Faults Handling in Chilled Water System Maintenance Program

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Abstract

Chilled water system can be considered as one of the critical systems in commercial buildings. One of its major components is addressed here, which is chiller system. The related faults of the said system normally make negative impact on its performance and accordingly reducing its life cycle. Addressing these faults by finding them while operating the buildings is recommended to make an efficient maintenance program. So, in this research, a quality engineering mechanism to address or to find these faults is proposed. Two tailed t-test is used as part of the proposed methodology. A case study of a building that contains five chillers is presented. During a particular period of time, the performance of one of those chillers has been found substantial for inspection. The proposed method has shown a significant outcome for the users at the said building from engineering management point of view.

Keywords
Chilled Water System, Chillers, Maintenance, Commercial Buildings, Engineering Management

1. Introduction

Business work is filling most people's time, employees, or workforces, who are working at commercial buildings (CBs)/ large facilities and spending most of their duty time inside these buildings, so, CB make up a formidable portion of the built environment for the people. The common-sense drives that the organizations/ owners must take care about these buildings; in order to avoid any negative impact on surrounding or on internal environment of these buildings.

CBs are different from city to city and could be massive or regular ones such as universities, offices buildings, shopping malls, hotels, factories, compounds, hypermarkets, etc, and are covering most of the land areas in the cities. University of Michigan (2020) reported that CB's floor spaces are foreseen to compass 124.7 billion square feet by 2050, which is 34 percent increase from 2019. Moreover, they are obviously playing a significant role towards the communities as a great CB can combine people together for a more social life and can generate more jobs. However, they are approximately consuming up to 40 percent of the total global energy demand (Kumar et al. 2016). Also, one of the main challenges that CB are facing is the climate change. Monge-Barrio and Gutierrez (2018) indicated that climate change has a significant impact on such buildings. Furthermore, climate change is predicted to have strong effects on the energy requirements of CB as their heating and cooling needs are highly related to temperature conditions and weather variations (Yau and Hasbi 2013). In addition, activities in buildings contribute to a major share of global environmental concerns (Urge-Vorsatz et al. 2013). These challenges motivate any facility manager or engineer to do valid actions towards building performance improvement and look after the associated operation and maintenance (O&M) costs; since CB are increasingly equipped with sophisticated engineering facilities as well like those are feeding energy supply, fire detection and protection, refrigeration, cooling, heating and ventilation, water supply and sewage, lighting, vertical transportation, communication, security, and alarm, etc (Lai and Man 2017). Looking to that, this paper is focused on Heat, Ventilation, and Air Conditioning (HVAC).

HVAC system is a technology of internal environmental ambience that supplies thermal comfort and agreeable indoor air quality (IAQ) at CBs (Proges 2020). It is based on the contrivances and the findings done by William Rankin, Nikolay Lvov, Willis Carrier, James Joule, and others (Swenson 2004). It is a critical system and is playing a big role in consuming a high percentage of energy in CBs, and accordingly, there will be an assertion on the electricity bill (Aswani et al. 2012). It takes more than thirty percent from the total energy used in CBs (Li et al. 2013). Cho et al. (2018) argue that energy consumption of HVAC system for large office building can take forty to fifty percent of the building's total energy use. It is, generally, worrying the organisers at CBs on the difficulty of replacing its components, when needed, so caring and making a planned control arrangement about that will save energy with minimal infrastructure investments (Dawson-Haggerty et al. 2010). However, doing a proper and well organised maintenance program for this system is totally required as many researchers found that the factor most often embroiled IAQ is a maintenance related (Greene et al. 1997).

The importance of HVAC is existing even before operating a particular CB where selecting the appropriate system with its components at the beginning of its project time is covering a significant part of its design. In this regard, Hassanain et al. (2014) argued that HVAC system is one of the most convoluted systems in buildings projects. The aforementioned HVAC components were listed by Sugarman (2020) such as water chillers, cooling towers, etc. Naturally, the selection of the said system is made based on three concepts, which are the configuration of that CB, the climate conditions, and the inclination of the owning organisation (Seyam 2018). One of the standards that HVAC's building design being created, selected, or studied is The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) through their handbooks (Denton et al. 1973, Barbaro et al. 1988, Humphreys and Hancock 2007, Kirkwood 2010, Persily 2015, Luo et al. 2020).

