An Optimization Model for Developing Time-Based Preventive Maintenance Strategy for Cooling Coils in Air Conditioning Systems Based on Genetic Algorithm

Abstract

With the rapid growth of China's air conditioning market, the issue of low energy efficiency in air conditioning usage has become increasingly prominent. One of the main reasons for this challenge is the lack of maintenance.

Fixed-period and corrective maintenance strategies, currently used in air conditioning coil maintenance, are no longer able to meet the actual usage requirements. The enhanced maintenance strategy should have the capability to ensure the operational performance of the air conditioning system, while also reducing costs and energy consumption. In addition, as a composite system, air conditioning comprises various subsystems, each with distinct properties, functions, and energy losses. This implies that various subsystems require distinct maintenance measures and strategies.

To address the aforementioned issues, this study proposes an optimization model for the coil, a subsystem in the air conditioning system. The optimization model can generate a time-based preventive maintenance strategy to fulfill the requirements of owners. The cost factor, operational performance factor, and environmental factor are taken into consideration.

This study addresses the research gap in optimization of coils in air conditioning systems. Furthermore, the study innovatively pointed out that when an enterprise participates in the carbon emission permit trading system, the operational cost of its air conditioning system includes not only the energy cost paid directly to the energy supplier, but also the potential loss in carbon emission permits, which represents an opportunity cost resulting from energy consumption. The study incorporates environmental factors into the cost analysis by including the cost of carbon emission permits to account for the impact of excessive emissions. The study's findings can address owners' needs for an enhanced maintenance strategy and fill the gap in current research on coil maintenance strategies.

Two simulation scenarios were designed to evaluate the model's performance. The genetic algorithm was employed to solve the model's objective function using Python. In contrast to the traditional fixed-period maintenance strategy, the new time-based preventive maintenance strategy generated from the model can ensure the minimization of total relevant cost (TRC) of the air conditioning system while still meeting performance criteria. Experimental simulations can be used to demonstrate the scientific validity and effectiveness of this model.

Key words: time-based preventive maintenance strategy, preventive maintenance strategy, HVAC, air conditioning system, coil maintenance, optimization, genetic algorithm, Python

Contents

1. Introduction

1.1 Background

1.1.1 The energy efficiency challenge in China's air conditioning sector and its causes

In the 21st century, air conditioning has become widely utilized in various types of buildings. According to CCTV Finance, citing the European Energy Agency (2023), China is among the top five countries and regions with the highest air-conditioning penetration rate in 2023. The countries with the highest percentages are Japan and the United States, both at 90%, followed by Saudi Arabia with approximately 63%. China's figure is 60%, which is identical to Canada's. Unlike the other four countries, China's air conditioning penetration rate is growing rapidly.

A report released by the IEA and Tsinghua University (2019) titled "The Future of Cooling in China" presents a comprehensive analysis of the cooling sector in China and highlight significant characteristics of this industry. The air conditioning market in China is still experiencing rapid growth. About 36% of the 1.7 billion new air conditioning systems installed worldwide in 2017 were in China. This growth will continue through the 2030s. Such a significant increase in installations is bound to be accompanied by a massive rise in energy consumption. This has raised concerns about China's energy efficiency in the air conditioning sector. The report highlights another aspect of this sector in China: the efficiency of air conditioning equipment is lower than its potential. A comprehensive dataset indicates that the performance of variable speed mini-split units sold in the Chinese air conditioner market from 2015 to 2017 was up to 20% lower than the market average and approximately 50-60% lower than the best available equipment. The combination of low energy efficiency and massive installed capacity will result in significant energy waste and put additional pressure on China's energy supply. The facts mentioned above indicate that it is imperative to improve energy efficiency in the Chinese air conditioning sector.

Improving energy efficiency is not only necessary to accommodate China's significant increase in air conditioning installation over the next decade but also essential for the global effort to address climate change. To address global climate change, it is essential to enhance energy efficiency in order to decrease carbon emissions.

Since the Industrial Revolution, global warming and significant changes in the world's climate caused by excessive emissions of greenhouse gases have become one of the most significant threats to humanity. Among them, carbon dioxide (CO_2) produced by burning fossil fuels constitutes the largest proportion of greenhouse gases, accounting for approximately 82.9% of total greenhouse gas emissions. Back in 2010, China had already become the world's largest emitter of greenhouse gases (ETA, 2010; USETA, 2010).

In response to climate change, world leaders signed the Paris Agreement on April 22, 2016. By 2030, China has committed to reducing carbon dioxide emissions per unit of GDP by 60-65% from 2005 levels, increasing the share of non-fossil fuels in primary energy consumption to about 20%, and increasing its forest stock by about 4.5 billion cubic meters from 2005 levels. Later, at the 75th session of the United Nations General Assembly, China formally proposed the objective of achieving a peak in carbon emissions by 2030 and carbon neutrality by 2060.

For China, it is important for the construction sector, which accounts for more than 7% of GDP, to make significant improvements in response to this commitment in order to achieve the dual carbon target (Chinanews, 2022). Carbon emissions from air conditioning systems are a crucial contributor to overall building carbon emissions. By 2022, the annual electricity consumption of various types of air conditioning equipment in use will account for approximately one-fifth of China's total power generation.

According to the China Building Energy Consumption Research Report (2019), air conditioning systems account for 60% to 70% of the total energy consumption of public buildings in China. Improving the energy efficiency of air conditioning systems will play a crucial role in reducing greenhouse gas emissions and mitigating global climate change.

The IEA and Tsinghua report explains the reason for the energy efficiency challenge: the installation and maintenance of equipment.

Several studies have supported the report's assertion that poor performance in operation and maintenance significantly contributes to the low energy efficiency in the Chinese cooling sector. Chao, Hao and Zhang (2016) conducted a study on the status of air conditioning operation and maintenance in Zhengzhou city. The survey revealed that only 23% of the respondents have professional staff dedicated to the daily operation and maintenance of air conditioning equipment. In the remaining 77% of the surveyed facilities, there are typically only 1-2 regular workers serving as operators. Their primary responsibility is to initiate and halt the operation of equipment in accordance with the specifications. Furthermore, they do not take on any maintenance responsibilities. When the equipment experiences an obvious fault, the initial response is to contact a private maintenance company to assess the fault. If it is a minor issue, such as parts replacement, it can be addressed directly by the private maintenance company. If a major issue arises that the private service company is unable to handle, they will reach out to the equipment manufacturer for diagnosis and maintenance. This is clearly one of the key reasons for the low energy efficiency of air conditioning systems. As the capital of Henan Province in China, Zhengzhou ranked 16th in GDP in 2023, a position typical of many cities in China and providing a useful reference for the national situation.

1.1.2 Issues in maintenance of air conditioning system and their causes

There are numerous studies on life cycle cost analysis (LCC) and life cycle assessment (LCA) indicating that for equipment with a long life cycle, the expenses and energy consumption incurred during the operation and maintenance phase of the equipment are significantly higher than those caused by the installation. Therefore, this study focuses on maintenance.

encompasses all planned and unplanned all activities procedures aimed at ensuring continuous access undertaken of operational equipment (Gackowiec, 2019). However, a "well-behaved" maintenance activity always requires a plan. Accordingly, a maintenance strategy is a planned approach to maintaining devices, which involves activities such as identifying, researching, and implementing repairs, replacements, and inspection decisions. Implementing the strategy requires executable, tactical plans (Velmurugan and Dhingra, 2015).

Currently, there are several issues with the maintenance of the air conditioning system.

First of all, many owners have neglected the maintenance of air conditioning systems. According to the research by Chao, Hao and Zhang (2016) mentioned above, only 23% of owners prioritize air conditioning maintenance and utilize professional personnel and methods.

One of the key reasons for this problem is that the maintenance of the air conditioning system has traditionally been seen as a "cost center," meaning it is considered a cost generator rather than a profit generator. It is managed by the logistics department. Traditionally, the management of the logistics department is separate from the main business of the enterprises (Stępień, 2016). Enterprises typically expand their core business by leveraging their expertise. Only when the profit margin of the main business has reached its limit, can they reduce the costs of non-production departments. In short, maintaining the air conditioning system does not yield clear profits for the owner.

Secondly, the commonly used maintenance strategy does not optimize the performance of air

conditioning systems.
Combining the study in Zhengzhou, China (Chao, Hao and Zhang, 2016) with a study in Owerri, Nigeria (Nkeleme et al., 2019), two maintenance strategies are widely used in practice. The first strategy is often referred to as the corrective strategy. The Zhengzhou study pointed out that the majority of owners investigated only take maintenance actions after the air conditioning system has a significant problem. In the Nigerian study, 68% of owners indicated that they operate assets without a specific maintenance plan and rely on corrective strategies. In the view of some researchers, this cannot be classified as "maintenance" but only as "repair." This approach, while the simplest maintenance strategy, actually has the highest overall cost. Another maintenance strategy can be summarized as a fixed-period maintenance strategy based on experience. This maintenance strategy is characterized by a set maintenance period. This maintenance strategy is typically based on the experience of the maintenance policy maker or a maintenance cycle that is generally accepted by the local air conditioning maintenance company. Compared with corrective maintenance, preventive maintenance can help avoid the high costs and functional decline caused by significant faults in air conditioning equipment. However, since this method relies more on human experience rather than on the specific performance of different brands and types of air conditioning systems, it still cannot optimize the performance of air conditioning systems.
It is worth noting that a significant air conditioning fault presents an opportunity for owners to transition from corrective maintenance to a fixed-period maintenance strategy, based on experience. To prevent future air conditioning failures, the owner may consult with an external team or a private maintenance company to determine the best maintenance strategy for the air conditioner. External teams and private companies often promote their fixed-period maintenance strategy based on their business experience.
In addition to the owner's subjective neglect, there are also objective reasons causing this problem. A successful operation and maintenance performance requires the collection of a large amount of non-intuitive data. However, most property owners often lack professional knowledge of maintenance and the ability to collect maintenance data. As a result, owners can only handle basic operation and maintenance management, which is often based on intuition and mechanical skills.
The third issue is that not all subsystems in an air conditioning system can be effectively maintained.
According to research in Owerri, Nigeria (Nkeleme et al., 2019), owners' maintenance behaviors primarily focus on the chiller, which is the main component of the air conditioning system. The maintenance behaviors of the chiller and its related subsystems are relatively comprehensive. However, other components of the air conditioning system, such as pumps, fan coil units, and distribution systems, do not receive the same level of attention.
It is known that air conditioning is a complex system, not just a single device. It usually consists of a cold source/heat pump system, a distribution system, and a terminal system. These subsystems contain lower-level subsystems, which in turn contain various devices, perform different functions, and operate in diverse environments. This indicates that the maintenance of the air conditioning system is quite complex. In practice, independent maintenance strategies are required for different subsystems.

1.1.3 Opportunities to solve problems in maintenance

The development and maturation of new technologies provide opportunities to solve or optimize the previously mentioned problems.
First, carbon emission permit trading is a burgeoning market today. It provides enterprises with a new perspective on the maintenance of air conditioning systems. A proper maintenance strategy can help conserve energy and decrease emissions. As the market for carbon permits continues to expand, enterprises will prioritize their own carbon emissions, creating new opportunities for corporate profits.

The company can directly sell its contribution to energy conservation and emission reduction as carbon emission rights. For some companies, the profits from selling carbon permits exceed those from their main business activities. For instance, in 2021, Tesla generated $1.465 billion from the sale of carbon credits. In the first quarter of this year, Tesla earned $679 million from selling carbon permits to other automakers, which is a 31 percent increase from the previous year. In contrast, in 2020, Tesla generated $1.58 billion from the sale of carbon permits, while its net profit for the year was only $720 million (Sina News, 2021). Excluding the revenue from the sale of carbon credits, Tesla incurs a financial loss. Enhancing the operation and maintenance capabilities of air conditioning systems can create new opportunities for business growth.

Second, the advancement of information technology (IT), including artificial intelligence (AI), the Internet of Things (IoT), and simulation technology, has significantly reduced the cost of acquiring data from air conditioning systems. Furthermore, simulation software for HVAC systems has been developed and is widely used. This enables owners to implement advanced, data-driven maintenance strategies.

1.1.4 conclusion

Improving energy efficiency in the air conditioning sector, particularly in China, is a pressing matter. One important approach is to enhance the maintenance of air conditioning systems. The current air conditioning and maintenance face three main problems: first, the air conditioning maintenance has been ignored by owners; second, the maintenance strategies currently used by owners cannot optimize the efficiency of the air conditioning system; and third, the current air conditioning maintenance does not cover all the components in the air conditioning system. The problems stem from subjective neglect by owners, a lack of professional operators and knowledge, and the objective complexity of the air conditioning system. However, with the passage of time, it is possible to optimize or resolve these problems.

1.2 Literature review

1.2.1 Study on the maintenance strategy

Different maintenance strategies result in varied maintenance decision-making. Therefore, it is essential to have a comprehensive understanding of maintenance strategies.

Some scholars have researched the history of maintenance strategy development and outlined the characteristics of different stages. In the study by Mikler (2011) and Teixeira and Landre (2016), maintenance strategies were categorized into three generations. In the first generation, maintenance activities were concentrated on repairs. The second generation is known as preventive maintenance, which involves planned and scheduled tasks. The third generation includes predictive and preventive activities, aiming to eliminate the negative consequences of failures, and is also referred to as "the reliability-centered maintenance culture." Some scholars define the fourth generation as encompassing prevention, early machinery control, reliability, and maintainability (Legutko, 2009).

Lee and Scott (2009) and Shin and Jun (2015) classify maintenance strategies based on their characteristics. One typical way of categorizing maintenance is corrective, preventive, and condition-based maintenance. They implemented this classification. In this classification, corrective maintenance is the most straightforward method. However, it is also the most expensive method because it is used in response to breakdowns and all the consequences of such incidents. Some scholars use the term "failure-based" or "unplanned" maintenance. Preventive maintenance is a response to the disadvantages of corrective actions. Scholars refer to this maintenance strategy as time-based maintenance, planned maintenance, or cyclic maintenance. The third strategy mentioned goes beyond simple visual observations and focuses on monitoring changes in crucial conditions.

(Mostafa et al., 2015) classified maintenance strategies as corrective, preventive, and design-out maintenance. Unlike the studies mentioned above, he included both condition-based and time-based maintenance in the preventative maintenance. The fundamental concept of design-out maintenance is to eliminate the necessity for maintenance during the entire life cycle of the product by integrating it into the design and manufacturing stages. This is also considered a design concept rather than a maintenance strategy.

It is worth noting that some scholars believe that condition-based maintenance is not a type of maintenance strategy on the same level as preventive maintenance, but rather that the former is included in the latter. For instance, Shin and Jun (2015) state that a condition-based strategy is similar to a preventative strategy because both methods aim to prevent failures before they occur.

(Wang, Chu, & Wu, 2006) provide a more detailed breakdown: corrective, time-based preventive, condition-based, and predictive maintenance.

Many scholars simply divide maintenance strategies into corrective and preventive maintenance. These two types of strategies also include subcategories. Legát et al. (2017) included condition-based maintenance and predictive maintenance as part of preventive maintenance. (Okoh et al., 2017) categorized preventive maintenance strategies into condition-based and opportunity-based approaches.

Some scholars also develop maintenance strategies for specific application scenarios.

(Wang, 2002) illustrated an age-dependent PM strategy. It is also known as time-based maintenance or manufacturing time-based maintenance strategy. This means that when the equipment processing time or processing capacity reaches a predetermined constant, equipment maintenance or replacement activity should be triggered. This is the simplest empirical preventive maintenance method to implement in small and medium-sized enterprises that lack equipment data, testing equipment, or understanding of equipment. However, this method is typically utilized for production equipment and may not be easily applicable to support equipment.

Lim et al. (2007) proposed that the periodic PM strategy refers to a fixed time interval for preventive maintenance. During periodic preventive maintenance, each maintenance activity can reduce the failure rate of equipment, but it cannot alter the pattern of change in the failure rate. Therefore, the optimal maintenance period is achieved by minimizing the maintenance costs.

Maintenance of equipment after a failure does not guarantee restoration to a pristine condition. The deterioration of equipment will be accelerated with the accumulation of operating time and the increase in maintenance time. It directly contributes to the increase in equipment maintenance costs and maintenance time (Yeh, 1998). Smeers et al. (1998) assumed that the costs of corrective maintenance (CM) are constant, and only the costs of preventive maintenance (PM) would change with equipment operating time. Based on the increasing failure rate, they determined the optimal maintenance cycle sequence within a finite lifespan.

In summary, there are currently diverse opinions among scholars regarding the classification of maintenance strategies, and no unified or dominant conclusion has been reached. This study analyzes and summarizes various perspectives on the classification of maintenance policies in detail, and establishes a classification of maintenance policies based on previous scholars' research. This is discussed in Section 2.2; the comparison of various maintenance strategies is discussed in Section 2.2.3 to determine the most suitable maintenance strategy for this study. Besides, it is evident that certain researchers have proposed universal preventive maintenance strategies based on time intervals. However, there is a lack of specific research applying these findings to the study of coil maintenance strategies. There is also no indication that owners use these effective coil preventive maintenance strategies on a daily basis.

1.2.2 Study on coil/ fan coil performance optimization

The coil in the air conditioning system is a component within the fan coil unit subsystem. Therefore, the literature review also includes literature about optimizing fan coil unit performance.

It should be noted that there is limited literature on the maintenance and performance improvement of coil/fan coil units. Matetić et al. (2022) pointed out that less than 6% of the literature in the air conditioning fault detection sector focused on coil analysis. In addition, Es-sakali et al. (2022) summarized nearly 50 pieces of literature related to predictive maintenance algorithms in the HVAC field, none of which included coil or fan coil systems. Here are some typical literature sources related to optimizing the performance of coils and fan coils.

