PERFORMANCE ASSESSMENT AND ROBUST OPTIMAL DESIGN OF DISTRIBUTED ENERGY SYSTEMS IN SUBTROPICAL REGIONS

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PERFORMANCE ASSESSMENT AND ROBUST OPTIMAL DESIGN OF DISTRIBUTED ENERGY SYSTEMS IN SUBTROPICAL REGIONS

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A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

Abstract of thesis entitled: Performance Assessment and Robust Optimal Design of Distributed Energy Systems in Subtropical Regions

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The distributed energy systems have been proven to be energy efficient and cost-effective in many regions. However, very few studies about the application of distributed energy systems in subtropical regions, where cooling demand dominates and heating demand can be ignored, are conducted. This thesis attempts to comprehensively study the application of distributed energy systems in such regions and address the following questions which are not well answered in existing studies:

- Are distributed energy systems more energy efficient when compared with existing centralized energy systems and what are the main constraints which limit the development of distributed energy systems in subtropical areas?
- How to design a distributed energy system that can maximize its potentials in energy saving and cost reduction compared with the existing centralized energy system?
- How to design a distributed energy system that can offer the best performance under uncertainties when the practical operating conditions may deviate from the predicted conditions?

Being an innovative energy supply technology, the performance of distributed energy system compared with the centralized energy system determines its future application. Performance assessment of distributed energy systems is conducted by comparing with centralized energy systems in subtropical areas. Characteristics of distributed energy systems in application are summarized after quantitative energy performance and economic performance analysis. The impacts of major design parameters and energy policies on the system performance are studied. The main constraints for the development of distributed energy systems in subtropical regions and the benefits of applying these systems are identified. Measures to improve the performance of distributed energy systems in terms of energy saving and cost reduction and suggestions for proper application in such regions are summarised based on the analysing the results.

The design for a distributed energy system is a complicated task due to the coupling operation and mutual constraints among its subsystems. An optimal method for distributed energy systems design is therefore developed to identify the best system that can maximize the benefits compared with centralized energy systems. The system operation and equipment sizing of the distributed energy system are optimized simultaneously in the design method to ensure that the system achieves maximum energy saving and economic profits. A case study of an energy system retrofitting project is adopted to test and demonstrate the optimal design method. Performance of the optimized distributed energy system and the advantages achieved by this system in reducing primary energy consumption and operating cost are assessed. The matching performance of on-site generations, which indicates the extent of matching between the generated energy and the energy demand, and the efficiency of electric chillers are analysed and compared with that of the centralized energy system.

In the practical operation of an energy system, actual operation condition variables, such as the electricity demand, are often very different from their predictions that used in the system design at planning and design stages. Such difference is taken as uncertainty. Uncertainties in design inputs (e.g. energy demand and energy price) and equipment degradations in operation result in that the actual performance of a distributed energy system deviates from the design expectations significantly. To ensure that distributed energy systems designed can operate at high performance when the actual working environment and equipment performance change over a large range, a robust optimal design method based on life-cycle performance analysis is developed. This method adopts a probabilistic approach, which is based on qualifying the uncertainties of design inputs and equipment degradations. Monte Carlo simulation method is adopted to model the uncertainty propagation and generate the probability distributions of the predicted system performance in the design process. The "probabilistic" life-cycle performance of distributed energy system is therefore obtained, and the method further identifies the optimum system which has the best life-cycle performance expectation under the above uncertain conditions concerned. A case study of a new development project is adopted to test and demonstrate the proposed robust optimal design method. The economic benefits and the performance robustness under different operating conditions of the designed distributed energy system is evaluated and analysed. Advantages of the proposed robust optimal design method compared with the design method that does not consider the life-cycle performance are identified by comparing the annual performance of distributed energy systems designed by those two methods, especially the performance in the latter years of life-cycle.

The robustness of an energy system performance is identified as the ability of the system to maintain stable performance when operating conditions deviate from the design conditions. By analysing this robustness, the impacts of uncertainties on the performance of distributed energy systems can be assessed and compared. An index is proposed to quantify the performance robustness of distributed energy systems based on the stochastic results of Monte Carlo simulation. Comparison on the impacts of different uncertainties on the system performance robustness is conducted and measures to improve the performance robustness for distributed energy systems in subtropical regions are summarized.

PUBLICATIONS ARISING FROM THIS THESIS

Journal Papers

2017 **Kang, J.**, Wang, S.W., & Gang, W.J. (2017). Performance of distributed energy systems in buildings in cooling dominated regions and the impacts of energy policies. *Applied Thermal Engineering*, *127*, 281-291.

2018 Gao, J.J., **Kang, J.**, Zhang, C., & Gang, W.J. (2018). Energy performance and operation characteristics of distributed energy systems with district cooling systems in subtropical areas under different control strategies. *Energy*, *153*, 849-860.

2018 **Kang, J.**, Wang, S.W., & Yan, C.C. (2018). A New Distributed Energy System Configuration for Cooling Dominated Districts and The Performance Assessment Based on Real Site Measurements. *Renewable Energy*, *131*, 390-403.

2018 **Kang, J.** and Wang, S.W. (2018). Robust Optimal Design of Distributed Energy Systems based on Life-Cycle Performance Analysis Using a Probabilistic Approach Considering Uncertainties of Design Inputs and Equipment Degradations. *Applied Energy*, *231*, 615-627.

2018 **Kang, J.** and Wang, S.W. (2018). Study on The Performance Robustness of Distributed Energy Systems under The Impacts of Uncertainties of Energy Demands and Energy Prices. (in prepare).

Conference Papers

2017 **Kang, J.**, Wang, S.W., & Gang, W.J. (2017). Performance and Benefits of Distributed Energy Systems in Cooling Dominated Regions: A Case Study. *Energy Procedia*, *143*, 1991-1996.

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NOMENCLATURE

Abbreviations

ATSE	annual total system energy efficiency
AC	absorption chiller
CES	centralized energy system
DCS	district cooling system
DES	distributed energy system
DG	distributed generation
EC	electric chiller
FHL	DES operation strategy of following hybrid load
FTL	DES operation strategy of following thermal load
LTC	life-cycle total cost
PBP	payback period
PDF	probability distribution function
PES	primary energy saving

Parameters

c	specific heat capacity of water (kJ/kg·K)
C_{annual}	annual total cost of the DES (USD)
C_d	cooling demand (kW)
$C_{d,peak}$	peak cooling demand (kW)
C_{AC}	generated cooling of absorption chiller (kW)
C_{CAP}	cooling capacity of the DES (kW)
C_{EC}	generated cooling of electric chiller (kW)

C_{EM}	cost of carbon emission (USD)
C_{INV}	initial cost of the DES investment (USD)
C_{PEN}	penalty of cooling demand dissatisfaction (USD)
CC_{AC}	capital cost of absorption chiller (USD)
CC_{CES}	capital cost of the CES (USD)
CC_{EC}	capital cost of electric chiller (USD)
CC_{DES}	capital cost of the DES (USD)
CC_{DG}	capital cost of DG (USD)
CC_{pump}	capital cost of pump (USD)
CC_{pipe}	capital cost of pipe (USD)
CEF	carbon emission factor of natural gas (kg/kWh)
CM_{DG}	maintenance cost of DG (USD/kWh)
COP_{ave}	average COP of electric chillers
COP_{AC}	COP of absorption chiller
COP_{EC}	practical COP of electric chiller
$COP_{EC,FL}$	full-load COP of electric chiller
$Cost_{certain}$	certain energy price (USD/kWh)
$Cost_{e}$	price of imported electricity from the utility grid (USD/kWh)
$Cost_{f}$	price of natural gas (USD/kWh)
$Cost_{e, sell}$	feed-in tariff (USD/kWh)
$Cost_{other}$	other cost for generating each unit electricity (USD/kWh)
$Cost_{uncertain}$	uncertain energy price (USD/kWh)
CP_{DG}	capacity of distributed generation (kW)
CP_{AC}	capacity of absorption chiller (kW)
CP_{CT}	capacity of cooling tower (kW)
CP_{EC}	capacity of electric chiller (kW)

CP_{pump}	capacity of pump (kW)
D_a	yearly degradation rate of equipment performance
D_{pipe}	diameter of pipe (mm)
$d_{certain}$	certain energy demand (kW)
$d_{uncertain}$	uncertain energy demand (kW)
$E_{bilding}$	building base electricity demand (kW)
E_{CHWP}	electricity demand of chilled water pump (kW)
E_{CT}	electricity demand of cooling tower (kW)
E_{CWP}	electricity demand of cooling water pump (kW)
E_d	electricity demand (kW)
$E_{d,\ CES}$	electricity demand of the CES (kW)
E_{DG}	generated electricity of DG in the DES (kW)
E_{EC}	electricity demand of electric chiller (kW)
E_{grid}	imported electricity from the utility grid (kW)
E_{sell}	exported electricity to the utility grid (kW)
$EC_{emission}$	carbon emission tax (USD/t Ce)
F_{CES}	fuel consumption of the CES (kWh)
F_{DES}	fuel consumption of the DES (kWh)
F_{DG}	fuel consumption of distributed generation (kWh)
F_{grid}	fuel consumption of centralized power plant (kWh)
F_{trend}	trend factor of variation in life-cycle
G	water flow rate (m^3/h)
g	gravitational acceleration (m/s^2)
H	water head (m)
INC	the total income of exporting electricity to the grid (USD)
L_{pipe}	length of pipe segment (m)

N	number of operating pumps
N_{DG}	number of distributed generations
N_{AC}	number of absorption chillers
N_{EC}	number of electric chillers
OC_{CES}	operating cost of the CES (USD)
OC_{DES}	operating cost of the DES (USD)
OEM_{DG}	On-site Energy Matching index of distributed generation
OEM_{AC}	On-site Energy Matching index of absorption chiller
OEF_{DG}	On-site Energy Fraction index of distributed generation
OEF_{AC}	On-site Energy Fraction index of absorption chiller
P	total pressure of fan (Pa)
Pen^C	penalty price of cooling demand dissatisfaction (USD/kW)
PS	government incentive for energy saving (USD/kWh)
Q_r	maximum recovered heat from distributed generations (kW)
$Q_{r,\,AC}$	recovered heat used by absorption chillers (kW)
r_P	part load ratio (%)
Rob_{index}	robustness index
$SCOP$	HVAC system coefficient of performance
UM^C	unmet cooling demand (kW)
α	ratio of the demand of HVAC terminal units to HVAC system
η_{DG}	practical electric efficiency of distributed generation (%)
$\eta_{DG,FL}$	full-load electric efficiency of distributed generation (%)
η_F	efficiency of fan (%)
η_{grid}	total efficiency of distributed generation (%)
η_P	efficiency of pump (%)
η_T	electric efficiency of centralized power plant (%)

λ	air-water ratio of cooling tower
ρ_a	density of air (kg/m^3)
ρ_w	density of water (kg/m^3)

CHAPTER 1 INTRODUCTION

This chapter, which consists of three sections, presents an introduction of this thesis. The background and motivation of this study are described in Section 1.1. The aim and objectives are presented in Section 1.2 in details. Section 1.3 shows the organization of this thesis and gives a brief description of each chapter.

1.1 Background and motivation

The world has been experiencing great risks from the depletion of existing energy reserves and dramatic growth of the pollutant and greenhouse gases (GHGs) emission due to the increasing energy consumption. In the past decade, the consumption of fossil fuels grows 1.7% per year in average, and this rate is even higher as 2.2% in 2018 (British Petroleum, 2016, 2018). More seriously, total GHGs emissions from fossil fuel combustion, which is the major cause of global warming, have risen more rapidly (2.2% per year) from 2000 to 2010 than that (1.3% per year) in the previous three decades (IPCC, 2014). These risks have brought urgent requirement and a great challenge for developing technologies of energy saving and GHG emission reduction.

Improving the efficiency of energy using and adopting renewable energy, or clear energy, are two valid ways to alleviate the above risks. Distributed energy system (DES) have been developing rapidly as a kind of high efficiency and high reliability energy system in the last decades (Paliwal et al., 2014). Integrating the supply of electricity, thermal energy and gas, DESs are able to achieve the effective control of energy distribution, and energy cascade utilization, which significantly improve the efficiency of energy using (Kang et al., 2017; Orehounig et al., 2015). Comparing the existing centralized energy system, DESs can better utilize renewable energy resources. Solar photovoltaic, wind power and other renewable energy technologies, which can reduce the primary energy consumption as well as the emission of GHGs significantly in the process of energy generation, are usually adopted in DESs through micro-grid or smart grid (Akorede et al., 2010; Sepponen et al., 2016).

DES technologies are experiencing an increasing application as a sustainable energy supply system worldwide. However, it does not mean that the DES can be used effectively in all climate regions without limits. A successful application of DES is restricted by many factors, such as energy resources, energy demands and local energy markets (Moradi et al., 2014; Tan et al., 2013). The selection of generators and the planning of the DES decide the energy efficiency and economic performance of this technology. Thus, studies of the DES feasibility and the approach to improve its benefits are essential efforts before using the DES in some specific regions.

Performance assessment is an important basis for the feasibility study of DES application (Allegrini et al., 2015; Mirakyan et al., 2013). Both the advantages and disadvantages of DES application can be quantitatively measured by assessing the DES performance. The corresponding recommendations for system design and optimization can also be obtained by analysing the DES performance. Particularly when applying DES in some specific climate regions, a comprehensive performance assessment should be conducted to identify the best DES option (Rizwan et al., 2008). Many studies focus on the application of DES in regions where both space heating and cooling are needed. However, the feasibility and the performance of DESs in subtropical regions, where space cooling is required almost all the year and demands of space heating is negligible, are rarely investigated yet. The operation characteristics, energy saving and economic benefits of DESs in subtropical regions are still unknown. A comprehensive study on the performance and the best application modes of DESs is essentially needed.

The DES design aims to decide the types of equipment adopted by the DES, the capacities of equipment and the operation strategies of the DES at the planning and design stage of the DES project (Sameti et al., 2017). A well-designed DES can further improve the system performance and ensure the benefits for the DES investor (Dehghanian et al., 2013; Saif et al., 2013). Various DES optimal design methods for different purposes, e.g., the energy system retrofitting and the new development of energy system, are developed and investigated.

Conventional optimal design methods for DES, however, only ensure the designed DES operates at the best performance in deterministic operating conditions. The designed DES may not operate at expected performance when operating conditions change. Robust optimal design method is proposed for the DES design to solve the above problem by considering the impacts of variable operating conditions (Yokoyama et al., 2014). Obtained by the proposed robust optimal design method, the DES is able to operate at high performance when the actual working environment and equipment performance change over a large range. However, there are still many shortcomings in the current research. Some important influential factors, e.g., the degradation of equipment performance, in DES life-cycle are ignored in the system optimal design. The DES, designed by a method which neglects these impacts, may only achieve the required performance in the first several years of installation, and get worse in the rest years.

To reduce CO_2 emission and meet the increasing electricity demand, the government in Hong Kong, a typical subtropical city of high density, has set it policy to replace coal gradually by natural gas as primary energy in power generation. The natural gas, a clean and low-carbon primary energy, is able to be utilized as energy resources in centralized power plants or delivered to users for distributed on-site generation. This provides an opportunity for the application of DESs in this subtropical region. However, the configuration and equipment of the DES that can satisfy energy demands effectively in this region are still unknown. The performance of DES should be assessed and analysed, and the constraints of DES application as well as their impacts on DES performance need to be identified. Potentials of the DES in energy saving should be studied, and optimal design methods which can identify the DES that creates maximum benefits should be developed.

1.2 Aim and objectives

This thesis, therefore, aims to investigate the application of DES in subtropical regions and develop a new robust optimal design method which identifies the DES that can operate with high performance through its life-cycle. The DES is proposed to supply energy for typical commercial buildings in Hong Kong. Based on the characteristics of the local energy demands and energy policies, the devices of DES are selected and the basic system configurations are determined. A performance assessing method for this specific DES is developed. By comparing the DES performance in different cases, the pros and cons of the DES are presented and its best application modes are determined. The planning of the DES for a district is adopted as the case for the study of DES design method. Two different application situations for DES planning, i.e., energy system retrofitting and new development, are considered and the corresponding optimal design methods are developed. The new methods should ensure the DES to maintain good performance when operating conditions change and equipment degradations occur in the DES life-cycle. Based on the results of analysis, recommendations for investors on the DES application in subtropical regions are given. The detailed objectives and research tasks of this thesis are presented as follows.

1. To introduce the typical DES configurations in subtropical regions and the energy fluxes in DESs. The models of the proposed DES, including the energy models, economic models, and system operation strategies, are developed.

2. To determine the assessment criteria using for evaluating the DES performance. Primary factors affecting the DES performance and the best application mode of the DES in subtropical regions are identified.

3. To develop an optimal design method for DES planning in a case of energy system retrofitting. This method aims to identify the optimum DES which can achieve the maximum energy saving and cost saving compared with the existing energy system. A case study is organized to test this method and evaluate the benefits of the optimum DES.

4. To develop a robust optimal design method for DES planning in a case of new development. This method aims to identify the optimum DES which can maintain a stable performance when operating conditions change significantly and operate with high performance throughout its life-cycle. A case study is conducted to test this method and identify the advantages of this method compared with a conventional optimal design method.

5. To assess the performance robustness of the optimized DES design option when operating conditions deviate from the design conditions. The impacts of different

uncertainties on the DES performance robustness is compared and the factors for achieving high performance robustness of DES are identified.

1.3 Organization of this thesis

This Chapter introduces the background and the motivation of the research by presenting the needs of a comprehensive study for the DES application in subtropical regions. The aim and main objectives are also presented in this chapter. Other chapters of this thesis are organized as follows.

Chapter 2 presents a comprehensive literature review of related existing studies, including the evaluation methods of the DES performance and optimization methods for DES in planning, design and operation. This chapter also elaborates the research gaps which are intended to be bridged in this thesis.

Chapter 3 describes recommended configurations and the operating principles of DESs for subtropical regions. Modelling and basic operation strategies of the DES are presented in detail.

Chapter 4 addresses the energy performance assessment of DESs in subtropical regions. Two performance criteria, which are the primary energy saving and the payback period, are defined and used to assess the DES performance. By comparing and analysing the DES performance, the influential factors for the DES application in subtropical regions can be identified and their impacts can be estimated.

Chapter 5 presents and elaborates the design optimization methods for DES planning in different situations. Two optimal design methods are developed for DES application in two situations concerning energy system retrofitting and new development respectively. In the first situation, the design objective is to identify the best energy saving and cost-efficient DES option comparing with the existing centralized energy system. In the second situation, the design objective is to identify the DES option that can operate with high performance through its life-cycle. Uncertainties of design inputs are considered and a robust optimal method is developed to perform this DES design.

Chapter 6 presents the test and validation of the DES optimal design method in a case of energy system retrofitting. A high density district including twelve buildings for multiple functions is considered in the case study. The energy demands of the district are collected by site monitoring and used as design inputs. The optimal design method is used to identify the optimum DES option. The energy benefits of replacing the existing energy system with the DES are presented. The matching performance of on-site generations and the efficiency of electric chillers are analysed. Corresponding advises for DES design in retrofitting case are also given.

Next two chapters present the test of the DES optimal design method in a case of new development DES. **Chapter 7** describes the application of the proposed robust optimal design method in DES planning. Uncertainties of design inputs are quantified based on previous study and information from energy markets. Assuming that the district elaborated in Chapter 6 is a newly developed adopting the same building design. The design of the DES for the new district is used as the second case study. The robust optimal design method is performed to identify the DES that has the best life-cycle performance expectation. The advantages of the optimum DES are presented by comparing its life-cycle performance with that of other DES schemes. A comparison with the DES identified by the uncertainty-based optimal design method (i.e., the method considers the uncertainty and does not consider the life-cycle performance) is conducted to validate that the DES identified by the proposed method can remain high performance in the latter years of its life-cycle.

Chapter 8 presents the studies on the DES performance robustness under the impacts of uncertainties. A robustness index is proposed to assess the robustness of DES performance and the robustness of the performance of the optimized DES at different stages over the entire life-cycle is compared quantitatively. A sensitivity study is conducted to investigate the impacts of different uncertainties on the system performance robustness.

Chapter 9 summarizes the main contributions of the work conducted in this PhD project and gives recommendations for future research on the subject concerned.

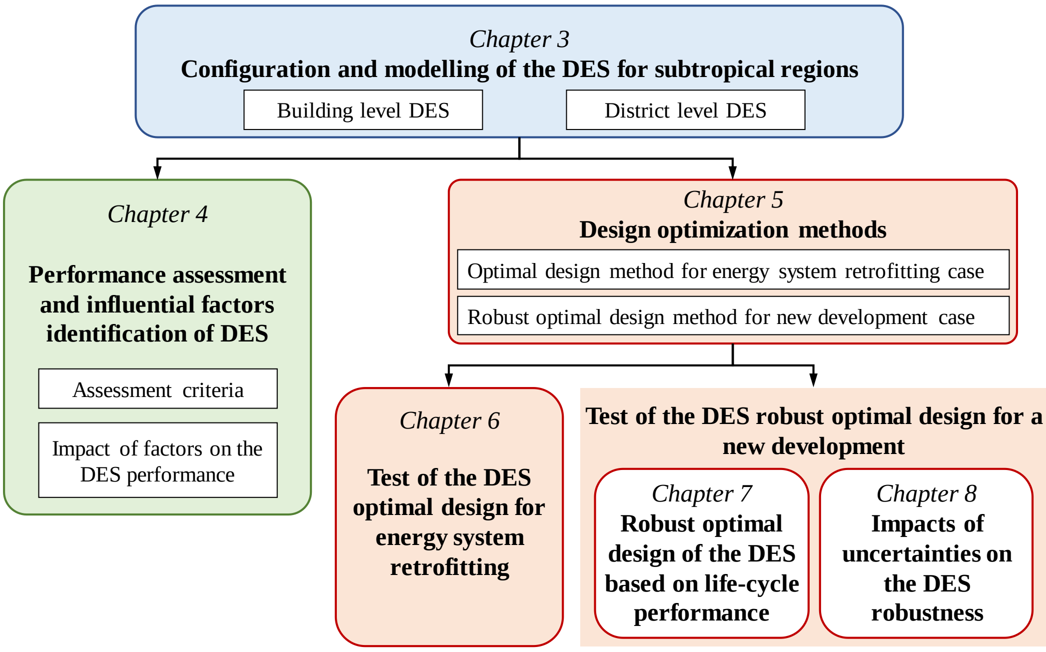


Figure 1.1 Organization of main chapters of the thesis

The interconnection between the main chapters of the thesis are illustrated in a flowchart in Figure 1.1. The determination of DES configurations, including building level DES (to serve an individual building) and district level DES (to serve building clusters in a district), and development of DES model are the basic tasks of this PhD study which are presented in Chapter 3. Using the DES model, the operation of DES can be simulated and the performance data, e.g., generated energy, can be obtained. In Chapter 4, assessment criteria of DES energy performance and economic performance are determined. Case studies are organized to assess the DES performance when some factors (e.g., design parameters or energy policies) vary. By comparing the performance of different DESs, the impacts of those factors can be assessed and recommendations for proper and optimized DES application in subtropical regions are presented. Two optimal design methods for DES planning in two different situations, i.e., energy system retrofitting and new development, are developed in Chapter 5. Chapter 6 presents the test of the optimal design method for energy system retrofitting in a case of replacing the existing CES in a district by DES. Chapter 7 presents the test of the robust optimal design method in a new development case of district level DES. Impacts of uncertainties on the DES robustness are assessed and analysed based on the stochastic performance data obtained in the proposed robust optimal design method in Chapter 8.

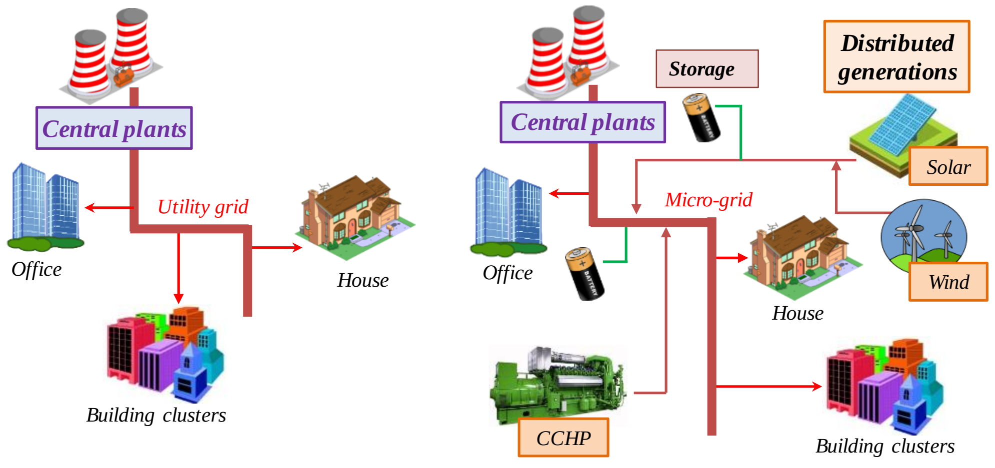
CHAPTER 2 LITERATURE REVIEW

Distributed energy system (DES) has been increasingly receiving interests and many DESs have been developed in recent decades. DESs can satisfy the energy demands of different end-users and achieve benefits that cannot be provided by conventional energy systems. This chapter presents a comprehensive literature review on the existing DES technologies and applications. Section 2.1 briefly introduces the basic information about the DES, including technologies, the operation mode and the advantages of the DES. Section 2.2 presents the review on current studies and efforts for DES performance assessment. The review of the studies on optimization methods for DES planning/design and on the uncertainties associated to DESs are presented in Section 2.3 and Section 2.4, respectively. Conclusive remarks of the reviews are given in Section 2.5.

