirical Chiller Models

An empirical model might be either of two types: (1) a black-box model type with coefficients that have no physical interpretations and are completely based on historically measured data; or (2) a hybrid model type in which all or a part of the coefficients have some physical meanings.

Efficiency empirical model

ASHRAE Research Project 1139 developed and compared four different mathematical models that could predict the fault-free performance of a vapor compression system. The evaluation used 5 months of data from a 220 Ton chiller from Toronto (800 samples) and about 1120 samples during 14 days from a 450-ton chiller located at Drexel University, which was instrumented to provide data collected specifically for that research.

The chiller models in ASHRAE RP 1139 were steady-state performance and models linear in the parameters (except for ANN) and had chiller efficiency as the only response variable. The ASHRAE RP 1139 has four chiller models:

- **Black-box models**: Linear empirical models, usually triquadratic multivariate polynomial (MP) models
- **Artificial neural network models**: Radial basis function (RBF) and multilayer perceptron (MLP)
- **Gray-box model**: Generic physical component model approach
- **Gray-box model**: Lumped physical Gordon–Ng model

The two online training models evaluated during this research are the following:

- **Ordinary recursive least squares (ORLS)**: All data are given the same weight in readjusting the parameter estimates.
- **Weighted recursive least squares (WRLS)**: More weight is given to newer data.

The objective of fault-free chiller models is to provide chiller performance predictions to compare with the observed performance.

- **Empirical model (simplest form)**:

$$COP = \alpha + \beta_1 T_{cdi} + \beta_2 T_{chi} + \beta_3 Q_{ch}$$

Where, T_{cdi} and T_{chi} are inlet water temperatures to the evaporator and condenser, respectively; and Q_{ch} is chiller evaporator production; and COP is chiller efficiency.

- **Multivariate polynomial model**:

Braun found that a second-order linear polynomial model with 10 coefficients is more appropriate. This is also called a multivariate polynomial model and is given by:

$$COP = \alpha + \beta_1 T_{cdi} + \beta_2 T_{chi} + \beta_3 Q_{ch} + \beta_4 {T_{cdi}}^2 + \beta_5 {T_{chi}}^2 + \beta_6 {Q_{ch}}^2 + \beta_7 T_{cdi} T_{chi} + \beta_7 T_{cdi} T_{chi} + \beta_8 T_{cdi} Q_{ch} + \beta_9 T_{chi} Q_{ch}$$

Electrical consumption empirical model

Wang (2017) compared his own empirical model with other models for chiller electrical consumption estimation. The short descriptions of each model are reviewed as below:

- **Yik model**:

$$PLR_{elec} = \alpha + \alpha_1 PLR + \alpha_2 PLR^2 + \alpha_3 T_{cwi} + \alpha_4 {T_{cwi}}^2 + \alpha_5 PLR.T_{cwi} + \alpha_6 PLR^2.T_{cwi} + \alpha_7 PLR.{T_{cwi}}^2 + \alpha_8 PLR^2.{T_{cwi}}^2$$

Where, PLR_{elec} and PLR are part-load ratios of chiller electricity consumption and cooling production, respectively; and T_{cwi} is the condenser inlet cooling water temperature.

- **Braun model**:

$$PLR_{elec} = \alpha + \alpha_1 PLR + \alpha_2 PLR^2 + \alpha_3 y + \alpha_4 PLR^2 + \alpha_5 y.PLR^2$$

$$y = \frac{\mathrm{T_{cwo}} - \mathrm{T_{chws}}}{(\mathrm{T_{cwo}} - \mathrm{T_{chws}})_{\mathrm{design}}}$$

Where, PLR_{elec} and PLR are part-load ratios of chiller electricity consumption and cooling production, respectively; and T_{cwo} and T_{chws} are the condenser water outlet and evaporator supply temperatures.

- **Chang model**:

$$N = \alpha + \alpha_1 PLR + \alpha_2 PLR^2 + \alpha_3 (T_{cwr} - T_{chws}) + \alpha_4 (T_{cwr} - T_{chws})^2 + \alpha_5 . (T_{cwr} - T_{chws}) . PLR$$

Where, N and PLR are chiller electricity consumption and cooling production part-load ratio, respectively; and T_{cwr} and T_{chws} are the condenser water inlet and evaporator supply temperatures.

- **Comstock model**:

$$N = \alpha + \alpha_1 T_{chws} + \alpha_2 T_{cwr} + \alpha_3 Q_e + \alpha_4 T_{chws} . Q_e + \alpha_5 T_{cwr} . Q_e + \alpha_6 {Q_e}^2$$

Where, N and Q_e are chiller electricity consumption and cooling production, respectively; and T_{cwr} and T_{chws} are the condenser water inlet and evaporator supply temperatures.

- **Wang model**:

$$N = \beta + \beta_1 \Delta p_{chw.p}^{0.5} + \beta_2 \Delta p_{chw.p} + \beta_3 \Delta T_{chw} + \beta_4 \Delta T_{chw}^2 + \beta_5 T_{cwo} + \beta_6 T_{cwo}^2 + \beta_7 \Delta T_{chw} \Delta p_{chw.p}^{0.5} + \beta_8 T_{cwo} \Delta p_{chw.p}^{0.5} + \beta_9 T_{cwo} \Delta T_{chw}$$

Where, N is chiller electricity consumption; ΔT_{chw} and $\Delta p_{chw.p}$ are chilled water temperature and pressure difference; and T_{cwo} is the condenser water outlet temperature.

The evaluation indicators of each method are shown in Figure II.3 for mean absolute error (MAE), coefficient of variation of root mean square error (CV), and mean relative error (MRE). In addition, the squared correlation coefficient (R^2) is addressed in Figure II.4.

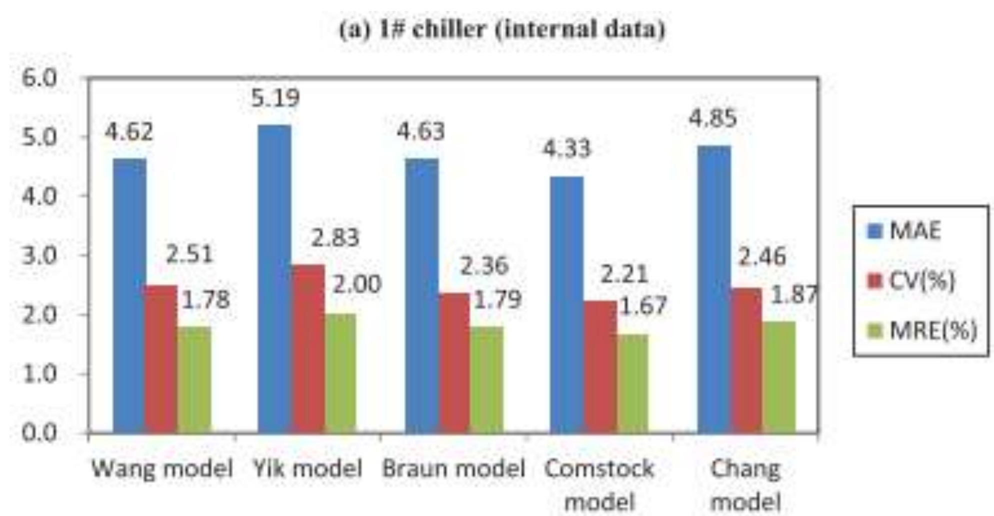

Figure II.3. Empirical model comparison for chillers. **Reprinted from H. Wang (2017).**

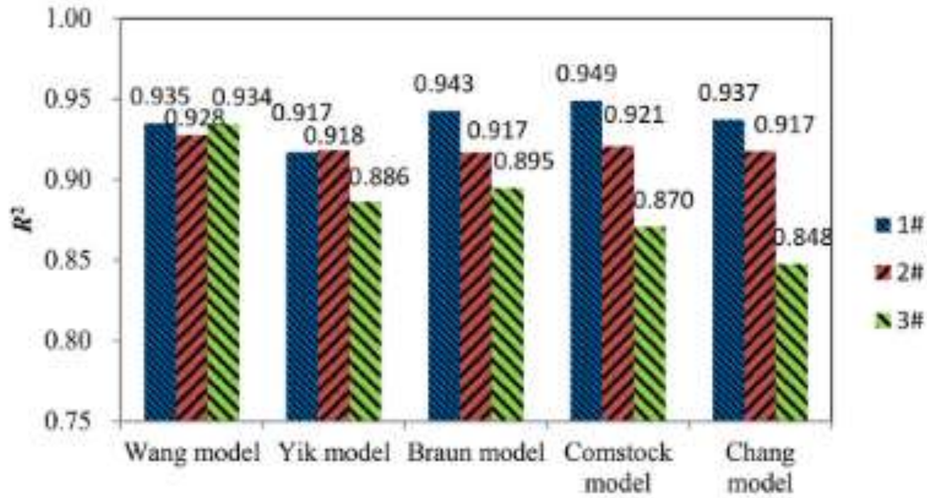

Figure II.4. R^2 comparison for chiller. **Reprinted from H. Wang (2017). 1#, 2#, and 3# are chiller numbers.**

Moreover, due to the broad variety of supplemental components, e.g., cooling towers (fan and heat exchanger), and primary and secondary pumps on chilled and cooling water loops, no widely recognized method for optimizing chiller plant approach temperatures is available. In addition, energy storage systems and different chiller types (steam chiller, absorption chiller, and heat recovery chiller) raise new questions about optimal sequencing and demand control of a chiller plant with chillers using completely different energy sources (i.e., steam, heat resources, heating demand, etc.). Complex chiller plants are often manually sequenced based on a time-schedule or run-time basis rather than automatic sequencing. Many researchers have proposed different approaches to solve that problem. Wang (1998) presented a dynamic model of a plant consisting of seawater-cooled centrifugal chillers with energy management control system (EMCS) control, and evaluated EMCS control strategies. Hydeman et al. (1999) demonstrated the implementation of a chiller plant model to predict performance of energy conservation measures (ECMs) in an upgraded plant and then verified as-installed performance with the model. Chang used different techniques to get optimal chiller sequencing using dynamic programming, neural networks, and branch and bound methods Y. C. Chang, Lin, and Lin (2005); Y.-C. C. Chang (2007); Y. C. Y.-C. Chang (2006). Wang proposed a data fusion scheme to improve the quality of cooling load measurement by using two types of building cooling load measurement: “direct measurement” consists of chilled water flow and temperature data, while “indirect measurement” is calculated from the instantaneous chiller electrical power input. Huang et al. (2009).

II.3 DATA MINING TECHNIQUES

Krarti (2003)is one of earliest authors to review the use of artificial intelligence (AI) applied to building energy systems to predict energy use for one or many buildings that have the same utility distribution source. Three methods—neural networks, fuzzy logic–based methods, and genetic algorithms—had been implemented in a few selected applications: weather forecasting, short-term load forecasting, fault detection and diagnostics, etc. Dounis (2010) reviewed AI techniques within two modern domains that are widely used as a design tool in building automation systems: computational intelligence (e.g., fuzzy logic and neural network) and distributed artificial intelligence (e.g., intelligent agents, multi-agent systems, and ambient intelligence). Reddy’s book (2011) covered a lot of analysis techniques, including unsupervised methods. Cam et al. (2014) used the data mining process to extract information from BAS measurements, then developed inverse models of building energy performance to figure out building operation, performance, and fault detection.

The most demanding data analysis task (possibly the most difficult in the whole optimization process) might be outlier and anomaly detection. This is the procedure that must ensure the reasonableness of the data values that are input to the system model or statistical analysis. This task is often described as noise removal/accommodation or as novelty detection and discord detection for statistical methods. While novelty detection deals with unexpected behavior, discord detection focuses on finding anomalous data subsets among the rest of the data. Chandola et al. (2009) surveyed research on anomaly detection, classified by the research approach used. Janetzko et al. (2013) compared several anomaly detection methods for power consumption data. Munir et al. (2017) created a pattern-based contextual anomaly detection approach for IoT (Internet of things) based on an anomaly score of several HVAC systems. Their pattern-based approach was used to detect anomalies in HVAC time-series data.

Clustering, which categorizes data into subgroups that are meaningful for further analytic tasks, is considered the most common approach among unsupervised data analytics research focusing on building performance data. Heidarinejad et al. (2014) examined simulated energy consumption of 134 offices that were certified as United States Leadership in Energy and Environmental Design, New Construction (LEED®-NC) to classify their energy use intensity into high, medium, and low clusters. Lavin and Klabjan (2015) used clustering methods with time-series data from smart meters. Iglesias and Kastner (2013) checked the effect of similarity measures when implementing clustering techniques where correlation might be an important factor. Bogen et al. (2013) established the framework for comparing the as-operated facility with expected usage patterns from sensor data sets. Li and Ju (2017) applied a hierarchical cluster method to the simulation data set of a chiller system.

Motif detection techniques are dedicated to time-series data investigation, which determines repeated patterns in data values according to time (i.e., daily, weekly, etc.) and is often used to form a baseline for discord detection. Miller et al. (2015) have implemented symbolic aggregate approximation (SAX) to analyze building electricity data. Patnaik et al. (2010) used sensor data to model cooling infrastructure in a data center.

Rule extraction techniques have the ability to automatically establish relationships between variables in a data set. May-Ostendorp et al. (2013) applied three different data-mining techniques to fine-tune supervisory control strategies on a mixed mode building during the cooling season. Domahidi et al. (2014) implemented unsupervised machine learning to extract prevalent information from simulation data to use with a hybrid model predictive controller. Yu et al. (2013) reviewed results of common data analysis methods applied to building-related data for exacting knowledge.

II.4 KNOWLEDGE EXTRACTION AND VISUALIZATION

Yu et al. (2013) proposed a step-by-step analysis method for extracting meaningful knowledge from a building-related database, and potential applications of this knowledge. Domahidi et al. (2014) and May-Ostendorp et al. (2013) extracted rules from modeling for model predictive control. Fan et al. (2015) applied several data mining techniques to identify dynamics, patterns, and anomalies in building operation along with temporal association rules within and between subsystems. Ahn and Park (2016) proposed wavelet coherence as a tool for investigating the relationship between occupants' presence and building energy consumption.

Visualization is the mandatory task for both pre- and post-processing when the decisions or follow-up tasks might be determined by engineers or operators. Duarte and Acker (2011) review how an energy management system (EMS) controls heating, ventilation, and air conditioning (HVAC) and lighting systems to conserve energy while maintaining human comfort and productivity. Marini et al. (2011) used a package of performance-monitoring software; data-acquisition hardware; and a communication system to collect, analyze and display energy information through an information dashboard.

II.5 SUMMARY

Since chiller plants are the biggest energy (electrical) consumer in a utility plant, a lot of research and testing has investigated chiller performance to evaluate efficiency, diagnose faults, and optimize operation. However, there are some deficiencies:

- **AHRI Standard 550/590**: While this standard is widely used by chiller manufacturers and energy codes, the waterside measuring tolerances are high at part-load conditions, particularly for low water temperature differences. For large utility plants, those inaccuracies are significant. However, it is still the most reliable method for evaluating chiller efficiency and fault data reporting since it is acknowledged by chiller manufacturers.
- **Chiller fault diagnostic database**: Most chiller faults require vapor compression cycle (refrigerant loop) evaluation; however, this is not readily accessible to testing by operating teams. The relatively high cost of chillers, especially for larger units,

limits the possible tests for fault detection. While the most comprehensive fault testing for chillers was conducted 20 years ago, newer chillers have been improved greatly—30% according to energy code requirements. To reach such high efficiency, the chiller configuration and operation practices are also much more diverse than before. As a result, the gas-side fault data are not widely used today.

- **Chiller empirical models**: The nature of inverse models is attractive whenever the operation data can be collected. Empirical models for chillers have been studied frequently. However, the utility plant often has multiple chillers running at different load ranges and weather conditions. This complexity makes empirical models unique to each machine even for identical chillers. In addition, the empirical model is of limited value for optimizing at the plant level when the interaction between chillers and plant loops is the main issue.
- **Machine learning (statistical-based) analysis**: The availability of data sets has increased lately with EMSs deployed in most utility plants. The statistical methods, which focus on data analysis, often lack a connection between the data model and a physical model. In contract, inverse empirical models are often characterized based on well-established engineering fundamentals. The statistical-based methods sometimes give dramatically changed results when new batches of data are delivered. For utility application, where stable operation is top priority, it may not be a viable option when most research is based on very small amounts of data rather than a full year's data.
- While a lot of research focuses on fault detection and diagnostics on the refrigerant side using data from water-side sensors, a data validation scheme is often absent

from procedures because laboratory data or short-term data were used. Research investigating sensor faults often adds artificial bias to good data to test detection schemes. Much of the reported research used a limited data set (less than 100 points with 15-minute frequency spread over two weeks of operation), which covers a very limited portion of an annual operation cycle.

Based on the issues mentioned, the priority in this study is to develop an "easy-to-understand" and flexible method for evaluation of chiller plant operation. My approach focuses on data filtering and developing an anomaly detection algorithm using real operation data with energy balance–based validation. It needs to be "easy-to-understand" with a close relationship between model output, the daily data, and work practices so the operating team can take needed actions to achieve efficient operation. It also needs to recognize that field conditions often limit the use of models that require laboratory-quality data. It must be flexible and use plant data and rulesets with simple validation. Considering plant optimizing as a continuous process, data validation is the basis of applying and validating not only my own but also other optimizing methods.

III. METHODOLOGY

The first section of this chapter describes the subject chiller plant, including all key equipment characteristics and plant control narratives. The chiller plant has been applying a plant optimization program, which has specialized control algorithms for all chilled and cooling water pumps and cooling tower fans using variable speed drives. The second section of the chapter explains the procedure for determining if a chiller is in operation. The third section identifies the procedure developed to examine a data set with possible faults and identify the reliable data by using energy balance. The fourth section shows the validation results of the data analysis process applying allowable tolerances from AHRI Standard 550/590. The remaining sections (fifth to eighth) describe the results and visualization procedures.

III.1 TEXAS A&M UNIVERSITY CHILLER PLANT

III.1.1 District Plant Layout and Description

The Texas A&M University campus has four main plants: Central Utility Plant (CUP), Satellite Utility Plant 1 (SUP1), Satellite Utility Plant 2 (SUP2), and Satellite Utility Plant 3 (SUP3). The CUP and SUP3 serve the East (Main) Campus, while SUP1 and SUP2 provide for the West Campus.

The tag, manufacturer, type, design capacity, and year of installation are shown for each chiller in Table III.1. Table III.2 shows their design characteristics. Overall, the four plants have installed capacity of about 58,000 cooling tons, and all 27 are centrifugal chillers.

Table III.1. Chiller list with data.

Plant	TAG	Manufacturer	Drive/Type	Capacity (tons)	Installed Year
CUP	001	Carrier	ELE/CNTRF	1500	1999
CUP	002	Carrier	ELE/CNTRF	1500	1999
CUP	003	York	ELE/CNTRF	2500	2008
CUP	004	York	ELE/CNTRF	2500	2008
CUP	005	York	ELE/CNTRF	2500	2008
CUP	006	York	ELE/CNTRF	2500	2008
CUP	007	York	ELE/CNTRF	3350	2015
CUP	008		STM/CNTRF	3350	
CUP	009		STM/CNTRF	3350	
CUP	010	York	ELE/CNTRF	3150	2015
SUP3	301	York	ELE/CNTRF	2500	2015
SUP3	302	York	ELE/CNTRF	2500	2015
SUP3	303	Trane	ELE/CNTRF	1100	1989
SUP3	304	Trane	ELE/CNTRF	1400	2004
SUP1	101	Trane	ELE/CNTRF	1000	2000
SUP1	102	Trane	ELE/CNTRF	1000	2000
SUP1	103	York	ELE/CNTRF	2500	
SUP1	104	Trane	ELE/CNTRF	2500	2010
SUP1	105	Trane	ELE/CNTRF	2500	2010
SUP1	106	Trane	ELE/CNTRF	2500	2010
SUP2	201	Trane	ELE/CNTRF	1334	1984
SUP2	202	Trane	ELE/CNTRF	1500	2009
SUP2	203	Trane	ELE/CNTRF	1334	1984
SUP2	204	York	ELE/CNTRF	2250	2007
SUP2	205	York	ELE/CNTRF	2250	2007
SUP2	206	York	ELE/CNTRF	2500	2015
SUP2	207	York	ELE/CNTRF	1178	2015

Table III.2. Chiller design performance characteristics.

Plant	TAG	Capacity (tons)	Published Efficiency	Design Water Return Conditions @ Condenser, Evaporator	NPLV	VSD
CUP	001	1500	0.606	@85°F,42°F		No
CUP	002	1500	0.606	@85°F,42°F		No
CUP	003	2500	0.615	@85°F,42°F	0.384	Yes
CUP	004	2500	0.615	@85°F,42°F	0.384	Yes
CUP	005	2500	0.613	@85°F,42°F	0.512	No
CUP	006	2500	0.613	@85°F,42°F	0.512	No
CUP	007	3350	0.613	@87°F,42°F	0.404	Yes
CUP	008	3350				No
CUP	009	3350				No
CUP	010	3150	0.595	@87°F,42°F	0.354	Yes
SUP3	301	2500	0.611	@87.6°F,42°F	0.37	No
SUP3	302	2500	0.611	@87.6°F,42°F	0.37	No
SUP3	303	1100	0.615	@85°F,42°F		Yes
SUP3	304	1400	0.599	@85°F,42°F		No
SUP1	101	1000	0.759/0.598	@87°F,42°F	0.484	No
SUP1	102	1000	0.759/0.598	@87°F,42°F	0.484	No
SUP1	103	2500	0.61	@85.5°F,42°F	0.381	Yes
SUP1	104	2500	0.582	@87°F,42°F	0.477	No
SUP1	105	2500	0.582	@87°F,42°F	0.477	No
SUP1	106	2500	0.582	@87°F,42°F	0.477	No
SUP2	201	1334	0.603	@86°F,42°F		No
SUP2	202	1500	0.588			Yes
SUP2	203	1334	0.603	@86°F,42°F		No
SUP2	204	2250	0.618	@85°F,42°F		Yes
SUP2	205	2250	0.618	@85°F,42°F		Yes
SUP2	206	2500	0.604	@85°F,42°F	0.379	No
SUP2	207	1178	1.538	@135°F,42°F	-	No

Some special chillers are excluded from this review due to their very different operational characteristics: chillers 104, 105, and 106 are duplex refrigerant cycle chillers; chillers 008 and 009 use steam driven compressors; and chiller 207 is a heat recovery chiller.

All chiller plants have a primary-buildings' pump distribution scheme for the chilled water side and primary-only for the cooling water side. The pumps are all headered, except the primary cooling water pumps of chillers 101, 102, and 103, which are each dedicated to their own chiller.

III.1.2 Plant Control System

The plant control system automatically controls key chiller and distribution plant setpoints as follows:

- **Chiller**:
    - Chilled water flow rate setpoint by using a valve on each chilled water line and a variable speed drive (VSD) on a headered primary chilled water pump.
    - Chilled water temperature setpoint using chiller manufacturer's control panel.
    - Chiller lift as the difference between condenser saturation and evaporator saturation temperatures or, where refrigerant temperatures are not available between evaporator and condenser leaving water temperatures, it is configurable using the condenser water flow rate setpoint.
    - Condenser water flow rate setpoint using a valve on each cooling water line and a VSD on the headered primary cooling water pump.
    - Chilled/condenser water flow rates, chilled water setpoints, and chiller lifts within individually assigned operation ranges with minimum and maximum values for each chiller. The ranges are based on the chiller datasheet and manual for each chiller.

A chiller group is considered *staged on* if its electrical loading ratio value is bigger than 0.95 in 5 consecutive minutes and the plant output ratio is higher than 0.95 for 10 consecutive minutes. It is considered *staged off* if measured plant load is less than the staged down capacity (after shutdown on priority chiller) and loop demand is below setpoint. There are several additional limits that ensure the chiller plant is stable during the chiller staging period.

- **Pump and cooling tower systems**:
  - There are two pump types in each chiller plant:
    - Primary pumps serve the evaporator (chilled) water loop of chillers.
    - Primary cooling water pumps circulate condenser water to cooling towers.
  - Two flow rate manipulation methods have been applied:
    - Constant speed pumps use valves
    - Variable speed pumps use pump speed
  - Each pump has its own initial control setpoint with three scenarios: START, STOP, and FAST START (when rapid response is desired). The control setpoints are the valve open ratio for valves or pump speed ratio for VSDs.
  - Each cooling tower has its own condenser setpoint temperature and fan speed setpoint range.
- **Building (loop) demand feedback**:
  - Building demand feedback is the control strategy that uses chilled water consumption feedback from key buildings to optimize pump pressure while

still delivering enough chilled water to meet loads. Each building has its own pump to meet chilled water demand.