Several scholars have examined the typical types of faults and specific maintenance methods for the fan coil unit, including studies by Wang and Wang (2005), Lin (2009), Wu (2009), and Zhang (2015). It also includes methods for maintaining coils. Some of these studies provide recommendations for coil maintenance strategies. Lin (2009) recommends cleaning the coil once every quarter. Zhang (2015) noted the importance of regularly cleaning the coil but did not specify the frequency. Wang and Wang (2009) suggested that the coil should be cleaned before using the air conditioner every summer. In these studies, the strategies are fixed-period maintenance strategies, which are based on the author's work experience. However, the author does not provide rational reasons for the development of these maintenance strategies.

Li, Zhang, and Bian (2014) aim to enhance the efficiency of air conditioning systems by focusing on operational aspects. For example, based on the measured data of Building Automation System (BAS). They utilized Simulink simulation software to flexibly develop various control strategies for achieving intelligent control of fan coil units, ultimately enhancing the efficiency of the units and reducing energy consumption. This type of research is valid, but it does not address coil maintenance, specifically, it does not directly consider how to prevent air conditioner malfunctions. This type of study offers a viable solution for improving coil efficiency. However, it does not directly address coil or fan coil unit faults, so it does not encompass the field of maintenance.

Matetić et al. (2023) attempted to integrate deep learning fault detection into coil maintenance to enhance coil efficiency. They explored three different DL models as fault detectors, including convolutional neural network (CNN), long short-term memory network (LSTM), and a combination of CNN and gated recurrent unit (GRU). They tested three DL models in a real-world dataset gathered from a smart hotel and compared the effectiveness of each, finding out that CNN+GRU method is most effective. The maintenance strategies they use are known as condition-based preventive maintenance or predictive maintenance strategies. This study addresses the research gap in the application of advanced maintenance strategies for coil/fan coil maintenance. However, his research also highlights the relative disadvantage of this maintenance strategy: it requires large amounts of real-time, high-frequency data, and obtaining such data is very challenging. The hotel has implemented a smart-room concept, utilizing microprocessor-controlled stations to effectively monitor and regulate key parameters, thereby ensuring the optimal functionality of the hotel rooms. Sensors in this smart hotel have the capability to collect data every five minutes. The sensors gather data for a maximum of five minutes at a time. After processing the data, a total of 60,052 samples from 2017 to 2019 were used in the study. Today, however, the vast majority of air conditioning owners do not have the capability to collect and manage such data, nor do they have the willingness to gather such a large amount of data.

1.2.3 Study on solving optimization problem

The formulation of a maintenance strategy typically aims to optimize certain objectives, making it essentially an optimization problem. Optimization is an ancient mathematical subject; therefore, there are many related areas that can be referenced. Coil maintenance strategy optimization is a single/multi-objective optimization problem. This type of optimization problem typically involves complex objective equations and a large number of feasible solutions. Heuristic algorithms are commonly employed to solve this type of problem. Heuristic algorithms are primarily simulated natural processes, including the ant colony algorithm, simulated annealing method, genetic algorithm, and others.

Katoch, Chauhan, and Kumar (2020) conducted a review of the development of genetic algorithms, providing detailed explanations of specific coding methods, selection techniques, crossover processes, and mutation strategies in genetic algorithms. The application scenarios of various enhanced genetic algorithms are also summarized. Santos, Ferreira, and Flintsch (2017) employed a genetic algorithm to determine the pavement maintenance strategy. In the objective function of his study, the parameters of the function are all constant. Brahim (2021) employed a genetic algorithm to address pavement optimization issues. In his research, the parameters such as the number of iterations and exchange rate were analyzed in detail. Ma, Hu, and Tao (2018) developed a GA-gray neural network to address the challenge of predicting pavement performance. Combining genetic algorithms with the gray neural network algorithm results in a very low degree of deviation.

Many scholars have utilized genetic algorithms to address optimization problems akin to coil maintenance strategies. The genetic algorithm itself has various variants that can be adjusted to meet different needs. Therefore, this study aims to use a genetic algorithm to solve the objective function.

1.2.4 Conclusion of literature review

Scholars have proposed universal strategies for preventive maintenance. However, these results have not been applied to coil maintenance in air conditioning systems. The accumulation of dirt over time is the most important factor affecting the variation in coil performance, and it must be taken into consideration when designing its maintenance strategy. After maintenance, coils can be restored to their original design performance, allowing maintenance strategies to be designed to overlook wear and tear. The genetic algorithm (GA) has been widely used to optimize maintenance strategies. This paper will initially explore the use of genetic algorithms and adjust the operators and operating parameters as necessary.

1.2 Research Gap

Two main research gaps can be identified from the literature review.

Firstly, there has been limited research on the implementation of advanced maintenance strategies for coils/fan coils in air conditioning systems. On one hand, there is little previous research in this field. On the other hand, not all advanced maintenance strategies have been studied: there is no evidence that the time-based preventive maintenance strategy has been applied in the field of coil/fan coil maintenance so far. Characteristics of the two advanced maintenance strategies: time-based preventive maintenance and condition-based preventive maintenance are discussed and compared in section 2.2. In the discussion, the former has less capability to accurately reflect the actual condition of the maintenance object compared to the latter. As a result, its maintenance effect is reduced compared to latter. However, the former has far lower data requirements, providing advantages in terms of usability and cost-effectiveness. Furthermore, the time-based preventive maintenance strategy has a more significant maintenance effect compared to the corrective and fixed-period maintenance strategies commonly used in the air conditioning industry today. Therefore, research on time-based preventive maintenance strategy should not be overlooked.

Second, studies on coil/fan coil optimization have not considered the economic factor. All relevant researches mentioned in literature review aim to maximize energy efficiency in their optimization models, and economic factors do not appear as a significant constraint in their optimization models. Most of the owners of air conditioning systems are economic players in the market, and all their behaviors are driven and influenced by the economic interests behind. The view that economic interests are the main driving force of market entities has been repeatedly proved by numerous economic studies and observed economic phenomena since the establishment of National Economics founded by Adam Smith. Maintenance behaviors for air conditioning system is naturally also influenced by the economic interests behind it. Although the maintenance of air conditioning systems, including the maintenance of coils, is beneficial for improving energy efficiency and reducing energy consumption. This, in turn, can alleviate the energy burden on society and help mitigate climate change. However, for an economic player in the market, the benefits of maintenance accrue to the entire society, rather than directly to the owners. For owners, the energy consumption resulting from air conditioning systems is an indirect cost that they must bear in order to generate economic benefits. This offers a reasonable explanation for the current lack of attention to air conditioning maintenance. Today, the introduction of carbon emission permits means that energy consumption can be given economic significance and become an economic growth point for enterprises. Therefore, economic factors need to be considered. Even if optimizing is not a goal for the model, it still needs to be included as a significant constraint. In this study, economic factors are directly considered as optimization objectives. That's the hope. Owners can realize significant economic benefits by saving energy. This can encourage them to make greater efforts in energy conservation and emission reduction.

1.3 Aim and objectives

Based on the existing issues with air conditioning maintenance and the research gaps, the aims and objectives of this study are as follows.

1.3.1 Aim

This study aims to develop an optimization model that can generate a preventive maintenance strategy for coil maintenance in an air conditioning system with the lowest net present value of the total relevant cost (TRC), while ensuring the cooling performance of the air conditioning system.

1.3.2 Objectives

To achieve the aim, the study has four objectives.

1) To establish a mathematical model for optimization, it is necessary to establish mathematical relationships between variables and set up an objective function.

2) To create simulation scenarios for testing the model's usability during implementation;

3) To solve the optimization model using the parameters of the simulation scenario on a computer;

4) Analyzing the results from simulation scenarios to evaluate the model's performance.

1.4 Novelty

1) This optimization model is specifically developed for coil maintenance strategies. This study addresses the neglected coil maintenance in the air conditioning field, improving the current situation. Additionally, it fills the research gap in the application of efficient maintenance strategies for coils. It is believed that this study will improve the efficiency of coil operation and reduce the costs of operation and maintenance. It is important to note that the new preventive maintenance strategy does not guarantee better cost performance. The previous strategy may have achieved better cost performance at the expense of operational performance. However, the new preventive maintenance strategy should offer better cost performance compared to any fixed-period maintenance strategy based on past experience, while still

meeting the operational performance requirement.

2) This study considers economic factors by examining the opportunity cost of operating an air conditioning system after participating in the carbon emission permit trading market. In this study, we consider the potential economic cost of coil performance loss in air conditioning systems after entering the carbon emission trading market. The investigation is more comprehensive and can better reflect the potential cost implications for enterprises as they transition to entities in the carbon emission trading market in the future.

3) This study integrates environmental and economic factors by using carbon emissions as the representative environmental factor. The study expresses carbon emissions from the operation of air conditioning systems in monetary terms through the carbon emission trading price. This shifts the responsibility for carbon emissions from enterprises directly from the realm of corporate social responsibility to the calculation of profit and loss. In this way, it can encourage businesses to enhance their profits by implementing energy conservation and emission reduction measures.

1.5 Research contents

The first part (Chapter 1) serves as the introduction. Firstly, the background and significance of the research on cooling coil maintenance strategy are explained to provide context for this study. Furthermore, the literature review encompasses the current research on maintenance strategy, coil fouling, genetic algorithms, and other related areas. Next, the research methodology and technical approaches are briefly summarized.

The second part (Chapter 2) involves the analysis of relevant theories. The current theoretical basis related to maintenance strategy and genetic algorithms is introduced, laying a foundation for the model design and solution below.

The third part (Chapter 3) covers the model's design. This section marks the transition from theoretical knowledge to practical application. The diagram illustrates the identification of factors in the model and their interrelationships. The high-level design of the model will guide the creation of the model below.

The fourth part (Chapter 4) covers the creation of the model. In this section, a general model for maintaining cooling coils will be developed. The selection of appropriate parameters is determined based on the optimization objective, and it involves combining relevant theoretical analysis and literature review. However, in this section, since there is no specific application scenario, only the types of parameters will be determined, rather than the specific parameter values.

The fifth part (Chapter 5) presents the solution and implementation of the model. The study does not include any test conditions based on actual air conditioning systems. Two simulation scenarios were proposed based on hypothetical and actual situations. The model was provided with adequate parameters, solved under the two simulation scenarios, and then the model's effectiveness was verified.

1.6 Research Methodologies

1) Literature research method

By collecting and reading relevant literature on maintenance strategy optimization and solution algorithms in other fields, analyzing and studying the literature, the similarity between maintenance optimization in other fields and coil maintenance strategy was found, and genetic algorithm was selected to solve the objective function.

2) Simulation method

Simulation method has been used to estimate the problem based on certain assumptions and data. Due to the large amount of computation, assistance by computer is required. Since the data of air conditioning systems in the real world cannot be obtained, this study uses simulation technology to build simulation scenarios in the HVAC simulation engine EnergyPlus, and solves the optimization model in these virtual scenarios.

3) Combination of qualitative and quantitative analysis

Through qualitative analysis of literature review and realistic background, the research question and research content were clarified. Quantitative analysis was used to determine the parameters of the simulation scene. Quantitative analysis is the basis for using EnergyPlus to construct the simulation, and it is also the basis for using Python to solve the model.

4) Interdisciplinary approach

Interdisciplinary approach is a research approach to conducting thorough research on a subject as a whole, utilizing multidisciplinary theories, methods, and results. The law of scientific development movement demonstrates that science is highly differentiated and highly integrated, forming a unified whole. This study integrated Heating, Ventilation and Air Conditioning (HVAC), management, economy, finance and other fields of knowledge and theories to solve the research question.

1.7 Roadmap of research

The technical roadmap for the study is shown in Figure 1-1.

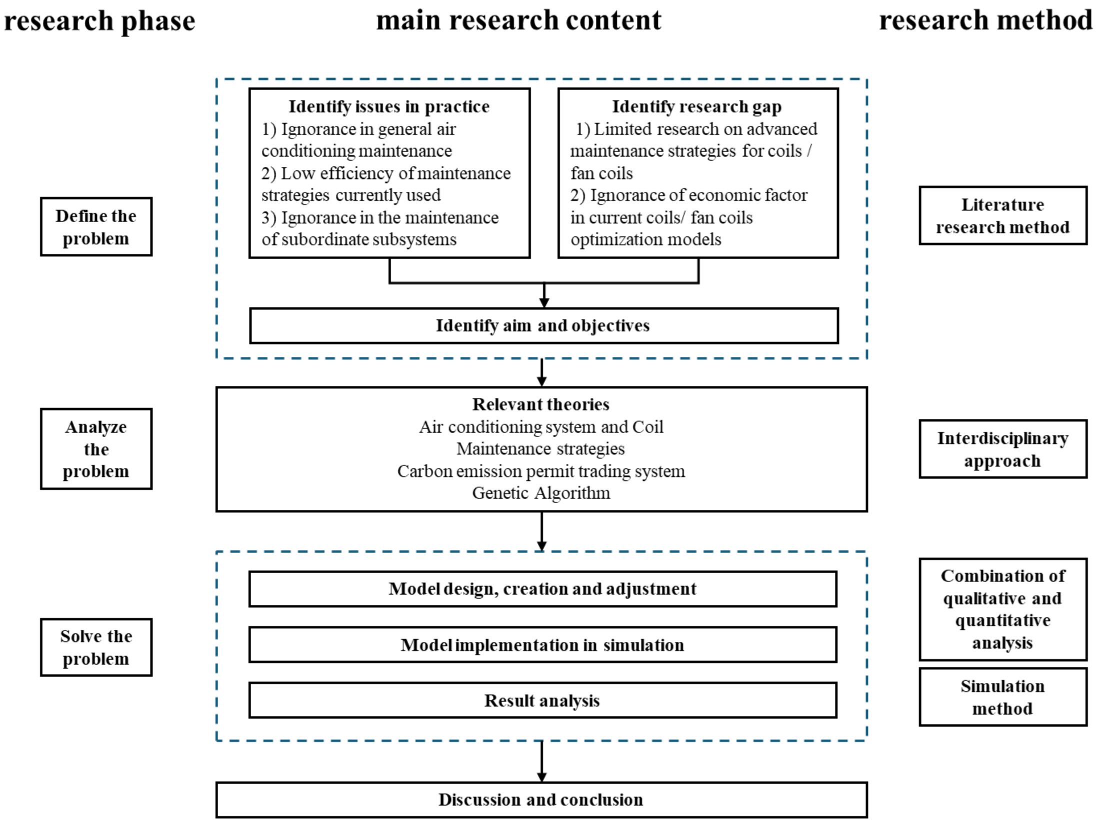


Figure 1-1: Roadmap of research

2. Relevant Theories

2.1 Air conditioning system and Coil

2.1.1 The composition of central air conditioning system

The central air conditioning system is divided into three subsystems according to their functions, which are the cold source/heat pump system, distribution system and terminal system.

A cold source system is a system that consumes a certain amount of energy and transfers heat from a low heat source to a high heat source. If the system that transfers heat from a higher to a lower heat source, it is called a heat pump system.

The central air conditioning system usually uses air or water as the carrier for heat/cold distribution. The air conditioning distribution system is the system that sends the treated air/water to the internal environment of the building.

An air conditioning terminal system is a system in which heat is exchanged with the air inside the building by using the air or water as a cold/heat carrier. The most common terminal device for air conditioning is the fan coil unit.

2.1.2 Working principle of cold source

Although the research object of this study is coil, which is a part of the air conditioning system. However, as the core part of the air conditioning system, it is necessary to understand the heat exchange principle of the cold source/heat pump system.

Chiller is one of the most common air conditioning systems. It exchanges the heat between water and air in the evaporator.

A chiller consists of four main large components, which are compressor, condenser, expansion valve and evaporator. These four main components form a closed loop system through a variety of pipes in a certain order. The refrigerant in the pipeline constantly changes the circulation state between gas and liquid to achieve the refrigeration effect. The thermodynamic cycle of refrigerant flowing in a closed-pipe can be divided into four phases: first, the compressor compresses the low-temperature and low-pressure gaseous refrigerant into high-temperature and high-pressure refrigerant vapor. The vapor then enters the condenser, where it is converted into a liquid with high temperature and pressure. This process is an exothermic process, and the heat is absorbed by the cooling water. The refrigerant from the condenser enters the expansion valve, reduces the temperature and pressure, and becomes a low-temperature, low-pressure gas-liquid mixture. Then the refrigerant enters the evaporator and absorbs the heat of the frozen water into a refrigerant gas with low temperature and low pressure. This repeated cycle completes the refrigerant in the chiller working stream.

2.1.3 Fan Coil Unit

A FCU consists of a fan and at least one air-water heat exchanger coil for heating or cooling airflow. Figure 2-1 is a diagram of a fan coil unit. To condition a space, hot or cold water is circulated through the FCU coil to add or remove heat from the airstream discharged to the space by the fan. The amount of heating or cooling is controlled primarily by controlling the water flow and secondly by controlling the fan speed. (ASHRAE, 2018). Figures 2-2 and 2-3 are the real product of the coil and fan coil unit (The picture originates from the Internet).