Furthermore, it is important system of buildings from wellbeing point of view; as it monitors environment related to occupant health such as the level of colorless odorless gas (CO_2) and humidity margins as well as occupant thermal comfort like ambient temperature and airflow (Schiavon et al. 2010). This system, especially its ventilation and cooling part, plays a big role in reducing the infection inside CBs during the recent global pandemic (COVID-19) if a proper maintenance management exists in monitoring airflow (Ding et al. 2020). Aebischer et al. (2007) underlined that due the impact of climate change, the need of cooling comfort inside CBs will be increased even in Europe until 2030 as the increment in temperature would be two-degree centigrade over time. The sub system highlighted in this research (CWS) is considered as one of the major functions in HVAC system and it usually consumes a significant amount of the total energy amortization used in the main system (Ma and Wang 2009). The above arguments have confirmed that HVAC is one of the critical and important systems at CBs, and it is worth to contribute towards the community by investigating its operation and predict the possible causes that affect its performance. This research focuses in framing a managerial PdM for the said system by addressing its components.

This research explains the said system based on ASHRAE handbook (2020). Its major components are listed below

1. Chillers
2. Cooling Towers.
3. Primary and Secondary Chilled Water Pumps.
4. Condenser Water Pumps
5. Air handling Units (AHUs) and Fan Coil Units (FCUs)

Here, the way of operating the said system is presented. Chillers produce the chilled water required to operate the AHUs/ FCUs and thereby to achieve the designed room conditions. Chillers, Primary Chilled water pumps are operated and sequenced to produce Chilled Water (CHW) at a set temperature whereas a specified temperature of water required by the condenser component of chillers is produced by the Cooling towers through the Condenser Water Pumps. The produced chilled water then is pumped by the Secondary Water Pumps to all the terminal units such as AHUs and FCUs and in case of variable flow system their speed is controlled to maintain a set differential pressure in the pipe network. Finally, the terminal units receive the chilled water and control their respective valve actuators to achieve the desired temperatures inside the rooms they are serving. Figure 1. shows a schematic drawing of CWS. This philosophy of addressing such system because it contains two essential life resources, energy power and water and this research aims to try contributing to optimize O&M through proposing PdM program for the same. The research question of this study is on how to identify the faults in chilled water system in order to make or build a predictive maintenance program for the same. Also, this research aims to cover the possible faults as much as possible to enrich the background of the concerned department for better dealing and arranging an efficient PdM program.

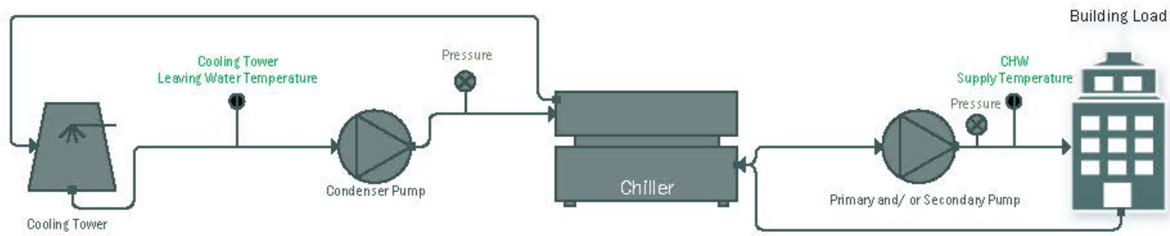

Figure 1. CWS Schematic (Source: Adopted from ASHRAE handbook 2020)

2. Literature Review

The research question of this research is how to address or handle the faults of CWS while planning to make a maintenance plan? Maintenance management for CWS were presented in many ways such as predictive maintenance (PdM) through faults detection. Operation research (OR) is one of the said ways, which was first used in maintenance arena during the second world war (McCloskey 1954). Wu et al. (2021) proposed a method to optimize the PdM scheduling for HVAC system by mixed-integer programming. The said method has two stages, the first one is the parameter generation through historical data and the second one is the optimization by linear programming. They did a case study on chillers and addressed their loads in Kilowatt (Kw). The idea of the first stage is to study the operational status and then listing the related constraints while the optimising model (second stage) has to be solved to present a high-quality PdM schedule; in order to detect the chillers' degradation. The model is a bit general and just tracing the chiller's load. It did not consider or discuss any precise faults or issues that lead to the chiller degradation. Another study, which its paradigm did not clearly focus on the possible faults nor clarify the system components that are addressed, is the one was done in a particular European hospital (Sanchez-Barroso and Sanz-Calcedo 2019). They proposed a quantitative method using Weibull distribution for determining the mean time between failures (MTBF). Their case study did not provide many details, but they argue that applying the said method will reduce the waste of the component's useful life. Yu and Chan (2012) did use clustering technique to assess the performance of five chillers. Their data were taken from a historical record of some parameters like chiller loads for every 30 minutes over one year. The target of their study is not exactly related to PdM but was to address the coefficient of performance of each chiller; in order to improve the operational status of the said parameters.