  - Building demand feedback uses the following inputs:
    - Building pumps control output
    - Differential pressure factor, which compensates when building differential pressure is below setpoint
    - Size factor, which gives correct coefficient for feedback based on building size
    - Other critical factors, such as the importance of a particular building or function

- **Optimizing strategies**:
  - *Chilled water (temperature) reset*: The chilled water temperature setpoint of a chiller is decreased if the chilled water flow rate is not at minimum value and chiller lift is less than its maximum limit. Otherwise, the chilled water temperature setpoint is increased.
  - *Lift setpoint reset*: The chiller lift is the difference between refrigerant evaporating and condensing temperatures. In order to keep running, a chiller should maintain a minimum lift setpoint, although increasing the lift makes a chiller operate less efficiently. The chiller lift setpoint is maintained by manipulating the condenser water flow rate with a pump and the return condenser temperature by cooling tower or bypass valve. The lift setpoint could be lowered by increasing the condenser water flow rate or lowering the condenser return temperature, e.g., cooling tower setpoint. When the chiller

lift setpoint needs to be increased, the condenser water flow rate is decreased. Once the condenser flow rate reaches its minimum value, the cooling tower setpoint should be adjusted to maintain the chiller lift setpoint.

- *Condenser temperature setpoint reset*: The condenser water temperature setpoint is permitted to increase in two situations with consideration of current outside wet bulb temperature:
  - If condenser water temperature setpoint is not at maximum value, and fan speed setpoint is above minimum value
  - If any chiller on the same header reaches minimum condenser water flow rate setpoint

  The condenser water temperature setpoint is decreased if it is not at minimum and fan speed is below its maximum value.
- *Chiller efficiency factor*: To optimize the runtime of efficient chillers while keeping rotation of the chillers in the same plant, efficiency factors would be applied individually to every chiller in number format with a maximum value of 2.0. If a chiller has efficiency factor 2.0, it would have number running time counted as 2 hours for every online hour, e.g., the annual operation time of the least efficient chiller (highest efficiency factor −2.0) would be half of the chiller with standard efficiency factor (1.0).

III.2 PROCEDURE TO PRESCREEN DATA FROM CHILLER PLANT SENSORS AND METERS TO IDENTIFY OBVIOUS PROBLEMS WITH SPECIFIC SENSORS/METERS

Chiller meter readings are recorded continuously, but data are evaluated only when the chiller is operating, since the chiller uses the highest percentage of chiller plant energy. While the multiple-chiller plant rarely turns on all chillers at the same time, each chiller should be reviewed individually.

III.2.1 Current Practice

The Utilities & Energy Services Department (UES) at Texas A&M University is the current operator of all energy facilities on the Texas A&M campus in College Station, Texas, which includes all district plants. The Analytical Services of UES, which is responsible for chiller plant performance monitoring and evaluation, is using an in-house template in spreadsheet format to evaluate all chiller performance in weekly, monthly, and annual reports, as shown in Table III.3. The number of monitored meters is very high, as each chiller is monitored by seven meters, as shown in Table III.4. Due to data acquisition system bandwidth capability that limits the amount of exported data and the number of concurrent connections, the data collected from the chillers is average hourly data, which provides inaccurate chiller performance indicators (kW/ton) during periods when one or more chillers are staged on and off. A chiller with many on/off stagings over the duration of a data set would have a very high (poor) performance indicator. In Table III.3, the average kW/ton of chillers 101 and 104 were very high due to low run-time hours and a high number of startup/shutdown times. Chiller 101 had run for only 19 hours in 3 shifts with an average efficiency at 0.72

kW/ton because kW/ton values during start/stop hours are much higher than normal values, e.g., more than 1.0 versus 0.5 kW/ton. Chiller 104 had run 2 hours, as it had started then immediately stopped with an average of 1.52 kW/ton. Figure III.1 shows the plots of chiller cooling production and efficiencies in SUP1 during the same period as the inaccurate chiller performance report, which is well described in Table III.3.

Table III.3. Performance report (March 27–April 2, 2018).

No.	Plant	Equipment	Total Production	Average	Run Hour	Efficiency
			Tons	Tons/hr	%	kW/ton
1	SUP1	CH101	15,342	807	11%	0.72
2	SUP1	CH102	22,429	748	18%	0.47
3	SUP1	CH103	357,164	2,126	100%	0.48
4	SUP1	CH104	770	385	1%	1.52
5	SUP1	CH105	0	0	0%	0.00
6	SUP1	CH106	146,669	1,982	44%	0.62
Total			542,373	1,990		0.52

Table III.4. Standard chiller meters.

Description	Symbol	Unit	Description	Symbol	Unit
Chilled Water Flow Rate	F_{chw}	gpm	Cooling Water Flow Rate	F_{cw}	gpm
Chilled Water Supply Temperature	T_{outchw}	°F	Cooling Water Supply Temperature	T_{outchw}	°F
Chilled Water Return Temperature	T_{inchw}	°F	Cooling Water Return Temperature	T_{incw}	°F
Electricity Consumption	P_{elec}	kWh			

Figure III.1. Chiller performance plots.

III.2.2 New Procedure for Chiller Production and Performance Reports

While the annual report of hourly average and total cooling production, and performance are insignificantly affected by the staging times, chiller characteristics data based on hourly values would have a lot of noise with the staging times included. In order to remove the unreasonable performance data at staging times, a new procedure for filtering out all staging hours of chillers is given in this section. The chart in Figure III.2 summarizes the workflow and steps from raw data to output chart. The process includes the following steps:

- Determine chiller operation shifts (continuous operation) and staging on/off hours
- Execute fault detection on data
- Use filtered data (in operation) as input for the following processes:
    - Chiller performance indicators
    - Energy balance validation
    - Chiller data histogram
- Use data analysis algorithms to create the following plots:
    - Chiller operation dashboard
    - Chiller operation plot
    - Chiller characterization map

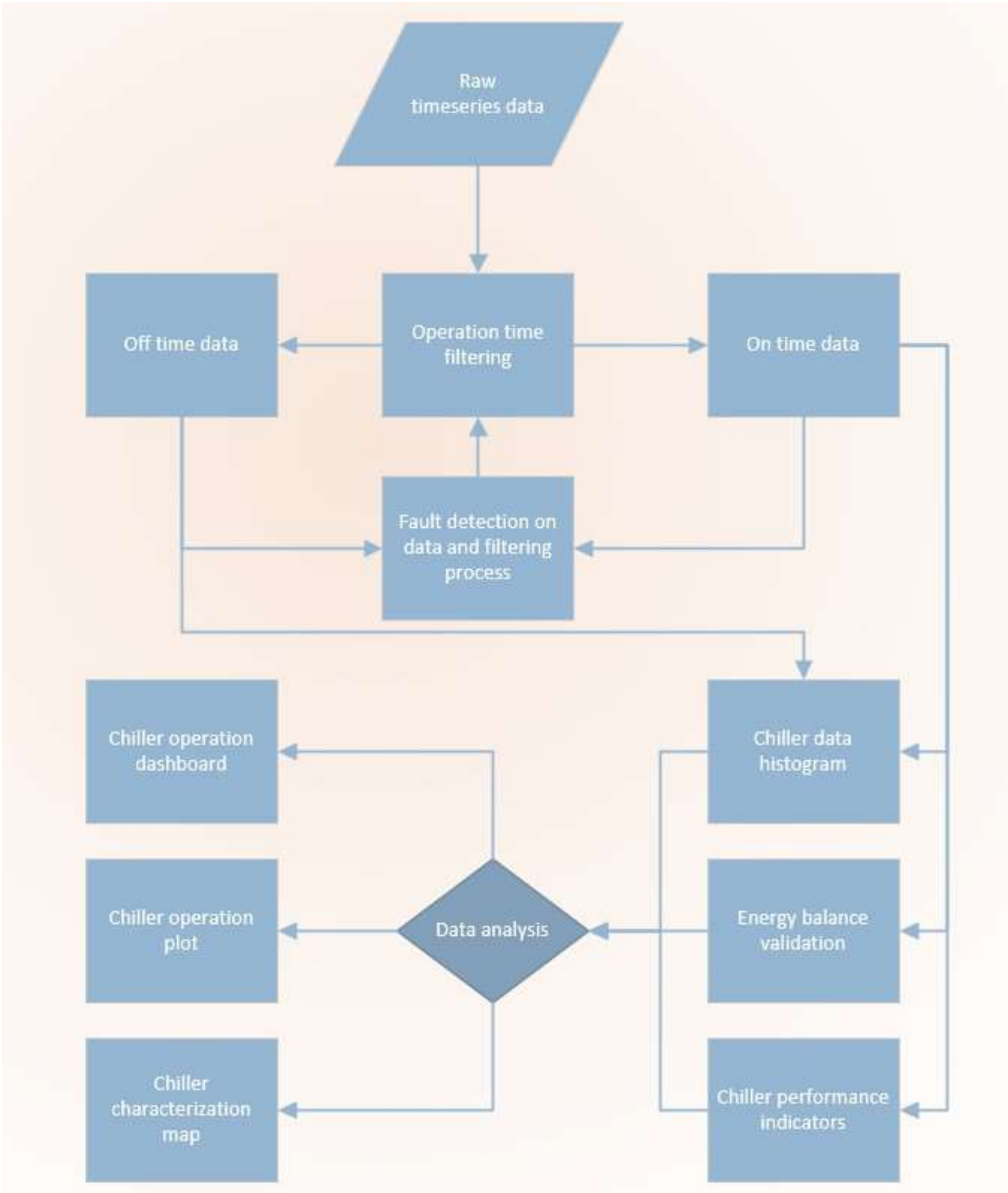

Figure III.2. Process flowchart.

III.3 DETERMINE CHILLER OPERATION SHIFTS (CONTINUOUS OPERATION) AND STAGING ON/OFF HOURS

On Lower Limit is the minimum value of a meter whose chiller is in operation. To ensure one chiller is in operation requires the following confirmations:

- Condition 1: Chiller evaporator flow rate is higher than On Lower Limit
- Condition 2: Chiller condenser flow rate is higher than On Lower Limit
- Condition 3: Chiller power meter is higher than On Lower Limit

The initial On Lower Limit for each chiller has been selected based on the design chiller cooling capacity as shown in Table III.5. For chillers with design evaporator and condenser water flow rates greater than 3500 gpm, the On Lower Limit is 300 gpm, and the remaining chillers, which have design evaporator and condenser water flow rates less than 3500 gpm, have limits of 200 gpm. The On Lower Limit for chillers with design electrical consumption values less than 1000 kW is 80 kW and 160 kW if the design electrical consumption is greater than 1000 kW. The initial On Lower Limits for flow and electrical consumption are based on typical values of those quantities during off times with consideration for averaged values during chiller start and stop hours. If a chiller had run 10 minutes in the monitored hours at the typical start-up demand limit (40%) and 20°F temperature differential lift, the chiller would have instantaneous power at 60% of design power, which is equivalent to about 10% (0.6×0.16) of the design value for average hourly electrical consumption. In order to simplify the procedure, each meter type has only one boundary grouping value. After initial filtering, the initial On Lower Limit values are reviewed by comparing with the identified fault hours.

Table III.5. Initial chiller on lower limits.

Chiller	Design Cooling Capacity, Tons	Evaporator Water Flow Rate, gpm		Condenser Water Flow Rate, gpm		Electrical Consumption, kW	
		Design	On Lower Limit	Design	On Lower Limit	Design	On Lower Limit
001	1500	2996	200	4500	300	909	80
002	1500	2996	200	4500	300	909	80
003	2500	6000	300	6675	300	1538	160
004	2500	6000	300	6675	300	1538	160
005	2500	6000	300	6675	300	1532	160
006	2500	6000	300	6675	300	1532	160
007	3350	6700	300	10050	300	2053	160
010	3150	6278	300	9770	300	1874	160
101	1000	2000	200	3000	200	598	80
102	1000	2000	200	3000	200	598	80
103	2500	5000	300	7500	300	1525	160
201	1334	5000	300	7500	300	1527	160
202	1500	3000	200	4500	300	883	80
203	1334	2286	200	4000	300	804	80
204	2250	4500	300	6000	300	1391	160
205	2250	4500	300	6000	300	1391	160
206	2500	5000	300	7500	300	1510	160
301	2500	5000	300	7500	300	1258	160
302	2500	5000	300	7500	300	1258	160
303	1100	2640	200	3315	200	676	80
304	1400	3344	200	4197	300	839	80

Each chiller has its operating data set established by finding all points of its data set which satisfy all three On conditions. Table III.6 shows a sample of operation data from chiller 103.

Table III.6. Sample of chiller 103 operation data.

Time		3/27/2018 0:00	3/27/2018 1:00	3/27/2018 2:00
F_{chw}	**CH103_1**	4759.68	4972.12	4737.06
T_{outchw}	**CH103_2**	43.03	42.98	42.96
T_{inchw}	**CH103_3**	54.26	53.94	53.95
P_{elec}	**CH103_5**	1155.29	1187.71	1113.55
F_{cw}	**CH103_6**	6941.29	6937.82	6927.86
T_{outcw}	**CH103_7**	87.37	87.92	87.36
T_{incw}	**CH103_8**	78.61	78.96	78.79

Based on three conditions (1, 2, and 3), a procedure is developed to find meter faults. If all three conditions are satisfied, the chiller is obviously on. If none of the three conditions are satisfied, the chiller is off. If one condition is satisfied and two are not, or two conditions are satisfied and one is not, then there may be a fault. The procedure is logically processed step-by-step as outlined below:

- All_On – all 3 conditions are satisfied. Value: True or False
- All_Off – all 3 conditions are not satisfied. Value: True or False
- Possible_Fault – Both All_On and All_Off are False. Value: True or False
- Possible_On – Possible_Fault or All_On are False. Value: True or False

The purpose of those validations is finding if any meter might have a problem by filtering out where the Possible_Fault condition is True.

Table III.7 shows a sample of data from chiller 004 where a possible fault was detected during 1/7/2017 1:00 – 1/7/2017 7:00 when the chiller evaporator flow rate is higher than the On Lower Limit while both electrical consumption and condenser flow rate are lower than their respective On Lower Limits. Table III.7 shows chiller meter values and in operation confirmations in:

- Column **CH004_1 Test** shows condition (1): Evaporator water flow rate values (column **CH004_1 –** Chilled Water Flow Rate, gpm), which are more than On Lower Limit (300 gpm)
- Column **CH004_6 Test** shows condition (2): Condenser water flow rate values (column **CH004_6 –** Cooling Water Flow Rate, gpm), which are more than On Lower Limit (300 gpm)
- Column **CH004_5 Test** shows condition (3): Electrical consumption values (column **CH004_5 –** Electrical Consumption, kWh), which are more than On Lower Limit (300 gpm)
- Column **CH004_All_On** checks if all three On conditions are satisfied – all three conditions are **True** while Column **CH004_All_Off** has **True** values while all are **False**
- Column **CH004_Possible_Fault** values are **True** when both columns **CH004_All_On** and **CH004_All_Off** have **False** values
- Column **CH004_Possible_On** values are **True** when either columns **CH004_All_On** or column **CH004_Possible_Fault** have **True** values

The chiller operating parameters during this possible fault time are shown in Figure III.3. Figure III.3 charts all seven physical meters listed in Table III.6. The red lines are flow rate type where the continuous red line is chilled water flow rate and the dashed red line is condenser flow rate. The lines with green circle markers are chilled water temperatures: supply temperature is represented by the filled circle, while the cross-circle is returned

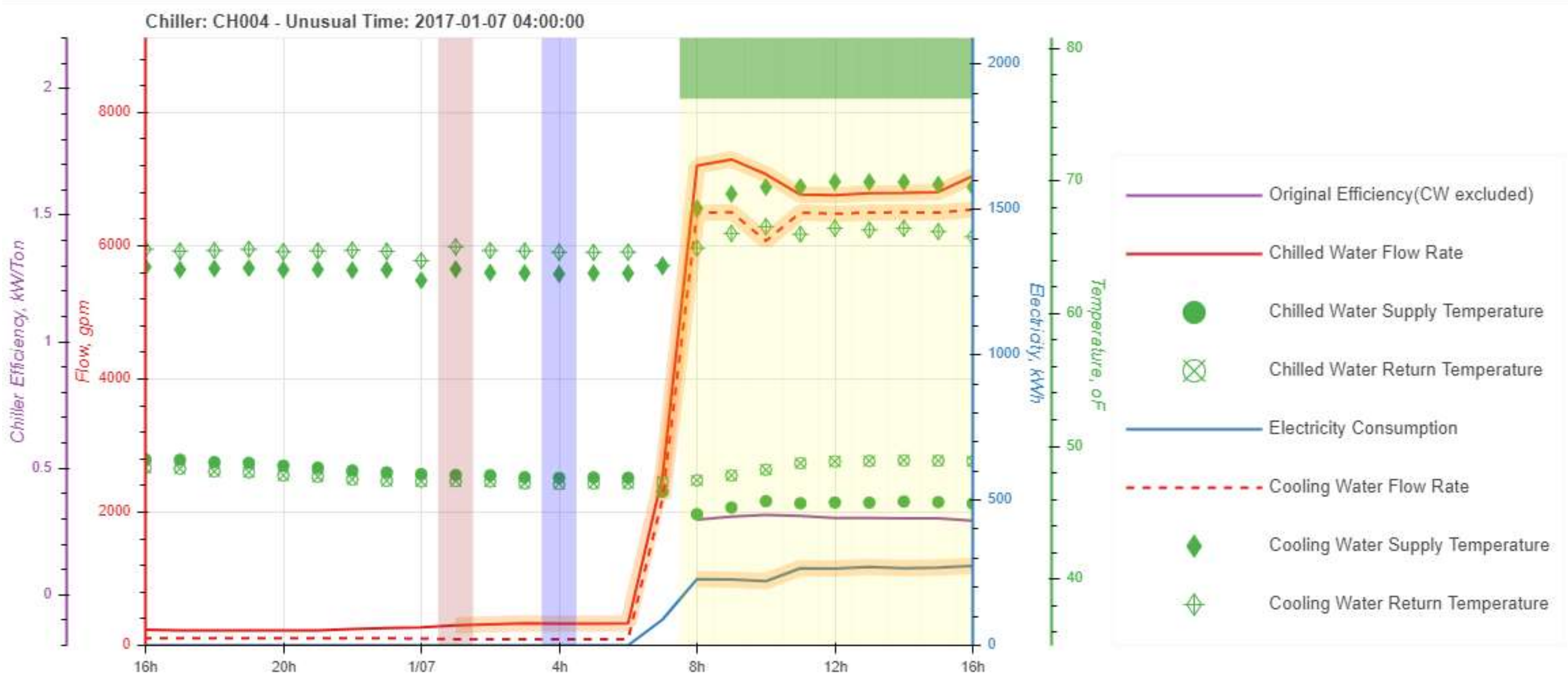

Figure III.3. Sample of chiller meter timeseries.

chilled water. Similarly, the diamond-shaped green lines illustrate the condenser water temperatures. The chiller electrical consumption is the blue line, while the violet line shows kW/ton. There are four axes that have color characterized by their units according to meter type. On the left boundary, the violet axis is the chiller efficiency value, while the red axis defines flow rate. On the right boundary, the blue axis shows electrical consumption values and the green axis characterizes temperature range. At the middle of the chart, two transparent color spans have been annotated: the pink span is start/stop time detected by the algorithm, while the violet shows the possible fault time detected. The yellow span on the right of the chart shows when all three On conditions were met. In addition, the blue span on top of the yellow span is the AHRI energy balance validation described in Section Four of this chapter. The chilled/cooling water flow rates and electricity consumption have transparent yellow spans when their values are above the On Lower Limits than their respective On Lower Limits. Table III.7 shows chiller meter values and in operation confirmations in:

- Column **CH004_1 Test** shows condition (1): Evaporator water flow rate values (column **CH004_1 –** Chilled Water Flow Rate, gpm), which are more than On Lower Limit (300 gpm)
- Column **CH004_6 Test** shows condition (2): Condenser water flow rate values (column **CH004_6 –** Cooling Water Flow Rate, gpm), which are more than On Lower Limit (300 gpm)
- Column **CH004_5 Test** shows condition (3): Electrical consumption values (column **CH004_5 –** Electrical Consumption, kWh), which are more than On Lower Limit (300 gpm)

Table III.7. Sample of operation detection.

Time (Local)	CH004_1	CH004_1 Test	CH004_5	CH004_5 Test	CH004_6	CH004_6 Test	CH004_Al l_Off	CH004_Al l_On	CH004_D T_range	CH004_Po ssible_Fau lt	CH004_Po ssible_On
1/6/2017 22:00	246.54	FALSE	0	FALSE	107.48	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
1/6/2017 23:00	258.49	FALSE	0	FALSE	106.98	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
1/7/2017 0:00	269.96	FALSE	0	FALSE	102.42	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
1/7/2017 1:00	300.83	TRUE	0	FALSE	91.99	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
1/7/2017 2:00	315	TRUE	0	FALSE	90.64	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
1/7/2017 3:00	329.33	TRUE	0	FALSE	89.92	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
1/7/2017 4:00	327.92	TRUE	0	FALSE	90.69	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
1/7/2017 5:00	327.94	TRUE	0	FALSE	91.28	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
1/7/2017 6:00	329.36	TRUE	0	FALSE	91.56	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
1/7/2017 7:00	2,538.8	TRUE	88.74	FALSE	2,204.4	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE
1/7/2017 8:00	7,201.4	TRUE	227.83	TRUE	6,492.9	TRUE	FALSE	TRUE	TRUE	FALSE	TRUE
1/7/2017 9:00	7,295.7	TRUE	227.12	TRUE	6,504.6	TRUE	FALSE	TRUE	TRUE	FALSE	TRUE
1/7/2017 10:00	7,074.0	TRUE	220.66	TRUE	6,071.5	TRUE	FALSE	TRUE	TRUE	FALSE	TRUE

- Column **CH004_All_On** checks if all three On conditions are satisfied – all three conditions are **True** while Column **CH004_All_Off** has **True** values while all are **False**
- Column **CH004_Possible_Fault** values are **True** when both columns **CH004_All_On** and **CH004_All_Off** have **False** values
- Column **CH004_Possible_On** values are **True** when either columns **CH004_All_On** or column **CH004_Possible_Fault** have **True** values

The chiller operating parameters during this possible fault time are shown in Figure III.3. Figure III.3 charts all seven physical meters listed in Table III.6. The red lines are flow rate type where the continuous red line is chilled water flow rate and the dashed red line is condenser flow rate. The lines with green circle markers are chilled water temperatures: supply temperature is represented by the filled circle, while the cross-circle is returned chilled water. Similarly, the diamond-shaped green lines illustrate the condenser water temperatures. The chiller electrical consumption is the blue line, while the violet line shows kW/ton. There are four axes that have color characterized by their units according to meter type. On the left boundary, the violet axis is the chiller efficiency value, while the red axis defines flow rate. On the right boundary, the blue axis shows electrical consumption values and the green axis characterizes temperature range. At the middle of the chart, two transparent color spans have been annotated: the pink span is start/stop time detected by the algorithm, while the violet shows the possible fault time detected. The yellow span on the right of the chart shows when all three On conditions were met. In addition, the blue span on top of the yellow span is the AHRI energy balance validation described in Section Three of this chapter. The chilled/cooling water flow rates and electricity consumption have transparent yellow spans when their values are above the On Lower Limits.

III.3.1 Fault Detection

Based on the chiller meter trends, the alarm points have been reviewed to find causes. Observing trend data gives us some ideas about how the lower and upper limits worked. The algorithm can detect this typical issue with chiller operation: *Evaporator or condenser water flow rates are still high when the chiller has been turned off.*

Whenever the evaporator or condenser flow rate remains high during chiller off time, energy is wasted for the pumping system and there is a cooling penalty due to mixing of return and supply chilled/cooling water. The cooling tower must work more than necessary when there is no heat rejection demand.

The possible reasons for these issues are:

- A leaking valve
- Faulty control action (manual or automatic)
- Faulty meter (physical sensor or acquisition system)

Figure III.4 shows a case when chiller 001 had a high condenser flow rate while the chilled water flow was nearly zero at 12h on 2017-01-11. The condenser flow rate (4000 gpm) is higher than the normal operation flow rate (3000 gpm). This situation with high condenser flow continued for 2 hours, then returned to normal flow.

Figure III.5 shows a case when the chilled water flow rate of chiller 001 unreasonably increased from zero to 3000 gpm without any other evidence of a running chiller at 7 am on 2017-09-26. Both condenser/cooling water flow rate and electrical consumption were zero, while there was no difference between return and supply temperatures at the evaporator, i.e., chiller 001 must have been out of operation at that time.

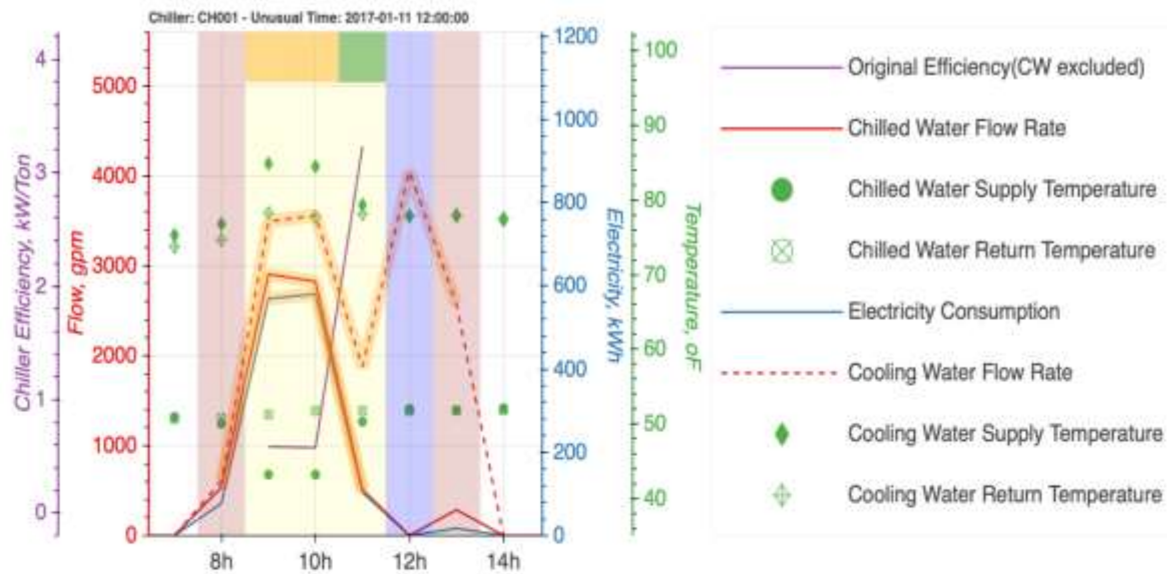

Figure III.4. Chiller 001 has problems with valve or cooling water flow meter.

