Intelligent Maintenance for Chilled Water System at Commercial Buildings: A Holistic Approach in Line with Industry 4.0

by

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DECLARATION OF AUTHENTICITY AND AUTHOR'S RIGHTS

This research thesis is an outcome of the author's original research. It has been written and composed by the author and has not previously been submitted for examination leading to the award of a postgraduate degree.

PUBLICATIONS

Many parts of this thesis, including research findings, have previously been presented and published in a well-known Q1 scientific journal, which is indexed within Scopus and SCIE, and at International and European conferences. The author notes that the first four publications have already cited by other research studies:

- Almobarek, M., Mendibil, K., and Alrashdan, A. (2022). Predictive Maintenance 4.0 for Chilled Water System at Commercial Buildings: A Systematic Literature Review, *Buildings,* 12, p. 1229.
- Almobarek, M., Mendibil, K., Alrashdan, A. and Mejjaouli, S. (2022). Fault Types and Frequencies in Predictive Maintenance 4.0 for Chilled Water System at Commercial Buildings: An Industry Survey, *Buildings,* 12, p. 1995.
- Almobarek, M., Mendibil, K. and Alrashdan, A. (2023). Predictive Maintenance 4.0 for Chilled Water System at Commercial Buildings: A Methodological Framework, *Buildings*, 13, p. 497.
- Almobarek, M., Mendibil, K. and Alrashdan, A. (2022, March). Faults handling in chilled water system maintenance program. In *Proceedings of the 12th International Conference on Industrial Engineering and Operations Management,* Istanbul, Turkey, 7–10 March 2022; Industrial Engineering & Operations Management (IEOM) Society International: Michigan, United States of America, pp. 1616–1625.
- Almobarek, M. and Mendibil, K. (2023, July). Most Occurred Faults in Chilled Water System: An Empirical Predictive Maintenance 4.0 Study. In *Proceedings of the 6th European Conference on Industrial Engineering and Operations Management,* Lisbon, Portugal, July 18-20, 2023; Industrial Engineering & Operations Management (IEOM) Society International: Michigan, United States of America, pp. 672–678.

AWARDS

Table 1 below shows the awards that the thesis author has gotten during the PhD studies.

Table 1: List of Awards

Award Title	Purpose	Awarding Body	Award Date	Award Amount (Pound Sterling)
Excellence Award #1	• Satisfactory progressive report from the thesis author’s supervisor. • Publishing the literature review part as a review paper in Q1 journal. • Presenting the introduction part of the research thesis in an international conference.	Saudi Arabian Cultural Bureau in the United Kingdom	December 16, 2022	1,231.47
Excellence Award #2	• Satisfactory progressive report from the thesis author’s supervisor. • Publishing the industry survey part of the research thesis in Q1 journal.	Saudi Arabian Cultural Bureau in the United Kingdom	January 03, 2023	1,239.59
Excellence Award #3	• Satisfactory progressive report from the thesis author’s supervisor. • Publishing methodological framework part of the research thesis in Q1 journal. • Presenting a part of the case study in a European international conference.	Saudi Arabian Cultural Bureau in the United Kingdom	October 16, 2023	1,218.87

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Yours Faithfully,

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Abstract

Commercial buildings are equipped with critical systems that need strong attention by applying efficient maintenance practices. One of these systems is the chilled water system (CWS), which contains sophisticated components and consumes significantly higher levels of energy and financial resources compared to other systems. Given the relevance of the issue, this research study started with the following guiding research question:

"*What are the approaches or methods to implement predictive maintenance (PdM) or fault detection for a chilled water system at commercial buildings?*"

The review of the literature (with more than 180 studies analysed) identified several research gaps, which are (1) the impact of the technical correlation between CWS components on fault detection remains unknown, (2) there is a significant level of variations in defining CWS faults and their importance, (3) the data measurement of these faults is not standardised leading to unclear data collection practice, and (4) the resolution of these faults remains inconclusive. Accordingly, four research questions were generated.

Two research methods were assigned to answer the generated four research questions: an industry survey and a case study. The industry survey adhered to construction guidelines and a pilot study. Subsequently, it was sent to 761 professionals of commercial buildings in the city of Riyadh, Kingdom of Saudi Arabia, out of which 304 responses were considered and analysed. For the second research method, a case study, a novel methodological framework has been developed and implemented. The framework contained three phases: set-up, machine learning and quality control. The first phase proposed arrangements to prepare the framework, while in the literature, studies were directly started with building the detection model. The second phase proposed a decision tree model to detect faults. The final phase suggested managerial steps for monitoring, controlling, and evaluating the maintenance framework which includes the detection model, while in the literature, studies were ended with presenting the model accuracy. In addition, a second case study has been conducted for external validity purposes.

This research project has proposed an intelligent maintenance framework for the whole CWS components in line with Industry 4.0, which includes a fault

detection model using machine learning. During three empirical periods, the research questions have been answered and verified, with the proposed detection model achieving greater than or equal to 20 per cent improvement in detecting faults at the two case study sites compared to the current building management system.

This thesis makes significant theoretical contributions, which are adding and recording additional faults to the ones mentioned by the literature, providing an action to fix each fault, providing fault frequencies that can be used in data collection and machine learning, and confirming the technical relevance between CWS components. Practically, this thesis makes significant contributions by proposing the said methodological framework, which contains an intelligent detection model. The framework inherently led to three other contributions, which are providing a simplified schematic for CWS, providing a proper location for each reading tool for data collection purpose, and providing a control plan for continuous monitoring for CWS. The aforementioned theoretical and practical contributions give a strong value for this research as they delivered a holistic maintenance guide for CWS at commercial buildings. At the end of this thesis, several areas for future research are suggested as well as the author's own reflection is shared.

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Chapter 1: Introduction

"Preservation of modern buildings and those that changed over time is a complicated and delicate undertaking."
(Jackson, 2017)

1.1 Background and Motivation of the Research

At commercial buildings or large facilities, business work fills most the time and occupies employees, who spend most of their workday inside these buildings. So, these buildings or facilities comprise a sizable portion of the built environment for people. Common sense drives the organisations or owners to take care of these buildings in efforts to avoid any negative impact on the external surrounding or internal environment of these buildings. Commercial buildings are clearly different city to city: they could be massive or regular sized, such as universities, offices buildings, shopping malls, hotels, factories, compounds, or hypermarkets, and they cover most of the land area in the cities. The University of Michigan (2020) reported that commercial building floor spaces are expected to encompass 124.7 billion square feet by 2050, a significant 34 per cent increase from 2019. Globally, as the number of commercial buildings rapidly increases, these require significant attention from a maintenance management point of view (Hauashdh et al., 2022).

In the author's view, commercial buildings are obviously playing a significant role in communities, as they enhance people's social life and serve to generate more jobs. However, they are consuming approximately 40 per cent of the total global energy demand (Kumar et al., 2016). Moreover, one of the main challenges that commercial buildings are facing is the climate change. According to Monge-Barrio and Gutierrez (2018), climate change has a significant impact on such buildings. Furthermore, climate change is predicted to have a strong effect on the energy requirements of commercial buildings, as their heating and cooling needs are inextricably related to temperature conditions and weather variations (Yau and Hasbi, 2013). In addition, activities in such buildings contribute to a major share of global environmental concerns (Urge-Vorsatz et al., 2013). These challenges should motivate any facility manager or engineer to take viable and practical actions toward building performance improvement and maintenance, as well as overseeing associated operation and maintenance costs. This is necessary since commercial buildings are increasingly equipped with sophisticated engineering facilities as well as heat, ventilation and air conditioning (HVAC) equipment or machines (Lai and Man, 2017). In doing this, facility managers or engineers can fulfil the sustainability of their commercial buildings (Gálvez et al., 2021).

Maintaining a particular building requires management of all systems within. Generally, it includes either mechanical or electrical systems. There are five major disciplines of buildings systems: 1) HVAC, which is highlighted in this research thesis; 2) plumbing and fire protection; 3) electrical power and telecommunications; 4) illumination; and 5) noise and vibration control (Janis and Tao, 2019). The *HVAC system* is defined by Porges as ''a technology of internal environmental ambience that supplies thermal comfort and agreeable indoor air quality'' (2020, p. 49). Historically, the HVAC system is based on the findings of William Rankin, Nikolay Lvov, Willis Carrier, James Joule and others (Swenson, 2004). As a critical system, it consumes a substantial percentage of energy in commercial buildings, that accordingly, is reflected on the electricity bill (Aswani et al., 2012). In fact. it consumes more than 30 per cent of the total energy used in commercial buildings (Li et al., 2013). Cho et al. (2018) argue that the energy consumption of an HVAC system for a large office building can consume 40 to 50 per cent of that building's total energy use. It is generally worrying to organisers or managers at commercial buildings because of the difficulty of replacing components, when needed, so caring and designing a planned control arrangement about the system to save energy, with minimal infrastructure investment, is critical (Dawson-Haggerty et al., 2010). However, conducting a proper and well-organised maintenance programme for this system is required, as many researchers have found that the factor most often embroiling indoor air quality is maintenance related (Greene et al., 1997).

The importance of HVAC system was evident even before operating a particular commercial building, where selecting the appropriate system with its components at the beginning of its project time covers a significant part of its design. In this regard, Hassanain et al. (2014) argue that the HVAC system is one of the most convoluted systems in buildings projects. This argument has been supported by Sugarman (2020) as well. Naturally, the selection of the said system is based on three concepts: the configuration of that commercial building, the climate conditions, and the inclination of the organisation that owns it (Seyam, 2018). The standards to which HVAC building designs are held when being created, selected or studied come from The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) (Luo et al., 2020a). Furthermore, it is an important system from well-being and safety points of view, as it monitors the environment related to occupant health, such as the level of colourless odourless gas (CO_2) and humidity margins, as well as occupant thermal comfort, including ambient temperature and airflow (Schiavon et al., 2009). This system, especially ventilation and cooling elements, played a significant role in reducing infection inside commercial buildings during the recent global pandemic (COVID-19) if proper maintenance management monitored the airflow (Ding et al., 2020). According to Aebischer et al. (2007), due to the impact of climate change, the need for cooling comfort inside commercial buildings will be increased even in Europe until 2030 as temperature increment will be two-degrees centigrade over time. Having noted the cooling part, this research study focused on one of the major systems of HVAC, the chilled water system (CWS). The next subsubsection provides an overview of this chilled water system as well as an additional research motivation from the author’s point of view from practical experience.

1.1.1 Chilled Water System

A chilled water systems (CWS), considered as one of the major functions in the HVAC system where it typically consumes a significant amount of the total energy amortisation used in the main system (Colmenar-Santos et al., 2013). The *ASHRAE Handbook* (2023) lists four components of CWS as follows:

1. Chillers;
2. Cooling Towers;
3. Pumps; and
4. Terminal Units.

As per ASHRAE (2023), the operation of CWS starts with chillers producing the chilled water required to operate the terminal units and thereby achieve the designed room conditions. Chillers, primary chilled water pumps, are operated and sequenced to produce chilled water 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 is then pumped by secondary water pumps to all terminal units, such as air handling units and fan coil units, and in case of a variable flow system, 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. Each component is manufactured by various industrial brands in different sizes, but the technical mechanism, function, and parts are same. Figure 1 shows a schematic drawing of the CWS (*ASHRAE Handbook*, 2023).

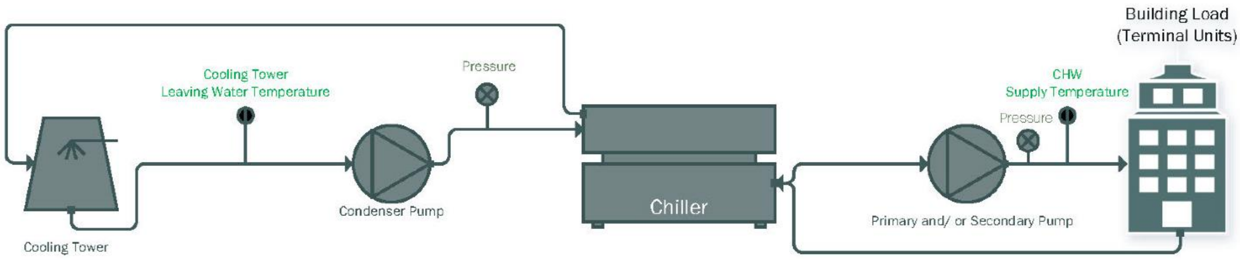

Figure 1: Schematic of chilled water system

During times of practical experience of more than ten years in facility management, the author repeatedly observed that the CWS plant broke down, and the real fault that caused the breakdown was not found in the original equipment manufacturer manual nor was the automotive control system like the building management system (BMS) able to guess or anticipate its occurrence correctly given the complex relationship among the various components of the plant. This led the author to seek a technological way that can replace BMS by an intelligent detection model to trace faults more efficiently and to see the possible ways to fix these faults when occurred in an effort to reduce plant breakdowns and thereby maintain the appropriate indoor conditions for occupants. In this context, this research project utilised machine learning to execute a predictive model as part of a maintenance management framework.

1.2 Research Thesis Aim

This research project aimed to explore innovations in observing and controlling the CWS at commercial buildings in accordance with the era of smart technologies. One of these technologies is faults detection, which is presented in this thesis. The objective of this research project is threefold: 1) to propose an intelligent maintenance via a methodological framework that could enhance CWS performance, 2) to build a fault detection model that performs better than BMS, and 3) to evaluate the intelligent maintenance framework in real-life setting. Consequently, the research project contributed to the development of a holistic fault detection strategic framework that employed a mechanism to collect additional faults and provide optimum solutions, building a decision tree model that has improved the detection accuracy over that of BMS. A fault detection strategy is in line with Industry 4.0, as explained in detail in the upcoming chapter.

1.2.1 The Significance of The Research

The significance for such a framework is that it will help users of commercial buildings to manage their building’s operation in an efficient manner by minimising the likelihood of any possible failure for the system in discussion, maximising the life cycle of the components of the said system, reducing the operation and maintenance costs, avoiding major component replacement costs, understanding the operational status of the said system, ensuring the system is operating in line with the design, clarifying the importance of the parameters of the said system, and ultimately, improving building occupant experience and comfort.

1.2.2 Guiding Research Question

The guiding research question underpinning this present research is **“What are the approaches or methods to implement predictive maintenance (PdM) or fault detection for a chilled water system at commercial buildings?”** The research project undertook a systematic literature review leading to four research gaps related to three specific points: fault description and handling, data collection and fault frequencies, and the coverage of the proposed maintenance frameworks. From this, four research questions are identified during the literature review process, and they are presented in detail in the next chapter.

1.3 Research Methods

This research project has assigned and employed two research methods to answer the aforementioned four research questions. The industry survey, the first research method, has been gone through two stages, namely survey construction and pilot study. The construction of the industry survey followed guidelines from the literature, while the pilot study included sending the draft survey to 10 experts in academia and industry for their review and advice. After that, the final draft of the survey was sent online via a web-based platform to 761 professionals of commercial buildings in Riyadh, Saudi Arabia. Those professionals were either facility managers, support services managers or operation and maintenance managers. The total considered responses of the industry survey is about 40 per cent out of 761 contacts (i.e. 304 responses) as the related commercial buildings have chilled water system within. Chapter 4 explains in detail the industry survey construction, its pilot study and its results.

With regard to the case study, Alfaisal University campus, which is located in Riyadh, Kingdom of Saudi Arabia, was chosen. A methodological framework for PdM strategy was proposed to implement the said case study. The aforementioned framework has three phases, namely set-up, machine learning and quality control. Each phase has an objective, explained in detail in Chapter 5 along with the case study results. Also, the said methodological framework has been implemented for another case study at a different building for external validity purposes, explained in detail in Chapter 5 as well. Three empirical periods were conducted: two periods were conducted at the building of the main case study for reliability and internal validity purposes, while the third period was conducted during the case study for the purpose of external validity.

1.4 Research Thesis Structure

This research thesis has been structured into six chapters as shown below in Table 2.

Table 2: Structure of research thesis

Chapter Number	Chapter Title	Chapter Description
1	**Introduction**	This chapter shows the research background and the motivation behind it, including an overview of the chilled water system. It highlights the research aim, the overall contribution to knowledge, and its significance as well as presenting the guiding research question. In addition, it gives a glimpse about the research methods assigned to answer the research questions of this thesis. Finally, it summarises the structure of this research thesis.
2	**Literature Review**	This chapter gives an overview of maintenance management at commercial buildings from a general view, maintenance strategies, maintenance in Industry 4.0, the PdM concept, the relationship between quality engineering and maintenance management, and then the applications that are in line with Industry 4.0. After that, it presents a systematic literature review of methodology that addresses the guiding research question. The said review has been built through four stages and focused on the previous applications of PdM or fault detection strategy on CWS. Then, it discusses the findings of the literature and lists the research gaps, and then generates the research questions for this thesis.
3	**Research Design**	This is a theoretical chapter exploring the research philosophy and its approach. It presents the assigned research methods that are intended to answer the generated research questions and shows how to design these methods. It also shows the research planning, ethical considerations and how to assess the research quality.
4	**Industry Survey**	This chapter explains the first research method of this research thesis. It shows how the industry survey has been constructed, how the pilot study has been implemented, and the outcome of these stages. Also, it shows how the industry survey has been distributed. Then, it presents the results of the industry survey in three parts: response rate, chilled water system faults and faults frequencies.
5	**Case Study: Development and Implementation of Maintenance Methodological Framework**	This chapter contains an overview about the location of the case study. It illustrates how the methodological framework has been proposed in order to apply it on the building under study. Then, it presents the results of implementing the framework. It contains discussions on reliability, internal validity and external validity.

6	**Discussion and Conclusion**	This final chapter discusses the results of both the industry survey and case studies and compares these results with the extant literature. It explains in detail how this research project has answered the research questions. Finally, it summarises the research in entirety, demonstrating how the quality of the research has been fulfilled. It lists the contribution to the knowledge theoretically and practically, the limitations, and then proposes a future research agenda accordingly. Finally, it ends with the author's own reflection.

Chapter 2: Literature Review

"Maintenance is everywhere, when there are systems, machines, elements that people use every day, requiring specific actions for functioning them correctly."
(De Carlo and Arleo, 2017)

2.1 Introduction

This chapter provides an overview about maintenance management at commercial buildings, maintenance strategies and the position of quality engineering in maintenance management. It also presents an overview about the concept of PdM and reviews applications of PdM or fault detection approaches that are in line with Industry 4.0.

After that, this chapter seeks to generate the theoretical foundation that is underpinning this research thesis by reviewing extant studies on CWS that were applied in PdM applications at commercial buildings in line with Industry 4.0. Having said that, this chapter contains the literature review methodology and the applications that are reviewed, and then discusses the findings, furnishes the research gaps, and thereafter, presents the generated research questions for this thesis.

2.2 Maintenance Management at Commercial buildings

2.2.1 An Overview

Wireman (2005) as well as Werbinska-Wojciechowska and Winiraska (2023) define *maintenance* as managing any assets that are owned by an organisation. Duffuaa et al. (2015) as well as Duffuaa et al. (2024) point out that maintenance can be regarded as a system with input and an associated output. The input part contains workforce, management, tools, equipment and machines, while the output part comprises the equipment or machines that are working perfectly, are fulfilling the reliability concepts, and are well configured to reach the scheduled operational time. According to the European Standard, maintenance connects all managerial actions required during the life cycle of the equipment of a particular commercial building (Márquez and Gupta, 2006; Márquez, 2007; Sandu et al., 2023).

Previously, attention afforded to maintenance was not sufficiently recognised, as it was considered a "Cinderella Function" due to historical reasons, but this changed gradually as maintenance involved new information technologies (Sherwin, 2000; Piniciroli et al., 2023). Up to around 1940, maintenance was considered an inescapable cost and once the failure of a particular piece equipment occurred, the maintenance technician would service the same equipment based on a call request (Murthy et al., 2002; Alhourani et al., 2023). In 1968, it was determined that better maintenance practices in the United Kingdom could have economised approximately 300 million pounds sterling per year of lost production because of the unavailability of a particular equipment (Kelly, 2006; Lundgren et al., 2023). In 1972, the significance of building maintenance was first recognised by the responsible authorities in the United Kingdom (Allen, 1993; Ogunbayo et al., 2023). Maintenance then became one of the important managerial departments or functions to be included in a company's organisational hierarchy (Pintelon and Gelders, 1992; Firdaus et al., 2023).

Maintenance in the 21st century is a substantial business: operating and maintaining commercial buildings takes significantly more time than designing and constructing the same building during its project time. The life cycle cost of operating and maintaining the same building is about 60 to 85 per cent of the total cost, whereas its design and its construction are about five to ten per cent (Lewis et al., 2010; Dahiya and Laishram, 2024). Moreover, alongside energy costs, maintenance costs can comprise the largest portion of an operational budget (Dekker, 1996; Goby et al., 2023). Many researchers have argued that implementing good and effective maintenance management would increase equipment performance, and this is definitely maximising the revenues, minimising the operation and maintenance costs, and ultimately growing an organisation's profits (Willmott, 1994; Alsyouf, 2007; Naidu et al., 2009; Xia et al., 2021a; Zeng et al., 2024). In this regard, Cholasuke et al. (2004) explain how to maximise organisational profit by implementing maintenance management. They list several factors such as attempting to minimise accidents or failures. Dhillon (2002) presents an approach containing steps and six important principles for managing maintenance in a cost-effective manner, which are 1) maximising productivity results, especially when each assigned person in a particular organisation has a defined maintenance task to perform in an effective manner; 2) scheduling the control points effectively, 3) ensuring measurement comes before control; 4) focusing on the customer service relationship; 5) controlling the work order of a particular maintenance activity by the responsible staff; and 6) performing the maintenance activity with an optimal technician number. Here in this research thesis, most of these principles have been considered while preparing the proposed methodological framework especially the third one where the researcher is advised to measure the situation within the building, which includes data collection and building a detection model, before controlling the maintenance activity. This will be shown in detail in Chapter 5.

2.2.2 Maintenance Strategies

Maintenance can be actioned in many ways, depending on the operational status of a building and the organisational strategy. Having said that, Seeley (1987) categorises maintenance types for buildings, suggesting that it be considered a planned/ scheduled activity which can be organised by scheduling the building operation and tracking its performance. So, it can be considered a scheduled activity as well (Patra and Kumar, 2024). In contrast, it can be also considered as an unplanned activity (Seeley, 1987; Tambe et al., 2013; Weidner 2023). In addition, it can be performed as a preventive task by controlling the building operation to reduce the probability of destruction, to avoid the failure of a mechanical or electrical system, or to maintain an item performance from any unexpected breakdown (Seeley, 1987; Gouiaa-Mtibaa et al., 2018; Zhang et al., 2024). This task can be considered as a planned/ scheduled or predictive activity (Seeley, 1987; Curcurù et al., 2010; Patra and Kumar, 2024).

In the event of a failure, maintenance serves as a corrective measure aimed at restoring a system to its normal operational state. In urgent situations, maintenance takes on the form of emergency tasks, such as promptly addressing significant water leaks or power outages. Furthermore, Kanisuru (2017) and Vasić et al. (2024) classify maintenance into four major types. The first is reactive, corrective or breakdown maintenance. The second is preventive maintenance, which he categorised into two major types: PdM, as considered in this research thesis, and periodic. The third major type of maintenance is the improvement or design maintenance; while the fourth is technology maintenance. Figure 2 illustrates the position of PdM along with other maintenance strategies (Kanisuru, 2017).

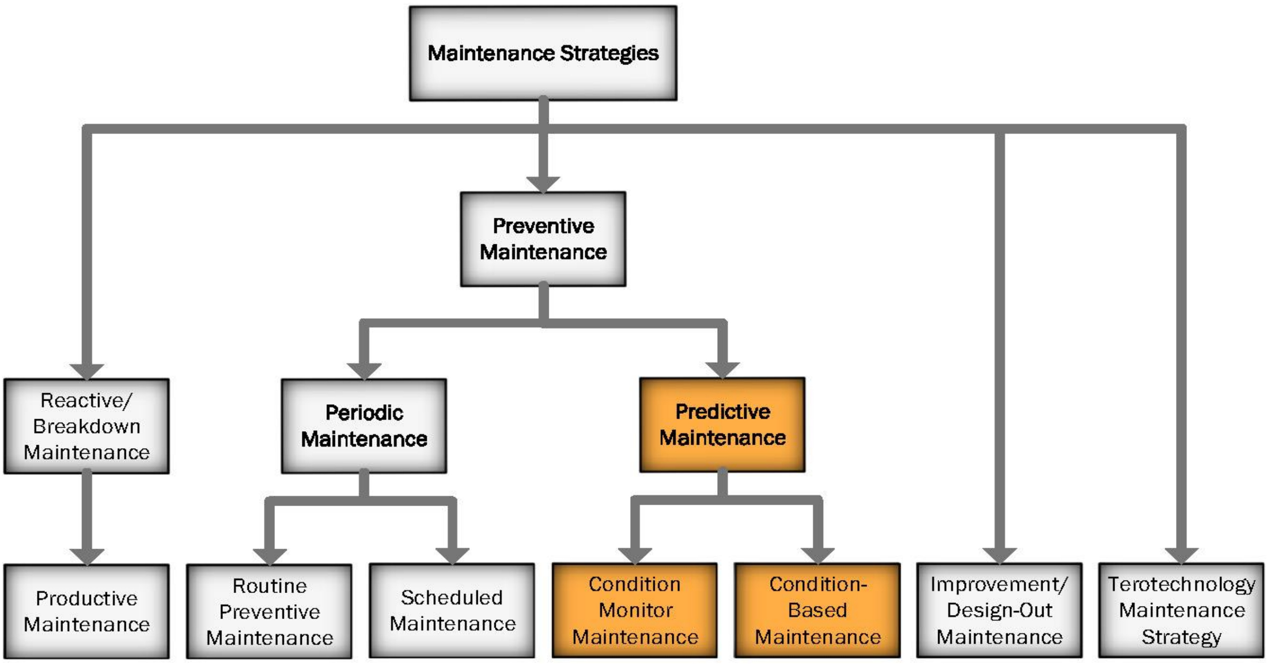

Figure 2: Structure of maintenance management strategies

Maintenance has been illustrated in different ways within the industrial revolutions. In the First Industrial Revolution, *reactive maintenance* was the primary strategy. This deals with an asset component on a daily basis as the aim is to respond to component malfunction or breakdown only after occurrence (Hegazy et al., 2010; Cachada et al., 2018; Sifat and Das, 2024). For this reason, it is referred to as 'corrective maintenance' as well (Campos Fialho et al., 2024). According to Swanson (2001), reactive maintenance can be described as a fire-fighting approach to maintenance, and she explains that a component or machine is allowed to run up to the point of failure. Then the failed component or machine is repaired or possibly be replaced (Swanson, 2001; Behera and Dave, 2024). Researchers also state that a temporary repair may be performed in order to return the said component or machine to its normal operation, thereby deferring a permanent solution until a later time (Swanson, 2001; Behera and Dave, 2024). Reactive maintenance strategy allows a particular plant to minimise the maintenance manpower and the amount of money spent to keep a component or machine running in a normal condition (Salvendy, 2001; Behera and Dave, 2024). However, the drawbacks of this strategy include unpredictable and fluctuating production capability, failure to meet the required tolerance level and output of scrap, and the rising overall maintenance costs that are needed to repair increasingly critical failures (Swanson, 2001; Behera and Dave, 2024).

Reactive maintenance strategy has been applied in many applications, for example, du Plessis et al. (2015) utilised the said strategy by implementing an energy management system on two case studies, the first for water reticulation systems and the second for cooling auxiliaries. The first case study was primarily performed to attend to the failure of the supervisory control and data acquisition system, while the second case study was performed to evaluate the coefficient of performance of refrigeration machines. Calves et al. (2005) implemented reactive maintenance on time critical systems using a mathematical modelling language called Petri Net graph. The modelling was structured on two steps. First, the precedence constraints provided by the process flow, which is the linear part of the graph, are modelled on the beginning and ending events of failure. After that, the model is completed with the resources required for the implementation of maintenance tasks. In thermal power plants, reactive maintenance strategy was applied on a component called regenerative air heater, used for heating the fresh air (Demet et al., 2019). In this regard, they proposed four actions: continue observing the component, replacing it when needed, grinding the shaft in case of axis shift mode, or cleaning the honeycomb by using appropriate chemicals. Bocewicz et al. (2024) implemented reactive maintenance approach by proposing a reference model for offshore wind farm equipment, and they claimed that the model can extend the lifespan of the said equipment. A reactive maintenance framework is made based on data mining process model that combine domain expertise with data science techniques to address the pervasive data issues in industrial datasets, and the researchers claimed that such models can enable the energy reduction (Ahern et al., 2022).

With regard to the Second Industrial Revolution, *planned/ scheduled maintenance* was the main strategic theme, a more proactive approach to maintaining the utility components or assets and minimising the downtime and costs associated with breakdowns of components (Cachada et al., 2018; García et al., 2022). The said strategic theme can be called 'routine preventive maintenance' as well, with the primary aim of this strategy to decrease workflow obstruction and failure of components or machines with minimal cost (Mirghani, 2001; Olsen, 2024). It assists in raising the reliability of components or machines and extending the life span of components or machines by determining and interacting with both consequence and technical-related aspects of certain failure modes (Mirghani, 2003; Matgorzata, 2016; Olsen, 2024). According to Akcamete et al. (2010) as well as Olsen (2024), planned/

scheduled maintenance lends itself to adequate solutions to avoid breakdowns or failures, by providing proper documentation of suitable tolerances of various utility components, machines or any other tools. In contrast, Lenahan (2011), in discussing the drawbacks of this maintenance strategy, insists that it requires more budget upfront while initialising the maintenance plan, and will cost the organisation more to regularly maintain the utility components or machines than implementing a reactive maintenance strategy. He further describes it as an over-maintenance activity because it has a regular plan where sometimes a component or machine may not require checking as often as planned (Lenahan, 2011; Trubetskaya et al., 2023). This strategy then requires more manpower because regular checks are a requirement in planned/ scheduled maintenance, while in case of reactive maintenance, the responsibility within the organisation is simply just to contact a technician or a contractor for a one-time inspection and repair. Therefore, planned/ scheduled maintenance strategy needs technicians to always be around the site and perform daily inspections (Lenahan, 2011; Trubetskaya et al., 2023). The difference between *preventive maintenance* and the planned/ scheduled one is minor, where the preventive one is made for a longer period like a year or so for multiple machines, while the planned/ scheduled maintenance is made for a specific task with period of time like maintaining an error in a particular machine (Al-Duais et al., 2022).

Planned/ scheduled maintenance strategy has been applied in many topics; for example, Tang et al. (2007) made a mathematical model that was formulated as a three-index integer programme. This model was presented to schedule the technicians who are responsible for utility services like elevators and HVAC systems. Another mathematical model was proposed by Wang (2012) to control the inventory of joint spare parts as a function of a planned/ scheduled maintenance programme. He considered multiple parameters in that model –such as the fixed cost of preventive maintenance inspection for all concerned items, the failure cost due to an absence of spare parts in stock, and the failure cost with the spare parts that are already in stock – and then conducted an empirical study using data from a local paper mill to claim the effectiveness of his mathematical model (Wang, 2012). In Italy, Tantardini et al. (2012) proposed a mathematical model to evaluate the costs for rescheduling maintenance interventions as part of planned/ scheduled maintenance programme. The said model considered three types of cost – those related to administrative, maintenance materials and maintenance manpower – and then took these into consideration when defining a maintenance service contract as well as when running it (Tantardini et al., 2012). Their mathematical model has been developed after a vast empirical analysis scattered in two phases, the first an exploratory phase intended to identify the variables of the rescheduling maintenance problem via interviewing the main maintenance service providers, and the second a confirmatory phase intended to validate the mathematical model using data from a real industrial setting. Finally, the results were analysed by the maintenance officers who were provided the data (Tantardini et al., 2012). Ukato et al. (2024) present a planned/ scheduled maintenance approach via artificial intelligence to optimise the logistics on offshore platforms that are related to oil and gas industry, and they indicated that such approaches could deliver a more sustainable operations outcomes. A routine preventive maintenance approach is made based on model methods of construction to mitigate the life cycle impact of construction for the concrete buildings structure in a harsh environment, and this approach has enhanced the sustainability by 86 per cent within the studied buildings (Sánchez-Garrido et al., 2024).

The main maintenance strategy in the Third Industrial Revolution was *productive maintenance,* defined as a holistic approach to the maintenance of utility components, equipment or machines that aims to attain exemplary production or performance (Agustiady and Cudney, 2018; Cachada et al., 2018; Samadhiya et al., 2024). The purpose of this maintenance strategy was to raise the productivity of any project by minimising the total cost of a particular component or machine over its entire life from design, production or fabrication, operation and maintenance, and the damages caused by the degradation of that component or machine (Ahuja and Khamba, 2008; Samadhiya et al., 2024). The key characteristics of this maintenance strategy are the reliability and maintainability focus of the utility component or machine, as well as cost awareness of maintenance activities (Almeanazel, 2010; Hallioui et al., 2023). This maintenance strategy aims to improve productivity of utility components or machines by performing other related strategies such as preventive maintenance, corrective maintenance and maintenance prevention during the life cycle of components or machines (Brah et al., 2004; Samadhiya et al., 2024). While the benefits of implementing this maintenance strategy might sound promising, it is quite challenging as it requires securing senior management support and allocating adequate resources to the maintenance programme. It requires the construction of a comprehensive plan as well as the development of a lean culture across the organisation and thorough preparation and training of all maintenance staff (Jain et al., 2014; Hallioui et al., 2023).

The literature contains numerous applications of the productive maintenance strategy; for example, Ireland and Dale (2001) illustrated the application of productive maintenance in three different companies. The first company is based in The United Kingdom within the field of rubber products. The company applied productive maintenance to maintain their machines and their successful strategic objectives were standardising the organisational models across the world: raising autonomy; assuring empowerment to all organisational levels and related departments; introducing effective and efficient teamwork; ensuring an excellent structure for the concerned team; improving flexibility and response time to the needs of customers; improving competitiveness, quality, output and current performance; and minimising all associated cost (Ireland and Dale, 2001).

The second company, specialising in packaging services, has 160 factories distributed throughout Europe, North America, Africa and Asia (Ireland and Dale, 2001). The company likewise applied productive maintenance improve the performance of their workforce, which was increased around 75 per cent. Their successful strategic objectives included extending the breakdown success to other departments; continuing to support autonomous maintenance; expanding the development of the computerised systems; continuing the reduction of stock; sustaining zone maintenance systems to other associated machines; developing thermal imaging systems to blend mechanical parts; communicating with relevant suppliers for other systems like vibration analysis; continuing the development of systems for controlling the budget tightly; and reviewing the associated maintenance costs continuously (Ireland and Dale, 2001).

The third company, focused on manufacturing motorised vehicles, applied productive maintenance to increase productivity and optimise work space. They succeeded with their strategic objectives by increasing the market share for all their products (Ireland and Dale, 2001). Another case study utilised productive maintenance strategy in a company that is interested in electronics manufacturing, and that strategy contained multiple steps that succeeded in three different functions: reducing the cleaning times of associated tools; reducing the checking times of associated machines; and simplifying the lubrication tasks (Chan et al., 2005). In the food industry, Tsarouhas (2007) discusses how productive maintenance can be applied, especially in preparing bakery products. He suggests that this maintenance strategy can detect and eliminate defects such breakdown losses, set up and adjustment losses, idling and minor stoppage losses, reduced speed losses, quality defects and rework losses, and start-up losses (Tsarouhas, 2007). Per Singh et al. (2022), implementing a productive maintenance approach in metal industry would improve the overall equipment efficiency. In Ethiopia, a qualitative framework is prepared by partial least square structural equation modeling, and then, it is presented to raise the awareness of implementing productive maintenance in manufacturing industries (Gelaw et al., 2024).

One of the last two maintenance strategies that are previously mentioned in Figure 2 is *design-out maintenance*, which is defined as a strategy that aims for improvement activities rather than just actioning maintenance tasks to ensure system functionality, and it focuses on the improvement of system design to minimise the maintenance burden or even eliminating maintenance totally (Kumaresan et al., 2024). Furthermore, it redesigns the parts of the equipment that consume huge levels of maintenance effort or require spare parts' available budget, or which have rejectable high failure rates (Psarommatis et al., 2023). This strategy was well applied in different industry's domains such as steel industry (Shahin et al., 2018; Torre and Bonamigo, 2024), and railways (Granström and Söderholm, 2024). The last maintenance strategy mentioned in Figure 2 is *terotechnology maintenance*, which is an engineering practice that leverages management and finance to optimise installation, operations, and upkeep of a particular equipment, where it merges multiple aspects of the said equipment's lifecycle from its design to installation to commissioning, operations, and maintenance, and therefore, it keeps this equipment maintained at an optimal level overtime (Chattopadhyay, 2024). It was used rarely reported by the literature, but there were some applications in maritime industry (Lazakis and Ölçer, 2016) as well as food and beverage industry (Onyejaka, 2024).

With regard to the Fourth Industrial Revolution (Industry 4.0), the associated maintenance strategy is *PdM,* which is applied in this research project as a fault detection approach. The next section presents overview of Industry 4.0, and then describes PdM from various aspects like definition, applications and other related points.

2.2.3 Building Management System (BMS)

Nowadays, *BMS* is one of the systems that is widely used in the maintenance management at commercial buildings (Gobinath et al., 2024). It is a computer-based control system that can be utilised to monitor and manage the mechanical, electrical and electro-mechanical systems or services in a particular facility or building (Ebirim et al., 2024). Such systems or services include power, HVAC, physical and security access control, fire safety and fighting systems, water pumps, irrigation system, lifts, and lights (Okwandu et al., 2024). In specific view of HVAC, BMS can enhance the comfort level for buildings' occupants where it can monitor the temperature setting based on the operational schedules (Borodinecs et al., 2024).

BMS is also called as a building automation system or a computerised maintenance management system (Yong, 2024). Its mechanism collects data from around a particular building or facility and monitor it for any abnormalities where in case the data falls outside the predetermined ranges/ values, the system, accordingly, sends an alert to the person in charge indicating possible problems (Obiuto et al., 2024).

Based on the standard operating procedure at a particular facility or building, BMS software can be installed as a standalone application or to be integrated with other monitoring programmes (Heidari et al., 2024). More advanced BMS applications can monitor and manage a range of facility services across multiple technical platforms or organisational protocols where they provide the stakeholders with a single shared view of the facility's operations on a daily basis (Seraj et al., 2024).

2.3 Maintenance in Industry 4.0

2.3.1 The Fourth Industrial Revolution (Industry 4.0)

The Fourth Industrial Revolution (Industry 4.0), the realisation of the digital transformation of a field or organisation, is delivering real-time decision making to a particular function thereby enhancing productivity, flexibility and agility (Ghobakhloo, 2020; Ancillai et al., 2023). Industry 4.0 is revolutionising the way that companies or organisations can manufacture, improve and distribute their products and outcomes whereby they are integrating new technologies and tools like Internet of Things, cloud computing and data analytics, Artificial Intelligence and machine learning into their production facilities and throughout their operations and maintenance activities (Dalenogare et al., 2018). Nowadays, smart factories or facilities are equipped with advanced sensors, embedding software and robotics that are collecting and analysing relevant data to allow the best decision-making outputs (Mubarak and Petraite, 2020). According to Bai et al. (2020), the tools of Industry 4.0 will create an even higher value when data from production operations are combined with operational data from enterprise resource planning platforms, supply chain zones, customer service records, and other enterprise systems such as BMS in order to render entirely new levels of visibility and insight from the previous idle information.

The advent of Industry 4.0 digital technologies fosters increased automation, facilitates the implementation of predictive maintenance strategies, enables self-optimisation of processes, and, ultimately, unlocks a new realm of efficiencies and responsiveness that were previously unimaginable to customers (Lasi et al., 2014). As authorities embark on the development of smart factories or other intelligent commercial structures, they pave the way for the business industry to fully embrace the Fourth Industrial Revolution. By harnessing vast quantities of data gathered from sensors strategically placed throughout building premises, real-time insights into asset management are secured. Moreover, these data-driven tools enable the implementation of PdM practices, effectively reducing downtime for building components and machinery (Silvestri et al., 2020).

Using high-tech Internet of Things devices in smart buildings will increase the productivity and enhance the quality of equipment, components and machines in these buildings (Sony and Naik, 2020; Jan et al., 2023). Replacing manual inspection business models like the models of preventive maintenance with artificial intelligence-powered visual insight will minimise the operational errors or faults of a building's machines or components, subsequently saving both money and time (Raj et al., 2020).

Even with limited resources, quality control personnel can establish a cost-effective solution by utilising a smartphone connected to the cloud. This setup empowers them to oversee operational processes, including manufacturing, from any location with internet connectivity (Devezas and Sarygulov, 2017).

Utilising machine learning algorithms, which are part of Industry 4.0 tools, maintenance officers can detect faults immediately, rather than at further stages when maintenance activity is certainly costlier (Silvestri et al., 2020).

This research project is grounded in the premise that Industry 4.0 concepts and technologies hold applicability across diverse industrial sectors and commercial settings. Consequently, this research thesis delves into an examination of both the advantages and drawbacks associated with Industry 4.0 concepts as presented by Sony (2020). Table 3 illustrates the pros and cons of Industry 4.0.

Table 3: Pros and cons of Industry 4.0 (Adopted from Sony, 2020)

Pros	Cons
Strategic competitive advantage	Negative impact of data sharing in a competitive environment
Organisational efficiency and effectiveness	Total implementation of Industry 4.0 is necessary for success
Organisational agility	Handling employee and trade union apprehensions
Manufacturing innovation	Need for highly skilled labours
Profitability	Socio-technical implications of Industry 4.0
Improved product safety and quality	Cybersecurity
Delightful customer experience	High initial cost
Improved operations	
Environmental and social benefits	

As the main maintenance strategy of this industrial revolution is the PdM, which is applied in this present research project, the following subsection presents an overview of this strategy.

2.3.2 Concept of Predictive Maintenance (PdM) Strategy

PdM, in general, was first devised back in the late 1940s (Prajapati et al., 2012), and is basically used to assist in determining the status of an operated equipment in order to estimate the time of performing the maintenance actions (Levitt, 2011). According to Selcuk (2017), PdM can be defined as an exercise of pre-empting failures depending on historical data in efforts to optimise maintenance efforts. Moreover, it is conditioned-based maintenance to predict the likelihood of the failure time of a particular piece of equipment and advise which maintenance task should be performed accordingly (Goriveau et al., 2016; Garcia et al., 2022).

As a subset of preventive maintenance, predictive maintenance (PdM) facilitates the strategic scheduling of reactive maintenance tasks, thus averting unforeseen equipment failures in commercial buildings. The core principle of PdM lies in assessing the real-time operational status of specific systems and components to streamline operations and minimise maintenance expenses (Mobley, 2002). Hence, PdM serves as an augmentation to both preventive and reactive maintenance strategies. Figure 3 visualises this argument (Ran et al., 2019). Moreover, this research posits that PdM constitutes a crucial aspect of maintenance programs for commercial buildings. By relying on real-time operational data, PdM enables swift identification of potential issues, surpassing reliance solely on average or projected equipment lifespans. Additionally, PdM facilitates the prediction of necessary maintenance actions upon fault detection, enhancing proactive management of building assets. Verbert et al. (2017) have assured that routine maintenance does not typically identify faults, but this can be sorted by implementing a PdM management programme. This assurance is also valid with fault detection approaches (Ji et al., 2024).

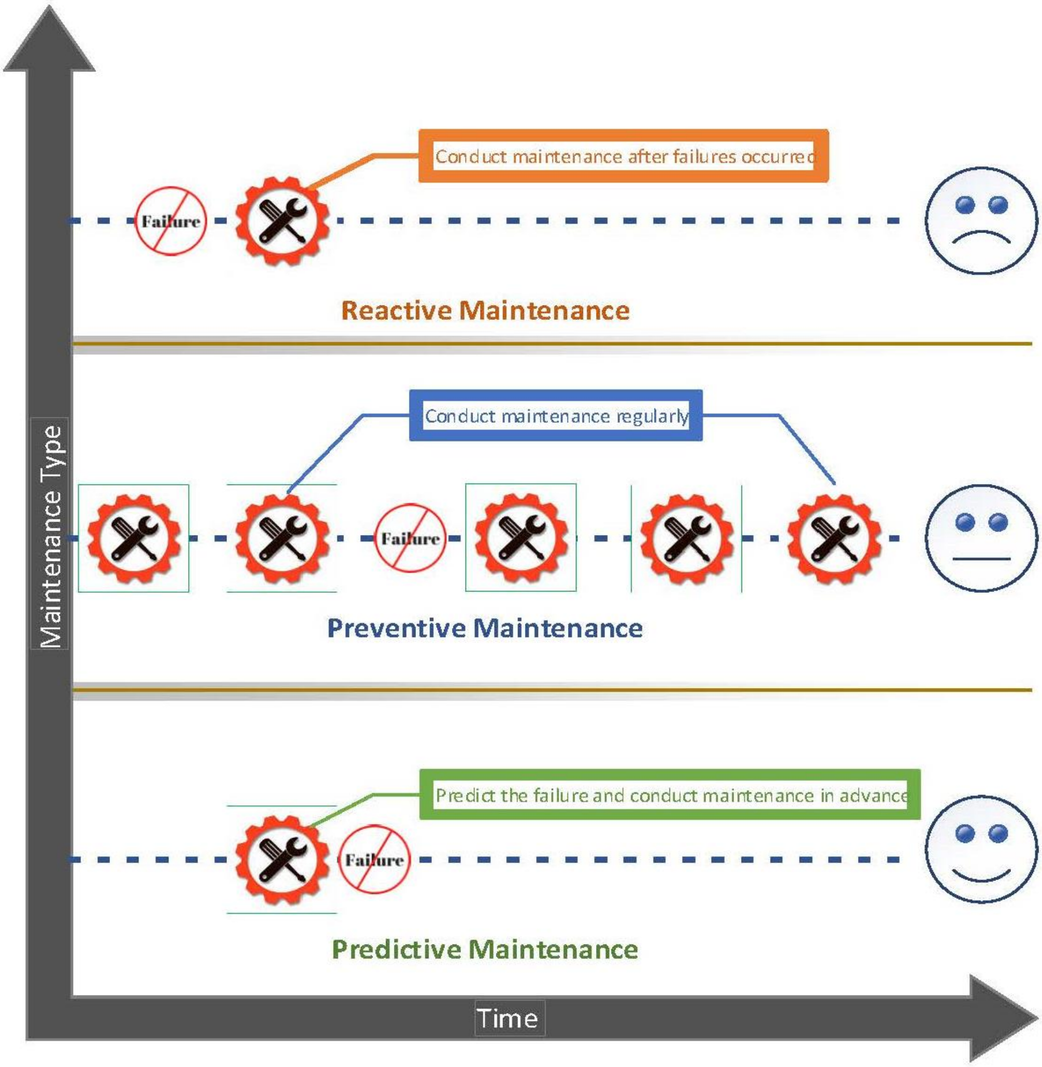

Figure 3: Effectiveness of predictive maintenance strategy

Having acknowledged PdM as a significant paradigm, well-known and key industrial manufacturers have invested in PdM to maximise machine parts and their uptime and disseminate maintenance to increase cost-efficiency (He et al., 2017). According to Wang et al. (2017a), scheduled and unscheduled shutdowns, astronomical operation and maintenance costs, avoidable inventory, and undue maintenance activities performed on particular equipment, machine, or system can be diminished with PdM. However, any technique has its own pros and cons: the main advantages of PdM or fault detection approaches include making repairs based on equipment condition, a potential savings of up to 20 per cent, as well as enriching safety aspects of equipment and equipment surrounding (Ramadan et al., 2024). Disadvantages of PdM result when an organisation's culture of hesitating neglects to assign a sufficient budget for the same (Hemmerdinger, 2014).

Large city downtowns are mainly comprised of commercial buildings, so owners or caretakers of these buildings make efforts to develop strategies and plans for their upkeep and to control their equipment. As mentioned previously, PdM is one of the said strategies, a strategical monitoring approach that optimises the usability of a particular piece of equipment or system (Kullu and Cinar, 2022). PdM strategy, in line with Industry 4.0, can determine the best time to detect equipment or system faults using machine learning models or artificial intelligence (Sahal et al., 2020). Bousdekis et al. (2019) have outlined the benefits of developing the said strategies, especially PdM strategy, suggesting that they have demonstrated a positive impact for improving many aspects related to various organisations, including maintenance and operation costs, replacement costs, repair downtime and verifications, machine failures, spare part stock, part service life, production, operator safety and overall profit. Using the outputs of a novel artificial intelligence approach, PdM strategy can serve as a control task that maintains buildings efficiently (Cotrufo et al., 2020). Moreover, PdM strategy ensures the sustainability of the buildings, as it allows humans and machines to be harmonised (Simon et al., 2022; Villa et al., 2022). In contrast, Achouch et al. (2022) note the challenges of PdM strategy regarding four aspects: financial and organisational limitations, the limitations of data sources, activity limitations for repairing machines, and the limitations in the deployment of industrial PdM models.

In line with Industry 4.0 concepts, PdM uses data analytics to predict and then detect equipment faults in an effort to rectify operational inefficiencies with a goal of eliminating the root cause of potential system flops (Tiddens et al., 2020). Amruthnath and Gupta (2018) suggest that observing equipment performance and monitoring the critical parameter of a particular system are one main PdM technique. Moreover, Huang and Wang (2016) consider component monitoring of a particular system as one preventive maintenance theme, which is the derived category of PdM. According to Nguyen and Medjaher (2019), fault detection and diagnosis and condition monitoring are critical components of PdM. To perform an automatic fault detection, PdM requires big data collection, an analytics platform and data sufficiency (Sharma et al., 2011). The analytics platform must incorporate domain expertise, so that the machine learning algorithms will have an intended application to the system that is under study (Faccio et al., 2014; Ogunbayo et al., 2023). According to Garg and Deshmukh (2006), data sufficiency is the availability of data from enough sensors, actuators, meters or control parameters so that a meaningful analysis can be performed accordingly.

Per Ran et al. (2019), maintenance in business industrial life is typically reactive maintenance and preventive maintenance, with the PdM strategy applied only in critical situations. Mallioris et al. (2024) believe that these maintenance strategies, which are reactive and preventive maintenance, do not consider the vast amount of data that can be generated as well as the available approaches that are aligned with Industry 4.0 principles, such as machine learning, Internet of Things, artificial intelligence, big data, advanced data analytics, data driven, cloud computing and augmented reality. Based on the thoughts of Chukwuekwe et al. (2016) as well as Wang (2016), PdM strategy aligns seamlessly with the principles of Industry 4.0, fostering a transformative shift in industrial processes driven by intelligent data processing methodologies. This paradigmatic evolution in maintenance practices has inspired confidence in the PdM concept within this research project. Specifically, it aims to assess the operational status of CWS and provide relevant stakeholders, including managers, maintenance engineers, and system users, with real-time insights into the health of these systems. This empowers proactive decision-making and facilitates timely interventions when necessary. To summarise, Figure 4 explains the idea behind PdM strategy (Cachada et al., 2018), while Table 4 represents the correlation between maintenance strategies and the industrial revolutions (Poór et al., 2019).