2.1 Overview of Distributed energy system (DES)

2.1.1 Configuration, technologies and benefits of DES

The distributed energy system (DES), which integrates distributed energy supply equipment and/or the utility grid, is considered as an innovative energy system with prospective development and benefits (Haikarainen et al., 2014). The main differences between DES and centralized energy system (CES, the conventional energy system which is the most common application) are shown in Fig. 2.1. In a CES, electricity is generated by large centralized power plants (gigawatts in size), which are often remote from buildings (or end-users), and transmitted to buildings through the utility grid. In a DES, distributed generations, which can be located in or near the building site, are adopted to produce electricity or other forms of energy. Energy storages reserve the surplus energy in the DES and release this energy when it is needed. Microgrid is usually used to connect the distributed generations, storages and buildings. A DES can operate either independently of the electrical grid as *stand-alone DES*, or being linked to the utility grid as *grid-connected DES* (Moradi et al., 2014; Nosratabadi et al., 2017; L. Wang et al., 2016). According to the number of buildings served by one DES, the DES can be divided into ***building level DES*** (provides energy for an individual building) and ***district level DES*** (provides energy for building clusters in a district). Building level DES is the most common DES application due to its cheaper investment cost and convenience in control. District level DES enables the improvement of energy saving and system operating reliability by using generations with large capacities and high efficiencies. However, the design method and the control strategy of the district level DES are more difficult than that of the building level DES due to its complicated configuration (M. Li et al., 2014).



(A) Centralized energy system (CES)　　(B) Distributed energy system (DES)

Figure 2.1 Schematics of centralized energy system (CES) and distributed energy system (DES)

The distributed generations in DESs are generally divided into two categories: renewable energy generations and low-carbon energy generations. The former includes solar photovoltaics, wind turbines, geothermal generations etc. The application of renewable energy reduces the consumption of fossil fuels significantly. It alleviates the risk of accelerating exploitation of energy reserves and greenhouse gas emission at the same time (Panwar et al., 2011). The latter mainly refers to multi-generation systems, also called CCHP (combined cooling, heating and power), powered by low-carbon energy resources (e.g., natural gas). It uses a distributed generation (usually a gas turbine or a reciprocating engine) to produce electricity, and recovers the lower temperature exhaust heat from the generation for heating or cooling simultaneously (Pepermans et al., 2005). Due to the high overall energy efficiency (usually above 80%) and high stability, multi-generation systems received more attentions than renewable energy resources in current DES applications, especially in urban areas (Cho et al., 2014; Gu et al., 2014).

Compared with CES, the DES has many benefits, including flexible modular assembly, significant advantages in energy efficiency, reliability, and power quality and emissions reductions. Main benefits of DESs employment can be summarized as follows:

- **Energy efficient and sustainable**: DESs typically use renewable energy resources instead of fossil fuels like that in CESs. Distributed generation and storage in DESs enable collection of energy from many sources and may improve efficiency and security of supply. By cascade utilization of energy, DESs can provide useful energy services to facilities with less primary energy consumption.
- **Economic benefits**: Lower consumption of primary energy in DESs directly leads to the reduction of energy related costs. In addition, DESs can significantly, and

when deployed on a large scale can comprehensively and profoundly, improve the resilience of electricity supply, thus reducing many kinds of social costs and risks. DESs can further achieve the reduction of operating cost by effective control among energy supplier and storages.

- **Reduction in emissions of GHGs and air pollutants**: DESs achieve the same levels of energy generation with lower levels of fossil fuel combustion and reduced emissions of carbon dioxide. Emissions of air pollutants, such as carbon monoxide (CO), nitrogen oxides (NO_x) and Sulphur dioxide (SO_2) are also reduced significantly when DESs replace CESs.

Moreover, DESs can reduce the cost of establishing a long-distance power network and the power loss in remote transmission. By coupling with the utility grid, DESs have increased reliability and decreased risks of power outages due to the addition of a separate power supply. Compared with a small number of large generations in central plants, multiple small generations in DESs are far less likely to fail simultaneously. Most distributed generations, especially renewables, tend not only to fail less than centralized plants, but also to be easier and faster to fix when they do fail.

2.1.2 Role of DESs in building energy saving

Buildings are one of the largest energy consumers, which account for 20~40 % of the total energy consumption worldwide and even 63% in some regions (EMSD Hong Kong, 2015; Pérez-Lombard et al., 2008). Therefore, reducing the energy consumption of buildings is a significant measure to alleviate the global energy problem (Bilgen, 2014). An appropriately designed DES can achieve substantial primary energy saving compared with existing CESs (Chen et al., 2013). As a result, DESs can play an important role in building energy saving (Viral et al., 2012). For instance, through combination with passive buildings or zero energy buildings (ZEBs), the DESs is expected to achieve 100% renewable energy supplies (Mathiesen et al., 2015). In addition, DESs can help building owners achieve short-term payback on investment by reducing the operating cost (Zhou et al., 2013a). Due to the fact that DESs reduce the GHGs emission to a great extent, more and more governments are beginning to encourage the application of DESs in buildings (Mancarella, 2012).

However, not all DES technologies can achieve the abovementioned benefits and the application in buildings is also subject to certain techniques and/or economic constraints. For example, due to the low efficiency and large installation area, renewable energy integrated DES is generally applicable in rural areas or places where building density is not high (Tan et al., 2013). In order to decrease the capital cost, the DES is recommended to use the existing energy distribution networks or reduce the length of newly developed networks (Ameri et al., 2016). Thus, appropriate DES technologies should be determined based on the characteristics of energy demands and the local economic environment. The feasibility of DESs and their best application modes should be studied comprehensively.

2.2 Performance assessment of DES

2.2.1 Purpose and approaches of DES performance assessment

The DES performance assessment can not only show the advantages of this technology directly, but also provide decision makers with meaningful recommendations for future planning. Extensive studies on DES performance have been conducted worldwide, such as in USA, European, Japan, China and India. These investigations focus on the applications of DESs, usually with some specific configurations or using some specific energy resources, in designated regions. Benefits of those applications can be identified based on the assessed DESs performance. Most existing approaches for DES performance assessment can be divided into two categories. The first category is *comparative assessment* and the second is *direct assessment*.

Comparative assessment approaches, also the most widely used approach, evaluate the DES performance by comparing with centralized energy systems (CESs) (Ghaebi et al., 2011; Paliwal et al., 2014; Zhou et al., 2013b). Fumo et al. introduced the basic numerical models and analysis method in a multi-generation system study, and evaluated the performance of DESs for large office buildings under various operation strategies in Chicago (Fumo et al., 2009; P. J. Mago et al., 2010). Compared with the CES, the DES can reduce 15.9% of annual primary energy consumption under an appropriate operation strategy. This approach is also effective in performance assessment for DESs in districts. Li et al. evaluated the economic and environmental performance of a DES at the neighbourhood level by comparing the annual cost and CO_2 emission of the DES with that of the reference CES (L. Li et al., 2016). Based on the evaluation results, an optimal operation strategy was also proposed for maximizing system benefits.

Direct assessment approach evaluates the DES performance by estimating its efficiency or environmental impacts directly. Exergy efficiency, which is the ratio of useful exergy extracted from the DES to its input exergy, is usually used for DES energy performance assessment considering the quality of the energy transferred (Laukkanen et al., 2016). This efficiency is used to identify the best choice from different DES technologies. Somma et al. compared the overall exergy efficiency of several DESs and an existing CES in a hotel in Beijing (Di Somma et al., 2015). Comparison results show that reasonably designed DESs are able to reduce energy costs and improve overall exergy efficiencies of energy systems significantly. An assessment of global and local emission impacts of DESs was comprehensively studied by Mancarella et al. They found that DESs can achieve substantial CO_2 reduction in most times, while DESs may increase pollutant emissions when operating in partial-load condition (Mancarella et al., 2009).

2.2.2 Feasibility study of DES based on performance assessment

The performance assessment can be used to analysis the feasibility of DES in different climate regions. By evaluating and comparing the performance of DESs, which usually have same configurations, their feasibility of application in different climate regions can be identified. Cho et al. evaluated the performance of DES in several cities in USA. Results have shown that DESs reduce the primary energy consumption and CO_2 emission compared with CESs in Columbus, Minneapolis and Miami (Cho et al., 2009). The climate can affect the users' energy demand and then have impacts on the performance of DESs. Wu et al. compared the DES performance among various climate conditions and indicated this system can obtain largest benefits in hot summer and cold winter zone in Japan (Q. Wu et al., 2014).

Appropriate application modes of DESs can also be identified through performance assessment studies. Mago et al. present that DESs have advantages particularly in the cases where the duration of thermal energy demands is long. Thermal energy demands should be considered as an essential factor in determining the feasibility of a DES. High-efficient thermal energy generations are supposed to be used in DESs (P. J. Mago et al., 2009). Li et al. used heat-to-electricity ratio and energy saving rate to identify potential users and application boundaries in different climate zones (M. Li et al., 2016). Results show that the DES application boundary can be wider with higher heating demand. In these heating dominated zones, DESs should use the existing district heat systems to improve the reliability and efficiency of supply where possible.

The local energy policy is another significant factor affecting the performance of DESs. Appropriate energy policies can inspire the development of DES technologies and encourage the adoption of on-site generations (Allan et al., 2015). According to Bush et al., the feed-in tariff scheme can improve the efficiency and economic benefits of small-scale renewable and low carbon non-renewable generation technologies in DESs (Bush et al., 2014). Zheng et al. investigated the effects of three different feed-in tariff policies on DES performance (Zheng et al., 2016). The results demonstrated that both system energy and economic performance were improved if the surplus electricity could be sold at a favourable price. Therefore, for the application of DES in a new region, the impacts of energy policies should be studied and the best energy policy should be identified.

2.3 Optimization of DES in design and operation

System design is one of the most important issues for the development and application of DES technologies (Alarcon-Rodriguez et al., 2010). A properly designed DES not only makes substantial economic benefits for investors, but also improves the energy efficiency of the system (Viral et al., 2012; Cao et al., 2016, 2017). Due to the diversity of power generation technologies and the complicated interactions among different equipment, DES design is a problem of high complexity, which should be addressed at the very beginning of the project (Ho et al., 2016; Ruan et al., 2009). The optimal design is an effective approach to solve the DES planning problem. With given design inputs, such as the energy demands and energy prices, the DES optimal design can be obtained by achieving the minimum or maximum objective functions (Mehleri et al., 2012). A matrix modelling approach was proposed by Liu et al. for DES design optimization under three different operation strategies (Liu et al., 2013). Ameri and Besharari optimally designed a DES by integrating renewable generations with a district thermal system, which achieved considerable costs saving and CO_2 emission reduction compared with the existing energy system (Ameri et al., 2016).

Similarly, some effective methods are developed to optimize the operation strategy of existing DESs. Wu et al. conducted a study on the optimization of operation strategies for a tri-generation system (J. Wu et al., 2012). A multi-objective approach was adopted for system optimization and the impacts of load conditions and price conditions on results were also analysed. Mohammadi et al. developed a decentralized power flow algorithm for collaborative operation of transmission and distribution systems in DESs (Mohammadi et al., 2018). The proposed algorithm was tested in standard systems and the results show that it can achieve the expected design goals with highly improved computation efficiency.

Useful experiences and effective guidelines for DES development can be achieved by analysing the performance of the optimally designed DES (Jiangjiang Wang et al., 2011). Stadler et al. used DER-CAModel for DES design optimization when retrofitting the energy system of an existing building in Australia (Stadler et al., 2014). They found that the simultaneous optimization of building shell and DESs can greatly reduce the operating costs and carbon emissions. Optimal design methods can also be used for DES planning in large scale districts. Falke et al. developed an optimization approach for DES design in a district of 150 buildings. They decomposed the optimization problem as an economic and ecological analysis, which could reduce the computation complexity while guaranteeing acceptable accuracy (Falke et al., 2016).

Currently, DESs, especially those serving building clusters in districts, are mainly used in regions where long duration of heating is needed in winter while very limited DES projects can be found in subtropical regions where cooling is the dominated or only requirement around the year. As a result, there is very few research on the structure/configuration, the design and the performance study of DES in subtropical regions in the literature.

District cooling systems have been approved as a promising cooling system for subtropical regions, where space cooling is required annually and the cooling demand density is relatively high. Compared with individual cooling systems, chillers in district cooling systems can operate with high efficiency and reliability so that their power consumption and operating cost are reduced. The energy loss in cooling distribution can also be reduced because the total length of distribution networks is significantly reduced when using district cooling systems in high demand density regions. In addition, the costs of district cooling systems can be further reduced when some incentive energy policies are adopted. For example, governments of subtropical regions provide economic incentives for district cooling systems and allow cooling trade between different suppliers (Wenjie Gang, Godfried Augenbroe, et al., 2016; Wenjie. Gang et al., 2016; Yan et al., 2015). Integrating a district cooling system within a DES sounds to be a potential option for energy saving in cooling dominated and high-density regions. To ensure that this specific DES achieves the maximum benefits compared with existing energy systems, an optimal design method for the DES should be developed and the benefits of such new option should be identified.

2.4 Research on uncertainties in DES

2.4.1 DES performance assessment considering uncertainty

In the model-based study of a DES, uncertainties, which can be defined as "*any deviation from the ideal deterministic knowledge of the relevant system*", are generally used to quantify the variations of design inputs (W. Tian et al., 2018; Walker et al., 2003). The stochastic nature of renewable energy, the inability to predict precisely the evolution of energy prices and the uncertain long-term energy and climate outlook render uncertainty considerations essential. Performance assessment of DES is usually performed in a deterministic condition assuming perfect knowledge of all the design inputs. Consequently, the results of the model and the success of the performance assessment are highly dependent on the values given to the deterministic parameters while any deviations due to uncertainty can potentially render inaccurate results.

Uncertainty analysis is used to predict the DES performance considering uncertainties of design inputs which should be concerned (Rysanek et al., 2013; Soroudi et al., 2013). In DES studies, uncertainties of design inputs can be divided into two main categories: 1) uncertainty of energy demands, and 2) uncertainty of energy prices. Li et al. adopted a probabilistic method to quantify the uncertainty of energy demands and used an uncertain programming model to investigate the impacts of uncertain demands on DES (C. Z. Li et al., 2008). They found that the uncertain demands have great impacts on the selection of equipment while having negligible impacts on annual energy performance. A. T. Rezvan et al. proposed a probabilistic method to analyse the impact of demand uncertainty on the economic performance of DESs in buildings (Rezvan et al., 2012, 2013). It not only identified the best DES operation strategy under uncertain demand, but also indicated that the capacity of DES should be decreased to lower the risk of over-spending when the uncertainty increases.

There are many uncertain factors in energy markets, which have great impacts on DES via energy policy and price (Yoon et al., 2011). Mavrotas et al. investigated the impacts of uncertainties of the economic parameters (e.g., the fuel costs and the interest rate) on the DES planning for a hospital (Mavrotas et al., 2010). It indicates that the probability distribution schemes of parameters have great impacts on the probability distributions of DES annual cost. A robust optimal design method is proposed by Aien et al to identify the optimum DES that can operate with high performance and robustness under variationally operating conditions (Aien et al., 2016; Mavromatidis et al., 2018a). However, few studies have considered both uncertainties of energy demands and prices together in the investigation of impacts of uncertainties on the DES performance. The extents of impacts of those two categories uncertainties on DES robustness are still unknown.

2.4.2 DES optimal design considering uncertainty

Conventional optimal design for DES is generally performed based on deterministic conditions. The design inputs, such as energy demands, initial costs and energy prices, are assumed as certain values and used to determine the best design options. However, these inputs may vary within a range rather than equal to deterministic values in practice because the variations of weather conditions, occupancy density and energy markets cannot be predicted accurately (C. Wang et al., 2016). Without taking the variations of design inputs into account, the designed DES may fail to operate as intended and cause poor performance when the actual operating conditions change. To overcome the shortage of the conventional optimal design methods, new optimal design methods that can ensure the DES operate with high performance under variable operating conditions is essentially needed.

Robust optimal design of DES is a new design method to identify the DES with high performance and robustness by considering uncertainties of design inputs. A robust optimally designed DES can maintain relatively high performance when the actual operating conditions change over a large range. Probabilistic approaches are often used to solve the objective functions and identify the robust design options for DES. Mixed integer nonlinear programming method and fuzzy-stochastic sampling are adopted for a DES robust optimal design in Ref. (Y. F. Li et al., 2010). It indicates that the optimized capacities of subsystems mainly depend on local energy resources and policies in DES planning. K. Akbari et al. proposed a stochastic programming method to determine the optimum capacities of DES in a building considering demand uncertainties (Akbari et al., 2014; Bertsimas et al., 2006).. Li et al. combined Monte Carlo method and multi-objective optimization model for DES sizing in buildings (C.-Z. Li et al., 2010). They found that the uncertainty has great impacts on the sizing of main equipment in DESs based on the sensitivity analysis.

In general, previous DES robust optimal design methods addressed the system performance of DES in the early years, i.e., the new installations, and ignored the system performance through life-cycle (Turconi et al., 2013). In fact, the operating conditions in the later years of the DES life-cycle may be totally different with that of the first years. Ensuring a DES operate with high performance in the whole life-cycle is an important issue. Huang et al. proposed an optimal design method for energy system in near-zero energy building based on the life-cycle performance. Results showed that the system can operate with high energy efficiency through its operating years (Huang et al., 2016; Huang et al., 2018). However, the DES design methods based on life-cycle performance assessment cannot be found in literature.

In a DES, performance degradation of equipment is almost inevitable. Degradation of equipment is defined as the reduction of its performance or outputs after a long time of operation. Studies on equipment degradation are conducted to prevent the energy system from operating in low efficiency (Xia et al., 2012). The design of distributed power generations considering efficiency degradation can decrease the risk of the reduction of annual power production (Radue et al., 2010; Z. Tian et al., 2011). The HVAC system is able to satisfy users' long-term cooling demand if correct efforts are implemented to prevent the degradation problem of chillers in the design stage (Huang et al., 2015). Therefore, the impacts of equipment degradation in DES life-cycle on the system performance should be studied and considered in the DES robust optimal design.

2.5 Summary

This chapter presents a comprehensive review on the current studies on DES. The basic configuration and components (e.g., energy generations and distribution networks) of DES are introduced briefly. System performance assessment and effective design optimization for DESs are two essential approaches to study the feasibility of DES application. Current investigations of these issues, however, mainly focus on the DESs used in regions where both space heating and cooling are needed. The performance and design methods for DES in subtropical regions, whose configuration is not clearly determined, still lack systematic research. Meanwhile, there are still many problems (e.g., the designed DES may operate with poor performance in the latter stage of its life-cycle) when using the existing DES optimal design methods. A new optimal design method that can overcome these shortages is essentially needed.

CHAPTER 3 CONFIGURATION AND MODELLING OF THE DISTRIBUTED ENERGY SYSTEM FOR SUBTROPICAL REGIONS

This chapter introduces the configurations of two typical application modes (i.e., building level and district level) of DESs for subtropical regions and the modelling of DES which is developed to simulate the operation of system. Section 3.1 presents and elaborates the typical configuration and the energy fluxes of the building level DES. Section 3.2 presents and elaborates the typical configuration and the energy fluxes of the district level DES. Section 3.3 presents the models for the DES, including energy models and economic models. Basic operation strategies of the DES are presented in Section 3.4. Conclusive remarks of this chapter are presented in Section 3.5.

3.1 Configuration of building level DES

Building level DES is a basic mode for the application of DES in subtropical regions. A typical configuration of a building level DES, as shown in Fig. 3.1, has distributed generations (DGs) and chillers (absorption chillers and electric chillers) located inside the facility room of the building. DGs and the utility grid, which connects centralized power plants, satisfy electricity demand (including the electricity demand of chillers (E_{EC}) and building ($E_{building}$)), and chillers satisfy cooling demand (C_d). In the energy system, a DG produces electricity (E_{DG}) and exhausts waste heat as flue gas around 600℃ simultaneously. A mixed-effect absorption chiller, which consists of a double effect (DE) absorption chiller and a single effect (SE) absorption chiller, uses the flue gas for thermal activated cooling (C_{AC}) directly (Jiang et al., 2015). When the energy demand cannot be satisfied by the DG or/and the absorption chiller, the utility grid or electric chillers are used to meet the electricity (E_{grid}) and cooling demands (C_{EC}).

It is worth noting that the cooling system of the building level DES is a common individual cooling system which is the same with that of the centralized energy system (CES). The auxiliary equipment, such as pumps, fans and cooling towers, of the cooling system in the building level DES and the CES can be regarded as the same.

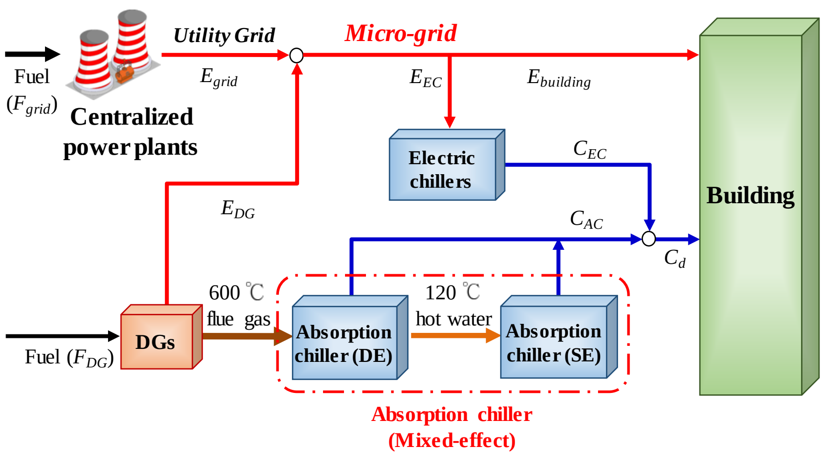


Figure 3.1 A typical configuration of the building level DES

3.2 Configuration of district level DES

District level DES is the other commonly used mode for the application of DES in subtropical regions, which has a more complicated configuration and flexible operation strategies. The typical configuration and the energy fluxes of a district level DES is shown in Fig.3.2, which actually is a combination of DES and district cooling system (DCS). As shown in Fig. 3.2(A), in the proposed DES, the needed electricity and cooling energy are generated mainly by a local energy station, which consists of DGs, absorption chillers and electric chillers. The micro-grid and the chilled water networks deliver the generated electricity and cooling energy to end-users (i.e., buildings) in the district respectively. Fig. 3.2(B) presents the energy fluxes among each component in the DES. The utility grid and DGs supply electricity (E_{grid} and E_{DG}) for the base electricity demands of buildings ($E_{building}$) and electricity demand of central cooling plant (including chillers (E_{EC}), chilled water pumps (E_{CHWP}) and the heat rejection system (E_{CWP} and E_{CT})) in the district. Absorption chillers (C_{AC}), which use the recovered heat from DGs ($Q_{r,AC}$) as the heat source, and electric chillers (C_{EC}) supply cooling for meeting the cooling demands of buildings (C_d) in the district. Subsystems and their corresponding equipment are described as follows.

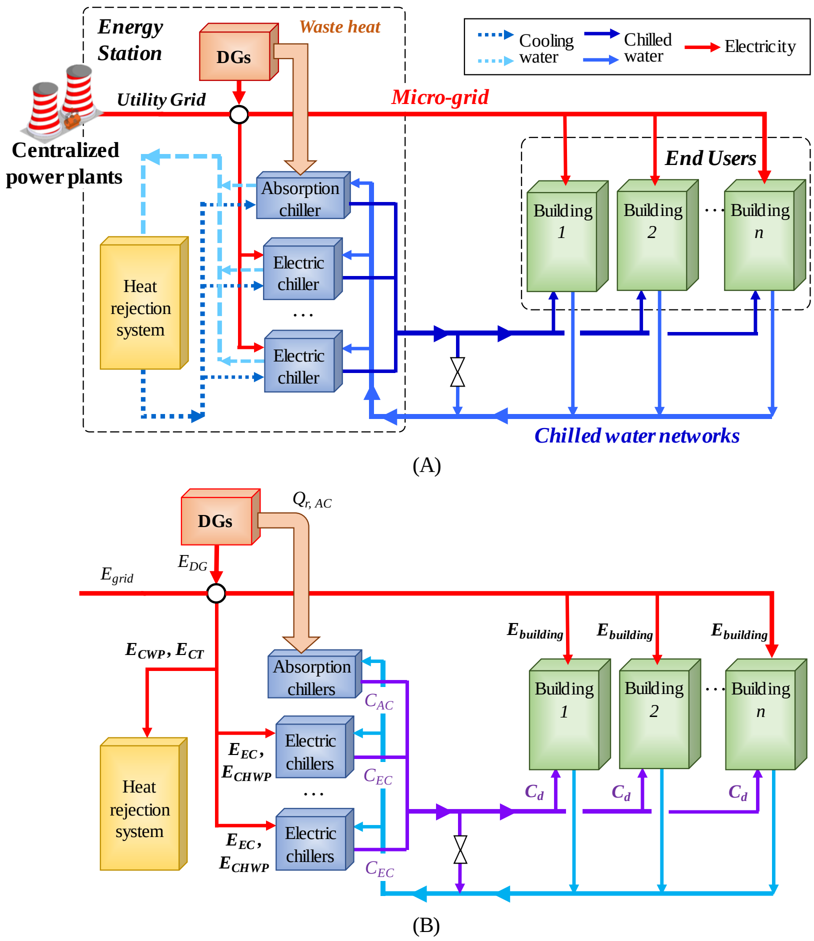


Figure 3.2 A typical configuration of a district level DES (A) and the energy fluxes in the DES (B)

It is important to mention that Hong Kong is a high population density city with high demands and limit place. Therefore, gas engines which have high efficiency and less place for installation are the priority of DGs in this PhD study.

Electric power system of the DES

The electric power system of the DES consists of power sources, including DGs as well as the utility grid, and the micro-grid. Electricity generated by DGs or imported from the utility grid is delivered to individual buildings through the micro-grid. The electricity generated by DGs should be with high priority. Only when the generated electricity cannot satisfy the demand of end-users, the insufficient power is imported from the utility grid. In contrary, the surplus electricity is exported to the utility grid.

District cooling system (DCS) in the DES

The cooling system of the DES, shown in Fig. 3.3, is actually a DCS that consists of three subsystems: chillers, chilled water networks and the heat rejection system.

- *Chillers*

Two types of chillers, including absorption chillers and electric chillers, are used in this DES. High temperature flue gas exhausted by DGs is directly used as the heat source by mixed-effect absorption chillers for cooling. Electric chillers are driven by the electricity generated by the DGs or imported from the utility grid. Generally, absorption chillers are used for cooling supply with high priority. When absorption chillers cannot satisfy cooling demand, electric chillers are used to provide the insufficient part.