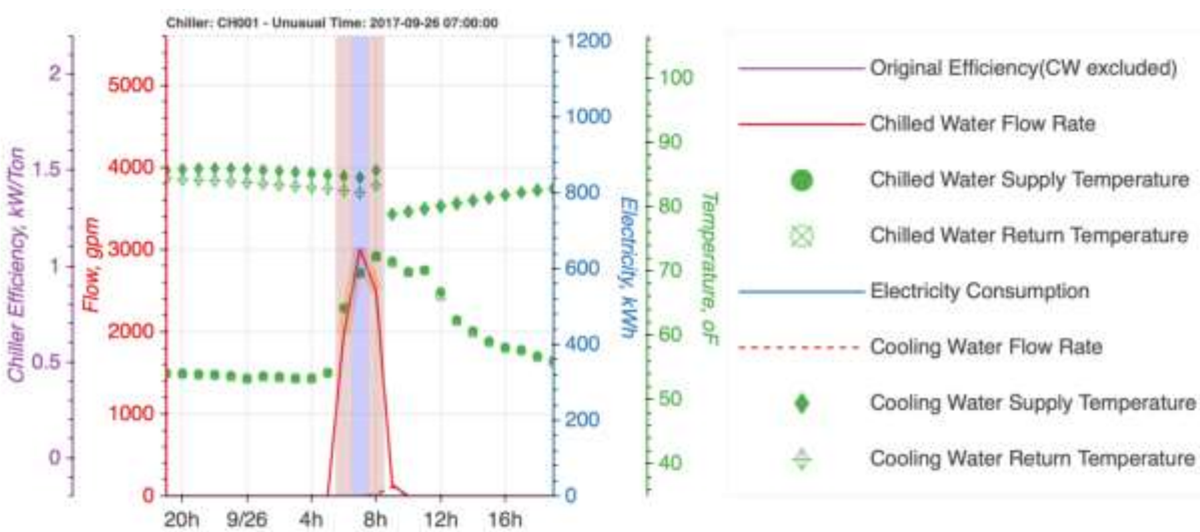

Figure III.5. Chiller 001 has high chilled water flow rate during off time.

To ensure all chiller operation hours were completely recorded and minimize the false alarms, the Possible_Fault alarms were reviewed to refine the On Lower Limit values for individual chillers.

The tuning procedure for chiller 004 is described in the sections below.

III.3.2 Possible Fault with Initial 'On Lower Limit'

Testing on the chiller 004 data set with the initial values for On Lower Limits gave 17 alarms with many false alarms. False alarms are typically caused when the On Lower Limits are too low or too high.

Case 1 – Chiller 004 at 2017-01-09 03:00

In Figure III.6, the chilled water flow rate value (375) during off time is more than the default On Lower Limit of 300 gpm, so it alarmed about possible faulty operation of chiller 004 while the cooling water flow rate and electrical consumption were not in the operational ranges (slim instead of thickened lines).

For chiller 004, the heat balance validation is good all year, so the chiller flow meter should not be the problem. Observing the histogram of all year chilled water flow rate during off time in Figure III.7, the normal value range is between 0 and 300 gpm. This case requires increasing the On Lower Limit so that false alarms will not be triggered any more. While flow meter acceptable tolerance is 5 percent of meter range (300 gpm) or 15 gpm, the On Lower Limit should be increased to 1.05 times the false-alarmed value.

Table III.8 shows the values of On Lower Limit for three meters—chilled and condenser water flow rates, and electrical meters—with their values for "*Alarmed Point*

(Time)" at the alarm time, along with their On Lower Limits. The values in the "*Down Row*" and "*Up Row*" columns are the hours when the alarmed meter has the largest hourly percent decrease and percent increase (relative to the previous hour) in the nearest 24 or 48 hours (12 or 24 hours before and after), respectively. The 24- or 48-hour time period is selected depending on the on/off characteristics of a particular metered point. Similarly, the "Max" and "Min" columns show highest and lowest values in the 24 or 48 surrounding hours. All values in Table III.8 are based on the 48 surrounding hours, e.g., 24 hours before and 24 hours after.

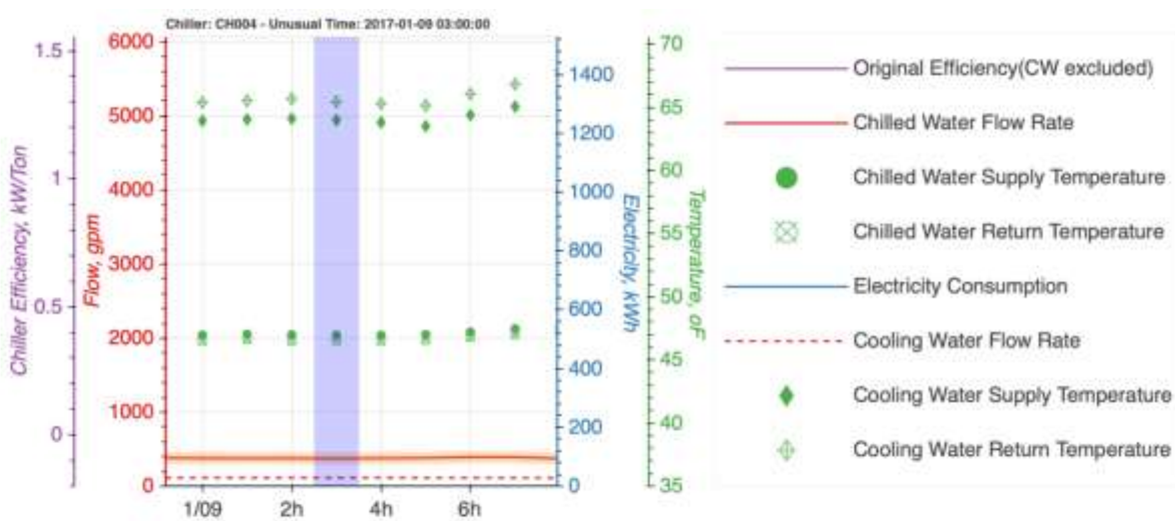

Figure III.6. Chiller 004 with false alarm while chilled water flow rate is more than the default On Lower Limit value.

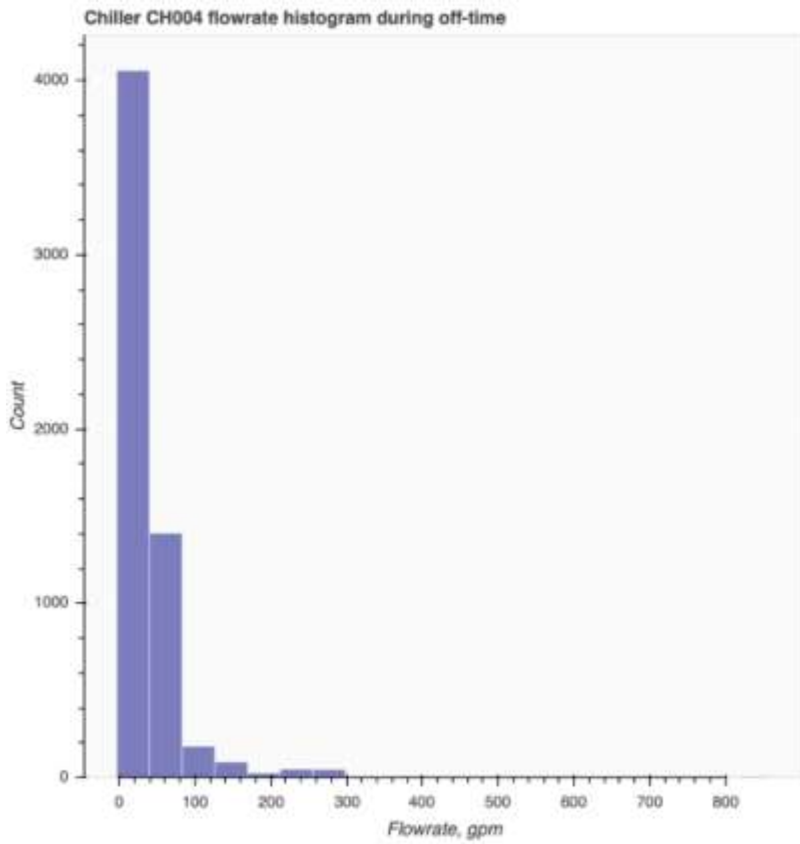

Figure III.7. Chiller 004 chilled water flow rate histogram.

Table III.8. Chiller data analysis at alarm time 2017-01-09 3:00.

Meter	On Lower Limit	Alarmed Point (Time)	Down Row (Time)	Up Row (Time)	Max	Min
		2017-01-19 03:00:00	2017-01-19 09:00:00	2017-01-08 15:00:00		
Chilled Water Flow Rate, gpm	300.0	375.29	341.77	347.24	405.7	340.5
Electrical Consumption, kWh	160.0	0	0.00	0.00	0	0.00
Cooling Water Flow Rate, gpm	300.0	112.63	110.89	105.18	115.26	102.39

Case 2 – Chiller 004 at 2017-01-09 16:00

Figure III.8 and Table III.9 show the alarm point when the condenser water flow rate value is 345.14 at 16:00 during the off time. The cooling water flow rate from 13:00 to 18:00 2017-01-09 is shown thickened. This case also requires increasing the On Lower Limit of the condenser water flow rate so false alarms will not be triggered any more.

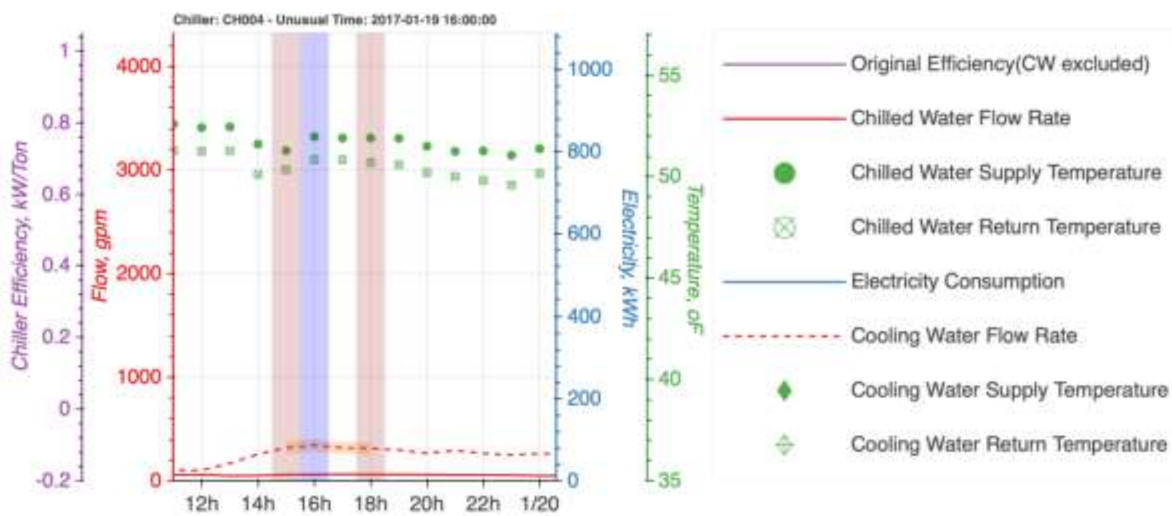

Figure III.8. Chiller 004 with high cooling water flow rate during off time.

Analogous to case 1, Figure III.9 shows a histogram of the condenser water flow rate for a time when the chiller was detected as offline. The typical high condenser flow rates during off time are in 300–350 gpm range.

Table III.9. Chiller data analysis at alarm time 2017-01-09 16:00:00.

Meter	On Lower Limit	Alarmed Point (Time)	Down Row (Time)	Up Row (Time)	Max	Min
		2017-01-19 16:00:00	2017-01-20 08:00:00	2017-01-19 13:00:00		
Chilled Water Flow Rate, gpm	300.0	62.4	61.02	49.19	65.05	49.19
Electrical Consumption, kWh	160.0	0	0.00	0.00	0	0.00
Condenser Water Flow Rate, gpm	300.0	345.14	265.56	170.24	345.14	103.19

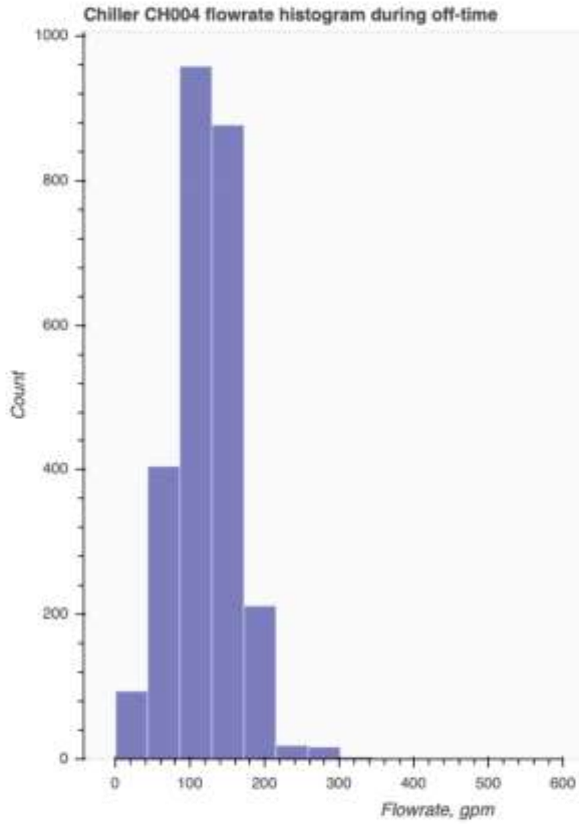

Figure III.9. Condenser water flow rate histogram of chiller 004 during off times.

Case 3 – On Lower Limit of electrical meter is too low

Figure III.10 and Table III.10 describe a false alarm when chiller 004 was running with both evaporator and condenser water flow rates, along with high evaporator and condenser difference temperatures, but the On Lower Limit of the electrical consumption meter had classified the chiller as being in off status. Based on the histogram of electrical meters in Figure III.11, the typical range of values is less than 100 kWh, so the On Lower Limit of chiller 004's electrical meter should be decreased accordingly.

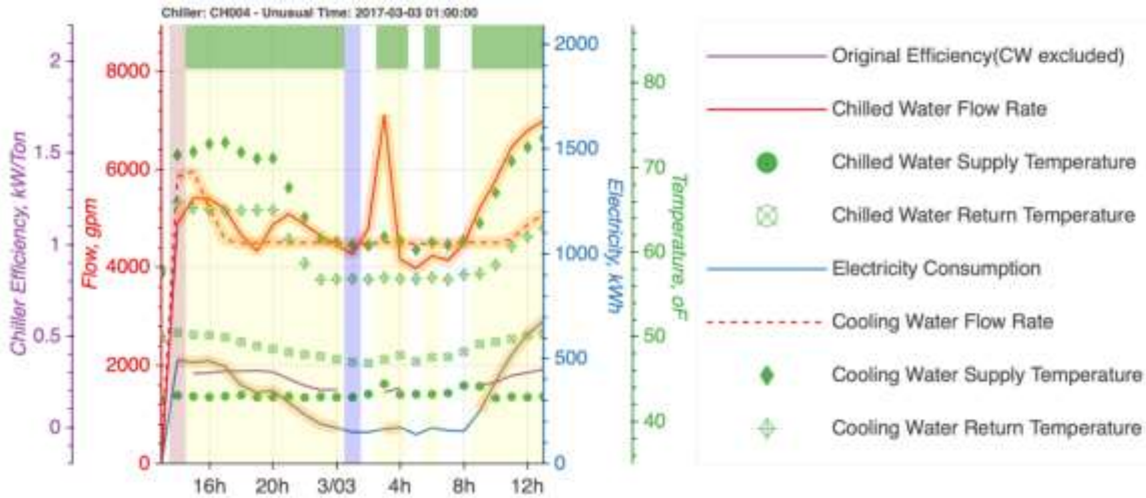

Figure III.10. Chiller 004 false alarm and missed operation point.

Table III.10. Chiller data analysis at 2017-03-03 1:00.

Meter	On Lower Limit	Alarmed Point (Time)	Down Row (Time)	Up Row (Time)	Max	Min
		2017-03-03 01:00:00	2017-03-02 04:00:00	2017-03-02 07:00:00		
Chilled Water Flow Rate, gpm	300.0	4271.45	4,165.42	−1.22	7,115.40	−1.22
Electrical Consumption, kWh	160.0	150.77	173.13	0.06	680.58	0.06
Cooling Water Flow Rate, gpm	300.0	4,499.51	4,506.59	143.76	5,961.34	143.76

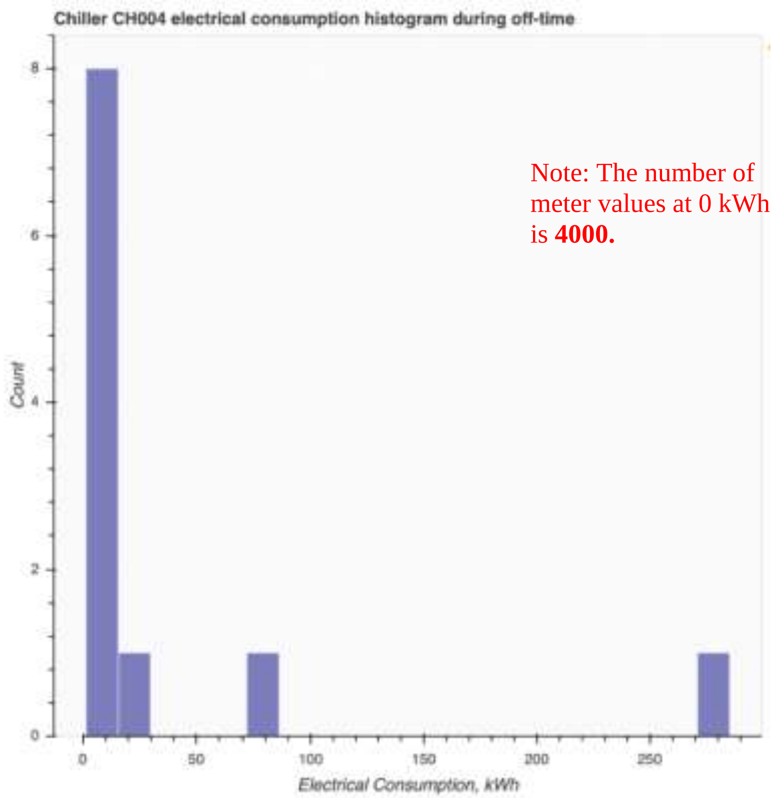

Figure III.11. Histogram of electrical meter for chiller 004.

III.3.3 Refining Chiller 'On Lower Limit'

Based on the three cases previously discussed, the On Lower Limits of chiller 004 have been refined. Table III.11 compares the initial and refined values. The refined values were increased or decreased to eliminate the unreasonable Possible Faults identified with the initial On Lower Limit values.

Table III.11. Optimizing chiller 004 on lower limit.

Meters	Unit	Initial On Lower Limit	Refined On Lower Limit
Chilled Water Flow Rate	gpm	300	420
Cooling Water Flow Rate	gpm	160	120
Electricity Consumption	kWh	300	520
Alarm Points	times	18	6

III.4 CHILLER PERFORMANCE RATING

All chillers at the Texas A&M UES plants are chilled water and heat pump water-heating packages using the vapor compression cycle. The current AHRI Standard 550/590 establishes the definitions, test requirements, rating requirements, and minimum data requirements for Published Ratings, marking and nameplate data, conversions and calculations, nomenclature, and conformance conditions. AHRI Standard 550/590 determines type and energy efficiency ratings of water chillers and heat pumps, and provides the mandatory requirements in the building energy code (ASHRAE S90.1) for installation in the United States, as seen in Table 6.8.1-3 of ASHRAE Standard 90.1. It also forms the mandatory (minimum) published requirements for datasheet and test report content that should be provided by chiller manufacturers and approved testing facilities for commercial purposes. The rating procedures described in AHRI Standard 550/590 are recognized by governmental agencies.

III.4.1 AHRI Standard 550/590 Performance Rating Allowance Limitations

To evaluate whether chiller efficiency test results match the submitted (published) data provided by manufacturers, AHRI Standard 550/590 determines test/fail limitation boundaries with four allowable tolerance limits:

- T_{ol1} – performance tolerance limit
- T_{ol2} – Integrated Part Load Value (IPLV) and Non-standard Part Load Value (NPLV) performance tolerance limit
- T_{ol3} – Tolerance on water side pressure limit
- T_{ol4} – Energy balance validity tolerance limit

These limits are intended to verify and confirm chiller performance ratings and take account of:

- *Uncertainty of measurement* due to instrumentation accuracy, installation conditions, and facility stabilities.
- *Uncertainty of test facilities* when the same unit is tested in multiple facilities with different setup variations, which may not give the same performance.
- *Uncertainty of manufacturing* because of production tolerances, which impact performance unit by unit.
- *Uncertainty of performance prediction models* when the manufacturer uses models to predict performance as a result of option complexity.

The application of tolerance limit T_{ol1} is described in Table III.12.

Table III.12. AHRI Standard 550/590 allowable tolerance limit application.

Value Type	Chiller Type	Limits
Capacity	Cooling or heating capacity for units with continuous unloading	Full load minimum:100% – T_{ol1} Full load maximum:100% + T_{ol1}
	Cooling or heating capacity for units with discrete capacity steps	Full load minimum: 100% – T_{ol1} Full load maximum: No limit (Full load shall be at the maximum stage of capacity)
Efficiency	EER	Minimum of: (rated EER) / (100% + T_{ol1})
	kW/tonR	Maximum of: (100% + T_{ol1}) · (rated kW/tonR)
	COP	Minimum of: (rated COP) / (100% + T_{ol1})
	IPLV.IP NPLV.IP EER	Minimum of: (rated EER) / (100% + T_{ol2})
	IPLV.IP NPLV.IP kW/tonR	Maximum of: (100% + T_{ol2}) · (rated kW/tonR)
	IPLV.IP NPLV.IP COPR	Minimum of: (rated COPR) / (100% + T_{ol2})

Based on the available meter data set, a performance tolerance limit (Tol1) and energy balance validity tolerance limit (Tol4) are chosen to validate the chiller meter set data using heat balance principles.

Performance tolerance limit of chiller (T_{ol1})

In AHRI Standard 550/590, the tolerance limits for net capacity and for full and part-load efficiency have been established and are given in Table 11 of the standard. It accounts for the calculated cooling variation based on accuracy of instrumental devices. Test validation tolerance limits are given in ARHI 550/590 Table 13. Figure III.12 shows the curves of T_{ol1} values, which depend on the part-load ratio and the temperature difference between supply and return water.

$$T_{ol1} = 0.105 - (0.07 * \%Load) + \left(\frac{0.15}{\Delta T_{FL} * \%Load}\right)$$

$$(100\% - T_{ol1}) * P_{chw} < P_{chwin} < (100\% + T_{ol1}) * P_{chw}$$

$$(100\% - T_{ol1}) * P_{cw} < P_{cwin} < (100\% + T_{ol1}) * P_{cw}$$

Where, T_{ol1} is the allowable tolerance of full and part-load point limits in decimal form; $\%Load$ is the part-load ratio in decimal form; ΔT_{FL} is the difference between supply and return water temperatures at full load, °F; P_{chwin}, P_{cwin} is the calculated chilled and cooling water production, tons; and P_{chw}, P_{cw} is the measured chilled and cooling water production, tons.