It has been noticed that fault detection for the cooling part of HVAC system is done using different approaches. In a residential facility, a study was done to detect the faults in HVAC system using simulation model (Turner et al. 2017). During seven days' study time, they focused on the outdoor temperature and the set indoor temperature parameters of AHUs; to detect selected faults like compressor failure. Their study is a data driven approach and they believe that tracking the said parameters can easily detecting the associated HVAC system's faults. Yang et al. (2018) presented a pragmatic simulation model to detect only four selected faults in HVAC system of forty-four buildings in Canada. Their solution relied on clustering work orders dataset, which were collected from occupants' complaints, and computing MTBF. The selected faults do not cover all mentioned HVAC components, and this can be considered as a limitation of the said solution. Simulation model within a stochastic system was presented by addressing the set temperature of a rooftop AHU (Holub and Macek 2013). The target of the said application is to detect a diagnostic fault that links to the fan. Frankly, the data used to simulate the aforementioned model were limited as they applied a hybrid system.

Sulaiman et al. (2015) developed a fuzzy fault detection model for centralized CWS using simulation. They implemented the said the model in air supply damper of an AHU, which is linked to two specific rooms. Three cases were studied in their research to simulate the said model. Two of them were related to damper's faults and the third one was at normal operation without any faults. They identified these faults by checking the room temperature variation. They mentioned that the developed model had resulted in detecting the damper faults but with no technical details. Another simulation model by Ahn et al. (2001) was done to detect cooling towers faults. Three chosen faults were detected via the deviations of three values such as the difference between the water temperatures that are leaving the tower and the temperatures that are entering the same. The only claim against this study is the data collection; as they did not clarify the source of their samples, which were used in the associated experiment.

Nowadays, the usage of machine learning is positively increasing with regard to fault detection. In Australia, an automatic fault detection system was developed in one of the large CBs (Guo et al. 2017). Machine learning was used there by merging two approaches, which are the hidden markov model and the support vector machine (SVM). In this regard, their data were collected through building management system (BMS) from fifteen distributed sensors in an AHU. Their system was trained based on selected faults over two business months. The study did not specify the parameters of the said AHU, which were addressed such as temperature or air flow. Sensors' false signal would be an added value if it was considered in their selected faults. Having said that, Luo et al. (2019) had perfectly offered a k-means clustering-based fault detection strategy for sensors of a certain CWS. Their collected data contained the return water temperatures of a particular chiller. That samples were gathered within four different seasons (Summer, Winter, Autumn, and Spring), one week each. The general goal was to check if the said temperature is complying with the designed one. With their study, organizations or researchers can catch the bias of sensors' faults. They suppose that such fault detection strategy can be dependent during operational hours if it mainstreamed with BMS platform, when needed.

Liang and Du (2007) proposed fault detection model of HVAC system using mixed methods. The under-study component was an AHU of a particular CB in Hong Kong. They combined simulation based-model method with SVM method. Three types of faults were addressed, which are return damper jam, cooling coil blockage, and speed reducing of the supply fan, noting that false signal fault is not considered in their study. Their method was built by collecting a data of multiple parameters like the set temperature and the indoor cooling load. The original sample size is small; as it was from ten operational hours but based on the qualitative output of a related research that was reviewed by Ding (2005), they assumed that the fault would arrive within one hour. So, they did depend on this assumption in finalising their required data and got a total of 576 samples, which were used to build the said model. Another study did use mixed methods to make PdM framework for mechanical, electrical, and plumbing (MEP) for building facilities (Cheng et al. 2020). They combined building information modelling (BIM) with IoT using machine learning algorithms. The algorithms used were Artificial Neural Network (ANN) and SVM. Their case study was to predict the condition of four chillers in one of Hong Kong's universities. Their proposal is comprehensive; as fifteen parameters were put into consideration to build their framework such as chiller type, temperature sensor value, and pressure sensor value. Two steps were conducted for the process of the said framework, which are data collection and then training the collected data using the said algorithms. The historical collected data were from two sides, BIM sensors and IoT sensors of fifteen months, but they did not specify the time interval of their data like hourly or so. They indicated that the one, who will use the said framework, may face some implementation difficulties with other MEP components where he/ she needs to consider the parameters differences. The said ANN and SVM methods were widely used to detect different selected faults especially on chillers and this has been remarked in diverse studies (Magoules et al. 2013, Han et al. 2011, Zhou et al. 2009, Namburu et al. 2007, Hou et al. 2006).