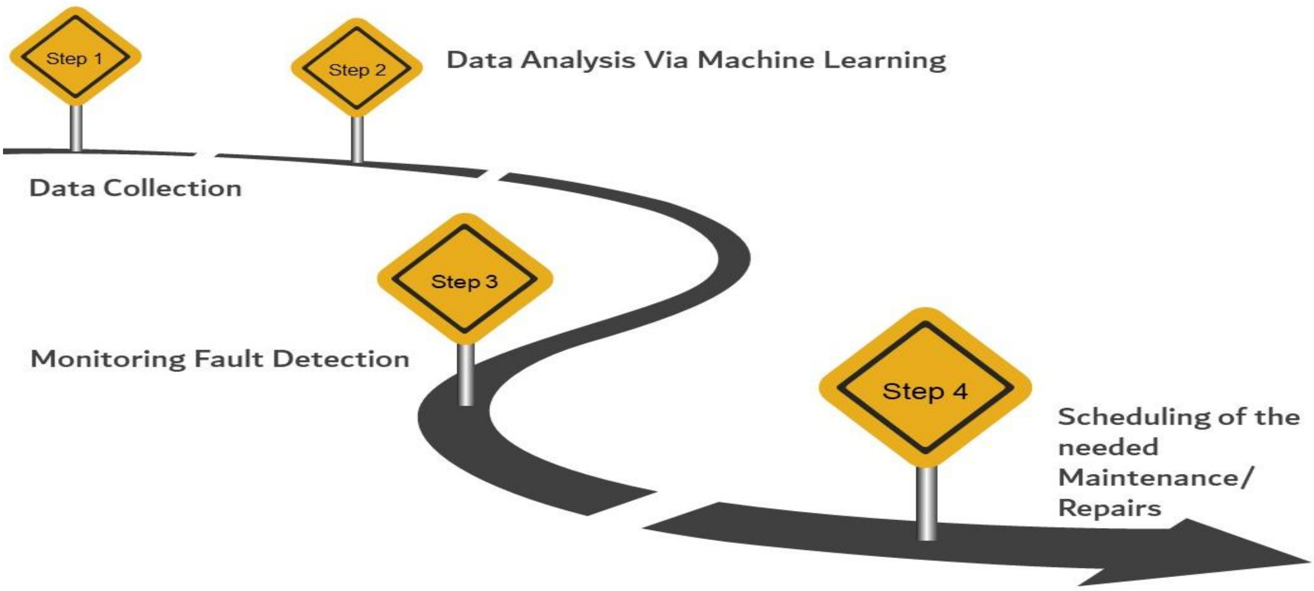

Figure 4: Proposed predictive maintenance strategy

Table 4: Correlation between maintenance and industrial revolutions

Industrial Revolution	Industry 1.0	Industry 2.0	Industry 3.0	Industry 4.0
Characteristics of the industry revolution	Mechanisation, steam power, and weaving loom	Mass production, assembly lines, and electrical energy	Automation, computers, and electronics	Cyber physical systems, Internet of Things, networks, cloud, machine learning, and bi-directional amplification system
Maintenance strategy	Reactive maintenance	Planned/ scheduled maintenance	Productive maintenance	PdM
Type of inspection	Visual	Instrumental	Sensor monitoring	Predictive analysis
Overall equipment/ system effectiveness	Less than 50%	Between 50% and less than 75%	Between 75% and 90%	Greater than 90%
Maintenance team reinforcement	Trained craftsmen	Inspectors	Reliability engineers	Data scientists

Before exploring the applications of PdM, which are discussed in subsection 2.3.4, the thesis author will examine the relationship between quality engineering and maintenance management, specifically with PdM, as the research has utilised quality engineering tools within the methodological framework, explained in detail in Chapter 5.

2.3.3 Quality Engineering in Maintenance Management

Applying quality engineering and industrial quality control concepts in maintenance management and processes is one key to making it a successful programme. Having said that, Márquez et al. (2009) presented a modelled framework containing eight phases linked to four blocks of effectiveness, efficiency, assessment and improvement. The philosophy behind this framework was to create a strategic plan for an organisation to improve the outcome of its maintenance programme. Applying the maintenance control function is another valuable technique for improving maintenance management (Duffuaa and Haroun, 2009; Ogunbayo et al., 2023). This function contains four phases: planning, organising, implementing and controlling. Specifically, this research relies on the paradigm of the last phase (controlling), which is measuring the performance of the maintained equipment, taking predictive and corrective actions, and reviewing the associated policies and procedures. Quality control is one of the main domains for evaluating the risks of maintenance activities (Kosztyan et al., 2019; Ertem et al., 2022). In fact, Chanter and Swallow (2008) as well as Nasr et al. (2023) argue that constructing industrial quality control procedures in maintenance projects will prevent the organisation from any managerial failure with any contractual party.

One important concept of maintenance management is process improvement, which is part of the industrial quality control. This was performed in many maintenance applications using the typical pattern of lean six sigma that has five phases: define, measure, analyse, improve and control (Wang et al., 2012b; Zasadzien, 2017; Schafer et al., 2019; Vaidya et al., 2020; Hamali et al., 2022). With specific regard to this project, the quality engineering approach is data driven in the PdM field. It is one important feature of the Fourth Industrial Revolution, defined previously here as Industry 4.0 (Kenett and Redman, 2019). Many research studies have proposed data driven PdM frameworks for multiple purposes as part of quality control such as in green manufacturing (Rodseth and Schjolberg, 2016); in railways (Gerum et al., 2019); in oil refinery plants (Antomarioni et al., 2019); in mechanical, electrical, and plumping components (Cheng et al., 2020); and in huge refineries (Pisacane et al., 2021). Zonnenshain and Kenett (2020) as well as Saihi et al. (2023) suggest that quality engineering is a crucial dimension of the processes in maintenance, and consequently should be a data driven. In line with this, they introduced a framework termed Quality 4.0. As per Zonta et al. (2020), the adoption of the PdM strategy emerges as a prevalent practice in the Quality 4.0 era. The associated data play a pivotal role in generating insights that can inform predictive decision-making processes. Therefore, within the realm of quality management, PdM is oriented towards cost reduction and failure prevention by pinpointing the components of a specific system that are prone to failure (Lee et al., 2019; Haleem et al., 2023).

Statistical quality control and statistical process control methods are two of the quality methods that support maintenance management. Escobar et al. (2024) applied these two methods in maintaining a manufacturing sector via three case studies, one for structured data, and two for unstructured data, they found that such methods could optimise the production processes and enhance the associated systems availability. Five steps were proposed as a procedure to show case how statistical process control could support the maintenance management, which are analysing particular components and assemblies as well as the associated production processes with regard to the utilisation of statistical process control as a test and control strategy, defining the function-critical test characteristics for the said components, planning and defining the statistical process control loops within individual production processes, carrying-out test process suitability, machine and process capability investigations, and continuing the monitoring of the production process utilising statistical process control (Bracke, 2024). Control charts method is also one of the quality engineering techniques that can support maintenance management. In one of the factories, the degradation of a particular manufacturing unit grows parallelly with the production rate and the time of its utilisation, which accordingly affects its reliability, availability, and the product quality, and in order to improve the entire process, which includes preventive maintenance for the said unit, and to minimise the cost, control charts method was utilised to build an optimisation model, and it showed a good effectiveness in such processes (Kammoun et al., 2024).

2.3.4 Applications of Predictive Maintenance in Line with Industry 4.0

In the age of Industry 4.0 and following what has been mentioned in previous subsections, maintenance officers require specific technical skills. They need the ability to manage maintenance processes, controlling the impact of PdM on a particular commercial building's organisation from several aspects such as business goals, on efficiency, on quality, and on safety points of view (Papcun et al., 2018; Antony et al., 2023). Nowadays, more and more resources are devoted to maintenance management, potentially leading the organisers of the commercial buildings to manage maintenance activities in a remote-control way. In this regard, the ability to analyse the huge amounts of data that are produced by a building's assets, machines or systems is one of the ongoing trends in the era of smart technologies (Achouch et al., 2022). Radio frequency identification, for example, and supervisory control, data acquisition, near field communication, wireless sensor actuator networks, simulation models, prediction models via machine learning algorithms, Internet of Things sensors and wireless sensor networks are several new innovative technologies that support fault detection and diagnosis as well as the overall health condition of a particular system in commercial buildings (Poór et al., 2019; Lambán et al., 2022).

The recent applications of the PdM strategy were in different domains. For instance, Righetto et al. (2021) reviewed many PdM strategic applications on multiple electrical systems. They refer to a study, for example, that was presented in a grey language model and used genetic algorithm to predict the tendency of gas content in the insulating oil of power transformers. They also note another study that applied an artificial neural network algorithm in a nuclear power system as part of the PdM strategic programme. In a small bottling plant, Kiangala and Wang (2018) applied supervisory control and a data acquisition approach to predict the early faults for a particular conveyor motor. Shukla et al. (2022), in discussing the thermography method widely used in PdM strategic applications, reviewed multiple studies that used the said method such as detecting the bearing damage of a particular induction motor and detecting the faults in the inner constructions of wind turbine rotor blades. Likewise, this method has been used to detect the faults of electrical transformers (de Faria Jr et al., 2015). On a real cutting machine woodworking machinery, PdM strategic technique was applied to predict the performance of the said machine using the random forest algorithm (Paolanti et al., 2018). The algorithm was also used to predict the faults of high sensitivity motors by analysing historical data of aircraft maintenance systems (Yan and Zhou, 2017). Cinar et al. (2020) suggest that machine learning algorithms such as random forest are beneficial for the development of PdM strategic programmes for electrical systems or equipment like motors.

The PdM strategy was implemented in water-related systems as well. In Egypt, for example, Saidy et al. (2020a) utilised a digital twin technique to predict the faults of a particular water desalination system, finding that the technique showed a very good accuracy. Once again, the faults of the said system were predicted by using statistical process control charts, but as per the authors, digital twin has a better prediction performance than the charts (Saidy et al., 2020b). Digital twin technique was also utilised in two other studies to predict the performance degradation in transmission unit of computer numerical control machine tools (Yang et al., 2022; Luo et al., 2020b). An experimental study by Him et al. (2019) collected data from 16 parameters like the pressure of incoming cooling water and then applied a decision tree algorithm to predict the faults of a can welding machine, concluding a good prediction accuracy. Furthermore, Wellsandt et al. (2022) suggest the use of a software called digital assistant as part of PdM strategic programme. In manufacturing sectors, a physical model-based approach was used as a PdM strategic application to predict the remaining useful life of multiple machines via a simulation model (Cao et al., 2022). In the railway domain, four studies recommended the use of a convolutional neural network algorithm to detect the defect of railway plugs, the wheels, the current collector strips of pantographs and the train bogies, respectively (Du et al., 2020; Krummenacher et al., 2018; Karaduman and Erhan, 2020; Kou et al., 2019). For airports facilities, the PdM strategy was utilised for various purposes via different techniques. For example, Verhagen and De Boer (2018) adopted a data driven approach by applying proportional hazard models that aimed to identify the operational factors affecting the reliability of nine aircraft components such as thermal actuator. The airport baggage system was also considered in a PdM strategy. In this regard, Koenig et al. (2020) applied the technical action research approach, while Gupta et al. (2023) applied supervised learning algorithms like random forest to predict the noise in the conveyors. The second study, that of Gupta et al. (2023), utilised Internet of Things sensors to capture the noise and considered the root mean square values of the signals, which were captured by the aforementioned sensors, in training their models.

These aforementioned studies were just some of the PdM strategic applications in a variety of fields. Here in this thesis, the studies, which were applied PdM strategic techniques for the CWS in commercial buildings, are highlighted. PdM can be supported by many intelligent maintenance approaches such as the combination of Convolutional Neural Network and Long Short-Term Memory (Liu et al., 2022a), artificial intelligence (Stanton et al., 2023; Ucar et al., 2024), Internet of things, digital twin, robotics, data fusion (Stanton et al., 2023), data balance and one-dimensional deep learning (Ileri et al., 2024). Jakubowski et al. mentioned that PdM can be supported by utilising data analytics tools and machine learning algorithms. They classified these algorithms into ''*neural networks*, *support vector machines*, which finds a hyperplane that separates different classes of observations in a high-dimensional space, *Tree-based models* recursively partition a feature space into subsets based on the most informative features in which the predictions of many weak learners are converted into one strong prediction, to increase the predictive capabilities and generalization, *Probabilistic models* capture uncertainty by modelling data distributions or sequences using probabilistic frameworks, commonly applied in areas such as anomaly detection, *Clustering* *algorithms* group similar data points according to their characteristics, allowing data exploration and pattern discovery in unlabelled data'' (2024, p. 5). The next section presents a systematic literature review for all four CWS components and examines the tools and methods utilised to predict the faults of the said system, as well as the fault detection strategic framework that were proposed and implemented. In addition to the motivation behind focusing on CWS, which was mentioned in the first chapter, CWS deserves to be focused on; because it has become a cornerstone of modern cooling technology where it offers efficient and reliable cooling solutions in buildings (Liu et al., 2024). Following that, the next section discusses the findings of the literature review and furnishes the related research gaps. Finally, the associated research questions of this thesis are presented in the closing section of this chapter.

2.4 Literature Review Methodology

The methodology of the literature review has been actioned by making a systematic literature review; outcomes have been finalised as detailed in the next two subsections.

2.4.1 Systematic Literature Review

Typically, a systematic literature review compiles varied research studies, delineated and discussed to find answers to a research question in adherence to careful, stringent methods (Briner and Denyer, 2012; Hiebl, 2023). Here in this research thesis, the protocol as outlined by Kitchenham (2004) has been followed. The systematic literature review underwent four stages. Table 5 gives a glimpse of these stages which are then explained in detail in upcoming subsubsections

Table 5: Stages of the systematic literature review

Stage Number	Stage Title	Description
1	Preparation	To determine the guiding research question
2	Base of the research	To determine how to access to the targeted research studies
3	Criterion of the literature selection	To determine which study should be considered in this research thesis
4	Quality assurance	To finalise the exact number of the considered studies

2.4.1.1 Stage #1 of Systematic Literature Review

This stage is the launching of the systematic literature review. It consisted of defining the guiding research question of this research project. A research question is defined as a question that a study or research project intends to answer (Qiu et al., 2020; Hunziker and Blankenagel, 2024). To generate a strong research question for any field, especially in technology, engineering and management, several principles are recommended for evaluation (Leong et al., 2015; Narula, 2024) (see Figure 5).

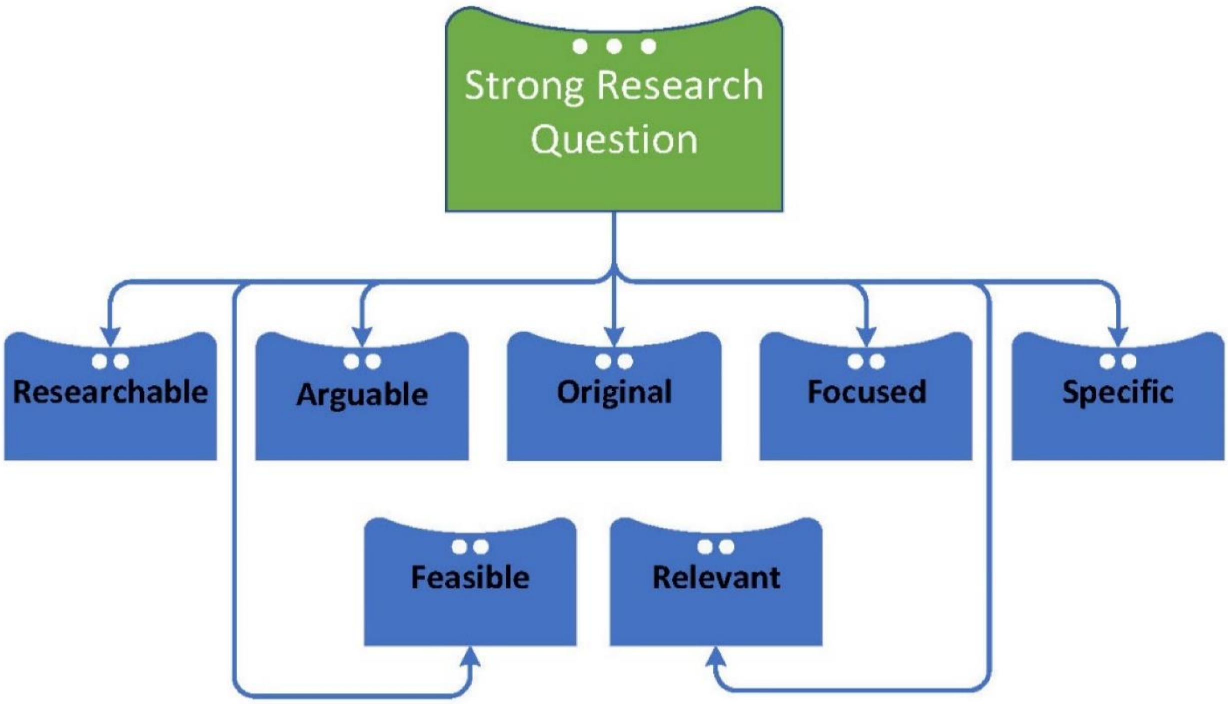

Figure 5: Principles of strong research questions

As the idea of this research thesis is to examine the studies that proposed a PdM strategy for CWS from a managerial point of view, the following guiding research question arose:

"What are the approaches or methods to implement predictive maintenance or fault detection for a chilled water system at commercial buildings?"

2.4.1.2 Stage #2 of Systematic Literature Review

This stage shows the search string and source selection. For the search string, operators called Boolean allow the researcher to use specific keywords with symbols such as "AND" and "OR" to limit the relevant research papers (Aliyu, 2017; Chigbu et al., 2023). Based on the information of the previous sections, Boolean operators were exercised in the search engines as shown below in Figure 6.

("Industry 4.0" OR "Quality 4.0") AND ("Machine learning" OR "Deep Learning" OR "Data Driven" OR "Artificial Intelligence") AND ("Predictive Maintenance" OR "Faults Detection" OR "Faults Diagnosis" OR "Condition Based Maintenance" OR "Condition Monitor Maintenance") AND ("Architecture" OR "Framework" OR "Management" OR "Program") AND ("Ontology" OR "Reasoning") AND ("Chilled Water System" OR "HVAC" OR "AC" OR "Chiller" OR "Cooling Tower" OR "Primary Pump" OR "Secondary Pump" OR "Condenser Pump" OR "Terminal Unit" OR "Air Handling Units" OR "Fan Coil Unit") AND ("Commercial Buildings" OR "Large Facilities").

Figure 6: Systematic literature review's Boolean operators

The search engines or database used in this research thesis, in addition to the Pure Database of the University of Strathclyde, are Scopus, Web of Science, Google Scholar, CrossRef, IEEE, Springer, ACM Digital Library, ProQuest, Inspec, ScienceDirect (Elsevier), EBSCO, Wiley Online Library, Taylor and Francis, and MDPI, as they are persuasive and reliable (Zonta et al., 2020; Dalzochio et al., 2020).

2.4.1.3 Stage #3 of Systematic Literature Review

Subsequent to the activities conducted in the preceding two stages, all studies deemed irrelevant to the objectives of this research project were excluded. The exclusion criteria outlined in Table 6 below were then applied to execute the subject stage.

Table 6: Exclusion criteria

Exclusion Criteria	Reference
Papers (journals or conferences) that are not related to PdM or fault detection in a beeline	Zonta et al., 2020; Dalzochio et al., 2020; Sajid et al., 2021; Divya et al., 2023
Papers that are not related to Industry 4.0 or Quality 4.0 or data driven analysis or data mining in a beeline	Zonta et al., 2020; Dalzochio et al., 2020; Sajid et al., 2021
Grey literature	Dolatabadi and Budinska, 2021
Non-English publications	Dolatabadi and Budinska, 2021
Pre-1999 publications	Cioffi et al., 2020
Papers that are not peer-reviewed	Inayat et al., 2015

2.4.1.4 Stage #4 of Systematic Literature Review

In this final stage, and as advised by Zonta et al. (2020), filtering processes have been implemented on the remaining papers where duplicate ones were removed; thereafter, titles and abstracts were analysed, and then entire texts were analysed. Also, double checking confirmed that the remaining articles fulfilled the basic research rules – presenting the purpose of the research clearly; using an ontology or reasoning; showing a framework, an architectural proposal or a research methodology; and presenting and discussing the results of the research – to uphold and ensure the quality of the literature review methodology (Kitchenham, 2004).

2.4.2 Search Results

From the second stage of the systematic literature review up to the fourth stage, a total of 168 studies were considered research papers in this research thesis. Table 7 below presents the paper selection journey and how many papers remain after each stage of the systematic literature review, while Figure 7 presents the number of journal articles and other considered literature.

Table 7: Journey of the systematic literature review

Action	Stage Number	Number of Studies
Initial Search	2	1,094
Exclusion Criteria	3	483
Quality Assurance	4	168

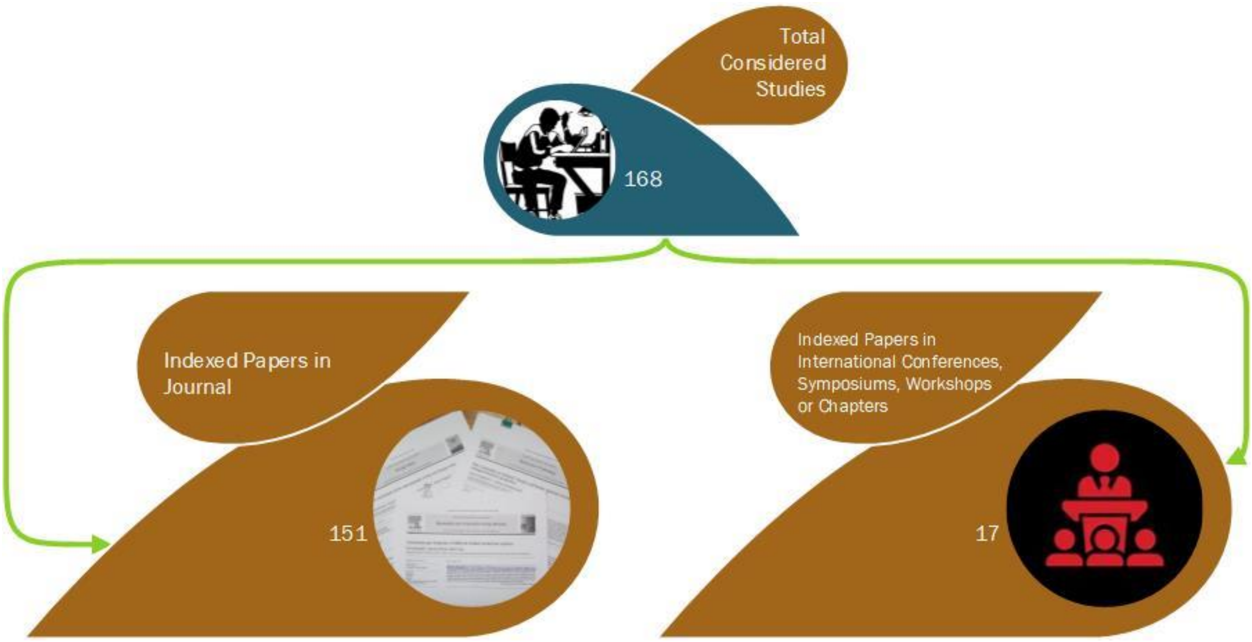

Figure 7: Considered studies in the main literature review

2.4.3 Literature Review Continuation

The literature review encompassed studies up to May 2022. However, to ensure the research thesis remains current, the focus has been extended beyond this timeframe. Consequently, the methodology outlined by Kitchenham (2004) was upheld, leading to the inclusion of an additional 14 research papers. This brings the total number of considered studies, up to June 2024, to 182.

2.5 Applications of PdM Strategy for Chilled Water System

This section delves into the studies outlined in the preceding section, organised into four subsections, each dedicated to a specific CWS component. The review presented here follows the PdM workflow advocated by Achouch et al. (2022). The said PdM workflow is summarised below in Table 8.

Table 8: Predictive maintenance workflow (Adopted from Achouch et al., 2022)

Step Number	Step Title	Step Description
1	Initial Stage	To understand the needs such as the maintenance issue that a particular facility is experiencing such as the faults in a particular system
2	Data Stage	To identify the source of data, its sample size and the period of data collection
3	Model Stage	To choose the method like the algorithm of machine learning, to evaluate the detection model, and then to control the under-study's system; in addition, this stage includes providing solutions to the occurred issues like systems faults

2.5.1 Chillers

PdM for chillers has been addressed through various approaches, ranging from overarching maintenance frameworks to specific fault detection and diagnosis protocols. These endeavors aim to align with the swift pace of industrial advancement. According to Rueda et al. (2005), the development of faults detection and diagnosis for liquid chillers is based on artificial intelligence techniques at one of the laboratory test facilities. By using an artificial neural network, they predicted the temperature increment of the water-cooled condenser with almost 99 per cent accuracy. In the United Kingdom, another study by Tassou and Grace (2005) applied artificial intelligence to predict the refrigeration leak fault of a particular liquid chiller at one of the large commercial buildings. This fault was also predicted by using the Kalman Filter algorithm (Navarro-Esbri et al., 2006). Han et al. (2020) integrated *k*-nearest neighbours, support victor machine and random forest algorithms into an ensemble diagnostic model to predict the said fault, and then also achieved around 99 per cent accuracy. According to Liu et al. (2022b), as a refrigeration leak fault seriously affects the reliability of chillers, they therefore proposed a predictive model based on the adaptive moment estimation algorithm with multi-layer feedforward neural networks trained with the error backpropagation neural network.

In Hong Kong and China, seven studies applied principal component analysis to predict several faults of sensors that are reading operational parameters, such as chilled water flow rate, condenser water flow rate and evaporating pressure (Hu et al., 2016a; Xiao et al., 2006; Mao et al., 2018; Wang and Cui, 2005; Xu et al., 2008; Wang et al., 2010; Hu et al., 2016b). Moreover, Hu et al. (2012) applied self-adaptive principal component analysis to enhance sensor fault detection and diagnosis efficiency. In contrast, Li et al. (2016a) report that support vector data description is better than principal component analysis, as it is not particularly efficient when it comes to predicting complex sensor faults, due to the weakness of Q-statistic plot, which is part of the principal component analysis. Xia et al. (2021b), however, did support this argument as they suggest that principal component analysis has a limited performance in predicting and then detecting the chiller faults. Accordingly, they enhanced the said method via two other methods – kernel density estimation and kernel entropy component analysis. Their study was built on data from an ASHRAE project to predict and then detect condenser fouling fault. Munir et al. (2023) used machine learning to predict the said fault, a condenser fouling, but they did not mention the algorithm that was utilised to make the prediction model nor include any clear information about the associated data.

Choi et al. (2005) utilised data from one of ASHRAE projects to predict multiple sensor faults by collecting data of one operational parameter, the evaporator water entering temperature. They applied three data driven techniques: multiway dynamic principal component analysis, multiway partial least squares and support vector machine. Based on their results, they determined that the first two techniques, which employed generalised likelihood ratio test, are more accurate than the neural network one, which is a support vector machine. This finding was corroborated by another study performed by Namburu et al. (2007) to predict eight different faults of chillers by using the same three techniques. From another ASHRAE project, Schein and Bushby (2006) applied a hierarchical rule-based fault detection and diagnosis to predict the faulty operation scheduling during three different weather seasons, but with no broaching of the data sample of their study nor providing a solution to fix that fault. Genetic algorithm was applied to present a fault detection model for sensor fault in a particular chiller, and their model was built without any characteristic assumption to detect and diagnose the said fault (Gao et al., 2023).

The faults mentioned above, like sensors faults or condenser fouling, were not the only faults considered in the previous studies. For example, at one commercial building in Hong Kong, chiller performance indices were utilised to predict evaporator fouling by applying a regression model (Zhou et al., 2009a). Performance indices of a particular chiller were again utilised to predict the other seven faults, such as condenser fouling, by applying fuzzy modelling and artificial neural network techniques (Zhou et al., 2009b). Both previous studies concluded that the utilisation of the performance indices may not be effective in fault diagnosis. On a related note, Comstock et al. (2001) presented data of one of the ASHRAE projects that had already tested the sensitivity of some chiller faults, but they did not specify these faults nor present any prediction model related information. Condenser fouling faults as well as evaporator fouling faults were predicted by applying support vector machines and *k*-nearest neighbours (Albayati et al., 2023). Although fault free mode was considered in this study as well as, the accuracy of their prediction model was around 93 per cent, but their sample size was too small as it just contained 30 observations of the supply air average humidity.

Han et al. (2011) applied faults detection and diagnosis protocol for multiple simultaneous faults of two chillers using combined support vector machine and multi-label techniques. These combined techniques showed high accuracy detection of the chillers' performance, although the experimental data were limited. On a separate note, such techniques require sufficient training data for a high-quality output (Shi and O'Brien, 2019; Mirnaghi and Haghighat, 2020). Per Ma and Wang (2011), significant degradation in chiller performance can be effectively detected through the application of a hybrid quick search method. This method involves characterising performance indices of specific operational parameters, such as the temperature of the condenser water supply.

A high chiller load affects the performance and leads to the appearance of faults such as condenser fouling. Yu and Chan (2012) suggest that via two studies, the first one pertained to improving chiller management using a regression model, while the other one proposed an assessment strategy of chiller performance using clustering analysis. According to Zhao et al. (2012), early identification of the said fault, the condenser fouling, is essential to highly maintain chiller performance; accordingly, they developed a virtual sensor for that fault. Similarly, Magoulès et al. (2013) proposed a significant fault detection and diagnosis strategy using a recursive deterministic perceptron neural network to predict faults related to chiller load. By utilising data of oil feed pressure, a regression model was built to detect the chiller faults and found that refrigeration leak and condenser fouling faults are mostly repeated faults (Ssembatya and Claridge, 2024).

Data from one ASHRAE project were utilised in 12 different studies to predict condenser fouling along with other unidentified faults (Zhao et al., 2013a; Zhao et al., 2013b; Zhao et al., 2013c; Yan et al., 2018a; Yan et al., 2020; Yan et al., 2017; Li et al., 2016b; Li et al., 2016c; Li et al., 2016d; Wang et al., 2020; Wang et al., 2017b; Li et al., 2016e). The first study applied exponentially weighted moving average control charts; the second one applied Bayesian belief network; the third one applied support vector data description; the fourth one used support vector machine; the fifth one applied conditional Wasserstein generative antagonistic networks; the sixth one combined extended Kalman filter and a recursive one-class support vector machine; the seventh one derived a tree-structured fault dependence kernel; the eighth one used principal component analysis along with support vector data description; and the ninth one adopted linear discriminant analysis. With regards to the tenth, one dimensional convolutional neural network and Gated Recurrent Unit were applied, while the eleventh one conjoined a distance rejection technique with Bayesian network by transforming the chiller's fault detection and diagnosis problem into a single-class classification problem. The last one in that group predicted seven different faults by using the large margin information fusion method, finding this method more accurate than others, such as multi-class support vector machine, artificial neural network, decision tree, quadratic discriminant analysis, Ada Boost and logistic regression. All of these research studies showed significant accuracies but did not include fault free situations in their data training. Extended Kalman filter algorithm was applied to present a fault detection model for a residential chiller, and it was successfully detected an undercharge fault with 70.6 per cent accuracy (Chintala et al., 2024).

Moreover, three additional studies used the same ASHRAE project to compare different models for the same purpose as the previous 12 studies (Tran et al., 2016a; Tran et al., 2016b; Tahmasebi et al., 2019). The first study presented two models, one by support vector machine and the second by combining nonlinear least squares support vector regression based on the differential evolution algorithm with exponentially weighted moving average control charts. It was determined that the second one has a better prediction. The second study, applying multiple linear regression, kriging algorithm and radial basis function, led to the conclusion that the radial basis function is better in prediction than the other two techniques. The outcome of the third study showed that an artificial neural network is more accurate than *k*-nearest neighbours and bagged tree algorithms. The considered faults in these three studies were not fully described. The impact of condenser fouling was discussed and, accordingly, a decoupling-based fault detection and diagnosis method was proposed to predict this fault (Zhao et al., 2014). This method was applied by observing the cooling capacity and suggested to clean the condenser water tubes before data collection. Later, this method was applied again alongside two other methods for efficiency comparison purposes in detecting multiple simultaneous chiller faults (Zhao, 2015). The aforementioned other two methods were multiple linear regression and simple linear regression, but it was determined that these two methods are not very effective.

Bonvini et al. (2014) argue that observing the energy consumption of a chiller is valuable for predicting the faults related to the high load. They introduced a fault detection and diagnosis approach based on an unscented Kalman filter, which is an advanced Bayesian nonlinear state estimation technique, to predict three of the aforementioned faults. Unscented Kalman filter is a proven technique which does not require long-time focused studies when applied in individual CWS components in different commercial buildings (Sun et al., 2013). This pretext came from a study that used and unscented Kalman filter to detect gradual chiller degradation based on the Grey-box model at the Jinmao tower of China (Sun et al., 2013). The said model is based on statistical process control by measuring and analysing two operational parameters – chilled water flow rate and chilled water returning temperature – where data were collected data every one hour for 20 days (Sun et al., 2013). Moreover, Karami and Wang (2018) integrated the Gaussian mixture model regression technique with the unscented Kalman filter to model a nonlinear system based on the measurement data of four operational parameters, finding this efficient in detecting chiller degradation and reducing the number of detecting sensors as well.

The chiller faults that are either related to the high load or from other issues can be linked to human interventions and, accordingly, can influence occupant satisfaction. Having said that, maintenance characteristics such as skills, knowledge and number of maintenance labourers were addressed by Au-Yong et al. (2014) at one of the office buildings by using mixed methods. Following a survey that was shared with selected occupants and key responsible staff, they predicted eight of the aforementioned maintenance characteristics via a regression model, and then found empirical evidence that such communications with the concerned parties can improve maintenance management and can enhance occupant satisfaction. With regard to high performance levels, it has been noticed that some commercial buildings are using BMS software in relation to their maintenance activities. For example, Alonso et al. (2019) suggest utilising BMS, in addition to plant management software, to control CWS performance; they applied this idea by observing the coefficient of chiller performance at a large hospital. Yan et al. (2014) proposed a chiller fault detection and diagnosis procedure to develop the BMS via a hybrid model that integrated a support vector machine with autoregressive exogenous variables, thereby obtaining high prediction accuracy with minimal false alarm rate. Identical results were presented by McIntosh and Mitchell (2000) using statistical analysis via modelling the log-mean temperature difference and condenser water temperature difference to predict six faults of chillers. In addition, two studies proposed a control strategy for chiller operation uncertainty by using the Monte Carlo simulation (Miyata et al., 2019; Liao et al., 2015).

To curb the deterioration of chillers, Beghi et al. (2016) proposed a semi data driven approach by using principal component analysis in differentiating anomalies from normal operation variability and a reconstruction-based contribution approach to segregate variables related to faults. To minimise fault prediction errors, Kocyigit (2015) claimed to use a fuzzy interference system and Levenberg–Marquart-type artificial neural network algorithm by evaluating two operational parameters: condenser pressure and evaporator pressure. In addition to fault free mode, he concentrated on faults such as refrigerant leak, evaporating fouling, compressor overcharging and condenser fouling. Additionally, Gao et al. (2019a) presented a fault detection and diagnosis strategy to detect sensor faults by combining a maximal information coefficient with a long short-term memory network.

Recently, it has been noticed in the market that multiple providers of maintenance solutions for commercial buildings are proposing building information modelling and a building automation system in addition to BMS. Cheng et al. (2020) utilised building information modelling with Internet of Things sensors to predict chiller faults through artificial neural network and support vector machine algorithms. However, their approach could not be applied for other CWS components due to differences in operational parameters. From BMS data, Escobar et al. (2020) used a fuzzy logic clustering approach for smart buildings, called the learning algorithm for multivariable data analysis, and succeeded in reaching a zero-error state for chiller control. Besides BMS, Srinivasan et al. (2021) have used explainable artificial intelligence for chiller fault detection and diagnosis, showing the significance of acquiring the trust of maintenance officers. Hu et al. (2019) used building automation system for collecting data of chiller operational parameters, such as condenser water flow, and then detected faults by using support vector machine algorithm. Considering the fault free situation in their model training, their approach detected only one single fault – compressor overcharging. The same fault was efficaciously detected by using a principal component analysis-based exponentially weighted moving average control chart and virtual refrigerant charge algorithm (Liu et al., 2017).

From BMS, Luo et al. (2019) collected the data of chilled water supply and return temperatures in per minute frequency for six days from four different weather seasons to predict sensors faults, in addition to fault free conditions, using *k*-means clustering. The said faults were not fully described, and as in some other studies, the frequencies of their data sampling were not justified even after the development of this approach by Luo and Fong (2020). Thieblemont et al. (2017) explored state-of-the-art control strategies. The first strategy, called 'model free control strategy', does not require building a model or the use of historical data. It can be performed by programming the ambient temperature based on the next day's weather forecast.

The second strategy is an intelligent one using artificial intelligence with a cold thermal energy storage system. This strategy suggests combining a fuzzy logic controller and a feed-forward controller with weather predictions. To do so, the authors listed 27 rules for this aforementioned second strategy (Thieblemont et al., 2017).

Advanced control is the third strategy, which includes two techniques: non-optimal advance predictive control and model predictive control. The unknown-but-bounded method is an example of the first technique, and its implementation is costly. The concept of model predictive control is to optimise the variables of CWS as a function of future horizon to satisfy the relevant constraints. Arteconi et al. (2012) suggested applying cold thermal energy storage for demand side management strategy, which can change the chiller load profile, to optimise the power system from generation to delivery. Model predictive control was presented by Wang et al. (2022) as a state-of-the-art strategy. They formulated a simulation model to primarily control the chiller performance using data of two main operational parameters, the water leaving temperature and water return temperature, but they did not state the chiller's faults, the time interval between the readings of these parameters or the study period.

Some studies used the ratio between the cooling load and energy consumed, which is called the coefficient of performance, as a data sample for scheduling PdM activities. In this regard, Wu et al. (2021) proposed a method to optimise the PdM scheduling for HVAC system by mixed integer programming. This method has two stages: the first one is parameter generation through historical data, and the second is optimisation by linear programming. They conducted a case study on chillers and addressed coefficient of performance. The idea of the first stage is to study the operational status and then listing the related constraints while the optimising model, which is the second stage, has to be solved to present a high quality PdM schedule to detect chiller degradation. This model is a bit general, nor does it consider any precise faults or issues that lead to chiller degradation. Li et al. (2022) proposed a fault detection and diagnosis method using a deep belief network. Their data were collected through an Internet of Things agent and processed through four different stages, including optimising them by a particle swarm optimisation algorithm. Moreover, in comparing deep belief network with deep neural network, *k*-nearest neighbours, and support vector machine, they obtained almost same prediction accuracy, but without clarifying the faults.

From coefficient of performance data, Motomura et al. (2019a) developed two simulation models to evaluate multiple chillers' faults. The first model calculated the increased amount of daily peak power, while the second one tracked the decrease rate of the performance coefficient. Sulaiman et al. (2020) observed a chiller coefficient of performance and developed a fault detection and diagnosis approach by using deep learning, multi-layer perceptron and support vector machine; they then determined that the multi-layer perceptron is more accurate than others. On a related note, multi-layer perceptron was integrated with a regression model to enhance the control of the chiller (Zabidi et al., 2023). In this study, the authors did not state any fault nor mention any detailed information about the data and its associated operational parameters (Zabidi et al., 2023). From a chiller coefficient of performance data sample, Ng et al. (2020) used Bayesian network to predict sensor bias of water flow temperature, but the results were not particularly encouraging as per the authors' conclusion. To obtain the usual promising results, Harasty et al. (2019) argued that the artificial neural network algorithm should be used in PdM strategic programmes. For a fuller picture, Sanzana et al. (2022) argued that a deep learning technique is the best to obtain higher prediction accuracy as compared to other PdM techniques.

At the end of this subsection, the research thesis has summarised in Tables 9 and 10 below what has been mentioned in the literature from three points of view: the faults, the operational parameters, and their frequencies or readings from which data were derived. The first table shows the faults that were stated in the literature as well as the number of times each fault is repeated across the considered studies. The second table is related to data collection and presents additional separate information pertaining to operational parameters presented or stated in the literature as well as their ranges from minimum and maximum frequencies points of view. This research thesis defines the duration or the time interval between each observation or reading of each operational parameter as 'minimum frequencies', while it defines study period, the duration of collecting the data, or the time span of collecting the data as 'maximum frequencies'. Data in the literature were utilised to build and train the prediction or detection models.

Table 9: Summary of chiller's faults

Fault Name	Number of Studies Addressing this Fault
Refrigeration leak	5
Evaporating fouling	3
Compressor overcharging	3
Faulty operation scheduling	1
Condenser fouling	16
High condenser temperature	1
Sensor bias	12

Table 10: Summary of chiller's frequencies utilised for data collection

Operational Parameter Name	Range of Minimum Frequency	Range of Maximum Frequency
Chilled water flow rate	Between 60 and 75 minutes	Between 20 days and two months
Condenser water flow rate	Between five and 75 minutes	Two months
Evaporating pressure	Not specified	Not specified

Evaporator water entering temperature	10 minutes	Five days
Supply air average humidity	Not specified	Not specified
Condenser water supply temperature	Not specified	Not specified
Chilled water leaving temperature	Not specified	Not specified
Chilled water returning temperature	One hour	20 days
Condenser pressure	Not specified	Not specified
Oil feed pressure	Not specified	Not specified

2.5.2 Cooling Towers

Compared to studies on chillers, studies on cooling towers were limited and were either part of the chiller studies or were discussed separately. Ahn et al. (2001) developed a simulation model to detect three faults of cooling towers. Their model was built based on the deviation of different operational parameters such as the difference between the chilled water temperatures that are leaving the tower and the temperatures that are returning to the same. The claims against this study, however, are the data collection and fault clarification as the authors did not clarify the source of their samples used in the associated experiment nor did not state the faults clearly. Zhou et al. (2009a) used a regression model to detect air fan degradation faults by formulating the performance index of the air flow rate’s reduction. The sample size of their data looked small, as it was generated during only five days in the summer season, including the fault free condition. Hu et al. (2019) collected data on fan power to detect the same fault, which is air fan degradation by using support vector machine, and their sample size also looked small as it contained 775 readings that were collected every five minutes during a study period of two months. From a qualitative method study, Chew and Yan (2022) suggested cleaning cooling tower fans before applying any fault detection and diagnosis approach, but this action cannot be considered as a solution to fix a particular fault where they did not mention any fault of the said CWS component, nor did they clarify the PdM technique. Khan and Zubair (2004) discussed another fault, fouling of fills, and predicted it by use of a regression model. Through this model, the correlation was analysed between the performance indices of different operational parameters, but they did provide a solution to fix the said fault when it occurred. Per Ma and Wang (2011), the said two faults, fouling of fills and air fan degradation, can be detected significantly using the hybrid quick search method by characterising the performance index of a selected operational parameter, the inlet condenser water temperature. Air fan degradation was also predicted by Sulaiman et al. (2020) when they compared multi-layer perceptron, support vector machine and deep learning methods, finding that multi-layer perceptron is more accurate than the other mentioned algorithms. However, they neglected to provide any solution to fix the fault when it appeared.

Human and organisational factors are obviously affecting PdM costs and its scheduling. In this regard, Jain et al. (2019) studied the failure conditions of a particular cooling tower by introducing a process resilience analysis framework. This framework utilised a Bayesian network model to integrate two factors, process parameter variations as a technical factor and human and organisational factors as a social one. Their framework illustrated the impact of their model on PdM management from cost and safety points of view. Melani et al. (2019) insisted that making a significant investment in a PdM programme is essential to maintaining the availability of the systems that are operating commercial buildings. Having said that, they developed a generalised stochastic Petri net model to predict multiple faults, such as those related to fans, including the operational errors caused by humans. Furthermore, Aguilar et al. (2020) proposed an autonomic cycle of data analysis tasks involving BMS to manage the failures of two cooling towers of an opera palace in Spain. They utilised three techniques – multi-layer perceptron, *k*-nearest neighbours and gradient boosting – to reach similar prediction accuracies of all three techniques. To diagnose such failures, Piot and Lancon (2012) suggested that commercial buildings use a SCANSITES 3D system as they surveyed several cooling towers in France and found the said system to be useful.

In contrast to what was performed in chillers, the fault detection and diagnosis of sensor faults was not studied much in regard to cooling towers. At the Oak Ridge National Laboratory in the United States of America, the air fan degradation fault of the high flux isotope reactor was predicted using wireless sensors (Hashemian, 2011). Wang et al. (2010) predicted the said fault by use of principal component analysis. Their data samples were collected through a sensor that read one of the operational parameters, the inlet condenser water temperatures, and per their results, the principal component analysis did not always record the occurrence timings of that fault, so accordingly, they could not evaluate the performance index of the aforementioned parameter. An experimental study had collected data from the same parameter to predict an air fan degradation fault using the Kalman filter method (Sun et al., 2013). Another study used the Kalman filter method to observe cooling tower performance at one of China's commercial buildings (Sun et al., 2018). To reduce the false alarm rate, the study analysed and measured some chosen parameters via a statistical process control technique. Motomura et al. (2019b) developed two simulation models to assess multiple cooling-tower faults. The first model checked the water flow and the outside air wet-bulb temperature, whilst the second model focused on the inlet and outlet condenser water temperatures. Data on air wet bulb temperature, which basically contained 5000 readings, were collected to predict a particular cooling tower's performance and to eliminate the severity of the related faults by use of the backpropagation neural network method (Xu et al., 2015). This method resulted in the obtainment of a very good correlation coefficient between the predicted values and experimental ones, but with no clarification about the predicted faults.

Similar to the close of the previous subsection regarding the chiller component, this thesis has summarised the literature of the cooling tower component as shown below in Tables 11 and 12. These tables have the same ideas of the previous tables (Tables 9 and 10), which were presented in the previous subsection.

Table 11: Summary of cooling tower's faults

Fault Name	Number of Studies Addressing this Fault
Air fan degradation	6
Fouling of fills	2
Sensor bias	1

Table 12: Summary of cooling tower's frequencies utilised for data collection

Operational Parameter Name	Range of Minimum Frequency	Range of Maximum Frequency
Chilled water leaving temperature	Not specified	Not specified
Chilled water entering temperature	Not specified	Not specified
Air flow rate	Not specified	Five days
Inlet condenser water temperature	Not specified	Not specified
Outlet condenser water temperature	Not specified	Not specified
Air wet bulb temperature	Not specified	Not specified
Fan power	Five minutes	Two months

2.5.3 Pumps

Following the literature on cooling towers, the number of studies on pumps is approximately the same. Karim et al. (2020) predicted five faults of pumps – out of which two were related to the cooling system – using artificial neural network method, arguing that their hypothetical data showed that such a method is capable of predicting the aforementioned faults, but they also did not clarify the predicted faults. Using *k*-means clustering method, Luo et al. (2019) studied the sensor bias of primary and secondary pumps, but their method has detected only one sensor fault. Through the high flux isotope reactor project at the Oak Ridge National Laboratory, Hashemian (2011) predicted three different faults using wireless sensors. These faults are excessive noise, faulty control switch and faulty starter, of which are related to the secondary pump.

From an installed building automation system, Hu et al. (2019) collected a data sample of the differential pressure every five minutes for two months to predict the degradation of the secondary pump using a support vector machine algorithm. However, they did not specify the fault that leads to pump degradation. To keep a control on the differential pressure of primary and secondary pumps, Ma and Wang (2009) developed a simulation model that recorded water flow rates of one year, but the time intervals between the readings were not clarified nor did they clarify the type of the fault. Miyata et al. (2019) used Monte Carlo simulation to detect operational uncertainty caused by the imponderable pressure, but data-related information was neglected.

Zhou et al. (2009a) used a regression model to detect a partial clogging fault in the secondary pump by formulating the performance index of the increase in the pipeline resistance. On the other hand, Wang et al. (2010) predicted the same fault, which is partial clogging by using the principal component analysis method. Moreover, Liu et al. (2022b) studied pipeline resistance and then predicted the primary pump's leakage fault by using adaptive moment estimation algorithm with multi-layer feedforward neural networks trained with the error backpropagation neural network. Motomura et al. (2019a) developed two simulation models to predict the faults of primary, secondary and condenser pumps. From the BMS data, their first model observed the water flow in litter per minute for almost a year, while the second focused on sensor errors and also studied the impact of pump specifications, such as the calibre. By using an Internet of Things technique on the subject CWS component, Domínguez-Cid et al. (2022) proposed a PdM framework for the hotel sector. Their framework contained an acquisition system that has three modules – single conditioning module, microcontroller-based system and microprocessor-based system – but they did not specify the data information and their related operational parameters nor stated the faults for which they were looking. Convolutional neural network transfer learning was applied to present a fault detection model for centrifugal pump, and it was successfully detected the motor faulty starter (Sunal et al., 2024).

The appearance of faults obviously affects the CWS performance, whether caused by human interventions or by an operational issue or by an unreliable sensor. Au-Yong et al. (2014) focused on pumps within their mixed-method study, which was explained in the section on chillers. Per the qualitative method research of Chew and Yan (2022), maintenance officers and researchers are advised to check the condenser pumps for corrosion before applying any fault detection and diagnosis approach. Moreover, Yang et al. (2017) proposed the usage of the fault detection and diagnosis strategy with the machine learning method, counting data samples via BMS that are related to pumps. However, they did not specify the associated operational parameters and the machine learning method nor the detected faults.

Yuan and Liu (2013) used a semi supervised learning technique to predict severe gear damage of a particular pump, which led to pump partial clogging, taking into consideration the fault free condition while training the model. Bouabdallaoui et al. (2021) introduced a PdM framework by using a long short-term memory network. As part of this framework, they collected data for three pumps via building automation system and Internet of Things devices, but they did not specify the associated operational parameters nor the predicted or detected faults. With regard to state-of-the-art control strategies, Thieblemont et al. (2017) suggested applying adaptive model predictive control to decrease the pumps' running time, but they did not clarify their PdM model nor mentioning the faults within their research.

Similar to chillers and cooling towers components, this thesis has summarised the literature of pumps in Tables 13 and 14 below with the same ideas as in the previous Tables 9 and 10.

Table 13: Summary of pump's faults

Fault Name	Number of Studies Addressing this Fault
Clogging	3
Faulty control switch	1
Pipeline leakage	1
High flow rate in cold exchange	1
Faulty starter	2
Low flow rate in cold exchange	1
Excessive or abnormal noise	1
Sensor bias	2

Table 14: Summary of pump's frequencies utilised for data collection

Operational Parameter Name	Range of Minimum Frequency	Range of Maximum Frequency
Differential pressure	Five minutes	Two months
Water flow rate	Not specified	360 days

2.5.4 Terminal Units

The subject component has the largest number of studies comparing it to other CWS components. Liang and Du (2007) proposed a fault detection and diagnosis model of the HVAC system using mixed methods. The under-study component was an air handling unit of a particular commercial building in Hong Kong. They combined a simulation-based model method with a support vector machine method. Three types of faults were addressed – return damper jam, cooling coil blockage and speed reducing of the supply fan – noting that false signal fault was not considered in their study. Their method was built by collecting data of multiple operational parameters, the set temperature and indoor cooling load. The original sample size was looking small because it was generated from 10 operational hours, but they assumed that the fault would arrive within one hour. They depended on this assumption when finalising their required data and obtained a bigger sample size, which was used to build the model.

Through building information modelling and Modelica software, Andriamamonjy et al. (2018) presented a simulation model to detect return damper jam fault of a particular air handling unit. Their model showed the potential of building information modelling for a significant reduction of the manual configuration needed to disseminate such a model, based on calculating the normalised root mean square error of multiple operational parameters (supply air temperature, space temperature, return air temperature and exhaust air temperature). The readings of each of these parameters contained three types of conditions or modes: faulty, uncertain and fault free. In contrast to a case study performed at a university, Alavi and Forcada (2022) argued that building information modelling cannot constitute complete information on maintenance activities when implementing decision making frameworks. The study, which discussed the impact of human interventions in the occurrence of faults and was explained in chillers and pumps subsections, also included air handling units (Au-Yong et al., 2014).