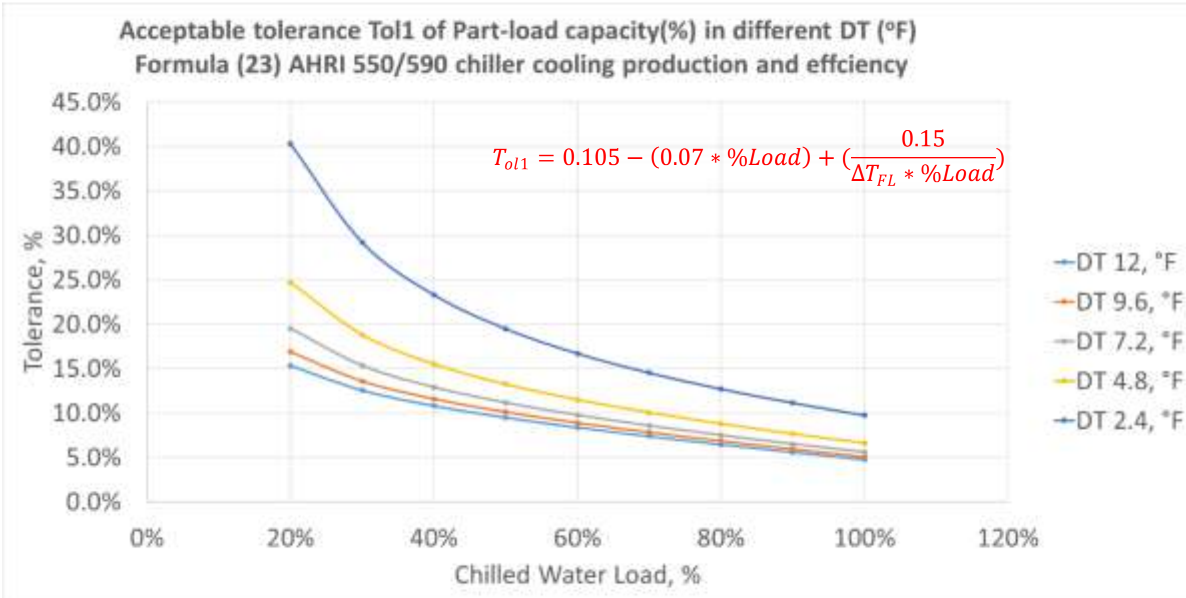

Figure III.12. Allowable tolerance of full and part-load T_{ol1}.

Energy balance validity tolerance limit (T_{ol4})

According to AHRI Standard 550/590, the validity tolerance's formula based on energy balance is:

$$T_{ol4} = 0.074 - (0.049 * \%Load) + \left(\frac{0.105}{\Delta T_{FL} * \%Load}\right)$$

$$|E_{bal}| \leq T_{ol4} * 100\%$$

$$E_{bal} = 2\,\frac{E_{in} - E_{out}}{E_{in} + E_{out}} * 100\%$$

Where, T_{ol4} is energy balance validity tolerance limit in decimal form; and E_{bal} is energy balance error, %.

Energy flows in and out of the system are calculated by the following formulas:

$$E_{in} = \sum_i E_{in_i} = Q'_{ev} + W_{refrig} * K$$

$$E_{out} = \sum_i E_{out_i} = Q'_{cd} + Q'_{hrc}$$

Where, E_{in}, E_{out} is energy input and output, tons; W_{refrig} is power, total of compressor work and auxiliary devices transferring energy into the refrigerant, kW; and K is [3.51685 – conversion rate from kW to tons].

The gross cooling, heating, and heat reclaim capacities have been measured as:

$$Q'_{ev} = m_w.[c_p.(T_{in} - T_{out}) + \frac{K9.\Delta p_{corrected}}{\rho}]$$

$$Q'_{cd} = m_w.[c_p.(T_{in} - T_{out}) + \frac{K9.\Delta p_{corrected}}{\rho}]$$

$$Q'_{hrc} = m_w.[c_p.(T_{in} - T_{out}) + \frac{K9.\Delta p_{corrected}}{\rho}]$$

Where, Q'_{ev}, Q'_{cd}, and Q'_{hrc} are, respectively, the gross capacity evaporator (cooling), condenser (heating), and heat recovery (heat reclaim), tons; $\frac{K9.\Delta p_{corrected}}{\rho}$ is the adjustments of pressure drop with $\Delta p_{corrected} = \Delta p_{test} - \Delta p_{adj}$, where $\Delta p_{corrected}$ is the corrected pressure, ft H_2O; Δp_{test} is the reading pressure, ft H_2O; Δp_{adj} is the piping pressure, ft H_2O; and ρ is the water density, $\frac{lb}{ft^3}$; and $K9$ is the conversion factor from $\frac{lb_f}{in^2}.\frac{ft^3}{lb_m}$ to $\frac{Btu}{lb_m}$ where lb_f and lb_m are pound-force and pound-mass.

To simplify data for monitoring purposes, the capacity adjustment for pressure drop, which is often minor and could fluctuate less than 0.4% of full-load capacity (1 ton difference at 430 tons full load) is neglected, so the gross capacities Q'_{ev}, Q'_{cd}, Q'_{hrc} might become net capacities P_{chw}, P_{cw}, and P_{elec}. Most of the chillers have semi-hermetic compressors so W_{refrig} becomes P_{elec}, so we get the following adjusted formulas:

$$E_{in} = \sum_i E_{in_i} = P_{chw} + \frac{P_{elec}}{K}$$

$$E_{out} = \sum_i E_{out_i} = Q_{cd} + Q_{hrc}$$

Figure III.13 shows the curves of T_{ol4} values, which depend on the part-load ratio and the water temperature difference between supply and return.

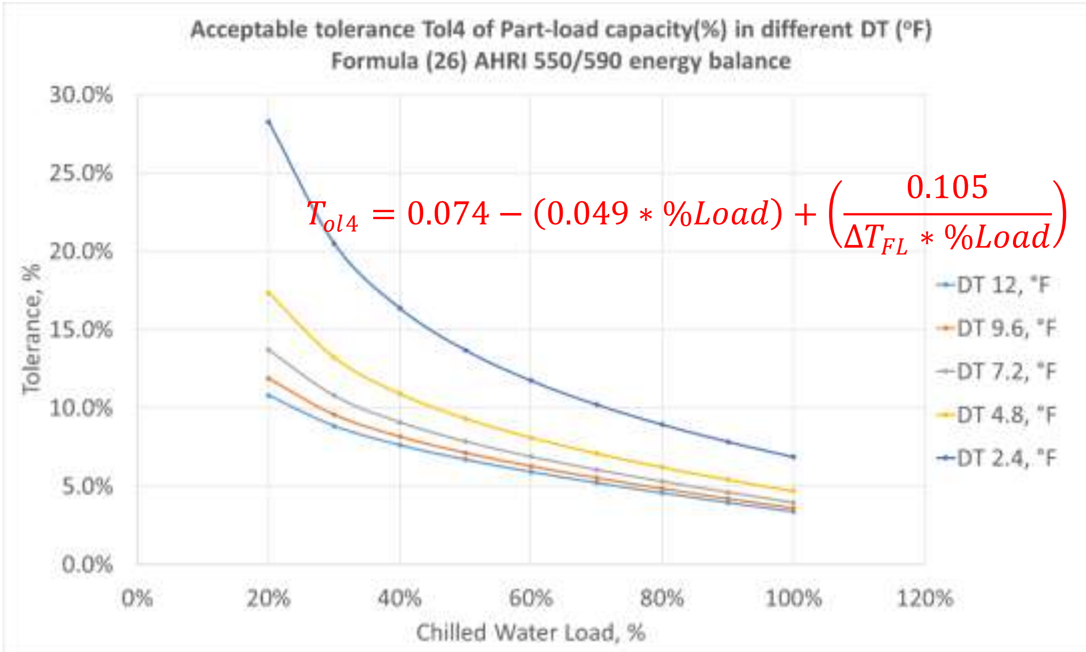

Figure III.13. Energy balance allowable tolerance T_{ol4}.

III.4.2 Using AHRI Standard 550/590 Allowable Tolerances to Evaluate the Reliability of Chiller Meter Datasets

The AHRI Standard 550/590 test procedure applied validation tolerance limits to chiller test results based on the chiller manufacturer's datasheet. In this thesis, those limits are the indicators for the chiller meter set validation. Table III.13 shows the differences between the AHRI Standard 550/590 performance rating and this thesis' meter validation.

Table III.13. Procedures with allowable tolerances.

Procedures with Allowable Tolerances	
Tolerance Limits	**Formula**
T_{ol1} For rating tests	$(100\% - T_{ol1}) * P_{chwdataset} < P_{chwmeasured}$
	$P_{chwmeasured} < (100\% + T_{ol1}) * P_{chwdatasheet}$
	$(100\% - T_{ol1}) * P_{cwdataset} < P_{cwmeasured}$
	$P_{cwmeasured} < (100\% + T_{ol1}) * P_{cwdatasheet}$
T_{ol1} For meter validation	$(100\% - T_{ol1}) * P_{ch} < P_{ch}$
	$P_{chwmeasuredindirect} < (100\% + T_{ol1}) * P_{chwmeasured}$
	$(100\% - T_{ol1}) * P_c < P_c$;
	$P_{cwmeasuredindirect} < (100\% + T_{ol1}) * P_{cwmeasured}$
	$P_{chwmeasuredindirect} = P_{cwmeasured} - \frac{P_{elec}}{K}$
	$P_{cwmeasuredindirect} = P_{chwmeasured} + \frac{P_{elec}}{K}$
T_{ol4}	$T_{ol4} = 0.074 - (0.049 * \%Load) + \left(\frac{0.105}{\Delta T_{FL} * \%Load}\right)$
	$\lvert E_{bal} \rvert \leq T_{ol4} * 100\%$
	$E_{bal} = 2\,\frac{E_{in} - E_{out}}{E_{in} + E_{out}} * 100\%$

For the equations in the table:

T_{ol1} – Allowable tolerance of full- and part-load points limit in decimal form

$\%Load$ – Part-load ratio of chiller design capacity in decimal form

ΔT_{FL} – Difference between supply and return water temperatures at full load, °F

$$P_{chw} = m_{chw} * \frac{T_{chwin} - T_{chwout}}{24}; P_{cw} = m_{cw} * \frac{T_{cwout} - T_{cwin}}{24}$$

Where,

P_{chw} – Chilled water production, tons

P_{cw} – Cooling water production, tons

m_{chw} – Chilled water flow rate, gpm

m_{cw} – Cooling water flow rate, gpm

T_{chwin}, T_{chwout} – Chilled water return and supply temperatures, °F

T_{cwin}, T_{cwout} – Condenser return and supply temperatures, °F

24 – Conversion rate from tons-hours to gpm-°F

P_{elec} – Electrical consumption, KWh with

$K = 3.51685\ - conversion\ rate\ from\ tons - hours\ to\ kWh$

$P_{chwdatasheet}$ – Chilled water production from manufacturing datasheet data, tons

$P_{chwdatasheet}$ – Condenser water production from manufacturing datasheet data, tons

$P_{chwmeasured}$ – Chilled water production from measurement data, tons

$P_{chwmeasured}$ – Condenser water production from measurement data, tons

$P_{chwmeasuredindirect}$ – Chilled water production derived from measured cooling water productions and electrical consumption, tons

$P_{cwmeasuredindirect}$ – Condenser water production derived from measured chilled water productions and electrical consumption, tons

E_{bal} – Energy balance

E_{in}, E_{out} – Energy input and output, tons

T_{ol4} – Energy balance validity tolerance limit in decimal form

$\%Load$ – Part-load ratio of chiller design capacity in decimal form

ΔT_{FL} – Different between supply and return water temperatures at full load, °F

While rating tests use tolerance limits for validating real measured values with the manufacturer's datasheet, the meter validations have those limits to validate real meter values with measured chiller cooling and heat recovery production using energy balance, which is calculated directly and indirectly based on the chiller meter data set.

III.4.3 Validation Results

The chiller validation plots are categorized into:

- By Validation Result
  - Good: Most measured tolerance values less than allowed

- Bad: Measured calculated limit more than allowed value
- Mixed: Have both

- By Time:
  - Winter: From 2017-01-01 00:00:00 to 2017-03-12 02:00:00 and from 2017-11-05 03:00:00 to 2017-12-31 23:00:00
  - Summer: From 2017-03-12 03:00:00 to 2017-11-05 02:00:00

The validation result is a group consisting of four scatter plots. Figure III.14 is the heat balance tolerance validation (T_{ol4}) for cooling (evaporator) production and Figure III.15 shows heating (condenser) production at the top right. Similarly, applying the allowable tolerance limit (T_{ol1}), the bottom left plot is the cooling production for chiller cooling production and the bottom right is for heating production. The validated tolerance (red dot) is the maximum allowable tolerance values based on the definition of T_{ol4} and T_{ol1}, while measured tolerance (blue dot) is calculated based on the difference between direct and indirect cooling/heating production values and electrical consumption. The meter data are considered reliable whenever the meter set has a validated tolerance (red dot) value bigger than the measured tolerance (blue dot).

The climate characteristics in which the Texas A&M plants operate are also considered by splitting the data set into winter- and summertimes, which help show the effect of ambient conditions on the chiller meters. The splitting points are daylight savings time changes, which also prevent discontinuity in data set values at time change moments.

Figures III.14 to III.17 show a sample of validation plots for chiller 001 with mixed results for the year 2018 for AHRI heat balance. Figure III.18 shows typical good results for chiller 010, while Figure III.19 shows bad results for chiller 204.

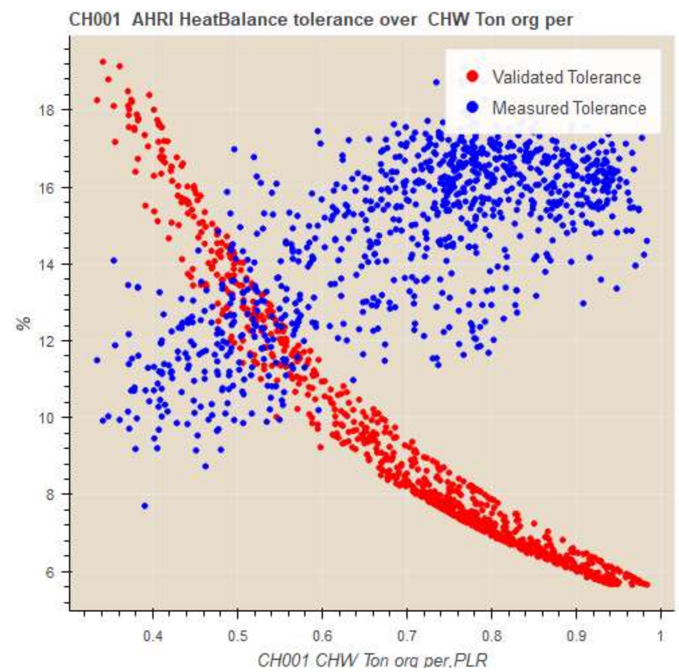

Figure III.14. Evaporator cooling load validation T_{ol4}.

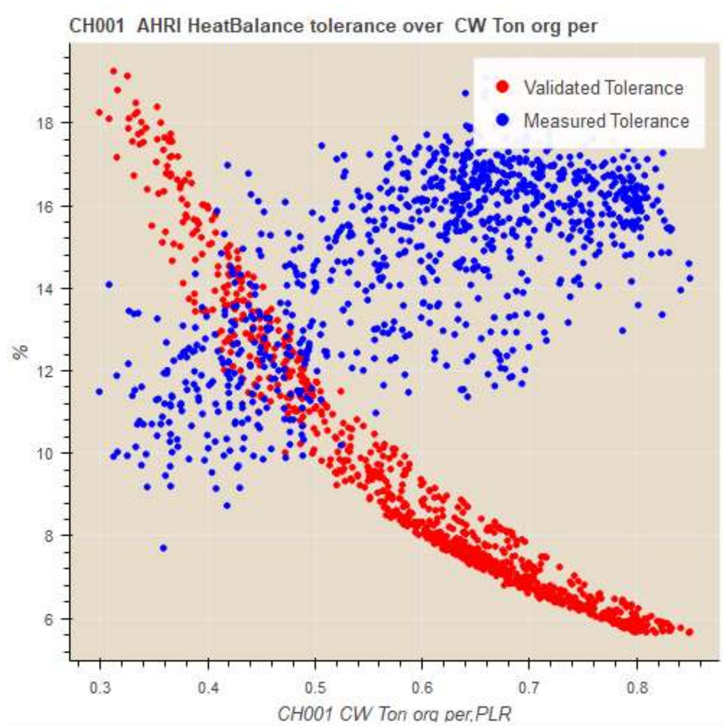

Figure III.15. Condenser cooling load validation T_{ol4}.

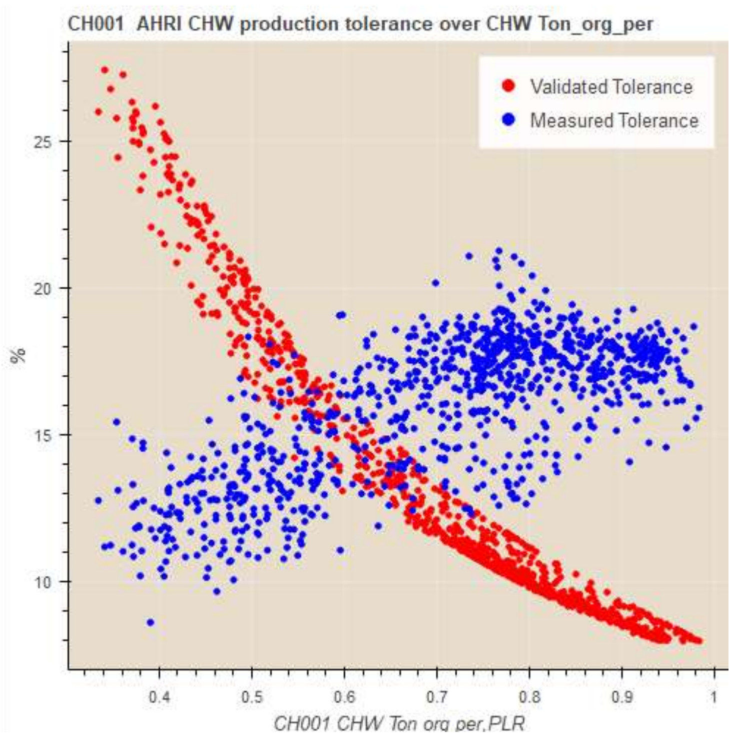

Figure III.16. Evaporator cooling load validation T_{ol1}.

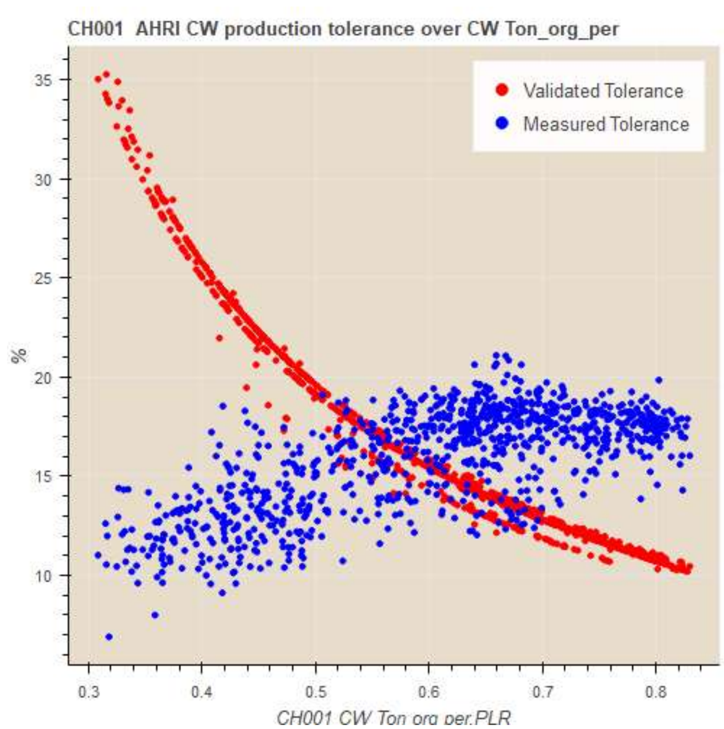

Figure III.17. Evaporator cooling load validation T_{ol1}.

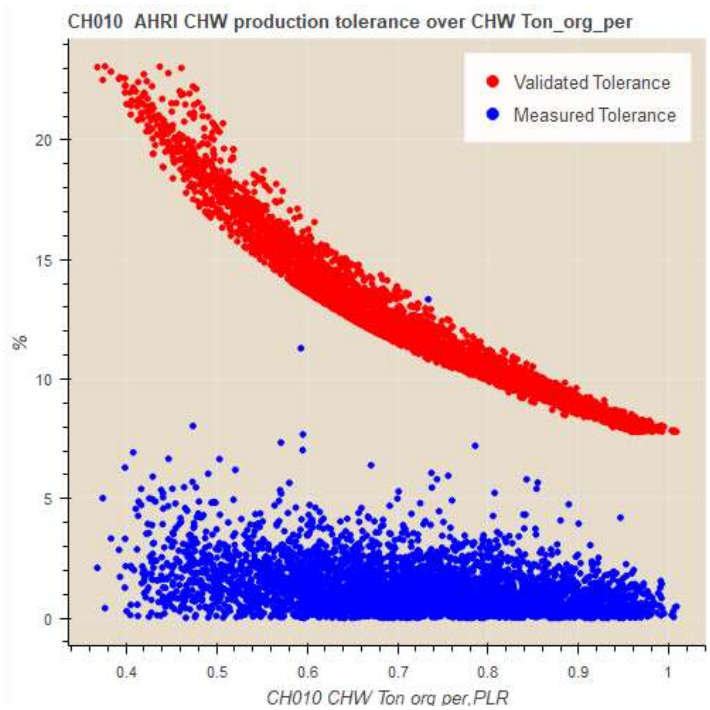

Figure III.18. Good validation – Chiller 010.

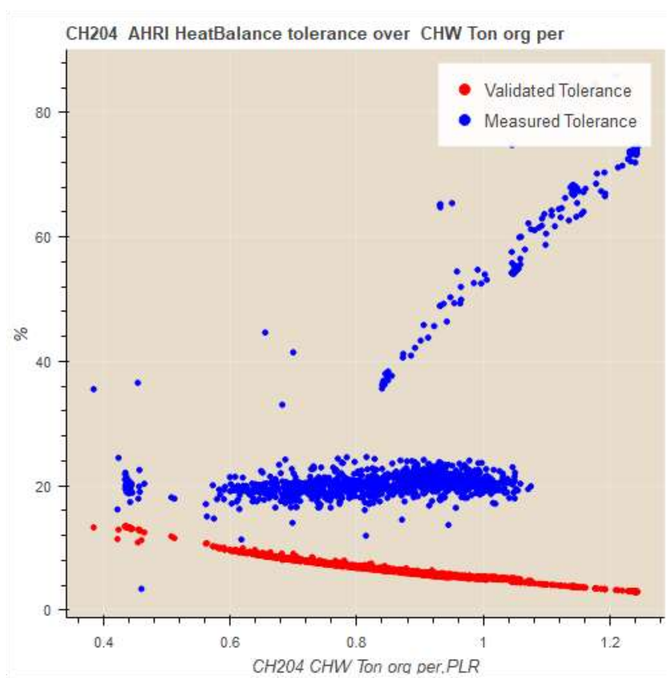

Figure III.19. Bad validation – Chiller 204.

Figures III.20 and III.21 contain data which show a sample of validation plots (chiller 001) in summer and winter, respectively. The results show that data from the meter set of chiller 001 has bad validation during the summertime and good validation during a portion of the wintertime. In addition, the chiller part-load ratio in the summertime is much higher than in the wintertime. This evidence might raise an issue of electrical meters calculated with fixed power factor values, e.g., those meters are not accurate enough over the whole performance range of their monitored chillers. In order to better detect errors, the chiller electrical meters should be recommissioned during the wintertime or upgraded using more suitable metering technologies.

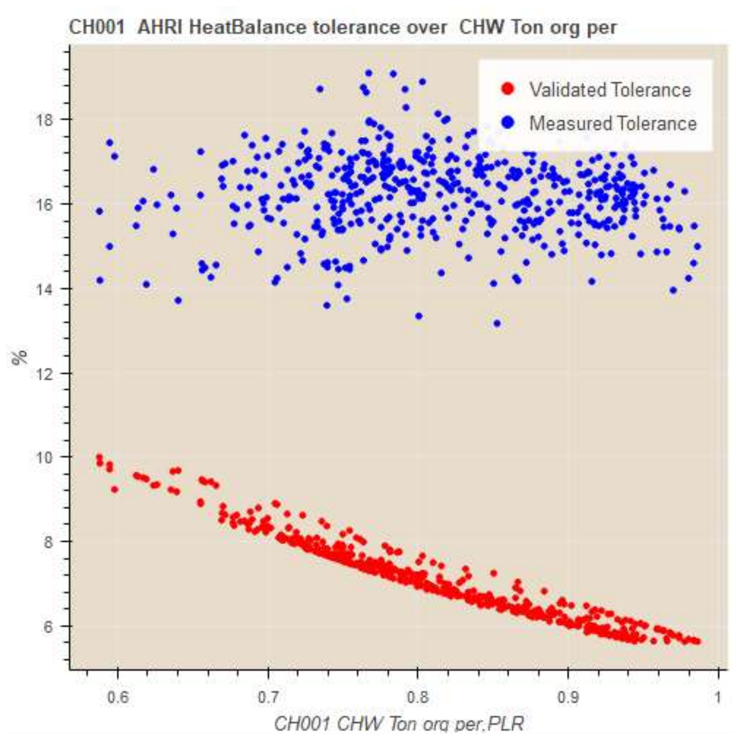

Figure III.20. Chiller 001 summer.