- *Chilled water networks*

Chilled water networks, which deliver chilled water from chillers to end-users, consist of three loops: the primary chilled water loop, secondary chilled water loops and in-building chilled water loops. Primary chilled water pumps used in the primary chilled water loop are constant speed pumps. The secondary chilled water loops distribute chilled water from the energy station to individual buildings. In each secondary chilled water loop, a group of variable speed pumps are used as secondary chilled water pumps. The in-building chilled water loops of individual buildings in the DES, which connect the secondary chilled water loops directly, are the same as that used in a common individual cooling system (ASHRAE, 2013).

- *Heat rejection system*

The heat rejection system of the DES (DCS) locates nearby the energy station and is used to reject the condensing heat of electric chillers as well as the heat for regeneration of absorption chillers. The waste heat is transferred from chillers to cooling towers by cooling water and rejected to the atmosphere in cooling towers.

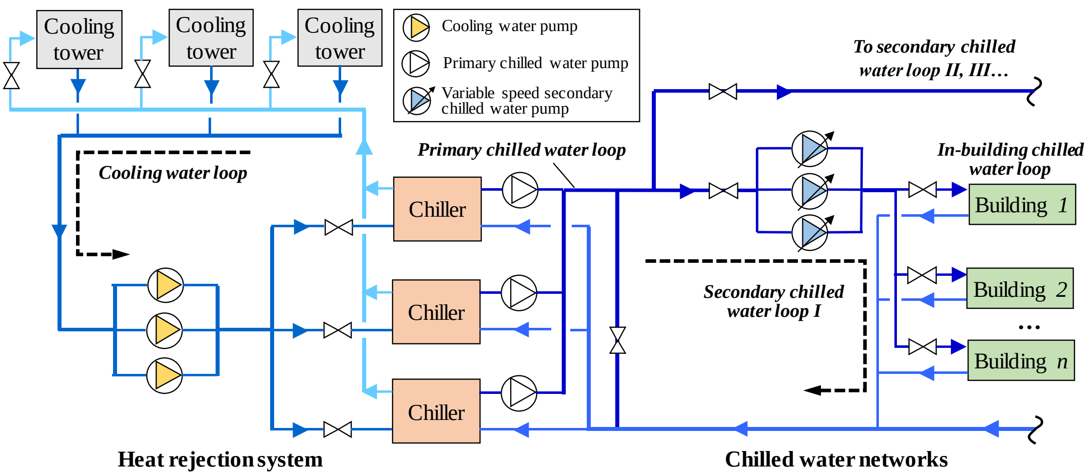


Figure 3.3 District cooling system in the DES

3.3 Modelling of DES

DES modelling is developed to simulate the operation of DES, and outputs corresponding information of the operation, like energy consumption and cost. In general, models for the DES includes two parts: energy models that are used to simulate the operation of equipment in the DES, and economic models that are used to calculate the equipment capital costs and energy prices concerned in this thesis.

3.3.1 Energy model of main equipment

Main equipment of a DES includes DGs, absorption chillers and electric chillers. In many previous studies, the full load (rated) efficiency and the partial load efficiency, i.e. electric efficiency of DGs and coefficient of performance (COP) of chillers, are often set as constant values for simplification. In fact, such simplifications may cause large inaccuracies because the equipment of different capacities will have different efficiencies and their efficiencies will change under different part loads. In this study, this divergence of efficiency is taken into account. Models of equipment as functions of capacities and part load ratios are developed.

i. Distributed generation (*DG*)

Natural gas engine is adopted as the distributed generation (DG) due to its high energy efficiency and high reliability in operation. Compared with renewable energy generations, e.g., PV and wind turbine, gas engines use reciprocating internal combustion engines to produce electricity with high conversion efficiency. Depend on its capacity, a gas engine has an electricity efficiency ranges from 30% to around 50%. Gas engines typically have thermal efficiencies between 35~45% by using multi-stage heat recovery technologies. The best engine can achieve a thermal efficiency of slightly more than 48%. In addition, the capacity of gas engine can change in a wide range, from 10 kW to 15 MW. This makes gas engines more suitable as DGs in DESs in high demand density regions.

Two types of energy efficiencies including the total energy efficiency η_T and the electric efficiency η_{DG} are used to represent the performance of a DG. Total energy efficiency is defined as the ratio of net generated electricity plus the net recovered waste heat to net primary energy consumption. Electric efficiency is defined as the ratio of net generated electricity to net primary energy consumption. For a certain type of DG, the total efficiency and electric efficiency under full load conditions are mainly determined by equipment capacity. For instance, the full load efficiencies of a typical gas engine are plotted in Fig. 3.4 based on manufacturer data (GE Co. Ltd., 2015). The relationship between full load efficiencies and DG capacities then can be fitted using the data in Fig. 3.4, as shown in Eqs. (3-1) and (3-2).

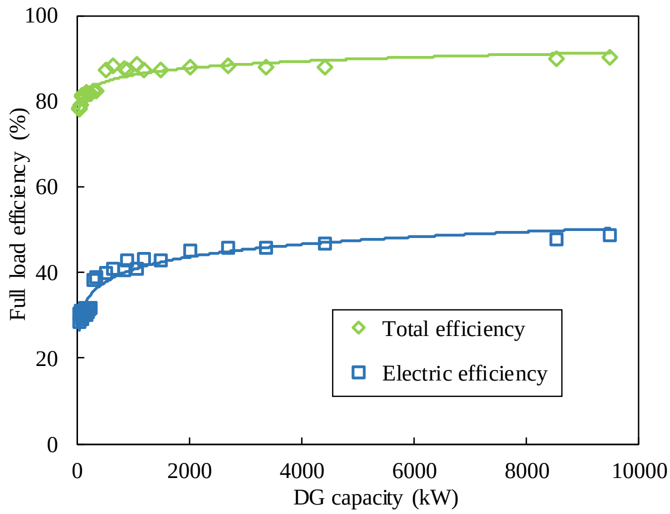


Figure 3.4 DGs full load efficiencies of different capacities

$$\eta_T = \frac{1}{100}[2.31 \cdot \ln CP_{DG} + 70.30] \quad (3\text{-}1)$$

$$\eta_{DG,FL} = \frac{1}{100}[4.24 \cdot \ln CP_{DG} + 11.50] \quad (3\text{-}2)$$

Based on a test study of a Capstone gas engine reported in reference (Capstone Co. Ltd., 2006), the DG electric efficiency reduces when the load ratio reduces, while the total efficiency keeps constant in part load conditions. Fig. 3.5 shows the variation of relative electric efficiency (α_{DG}), i.e., the ratio of partial load efficiency to the full load efficiency of the DG in that test. Eq. (3-3) is the relative electric efficiency of DGs by fitting the data presented in Fig. 3.5. Where r_p is the part load ratio (the ratio of practical electricity output and the rated capacity). It is assumed that all DGs perform with the same relative electric efficiency. Thus, the practical electric efficiency of DGs at any part load can be estimated by Eq. (3-4). The primary energy consumption of the DG (F_{DG}) and centralized power plants (F_{grid}), and the amount of recoverable waste heat (Q_r), which can be used by absorption chillers, are estimated by Eqs. (3-5) to (3-7), respectively. η_{grid} is the electric efficiency of centralized power plants which use Combined Cycle Gas Turbine (CCGT) as generations. According to the statistical data in Ref. (Eurelectric et al., 2003), this value is fixed to be 50%.

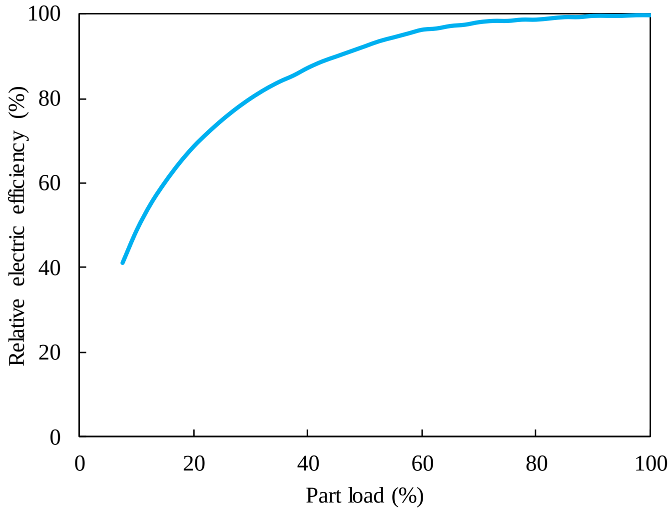


Figure 3.5 The relative electric efficiencies of DG at part loads

$$\alpha_{DG} = 1.33r_p^3 - 3.21r_p^2 + 2.61r_p + 0.27 \tag{3-3}$$

$$\eta_{DG} = \alpha_{DG} \cdot \eta_{DG,FL} \tag{3-4}$$

$$F_{DG} = \frac{E_{DG}}{\eta_{DG}} \tag{3-5}$$

$$F_{grid} = \frac{E_{grid}}{\eta_{grid}} \tag{3-6}$$

$$Q_r = F_{DG}(\eta_T - \eta_{DG}) \quad (3\text{-}7)$$

ii. Absorption chiller

LiBr-H_2O absorption chillers are commonly used thermal driven chillers. By increasing the number of desorption process, the absorption chiller can use high temperature heating source (above 500 ℃) and achieve a COP as high as 1.4. The mixed-effect absorption chiller, which is adopted in the DES, couples single effect process and double effect process in one chiller unit. It uses both the exhaust flue gas with high temperature (400~600 ℃) and the jacket water with a lower temperature (around 90 ℃) as the heating source. Thus, it improves the recovery of waste heat form DGs in a grate extend. Due to that the lack of mechanical driving components, the chiller can operate with stable efficiency and is hardly affected by part load ratios. Different from electric chillers, the capacity of equipment has very limited effects on the COP of absorption chiller. As a simplification, the COPs of absorption chillers with different capacities are assumed to be the same in this study.

The absorption chillers use the recovered waste heat ($Q_{r,AC}$) for cooling. The cooling output of these chillers is calculated by Eq. (3-8). The COP of absorption chiller (COP_{AC}) is assumed to be a constant as 1.2, based on the results of an experimental study (J. L. Wang et al., 2015).

$$C_{AC} = Q_{r,AC} \cdot COP_{AC} \quad (3\text{-}8)$$

iii. Electric chiller

Water-cooled centrifugal chiller is adopted as the electric chiller in the DES. Comparing with other types of chiller, the centrifugal chiller has a higher rated COP (higher than 5.8), a lower failure rate and a simpler maintenance requirement. Water cooling improves the heat exchange efficiency and reduces the surface area of the heat exchanger in the chiller. The capacity of water-cooled centrifugal chiller can be as high as 8800 kW (2500 TR), so that it is commonly used for cooling in large-scale buildings or district cooling systems.

Based on the data provided by a major manufacturer (Carrier Co. Ltd., 2015), as presented in Fig. 3.6, the full load COP of chiller with different capacity (CP_{EC}) can be estimated by the fitting function (Eq. (3-9)). The relative COP, which is the ratio of practical COP to full load COP, for a typical chiller under different part load ratio (r_p) is presented here as an example, as shown in Fig. 3.7 (Wenjie Gang, Shengwei Wang, et al., 2016). All of the chillers in this study follow the same curve of relative COP, which is fitted by Eq. (3-10). The practical COP is the product of full load COP and relative COP as shown by Eq. (3-11). The electricity consumption of chillers can be estimated by Eq. (3-12).

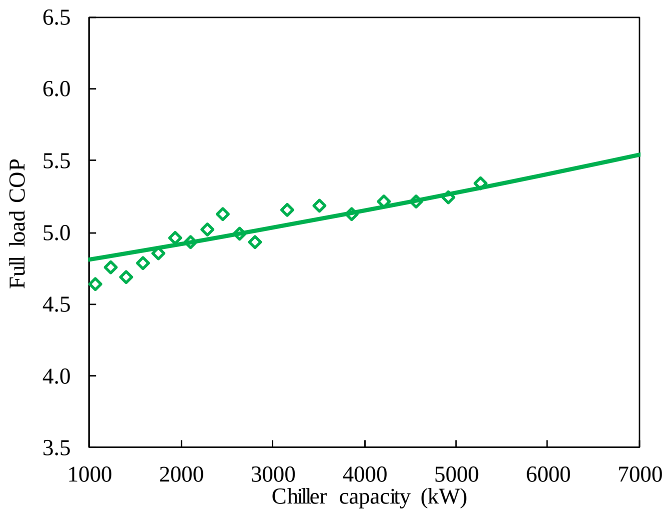


Figure 3.6 Electric chillers full load COP of different capacities

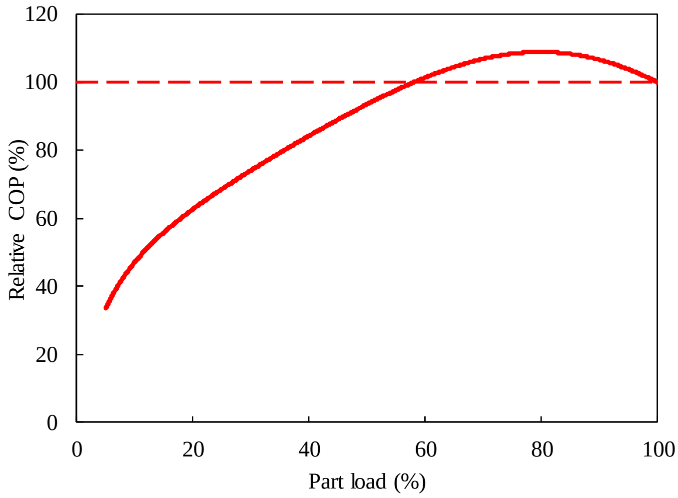


Figure 3.7 The relative COP of electric chiller at part loads

$$COP_{EC,FL} = 2.89 \times 10^{-9} CP_{EC}^{2} + 0.21 \times 10^{-4} CP_{EC} + 4.71 \tag{3-9}$$

$$\alpha_{EC} = -0.57 r_p^3 - 0.26 r_p^2 + 1.52 r_p + 0.32 \tag{3-10}$$

$$COP_{EC} = \alpha_{EC} \cdot COP_{EC,FL} \tag{3-11}$$

$$E_{EC} = \frac{C_{EC}}{COP_{EC}} \tag{3-12}$$

3.3.2 Energy model of auxiliary equipment

Auxiliary equipment of a DES includes water pumps and cooling towers.

i. Water pumps

Water pumps are used to deliver water (i.e., chilled water and cooling water) from chillers to HVAC terminal units (e.g., AHU) in cooling systems. The electricity demand of a water pump can be estimated by Eq. (3-13). Where H is the pressure head, G is the flow rate of water, m^3/h, g is the acceleration of gravity, 9.8 $kg \cdot m/s^2$. η_P is the pump efficiency, 0.85 as Ref (EMSD Hong Kong, 2007a).

$$E_{pump} = H \cdot G \cdot g/(3600 \cdot \eta_P) \tag{3-13}$$

ii. Cooling towers

Cooling towers are the main equipment in a heat rejection system. The electricity demand of cooling towers can be estimated by Eq. (3-14). Where *P* is the total pressure of fans (400 Pa is used in the estimation). λ is the air-water ratio of cooling towers (0.65 is used in the estimation), which is the ratio of the air mass flow rate to the water mass flow rate. ρ_w is the density of water, 1000 kg/m^3, and ρ_a is the density of air, 1.21 kg/m^3. η_F is the efficiency of fans used in cooling towers, 0.78.

$$E_{CT} = G \cdot \rho_w \cdot \lambda \cdot P/(3600 \cdot \eta_F \cdot \rho_a) \tag{3-14}$$

3.3.3 Economic models

i. Equipment capital costs

The total equipment capital costs of a DES are the sum of initial investments of all equipment, including the investment of main equipment (i.e., the DG, the absorption chiller and electric chiller), the investment of auxiliary equipment (i.e. the water pumps, and the cooling tower in the heat rejection system), and the investment of the pipes in chilled water network. Eqs. (3-15) to (3-17) present the investment of DG, absorption chiller and electric chiller respectively. Where *CC* is the equipment investment and *CP* is the capacity of this equipment (U.S. Environmental Protection Agency, 2015a; Zheng et al., 2016).

$$CC_{DG} = [3711.78 - 280.47 \cdot \ln CP_{DG}] \cdot CP_{DG} \tag{3-15}$$

$$CC_{AC} = [369.50 - 36.78 \cdot \ln CP_{AC}] \cdot CP_{AC} \tag{3-16}$$

$$CC_{EC} = 150.45 \cdot CP_{EC} \tag{3-17}$$

The investment of auxiliary equipment can be estimated by Eqs. (3-18) to (3-20). Eq. (3-18) presents the investment of water pumps, including chilled water pumps and cooling water pumps (Wilo Co. Ltd., 2015). Eq. (3-19) presents the investment of cooling tower (liangken Co. Ltd., 2015). The investment of pipe is shown in Eq. (3-20).

$$CC_{pump} = 1.63 \cdot CP_{pump}^2 + 133.72 \cdot CP_{pump} + 500.37 \tag{3-18}$$

$$CC_{CT} = 29.85 \cdot CP_{CT} \tag{3-19}$$

$$CC_{pipe} = [0.889 \cdot D_{pipe}^2 + 6.52 \cdot D_{pipe} + 63.65] \cdot L_{pipe} \tag{3-20}$$

where, CP_{pump} is the rated power of the pump, kW, CP_{CT} is the rated air flow, m^3/h. D_{pipe} is the diameter of the pipe, mm, and L_{pipe} is the length of the pipe segment, m.

ii. Equipment maintenance costs

Compared with other equipment, DGs need frequent maintenance during operation. The maintenance cost coefficient (CM_{DG}) is the maintenance cost of DGs associated with each unit of electricity generation as shown in Eq. (3-21), USD/kWh.

$$CM_{DG} = 0.0394 - 0.0031 \cdot \ln CP_{DG} \tag{3-21}$$

iii. Energy prices

Energy prices include the price of primary energy, and the price of secondary energy, i.e., grid electricity price. Energy prices are mainly determined by local energy markets. Hong Kong is currently using coal-fired power plants to generate electricity, and intends to replace those plants by natural gas generations in the future years (CLP Hong Kong, 2015c; Fong et al., 2015). Due to the difference between coal price and gas price, the current electricity price cannot be used directly in the economic models and an appropriate electricity price need to be deduced. The current electricity price in Hong Kong consists of the total energy cost and the other cost ($Cost_{other}$) (CLP Hong Kong, 2015d). In this study, the other cost, which is assumed to be an independent value, is deduced by subtracting the total energy cost from the electricity price. According to the tariff data of China Light and Power Company (CLP), the major utility company in Hong Kong, the other cost for generating each unit electricity is estimated to be 0.078 USD/kWh (CLP Hong Kong, 2015a, 2015b). When natural gas is used as the fuel, the grid electricity price ($Cost_e$) equals the sum of the natural gas cost ($Cost_f$) and the other cost as shown in Eq. (3-22). The natural gas price is the price of natural gas which is directly purchased by CLP from international energy market, 0.057 USD/kWh, where kWh is the higher heating value of natural gas. In the DES, the feed-in tariff ($Cost_{e,sell}$), or the selling price of electricity, is assumed to be 80% of the grid electricity price as shown in Eq. (3-23). Thus, the electricity price and the feed-in tariff are 0.192 USD/kWh and 0.154 USD/kWh, respectively.

$$Cost_e = Cost_{other} + Cost_f \cdot \frac{1}{\eta_{grid}} \tag{3-22}$$

$$Cost_{e,sell} = 0.8 \cdot Cost_e \tag{3-23}$$

3.4 Operation strategies of DES

The DES operation is a complex issue because of the energy conversion and the coupling operation among the energy supply equipment and the utility grid. A DES may perform in a totally different way if it controlled by different operation strategies. Thus, to ensure high energy efficiency of the DES during operation while satisfying various demands, an appropriate operation strategy is essential.

In DES application, two common energy policies with respect to the grid interaction are distinguished by the permission of selling the surplus electricity:

EP_1: Selling electricity is not permitted;

EP_2: Selling electricity to the grid is allowed if DGs produce surplus electricity.

The choice of operation strategy is governed by the energy policy. Two basic operation strategies, namely following hybrid load (FHL) and following thermal load (FTL), are employed to control the operation of DES. Besides, other operation strategies, such as following electric load (FEL), can be adopted in the DES control. However, a feasibility study was conducted and presented that these strategies cannot control the proposed DES in a good operation mode in such subtropical regions. Therefore, the application of these strategies is not discussed in this thesis.

i. FHL strategy

Fig. 3.8 (a) illustrates the following hybrid load (FHL) operation strategy adopted in EP_1. The *x*-axis represents the electricity demand, and the *y*-axis shows the cooling demand. The black curve represents the outputs of absorption chillers (ACs), C_{AC}, depends on the electricity output of DGs. The left side of this line ends at a minimum output value (25% of the DG rated capacity) as DGs should not be operated beyond this limit due to its low efficiency (Chamra et al., 2008). The right side of this line ends at the maximum output or the rated capacity of DGs. The DES operating condition can be divided into four areas. The FHL strategy is presented as four cases associated with the four areas as follows.

Case 1h ($E_d \geqslant E_{max}$; $C_d \geqslant C_{max}$): Both DGs and absorption chillers operate at the maximum load. However, their outputs are not sufficient to meet the energy demands.

The gap of electricity supply will be imported from the grid and the cooling will be supplied by electric chillers.

Case 2h ($E_d \geqslant E_{min}$; $C_{min} < C_d < C_{ac}$): The cooling demand is less than the cooling supplied by absorption chillers when the output of DGs match the electricity demand, as the point B_1 shows. In this case, absorption chillers operate to meet the cooling load at the point B while the DGs produce a corresponding amount of electricity. The gap of electricity supply will be imported from the grid.

Case 3h ($E_{min} < E_d < E_{max}$; $C_d \geqslant C_{ac}$): The cooling demand is larger than the cooling supplied when the output of DGs match the electricity demand, as the point A_1 shows. In this case, the DGs operate to meet the electricity load at the point A while absorption chillers produce a corresponding amount of cooling. The gap of cooling supply will be supplied by the electric chillers.

Case 4h ($E_d < E_{min}$ or $C_d < C_{min}$): DGs are off because the power demand is lower than the minimum output of DGs. The electricity is imported from the grid and the cooling is supplied by the electric chillers.

ii. FTL strategy

Fig. 3.8 (b) illustrates the following thermal load (FTL) operation strategy which is adopted in EP_2. The detail is presented in the following ways:

Case 1t ($C_d \geqslant C_{max}$): Both DGs and absorption chillers operate at maximum load. The gap of electricity supply will be imported from the grid if it is insufficient and the surplus of electricity generated can be sold to the grid if it is more than the power demand. The insufficient cooling will be supplied by electric chillers.

Case 2t ($C_{min} < C_d < C_{max}$): In this case, absorption chillers operate to match the cooling load while DGs produce a corresponding amount of electricity. The gap of electricity supply will be imported from the grid (from operation point B to demand point B_1) while the surplus generated electricity is sold to the grid (from operation point A to demand point A_1).

Case 3t ($C_d < C_{min}$): DGs are off because the energy demand is lower than the minimum output. The electricity is imported from the grid and the cooling is supplied by electric chillers.

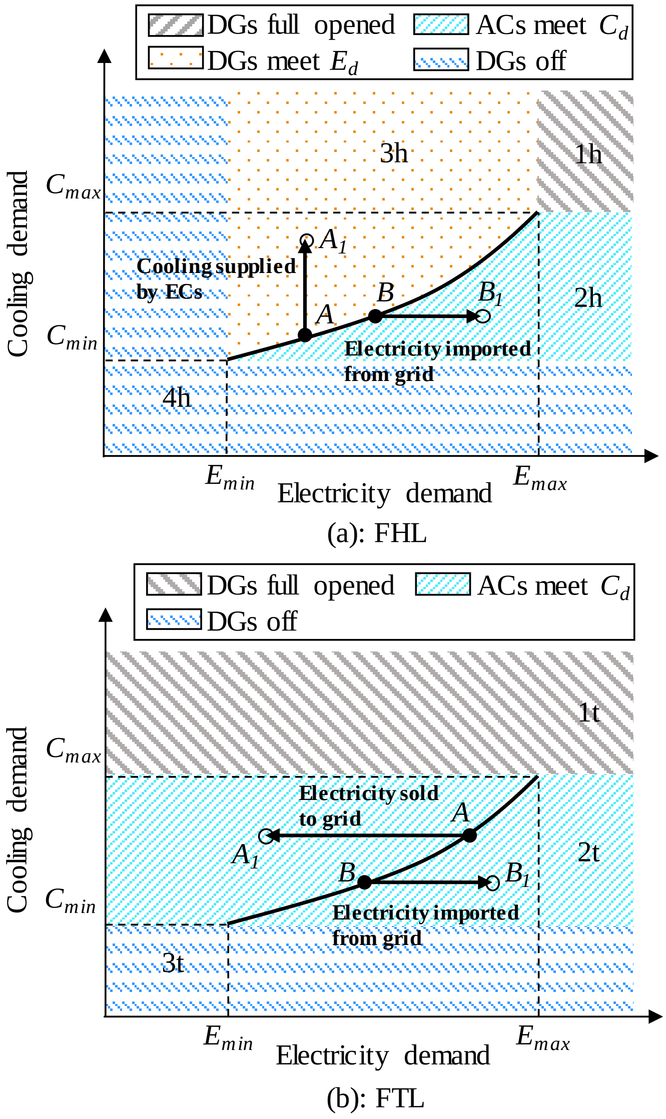


Figure 3.8 DES operation strategies employed in this study

3.5 Summary

In subtropical regions, electricity and space cooling are the dominated energy demands while space heating can be ignored. DGs and chillers with high energy efficiency and large capacities are the best choices as DES technologies in these regions. Mixed-effect absorption chillers convert waste heat into available cooling energy with a high COP. They not only satisfy the cooling demand of users but also improve the overall energy efficiency of DES. The DES is connected to the utility grid so that the DES can purchase electricity from the utility grid. The proposed building level DES uses a commonly-used individual cooling system, which is the same as that of the CES for the cooling of the buildings. The proposed district level DES is actually a combination of DES technologies and DCS. Additional chilled water networks are needed for distributing chilled water to the building in the district.