The PdM framework of Bouabdallaoui et al. (2021), discussed in the pumps section, was also embedded with two air handling units, but they did not define the predicted faults in their case study that was performed at a sport facility in France. Bruton et al. (2013) proposed a procedure for choosing the appropriate machine learning technique based on air handling unit conditions. After that, they developed an automated fault detection and diagnosis for air handling units, the contents of which are data access layer to be flexible with BMS, business layer to be flexible with any combination of sensors with operational parameters, and graphical user interface to evaluate the performance of air handling units (Bruton et al., 2014).

Sittón-Candanedo et al. (2018) used a decision tree technique for evaluating an early stage PdM model of terminal units. In a set of buildings that are between zero and 30 years old, they obtained historical data of the indoor temperatures to compare with the newly designed ones, and then to identify any abnormal behaviour. After utilising the sample size of 8000 readings, they indicated that decision tree algorithm showed an exceedingly high accuracy in covering fault possibilities. On a related note, Hodavand et al.

(2023) concluded that the decision tree algorithm provides a practical solution to smart building management, enabling real-time data collection and analysis to enhance occupant comfort and ensure sustainable operations and maintenance. They also indicated that the decision tree technique is the best for PdM as it can improve fault detection and diagnosis by allowing real-time monitoring of building components and systems and can enhance stakeholder collaboration and communication (Hodavand et al., 2023).

In pursuit of thermal comfort within commercial buildings, an experiment was conducted, involving the collection of occupant skin temperatures. This data was utilised to predict the optimal speed reduction for the supply fan in air handling units. Support vector machine and extreme learning machine techniques were employed, yielding satisfactory results from both methodologies (Chaudhuri et al., 2017). For achieving high accuracy in fault detection and diagnosis models, it is recommended to clean the impeller, fan scroll, and blower blade of air handling units prior to the application of the model (Chew and Yan, 2022). Arteconi et al. (2012) suggested a state-of-the-art control strategy using demand-side management to reduce the required air handling unit's size up to 40 per cent, resulting in energy saving.

The variable air volume of air handling units was discussed in numerous studies. For instance, in a multi-purpose research and test facility called an environmental chamber, Cho et al. (2005) conducted two studies on a number of rooms that represent commercial building standards. In addition to the fault free condition, their first study used artificial neural network to predict some faults linked to air handling unit parts, including the variable air volume, while the second study applied transient pattern analysis to isolate the said faults to reach steady-state condition. The study of Schein and Bushby (2006), which was mentioned previously in the chiller subsection, predicted a variable air volume sensor fault when reading the discharge air temperature. At a large academic office building in Canada, Gunay et al. (2022) developed a simulation model to detect variable air volume sequencing logic faults in two air handling units. Using data of ASHRAE projects, another simulation model was developed by Norford et al. (2002) to detect multiple air handling unit faults related to the variable air volume's damper, fan and filter coil system. Moreover, Li et al. (2021) proposed a simulation model to predict 11 variable air volume faults at a particular commercial building in China, succeeding in detecting nine faults, including outdoor air damper stuck and multiple sensors faults. Two more research studies predicted the return damper jam fault at two different commercial buildings: the first one applied random forest, while the second one developed a simulation model (Gao et al., 2019b; Deshmukh et al., 2019). In addition, Lin et al. (2023) claimed success in predicting the faulty variable air volume of an air handling unit by applying a fully automated control hunting correction algorithm, developed by utilising lambda open-loop tuning rules. The source of data used was discharge air temperature, and the readings of this operational parameter were taken every 30 minutes during the summer of 2022. A similar study to Lin et al. (2023) one was conducted at the Oak Ridge National Laboratory but by applying a digital twin technique (Xie et al., 2023).

At other various commercial buildings, 13 research studies used data from one ASHRAE project to predict several faults of air handling units and fan coil units, including ones related to the variable air volume, and obtained an acceptable prediction accuracy for each (Piscitelli et al., 2020; Zhao et al., 2015; Zhao et al., 2017; Yuwono et al., 2015; Yan et al., 2016a; Yan et al., 2018b; Yan et al., 2019; Tun et al., 2021; Pourarian et al., 2017; Li et al., 2010; Li and Wen, 2014; Fan et al., 2021; Mulumba et al., 2015). The first study applied the temporal association rules mining algorithm, while both the second and third ones applied Bayesian network. The fourth study applied ensemble rapid centroid estimation; the fifth study applied simulation model; and the sixth applied support vector machine. With regard to the seventh, the generative adversarial network was applied, and the eighth one combined random forest with support vector machine. The ninth utilised simulation software called HVACSIM+; the tenth derived large margin information fusion; the eleventh applied principal component analysis; the twelfth applied semi supervised learning; and the last one applied support vector machine algorithm with autoregressive exogenous variables technique. In contrast, Zhao et al. (2019) criticised the same ASHRAE project because its data did not cover a vast range of operating conditions.

Combining the fault detection and diagnosis approach with a fault isolation approach is one of the PdM ideas. A study in Canada presented this idea by applying the principal component analysis to detect two selected faults of air handling units and active functional testing to isolate the same faults (Padilla and Choinière, 2015). Two more studies applied principal component analysis, but in both detecting and isolating a number of faults on air handling units (Wang and Xiao, 2004; Qin and Wang, 2005). Ranade et al. (2019) developed a simulation model to predict some selected faults of fan coil unit and variable air volume, including fault free condition. They argued that these faults can be isolated easily by applying decision tree algorithm. Using data of air handling unit outlet water temperature and supply air temperature, collected for three days, Shahnazari et al. (2019) applied a recurrent neural network to detect and isolate the faults of the associated sensors. Moreover, Wang and Chen (2016) conducted a case study at a particular commercial building with 36 floors by applying exponentially weighted moving average control charts for the same purpose – detecting sensor faults.

Wang et al. (2012a) applied a genetic algorithm to predict and isolate the faults of air handling unit supply fans and variable air volume. Data from BMS were utilised to predict and isolate 10 selected faults of air handling units using Bayesian network (Xiao et al., 2014). At a green commercial building, an experimental study resulted in developing four simulation models to detect and isolate four faults of air handling units by one model for each fault (Yang et al., 2008). Yang et al. (2018b) presented a pragmatic simulation model to detect only four selected faults at 44 buildings in Canada. Their solution relied on clustering work orders datasets collected from occupant complaints, and then they computed mean time between failure. Mean time between failure was also computed by Sanchez-Barroso and Sanz-Calcedo (2019). To detect and isolate small bias sensor faults, an experimental study advised using a hybrid-model-based fault detection and diagnosis that combines the fractal correlation dimension algorithm with support vector regression (Yang et al., 2013). Zhang and Hong (2017) explained the background of faults related to variable air volume in air handling units, which will help the researchers or commercial building officers take that into consideration while making PdM programmes.

By recalling what has been mentioned in the chillers subsection about how commercial buildings are using BMS to control CWS performance, it has been noted that Hosamo et al. stated that "in systems like Air Handling Unit (AHU) which is considered as a complex system, many faults cannot be detected by BMS" (2022, p. 2). Having said that, they conducted a case study on four air handling units at a particular university which proposed a digital twin technology utilising building information modelling and Internet of Things sensors, noting that this technology is an artificial neural network-based technique. On a related note, Lee et al. (2004) predicted sensor faults using a general regression neural network model. Gao et al. (2016) studied the impact of the system's water temperature difference (called delta T) on air handling unit performance. They developed a simulation model that generates the performance indices of various operational parameters, but they did not clarify the faults that may appear due to the aforementioned temperature difference.

Choi and Yeom (2019) introduced a thermal satisfaction prediction model that combines human factors and physiological signals. Their data were collected from volunteer students through a LabVIEW based data acquisition system and were analysed by multiple statistical analysis and data mining software called WEKA. Their study showed a significant correlation between the said factors and signals. A similar study discussed indoor air quality and used simulation model and statistical tests to diagnose air handling unit sensor faults (Najeh et al., 2021). Shaw et al. (2002) studied the correlation between multiple operational parameters of an air handling unit to obtain reliable fault detection and diagnosis results in detecting faults related to fan, damper and filter coil system.

In Australia, an auto fault detection and diagnosis model, developed by Guo et al. (2017) in one of the large commercial buildings, merged the hidden Markov model and support vector machine. Their data were collected through BMS from 15 air handling unit sensors, and their model was trained based on selected faults over two business months. Unfortunately, they did not specify which parameters of the air handling unit were studied, nor did they consider the sensor's false signal in their model. Holub and Macek (2013) presented a simulation model within a stochastic system by addressing the set temperature of a rooftop air handling unit. The target of their application was to detect a diagnostic fault that links to the fan. Frankly, the data used to simulate the model were limited where they applied a hybrid system.

To obtain an active simulation model, Deshmukh et al. (2020) suggested holding three operational conditions and closing the cooling valve while collecting the air handling unit's data of fault free mode. Ma et al. (2020) introduced a PdM framework which integrated building information modelling, geographic information system and reliability-centred maintenance technologies by implementing a quantitative decision-making model along with a Monte Carlo simulation model. Their case study, performed on a virtual university campus that included air handling units, determined it difficult to acquire a large data sample size. Gourabpasi and Nik-Bakht (2021) indicated that the lack of knowledge in locating sensors causes difficulty for both data collection and sensor fault detection and diagnosis.

Terminal unit fault detection and diagnosis can be considered a probabilistic approach. In the USA, Dey and Dong (2016) applied Bayesian belief network in a probabilistic way to predict some air handling unit faults at one university. Du et al. (2008) applied the wavelet neural network to fix the air handling unit's sensor bias. A subtractive clustering technique and backpropagation neural network were combined to catch the missing alarm when an air handling unit's fault occurred (Du et al., 2014a). For missing alarm issues, a study suggested applying Levenberg–Marquart-type artificial neural network to eliminate that (Du et al., 2014b). To enhance the thermal comfort, Dudzik et al (2020) suggested the use of a building automation system and applied artificial neural network to examine the environmental quality management system. In Jordan, Al-Aomar et al. (2023) utilised BMS to retrieve three days' historical data of the air flow of a particular air handling unit at a hospital. Then, they applied two probabilistic algorithms, prophet forecasting and seasonal auto-regressive integrating moving average, and then noted that the second has a better accuracy, but they did not clarify the type of the fault.

At one of Qatar's sport facilities, Elnour et al. (2022) applied a neural network that clustered the normalised root mean square error of some operational parameters, and then compared that with support vector machine, *k*-nearest neighbours and decision tree techniques. They found their approach to be more efficient than the aforementioned three techniques in controlling air handling unit operation. Through virtual sensors of multiple operational measurements, Kim and Braun (2020) presented a fault detection and diagnosis approach via virtual sensors to predict the compressor failure. Their study discussed a rooftop air conditioner that works as a terminal unit; the sensors were linked to the measurements of three operational parameters, refrigerant mass flow, refrigerant charge and air flow. Lauro et al. (2014) used fuzzy logic clustering to predict the abnormal behaviour of a particular building's fan coil unit. Li and Wen (2014) used wavelet transform with the principal component analysis technique to predict some air handling unit faults. Liu et al. (2021) applied the Markov Chain Monte Carlo algorithm to drive the statistical characteristics of an air handling unit's faults levels.

On a single terminal unit, Lo et al. (2007) applied fuzzy genetic algorithm to eliminate sensor false signals. The study of Luo et al. (2019), as explained in the chillers and pumps subsections and using *k*-means clustering algorithm, also focused on terminal units by detecting sensors faults. By utilising ASHRAE's thermal comfort database, an experimental study compared the thermal sensation vote and the predicted mean vote by use of a random forest model, resulting in approximately 65 per cent accuracy in the thermal sensation vote prediction but with no clarification on any fault (Luo et al., 2020a). The study of Miyata et al. (2019), as mentioned in the chiller and pump subsections, included air handling units, but they did not define the related faults. From an ASHRAE project dataset, Montazeri and Kargar (2020) applied six algorithms (namely support vector machine, radial basis function, kernel principal component analysis, decision tree, deep belief network and shallow neural network) to detect the sensor and actuator faults, insisting that the decision tree model had the best prediction accuracy.

ASHRAE datasets were not the only source in developing fault detection and diagnosis within the literature. Novikova et al. (2019) utilised a dataset called 'VAST Challenge 2016' to develop a simulation model that monitored and assessed terminal unit performance at a three-floor commercial building. The data of residential complex buildings were utilised by Parzinger et al. (2020) for air handling unit fault detection and diagnosis, using autoregressive exogenous variables and random forest techniques. Both techniques showed similar and acceptable prediction accuracy. Rafati et al. (2022) utilised non-intrusive load monitoring software in terminal unit fault detection and diagnosis. Extended Kalman filter algorithm was applied to present a fault detection model for a residential air handling unit, and it was successfully detected an undercharge fault with 70.6 per cent accuracy (Chintala et al., 2024).

In collaboration with a leading building management company, Satta et al. (2017) proposed a PdM approach for the cohort of 17 appliances that are similar to terminal units, and then examined this cohort at an Italian hospital. Using historical data of different variables such as indoor temperature, they used decision tree to detect the abnormal behaviour of these appliances. They argued that the reciprocal dissimilarities between appliance behaviour can expose an upcoming fault with enough anticipation to allow for a proactive meddling to avert breakage in operation. Tehrani et al. (2015) addressed one fault related to a particular terminal unit at one Canadian university. The fault was the filter blockage, and the associated data sample size was more than 3000 readings of fan speed, taken every 30 minutes. Moreover, they indicated that the performance of the unit in discussion improved using decision tree instead of artificial neural network. Furthermore, Shakerian et al. (2021)

recommended applying the synthetic minority oversampling technique to improve the prediction accuracy.

Sulaiman et al. (2015) developed a fuzzy fault detection model for centralised CWS, using simulation. They implemented the model in the air-supply damper of an air handling unit, linked to two specific rooms. Three cases were studied in their research to simulate the model. Two were related to damper faults, and the third was at normal operation, without any faults. They identified these faults by checking the room-temperature variation. They noted that the developed model resulted in detecting the damper faults, but with no technical details. Another fault detection and diagnosis approach, presented further by them and explained in the chillers and cooling towers section, also covered air handling units (Sulaiman et al., 2020). This study addressed the faults related to the compressor and damper. Thumati et al. (2011) developed a generic simulation model to detect terminal unit faults and to isolate the associated residual errors. Their idea could be presented perfectly by using virtual sensor approaches such as the one by Verbert et al. (2017).

At a residential facility, Turner et al. (2017) developed a simulation model for the fault detection and diagnosis of air handling units. During seven days' study time, they focused on the outdoor temperature and the set of indoor temperature parameters to detect a selected fault, compressor failure. They believe that using such data driven approaches for tracking these parameters can help easily detect associated faults. Van Every et al. (2017) applied Gaussian regression and a support vector machine to estimate air handling unit sensor values and to detect associate faults, respectively. With no clarification to the faults and frequencies, Velibeyoglu et al. (2018) applied a directed acyclic graph to assess the detectability of air handling unit simultaneous faults, claiming they have obtained a promising accuracy of results.

The usage of one or more software or systems – such as LabVIEW-based data acquisition system, building information modelling, Internet of Things sensors, building automation system and BMS – is important in controlling CWS performance that is part of PdM programmes. Villa et al. (2022) extolled the usage of such software in air handling unit fault detection and diagnosis purposes, and accordingly, they introduced a PdM management framework using an automatic machine learning platform called H2O. Using fuzzy logic clustering, Wijayasekara et al. (2014) assessed BMS performance in controlling the thermal comfort inside selected rooms. Alongside BMS, decision tree and regression tree algorithms were used by Yan et al. (2016b) to develop a diagnostic strategy for air handling units. For this experiment, they used data recorded from one of the ASHRAE projects to predict faults related to cooling coil and fan, including fault free mode. They emphasised that data driven methods are unique to glean the useful information from large datasets and for modelling the behaviour of HVAC systems. Yu et al. (2012) proposed association rule mining, which is a data-mining technique, to test the correlation between air handling unit operational parameters at one of the complex buildings that contains offices and chemical labs. It seems they faced some difficulties regarding data collection; the absence of data sources such as sensors or any other reading tools of operational parameters weakens any machine learning model in detecting and diagnosing faults of any system (Shi et al., 2017).

Similar to the summary of other three components in the previous subsections (chillers, cooling towers and pumps), Tables 15 and 16 present the same ideas as in Tables 9 and 10 but concerning literature on terminal units.

Table 15: Summary of terminal unit's faults

Fault Name	Number of Studies Addressing this Fault
Faulty variable air volume	22
Faulty fan	5
Compressor failure	3
Filter blockage	1
Faulty filter coil system	2
Cooling coil blockage	2
Return damper jam	8
Speed reducing the supply fan	3
Sensor bias	12

Table 16: Summary of terminal unit's frequencies utilised for data collection

Operational Parameter Name	Range of Minimum Frequency	Range of Maximum Frequency
Set/space/ indoor temperature	Not specified	Between 10 hours and seven days
Indoor cooling load	Not specified	10 hours
Supply air temperature	Not specified	Three days
Outlet water temperature	Not specified	Three days
Return air temperature	Not specified	Not specified
Exhaust air temperature	Not specified	Not specified
Discharge air temperature	30 minutes	Not specified

Air flow	Not specified	Three days
Outdoor temperature	Not specified	Seven days
Refrigerant charge	Not specified	Not specified
Refrigerant mass flow	Not specified	Not specified

2.6 Discussion

2.6.1 General View

From the previous section, it is observed that chillers and terminal units were mainly researched, while there was little research on cooling towers and pumps. Following the systematic literature review, the maximum number of research studies on chillers was carried out from 2016 to 2019, whereas on terminal units, research was primarily conducted in 2020. Regarding cooling towers and pumps, 2019 recorded the maximum number of research studies for both components. Figure 8 highlights the research trends from 1999 onward.

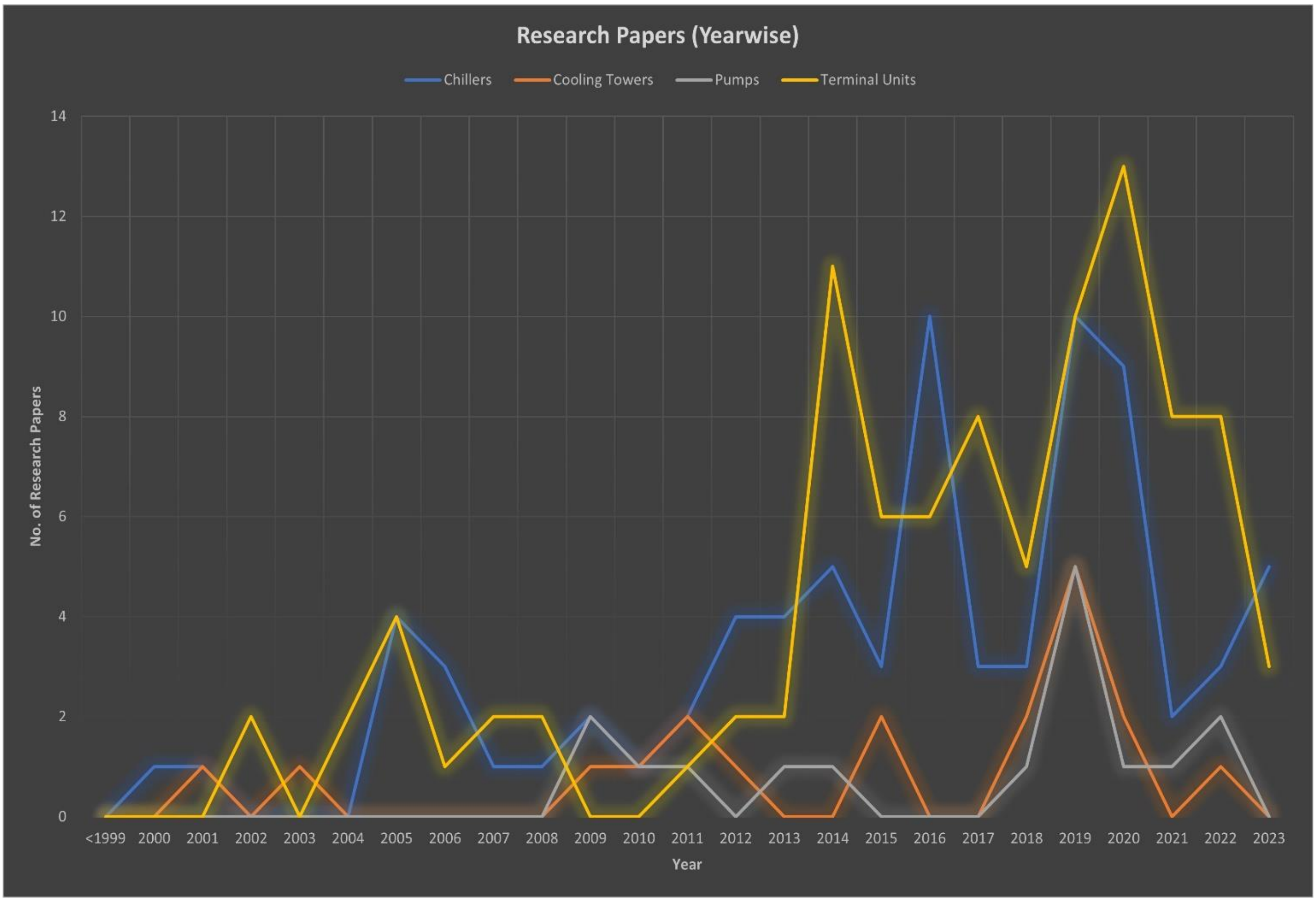

Figure 8: Research trends

The systematic literature review aims to address the guiding research question outlined in this chapter, which focuses on exploring methods of implementing a PdM programme and fault detection framework for a CWS. The primary objective of the research question is twofold. Firstly, it seeks to understand the preparatory measures undertaken by researchers for the implementation of the PdM or fault detection framework. This involves examining how researchers identify and analyse system faults, which forms the foundational basis for implementing the PdM or fault detection framework. Additionally, it involves identifying operational parameters that enable researchers or users to monitor the system and detect faults, as well as understanding the sample size and data sources utilised in this process. Secondly, the research question aims to investigate the tools, methods, programmes or control strategies employed in the development of the PdM or fault detection framework. So, the fifth section of this chapter (Applications of PdM Strategy for CWS) is presented based on these two aims of the guiding research question. In addition, the systematic literature review has been prepared and then written following the proposed PdM workflow by Achouch et al. (2022), as presented in Table 8. So, each considered study has undergone these activities unless information is missing.

The considered studies occasionally addressed CWS components independently and other times in combinations. From a combination point of view, some addressed either two components or three components in total although no research study addressed the whole system (i.e., four components) at once, and for this reason, the previous section was divided into four subsections, a subsection for each CWS component. As stated previously in this subsection, the majority of the considered research studies investigate terminal units (approximately 48 per cent of the total number of studies), and the next is chillers (approximately 32 per cent of the total number of studies). Table 17 presents the number of considered studies that addressed either a single component or more than one within the same study. Table 18 summarised the key findings of the considered studies that are addressed more than one CWS component within their studies.

Table 17: Breakdown of the considered research studies of the literature

CWS Components	Number of Considered Studies
Just chillers	63
Just cooling towers	6
Just pumps	6
Just terminal units	86
Chiller and cooling towers	5
Chillers and pumps	2
Chillers and terminal units	5
Cooling towers and pumps	1
Pumps and terminal units	1
Chillers, cooling towers and pumps	3
Chillers, pumps and terminal units	2
Chillers, cooling towers and terminal units	1
Cooling towers, pumps and terminal units	1
Total	182

Table 18: Key findings of the literature considered more than one chilled water system component

Reference	CWS components addressed	Key findings
Bouabdallaoui et al. (2021)	Pump and Terminal Unit	• Internet of Things devices are crucial for fault detection techniques.
Wang et al. (2010)	Chiller, Cooling Tower, and Pump	• Principal component analysis algorithm is valid to detect the clogging fault in pumps. • The said algorithm is also valid to detect the sensor bias in chillers. • The said algorithm is valid to detect the air fan degradation fault in cooling tower as well.
Miyata et al. (2019)	Chiller, Pump, and Terminal Unit	• The operational uncertainty in the aforementioned CWS components can be well detected by utilising the Monte Carlo simulation.
Motomura et al. (2019a)	Chiller and Pump	• Applying simulation models in association with BMS is useful to monitor the chillers and to detect their faults. • It is important to understand the pump specifications before implementing fault detection techniques.

Luo et al. (2019)	Chiller, Pump, and Terminal Unit	• *k*-means clustering algorithm is ideal to detect the sensor bias in the aforementioned CWS components.
Hashemian (2011)	Cooling Tower and Pump	• Wireless sensors technique is applicable to detect the air fan degradation in cooling tower. • The said technique is valid for secondary pump maintenance as well as it can detect excessive noise, faulty control switch and faulty starter faults.
Sulaiman et al. (2020)	Chiller, Cooling Tower, and Terminal Unit	• Multi-layer perception algorithm is more accurate than deep learning and support vector machine in detecting the faults in the aforementioned CWS components.
Ma and Wang (2011)	Chiller and Cooling Tower	• The degradation of the aforementioned CWs components can be effectively detected by utilising a hybrid quick search method.
Hu et al. (2019)	Chiller, Cooling Tower, and Pump	• Support vector machine algorithm can make a detection model even with small data size.
Zhou et al. (2009a)	Chiller, Cooling Tower, and Pump	• By formulating the performance index of any chiller’s operational parameter, the evaporating fouling fault can be detected by making a regression model. • The air fan degradation fault in cooling tower can be detected by making a regression model via formulating the performance index of any operational parameter.

		• In pump, the partial clogging fault can be detected by building a regression model, which can be built through formulating the performance index of any operational parameter.

From the above and, as stated previously in this subsection, it has been deduced that no research from the considered studies has addressed the entire CWS within the same study, and therefore, the first research gap of this thesis is presented as follows:

Research Gap #1: *The impact of the technical correlation between all four CWS components on fault detection remains unknown.*

The following three subsections discuss the three stages of the PdM workflow, proposed by Achouch et al. (2022) and presented in this chapter in Table 8.

2.6.2 Chilled Water System Faults

To begin, the *faults* considered in this literature can be defined as any failure that may lead to a CWS breakdown over time. In this regard, it has been observed that some studies were focused on only one fault, such as the condenser fouling of chillers. Significant variations exist among the studies regarding the number of faults addressed for all CWS components. While some studies focus on specific faults, others cover a broader range. Moreover, certain studies may address the same faults, while others target different ones. Conversely, some studies either do not specify the faults addressed or provide inadequate descriptions, often citing "abnormal behavior" as a fault, for instance. Additionally, certain studies may list multiple faults but fail to address or predict all of them in their case studies.

For chiller related studies that stated the faults, most addressed primarily the condenser fouling fault and secondly the refrigeration leak fault. On a related note, some of the studies extended their discussion by clarifying the reason behind the occurrence of condenser fouling and compressor overcharging faults. Those studies indicated that high chiller load is affecting the chiller performance and leading to the aforementioned faults, which are condenser fouling and compressor overcharging. Some of the studies indicated that the condenser fouling fault as well as the refrigeration leak fault were determined as the faults with the most negative impact on CWS reliability and on occupant satisfaction. For the cooling towers section, fouling of fills and air-fan degradation are the most addressed faults. The most addressed fault of the pumps is pump clogging. For the terminal units, the most addressed faults were related the variable air volume in addition to other faults like return damper jam, cooling coil blockage, and speed reducing of the supply fan. Sensor bias or controller false alarms were considered in some of the aforementioned studies as a fault. According to most of the reviewed literature, fault free mode must be considered in any research to increase prediction reliability. Some studies discussed human factors that have a significant impact on fault appearance, such as skills of the maintenance officer who manages the system, but they did not present any related fault. Figure 9 below summarises the faults presented by the literature for each CWS component.

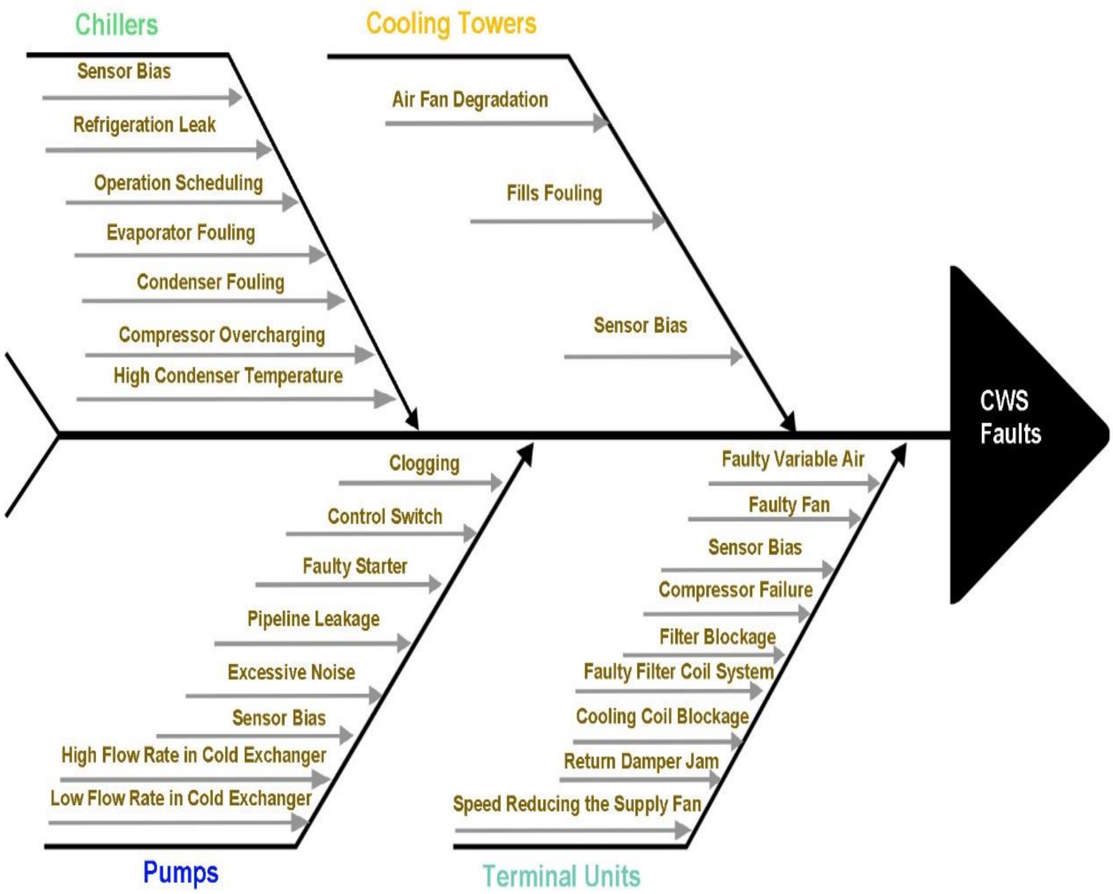

Figure 9: Chilled water system faults presented in the literature

During the review of studies concerning system faults, despite the wealth of valuable information they provided, the disparities between the studies highlighted the emergence of the second research gap in this thesis. This gap can be summarised as follows:

Research Gap #2: *There is a significant level of variations in defining CWS faults and their importance/ impact.*

2.6.3 Operational Parameters, Frequencies and Data Collection

Operational parameters are the measurable technical factors that provide numerical data of the system performance (Levitt, 2011). The readings of any of these operational parameters can give a clear glimpse of the health condition of the related CWS component as they are linked technically to the operation of CWS components (*ASHRAE Handbook,* 2023; Chang et al., 2023). Furthermore, the considered literature did not claim that there is a technical correlation between a particular operational parameter and a particular fault. Some of the reviewed studies in the literature have chosen different operational parameters for their data collection plan such as the chilled water leaving temperature for chillers and for cooling towers, the differential pressure for the pumps, and the space temperature for the terminal units. Data collection serves as the primary activity in constructing the detection model, as it necessitates the acquisition of datasets. These datasets typically comprise readings of operational parameters along with associated information regarding faults. The process of creating datasets involves determining frequencies. As per the understanding gleaned from the literature, frequencies refer to the time intervals between readings of operational parameters. This thesis refers to the shortest time interval between readings as the 'minimum frequency'. Additionally, the duration over which data is collected, representing the study period, is termed the 'maximum frequency'.

During the review of the considered literature, it has been found that some of the studies did not specify which operational parameter their data came from. In addition, some of the studies stated the operational parameters but did not provide detailed information about the associated data, such as sample size or frequencies. Some studies did not address the operational parameters, nor the data information used in building the prediction model. With regard to the data source, some of the studies used ASHRAE projects, some counted on the sensors, and others relied on historical records of other sites. Moreover, some of the considered studies utilised Internet of Things sensors, BMS, or building automation systems as sources to obtain their data and to control the addressed CWS components. The considered studies using these sources either did not offer many details about the minimum or maximum frequencies, or these frequencies were not the same between the studies that clarified them. A review of the studies in the literature makes apparent that the methods of data collection vary among them. Differences in sample size, minimum frequencies, and maximum frequencies exist across the studies. This variability poses a challenge for future research endeavors aiming to create datasets, especially when studying CWS in buildings. Clarifying the optimal approach for dataset creation in such cases becomes essential for researchers.

Further to the above, it is evident that the collected data in the considered studies were used to simply build and train the prediction model. In view of the final stage of the PdM workflow of Achouch et al. (2022), the considered studies have evaluated their prediction models by showing their prediction accuracies, calculated based on the collected and utilised data. For this research project, evaluating the prediction model requires undertaking experimental studies to check its reliability and validity in predicting and then detecting faults. So, this thesis has addressed this weakness by conducting empirical studies, as will be shown in Chapter 5.

With regard to the reading tools of the operational parameters such as sensors, meters and gauges, it has been observed that no considered study has suggested or referred to managerial or technical procedures for installing such reading tools in the case of their unavailability at a particular building. But considering the nature of this shortcoming in the literature, this research thesis addressed this weakness by presenting a proper location for selected operational parameters, as will be shown in Chapter 5. On a separate note, some literature advised the cleaning of some CWS critical parts such as the air handling unit fan scroll and chiller condenser water tubes before collecting the data to ensure an excellent machine learning model, but they neglected to provide information about how exactly the data should be collected. Some studies emphasised that having an excellent machine learning model would be challenging if the data sample size is inadequate. This challenge, along with the differences between the studies with regard to frequencies, encouraged this research thesis to explore justified frequencies that can allow the creation of datasets of the prediction model by identifying proper time intervals between the readings of operational parameters (minimum frequency) as well as a proper time span for data collection, which is the study period (maximum frequency).

Reviewing the considered studies from operational parameters, frequencies and data collection points of view, led to the third research gap to be addressed by this thesis, summarised as follows:

Research Gap #3: *The measurement of CWS faults is not standardised leading to inconsistent fault detection practice.*

2.6.4 Detection Tools and Management

This subsection gives a swift overview on PdM, and fault detection tools applied within the considered studies and highlights the major findings. The primary methods used are a simulation model, principal component analysis, support vector machine, decision tree and artificial neural network (as furnished in Appendix A) along with others which are not as common. The Appendix showcases which method is applied for which CWS component along with the related references. As per the second stage of the PdM workflow of Achouch et al. (2022), most of the considered studies have already stated the chosen machine learning algorithm but ended their work with building and training a model, showing the prediction accuracy but lacking solutions to fix the faults in stated cases.

Other studies include a comparison between several machine learning tools from an accuracy point of view. In most, decision tree and artificial neural network scored the highest accuracy percentage in predicting faults. Generally, per the claims within literature, all machine learning techniques showed very good accuracies in predicting faults. Similarly, some of the studies combined machine learning techniques in PdM applications such as autoregressive exogenous variables with support vector machine, suggesting that such combinations have positive outcomes in predicting the CWS faults. But again, it is worth noting that the studies reviewed in this context concluded their PdM programmes or fault detection models after establishing and training the prediction model, as well as demonstrating its accuracy in predicting faults. However, a notable gap exists in these studies as they often neglect to offer solutions for addressing the identified faults. Some studies indicated the benefits of applying control strategies like demand-side management in saving energy but likewise, did not offer solutions for fixing the faults when one occurred. From a management point of view and following the third stage of the proposed PdM workflow, presented in this chapter in Table 8, the intelligent maintenance framework must provide solutions to fix the occurrence of faults, but the reviewed literature confirmed that the previously proposed PdM programmes or fault detection approaches ended with building and training a prediction or a detection model, devoid of management solutions for rectifying faults.

From the above finding, the fourth research gap of this thesis can be summarised as follows:

Research Gap #4: *CWS fault resolution remains inconclusive.*

2.7 Conclusion

At the beginning of this chapter, an overview of maintenance management in commercial buildings was provided. After that, this chapter explored maintenance strategies. Then, the chapter presented an overview of the maintenance strategy selected for this research project, which is PdM, defining the strategy from an Industry 4.0 point of view. Also, the relation between maintenance management and quality engineering was discussed as well. Further, this chapter explored multiple applications on PdM strategy for various systems and domains.

This chapter aimed to answer the guiding research question, addressing the literature from a managerial point of view. The first goal of the guiding research question is to check the arrangements or the preparations to identify faults, and the second goal is to inquire about predictive tools applied in line with Industry 4.0. This chapter implemented a systematic literature review that included four stages, and then based on the systematic review, it highlighted the studies conducted post-1999 on PdM or fault detection for CWS in commercial buildings, exploring numerous frameworks, programmes, approaches and methods. Following the PdM workflow of Achouch et al. (2022), this chapter also identified the gaps discernible from the literature from a managerial perspective.

Following the systematic literature review, especially at the end of its second stage, a lack of research covering the entire CWS was noted. The considered studies cover either one, two or three components only. Therefore, this chapter focused on all four CWS components. From a maintenance management point of view, this research project intends to consider the entire system (i.e., *all* CWS components in the same PdM programme or fault detection framework). So, the first research gap, as mentioned in the previous section, arose with this finding, deliberating on the importance of covering the entire system rather than only partial coverage of one, two or three CWS components. To justify this importance, this research project intended to check if there is a correlation between CWS components. So, the first research question can be presented as follows:

First Research Question: *Is there a correlation between the components of a CWS that makes it important to cover all of them within the same maintenance framework?*

With regard to the second research gap, mentioned in the previous section as well, it is concluded that CWS may have other faults different from those studied in the literature, and therefore, the second research question generated for this research project is as follows:

Second Research Question: *Are there any other faults rather than the ones mentioned by the literature?*

While following the second stage of the proposed PdM workflow, the data stage, it has been noted that the considered studies of the literature were not similar with regard to the frequencies used in building and training the detection models where the time interval between the readings of the operational parameters or the study period were not same, even in studies addressing the same CWS components. It has been also noted that the rest of considered studies either did not provide the time interval between readings of operational parameters, did not provide the study period, did not give clear information about data collection methodology, or did not identify the source of the data. This finding can be extracted from Tables 10, 12, 14, and 16 in this chapter. Also, some of the considered studies which utilised data from ASHRAE projects, for example, did not provide details of data from the time interval between the readings of operational parameter or did not clarify the time span of these data (study period). Therefore, the third research gap arose according to this observation. This research intends to propose a base that can provide fault frequencies and then utilise this for building and training the proposed detection model. Accordingly, the third research question of this research investigation can be presented as follows:

Third Research Question: *How can an intelligent detection model be built and validated?*

The final stage of the proposed PdM workflow is to complete the maintenance framework by rectifying the occurred faults or issues. The considered research studies of the literature, however, did not provide solutions for detected faults, ending instead by only tracing the faults or showing the accuracy of the detection model. Therefore, the fourth research gap arose, as mentioned in the previous section as well, and accordingly, this thesis sought to find actions to fix CWS faults. So, the fourth research question of this thesis can be presented as follows:

Fourth Research Question: *What are the actions required to fix the CWS faults?*

The aim of this research is to propose a holistic fault detection framework for CWS at commercial buildings in line with Industry 4.0. To accomplish this, the thesis proposed a methodological framework with three phases – set-up, machine learning and quality control – as explained in detail in Chapter 5. The main goal of the proposed framework is to create a detection model by utilising a machine learning algorithm. In accordance with the PdM workflow proposed by Achouch et al. (2022) and presented in this chapter (Table 8), the third stage of the workflow was to evaluate the prediction model, which means assessing its performance in tracing and detecting faults. Based on that, the above research question of this thesis can cover the said task.

This thesis has performed further actions to answer the above research questions as will be explained in Chapters 3, 4 and 5. These research questions have been re-numbered for a logical order to match this research flow. From a fault point of view, this research has performed an action to identify new faults and another action to validate that identification. Also, this research project has performed an action to provide a solution for each identified CWS fault. For data collection, this research project performed an action to verify the required sample size as well as the frequencies of data readings and records and recommends creating the datasets from the building under study to obtain more accurate data about the current operational situation and to avoid dependence on historical records from other buildings or projects. In addition, this research has established a control plan after building, training and testing the detection model to maintain continuous and meticulous tracking of the building's operation and maintenance.

Chapter 3: Research Design

"A well-structured maintenance programme for HVAC systems is not optional but it is compulsory."
(Suttell, 2006)

3.1 Introduction

This chapter explores aspects of designing this present study from a research point of view. It explores the philosophical perspective, the research approach, the research planning, the assigned research methods, the ethics of the research, and finally, the quality of the research. To recall the main goal of the previous chapter, this thesis has included a comprehensive, systematic literature review which investigated studies that proposed PdM frameworks, approaches or fault detection and diagnosis protocols in line with Industry 4.0. The aforementioned systematic literature review study explained and focused on CWS with four components: chillers, cooling towers, pumps and terminal units. Based on the guiding research question, mentioned in the previous two chapters, the systematic literature review considered 182 studies that applied different methods or machine learning algorithms to predict CWS faults. After reviewing the literature and the associated four research gaps, four research questions were developed, as presented in the previous chapter. In this chapter, those research questions are recalled in Table 19 below into the same logical order as the outcome of this research project.

Table 19: Logical order of the research questions

Research Questions	Order Number
Is there a correlation between the components of a CWS that makes it important to cover all of them within the same maintenance framework?	1
Are there any other faults rather than the ones mentioned by the literature?	2
How can an intelligent detection model be built and validated?	3
What are the actions required to fix the CWS faults?	4

3.2 Philosophical Perspective

This section illustrates the philosophical perspective of this research. First of all, *research philosophy* is defined as a framework that directs the manner of conducting research according to notions of reality and nature of knowledge (Collis and Hussey, 2021). It emphasises the system of beliefs, the assumptions and the rationale across knowledge development in a specific field or domain (Saunders et al., 2019). Awareness of philosophical assumptions is required for researchers while choosing a research topic. Saunders et al. (2019) confirm the importance of a philosophical commitment from several points of view such as the philosophical position of the researcher and the manner of undertaking research; the nature and background of the topic that assists the researcher in forming all facets of the planned study; and the selection of the research methodology, the research strategy, the technique of data collection and the associated analysis procedures that allow the designing of a cohesive research study or project.

Research philosophy encompasses the development of research assumptions alongside an understanding of research knowledge and its nature (Saunders et al., 2019). According to Saunders et al. (2019), assumptions are acknowledged as a primary statement of reasoning, but are based on the philosophising researcher's knowledge and visions generated as a result of intellectual thoughts. Also, Hitchcock and Hughes (2002) explain that all research arises from assumptions. Therefore, it is understood that assumptions may differ between researchers based on the nature of knowledge and its gain (Lancaster, 2007). Zukauskas et al. (2018) list three main trends of research philosophy: the positivist, the interpretivist, and the pragmatist philosophies. The scientific research paradigm assists to define the scientific research philosophy. Literature on scientific research explains that a researcher must have a visible sight of the paradigms that offer philosophical, theoretical, instrumental and methodological foundations (Zukauskas et al., 2018). Alghamdi and Li (2013) assure that the scientific research paradigm depends on the aforementioned foundations. According to Cohen et al. (2017), the scientific research paradigm can be defined as a wide structure comprising visualisation, beliefs and outreach of different theories and practices used to carry out a particular scientific research study. Gliner et al. (2011) depict the scientific research paradigm as a way of thinking about research, the process of accomplishing it, and implementing that process via research methods.

Easterby-Smith et al. (2018) list three main components of the scientific research paradigm in order to comprehend the philosophy of any research, as shown below in Table 20. Similarly, Zukauskas et al. (2018) compared the aforementioned trends of research paradigms from the point of view of each component, as summarised below in Table 21.

Table 20: Components of the scientific research paradigm

Research Paradigm Component	Description
Epistemology	General parameters and assumptions associated with an excellent way to explore the real-world nature
Ontology	General assumptions created to perceive the real nature of society (to understand the real nature of society)
Research Method	Combination of different techniques used by the scientists or the researchers to explore different situations

Table 21: Comparison of main paradigms with regard to components

Research Paradigm	Positivism	Interpretivism	Pragmatism
Ontology	Reality is objective and perceived	Researcher and reality are inseparable	Reality is vague, but based on language, history, and cultural respect
Epistemology	Acquisition of knowledge is not related to values and moral content	Knowledge is based on the abstract descriptions of meanings, and formed of human experiences	Knowledge is derived from experience. The researcher restores subjectively assigned and “objective” meaning of other actions
Research Methods	Surveys, experiments, quasi-experiments	Case studies, interviews, phenomenology, ethnography, and ethnomethodology	Interviews, case studies, and surveys

Following the above information, this research thesis adopted the pragmatist paradigm introduced by William James in 1898 (Malachowski, 2014). The *pragmatist paradigm* is defined as a philosophical tradition that considers ideologies as instruments for prediction as well as for problem solving (Bacon, 2012). This research paradigm tries to enhance the understanding of the industry to be more practical in providing more appropriate practices (Korte, 2022). According to Sakib and Wuest (2018), this pragmatist research paradigm is ideal for PdM research. Table 22 illustrates the assumptions of the pragmatist paradigm and implications for this research thesis.

Table 22: Implications of pragmatist assumptions

Assumption	References	Implication in this research thesis
The epistemological pragmatist assumption is that knowledge is always based on experience	(Kaushik and Walsh, 2019)	Based on the research gaps and generated research questions, professionals from several commercial buildings were contacted about the CWS faults and their occurrence frequencies, which is explained in detail in Chapter 4.
The ontological pragmatist assumption is that reality is ambiguous, but it is based on the history	(Creswell and Creswell, 2017)	Following the research gaps and in light of the generated research questions, faults with their occurrence frequencies of CWS are unknown in advance but can detected by utilising historical data. This course of action is explained in detail in Chapter 5.
The methodological pragmatist assumption is to employ a survey or an experimental case study	(Aneta and Jerzy, 2013; Saunders et al., 2019)	To answer the generated research questions, this thesis has conducted an industry survey followed by a case study via methodological framework. Chapters 4 and 5 show this in detail.

3.3 Research Approach

Research approach is defined as a systematic and structured way for conducting a research study, and each approach differs in terms of its inherent logic and methods of investigations (Okoli, 2023). There are three main research approaches: deductive, inductive, and abductive (Kennedy and Thornberg, 2018). Performing a research study via a conceptual structure and theoretical background developed from the scientific literature, and then testing that with empirical observation is referred to as a deductive research approach (Saunders et al., 2019; Fife and Gossner, 2024). On the other hand, the inductive research approach strives to generate a theory with the collection of related data in an effort to explore a phenomenon (Saunders et al., 2019; Gupta et al., 2022). With regard to the third type of research study, the abductive approach, the researcher begins by collecting relevant data to explore a topic, determine themes or expound patterns (Saunders et al., 2019; Bürger and Fiates, 2024). The abductive approach lets the researcher generate a new theory or amend an existing one by testing via a supplementary data collection (Saunders et al., 2019; Zheng and Pee, 2024). Table 23 below summarises the key facets of these three research approaches (Saunders et al., 2019).

Table 23: Facets of the three research approaches

Research Approach	Deductive	Inductive	Abductive
Logic	In a deductive inference, when the premises are true, the conclusion must be true as well	In an inductive inference, known premises are used to generate untestable conclusions	In an abductive inference, known premises are used to generate testable conclusions
Generalising from/to	Generalising from the general to the specific	Generalising from the specific to the general	Generalising from the interactions between the specific and the general
Data usage	Data collection is used to evaluate propositions or hypotheses related to an existing theory	Data collection is used to explore a phenomenon, identify themes and patterns, and to create a conceptual framework	Data collection is used to explore a phenomenon, identify themes and patterns, locate these in a conceptual framework and test this via subsequent data collection
Theory	Theory falsification or verification	Theory generation and building	Theory generation or modification; incorporating existing theory, where appropriate, to build new theory or amend existing theory

This research thesis employs the abductive research approach in line with the adopted scientific research paradigm, which is pragmatism. Based on the systematic literature review, the employed research approach is developed in a conceptual and theoretical way, and therefore, two research methods – an industry survey and a case study – have been assigned to fill the research gaps and accordingly, to answer the generated research questions as presented in the next sections of this chapter as well as in Chapters 4 and 5.

3.4 Research Planning

This section shows the road map created for this research project. According to Leedy and Ormrod (2018), research planning starts by identifying the idea based on the research motivation and the background of the topic, and accordingly, the guiding research questions should be finalised prior to beginning the literature review. Based on the outcome of the literature review, the research gaps are recorded and then research questions generated to guide the study in discussion. After that, the research methods are selected based on the epistemological and ontological assumptions, which include data collection and analysis. Buie (2018) suggests the use of an input-process-output diagram for problem solving planning, and accordingly, Figure 10 below shows a simple view of planning this research thesis via three phases. Each step of the road map of this research has either been explained in previous chapters or will be explained in upcoming chapters.