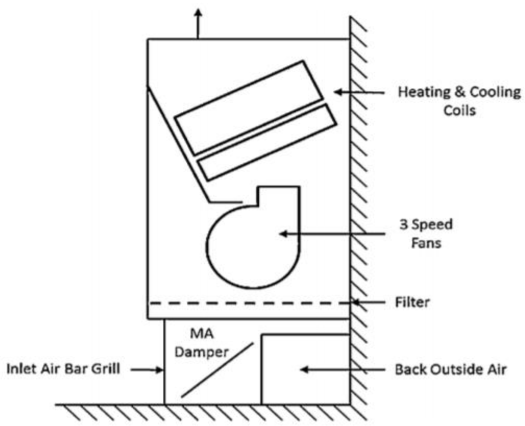


Figure 2-1: diagram of a fan coil unit (ASHRAE, 2018)


Figure 2-2: Real products of cooling coil   Figure 2-3 Real product of Fan coil unit

(The picture originates from the internet)

2.1.4 Coil

It should be emphasized that fan coil unit and coil are not the same concept. Fan coil unit belongs to the air conditioning distribution system, and coil is a component of fan coil. The relationship between the above concepts is shown in Figure 2-4. It is still part of the air conditioning system. The chilled or hot water in the coil tube can exchange heat with the air outside the tube, so that the air can be cooled, dehumidified or heated to adjust the indoor air parameters.

A coil is cooled or heated by the exchange of heat between water and air. No matter the water side or the air side, fouling will occur in use, which will affect the heat transfer effect. When coil fouls, heat transfer efficiency decreases and the air conditioning system increases power to maintain the preset cooling/heating effect, increasing energy consumption and increasing the owner's operating costs.

The coil must be maintained independently of the rest of the air conditioning system. First, as part of the end system, coil performance directly affects the indoor heat exchange effect with the air conditioning system. Secondly, because the coil is located indoors, its operating environment is significantly different from that of the outdoor heat exchanger. Therefore, the maintenance time of the two is different. Third, the coil is located at the end device. Compared to other devices, the coil is easier to reach. This means that the maintenance of the coil is simpler than that of other devices. In addition, the effect of coil fouling on the air conditioning system is significant. This effect can be seen in the simulation results (Chapter 5).

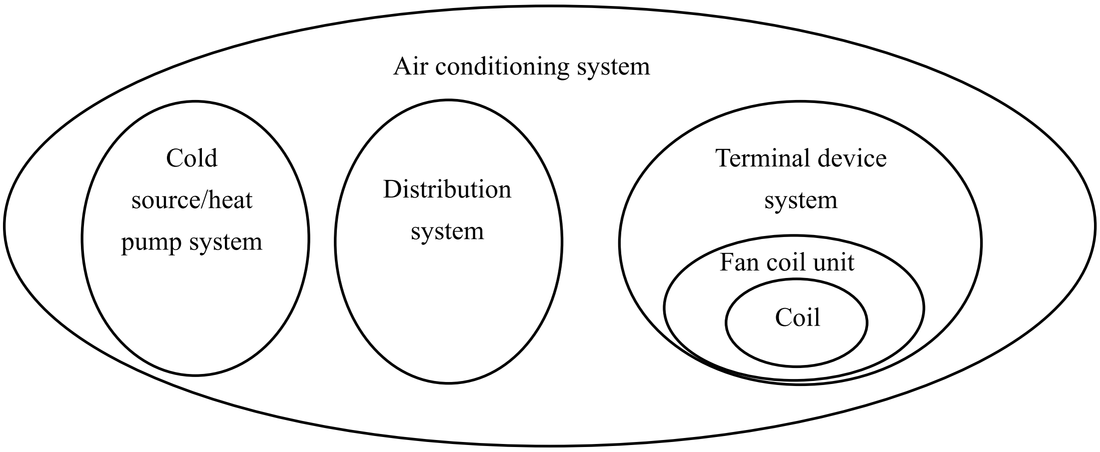


Figure 2-4: Relationships between air conditioning system, terminal device system, fan coil unit and coil

2.1.5 Coil fouling

As heat exchangers, coils have the same type of failure as other heat exchangers. Its long-term performance deterioration is mainly influenced by dust accumulation, salt spray corrosion, intermittent system operation and microbial pollution (Zhan, 2015), among which dust accumulation, that is to say "fouling", is the most important factor for the long-term performance decline of heat exchangers (Zhang et al, 2015). After working for a period of time, a large amount of dust and scale will be deposited on the fin surface of the heat exchanger, which will gradually accumulate and form a massive scale after natural action, leading to serious deterioration of the performance of the air conditioning system. On the one hand, long-term dust deposition and scaling can block the fin gap of the heat exchanger, thus reducing the convective heat transfer area and increasing the resistance of air flow during air flow (Hernandez-Arrieta et al., 2017). On the other hand, dust and dirt adhering to the fin surface of the heat exchanger increases the thermal resistance on the fin side, reduces the heat transfer coefficient on the air side, and the heat transfer efficiency on the surface of the heat exchanger drops sharply, finally leading to a decrease in the heat transfer efficiency of the air conditioner system (Thatcher, 1995). However, in order to make the indoor environment under the action of air conditioning system achieve the same cooling or heating effect, only by increasing energy consumption can achieve the air conditioning effect with low energy efficiency.

In addition, when the coil is fouled to a certain extent, the fouling may lead to refrigerant or water leakage (Wu, 2009).

2.1.6 *Energy performance change of coil with time*

Pak et al. (2003) tested the collected condenser coils and found that when dust was deposited in the air duct, the pressure drop of the single-row heat exchanger would increase by 28%-31% and the heat transfer performance would decrease by 7%-12% at the standard air speed of 1.53m/s, while the pressure drop of the double-row heat exchanger would increase by 22%-37%. The heat transfer performance will decrease by 4-5%. After standard cleaning of the coil with a chemical cleaning agent, the heat exchanger performance will basically recover. Zhang et al. (2015) tested an indoor and outdoor fan of an air conditioner that had been used for two years, and found that the air supply volume of the fan decreased, and at the same time, the refrigeration and heating capacity of the air conditioner also decreased sharply. The important conclusion to be drawn from the above studies is that fouling caused by fouling is the most important factor causing the performance degradation of the coil. Without maintenance, the performance of the coil will deteriorate dramatically. In addition, coil performance can be restored to the original design specifications through maintenance.

2.1.7 *Coil maintenance measure*

Coil maintenance measure is not complicated. According to the study of Lin (2009); Wang and Wang (2005), the maintenance measure for foiling is "cleaning". For the situation that coil fouling is not severe, Cleaning should be conducted by a powerful vacuum cleaner or by high pressure water; For oil or other chemical pollution, the appropriate chemical cleaning agent should be used. When the coil is severely fouled, the coil should be removed from the fan coil unit for thorough cleaning. When the coil leaks or is damaged so that its performance cannot meet the requirements of use, the coil needs to be replaced.

2.2 Maintenance strategies

From the literature review, it is evident that various scholars hold different opinions on the classification of maintenance strategies at present, and there is no unified or dominant conclusion. The aim of this study is not to categorize maintenance strategies, but to suggest an improved maintenance strategy for the coil in the air conditioning system. Therefore, this article will argue that the effectiveness of a maintenance strategy depends on its ability to accurately reflect the specific conditions of the equipment being maintained. This position is consistent with that presented in the articles by Es-sakali et al. (2022)

and Ahmad and Kamaruddin (2012). To accurately represent the specific conditions of the equipment being maintained, there must be a sufficient amount of data about the equipment. A sound maintenance strategy should be grounded in this data, rather than the experience or habits of maintenance policy makers. Based on the research objectives and positions outlined above, the classification of maintenance strategies in this paper is illustrated in Figure 2-5.

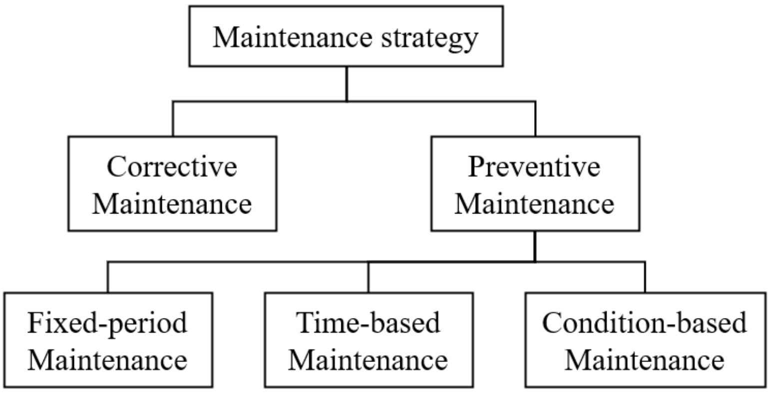


Figure 2-5: Classifications of maintenance strategies

2.2.1 Corrective maintenance strategy

Maintenance strategies fall into two main categories. Includes preventive maintenance (PM) and restoration corrective maintenance (CM) (Duffuaa et al., 2001).

Corrective maintenance refers to the maintenance strategy in which maintenance activities are carried out at the time of equipment failure to restore it to a specific level of performance. It is a passive maintenance strategy with no predetermined schedule or expectations.

Merely adopting a condition monitoring (CM) strategy cannot effectively ensure the reliability of equipment. This approach may lead to sudden disruptions in production, impact workshop scheduling, and disrupt the smooth flow of the production process. CM is not suitable for air conditioning maintenance. This is because the decline in the performance of the air conditioning system is a gradual process, and when the decline is not noticeable, the cooling/heating capacity of the air conditioning is not significantly affected. The air conditioning system boosts power to meet predetermined cooling/heating needs, resulting in increased power and energy consumption. By the time users feel the need for maintenance, the optimal time has already passed. Corrosion-resistant material (CM) is also not suitable for coil maintenance. Users often only notice a decline in the overall performance of the air conditioning system and are unable to pinpoint which part or parts of the system are failing. As a result, they can only conduct extensive maintenance. Coil maintenance is only one aspect of large-scale maintenance.

2.2.2 Preventive maintenance strategy

PM, in a broad sense, refers to a maintenance approach that aims to prevent equipment or system failure by monitoring, checking, and measuring equipment status. It involves taking proactive maintenance actions based on preset strategies before equipment failure occurs. Broadly speaking, the following maintenance strategies, which encompass maintenance activities or behaviors conducted before equipment failure, are generally considered as preventive maintenance (PM). These include time-based maintenance, condition-based maintenance, predictive maintenance, and reliability-centered maintenance.

2.2.2.1 *Fixed-period maintenance strategy*

In a narrow sense, preventive maintenance strategy is understood as scheduled maintenance. This understanding is widely accepted by equipment manufacturers (Ahmad and Kamaruddin, 2012). As per the equipment manufacturers' recommendation, preventive maintenance (PM) should be carried out at regular intervals, such as every 500 hours or annually. In this sense, it can be redefined as a fixed-period maintenance strategy. Its distinctive feature is that the maintenance period is fixed, and the development of the maintenance period does not involve the specific equipment's data. Therefore, the actual situation of the equipment has not been considered. This maintenance strategy has been shown by many studies to be ineffective in minimizing operation costs and maximizing machine performance. Labib's research (2004) highlights the reasons for different PM schedules for each equipment, as they operate in distinct environments. Secondly, the designers of the equipment often do not understand how failures occur in practice, and they have less knowledge about preventing equipment failure than the people who operate and maintain these machines. Finally, equipment manufacturers may intentionally maximize spare parts replacement through frequent preventive maintenance (PM).

Compared to corrective maintenance (CM), preventive maintenance (PM) can significantly reduce downtime, prolong the service life of equipment, lower maintenance costs, and ensure production safety. As a result, PM is more widely utilized in equipment maintenance management.

2.2.2.2 *Condition-based maintenance and Time-based maintenance strategy*

According to established triggers, PM can be categorized in two ways based on its implementation. They are condition-based maintenance (CBM) and time-based maintenance (TBM) (Ahmad and Kamaruddin, 2012).

TBM, also known as time-based maintenance, is a maintenance strategy in which maintenance activities or behaviors are determined based on analyses of failure times. In other words, the expected lifetime of certain equipment is estimated using failure time data or usage-based data. TBM is based on an important assumption: that equipment failure is predictable.

CBM is a maintenance strategy that recommends maintenance activities or behaviors based on the information collected through the condition monitoring process. In condition-based maintenance (CBM), equipment aging is monitored through its operating condition, which can be measured based on various monitoring parameters. The central concept of CBM is condition monitoring, which involves the continuous monitoring of signals using specific types of sensors or other appropriate indicators (Campos, 2009).

Compared to CBM, the primary advantage of TBM is its ease of planning and implementation, which facilitates aligning maintenance resources with production plans and coordinating with other organizational strategies and plans. Therefore, Time-Based Maintenance (TBM) is the most common maintenance plan when there is insufficient previous production data and when diagnosing equipment failures and predicting conditions is difficult. Even today, there is still a large user base due to its ease of use and low cost. However, at the same time, because the maintenance plan is created in advance without considering the actual condition of the equipment at the time of maintenance, it is easy to cause "inadequate maintenance" and "excessive maintenance" of the equipment. This may lead to safety accidents and product quality issues due to insufficient maintenance, or result in the wastage of maintenance resources and reduced equipment availability.

In the context of condition-based maintenance (CBM), it is important to note that most equipment will undergo a degradation process before failure. CBM can diagnose early, potential, and minor failures based on specific degradation characteristics, allowing for appropriate maintenance operations to be performed before they escalate into significant, severe, and functional failures (Liu, 2016). Compared to traditional maintenance methods (TBM), condition-based maintenance (CBM) can effectively prevent the issues of "over-repair" and "under-repair". However, CBM also has some disadvantages, including high hardware and software costs, challenging implementation, and complex operation. In general, TPM and CBM have their own specific use cases. CBM is suitable for situations where the organization has advanced detection devices, the target equipment itself is highly technological, and the organization employs highly skilled technical personnel.

Ye (2021) identifies the essential technical connections required to implement CBM. Owners can collect maintenance data using the following technologies.

1) Data acquisition and transmission technology

Obtaining signal data that can characterize the device's status is a prerequisite for fault diagnosis.

2) Signal Feature Extraction

Various processing methods are necessary to extract characteristic information that can characterize the device state in order to obtain the original signal. This lays the foundation for subsequent analysis of the device's condition state.

3) Equipment Fault Diagnosis

Diagnosing early equipment faults and predicting the deterioration trend are the primary challenges of preventive maintenance.

Compared to Condition-Based Maintenance (CBM), Time-Based Maintenance (TBM) processes and analyzes historical data of maintenance objects. As a result, TBM has lower requirements for information timeliness. The demand for real-time data transmission and fault diagnosis technology is also decreasing. However, it also requires sensors to collect and process data from maintenance equipment. In this scenario, while the accuracy is typically lower than that of CBM, TBM demonstrates greater adaptability to various air conditioning systems. Therefore, as a standard model for typical air conditioning system owners, the TBM strategy was chosen for this study, and the optimization model's construction is based on the TBM strategy.

2.2.3 Comparation and selection of maintenance strategy

Table 2-1 compares the four maintenance strategies in terms of data requirement, technical requirements, and maintenance effects. Both the Time-Based Preventive Maintenance Strategy (TBM) and the Condition-Based Preventive Maintenance Strategy (CBM) rely on the adequate collection of maintenance object data. Both can reflect the characteristics of maintenance objects, improving the efficiency of maintenance and reducing maintenance costs. The main difference between the two strategies is that CBM monitors and maintains the object's real-time data, while TBM makes predictions based on the object's historical data. It is evident that while TBM is less effective than CBM in reducing downtime and maintenance costs, it is more suitable for maintaining low-complexity equipment due to its lower cost and technical threshold. However, it is much better than the previous two maintenance strategies. Moreover,

Given that the coil is not a highly complex device, it is challenging to collect real-time data on coil fouling. This study creates an optimization model based on TBM. This decision aligns with the current situation and offers high cost performance.

Table 2-1: Comparation of 4 maintenance strategies

Name of Maintenance Strategy	Data Requirement	Technical Requirement	Maintenance Effects
Corrective Maintenance	None	Low	Low
Fixed-Period Maintenance	Based on the subjective experience of the maintainers or overall industry experience	Low	Medium
Time-based Preventive Maintenance	Based on historical data of Maintenance objects	Medium	Relatively high
Condition-Based Preventive Maintenance	Based on real-time data of Maintenance objects	High	High

2.3 Carbon emission permit trading system

China has formally pledged to the world to achieve a peak in carbon emissions by 2030 and carbon neutrality by 2060. Traditionally, enterprises have sought to reduce carbon emissions due to corporate social responsibility or mandatory policy requirements. In the implementation of emission reduction, enterprises are typically passive, resulting in an insignificant effect on emission reduction.

The following paragraphs will introduce the carbon emission permit trading system and its theoretical foundation. Some empirical studies on carbon emission trading are also referenced. Carbon emission permit trading provides an economic incentive for enterprises to conserve energy and reduce emissions. Enterprises may seek higher profits from trading carbon emission permits in order to proactively reduce their carbon emissions.

2.3.1 Theory basic of Carbon emission trading system

2.3.1.1 Coase's property right theory

Coase's theory of property rights is the primary theoretical foundation for the carbon emission permit trading system. In "The Problem of Social Costs," Coase refuted Pigou's theory that the losses caused by negative externalities should be borne by the corresponding people. He pointed out that in solving environmental problems, the focus should be on reducing the greater damage (Coase, 1960).

Coase considered environmental factors to be a significant aspect of production. He believed that the primary cause of environmental problems, from the perspective of property rights, is the lack of clear ownership or the high cost of determining ownership. Only when the ownership of environmental resources is clearly defined, can they be freely traded in the market, in order to mitigate the externality of environmental resources. Coase's theory is an important theoretical foundation for many governments when making decisions regarding environmental management. By clarifying property rights, external costs are internalized. At the same time, Coase also points out that transaction costs may have a certain impact on the definition of property rights. Based on this theoretical foundation, carbon emission trading can mitigate negative externalities by allowing the free exchange of carbon emission credits in the carbon trading market. This not only enhances the mechanisms for environmental regulation but also offers an effective approach to environmental governance.

2.3.1.2 Theory of sustainable development

The concept of sustainable development was first proposed at the 1972 Conference on the Human Environment. The theory emphasizes that human economic production activities should consider both the present and future, and adhere to scientific and sustainable development. Carbon emission trading, as a market-oriented environmental regulation, is also developed within the context of sustainable development (Shi et al., 2019).