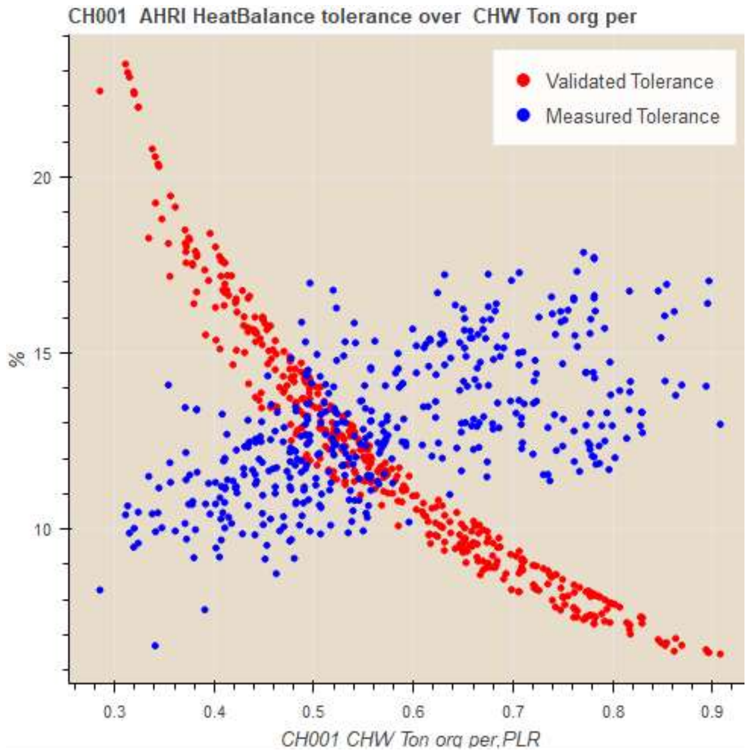

Figure III.21. Chiller 001 winter.

The summary of chiller validation results and their annual cooling production values and efficiencies are shown in Table III.14. From the results in Table III.14, scatter plots of total annual cooling production and average cooling production vs. their efficiency with colors indicating the data validation results are presented in Figure III.22 and Figure III.23, respectively.

It is evident that both worst and best chiller input power–to-output ratios (kW/ton) come from the “Bad” group. While chillers 204 and 205 have exceptionally good input power–to-output ratios at about 0.28 kW/ton, their bad validation results demand recalibration of their meter set. The same recalibration is also recommended for chiller 206, which has an unusually high input power–to-output ratio of 1.26 kW/ton. The current validation classification procedure can point out abnormalities in chiller performance data.

In addition, chiller 003 with a bad validation result may require calibration later, even though its input power–to-output ratio is like that of other chillers

Table III.14. Chiller annual summary.

Chiller	All Year	Summer	Winter	Total Cooling Production, tons-hours	Average Cooling Production, tons	Efficiency, kW/ton
001	Mixed	Bad	Mixed	1,056,511	1,052	0.59
002	Good	Good	Good	1,094,739	1,005	0.62
003	Bad	Bad	Bad	8,625,556	1,911	0.55
004	Good	Good	Good	7,761,593	1,955	0.52
005	Good	Good	Good	8,707,785	1,997	0.64
006	Good	Good	Good	9,244,471	1,983	0.57
007	Mixed	Mixed	Bad	10,515,725	2,843	0.43
010	Good	Good	Good	9,599,117	2,249	0.42
101	Mixed	Bad	Mixed	805,982	822	0.65
102	Good	Good	Good	1,099,978	827	0.41
103	Good	Good	Good	11,504,428	1,981	0.51
201	Mixed	Mixed	Mixed	6,840,940	2,028	0.51
202	Good	Good	Good	2,104,962	1,126	0.6
203	Mixed	Bad	Mixed	621,016	786	0.79
204	Bad	Bad	Bad	2,633,546	1,955	0.28
205	Bad	Bad	Bad	3,331,230	1,674	0.29
206	Bad	Bad	Bad	7,148,606	1,924	1.26
301	Good	Good	Good	14,287,567	2,159	0.51
302	Good	Good	Good	14,638,211	2,132	0.49
303	Mixed	Mixed	Bad	452,335	896	0.65
304	Mixed	Bad	Mixed	1,091,519	935	0.35

From these two scatter plots, three groups of chillers can be identified based on their annual total cooling production:

- *Low usage* – total annual cooling production less than 4 million ton-hours: Chillers 001, 002, 101, 102, 202, 203, 303, and 304
- *Average usage* – total annual cooling production from 7 million to 12 million ton-hours: Chillers 004, 005, 006, 007, 010, 103, and 201
- *High usage* – total annual cooling production higher than 12 million ton-hours: Chillers 301 and 302

The scatter plot of total annual cooling production (Figure III.22) clearly shows the utilization rate of the chillers. It shows a good management of chiller operating time, with most chillers in the good validation group having higher cooling production rates than the mixed and bad groups. The control systems should increase the runtime of chiller 102, as it has both good efficiency and a reliable meter data set.

Three of the six chillers in SUP2 (50%; 204, 205, and 206) have problems with their validation results. While they provided about 50% of the plant's total annual cooling production, recalibration of their meter set should be planned, especially chiller 206 with a high cooling production rate of about 7 million ton-hours in 2017.

Figures III.23 to III.25 describe the annual average cooling production per operating hour in tons and in part-load ratio (of design chilled water capacity). While Figures III.26 and III.27 show the typical average chiller production rate is about 2000 tons with input-to-output ratios in the range 0.5–0.65 kW/ton as validated data input, metering upgrades would be beneficial for production estimation. In terms of chiller utilization rate, the 0.7–0.85 part-load ratio (PLR) is typical for most of the chillers.

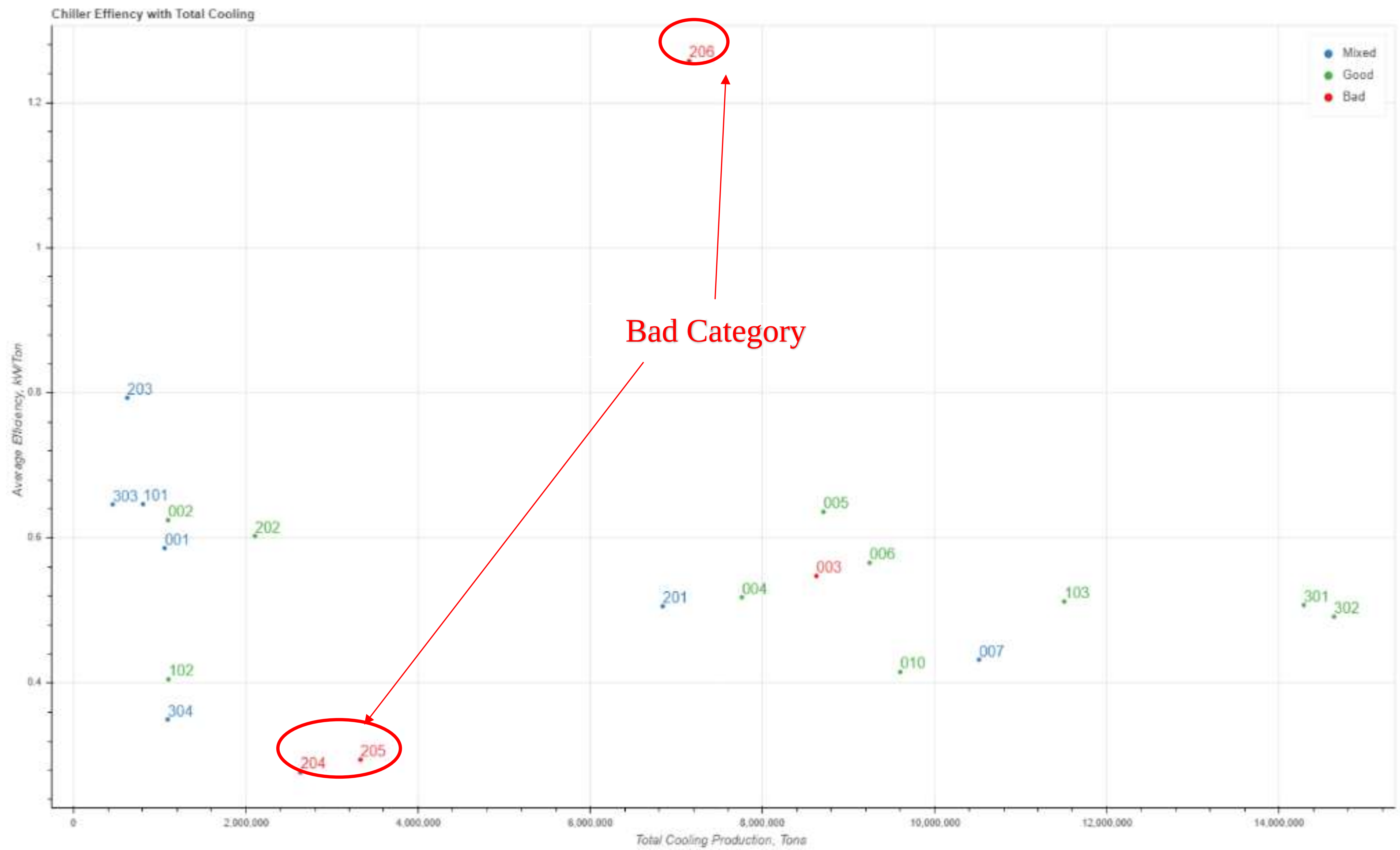

Figure III.22. Chiller input-to-output ratio vs. total cooling production with AHRI validation category.

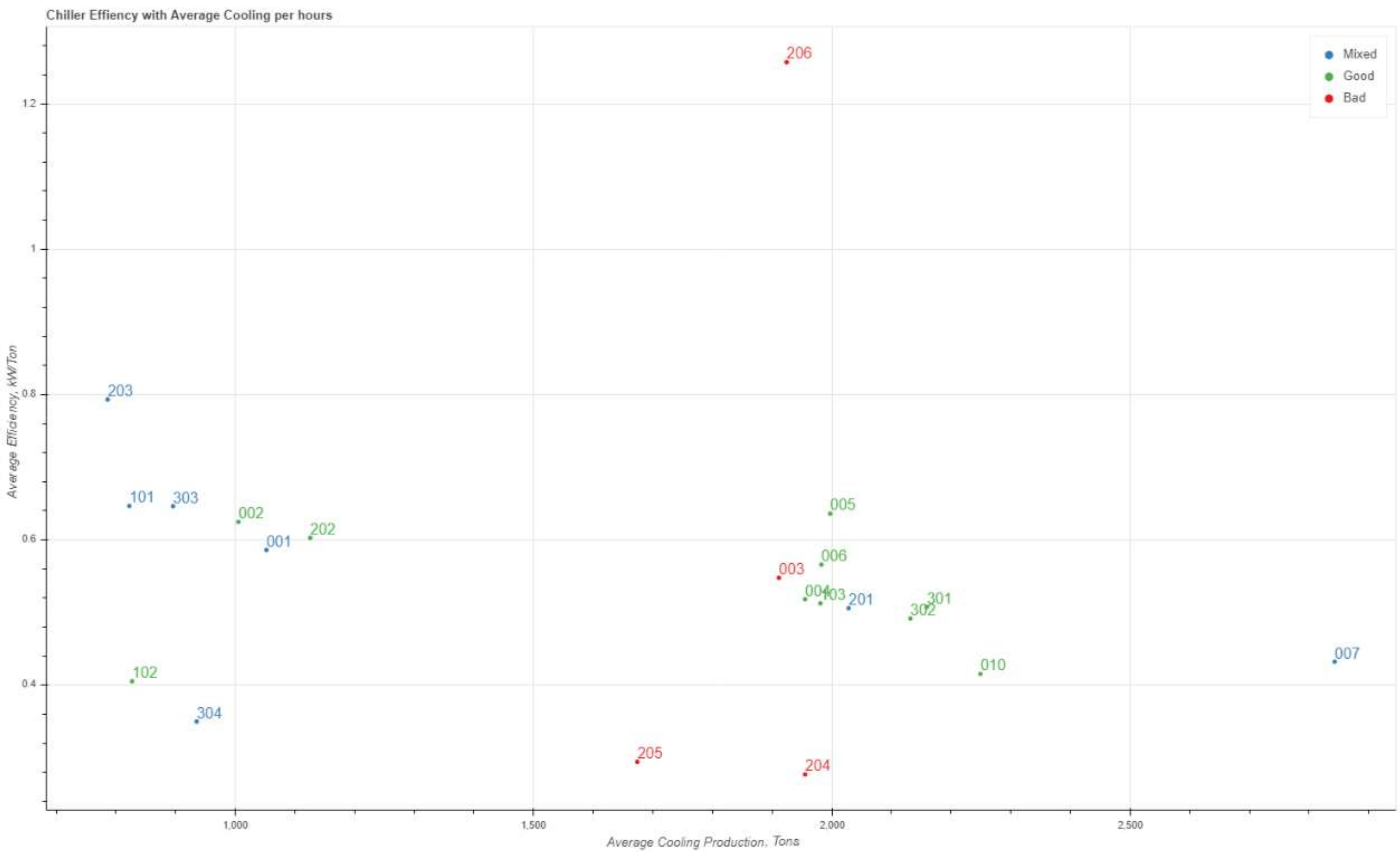

Figure III.23. Average chiller input-to-output ratio vs average cooling production with AHRI validation category.

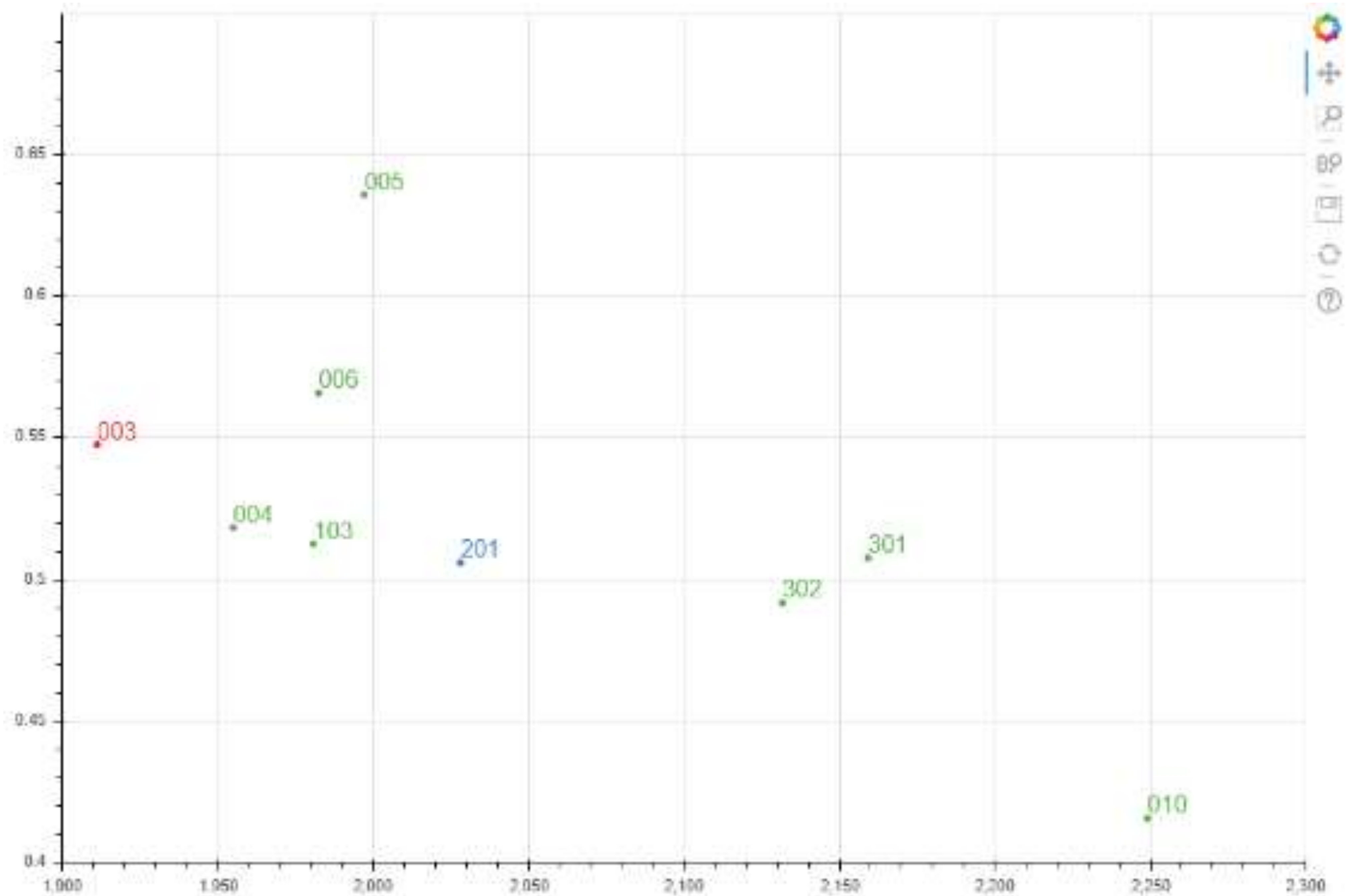

Figure III.24. Chiller average cooling production – Enlarged.

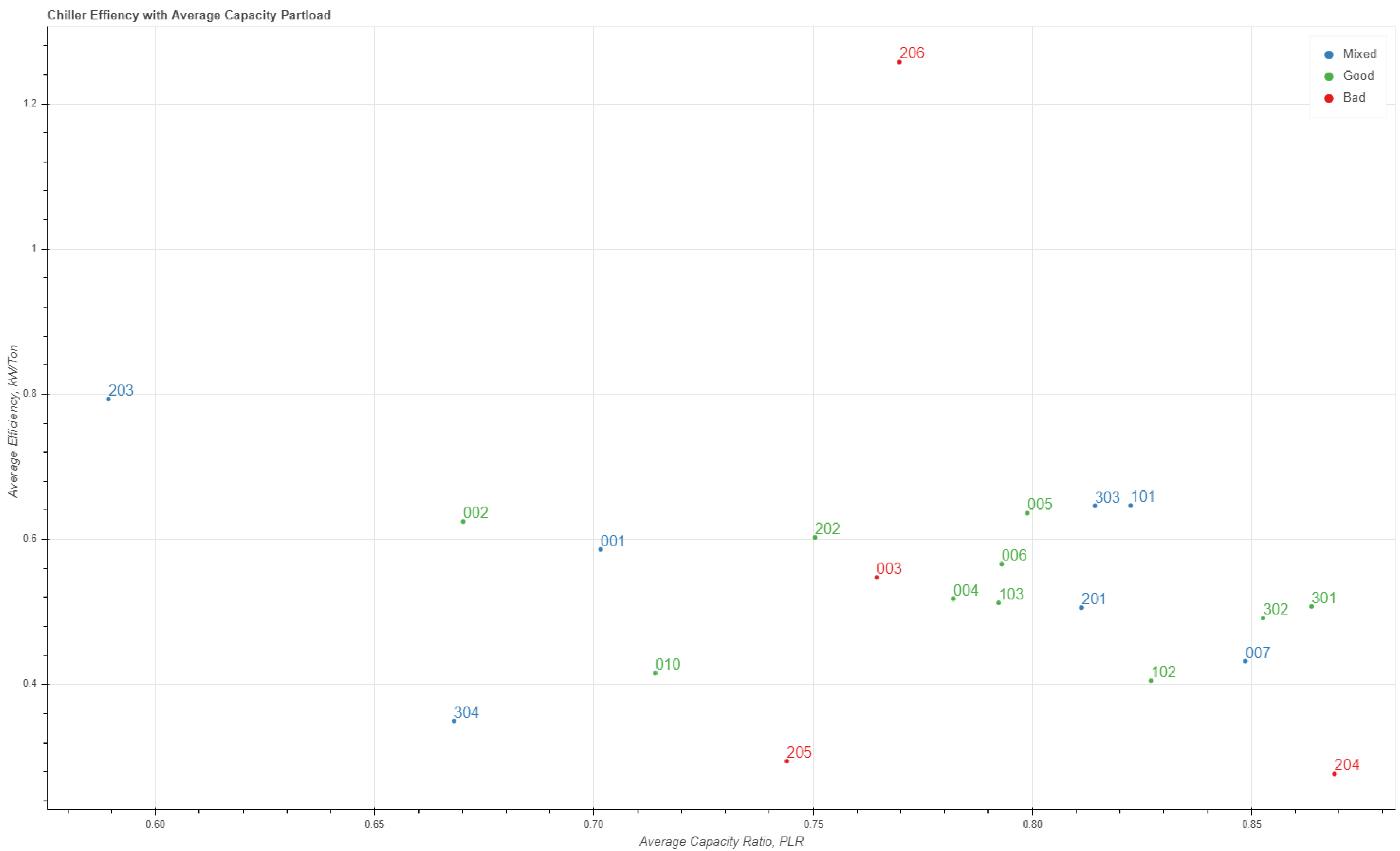

Figure III.25. Average annual input-to-output ratio vs. part-load ratio of design chilled water capacity, PLR.

III.5 CHILLER OPERATIONAL CHARACTERISTICS

III.5.1 Chiller Meter Set

Each chiller has seven physical meters with characteristics as shown in Table III.15. The meters have been calibrated periodically and as requested by professional technical staff of the Texas A&M UES team. While the meters are industrial grade, the constraints in installation locations and complexity of accurate measurement have affected the commissioning process, as the accuracy of the meter calibrations in the field is much lower than the requirements of AHRI Standard 550/590.

Table III.15. Chiller-installed meters.

Symbol	Description	Index	Unit
F_{chw}	Return chilled water flow rate	_1	gpm
T_{outchw}	Supply chilled water temperature	_2	°F
T_{inchw}	Return chilled water temperature	_3	°F
P_{elec}	Electrical consumption	_5	kW
T_{incw}	Supply condenser water temperature	_7	°F
T_{outcw}	Return condenser water temperature	_8	°F
F_{cw}	Return condenser water flow rate	_6	gpm

Table III.16 shows the meter requirements in normal practice and AHRI Standard 550/590 requirements. The big differences between laboratory and practical measurement have been compensated by multiplying the AHRI allowable tolerance limits (T_{ol1}, T_{ol4}) by 1.5.

Table III.16. Meter allowable tolerance requirement.

Meter type	Commissioning Requirement	AHRI 550/590 Requirement[2]
Electricity, percent of reading (RDG)	±5%[1]	±2%
Flow rate, percent of reading (RDG)	±10%	±1%
Temperature, °F	±0.5	±0.2

[1] Chiller electrical consumption is often derived from chiller current percent, voltage, and power factor: $P_{elec\,(\mathrm{kW})} = \sqrt{3} \times PF \times I_{(\mathrm{A})} \times V_{\mathrm{L\text{-}L}\,(\mathrm{V})} / 1000$. *However, power factor (PF) is also varied frequently, so the generalized 5% accuracy has been chosen.*

[2] Table C1. Requirements for Test Instrumentation – AHRI Standard 550/590.

III.5.2 Chiller Performance Evaluation

From seven chiller meters, 23 performance indicators have been derived for all points when a chiller is in operation. Many of these indicators are important for chiller operation and evaluations:

- *Chiller "efficiency"*, kW/ton: The ratio between chiller energy consumption and production. It is the signature value of a chiller's performance rating.
- *Chilled water capacity* P_{chw}, tons: The chilled water capacity or how much the chiller can produce in 1 hour.
- *Chilled and condenser water temperature differences $\Delta T_{chw}/\Delta T_{cw}$*, °F: The differences between return and supply water temperatures of evaporator and condenser. They indicate how well the heat exchangers (evaporator and condenser) work and have a big impact on chiller efficiency; typically, larger differences are better. Moreover, chilled and condenser water flow rates are directly affected by

those temperature differences. The cooling tower fan work is also directly proportional to condenser water temperature difference.

- *Chilled and condenser water flow rates F_{chw} /F_{cw}*, gpm: the flow rates of water passing through the evaporator and condenser. The primary pump production and efficiency are greatly affected by those flow rates. Any primary pump should manipulate its pressure setpoint to ensure that evaporator and condenser flow rates are maintained. As the pressure ratio is proportional to the square of the flow rate ratio per the Pump Law, the flow rate setpoint is critically important, not only for chiller efficiency, but also for the whole plant efficiency.

To compensate for the differences between actual performance and the design specifications (i.e., chilled water capacity, evaporator and condenser, water flow rates, electrical consumption), the part-load ratios relative to the design values have been calculated to better check the utilization rate and better understand the design limits of the chillers. All performance indicators are listed in Table III.17.

Table III.17. Chiller performance indicators.