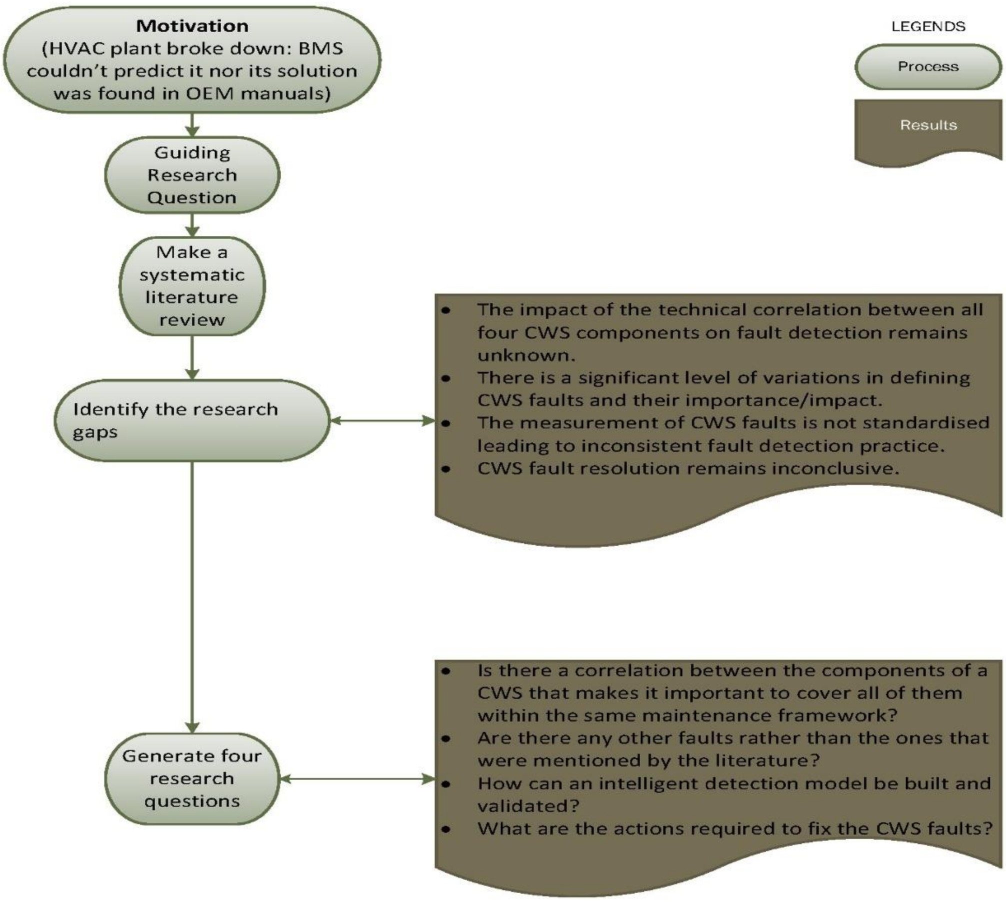

Figure 10a: Research thesis road map (phase 1)

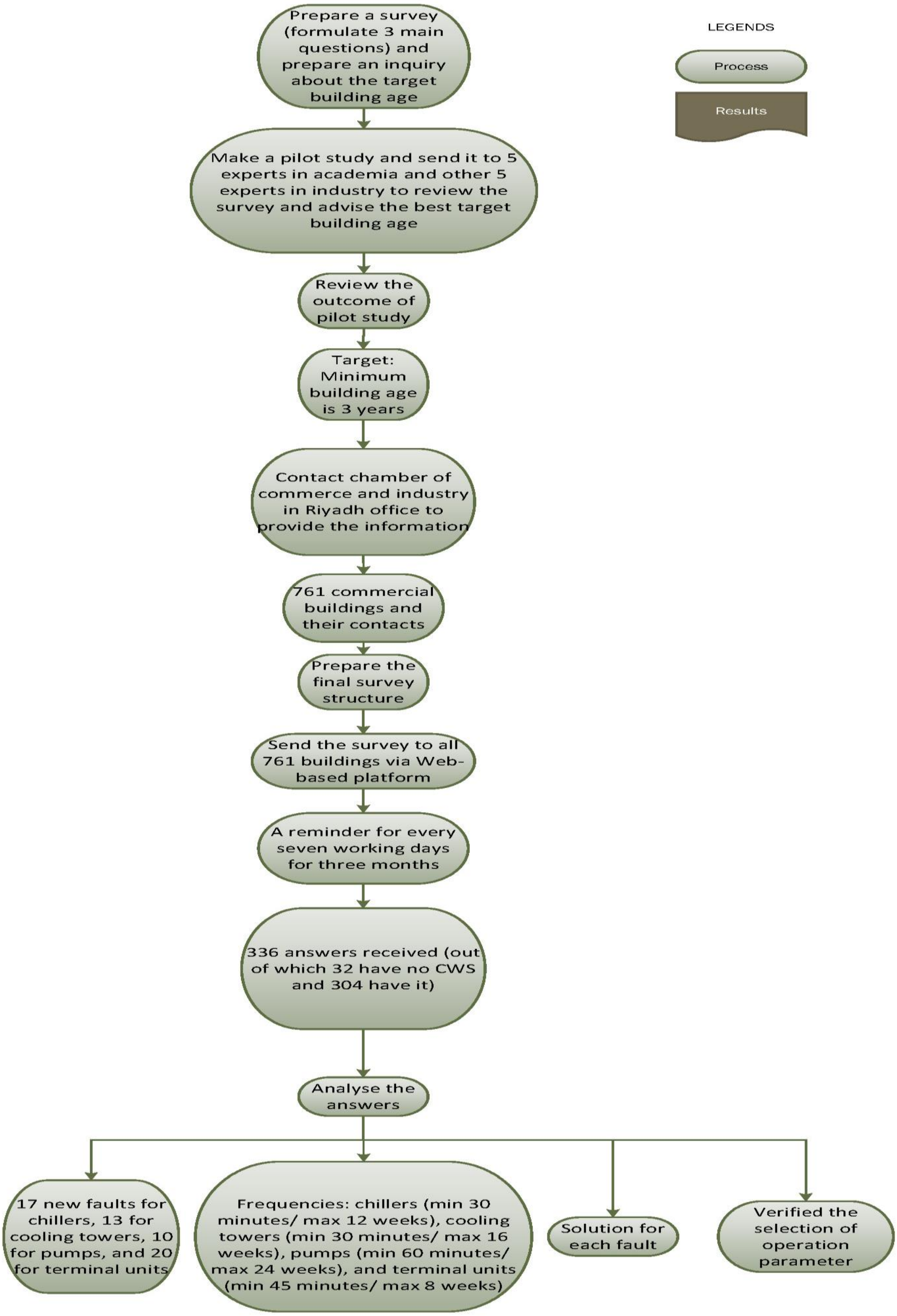

Figure 10b: Research thesis road map (phase 2)

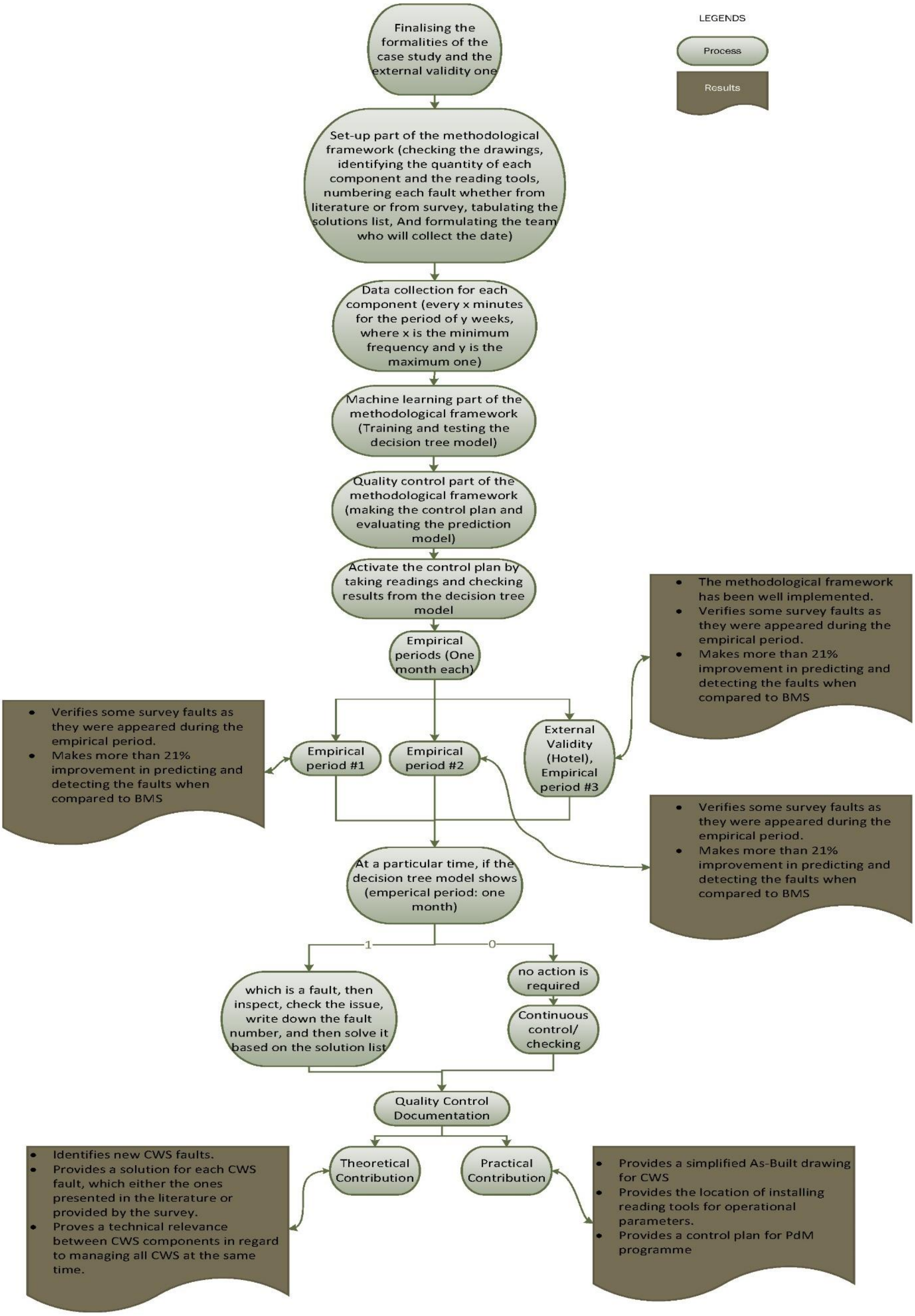

Figure 10c: Research thesis road map (phase 3)

3.5 Assigned Research Methods

A glance at the four research questions generated highlights two keywords; these are the main pillars of this research. The first one is ‘faults’, which are descriptive data, and the second is ‘frequencies’, which are the readings of the operational parameters as well as the study period. These are numerical data, so this research thesis has opted for mixed methods methodology in line with epistemological and ontological assumptions. *Mixed methods* can be defined as an integration between quantitative and qualitative approaches (Heyvaert et al., 2013). A quantitative approach uses numerical data while a qualitative approach uses descriptive data (Saunders et al., 2019). Table 24 outlines the main characteristics of a mixed methods approach (Creswell and Tashakkori, 2007; Mitchel, 2018; Saunders et al., 2019).

Table 24: Main characteristics of mixed methods methodology

Characteristics	Mixed Methods Research Design
Research philosophy	It is associated with the epistemological and ontological pragmatism approach
Research approach	Abductive approach can be used
Typical goals	Producing a robust description and interpretation of data, making the quantitative results more understandable, and understanding wider snap of qualitative findings
Data collection	Uses structured and validated instruments for data collection
Role of the researcher	To answer the research questions that neither quantitative nor qualitative methods could answer alone, and to explain the statistical results more deeply
Research strategy	Generally associated with experimental case study and survey research strategy
Main advantage	Flexibility
Main disadvantage	Workload

Following the systematic literature review, four research gaps were listed with four research questions generated accordingly. Table 25 presents the assigned research method that intended to answer each research question.

Table 25: Thesis research methods

Research Questions	Assigned Research Method
1) Is there a correlation between the components of a CWS that makes it important to cover all of them within the same maintenance framework?	Industry survey and case study
2) Are there any other faults rather than the ones mentioned by the literature?	Industry survey and case study
3) How can an intelligent detection model be built and validated?	Industry survey and case study
4) What are the actions required to fix the CWS faults?	Industry survey and case study

3.5.1 Industry Survey Design

With regard to the first research method, which intended to answer the research questions displayed in Table 25, a *survey* is defined as a research method utilised to collect data from a predetermined group of participants to solicit information and thoughts on diverse topics of interest (Schouten et al., 2017). It lets the researcher collect quantitative and qualitative data which can be illustrated and analysed using descriptive and inferential statistics (Saunders et al., 2019). Collecting data related to any study is important in terms of harmonisation with research goals (Ramakrishnan et al., 2012).

According to Levy and Lemeshow (2013), survey design comprises two steps: 1) developing the sampling plan, and then 2) establishing the procedures for obtaining population estimates from the sample data as well as for estimating the reliability of those population estimates. The sampling plan is the methodology that will be utilised to choose the sample from the population (De Leeuw et al., 2012). The sampling plan depicts the approach that should be used to select the sample, how an adequate sample size should be determined, and the choice of media through which the survey should be administered and distributed (Laaksonen, 2018). This might be telephonic or face-to-face interviews, for example, or mailed surveys using either postal or electronic mail, or a web-based survey (Laaksonen, 2018). Anseel et al. (2010) advise that while crafting the survey, the researcher must determine the method of administrating the survey such as self-completed questionnaire. For the second step of the survey design, the process involves identification of the desired response rate and the required level of accuracy for the survey (Salant and Dillman, 1994; Laaksonen, 2018). Survey design procedures require input from stakeholders who will utilise the survey data and from those who will conduct the survey. Ghauri and Gronhaug (2005) advise specifying the required data while crafting the survey. According to Levy and Lemeshow (2013), data users should determine the measurable variables, the required estimates, the needed reliability and validity to ensure usefulness of the estimates, and any resource limitations that could impact survey implementation. Levy and Lemeshow (2013) suggest that the people who will conduct the survey may furnish additional inputs regarding resource requirements and offer alternative sampling procedures they deem practical and adequate to the task.

The main instrument of any survey is the questions, which can be open-ended or closed-ended. They should, of course, be harmonised with the educational level of the intended participants (Fowler, 1995). Open-ended questions let participants answer in their own words and allow the researcher who is conducting the survey to explore ideas that would not otherwise be readily in mind (Salant and Dillman, 1994). In contrast, closed-ended questions require participants to select responses from among a given group of response options (Salant and Dillman, 1994). The wording and the logical order of the questions should be scrutinised while constructing the survey (Ghauri and Gronhaug, 2005). According to Anseel et al. (2010), the survey must be pre-tested, and to do so, a pilot study conducted. In this regard and in order to execute the survey, according to Levy and Lemeshow (2013), a pilot study is vital prior to distributing or conducting the survey. A pilot study is used to assess and review the survey questions and the choice of the targeted participants either by dependable experts in the field or via group discussion of stakeholders who are familiar with the aim of the survey (Fowler, 1995).

Based on the above valuable information, the industry survey of this research has been carefully constructed and a pilot study undertaken before sending the survey to the research participants, as explained in detail in the next chapter. On a related note, the author of this thesis has added the word 'industry' to 'survey' to be 'industry survey' as the target respondents are from industry and the survey has technical information and questions. According to this present study, data collected from the industry survey will open a space to investigate the operational circumstances at buildings managed by the participants. As concluded by the systematic literature review, an industry survey investigates commercial buildings in the areas and cities in which buildings will be studied, and here in this research thesis, the city of Riyadh in the Kingdom of Saudi Arabia has been chosen.

3.5.2 Case Study Design

With regard to the second research method intended for answering the research questions and to verify the answers of the industry survey, and to present a holistic intelligent maintenance via methodological framework, a case study method was identified. *Case study* is defined as a strategy for undertaking research that involves an empirical investigation of a particular trendy phenomenon within its real-life context using multiple sources of evidence (Woodside, 2010). From an engineering management point of view, case study is a discussion of real-life situations that business executives encounter (Schwartz-Shea and Yanow, 2013). The case study is an appropriate method for describing, predicting and controlling processes that are associated with a phenomenon at the organisational level (Beach and Pedersen, 2016). It can produce an in-depth analysis of phenomenon in a framework, strengthening the development of historical perspectives, and guaranteeing internal validity (Gagnon, 2010). Case study is typically applied when three criteria are met: the first, answering the *how* and *why* questions; the second, when the researcher has little or no control over behavioural events; and the third, when the focus of the associated study is neoteric, contrary to historical phenomenon (Ridder, 2017).

There are several approaches for designing case study research, several suggested by Robert Yin, Robert Stake and Kathleen Eisenhardt. Yin (2018) lists five main steps to design the case study: defining the research questions, determining the theoretical propositions, identifying the actual case that the researcher would study, linking that case to research questions via data analysis, and then reporting the strength of the findings. His approach is created primarily for qualitative research. Yin (2018) emphasises that the initial step in the research design process should be guided by the research questions. Researchers are advised to dedicate significant time and effort to formulating these questions thoughtfully. Once the research questions are defined, Yin (2018) advises the development of theoretical propositions stating what the researcher expects to discover. These propositions are something like hypotheses but are not formulated in the exact same way (George, 2019). For the third step, Yin (2018) insists that the researcher should identify where information will be collected from. After that, for the fourth step, Yin (2018) suggests different ways of linking data to the research questions, propositions or purpose, such as pattern matching, explanation building, time-series analysis, logic models and cross-case synthesis. Yin (2018) advises that sufficient data be collected for better linking and analysis. On a related note, Stake (1995) suggests two ways to analyse the collected data: categorical aggregation and direct interpretation. Yin's approach (2018), though, advises that data be collected first, followed by data analysis, while Stake's approach (1995) does not suggest a specific point of time during the research process for data collection and analysis to begin. The final step of Yin's approach (2018) is to interpret the strength of the case study; this step, he insists, applies statistical benchmarks to prove the strength of the case study findings.

With regard to Eisenhardt's approach (1989), she suggests five steps to design the case study research. The first step is defining the research questions, the 'getting started' step as she refers to it. She emphasises an important component of this step – that researchers do their best to avoid having a theory or theoretical proposition in advance, meaning that the researcher should not propose a theory or a relationship prior to collecting data. The second step involves selecting the precise case that will be used. After that, she suggests collecting the data, referring to third step as the 'crafting instruments and protocol' step. With regard to this step, she does not restrict case study research as a qualitative study as she claims there is no frontier in such research, and therefore, the utilisation of both qualitative and quantitative data collection tools is permitted. This differs from the previous two approaches (Yin, 2018; Stake, 1995), which concentrate solely on qualitative studies. The fourth step of Eisenhardt's approach (1989) entails analysing the collected data, the backbone of the case study research she explains. Again, in contrast to Yin's approach (2018), Eisenhardt (1989) claims that data analysis can be undertaken even while collecting the data and not only after the data collection. The main tactic for analysing the data is hypothesis testing, assessing the plausibility of a hypothesis using sample data (Eisenhardt, 1989). After stating the hypotheses, which are null hypothesis and the alternative one, and collecting the data, the test can be conducted either by statistical analysis like analysis of variance, called ANOVA test (Walpole et al., 2016) or via machine learning algorithms (Fazai et al., 2019). The final step of Eisenhardt's approach (1989) is reporting the case study findings and their strengths. In this step, she suggests a comparison of findings with the extant literature in order to avoid having those interested in such studies vacillate between two different findings that may result in questioning the generalisability of a particular study. Rather, researchers are encouraged to think critically and are furnished the opportunity to extend an existing theory or to enhance findings of the extant literature.

In this current research, the case study takes the first research method a step further. A methodological framework is proposed to implement the said method. The framework contains three phases: the set-up, machine learning and quality control. Two case studies have been implemented following Eisenhardt's approach (1989). One was in a university in Riyadh, Saudi Arabia, while the second one was in a hotel; two are investigated for external validity purposes. This is explained in detail in Chapter 5.

3.6 Ethics of the Research

This research thesis considered the ethics of research. Saunders et al. (2019) assert that participants engaged in research should be fully informed that they are subjects of study. This awareness fosters a sense of cooperation and encourages participants to willingly share the necessary information (He, 2023). Table 26 shows the course of actions in terms of the ethics of the research.

Table 26: Ethical considerations

Research Method	Actions
Industry survey	• Contact details of participants were received officially from the concerned authority (Chamber of Commerce, Riyadh City). Appendix B contains an e-mail of the correspondence between the thesis author and the said authority. • Participants were promised anonymity. A clear statement was included in the body of the e-mail sent to targeted participants. • Participants gave consent. At the end of the industry survey, a message appears to the participants in the web-based platform of the survey confirming that submission means approval.
Case study via methodological framework	• Executive management gave approval. An official letter was sent to senior management of the building under study, and in return, written approval was received.

3.7 Quality of the Research

Here in this last section of this chapter, the author checks and affirms the quality of the research outcomes. The outcomes, presented in detail in Chapters 4 and 5, are primarily a list of CWS faults, their solutions, the proposed faults frequencies and the proposed decision tree's detection model. Saunders et al. (2019) list and define three courses of action for evaluating the quality of research: reliability, internal validity and external validity (Table 27).

Table 27: Evaluation elements of research quality

Element	Description
Reliability	Reliable research should be reproducible, meaning that the techniques of the data collection and analytical procedures can produce the same findings if repeated by another researcher at another time
Internal validity	The extent of confidence in research outcomes
External validity	The ability of the research findings to be generalised and implemented somewhere else.

Amaratunga et al. (2002) also made a comparison between research reliability and validity as shown below in Table 28.

Table 28: Comparison between research reliability and validity

Reliability	Validity
The extent to which the research results can be reproduced when the research study is reiterated under similar circumstances	The extent to which the results really measure what they are supposed to measure
To check the consistency of the research results across periods of time, across different investigators, and across parts of the study itself	To check how well the research results conform to the founded theories and other actions or measures of the same concept
A reliable measurement is not necessarily always valid where the results are likely reproducible but they are not inevitably correct.	A valid measurement is typically reliable where if a test, a framework or a theory produces accurate results, they must be reproducible

In this research thesis, the course of action is prepared for assessment as presented below in Table 29.

Table 29: Quality of research activity in this research project

Element	Element Implementation
Reliability	To check if the proposed detection model can trace CWS faults over time; also, to check if the solutions provided by the industry survey are useful for fixing the occurred faults.
Internal validity	To check if the proposed detection model is better than the existing PdM tool at the building under study.
External validity	To apply the methodological framework at another site and check the performance of the detection model; in this current research project, a second case study is conducted for this explicit purpose.

Chapter 4: Industry Survey

"Predictive maintenance is, essentially, the gold star of the maintenance world - it ensures that tasks are performed at just the right time."
(Eisner, 2022)

4.1 Introduction

The industry survey is the first research method that is assigned to answer the research questions as mentioned in the previous chapter. The type of the survey chosen for this research project is an online one as explained in detail in the next sections. Table 30 below illustrates the benefits of this online survey research method (Fricker and Schonlau, 2002; Easterby-Smith et al., 2018).

Table 30: Benefits of online surveys

Benefit	Description
Cost	Surveys are proportionately not expensive, with only a minor cost per participant. Even if motivations are given to participants, the cost per response is significantly less than the cost of administrating paper or phone surveys, and the number of potential responses is typically greater.
Extensive	Surveys are meaningful in describing attributes of a significant population. No other research method can provide this vast capability, with a more accurate sample size to collect targeted results in which to plot conclusions and to render substantial decisions.
Dependable and flexible	The anonymity of surveys allows participants to answer with more explicit and valid responses. Surveys conducted anonymously offer a space for clear and truthful responses more than other research methodologies, particularly visibly stated that survey responses will remain discrete and classified.

In this present research, the industry survey serves multiple objectives aligned with the identified research gaps and associated research questions. The primary aim is to validate the faults identified in the existing literature. Based on the findings of the systematic literature review, which revealed the possibility of additional or different faults in CWS, the survey seeks to identify any new or overlooked faults. To recall the definition of *fault,* it is any failure that may lead to a CWS breakdown over time. The second point is to identify the occurrence timings of minimum and maximum faults. These timings assist in determining the frequencies, which can then be used in creating the dataset of the decision tree model for heightened prediction accuracy. To recall the definition of *frequencies*, these are the time intervals between readings of the operational parameters as well as the whole study period. The final point is to understand how to fix the faults, either those identified by the literature or by the industry survey. The industry survey has undergone a careful crafting procedure as well as a pilot study, as shown in the next two sections.

4.2 Industry Survey Construction

The proposed industry survey contains four parts which solicit both quantitative and qualitative data. The survey began a with close-ended question asking the participants about the availability of CWS in their facilities. The answer required is black or white, either 'yes' or 'no', and if 'yes', participants were asked to complete the survey. The second part of the industry survey, containing open-ended questions, is related to the faults: the definition of the *fault* is given to the participants, and they are asked about their observations of listed faults as collected from the literature for each CWS component. Then, they are asked to provide additional faults that have occurred in their buildings. Then, participants were asked to suggest a solution for each listed fault.

The third part of the survey is related to fault frequencies: participants were asked which fault occurred most commonly, and to specify its frequency occurrence time (minimum frequency); and then, which fault occurred most infrequently and its frequency occurrence time (maximum frequency). The further action of this survey portion is to select the minimum value frequencies of the faults that occur often for all responses, and to select the maximum value frequencies of the faults that occur infrequently for all responses. The innovative idea here is to utilise these two values in creating the dataset that is will be used in building any machine learning model, and in particular, a decision tree model for this present research. The minimum frequency is proposed as a time interval in collecting data for each component, for example, the readings should be taken every 45 minutes. In contrast, the maximum is to be used as a study period, for example, the readings should be taken over three months. Asking the participants to state those two faults and frequencies makes obtaining the frequency information simple and avoids any misunderstandings. Following the systematic review of literature, the source of the associated data are the readings of any chosen operational parameter of each component, as these operational parameters reflect the health conditions of CWS components.

The fourth part of the survey solicits the opinions of participants about the chosen operational parameter of each CWS component for validation purposes. Although that any operational parameter can give a glimpse about the health condition of the related CWS component as mentioned in Chapter 2, and therefore, it can help building the machine learning model and lead to the fault in the component (*ASHRAE* Handbook, 2023), this part of the survey is intended to check the view of the participants about the best operational parameter of each CWS component that its readings can build the detection model of each CWS component (see Appendix C, part 4). In this research, the chosen operational parameters are the chilled water leaving temperature for chillers and cooling towers, the pressure for pumps, and the space temperature for terminal units. These operational parameters were utilised in some of the considered literature to build the associated detection models, and they are selected here based on the thesis author’s practical experience. Up to this point, the guidelines as suggested by Anseel et al. (2010) as well as by Ghauri and Gronhaug (2005) related to the specification of the data type and the consideration of question wording and logical order, were fulfilled. Regarding the guideline suggested by Anseel et al. (2010) related to the method of administration, the self-completed questionnaire is selected as the data collection instrument. With regard to the guideline related to pre-testing the survey as suggested by Levy and Lemeshow (2013) and Ghauri and Gronhaug (2005), a pilot study was performed, as explained below.

4.3 Pilot Study

To adhere to the fourth guideline of survey construction, the draft questionnaire was disseminated to 10 experts from academia and industry for their review and advice. In addition to the questions, the draft included an explanation of the research goal and expectations. This is to ensure that the survey questions are fulfilling the requirements for validity and reliability, and to raise the response rate (Easterby-Smith et al., 2018; Saunders et al., 2019). The experts from academia were from a variety of departments – industrial engineering, mechanical engineering, electrical engineering, economics and operation management. Also, a manufacturer of each CWS component as well as an operation and maintenance contractor were the industry experts. These experts were allotted one month to reply with their feedback. Table 31 below presents the main comments from both sides, academia and industry.

Table 31: Pilot study outcomes

Academia	Industry
The anonymity of the participants and their organisations must be protected by adding a statement in this regard	The minimum age of the commercial buildings that are managed by the respondents should be three years
The recommended duration for receiving responses is three months	The commercial buildings should have valid commercial registration with the concerned authority
Clarify the questions that are related to the frequency part with an example	Each component should have its own questions
The form of writing the solutions for the new faults should be made the same for every participant	Avoid using abbreviations

After addressing the experts' comments, the industry survey was finalised (as shown in Appendix C) and inserted into a web-based platform, as explained in the next section.

4.4 Targeted Participants and Survey Distribution

Following the outcome of the pilot study, the concerned authority in Riyadh was contacted, and accordingly, the professionals' contacts of 761 commercial buildings were received containing e-mails and phone numbers. The professionals are facility managers, operation and maintenance managers and support services managers.

For industry survey distribution, the associated technique of survey administration, as part of the survey construction guidelines, is the SurveyMonkey platform for web-based questionnaires. This platform generates e-mails to participants. Following the recommendations of Andrews et al. (2003), the e-mail was given an informative title and the body of the e-mail carefully worded to encourage the participants to open the e-mail and click on the survey link. Likewise, the burden of the survey was minimised for participants. The agreement with participants that answers would be anonymous was conveyed with a written statement in the body of the e-mail.

As recommended by the pilot study, the duration of the industry survey was three months' time, including weekends, and auto reminders were sent every seven working days. In addition to auto reminders, a follow-up nudge with phone calls encouraged a higher response rate (Hudson et al., 2004).

4.5 Industry Survey Results

This section illustrates the results of the aforementioned industry survey. It contains four subsections discussing response rate, analysis of survey responses, CWS faults and CWS fault frequencies.

4.5.1 Response Rate

From the 761 participants connected to commercial buildings who were contacted, 336 responses were received within the allotted time, out of which 304 respondents have CWS at their facilities. These are then considered in this research thesis. Figure 11 below illustrates the response rate of the survey.

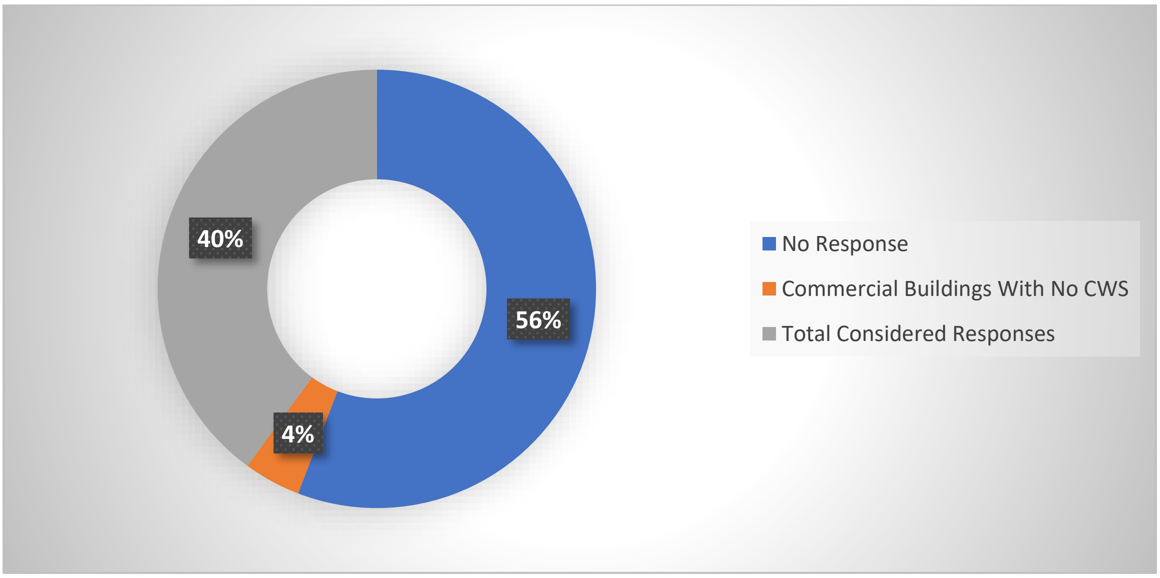

Figure 11: Industry survey response rate

The auto reminders and follow-up phone calls appear to have been beneficial as responses increased during the second and the third months, respectively. Figure 12 shows the number of responses for each month of the survey.

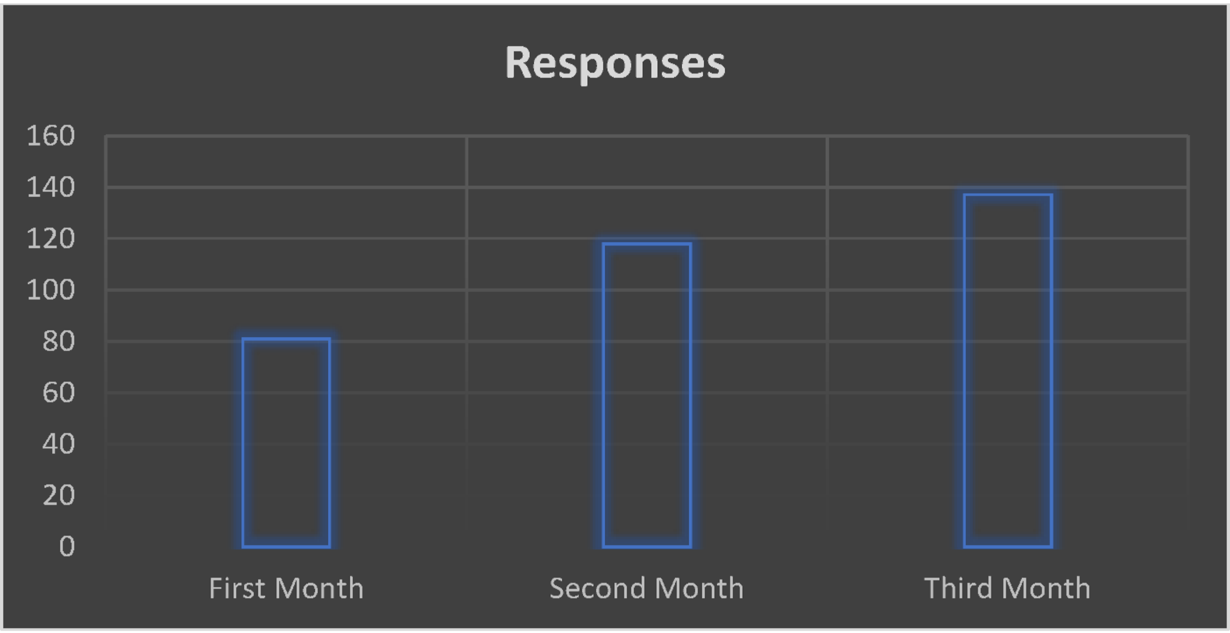

Figure 12: Monthly number of responses

4.5.2 Analysis of Industry Survey Responses

As mentioned previously in this chapter, data gathered from the survey are both quantitative and qualitative. The faults and their solutions are qualitative as these are text-based answers, while the frequencies are quantitative as they are numerical responses. The analysis of the survey outcomes took 22 working days, excluding weekends (Fridays and Saturdays) by an assigned team. The team divided into two sub-teams, referred to for this research as internal and external sub-teams. The internal sub-team included the thesis author, who is separating the responses of CWS components in one sheet for each component, analysing the answers, and then summarising the required information, two operation and maintenance managers, who are refining the information, and the external supervisor of the thesis author, who is supervising the whole process, whereas the external sub-team included several experts who participated in the pilot study. Regarding the aforementioned two managers in the internal sub-team, one is managing the operation and maintenance at a university building (the main case study), while the second is managing the same at a hotel building (the case study for external validity). With regard to the experts in the external sub-team, they are an operation and maintenance contractor as well as a manufacturer of each CWS component. The summary provided by the internal sub-team for each

CWS component is screened, reviewed, and approved by the operation and maintenance contractor. After that, each summary is sent to the concerned manufacturer for validation. Those experts are already engaged in operation and maintenance activities through annual contracts for both buildings.

As mentioned in the previous subsection, 336 responses were received during the industry survey, out of which 304 responses were considered in this research project due to the initial 'yes' answer by those participants, affirming that they have CWS in their facilities or buildings, so the analysis of the first part of the industry survey was straightforward. The second part of the industry survey contains the faults and respective solutions which were analysed with a coding approach. Corbin and Strauss (2014) call this approach a traditional one in analysing text answers of surveys. In this present research, coding began by the internal sub-team by reading through the answers of the second part of the survey containing the faults and their corresponding solutions. They then identified main categories for faults and solutions. This was done by grouping similar words or statements, refining them, and then linking the result to each fault and its solution. After that, the internal sub-team wrote a concise text for each fault and its solution. The faults gathered from the literature were delineated in their same written format. The final step of this analysis entailed writing a summary for each CWS component that contains the list of faults, includes those from the literature and the new ones from the survey, and beside each fault, a solution was noted as well.

Subsequently, the summary was sent to the external sub-team for review and validation. For example, the summary of the cooling towers was sent to the operation and maintenance contractor and cooling tower manufacturer. Table 32 below summarises the analysis of one chiller's fault and its solution. This table contains four columns, the first from the left showing a sample of texts written by participants; these texts are related to one of the chiller's faults. The second column from the left shows how this research thesis described this fault to reflect the outcome of the analysis of the sample in the previous column. This was done by the internal sub-team and verified by the external sub-team. The third column from the left shows a sample of texts written by the participants; these are related to the solution of each fault. The fourth column from the left shows the outcome of the analysis of the sample in the previous column, done by the internal sub-team and verified by the external sub-team.

Table 32: Sample of text answer analysis and outcome

Fault as named by participants	Fault name post analysis activity	Solution as presented by participants	Description of solution post analysis activity
Condenser approach over the limit	High condenser approach	The associated operating cooling tower needs to be checked	The connected tunnel of the cooling tower in operation should be checked and serviced by cleaning the fills
Condenser approach breached		The tunnel that is connected to the cooling tower requires checking the fills and do cleaning for them	
The approach of the condenser is going up		The pipeline that is linked as a tunnel between the cooling tower and the chiller needs to be inspected by checking the fills and clean them	
The high difference between condenser liquid and refrigerant temperature and leaving water temperature		Servicing the cooling tower tunnel is surely required	
Undesirable condenser approach		The technician must inspect the tunnel of the cooling tower	
Condenser approach needs attention		The person in charge of CWS should be asked to go to the cooling tower associated with that chiller and do some servicing by cleaning the fills	

For the third part of the industry survey, four pieces of information were requested from the participants for each CWS component (see Appendix C). All participants provided the fault that occurred often in their building and the frequency of occurrence, as well as the fault that occurred infrequently and its frequency of occurrence for each CWS component. Then, these timings were shifted to an Excel file. A column for each CWS component contains 304 values of the frequency occurrence time of the faults that occur often, and another column for each CWS component containing 304 values of the frequency occurrence time of the faults that occur infrequently. This research thesis named the frequency occurrence time of the faults that occur often as 'minimum frequency' and nominated it as 'x', and called the frequency occurrence time of the faults that occur infrequently as 'maximum frequency' and nominated it as 'y'. After that, these values (x and y) were inserted in the two separate columns, and then the minimum value of x has been determined using the Min function in the Excel, while the maximum value of y has been determined using the Max function in Excel. Here, and as mentioned in the second section of this chapter, this research thesis proposed an innovative utilisation of these two values, x and y. The idea of determining the minimum of values of the x and maximum value of the y is to ascertain the most possible proper frequencies that can be used in creating a dataset of a machine learning detection model. By getting the minimum value of x's, the guarantee will be raised for picking a proper time intervals between the readings of the operational parameter of each component, and the guarantee will be raised for picking a proper study period for collecting the data by getting the maximum value of y's, and therefore, a proper dataset for each CWS component can be made. The detail of creating the dataset is provided in the next chapter. This research thesis proposed utilising the 'minimum frequency' as a time interval between the readings of a particular operational parameter in a particular CWS component, while it proposed utilising the 'maximum frequency' as a study period for a particular CWS component. The proposed minimum and maximum frequencies for each CWS component are shown in section 4.5.4 of this chapter.

For the final segment of the industry survey, participants were given an operational parameter for each CWS component and asked a close-ended question: if the selected operational parameters are the best to predict the health condition of CWS components or not. The analysis here is to count the number of participants in agreement with these selected operational parameters and then to determine the percentage out of the total number of participants: 304. The percentage for each operational parameter is shown in section 4.5.4 of this chapter. As mentioned in the second section of this chapter, this activity is for validation purposes of the selected operational parameters. In cases where the answer to the question of this fourth part of the survey is 'no', participants were asked to suggest an alternative operational parameter for the related CWS component. These data were analysed using the same coding approach as the second part of the industry survey.

4.5.3 Chilled Water System Faults

To recall the CWS faults that were presented post systematic literature review, there were seven faults for chillers, three faults for cooling towers, eight faults for pumps, and nine faults for terminal units. In contrast, the argument that the systematic literature review is incomplete has been proven here as the survey divulged additional faults for each CWS component. The survey outcome provided the research community with 17 faults for chillers, 13 faults for cooling towers, eight faults for pumps and 20 faults for terminal units. Figure 13 below illustrates the total number of CWS faults and the increment between the literature and the industry survey outcomes where these faults are all distinct.

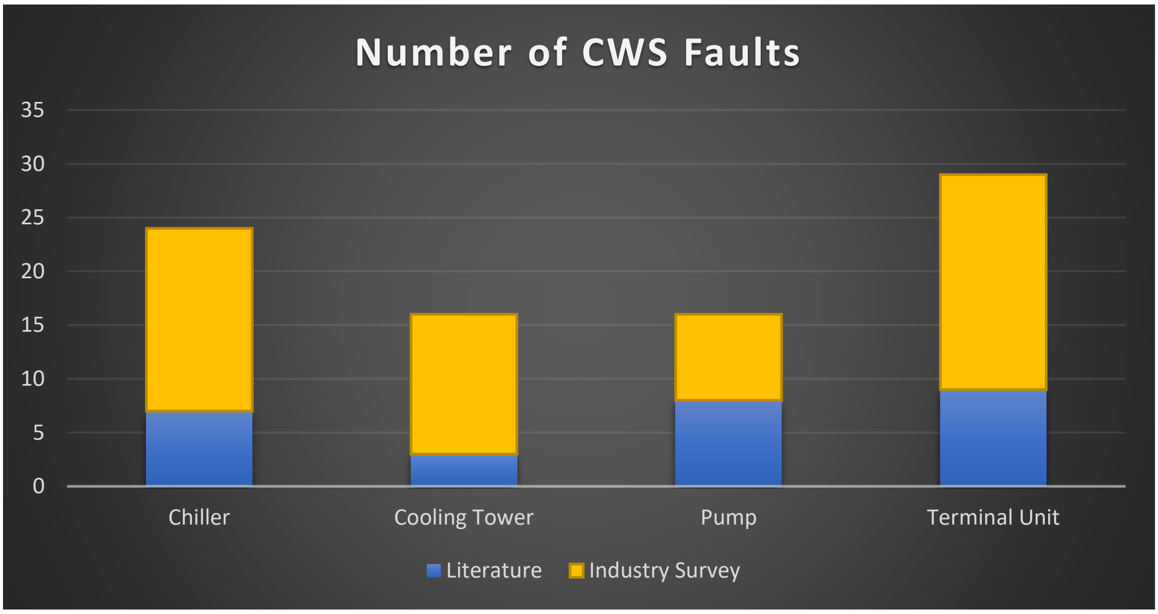

Figure 13: Number of chilled water system faults post industry survey

As stated previously in this chapter, the faults addressed in the literature were listed in the survey for each component and the participants were asked if they observe them. Then they were asked to state other faults beyond those listed. Furthermore, the survey provided managerial solutions for both the faults studied in the literature and the new faults emanating from the survey, whereas the previous studies of the literature ended their proposed PdM or faults detection and diagnosis programmes by tracing the faults but without solutions to rectify the faults. To summarise these outcomes, a table for each CWS component describes the faults and its source, either from literature or from the industry survey, as well as a solution or action for each fault. Table

33 is for chillers, and Table 34, Table 35 and Table 36 are for cooling towers, pumps and terminal units, respectively.

Table 33: Chiller faults and solutions

Fault	Identified By	Solution/Action
Refrigeration leak	Literature	All the components of refrigeration system including tube, joints and valves should be checked, tested and rectified as appropriate.
Evaporating fouling	Literature	The associated parameters should be checked, and then the evaporator tubes should be descaled.
Compressor overcharging	Literature	The factory sheet should be checked and then the charge reduced accordingly.
Faulty operation scheduling	Literature	The control switch should be reset.
Condenser fouling	Literature	The associated parameters should be checked, and then the condenser tubes should be descaled.
High condenser temperature	Literature	The return chilled water temperature should be checked, and then the tubes should be descaled.
Sensor bias	Literature	The controller, the artificial agent, or the sensor should be checked, verified and replaced if needed.
Low discharge superheat	Industry survey	The liquid refrigerant flow in the compressor should be checked and adjusted.
Low evaporator refrigerant temperature	Industry survey	The expansion valve and the filter should be checked and cleaned.
Low oil pressure	Industry survey	The oil filters should be cleaned, and the oil pump with its quality should be checked and rectified.
Low condenser flow	Industry survey	The pressure of the condenser pump in operation should be checked and rectified.
Low chilled water flow	Industry survey	The pressure of the secondary pump in operation should be checked and rectified.
Low cooler water temperature difference (low cooler delta-t)	Industry survey	The lowering efficiency of the primary pump in operation should be checked and the pressure reset.
High cooler water temperature difference (high cooler delta-t)	Industry survey	The accuracy of the water flow’s control should be checked and rectified.
High compressor lift	Industry survey	The water flow should be checked.
High motor temperature	Industry survey	The compressor parameters should be checked.
High motor ampere	Industry survey	The linked mechanical system and the motor winding should be checked and rectified.
High condenser approach	Industry survey	The connected tunnel of the cooling tower in operation should be checked and serviced by cleaning the fills.
High evaporator approach	Industry survey	The assigned water temperature set-point should be checked and reset if needed.
High condenser pressure	Industry survey	The strainer should be checked and cleaned.
Relief valve discharge	Industry survey	The pressure sensors should be checked and fixed.

Vibration	Industry Survey	The supply water temperature should be checked, and the mountings should be reassembled.
Imbalanced line current	Industry survey	The loose connection at the terminals should be rectified.
Incorrect manual guide vane target	Industry survey	The override sittings should be checked and reset.

Table 34: Cooling tower faults and solutions

Fault	Identified By	Solution/Action
Air fan degradation	Literature	The fan should be checked physically, and then repaired by grinding or replaced if needed.
Fouling of fills	Literature	The fills should be cleaned or replaced if needed.
Sensor bias	Literature	The controller, the artificial agent or the sensor should be checked, verified and replaced if needed.
Unusual sound	Industry survey	The bearings of the motor in operation should be checked.
Malfunctioning blowdown system	Industry survey	The solenoid valves should be checked.
High water total dissolved solid	Industry survey	The chemical treatments should be checked.
Fills clogging	Industry survey	The chemical treatments should be checked, and then the required chemicals refilled if needed.
Low circulating water flow rate	Industry survey	The stainer of the associated condenser pump or condenser tubes inside the chiller should be checked and cleaned.
Vibration	Industry survey	The motor in operation and its blade alignment should be checked.
Over current	Industry survey	The phase voltage and other electrical connection should be checked.
Rise in circulating water temperature	Industry survey	The filters should be checked and cleaned or replaced if needed.
Damaged fan	Industry survey	The associated motor should be replaced. In addition, the fan should be grinded or replaced, if needed.
Faulty water level valve	Industry survey	The valve should be replaced.
Faulty isolation valve	Industry survey	The valve should be replaced.
Motor overheating	Industry survey	The voltage should be checked and adjusted.
Low water basin level	Industry survey	The water makeup system should be checked, and the water level should be increased.

Table 35: Pump faults and solutions

Fault	Identified By	Solution/Action
Clogging	Literature	The strainer filtering the water coming from the associated cooling tower should be checked and cleaned in case of partial clogging, and deep cleaned with chemicals and high-pressured water in case of full clogging.
Faulty control switch	Literature	The switch should be troubleshooted or replaced if needed.
Faulty starter	Literature	The electrical connection should be checked and rectified.
Pipeline leakage	Literature	The pipe joint and its fittings should be checked, and then welded or replaced if needed.
High flow rate in cold exchange	Literature	The right pump speed should be checked and adjusted.
Low flow rate in cold exchange	Literature	The right pump speed should be checked and adjusted.
Abnormal or excessive noise	Literature	The associated bearings and shaft should be checked and fixed.
Sensor bias	Literature	The controller, the artificial agent, or the sensor should be checked, verified and replaced if needed.
Motor vibration	Industry survey	The bearings and the foundation support should be checked and rectified.
Motor Heat-up	Industry survey	The bearings and the associated fan should be checked and rectified, ground or replaced if needed.
Leakage from pump set	Industry survey	The associated gland and joints should be checked and reassembled.
Leakage from valves	Industry survey	The associated joints should be checked, reassembled or the valve replaced if needed.
Pump runs but provides no water	Industry survey	The valves should be checked and made free of air.
Pumps run at reduced capacity	Industry survey	The stainer should be checked and cleaned.
Noisy non-return valve	Industry survey	The valve set-up should be checked and replaced if needed.
Improper pump water alignment	Industry survey	Realignment.

Table 36: Terminal unit faults and solutions

Fault	Identified By	Solution/Action
Faulty variable air volume	Literature	The damper connection and controller should be checked and rectified.
Faulty fan	Literature	The fan should be checked, rectified and replaced if needed.
Compressor failure	Literature	The voltage and related control accessories should be checked before replacing formalities.
Filter blockage	Literature	The filter should be cleaned or replaced if needed.
Faulty filter coil system	Literature	The dirt and debris should be cleared.

Cooling coil blockage	Literature	For outer blockage, the fresh air damper position should be checked, and air speed reduced if needed. For inner blockage, the chilled water quality coming from the associated chiller or from the primary pump should be checked and rectified.
Return damper jam	Literature	The damper should be serviced and replaced if needed.
Speed reducing the supply fan	Literature	The blower tips should be checked and cleaned.
Sensor bias	Literature	The controller, the artificial agent or the sensor should be checked, verified and replaced if needed.
Dirty air flow	Industry survey	The bag filer section should be checked and cleaned.
Faulty supply air damper	Industry survey	The damper should be replaced.
Loose belts	Industry survey	The associated pulleys, mountings and V. belt quality should be checked and rectified.
Air trapped in cooling coil	Industry survey	The coil should be checked and cleaned. The pressure of associated secondary pump should be checked and amended as well.
Faulty control valve	Industry survey	The associated voltage should be checked, and the valve replaced if needed.
Broken belts	Industry survey	The associated pulley should be checked and rectified, and then the belt should be replaced.
Noisy motor	Industry survey	The blower bearings should be checked and fixed.
Faulty bearing	Industry survey	The bearing should be replaced.
Motor overload	Industry survey	The power voltage and electrical accessories should be checked and rectified.
Noisy contactors	Industry survey	The terminal in operation should be cleaned.
Vibration	Industry survey	The associated blowers should be aligned.
Motor overheating	Industry survey	The voltage and rated amperes should be checked and adjusted.
Damaged Insulation on pipe	Industry survey	The insulation material should be replaced and then sealed properly.
Faulty variable frequency drive soft starter	Industry survey	The associated parameters should be reset.
Low static pressure	Industry survey	The air flow rate should be checked and decreased.
Damaged Insulation on duct	Industry survey	The duct should be vacuumed, and the defective insulation should be replaced.
Faulty fresh air damper	Industry survey	The air speed should be reduced, or the damper should be replaced if needed.
Faulty exhaust air damper	Industry survey	The connected duct should be vacuumed, or the damper should be replaced if needed.
Faulty cooling valve actuator	Industry survey	The voltage should be checked and adjusted.
Faulty damper actuator	Industry survey	The voltage should be checked and adjusted, and the air flow rate should be minimised.

The occurrence of faults differs between the commercial buildings managed by participants, who repeated some faults for each component and listed some other faults either once or a few times. Furthermore, all considered responses confirmed the occurrence of the faults that are mentioned by the literature and furnished in Figure 9. Table 37 below reveals the most repeated fault for each CWS component in the commercial buildings managed by participants. This table has three columns: the first from the left lists the CWS components; the second from the left shows the most repeated fault by the participants for each CWS component; while the third from the left shows the percentage of participants who listed the faults in the previous column out of the total number of participants (304).

Table 37: Most repeated faults

CWS Component	Fault	Repeating Percentage
Chillers	Refrigeration leak	100%
Cooling towers	Malfunctioning blowdown system	89%
Pumps	Noisy non-return valve	91%
Terminal units	Low static pressure	84%

This table shows refrigeration leak as the most common fault for chillers as all the respondents confirmed its appearance at their commercial buildings; this is not in alignment with the systematic literature review wherein the condenser fouling was the most frequently noted chiller fault in the literature. For the cooling towers, the literature primarily addressed fills fouling and air fan degradation faults, while the industry survey showed that the malfunctioning blowdown system fault is the most repeated. The same is evident with pumps and terminal units, wherein the literature mainly addressed the pump clogging fault and the terminal unit return damper jam fault, while the industry survey showed other faults noted by the majority of the participants: noisy non-return valve and low static pressure for pumps and terminal units, respectively. The literature has overlooked the aforementioned faults as it might be the focus was on how to build a detection model and on determining the detection accuracy of that model rather than paying attention to the type of fault.