Modelling is the basic task for the feasibility study on DESs to be applied in subtropical regions. Energy models are developed to simulate the operation of devices/subsystems in the DES and economic models are developed to evaluate various costs of the DESs. Two basic operation strategies with respect to the energy policies are adopted to control the DES operation. The performance assessment methods of DES need to be developed. The advantages as well as disadvantages of using DESs in subtropic regions need to be identified based on the system performance.

CHAPTER 4 PERFORMANCE ASSESSMENT AND INFLUENTIAL FACTORS IDENTIFICATION OF DES

Performance assessment is an effective approach for DES feasibility study. It can be adopted not only to evaluate the pros and cons of the DES in a quantitative mean but also to provide useful recommendations for DES design. Based on the simulation results, the DES performance can be quantified with given assessment criteria. The advantages and the limitations of DESs can be then identified by comparing the performance of DESs adopting different design options.

In this chapter, performance assessment methods of DESs in subtropical regions is developed. The main factors affecting DES application and the extent of impacts are identified using these assessment methods. Section 4.1 introduces the assessment criteria to quantify the DES performance. Section 4.2 presents the arrangement of case studies for identifying influential factors that affect the performance of DESs in applications. Impacts of those factors on DES performance are evaluated and analysed in Section 4.3. The results of performance assessment and suggestions for DES applications in subtropical regions are summarized in Section 4.4.

4.1 Performance assessment criteria of the DES

Two values, the primary energy saving and the payback period, are used as the assessment criteria to evaluate the energy performance and the economic performance of DES, respectively.

4.1.1 Primary energy saving (PES)

The primary energy saving (*PES*) of DES is the energy saving of DES compared with the centralized energy system (CES). It is the ratio of annual saved energy by the DES and the annual energy consumption of CES, as shown in Eq. (4-1). Where F_{DES} is the primary energy consumption of DES as shown in Eq. (4-2). F_{CES} is the corresponding CES consumption for generating the same amounts of electricity and cooling as shown in Eq. (4-3). *d* and *h* are the number of day and hour, respectively. A higher value of primary energy saving denotes better energy performance of a DES.

$$PES = \frac{F_{CES}-F_{DES}}{F_{CES}} \times 100\% \tag{4-1}$$

$$F_{DES} = \sum_{d=1}^{365}\sum_{h=1}^{24}\left(F_{DG} + F_{grid}\right) \tag{4-2}$$

$$F_{CES} = \sum_{d=1}^{365}\sum_{h=1}^{24}\frac{1}{\eta_{grid}}\left(E_d + E_{sell} + \frac{C_d}{COP_{ec}}\right) \tag{4-3}$$

4.1.2 Payback period (PBP)

The payback period (*PBP*) indicates the number of years needed for the payback of the surplus capital cost when DES replaces CES. Thus, shorter payback period indicates better economic performance of the DES. This value is the ratio of the capital cost difference and the operating cost difference as shown in Eq. (4-4). Where ΔCC and ΔOC are the increase of system capital cost and the annual operation cost saving shown in Eqs. (4-5) and (4-6), respectively. CC_{eq} is the equipment capital cost, which is the product of unit price and capacity. n_1 and n_2 are the equipment number for the DES and the CES. The first part of the right side in Eq. (4-6) is the annual operation cost of CES, and the second part is that of the DES which includes the energy cost and the maintenance cost.

$$PBP = \frac{\Delta CC}{\Delta OC} \tag{4-4}$$

$$\Delta CC = \sum_{m=1}^{n_1} CP_m \cdot CC_{m,eq} - \sum_{n=1}^{n_2} CP_n \cdot CC_{n,eq} \tag{4-5}$$

$$\Delta OC = \sum_{d=1}^{365} \sum_{h=1}^{24} \left\{ \left(E_d + \frac{C_d}{COP_{EC}} \right) \cdot Cost_e - \left[\left(E_{grid} \cdot Cost_e + F_{DG} \cdot Cost_f - E_{sell} \cdot Cost_{e,sell} \right) + CM_{DG} \cdot E_{DG} \right] \right\} \tag{4-6}$$

4.2 Identification of influential factors of DES

Building level DES is the most typical application of DESs. Its performance can represent the advantages and the disadvantages of DESs using in subtropical regions. In this study, energy performance and economic performance of building level DESs are assessed and main factors affecting the DES performance are identified by analysing the assessment results. The procedures for identifying the main influential factors on DES performance is shown in Fig. 4.1.

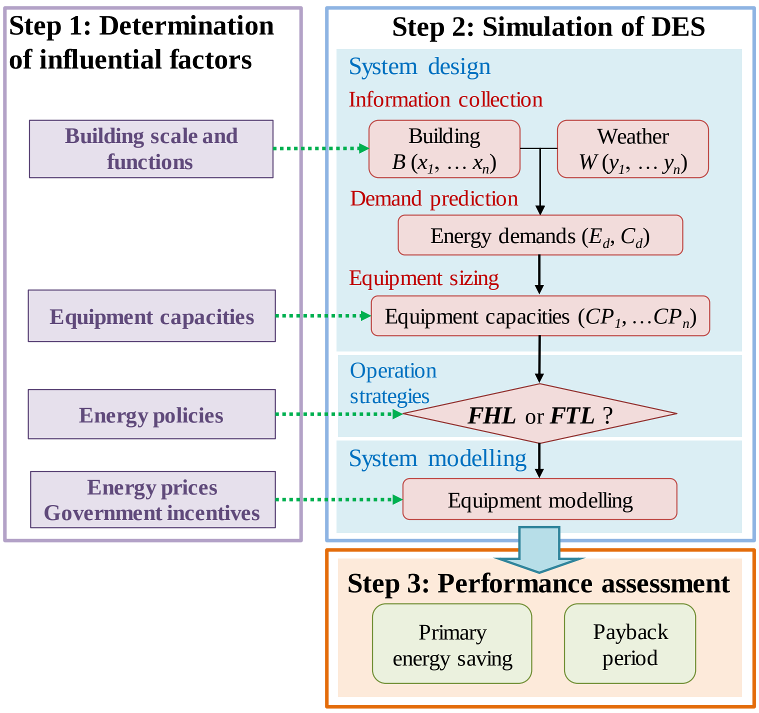


Figure 4.1 Procedures for identification of influential factors on DES performance

The influential factors are determined, and the corresponding case studies, which investigate the impacts of specific factors on the DES performance, are organized in Step 1. Step 2 is the DES simulation which includes three subtasks: system design, selection of operation strategies and system modelling. The DES performance is assessed in Step 3. The impacts of those influential factors are demonstrated by comparing and analysing the DES performance of case studies.

4.2.1 Determination of influential factors

The factors may affect DES performance include four categories. Description of these factors and organization of the corresponding case studies are presented as follows.

i. Building scales and functions

A commercial building is selected for analysis the impacts of building scale on DES performance. Its floor area changes within a range between 2,000 and 250,000 m^2. Five public buildings with different functions, including the commercial building, the office building, the school, the hotel and the hospital, are chosen for analysis the impacts of building functions. In this case, all the buildings are assumed to have a floor area of 60,000 m^2.

ii. Equipment capacities

Equipment capacities refer to the capacities of DGs, absorption chillers and electric chillers. In the DES, it is assumed that the absorption chillers have the capacity to use all the recoverable waste heat when the DGs are operating at full load, and the capacity of electric chillers is then chosen to fill the gap of absorption chillers in satisfying the cooling demand at the design load condition, as shown in Eqs. (4-7) and (4-8). Where N_{DG}, N_{ac} and N_{ec} are the numbers of DGs, absorption chillers and electric chillers, respectively. $C_{d,peak}$ is the annual peak cooling demand and α is the safety factor, 1.1.

When DGs capacities are determined, corresponding chillers capacities can be estimated by the above equations. In this case study, DGs capacities are changed within a range, then chillers capacities change consequently.

$$CP_{AC} = CP_{DG} \frac{(\eta_T - \eta_{DG,FL})}{\eta_{DG,FL}} COP_{AC} \cdot \frac{N_{DG}}{N_{AC}} \tag{4-7}$$

$$CP_{EC} = \frac{C_{d,peak} \cdot \alpha - N_{AC} CP_{AC}}{N_{EC}} \tag{4-8}$$

iii. Energy policies

Two energy policies, i.e., EP_1 (selling electricity is not allowed) and EP_2 (Selling electricity is allowed), are adopted to invest the impacts of energy policies. When the energy policy is determined, the DES runs in the corresponding operation strategy (i.e., following hybrid load (FHL) strategy or following thermal load (FTL) strategy).

iv. Energy prices and government incentive

The natural gas price in the market can affect the operation cost of DES. Three natural gas prices are adopted to analyse such impacts. Gas price I is the gas price used in this thesis, 0.057 USD/kWh. Gas price II is the current natural gas price given by the local supplier in Guangzhou near Hong Kong, which is a metropolis in Mainland China, 0.072 USD/kWh (Guangzhou Municipal Development and Reform Commision, 2016). Gas price III is the current natural gas price given by the local supplier in Hong Kong, 0.108 USD/kWh (Towngas Hong Kong, 2017).

To encourage to reduce the energy consumption, governments may provide some financial support as economic incentives to the DES investors according to primary energy saving (Dong et al., 2015). In this study, the impacts of this incentive on the performance of local DESs are investigated. It is assumed that the economic incentive, which is given by the government, is proportional to the primary energy saving of the DES. The adjusted operation cost, which can be calculated by Eq. (4-9), equals the sum of system energy cost and the maintenance cost, subtracted by the energy saving incentive. In Eq. (4-9), *PS* is the incentive coefficient of energy saving. It is the amount of money which the government intends to subsidize for each unit of primary energy saving. In this study, the incentive coefficient is chosen as 0.029 USD/kWh, i.e., 50% of the fuel price.

$$OC = \sum_{d=1}^{365}\sum_{h=1}^{24}\left[\left(E_{grid}\cdot Cost_e + F_{DG}\cdot Cost_f - E_{sell}\cdot Cost_{e,sell}\right) + CM_{DG}\cdot E_{DG} - (F_{CES} - F_{DES})\cdot PS\right] \tag{4-9}$$

4.2.2 Simulation of DES and its performance assessment

The first subtask in the DES simulation is system design. Users' energy demands are predicted and the capacities of equipment in the DES are identified as follows.

i. Information collection

Collecting the building information B (x_1, x_2… x_n) and the outdoor weather parameters W (y_1, y_2… y_n). B includes the building function, building physical parameters, the indoor environment settings, etc. W includes the outdoor temperature, the relative humility, etc. For DES design, these are primary design parameters.

ii. Demand prediction

Several available software, such as EnergyPlus, DesT and TRNSYS, are commonly used for buildings energy demand prediction. TRNSYS is a user-friendly simulation program with better flexibility in including energy systems in simulation (TRNSYS, 2015). With the building information (working schedule and physical parameters) and outdoor weather parameters (TMY data of Hong Kong), the hourly cooling demand

(C_d) can be predicted using TRNSYS building model, Type 56, in this study. The electricity demand of each building (E_d) includes the base demand of building ($E_{building}$) and the demand of the auxiliary equipment of HVAC systems (E_{aux}), such as pumps, cooling towers, and fans. The $E_{building}$ can be calculated according to the guidelines on building energy codes published by the Hong Kong government (EMSD Hong Kong, 2007c). The E_{aux} can be predicted by a simplified method which is explained in reference (Kong et al., 2005). For an individual building, the electricity demand of auxiliary equipment of HVAC system (E_{aux}) in the CES and the DES are the same.

iii. DES equipment sizing

A common design method, named maximum rectangle method (MRM), to determine the equipment capacities in DES according to user's energy demands in the study of performance. This method is based on the electricity demand as described in reference (Sanaye et al., 2014). Fig. 4.2 illustrates the process of this method. A rectangle can be drawn under the cumulative curve of annual electricity demand limited to the time and the demand axis. The demand, i.e. the value at the x-axis, associated with the intersection of the rectangle with the maximum area determines the DG capacity.

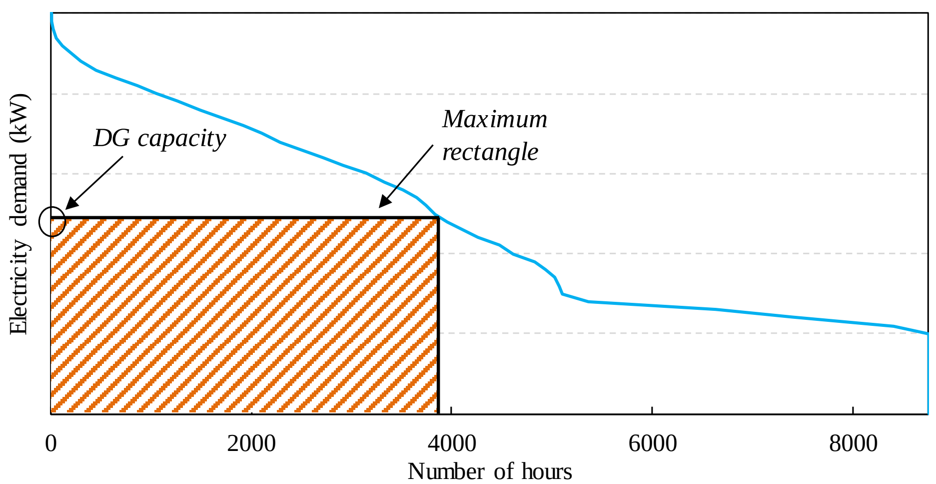


Figure 4.2 Cumulative curve and the application of MRM

The DG capacity is selected within a range between 50 and 8500 kW with an interval of 50 kW. The absorption chiller capacity ranges from 100 to 2500 kW and the electric chiller capacity ranges from 100 to 7500 kW.

After the DES is designed and the operation strategy is determined, the operation of the system can be simulated and the system performance data (e.g., operating cost, energy consumption and energy generation) can be obtained using the DES model. The performance of DES can be evaluated using the assessment criteria based on the simulation results.

4.3 Impacts of main influential factors on DES performance

4.3.1 Building scale and functions

The buildings with different scales and functions result in different energy demands. Thus, the impacts of these factors on the performance of the building level DES are significant. When selling generated electricity is not permitted, i.e. energy policy EP_1 is adopted, the system follows the FHL operation strategy. For commercial buildings with different scales, whose floor areas change within a range between 2,000 and 250,000 m^2, the capacities and the number of equipment are presented in Table 4.1 based on the constraints of equipment capacity assumed above. It can be seen that DGs and chillers, applied in large-scale buildings, have larger capacities with higher efficiencies, both total efficiency η_T and electric efficiency $\eta_{DG,FL}$. The annual primary energy savings of DESs in buildings of different scales are shown in Fig. 4.3. A positive value denotes that the DES saves primary energy compared with the corresponding CES, while the negative denotes that the DES consumes more than the CES. In small-scale buildings (i.e., the floor area is less than 40,000 m^2), the ratio is negative. It decreases when the building scale decreases. This indicates that the DES is inapplicable in small-scale buildings because the DES used in those buildings is equipped by small capacity devices with lower energy efficiencies, and consumes more primary energy than the CES as a result. The saving increases when the building scale increases. It reaches 6.15% when the scale is 100,000 m^2. However, this value is saturated at 6.43%, indicating that the DES cannot achieve very significant energy saving in this subtropical region when selling electricity is not permitted.

Table 4.1 Detailed equipment selection for the building energy systems

Building scale (m^2)	DES								CES	
	DG (kW)	$\eta_{DG,FL}$ (%)	$\eta_{T,}$ (%)	N_{DG}	Absorption chiller (kW)	N_{AC}	Electric chiller (kW)	N_{EC}	Electric chiller (kW)	N_{EC}
2,000	100	30.56	80.60	1	140	1	120	3	130	4
5,000	250	34.35	82.71	1	300	1	280	3	280	4
10,000	450	37.28	85.53	1	535	1	620	3	600	4
20,000	850	40.17	85.53	1	950	1	1270	3	1200	4
40,000	1750	43.11	87.19	1	1720	1	2600	3	2380	4
60,000	2550	44.69	88.06	1	2370	1	3970	3	3570	4
100,000	4550	47.16	89.39	1	1310	2	6610	3	5940	4
250,000	5400	47.90	89.78	2	1525	3	6290	8	5940	10

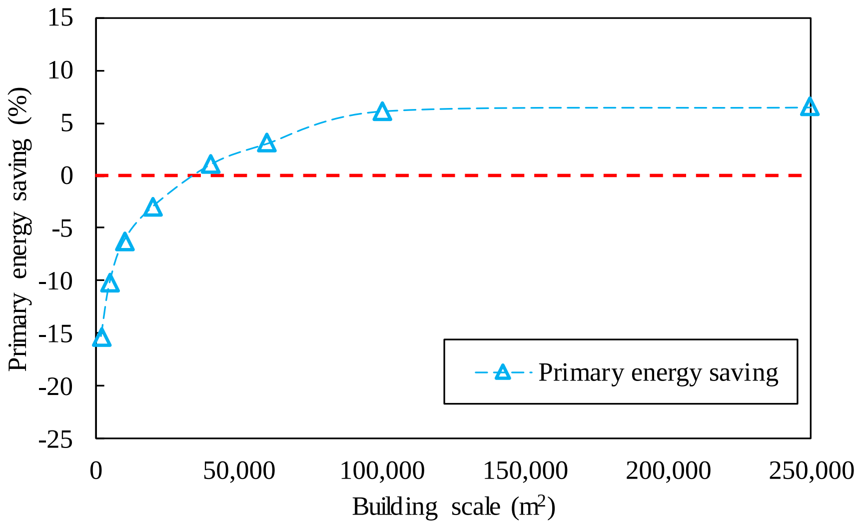


Figure 4.3 Performance of DESs *vs* building scale when selling electricity is not permitted

Fig. 4.4 presents the DES energy performance of different functions of buildings. Due to the difference of building functions and working schedules, the annual primary energy consumptions of buildings are different. For example, the primary energy consumed by the commercial building is 58298 MWh in a year and it is about half for the school (28567 MWh). This is because the commercial building has significantly higher energy demands during the night-time and weekends compared with the school building. Compared with the CES, the ranking order of the DES in terms of primary energy saving is: the commercial building (3.07%), the office building (2.98%), the hotel (2.49%), the hospital (2.06%) and the school (1.43%). Main reason is that DESs may operate with different part load ratios using in different buildings. For example, DESs in commercial buildings may operate with higher part load ratios and higher efficiency, while DESs in schools may operate with lower part load ratios and lower efficiency, and consume more energy as a result. This case indicates that the building level DES is not practically beneficial to all buildings in term of energy saving.

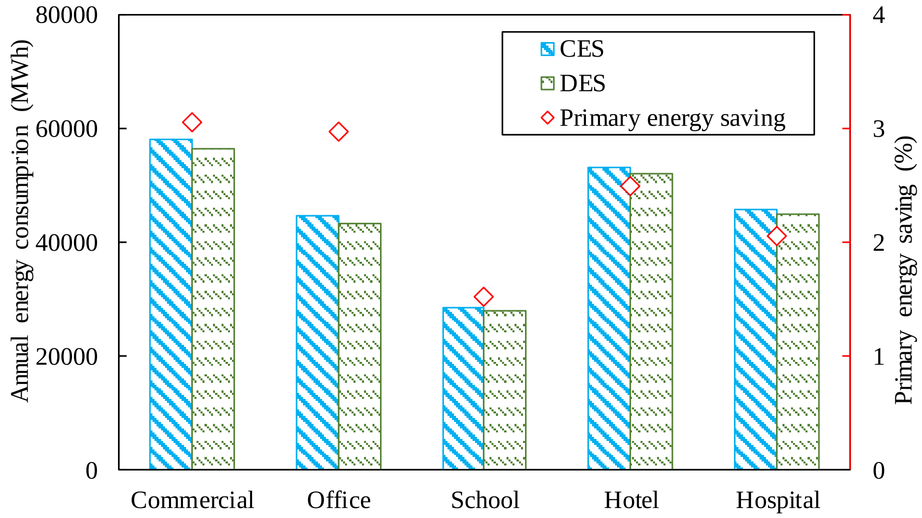


Figure 4.4 Performance of DESs in buildings of different functions when selling electricity is not permitted

4.3.2 Equipment capacities

Capacities of DESs affect the system energy production and the energy consumption. A hypothetic commercial building of 100,000 m^2 floor area is regarded as the case building. The DG capacity varies from 2000 kW to 8000 kW, and capacities of chillers vary consequently according to Eqs. (4-7) and (4-8). Compared with the CES, the primary energy saving of the DES with various DG capacities, when selling electricity is not permitted, is shown as Fig. 4.5. It can be seen that, when the DG capacity increases, the system energy saving increases because of the raise in equipment efficiency. The saving reaches the maximum value, 6.54%, when the DG capacity is 5350 kW, and reduces when the capacity continues to increase. This is because the oversized DG will operate under part loads with relatively lower efficiency. Therefore, the primary energy consumption of the DES increases so that the system energy performance decreases.

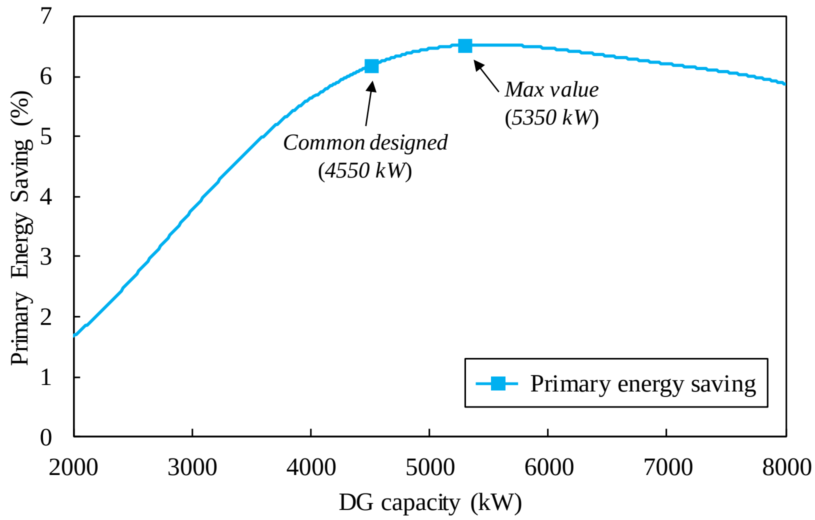


Figure 4.5 Energy performance of DESs of variable DG capacities when selling electricity is not permitted

Fig. 4.6 illustrates the system payback period with different DG capacities in the same case. The results indicate that the system payback period remains a relatively high value when the DG capacity is either undersized or oversized. When a DG of small capacity is adopted, the operation cost cannot be reduced apparently. Thus, the additional capital cost of DES cannot be recovered within a short time. When the DG is oversized, the capital cost increases but the operation cost will not reduce, or only reduce slightly. Thus, the payback period increases. For this building, the minimum payback period is 1.98 years when the DG capacity is 4100 kW. Meanwhile, the marked points in Fig. 4.5 and Fig. 4.6 indicate that the DES achieved by the common design method cannot realize the potential of energy saving or achieve the maximum economic performance.

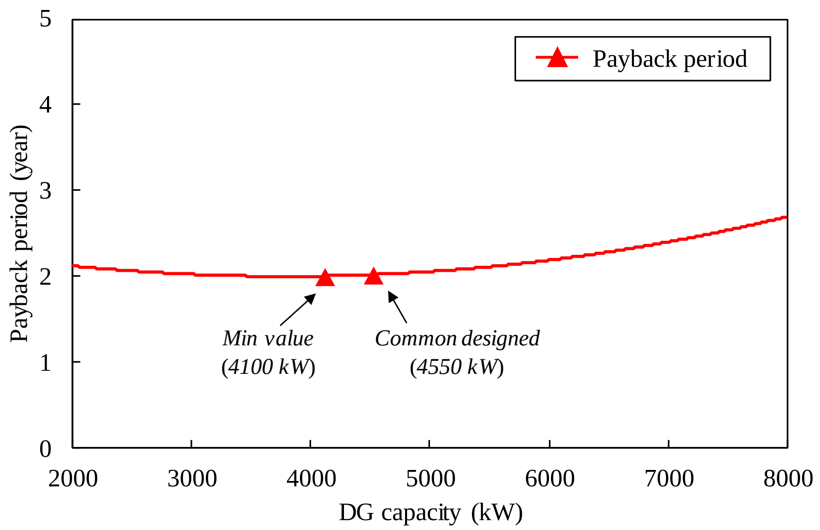


Figure 4.6 Economic performance of DES of variable DG capacities when selling electricity is not permitted

4.3.3 Energy policies

When selling generated electricity is permitted, i.e. energy policy EP_2 is adopted, the system follows the FTL operation strategy. Fig. 4.7 and Fig. 4.8 present the comparison of DES energy saving and the annual electricity generation respectively, under two different grid interaction policies. When the surplus electricity can be sold to the grid, the primary energy saving increases significantly and this increase becomes larger when the DG capacity increases. For example, the primary energy saving increases by 1.59% (from 5.73% to 7.32%) when the DG capacity is 4000 kW, and increases by 7.67% (from 5.88% to 13.55%) when the DG capacity increases to 8000 kW. From Fig. 4.8 we can see that the annual electricity generation of DESs increases in EP_2. It indicates that: 1) the practical electric efficiency of DGs increases while less primary energy will be consumed; 2) more recovered heat can be used for cooling due to the increase of DG production. Thus, the electricity consumption of electric chillers in the DES reduces.