Bouabdallaoui et al. (2021) proposed a PdM framework for HVAC system based on machine learning research, which took place at one of the sport facilities in France. The said framework contains five steps, which are data collection, data processing, model development, fault notification, and improving the said model. Data of the cooling part of their study were collected from maintenance record of forty-five days found on Building Automation system (BAS) and IoT sensors. It would have been great had the faults were defined in their case study, which was applied on two AHUs. Similar two AHUs were addressed in other study using machine learning; to enhance the thermal comfort inside CBs (Du et al. 2014). The historical data of some parameters (for example, return chilled water temperature and chilled water flow rate) were the key of developing their model to detect the abnormalities in the said AHUs. The proposed model was based on combining a pair (basic and auxiliary) of neural networks. Six selected faults were focused on including the false alarm. According to them, the idea behind that integration of both networks was to detect the missing and/ or the false alarms that may occur during the operating time.

In Singapore, Yan et al. (2020) did use one of its techniques to detect seven selected chiller faults such as refrigerant leak and overcharge. Their data were collected from one of ASHRAE projects, which were gathered in every two minutes. The sample size contains 24,192 readings of some monitoring parameters like water temperatures. Clustering technique was applied through Generative Adversarial Network (GAN) to execute the said fault detection model. They believe the classification accuracy that resulted from the clustering can be enhanced by extending GAN skeleton in utilizing more assorted deep learning techniques like convolutional neural network (CNN) and long short-term memory (LSTM) neural networks; in order to gain a dataset that comprises of faults occurring over a vast domain of operating conditions. Another deep learning technique was used for faults detection in HVAC system (Shahnazari et al. 2019). They applied recurrent neural network (RNN) in clustering the faults by estimating the faults occurrence based on trial and error. Beghi et al. (2016) proposed a method that tapped principal component analysis for HVAC system; to distinguish anomalies from normal operation variability, and a reconstruction-based contribution approach; to insulate variables related to the said system's faults. Four selected faults of a particular chiller were addressed to be detected using a semi-supervised machine learning method. The proposed method looks interesting, but they did not clarify the source nor the sample size of their data that was used in their study.

Candanedo et al. (2018) did use supervised machine learning algorithm through Decision Tree (DT) technique for evaluating an early stage PdM model of HVAC system. In a set of buildings that are between zero and thirty years old, they got a historical data of the indoor temperatures; in order to compare them with the targeted ones, and then to identify any abnormal behaviour. They indicated that DT showed its accuracy in covering the faults possibilities. According to Lin et al. (2017) and Liu et al. (2018), DT is one of the most successful supervised learning techniques for classification. Trivedi et al. (2019) applied DT and SVM techniques; to detect two common faults in fifteen ACs of different rooms at a particular university. The relevant data, even though they were limited, revealed the status of those ACs over one week time. They reached to a result that DT is more accurate than SVM in predicting the said faults. In cooperation with a leading building management company, a PdM approach was proposed for the cohort of seventeen appliances related to HVAC systems, which were installed in one of the Italian hospitals (Satta et al. 2017). Using historical data of different variables like indoor temperature, they used DT to detect the abnormal behaviour of these appliances. They argued that the reciprocal dissimilarities between appliances' behaviour can expose an upcoming fault with enough anticipation to allow for a proactive meddling and avert breakage in operation. Tehrani et al. (2015) addressed one fault related to an HVAC system at one of the Canadian universities. The said fault was filter blockage and they used ANN to predict the behaviour of the said system. Also, they reached out that the performance of the system in discussion has improved by using DT instead of ANN. Furthermore, DT was used to develop a diagnostic strategy for AHUs (Yan et al. 2016). Nine cases were addressed for their related experiment, which are eight faults like duct leakage and one case for normal operation (fault free). For this experiment, they used data that were recorded from one of the ASHRAE projects. They emphasised that data-driven methods are unique to glean the useful information from large data sets and modelling the behaviour of HVAC systems.

As a summary of the presented literature, selecting the faults based on the historical data or previous records was the main mechanism of addressing those faults. The next section shows the proposed mechanism to address the same.

3. Methodology

In this paper, chillers are addressed out of the five main components of CWS. The methodology contains two parts, one is set-up and the other is execution. Both parts contain several steps to give any concerned user/ manager a simplified way to understand the system in discussion and how to enrich the likelihood of catching faults that make issues to the same system. This will lead to have a proper maintenance plan through PdM program or so.

3.1 Set-up Part

The following steps are recommended to go through by the user as per their sequence.