In addition to a fixing action for each CWS fault in the industry survey, it is evident from Tables 33-36 that there are technical correlations between CWS components, as faults in a particular CWS component appear to be a consequence of the health condition of another CWS component. The low condenser flow fault in the chiller component, for example, can be fixed by investigating the related pump component in operation. The solution of this fault can be executed by checking and rectifying the pressure of the condenser pump in operation. The low chilled water flow fault in the chiller component can be fixed by investigating the related pump component. The solution for this fault can be executed by checking the rectifying the pressure of the secondary pump in operation. The high condenser approach fault in the chiller component can be fixed by investigating the related cooling tower component in operation. The solution to this fault can be executed by checking and servicing the connecting tunnel of the cooling tower in operation via cleaning the fills.

The low circulating water flow rate fault in the cooling tower component can be fixed by investigating the related chiller or pump components in operation. The solution for this fault can be executed by checking and cleaning the stainer of the associated condenser pump or by checking and cleaning the condenser tubes inside the associated chiller. The clogging fault in the pump component can be fixed by investigating the related cooling tower component in operation. The solution to this fault can be executed by checking and cleaning the strainer filtering the water from the associated cooling tower in case of partial clogging, and by cleaning deeply with chemicals and high-pressured water in case of full clogging.

The air trapped in cooling coil fault in the terminal unit component can be fixed by investigating the related pump component in operation. The solution to this fault can be executed by checking and cleaning the coil and by checking and amending the pressure of associated secondary pump. The cooling coil blockage fault in the terminal unit component can be fixed by investigating the related chiller or pump components in operation. The solution for this fault can be executed by checking the fresh air damper position and by reducing the air speed in case of the outer blockage. In case of inner blockage, it can be fixed by checking and rectifying the chilled water quality from the associated chiller or the primary pump in operation. To justify the technical correlation between CWS components quantitatively, *Pearson r* test is used for this purpose. Yu and Hutson (2024) define it as a statistical correlation test that can estimate the strengths between different variables and their relationships. The correlation coefficient '*r*' can be easily calculated in Excel software via '*PEARSON*' function (Mustafy and Rahman, 2024). Table 38 below shows the interpretations of different *r* values (Fox and Sturdivant, 2024).

Table 38: Interpretations of different correlation coefficient values

Correlation coefficient value	Strength	Direction
Greater than 0.50	Strong	Positive
Between 0.30 and 0.50	Moderate	Positive
Between Zero and 0.30	Weak	Positive
Zero	None	None
Between Zero and – 0.30	Weak	Negative
Between – 0.30 and – 0.50	Moderate	Negative
Less than – 0.50	Strong	Negative

The quantitative analysis is arranged through Excel sheet for each of the fault relations between the components that are mentioned previously in this subsubsection. Each sheet includes three columns, the first column contains the serial numbers of the persons surveyed, who are stated the fault, for example the low chilled water fault in chiller, the second column contains either '1', which means the person mentioned that the said fault can be fixed by investigating the related pump in operation for the said fault, or '0', which means the person gives different action, and the third column contains the cumulative values of the second column. After that, the first and third columns are assigned as variables for *Pearson r* test. Appendix D shows these sheets along with the correlation coefficient values and their plots. Table 39 below summarised the *r* values between CWS components, and the associated confidence level is ninety-nine per cent.

Table 39: Correlation Coefficient Values (Industry Survey)

CWS component experiencing a fault	Fault	CWS component to be investigated	Correlation Coefficient Value
Chiller	Low condenser flow	Pump	0.9707
Chiller	Low chilled water flow	Pump	0.9806
Chiller	High condenser approach	Cooling Tower	0.9307
Cooling Tower	Low circulating water flow rate	Chiller	0.9525
Cooling Tower	Low circulating water flow rate	Pump	0.9623
Pump	Clogging	Cooling Tower	0.8922
Terminal Unit	Air trapped in cooling coil	Pump	0.9880
Terminal Unit	Cooling coil blockage	Chiller	0.9599
Terminal Unit	Cooling coil blockage	Pump	0.9413

All *r* values in the above table are greater than 0.50, which means the correlation is strong and positive for each. So, from this analysis, it can be concluded that covering the whole CWS within the same maintenance framework is exceedingly important and highly significant.

4.5.4 Chilled Water System Fault Frequencies

This subsection is related to the third part of the survey, whose concept was explained previously in this chapter. Participant responses were counted by tabulating the frequency values of the faults that are occurring often (x's) as well as the frequency values of the faults that occurred infrequently (y's). Then, the smallest value of the x and the biggest value of the y are identified. In addition, these two values were scored by the majority of the participants. Table 40 below summarises these outcomes: each CWS component has two values (x and y) and shows the highest percentage of times each value is repeated by the participants. Figure 14 is for chiller as an example, showing how the values of x and y in Table 40 are derived, and the same applies for other CWS components. These frequencies will be used for data collection to create a dataset for each CWS component, which will then be used in building the detection model. Data collection related details will be discussed in the next chapter.

Table 40: Fault frequency outcomes

CWS component	X (minutes)	Percentage of 304 participants who stated the value x	Y (weeks)	Percentage of 304 participants who stated the value y
Chillers	30	75%	12	56%
Cooling towers	30	68%	16	39%
Pumps	60	49%	24	34%
Terminal units	45	40%	8	39%

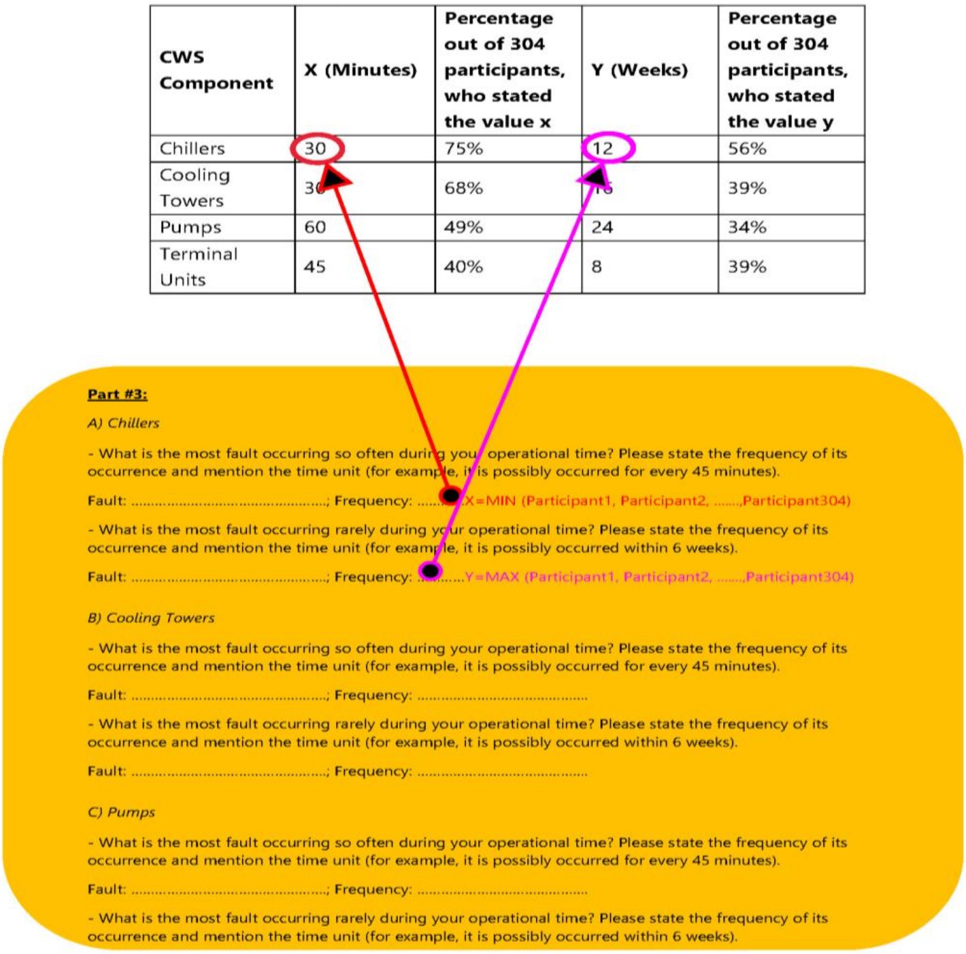

Figure 14: Source of frequency values

The above table clarifies the time interval of the proposed readings of each chosen operational parameter for the chiller in operation – the leaving water temperature – as every 30 minutes over a study period of 12 weeks. For the cooling tower, the readings of the water leaving temperature should be taken every 30 minutes over a study period of 16 weeks. For the pumps, the readings of the pressure should be taken every hour over a study period of 24 weeks. For the terminal unit, the readings of the space temperature should be taken every 45 minutes over a study period of eight weeks. These frequencies provide a technical element to building the machine learning model, which in this research is a decision tree, to detect the faults and control the entire CWS. Having noted the operational parameters, the survey asked participants in its fourth segment to share their opinion on specific operational parameters for each CWS component. This is to ensure that these operational parameters are valid and are the best to provide the health condition of the CWS components, and accordingly, to find and detect the faults. Table 41 below shows the majority of participants identified the chosen operational parameters as the best to detect the health condition of CWS components. Appendix E contains the alternative operational parameters recommended by the remainder of the participants.

Table 41: Chilled water system operational parameters

Component	Operational Parameters	Participants with the choice
Chillers	Chilled water leaving temperature (°C)	98%
Cooling towers	Chilled water leaving temperature (°C)	96%
Pumps	Pressure (bar)	100%
Terminal units	Space temperature (°C)	90%

4.6 Conclusion

This chapter presented the first research instrument in this research project, the industry survey. The industry survey, adhering to construction guidelines and a pilot study, was disseminated to 761 professionals who manage commercial building in Riyadh, Saudi Arabia. The duration of the industry survey was three months, and 336 responses were received during that time. Of those, 304 participant responses were considered by this research project as these participants have CWS in their commercial buildings. After that, the responses were analysed by an assigned team. Following the analysis, the industry survey provided the research community with new faults: 17 faults for chillers, 13 faults for cooling towers, eight faults for pumps, and 20 faults for terminal units. Also, the industry survey provided a solution to fix each fault, all faults listed in either the literature or noted by the industry survey. The solutions reveal a correlation between CWS components, underscoring the importance of involving the entirety of CWS components when managing operations. For example, to fix a chiller fault such as high condenser approach, the cooling tower in operations needs to be inspected.

With regard to the frequencies, this research project proposed time frequencies to create the dataset for use in building the detection model. These frequencies, as presented in Table 40, are two types, minimum and maximum. This research proposed an innovative approach to create the dataset that will be used in building the detection model by applying the minimum frequency as a time interval between the readings of the operational parameter for each CWS component, and by using the maximum frequency as a study period. This chapter explains how these frequencies were calculated (see Figure 14 for an example). The findings from the concluding segment of the industry survey have reinforced the selection of operational parameters for this research project. These parameters will serve as the primary source of data required for constructing the detection model. The subsequent chapter will demonstrate how the outcomes of the survey, including the identified frequencies, are utilised in developing the methodological framework. This framework will be implemented through the second research method employed in this project, namely, a case study. The subsequent Chapter will also show that the chosen operational parameter of each CWS component can be taken care of any fault category in the associated component.

Chapter 5: Case Study: Development and Implementation of Maintenance Methodological Framework

"Save money by relying on predictive maintenance."
(Theissler et al., 2021)

5.1 Introduction

As discussed in the first chapter, the goal of this research project is to present a holistic intelligent maintenance for CWS via a methodological framework. This chapter utilised the outcomes of the industry survey (see the previous chapter) in building this framework. The industry survey provided two inputs applicable to this research, which were the fault frequencies and fault solutions. The utilisation of these inputs is explained in the next sections. This chapter presents the second research method of this present research project, which is a case study, one main case study and another for external validity purpose. To implement the main case study, a methodological framework is proposed in this chapter. Partelow (2023), defining *framework* as a supporting structure around which something can be created and built, considers it a system of rules, steps, ideas or beliefs utilised to plan or decide something for any scientific topic. From a research point of view, frameworks are typically utilised to understand and investigate a research problem and lead the development and analysis of the research topic (Ravitch and Riggan, 2016). Also, it can be presented as a roadmap to conceptualise and structure the research work by providing a schema that links different ideas, concepts or theories within the area of a research topics to facilitate the execution of the related empirical studies (Kirk et al., 2015). From a practical point of view, constructing management frameworks for projects, continuous activities or any other core programme of a building's facility management gives a structure to the programme and allows corrective measures that can achieve related goals (Wildenauer et al., 2022).

Structuring a methodological framework for this research project serves several objectives. The primary goal is to assess the suitability of the proposed frequencies, which emerged as a key finding from the industry survey. It aims to determine whether these frequencies are appropriate and capable of facilitating the development of a detection model with high accuracy. These frequencies, shown in the previous chapter, will be used for data collection purpose. As mentioned in the previous chapter, this research project proposed an innovative way for data collection where the minimum frequency for each CWS component will be used as a time interval between the readings of the operational parameters, while the maximum frequency will be considered as a study period or the total time of collecting the data. Accordingly, a dataset for each CWS component will be provided. Then, each dataset of each CWS component will be used in building and training the detection model that will be presented via machine learning. The second goal is to verify the faults presented in this thesis especially the ones resulted from the industry survey and that will be checked during empirical periods. Overall, the methodological framework will allow this research project to address all the research gaps and will give a structure for the second research method, which is the case study, to answer all the research questions, and to verify the outcomes of the industry survey that were mentioned in the previous chapter. The next section shows the structure of the proposed methodological framework.

5.2 Methodological Framework

The methodological framework in this research project is built from a managerial perspective; each phase of the framework contains multiple managerial steps. Table 42 below describes the phases of the proposed methodological framework as well as the objectives of each phase.

Table 42: Methodological framework structure

Phase	Objectives	Supporting References
Set-up	• To understand the as-built drawing of the under-study building. • To identify the number of each CWS components and their location at the site. • To ensure the data reading tools are in the right locations. • To prepare the data collection plan, including data collection tools, the schedule of data collection, and the team who will collect the data.	(Maree et al., 2021; Sala et al., 2019; Hauashdh et al., 2024)
Machine learning	• To formulate the algorithm, build the detection model and train it.	(Sharma et al., 2024; Cummins et al., 2024)
Quality control	• To make a control plan for the maintenance framework. • To evaluate the detection model.	(Gan et al., 2024; Arena et al., 2024)

It is suggested that the above phases are followed in the same logical order as shown, as detailed in the next subsections.

5.2.1 Set-up Phase

In preparing the methodological framework, three stages are to be followed in the same order as listed in the below subsubsections.

5.2.1.1 Chilled Water System Drawing

The first step of the framework suggested by this research project is to understand the as-built drawing of the CWS in the building that will be studied. This drawing, showing the actual building layout, is normally handed over to the facility management after completion of the building construction (Ellis, 2021). Following ASHRAE standards (2023), this research proposed a simplified schematic CWS drawing to easily identify the numbers of each CWS component and recognise their location at the site (see Figure 15 below). The proposed schematic serves as a guide while the researcher or user is reviewing the original as-built drawing. The as-built drawing, typically quite complicated, has many pages that contain other utility systems. The proposed schematic has been made to recognise the look of each CWS component in the drawing, so the user of the researcher can identify each easily in the main as-built drawing, noting the number of each CWS component at the building and their locations at the site.

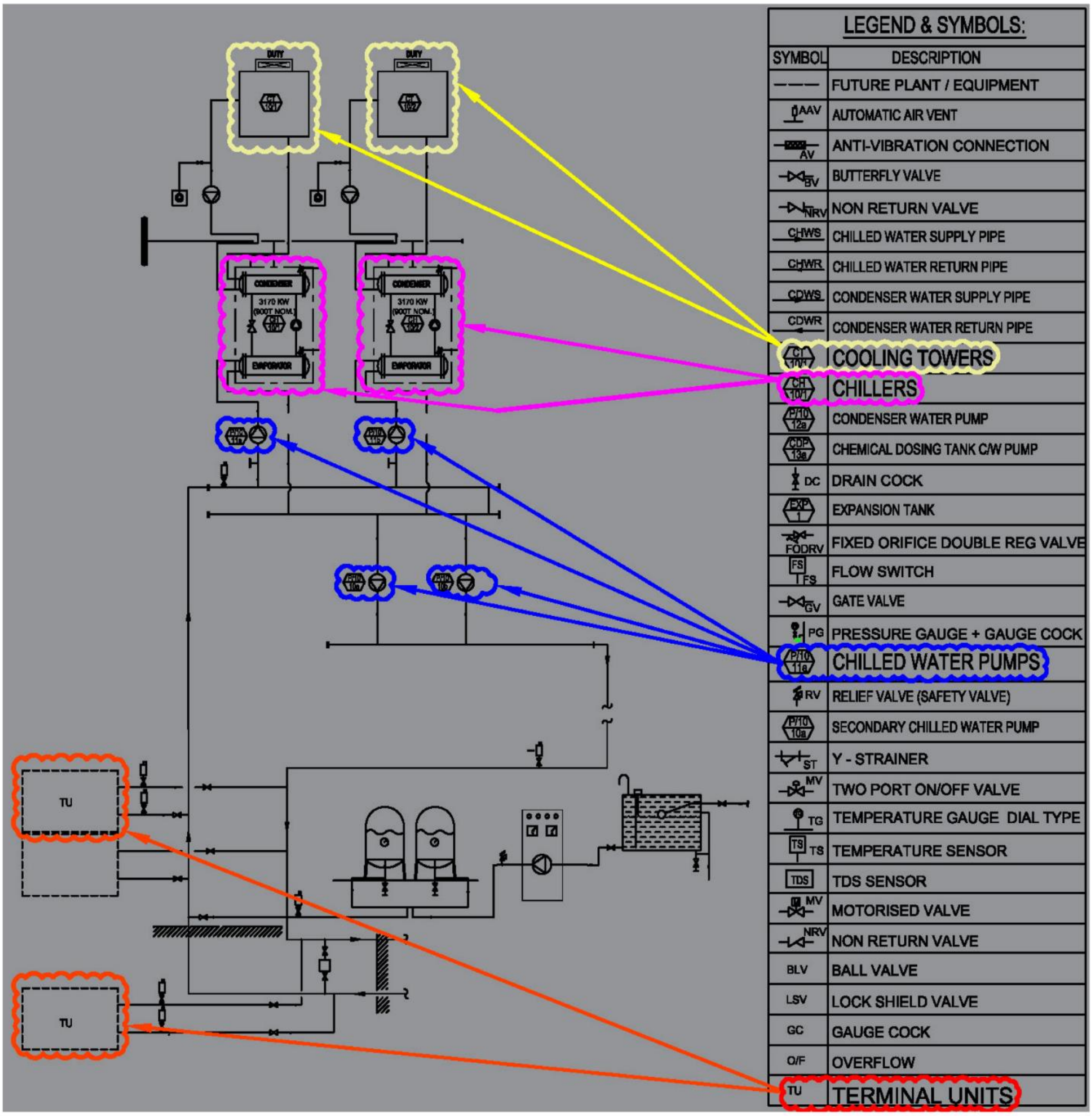

Figure 15: Chilled water system simplified as-built drawing

5.2.1.2 Reading Tools of Operational Parameters

Following on the previous two chapters, one fundamental of PdM strategy is the datasets that contain the readings of the CWS operational parameters. As discussed in the systematic literature review, *operational parameters* are defined as quantifiable factors that offer numerical data about the performance of the CWS. In this research project, the operational parameters chosen are the temperature of water leaving the chillers and cooling towers, the pressure for pumps, and the space temperature for terminal units as these are the best for conveying the health condition of these components as proven by the industry survey (Chapter 4, Table 41).

To collect these parameter readings, the associated tools were assumed to be available at the building under study. Measurement tools can include meters, gauges, sensors, thermostats or any other agent such as BMS. In case of the unavailability of these reading tools, Lam et al. (2011) as well as Beckmann et al. (2004) outlined procedures for installing such tools. Following the standard operating procedure of ASHRAE (2023), this research project suggests a proper location for installing the reading tool for each CWS component in the building under study (see Table 43).

Table 43: Proper locations for reading tools

Chilled Water System Component	Location
Chiller	Chilled water supply header
Cooling tower	Straight pipeline entering the condenser
Pump	Discharge pipeline
Terminal unit	1.50 m above the floor level in a space, or in the return air duct

Once the reading tools are installed, they must be connected to an assigned computer unit that will be used in the maintenance framework. Kayastha et al. (2014) as well as Trivedi et al. (2019) outlined a procedure for connecting such tools to computers. This course of action is undertaken, as explained in the third subsection of the methodological framework section (Quality Control).

5.2.1.3 Data Collection

After determining the number of each component and finalising the reading tools, the last stage of the set-up is the data collection. The previous chapter proposed time frequencies to collect data of selected operational parameters in commercial buildings (see Table 40) and supported the choice of the operational parameters (see Table 41). Following these proposals, the readings of chilled water temperature leaving a particular chiller should be taken every 30 minutes over a study period of 12 weeks. The same should be applied for cooling towers, but over a study period of 16 weeks. With regard to pumps, the readings of pressure should be taken every hour over a study period of 24 weeks. For terminal units, the readings of space temperature should be taken every 45 minutes over a study period of eight weeks.

This research project uses a check sheet to collect data for each CWS component. According to Tarí and Sabater (2004), a check sheet is one of the seven basic quality control tools. The check sheet should contain the readings and inspection results. According to Zhang et al. (2019), such readings must cover two modes, fault existing and fault free, and therefore, the inspection results will be either '1' in a case of fault or '0' in a case of no fault. This research project suggests that the check sheet be completed by experienced technicians or users. Each check sheet, it is proposed, is to be recorded by two team members, one for the morning and part of the afternoon shift, and one for the evening and the second part of the afternoon shift. Appendix F presents a proposed check sheet for terminal units, and the same should be applied for other CWS components, taking into consideration the differences in time intervals and the unit of operational parameters between components.

After collecting the data, a file for each particular component is proposed to be created in Excel software, and then the information from the related check sheet should be logged. Thus, each file should contain two columns – one for the readings and the another for the inspection results – and then be saved in the assigned computer unit in *csv* format. These files contain the required datasets, and at this point, the set-up phase is completed. Accordingly, the machine learning part can then be started.

5.2.2 Machine Learning Phase

This research has utilised decision tree, a common machine learning algorithm primarily used for classification, prediction and regression applications. It has many benefits; for example, Sharma and Kumar (2016) insist that it can be used to predict continuous and discrete values. They also indicate that it can capture nonlinear relationships while being easier to use than other machine learning algorithms for understanding, interpretation and visualisation (Sharma and Kumar, 2016). In addition to these benefits, the literature review concluded that decision tree and artificial neural network algorithms provide high prediction accuracy compared to other algorithms, and therefore, this research project has chosen decision tree, as its graphical binary representation can be easily interpreted by both technical and nontechnical decision makers. Moreover, decision trees excel in capturing nonlinear relationships within data, providing a valuable tool for tasks requiring pattern recognition (Priyanka and Kumar, 2020). Simultaneously, the research recognises the alternative methodology of artificial neural networks inspired by the sophisticated architecture of the human brain, consisting of interconnected nodes in layers (Graupe, 2013). Each connection between nodes has a weight, and the model learns by adjusting these weights during the training process (Wu and Feng, 2018). Artificial neural networks are adequate for learning complex patterns and relationships in data, making them suitable for tasks like image and speech recognition, natural language processing and detailed decision-making processes (Gurney, 2018). However, artificial neural networks can be computationally intensive, especially for large and deep networks, and may lack the interpretability offered by the decision trees (Worden et al., 2023). With these considerations, this thesis acknowledges the distinctive advantages of decision trees, such as interpretability and simplicity, rendering them a valuable choice in capturing intricate relationships within data.

The decision tree has a tree-like structure, with a root node and intermediate nodes that split into branches. The last intermediate node, split into leaves, is terminated with an end node. Each node represents a classification or prediction feature. A branch or a leaf represents the possible value of the feature. The path from the root node to the end node is labelled using the predicted outcome or target classification, which is assigned using an existing training dataset. Using supervised training algorithms, the features are split recursively from top down according to certain criteria. Figure 16 below depicts the general structure of the decision tree (Fletcher and Islam, 2019).

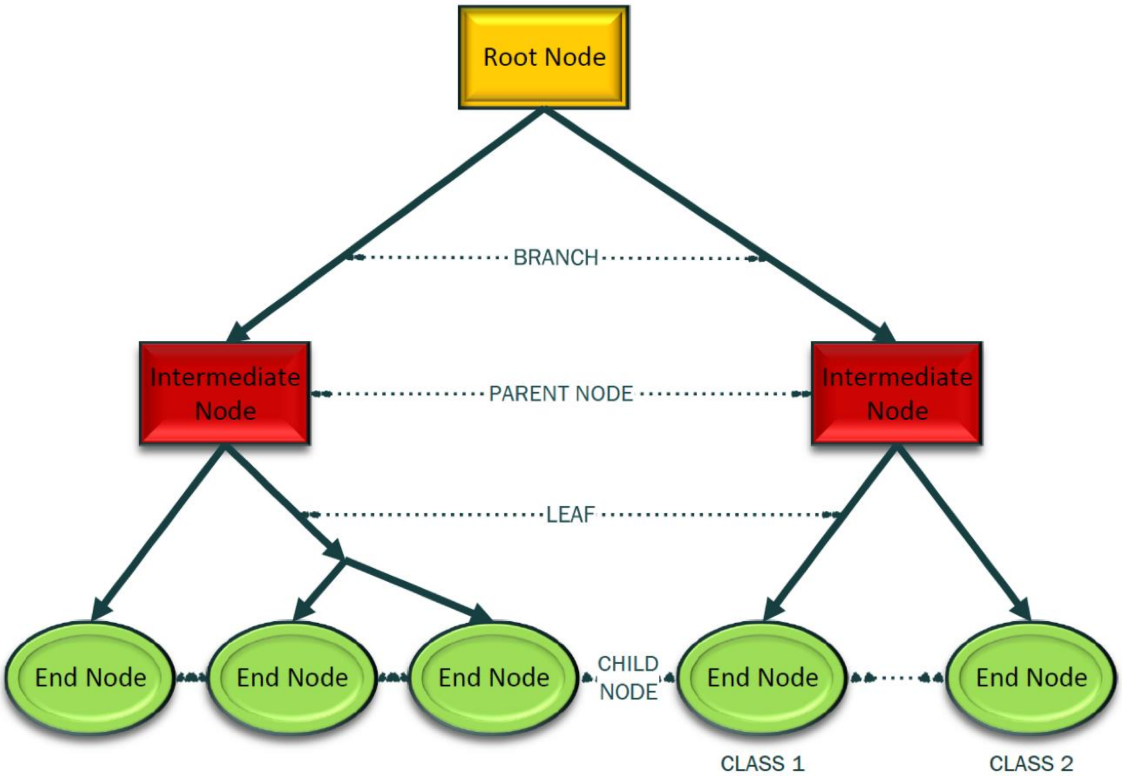

Figure 16: General structure of the decision tree

In this research, two decision tree algorithms are proposed for use – the C4.5, a successor of the iterative dichotomiser 3 (ID3), and the classification and regression tree (CART) algorithm – as they are efficient for splitting the trees (Javed Mehedi Shamrat et al., 2022). The basic principle of the splitting mechanism is to select a root node from the 'N' features and subsequently decide which attribute should be used next as the intermediate node. Different statistical criteria should be used to make these decisions, such as the Gain Ratio and the Gini Index. According to Grąbczewski (2014), the Gain Ratio criterion is mainly used in the C4.5 algorithm, while the Gini Index is used in the CART algorithm. The Gain Ratio is calculated as in Equation 1 below:

$$Gain\ Ratio_{(A)} = \frac{Information\ Gain}{SplitInfo} = \frac{Entropy(parent) - \sum_{j=1}^{k} Entropy(j,child)}{\sum_{j=1}^{k} \frac{D_j}{D} log_2 \frac{D_j}{D}} \quad (1)$$

In information theory, entropy measures the uncertainty in data. The entropy (parent) measures the amount of randomness (impurity) in the parent node before it splits. D is the number of instances in the parent node and D_j is the number of instances in the child j, and k is the number of discrete values of an attribute A, which is tested at the parent node for splitting. The entropy at each child node is found using Equation 2 below:

$$Entropy = -\sum_{i=1}^{n} p_i \, log_2 \; p_i \tag{2}$$

Where p_i is the probability of selecting an instance in class i, and n is the number of classes. The attribute that is selected for splitting at the parent node is the one with the highest Gain Ratio. Similarly, the Gini Index for the CART algorithm can be found by Equation 3 below:

$$Gini\ Index_{(A)} = \sum_{j=1}^{k} \frac{D_j}{D} Gin(j, child) \tag{3}$$

Similarly, to the entropy, the Gini Index measures the impurity at the parent node. The Gini of a child node is found by Equation 4 below:

$$Gini = 1 - \sum_{i=1}^{n} p_i^2 \tag{4}$$

The attribute that is selected for splitting at the parent node is the one with the smallest Gini Index. In this research project, this attribute is the selected operational parameter of each CWS component. As a reminder of these operational parameters or attributes, they are the water leaving temperature for chillers and cooling towers, the pressure for pumps, and the space temperature for terminal units. Many programming languages or software can read the collected data and train the detection model, such as Python (Guttag, 2017). The software should be installed in the assigned computer unit and the required codes should be written in a way that allows reading the files (datasets) for each CWS component, as listed in the data collection stage of the setup phase, and then to train and test the model. In terms of the process of utilising decision trees for detection, Figure 17 below shows sequential steps that guide the development, training and evaluation of the decision tree model.

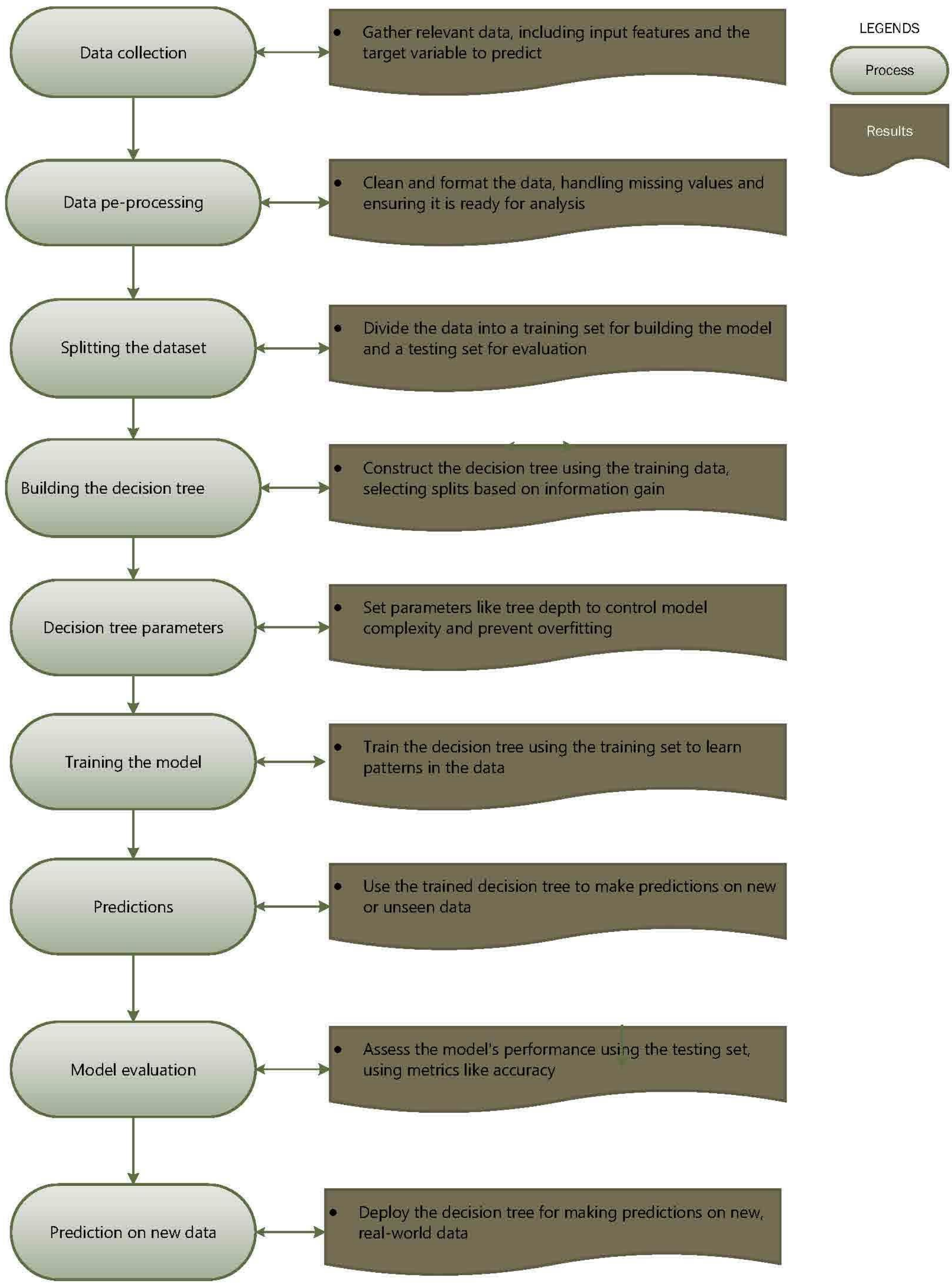

Figure 17: Building of decision tree model

5.2.3 Quality Control Phase

Th quality control phase is the final part of the proposed framework; its goal is to ensure the detection model is working correctly and to rectify faults immediately. To do so, this research project suggests crafting a control plan which contains monitoring and response actions (Almobarek and Alrashdan, 2022). Table 44 below clarifies the descriptions of these two actions, noting who is responsible for executing each action.

Table 44: Control plan

Quality Control Action	Description	Responsible
Monitoring	The detection model should be connected to the reading tools, which are already connected with the computer unit during set-up. This ensures that the computer unit shows continuous reading for each CWS component.	Information Technology Department or Service Provider or Specialised Supplier
Response	When the detection model shows fault, which is '1', as a result of a particular reading, the related component should be inspected and then be rectified as per the actions tabulated in the previous chapter (Tables 33-36).	Facility Department's Officer and Technician

While the response action contains fixing the occurred faults by implementing the actions provided by this research thesis in Tables 33-36, this research project recommends applying measures that examine if these actions are satisfactory or not. When detecting a fault, and after implementing the provided action to fix that fault, the inspector at site should immediately observe the effected part of the component, and then report the outcome to the officer. The outcome would be either satisfactory, which means the fault is fixed and cleared, or unsatisfactory, which means the provided action is unable to fix the fault. In case of unsatisfactory, the inspector should re-implement the action again and observe the effected part – in case the fault continues, then the inspector should report that to the officer, and accordingly, the officer should double check the situation at site to validate the report of the inspector. Once validated, the officer should call specialised team like the operation and maintenance contractor to look at the case and fix it. Furthermore, Montgomery (2020) advises it best to document the outcome of the response action for future improvement. This research proposed a documentation process which involves listing the lessons learned from the proposed intelligent maintenance framework, ensuring that the computer unit is working efficiently, tracking spare parts stock, training more technicians to be familiar with the detection model, and writing regular reports about the performance of the proposed intelligent maintenance framework for future improvements.

5.3 Case Study: Methodological Framework Implementation and Results

This section presents a case study on the proposed framework. The case study was performed at Alfaisal University in Riyadh, Kingdom of Saudi Arabia. The implementation of the framework has been carried out as per the three parts proposed in the previous section comprising the methodological framework.

Alfaisal University is a King Faisal Foundation project, a private, not-for-profit, research university, comprising the Colleges of Engineering, Science and General Studies, Medicine, Pharmacy, Business, and Law and International Relations. It has a range of state-of-the art amenities and equipment spread across seven major buildings on a 36.7-acre (≈149,000 square meter) campus. These facilities provide students, faculty members and other admin staff a venue for study and research while accommodating various other social activities too. The following subsections will explain the implementation of each part of the methodological framework.

5.3.1 Implementation of Set-up Phase

5.3.1.1 Chilled Water System Drawing

The main goal of the proposed framework is to design an intelligent maintenance framework that considers the whole CWS, all CWS components. Therefore, to begin implementing the framework, the CWS as-built drawing was collected and then, following Figure 15, the numbers of each CWS component were determined (see Table 45) as well as their locations around the site. Figure 18 shows a panoramic view of CWS at Alfaisal University.

Table 45: Number of chilled water system components

CWS Component	Quantity
Chiller	5
Cooling tower	7
Pump	19
Terminal unit	72

Figure 18: Panoramic view of chilled water system

5.3.1.2 Reading Tools of Operational Parameters

At this stage, the standard presented in Table 43 has been followed, ensuring that the reading tools for the operational parameters of each CWS component were in the best location. Figures 19-22 show the reading tool location for each CWS component. As previously stated, these tools read the temperature for water leaving each chiller and cooling tower, the pressure for pumps, and the space temperature for terminal units. Through the Information Technology Department of the university in discussion, these reading tools were connected via sensors to a computer unit to be prepared for the quality control phase.

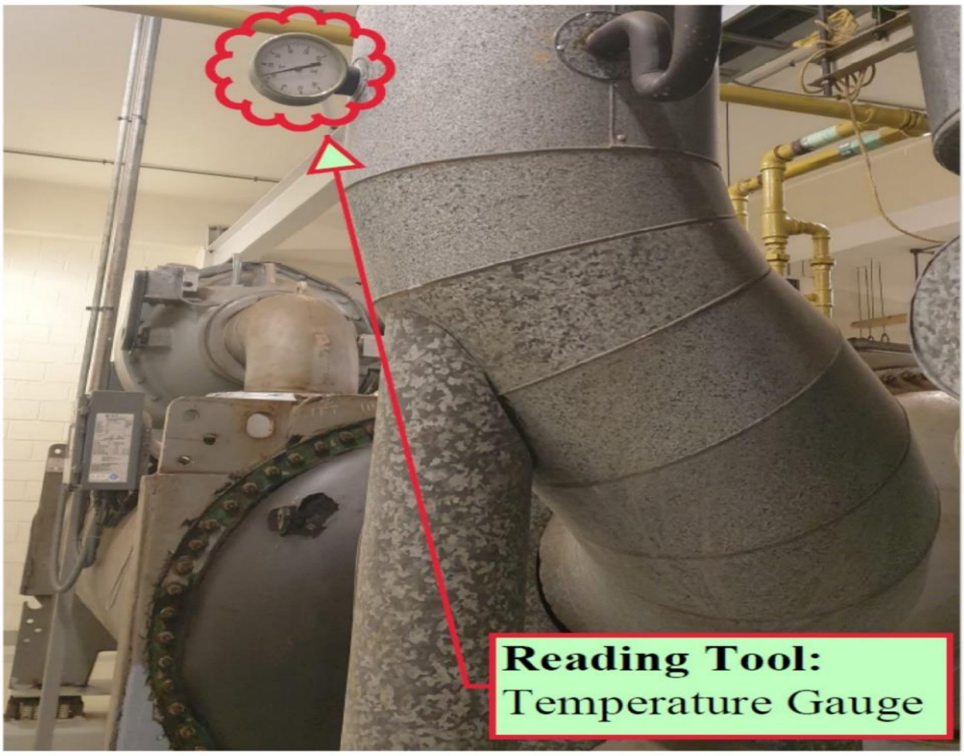

Figure 19: Chiller reading tool

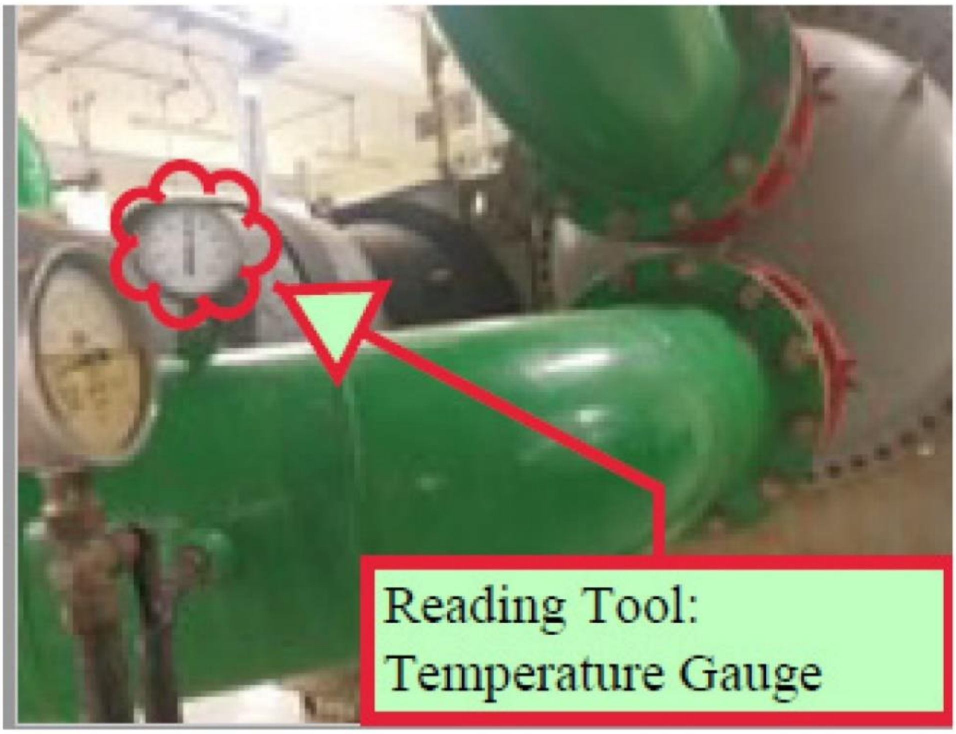

Figure 20: Cooling tower reading tool

Figure 21: Pump reading tool

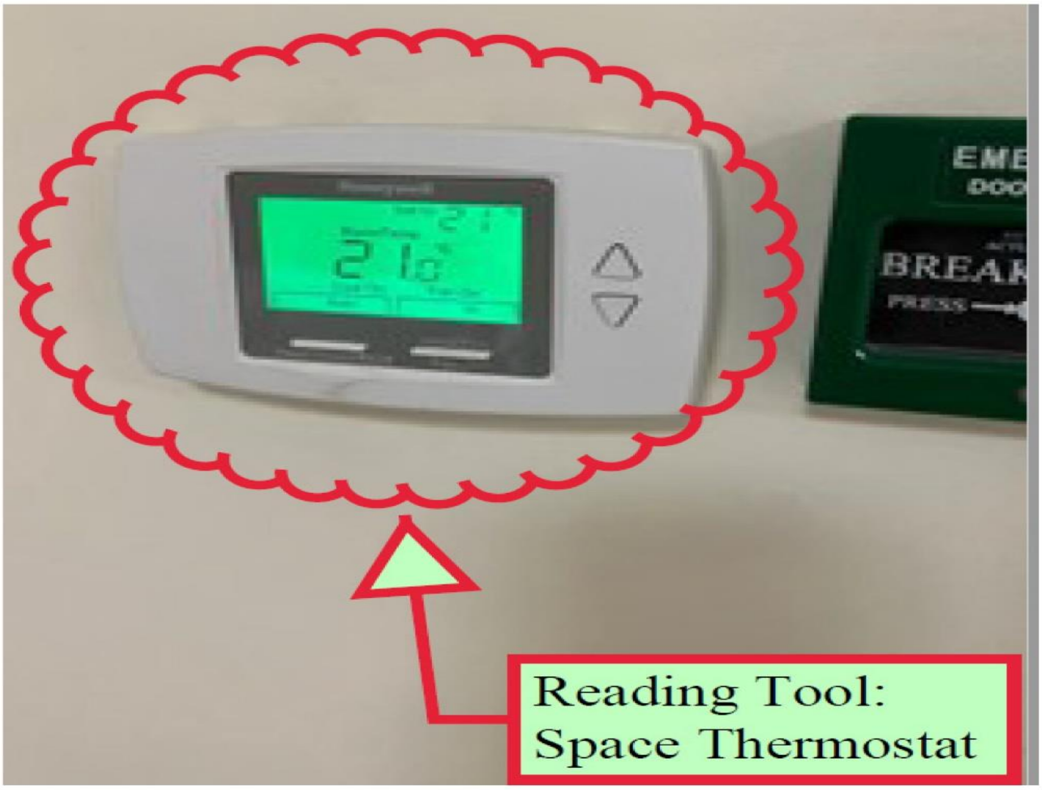

Figure 22: Terminal unit reading tool

5.3.1.3 Data Collection

The most important stage in setting up the intelligent maintenance framework pertains to the datasets required to build the detection model. As the previous two stages had been finalised, data collection was initiated as per the outcomes of the industry survey. This research project adhered to the recommended minimum frequencies as time intervals when collecting data; likewise, the recommended maximum frequencies were used as study periods for each CWS component. Twelve qualified technicians from the university were assigned for the subject matter, and one operational unit for each CWS component was selected. The readings for the chilled water leaving temperatures of each chiller and cooling tower were collected manually using check sheets. The same was performed for the pressures for each pump and the space temperatures for each terminal unit. In addition, the inspection result, which was either a fault “1” or fault free “0”, was included for each check sheet. Appendix G illustrates a fully filled one day check sheet for a particular pump, and Table 46 below shows the data collection plan.

Table 46: Data collection plan

Chilled Water System Component	Time Interval for Reading and Inspection (Minutes)	Total Study Time (Weeks)	Study Period
Chiller	30	12	29 May 2022 to 20 August 2022
Cooling tower	30	16	29 May 2022 to 17 September 2022
Pump	60	24	29 May 2022 to 12 November 2022
Terminal unit	45	8	29 May 2022 to 23 July 2022

After that, an Excel file was created for each component, and the information in all the related check sheets was transferred to the appropriate Excel files. Following the procedure proposed in the methodological framework section, each Excel file represented a dataset that contained two cells, one for the readings and another one for the inspection results (see Appendix H for an example of a cooling tower). Next, each file was named and saved in *csv* format. For example, for a particular pump, the file was named and saved as ”pu.csv’’; so, it can be read when training the detection model, as shown in the next section.

5.3.2 Implementation of Machine Learning Phase

A decision tree was built for each selected CWS component. As explained in the methodological framework section, the faults of each component were predicted using the related attributes. Table 47 shows the attribute and training data size for each unit of the selected CWS components that were in an operational mode. The data size for the whole CWS is 10,248 observations.

Table 47: Main inputs of the detection model

CWS Component	Attribute	Data Size for Each Unit
Chiller	Chilled water leaving temperature (°C)	2,688
Cooling tower	Chilled water leaving temperature (°C)	3,584
Pump	Pressure (bar)	2,688
Terminal unit	Space temperature (°C)	1,288

The C4.5 and CART algorithms were used to train the tree. Various training parameters were used to optimise tree accuracy. The parameters included the training to testing ratio and the level of pruning. The model was executed in Python, with the pseudocode shown below in Figure 23 for a particular pump. The same was done with other CWS components, taking into consideration the changes in file reading and loading.

```
BEGIN

  # Import necessary libraries
  IMPORT necessary libraries (numpy, pandas, sklearn, matplotlib, csv)

  # load dataset
  LOAD pump dataset into X (features=pressure) and y (target=1 for fault observed
OR= 0 for no fault)

  # Split the dataset into training and testing sets
  SPLIT X and y into X_train, X_test, y_train, y_test using train_test_split with test_size =
0.3 and random_state =1

  # Initialise the DecisionTreeClassifier with Gini index
  CREATE DecisionTreeClassifier object clf with criterion = 'gini' and max_depth =
set_by_user

  # Train the model
  FIT clf on X_train and y_train

  # Predict the results
  PREDICT y_pred using clf on X_test

  # Evaluate the model
  CALCULATE accuracy using accuracy_score with y_test and y_pred
  PRINT "Accuracy: ", accuracy * 100, "%"

  # Write results to CSV file
  OPEN file results.csv for writing
  WRITE X_test and y_pred to results.csv in comma-separated format
  CLOSE file results.csv

  # Plot the decision tree
  IMPORT matplotlib.pyplot as plt and plot_tree from sklearn.tree
  SET plot figure size with custom dpi
  PLOT decision tree using plot_tree with clf, feature_names, and class_names
  SHOW plot

  END
```

Figure 23: The Pseudocode of Pump's Decision Tree

The initial run of the training stage was performed without pruning, which led to prediction overfitting, as can be seen for the chiller tree in Figure 24, and in Figures 25, 26 and 27 for the cooling tower tree, the pump tree and the terminal unit tree, respectively, noting that these trees are for one selected CWS component in an operational mode. From these figures, it can be seen that at the end of each intermediate node, there is an interval of two values where the left-side value is the total observation of fault free, while the right-side value is the total observation of faults. The total number of observations is also mentioned in each intermediate node. After completing the run of the training, the pre-pruning of the decision tree shows the end node for each CWS component.

Pruning is a technique used in decision trees to prevent overfitting, a phenomenon whereby the model performs well on the training data but fails to generalise effectively to new and unseen data. Overfitting occurs when the decision tree becomes too complex, capturing noise or abnormalities in the training data that do not represent true patterns. In this research, the branches that provide minimal improvement in detection accuracy are pruned after the tree is fully constructed. Similar to the pre-pruning of decision tree, each intermediate node clarifies the sample size, and it has an interval of two values, one for fault free observations after pruning, and the other one for fault observations after pruning. Examining the different pruning methods, the optimally trained trees for each studied CWS component were found in Python as shown in Figure 28 for the same selected chiller, and in Figures 29, 30 and 31 for the same selected cooling towers, pumps and terminal units, respectively.