Enterprises are key players in social and economic development. The goal of enterprise development is to maximize the company's interests, but blindly pursuing economic benefits comes at the cost of destroying the ecological environment. In recent years, businesses have faced growing constraints due to environmental regulations. The concept of sustainable development requires enterprises to shift their perspective, find ways to comply with environmental regulations, and strike a balance between environmental protection and business profitability.

Under the theory of sustainable development, the implementation of a carbon emission trading system requires enterprises to consider both the current economy and future benefits.

2.3.1.3 Relation between environment regulation and enterprise financial performance

With the exception of a few social enterprises, most enterprises that dominate the market and prioritize commercial profit are not inclined to join the carbon emission permit trading system, even with a moral appeal. Only economic benefits can increase the attention of business owners and entrepreneurs to an environmental regulation, whether they are based on market incentives or direct government requirements.

There are two fundamental hypotheses regarding the relationship between environmental regulation and the financial performance of businesses.

According to neoclassical economic theory, when a company has already made the optimal allocation of resources based on market conditions, environmental protection regulations will inevitably lead to a sacrifice in the company's economic profits. Any rise in investment and management expenses for environmental protection, including both direct and indirect costs, will to some extent impede the achievement of the economic interests of the enterprise.

However, in 1995, Porter rejected the traditional neoclassical economic theory and proposed the "Porter hypothesis," which suggests that sensible environmental regulations can stimulate enterprise creativity and enhance competitiveness. The costs of innovation can be offset by product and process improvements, and long-term economic benefits can result from it. (Porter, 1995) Several studies support this view. Lanoie (2011) conducted empirical research using observational data from seven OECD countries, including the United States and Canada. The study found that environmental regulation policies had an impact on the relative prices of environmental production factors to some extent. Additionally, it concluded that incentive-based environmental regulation was more effective than command-based environmental regulation in stimulating enterprise innovation. Woo-yong and Bongsuk (2014) focused on South Korea's manufacturing industry in their research. They concluded that environmental regulation policies could stimulate R&D investment growth. The results demonstrated significant positive effects on the productivity growth rate of all factors.

2.3.2 Carbon emission permit trading system

In response to the existing air pollution problems, governments around the world are implementing stricter environmental policies.

The fundamental concept of the carbon emission permit trading system is that each covered entity is allocated a specific emission limit, which can be met through the receipt of emission allowances, offsetting activities, market purchases, or any combination of these options. The total emissions of all entities are subject to a "permit." The permit can be exchanged within a permit-and-trade system, which establishes a specific limit on carbon emissions in a particular jurisdiction while allocating emissions allowances to participating entities in a quantity that aligns with the permit (Carmody, 2019).

Carbon emission permits are a form of environmental regulation that relies on market incentives, in contrast to the previous command-based environmental regulations that established standards and regulations, including emission limits. Some scholars argue that carbon emission trading can incentivize enterprises to enhance technological innovation and achieve economic gains, while also facilitating the long-term adjustment of an economy's industrial structure (Fan, 2018).

As an environmental policy with market incentives, scholars generally believe that the operating costs of enterprises will increase in the short term due to carbon emission trading. However, the long-term relationship of carbon emission trading with technological innovation activities or the financial performance of enterprises has not been determined. Karin et al. (2011) examined the industry reform in Sweden's pulp and paper industry over the last decade and concluded that the EU carbon emission trading scheme has facilitated industry reform and expanded business income prospects. Li et al. (2021) argue that carbon emission trading can substantially enhance a company's short-term business performance. They also suggest that the negative impact on long-term performance can be mitigated by enhancing the liquidity of the carbon market.

Furthermore, what is commendable is that, in comparison to traditional government policies that directly impose energy reduction requirements on enterprises, carbon emissions trading is a market-driven environmental regulation policy. It brings the external environmental costs caused by carbon dioxide emissions into the enterprise and reduces pollutant emissions by internalizing costs. This aligns with the growing environmental protection standards set by major countries and political bodies worldwide in recent years. This aligns with the growing demand for stricter environmental protection regulations from major countries and political entities in recent years.

2.3.3 The impact of carbon emission trading on enterprise decision making.

The emergence of carbon emission trading means that the external costs of enterprises can be transferred. For example, negative externalities can be mitigated by purchasing additional carbon emission permits, while positive externalities can be leveraged to reap benefits through energy conservation and emission reduction by selling the surplus of carbon emission permits. The expansion of the scope of carbon emission trading is expected to have a significant impact on the energy conservation and emission reduction behavior of enterprises. Since carbon emission permits are monetized, this implies that there will be a price in the carbon permit market for any potential carbon emissions by an enterprise.

As a result, when enterprises entered the carbon emission rights market, the cost per unit of energy consumption for enterprises changed significantly. A new approach must be used to analyze costs in order to conduct cost accounting analysis accurately and efficiently. In cost management, in addition to accounting costs, economic costs are also important indicators for guiding decision-making. Accounting costs are the explicit and tangible costs that are recorded in the company's books by the accounting department. Economic cost refers to the total expenses incurred in achieving a goal. When a resource is used for one purpose, it cannot be used for another purpose, potentially resulting in a loss. Therefore, the greatest benefit a resource can gain from being used elsewhere is its opportunity cost. The significance of economic cost lies in its ability to demonstrate the trade-offs made by an entity in its economic activities. Focusing solely on accounting costs may result in overlooking other uses of a resource when making a decision. Economic cost consists of accounting cost and opportunity cost.

$$Economic\ Cost = Accounting\ Cost + Opportunity\ Cost \tag{2-1}$$

After an enterprise joins the carbon emission permit trading system, when it consumes resources for a specific purpose, it implies that the enterprise forfeits a carbon emission permit equivalent to the carbon emissions produced during the resource's production for that purpose.

Suppose an organization consumes n units of energy during a specific period while utilizing the air conditioning system after participating in the carbon emission permit trading system. Let's assume the price of energy is A per unit. Each unit of energy produces "b" units of carbon emissions, and each unit of carbon permit is traded at a price of "B." There are two possibilities:

1The enterprise needs to purchase additional carbon emission rights because its allocated carbon emission permit has already been used up. In order to obtain n units of energy, the enterprise needs to pay an accounting cost of nA directly to the energy supplier and nbB to the seller of carbon emission permits. In this scenario, there are no carbon emission rights to sell, so the opportunity cost is 0.

$$Economic\ Cost_1 = nA + nbB \tag{2-2}$$

2) The Enterprise still has unused carbon emission permits. This means that enterprises do not need to buy additional carbon emission permits. But consuming carbon emission permits means they cannot be sold in the trading market. In this scenario, the accounting cost is nA, paid directly to the energy supplier. The opportunity cost of forgoing the sale of equivalent carbon emission rights is nbB.

$$Economic\ Cost_2 = nA + nbB \tag{2-3}$$

If the enterprise does not participate in the carbon emission permit market. It has no carbon emission permits to sell and does not need to purchase carbon emission permits for its excess emissions. Thus, the accounting cost is represented by nA, which is paid directly to the energy producer. The opportunity cost is 0.

$$Economic\ Cost_0 = nA \tag{2-4}$$

By comparing the three, two conclusions can be drawn:

1) When enterprises join the carbon emission trading system, they will incur additional economic costs compared to their previous expenses.

2) When participating in the carbon emission system, the economic cost remains constant whether the carbon emission permits have been exhausted or there is still a balance of available permits.

It should be noted that some businesses, especially small and medium-sized enterprises, have not adapted to the changes after entering the carbon emission permit trading market.

Currently, most companies classify the total purchase or sale of carbon emission permits as non-operating expenses or income. This practice separates the trading of carbon emission permits from the company's daily operations, which prevents the company from aligning its behavior with the financial implications of carbon emission permits. When an air conditioning system operates improperly and is not maintained, it leads to higher energy consumption. Consequently, the company experiences losses in two ways: it must cover additional energy costs and buy extra carbon emission permits. If an enterprise considers its total carbon emissions permit as a single cost/income item, it cannot identify the specific source of this cost/income and, as a result, cannot manage it effectively. The concept of "relevant cost" is utilized to assign the cost of additional carbon emission permits to the equipment responsible for generating the carbon emissions.

2.4 Genetic Algorithm (GA)

Genetic algorithm (GA) is a general framework that can solve optimization problems with a relatively low cost. it is a global search algorithm for optimization.

2.4.1 The theoretical basis of genetic algorithm

The concept of genetic algorithms is derived from the process of "evolution," a well-known principle in biology. Evolution is a phenomenon in which organisms gradually adapt to their environment and improve their ability to survive. Creatures evolve within populations. Individuals in a population have varying capacities to adapt to the environment, and this capacity is referred to as fitness. Darwin's theory of natural selection seeks to explain the mechanism of "inheritance" in evolution. It suggests that genes may be exchanged between organisms for various reasons, and during this exchange, genes may undergo mutations. These exchanged and mutated genes will be passed on to the next generation. New genes can lead to various adaptations to the environment. Eventually, there will be an increase in genes that enable individuals to adapt to the environment and a decrease in genes that hinder their survival. Through the process of natural selection, the population will gradually evolve to better adapt to its environment.

Heredity and evolution have the following characteristics:

1) All genetic information of an organism is contained in chromosomes, which determine the characteristics of the organism.

2) Chromosomes consist of a regular arrangement of genes.

3) Organisms reproduce through the process of genetic replication.

4) Crossover or mutation between homologous chromosomes can lead to the emergence of new species and traits.

5) Genes that are more suited to the environment are more likely to be passed on to the next generation than genes that are less well-adapted.

The use of genetic algorithms to solve similar optimization problems has a long history. Professor John Holland first introduced the concept of genetic algorithms in 1975. Through numerous experiments, his students are attempting to apply the concept of genetic algorithms to solve optimization problems. The goal is to develop an adaptive probabilistic optimization technology that is based on biological genetic and evolutionary mechanisms, and is suitable for optimizing complex systems.

2.4.2 The advantages of genetic algorithm

The genetic algorithm (GA) was selected as the optimization tool for this study because of the following advantages:

1) Genetic algorithms have strong versatility and wide-ranging applications, enabling them to quickly obtain optimal solutions for complex problems. The selection, crossover, and mutation operators are crucial for simulating the genetic evolution process of biological chromosomes. They are also convenient for solving various optimization problems in fields such as production scheduling, image processing, and function optimization.

2) A genetic algorithm is a global search optimization algorithm that is resistant to getting trapped in local optimal solutions. In the process of solving a genetic algorithm, the search begins with a population consisting of multiple chromosomes. In other words, the search begins from multiple points simultaneously instead of starting from a single point. In addition, other heuristic algorithms that search from a single point may easily converge to a local optimal solution when the search space does not have a single peak. However, a genetic algorithm can find the optimal solution in cases where the search space has multiple peaks, thus avoiding this situation. It can quickly find the optimal solution in both single-peak and multi-peak distributions. Even if the fitness function of the genetic algorithm is irregular and discontinuous, it can still find the global optimal solution.

3) Most objective functions in practical problems are either difficult to derive or do not have derivatives. When using a genetic algorithm, the search for the optimal solution is based on a fitness function, and there is no need to differentiate the objective function. The fitness function serves as the foundation for

searching the optimal solution. It is unaffected by the continuous differentiability of the function, allowing for flexibility in setting the function's scope.

4) The three operators of a genetic algorithm, namely selection, crossover, and mutation, are implemented using random probabilities rather than deterministic rules. Random probability changes are utilized to continually adjust the search direction, aiming to generate more adaptable individuals. The genetic algorithm, as a probabilistic method, provides greater flexibility in finding the optimal solution, with the characteristics of variables themselves having minimal impact on the search process.

2.4.3 The process of genetic algorithm

The application of a genetic algorithm involves the following steps.

1) Encoding and decoding

When using genetic algorithms, the initial step involves encoding feasible solutions into symbolic strings. Symbol strings are similar to the chromosomes of natural organisms. The genetic algorithm is not optimized for single genes, but for entire chromosomes or individuals. The quality of the code affects the selection, crossover, and mutation operations, thus influencing the optimal solution. Therefore, it is essential to adhere to the principles of non-redundancy, completeness, and soundness when designing coding strategies. Decoding is the process of converting the string back to its original form.

2) Identify the initial population

The evolution of organisms is driven by population dynamics. The initial population consists of the encoded individuals, and these individuals constitute the initial solution for the genetic algorithm. The initial population size will impact the calculation speed and the quality of the optimal solution in the genetic algorithm. The initial population size is usually set between 30 and 200 in practical applications. If the population is too small, the genetic algorithm tends to converge prematurely and settle for local optima. Conversely, if the population is too large, the computational burden of using the genetic algorithm will increase, leading to longer solving times.

3) Identify the fitness function.

The fitness function is utilized to assess the quality of chromosomes. The fitness function is closely related to the objective function. When the objective function is non-negative, it can be directly used as a fitness function. When the objective function produces a negative value, it cannot be directly used as the fitness function because fitness values cannot be negative. However, the objective function can be transformed into a positive number through a transformation process and then used as the fitness function. The higher the fitness level, the better the quality of the population, the greater the likelihood of inheritance to the next generation, and the closer the solution is to the optimal outcome.

4) Selection

The selection is determined by evaluating the size of the fitness. The fitness function is used to evaluate the fitness of individuals, and those with high fitness levels are selected for the next generation of the population. As the population continues to evolve, more favorable genes are passed on to the next generation, leading to offspring with greater fitness. The solution obtained at this stage is closer to the optimal solution.

5) Crossover

The crossover process involves selecting crossover points on chromosomes based on a specified probability of crossover. It then exchanges gene fragments between two chromosomes at the crossover points to create new chromosomes. A new population will be established. The chromosomes formed after the crossing operation will show increased fitness and improved genetic composition. As a result, the offspring obtained after each iteration will be closer to the optimal solution of the objective function. The process of crossover involves using the parent generation as the starting point to form a new chromosome by combining the characteristics of the parent chromosomes. This process can be viewed as a method for uncovering an optimal solution that is currently unknown, based on the magnitude of the known optimal solution.

6) Mutation

A genetic algorithm performs mutation after the selection and crossover operations. The mutation operation involves exchanging a small portion of a chromosome with a low probability of a few alleles. Mutation manipulation can increase chromosome diversity and effectively prevent the loss of genetic information during the process of selection and crossbreeding.

2.5 Conclusion

In this chapter, the relevant fields and theories involved in this study are explained, laying a solid foundation for the creation of the following model. Firstly, the text introduces the relationship between the coil and the entire air conditioning system, as well as the characteristics of coil failure. Secondly, two preventive maintenance strategies, along with their technical support requirements, and the rationale for selecting TPM are introduced. Thirdly, the theoretical foundation of the carbon emission permit trading system and the significance of integrating carbon emission permits into enterprise decision-making were introduced. Finally, the concept of genetic algorithms, operators, and the basic execution process of genetic algorithms are introduced.

3. Model design

3.1 Optimization factors of the model

1) Performance Factor

A coil has practical utility. The performance of a coil determines its ability to meet the needs of users, which is its functional value. Therefore, the performance factor of the coil must be taken into consideration.

2) Economic Factors

Under market economic conditions, owners must use currency to exchange energy, materials, and labor in the market, as they are usually unable to obtain the energy needed to operate the air conditioning system and the materials and labor required to maintain it. The currency paid by the owners is the cost of the activity. Therefore, the costs associated with operating and maintaining coils must be taken into account.

3) Environmental Factors

In the preceding introduction, pertinent theories of carbon emission permit trading were discussed. It was emphasized that all market entities' activities have externalities, and thus, the impact of their activities on the external environment should be taken into consideration.

In addition to conducting background analysis, this study also integrates existing research on maintenance strategies. All relevant research includes performance and economic factors. Although the environmental factor is not always considered, it is still one of the most significant factors. Therefore, the three factors mentioned above have a certain universality. For example, Santos, Ferreira, and Flintsch (2017) conducted research on pavement maintenance strategies. They used life cycle cost (LCC) as an economic factor, government requirements (established by the Virginia Department of Transportation) on pavement as a performance factor, and the findings of life cycle analysis (LCA) as an environmental factor. Sharifa and Hammad (2019) also take into account life cycle cost (LCC) and life cycle assessment (LCA) when researching optimized building renovation plans. This includes lighting, ventilation, HVAC systems, and ensuring that all contingency plans already meet the owner's minimum performance requirements. Wu et al. (2021) conducted a study on optimizing predictive maintenance scheduling. The study examined the overall cost of the HVAC system as an economic factor, the health of the equipment as a performance factor, and energy consumption as an environmental factor. Sánchez-Barroso and Sanz-Calcedo (2019) conducted a study on predictive maintenance strategies for hospital HVAC systems. They analyzed the failure density of the HVAC system as an indicator of its performance and compared the inspection costs to the maintenance costs. No environmental factors were manipulated in the study, although the research indicated that the new strategy is effective in reducing waste. However, a specific environmental factor was not introduced.

3.2 Connection between coil fouling and factors

The coils in the air conditioner will accumulate fouling over time, leading to a decrease in the air conditioner's thermal conductivity. As a result, the air conditioner's energy consumption increases, while its cooling effect decreases. This highlights the importance of coil maintenance. Restoring the coil's thermal conductivity also results in additional maintenance costs. Therefore, a practical maintenance strategy is required to balance the impact of coil clogging with the cost of coil repair. In Chapter 3, it is noted that carbon emissions can be monetized based on the price of the corresponding carbon emission permit. Therefore, in this study, the carbon emissions from energy consumption, which have been used to represent environmental factors, are replaced by the price of carbon emission permits, which can be measured in currency, and are combined into economic factors. The economic factor in this study includes the direct cost of energy consumption and opportunity cost. Therefore, the costs examined in this study are economic costs rather than accounting costs. Potential losses in the carbon emission permit market resulting from the increase in carbon emissions are also considered.