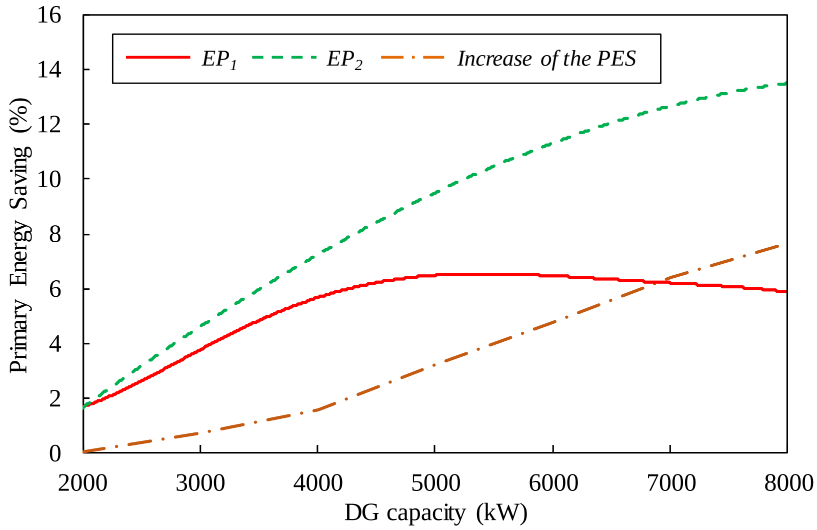


Figure 4.7 Energy performance of DESs under different grid interaction policies

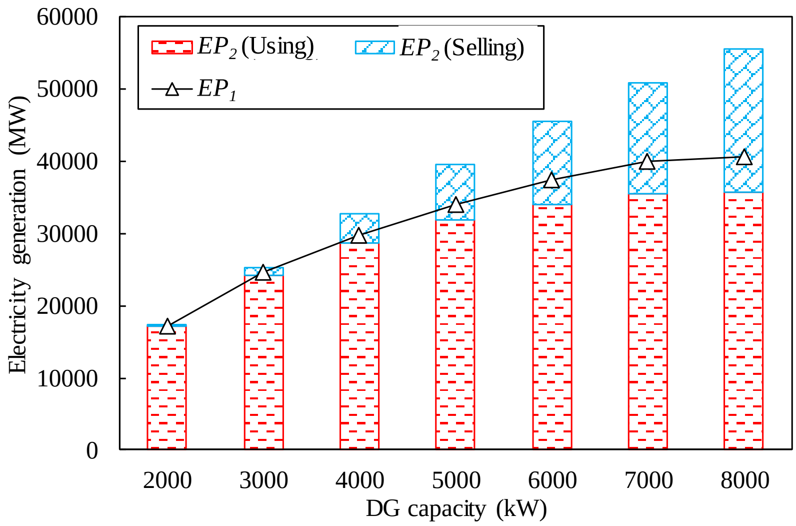


Figure 4.8 Annual electricity generations of DESs under different grid interaction policies

Fig. 4.9 shows that the payback period decreases due to the use of energy policy EP_2. By selling the generated electricity with an appropriate feed-in tariff, the DES can reduce its operation cost according to Eq. (4-6). This reduces the payback period and improves the system economic performance. When the DG capacity is 4000 kW, for instance, the payback period reduces by 0.14 years (from 1.99 years to 1.85 years). This reduction is enlarged with the increase of the DG capacity, and reaches 0.75 year when the DG capacity is 8000 kW (from 2.71 years to 1.96 years). In subtropical regions, the building level DES can achieve higher energy and economic performance when selling electricity of DES is permitted.

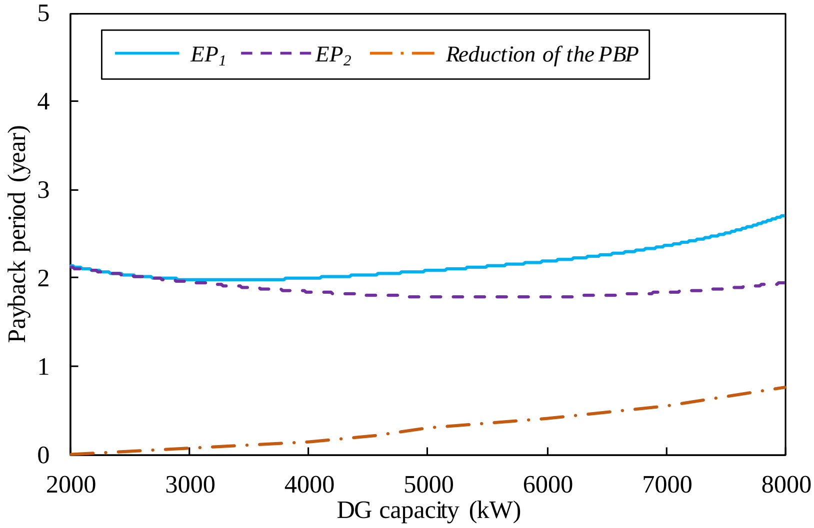


Figure 4.9 Economic performance of DESs under different grid interaction policies

4.3.4 Energy prices

Comparing the operation cost of DESs and CESs, the operation cost saving can be estimated by Eq. (4-6). Fig. 4.10 shows the cost savings when different gas prices are adopted. The positive value denotes that the system operation cost reduces due to the application of DES. The DES achieves economic benefits and the surplus capital cost of the DES can be recovered. While the negative value denotes that the system operation cost increases. Thus, the DES losses the economic benefits and the surplus capital cost cannot be recovered. When Gas price I is adopted, the operation cost saving of the system is larger than the case when Gas price II is adopted. This indicates that the DES can achieve economic advantages in both situations and the cost benefit is improved in the first situation (i.e., Gas price I is adopted). When Gas price III (i.e., the current gas price in Hong Kong) is used, the operation cost saving is negative, indicating that the use of DES increases the building energy system operation cost.

The application of DESs is limited in this situation because both the capital cost and the operation cost increase.

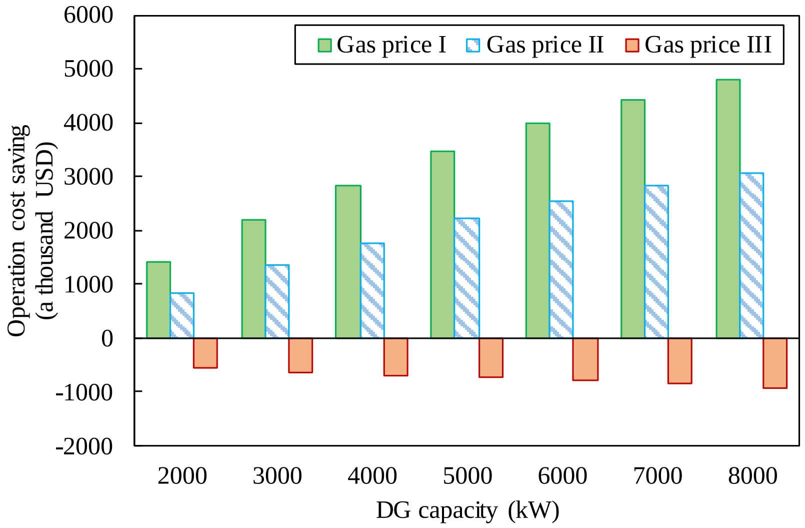


Figure 4.10 The operation cost savings under different gas prices

4.3.5 Government incentives

The commercial building introduced in Section 4.3.2 is regarded as the case building. EP_2 is adopted and the DES can sell the generated electricity to the grid. Fig. 4.11 presents the system payback period of two cases: EP_2 and EP_2 with government incentive. It can be seen that the payback period reduces when the government subsidizes for the primary energy saving. The surplus capital cost of the DES can be recovered within 2 years when the DG capacity varies from 2000 kW to 8000 kW. It is because that the incentive for energy saving results in the reduction of the system operation cost, so that the payback period is reduced consequently. Another impact is the improvement of economic performance of the DES with larger DGs. When the largest DG (8000 kW) is adopted, the payback period reduces to 1.67 years, which corresponds closely to the minimum value, 1.64 years. This indicates that the government incentive is an effective policy to improve the benefits of DESs in subtropical regions.

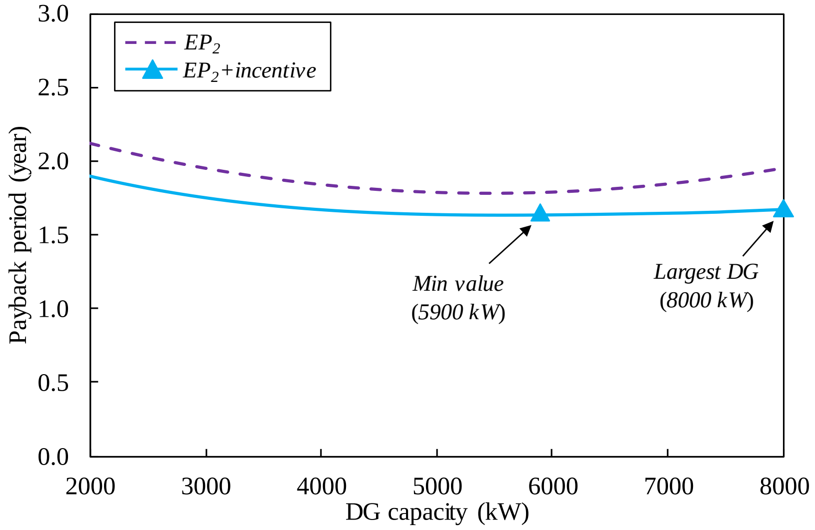


Figure 4.11 Impact of government incentive on the payback period

4.4 Summary

Building level distributed energy systems (DESs) in a subtropical region are studied, and their performance is quantified and evaluated. The impacts of major design parameters and energy policies on the performance of DESs are investigated. The building level DESs can achieve substantial benefits (i.e., up to 13.55% of primary energy saving and 1.64 years of payback period) in this region under certain situations, while the scale and function of buildings, the design capacity of DES as well as the energy policy and gas price have significant impacts on the practical benefits of DESs. Based on test results, some detailed conclusive remarks can be drawn as follows:

- The scale of building affects the benefits of using DESs significantly. The use of DESs is found to be beneficial only when a building scale is larger than 40,000 square meters. When the scale of building increases, the energy saving of DES increases to the maximum then remain unchanged.

- The function of buildings also has obvious impacts on the benefits of using DESs. It is found that the use of DESs in the commercial building has more benefit. It is less for office buildings and it is the least for public buildings like schools.
- For a given building, both undersized and oversized DGs will result in reduced DES performance. With proper design, the use of DES can achieve 6.54% primary energy saving and 1.98 years of payback period when selling electricity is not permitted.
- Permission for selling electricity to the grid can improve the benefits of using DES effectively. The primary energy saving of using DESs can be increased by 7.01% (from 6.54% to 13.55%) when selling electricity is permitted.
- Reasonably low gas price is a prerequisite for cost-effective operation and application of DESs. The current gas price in Hong Kong consumer market cannot allow cost-effective application while the current price of gas purchased from the international market allows rather cost-effective application of DESs.

In summary, the prerequisites or favourable conditions which allow that DESs can profit in subtropical regions include: 1) the energy demands of users concerned are high; 2) the surplus electricity generated by DGs can be sold to the utility grid; and 3) the gas price is much lower than the electricity price. Main conclusions of this performance study can be used as references for the feasibility judgment of DESs in development projects. In the following DES design studies, it is assumed that selling electricity is allowed (i.e., EP_2 is used as the energy policy) and the lowest gas price (i.e., the Gas price I) is adopted. The optimal design methods for the DES need to be developed. The potentials of the DES in energy saving and cost reduction need to be studied.

CHAPTER 5 DESIGN OPTIMIZATION METHODS

DES design optimization aims to identify the optimum system capacities and operation strategies in the planning and design stages. Chapter 5 presents two DES optimal design methods for two different application situations. Method I, elaborated in Section 5.1, can be used to design the DES in case of energy system retrofitting. The design inputs of this method can be obtained by measuring the energy demands of the existing energy system. The purpose of this design optimization is to maximize the DES benefits comparing with the existing energy system. Method II, elaborated in Section 5.2, is a robust optimal design method which is used to design the DES in case of new development projects. Uncertainties of design inputs throughout the DES life-cycle are considered in this design method. A probabilistic approach is developed to identify the optimum DES, which can operate with high life-cycle performance when operating conditions change. For each method, the detailed procedures of the optimization process are presented in the corresponding section. Conclusive remarks of this chapter are presented in Section 5.3.

5.1 DES optimal design method for energy system retrofitting

5.1.1 Objective of DES optimal design in retrofitting cases

As an efficient and eco-friendly energy system, the DES is commonly planned to replace the existing energy system (i.e., the CES) in an energy system retrofitting case. The objective of the optimal design in this case is to develop a DES that can achieve maximum energy saving and economic benefits compared with the CES. An optimal method is developed for the design of the DES using practical electricity and cooling demands of users, which can be monitored by on-site energy measurement system.

5.1.2 Procedures of the optimal design

The design procedure consists of three steps as shown in Fig. 5.1.

Step 1. Identification of possible DES schemes: One DES with certain equipment capacities is regarded as one DES scheme. Based on the coupling effects between equipment and ranges of their capacities, equipment capacities of a DES scheme can be determined. All DES schemes can be identified and collected as a set of schemes, CP_{DES}.

Step 2. Operation optimization of each DES scheme: For a DES scheme, appropriate operating schedule can reduce the primary energy consumption of the system. The optimal operating schedule of each DES scheme is determined by this optimization process. The energy generation and the energy consumption of each DES scheme are obtained in this step. MATLAB is used to solve the objective function in this step.

Step 3. Selection of optimal design scheme: With results in the second step, the economic performance of each DES scheme can be evaluated. The purpose of this third step is to identify the DES with the best economic performance among all DES schemes. This step is a sizing optimization actually.

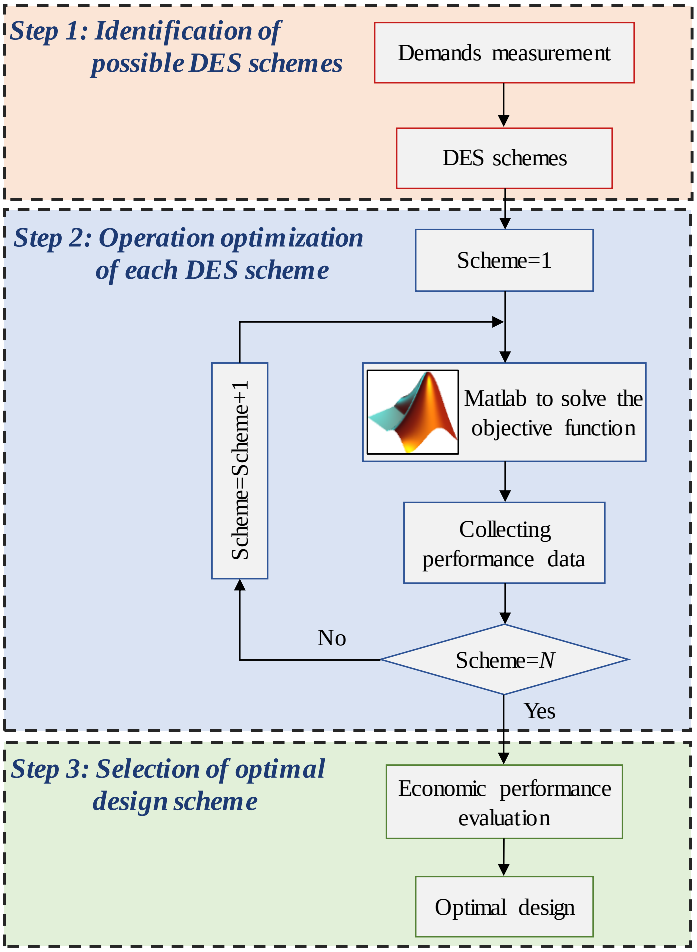


Figure 5.1 Flow chart of the optimal design for energy system retrofitting

<u>Step1 - Identification of possible DES schemes</u>

All DES schemes with different capacities of DGs (CP_{DG}), absorption chillers (CP_{AC}) and electric chillers (CP_{EC}) are identified in this step. Due to the coupling effects among these three equipment, their capacities are subject to two constraints: 1) absorption chillers have the capacity to use the recoverable heat when DGs are operating at full load; 2) electric chillers have the capacity to cooperate with absorption chillers in satisfying the peak cooling demand. The DG capacity is assumed as discrete ranged between 1000 and 8500 kW with size interval of 50 kW while the capacity of chillers is assumed as continuous. Once the DG capacity is determined, capacities of chillers can be estimated by Eqs. (4-30) and (4-31) respectively, thus a certain DES scheme is identified. Searching in the range of DG capacity, all of DES schemes can be identified and collected as a scheme set, CP_{DES}.

<u>Step 2 - Operation optimization of the DES</u>

Operating schedule of a DES determines the actual energy generation of equipment (i.e., DGs (E_{DG}), absorption chillers (C_{AC}) and electric chillers (C_{EC})) in operation, as well as the amount of exported electricity (E_{sell}) and imported electricity to/from the utility grid. An appropriate operating schedule helps the DES save primary energy compared with the CES in operation. The operation optimization aims to ensure that each DES scheme can operate in the best mode for energy-efficient operation.

i. Objective function

The objective of operation optimization is to ensure that each DES scheme can achieve maximum energy saving compared with the CES in each time interval (i.e., each hour) as shown in Eq. (5-1). Where, the energy consumption of DES (F_{DES}) is the sum of gas consumption of DGs and associated energy consumption of imported electricity (shown in Eq. (5-2)). The energy consumption of CES (F_{CES}) is the energy consumption for generating the same energy (shown in Eq. (5-3)). The efficiency of central power plants, η_{grid}, is simply fixed to be 50%. Meanwhile, the output of Eq. (5-1) can be used as the assessment of the DES energy saving.

$$Maximize \ \frac{(F_{CES}-F_{DES})}{F_{CES}} \tag{5-1}$$

$$F_{DES} = \sum F_{DG} + \frac{1}{\eta_{grid}} \cdot E_{grid} \tag{5-2}$$

$$F_{CES} = \frac{1}{\eta_{grid}} (E_{d,CES} + E_{sell}) \tag{5-3}$$

ii. Constraints

Energy balance constraints guarantee that the supply equals to (or be slightly larger than) the demand for each form of energy. The electricity demand of the DES, as shown in Eq. (5-4), is the sum of the building base demand ($E_{building}$), the electricity requirement of chillers (E_{EC}), pumps (including chilled water pumps, E_{CHWP}, and cooling water pumps, E_{CWP}) and cooling towers (E_{CT}). While the electricity supply in the DES is the sum of imported and generated electricity subtracted by the exported electricity. It is worth noting that electricity cannot be imported and exported simultaneously. Eq. (5-5) describes that the cooling generated by absorption chillers and electric chillers satisfies the cooling demand.

$$E_d = E_{building} + \sum E_{EC} + E_{CHWP} + E_{CWP} + E_{CT} = E_{grid} + \sum E_{DG} - E_{sell} \quad (5\text{-}4)$$

$$C_d = \sum C_{EC} + \sum C_{AC} \quad (5\text{-}5)$$

Capacity constraints in determining the energy generation, consumption and minimum loads of equipment in operation are described as follows.

- *Distributed generations*

Gas engines generate electricity and provide recoverable heat for absorption chillers at the same time. The electricity generation cannot exceed the installed capacity of DG, and an equipment should be shut down to avoid operating at low efficiency when its load ratio is below 25%, as shown in Eq. (5-6). With the electricity generation of one DG, the primary energy consumption (F_{DG}) and the recoverable heat (Q_r) can be estimated by DG model introduced in Chapter 4. The former is a significant part of system energy consumption and the latter is used to restrain the operation of absorption chillers.

$$25\% \cdot CP_{DG} \leq E_{DG} \leq CP_{DG} \quad (5\text{-}6)$$

- *Chillers*

The cooling generated by electric chillers cannot exceed their capacities as shown in Eq. (5-7). The electricity consumption and the coefficient of performance (COP_{EC}) of electric chillers are estimated by the electric chiller model. Absorption chillers use the recovered heat ($Q_{r,AC}$, which can be estimated by the absorption chiller model) from DGs for thermal energy activated cooling. Thus, two constraints must be satisfied simultaneously: 1) generated cooling cannot exceed the equipment capacity; and 2) the recovered heat cannot exceed maximum recoverable heat from DGs. Eqs. (5-8) and (5-9) present the upper limit of absorption chiller generation and the upper limit of recovered heat, respectively.

$$C_{EC} \leq CP_{EC} \tag{5-7}$$

$$C_{AC} \leq CP_{AC} \tag{5-8}$$

$$\sum Q_{r,AC} \leq \sum Q_r \tag{5-9}$$

- *Pumps and cooling towers*

When the capacities of the chillers ($CP_{chiller}$) are determined, the maximum flow rates (G) of chilled water and cooling water can be calculated by Eq. (5-10). The capacities of pumps, i.e., primary chilled water pumps and cooling water pumps, can be determined by Eq. (5-11). The capacity of cooling towers, CP_{CT}, can be estimated by Eq. (5-12).

$$G = \frac{CP_{chiller} \cdot 3600}{\rho_w \cdot c \cdot \Delta t} \tag{5-10}$$

$$CP_{pump} = \frac{G \cdot g \cdot H}{3600 \cdot \eta_p} \tag{5-11}$$

$$CP_{CT} = G \cdot \rho_w \cdot \lambda / \rho_a \tag{5-12}$$

Where, ρ_w is the density of water, 1000 kg/m^3, c is the specific heat capacity of water, 4.2 kJ/(kg·K), and Δt is the difference between inlet and outlet temperatures, 5 ℃. λ is the air-water ratio of cooling towers, 0.65, and ρ_a is the density of air, 1.21 kg/m^3.

<u>Step 3 - Selection of optimal design scheme</u>

The objective of this step is to identify the DES with the optimum economic performance among all available DES schemes. In this study, the payback period (PBP) of the DES, which is the ratio of the additional capital cost to the saving of operating cost of the DES compared with the CES as shown in Eq. (5-13), is used to evaluate the economic performance of the system. The capital cost of the CES (Eq. (5-14)) is the sum of costs of chillers, pumps and cooling towers in each building. The capital cost of the DES (Eq. (5-15)) is the sum of costs of DGs, chillers, pumps and cooling towers as well as pipe networks. Annual operating cost of the CES (Eq. (5-16)) is the cost of electricity purchasing while annual operating cost of the DES (Eq. (5-17)) is the sum of system energy cost and the maintenance cost, subtracted by the energy saving incentive. Where y and h stand for the number of days in one year and the number of hours in one day respectively. CM_{DG} is the maintenance cost coefficient. PS is the incentive coefficient of energy saving. According to the definition, the DES with minimum value of payback period has the best economic performance. The optimal designed DES can be identified from all of DES schemes based on Eq. (5-13).

$$Minimize\ \ PBP = \frac{\Delta CC}{\Delta OC} = \frac{CC_{DES} - CC_{CES}}{OC_{CES} - OC_{DES}} \tag{5-13}$$

$$CC_{CES} = \sum_n \left(\sum CC_{EC} + \sum CC_{pump} + \sum CC_{CT}\right) \tag{5-14}$$

$$CC_{DES} = \left(\sum CC_{DG} + \sum CC_{AC} + \sum CC_{EC} + \sum CC_{pump} + \sum CC_{CT}\right) + CC_{pipe} \tag{5-15}$$

$$OC_{CES} = \sum_y \sum_h E_{d,CES} \cdot Cost_e \quad (5\text{-}16)$$

$$OC_{DES} = \sum_y \sum_h [(E_{grid} \cdot Cost_e + \sum F_{DG} \cdot Cost_f - E_{sell} \cdot Cost_{e,sell}) + \sum CM_{DG} \cdot E_{DG} - (F_{CES} - F_{DES}) \cdot PS] \quad (5\text{-}17)$$

5.2 DES robust optimal design method for new development

5.2.1 Objective of DES robust optimal design in new development cases

In the case of new development of DES, design inputs (e.g., the energy demands of buildings) can only be obtained by predicting instead of measuring. The conventional demands predicting method estimates the building energy demands in a deterministic situation, i.e., the typical meteorological year (TMY). The practical energy demands, however, do not equal the predicted values in most cases but vary within a range with some probabilities. Uncertainty is a probabilistic method used to quantify the variations of design inputs. The robust optimal design is such a DES design method considering uncertainties of design inputs.

The DES robust optimal design is proposed to identify the DES which has the best performance and can operate at high performance when the actual working conditions, e.g., the energy demands and the energy prices, change over a large range. Fig. 5.2 illustrate the comparison of the performance of different optimal designs. The performance indices shown by the *y*-axis may refer to the thermal comfort, the energy consumption or the total monetary cost of the designed DES. For *Design A*, i.e., the conventional optimal design, the performance is very good at the design condition x_1 but the design is not robust. When the inputs or conditions change due to the uncertainties or noises (±*a*), the performance of *Design A* will decrease sharply. For

Design B, i.e., the robust optimal design, its performance is good and it can keep stable even though the inputs deviate from the pre-assumed value.

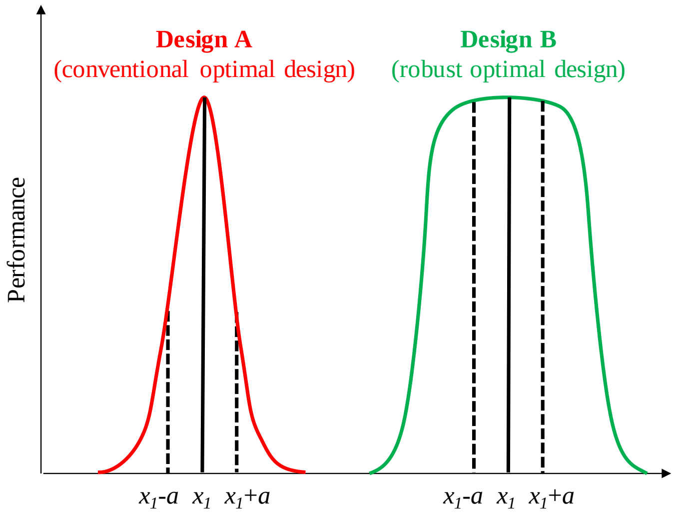


Figure 5.2 Illustration of the performance of robust optimal design

Note: x_1 is the pre-assumed design inputs of condition; a is the noise for x_1

5.2.2 Purpose of adopting life-cycle performance analysis

The commonly optimal design method considering uncertainty, namely the uncertainty-based optimal design, uses maximization of the DES performance in the first operating year as the optimization objective. Actual energy demands and prices, however, will change, i.e., increase or decrease, rather than staying at the same level through the DES life-cycle. After a long time of operation, devices in the DES are affected by degradation, and their efficiencies as well as power productions reduce. Therefore, The DES that designed by the uncertainty-based optimal design method may only achieve the required performance in the first several years of installation and get worse in the rest years.