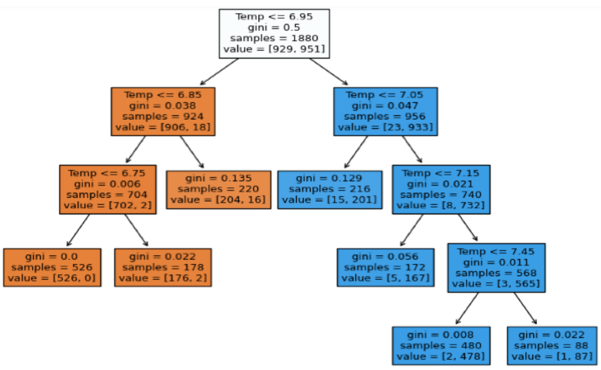

Figure 24: Chiller tree without pruning

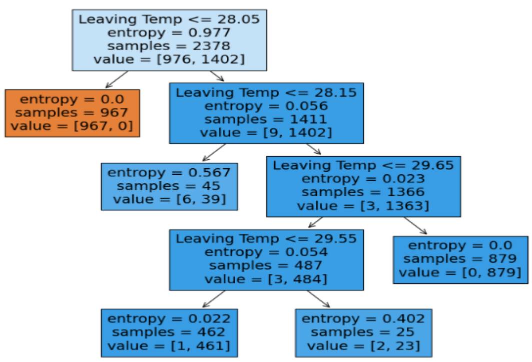

Figure 25: Cooling tower tree without pruning

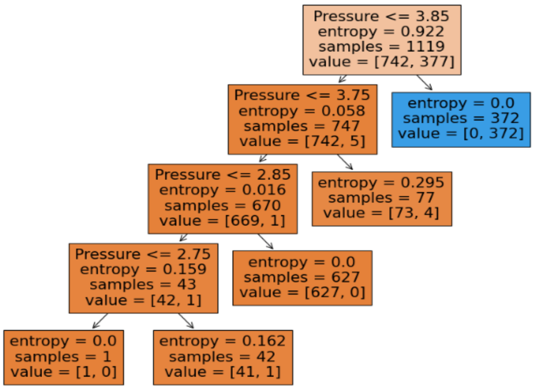

Figure 26: Pump tree without pruning

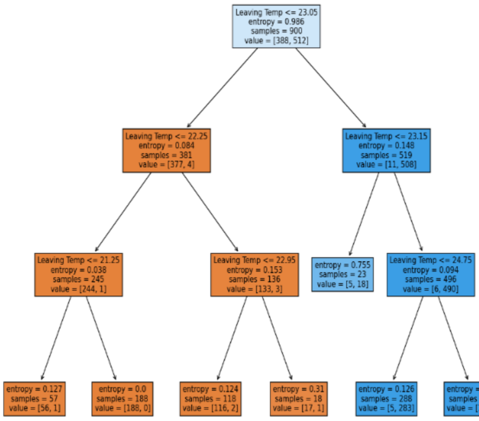

Figure 27: Terminal unit tree without pruning

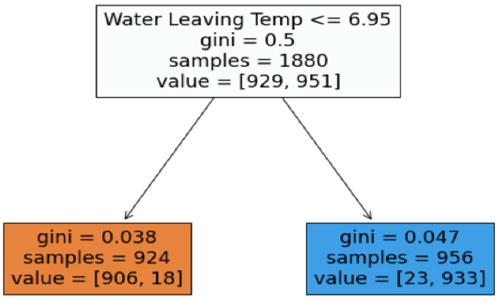

Figure 28: Chiller decision tree

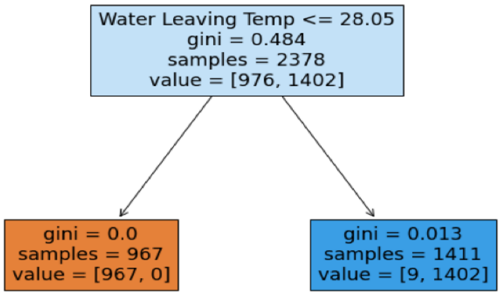

Figure 29: Cooling tower decision tree

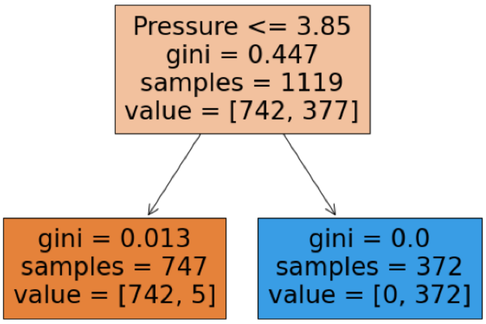

Figure 30: Pump decision tree

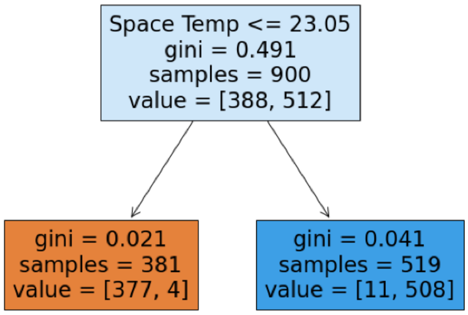

Figure 31: Terminal unit decision tree

Changing the training-to-testing ratio and the training algorithms had a very small impact on the prediction accuracy between C4.5 and CART. A 70-to-30 per cent training-to-testing ratio was adopted using the CART training algorithm. The detection accuracy of a decision tree model can be calculated by Equation 5 below:

$$\text{Accuracy} = \frac{\text{Number of Correct Detections}}{\text{Total Number of Detections}} \times 100 \tag{5}$$

Where, ''Number of Correct Detections'' is the count of instances where the model's prediction matches the actual target values in the test set, and ''Total Number of Detections'' is the total number of instances in the test set.

The optimal model demonstrates that similarly high accuracy was attained for both C4.5 and CART. Importantly, achieving this level of accuracy required only one level of decision branching, indicating that minimal depth was enough to produce accurate results, irrespective of the training algorithm employed. The detection accuracies for all CWS components at optimal decision tree settings are presented below in Table 48. These high accuracies proved that the proposed frequencies shown in previous chapter (Table 40) are proper to create the dataset for each CWS component.

Table 48: Detection accuracies of chilled water system components

Chilled Water System Component	Detection Accuracy (%)
Chiller	98.50
Cooling tower	99.60
Pump	99.80
Terminal unit	99.20

5.3.3 Implementation of Quality Control Phase

After successfully building the detection model, the control plan presented in Table 44 was actioned. In the monitoring stage of the control plan, the detection model was connected to a computer unit (see Figure 32) to initiate the second stage of the control plan (response). In this stage, the Facility Department at the university was advised to continue observing the readings as per convenient and to inspect the site in case of a fault '1', fixing it as per the actions provided in the previous chapter (Tables 33-36) and measuring the outcomes as shown in subsubsection 5.2.3. In addition, the department were advised to document the response action of the control plan by listing the lessons learned from the proposed intelligent maintenance framework, ensuring that the computer unit is working efficiently, tracking the spare parts stock, training more technicians to be familiar with the detection model, and writing regular reports about the performance of the proposed intelligent maintenance framework for future improvements.

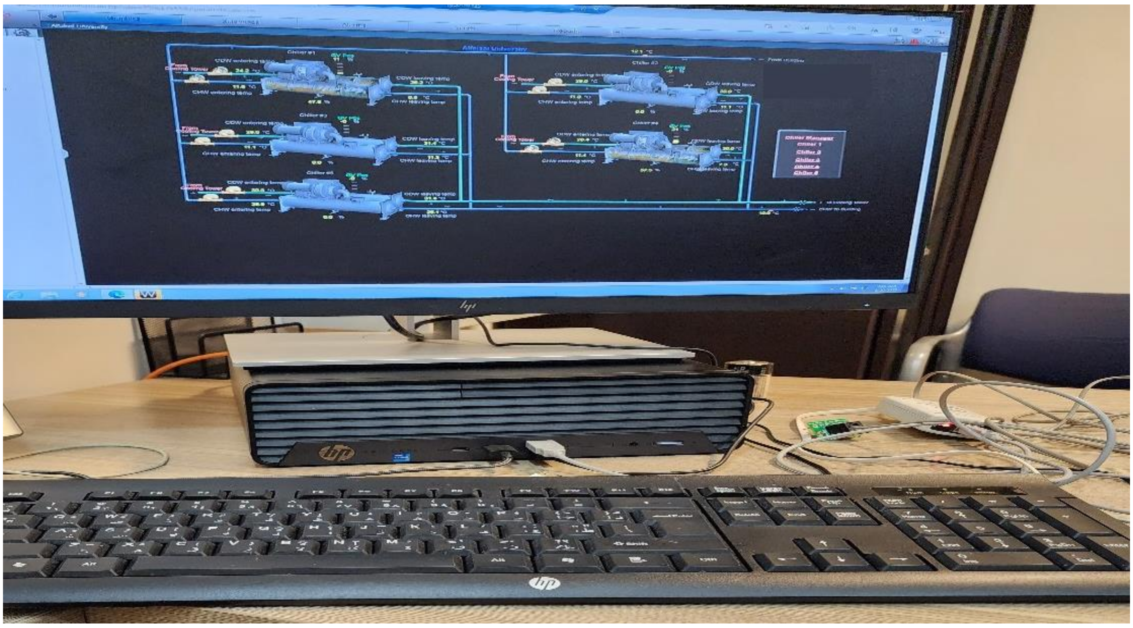

Figure 32: Computer unit for intelligent maintenance framework

5.4 Reliability and Internal Validity

After successfully implementing the methodological framework, an empirical study divided into two periods (one month each, including weekends) was conducted for reliability and internal validity purposes. During each empirical period, the same unit of each CWS component was considered, and the readings of the related operational parameters were recorded. As stated previously in Chapters 3 and 4, a single operational parameter is used to build the dataset of each CWS component. During the first empirical period, the decision tree model of each CWS component predicted 56 faults in the chiller, 61 faults in the cooling tower, 39 faults in the pump, and 73 faults in the terminal unit. All fault signals from the computer unit, which were displayed as '1', led primarily to real faults around the site, which are part of the faults listed either by the literature or by the industry survey. Figure 33 displays a fault signal for the cooling tower, which means unknown fault is predicted by the decision tree model. After each fault signal, the assigned specialised technician should inspect the associated CWS component physically where each CWS component has an assigned specialised technician for inspection. The thesis author was involved in the inspection as well as attending to fault signals. This inspection has two goals: the first is to check if there is a real fault, which means the decision tree model has detected that fault; and the second is to fix that fault by applying the solutions mentioned in the previous chapter (Tables 33-36) which are an outcome of the industry survey. Table 49 below shows a breakdown of the name and number of chiller faults detected by the decision tree model during the first empirical period, while Tables 50-52 are related to the decision tree's model of cooling tower, pump and terminal unit, respectively. Each table has three columns, the first one contains the fault name, the second one contains its source whether from the literature or the survey, and the third column, which is titled as "Number of Times Detected", shows how many times this fault had appeared and detected during the said empirical period.

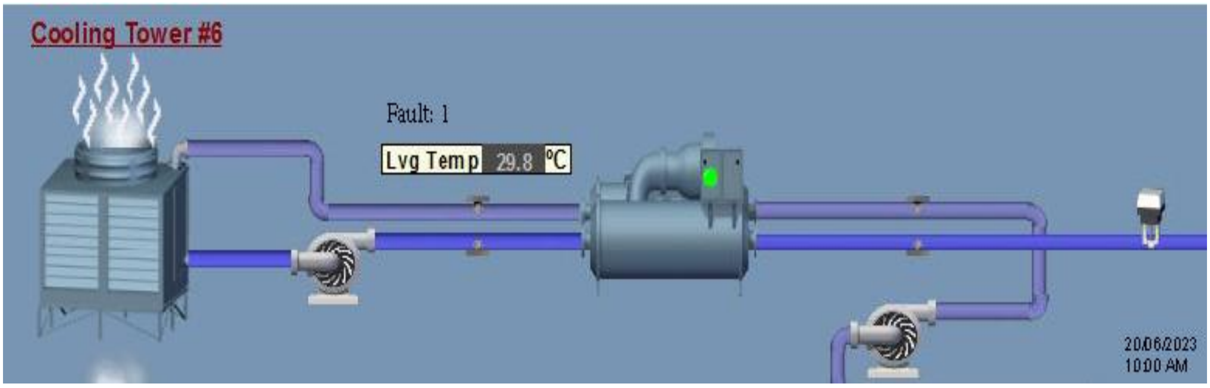

Figure 33: Fault signal for cooling tower

Table 49: Summary of the first empirical period for chiller

Fault	Source	Number of Times Detected
Refrigeration leak	Literature	9
Condenser fouling	Literature	8
Evaporating fouling	Literature	7
High compressor lift	Industry survey	7
Compressor overcharging	Literature	6
High motor ampere	Industry survey	5
Relief valve discharge	Industry survey	5
High condenser approach	Industry survey	4
Incorrect manual guide vane target	Industry survey	2
High evaporator approach	Industry survey	1
	Total	54

Table 50: Summary of the first empirical period for cooling tower

Fault	Source	Number of Times Detected
Malfunctioning blowdown system	Industry survey	11
Low water basin level	Industry survey	10

High water total dissolved solid	Industry survey	10
Vibration	Industry survey	9
Rise in circulating water temperature	Industry survey	5
Faulty isolation valve	Industry survey	4
Low circulating water flow rate	Industry survey	4
Motor overheating	Industry survey	3
Fouling of fills	Literature	2
Over current	Industry survey	1
Unusual sound	Industry survey	1
	Total	60

Table 51: Summary of the first empirical period for pump

Fault	Source	Number of Times Detected
Noisy non-return valve	Industry survey	10
Pump runs but provides no water	Industry survey	7
Leakage from Valves	Industry survey	7
Motor vibration	Industry survey	3
Low flow rate in cold exchange	Literature	3
Improper pump water alignment	Industry survey	1
Motor heat-up	Industry survey	2
Clogging	Literature	4
	Total	37

Table 52: Summary of the first empirical period for terminal unit

Fault	Source	Number of Times Detected
Low static pressure	Industry survey	13
Loose belts	Industry survey	8
Air trapped in cooling coil	Industry survey	9
Noisy contactors	Industry survey	6
Faulty fresh air damper	Industry survey	6
Speed reducing the supply fan	Literature	6
Vibration	Industry survey	1
Faulty exhaust air damper	Industry survey	5
Dirty air flow	Industry survey	2
Faulty damper actuator	Industry survey	4
Faulty control valve	Industry survey	3
Damaged insulation on pipe	Industry survey	1
Cooling coil blockage	Literature	4
	Total	71

The above four tables make evident the reliability of the decision tree model of each CWS component as 54 faults for the chiller, 60 faults for the cooling tower, 37 faults for the pump, and 71 faults for the terminal unit were detected. In addition, detecting these real faults conveyed the reliability of the proposed frequencies as shown in the previous chapter (Table 40). They were utilised to create the datasets for CWS components, which were used to build and train the detection models. Also, the above four tables validated the new faults that were provided by the industry survey where six different chiller faults, 10 different cooling tower faults, six different pump faults, and 11 different terminal unit faults appeared during this empirical period, the majority of these detected faults from the lists of the new faults provided by the industry survey (see Tables 33-36).

The solutions suggested by the industry survey, as mentioned in the previous chapter (Tables 33-36), verified their validity in fixing the occurred faults to the satisfaction of the concerned department. Regarding the finding mentioned previously about the technical correlation between CWS components, the importance of covering the all the CWS components within the same intelligent maintenance framework has been confirmed during this empirical phase where the chiller fault that occurred, which is the high condenser approach, had been successfully fixed by investigating the associated cooling tower and then by implementing the suggested solution (Table 33). This fault appeared four times during the said empirical period (See Table 49), and it was identified and fixed by the technician, who inspected the site, where he cleaned the effected fills of the associated cooling tower. With regard to the occurred cooling tower fault, which is the low circulating water flow rate, it was successfully fixed by investigating the associated chiller and/ or pump, and then by implementing its suggested solution (Table 34). This fault appeared four times during the said empirical period (see Table 50), out of which, two times were fixed by cleaning the stainer of the associated condenser pump, and two times were fixed by cleaning the condenser tubes inside the associated chiller. With regard to the occurred pump fault, which is pump clogging, it was successfully fixed by investigating the associated cooling tower, and then by implementing its suggested solution (Table 35). This fault appeared four times (see Table 51), and it was a partial type and it was identified by the assigned technician and fixed by cleaning the strainer filtering the water coming from the associated cooling tower. The occurred terminal unit faults, which are the cooling coil blockage and air trapped in cooling coil, were successfully fixed by investigating the associated chiller and pump, and then by implementing their suggested solutions (Table 36). For example, the first fault, which is the cooling coil blockage, appeared four times during the empirical period in discussion (see Table 52), and it was an outer type and fixed by reducing the air speed that linked to the associated chiller.

A quantitative analysis is made to confirm the above-mentioned technical correlation between CWS components. Similar to the analysis of the industry survey's outcome (see Table 39), the analysis of the case study's outcome with regard to the correlation is made through Excel sheets using *Pearson r* test. Each sheet contains three columns, the first one contains the serial number of fault occurrence, for example, the first detection time of the high condenser approach fault in chiller is numbered as '1', the second detection time of the same fault is numbered as '2', etc. With regard to the second column of the aforementioned sheets, it contains either '1', which means that the said fault is successfully fixed by investigating the associated cooling tower, or '0', which means fixing the fault was not required to investigate the associated cooling tower. The third column contains the cumulative values of the second column. Appendix I shows these sheets along with the correlation coefficient values and their plots. Table 53 below summarised the *r* values between CWS components during the first empirical period with ninety-nine per cent confidence level. All correlation coefficient values are greater than 0.50. which means the correlation is strong and positive.

Table 53: Correlation Coefficient Values for the first empirical period

CWS component experiencing a fault	Fault	CWS component to be investigated	Correlation Coefficient Value
Chiller	High condenser approach	Cooling Tower	0.9439
Cooling Tower	Low circulating water flow rate	Pump	0.9486
Pump	Clogging	Cooling Tower	0.9307
Terminal Unit	Cooling Coil Blockage	Chiller	1

Similarly, the existing monitoring system implemented by the department is BMS. They were asked to give a report for the same empirical period during which the CWS components via the decision tree model were observed. The report contained the total number of faults predicted and detected by the BMS for the same selected CWS components. For internal validity purposes, Figure 34 shows a comparison between the decision tree model and BMS in tracing and detecting faults after inspecting the site within the same period. The Figure's bar chart confirms the internal validity of the decision tree model; each CWS component was fulfilled as there is an improvement in detecting the faults when compared to BMS. As a result of this empirical period, the improvement in chiller is 24 per cent, while the improvements in cooling tower, pump and terminal unit are 22, 30 and 24 per cent, respectively.

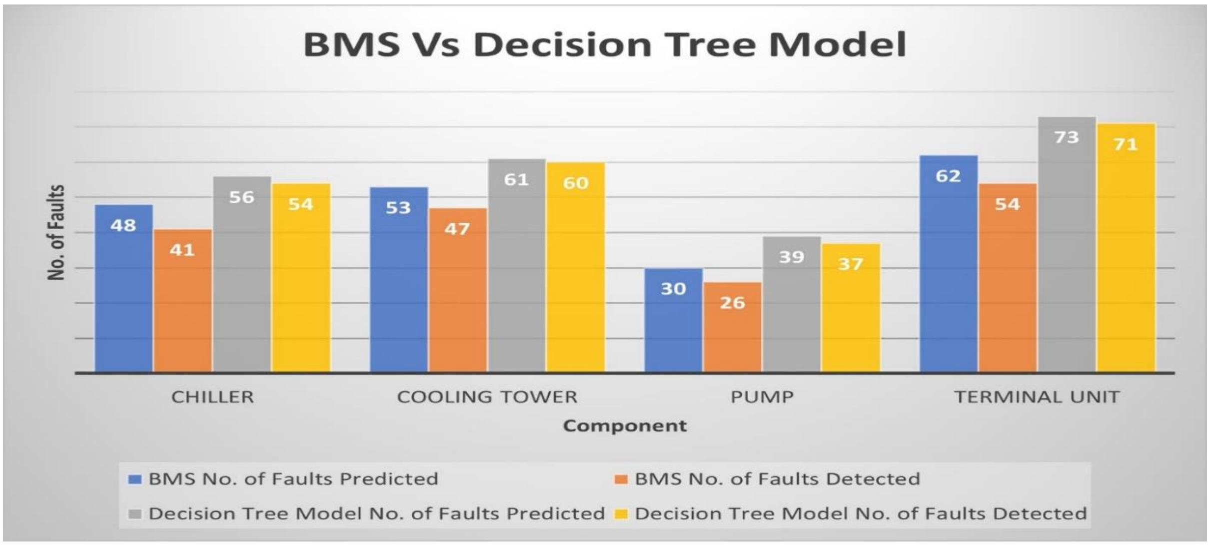

Figure 34: Comparison of detection performance during first empirical period

The above process has been repeated during the second empirical period. The decision tree model predicted 47 faults in the chiller, 53 faults in the cooling tower, 44 faults in the pump and 68 faults in the terminal unit. Table 54 below shows a breakdown of the name and number of chiller faults that were detected by the decision tree model during the second empirical period, while Tables 55, 56 and 57 reflect the decision tree's model of cooling tower, pump and terminal unit, respectively. The third column on the right of these tables, which is titled as "Number of Times Detected'' shows how many times each fault had appeared and detected during the said empirical period.

Table 54: Summary of the second empirical period for chiller

Fault	Source	Number of Times Detected
Refrigeration leak	Literature	8
Low condenser flow	Industry survey	7
High condenser temperature	Literature	7
High evaporator approach	Industry survey	5
Low oil pressure	Industry survey	5
High motor temperature	Industry survey	5
Vibration	Industry survey	3
Imbalanced line current	Industry survey	3
Low evaporator refrigerant temperature	Industry survey	2
Faulty operation scheduling	Literature	1
	Total	46

Table 55: Summary of the second empirical period for cooling tower

Fault	Source	Number of Times Detected
Malfunctioning blowdown system	Industry survey	10
Over current	Industry survey	8
Fills clogging	Industry survey	7
Faulty water level valve	Industry survey	9
Motor overheating	Industry survey	4
Faulty isolation valve	Industry survey	4
Low circulating water flow rate	Industry survey	8
Damaged fan	Industry survey	2
	Total	52

Table 56: Summary of the second empirical period for pump

Fault	Source	Number of Times Detected
Noisy non-return valve	Industry survey	9
Low flow rate in cold exchange	Literature	9
Pump runs but provides no water	Industry survey	7
Leakage from pump set	Industry survey	4
Motor heat-up	Industry survey	4
Pump runs at reduced capacity	Industry survey	3
Faulty control switch	Literature	3
Pipeline leakage	Literature	2
Abnormal or excessive noise	Literature	1
	Total	42

Table 57: Summary of the second empirical period for terminal unit

Fault	Source	Number of Times Detected
Low static pressure	Industry survey	11
Loose belts	Industry survey	10
Air trapped in cooling coil	Industry survey	8
Faulty cooling valve actuator	Industry survey	6
Return damper jam	Literature	6
Motor overload	Industry survey	6
Vibration	Industry survey	6
Faulty supply air damper	Industry survey	4
Faulty filter coil system	Literature	3
Faulty variable air volume	Literature	3
Damaged insulation on duct	Industry survey	1
Compressor failure	Literature	1
Filter blockage	Literature	1
Broken belts	Industry survey	1
	Total	67

These four tables give evidence that the decision tree model of each CWS component shows reliability as 46 faults for the chiller, 52 faults for the cooling tower, 42 faults for the pump and 67 faults for the terminal unit were detected. In addition, detecting these real faults showed again the reliability of the proposed frequencies, noted in the previous chapter (Table 40), as they were utilised to create the datasets for CWS components, which were then used to build and train the detection models. Also, the above four tables again validated the new faults provided by the industry survey where seven different chiller faults, nine different cooling tower faults, five different pump faults, and nine different terminal unit faults appeared during this second empirical period. The majority of these detected faults are from the lists of new faults emerging through the survey and shown in the previous chapter (Tables 33-36).

The solutions suggested by the industry survey (Tables 33-36) again confirmed their validity in fixing the occurred faults to the satisfaction of the concerned department. Regarding the finding mentioned in the previous chapter regarding the technical correlation between CWS components, the importance of covering all the CWS components within the same intelligent maintenance framework has been confirmed again during the empirical period. The occurred chiller fault, for example, which is the low condenser flow, has been successfully fixed by investigating the associated pump and then by implementing its suggested solution (Table 33). With regard to the cooling tower fault that occurred, the low circulating water flow rate, it has been successfully fixed by investigating the associated chiller and pump, and then by implementing its provided solution (Table 34). The terminal unit fault that occurred, which is the air trapped in cooling coil, has been successfully fixed by investigating the associated chiller and pump, and then by implementing its suggested solution (Table 36). Similar to the first empirical period, a quantitative analysis is made to confirm the above-mentioned correlation (see Appendix I). Table 58 below summarised the *r* values between CWS components during the second empirical period with ninety-nine per cent confidence level. All correlation coefficient values are greater than 0.50. which means the correlation is strong and positive.

Table 58: Correlation Coefficient Values for the second empirical period

CWS component experiencing a fault	Fault	CWS component to be investigated	Correlation Coefficient Value
Chiller	Low condenser flow	Pump	0.9799
Cooling Tower	Low circulating water flow rate	Chiller	0.9439
Cooling Tower	Low circulating water flow rate	Pump	0.9439
Terminal Unit	Air trapped in cooking coil	Chiller	1
Terminal Unit	Air trapped in cooking coil	Pump	0.9439

Concerning the new faults emerging from the survey and shown in the previous chapter (Tables 33-36), and after these two empirical periods, out of the 17 new chiller faults from the survey, 12 faults occurred. With regard to cooling towers, of the 13 new faults provided by the survey, 12 faults occurred. With regard to the pump, all eight new faults emerging from the survey occurred. For the terminal unit, of the 20 new faults provided by the survey, 16 faults occurred. This also validated the outcomes of the industry survey about these new faults. In addition, it has been observed that the faults occurring most frequently for CWS during these two empirical periods are the refrigeration leak fault for the chiller component, the malfunctioning blowdown system fault for the cooling tower component, the noisy non-return valve for the pump component, and the low static pressure for the terminal unit component (Tables 49-52 and 54-57). This observation matches the outcome of the industry survey with regard to the CWS faults repeated the most by the participants (Table 37).

For internal validity purposes, a comparison between the decision tree model of each CWS component and the BMS in predicting and detecting CWS faults has been conducted in the same procedure as the first empirical period. Figure 35 presents this comparison. As a result of this empirical period, the improvement rate in chiller is 28 per cent, while the improvements in cooling tower, pump and terminal unit are 21, 26 and 22 per cent, respectively. After all the above activities, a discussion was conducted with the head of maintenance as well as with the operation and maintenance manager at the university to ascertain their views about the proposed methodological framework, a holistic intelligent maintenance for CWS. The outcome of the proposed intelligent maintenance framework was to their satisfaction, particularly seeing the improvement made by the proposed decision tree model of each CWS component when compared to BMS.

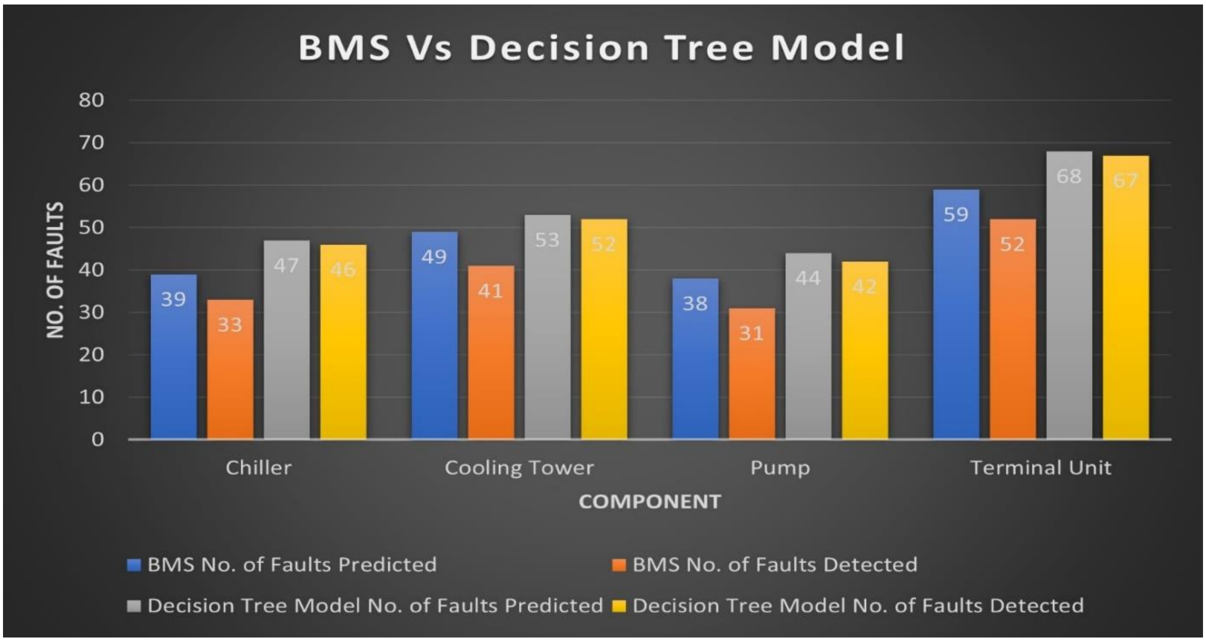

Figure 35: Comparison of detection performance during second empirical period

5.5 External Validity

The methodological framework has been implemented at another site for external validity purposes. The second case study was conducted in a hotel owned by the same foundation that manages the university. The hotel has a complete CWS, which means it has chillers, cooling towers, pumps and terminal units. The three methodological framework phases were applied in parallel with main case study, so the data collection plan was same for both case studies. Following the same procedure as implemented in the main case study, Figures 36-39 show the outcomes of the hotel's decision trees without pruning for a selected chiller, cooling tower, pump and terminal unit, respectively.

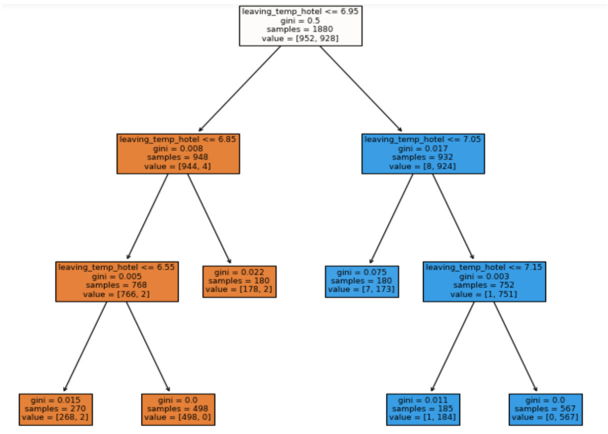

Figure 36: Hotel chiller tree without pruning

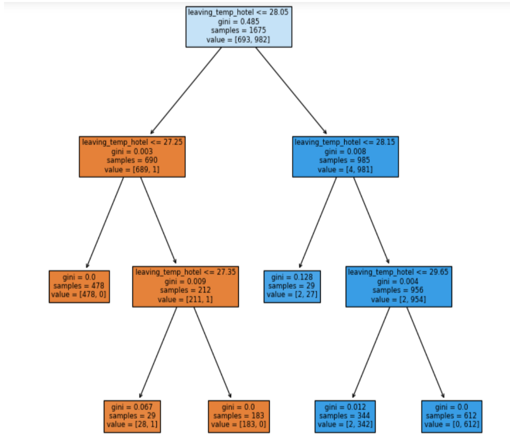

Figure 37: Hotel cooling tower tree without pruning

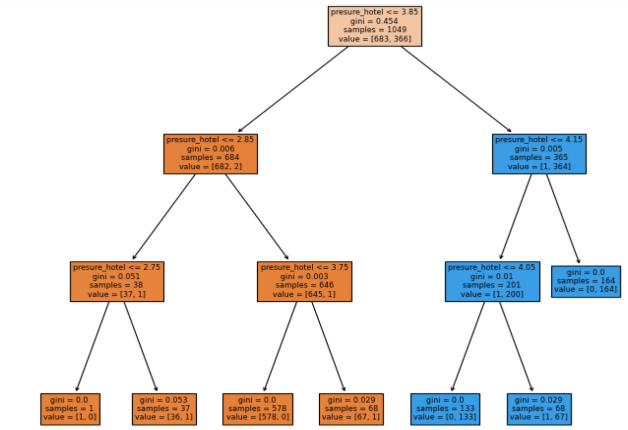

Figure 38: Hotel pump tree without pruning

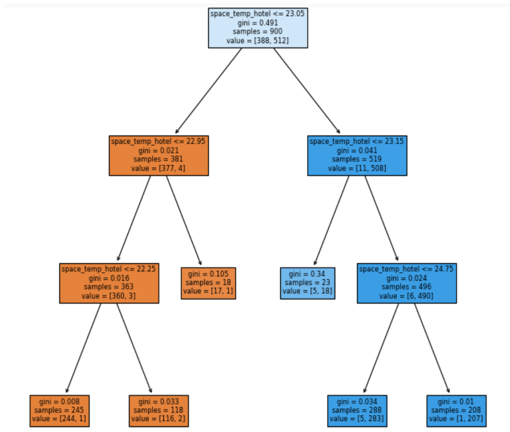

Figure 39: Hotel terminal unit tree without pruning

Examining the different pruning methods, the optimally trained trees for each studied CWS component were once again found in Python (see Figure 40) for the same selected chiller, and for the same selected cooling tower, pump and terminal unit, respectively (Figures 41-43).

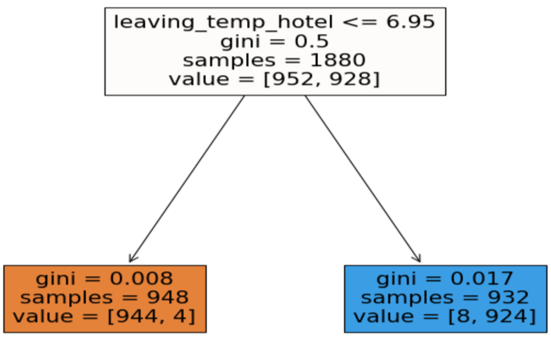

Figure 40: Hotel chiller decision tree

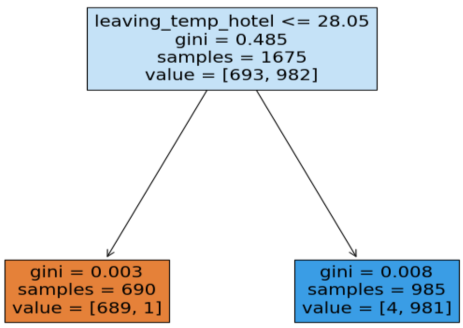

Figure 41: Hotel cooling tower tree

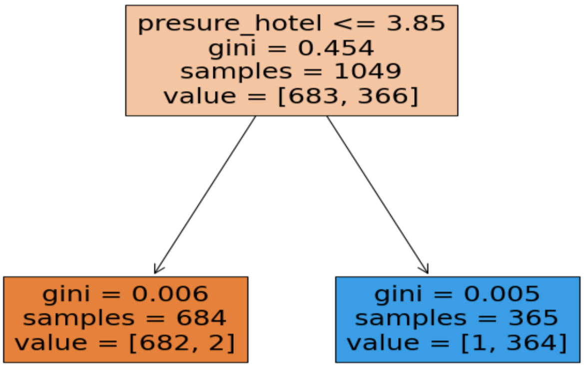

Figure 42: Hotel pump decision tree

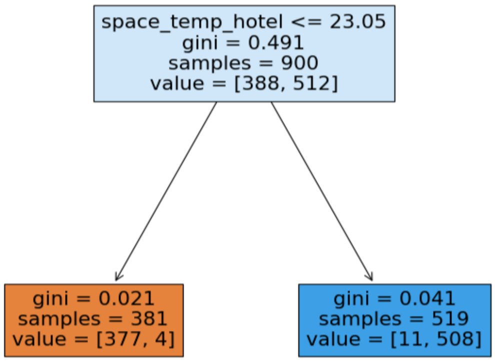

Figure 43: Hotel terminal unit decision tree

Similar to the main case study, changing the training-to-testing ratio and the training algorithms had an insignificant impact on the detection accuracy. A 70-to-30 per cent training-to-testing ratio was adopted using the CART training algorithm. By utilising Equation 5 as in the main case study, the detection accuracies of each CWS component at the optimal decision tree setting were determined and presented below in Table 59. Again, these high accuracies prove that the proposed frequencies, as shown in previous chapter (Table 40), are proper to create the dataset for each CWS component. After that, the Support Services Department at the hotel site successfully actioned the monitoring and response actions of the quality control phase.

Table 59: Hotel chilled water system component detection accuracies

CWS Component	Detection Accuracy (%)
Chiller	98.90
Cooling tower	99.70
Pump	99.85
Terminal unit	99.35

After implementing the phases of the methodological framework, an empirical study was conducted for one month, including weekends, for validity purposes. The decision tree model of the chiller predicted 41 faults, while the decision tree model of the cooling tower predicted 43 faults. With regard to the decision tree model of the pump, it predicted 44 faults, while the decision tree model of the terminal unit predicted 48 faults.

Following a site inspection by assigned technicians, Table 60 below shows a breakdown of the name and number of chiller faults that were detected by the hotel's decision tree model during the empirical period, while Tables 61, 62, and 63 below are for the decision tree's model of cooling tower, pump and terminal unit, respectively. The column titled “Number of Times Detected” in these tables shows how many times each listed fault had appeared and detected on site.

Table 60: Summary of the hotel empirical period for chiller

Fault	Source	Number of Times Detected
Refrigeration leak	Literature	7
High condenser temperature	Literature	7
Evaporator fouling	Literature	6
Low chilled water flow	Industry survey	5
Compressor overcharging	Literature	5
High cooler delta-t	Industry survey	3
Vibration	Industry survey	2
Low oil pressure	Industry survey	1
Low discharge superheat	Industry survey	1
Incorrect manual guide vane target	Industry survey	1
Relief valve discharge	Industry survey	1
	Total	39

Table 61: Summary of the hotel empirical period for cooling tower

Fault	Source	Number of Times Detected
Malfunctioning blowdown system	Industry survey	11
Rise in circulating water temperature	Industry survey	8
Low water basin level	Industry survey	6
Fills fouling	Literature	6
Vibration	Industry survey	4
Faulty isolation valve	Industry survey	2
Faulty water level valve	Industry survey	2
Unusual sound	Industry survey	1
	Total	40

Table 62: Summary of the hotel empirical period for pump

Fault	Source	Number of Times Detected
Noisy non-return valve	Industry survey	15
Motor vibration	Industry survey	11
Leakage from valves	Industry survey	4
Improper pump water alignment	Industry survey	3
High flow rate in cold exchange	Literature	3
Pump runs but provides no water	Industry survey	3
Clogging	Literature	4
	Total	43

Table 63: Summary of the hotel empirical period for terminal unit

Fault	Source	Number of Times Detected
Low static pressure	Industry survey	12
Faulty control valve	Industry survey	11
Faulty variable air volume	Literature	8
Faulty cooling valve actuator	Industry survey	4
Faulty exhaust air damper	Industry survey	4
Noisy motor	Industry survey	4
Damaged Insulation on pipe	Industry survey	1
Faulty bearings	Industry survey	1
Faulty fan	Literature	1
	Total	46

These tables make it clear that the decision tree model of each CWS component shows reliability as 39 faults for the chiller, 40 faults for the cooling tower, 43 faults for the pump, and 46 faults for the terminal unit were detected. Additionally, detecting these real faults confirms the reliability of the proposed frequencies (Table 40) as they were utilised to create the datasets for CWS components, which were then used to build and train the hotel's detection models. Also, the above four tables validated again the new faults that were provided by the industry survey as seven different chiller faults, seven different cooling tower faults, five different pump faults, and six different terminal unit faults appeared during this hotel's empirical period, with the majority of these detected faults on the lists of the new faults identified by the survey and shown in the previous chapter (Tables 33-36).

Furthermore, the provided actions by the industry survey again had their validity verified in fixing the occurred faults to the satisfaction of the concerned department. Regarding the finding mentioned in the previous chapter about the technical correlations between CWS components, the importance of covering all the CWS components within the same intelligent maintenance framework has been confirmed yet again during the empirical period where the occurred chiller fault, which is the low chilled water flow, has been successfully fixed by investigating the associated pump and then by implementing its provided solution. With regard to the pump fault occurring, which is clogging, it has been successfully fixed by investigating the associated cooling tower, and then by implementing its solution that was shown in the previous chapter (Table 34). Similar to the previous two empirical periods, a quantitative analysis is made to confirm the above-mentioned correlation (see Appendix I). Table 64 below summarised the *r* values between CWS components during the hotel empirical period with ninety-nine per cent confidence level. All correlation coefficient values are greater than 0.50. which means the correlation is strong and positive.

Table 64: Correlation Coefficient Values for the hotel empirical period

CWS component experiencing a fault	Fault	CWS component to be investigated	Correlation Coefficient Value
Chiller	Low chilled water flow	Pump	1
Pump	Clogging	Cooling Tower	0.9487

In terms of the new faults emerging from the survey and shown in the previous chapter (Tables 33-36), and after these three empirical periods (two at the university and one at the hotel), of the 17 new chiller faults that were provided by the industry survey, 15 faults occurred. With regard to cooling tower component, all 13 new faults that were provided by the industry survey occurred. The same is true with regard to the pump component: all eight new faults provided by the industry survey already occurred. For the terminal unit component, of the 20 new faults provided by the industry survey, 18 faults occurred. This further validates the outcomes of the industry survey concerning the new faults. In addition, it has been observed that the most frequently occurring faults for CWS components during the hotel empirical period are refrigeration leak fault for the chiller component, the malfunctioning blowdown system fault for the cooling tower component, the noisy non-return valve for the pump component, and the low static pressure for the terminal unit component (see Tables 60-63). Like the empirical periods of the main case study, this observation again matches the outcome of the industry survey with regard to the CWS faults listed the most by participants, as shown in Chapter 4 (Table 37).

For validity purposes, a comparison between BMS, which is similar to the monitoring system at the university, and the hotel's decision tree model of each CWS component in predicting and detecting CWS faults, has been conducted in the similar procedure as the two previous empirical periods. Figure 44 shows the comparison. As a result of this hotel's empirical period, the improvement in chiller is 21 per cent, while the improvement in cooling tower, pump and terminal unit are 25, 26 and 22 per cent, respectively. As with the previous empirical periods, a discussion was held with the hotel stakeholders to ascertain their views about the proposed methodological framework, a holistic intelligent maintenance for CWS. The outcome of the proposed intelligent maintenance framework was to their satisfaction, particularly with the improvements by the proposed decision tree model of each CWS component when compared to BMS. With this, the external validity of this research project has been fulfilled.

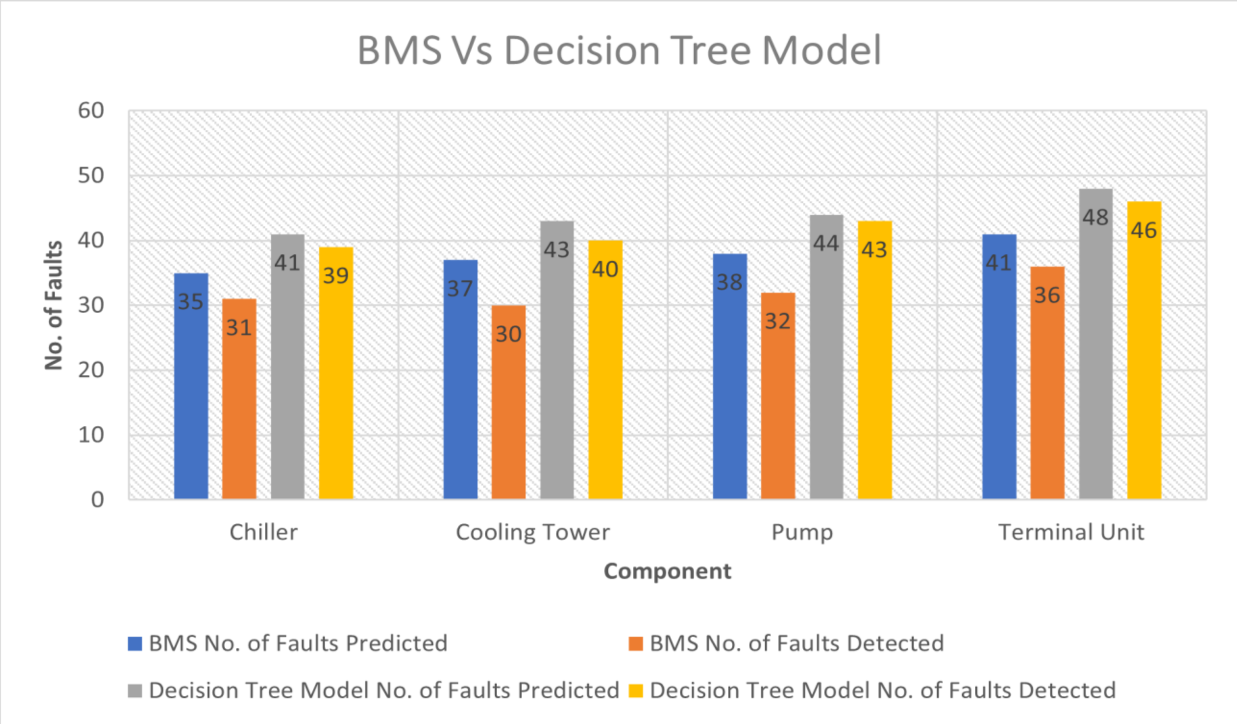

Figure 44: Comparison of the detection performance during the hotel empirical period

5.6 Conclusion

This chapter presented the second research instrument in this research project, the case study. The case study is implemented through a proposed methodological framework (see Table 42). Three empirical periods were conducted, and the detection model for each CWS proved its reliability and validity in tracing the faults. Though such faults have a minimal impact on CWS components, but they may lead to major breakdown as defined in Chapters 2 and 4. So, the detection models and the actions provided by this research project have managed to protect the said components from major failures. The methodological framework can be considered as a guide for operation and maintenance professionals where it contains several managerial and technical steps. Table 65 below presents a step-by-step guideline for implementing the proposed methodological framework.

Table 65: Step-by-step guideline

Step Number	Step	Remarks
1	Looking at the As-built drawing and then matching it with the simplified CWS drawing (see Figure 15).	This step is to understand the assembly of CWS at site, and to determine the number of each CWS component installed at site.
2	Ensuring the reading tools are installed properly (see Table 43).	Here, the reading tools are the source of collecting the data, and this step is to make sure the data collection can start conveniently.
3	Determining the data collection plan.	A schedule for each CWS component should be here as per the proposed minimum and maximum frequencies (see Table 40).
4	Preparing the required copies of the check sheets for each CWS component (see Appendix F)	The number of check sheets is based on the number of days that are determined from the previous step.
4	Forming the team members who are going to collect the data.	As per the work load, the concerned person should assign the technicians for each CWS component.
5	Transferring the collected data to Excel sheet for each CWS component.	The Excel sheets are considered as datasets for building the machine learning model.
6	Building the machine learning model (see Figure 17).	For example, in this research project, decision tree algorithm is formulated to be a detection model for each CWS component.
7	Making and implementing a quality control plan (see Table 44).	At the end of this methodological framework, the quality control plan ensures evaluating the detection model from faults tracing point of view, fixing the occurred faults by the provided actions, examining these actions, and documenting the lesson learned for continuous improvements.

The next chapter analyses and summarises the outcomes and findings of this research and interprets the answers of the four research questions. Also, it acknowledges the contribution of this present work to the extant knowledge both theoretically and practically, summarises the assessment of the quality of this research thesis, denotes the limitations of this research, and suggests future research. It then wraps up with the author’s personal reflection.

Chapter 6: Research Thesis Discussion and Conclusion

"Fault detection is one of the critical components of predictive maintenance where it is very much needed for industries to detect faults early and accurately."
(Amruthnath and Gupta, 2018)

6.1 Introduction

This chapter interprets and discusses the results of the two applied research methods of this research project. The discussion centres primarily on the four research questions answered by the project. Following the approach of Eisenhardt (1989), the discussion includes a comparison of findings of this research with extant literature. Each of the next four subsections is related to one research question and its answer. Thereafter, the chapter concludes with several subsections: a general summary of this research project, the contribution to theoretical and practical knowledge, the research limitations, a future research agenda, and finally, with the author's reflections.

6.2 Discussion

6.2.1 Answer to Research Question #1

The first research question generated after the systematic literature review and shown in Chapter 3 (Table 19) is as follows:

Research Question #1: *Is there a correlation between the components of a CWS that makes it important to cover all of them within the same maintenance framework?*

The main point of investigation in this research project is the chilled water system (CWS) and the aim of this research is to propose a holistic intelligent maintenance framework for CWS components, which means managing all components of the system within the same framework and at the same time. In light of the definition of CWS in Chapter 1, the four components – chiller, cooling tower, pump and terminal unit – all contribute to the system at the same time and linked to each other from an operational point of view.

But the systematic literature review revealed that no study under consideration focused on all CWS components within the same research (see Chapter 2, Table 17). Information in Table 17 indicates that the majority of the relevant studies (approximately 50 per cent) addressed only one CWS component, the terminal unit. The chiller component was second with approximately 32 per cent of the considered studies investigating this component. The remaining 18 per cent were distributed between addressing only one CWS component, either the cooling tower or pump, or by addressing two or three CWS components at the most. No evidence indicated coverage of all CWS components in their entirety within the same studies. This could potentially be due to the complexity of the CWS system, as shown in Chapter 5 (Figure 18), or perhaps to the difficulty of accessing data for all four CWS components. On a side note, the studies that addressed more than one CWS component, which are summarised in Table 18, did not mention any technical relevance between the components. For example, Zhou et al. (2009a), Hu et al. (2019), and Motomura et al. (2019a) focused on three CWS components – chiller, cooling tower and pump – but none of these three studies clarified any technical link or relevance among the three CWS components. Sulaiman et al. (2020) also explored three CWS components – chiller, cooling tower and terminal unit – but also neglected to examine any relevance between these components or to clarify the reason for addressing these particular three components in the same research. Miyata et al. (2019) as well as Luo et al. (2019) focused on three CWS components – chiller, pump and terminal unit – but also failed to mention any rationale for addressing these particular three components in their studies or to clarify any technical relevance among them. Based on that, the first research gap emerged for this research project: "*The impact of the technical correlation between all four CWS components on fault detection remains unknown*". This created a question about the benefit and significance of covering all CWS components at the same time within any proposed fault detection framework, and accordingly, the above research question was generated.

The research methods assigned to answer this first research question were the industry survey (explained in Chapter 4) and the case study (explained in Chapter 5). By examining the fault solutions solicited from the industry survey (see Chapter 4, Tables 33-36), it was noticed that faults in a particular CWS component seem to be due to the health condition of another CWS component, which means there is likely some degree of technical relevance between CWS components wherein the faults that occur in a particular CWS component could potentially be fixed by investigating another CWS component. A quantitative analysis is conduced to confirm the correlation between CWS components based on the industry survey outcomes (see Table 39 and Appendix D). Based on the correlation coefficient values mentioned in the said table and appendix, the correlation is strong and positive with ninety-nine per cent confidence level. In addition, a quantitative analysis is conducted to reconfirm the correlation between CWS components based on the case study outcome (see Tables 53, 58, and 64 as well as Appendix I). Based on the correlation coefficient values mentioned in the said tables and appendix, the correlation is strong and positive as well with ninety-nine confidence level, and accordingly, the case study has validated the outcome of the industry survey in this regard. Table 66 below summarises the relevance of faults and their fixing actions between CWS components, as noted after the industry survey and confirmed by the case study at both sites.

Table 66: Relevance between chilled water system components

CWS component showing fault	Fault	CWS component to be investigated
Chiller	Low condenser flow	Pump
Chiller	Low chilled water flow	Pump
Chiller	High condenser approach	Cooling tower
Cooling tower	Low circulating water flow rate	Chiller and/or pump
Pump	Clogging	Cooling tower
Terminal unit	Air trapped in cooling coil	Pump
Terminal unit	Cooling coil blockage	Chiller and/or pump

During the three empirical periods of this study, faults that occurred in a particular CWS component were fixed by rectifying something in another component. Part of these faults were the same faults as presented in the above table. For example, the low condenser flow fault that occurred in the chiller during one of the empirical periods at the university building was successfully fixed by implementing an action furnished by the industry survey (see Chapter 4, Table 33). With the action to fix this fault, the technical relevance between the chiller and the pump has been confirmed; the associated condenser pump in operation has been investigated and then its pressure has been checked and rectified. Low chilled water flow fault occurred in the chiller during the hotel's empirical period and was successfully fixed by implementing its solution supplied by the industry survey (see Chapter 4, Table 33). With the action to fix this fault, the technical relevance between the chiller and the pump has been confirmed, again where the associated secondary pump in operation has been investigated and then its pressure checked and rectified.

A high condenser approach fault occurred in the chiller during one of the empirical periods at the university building and was successfully fixed by implementing its solution provided by the industry survey (see Chapter 4, Table 33). As per the action to fix this fault, the technical relevance between the chiller and the cooling tower has been confirmed where the connected tunnel of the associated cooling tower in operation has been checked and then serviced via cleaning the fills.

The cooling tower fault, which is low circulating water flow rate, occurred during both empirical periods at the university building and was successfully fixed by implementing its action as provided by the industry survey (see Chapter 4, Table 34). As per the action to fix this fault, it is again confirmed that technical relevance exists between the cooling tower and the chiller where the associated chiller in operation has been investigated and then the condenser tubes inside the associated chiller have been checked and cleaned. Also, for the same fault, the technical relevance between the cooling tower and pump has been confirmed where the associated pump in operation has been investigated as well, and then the stainer of the associated condenser pump has been checked and cleaned. A clogging fault occurred in the pump during one of the empirical periods at the university building as well as during the hotel's empirical period. This fault was successfully fixed by implementing its solution as furnished by the industry survey (see Chapter 4, Table 35). With the action to fix this fault, the technical relevance between the pump and the cooling tower has again been confirmed: the associated cooling tower in operation has been investigated, and then the strainer, which is filtering the water coming from that cooling tower, has been checked and cleaned as the status of the clogging was partial when detected.