In addition to the economic factor, maintenance strategies also need to consider the coil's performance. The performance of a heat exchanger is reflected in its heat transfer efficiency. Even if the goal of minimizing costs is not achieved, maintenance is still necessary when the cooling performance of the air conditioner has been reduced to a certain extent, in order to ensure its continued performance.

3.3 Conclusion

In summary, the model aims to develop a time-based preventive maintenance strategy for the heat exchange coil in the air conditioning system that minimizes economic costs while ensuring the performance of the air conditioning system. Environmental factors have been integrated into economic considerations.

4. Model Creation

4.1 Description the model question

The Remain Service Life (RSL) of the coil is divided into equal parts with a consistent time period, and each equal part is considered a node for applying maintenance activities. For example, a coil with a rated service life (RSL) of 2 years can be divided into 24 periods in terms of months. If we consider the start of each period as a time node for maintenance activity, there are 24 nodes available for performing maintenance. In each period, there is an equal number of coil maintenance activities to choose from, including the option of "no maintenance." Various maintenance activities during each period will lead to varying total costs. The objective of the optimization model is to determine the most cost-effective maintenance activity to perform during specific periods, minimizing the net present value (NPV) of the total cost while adhering to performance constraints.

4.2 Parameter determination

For ease of reading, the parameters used to construct the model below are listed in advance.

Table 4-1: Parameters of optimization model

Symbol of Parameter	Definition
X_{ti}	Decision variable
t	Time period
i	serial number of Maintenance activity
d	Discount rate at period *t*
E_{ti}	Energy consumption of activity *i* at period *t*
EC	Operation cost factor
MC_i	maintenance cost of activity *i*
FOH_{ti}	Failure operation hour if activity i is apply at *t*
H_t	Total running hour of period *t*
θ_{min}	The allowed rate of minimum failure operation hour
Matrix E	Energy consumption matrix
Matrix A	FOH matrix
$t^{'}$	Last maintenance period of *t*
v	The number of fouling rate values

EC: Operation cost factor (EC) consists of energy price and carbon emission permit price. It is a fixed value. FOH_{ti} represents the number of hours that operation temperature is not meet the requirement in the period t after performing maintenance activity. t' means the latest period that maintenance activity has been applied before period *t*.

4.3 Preliminary modeling of objective function

An equal fraction of RSL is taken as a period *t*. In each period *t*, the coil may have *i* possible maintenance activities. At the beginning of each period *t*, it can be chosen to perform only one of *i* maintenance activities. a (0,1) type decision variable X_{ti} is used to indicate whether the maintenance activity *i* is applied in period *t*. $X_{ti} = 0$. if is not applied, and $X_{ti} = 1$ is applied.

From the above description of the problem, a basic objective function can be constructed.

$$Minimize\ TC = \sum_{t=1}^{RSL} \sum_{i=1}^{\mathrm{I}} \frac{1}{(1+d)^{t-1}} \cdot C_{ti} \cdot X_{ti} \tag{4-1}$$

The decision variable X_{ti} is the variable that controls whether the maintenance activity *i* is performed in period *t*. *t* represents a one-month period of Remaining Service Life (RSL). It is important that the maintenance activity should occur at the beginning of the period. *i* represents all the maintenance actions that can be performed at the beginning of period *t*. *d* represents the discount rate at period *t*. C_{ti} represents the costs occur at month *t* when activity *i* has been applied.

In the whole RSL, the number of decision variable X_{ti} is t^i.

In addition, it should be noted that a coil may have multiple potential failure types, such as fouling and abrasion. It is also possible that different levels of maintenance activities will have different effects on performance recovery. As a result, multiple maintenance activities may exist on the coil at the same time. In these circumstances, I should represent a portfolio rather than different maintenance activities that may occur in each t. For example, a coil has 2 potential faults, A and B. Therefore, there should be 4 maintenance portfolios:

I_1: nothing needs to be maintained;

I_2: failure A needs to be maintained;

I_3: failure B needs to be maintained;

I_4: both failure A and B need to be maintained.

4.4 Model Hypothesis

According to the literature analysis, some assumptions can be made about the model. Thus, the solution of the model is simplified in a reasonable level. The establishment of this model needs to follow several assumptions:

1) Assumption 1: Except the coil, the rest of the air conditioning system is well maintained without affecting the change of energy consumption of the system;
2) Hypothesis 2: Coil performance can be restored to the optimal state through maintenance behavior;
3) Hypothesis 3: the change in energy consumption of the air conditioner operation is only affected by coil fouling;
4) Hypothesis 4: The degree of fouling in the coil has a maximum level. When the coil blockage reaches its maximum level, it will remain at that level until maintenance is performed.
5) Hypothesis 5: The air conditioner user requires the air conditioner to keep the indoor temperature stable at a certain temperature. Thus, the external operating conditions of the coil itself are stable. Therefore, the fouling rate of coil changes with time, and the fouling rate is only affected by time changes. The influence of external environment on the rate of fouling change can be ignored in this study.
6) Hypothesis 6: The weather change outside the building is a yearly cycle.

Hypothesis 1 is derived from the objectives of the optimization model. Since the focus of optimization is the coil, the remaining components of the air conditioning system should be kept constant as control variables. This assumption makes it possible to optimize the coil, a subsystem of the air conditioning system, by considering the overall relevant cost and energy consumption of the air conditioning system. Hypothesis 2 is based on the literature review. After two years of not being maintained, the performance of coils can still be restored to their original design standard following maintenance activities. Hypothesis 3 is formulated based on the literature review, which indicates that fouling has a significant impact on coil performance, while other factors have minimal influence and make a low contribution to maintenance behavior decisions. Therefore, these factors are disregarded in this study. Hypothesis 4 is based on the research results in the literature review, suggesting that the heat exchange capacity of the heat exchanger will not decrease indefinitely but will approach a certain value. Hypothesis 5 is based on a common behavior among air conditioner users. The need for maintaining a constant temperature is widely utilized in commercial buildings, industrial plants, laboratories, and other air conditioning settings. Hypothesis 6 is formulated to leverage energy simulation software. The simulation software used in this study, EnergyPlus, can only provide weather data for a one-year period.

Based on hypotheses 2, 3, 4, and 5, it can be concluded that the curve of coil fouling rate without maintenance increases monotonically before reaching the maximum value, and remains at the maximum value until the next maintenance reduces the fouling rate to zero.

4.5 Model Adjustment

4.5.1 Preliminary adjustment

i represents all the maintenance actions that can be performed at the beginning of period t. In this study, i represents 2 activities: “maintenance” and “no maintenance.” Therefore $i = 1, 2$. This is because the coil performance can be restored to the best situation only by cleaning.

Consuetudinary, the annual discount rate is 5%. Since t in this study represents a one-month period, the value of d in this paper is 5%/12.

4.5.2 Cost analysis

It is important to consider the total cost of the coil, which includes both maintenance and operation costs, when the study focuses on coil issues. In practice, it is challenging to allocate the operational cost of the coil, a smaller component of the air conditioning system, in accounting. Therefore, in this study, the variable control method has been utilized to ensure that the variation in air conditioning system operation costs reflects the variation in coil operating costs. Based on Hypothesis 1, it was assumed that all the air conditioning parts, except the coil, have been properly maintained. This means that the performance of the other parts, except the coil, remains unchanged. Under these conditions, when the performance of the entire air conditioning system changes, it can be approximately attributed to the change in the coil. Therefore, optimizing the overall operation cost of the air conditioning system can also help achieve the goal. This study refers to the combined cost of coil maintenance and the overall air conditioning system operation as the relevant cost (RC) of the coil.

Therefore, the modified expression of the target equation is:

$$Minimize\ TRC = \sum_{t=1}^{RSL} \sum_{i=1}^{2} \frac{1}{(1+d)^{t-1}} \cdot \mathrm{R}C_{ti} \cdot X_{ti} \tag{4-2}$$

TRC, which is the sum of the net present value of the relevant cost (RC) for each period *t*. $\mathrm{R}C_{ti}$ is the combination of the air conditioning system operation cost and coil maintenance cost in *t* when activity *i* has been applied.

For a certain period *t*, the formula of RC is:

$$\begin{aligned} RC_{ti} &= \sum_{i=1}^{2} (EC \cdot E_{ti} + MC_i) \cdot X_{ti} \\ &= (EC \cdot E_{t1} + 0) \cdot X_{t1} + (EC \cdot E_{t2} + MC_2) \cdot X_{t2} \end{aligned} \tag{4-3}$$

EC is the operating cost factor, which is composed of energy price (accounting cost) and carbon emission permit price (opportunity cost), and it is constant for any *t* and *i*. E_{ti} represents the energy consumption in period *t*. E_{t1} represents the energy consumption when maintenance is not applied; E_{t2} represents the energy consumption when maintenance is applied. MC_i represents the maintenance related cost.

X_{ti} is the control variable that decide whether maintenance activity is applied or not. According to the literature review, the coil performance can be restored to the optimal after cleaning. Therefore, there is only one maintenance method, namely cleaning. However, for the purpose of mathematical modeling, this study sets two maintenance activities for each *t*. *i* represents the serial number maintenance activities. *i* = 1, represents that activity 1*: no* cleaning; *i* = 2, represents that activity 2: do the cleaning. $X_{ti} = 0$ means activity *i* is not applied; $X_{ti} = 1$means activity *i* is applied. To be specific, if maintenance activity is not applied, $X_{t1} = 1,\ X_{t2} = 0$; if maintenance activity is applied, $X_{t1} = 0,\ X_{t2} = 1$. Since not performing maintenance (i= 1) and performing maintenance (i=2) are regarded as two activities that cannot happen at the same time, thus $X_{t1} + X_{t2} = 1$.

To each period *t*, there are only two possible valued for MC_i: if no maintenance is applied, namely MC_1=0; If maintenance is applied, MC_2 is a given fixed value.

In conclusion, the final target equation is:

$$Minimize\ TRC = \sum_{t=1}^{RSL} \sum_{i=1}^{2} \frac{1}{(1+d)^{t-1}} (EC \cdot E_{ti} + MC_i)\, X_{ti} \tag{4-4}$$

In the expression of TRC, EC and d are fixed values; X_{ti} is the decision variable; the value of MC_i is known. Only the value of E_{ti} has not been determined. Obtaining the value of E_{ti} is the key to solving the objective equation.

4.5.3 Determination of the Value of Energy Consumption

The energy consumption (E_{ti}) is different under different fouling conditions for a certain period *t* due to the fouling condition of the coil changes.

According to hypotheses 3 and 4, the energy consumption of air conditioning operations is only affected by weather factors and the degree of coil fouling. The weather of air conditioning operation is a one-year cycle, that is, for the same period of each year, the energy consumption will be the same if the coil is not fouling.

However, the fouling of the coil will affect its thermal conductivity. The fouling rate of the coil will increase monotonically according to a certain rule until the fouling rate reaches the maximum. According to hypothesis 2, after the maintenance activity, the fouling rate will return to 0%, and based on hypothesis 5, the coil will repeat the fouling process again until the next maintenance activity resets the fouling rate. Since the unit of time in this study is one month, value of the fouling rate is discrete rather than continuous. Because there is an upper limit to the fouling rate, and the value of the fouling rate is discrete and monotonically increasing. Therefore, the number of fouling rate values (v) can be known.

If the change curve of the fouling is known, by inputting the value of the fouling rate into the simulation software, the energy consumption of each month in a year under different fouling rates can be obtained in advance. Based on this data, the optimization model can develop a time-based preventive maintenance strategy. A matrix (Matrix *E*) can be formed by obtaining the energy consumption values for each month in a year in different fouling rates.

Each column in the matrix corresponds to a period in a year; each column corresponds to a value of the fouling rate. The number of values of the fouling rate (v) determines the number of rows. Since this study takes one month as a period, the number of columns in the matrix is 12. The matrix *E* is shown below:

$$E=\begin{matrix} e_1^1 & e_1^2 & e_1^3 & e_1^4 & e_1^5 & e_1^6 & e_1^7 & e_1^8 & e_1^9 & e_1^{10} & e_1^{11} & e_1^{12} \\ e_2^1 & e_2^2 & e_2^3 & e_2^4 & e_2^5 & e_2^6 & e_2^7 & e_2^8 & e_2^9 & e_2^{10} & e_2^{11} & e_2^{12} \\ e_3^1 & e_3^2 & e_3^3 & e_3^4 & e_3^5 & e_3^6 & e_3^7 & e_3^8 & e_3^9 & e_3^{10} & e_3^{11} & e_3^{12} \\ e_4^1 & e_4^2 & e_4^3 & e_4^4 & e_4^5 & e_4^6 & e_4^7 & e_4^8 & e_4^9 & e_4^{10} & e_4^{11} & e_4^{12} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots & \vdots \quad \vdots \\ e_v^1 & e_v^2 & e_v^3 & e_v^4 & e_v^5 & e_v^6 & e_v^7 & e_v^8 & e_v^9 & e_v^{10} & e_v^{11} & e_v^{12} \end{matrix} \tag{4-5}$$

The value of E_{ti} selects elements from the matrix *E* according to the change of *t* and *i*. For any E_{ti}, the column of the element is the remainder of *t* divided by 12. To select row for an element, there are three situations to consider.

1) apply maintenance activity (i = 2). As a result of the maintenance activity, the performance reverts to the optimal, thus first row should be taken.
2) not apply maintenance activity (i =1) and the fouling rate reaches its maximum $(if\ t-t'\geq v)$. There is no maintenance activity, thus the row number is moved down based on the number of periods since the last maintenance period t'.
3) not apply maintenance activity (i = 1) and the fouling rate is not at its maximum ($t-t'<v$); Since the fouling has reached its maximum, take the last row.

To sum up, the formula for energy consumption $E_{t,1}$ is:

$$\begin{cases} E_{t,1}=e_{1+t-t'}^{(t)\%12}(if\ t-t'<v) \\ E_{t,1}=e_{v}^{(t)\%12}(if\ t-t'\geq v) \\ E_{t,2}=e_{1}^{(t)\%12} \end{cases} \tag{4-6}$$

4.5.4 Constraint

4.5.4.1 Constraint of maintenance activity

Since the two preset maintenance activities represent maintenance and non-maintenance, they are mutually exclusive, thus there is one and only one maintenance behavior can be performed in each period *t*. The mathematical expression for this constraint is:

$$\sum_{i=1}^{2} X_{ti} = 1, X_{ti} \in [0,1], \forall t = 1, 2, \dots, RSL \tag{4-7}$$

4.5.4.2 *Constraint of air conditioner performance*

In addition to the cost requirements, the performance requirements of air conditioner also need to be reflected in the model. Because the coil has only the function of heat exchange, the indoor temperature is taken as the factor representing the performance of the coil. In this study, the heat exchange performance requirement is reflected in the number of hours that operation temperature is not meet the requirement (FOH_{ti}) and there is no maximum requirement for this requirement, only a certain performance level needed to be reached. Thus, it doesn't appear as another objective function, but as a constraint. The requirement for performance is that FOH_{ti} compares to total running hour of period *t* (H_t) should be less than a specific ratio. That is:

$$\frac{FOH_{ti}}{H_t} < \theta_{min} \tag{4-8}$$

The calculation of FOH_{ti} follows the same methodology as energy consumption, because the change in FOH_{ti} is also caused by the fouling of the coil. The value matrix of FOH_{ti} and mathematical expression of the calculation of FOH_{ti} are：

$$A=\begin{matrix} a_1^1 & a_1^2 & a_1^3 & a_1^4 & a_1^5 & a_1^6 & a_1^7 & a_1^8 & a_1^9 & a_1^{10} & a_1^{11} & a_1^{12} \\ a_2^1 & a_2^2 & a_2^3 & a_2^4 & a_2^5 & a_2^6 & a_2^7 & a_2^8 & a_2^9 & a_2^{10} & a_2^{11} & a_2^{12} \\ a_3^1 & a_3^2 & a_3^3 & a_3^4 & a_3^5 & a_3^6 & a_3^7 & a_3^8 & a_3^9 & a_3^{10} & a_3^{11} & a_3^{12} \\ a_4^1 & a_4^2 & a_4^3 & a_4^4 & a_4^5 & a_4^6 & a_4^7 & a_4^8 & a_4^9 & a_4^{10} & a_4^{11} & a_4^{12} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots & \vdots \; \vdots \\ a_v^1 & a_v^2 & a_v^3 & a_v^4 & a_v^5 & a_v^6 & a_v^7 & a_v^8 & a_v^9 & a_v^{10} & a_v^{11} & a_v^{12} \end{matrix} \tag{4-9}$$

$$\begin{cases} FOH_{t,1} = a_{t-t'+1}^{(t)\%12} (if\ t - t' < v) \\ FOH_{t,1} = a_v^{(t)\%12} (if\ t - t' \geq v) \\ FOH_{n,2} = a_1^{(n)\%12} \end{cases} \tag{4-10}$$

4.5.5 *Final optimization model*

The complete optimization model is as follows:

Objective function:

$$Minimize\ TRC = \sum_{t=1}^{RSL} \sum_{i=1}^{2} \frac{1}{(1+d)^{t-1}} (EC \cdot E_{ti} + MC_i) X_{ti} \tag{4-11}$$

$$\begin{cases} E_{t,1} = e_{t-t'+1}^{(t)\%12} (if\ t - t' < v) \\ E_{t,1} = e_v^{(t)\%12} (if\ t - t' \geq v) \\ E_{t,2} = e_1^{(t)\%12} \end{cases} \tag{4-12}$$

$$\begin{cases} MC_1 = 0 \\ MC_2 = MRC + MCEF \end{cases} \tag{4-13}$$

$$E=\begin{matrix} e_1^1 & e_1^2 & e_1^3 & e_1^4 & e_1^5 & e_1^6 & e_1^7 & e_1^8 & e_1^9 & e_1^{10} & e_1^{11} & e_1^{12} \\ e_2^1 & e_2^2 & e_2^3 & e_2^4 & e_2^5 & e_2^6 & e_2^7 & e_2^8 & e_2^9 & e_2^{10} & e_2^{11} & e_2^{12} \\ e_3^1 & e_3^2 & e_3^3 & e_3^4 & e_3^5 & e_3^6 & e_3^7 & e_3^8 & e_3^9 & e_3^{10} & e_3^{11} & e_3^{12} \\ e_4^1 & e_4^2 & e_4^3 & e_4^4 & e_4^5 & e_4^6 & e_4^7 & e_4^8 & e_4^9 & e_4^{10} & e_4^{11} & e_4^{12} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots & \vdots \; \vdots \\ e_v^1 & e_v^2 & e_v^3 & e_v^4 & e_v^5 & e_v^6 & e_v^7 & e_v^8 & e_v^9 & e_v^{10} & e_v^{11} & e_v^{12} \end{matrix} \tag{4-14}$$

Constraint (1):

$$\sum_{i=1}^{2} X_{ti} = 1, X_{ti} \in [0,1], \forall t = 1, 2, \dots, RSL \tag{4-15}$$

Constraint (2):

$$\frac{FOH_{ti}}{H_t} < \theta_{min} \tag{4-16}$$

$$\begin{cases} FOH_{t,1} = a_{t-t'+1}^{(t)\%12}(if\ t-t' < v) \\ FOH_{t,1} = a_{v}^{(t)\%12}(if\ t-t' \geq v) \\ \qquad FOH_{n,2} = a_{1}^{(n)\%12} \end{cases} \tag{4-17}$$

$$A=\begin{matrix} a_1^1 & a_1^2 & a_1^3 & a_1^4 & a_1^5 & a_1^6 & a_1^7 & a_1^8 & a_1^9 & a_1^{10} & a_1^{11} & a_1^{12} \\ a_2^1 & a_2^2 & a_2^3 & a_2^4 & a_2^5 & a_2^6 & a_2^7 & a_2^8 & a_2^9 & a_2^{10} & a_2^{11} & a_2^{12} \\ a_3^1 & a_3^2 & a_3^3 & a_3^4 & a_3^5 & a_3^6 & a_3^7 & a_3^8 & a_3^9 & a_3^{10} & a_3^{11} & a_3^{12} \\ a_4^1 & a_4^2 & a_4^3 & a_4^4 & a_4^5 & a_4^6 & a_4^7 & a_4^8 & a_4^9 & a_4^{10} & a_4^{11} & a_4^{12} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots & \vdots \\ a_v^1 & a_v^2 & a_v^3 & a_v^4 & a_v^5 & a_v^6 & a_v^7 & a_v^8 & a_v^9 & a_v^{10} & a_v^{11} & a_v^{12} \end{matrix} \tag{4-18}$$

4.6 Genetic Algorithm design and solving process

4.6.1 Design of genetic algorithm

Through the introduction of the objective function above, it can be known that this is an optimization with a single objective and multiple constraints. The dimension of the solution corresponds to the number of periods, *t*. For example, if Remain Service Life has 12 periods, the solution of the objective function has 12 dimensions. It is means that there are 2^{12} possible solutions. The use of accurate algorithm to such a question will involve a large amount of computation. To solve a problem with a large number of possible solutions, the modern heuristic algorithm is the most widely used algorithm at present. Genetic algorithm is one of the modern heuristic algorithms, which can solve the objective function. In this study, the application of genetic algorithm was supported to by Python.

In order to achieve the solution, it is necessary to design the genetic algorithm in a reasonable way, so that it can better integrate into the problem that needs to be solved, so as to obtain the optimal solution, or approximate optimal solution. The design of genetic algorithm requires to determine the operation parameters such as population size, crossover probability, mutation probability and termination conditions, and then determine the initial population, as well as the methods used in a series of steps including selection, crossover, mutation, and fitness evaluation.

1） Coding

Coding involves translating the actual optimization problem into a language that the computer can recognize. Coding is the initial step in all genetic algorithm problems. The decision variable is a binary variable, meaning it can only take on two possible values: 0 and 1, representing "no maintenance" and "maintenance" respectively. As a result, there is no need for complex encoding and decoding operations in this study. The value 0 indicates no maintenance, while the value 1 indicates maintenance.

2） Generate the initial population

The initial population is generated based on the subsequent population iteration. The initial population size usually ranges from 30 to 200. The initial population must be established correctly. If the population size is too small, it is easy to become trapped in a local optimum during the subsequent iteration. On the other hand, if the population size is too large, it will increase the difficulty of calculating fitness, reduce the overall calculation speed, expand the range of optimal solution search, decrease the efficiency of finding the optimal solution, and hinder premature convergence during the search for the optimal solution. There is no widely accepted standard for the size of the initial population chosen; it depends more on the user's experience. The population size used in this study was 100. Due to the large number of alternative solution sets, the initial population is selected randomly during initialization. An array consisting of only elements 0 and 1, with a length equal to RSL, will be randomly generated as the initial individual. This process continues until the desired population size is achieved.

3） Fitness Function

Fitness function is used to judge the quality of each chromosome. The objective function takes the minimum total relevant cost as the objective. Therefore, the smaller the objective function value is, the larger the fitness is. The inverse of the objective function is used as the fitness value.

Importantly, since there are only two maintenance activities has been used in this paper (maintenance/no maintenance), the construction of the objective function in Python is not modeled exactly according to the objective function in this paper, but is further simplified. The purpose of this is to improve the running speed of the genetic algorithm program. In the function programing, 0 of type (0,1) decision variable represents no maintenance activity in month t, and 1 represents applied maintenance activity in month t. This simplification reduces the number of target variables from 2t to t: the number of target variables is halved. In this paper, the objective function does not carry out this simplification. This is because the objective function in the article needs to show the derivation process of the objective function, and when the value of i is greater than 2, such simplification cannot be carried out. This is because the objective function designed in this study is only applicable to decision variables of type (0,1). A variable of type (0,1) can only indicate “yes” or “no”, there is no third possibility.

4） Selection operator

Selection is determined based on fitness size. Fitness is determined by a fitness function. Chromosomes with high fitness values are selected to replace those with low fitness in order to integrate them into the population. Chromosomes that carry excellent genes will be selected and passed on to the next generation, leading to increased fitness values and bringing us closer to the optimal solution through continuous iteration. The selection operator utilized in this study is known as the roulette algorithm. In this approach, the likelihood of an individual in a population being chosen is directly related to its fitness. It is necessary to calculate the sum and normalize the fitness values of all individuals in the population. A random number will be generated to select individuals corresponding to the randomly selected area.

5） Crossover operator

The crossover process in a genetic algorithm involves selecting crossover points based on a specified crossover probability. Gene fragments are then exchanged at these points to create new chromosomes, thereby generating a new population. The exchange method in this study involves swapping some elements of two adjacent chromosomes, such as chromosomes 0 and 1, and individuals 2 and 3. Each allele in each pair of individuals is exchanged at a certain percentage. The crossover rate used in this study was 50%. The specific implementation method involves generating a random number between 0 and 1 for each pair of alleles. If the random number is greater than 0.5, the exchange will take place.

6） Mutation operator

Genetic algorithm variation involves replacing genetic fragments of the previous generation of chromosomes with other genetic fragments, resulting in a chromosome sequence that is different from the parental chromosome. Mutation can cause the solution process to escape from the local optimal solution. The mutation operator utilized in this study is based on probability. First, determine whether a chromosome has a mutation based on a specific mutation rate, and then determine whether a gene on the chromosome has a mutation using the same mutation rate. It is important to point out that the rate of variation is too low to achieve the goal of escaping the local optimal solution. If the rate of variation is too high, it is easy to overlook the optimal solution during the solving process, leading to a missed opportunity for the optimal solution or a decrease in solving speed.

In this study, the initial mutation rate was set at 5%. The GA results indicated that the optimal solution was skipped. After resetting the mutation rate to 2%, GA can run normally.

7) Terminal condition

There are typically two ways to terminate a genetic algorithm. Firstly, the optimal solution is achieved through iteration. If no improvement is observed after n iterations, the genetic algorithm can be terminated. Second, the iteration ends when the specified number of iterations is reached. Since the random initialization method is used for iteration in this study, the final result may be a local optimal solution rather than the global optimal solution. In order to achieve the global optimal solution to the greatest extent possible, this paper employs the approach of setting a maximum number of iterations to terminate the genetic algorithm. After several adjustments, the final iteration used in this study was 5000 times.

4.6.2 The solving process of genetic algorithm

The genetic algorithm needs to search for the optimal solution using three operators: selection, crossover, and mutation. During the solving process, if the number of iterations of the population or other termination criteria is reached, the solving process will be terminated. At this point, the population will cease to evolve, and the optimal solution will be output.

The detailed process of solving genetic algorithms mainly includes the following 8 steps.

Step 1: Transform the optimization problem into a format recognizable by the computer. After that, the solution set for the actual problem is evaluated and then coded.

Step 2: Screen the encoded chromosomes and randomly generate the initial population. The number of chromosomes in the primary population (P0) should be set appropriately.

Step 3: Determine the fitness function of the problem based on the objective function;

Step 4: Calculate the fitness value of each chromosome in the initial population based on the fitness function established in Step 2.

Step 5: The initial chromosome is selected, crossed, and mutated to generate a new generation of the population (P1). A second decoding was conducted to calculate the fitness value of each newly generated chromosome.

Step 6: Based on the fitness value of each chromosome in the new generation population, a new round of selection, crossover, and mutation operations is carried out.

Step 7: Repeat the sixth step until the specified number of iterations is reached and the termination condition is satisfied to stop the iteration. Proceed to step 8.

Step 8: When the termination condition is met, the population stops iterating, and the results of the iteration are calculated and outputted.

5. Model implementation and optimization results analysis

Due to the time constraints of this study, it is not feasible to conduct experiments in real-world environments or observe the performance of actual air conditioning systems. To validate the usability and effectiveness of the model, we will create simulation scenarios. These scenarios will involve a house model, external weather data for the house, a compatible air conditioning system, and the owner's usage environment. The hypothetical air conditioning system's operation would be simulated using EnergyPlus, which is an HVAC simulation engine. The purpose of using this engine is to collect data on energy consumption and FOH (failure operation hour) under various weather conditions and levels of coil fouling. EnergyPlus was selected to conduct the simulation in this study because it is one of the most widely used building energy simulation engines in the HVAC industry. It can calculate the heating and cooling load of a building based on its physical structure and HVAC systems. Importantly, EnergyPlus

has the capability to simulate scenarios involving coil fouling.
Factors related to the owner's usage environment, such as energy costs, carbon emission prices, and maintenance expenses, are determined based on realistic criteria.

5.1 Simulation Scenario 1

5.1.1 EnergyPlus Simulation

5.1.1.1 Modelling approach of coil fouling

EnergyPlus offers two methods to simulate coil clogging: Fouled UA Rated or Fouling Factor. The study adopts the method of setting the fouling factor. This method requires setting the fouling coefficient for the air side and the water side of the coil when fouling has reached its maximum. The unit for these two parameters is m^2-K/W. The principle is that when the coil is fouled, the heat transfer capacity of the coil will be affected. This influence is reflected by the fouling thermal resistance factor (R_{foul}), which is the reciprocal of a heat transfer coefficient.

$$R_{foul} = \frac{r_{air}}{A_{air}} + \frac{r_{water}}{A_{water}} \tag{5-1}$$

Where,
r_{air} is the air side fouling factor, m^2-K/W.
r_{water} is the water side fouling factor, m^2-K/W.
A_{air} is the air side coil surface area, m^2.
A_{water} is the water side coil surface area, m^2.
The EnergyPlus system's built-in auto-sized program generates variable areas for both the air-side and water-side parameters out of the four parameters. In this study, r_{air} is set at 0.01 and r_{water} is set at 0.001. It should be noted that the data in this study exceeds the design index of the fouling coefficient in the typical air conditioner. The design index of the air conditioner takes into account the general operating conditions, and this study needs to consider the upper limit of the coil fouling condition.

5.1.1.2 Description of building model and air conditioner model in the simulation

The building model input in the simulation is a single-floor rectangular storage building with zones measuring 100 ft x 50 ft and a height of 8 feet. The building contains four exterior and one interior conditioned zone. The total area is 5000 ft^2 (463.6 m^2). This building is equipped with a standard Variable Air Volume (VAV) system, including outside air intake, hot water reheat coils, and a central chilled water cooling coil. The central plant consists of a single hot water boiler and an electric compression chiller with an air-cooled condenser. All equipment is automatically sized by the EnergyPlus built-in program. The heating and cooling coil may become fouled during operation of the HVAC system.

5.1.1.3 Weather Data

The default location is Chicago, IL, USA (41°39′ N, 87°34′ W), a city situated on the shores of the Great Lakes. As a city with a typical temperate continental climate, Chicago experiences a very distinct climate throughout the year. In July, the warmest month of the year, the average high temperature is 29°C, and the average low temperature is 17°C. The coldest month is January, with an average maximum temperature of 2°C. The weather data used in this study was downloaded from the official EnergyPlus website. It's a complete year of weather data.

5.1.1.4 Fouling rate

The degree of fouling change is closely related to the model's ability to accurately reflect the actual situation of the air conditioning system. Unfortunately, due to constraints in time and experimental conditions in this study, it is impossible to obtain an accurate fouling rate curve. This curve is based on assumptions from previous studies.

According to the study by Shi et al. (2016). The clogging rate of the home air conditioning system was tested by running it continuously for five months, starting with no clogging. They found a blockage rate of 16.1% in the second month and 67.8% in the fifth month. The study only provided five months of data on clogging rates and did not cover a full year of changes in fouling rates. According to Zhan et al.'s (2015) research, the accumulation of fouling in air conditioning heat exchangers will not continue to increase indefinitely. The decline in operating performance of air conditioning heat exchangers will eventually stabilize, as the accumulated dust will increase in weight and be easily blown away. Combined with the study of both, it can be observed that the fouling rate of the air conditioning heat exchanger gradually increases, reaches a threshold, and then gradually decreases before finally stabilizing.

In this simulation, while it is acknowledged that various air conditioning systems exhibit different fouling rate curves, for the purpose of simplified calculation, a linear curve is utilized in this study. The monthly blockage rate is generally comparable to that shown in the study by Shi et al. (2016). At the end, the blockage rate stabilizes at a fixed value.

It is assumed that the cooling coil fouling reaches 80% of the maximum value six months after the start of the operation of the air conditioning system, and the fouling level will remain at the maximum if no maintenance is performed. It is assumed that fouling accumulates evenly over the six-month period. Therefore, there are six possible values for the fouling rate: 0%, 16%, 32%, 48%, 64%, and 80%. The energy consumption and FOH matrix has 6 rows, denoted as v. The fouling rate is shown in Figure 5-1. This fouling rate curve is only applicable to this simulation. When the model is applied in practice, certain methods should be employed to obtain the accurate or nearly accurate curve of the blockage rate. For instance, the fouling rate is tested monthly, or the manufacturer measures the change in the blockage rate under standard conditions and provides the information to the owners to estimate the true fouling rate.

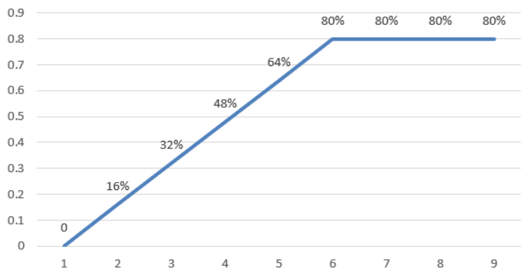


Figure 5-1: Curve of the fouling rate

5.1.1.5 *energy consumption Matrix*

After inputting the weather data, fouling coefficient, and fouling rate into the simulation system, the energy consumption matrix is obtained (see Table 5-2). Energy consumption is measured in joules.

In June, for example, when the coil was at its most fouled level, the system's overall energy consumption increased by 25%. This shows that coil maintenance cannot be ignored. Its maintenance should be handled separately.

Table 5-2: Energy consumption Matrix

	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
												Unit: Joule
F=0	981488158	887246651	987876258	965857475	1021731788	1018782384	1067157206	1051470177	996332330	1022228659	958313706	981812388
F=16%	981488165	887246569	987876412	985874136	1080370586	1134648561	1231716907	1165405358	1052480926	1022298094	958314913	981812390
F=32%	981488153	887245765	988210576	1020288004	1176996304	1260435488	1332239416	1304847434	1149506472	1036555619	958706973	981812283
F=48%	981487595	887245868	989956221	1042124676	1238920496	1319948874	1368487471	1363178317	1200895693	1057044162	962556675	981811789
F=64%	981487272	887245526	992766958	1057452280	1274016605	1343684828	1388389720	1389223713	1235807887	1071950976	968448832	981811647
F=80%	981487362	887245442	994613951	1070575924	1296922319	1358555851	1396202048	1403987597	1257375549	1086406411	974108774	981811981

Table 5-3: FOH Matrix

	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
												Unit: hour
F=0	1	3	0	0	0	0	0	0	5	21	4	3
F=0.16	1	3	0	17	44	110	157	97	56	21	4	3
F=0.32	1	3	0	41	121	192	204	200	127	30	5	3
F=0.48	1	3	2	55	155	215	217	222	155	45	13	3
F=0.64	1	3	3	63	175	219	220	229	173	59	15	3
F=0.8	1	3	6	67	184	223	221	237	183	71	20	3

5.1.1.1 FOH Matrix

After inputting the weather data, fouling coefficient, and fouling rate into the simulation system, the FOH matrix is obtained (Table 5-3). The unit of measurement is hours. From May to September, when fouling is at its peak, the number of hours it fails to meet performance requirements approaches or exceeds 30%. During June, July, and August, when the coil is only slightly dirty, the performance of the air conditioning is significantly reduced. Especially in July, when the fouling rate is only 16%, 21% of the hours already fail to meet the performance requirements. This also demonstrates that coil clogging significantly impacts the performance of the air conditioning system.