To address above problems, the life-cycle performance of DES should be analysed and considered in the DES design, and an optimal design method that considers both uncertainties and life-cycle performance is proposed, namely the robust optimal design. The objective of this proposed robust optimal design method is to achieve a design option which provides the system with the capability to operate at high performance through its life-cycle, i.e., to operate with higher performance in the late years of life-cycle, as shown in Fig. 5.3. Compared with the uncertainty-based optimal design method, the robust optimal design method uses maximization of the DES life-cycle performance as the optimization objective. The DES life-cycle performance is assessed in the optimization process, and the optimum DES is identified as the design option that has the best life-cycle performance.

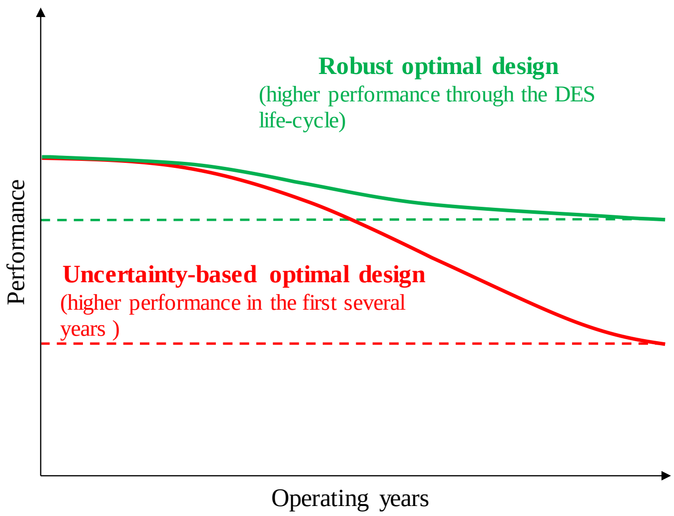


Figure 5.3 Illustration of the DES performance in its life-cycle

5.2.3 Procedures of robust optimal design

The objective of DES robust optimal design is to identify the DES which has best economic performance through its life-cycle. This design method uses uncertain working conditions as the inputs. A probabilistic approach is developed to solve the objective function considering uncertainties and identify the optimum DES based on the probabilistic results. The detailed procedures of the method are presented in this section.

The proposed robust optimal design method consists of four steps as shown in Fig. 5.4. Step 1: predict the uncertain energy demands based on the uncertainty modelling; Step 2: determine the alternative DES schemes based on the uncertain cooling demand. Step 3 and Step 4 are the process of robust optimization considering uncertainties. Where, the operation of a DES scheme over its life-cycle is optimized firstly in Step 3. Monte Carlo simulation is conducted to solve the objective function in this step concerning uncertainties and obtain probabilistic DES performance data. Then, the life-cycle performance of DESs is evaluated and the optimum DES scheme is identified in Step 4. The uncertainty-based optimal design only optimizes the DES operating in the first year in Step 3, while other steps in this method are the same with that of the robust optimal design method.

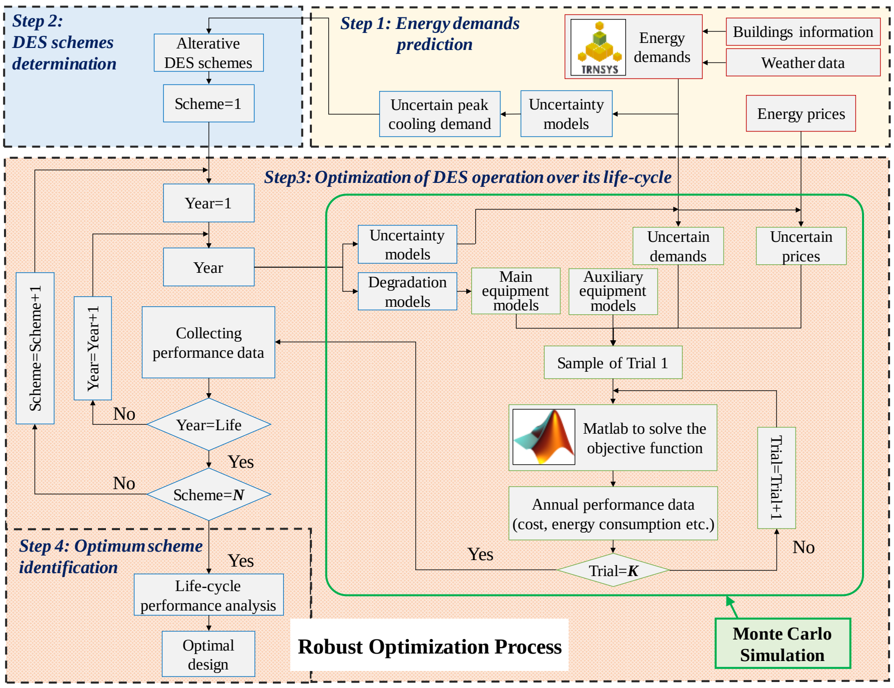


Figure 5.4 Flowchart of the proposed robust optimal design method

<u>Step 1 - Quantification of design inputs uncertainties through the DES life-cycle</u>

As the design inputs, energy demands of users and energy prices should be predicted at the start of the design process. By collecting information of buildings and weather data, the annual cooling demand and the annual electricity demand can be predicted by Building Performance Simulation tools and building energy performance equations in Energy Code (EMSD Hong Kong, 2007b), respectively. The energy prices can be obtained based on the local energy market. A probabilistic method is adopted to quantifies the uncertainties of these design inputs.

i. Uncertainty of energy demand

Uncertain demands can be predicted by assigning proper probability distribution functions (PDFs), which describe the uncertainties, to certain demands as shown in Fig. 5.5(a) (Mavromatidis et al., 2018b). The uncertain energy demand is the production of certain demand of year *t* and the *PDF* as shown in Eq. (5-18). The certain demand of year *t* is estimated as $(F_{trend})^{(t-1)} \cdot d_{certain}$. Where, F_{trend} is the time-independent trend factor which indicates the annual increase (larger than 1) and decrease (smaller than 1) of a parameter, *t* is the year of operation and $d_{certain}$ is the certain demand of the first operation year which is predicted by simulation tools. Monte Carlo simulation is adopted to generate sufficient uncertain demands by repeating the uncertainty modelling. Let the *t* be valued from 1 to 20 (the life-cycle of DES), the uncertain cooling demand of the 20 years can be obtained. The uncertain peak cooling demands in the DES life-cycle are identified and used to determine alternative DES schemes.

$$d_{uncertain} \sim (F_{trend})^{(t-1)} \cdot d_{certain} \cdot PDF \tag{5-18}$$

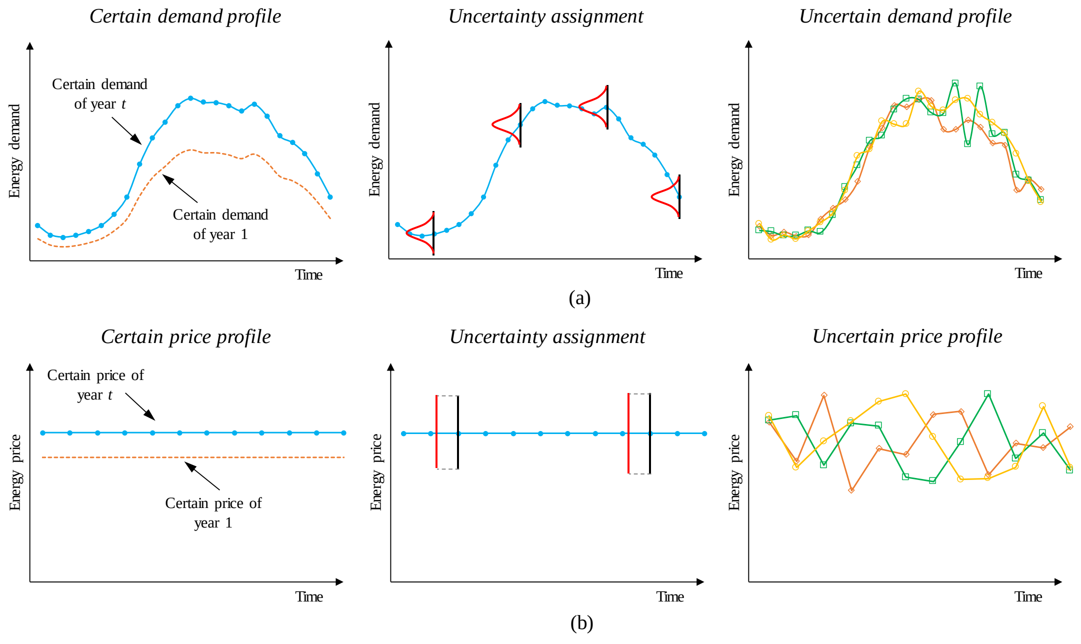


Figure 5.5 Generation of uncertain demands in DES design

ii. Uncertainty of energy price

Fig. 5.5(b) illustrates the generation of uncertain energy price. The uncertain price can be estimated by Eq. (5-19). Where, $Cost_{certain}$ is the energy price from local energy market in the first operating year. It is worth noting that the energy price changes every month. Thus, what estimated by Eq. (5-19) is the monthly uncertain prices.

$$Cost_{uncertain} \sim (F_{trend})^{(t-1)} \cdot Cost_{certain} \cdot PDF \tag{5-19}$$

The energy prices considering uncertainties are the natural gas price ($Cost_f$), the electricity price ($Cost_e$), the feed-in tariff ($Cost_{e,sell}$), and the penalty price of cooling demand dissatisfaction (Pen^C). According to Section 3.3.3, the electricity price and feed-in tariff are deduced from the price of natural gas. Therefore, Eq. (5-19) is used to estimate the uncertain gas price, while other prices are estimated by correlation equations.

<u>Step 2 - Determination of alternative DES schemes</u>

The determination of alternative DES schemes must consider the characteristics of energy demands throughout the DES life-cycle. A cumulative probability analysis-based method including two subtasks are developed for schemes identification.

i. Determination of cooling capacity

The peak cooling demand with uncertainty is a set of stochastic values instead of a deterministic value. The probability distribution of this variable is shown as the curve in Fig. 5.6. The cooling capacity of DES can be determined for the purpose of satisfying the peak cooling demand in a particular certain extent. The extent of satisfaction is denoted by a dimensionless threshold, β_i, as described by Eq. (5-20). Where, Φ is the cumulative probability function of peak cooling demand $C_{d,peak}$. $C_{CAP,i}$ is the corresponding cooling capacity of the threshold β_i. n stands for the number of different cooling capacity. The value of β indicates that the corresponding DES has a probability of β to cover the peak cooling demand over its life-cycle. In the framework of statistics, the DES cooling capacity will be sized by selecting a capacity $C_{CAP,i}$ to satisfy Eq. (5-20). n values of β (with a value between 0 and 1) are initialized so that n different cooling capacities will be determined.

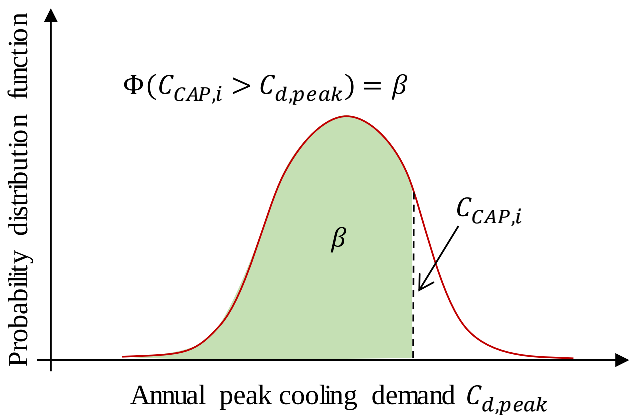


Figure 5.6 Determination of DES cooling capacity by a statistic method

Note: $C_{CAP,i}$: the cooling capacity of DES scheme i; β: the threshold; Φ: the cumulative probability function

$$\Phi\left(C_{CAP,i} > C_{d,peak}\right) = \beta_i, i = 1, \dots, n. \tag{5-20}$$

ii. Determination of equipment capacity

Based on the cooling capacity, the equipment capacities of the DES can be determined as follows.

- *Determine the initial DES scheme*

Making β_{k+1} equals 0.5, so that the corresponding cooling capacity $C_{CAP,k+1}$ can be estimated. Let the cooling capacity of the initial DES scheme equals $C_{CAP,k+1}$, and the electric chillers and the absorption chillers cover 50% of this cooling capacity respectively, one can get the total capacities of these two chillers. Based on the energy balance, i.e., the recoverable exhaust heat from DGs is the heat that can be used by absorption chillers, the capacities of DGs can be obtained. For simplification, the numbers of generation in each scheme are identical as two DGs, six absorption chillers and six electric chillers. Thus, the number and capacity of each equipment of the initial DES scheme are determined.

- *Obtain the scheme matrix*

Other schemes are obtained by changing the equipment capacities. Assumed that there is an n×n (n=2k+1) matrix of DES schemes as shown in Fig. 5.7. The initial scheme is located in the middle, i.e., $S_{E(k+1)\,A(k+1)}$. For the column of the initial scheme, we can only change the capacities of the electric chillers to satisfy that the cooling capacity of the DES equals to $C_{CAP,i}$ (i is the number of the row) so that capacities of both absorption chillers and electric chillers can be determined. For example, $S_{E(k)\,A(k+1)}$ is in the same column with the initial scheme but different row ($\boldsymbol{S_{E(k)}}$). As above concerned, this DES scheme has the same absorption chillers capacities with the initial DES scheme. Its electric chiller capacities are the difference between the cooling capacity ($C_{CAP,k}$) and absorption chillers capacities. For the row of the initial scheme, we can only change the capacities of the absorption chillers to satisfy the same rule. The capacities of DGs are determined consequently according to the constraint of the energy balance among equipment. By ensuring that the capacities of electric chillers in each row ($\boldsymbol{S_{E(k)}}$) remains the same and the capacities of absorption chillers as well as DGs in each column ($\boldsymbol{S_{A(k)}}$) remain the same, other elements ($S_{E(i)\,A(j)}$, $i, j \in 1, 2, \ldots, n$) in this matrix are determined.

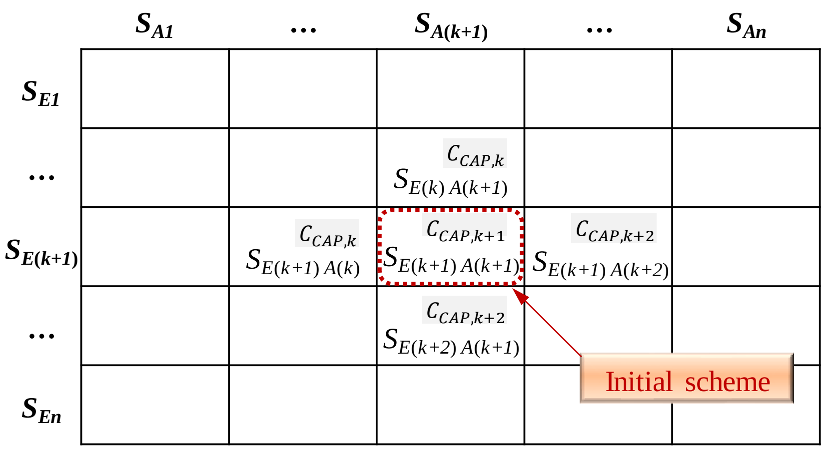


Figure 5.7 The illustration of the matrix of alternative DES schemes

Note: the capacities of electric chillers in each row ($\boldsymbol{S_{E(i)}}$) are same, and the capacities of absorption chillers as well as DGs in each column ($\boldsymbol{S_{A(j)}}$) are same. ($i, j \in 1, 2, \cdots$, n)

Step 3 - Optimization of DES operation over life-cycle

The optimization of DES operation aims to ensure that the DES can operate in the best mode over its life-cycle. For a certain DES scheme, the process of operation optimization needs to be repeated until the last operating year of its life-cycle. The annual performance data of the DES, for example, the costs and the energy consumption, are obtained by modelling, and the life-cycle performance data is collected as a database. For a certain operating year, the energy demands and energy prices, i.e., the design inputs, are estimated by uncertainty models. The degradation of equipment performance due to aging process can be estimated by degradation models as follows.

i. Degradation modelling

Performance degradations of main equipment in DES affect the system operation to a great extent. The degradation of DG is caused by several mechanisms in components (Kurz et al., 2009; Volponi, 2014). Fouling of the air filtration system leads to increased pressure drop in the inlet system, resulting in the reduction of engine efficiency. The compressor in DG suffers efficiency reduction due to the erosion in blade surfaces and the corrosion caused by combustion. Meanwhile, the DG capacity is significantly impacted by combined effects of these mechanisms. Chillers degradation leads to more serious efficiency deterioration of the whole HVAC systems (Djunaedy et al., 2011). The degradation of coefficient of performance (COP) of chillers may even reach 20% after operating for 20 years (Hendron, 2006).

Several existing models are available for describing the degradation of equipment specifications (De Wilde et al., 2011; Van Noortwijk, 2009). A random degradation rate method, which has no requirement for on-site date and can be used at the early design stage, is used to model the degradation in this study. It indicates that the specification reduces by a degradation rate per operating year, which is presented by a random quantification. The specifications of equipment in Year t can be estimated by Eq. (5-21).

$$Q_t = Q_0 \times (1 - D_a t) \tag{5-21}$$

Where, Q_0 is specification when newly installed. D_a is the yearly degradation rate while t is the year of operation. The uncertainty of degradation rate (D_a) can be quantified as a stochastic distribution either by fitting measured data (De Wilde et al., 2011), or deducing by mathematic method (Huang et al., 2016). Huang et al. indicated that the uncertainty of degradation rate of equipment in buildings fits a normal distribution in their recent study of life-cycle prediction of building energy use (Huang et al., 2016; Huang et al., 2015). In this study, the same degradation rates of chillers efficiencies in Ref. (Huang et al., 2016) are used. The degradation rates of DG efficiency and capacity are deduced according to a study on the deterioration of gas engines (R Kurz et al., 2001). Table 5.1 presents the specifications of these degradation rates.

Table 5.1 Degradation rates of equipment specifications

Equipment		**Parameter**	**Unit**	**Degradation rate**
Chillers	Electric chiller	COP	W/W	$N\,(0.0025, 0.00025^2)$
	Absorption chiller	COP	W/W	$N\,(0.0025, 0.00025^2)$
DG		Electricity efficiency	%	$N\,(0.0014, 0.00014^2)$
		Generation capacity	W	$N\,(0.0039, 0.00039^2)$

ii. Monte Carlo simulation

Monte Carlo simulation is used to model the probability of different outputs in a process that cannot easily be predicted due to the uncertainty of inputs. With a mathematical model, the Monte Carlo simulation uses repeated stochastic samplings with enough sample size (usually 100-1000) to generate modelling results. As Eq. (5-22) presents, $\boldsymbol{Y} = f\,(\boldsymbol{X})$ is the mathematical model already known, where x_1 to x_n are inputs and y_1 to y_k are outputs. A set of samples $\boldsymbol{S} = (1, 2, 3\ldots)$ is used to gather all stochastic samplings of inputs. The probability that sample s happens is represented by $P(\boldsymbol{X}_s)$ and we have $\sum P(\boldsymbol{X}_s) = 1$. For each sample $\boldsymbol{X}_s$, the corresponding result $\boldsymbol{Y}_s$ can be obtained by the model and the probability of output equals the probability of input, i.e., $P(\boldsymbol{Y}_s) = P(\boldsymbol{X}_s)$. Monte Carlo simulation is to run the model for all input samples, then estimate the value and probability of corresponding outputs. By aggregating or assessing the outputs from Monte Carlo simulation, probabilistic characteristics of simulation results, e.g., the expectation, the distribution and the extreme values, are obtained and used as modelling results or for analysis.

In this step. the optimal operation strategy of each DES scheme is found out by solving the objective function as shown in Eq. (5-23). According to Monte Carlo simulation, sufficient samples of uncertain design inputs are obtained (the number of samples is $\boldsymbol{K}$) by the uncertainty model. The solving of function $\sigma(\boldsymbol{X})$ should be repeated $\boldsymbol{K}$ times based on samples of uncertain inputs. The stochastic DES performance data with probability distributions are therefore obtained under above concerned. By repeating the process of operation optimization from Scheme 1 to Scheme N (N stands for the last DES scheme), the performance data of all the alternative DES schemes are generated to form the database.

$$\begin{cases} \boldsymbol{Y} = f(\boldsymbol{X}) \\ (y_1, y_2, y_3 \dots y_k) = f(x_1, x_2, x_3 \dots x_n) \\ \boldsymbol{Y}_s = (y_{s1}, y_{s2}, y_{s3} \dots y_{sk}) = f(x_{s1}, x_{s2}, x_{s3} \dots x_{sn}) = f(\boldsymbol{X}_s) \qquad \forall\, s \in \boldsymbol{S} \\ P(\boldsymbol{Y}_s) = P(\boldsymbol{X}_s) \end{cases} \tag{5-22}$$

$$Min\ \ \sigma(\boldsymbol{X}) = \sigma(x_1, x_2, x_3 \dots x_n) \tag{5-23}$$

iii. Objective function

The objective of the DES operation optimization is to minimize the system annual total cost (C_{annual}) which is what the investors should pay in each year. As shown in Eq. (5-24), C_{INV} is the annualized investment cost of investment and OC_{DES} is the cost which satisfies the DES operation. The term C_{EM} presents the cost of carbon emission and INC presents the total income of exporting electricity to the grid. C_{PEN} is the penalty of cooling demand dissatisfaction.

$$C_{annual} = C_{INV} + OC_{DES} + C_{EM} - INC + C_{PEN} \tag{5-24}$$

The investment cost of the DES includes the capital cost of distributed energy generations, the cost of chilled water networks and the cost of the heat rejection system. Considering the dynamic of cash flow, the initial cost of investment can be estimated in Eq. (5-25). Where r is the interest rate, 10%, and y is the lifetime of the system, 20 years.

$$C_{INV} = \frac{r(1+r)^y}{(1+r)^y-1}\left(CC_{generation} + CC_{CHW\_networks} + CC_{heat\_rejection}\right) \tag{5-25}$$

The annual operating cost of the DES, as shown in Eq. (5-26), includes the annual operating cost which contains the electricity cost. the primary energy cost, and the maintenance cost which associates to the generation of electricity (E_{DG}).

$$OC_{DES} = \sum_m \sum_d \left[\left(E_{grid} \cdot Cost_e + F_{DG} \cdot Cost_f\right) + CM_{DG} \cdot E_{DG}\right] \tag{5-26}$$

The carbon emission tax is the penalty charged by governments for emitting carbon into the atmosphere. The development of renewable energy and the utilization of energy saving technologies are encouraged by the implementation of carbon emission tax policy. In this study, the cost of carbon emission is the carbon emission tax that the DES investors pay to the government due to combustion of primary energy (natural gas) in a year, as shown in Eq. (5-27). Where CEF is the carbon emission factor of natural gas, 0.055 kg/kWh based on Ref. (IPCC, 2006). It presents the weight of emitted carbon by combusting per energy basis (heat) of natural gas. $EC_{emission}$ is the carbon emission tax, 132 USD/t Ce, per ton of emitted carbon, which is chosen from a global report about carbon pricing (The World Bank, 2015).

$$C_{EM} = \sum_m \sum_d [\left(F_{DG} + F_{grid}\right) \times CEF \times EC_{emission}] \tag{5-27}$$

The risk of demand dissatisfaction of DES is considered in the design optimization and converted into an economic penalty in this objective function. Reducing the penalty helps a DES to achieve higher economic performance. Eqs. (5-28) and (5-29) calculate the income of exporting electricity to the grid (*INC*) and the penalty of cooling demand dissatisfaction (C_{PEN}), respectively. Where UM^C is the unmet cooling demand. Both the feed-in tariff ($Cost_{e,sell}$) and the penalty price (Pen^C) are concerned with the local electricity price.

$$INC = \sum_h (E_{sell} \times Cost_{e,sell}) \tag{5-28}$$

$$C_{PEN} = \sum (Pen^C \times UM^C) \tag{5-29}$$

Energy balance constraints of the system in operation are presented by Eqs. (5-30) and (5-31): the net value of energy inputs, including the exchanged energy and self-generated energy, equals the hourly demands of the DES.

$$E_{building} + \sum E_{EC} + E_{CHWP} + E_{CWP} + E_{CT} = E_{grid} + \sum E_{DG} - E_{sell} \tag{5-30}$$

$$C_d = \sum C_{AC} + \sum C_{EC} + UM^C \tag{5-31}$$

The electricity demand (including electricity demand of buildings ($E_{building}$), chillers (E_{EC}), pumps (including chilled water pumps, E_{CHWP}, and cooling water pumps, E_{CWP}) and cooling towers (E_{CT}) equals to the sum of the imported electricity (E_{grid}) and the generated electricity by DGs (E_{DG}), subtracted by the exported electricity (E_{sell}). The cooling demand (C_d) equals the sum of the cooling generated by absorption chillers

(C_{AC}) and electric chillers (C_{EC}) as well as the unmet cooling demand (UM^{C}). The unmet cooling demand is the different between the cooling demand and the maximum cooling which chillers can provide when and only when the cooling demand is larger than the total capacities of chillers. So that UM^{C} can be estimated by functions as shown in Eq. (5-32).

$$UM^{C} = \begin{cases} C_d - \left(\sum CP_{AC} + \sum CP_{EC}\right) & if\ \ C_d > \sum CP_{AC} + \sum CP_{EC} \\ 0 & if\ \ C_d \leq \sum CP_{AC} + \sum CP_{EC} \end{cases} \tag{5-32}$$

The exported electricity cannot exceed the total generated electricity (Eq. (5-33)). Exported and imported electricity at the same time is not allowed in this study, which is presented in Eq. (5-34).

$$E_{sell} \leq E_{DG} \tag{5-33}$$

$$E_{sell} \cdot E_{grid} = 0 \tag{5-34}$$

<u>Step 4 - Optimum scheme identification</u>

At this step, the life-cycle performance of each DES scheme is assessed based on the performance database obtained in the previous step. The DES life-cycle performance is analysed and the optimal design is identified eventually.

i. Evaluation of the life-cycle performance

The expectation of a stochastic variable is the probability-weighted average which can be regarded as the expected value of this variable. In this robust optimal design, the expectation of probabilistic life-cycle performance is calculated as the value which represents the DES life-cycle performance. The life-cycle total cost (LTC) is the total cost that investors must pay for the DES through its life-cycle. The expectation of this variable is shown in Eq. (5-35).

$$LTC = \sum_{s \in S}(P_s \cdot \sum_{y=1}^{20} C_{annual,y,s}) \qquad (5\text{-}35)$$

Where, $C_{annual,y,s}$ is the annual cost of Year y corresponding to sample s. P_s is the probability of sample s and S is the number of inputs samples. Higher the LTC is, more money will be paid for the DES. On the contrary, lower the LTC is, less money will be paid for the DES and better performance the DES has. The purpose of this optimal design is to identify the DES which can achieve the best life-cycle performance. Thus, the DES scheme with the minimum LTC is identified as the optimum DES based on above analysis.