Description	Symbol	Formula	Unit
Chilled Water Temperature Difference	ΔT_{chw}	$T_{inchw} - T_{outchw}$	°F
Condenser Water Temperature Difference	ΔT_{cw}	$T_{incw} - T_{outcw}$	°F
Chiller Lift Temperature Difference	ΔT_{lift}	$T_{outcw} - T_{outchw}$	°F
Original Chilled Water Capacity	P_{chw}	$P_{chw} = F_{chw}*(T_{outchw} - T_{inchw})/24$	tons
Original Cooling Water Capacity	P_{cw}	$P_{cw} = F_{cw}*(T_{outcw} - T_{incw})/24$	tons
Original Electricity Consumption	P_{elec}	Same as Electricity Consumption (P_{elec})	kWh
Indirect Electricity Consumption	$P_{chw\text{-}in}$	$P_{chw\text{-}in} = P_{cw} - P_{elec}*0.284$	kWh
Indirect Cooling Water Capacity	$P_{cw\text{-}in}$	$P_{cw\text{-}in} = P_{chw} + P_{elec}*0.284$	Tons
Indirect Chilled Water Capacity	$P_{elec\text{-}in}$	$P_{elec\text{-}in} = (P_{cw} - P_{chw})/0.284$	Tons
Original Efficiency (CW excluded)	COP_1	$COP_1 = P_{elec}/P_{chw}$	kW/ton
Indirect Efficiency (CHW excluded)	COP_2	$COP_2 = P_{elec}/(P_{cw} - P_{elec\text{-}}*0.284)$	kW/ton
Indirect Efficiency (ELEC excluded)	COP_3	$COP_3 = (P_{cw} - P_{chw})/(0.284*P_{chw})$	kW/ton
Chilled Water Capacity Original vs Indirect Difference	P_{chw_diff}	$(P_{chw\text{-}in} - P_{chw})/P_{chw} * 100$	%
Cooling Water Capacity Original vs Indirectly Different	P_{cw_diff}	$(P_{cw\text{-}in} - P_{cw})/P_{cw} * 100$	%
Electricity Consumption Original vs Indirectly Different	P_{elec_diff}	$(P_{elec\text{-}in} - P_{elec})/P_{elec} * 100$	%
Chilled Water Design Flow Ratio	F_{chw_per}	$F_{chw}/F_{chw\text{-}desg}$	PLR
Original Chilled Water Design Capacity Ratio	P_{chw_per}	$P_{chw}/P_{chw\text{-}desg}$	PLR
Chilled Water Design Temperature Difference Ratio	ΔT_{chw_per}	$(T_{inchw} - T_{outchw})/(T_{inchw} - T_{outchw})_{desg}$	PLR
Original Design Efficiency Ratio (CW excluded)	COP_{1_per}	$COP_1/COP_{1\text{-}desg}$	PLR
Cooling Water Design Flow Ratio	F_{cw_per}	$F_{chw}/F_{chw\text{-}desg}$	PLR
Original Cooling Water Design Capacity Ratio	P_{cw_per}	$P_{cw}/P_{cw\text{-}desg}$	PLR
Cooling Water Design Temperature Difference Ratio	ΔT_{cw_per}	$(T_{incw} - T_{outcw})/(T_{incw} - T_{outcw})_{desg}$	PLR
Design Electricity Consumption Ratio	P_{elec_per}	$P_{elec}/P_{elec\text{-}desg}$	PLR

III.5.3 Chiller Performance Dashboard

To rapidly determine chiller performance, a dashboard for chiller operation has been established to review historical chiller performance. That dashboard is selectable with four scatter charts. The chart options are drop-down lists, text input, and range bars, which include the selectable list as shown in Figures III.26 and III.27.

There are drop-down list options:

- **First Column**:
  - ***Chiller***: The number of the chiller whose data is shown on the chart (Chiller 103 as in Figure III.26). It is selectable from a list of all chillers in the data sheet.
  - ***Color***: The indicator, e.g., Original Design Efficiency Ratio (CW excluded) as in Figure III.27, is selectable from the list of indicators shown in Table III.17. The data range of the original design efficiency ratio is observed to set up a color bar as a legend. The chart program will review its range to set the color of each value (dot) on scatter plots, as seen in Figure III.28. The original design efficiency ratio for chiller 103 has the name "**CH103_COP1_per**" with a value range from 0.38 to 1.13.
  - ***Split Range* and *Boundary***: The range number is a slide bar, which has two inputs (e.g., 6…8 in Figure III.26), and the boundary is the number input (e.g., 0.9 in Figure III.26). Those inputs determine the number of indicator range groups (**8 colors**) based on the value of the boundary (0.9). It means the range 0.33(min)–0.9(boundary value) will have **6** groups (0.38–0.62), (0.62–0.73), (0.73–0.81), (0.81–0.84), (0.84–0.88), and (0.88–0.9) with the

number of points in each group (range) the same. A similar rule is applied for **2** (of **8**) remaining groups that have an indicator value, (0.9–0.94) and (0.94–1.13). This function is helpful to prevent the overconcentration issue for the scatter chart.

  - ***Filter rate***: The input number (e.g., 2.5 in Figure III.26) is the filter rate for extremely high and low data in percentage. It means the chart will remove points (time), which are in the 2.5% lowest and highest value ranges of the original design efficiency ratio (color indicator). This function will remove extreme (i.e., unreasonably high and low) values from the data set that might oversize the axis.
  - ***Update***: The green "Update" button resets the chart with all new input as selectable from the dashboard.

- **Second Column**:
  - ***Top_Left_Chart***: Two drop-down lists specify the y and x coordinate values. The list of indicators with their formulas is compatible with Table III.17. The Top_Left_Chart is described in Figure III.29.
    - ***Top_Left_y_axis***: e.g., "Original Design Efficiency Ratio(CW excluded)" as selected in Figure III.27.
    - ***Top_Left_x_axis***: e.g., "Chilled Water Design Flow Ratio" as selected in Figure III.27.
  - ***Bottom_Left_Chart***: Similar to **Top_Left_Chart** for bottom left scatter plot with y-axis as "Original Design Efficiency Ratio(CW excluded)" and x-axis as "Original Chilled Water Design Capacity Ratio"

- **Third Column**: Similar to the second column, setup for the top right scatter plot in **Top_Right_Chart** and bottom right scatter plot in **Bottom_Right_Chart**.

After selecting the **Update** button, the new chart is refreshed and shown as in Figures III.29 to III.32.

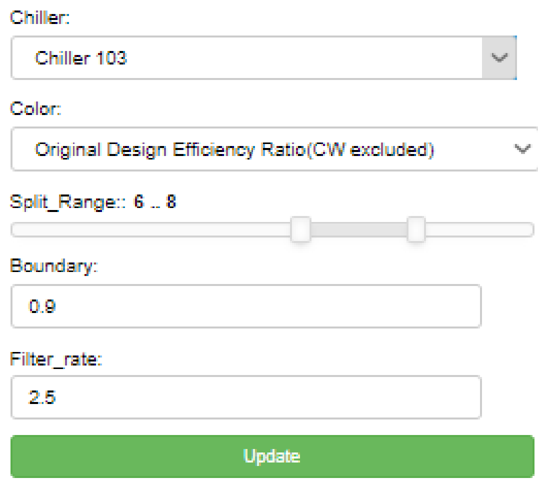

Figure III.26. Dashboard selection – First column.

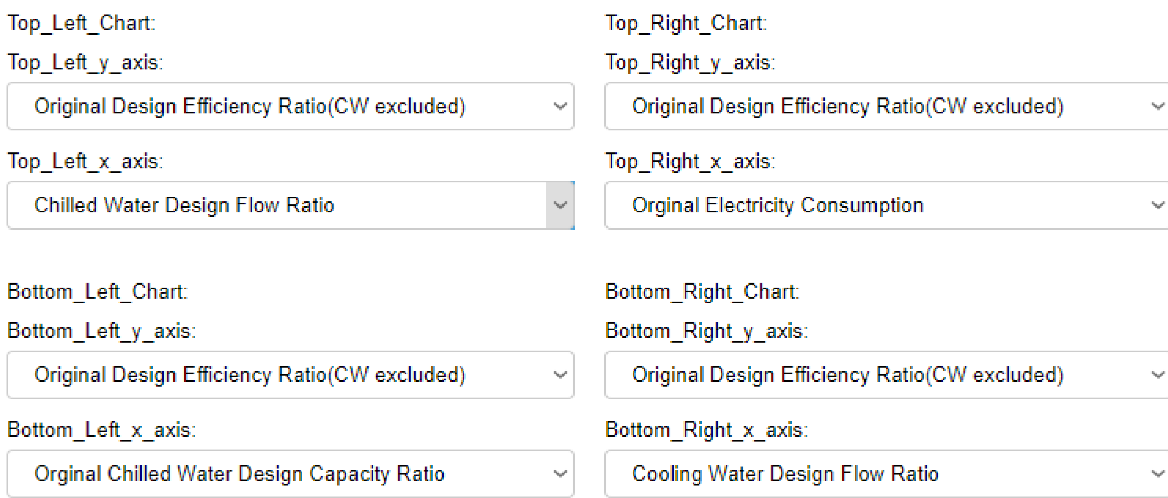

Figure III.27. Dashboard selection – Second and third columns.

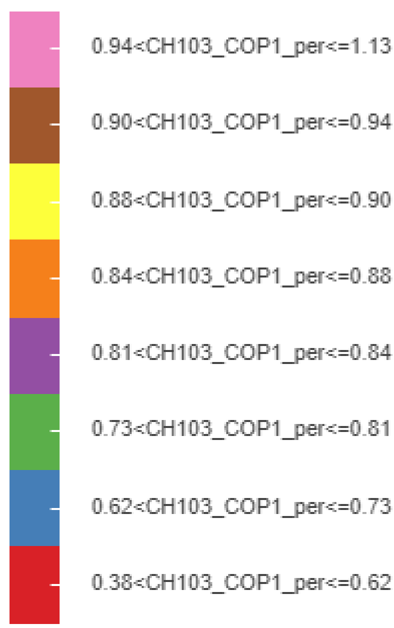

Figure III.28. Color range.

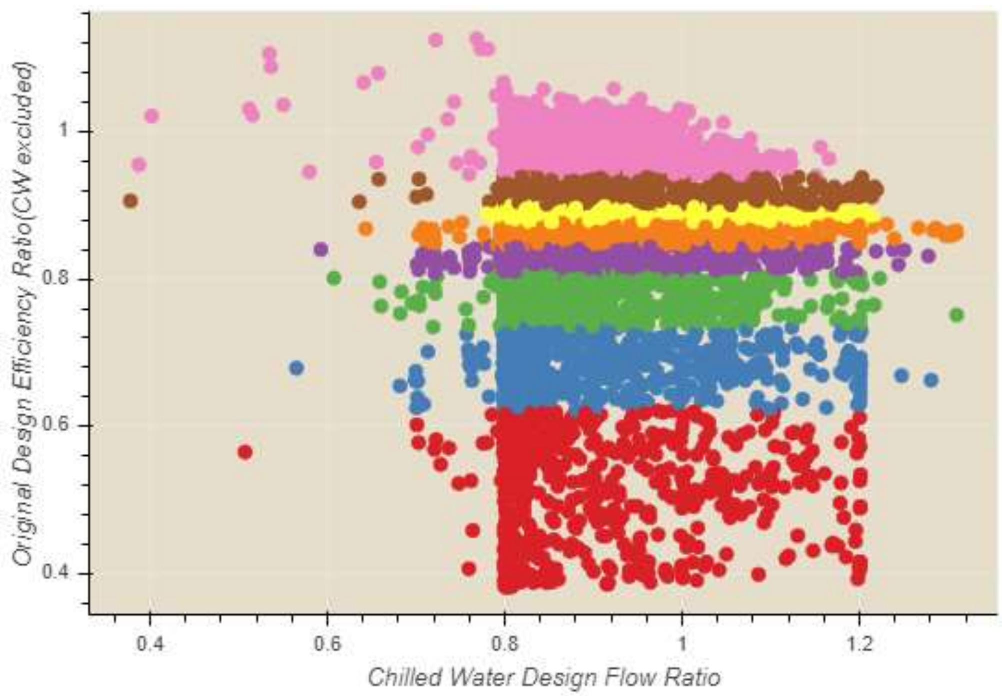

Figure III.29. Top left chart – Chiller efficiency ratio versus chilled water design flow ratio plots.

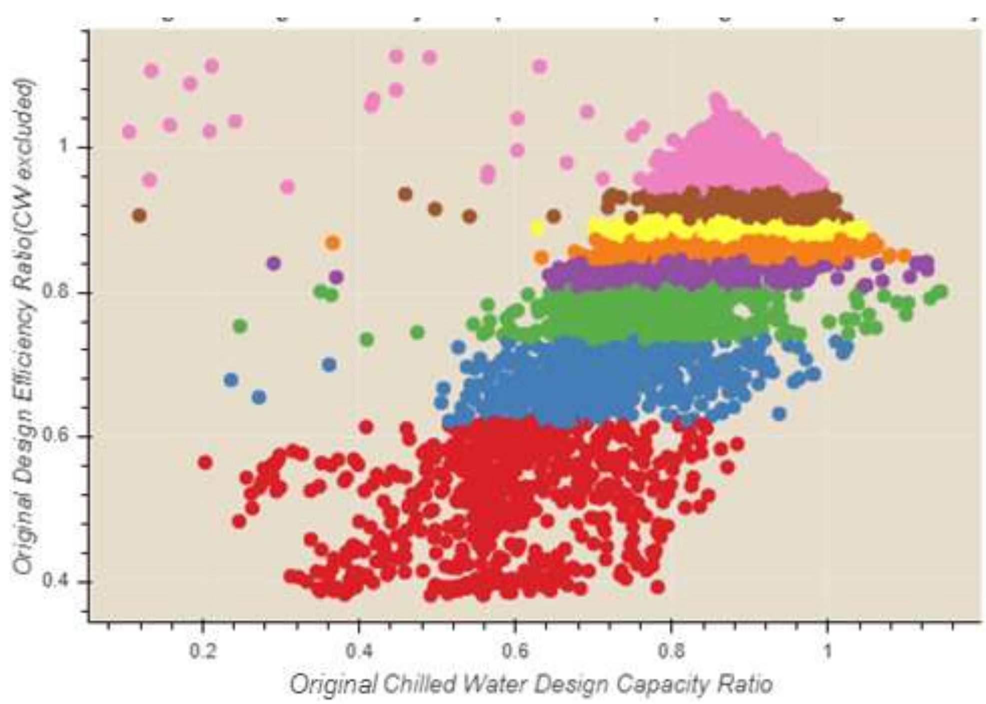

Figure III.30. Bottom left chart – Chiller efficiency ratio versus chilled water design capacity ratio plots.

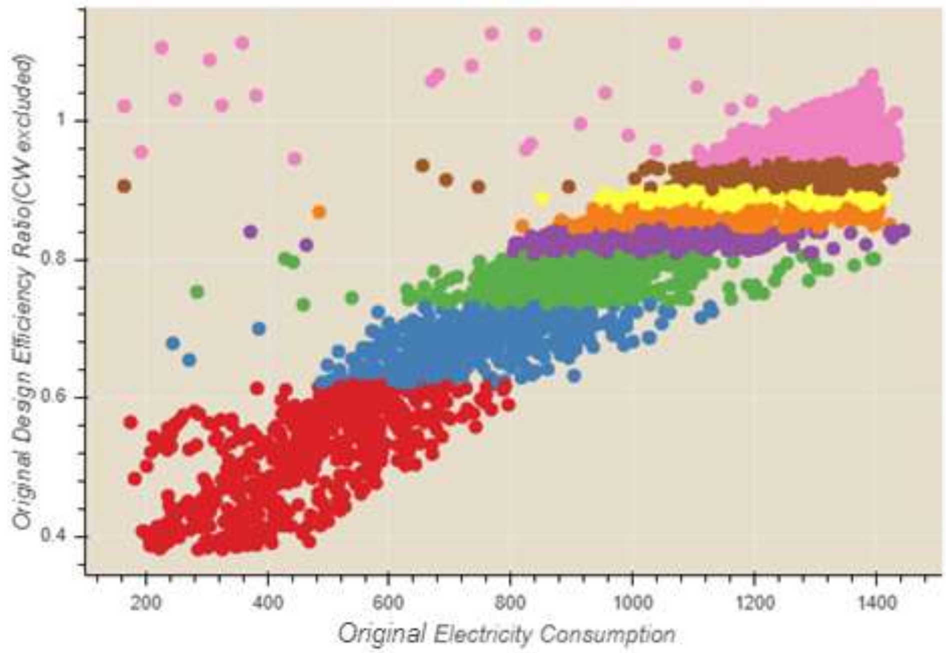

Figure III.31. Top right chart – Chiller efficiency ratio versus original electricity consumption(kWh) plots.

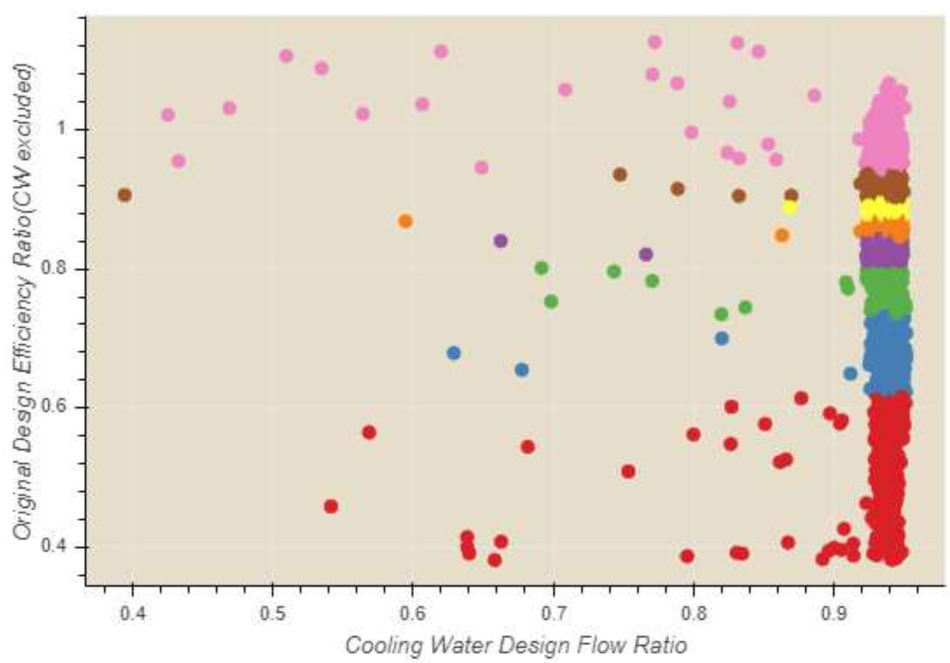

Figure III.32. Bottom left chart – Chiller efficiency ratio versus cooling water design capacity ratio plots.

III.6 CHILLER CHARACTERISTIC RULESET

In general, the relationship of values from different meters is described as a function that has input and output as below:

- **Input**:
    - Chilled water return temperature
    - Condenser water return temperature
    - Chilled water flow rate
    - Condenser water flow rate
- **Output**:
    - Chilled water supply temperature
    - Condenser water supply temperature
    - Electrical consumption

Typically, chilled water and condenser supply temperatures are the given setpoints of the chiller and cooling tower, respectively, while chiller efficiency is the ratio of chilled water production and electrical consumption. Therefore, the chiller performance might be based on the following indicators in relationship to chiller efficiency:

- Chilled water flow rate
- Chilled water temperature difference
- Chiller lift temperature
- Chiller chilled water production

To normalize the different chiller sizes (range from 1000 to 3500 tons), the chilled water flow rate and chilled water capacity are ratio values in decimal form based on design performance data. The ratios were specified in the last eight rows of Table III.17. After all plots have been established, we can start to review their plots to extract rules.

Four scatter plots show chiller performance plots for the chiller as in Figures III.34 to III.37. All the plots have the design chiller efficiency ratio[1] as vertical axes and the four mentioned indicators in the design ratio as horizontal axes. The legends indicate about the AHRI allowable tolerance validation, with green as UnValidated (unsatisfied) and blue as Validated (satisfied).

III.6.1 Case 1 – Chiller 001

The ruleset extracted from Figures III.33 to III.36 for chiller 001 is as follows:

- Figure III.33: Efficiency value is not proportional to the chiller flow rate.
- Figure III.34: Efficiency ratio is proportional when chilled water temperature difference is higher than 6°F and inversely proportional when less than 6°F.
- Figure III.35: Efficiency ratio is proportional when lift temperature difference value is higher than 30°F.
- Figure III.36: Efficiency ratio is inversely proportional when design chilled water capacity ratio is less than 0.6.

[1] Design chiller efficiency ratio is the ratio of actual chiller efficiency to design chiller efficiency. It gives an idea of how well the chiller is running compared to its own design data.

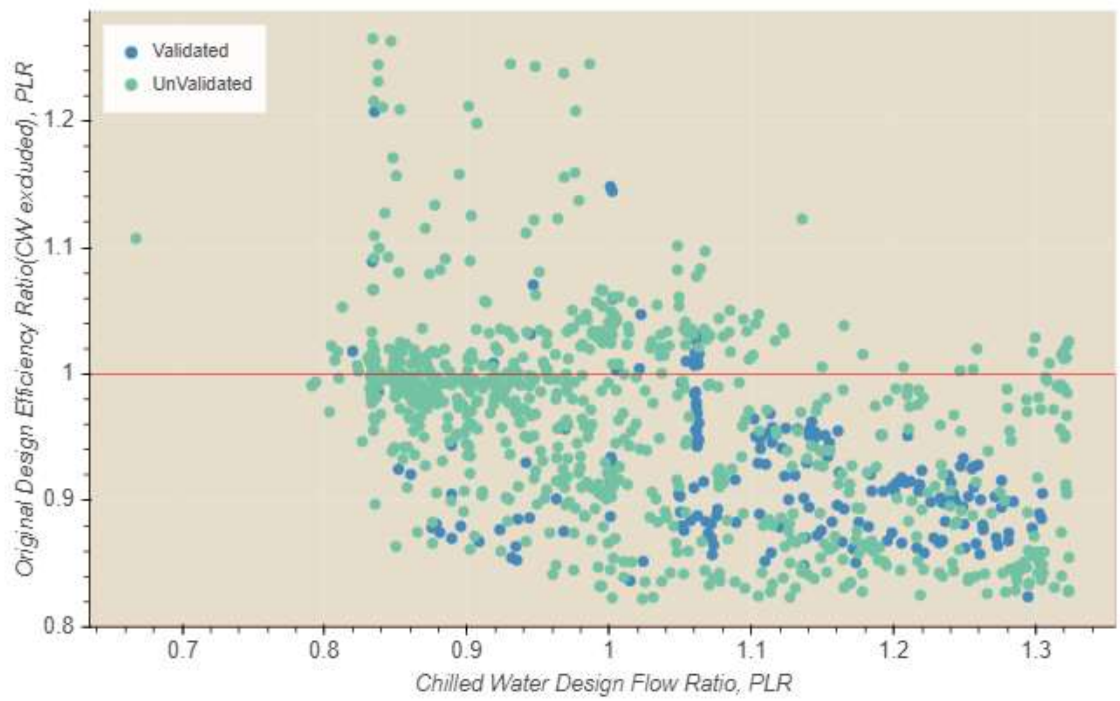

Figure III.33. Chiller efficiency versus chilled water flow ratio.

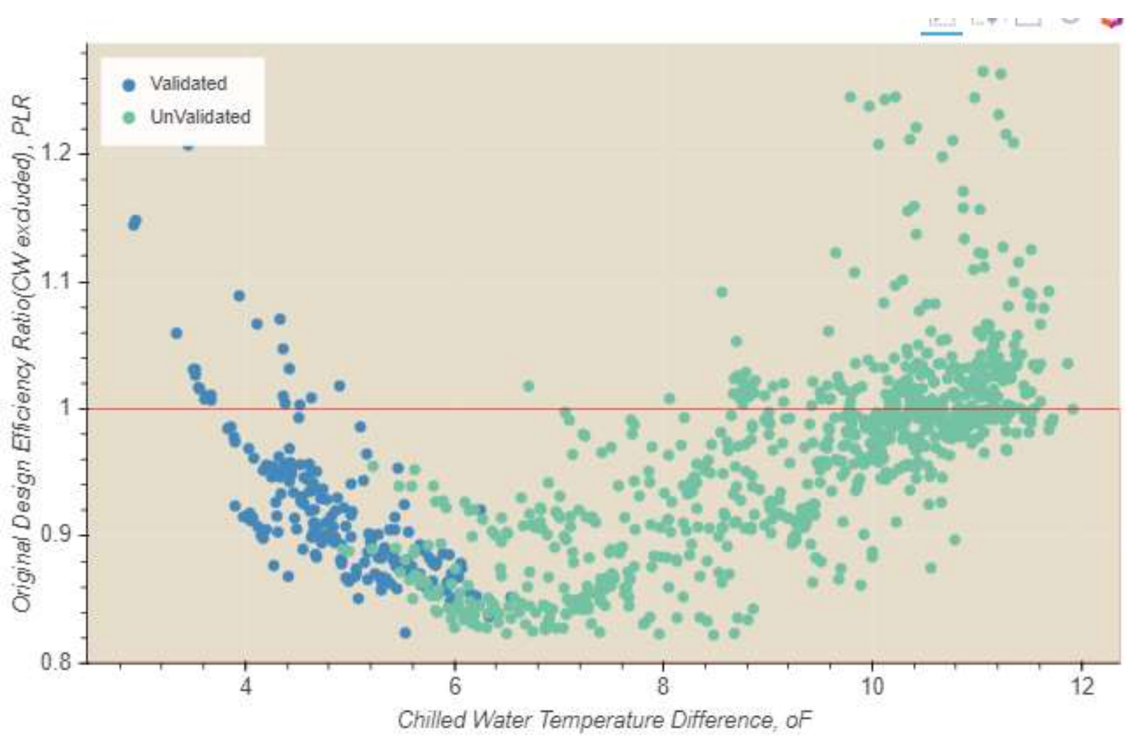

Figure III.34. Chiller efficiency ratio versus chilled water temperature difference.