5.1.2 Other parameters

Table 5-4: Parameters for Simulation Scenario 1

parameter	Value
RSL	36
d	5%
EC	0.000000004722
MC_2	50
H_t	744, 672, 744, 720, 744, 720, 744, 744, 720, 744, 720
θ_{min}	20%
v	6

Table 5-4 shows the rest parameters of the optimization model. Assume that the Remaining Service Life of the coil is 3 years. Therefore, there are 36 one-month periods t in RSL. The discount rate d for t is based on the general annual discount rate, which is 5%. Since t in this paper represents a one-month period, the value of d in this paper is 5%/12 = 0.004166666667. Based on the data from U.S Energy Information Administration (2022), the average price of electricity to ultimate customers in 2021 is 13.72 USD/Kwh. Operating cost factor (*EC*) consists of energy price and carbon price. The carbon emission of electricity is related the It's related to the way of electricity generation. Depending on the data of U.S EIA (2022), the Carbon Emissions of Illinois, where Chicago located in, ranged from 500 lbs. CO_2/MWh to 1,000 lbs. CO_2/MWh. This range means that this region has a mix of renewable, natural gas-fired, and nuclear generation that keeps their carbon intensities low relative to the average of USA. In this experiment, the value of carbon emissions is the median of this range. After the conversion, the Carbon Emission is 0.34 Kg/Kwh.

Table 5-4 displays the remaining parameters of the optimization model. Assuming that the remaining service life of the coil is 3 years. Therefore, there are 36 one-month periods, denoted as t, in RSL. The discount rate *d* for *t* is based on the general annual discount rate of 5%. Since *t* in this paper represents a one-month period, the value of *d* in this paper is 5%/12 = 0.004166666667. According to the U.S. Energy Information Administration (2022), the average price of electricity for ultimate customers in 2021 was 13.72 USD/kWh. The operating cost factor (*EC*) comprises energy prices and carbon prices. The carbon emissions of electricity are related to the method of electricity generation. Depending on the data of U.S EIA (2022), the Carbon Emissions of Illinois, where Chicago located in, ranged from 500 lbs. CO_2/MWh to 1,000 lbs. CO_2/MWh. This diversity indicates that the region utilizes a combination of renewable, natural gas-fired, and nuclear generation, which helps maintain lower carbon intensities compared to the national average in the USA. In this experiment, the median of this range represents the value of carbon emissions. After the conversion, the carbon emission is 0.34 kg/kWh.

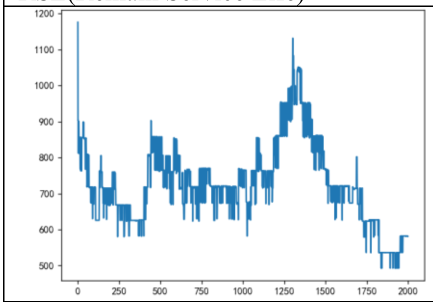
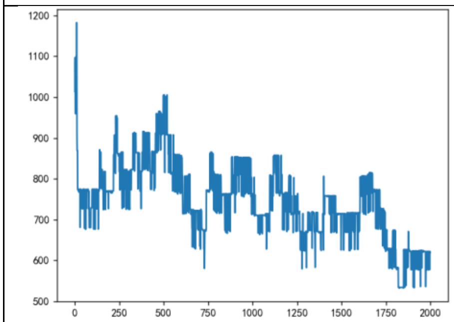
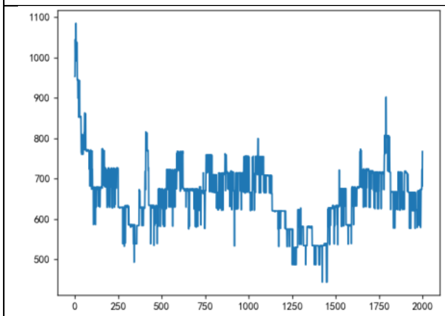
The price of carbon emission permits is determined by the supply and demand of buyers and sellers in the carbon emission permit market. Therefore, it is always changing. Carmody (2019) cited Environment and Climate Change Canada's Pan-Canadian Framework on Clean Growth and Climate Change Annex 1, which states that the initial price for CO2 emissions should increase to $50 per tonne by 2022. The initial price will be used in this experiment. Combining the above three sub-parameters, the EC is 0.000000004722. Coil maintenance cost is 50 USD. According to experience, the overall cost of door-to-door air conditioner maintenance in the United States ranges from $150 to $350. This typically includes travel expenses, labor costs, materials costs. This simulation assumes that the cost of coil maintenance is $50. Assuming that the building's users require the air conditioning to operate 24 hours a day. In reality, certain facilities, such as storage warehouses with refrigeration requirements, hospital rooms, require a constant temperature 24 hours a day. The total running time for each month in a year is 744, 672, 744, 720, 744, 720, 744, 720, 744. The allowed rate of the minimum Failure Operation Hour (θ_{min}) is set 20%.

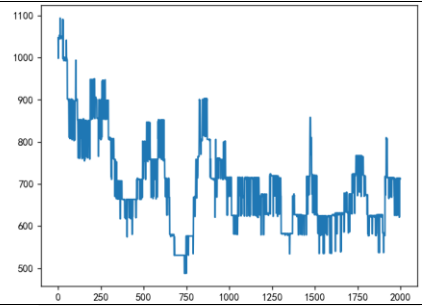
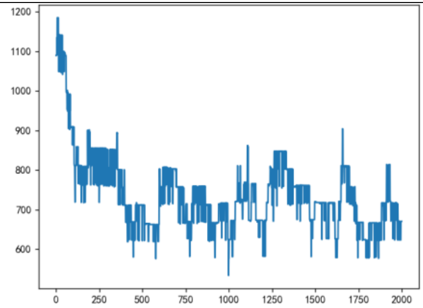
5.1.3 *Solving of Genetic algorithm*

The parameters mentioned above are input into the genetic algorithm and solved using Python programming. Run the program 5 times according to the Genetic algorithm parameters of population size of 100, crossover rate of 50%, mutation rate of 5%, and 2000 iterations. The results of the run and the image are shown in Table 5-5.

Table 5-5: Results of Genetic algorithm

(Simulation Scenario1, population scale:100, crossover rate: 50%, mutation rate: 5%, iteration: 2000)

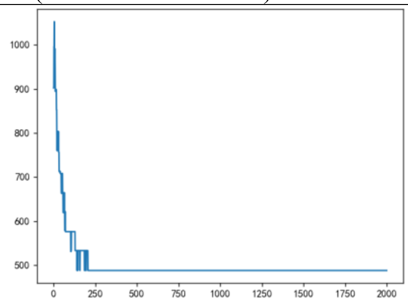
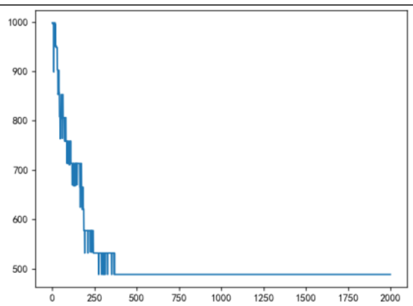
RSL(Remain Service Life)	TRC	Solution
	492.64238786109667	[0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 1. 0. 0.]
	532.2083464900843	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0.]
	444.0854984276671	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0.]

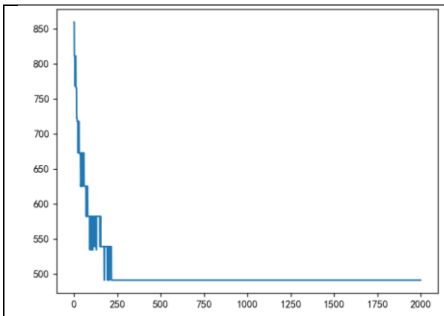
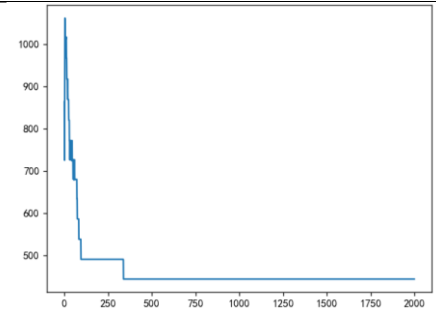
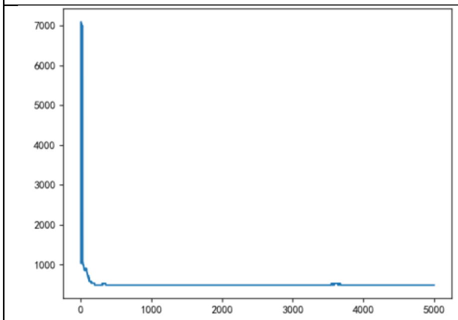
	487.91063184363173	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 1. 0. 0. 0. 0.]
	533.9779424435822	[0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 1.]

The running results do not converge. It is speculated that the genetic algorithm may skip the optimal solution due to a mutation operator that is set too high. Therefore, the mutation operator has been modified to 2%. With a crossover rate of 50% and a mutation rate of 2% and the number of iterations in 2000, the genetic algorithm was run again 5 times. The results are shown in Table 5-6.

Table 5-6: Results of Genetic algorithm

(Simulation Scenario1, population scale:100, crossover rate: 50%, mutation rate: 2%, iteration: 2000)

RSL(Remain Service Life)	TRC	Solution
	487.91063184363173	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0.]
	488.55891112653484	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 1. 0.]

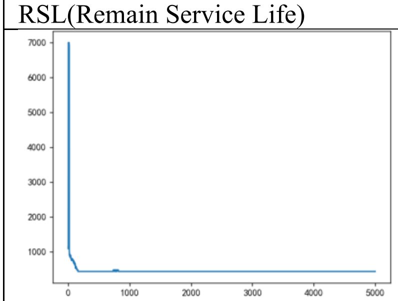
	444.0854984276671	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0.]
	487.91063184363173	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 1. 0. 0. 0. 0.]
	487.91063184363173	[0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0.]

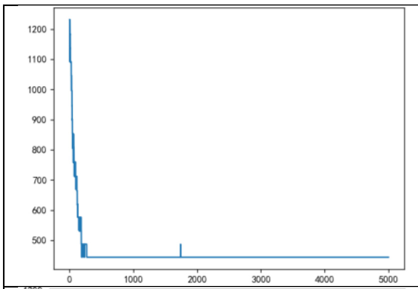
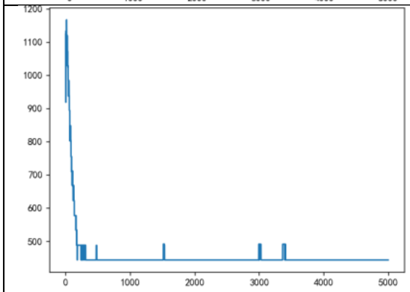
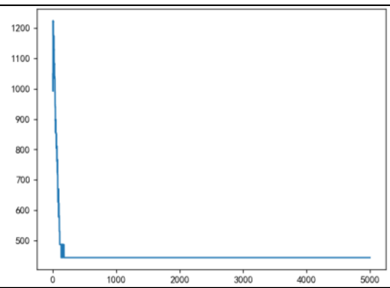
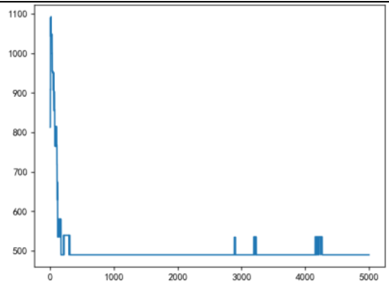
After adjusting the variance rate, the image converges. The lowest Total Related Cost of the five results is 444.0854984276671. Considering the inconsistent results of all five runs, and based on the image of the fourth run showing the lowest total relevant cost, it is evident that the genetic algorithm reached a local optimal solution for over 100 consecutive iterations before it further obtained a better solution. In view of this situation, the number of iterations was adjusted to 5000. This means that the genetic algorithms will run five times, with a crossover rate of 50%, mutation rate of 2%, and iteration number of 5000. The results are shown in Table 5-7.

Four out of the five runs yielded an approximate result. The minimum relevant cost is approximately 444.0854984276671.

Table 5-7: Results of Genetic algorithm

(Simulation Scenario1, population scale:100, crossover rate: 50%, mutation rate: 2%, iteration: 5000)

RSL(Remain Service Life)	TRC	Solution
	444.0854984276671	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0.]

	444.0854984276671	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 1.]
	444.0854984276671	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0.]
	444.0854984276671	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0.]
	490.15280902761737	[0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0.]

These solutions share the same feature, that is, they are all maintained in May and July each year. 6 solutions are shown in Table 5-8. Solution No. 3 needs to be maintained for the fewest number of times, only 6 times, in May and July. Therefore, this solution has been selected as the optimal result.
Select the option that requires the least maintenance. The solution labeled as 3 needs to be maintained as few as 6 times. Therefore, this solution has been chosen as the ultimate optimization result.
To summarize, according to the optimized model, maintenance should be conducted in the 5^{th}, 7^{th}, 17^{th}, 19^{th}, 29^{th}, and 31^{st} months, specifically the 5th and 7th months of each year. The total relevant cost of using this maintenance strategy is 444.0854984276671.

Table 5-8: Combination of 6 Alternative optimal solution

t		1	2	3	4	5	6	7	8	9	10	11	12
Month		Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov	Dec.
No.	①					1		1					
	②					1		1					
	③					1		1					
	④					1		1					
	⑤					1		1					
	⑥					1		1					
		13	14	15	16	17	18	19	20	21	22	23	24
		Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov	Dec.
No.	①				1	1		1			1		
	②					1	1	1					
	③					1		1					
	④					1		1					
	⑤			1		1		1					
	⑥					1		1					
		25	26	27	28	29	30	31	32	33	34	35	36
		Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov	Dec.
No.	①					1		1					
	②					1		1					
	③					1		1					
	④					1		1					1
	⑤			1		1		1					
	⑥					1		1		1			

5.1.4 *Results analysis*

In order to compare the maintenance strategy optimized by the model with the fixed-period maintenance strategy based on the decision-maker's experience, it is necessary to develop one or more relatively reasonable fixed-period maintenance strategies for the simulated building. Currently, most property owners use a fixed-period maintenance strategy that usually involves maintaining the coil once a year. The simulated building is located in Chicago, where the summer season spans from June to August. Three maintenance strategies have been designed.

Strategy A: Maintenance after the summer. Maintenance is conducted in September every year.

Strategy B: Maintenance in the middle of each year. That is, maintenance is conducted in June every year.

Strategy C: Perform maintenance before and after each summer. Maintenance is conducted in May and September each year.

Table 5-9: Competition between 3 fixed-period strategy and optimized Strategy for simulation scenario 1

	Total Relavant Cost (USD)	Number of Month that Operation requirement not met	Total Failure Operation Hour (Hour)	Total Energy Consumption (J)
Strategy A	313.84	12	2898	39988460447
Strategy B	311.13	12	2538	38987119031
Strategy C	446.42	6	1923	38199756965
Optimized Strategy	444.08	0	1368	37404178421

The combination of the above 4 strategies is illustrated in Table 5-9. Of the four maintenance strategies, A and B are maintained only once a year, while C and the optimized strategy are maintained twice a year. Compared to the optimized strategy, the A and B can save more than 100 USD. However, 6 months failed to meet the performance requirements of strategy C, while 12 months failed for both strategy A and B. Thus, all strategy A, B, and C should be rejected. In additional, the number of hours that not meet the performance requirements of all non-optimized strategies are 2898, 2539, and 1923 hours, while optimized strategy is only 1368. Compared to strategy C, which is the best performing among the three non-optimized strategies, the optimized strategy saved $2.34 and reduced the total FOH by 555 hours. The optimized strategy also has the lowest energy consumption among the four strategies.

None of the three non-optimized strategies meet the performance requirements. That's because the simulations used weather data from Chicago, which experiences hot summers. As the fouling degree increases, the coil's heat transfer performance gradually decreases, leading to failure to meet the minimum requirements of θ_{min}. In addition, the air-conditioning system is also sensitive to maintenance costs. In all four strategies, the proportion of maintenance costs in the total relevant cost is 33.6%, 33.7%, 47.8%, and 48.2%, respectively. The reason why the TRC of strategy A and B can be 100 USD lower than the latter two, even though the energy consumption is higher, is that the former two have only been maintained 3 times in the entire remaining service life (RSL), while the latter two have been maintained 6 times.

Considering the situation mention above, this study designed a simulation scenario 2 by modifying some parameters, so as to comprehensively investigate the application of the optimization model in various scenarios.

In addition, it should be pointed out that even if the optimal solution obtained in this scenario is in the form of a fixed-period strategy, maintenance will be applied in May and July every year. However, it is fundamentally different from the fixed-period maintenance strategy because the two strategies are based on different principles. This situation should be considered a coincidence. The periodic form of the optimal solution is not caused by the use of year-cycled weather data. This is because as the air conditioning system operates in January of the second year, its fouling rate is likely to differ from the state of the first month of the first year.

5.2 Simulation Scenario 2

The energy consumption and FOH data are consistent with those in simulation scenario 1.