The terminal unit fault, air trapped in cooling coil, occurred during both empirical periods at the university building and was successfully fixed by implementing its solution provided by the industry survey (see Chapter 4, Table 36). As per the action to fix this fault, the technical relevance between the terminal unit and the pump has been confirmed: the associated pump in operation has been investigated, and then the coil has been cleaned and the pressure of the associated secondary pump has been checked and amended. A cooling coil blockage fault occurred in the terminal unit during one of the empirical periods at the university building and was successfully fixed by implementing the action to fix this fault supplied by the industry survey (see Chapter 4, Table 36). As per the action to fix this fault, a technical relevance between the terminal unit and the pump is confirmed; the associated pump in operation has been investigated and then the chilled water quality from the associated primary pump has been checked and rectified as the blockage was an inner one when detected. Also, for the same fault, the technical relevance between the terminal unit and the chiller has been confirmed where the associated chiller in operation has been investigated, and then the chilled water quality from the associated primary pump has been checked and rectified as the blockage was also an inner one when detected.

In view of the above discussion, the industry survey and the case studies have answered the first research question: both methods resolved a confirmation that there indeed is technical relevance between CWS components, and accordingly, covering all these components simultaneously within the same intelligent maintenance framework is imperative. Therefore, the answer to the first research question is *'yes, there is a strong and positive correlation between CWS components, and therefore, it is important to cover them within the same intelligent maintenance framework'*.

6.2.2 Answer to Research Question #2

The second research question generated after the systematic literature review and shown in Chapter 3 (Table 19) is as follows:

Research Question #2: *Are there any other faults rather than the ones mentioned by the literature?*

The above question intended to check if there are CWS faults not addressed or stated by the considered literature. Identifying new faults will open a space that can expand the knowledge about the issues of CWS. As mentioned after the systematic literature review, the term *fault* is defined as any failure that may lead to a CWS breakdown over time, so taking care of CWS components would be inefficient without the awareness and knowledge of issues that engender their breakdown.

The considered studies in the literature have addressed various faults for CWS components. For the chiller component, the total number of considered studies that addressed faults is 81. Most of these have pinpointed the condenser fouling and refrigeration leak as chiller faults. Also, sensor bias is addressed as a chiller fault by most of the literature where several studies suggested installing sensors via multiple approaches such as Internet of Things to detect chiller faults. Table 67 below summarised the chiller faults that are mentioned by the literature. The table contains the fault along with the reference(s). Some of the studies neglected to describe the chiller faults clearly; for example, Ma and Wang (2011), Sun et al. (2013), Karim and Wang (2018), and Wu et al. (2021) addressed the degradation of the chiller but did not proffer more detail about the faults that lead to that degradation. The remainder of the literature did not state or clarify chiller faults within their proposed intelligent maintenance frameworks.

Table 67: Summary of chiller faults presented by the literature

Fault	References
Condenser fouling	Zhou et al. (2009b), Yu and Chan (2012), Zhao et al. (2012), Zhao et al. (2013a), Zhao et al. (2013b), Zhao et al. (2013c), Kocyigit (2015), Li et al. (2016a), Li et al. (2016b), Li et al. (2016d), Li et al. (2016e), Wang et al. (2017b), Yan et al. (2018a), Wang et al. (2020), Xia et al. (2021b), Munir et al. (2023), Albayati et al. (2023), and Ssembatya and Claridge, (2024)
Refrigeration leak	Tassou and Grace (2005), Navarro-Esbri et al. (2006), Kocyigit (2015), Han et al. (2020), Liu et al. (2022b), and Ssembatya and Claridge, (2024)
Faulty operation scheduling	Schein and Bushby (2006)
High condenser temperature	Rueda et al. (2005)
Evaporating fouling	Zhou et al. (2009a), Kocyigit (2015), and Albayati et al. (2023)
Compressor overcharging	Kocyigit (2015), Liu et al. (2017), and Hu et al. (2019)
Sensor bias	Wang and Cui (2005), Choi et al. (2005), Xiao et al. (2006), Xu et al. (2008), Wang et al. (2010), Hu et al. (2012), Hu et al. (2016a), Hu et al. (2016b), Mao et al. (2008), Hu et al. (2019), Mao et al. (2018), Gao et al. (2019a), Luo et al. (2019), and Ng et al. (2020)

The literature did not reveal much of a focus on the cooling tower component: the total number of the considered studies was 17. Most of these studies found air fan degradation as one cooling tower fault. Table 68 summarised the references that were mentioned the air fan degradation as well as other faults. Miyata et al. (2019) utilised the Monte Carlo simulation technique to detect operational uncertainty caused by imponderable pressure, but like others, they neglected to describe the faults that rendered such uncertainty. The remainder of the literature did not state or clarify cooling tower faults within their proposed PdM programmes or fault detection models.

Table 68: Summary of cooling tower faults presented by the literature

Fault	References
Air fan degradation	Zhou et al. (2009a), Ma and Wang (2011), Hashemian (2011), Sun et al. (2013), Wang et al. (2010), Hu et al. (2019), Melani et al. (2019), and Sulaiman et al. (2020)
Fouling of fills	Ma and Wang (2011) as well as Khan and Zubair (2004)
Sensor bias	Sun et al. (2018)

As mentioned in Chapter 2, the consideration of the literature towards the pump component is similar to the cooling tower component; the total number of considered studies is 16. Table 69 presents a summary of the pump faults that were highlighted by the literature. Hu et al. (2019) addressed the degradation of the secondary pump but did not proffer the necessary detail about the faults resulting in that degradation. The remainder of the considered studies did not state any fault in their proposed PdM or fault detection approaches with regard to the pump component.

Table 69: Summary of pump faults presented by the literature

Fault	References
Clogging	Yuan and Liu (2013), Zhou et al. (2009a), and Wang et al. (2010),
Excessive or abnormal noise	Hashemian (2011)
Faulty control switch	Hashemian (2011)
Faulty starter of the pump	Hashemian (2011)
Pipeline leakage	Liu et al. (2022b)
High flow rate in cold exchange	Ma and Wang (2009)
Low flow rate in cold exchange	Ma and Wang (2009)
Sensor bias	Luo et al. (2019), and Motomura et al. (2019b)

A review of the identified literature studies determined that the terminal unit was the CWS component most addressed, along with the chiller component. The total number of considered studies pertaining to the terminal unit fault is 97. While the literature has provided many faults for the terminal unit component, the most stated one is the faulty variable air volume. Table 70 shows the terminal unit faults that were stated by the literature along with the supporting references. Several studies failed to describe the faults they addressed, simply noting these as ‘abnormal behaviour’ of the terminal unit

(Lauro et al., 2014; Satta et al., 2017; Candanedo et al., 2018). The rest of the studies did not state the faults within their proposed PdM programmes for the terminal unit component.

Table 70: Summary of terminal unit faults presented by the literature

Fault	References
Faulty variable air volume	Norford et al. (2002), Cho et al. (2005), Schein and Bushby (2006), Li et al. (2010), Wang et al. (2012a), Li and Wen (2014), Zhao et al. (2015), Mulumba et al. (2015), Yuwono et al. (2015), Yan et al. (2016a), Zhao et al. (2017), Pourarian et al. (2017), Zhang and Hong (2017), Yan et al. (2018), Yan et al. (2019), Ranade et al. (2019), Piscitelli et al. (2020), Fan et al. (2021), Li et al. (2021), Gunay et al. (2022), Lin et al. (2023), and Xie et al. (2023)
Faulty fan	Norford et al. (2002), Shaw et al. (2002), Wang et al. (2012a), Holub and Macek (2013), and Yan et al. (2016b)
Compressor failure	Turner et al. (2017), Kim and Braun (2020), and Sulaiman et al. (2020)
Filter blockage	Tehrani et al. (2015)
Faulty filter coil system	Norford et al. (2002), and Shaw et al. (2002)
Cooling coil blockage	Liang and Du (2007), and Yan et al. (2016b)
Speed reducing the supply fan	Liang and Du (2007), Yan et al. (2016b), and Chaudhuri et al. (2017)
Return damper jam	Shaw et al. (2002), Liang and Du (2007), Sulaiman et al. (2015), Yan et al. (2016b), Andriamamonjy et al. (2018), Gao et al. (2019b), Deshmukh et al. (2019), and Sulaiman et al. (2020)
Sensor bias	Lee et al. (2004), Lo et al. (2007), Du et al. (2008), Yang et al. (2013), Du et al. (2014), Van Every et al. (2017), Shahnazari et al. (2019), Luo et al. (2019), Montazeri and Kargar (2020), Li et al. (2021), Gourabpasi and Nik-Bakht (2021), and Najeh et al. (2021)

As evident from the above discussion, one of the clear research gaps arising was, "*There is a significant level of variations in defining CWS faults and their importance/ impact*''. Accordingly, this initial research question has been generated. The research methods assigned to answer this research question are the industry survey (explained in Chapter 4) and the case study (explained in Chapter 5). Results of the industry survey have provided the research community with additional faults for each CWS component. They are 17 faults for chiller, 13 faults for cooling tower, 8 faults for pump, 20 faults for terminal units, which is more than those identified as an outcome of the systematic literature review where they are 7 faults for chiller, 3 faults for cooling tower, 8 faults for pump, 9 faults for terminal unit (see Figure 13). To recall, the faults that are mentioned by the literature were presented in Chapter 2 (Figure 9), while the faults that are mentioned by the industry survey are mentioned above (see Tables 67-70). Furthermore, and as mentioned in Chapter 4, all participants in the industry survey confirmed the occurrence of the faults mentioned by the literature at their sites, but they differ with literature in the most repeated faults. The considered studies of the literature were mostly mentioned the condenser fouling and sensor bias faults in chiller, the air fan degradation fault in cooling tower, the clogging fault in pump, and the faulty variable air volume in terminal unit, while the responses of industry survey were mostly stated the faults mentioned in Table 37.

Following the survey, the case study method was applied using a proposed methodological framework. The framework is comprised of three phases: set-up, machine learning and quality control. After implementing the last phase of the framework, three empirical periods were conducted at two different sites, out of which two periods for reliability and internal validity purposes were undertaken for the main case study in a university building, and one period for external validity purpose was undertaken in a hotel building. The result of these empirical periods with regard to the faults has validated the outcome of the industry survey as 15 faults for the chiller component occurred out of the additionally recorded 17 faults. The two faults that did not occur were low cooler delta-T and high condenser pressure. By contrast, the 15 faults that occurred were low discharge superheat, low evaporator refrigerant temperature, low oil pressure, low condenser flow, low chilled water flow, high cooler delta-T, high compressor lift, high motor temperature, high motor ampere, high condenser approach, high evaporator approach, relief valve discharge, vibration, imbalanced line current, and incorrect manual guide vane target.

With regard to the cooling tower component, the outcome of the three empirical periods has fully validated the outcome of the industry survey as all additional 13 faults occurred. These faults were the malfunctioning blowdown system, unusual sound, high water total dissolved solid, fills clogging, low circulating water flow rate, vibration, over current, rise in circulating water temperature, damaged fan, faulty water level valve, faulty isolation valve, motor overheating, and low water basin level. Likewise, with regard to the pump component, the outcome of the three empirical periods has fully validated the outcome of the industry survey as all the additional eight faults occurred. These faults were motor vibration, motor heat-up, leakage from the pump set, leakage from the valves, pump runs but provides no water, pump runs at reduced capacity, noisy non-return valve, and improper pump water alignment.

With regard to the terminal unit component, the result of the three empirical periods has somewhat validated the outcome of the industry survey as 18 faults occurred out of the 20 additionally identified faults. The two faults that did not occur were the motor overheating and the faulty variable frequency drive soft starter. The faults that did occur were dirty air flow, faulty supply air damper, loose belts, air trapped in cooling coil, faulty control valve, broken belts, noisy motor, faulty bearing, motor overload, noisy contactors, vibration, damaged insulation on pipe, low static pressure, damaged insulation on duct, faulty fresh air damper, faulty exhaust air damper, faulty cooling valve actuator, and faulty damper actuator.

From the above discussion, the reasonable conclusion after a comprehensive systematic literature review concerning the existence of additional faults is proven by the industry survey and the case study, and therefore, the answer to the second research question of this research project is '*yes*'.

6.2.3 Answer to Research Question #3

The third research question generated after the systematic literature review, shown in Chapter 3 (Table 19), is as follows:

Research Question #3: *How can an intelligent detection model be built and validated?*

The maintenance strategy utilised in this research project is an intelligent one based on fault detection approach, as this is in line with Industry 4.0. One of the proposed methodological framework phases is machine learning. The machine learning phase includes building and training a detection model, which happens via a decision tree algorithm in this research project. To build and train a detection model for each CWS component, a dataset for each CWS component is required. For this research project, an Excel file was created for each dataset to be read by the chosen machine learning platform, Python. Each file contains two columns, one with the readings of the chosen operational parameters, and another one for the inspection result, which is either '1' in a case of fault, or '0' in a case of no fault. The chosen operational parameters in this research project are the chilled water leaving temperatures for the chiller and the cooling tower components, the pressure for the pump component, and the space temperature for the terminal unit component. These readings, along with the inspection results, were recorded by experienced technicians by means of check sheets. To collect data, which includes these readings and inspection results, a time interval between the readings is established, referred to in this research as minimum frequency; likewise, a study period or time span for data collection is established, referred to in this research as maximum frequency. In this regard, it has been noted after the systematic literature review that there are variances in addressing the frequency point of view. Some studies from the literature clarified both minimum and maximum frequencies, but these frequencies were not same in all the literature, nor were operational parameters the same with all reviewed studies. Some studies clarified the operational parameters but did not specify either one of the frequencies or both. The rest of the literature did not specify operational parameter or frequencies.

For the chiller, Sun et al. (2013) collected data of two operational parameters, chilled water flow rate and chilled water returning temperature, every hour for 20 days. Chilled water flow rate was considered again by Mao et al. (2018) but the readings were collected every 75 minutes for two months. Xiao et al. (2006) considered the same parameter but did specify the frequencies. Another study considered the parameter and specified the sample size of the collected data but did not provide information about the frequencies (Hu et al., 2016) Condenser water flow rate is another operational parameter for which one study collected readings every five minutes for two months (Hu et al., 2016), and another study collected readings but every 75 minutes for two months (Wang et al., 2010). Wang and Cui (2005) collected data of evaporating pressure but did not provide information about the frequencies. Kocyigit (2015) addressed the same operational parameter along with the condenser pressure, but with information provided about the frequencies. The study of Choi et al. (2005) collected readings of the evaporator water entering temperature every 10 minutes for five days. One of the studies addressed the supply air average humidity as an operational parameter where its sample size was clarified, but information about the frequencies was absent (Albayati et al., 2023). Ma and Wang (2011) considered the condenser water supply temperature but did not clarify the frequencies. The readings of the chilled water leaving temperature and the chilled water returning temperature were collected in the study of Wang et al. (2022), but frequencies were not specified. The readings of oil feed pressure were combined to create a dataset to detect chiller fault, but the frequencies were not clarified as well (Ssembatya and Claridge, 2024). The rest of the chiller studies failed to clarify data-related information.

For the cooling tower, Ahn et al. (2001) explained that the data for building their simulation model are the readings of the chilled water leaving temperature and the chilled water returning temperature, but they did not clarify the frequencies. Zhou et al. (2009a) collected data of the air flow rate and clarified only the maximum frequency, which is five days. Data of the fan power were collected during two months with a time interval between the readings of five minutes (Hu et al., 2019). Three studies from the literature addressed inlet condenser water temperature as an operational parameter for their data collection purpose in building their prediction models, but they did not specify the frequencies (Ma and Wang, 2011; Wang et al., 2010; Motomura et al., 2019a). The study of Motomura et al. (2019b) addressed another operational parameter, the outlet condenser water temperature, but the associated frequencies were not specified. One study collected data of air wet bulb temperature that have a sample size of five thousand readings, but the frequencies were not clarified (Xu et al., 2015). The rest of the cooling tower studies did not clarify the data-related information. For the pump, Hu et al. (2019) utilised a building automation system to obtain differential pressure data every five minutes for two months. Water flow rates of one year were utilised in building a simulation model, but the time intervals between the rate readings were not specified (Ma and Wang, 2009). The rest of the pump studies did not clarify the data-related information.

For the terminal unit, the indoor set temperature or the space temperature was addressed in four studies from the literature (Turner et al., 2017; Liang and Du, 2007; Sittón-Candanedo et al., 2018; Andriamamonjy et al., 2018). The first and second study clarified only the maximum frequency, which is seven days and 10 hours, respectively; the third study clarified the sample size but they did not specify the frequencies; while the fourth study did not clarify both frequencies. The outdoor temperature is another operational parameter that was considered by Turner et al. (2017), but only the maximum frequency of its readings was clarified, which is seven days. A sample size of the indoor cooling load was collected during 10 hours for one of the studies, but the time intervals between the loads were not specified (Liang and Du, 2007). The supply air temperature was chosen as an operational parameter by two studies from the literature (Andriamamonjy et al., 2018; Ranade et al., 2019). The first study did not specify the frequencies, while the second study specified the maximum frequency only, which is three days. Ranade et al. (2019) considered another operational parameter, the outlet water temperature, and only clarified the maximum frequency, which is three days. Andriamamonjy et al. (2018) considered two more operational parameters, the return air temperature and the exhaust air temperature, but they did not clarify the frequencies. Discharge air temperature is an operational parameter considered by two studies from the literature (Schein and Bushby, 2006; Lin et al., 2023). The first study did not clarify the frequencies, while the second study specified only the minimum frequency, which is 30 minutes. The air flow was considered as an operational parameter by two studies from the literature (Kim and Braun, 2020; Omar et al., 2023). But the first study did not clarify the frequencies, while the second one clarified only the maximum frequency, which is three days. The study of Kim and Karim (2020) considered two more operational parameters, the refrigerant charge and the refrigerant mass flow, but they did not clarify the associated frequencies. The study of Chaudhuri et al. (2017) did not consider the parameters linked technically to the terminal unit operation where they collected occupant skin temperatures and considered these readings in building their support vector machine model. The rest of the terminal unit studies did not clarify the data-related information.

Based on the above discussion, another research gap arose for this research project: ''*The measurement of CWS faults is not standardised leading to inconsistent fault detection practice.*". The noted differences cause obscurity for future research on the proper way to create datasets in case the researcher needs to collect new data for a building to study its CWS. The differences between the studies with regard to the frequencies have encouraged this research to think about confirming justified frequencies that allow the creation of datasets of the detection model by identifying proper time intervals between readings of the operational parameters (minimum frequency) as well as a proper time span of collecting the data, which is the study period (maximum frequency). Also, this research believes that random selections of the frequencies cannot guarantee a high detection accuracy of a detection model, so research requires logical and justifiable frequencies for data collection purposes. Accordingly, the aforementioned fourth research question has been generated.

Similar to the previous research questions, the research methods assigned to answer the third research question are the industry survey (explained in Chapter 4) and the case study (explained in Chapter 5). In the industry survey, this research project devised an innovative way to identify minimum and maximum frequencies. The participants were asked in the third part of the industry survey to state the fault for each CWS component that is occurring often and then state its frequency of occurrence in their commercial buildings. They were also asked to state the fault for each CWS component that is occurring only rarely and then state its frequency of occurrence in their commercial buildings. After considering 304 responses, the minimum value of the minimum frequencies and the maximum value of the maximum frequencies were identified as the proposed frequencies in this research project, where the minimum value of each CWS component is for the time interval between the readings of the chosen operational parameters and the maximum value of each CWS component is for the time span for data collection. This ensures coverage of the possibility of fault occurrence as much as possible within the city in which a particular building to be studied is located. This innovative idea was discussed in Chapter 4 (Figure 14). So, this research project has proposed frequencies applicable to data collection for each CWS component (see Chapter 4, Table 40).

After determining the outcomes of the industry survey, the case study method via methodological framework was conducted. Two case studies were conducted, a main one in a university building and another in a hotel building for external validity purposes. As shown in Chapter 5 (Table 46), the data collection plan was implemented as per the proposed frequencies. Accordingly, a dataset for each CWS component was created to build and train its decision tree model. The detection accuracy for the decision tree model of each CWS component at both sites was calculated based on the collected data using Equation 5. As shown in Chapter 5 (Tables 48 and 59), the detection accuracy for the decision tree model of each CWS component at both sites was more than 98 per cent, results which validate the proposed frequencies. Because these frequencies were applied as a guide for data collection, attaining such high accuracy confirms the significance of these frequencies. At the time of implementing the case study method via methodological framework, three empirical periods were conducted, two periods for reliability and internal validity at the main case study building (Alfaisal University), and one period as an external validity case study at another building (a hotel). As shown in Chapter 5 (Tables 49-52, 54-57, and 60-63), the decision tree model of each CWS component verifies its reliability in tracing and detecting faults. This confirms that the proposed frequencies are valid in creating datasets for building detection models. Also, the accuracy outcome of each CWS component validated the chosen operational parameters of this research project; these are the chilled water leaving temperature for chiller and cooling tower, the pressure for pump, and the space temperature for terminal unit. Moreover, it validated the outcome of the industry survey where the majority of participants were advised to select these operational parameters (see Chapter 4, Table 37).

In light of the above, the industry survey and the case studies have fulfilled the way of building the detection model, which is highlighted in the third research question. This research thesis has proposed proper frequencies that were utilised in collecting data that built a reliable detection model for each CWS component. These frequencies are summarised below in Table 71.

Table 71: Chilled water system fault frequencies

CWS Component	Minimum Frequency (Minutes)	Maximum Frequency (Weeks)
Chiller	30	12
Cooling tower	30	16
Pump	60	24
Terminal unit	45	08

The primary intention of the proposed intelligent maintenance framework is to detect the faults of CWS and then to fix them when occurring. To do so, a detection model was built and trained for each CWS component. In line with Industry 4.0, machine learning is one of the phases of the proposed methodological framework; it entails building and training the detection model. The PdM workflow proposed by Achouch et al. (2022) contains in its final stage the evaluation of the detection model. To evaluate the detection model of this research project, it is necessary to assess the model's performance in tracing and detecting faults of CWS components. A review of the literature revealed that evaluating the detection model was completed by calculating the prediction accuracy based on the data. As mentioned in Chapter 2, this research believes that evaluating the detection model requires the undertaking of experimental studies to check its reliability and validity in tracing and detecting faults.

The assigned research method to validate the outcome of the industry survey and the built detection model is the case study (explained in the previous chapter). As mentioned previously, this method has been implemented via a methodological framework containing three phases: set-up, machine learning and quality control where two case studies were implemented, the main one at a university building and another at a hotel building for external validity purposes. As part of the second phase, the machine learning phase, a decision tree model for each CWS component was built and trained as per the steps mentioned in the previous Chapter (see Figure 17) with the sample size mentioned in the previous chapter (Table 47). Some of the reviewed studies have encouraged this research to use the decision tree algorithm. According to Hodavand et al. (2023), decision tree algorithm provides a practical solution to smart building management; in fact, they emphasise that decision tree algorithm is the best for PdM and for fault detection. Montazeri and Kargar (2020) compared the decision tree algorithm with five other machine learning algorithms, finding that the decision tree algorithm has the highest prediction accuracy. One of the reviewed studies indicated that decision tree algorithm shows a high accuracy in covering fault possibilities, an excellent algorithm for evaluating the intelligent maintenance framework (Sittón-Candanedo et al., 2018). In a general view of other machine learning algorithms, the decision tree algorithm was chosen as its graphical binary representation can be easily interpreted by technical users as well as nontechnical decision makers.

In this second phase, the researcher calculated the detection accuracy of the decision tree model of each CWS component at both sites with promising results: the lowest accuracy was 98.5 per cent (see previous chapter, Tables 48 and 59). This is in agreement with several other studies determining high prediction accuracy by applying the decision tree algorithm such as the studies of Satta et al. (2017), Ranade et al. (2019), and Elnour et al. (2022). While implementing the last phase of the methodological framework, a computer unit at each site was integrated with the decision tree model for continuous monitoring. When the screen of the computer unit shows a signal with ‘1’ (see Figure 31), this means the decision tree model has predicted a fault. The next course of action is to inspect the site and verify that signal, and in the case of a real fault, this confirms the decision tree model has detected a fault.

During the first empirical phase, conducted at the university after implementing the last phase of the methodological framework, the decision tree model of the chiller predicted 56 faults, out of which 54 faults were detected. The decision tree of cooling tower predicted 61 faults, out of which 60 faults were detected. With regard to the decision tree of the pump, 39 faults were predicted, out of which 37 faults were detected. For the terminal unit, its decision tree model predicted 73 faults, out of which 71 faults were detected. These results confirm the reliability of the detection model of each CWS component as most of the predicted faults were real faults at the site. This also verifies that the proposed frequencies (Chapter 4, Table 40; Chapter 6, Table 71) are appropriate for data collection for datasets upon which the detection model was built and trained.

With regard to the second empirical period, the decision tree of the chiller predicted 47 faults, out of which 46 faults were detected. For the cooling tower, its decision tree model predicted 53 faults, out of which 52 faults were detected. The decision tree model of the pump predicted 44 faults, out of which 42 faults were detected. For the terminal unit, its decision tree model predicted 68 faults, out of which 67 faults were detected. Similar to the first empirical period, these results confirm the reliability of the prediction model of each CWS component as nearly all the predicted faults were real faults at the site. Also, this verifies the proposed frequencies that were utilised in creating the prediction models. With regard to the third empirical period, which was conducted at the case study building for external validity (the hotel), the chiller's decision tree model predicted 41 faults, out of which 39 faults were detected. For the cooling tower, its decision tree model predicted 43 faults, out of which 40 faults were detected. For the pump, its decision tree model predicted 44 faults, out of which 43 faults were detected. The terminal unit's decision tree model predicted 48 faults, out of which 46 faults were detected. These outcomes have the same encouraging impact as the previous two empirical periods, confirming the reliability of the prediction model of each CWS component. Again, nearly all predicted faults were real faults at the site. And again, this validates the proposed frequencies utilised in creating the prediction models.

After the empirical periods, a comparison activity was conducted at both sites between BMS and the decision tree model of each CWS component. Clear improvement was evident in fault detection (see Table 72). The stakeholders at both sites expressed satisfaction with the decision tree model of each CWS component as it traced and detected numerous faults, showing encouraging improvement in tracing and detecting faults when compared to BMS.

Table 72: Faults detection improvement by the decision tree model

CWS Component	First Empirical Period Improvement (%)	Second Empirical Period Improvement (%)	Third (Hotel) Empirical Period Improvement (%)
Chiller	24	28	21
Cooling tower	22	21	25
Pump	30	26	26
Terminal unit	24	22	22

Based on the above discussion, the industry survey and case study methods have answered the third research question *by providing the frequencies mentioned in Table 71, which can create the required datasets that build the intelligent detection model. The empirical periods activities have validated the detection model very well.*

6.2.4 Answer to Research Question #4

The fourth research question that was generated after the systematic literature review and shown in Chapter 3 (Table 19) is as follows:

Research Question #4: *What are the actions required to fix the CWS faults?*

Following the PdM workflow proposed by Achouch et al. (2022), the intelligent maintenance framework would be inefficient without understanding how to fix any issues or faults occurring in a building's systems. So, proposing a holistic intelligent maintenance framework for CWS would necessitate an immediate to fix each occurred fault. As a result of the literature review, it was noted that studies ended their PdM programmes or approaches with building and training the prediction models, and then with calculating its accuracy in predicting or detecting the investigated faults, but without providing solutions to the CWS faults. Also, two of the studies advised some actions before collecting the data that will be utilised in building and training the prediction models for chiller, cooling tower and terminal unit components, but those actions are not solutions for fixing the faults of the said CWS components; instead, they were proposed for data collection purposes. The first study advised the cleaning of the condenser water tubes in the chiller (Zhao et al., 2014), while the second study advised the cleaning of the cooling tower fan and the impeller, the fan scroll, and the blower blade of the air handling unit (Chew and Yan, 2022). Based on this, another research gap arose: "*CWS fault resolution remains inconclusive*". Therefore, a fourth research question has been generated.

The assigned research methods to answer the subject research question are the industry survey (explained in Chapter 4) and the case study (explained in Chapter 5). The industry survey has provided an action to fix each CWS fault that was presented in the literature. Also, the industry survey provided an action to fix each additional CWS fault that was presented by the same industry survey. Table 73 shows the total number of actions for each CWS component.

Table 73: Number of actions to fix CWS faults

CWS Component	Total Number of Fault Solutions
Chiller	24
Cooling tower	16
Pump	16
Terminal unit	29

The fault occurring during the three empirical periods for each CWS component, as presented in the previous chapter (Tables 49-52, 54-57, and 60-63), were successfully fixed by implementing the actions that were furnished by the industry survey and mentioned in Chapter 4 (Tables 33-36). After implementing the quality control phase, which includes measuring the provided actions to fix the occurred faults (see subsubsection 5.2.3), the concerned departments at the main case study site (the university) and at the external validity site (the hotel) scrutinised if the said actions are applicable and beneficial in fixing the faults. Indeed, all the actions to fix the faults occurring were to the satisfaction of the concerned departments at both sites.

In view of the faults occurring during the empirical periods for CWS components, as mentioned in the previous chapter (Tables 49-52, 54-57, and 60-63), the majority were from the new faults supplied by the industry survey and only a few faults were from the list generated from the literature, as mentioned in Chapter 2 (Figure 9). To highlight the faults occurred during the empirical periods from the lists generated from the considered literature, the chiller faults occurring were refrigeration leak, condenser fouling, compressor overcharging, evaporating fouling, high condenser temperature, and faulty operation scheduling. For the cooling tower component, one fault occurred from the list presented by the considered literature, the fouling of fills. For the pump component, the faults occurred from among those listed by the literature were clogging, low flow rate in cold exchange, faulty control switch, pipeline leakage, abnormal or excessive noise, and high flow rate in cold exchange. For the terminal unit component, the faults that occurred from among those generated by the literature were cooling coil blockage, speed reducing the supply fan, return damper jam, faulty variable air volume, compressor failure, and filter blockage.

During the empirical periods, the refrigeration leak fault for the chillers was detected 24 times by the decision tree models. This fault was presented by several studies from the considered literature (Tassou and Grace, 2005; Navarro-Esbri et al., 2006; Kocyigit, 2015; Han et al., 2020; Liu et al., 2022b). These studies have proposed various PdM tools to predict or detect the fault, but again, they neglected to suggest a solution or an action to fix the fault. In this research project, an action was provided for the fault (see Chapter 4, Table 33). After detecting the fault by the proposed decision tree models, it has been successfully fixed by implementing the provided solution, which is by checking, testing and rectifying the tube, joint, and valves of the refrigeration system of that chiller. The condenser fouling fault is another chiller fault that occurred during the empirical periods. This fault was detected eight times by the decision tree models. This fault was presented by 16 studies from the considered literature (Zhou et al., 2009a; Yu and Chan, 2012; Zhao et al., 2012; Zhao et al., 2013a; Zhao et al., 2013b; Zhao et al., 2013c; Kocyigit, 2015; Li et al., 2016a; Li et al., 2016b; Li et al., 2016c; Li et al., 2016d; Wang et al., 2017b; Wang et al., 2020; Xia et al., 2021b; Munir et al., 2023; Albayati et al., 2023). These studies proposed a variety of PdM tools to predict or detect the fault, but they did not provide any solution to fix it. In this research project, the said chiller fault has been successfully fixed by implementing the action furnished by the industry survey (Chapter 4, Table 33): descaling the condenser tubes.

The proposed decision tree models for chillers have detected compressor overcharging six times during the empirical periods of this research. This fault was presented by three studies from the considered literature (Kocyigit, 2015; Liu et al., 2017; Hu et al., 2019). These studies have proposed various PdM tools to predict or detect this fault, but they did not provide any viable solution for fixing it. In this research project, this chiller fault has been successfully fixed immediately after its detection by the decision tree model. It was fixed by implementing the action furnishes by the industry survey

(Chapter 4, Table 33) – by checking the factory sheet and then by reducing the charge accordingly.

The evaporating fouling fault, another chiller fault occurring during the empirical periods, was detected 13 times by the decision tree models. This fault was presented in the considered literature by three studies (Zhou et al., 2009b; Kocyigit, 2015; Albayati et al., 2023). These studies have proposed different PdM tools to predict or detect this fault but stopped prior to proffering any solution to fix it. In this research project, an action was furnished for this fault (Chapter 4, Table 33). It has been successfully fixed immediately after its detection by descaling the evaporator tubes.

As mentioned previously in this subsection, high condenser temperature is a chiller fault that occurred during the aforementioned empirical periods; this fault was detected 14 times by the decision tree models. As noted in the literature, Rueda et al. (2005) proposed a fault detection technique by applying an artificial neural network algorithm for this fault, but as with the others, they did not provide a solution to fix it this fault at the time of its detection. In this research project, a viable action was supplied for fixing this fault (Chapter 4, Table 33). After detection of this fault by the decision tree model, it has been successfully fixed by implementing that solution – by checking the return chilled water temperature and then the condenser tubes were descaled.

The final fault that occurred fault from the list of chiller faults that was generated from the literature is the faulty operation scheduling. This fault has been detected once by the decision tree model during the empirical periods. This fault was presented by Schein and Bushby (2006) where they applied a hierarchical rule-based fault detection and diagnosis to predict this fault. But as with the other studies, no solution for fixing this fault was indicated. In this research project, this fault was successfully fixed after detection by implementing the action furnished through the industry survey (Chapter 4, Table 33), which was by resetting the control switch.

As mentioned previously in this subsection regarding the cooling towers faults that were listed by the literature, one fault has occurred eight times during the empirical periods: the fouling of fills. In the literature, this fault was detected by applying a regression model in one of the studies and by the hybrid quick search method in another study, but with no solution provided to fix it (Khan and Zubair, 2004; Ma and Wang, 2011). This present research has furnished an action to fix this fault (Chapter 4, Table 34), and this solution has been implemented after the fault's detection by the decision tree model. This fault has been successfully rectified by cleaning the fills.

With regard to the pump component, the clogging fault has occurred three times during the empirical periods, and it is one of the faults that were presented by the literature in three studies, the research studies of Yuan and Liu (2013), Wang et al. (2010), and Zhou et al. (2009a). These studies have applied various PdM models to predict this fault, but without the suggestion of a solution to fix it in case of its occurrence in real life. In this present research project, an action to fix this fault was one evident and beneficial outcome of the industry survey (Chapter 4, Table 35). The action was implemented immediately after detecting the fault by the decision tree models. The status of the clogging was partial, and it has been successfully fixed by cleaning the strainer that is filtering the water coming from the associated cooling tower.

During the empirical periods, low flow rate in cold exchange fault and high flow rate in cold exchange fault, both presented in the literature by Ma and Wang (2009), have been detected by the decision tree models 15 times: 12 for the low flow rate fault and three for the high flow rate fault. Ma and Wang (2009) proposed a simulation model to predict both faults, but without giving a solution to fix them if they occurred while operating the CWS in any building. In this research project, actions to fix both faults have been provided (Chapter 4, Table 35), and both actions were utilised during the empirical periods. Both faults have been successfully fixed by adjusting the pump speed.

The faulty control switch and excessive noise faults have occurred during the empirical periods, two pump faults from the list generated from the literature. Hashemian (2011) presented these faults and predicted them using wireless sensors, but as with other studies, his research did not include solutions for those faults. As shown in the previous chapter, the faulty control switch was detected three times by the decision tree model during the empirical periods, and its fixing action (Chapter 4, Table 35) has been successfully implemented, fixing the fault by troubleshooting the switch. With regard to the excessive noise fault, it was detected once by the decision tree model during the empirical periods. As this present research has provided an action to fix this fault (Chapter 4, Table 35), this action has successfully cleared that fault by fixing the associated bearings and shaft.

The pipeline leakage fault also occurred during the empirical periods; it has been detected twice by the decision tree model. In the considered literature, this fault was presented by Liu et al. (2022b) who predicted it by applying an adaptive moment estimation algorithm with multi-layer feedforward neural networks trained with the error backpropagation neural network, but their PdM proposal did not contain a solution or an action to fix this fault. In contrast, this research project has furnished an action to fix this fault (Chapter 4, Table 35) which resulted in a successful fix of this fault by welding multiple pipe joints.

With regard to the terminal unit faults presented in the considered literature and which occurred during the empirical periods as mentioned above in this subsection, cooling coil blockage and speed reducing the supply fan were two specific faults. Both faults were presented by Liang and Du (2007) as well as by Yan et al. (2016b). The study by Liang and Du (2007) combined a simulation-based model method with a support vector machine method to predict these faults, while the study of Yan et al. (2016) utilised decision tree algorithm for fault prediction. But both studies have neglected to proffer a solution for either of these two faults. During the empirical periods, the proposed decision tree model of this present research has detected the cooling coil blockage once and the speed reducing the supply fan six times. After detection, both faults were successfully fixed by implementing the actions provided by this research (Chapter 4, Table 36). The first fault, an inner blockage, was fixed by rectifying the chilled water quality coming from the associated chiller as well as from the associated primary pump. The second fault was fixed by cleaning the blower tips.

A return damper jam was another fault occurring during the empirical periods. This fault was presented by seven studies in the literature (Shaw et al., 2002; Liang and Du, 2007; Sulaiman et al., 2015; Yan et al., 2016b; Gao et al., 2019b; Deshmukh et al., 2019; Sulaiman et al., 2020). These studies have applied different PdM tools to predict the fault, but none proposed any solution to fix the same. In this research, an action was provided (Chapter 4, Table 36), which is servicing the damper or replacing it as needed. This fault was detected six times by the decision tree model of this research project, and its aforementioned solution successfully rectified the fault after detection.

Three more faults occurring during the empirical periods were from the fault lists presented by the literature. First, the faulty variable air volume was presented by 22 studies (Norford et al., 2002; Cho et al., 2005; Schein and Bushby, 2006; Li et al., 2010; Wang et al., 2012a; Li and Wen, 2014; Zhao et al., 2015; Mulumba et al., 2015; Yuwono et al., 2015; Yan et al., 2016a; Zhao et al., 2017; Pourarian et al., 2017; Zhang and Hong, 2017; Yan et al., 2018b; Yan et al., 2019; Ranade et al., 2019; Piscitelli et al., 2020; Fan et al., 2021; Li et al., 2021; Gunay et al., 2022; Lin et al., 2023; Xie et al., 2023). These studies have applied a variety of PdM tools to predict this fault, but with no solution provided to fix it in case it appeared in the terminal units of any commercial building. As shown in Chapter 4 (Table 36), this research project has filled this absence by providing an action to fix that fault, which is by rectifying the damper connection and controller. During the empirical periods, this fault was detected 11 times by the decision tree model for this research. It was successfully fixed by implementing the aforementioned action.

Second, the compressor failure fault was presented by three studies from the considered studies (Turner et al., 2017; Kim and Braun, 2020; Sulaiman et al., 2020). The first study applied a simulation mode; the second applied virtual sensors; while the third applied multi-layer perceptron to predict this fault, but none proffered a viable solution for the fault. This research project has provided an action (Chapter 4, Table 36), acknowledging that the voltage and related control accessories should be checked before replacing formalities. By the proposed decision tree model of this research, this fault was detected once during the empirical periods and was successfully repaired by implementing the provided action. The filter blockage fault is the last fault that occurred during the empirical periods from the lists presented by the considered literature. It was presented by Tehrani et al. (2015) and was predicted by utilising the decision tree algorithm, but with no solution provided to fix it in case it appeared in the industry life. This research has completed this task by providing an action to fix this fault (Chapter 4, able 36). During the empirical periods, this fault was detected once by the proposed decision tree model of this research, and then successfully fixed by implementing its action, which is by cleaning the filter.

A cursory perusal of Figure 13 in Chapter 4 shows the total number of chiller faults presented by the literature as seven faults, out of which, six faults occurred during the empirical periods (see previous chapter). The total number of the additional chiller faults provided by the industry survey is 17, out of which 15 faults occurred during the study’s empirical periods. So, 21 types of chiller faults were successfully fixed by implementing the furnished actions (see Chapter 4, Table 33). For the cooling tower, the total number of faults that were presented by the literature is three, out of which one fault occurred during the study's empirical periods (see previous chapter). The total number of additional cooling tower faults emerging from the industry survey is 13 faults, and all occurred during the empirical periods. So, 14 types of cooling towers faults were successfully fixed by implementing the furnished actions (see Chapter 4, Table 34). For the pump component, the total number of faults that were presented by the literature is eight faults, out of which six occurred during the study's empirical periods. The total number of additional pump faults that were provided by the industry survey is eight, all of which occurred during the empirical periods. So, 14 types of pump faults were successfully fixed by implementing the furnished actions (see Chapter 4, Table 35). For the terminal unit component, the total number of faults that were presented by the literature is nine, out of which eight faults occurred during the study's empirical periods. The total number of additional terminal unit faults emerging from the industry survey is 20, out of which 18 faults occurred during the study's empirical periods. So, 26 types of terminal unit faults were successfully fixed by implementing the furnished actions (Chapter 4, Table 36). In general, this present research project has provided a viable action to fix each listed type of fault, whether its source is from the literature or from the industry survey (see Table 73).

In light of the above, the industry survey and case studies have supplied an answer for the fourth research question of this research project, *beneficially providing an action to fix each listed CWS fault in order to ensure a holistic intelligent maintenance framework*. These actions are presented Chapter 4: Table 33 presents an action to fix each listed chiller fault, and Tables 34-36 present actions to fix each listed fault of cooling tower, pump and terminal unit, respectively.

6.3 Conclusion

6.3.1 Summary of Research Thesis Aim and Objective

This research proposes a holistic intelligent maintenance framework for CWS at commercial buildings. It conducted a four-stage systematic literature review. The guiding research question of this research project was as follows:

“What are the approaches or methods to implement predictive maintenance or fault detection for a chilled water system at commercial buildings?”

The intention of the above question was to gain an understanding of the mechanism of identifying a system’s faults during operation and exploring the methods used to detect these faults. Following the above guiding question, the systematic literature review began and extending to 182 studies that were performed more recently than 1999. This review of these studies followed the PdM workflow proposed by Achouch et al. (2022). Four research gaps were highlighted from a management perspective. These gaps (explained in Chapter 2) are related to three parts (fault description and handling, data collection and frequency, and the coverage of the proposed maintenance frameworks) and accordingly, four research questions were generated. To answer these questions, two research methods were assigned: industry survey and case study (Chapter 3, Table 19). The industry survey, adhering to constructive guidelines and a pilot study, was disseminated to 761 participants at commercial buildings in Riyadh, Saudi Arabia, which have valid registration certificates with the proper authority. As recommended by the pilot study, the commercial buildings that were contacted have a minimum age of three years. As advised by the pilot study, three months were given to receive survey responses, and as a result, 336 response were received, out of which 304 responses were examined for this research project as they have CWS in their commercial buildings. The industry survey produced four outcomes: 1) recording additional faults for each CWS component; 2) an action to fix each listed CWS fault whether its source was the literature or the survey; 3) frequencies for all CWS components that can be used in data collection to build a detection model; and 4) validation of the chosen operational parameters with readings viable for creating the datasets upon which the detection model can be built and trained.

In light of the above, the aim of this research project was to explore innovations in observing and controlling the CWS at commercial buildings in accordance with the era of smart technologies, and it is achieved by gaining the knowledge of other researchers from conducting the said literature review. 182 considered studies are illustrated various ideas in detecting the faults of CWS components and opened a gate to present further knowledge by filling the associated research gaps. The aim of this research project is also achieved post conducting the industry survey where valuable insights and information were gathered from 304 professionals. The industry survey looked like a drone that captured the CWS at different commercial buildings where each professional submitted the answers of the provided four parts, which can be considered as a sight of operation and maintenance management for CWS at the professional's building. These answered are helped to answer the research questions of this research project.

With regard to the case study, a methodological framework was proposed for conducting the research. Two case studies were conducted in tandem, the primary one a university building, and the other a hotel building for external validity purposes. The methodological framework entailed three phases: the set-up, machine learning and quality control. Each phase of this methodological framework has multiple managerial stages or steps to build the intelligent maintenance framework. The set-up phase of the proposed methodological framework contained three stages. The first stage was understanding the building under study in an efficient way by analysing its as-built drawing. By doing so, determining the unit numbers of each CWS component in the building, and knowing their locations on site was easier. This proposed simplified schematic (see Chapter 5, Figure 15) allowed users to find each CWS component and determine their quantities. The second stage of the set-up pertained to the reading tools for the CWS operational parameters: how to make the reading tools available and the proper location for each tool. The readings of the operational parameters were essential for creating the datasets used in the second phase of the methodological framework, the machine learning. The operational parameters chosen in this research were the chilled water temperatures for chillers and cooling towers, the pressures for pumps, and the space temperatures for terminal units. The third and final stage of the set-up addressed data collection, presenting the data required and proposing a complete plan for collecting data. Therefore, the main goal of the set-up phase was to provide datasets required to build and train the detection model, as explained in the second phase of this framework, which is machine learning. With this, the first objective of this research project, which was mentioned in Chapter 1 (see section 1.2), is fulfilled.

As this research project intended to implement an intelligent maintenance framework in line with Industry 4.0, the second phase of the methodological framework relied on machine learning. The decision tree technique was chosen to build and train a model for predicting and detecting CWS faults by utilising datasets created based on the proposed frequencies. Two decision tree algorithms, C4.5 and CART, were proposed to build, train and test the detection model. The detection accuracy for each decision tree model was calculated with encouraging results: the detection accuracy was more than 98 per cent for the decision tree model of each CWS component. The last phase of the methodological framework, quality control, proposed a control plan for continuous evaluation of the detection models. The control plan contained two actions, monitoring and response. Both actions proposed executing the decision tree model while operating the CWS, and then controlling the system via aspects such as fixing the detected faults and documenting the outcomes of the detection model from a managerial perspective.

To conduct the research quality aspects that were mentioned in Chapter 3 (Table 27), three empirical periods (one month each) were executed: two periods at the main case study building (the university) for reliability and internal validity purposes, and the third at another site (the hotel) for external validity purposes. Following the assessment activities of this research project as discussed in Chapter 3 (Table 29), the reliability segment was assigned to check if the proposed detection model, the decision tree, can trace CWS faults over time. The reliability part was proven during the first two empirical periods implemented at the main case study building (the university). During the first empirical period, which was conducted at the university, the decision tree model of the chiller predicted 56 faults, out of which 54 faults were detected, with a breakdown of nine times for the refrigeration leak fault, eight times for the condenser fouling fault, six times for the compressor overcharging fault, seven times for evaporating fouling fault, seven times for the high compressor lift fault, five times for the high motor ampere fault, five times for the relief valve charge fault, four times for the high condenser approach fault, two times for the incorrect manual guide vane target fault, and one time for the high evaporator approach fault.

The decision tree of the cooling tower predicted 61 faults, out of which 60 faults were detected, with a breakdown of 11 times for malfunctioning blowdown system fault, 10 times for the low water basin level fault, 10 times for the high water total dissolved solid fault, nine times for the vibration fault, five times for the rise in circulating water temperature, five times for the faulty isolation valve, three times for the low circulating water flow rate fault, three times for the motor overheating fault, two times for the fouling of fills fault, one time for the over current fault, and one time for the unusual sound fault.

With regard to the decision tree of the pump, 39 faults were predicted, out of which 37 faults were detected, with a breakdown of 10 times for noisy non-return valve fault, seven times for pump runs but no water provision, seven times for leakage from valves, six times for motor vibration fault, three times for low flow rate in cold exchange fault, one time for the improper pump water alignment fault, two times for motor heat-up fault, and one time for clogging fault.

For the terminal unit, its decision tree model predicted 73 faults, out of which 71 faults were detected, with a breakdown of 13 times for the low static pressure fault, eight times for the loose belts fault, nine times for air trapped in cooling coil, six times for noisy contactors fault, six times for faulty fresh air damper, six times for speed reducing the supply fan, five times for vibration, five times for faulty exhaust air damper, two times for dirty air flow fault, four times for faulty damper actuator, three times for faulty control valve, one time for damaged insulation on pipe, and one time for cooling coil blockage fault. These results confirmed the reliability of the detection model of each CWS component as it was able to predict faults, and most of the predicted faults were real faults at the site.

With regard to the second empirical period, which was also conducted at the university, the decision tree of the chiller predicted 47 faults, out of which 46 faults were detected, with a breakdown of eight times for a refrigeration leak fault, seven times for the low condenser flow fault, seven times for the high condenser temperature fault, five times for the high evaporator approach fault, five times for the low oil pressure fault, five times for the high motor temperature fault, three times for the vibration fault, three times for the imbalanced line current fault, two times for low evaporator refrigerant temperature fault, and one time for the faulty operating schedule. For the cooling tower, its decision tree model predicted 53 faults, out of which 52 faults were detected, with a breakdown of 10 times for a malfunctioning blowdown system fault, eight times for the over current fault, seven times for the fills clogging fault, nine times for faulty water level valve, six times for the motor overheating fault, six times for the faulty isolation valve, five times for the low circulating water flow rate fault, and one time for the damaged fan fault.

The decision tree model of the pump predicted 44 faults, out of which 42 faults were detected, with a breakdown of nine times for a noisy non-return valve fault, nine times for the low flow rate in cold exchange fault, seven times for pump runs but no water provision, four times for leakage from pump set, four times for the motor heat-up fault, three times for pump runs at reduced capacity, three times for the faulty control switch, two times for the pipeline leakage fault, and one time for abnormal or excessive noise fault. For the terminal unit, its decision tree model predicted 68 faults, out of which 67 faults were detected, with a breakdown of 11 times for a low static pressure fault, 10 times for the loose belts, eight times for air trapped in cooling coil, six times for the faulty cooling valve actuator, six times for the return damper jam fault, six times for the motor overload fault, six times for the vibration fault, four times for the faulty supply air damper, three times for the faulty filter coil system, three times for the faulty variable air volume, one time for damaged insulation on duct, one time for the compressor failure, one time for the filter blockage fault, and one time for the broken belts fault.

Similar to the first empirical period, these results again confirmed the reliability of the detection model of each CWS component as it was able to detect faults, and most of the signal alerts “1” were real faults at the site. In addition, detecting these real faults demonstrated the reliability of the proposed frequencies (Chapter 4, Table 40, and Chapter 6, Table 71) as they were utilised to create the datasets for CWS components, which were then used to build and train the detection models. Also, the actions listed in Chapter 4 (Tables 33-36) for chiller, cooling towers, pumps and terminal units, respectively, were reliable for fixing the fault that occurred faults sufficiently to the satisfaction of stakeholders of university building of the main case study.

With regard to internal validity, assigned to check if the proposed detection model is better than the existing PdM tool at the building under study, the decision tree model of this research project for each CWS component has demonstrated clear improvement in predicting and detecting CWS faults as compared to the existing system at the building of the main case study, which is BMS. During the two empirical periods, and as shown in Chapter 5 (Figures 34-35), and in this chapter (Table 72), the decision tree model is better than BMS by greater than or equal to 21 per cent for all CWS components.

With regard to external validity, this occurred via the application of the methodological framework at another site and by assessing the performance of the detection model. The methodological framework has been implemented at another site for this purpose. The second case study was conducted in a hotel owned by the same foundation that manages the university (the main case study). The hotel has a complete CWS, which means it has chillers, cooling towers, pumps and terminal units. The methodological framework phases were applied in tandem with the main case study, so the data collection plan was same for both case studies. After creating the datasets and then building and training the decision tree models, the prediction accuracy of each detection model was calculated by Equation 5. The results were encouraging as the detection accuracy of each CWS component was found greater than or equal to 98.90 per cent. After implementing the methodological framework, an empirical period was conducted for reliability and validity purposes.