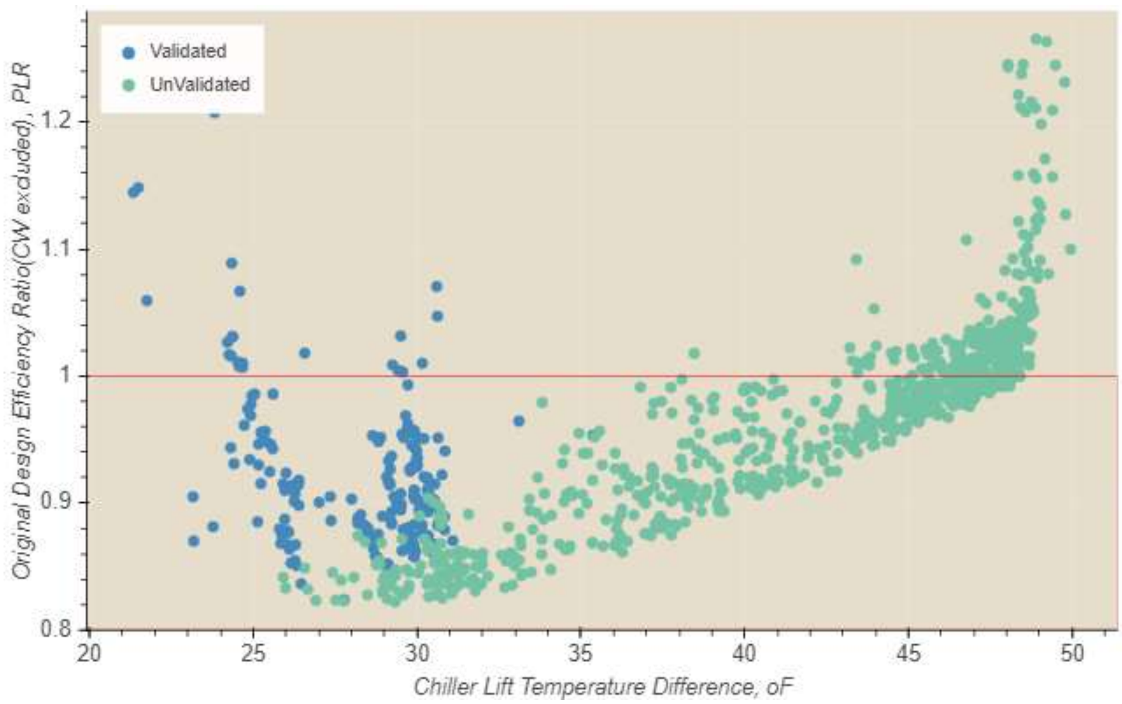

Figure III.35. Chiller efficiency versus chiller lift temperature difference.

Figure III.36. Chiller efficiency ratio versus design chilled water capacity ratio.

III.6.2 Case 2 – Chiller 202

In general, in case 2 there are some abnormalities in the four plots. which mostly relate to low design chilled water capacity ratio:

- *Figure III.37*: Efficiency ratio has a large negative slope when chilled water flow rate ratio is less than 0.82.
- *Figure III.38*: Efficiency ratio is best (lowest) when chilled water temperature difference is in the range 4–6°F.
- *Figure III.39*: Efficiency ratio is proportional (worsens) when lift temperature difference is higher than 30°F.
- *Figure III.40*: Efficiency ratio is poor when design chilled water capacity ratio is less than 0.3.

III.6.3 Case 3 – Chiller 004

The following ruleset was extracted from Figure III.41:

- While chiller 004 has very good validation and uses a variable speed drive (VSD), the data show no strong correlation between chiller efficiency ratio and other performance indicators except the efficiency ratio is proportional to the lift temperature difference, as shown in the bottom left plot.
- The chiller efficiency ratio reaches the best possible values while the chilled water difference is from 2–4°F.

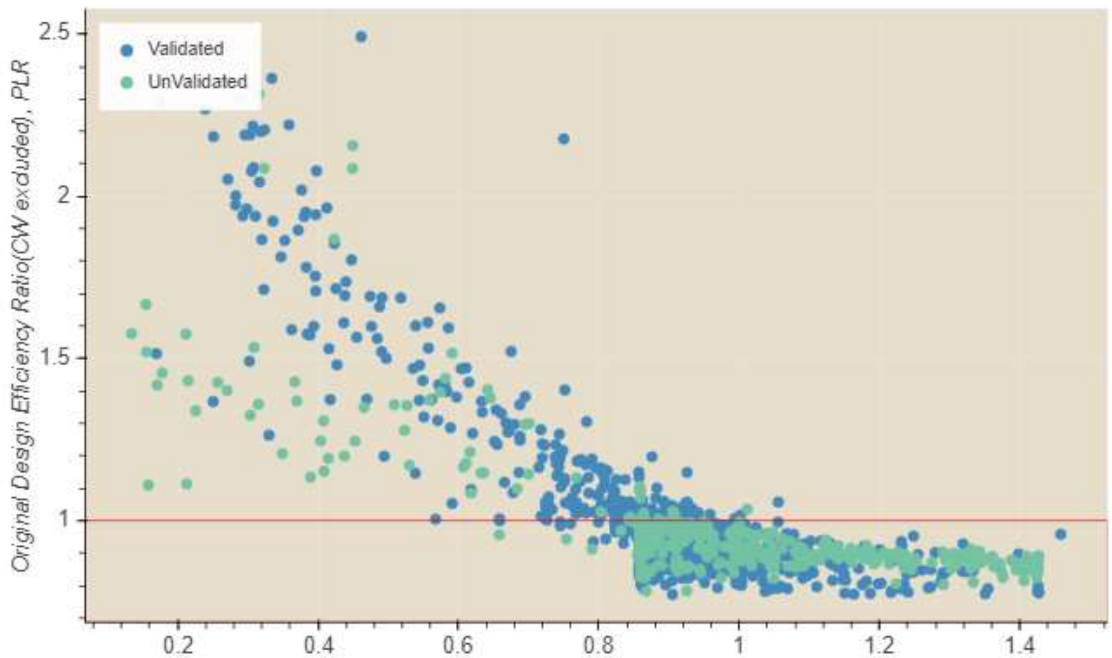

Figure III.37. Chiller efficiency ratio versus design chilled water capacity ratio.

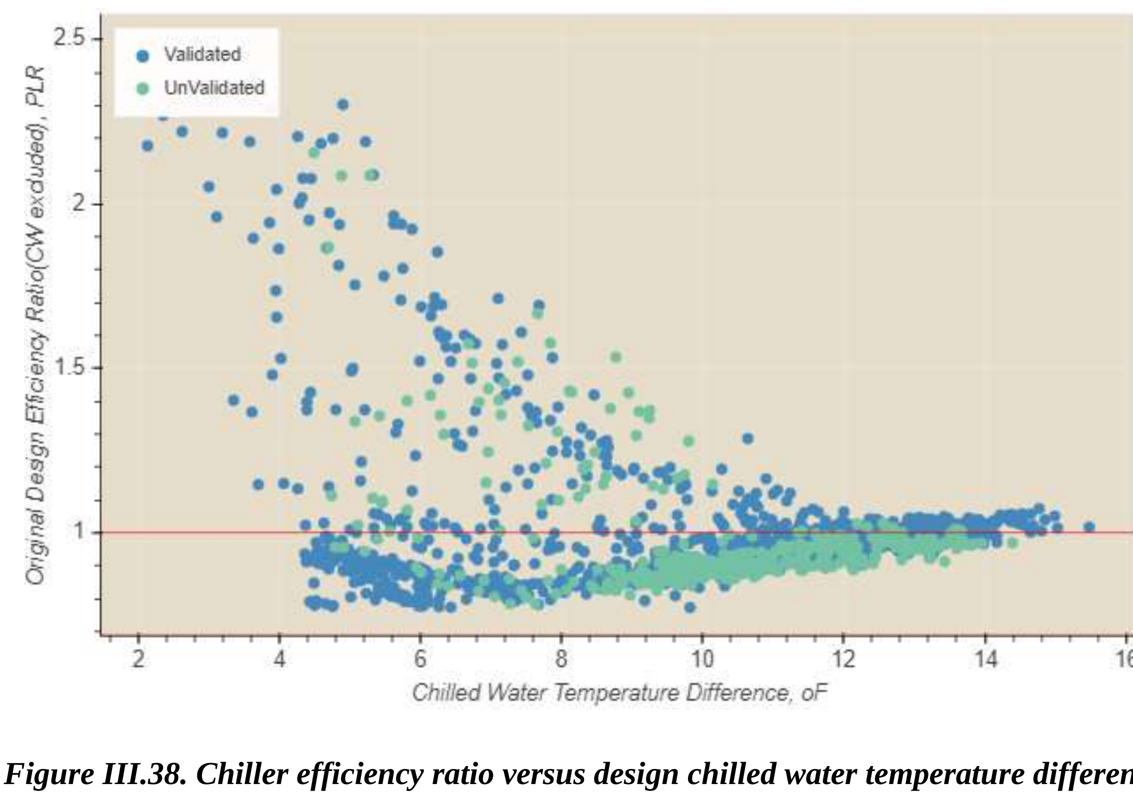

Figure III.38. Chiller efficiency ratio versus design chilled water temperature difference.

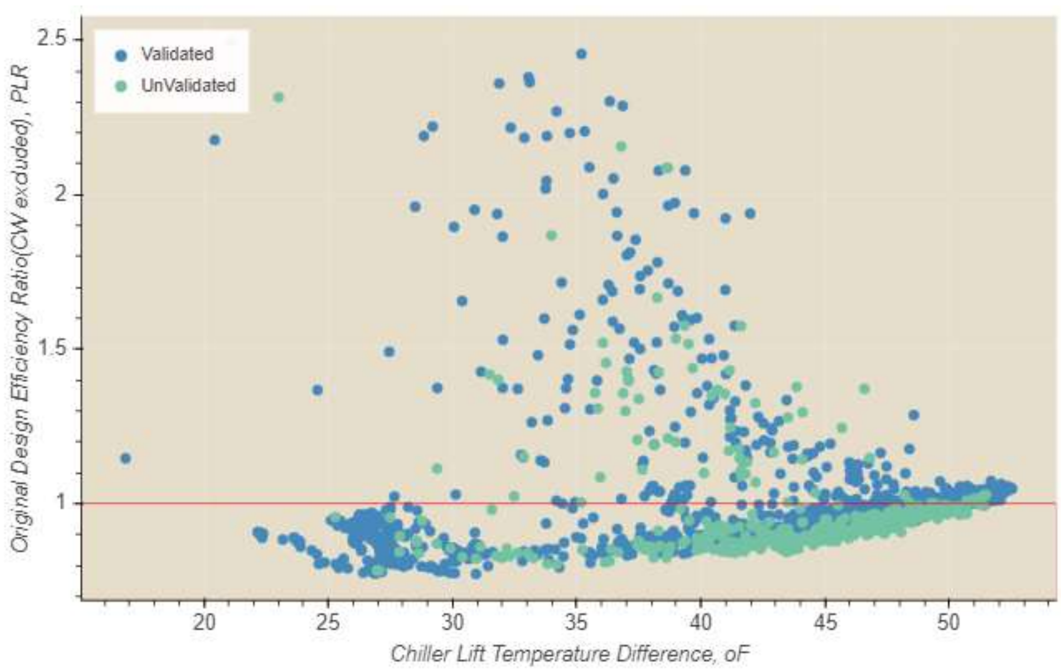

Figure III.39. Chiller efficiency ratio versus design chiller lift temperature difference.

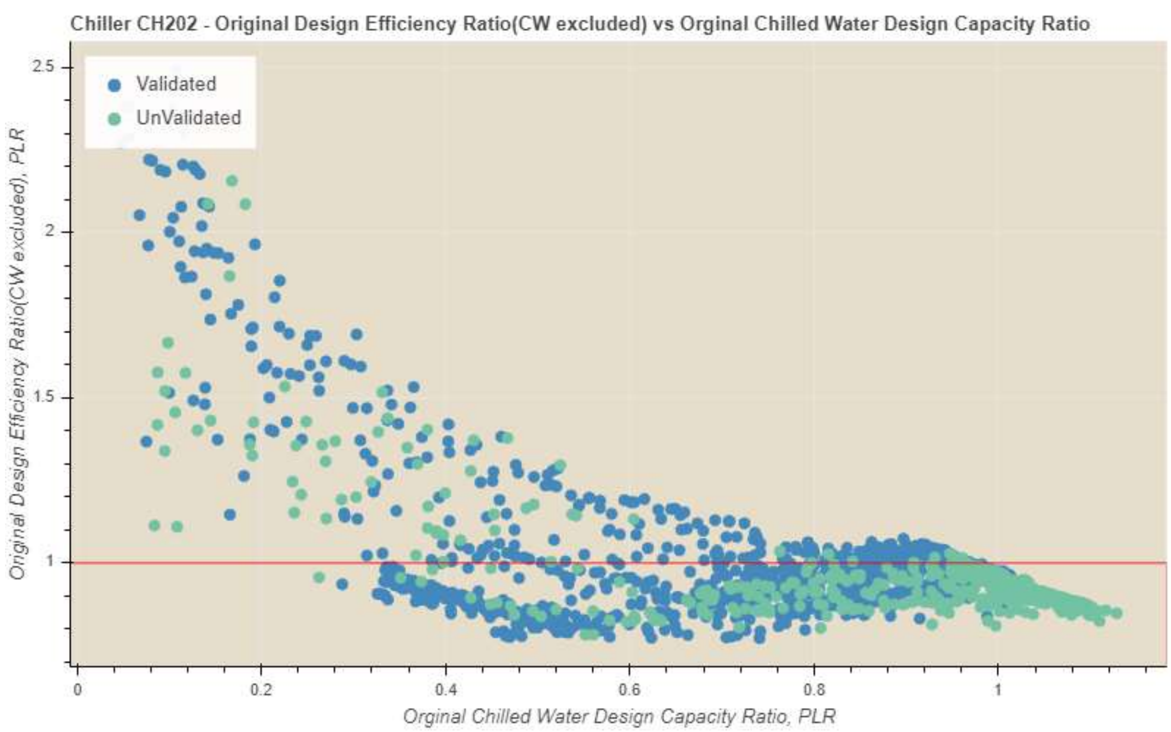

Figure III.40. Chiller efficiency ratio versus design chilled water design capacity ratio.

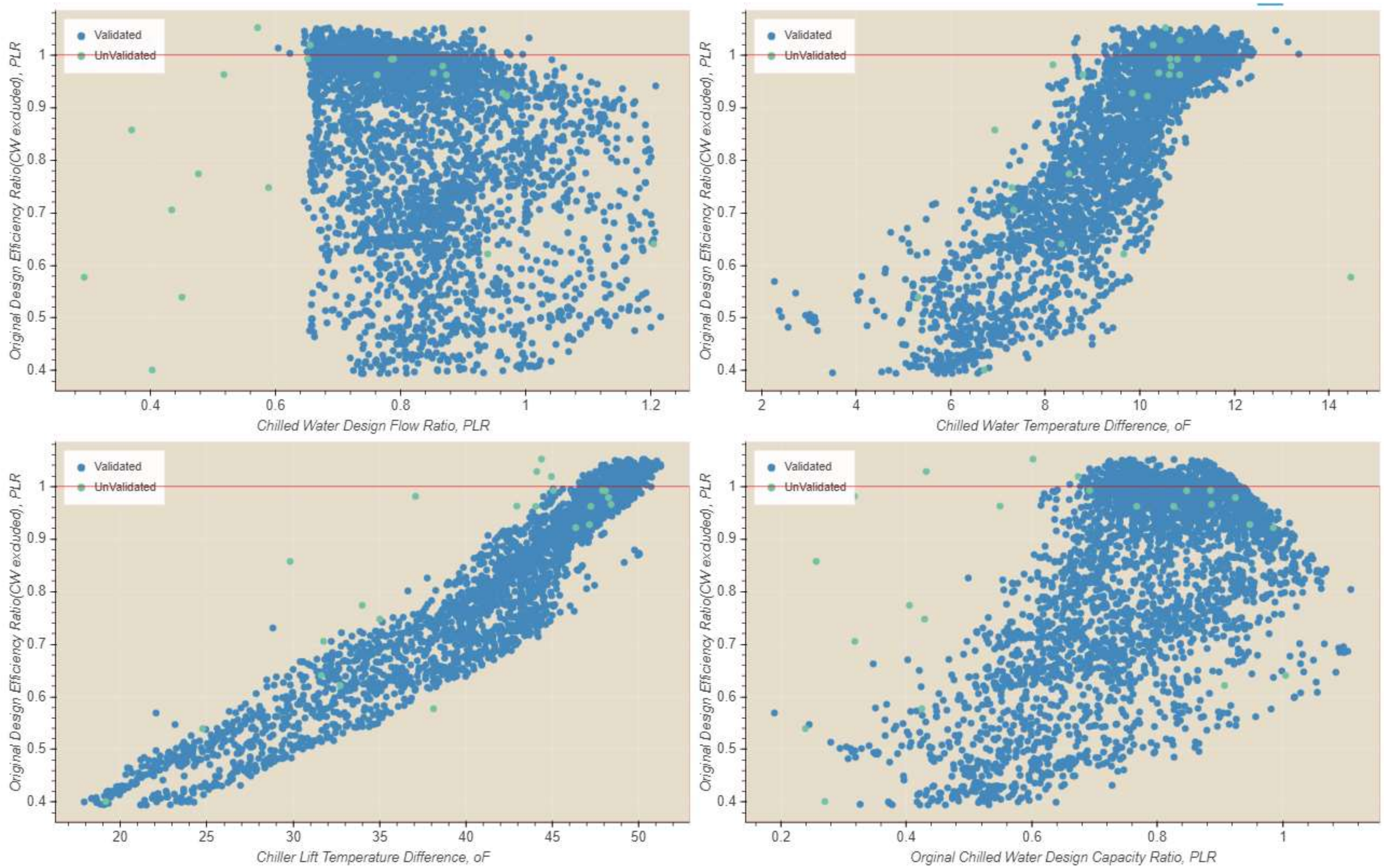

Figure III.41. Chiller 004 performance map.

III.7 CHILLER HISTOGRAMS

Using histograms of chiller efficiency ratio and capacity ratio, we can see the big difference between a "bad" and "good" chiller: While the good chiller (010) in Figure III.42 has similar histogram plot shapes for efficiency and chilled water capacity ratios, the bad chiller (204) has dramatic differences in shape.

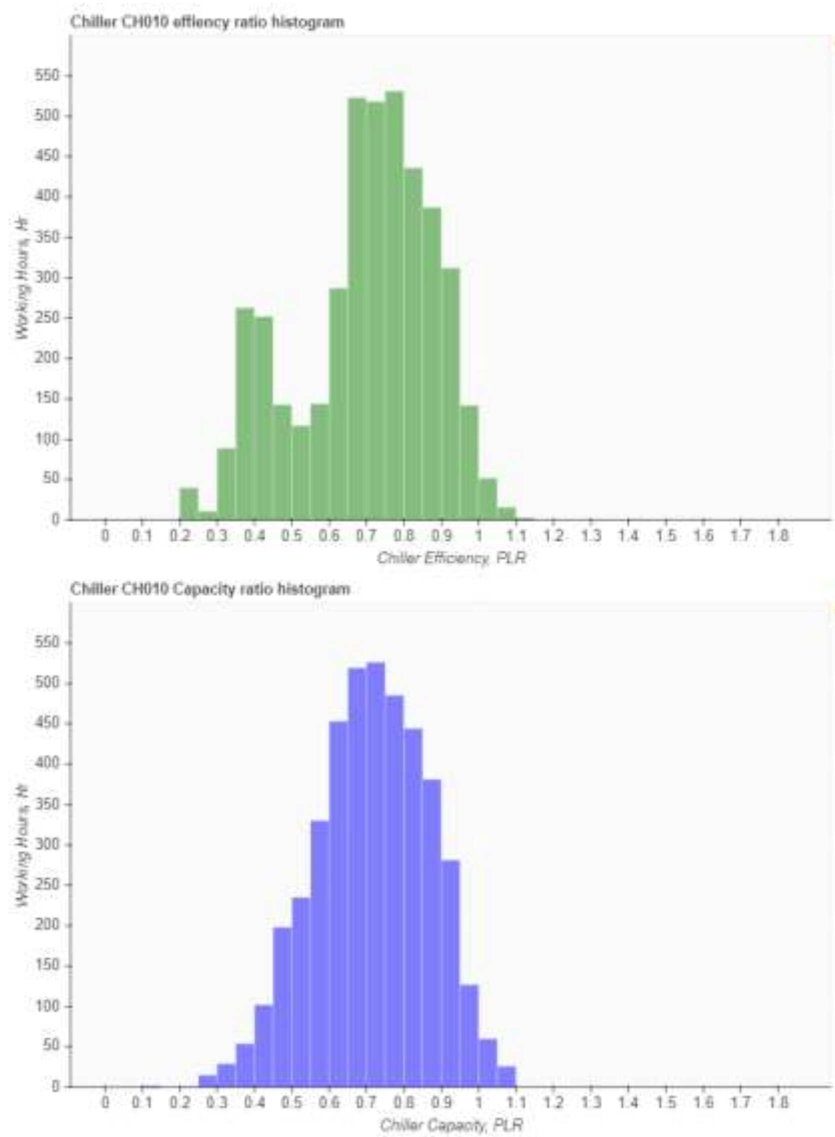

Figure III.42. Chiller 010 histogram.

There is no correlation between the efficiency and chilled water-cooling production rate ratios in Figure III.43 when chiller 204 has the highest number of operation hours near the design chilled water capacity ratio of 1.0 but the chiller efficiency ratio maxes out at 0.6. Those values for chiller 204 are unreasonable

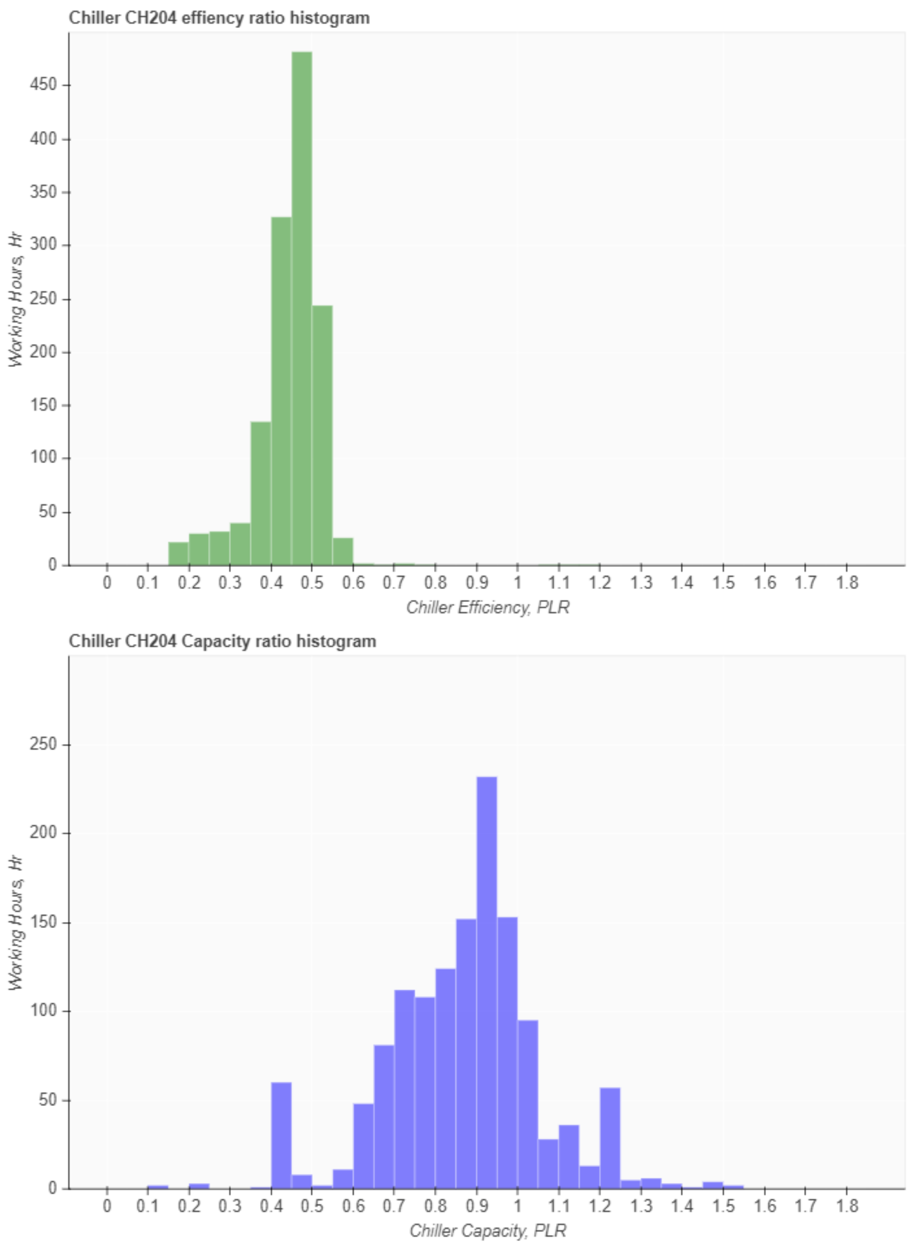

Figure III.43. Chiller 204 histogram.