5.3 Summary

Two optimal design methods for DESs in two different application situations are presented in this chapter. In the first situation, namely retrofitting case, the end users are served by an existing CES and a DES is proposed to replace the CES for energy supply. The design objective is to identify the optimum DES that can maximize the energy saving while minimizing the payback period of investment compared with the existing CES. The measured energy demands of the end-users are used as inputs of the optimal design method, and the optimal design is performed based on these data. In the second situation, namely new development case, a new DES is going to be developed for a building or building clusters in a district to be built. The design objective is to identify the DES that can operate with high performance through its life-cycle. To ensure that the designed DES can remain stable performance when practical operating conditions deviate from the pre-amusing conditions, uncertainties of design inputs are quantified and considered in the design process as there is no actual load records and the loads need to be predicted. A robust optimal design method using Monte Carlo simulation is developed to identify the optimum DES with above concerned. These two methods need to be tested in DES design cases and advantages of the methods should be confirmed.

CHAPTER 6 IMPLEMENTATION AND TEST OF THE PROPOSED DES OPTIMAL DESIGN FOR ENERGY SYSTEM RETROFITTING IN A DISTRICT

In this chapter, the DES optimal design method for energy system retrofitting is implemented and tested through a case study, i.e., developing a DES to replace the existing CES in a district. Practical energy demands of the district are monitored and collected, and the proposed DES is identified by the optimal design method. The performance of the optimum DES is assessed and the performance of this DES is compared with that of the existing CES. The aim and the organization of this chapter are presented in Section 6.1. Section 6.2 elaborates the energy user, i.e., a district in Hong Kong, and presents the monitoring process of energy demands. Section 6.3 presents the use of the optimal design method and the performance evaluation of the optimum DES. The energy saving potentials and economic benefits of the DES identified are also evaluated. Conclusive remarks of this case study are given in Section 6.4.

6.1 Introduction

The Hong Kong government has been increasingly encouraging the utilization of energy-efficient technologies and willing to replace ageing energy systems with these technologies over the last few years. The district level DES, which uses a district cooling system for cooling supply, seems to be a potential option for energy saving comparing the existing CES in a district. However, the design method and benefits of this DES are not investigated yet. This chapter aims to test the optimal design method for DES planning and identify the advantages of the designed DES. A case study of designing a DES replacing the CES to supply energy for a district is developed. Optimal design method introduced in Section 5.1 is used to identify the DES. This case study is organized is as follows.

i. Description of the energy user and measurement of energy demands

A district in Hong Kong is chosen as the energy user. The annual energy demands, i.e., electricity demand and cooling demand, of the district are measured. However, these measured data cannot be used as the design inputs directly. Some data pre-treatments should be performed to obtain the design inputs.

ii. Determination of the district level DES

Based on the layout of buildings, the place of the energy station and the layout of distribution networks in the DES are determined. The size of pipes and the capacities of secondary chilled water pumps can be predetermined according to the cooling demand.

iii. DES design using the optimal design method and performance assessment

The optimal design method in Section 5.1 is adopted to size the DES and determine its operation strategy. The performance of DES is assessed based on the modelling results. The matching performance of on-site generations and the efficiency of electric chillers are analysed and compared with that of the CES.

6.2 The district of concern and monitoring of its energy demands

6.2.1 Description of the district and the existing energy systems

The main campus of the Hong Kong Polytechnic University, located in the centre area of Kowloon in Hong Kong with a total site area of 94,600 m^2, is the district used in this case study. The layout of this campus is illustrated by the site map (Fig. 6.1). Twelve buildings, named 'Phase 1', 'Phase 2', etc., with different functions, such as classrooms, laboratories, offices and library are involved. Table 6.1 presents the floor areas and main functions of all buildings in this district. To support the routine university activities, space cooling is required all year around.

Table 6.1 The floor areas and functions of buildings

Building	**Area (m^2)**	**Functions**
Phase 1	55,251	Classroom, office, library, laboratory, canteen, stadium
Phase 2	24,419	Classroom, office, dental clinic,
Phase 3A	16,782	Clinic, lecture hall, office
Phase 3B	23,400	Classroom, office, canteen, stadium
Phase 4	19,330	Classroom, office, lecture hall, laboratory,
Phase 5	10,078	Classroom, office, laboratory
Phase 6	12,307	Meeting room, classroom, office
Phase 7	25,000	Classroom, office, laboratory, lecture hall
Phase 8	44,000	Classroom, office, laboratory, lecture hall, canteen
JCA	4,800	Auditorium
JCIT	15,318	Classroom, office, activity room, lecture hall
PCD	10,196	Classroom, office
Total	**252,901**	

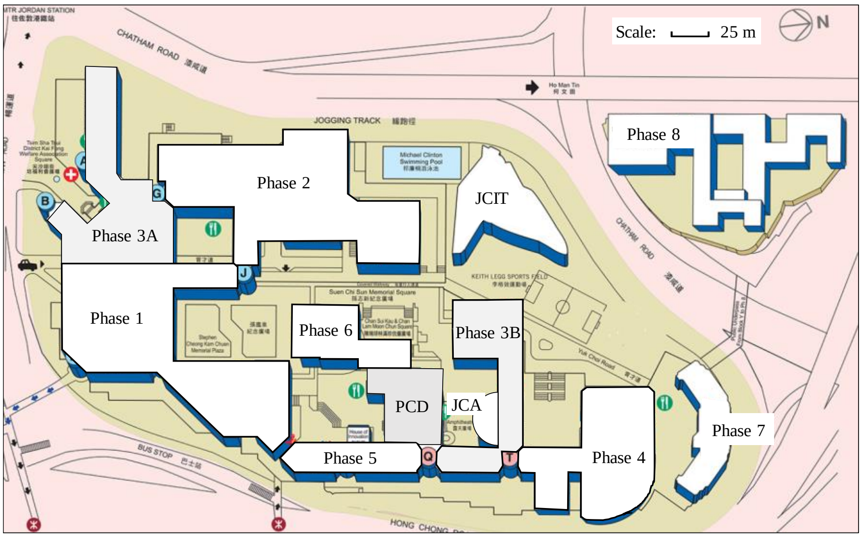


Figure 6.1 Campus map of the Hong Kong Polytechnic University

The existing energy system in this district relies on the centralized energy system (CES) as shown in Fig. 6.2. For an individual building, the electricity demand (including that of lighting, equipment, the HVAC system etc.) is supplied by the utility grid, which connects the central power plants and transmits the electricity from plants to buildings. The cooling demand of a building is supplied by an individual cooling system, which is installed in the building concerned. Fig. 6.3 illustrates a typical individual cooling system in a building, which includes electric chillers, an in-building chilled water loop and a heat rejection system. Electric chillers (typically water-cooled centrifugal chillers have the cooling capacities ranging from 500 kW to 1200 kW), which are located in the plant room, are used as the cooling source in each building to generate chilled water. The in-building chilled water loop consists of variable speed or constant speed chilled water pumps and HVAC terminal units, such as AHU, PAU and fans. Chilled water is delivered by these chilled water pumps to HVAC terminal units for space cooling. The heat rejection system consists of cooling water pumps and cooling towers. The condensing heat is transferred from chillers to cooling towers by cooling water, and rejected to the atmosphere in cooling towers. Based on the district planning, the details of chillers of all buildings in the district are shown in Table 6.2. The operation of this CES is modelled and its performance data is used for the DES performance evaluation to analyse the benefits made by the DES.

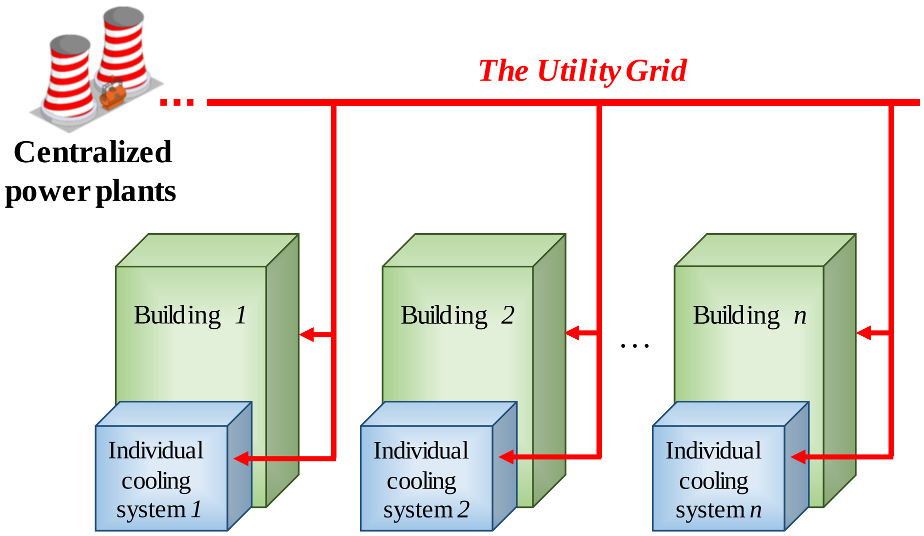


Figure 6.2 District power distribution architecture of the existing centralized energy system

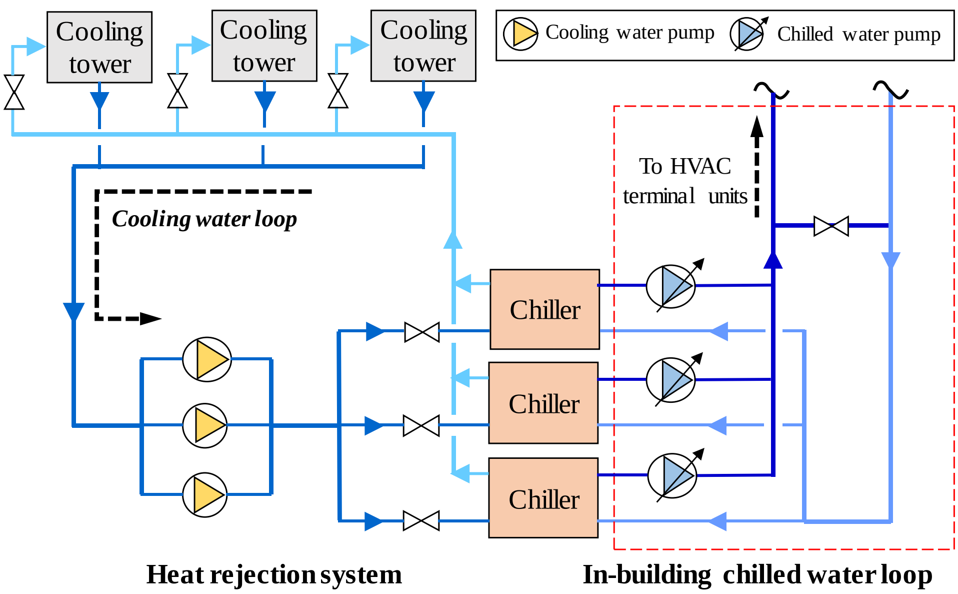


Figure 6.3 Schematic of typical individual cooling systems of buildings in the centralized energy system

Table 6.2 Existing chiller specifications of buildings in the district

Building	Capacity (kW)	Number	Full load COP	Building	Capacity (kW)	Number	Full load COP
Phase 1	1110	5	4.83	Phase 6	1140	4	4.83
Phase 2	845	4	4.80	Phase 7	990	4	4.81
Phase 3A	680	3	4.78	Phase 8	1670	4	4.89
Phase 3B	1110	3	4.83	JCA	445	2	4.76
Phase 4	1138	3	4.83	JCIT	890	3	4.80
Phase 5	730	2	4.79	PCD	650	3	4.78

6.2.2 Site monitoring and processing of energy demand data

Cooling demands of buildings

The building-integrated BMS (building management system) is a computer-based management system installed in buildings that controls and monitors the building's mechanical and electrical equipment such as HVAC systems, power systems and security systems. It records a large number of operational data of chillers, such as flow rates of chilled water, inlet and outlet temperatures, etc., in each time interval, e.g., one hour with sufficient accuracy. Based on these recorded data, the cooling provided by chillers, which is regarded as the actual cooling demand, of each building can be calculated by Eq. (6-1). Where, c is the specific heat capacity of water, 4.2 kJ/(kg·K), G is the flow rate of chilled water, m^3/h, ρ_w is the density of water, 1000 kg/m^3, and Δt is the difference between inlet and outlet temperatures.

$$C_d = c \cdot G \cdot \rho_w \cdot \Delta t/3600 \quad (6\text{-}1)$$

The hourly cooling demand of the district is calculated as the sum of all buildings as presented in Fig. 6.4(A). It is observed that the cooling in this district is required in 24 hours each day and there is a very large difference between the maximum (annual maximum: 32913 kW) and minimum demand (annual minimum: 681 kW) over a year and within a day. The total annual cooling consumption of this district is 102903 MWh. It indicates that cooling is abundantly required in this subtropical region. Fig. 6.4(B) shows the cooling demands of three representative buildings in two days (05/July and 06/July/2015). It is obvious that the building function has great impacts on the pattern of cooling demand. Phase 1 mainly consists of classrooms and libraries. The cooling demand of this building is higher on weekdays (06/July) and lower on weekends (05/July). Phase 7 has a lot of laboratories which need cooling over 24 hours each day. The cooling demand of this building is still high in the evening. JCIT is a public building which opens for public activities on weekends. Thus, this building requires high cooling on a weekend.

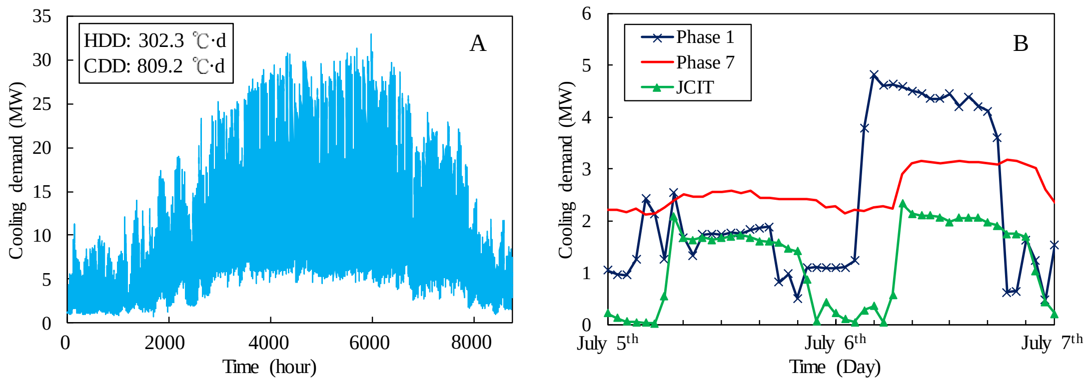


Figure 6.4 Annual profile of total cooling demand (A) and the cooling demands of three different buildings (B) of the district (Year: 2015)

Note: HDD is the heating degree days and its base temperature is 18 °C; CDD is the cooling degree days and its base temperature is 24 °C.

<u>Monitoring and breaking-down of building base electricity demands of buildings</u>

The electricity demand of a building is different for different energy system designs concerned in this case study (i.e., choice of DES or CES). To separate the electricity demand independent from system design from that dependent on the system design, the electricity demand of a building is divided into two parts, i.e., the cooling plant electricity demand, which depends the energy system design, and the building base electricity demand, which is independent from the energy system design, as shown in Fig. 6.5. The cooling plant electricity demand consists of demands of electric chillers (E_{EC}) and heat rejection systems (consists of cooling water pumps (E_{CWP}) and cooling towers (E_{CT})). The building base electricity demand ($E_{building}$) is the demand of all electricity consumers other than the cooling plants, such as IT equipment, lighting and in-building chilled water loop. In this case study, the building base electricity demand is calculated and used as one of the inputs for the DES design.

In the district, the hourly electricity demand of the district ($E_{d,CES}$) is the sum of demands of individual buildings, which are measured by power meters and collected by the BMS. The building base electricity demand is the difference between the hourly electricity demands and cooling plant demands of all buildings as shown in Eq. (6-2), where n stands for the number of buildings. Based on the measured cooling demand and specifications of electric chillers, the electricity demand of chillers can be estimated by chiller models. The electricity demand of cooling water pumps as well as cooling towers can be estimated by Eqs. (6-3) and (6-4) respectively. Where P is the total pressure of fans (400 Pa is used in the estimation). λ is the air-water ratio of cooling towers (0.65 is used in the estimation), ρ_a is the density of air, 1.21 kg/m^3. Efficiencies of pumps (η_P) and fans (η_F) used are 0.85 and 0.78, respectively. Fig. 6.6 shows the profile of overall annual building base electricity demand of the entire district. The annual minimum building base electricity demand was 2977 kW while the annual maximum is 14120 kW. The annual building base electricity consumption of this district is 40563 MWh.

$$E_{building} = E_{d,CES} - \sum_n (E_{EC} + E_{CWT} + E_{CT}) \tag{6-2}$$

$$E_{pump} = N \cdot H \cdot G \cdot g/(3600 \cdot \eta_P) \tag{6-3}$$

$$E_{CT} = G \cdot \rho_w \cdot \lambda \cdot P/(3600 \cdot \eta_F \cdot \rho_a) \tag{6-4}$$

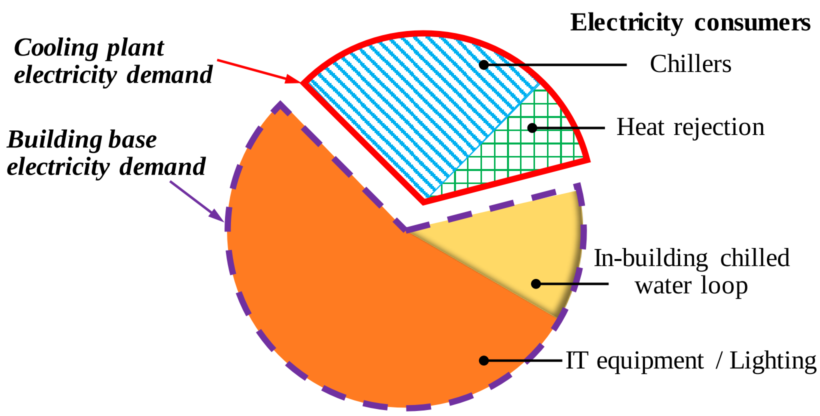


Figure 6.5 Categorization of major electricity consumers in buildings

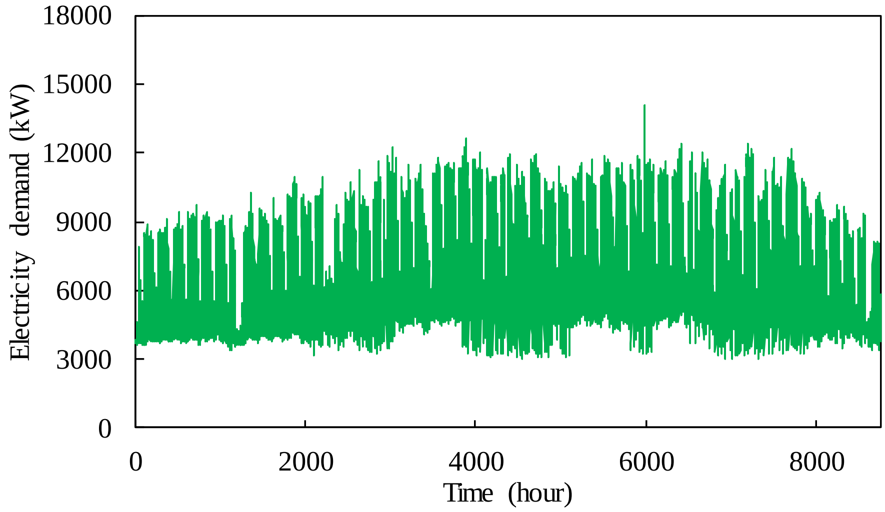


Figure 6.6 Annual profile of the overall building base electricity demand of the district

6.3 Configuration of the proposed DES for the district

The layout of the proposed DES for the district should be determined before the optimal design. Based on the DES typical configuration and the layout of buildings, an energy station, which consists of distributed generations (DGs), absorption chillers and electric chillers, is developed in the middle location of the district, and the heat rejection system is located nearby the energy station, as shown in Fig. 6.7. According to the scale of district and basic rules in a DES design guide, two DGs, six absorption chillers and six electric chillers are selected. Chilled water networks, which has three secondary loops, loop I to loop III, are proposed to deliver chilled water in the district. The required flow rate of chilled water in each pipe segment is estimated by Eq. (6-1), based on the cooling demands of buildings and a given design supply and return temperatures of chilled water (i.e., 7 ℃/12 ℃.) (Yan et al., 2016). The sizes of pipe segments in each secondary chilled water loop can be determined based on the water flow rate, as shown in Table 6.3. According to the length of pipe segments and the flow rate of chilled water, the secondary chilled water pumps can be selected as shown in Table 6.4.

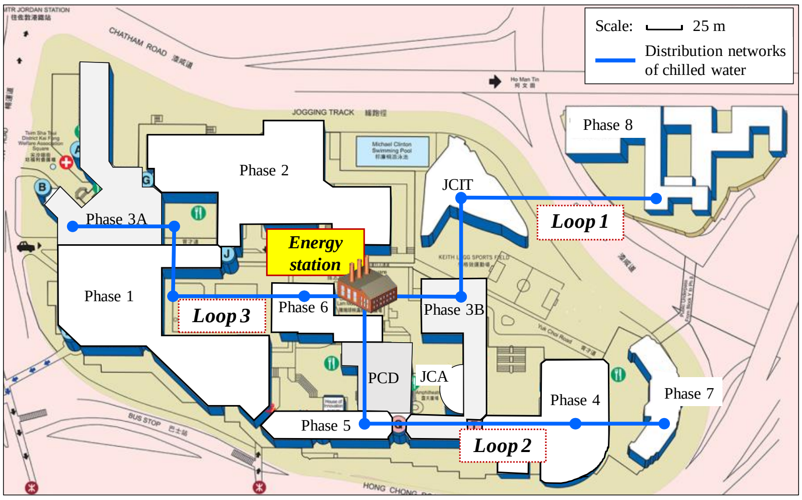


Figure 6.7 Schematic of the layout and the distribution networks of the DES

Table 6.3 Specifications of pipe segments in secondary chilled water loops

	Segment	Starting/ ending nodes	Distance (m)	Diameter (mm)	Price (USD/m)	Investments (USD)
Loop 1	1	Station/ Phase 3B	54	550	690	74,540
	2	Phase 3B/ JCIT	59	450	536	63,724
	3	JCIT/ Phase 8	110	400	466	102,367
Loop 2	1	Station/ Phase 5	72	450	536	77,242
	2	Phase 5/ Phase 4	139	400	466	129,218
	3	Phase 4/ Phase 7	54	350	400	43,236
Loop 3	1	Station/ Phase 6	36	600	774	55,708
	2	Phase 6/ Phase 1	79	500	611	96,795
	3	Phase 1/ Phase 2	50	400	466	46,988
	4	Phase 2/ Phase 3A	61	250	282	34,515

Table 6.4 Specifications of secondary chilled water pumps in the DCS

	Head (kPa)	Number	Q (m^3/h)	W (kW)	Price (USD)
Secondary pumps (in Loop 1)	140	5	380	17.1	4,697
Secondary pumps (in Loop 2)	160	5	312	16.0	4,525
Secondary pumps (in Loop 3)	140	6	377	16.9	4,679

6.4 The optimum DES and its performance assessment

6.4.1 Implementation of the DES optimal design

Based on the measured energy demands of the district, the size and the operation strategy of the proposed DES are determined using the optimal design method described in Section 5.1. Table 6.5 shows the capacities of equipment of the DES designed, and the peak energy demands of the energy system. Two identical DGs of the capacity of 5900 kW each are adopted for electricity generation. It can be found that electricity should be imported from the utility grid when DGs cannot satisfy the demand. Six identical absorption chillers, the total capacity of 12324 kW, and six identical electric chillers, the total capacity of 23880 kW, are adopted for cooling supply. In the later part of this section, the energy and economic performance of the DES is evaluated and analysed. Comprehensive analysis on the annual electricity consumption of the DES is conducted. The matching performance of on-site generations, i.e., DGs and absorption chillers, is assessed by using on-site matching indices. Energy efficiencies of electric chillers in the DES and the CES are compared. Meanwhile, the impacts of chiller design on chiller performance are studied.

Table 6.5 Equipment capacities and the peak energy demands of the optimally designed DES

Equipment	**Equipment capacity (kW)**			**Peak electricity demand (kW)**	**Peak cooling demand (kW)**
	DGs	**Absorption chillers**	**Electric chillers**		
Configuration	5900×2	2054×6	3980×6	16543	32914
Total capacities	11800	12324	23880		

6.4.2 Energy saving and economic benefits of the DES

The energy performance of the DES is evaluated by comparing with the CES. Primary energy saving (PES) is adopted to quantify the energy performance of DES in this case study. As shown in Eq. (6-5), the assessment criterion used is the ratio of saved primary energy and the energy consumption of CES over a period of time. Where, *A* stands for the number of days in that period. Higher value of primary energy saving means better energy performance of the DES.

$$PES = \frac{\sum_A \sum_h (F_{CES} - F_{DES})}{\sum_A \sum_h F_{CES}} \tag{6-5}$$

The monthly primary energy consumptions of these two energy systems (i.e., DES and CES) and the corresponding monthly primary energy saving is shown in Fig. 6.8. The DES consumes less primary energy, i.e., natural gas, than the CES in all months. The monthly primary energy saving ranges from 7.36% to 10.32% and the annual primary energy saving of DES is 9.58%. Table 6.6 and Table 6.7 present the details of the capital cost and the operating cost of these two energy systems. Due to the high investment of DGs and the additional cost of chilled water networks, the capital cost of the DES is about three times of the CES. However, the annual operating cost is reduced by 44.2% when the DES replaces the CES. It indicates that the investors must pay a lot for the high DES investment, and will profit immediately due to the significant reduction of operating cost. According to the concept of payback period, the extra capital cost of the DES can be recovered in 1.93 years, which means that the DES will achieve obvious cost saving after two years of operation. Results of the performance evaluation indicate that the DES is a cost-effective energy system with substantial primary energy saving.