The decision tree model for the hotel chiller predicted 41 faults, out of which 39 faults were detected, with a breakdown of seven times for a refrigeration leak fault, seven times for the high condenser temperature, six times for the evaporator fouling fault, five times for the low chilled water flow, five times for the compressor overcharging fault, three times high cooler delta-T, two times for the vibration fault, one time for the low oil pressure fault, one time for the low discharge superheat fault, one time for the incorrect manual guide vane target, and one time for the relief valve discharge fault. For the hotel's cooling tower, its decision tree model predicted 43 faults, out of which 40 faults were detected, with a breakdown of 11 times for the malfunctioning blowdown system fault, eight times for the rise in circulating water temperature, six times for the low water basin level fault, six times for the fills fouling fault, four times for the vibration fault, two times for the faulty isolation valve, two times for the faulty water level valve, and one for the unusual sound fault.

For the hotel pump, its decision tree model predicted 44 faults, out of which 43 faults were detected, with a breakdown of 16 times for the noisy non-return valve fault, 12 times for the motor vibration fault, four times for the leakage from valves, three times for the improper pump water alignment fault, three times for the high flow rate in cold exchange, three times for pump runs but no water provision, and two times for the clogging fault. The hotel's terminal unit decision tree model predicted 48 faults, out of which 46 faults were detected, with a breakdown of 12 times for the low static pressure fault, 11 times for the faulty control valve, eight times for the faulty variable air volume, four times for the faulty cooling valve actuator, four times for the faulty exhaust air damper, four times for the noisy motor fault, one time for the damaged insulation on pipe, one time for faulty bearings, and one time for a faulty fan.

As with the first two empirical periods, these results again confirmed the reliability of the detection model of each CWS component as it was able to predict the faults, and nearly all the predicted faults were real faults at the site. In addition, detecting these real faults verified the reliability of the proposed frequencies (Chapter 4, Table 40, and Chapter 6, Table 71) as they were utilised to create the datasets for the hotel CWS components, which were then used to build and train the detection models. Also, the solutions listed in Chapter 4 (Tables 33-36), for chiller, cooling towers, pumps and terminal units, respectively, were reliable for fixing the faults that occurred faults to the satisfaction of the stakeholders of the hotel building. Furthermore, the existing PdM system at the hotel is BMS, which is similar to one at the university; a comparison between BMS and the hotel's decision tree model of each CWS component was conducted during the empirical period, demonstrating clear improvement in tracing and detecting CWS faults by the decision tree model. As shown in the previous chapter (Figure 44) and in this chapter (Table 72), the decision tree model is undeniably better than BMS, with greater than or equal to 21 per cent for each hotel's CWS component. Implementing the framework successfully in two sites, building a detection model for each CWS component that performed better than BMS, and meeting the satisfaction of the stakeholders at both sites have fulfilled the second and third objectives of this research project, which was mentioned in Chapter 1 (see section 1.2).

6.3.2 Theoretical Contributions to The Knowledge

"Enriching the research community with additional faults for each CWS component"

The systematic literature review showed that the literature could be grouped into four parts: the first part addressed similar faults, the second part addressed different faults, the third part did not fully describe the faults but referred to faults as 'abnormal behaviour', and the last part did not clarify the faults. In total, the literature presented seven faults for the chiller, three faults for the cooling tower, eight faults for the pump, and nine faults for the terminal unit. Based on that, the research project sought out the existence of other faults, and then assigned two research methods to discover new faults: an industry survey and a case study via methodological framework. After analysis of the survey results, this research project identified and recorded additional faults for each CWS component, noting 17 additional faults for the chiller, 13 additional faults for the cooling tower, eight additional faults for the pump, and 20 additional faults for the terminal unit. At the time of implementing the case study method at two sites, 15 faults occurred out of the 17 additional faults for the chiller; all 13 additional faults for the cooling tower occurred; all eight additional faults for the pump occurred; and 18 faults occurred out of the 20 additional faults identified for the terminal unit. Looks like the literature has overlooked the aforesaid additional faults due to their focus on building and training detection model and on calculating the detection accuracy of that model rather than paying attention to the type of fault. In addition, the datasets, which were utilised to build and train their models, contained observations of a specific fault like the ones mentioned in Tables 67-70 or contained a fault that is undefined.

So, the first theoretical contribution to the knowledge by this research project is the identification and recording of additional faults for each CWS component (see Chapter 4, Tables 33-36).

"Providing an action to fix each listed CWS fault"

In accordance with the PdM workflow proposed by Achouch et al. (2022), the last stage of that workflow focused on fixing the faults or issues that occurred faults, but while reviewing the literature, it was noted that not a single study provided a solution for the faults addressed. As the aim of this research project is to propose a holistic intelligent maintenance framework, it is essential to complete the intelligent maintenance activity by fixing the faults when they occur. Based on this essential understanding, this present research project explored viable actions to fix CWS faults by assigning two research methods, as industry survey and a case study, to investigate solutions. After analysing the survey results, the research project provided an action to fix each listed fault (see Chapter 4, Tables 33-36). To summarise the number of listed faults, the chiller has seven faults identified from the considered literature and 17 additional faults from this research; the cooling tower has three faults from the considered literature and 13 additional faults from this research; the pump has eight faults from the considered literature and eight additional faults from this research; and the terminal unit has nine faults from the considered literature and 20 additional faults from this research. This research project has recommended measures to assess the provided actions as part of the quality control phase of the proposed methodological framework. When detecting a fault and after implementing the provided action to fix that fault, the inspector at site should immediately observe the effected part of the component and report the outcome to the officer. The outcome would be either satisfactory, which means the fault is fixed and cleared, or unsatisfactory, which means the provided action is unable to fix the fault. In case of unsatisfactory, the inspector should re-implement the action again and observe the effected part – in case the fault continues, then the inspector should report that to the officer, and accordingly, the officer should double check the situation at site to validate the report of the inspector. Once validated, the officer should call specialised team like the operation and maintenance contractor to look at the case and fix it. At the time of implementing the case study at two sites, all faults that occurred were successfully fixed by implementing the provided actions, as confirmed by the stakeholders, who are the operation and maintenance managers, of both sites. So, the second theoretical contribution to the knowledge by this research project is the provision of a viable action to fix each listed CWS fault (see Chapter 4, Tables 33-36).

"Confirming technical relevance between CWS components"

The studies reviewed from the literature were primarily focused on one CWS component, although a few studies focused either on two CWS components or three components at the most. This observation triggered a question about the significance of covering the whole CWS by addressing all its components. While analysing the survey results with regard to the solutions of CWS faults, it was noted that some faults for one particular CWS component are due to the health condition of another component. A quantitative analysis for the responses was made to justify this notice, and the result showed strong and positive correlation (see Table 39, and Appendix D). This result was confirmed during the empirical periods as part of the case study method as fixing some faults of a particular CWS component required investigating another component. In this regard, a quantitative analysis was again made to illustrate the correlation, and the result showed strong and positive correlation as well (see Tables 53, 58, and 64 as well as Appendix I). So, the third theoretical contribution to the knowledge by this research project is illustrating and confirming the technical relevance between CWS components.

"Providing valid frequencies for each CWS component"

The main part of intelligent maintenance framework is the detection model. Datasets are required to build and train that model. These datasets can be either ready for utilisation, which means the data are historical, or the data should be collected from the building that will be studied. To collect the data, three factors are required: determining the operational parameter of each CWS component, determining the time interval between the readings of the operational parameter, referring to in this research as minimum frequency, and determining the study period, referred to in this research as maximum frequency. During the systematic literature review, it was observed that there is great variance in the studies with regard to data collection related information. The studies can be placed into five groups: the first clarified the operational parameter and the frequencies but these were not usually the same information; the second clarified the operational parameter and one of the frequencies; the third clarified the operational parameter but without clarifying the frequencies; the fourth clarified the sample size of the data but not the operational parameter or the frequencies; and the last did not clarify any data collection-related information.

The difference between the studies with regard to the frequencies obscures which frequencies are proper for building and training a new detection model. So, this research project, noting this observation, included a section in the industry survey to ask participants about faults that occurred often (and to state the frequency) and about faults that rarely occur (and to state the frequency) for each CWS component. The research project designed an innovative way to determine the frequencies, by identifying the minimum value of all minimum frequencies provided by the participants, as well as by identifying the maximum value of all maximum frequencies provided by the participants. These two values for each CWS component serve as the proposed frequencies by this research project. The case study method, the second research method assigned by this research project, was implemented at two sites post analysing the results of the industry survey, the first site is a university building, which is for the main case study, and the second site is a hotel building for external validity purposes. The proposed frequencies (Chapter 4,

Table 40, and Chapter 6, Table 71) were utilised in the data collection for both sites. After building and training the detection model, the decision tree, for each CWS component, the detection accuracy was calculated with encouraging results: the accuracy was greater than or equal to 98.5 per cent for both sites. This confirms that the proposed frequencies are proper for the data collection activity, and they helped to create the datasets that built and trained a detection model for each CWS component. In addition, the detection models show their reliability in detecting faults (Chapter 5, Tables 49-52, 54-57, and 60-63), and this validated the proposed frequencies where the detection model of each CWS component was built and trained based on these frequencies. So, the fourth theoretical contribution to the knowledge by this research project is providing valid frequencies for each CWS component that can be utilised in creating the datasets to build and train the detection model.

6.3.3 Practical Contributions

"Providing a methodological framework that presents a holistic intelligent maintenance for CWS at commercial buildings"

The methodological framework itself is a practical contribution where it presents a holistic intelligent maintenance framework for CWS. This research project proposed three phases (shown in Chapter 5) that present a road map for the intelligent maintenance framework. These phases are set-up, machine learning and quality control, and they contain multiple management steps to build the intelligent maintenance framework. The said framework can be considered as a guide for operation and maintenance professionals as shown in the previous chapter (see Table 65). So, the first practical contribution is presenting a holistic intelligent maintenance via a methodological framework.

"Providing a simplified schematic for CWS"

Practically, this research thesis delineated technical guidelines when implementing the methodological framework as shown in the previous chapter (see Table 65). With regard to the first phase of the methodological framework, the research project advised the value of thoroughly understanding the building to be studied by assessing the as-built drawing, but since such drawings are complicated with many pages and much information, this research created a simplified schematic for CWS to show how each CWS component looks in such drawings for easy visualisation and identification of each component, the number of each CWS component, and the location of each unit at the site. The schematic was created based on the guidelines of the *ASHRAE Handbook* (2023) as shown in Chapter 5 (Figure 15). So, the second practical contribution to the knowledge by this research project is the provision of a simplified schematic for CWS.

"Providing a proper location for each reading tool of selected operational parameters"

While reviewing the literature with regard to data collection-related information, an inadequacy was noted: no research suggested reading tool locations of operational parameters. Operational parameters presented one of the values of the datasets that built the detection model for each CWS component. These values are the chilled water leaving temperatures for both chiller and cooling tower, the pressure for pumps, and the space temperature for terminal units. The second values of the datasets are the inspection results, which are fault ('1') or fault free (''0). This research has addressed the aforementioned weakness by proposing a proper location for the reading tool of each operational parameter based on the standard operating procedure of the *ASHRAE Handbook* (2023). Reading tools can be sensors, meters or gauges, and their proposed locations were provided in Chapter 5 (Table 43). So, the third practical contribution to the knowledge by this research is the provision of a proper reading tool location for each operational parameter. These locations will advise the researcher or user as to where to install such tools if they are not already installed at site, or to ensure they are in their proper locations if they are already installed. This practical contribution is a part of the proposed guide, which is mentioned in the previous chapter (see Table 65).

"Providing a control plan for continuous CWS monitoring"

The fourth practical contribution of this research project is related to the third phase of the proposed methodological framework, quality control. In the previous chapter (Table 44), this research project devised a control plan that can be conducted after building and training the detection model to continue observing and monitoring the said model, while the studies from the literature ended their proposed intelligent maintenance frameworks by calculating the detection accuracy of their detection models. The said plan is part of the guide that is provided in the previous chapter (see Table 65). In addition, this research project provided a documentation process (as shown in the previous chapter) which involves listing the lessons learned from the proposed intelligent maintenance framework, ensuring that the computer unit is working efficiently, knowing which the detection model is installed on it, tracking the spare parts stock, training more technicians for familiarity with the detection model, and writing regular reports about the performance of the proposed intelligent maintenance framework. This process is advised to be actioned after conducting the aforementioned control plan. These processes are required within the intelligent maintenance framework to ensure continuous control and improvement to the maintenance management framework of the CWS. Also, this research project suggests that such process can implemented in any other maintenance strategy.

6.3.4 Quality of The Research

Three elements determine the quality of research: reliability, internal validity and external validity (see Chapter 3, Table 27). This present research project has explained how it has fulfilled these requirements (Chapter 3, Table 29). Accordingly, the outcomes of this thesis have fulfilled the quality of the research as shown below in Table 74.

Table 74: Research quality accomplishment

Element	Research Thesis Outcome
Reliability	The proposed detection model of each CWS component has shown its reliability by tracing the faults where after inspecting the site (university), most of the predicted faults were detected. Also, the solutions furnished by this research were useful in fixing the faults that occurred.
Internal Validity	The proposed detection model of each CWS component has improved fault prediction and detection compared to the existing system (BMS) at both sites.
External Validity	The proposed methodological framework has been successfully implemented at a second site, a hotel. The detection model of each CWS component at that site has demonstrated similar performance to the one at the university in tracking faults, detecting them, and improving fault detection over the existing system, BMS.

6.3.5 Limitations

Both research methods assigned to answer the four research questions of this research project have limitations. The industry survey, for example, required significant effort to receive responses by implementing a follow-up strategy (outcome shown in Chapter 4, Figure 12). Although the number of the responses was 336 out of 761 contacts at commercial buildings, there may have been invalid e-mail addresses or phone numbers, one potential limitation reducing the number of responses. Another limitation besets the survey as well, in that it was conducted in Riyadh, Saudi Arabia. Though the industry survey structures the pillars of this research project – which are CWS faults, the actions to fix the faults, and the frequencies – these may be limited by the city surveyed. Considering the climate in Riyadh and climate difference between Riyadh and other cities (whether inside Saudi or outside Saudi), there may be other faults or different faults frequencies elsewhere. So, the next subsection considers this limitation as part of the future research agenda.

After analysing the considered studies of the literature, this research project defined the *fault* as any failure that may lead to a CWS breakdown over time, which means that the listed faults in this research thesis have a minimal impact on the operation of CWS as confirmed during the empirical periods. Accordingly, this definition is included in the second part of the industry survey as a note for the participants (see Appendix C). So, this research project is limited to such type of faults, and it did not consider other types of faults that may completely shut-down the CWS when occurred or the ones that may have a major impact, if any. So, the next subsection is also considered this third limitation as part of the future research agenda.

The fourth limitation is related to case study methodology. The three empirical periods which were conducted at two sites have validated most of the outcomes of the industry survey, especially with regard to the faults and the actions to fix such faults. From the 17 additional chiller faults, which were furnished by the survey, 15 faults occurred, and from the 20 additional terminal unit faults, 18 faults occurred. All the additional faults of cooling tower and pump occurred. Although only two additional faults of the chiller and terminal unit did not occur during the said periods, it would be useful to allow for more empirical periods to attempt to validate the remaining faults.

6.3.6 Future Research Agenda

From the systematic literature review, it was noticed that the number of studies pertaining to cooling towers and pumps were far fewer than those pertaining to chillers and terminal units; therefore, this research project encourages researchers to pay more attention to these two components (cooling tower and pump) if their studies are not planned for the entire CWS. Another suggestion for future research, in light of the first limitation mentioned in the previous subsection, is to expand the reach of the industry survey, distributing it into other cities in the Kingdom of Saudi Arabia, like Jeddah or Dammam; or surrounding countries like Kuwait, Bahrain or Qatar; or other countries farther afield on the same continental, Asia; or even to other continents such as South America or Africa. This agenda may enrich the research community with more faults beyond those listed in this research project (Chapter 4, Tables 33-36). The same agenda will also allow for exploring fault frequencies of different operational parameters, including the ones chosen by this research project, which can be utilised in building and training detection models if the researchers intend to utilise machine learning.

The third future research agenda is related to the operational parameters that their readings can help in building and training the detection model. Although Chapter 2 showed that any operational parameter is generally giving a glimpse about the health condition of the related CWS component, this research project encourages researchers to explore how different operational parameters may lead to different faults, and accordingly, a fish-bone diagram like Figure 9 can be presented. One more suggestion for future work, in light of the third limitation mentioned in the previous subsection, is to explore the faults that partially and/or completely do shut-down the CWS. This includes building detection models based on the frequencies of such faults. While this research project has proven that there is a technical relevance between CWS components as shown in Table 66 and has proposed a simplified schematic for CWS as shown in Figure 15, future works are encouraged to deeply investigate the complexity of such a system to explore more relationships between its components.

The sixth research agenda suggested by this research project is to focus more on the faults occurring more frequently for each CWS component. As shown in Chapter 4 (Table 37), as well as in the previous chapter (Tables 49-52, 54-57, and 60-63), researchers are encouraged to investigate the repeated occurrence of the refrigeration leak fault in the chillers, the malfunctioning blowdown system fault in the cooling towers, the noisy non-return valve fault in the pumps, and the low static pressure fault in the terminal units, and to explore the reasons for these occurrences. For the machine learning related tasks, three research agendas are suggested by this research project. The first is to discuss how to integrate the machine learning models with the building automation and management systems, such as BMS, for more efficient detection models. The second is to propose an intelligent system for updating the datasets required to build and train the detection model in order to raise the control efficiency of commercial buildings. While this research project has built a separate detection model for each component, the third research agenda is to address the complexity of CWS and to try building one detection model that look after all CWS components. Finally, another suggestion is for researchers to apply the ideas of the proposed methodological framework and extend the framework to other HVAC systems such as heating systems and to other utility systems such as electrical systems.

Future research agendas are suggested to show how to motivate more participants – professionals who participate in such industry surveys – to reply. The professionals for this research were either support services managers, facilities managers, or operation and maintenance managers, and their workload may deter them from taking the time to answer survey questions. Also, future research agendas are suggested to place more attention on the availability of data sources; the experience of the team who will collect the data; the organisational culture at the building under study which may not be cooperative; and the associated costs such as arranging the reading tools, the computer unit of the detection model, and the labour.

In line with Sanzana et al. (2022), researchers are encouraged to explore further development in deep learning applications towards the PdM of HVAC system of which CWS is a part. This present research has implemented its methodological framework in two different types of commercial buildings – a university campus and a hotel – so it would be useful for future research to implement the proposed framework in other types of commercial buildings like hospitals. According to Al-Aomar et al. (2023), machine learning applications in PdM require more attention in hospital facilities. Hodavand et al. (2023) insist that fault data from complex systems such as HVAC systems are scarce, so more research studies are required to investigate machine learning technique for fault detection, especially unsupervised and deep learning methods. Therefore, they suggest searching for a standardised solution for integrating data from various sources like building automation systems, building information systems and BMS to ensure the effectiveness of machine learning algorithms like decision tree. As this research project presented an intelligent system for the maintenance of CWS at commercial buildings, the last research agenda suggested for the researchers is to explore what could be done to move from such an intelligent system that detect the faults to a PdM that can anticipate the faults way before their occurrence.

6.3.7 Thesis Author's Own Reflection

In the author's current position in the industry, a great deal of effort in maintenance planning goes toward CWS due its complexity. At the start of the PhD study on October 01, 2020, the author intended to address this complex system to improve the maintenance practice at the current job. The research process helped the author explore a myriad of ideas about developing an intelligent maintenance framework for such a system, and then investigating how and where to improve the current maintenance procedure on CWS on site. In terms of personal and professional aspects, the author has benefited tremendously from the research experience, particularly by improving time management skills. Specifically, the research process required extensive preparation and planning for each stage of the study, and each stage had to be conducted in an organised manner from a time perspective. The University of Strathclyde has a reputable PhD programme with students taking five modules of researcher professional development activities: knowledge and intellectual abilities; personal effectiveness; research governance and organisation; engagement, influence, and impact; and an elective module which included attendance at international conferences. These modules helped the author conduct the research efficiently as well as write this thesis properly.

After finalising this thesis, the author carries an overwhelming excitement to present a holistic intelligent maintenance framework for CWS at commercial buildings. The presented programme evolved through a long journey: conducting a systematic literature review, constructing an industry survey, analysing its outcomes, and proposing and implementing a methodological framework at two sites. The framework is a holistic one as it begins with an understanding of the engineering drawing of CWS, showing the proper location of each reading tool. Thereafter, the journey continued through the process of data collection, the implementation of machine learning algorithm to make the detection model, and then the quality control process that with viable and pragmatic actions to fix the faults that have occurred faults. It also replied on monitoring and improvement actions via a control plan and documentation process. So, the final product of this research project is a methodological framework that represents an intelligent maintenance framework for CWS at commercial buildings.

Although the author of this thesis is a senior manager of a facility department, the industry survey allowed him to explore the operational situations at other commercial buildings in Riyadh and to ascertain the managerial knowledge of the professionals at these other commercial buildings. The research thesis provided a list of faults and actions to fix them that are not in the original equipment manufacturer manual, presenting a decision tree model that enhanced the maintenance practice at the university building under study with regard to fault detection, undeniably more effective than the existing maintenance system, BMS.

The PhD journey taught the author a great deal about machine learning and choosing a proper algorithm. The author has agreed with senior management of his current occupational position to implement the proposed methodological framework and utilise the proposed detection model at the site after his doctoral graduation ceremony.

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Appendices

Appendix A: Summary of CWS predictive maintenance and fault detection tools across the literature

Technique	Component(s)	Reference(s)
Artificial Neural Network	Chiller, pump and terminal unit	(Rueda et al., 2005; Zhou et al., 2009b; Li et al., 2016a; Kocyigit, 2015; Tahmasebi et al., 2019; Cheng et al., 2020; Harasty et al., 2019; Karim et al., 2020; Cho et al., 2005; Hosamo et al., 2022; Dudzik et al., 2020; Tehrani et al., 2015)
Kalman Filter	Chiller and cooling tower	(Navarro-Esbri et al., 2006; Sun et al., 2013; Sun et al., 2018)
k-nearest neighbours	Chiller, cooling tower and terminal unit	(Han et al., 2020; Albayati et al., 2023; Tahmasebi et al., 2019; Aguilar et al., 2020; Elnour et al., 2022)
Support Vector Machine	All CWS components	(Choi et al., 2005; Albayati et al., 2023; Han et al., 2011; Yan et al., 2018a; Tran et al., 2016a; Yan et al., 2014; Cheng et al., 2020; Hu et al., 2019; Li et al., 2022; Sulaiman et al., 2020; Liang and Du, 2007; Chaudhuri et al., 2017; Yan et al., 2018b; Tun et al., 2021; Mulumba et al., 2015; Guo et al., 2017; Elnour et al., 2022; Montazeri and Kargar, 2020; Van Every et al., 2017)
Random Forest	Chiller and terminal unit	(Gao et al., 2019b; Han et al., 2020; Tun et al., 2021; Parzinger et al., 2020; Luo et al., 2020a)
Adaptive Moment Estimation	Chiller and pump	(Liu et al., 2022b)
Backpropagation Neural Network	Chiller and pump	(Xu et al., 2015; Du et al., 2014a)
Principal Component Analysis	All CWS components	(Hu et al., 2016a; Xiao et al., 2006; Mao et al., 2018; Wang and Cui, 2005; Xu et al., 2008; Wang et al., 2010; Hu et al., 2016b; Li et al., 2016b; Beghi et al., 2016; Wang et al., 2010; Li et al., 2010; Padilla and Choinière, 2015; Wang and Xiao, 2004; Qin and Wang, 2005)
Multiway Partial Least Squares	Chiller	(Choi et al., 2005)
Multiway Dynamic Principal Component Analysis	Chiller	(Choi et al., 2005)
Fuzzy Modelling	Chiller and terminal unit	(Zhou et al., 2009b; Sulaiman et al., 2015)
Multi-Label	Chiller	(Han et al., 2011)

Hybrid Quick Search	Chiller and cooling tower	(Ma and Wang, 2011)
Regression	Chiller, cooling tower and pump	(Zhou et al., 2009a; Yu and Chan, 2012; Au-Yong et al., 2014; Zabidi et al., 2023; Khan and Zubair, 2004; Ssembatya and Claridge, 2024)
Clustering	Chiller and terminal unit	(Yu and Chan, 2012; Yan et al., 2016a; Yang et al., 2018; Du et al., 2014a; Elnour et al., 2022)
Recursive Deterministic Perception Neural Network	Chiller	(Magoulès et al., 2013)
Multi-layer perceptron	Chiller	Sulaiman et al., 2020; Zabidi et al., 2023)
Exponentially Weighted Moving Average Control Charts	Chiller and terminal unit	(Zhao et al., 2013a; Tran et al., 2016b; Wang and Chen, 2016)
Bayesian Belief Network	Chiller and terminal unit	(Zhao et al., 2013b; Dey and Dong, 2016)
Support Vector Data Description	Chiller	(Zhao et al., 2013c; Li et al., 2016c)
Wasserstein Generative Antagonistic Network	Chiller	(Yan et al., 2020)
Extended Kalman Filter	Chiller and terminal unit	(Yan et al., 2017; Chintala et al., 2024)
Recursive One-class Support Vector Machine	Chiller	(Yan et al., 2017)
Linear Discriminant Analysis	Chiller	(Li et al., 2016e)
One Dimensional Convolutional Neural Network	Chiller and pump	(Wang et al., 2020; Sunal et al., 2024)
k-means clustering	Chiller, pump and terminal unit	(Luo et al., 2019)
Wavelet Neural Network	Terminal unit	(Du et al., 2008)
Kernel Principal Component Analysis	Terminal unit	(Montazeri and Kargar, 2020)
Synthetic Minority Oversampling	Terminal unit	(Shakerian et al., 2021)
Directed Acyclic Graph	Terminal unit	(Velibeyoglu et al., 2018)
Distance Rejection	Chiller	(Wang et al., 2017b)
Bayesian Network	Chiller, cooling tower and terminal unit	(Wang et al., 2017b; Xiao et al., 2014; Zhao et al., 2015; Zhao et al., 2017; Jain et al., 2019; Ng et al., 2020)
Large Margin Information Fusion	Chiller and terminal unit	(Li et al., 2016d; Li et al., 2010)
Multi-Class Support Vector Machine	Chiller	(Li et al., 2016)

Decision Tree	Chiller and terminal unit	(Li et al., 2016; Sittón-Candanedo et al., 2018; Hodavand et al., 2023; Ranade et al., 2019; Elnour et al., 2022; Montazeri and Kargar, 2020; Satta et al., 2017; Tehrani et al., 2015; Yan et al., 2016b)
Self-adaptive Principal Component Analysis	Chiller	(Hu et al.,2012)
Quadratic Discriminant analysis	Chiller	(Li et al., 2016a)
Tree-Structured Fault Dependence Kernel	Chiller	(Li et al., 2016a)
Ada Boost	Chiller	(Li et al., 2016a)
Logistic Regression	Chiller	(Li et al., 2016a)
Support Vector Regression	Chiller and terminal unit	(Tran et al., 2016a; Yang et al., 2013)
Differential Evolution	Chiller	(Tran et al., 2016b)
SCANSITES 3D	Cooling tower	(Piot and Lancon, 2012)
Multiple Linear Regression	Chiller	(Tran et al., 2016a; Zhao, 2015)
Kriging	Chiller	(Tran et al., 2016a)
Wireless Sensors	Cooling tower and pump	(Hashemian, 2011)
Radial Basis Function	Chiller and terminal unit	(Tran et al., 2016a; Montazeri and Kargar, 2020)
Bagged Tree	Chiller	(Tahmasebi et al., 2019)
Simple Linear Regression	Chiller	(Zhao, 2015)
Unscented Kalman Filter	Chiller	(Bonvini et al., 2014; Sun et al., 2013; Karami and Wang, 2018)
Statistical Process Control	Chiller and cooling tower	(Sun et al., 2013; Sun et al., 2018)
Gaussian Mixture Model Regression	Chiller	(Karami and Wang, 2018)
Autoregressive Exogenous Variables	Chiller and terminal unit	(Yan et al., 2014; Mulumba et al., 2015; Parzinger et al., 2020)
Monte Carlo Simulation	Chiller, pump, and terminal unit	(Miyata et al., 2019; Ma et al., 2020)
Decoupling	Chiller	(Zhao et al., 2014)
Fuzzy Interference System	Chiller	(Kocyigit, 2015)
Levenberg Marquart Type Artificial Neural Network	Chiller and terminal unit	(Kocyigit, 2015; Du et al., 2014b)
Maximal Information Coefficient	Chiller	(Gao et al., 2019a)
Virtual Sensor	Chiller and terminal unit	(Zhao et al., 2012; Kim and Braun, 2020; Verbert et al., 2017)
H2O (Automatic Machine Learning Platform)	Chiller and terminal unit	(Villa et al., 2022)

Association Rule Mining	Terminal unit	(Yu et al., 2012)
Temporal Association Rules Mining	Terminal unit	(Piscitelli et al., 2020)
Ensemble Rapid Centroid Estimation	Terminal unit	(Yuwono et al., 2015)
Regression Tree	Terminal unit	(Yan et al., 2016b)
HVACSIM+ (Simulation Software)	Terminal unit	(Pourarian et al., 2017)
Fuzzy Logic Clustering	Chiller and terminal unit	(Escobar et al., 2020; Lauro et al., 2014; Wijayasekara et al., 2014)
Active Functional Testing	Terminal unit	(Padilla and Choinière, 2015)
Explainable Artificial Intelligence	Chiller	(Srinivasan et al., 2021)
Virtual Refrigerant Charge	Chiller	(Liu et al., 2017)
Gated Recurrent Unit	Chiller	(Wang et al., 2020)
Mixed Integer Programming	Chiller	(Wu et al., 2021)
Deep Belief Network	Chiller and terminal unit	(Li et al., 2022; Montazeri and Kargar, 2020)
Deep Neural Network	Chiller	(Li et al., 2022)
Principal Component Analysis-based exponentially weighted moving average control charts	Chiller	(Liu et al., 2017)
Multi-Layer Perceptron	Chiller and cooling tower	(Sulaiman et al., 2020; Aguilar et al., 2020)
Simulation	All CWS components	(Wang et al., 2022; Motomura et al., 2019a; Ahn et al., 2001; Motomura et al., 2019b; Ma and Wang, 2009; Liang and Du, 2007; Andriamamonjy et al., 2018; Gunay et al., 2022; Norford et al., 2002; Li et al., 2021; Deshmukh et al., 2019; Yang et al., 2008; Yang et al., 2018; Gao et al., 2016; Deshmukh et al., 2020; Najeh et al., 2021; Holub and Macek, 2013; Novikova et al., 2019; Sulaiman et al., 2015; Thumati et al., 2011; Turner et al., 2017; Yan et al. 2016a)
Gradient Boosting	Cooling tower	(Aguilar et al., 2020)
Autonomic Cycle of Data Analysis Tasks	Cooling tower	(Aguilar et al., 2020)
Generalised Stochastic Petri Net	Cooling tower	(Melani et al., 2019)
Particle Swarm Optimisation	Chiller	(Li et al., 2022)

Deep Learning	Chiller and cooling tower	(Sulaiman et al., 2020; Sanzana et al., 2022)
Shallow Neural Network	Terminal unit	(Montazeri and Kargar, 2020)
Semi Supervised Learning	Pump and terminal unit	(Yuan and Liu, 2013; Fan et al., 2021)
Non-intrusive Load Monitoring Software	Terminal Unit	(Rafati et al., 2022)
Wavelet Transform with the Principal Component analysis	Terminal Unit	(Li and Wen, 2014)
Markov Chain Monte Carlo	Terminal Unit	(Liu et al., 2021)
Kernel Density Estimation	Chiller	(Xia et al., 2021b)
Kernel Entropy Component Analysis	Chiller	(Xia et al., 2021b)
Genetic Algorithm	Chiller and Terminal Unit	(Wang et al., 2012a; Lo et al., 2007; Gao et al., 2023)
Generative Adversarial Network	Terminal Unit	(Yan et al., 2019)
General Regression Neural Network	Terminal Unit	(Lee et al., 2004)
WEKA (Data Mining Software)	Terminal Unit	(Choi and Yeom, 2019)
Hidden Markov Model	Terminal Unit	(Guo et al., 2017)
Digital Twin Artificial Neural Network	Terminal Unit	(Hosamo et al., 2022; Xie et al., 2023)
Recurrent Neural Network	Terminal Unit	(Shahnazari et al., 2019)
Fractal Correlation Dimension	Terminal Unit	(Yang et al., 2013)
Demand Side Management	Chiller and Terminal Unit	(Arteconi et al., 2012)
Multi-layer Feedforward Neural Network	Chiller and Pump	(Liu et al., 2022b)
Error Backpropagation Neural Network	Chiller and Pump	(Liu et al., 2022b)
Long Short-term Memory Network	Chiller and Pump	(Gao et al., 2019a; Bouabdallaoui et al., 2021)
Extreme Learning Machine	Terminal Unit	(Chaudhuri et al., 2017)
Lambda Open-loop Tuning Rules (fully automated control hunting correction algorithm)	Terminal Unit	(Lin et al., 2023)
Prophet Forecasting	Terminal Unit	(Al-Aomar et al., 2023)

Seasonal Auto-Regressive Integrating Moving Average	Terminal Unit	(Al-Aomar et al., 2023)

Appendix B: Correspondence on data gathering of survey participants

Malek Al Mobarek

From:	Abdulaziz Al-Turki
Sent:	Monday, December 20, 2021 11:07 AM
To:	Malek Al Mobarek
Subject:	RE: قائمة المباني التجارية المسجلة ومعلومات الاتصال
Attachments:	قائمة المباني التجارية ومعلومات الاتصال.xlsx

م. مالك ، تحية عطرة ،

تجد برفقه ملف اكسل يحتوي على المعلومات المطلوبة.

أتمنى لك التوفيق في رسالتك البحثية.

عبد العزيز التركي - مدير علاقات العملاء

On Dec 16, 2021, at 9:13 AM, Malek Al Mobarek <malmobarek@alfaisal.edu> wrote:

المكرم الأستاذ / عبد العزيز التركي المحترم ،

تحية طيبة ،

أود شكركم أولاً على استقبالكم لي يوم أمس بمكتبكم ، وحسب المفاهمة أثناء اللقاء ، أرجو التكرم بتزويدي بقائمة المباني التجارية المسجلة لديكم بغرفة الرياض ومعلومات الاتصال الخاصة بالمشغلين ، يرجى الإحاطة بأن يكون عمر كل مبنى من تاريخ تسجيله هو ثلاث سنوات فما فوق. سيتم الاستفادة من تلك المعلومات لعمل استبانة خاصة برسالة الدكتوراه الخاصة بي.

شكراً جزيلاً مرة أخرى على تعاونكم ودعمكم ،،،

مالك المبارك (طالب دكتوراه)

Please consider the environment before printing this e-mail.

Appendix C: Final questions form of the industry survey

Part #1:

- Do you have chilled water system at your facility?

  ○ Yes
  ○ No

If yes, then please complete the following parts:

Part #2:

- Please choose from the below furnished faults for each component of the chilled water system that you encounter at your facility and provide the details. Kindly add those that you encounter but are not listed here as new. Also, beside each fault, kindly propose a managerial solution to fix that fault in a timely manner. Please note that this part is looking for the fault, which is defined as any failure that may lead to a chilled water system component breakdown over time.

A) Chillers

Fault	Do you encounter this at your facility?	Solution
Sensor Bias	○ Yes ○ No	
Refrigeration Leak	○ Yes ○ No	
Operation Scheduling	○ Yes ○ No	
Evaporating Fouling	○ Yes ○ No	
Condenser Fouling	○ Yes ○ No	
High Condenser Temperature	○ Yes ○ No	
Compressor Overcharging	○ Yes ○ No	
New Faults and their solutions: (Please write this form: (Fault: Solution), (Fault: Solution)		

B) Cooling Towers

Fault	Do you encounter this at your facility?	Solution
Air Fan Degradation	○ Yes ○ No	
Fills Fouling	○ Yes ○ No	
Sensor Bias	○ Yes ○ No	
New Faults and their solutions: (Please write this form: (Fault: Solution), (Fault: Solution)		

C) Pumps

Fault	Do you encounter this at your facility?		Solution
Clogging	○ Yes	○ No	
Control Switch	○ Yes	○ No	
Faulty Starter	○ Yes	○ No	
Pipeline Leakage	○ Yes	○ No	
High Flow Rate in Cold Exchange	○ Yes	○ No	
Low Flow Rate in Cold Exchange	○ Yes	○ No	
Excessive or Abnormal Noise	○ Yes	○ No	
Sensor Bias	○ Yes	○ No	
New Faults and their solutions: (Please write this form: (Fault: Solution), (Fault: Solution)			

D) Terminal Units

Fault	Do you encounter this at your facility?		Solution
Sensor Bias	○ Yes	○ No	
Faulty Variable Air Volume (VAV)	○ Yes	○ No	
Faulty Fan	○ Yes	○ No	
Compressor Failure	○ Yes	○ No	
Filter Blockage	○ Yes	○ No	
Faulty Filter Coil System	○ Yes	○ No	
Cooling Coil Blockage	○ Yes	○ No	
Return Damper Jam	○ Yes	○ No	
Speed Reducing the Supply Fan	○ Yes	○ No	
New Faults and their solutions: (Please write this form: (Fault: Solution), (Fault: Solution)			

Part #3:

A) Chillers

- What is the most fault occurring so often during your operational time? Please state the frequency of its occurrence and mention the time unit (for example, it is possibly occurred for every 45 minutes).

Fault: ....; Frequency: ....

- What is the most fault occurring rarely during your operational time? Please state the frequency of its occurrence and mention the time unit (for example, it is possibly occurred within 6 weeks).

Fault: ....; Frequency: ....

B) Cooling Towers

- What is the most fault occurring so often during your operational time? Please state the frequency of its occurrence and mention the time unit (for example, it is possibly occurred for every 45 minutes).

Fault: ....; Frequency: ....

- What is the most fault occurring rarely during your operational time? Please state the frequency of its occurrence and mention the time unit (for example, it is possibly occurred within 6 weeks).

Fault: ....; Frequency: ....

C) Pumps

- What is the most fault occurring so often during your operational time? Please state the frequency of its occurrence and mention the time unit (for example, it is possibly occurred for every 45 minutes).

Fault: ....; Frequency: ....

- What is the most fault occurring rarely during your operational time? Please state the frequency of its occurrence and mention the time unit (for example, it is possibly occurred within 6 weeks).

Fault: ....; Frequency: ....

D) Terminal Units

- What is the most fault occurring so often during your operational time? Please state the frequency of its occurrence and mention the time unit (for example, it is possibly occurred for every 45 minutes).

Fault: ....; Frequency: ....

- What is the most fault occurring rarely during your operational time? Please state the frequency of its occurrence and mention the time unit (for example, it is possibly occurred within 6 weeks).

Fault: ....; Frequency: ....

Part #4:

- Please tick appropriately if the furnished parameter best predicts the chiller's health condition and if not, please recommend an alternative.

Chilled Water Leaving Temperature (ºC)	Is it the best to predict the health condition?		Alternative
	○ Yes	○ No	

- Please tick appropriately if the furnished parameter best predicts the cooling tower's health condition and if not, please recommend an alternative.

Chilled Water Leaving Temperature (ºC)	Is it the best to predict the health condition?		Alternative
	○ Yes	○ No	

- Please tick appropriately if the furnished parameter best predicts the pump's health condition and if not, please recommend an alternative.

Pressure (Bar)	Is it the best to predict the health condition?		Alternative
	○ Yes	○ No	

- Please tick appropriately if the furnished parameter best predicts the terminal unit's health condition and if not, please recommend an alternative.

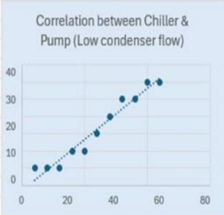
Space Temperature (ºC)	Is it the best to predict the health condition?		Alternative
	○ Yes	○ No	

Important Note: By clicking submit, you are approving to participate in this survey anonymously.

Appendix D: Correlations between CWS components (Industry Survey)

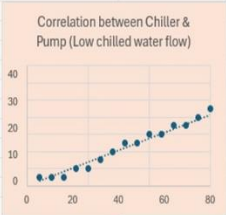
Correlation Coefficient 0.94131623

Person Surveyed	Response	Cumulative Respose
1	1	1
2	0	1
3	0	1
4	1	2
5	0	2
6	1	3
7	1	4
.	1	5
.	0	5
.	1	6
67	0	6



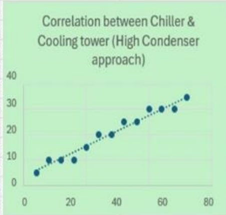
Correlation Coefficient 0.970459089

Person Surveyed	Response	Cumulative Respose
1	1	1
2	0	1
3	0	1
4	1	2
5	0	2
6	1	3
7	1	4
.	1	5
.	0	5
.	1	6
59	0	6



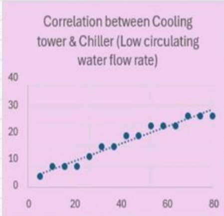
Correlation Coefficient 0.892222621

Person Surveyed	Response	Cumulative Respose
1	1	1
2	1	2
3	0	2
4	0	2
5	1	3
6	1	4
7	0	4
.	1	5
	0	5
.	1	6
62	0	6



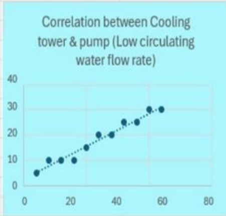
Correlation Coefficient 0.933962174

Person Surveyed	Response	Cumulative Respose
1	1	1
2	1	2
3	0	2
4	0	2
5	1	3
6	1	4
7	0	4
.	1	5
.	0	5
.	1	6
71	0	6



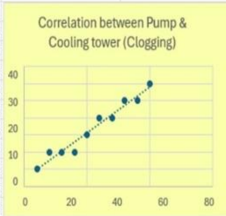
Correlation Coefficient 0.956167729

Person Surveyed	Response	Cumulative Respose
1	1	1
2	1	2
3	0	2
4	0	2
5	1	3
6	1	4
7	0	4
.	1	5
.	0	5
.	1	6
68	0	6



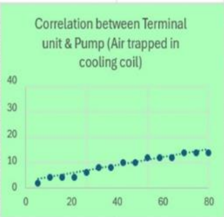
Correlation Coefficient 0.961398664

Person Surveyed	Response	Cumulative Respose
1	1	1
2	1	2
3	0	2
4	0	2
5	1	3
6	1	4
7	0	4
.	1	5
	0	5
.	1	6
55	0	6



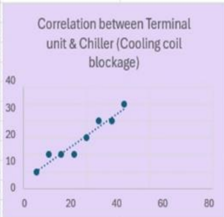
Correlation Coefficient 0.989646004

Person Surveyed	Response	Cumulative Respose
1	1	1
2	1	2
3	0	2
4	0	2
5	1	3
6	1	4
7	0	4
.	1	5
.	0	5
.	1	6
77	0	6



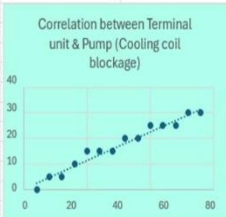
Correlation Coefficient 0.922680721

Person Surveyed	Response	Cumulative Respose
1	1	1
2	1	2
3	0	2
4	0	2
5	1	3
6	1	4
7	0	4
.	1	5
.	0	5
.	1	6
49	0	6



Correlation Coefficient 0.971941546

Person Surveyed	Response	Cumulative Respose
1	0	0
2	1	1
3	0	1
4	1	2
5	1	3
6	0	3
7	0	3
.	1	4
	0	4
.	1	5
51	0	5



Appendix E: Alternative operational parameters

Chilled Water System Component	Operational Parameters
Chiller	• Water Return Temperature • De-coupler Temperature
Cooling Tower	• Wet Bulb Temperature • Fan static Pressure
Pump	No alternatives were provided as 100 per cent of the participants were with choosing the pressure.
Terminal Unit	• Air Supply Temperature • Air Return Temperature • Mixed Air Temperature

Appendix F: Check sheet for terminal units

Check Sheet (Building Name: ………………)

Component: Terminal Unit #…….

Day & Date: ………………………………

Time	Space Temperature (°C)	Fault Free (0) Fault (1)	Time	Space Temperature (°C)	Fault Free (0) Fault (1)
6:30			14:45		
7:15			15:30		
8:00			16:15		
8:45			17:00		
9:30			17:45		
10:15			18:30		
11:00			19:15		
11:45			20:00		
12:30			20:45		
13:15			21:30		
14:00			22:15		
Inspector Name: Signature:			23:00		
			Inspector Name: Signature:		

Appendix G: Duly filled check sheet for a particular pump

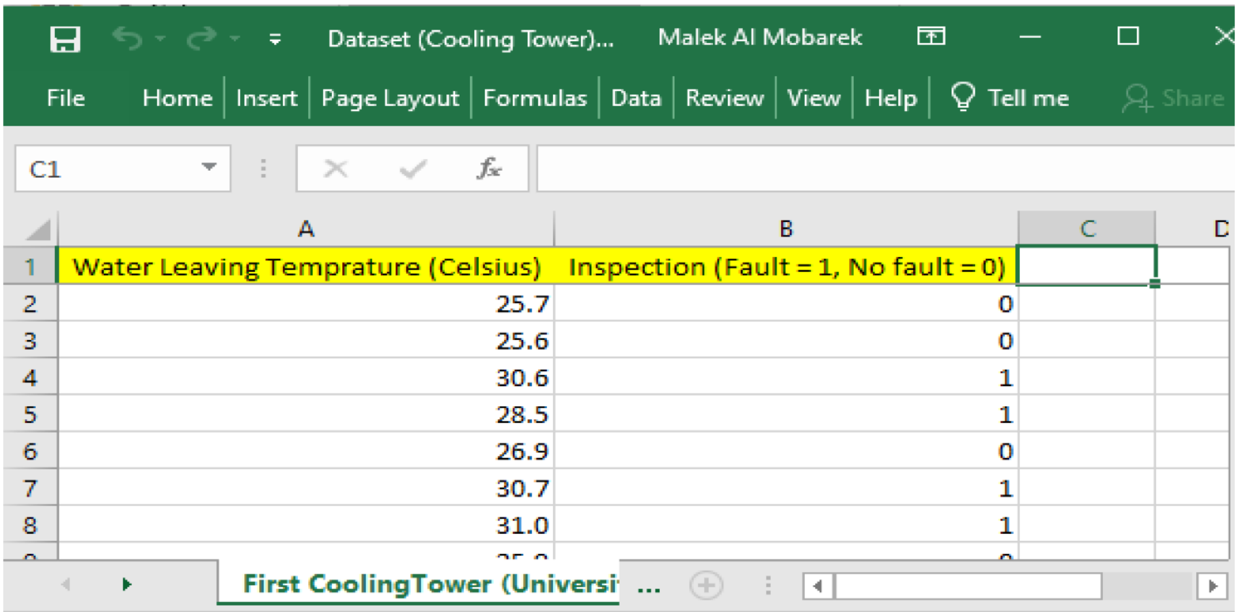
Check Sheet (Building Name: Students Center)

Component: Pump #1

Day & Date: Thursday November 10, 2022

Time	P (bar)	Fault Free (0) Fault (1)	Time	P (bar)	Fault Free (0) Fault (1)
7:00	4.0	1	15:00	3.8	0
8:00	4.0	1	16:00	3.9	1
9:00	3.8	0	17:00	3.7	1
10:00	3.7	0	18:00	4.0	1
11:00	3.8	0	19:00	4.3	1
12:00	4.4	1	20:00	4.1	1
13:00	4.3	1	21:00	3.7	0
14:00	4.5	1	22:00	3.6	0
Inspector Name: SABIR AHMED			Inspector Name: Mohd Younus		
Signature:			Signature:		

Appendix H: Snapshot of cooling tower dataset

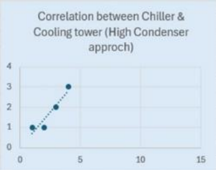


Water Leaving Temprature (Celsius)	Inspection (Fault = 1, No fault = 0)
25.7	0
25.6	0
30.6	1
28.5	1
26.9	0
30.7	1
31.0	1

Appendix I: Correlations between CWS components (Case Study)

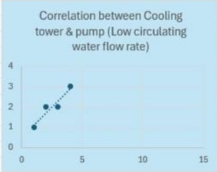
SN of Fault occurance	Fixing Status	Cumulative Status
1	1	1
2	0	1
3	1	2
4	1	3

Correlation Coefficient 0.943879807



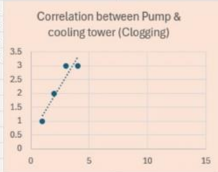
SN of Fault occurance	Fixing Status	Cumulative Status
1	1	1
2	1	2
3	0	2
4	1	3

Correlation Coefficient 0.948683298



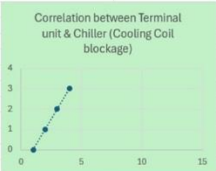
SN of Fault occurance	Fixing Status	Cumulative Status
1	1	1
2	1	2
3	1	3
4	0	3

Correlation Coefficient 0.943879807



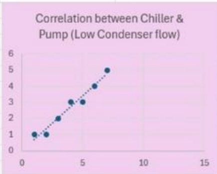
SN of Fault occurance	Fixing Status	Cumulative Status
1	0	0
2	1	1
3	1	2
4	1	3

Correlation Coefficient 1



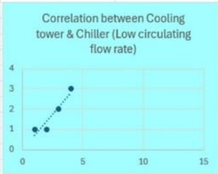
SN of Fault occurance	Fixing Status	Cumulative Status
1	1	1
2	0	1
3	1	2
4	1	3
5	0	3
6	1	4
7	1	5

Correlation Coefficient 0.979850184



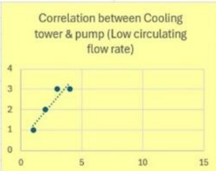
SN of Fault occurance	Fixing Status	Cumulative Status
1	1	1
2	0	1
3	1	2
4	1	3

Correlation Coefficient 0.943879807



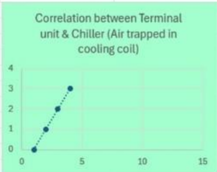
SN of Fault occurance	Fixing Status	Cumulative Status
1	1	1
2	1	2
3	1	3
4	0	3

Correlation Coefficient 0.943879807



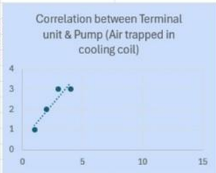
SN of Fault occurance	Fixing Status	Cumulative Status
1	0	0
2	1	1
3	1	2
4	1	3

Correlation Coefficient 1



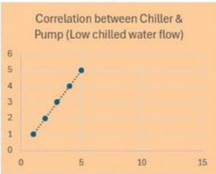
SN of Fault occurance	Fixing Status	Cumulative Status
1	1	1
2	1	2
3	1	3
4	0	3

Correlation Coefficient 0.943879807



SN of Fault occurance	Fixing Status	Cumulative Status
1	1	1
2	1	2
3	1	3
4	1	4
5	1	5

Correlation Coefficient 1



SN of Fault occurance	Fixing Status	Cumulative Status
1	0	0
2	1	1
3	0	1
4	1	2

Correlation Coefficient 0.948683298