III.8 DETECTION OF INCONSISTENT CHILLER OPERATION

An algorithm to detect inconsistent chiller operation has been implemented to identify gradual chiller performance changes based on the change in percentage between three continuous timesteps. It identifies any timestep for which the chiller is in operation during the previous and next timesteps, but where the chilled water flow rate, electrical consumption, and cooling water flow rate fluctuate widely during the previous and/or next timesteps.

The sharp change timestep is determined based on following sources:

- *Data observation*: Three meter readings are observed for each chiller to evaluate the hour-to-hour slopes in percentage:

$$\%Change = \frac{V_{current} - V_{previous}}{100}$$

  In most cases, these three key meter readings have a *%Change* value less than 50%, as shown in Figure III.44 for chiller 301. While these three meters readings are input, *%Change* values for the three meters of more than 50% at the same time may indicate a chiller short cycle condition. This can be verified by finding if *the hours with the sum of percentage change of all three monitored meters in the current timestep larger than 150% (3 × 50%) in absolute value when comparing with previous timestep.*

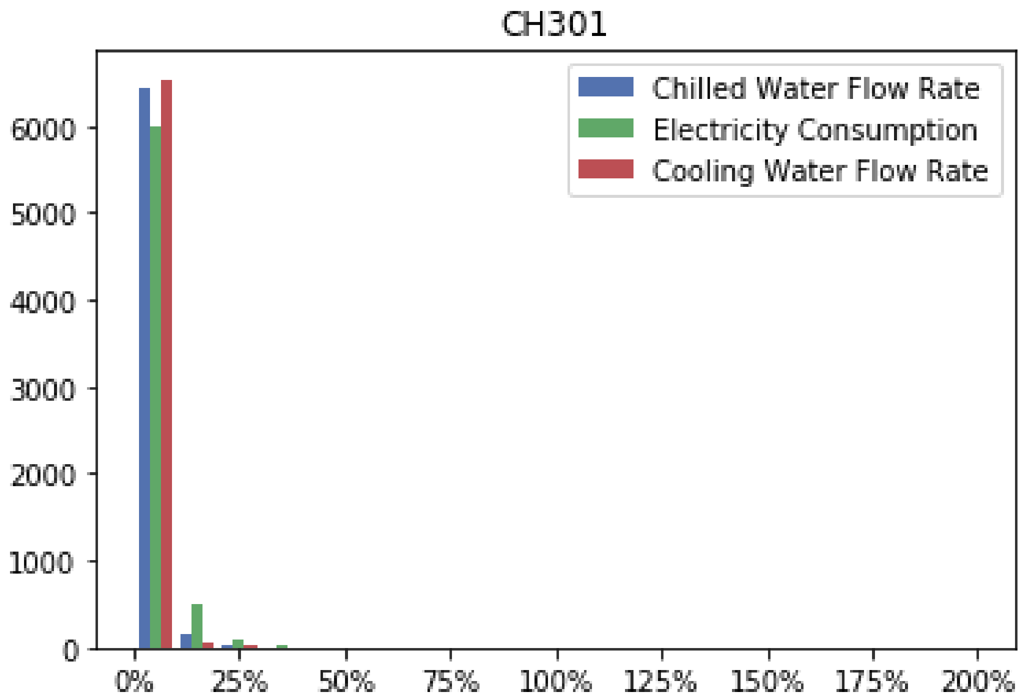

Figure III.44. Chiller 301 histogram of percentage change.

- *Inconsistent pattern*: Inconsistent chiller operation will show a V-shaped sketch on a timeseries plot of flow rate and electrical meters, as a short-cycled chiller is usually restarted immediately to meet the load demand since it is not a planned shutdown.

To catch a V-shaped pattern, the second condition is established if the absolute value of percentage change of meter readings from the current to the next timestep is higher than 150% when the flow rates and electricity consumption values at short-cycled timestep are close to off range. From this assumption, we get the second condition: *sum of percentage changes of all three monitored meters in the next timestep are more than 450%*.

- *Chiller plant control*: The typical chilled water and cooling water flow rates should be adjusted by less than 30% of design flow during any hour because of the following:
  - The interaction of primary and secondary chilled water loops would be negatively affected when flow rate is quickly adjusted.
  - Due to the thermal mass of the chilled water in the loops and chilled water storage tanks, time response of chilled water demand would limit the gradual increase or decrease of chilled water demand and limit changes in the chilled and cooling water flow rates and electricity consumption except during the start-up and shut-off moments (hours).
  - Chillers, especially old ones, might not respond to rapid change in demand.

  An additional condition is set by reviewing if the sum of percentage changes of monitored meter value is increased more than six times ($200 \times 3 = 600\%$) after 2 hours (timesteps) from a possible fault timestep.

  When all three conditions are triggered, the alarm should be established.

Figure III.45 shows an inconsistent data point of chiller 001 at 2017-07-09 16:00 when the chiller was suddenly stopped and then started. This point was identified by the algorithm described above.

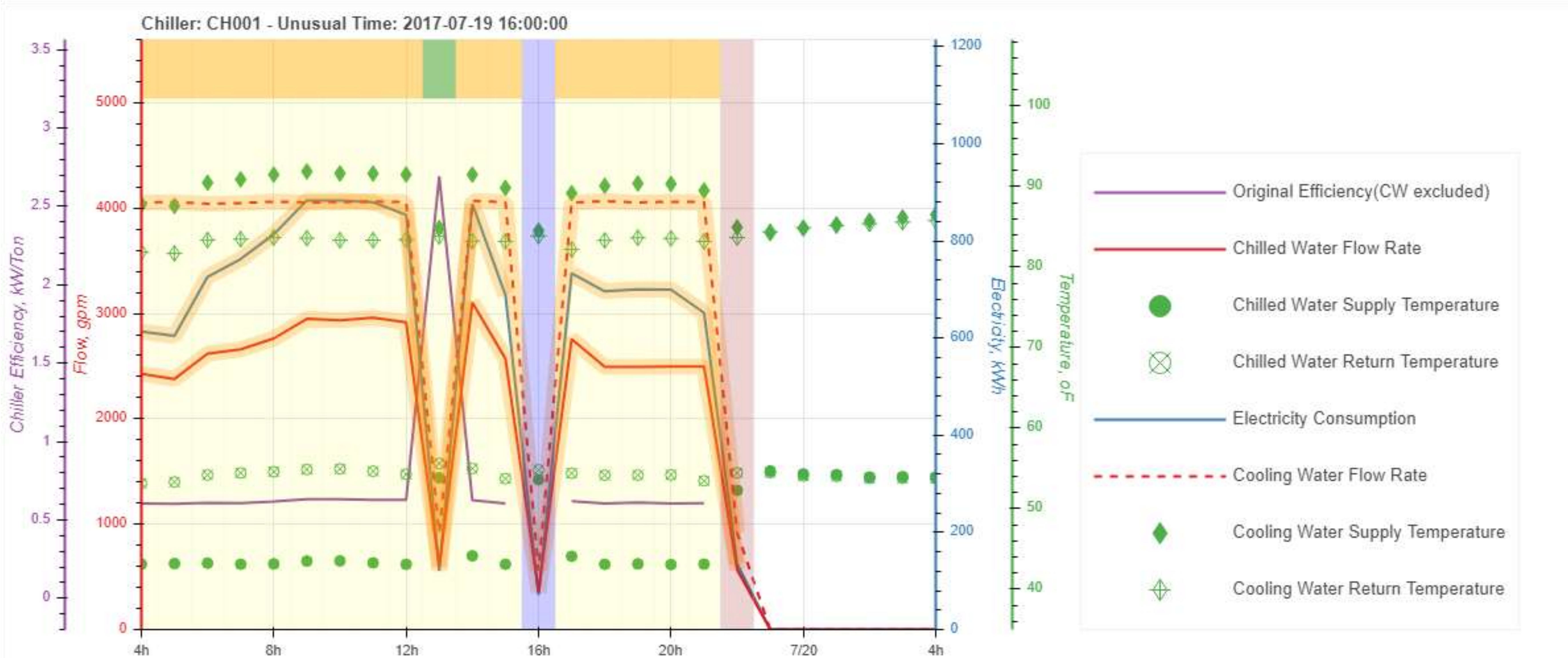

Figure III.45. Chiller 001 inconsistent detection.

IV. SUMMARY

Based on the results of the algorithms described above, the following assertions and rulesets have been established.

IV.1 GENERAL RESULTS

All chiller data sets have been filtered into on and off operation data collections. The fault detection and boundary limit reviews have been applied to find possible faulty records and optimize the boundary values.

The on (in operation) chiller data have been validated using AHRI Standard 550/590 energy balance and capacity tolerance limits. The annual performance report output indicated that the highest and lowest chiller power per capacity ratios are unreasonable values, and this data was identified as bad data using the validation algorithms. Hence, the validation results may be applied as indicators for chiller meter data fault detection and diagnostics.

Analysis of the operating data set has determined the following regarding the chiller operational characteristics.

IV.2 DETAILED RESULTS

IV.2.1 Validation Report

Chillers with validated good data output

- CUP: 002, 004, 005, 006, 010
- SUP1: 102, 103
- SUP2: 202
- SUP3: 301, 302

Chillers with mixed data validation output

- CUP: 001 – Bad in hot weather period; 007 – Bad in cold weather period
- SUP1: 101 – Bad in hot weather period
- SUP2: 201, 203 – Bad in hot weather period
- SUP3: 303 – Bad in cold weather period; 304 – Bad in hot weather period

It is recommended that the power meters of the chillers above be checked when the chiller validation result is bad, since the chiller electrical consumption range between hot and cold periods is well divided with different chiller lift.

Chillers with bad data output

- CUP: 003
- SUP2: 204, 205, 206

It is recommended that those chiller meters be calibrated to achieve more reliable results.

IV.2.2 Chiller Ruleset

- Most chillers have power per cooling production ratios (kW/ton) proportional to the chiller lift.
- Chillers 001 and 002 have power per cooling production ratios that gradually increased when the chiller lift is higher than 45°F.
- Chillers 001, 101, and 102 have power per cooling production ratios that increased when chiller lift was less than 30°F or the chiller water temperature difference was less than 6°F or the chilled water production ratio was less than 60% of the design production.
- Chillers 004 and 010 have power per cooling production ratios that increased with chilled water difference and chilled water production rate.
- Chiller 202 has a power per cooling production ratio that increased when the chilled water design flow rate ratio was less than 0.8.
- Chiller 203 should keep chiller lift more than 40°F and chilled water temperature difference higher than 6°F and chilled water design flow rate ratio higher than 0.4.
- Chiller 303 has power per cooling production ratio values proportional to the chilled water temperature difference. Its power per cooling production ratio range is also very narrow (0.95–1.1).

- Chiller 304 has a power per cooling production ratio inversely proportional to chiller lift, chilled water temperature difference, and chilled water production capacity.

IV.3 FUTURE WORK

Recommendations for future research are as follows:

- Develop a new algorithm for timeseries pattern recognition based on hourly profiles of chiller meters to identify issues in real time or on a daily or weekly basis.
- Establish an ordered list from the chiller power per cooling production ratio based on a combination of independent variables (chilled water flow rate, chiller lift, chilled water return temperature) to support the operation team in staging chillers on and off.
- Investigate possible meter faults for the invalid data to identify exactly which meters need repair or recalibration.

REFERENCES

Afroz, Zakia, G. M. GM Shafiullah, Tania Urmee, and Gary Higgins. 2017. "Modeling Techniques Used in Building HVAC Control Systems: A Review." *Renewable and Sustainable Energy Reviews* 83 (December 2017): 64–84. https://doi.org/10.1016/j.rser.2017.10.044.

Ahn, Ki-Uhn, and Cheol-Soo Park. 2016. "Correlation between Occupants and Energy Consumption." *Energy and Buildings* 116 (March): 420–33. https://doi.org/10.1016/J.ENBUILD.2016.01.010.

Air Conditioning Heating and Refrigeration Institute. 2015. "AHRI 550/590 Standard" 590.

ASHRAE. n.d. "Chap 40. Supervisory Control Strategies and Optimization." In *ASHRAE Handbook*.

Baillie, Brian P., and George M. Bollas. 2017. "Development, Validation, and Assessment of a High Fidelity Chilled Water Plant Model." *Applied Thermal Engineering* 111: 477–88. https://doi.org/10.1016/j.applthermaleng.2016.09.125.

Bogen, A. Christopher, Mahbubur Rashid, E. William East, and James Ross. 2013. "Evaluating a Data Clustering Approach for Life-Cycle Facility Control." *Journal of Information Technology in Construction* 18: 99–118.

Braun, J.E., and M.C Comstock. 1999. "Development of Analysis Tools for the Evaluation of Fault Detection and Diagnostics in Chillers, ASHRAE Research Project 1043-RP."

Browne, M.W., and P.K. Bansal. 1998. "Steady-State Model of Centrifugal Liquid Chillers: Modèle Pour Des Refroidisseurs de Liquide Centrifuges En Régime Permanent." *International Journal of Refrigeration* 21 (5): 343–58. https://doi.org/10.1016/S0140-7007(98)00003-6.

———. 2002. "Transient Simulation of Vapour-Compression Packaged Liquid Chillers." *International Journal of Refrigeration* 25 (5): 597–610. https://doi.org/10.1016/S0140-7007(01)00060-3.

Cam, Mathieu Le, Radu Zmeureanu, and Ahmed Daoud. 2014. "Application of Data Mining Techniques for Energy Modeling of HVAC Sub-Systems." *ESim IBPSA-Canada*.

Chandola, Varun, Arindam Banerjee, and Vipin Kumar. 2009. "Anomaly Detection." *ACM Computing Surveys* 41 (3): 1–58. https://doi.org/10.1145/1541880.1541882.

Chang, Yung-Chung, Chao-Yuan Chen, Jyun-Ting Lu, Jin-Kwei Lee, Tian-Shuen Jan, and Ching-Liang Chen. 2013. “Verification of Chiller Performance Promotion and Energy Saving.” *Engineering* 05 (01): 141–45. https://doi.org/10.4236/eng.2013.51A020.

Chang, Yung-Chung Chung. 2007. “Sequencing of Chillers by Estimating Chiller Power Consumption Using Artificial Neural Networks.” *Building and Environment* 42 (1): 180–88. https://doi.org/10.1016/j.buildenv.2005.08.033.

Chang, Yung Chung, Fu Ann Lin, and Chin Huang Lin. 2005. “Optimal Chiller Sequencing by Branch and Bound Method for Saving Energy.” *Energy Conversion and Management* 46 (13–14): 2158–72. https://doi.org/10.1016/j.enconman.2004.10.012.

Chang, Yung Chung Y.-C. 2006. “An Outstanding Method for Saving Energy - Optimal Chiller Operation.” *IEEE Transactions on Energy Conversion* 21 (2): 527–32. https://doi.org/10.1109/TEC.2006.871358.

Domahidi, Alexander, Fabian Ullmann, Manfred Morari, and Colin N. Jones. 2014. “Learning Decision Rules for Energy Efficient Building Control.” *Journal of Process Control* 24 (6): 763–72. https://doi.org/10.1016/j.jprocont.2014.01.006.

Dounis, Anastasios I. 2010. “Artificial Intelligence for Energy Conservation in Buildings.” *Advances in Building Energy Research* 4 (1): 267–99. https://doi.org/10.3763/aber.2009.0408.

Du, Zhimin, and Xinqiao Jin. 2007. “Detection and Diagnosis for Sensor Fault in HVAC Systems.” *Energy Conversion and Management* 48 (3): 693–702. https://doi.org/10.1016/j.enconman.2006.09.023.

Duarte, C, and Brad Acker. 2011. “Prioritizing and Visualizing Energy Management and Control System Data to Provide Actionable Information for Building Operators.” *Western Energy Policy Research Conference*. http://mhrg.if.uidaho.edu/papers/2011/WEPC11_DuarteAckerKevin_EMSDataVisualisation.pdf.

Fan, Cheng, Fu Xiao, Henrik Madsen, and Dan Wang. 2015. “Temporal Knowledge Discovery in Big BAS Data for Building Energy Management.” *Energy and Buildings* 109 (December): 75–89. https://doi.org/10.1016/j.enbuild.2015.09.060.

Heidarinejad, Mohammad, Matthew Dahlhausen, Sean McMahon, Chris Pyke, and Jelena Srebric. 2014. “Cluster Analysis of Simulated Energy Use for LEED Certified U.S. Office Buildings.” *Energy and Buildings* 85: 86–97. https://doi.org/10.1016/j.enbuild.2014.09.017.

Huang, Gongsheng, Shengwei Wang, Fu Xiao, and Yongjun Sun. 2009. “A Data Fusion Scheme for Building Automation Systems of Building Central Chilling Plants.” *Automation in Construction* 18 (3): 302–9. https://doi.org/10.1016/j.autcon.2008.09.003.

Hydeman, M, P Sreedharan, N Webb, and S Blanc. n.d. “Development and Testing of a Reformulated Regression-Based Electric Chiller Model.” *ASHRAE Trans* 108 (2): 1118–1127.

Hydeman, Mark, Steven T. Taylor, and Carl D. Speck. 1999. “Commissiong Tools and Techniques Used in a Large Chiller Plant Optimization Project.”

Iglesias, Félix, and Wolfgang Kastner. 2013. “Analysis of Similarity Measures in Times Series Clustering for the Discovery of Building Energy Patterns.” *Energies* 6 (2): 579–97. https://doi.org/10.3390/en6020579.

Janetzko, Halldór, Florian Stoffel, Sebastian Mittelstädt, and Daniel A Keim. 2013. “Computers & Graphics Anomaly Detection for Visual Analytics of Power Consumption Data.” *Computers and Graphics* 38: 1–11. https://doi.org/10.1016/j.cag.2013.10.006.

Krarti, Moncef. 2003. “An Overview of Artificial Intelligence-Based Methods for Building Energy Systems.” *Journal of Solar Energy Engineering* 125 (3): 331. https://doi.org/10.1115/1.1592186.

Lawrence Berkeley National Laboratory. 1980. *DOE2 Reference Manual, Part 1, Version 2.1*. Department of Energy (DoE).

Lavin, Alexander, and Diego Klabjan. 2015. “Clustering Time-Series Energy Data from Smart Meters.” *Energy Efficiency* 8 (4): 681–89. https://doi.org/10.1007/s12053-014-9316-0.

Lee, T S. 2004. “Thermodynamic Modeling and Experimental Validation of Screw Liquid Chillers.” *ASHRAE Trans* 110 (1): 206–216.

Li, Manfeng, and Yonglin Ju. 2017. “The Analysis of the Operating Performance of a Chiller System Based on Hierarchal Cluster Method.” *Energy and Buildings* 138: 695–703. https://doi.org/https://doi.org/10.1016/j.enbuild.2016.12.076.

Marini, Kyle, Girish Ghatikar, Rick Diamond, Steve Greenberg, Steven Lanzisera, Dale Sartor, Lonny Simonian, and Dave Watson. 2011. “Using Dashboard to Improve Energy and Comfort in Federal Buildings,” no. February: 22. https://doi.org/10.2172/1007230.

May-Ostendorp, Peter T., Gregor P. Henze, Balaji Rajagopalan, and Charles D. Corbin. 2013. “Extraction of Supervisory Building Control Rules from Model Predictive Control of Windows in a Mixed Mode Building.” *Journal of Building Performance Simulation* 6 (3): 199–219. https://doi.org/10.1080/19401493.2012.665481.

Mclntosh, I.B.D., J.W. Mitchell, and W.A. Beckman. 2000. “Fault Detection and Diagnosis in Chillers—Part I: Model Development and Application.” In *ASHRAE Transaction*, edited by ASHRAE, 106:268–82. Atlanta: ASHRAE.

Miller, Clayton, Zoltán Nagy, and Arno Schlueter. 2015. "Automated Daily Pattern Filtering of Measured Building Performance Data." *Automation in Construction* 49 (PA): 1–17. https://doi.org/10.1016/j.autcon.2014.09.004.

Munir, Mohsin, Steffen Erkel, Andreas Dengel, and Sheraz Ahmed. 2017. "Pattern-Based Contextual Anomaly Detection in HVAC Systems." *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*, 1066–73. https://doi.org/10.1109/ICDMW.2017.150.

Ng, K C, H T Chua, W. Ong, S S Lee, and J M Gordon. 1997. "Diagnostics and Optimization of Reciprocating Chillers: Theory and Experiment." *Applied Thermal Engineering* 17 (3): 263–76. https://doi.org/10.1016/s1359-4311(96)00031-2.

Patnaik, Debprakash, Manish Marwah, Ratnesh K. Sharma, and Naren Ramakrishnan. 2010. "Data Mining for Modeling Chiller Systems in Data Centers." In *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 6065 LNCS:125–36. https://doi.org/10.1007/978-3-642-13062-5_13.

Reddy, T. Agami. 2011. *Applied Data Analysis and Modeling for Energy Engineers and Scientists*. https://doi.org/10.1007/978-1-4419-9613-8.

Reddy, T. Agami, and Klaus K Andersen. 2002. "An Evaluation of Classical Steady-State off-Line Linear Parameter Estimation Methods Applied to Chiller Performance Data." *HVAC Res* 8 (1): 101–124. https://doi.org/10.1080/10789669.2002.10391291.

Shan, Kui, Shengwei Wang, Dian-ce Gao, and Fu Xiao. 2016. "Development and Validation of an Effective and Robust Chiller Sequence Control Strategy Using Data-Driven Models." *Automation in Construction* 65: 78–85. https://doi.org/https://doi.org/10.1016/j.autcon.2016.01.005.

Sun, Yongjun, Shengwei Wang, and Gongsheng Huang. 2009. "Chiller Sequencing Control with Enhanced Robustness for Energy Efficient Operation." *Energy and Buildings* 41 (11): 1246–55. https://doi.org/10.1016/j.enbuild.2009.07.023.

———. 2010. "Online Sensor Fault Diagnosis for Robust Chiller Sequencing Control." *International Journal of Thermal Sciences* 49 (3): 589–602. https://doi.org/10.1016/j.ijthermalsci.2009.10.003.

Swider, D.J., M.W. Browne, P.K. Bansal, and V. Kecman. 2001. "Modelling of Vapour-Compression Liquid Chillers with Neural Networks." *Applied Thermal Engineering* 21 (3): 311–29. https://doi.org/10.1016/S1359-4311(00)00036-3.

Wang, Handong. 2017. "Empirical Model for Evaluating Power Consumption of Centrifugal Chillers." *Energy and Buildings* 140 (April): 359–70. https://doi.org/10.1016/j.enbuild.2017.02.019.

Wang, Shengwei. 1998. “Dynamic Simulation of a Building Central Chilling System and Evaluation of EMCS On-Line Control Strategies.” *Building and Environment* 33 (1): 1–20. https://doi.org/10.1016/S0360-1323(97)00019-X.

Wang, Shengwei, and Jingtan Cui. 2005. “Sensor-Fault Detection, Diagnosis and Estimation for Centrifugal Chiller Systems Using Principal-Component Analysis Method.” *Applied Energy* 82 (3): 197–213. https://doi.org/10.1016/j.apenergy.2004.11.002.

———. 2006. “A Robust Fault Detection and Diagnosis Strategy for Centrifugal Chillers.” *HVAC and R Research* 12 (3): 407–28. https://doi.org/10.1080/10789669.2006.10391187.

Wang, Shengwei, and Jin Bo Wang. 2002. “Robust Sensor Fault Diagnosis and Validation in HVAC Systems.” *Transactions of the Institute of Measurement and Control* 24 (3): 231–62. https://doi.org/10.1191/0142331202tm030oa.

Wang, Shengwei, and Fu Xiao. 2004. “AHU Sensor Fault Diagnosis Using Principal Component Analysis Method.” *Energy and Buildings* 36 (2): 147–60. https://doi.org/10.1016/j.enbuild.2003.10.002.

Wei, Xiupeng, Guanglin Xu, and Andrew Kusiak. 2014. “Modeling and Optimization of a Chiller Plant.” *Energy* 73: 898–907. https://doi.org/https://doi.org/10.1016/j.energy.2014.06.102.

Yik, Francis W H, and Vincent K C Lam. 1998. “Chiller Models for Plant Design Studies.” *Building Services Engineering Research and Technology* 19 (4): 233–41. https://doi.org/10.1177/014362449801900407.

Yu, Zhun, Benjamin C.M. Fung, and Fariborz Haghighat. 2013. “Extracting Knowledge from Building-Related Data - A Data Mining Framework.” *Building Simulation* 6 (2): 207–22. https://doi.org/10.1007/s12273-013-0117-8.

Zhao, Ling-Xiao Xiao, Liang-Liang Liang Shao, and Chun-Lu Lu Zhang. 2010. “Steady-State Hybrid Modeling of Economized Screw Water Chillers Using Polynomial Neural Network Compressor Model.” *International Journal of Refrigeration* 33 (4): 729–38. https://doi.org/10.1016/j.ijrefrig.2009.12.028.

Zhao, Yang, Fu Xiao, and Shengwei Wang. 2013. “An Intelligent Chiller Fault Detection and Diagnosis Methodology Using Bayesian Belief Network.” *Energy and Buildings* 57: 278–88. https://doi.org/10.1016/j.enbuild.2012.11.007.

Zmeureanu, Radu, and Hadrien Vandenbroucke. 2015. “Use of Trend Data from {BEMS} for the Ongoing Commissioning of {HVAC} Systems.” *Energy Procedia* 78: 2415–20. https://doi.org/https://doi.org/10.1016/j.egypro.2015.11.207.