5.2.1 Other parameters

Simulation scenario 2 modifies the preset maintenance cost (MC_2) from 50 USD to 10 USD and the allowed rate of the minimum Failure Operation Hour (θ_{min}) from 20% to 30%. The aim is to reduce the sensitivity of the air conditioning system to performance requirements and maintenance costs. The remaining parameters remain the same. The parameters are set as shown in Table 5-10.

parameter	Value
RSL	36
d	5%
EC	0.000000004722
MC_2	10
H_t	744, 672, 744, 720, 744, 720, 744, 744, 720, 744, 720
θ_{min}	30%
v	6

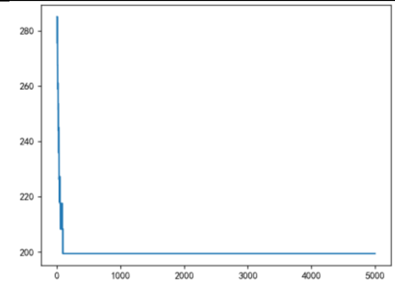
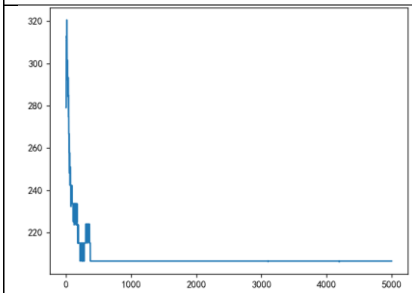
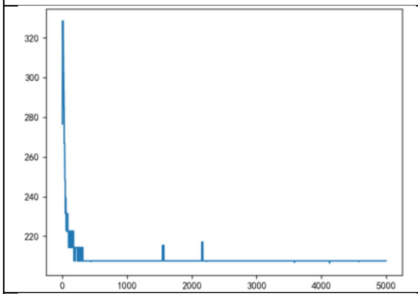
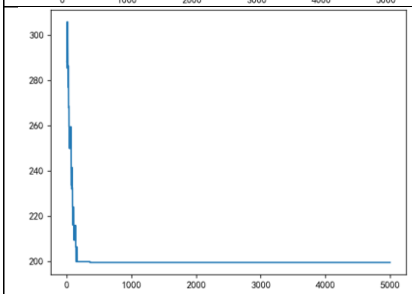
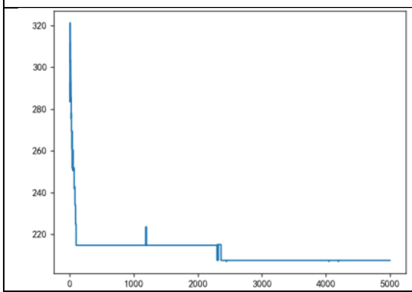
Table 5-10: Parameters of Simulation Scenario 2

5.2.2 *Solving of Genetic algorithm*

Based on the experience from Simulation Scenario 1, run the program 10 times using the genetic algorithm parameters of population number of 100, a crossover rate of 50%, a mutation rate of 2%, and 5000 iterations. The results of the run and the image are shown in Table 5-11.

Table 5-11: Results of Genetic algorithm

(Simulation Scenario2, population scale:100, crossover rate: 50%, mutation rate: 2%, iteration: 5000)

RSL(Remain Service Life)	TRC	Solution
	199.47363875452376	[0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
	206.11610537113432	[0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 0.]
	206.4768754595986	[0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
	198.36826126047201	[0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
	206.91832038472026	[0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]

It can be seen that all five results converge. Choose the solution with the lowest total associated cost. Its total related cost is 198.36826126047201 USD. Solution is [0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]. That is to say, the maintenance should be occurred in the 6th, 18th and 27th month.

5.2.3 *Result analysis*

Continue to implement the three fixed-period maintenance strategies in Scenario 1

Strategy A: Maintenance after the summer. Maintenance is carried out in September every year.

Strategy B: Maintenance in the middle of each year. Maintenance is conducted in June every year.

Strategy C: Perform maintenance before and after each summer. Maintenance is conducted in May and September each year.

Table 5-12: Competition between 3 fixed-period strategy and optimized Strategy for simulation scenario 2

	Total Relavant Cost (USD)	Number of Month that Operation requirement not met	Total Failure Operation Hour (Hour)	Total Energy Consumption (J)
Strategy A	203.33	6	2898	39988460447
Strategy B	199.23	0	2538	38987119031
Strategy C	223.54	0	1923	38199756965
Optimized Strategy	198.36	0	2523	39036015608

As shown in Table 5-12, Strategy A was rejected because it could not meet performance requirements for 6 periods. All three remaining strategies meet the performance requirements. Thus, the optimization effect of the model can be examined when the air conditioning performance requirement is not sensitive. Meanwhile, for the three strategies other than strategy A, the proportion of maintenance costs in the Total Relevant Cost is 15.0%, 26.8%, and 15.1%. Compared to scenario 1, it has decreased significantly. The optimization effect can be examined when maintenance costs are not significant. Strategy C was maintained twice in one year. According to the Total Failed Operation Hour, Strategy C conducted excessive maintenance, leading to a high Total Relevant Cost. Compared to Strategy C, the optimized strategy can save 25.18 USD, which is 11.26% of the Total Relevant Cost when Strategy C is selected. Strategy A is very similar to the optimized strategy. Both of them decide to do maintenance in the 6th and 18th months. The difference is that the third maintenance for strategy B occurs in the 28th month, while the third maintenance for the optimized strategy occurs in the 27th month. Comparing the Total Relevant Cost of the two, it can be seen that the optimized solution is $0.87 less than strategy B. It can be concluded that the optimized strategy is superior to the three fixed-period strategies.

It should be noted that even though Strategy B is very similar to the optimized strategy and their Total Relevant Cost is very close, the basis for the two strategies is still very different. Strategy B is mechanistic fixed-period maintenance with the maintenance period equally divided into years, while the optimization strategy is based on the results of data analysis. Furthermore, scenario 2 is not intended to completely negate the fixed maintenance strategy. Most fixed-period maintenance strategies are developed in the absence of data and are based on the long-term experience of decision-makers, which is reasonable but can still be optimized. The solution to scenario 2 also confirms the point mentioned in the previous section that the results obtained from this optimization model may not necessarily exist in a periodic form: maintenance is conducted in June of each of the two years of the operating cycle, and in May of the third year of the operating cycle.

It is worth noting the performance in energy consumption. The best energy consumption performance is strategy C, which involves maintenance conducted twice a year, and the energy consumption of the optimized strategy is slightly higher than that of strategy B.

The energy consumption of the optimized strategy is higher than that of strategy C because the air conditioning performance requirements are reduced in Scenario 2, and θ_{min} is set to 30% instead of 20% in scenario 1. Therefore, in scenario 2, only one maintenance is required to meet the operational requirements. After optimization, the energy consumption of the strategy is slightly higher than that of strategy B, but the TRC is slightly lower than that of strategy B due to the consideration of the discount rate d in the maintenance model. The optimization model indicates that conducting maintenance in May of the third year of the operating cycle, rather than in June, will be more cost-effective, despite the higher energy consumption. The reason for considering the discount rate d is that the inclusion of carbon emission rights in the model provides economic value to carbon emissions.

5.3 Conclusion

In this chapter, two specific simulation scenarios are designed, and a genetic algorithm is employed to solve the model. Two simulation scenarios demonstrate the scientific validity and effectiveness of the model and genetic algorithm. Under the condition that different parameters exhibit different sensitivities, it is possible to obtain an optimal solution that surpasses the common fixed-period maintenance strategy. In other words, if the basic performance requirement is met, it is possible to achieve a better solution for Total Relevant Cost.

The model also offers flexibility. When parameters such as energy prices, carbon emission prices, or maintenance costs change, the model can be solved by adjusting the corresponding parameters. This is crucial for effectively managing carbon emissions and assisting businesses in the low-carbon era.

Furthermore, when adapting the genetic algorithm to solve the optimization model, it becomes evident that variations in algorithm parameters will impact the efficiency and outcomes of the solution. Therefore, in the practical application of the algorithm and model, the algorithm parameters should be adjusted based on the specific requirements of the situation.

6. Discussion

Compared to previous studies, this study has made progress in the following areas.

Most of the previous studies on air-conditioning system maintenance optimization, whether based on advanced maintenance strategies or not, took energy consumption as the optimization goal. For the research of production equipment maintenance optimization, performance or economic factors are usually taken as optimization objectives. The main difference between this study and them is the introduction of the concept of carbon emission trading, which gives economic attributes to energy consumption, thus introducing economic factors into the optimization model and acting as direct optimization targets.

This consideration is based on the economic fact that the vast majority of air conditioning owners are economic players in the market and their primary concern is economic gain and loss. The maintenance behavior of air conditioning is also a part of its economic behavior, which is encouraged and restricted by economic factors. In the traditional concept, the maintenance of air conditioning belongs to the cost center, rather than the profit center, that is, it is not the key to economic growth of economic entities, which is one of the important reasons for the neglect of maintenance behavior. The introduction of the concept of carbon emission trading means that owners can get real economic benefits from saving energy, so as to encourage owners to make greater efforts in energy conservation and emission reduction.

The incorporation of economic factors into the optimization model and as the optimization target does not imply an over-amplification of the role of economic factors. Therefore, this study also considers the performance factors of air conditioning operation in relation to environmental factors. The final optimization model is the result of the combined influence of economic, environmental and performance factors. For example, in scenario 1, while the TRC of strategies A and B is significantly lower than that of the optimized strategy, their performance and environmental indicators are also much lower than those of the optimized strategy. In scenario 2, while the performance and environmental indicators of strategy C are better than those of the optimized strategy, its TRC is worse than that of the optimized strategy. The time-based preventive maintenance strategy generated by the optimization model in this study is superior to various fixed-period maintenance strategies based solely on experience.

In addition, this study focuses on the maintenance strategy for an overlooked subsystem, the coil, rather than the maintenance strategy for the entire air conditioning system. Firstly, it addresses the research gap of limited studies on advanced coil maintenance strategies, especially the time-based maintenance strategy at present. Secondly, it also partially addresses the issue of owners only focusing on maintaining the main subsystems of air conditioning (such as condensers and pipes) in practical air conditioning maintenance scenarios.

This study also has the following shortcomings.

Firstly, this study does not demonstrate its feasibility based on an actual air conditioning system. The simulation model used in this study is relatively simple. The current air conditioning system may actually have a more complex cost structure, more complex components and more variable weather conditions. Moreover, simulation models cannot fully reflect reality. The environment that supports the simulation model itself is only an abstraction of reality. Finally, this study is not based on actual fouling rate data and can only be hypothesized based on previous relevant studies. In practical applications of this model, it is essential to obtain actual or nearly actual coil fouling rate data whenever possible. In order to accurately reflect the actual situation of the coil. For instance, the frequency of fouling is assessed monthly; or the producer evaluates changes in the obstruction rate within established parameters and provides this data to the owners to estimate the actual fouling rate. In practice, however, manufacturers often do not want to share the relevant data with owners. Instead, they prefer owners to perform maintenance more frequently in order to increase profits. Therefore, if the manufacturer is expected to provide fouling rate data, it may be necessary for the government or relevant agencies to establish industry standards and enforce them with appropriate measures. However, this could actually be done in laboratories commissioned by companies or governments, some of which are already capable of the same. Therefore, future research should aim to obtain actual data on air conditioning systems, further demonstrating the feasibility and scientific basis of the model.

Secondly, the cost factors used in this study is relatively straightforward. It only includes the operational cost, maintenance cost, and cost of carbon emission permit of air conditioning. In reality, there may be extra cost factors such as administrative expenses. Besides, maintenance may lead to equipment shutdowns and corresponding losses. Therefore, future studies should aim to broaden the cost items to more accurately reflect reality.

Thirdly, the coil fouling rate curve used in this study only accounts for the change over time. In more complex situations, the change in coil fouling may also be influenced by ambient temperature, humidity, air quality, fluid dynamics, and other factors. Currently, these factors still require further study.

Finally, in this study, the duration of each period t is one month. In most cases, this configuration can already meet the requirements for coil maintenance. But when the precision is increased further, such as when the duration of each period is a day or an hour, the scale of energy consumption and FOH matrix will become very large. It is theoretically possible to continue using this model, but it will require a large amount of computation.

7. Conclusion

Based on a literature analysis and background investigation, this study identifies current research gaps and practical needs in the field of air conditioning coil maintenance strategies. According to the literature and practical experience, this study proposes an optimization model to minimize the total relevant cost of air conditioning systems, based on their operational performance. The model's performance is based on the simulation method. In this study, two simulation scenarios based on real situations were constructed, and a genetic algorithm was used to solve the optimization model in two scenarios.

Scenario 1 tests the performance of the model under the situation of high maintenance cost and high air conditioning performance constraint. Scenario 2, on the contrary, tests the performance of the model under the situation of low maintenance cost and low air conditioning performance constraint.

In each scenario, three fixed-period maintenance strategies A, B, and C are compared with the optimized strategy generated using the optimization model. In scenario 1, non-optimized Strategies A, B, and C fail to meet the air conditioning performance constraint and are therefore rejected. Only the optimized strategy will be accepted. Furthermore, the energy consumption of the optimized strategy is the lowest among the four strategies. In scenario 2, strategies B, C, and the optimized strategy meet the constraint. Although the optimized strategy has the highest energy consumption of the three, its TRC is the lowest.

The results indicate that the time-based preventive maintenance strategy, established by the optimization model, outperforms the fixed-period maintenance strategy. Compared to the fixed-period maintenance strategy, the new approach can ensure that the total relevant cost of the air conditioning system is minimized while meeting performance requirements. Experiments conducted with simulated scenarios can demonstrate the scientific validity and effectiveness of the model.

When formulating cost optimization objectives, this study asserts that enterprises should factor in the purchase of carbon emission permits for any additional carbon emissions, thereby incorporating the cost of purchasing carbon emission permits into the cost optimization objective. This design helps enterprises fully understand the impact of carbon emissions. According to the optimization model's requirements, the coding, selection, crossover, and mutation operators of the genetic algorithm are well designed. During the process of solving the objective function with a genetic algorithm, the parameters are adjusted based on the actual circumstances. The genetic algorithm utilized in this study is stable and fast, successfully achieving the intended objective.

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9. Appendix A: Code for Genetic Algorithm

```
import numpy as np
import matplotlib.pyplot as plt
from pylab import *
import pandas as pd
mpl.rcParams['font.sans-serif'] = ['SimHei']
mpl.rcParams['axes.unicode_minus'] = False
####################data input####################
EE = pd.read_excel('data_set/data.xlsx', sheet_name='EC')
FOH = pd.read_excel('data_set/data.xlsx', sheet_name='FOH')
Fmin = pd.read_excel('data_set/data.xlsx', sheet_name='Fmin')
EE = EE.values
FOH = FOH.values
Fmin = Fmin.values
#################### initialization of parameter ####################
NP=100          # population size
L=60            # RSL
Pc=0.5          #Crossover rate
Pm=0.1          #mutation rate
G=2000          # iterations
EC=(0.34/3600000)*(50/1000)
d=0.004166667
Xd=1/(1+d)
MC=[0,50]

#data saving
f=np.random.randint(0,2,(NP,L))
x=np.zeros((NP,1))
#nf=f.copy()
nf=np.zeros((NP,L))
Fit=np.zeros((NP,1))
bestneess=np.zeros((G,1))
fitneess_value_list = []
fibest=np.zeros((G,L))
####################fitness function####################
def func1(x):
   fit = -x
   return fit
####################main body of Genetic Algorithm ####################
for k in range(G):
    for i in range(NP):
        U=f[i,:]
```

```
    TRC=0
    m=0
    jj=0
    v=0
    for j in range(L):
        pp=j%12
        v=j-jj
        cc=0
        eer=0
        if U[j] == 1:
            v=0
            jj=j
            cc=50
        if v>5:
            v=5
        if Fmin[0,pp]<FOH[v, pp]:
            eer=6000   #the penalty for violating the constraint 2
        m = Xd**j*(EC*EE[v, pp]+cc)+eer
        TRC += m
    Fit[i] = func1(TRC)

maxFit = np.max(Fit)
minFit = np.min(Fit)
rr = np.argwhere(Fit == maxFit)[0][0]
fBest = f[rr,:]
Fit = (Fit - minFit) / (maxFit - minFit)

################# selection operator#################
sum_Fit = sum(Fit)
fitvalue = Fit/ sum_Fit
fitvalue = np.cumsum(fitvalue)
ms = np.random.random((NP, 1))
ms = sort([i for i in ms[:, 0]])
fiti = 0
newi = 0
while newi < NP:
    if ms[newi] < fitvalue[fiti]:
        nf[newi,:]=f[fiti,:]
        newi = newi + 1
    else:
        fiti = fiti + 1

#################crossover operator#################
for i in range(0,NP,2):
```

```
        p=np.random.random()
        if p<Pc:
            q=np.random.randint(0,2,(1,L))
            for j in range(L):
                if q[:,j]==1:
                    temp=np.int(nf[i+1,j])
                    nf[i+1,j]=nf[i,j]
                    nf[i,j]=temp

    ################# mutation operator#################
    i=0
    while i <=np.round(NP*Pm):
        h=np.random.randint(0,NP,1)[0]

        for j in range(int(np.round(L*Pm))):
            g=np.random.randint(0,L,1)[0]
            nf[h,g]=np.abs(1- nf[h,g])
        i+=1

    f=nf
    f[0,:]=fBest
    fibest[k,:]=fBest
    fitneess_value_list.append(maxFit)
    bestneess[k,0]=maxFit

plt.plot(np.array(fitneess_value_list))
plt.title('iteration Curve')
plt.show()

bestFit = -np.max(fitneess_value_list)
rrr = np.argwhere(bestneess == -bestFit)[0][0]
bestnn=fibest[rrr, :]
print('TRC',bestFit )
print('Solution',bestnn )
```