- The user to ask for mechanical drawings of the building under study to have a look.
- From the previous step, the number of chillers should be determined.
- This research argues that the leaving temperature (LT) from the chiller is giving a clear picture on its health condition, so the user should check the said drawings and the manufacturer manuals about the set point of each chiller and write it/ them down.
- The core method that is used in this research is the hypothesis test. Here, two tailed t-test is recommended, and the statement of this test is as follows:
  H_0: $\mu = \mu_0$

H_1: $\mu \neq \mu_0$

Where:
H_0: The null hypothesis.
H_1: The alternative hypothesis.
μ: The mean value of a particular LT sample (°C).
μ_0: LT of a particular chiller (°C).

3.2 Execution Part

In this part, the first thing for the user to do is collecting the readings/ data of LT for each chiller. In order to do so, the user should check what are the available reading tools or prepare the same in case of they are unavailable. The tools here can be defined as sensors to determine LT for each chiller. The sample data is recommended to be more than 30 readings for each under study period. In this research, R language is used to run the aforementioned test, Schmuller (2017) explained the benefits of R and how to use it. Therefore, the said data should be formed as shown in Table 1 for each chiller; in order to support the process of running the t-test. After that, the user is recommended to use MS Excel to enter the mentioned table and save a file for each chiller and name that file as "Chiller**i**", where "**i**" means the understudy chiller. For instance, chiller #4 in a particular building, the file name should be "Chiller4". It should be saved as type of CSV in "Documents" part of the device/ computer that the user is using. Accordingly, the file name must appear as "Chiller4.csv". This arrangement is also to support and simplify the process of the running the t-test.

Table 1. Data Form

Chiller.i
X_1
X_2
.
.
.
.
.
X_n

Where:

X: LTs during the understudy period (°C).
n: sample size.

Now, it is the time to test the collected data in R. The following arrangements are proposed to do so:

- The user needs to open RStudio and go to "Session" in toolbar, press "Set Working Directory" and then select "To Source File Location".
- Then, the user needs to write the following arguments in R Script for each Chiller:

```
# Testing of Chilleri
read.csv("Chilleri.csv")
install.packages("DAAG")
require(DAAG)
Chilleri <- read.csv("Li.csv")
Chilleri
t.test(Chilleri, mu = μ0, alternative = "two.sided")
```

- Lastly, the user must highlight all the above arguments/ expressions and then click on "Run" on the toolbar.

After that, the user can read the result of the said test. The result of the test will appear automatically in Console, the important one is probability value (P-Value), which is the smallest level of significance that would lead to rejection of H_0 with the given data. If P-Value is less than or equal the significance level, which is set typically five percent, then H_0 will be rejected and accordingly the test result will be substantial (Almobarek et al. 2020) That means LT at chiller i is not aligned with the set point and accordingly, an immediate inspection is needed. Once run the test for each chiller, the results are recommended to be formed as Table 2. To keep a record, it is better to add the period time of the sample size to the said table. An application is shown in the next section to give a glimpse on this methodology.

Table 2. Results Form

Study Period: From …… am/ pm …..day until …… am/ pm ……day, Date …..					
Chiller#	1	2	. . . .		n
Substantial?	Yes		Yes		Yes
Insubstantial?		Yes		Yes	
Inspector	Mr./Ms.		Mr./Ms.		Mr./Ms.

4. Application/ Case Study

This research got a chance to apply the said methodology at one of Riyadh city universities, Kingdom of Saudi Arabia. This university has five chillers, and the set points of each chiller is 6 °C, which is the value of μ_0 in the hypothesis test. LT's readings have been taken for every minute of each chiller during three weekdays. After running the t-test for each chiller, the performance of one chiller has been found substantial (chiller# 2) and therefore, an inspector from the same university has been assigned for further action from the concerned department. The Table 3. Shows the results of study period from 6am Monday until 11pm Wednesday of October 4-6, 2021.

Table 3. Results

Study Period: From 6 am Monday until 11 pm Wednesday of October 4-6, 2021					
Chiller#	1	2	3	4	5
Substantial?		Yes			
Insubstantial?	Yes		Yes	Yes	Yes
Inspector		Mr. Aron			

5. Conclusion

This paper showed a significant way on how to find the chiller that having issue or that not aligned with the designed set point. The philosophy of this research is to have a mechanism that leads the user to the faults in CWS (chiller here). The gap of previous research is selecting the faults based on previous data/ record with no consideration to the building current situation. The method can easily be used for other components like cooling towers considering the differences of the related parameters. The limitation here is that the inspector has to be qualified to interpret the inspection outcome and therefore, the future agenda of this research is to explore logical ideas and tools to recognize the faults and accordingly to make a comprehensive predictive maintenance program for CWS in CBs that will be aligned with the fourth quality evolution.

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