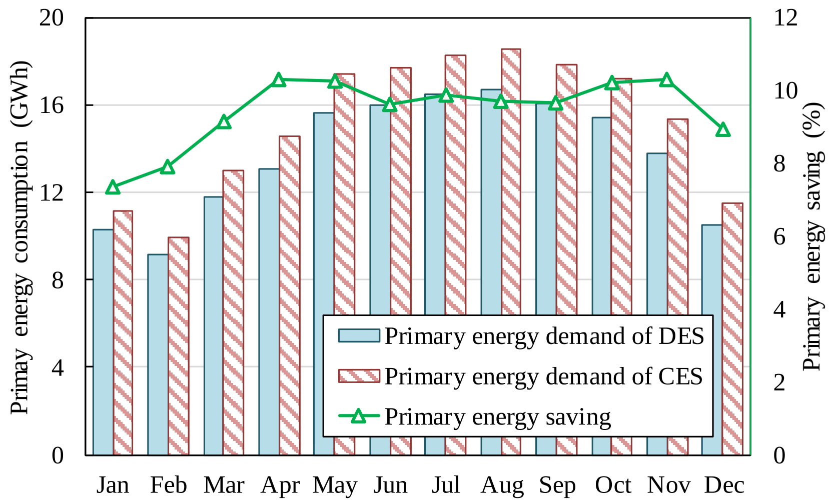


Figure 6.8 Monthly primary energy consumptions of energy systems and primary energy saving of the DES

Table 6.6 Detailed capital costs (10^3 USD) of two energy systems

Items	**DES**	**CES**	**Difference (%)**
DG	15063		—
Chiller			
Absorption Chiller	1096		
Electric Chiller	3591	6606	-29.0
Cooling water pumps	79	346	-77.3
Cooling towers	49	266	-81.7
Chilled water pumps (chilled water networks)			
Primary pumps	95		—
Secondary pumps (loop 1)	22		—
Secondary pumps (loop 2)	21		—
Secondary pumps (loop 3)	26		—
Pipes (chilled water networks)			
Secondary loop 1	241		—
Secondary loop 2	250		—
Secondary loop 3	199		—
Total	**20732**	**7218**	**187.2**

Table 6.7 Detailed annual operating costs (10^3 USD) of two energy systems

Items	**DES**	**CES**	**Difference (%)**
Imported electricity	1443	16561	-91.3
Fuel	8612		—
Exported electricity	913		—
Maintenance	905		—
Incentive	803		—
Total	**9245**	**16561**	**-44.2**

The electricity demand of the CES includes the building base demand, the demand of chillers, cooling water pumps and cooling towers. For the DES, besides the demands mentioned above, the electricity demand also includes the additional demand of pumps in chilled water networks. Fig. 6.9 compares electricity demand profiles of the cooling subsystems in the CES and the DES in a typical summer week. It can be observed that the demand of electric chillers is obviously reduced in the DES, especially in the night-time. However, the electricity demand of cooling towers and cooling water pumps increases. It is because that the use of absorption chillers in the DES increases the condensing heat of the heat rejection system, which increases the power demand of the heat rejection system consequently. Chilled water pumps in the DES consume additional electricity to deliver the chilled water, this part is not as high as the demand of cooling water pumps. It is due to two facts. One is that the length of chilled water pipes is not long and the resistance is not large due to the high cooling demand density. The second is that the district cooling system connects the end-users directly without heat exchangers. The chilled water pumps need not provide extra hydraulic head to offset the resistance of heat exchangers.

The annual electricity consumption of these two energy systems is compared as shown in Table 6.8. It can be observed that the total electricity consumption of the DES is reduced by 13.6% compared with that of the CES. The electricity consumption of electric chillers is significantly reduced by 72.4%. However, the electricity consumption of cooling water pumps and cooling towers increases by 36.1%. This indicates that the difference between electricity consumption of heat rejection systems in the DES and the CES cannot be neglected. In addition, the annual consumption of chilled water pumps in chilled water networks (excluding chilled water loops within buildings) is 1845 MWh, which accounts for around 2.5% of the total consumption of the DES. It indicates that the additional energy consumption for chilled water distribution is not very significant when DESs are used in such a high demand density district.

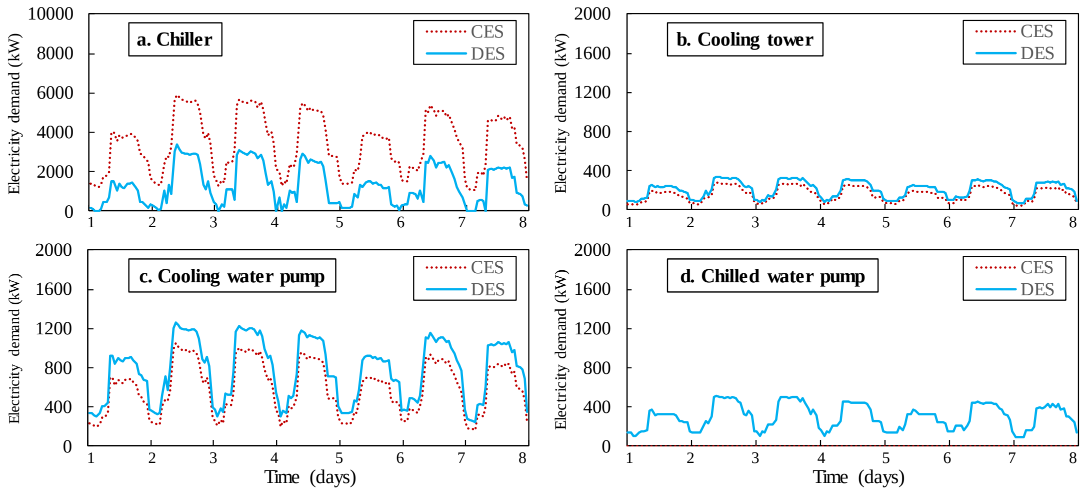


Figure 6.9 Electricity demand of electric chillers, cooling towers, cooling water pumps and chilled water pumps of two energy systems in a typical summer week

Table 6.8 Detailed annual electricity consumptions (MWh) of two energy systems

Items	**DES**	**CES**	**Difference (%)**
In-building	60680	60680	0
Heat rejection system			
Cooling water pumps	4817	3539	36.1
Cooling towers	1297	953	36.1
Chilled water pumps (Chilled water networks)			
Primary pumps	1016		—
Secondary pumps (Loop 1)	247		—
Secondary pumps (Loop 2)	301		—
Secondary pumps (Loop 3)	281		—
Chillers	5778	20947	-72.4
Total	**74418**	**86118**	**-13.6**

6.4.3 Matching performance of on-site generations

Two indices, On-site Energy Matching index (OEM) and On-site Energy Fraction index (OEF), are introduced to assess the matching performance of on-site generations (Cao et al., 2013). The definition of OEM and OEF indices of DGs and absorption chillers are given by Eqs. (6-6) to (6-9), where *m* stands for the number of days in a month. The value of OEM represents how much (i.e., the proportion) on-site generated energy is used rather than being dumped or exported. The value of OEF represents the contribution of on-site generated energy to the energy demand. According to these definitions, it is can be seen that the values of these indices range from 0 to 1. By analysing the values of these two indices, the matching performance of on-site generations under four typical situations is evaluated as follows.

Situation 1: Values of both OEM and OEF are large, i.e., larger than 0.8. This indicates that most part of the generated energy from on-site generations can be used, and most part of demand can be satisfied by generations. Generations can match the energy demand well.

Situation 2: OEM is large while OEF is small, i.e., smaller than 0.6. This indicates that most part of the generated energy can be used by users locally. However, generated energy cannot satisfy most part of demand. Demand is higher than the supply from on-site generations and energy from other energy sources is therefore needed.

Situation 3: OEF is large while OEM is small. This indicates that generations can satisfy most part of the demand but a large portion of generated energy should be exported (such as electricity) or dumped (such as heat). Energy is likely wasted in this situation.

Situation 4: Values of both OEM and OEF are small. This indicates that not only generated energy from on-site generations may be wasted, but also on-site generations cannot satisfy most of the demand. The probability of such situation is very low unless the system operation/control is very poor or totally unreasonable.

$$OEM_{DG} = \frac{\sum_m \sum_h (E_{DG} - E_{sell})}{\sum_m \sum_h E_{DG}} \tag{6-6}$$

$$OEF_{DG} = \frac{\sum_m \sum_h (E_{DG} - E_{sell})}{\sum_m \sum_h E_d} \tag{6-7}$$

$$OEM_{AC} = \frac{\sum_m \sum_h C_{AC}}{\sum_m \sum_h (Q_r \cdot COP_{AC})} \tag{6-8}$$

$$OEF_{AC} = \frac{\sum_m \sum_h C_{AC}}{\sum_m \sum_h C_d} \tag{6-9}$$

These two indices are used to assess the matching performance of the optimal option and the results are presented in the rest of this session. Fig. 6.10 presents the monthly matching indices of DGs in a year. The OEM_{DG}, which fluctuates between 0.87 and 0.98, denotes that most part of generated electricity is used in the district while only a small portion of electricity is exported. The OEF_{DG}, which fluctuates between 0.84 and 0.96, denotes that around 90% of monthly electricity demand is satisfied by the DGs and the rest should be satisfied by the utility grid. Results also indicate that DGs can match the electricity demand very well over the year.

Fig. 6.11 presents the matching indices of the absorption chillers in a year. In the winter months, i.e., January and February, OEF_{AC} is large while OEM_{AC} is small. It indicates that the absorption chillers can satisfy nearly all the cooling demand in winter months. However, part of recoverable heat from DGs cannot be used for cooling but dumped, which leads to energy waste. In the summer months, i.e., May to October, OEF_{AC} is small while OEM_{AC} almost equals 1. This denotes that all the recoverable heat is used for cooling, however, the cooling generated by absorption chillers is far from what needed to satisfy the cooling demand. In summer months, electric chillers are used frequently and they provide up to 43% of the cooling. In other transition months, while both OEM_{AC} and OEF_{AC} are large and fluctuates between 0.81 and 0.98, the absorption chillers match the cooling demand very well. According to the above analysis, it can be found that the DES could waste thermal energy in winter months. Thermal energy storages are seen to be potential options for reusing this part of energy. This technology can store the waste heat and use it for domestic hot water production. The applications of thermal energy storages and their benefits in energy saving need to be studied further.

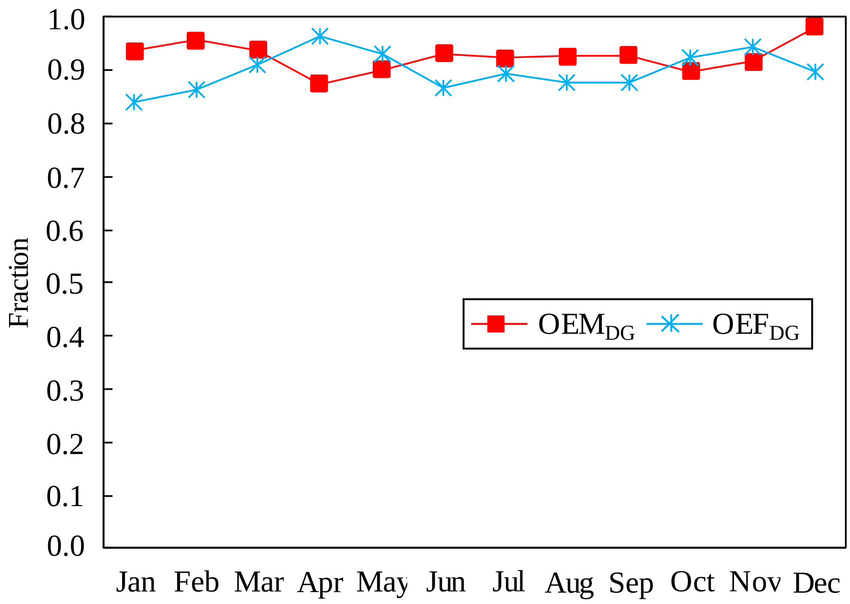


Figure 6.10 Matching indices of DGs in a year

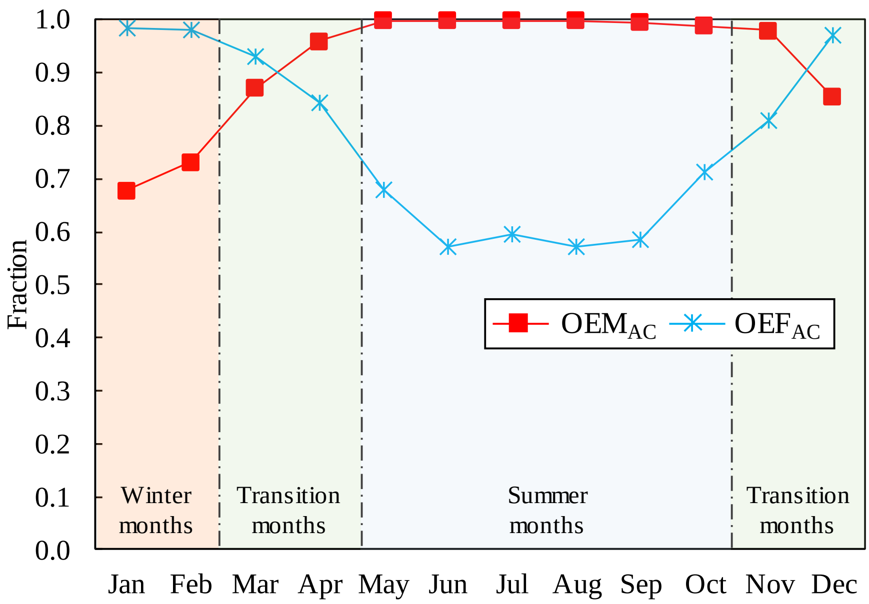


Figure 6.11 Matching indices of absorption chillers in a year

6.4.4 Performance of electric chillers and impacts of their design

In the DES, electric chillers with larger capacity and higher full load COP are used compared with CES. Thus, electric chillers in the DES can operate with higher performance and consume less electricity than those in the CES theoretically. In fact, the practical performance of electric chillers is affected by the cooling demand. For example, chillers operate at high efficiency when cooling load (part load ratio) is high while, they will operate at low efficiency when cooling load is low. Average COP is adopted to evaluate the performance of electric chillers as shown in Eq. (6-10).

$$COP_{ave} = \frac{\sum_A \sum_h C_{EC}}{\sum_A \sum_h E_{EC}} \tag{6-10}$$

The monthly average COP of electric chillers in the DES and the CES is compared as shown in Fig. 6.12. It can be observed that average COP of the DES is higher than that of the CES from April to November. However, the average COP of the DES, with a minimum of 3.18, is lower than that of the CES in January, February and December, due to the small cooling demand in these months. The annual average COP (5.36) of the chillers in the DES is higher than that of the CES (4.91).

The average COP of electric chillers of DESs using two electric chiller design options is compared to study the impacts of chiller design on the energy performance. The configurations of DGs, absorption chillers and the total capacities of electric chillers of the DESs of two chiller options (*Option 1* and *Option 2*) are the same, as shown in Table 6.9. The only difference between the DESs of two options is the electric chiller number and the capacity of individual electric chillers, as presented in Table 10. The average COP of the electric chillers of the DESs of two options in the same operation condition is presented in Fig. 6.13. It can be seen that the monthly average COP is improved when the selection of chillers is optimized. In winter months, such as January for example, the average COP increases from 3.18 to 4.79. In summer months, the performance of chillers is also improved although the improvement is not obvious. The selection of electric chillers certainly affects their performance in operation, and an appropriate configuration of electric chillers, like *Option 2*, can improve the performance and reduce their energy consumption.

Table 6.9 Specifications of electric chillers in *Option 1* and *Option 2*

Option 1		**Option 2**	
Capacity (kW)	**Full load COP**	**Capacity (kW)**	**Full load COP**
3980×6	5.15	4342×5	5.20
		2170×1	4.94

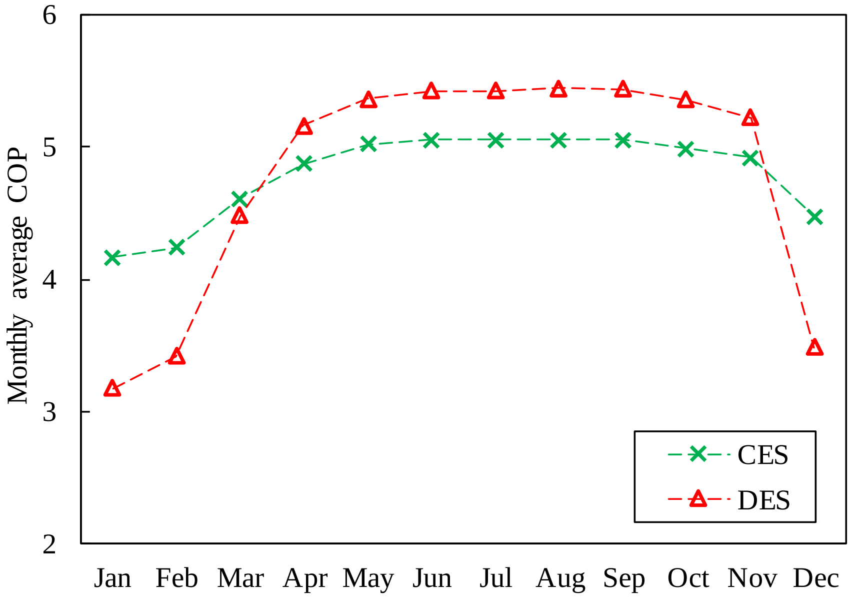


Figure 6.12 Monthly average COP of electric chiller in the DES (*Option 1*) and the CES

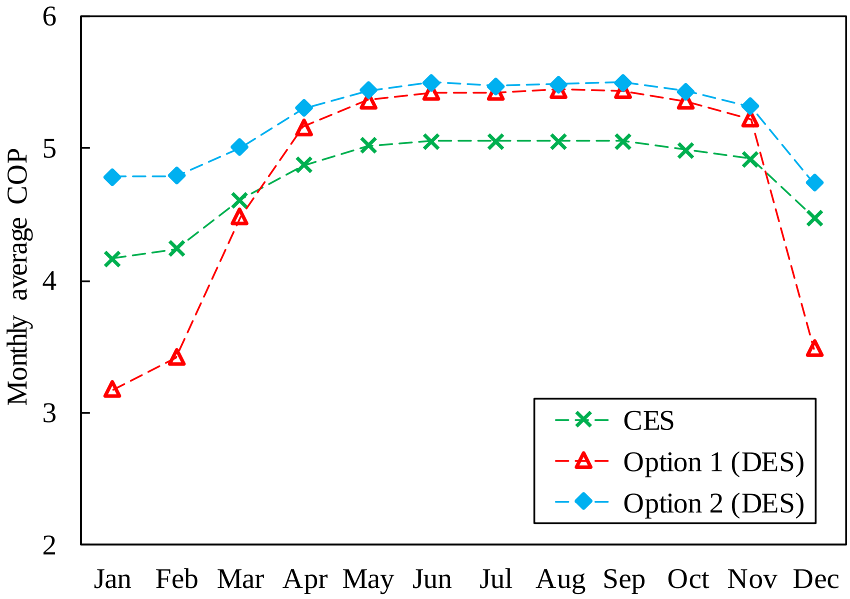


Figure 6.13 Comparison of monthly average COP of electric chillers of *Option 1* (DES) and *Option 2* (DES)

6.5 Summary

The optimal design method for distributed energy systems (DESs) in subtropical regions is implemented and tested in an energy system retrofitting case. An existing district that served by CES is selected, and the energy demands of this district are collected by real site monitoring. Then the optimal design method is performed based on those measured energy demand profiles. The equipment capacities and operating schedule of the optimum DES are determined during the design process. The energy saving and economic benefits of the DES, the matching performance of on-site generations and the performance of electric chillers are evaluated. Based on the experience and the results of the case studies on a practical district, conclusive remarks can be drawn as follows:

- The proposed district level DES is a cost-effective and energy-efficient technology in subtropical regions. The DES can achieve 9.6% of primary energy saving and substantial economic benefits, i.e., the annual operating cost reduces greatly so that the extra capital cost can be recovered within 1.93 years.
- The annual electricity consumption, in particular, the electricity consumption of chillers, of the district is reduced significantly (13.6% and 72.4% respectively) of the DES compared with the CES (centralized energy system). The low proportion of the electricity consumption of pumps in chilled water networks (2.5% of the overall electricity consumption in this case study) indicates that this part of consumption is not very significant when the DES/DCS (district cooling system, working as part of DES to provide cooling) is used in the districts of high cooling demand density.

- In this typical case, the DGs can match the electricity demand of the district very well. However, the absorption chillers can only match cooling demand well in transition months. In winter months, the absorption chillers may dump a substantial part of the recoverable heat (around 30% in this case study), and in summer months, the absorption chillers can only satisfy around 50% of cooling demand while the insufficient cooling needs to be supplied by electric chillers.
- In the DCS, electric chillers operate with higher efficiency than that in the individual cooling systems, i.e., the COP of chillers is improved by 9.2% (from 4.91 to 5.36). Using chillers with appropriate design enable the part load ratios of chillers to be increased. The monthly average COP of electric chillers can be improved by up to 50.6% (from 3.18 to 4.79), especially in winter months.

CHAPTER 7 IMPLEMENTATION AND TEST OF THE PROPOSED ROBUST OPTIMAL DESIGN OF DES FOR A NEW DISTRICT DEVELOPMENT

In this chapter, the DES robust optimal design method is implemented and tested through a case study based on a new development project. Uncertainty is concerned to quantify the possible variations of energy demands and prices. Degradation model is adopted to predict the reduction of the equipment production and performance throughout the life-cycle. The proposed robust optimal design method is therefore used to identify the optimum DES which has the best life-cycle performance expectation under the above conditions concerned. The aim and the organization of this chapter are presented in Section 7.1. Section 7.2 presents the quantification of uncertainties in design inputs. Section 7.3 presents the life-cycle performance and robustness of the optimum DES. Section 7.4 analyses advantages of the proposed robust optimal design method and the associated performance benefits of DES. Conclusive remarks of this case study are given in Section 7.5.

7.1 Introduction

Robust optimal design is a DES optimal design method considering the impacts of uncertainties. This method can identify the best DES which can operate at high performance when the actual working environment change over a large range. In the case of designing a DES in a new development project, same design parameters (e.g., energy demands) can only be obtained by prediction. The DES designed by using these predicted values may operate with poor performance in practical conditions due to the impacts of uncertainties. Thus, the robust optimal design is a more appropriate approach for guiding the DES design in this situation. Recent robust optimal design methods, however, only consider uncertainties in the first operating year without considering uncertainties in the DES life-cycle. In fact, energy demands and energy prices cannot be kept at constants but vary following some trends throughout the life-cycle. Equipment production and performance will reduce and degrade due to the aging effect. The DES, designed by a method which does not consider uncertainties in the life-cycle, may only achieve the required performance in the first several years of installation, and get worse in the rest years. To solve the above problems, a robust optimal design method based on life-cycle performance analysis for DES planning is developed (elaborated in Section 5.2). This chapter aims to test the feasibility of this method in DES design and analyse the advantages of this method by comparing other design methods. A case study of designing the DES in a new district development is developed. This case study is organized as follows.

i. Prediction of the certain energy demands and generation of the uncertain design inputs

The same district in Chapter 6 is used as the energy user. Although the measurements of actual building demands of the existing district are available, the predicted demands by simulation are used in this case study to simulate the design process of DES when developing a new district. The uncertain design inputs are generated by the uncertainty models based on the certain values.

ii. Identification of the alternative DES schemes

Sufficient samples of uncertain cooling demand can be obtained through stochastic sampling. Alternative DES schemes, which the optimum DES is identified from, are determined based on the probability distribution of those samples.

iii. DES design using the proposed robust optimal design method and performance assessment the of DES

The proposed robust optimal design method in Section 5.2 is performed to identify the optimum DES design. The life-cycle total costs of all alternative DES schemes are compared and the cost savings of the optimum DES are analysed and discussed. A sensitivity study is also conducted to present the robustness of the optimum DES. By comparing with the DES achieved by using an uncertainty-based optimal design method (i.e., the design method only considers uncertainty and does not consider the DES life-cycle performance), the performance advantages of the DES achieved by this proposed design method are identified.

7.2 Quantification of uncertain design inputs

7.2.1 Prediction of certain energy demands

The certain cooling demand of the district, which is described in Chapter 6, is predicted by TRNSYS. Type 56, the multi-zone building modelling component in TRNSYS, is adopted to build the model of buildings. The indoor temperature is set between 22 and 26 ℃ according to building functions, and the indoor relative humidity is set as 50%. The operating schedule and energy demand density, including the occupants, equipment and lighting, of each building can be obtained based on the Building Energy Code published by the local government as partially shown in Table 7.1. Based on this information and outdoor weather parameters of a typical meteorological year (TMY), annual cooling demands of those buildings can be estimated by the simulation model. The building base electricity demand consists of the electricity demand of lighting, equipment and HVAC terminal units (i.e., PAUs, AHUs and chilled water pumps inside the building), as shown in Eq. (7-1). The electricity demands of former two items, which are assigned with probabilities of electricity demand uncertainty, are estimated according to equations introduced in government guidelines (EMSD Hong Kong, 2007b). The power consumption of HVAC terminal units in a building can be estimated by Eq. (7-2) according to an on-site study of Yan et al. on an HVAC system in a commercial building (C. C. Yan et al., 2015). Where *SCOP*, short for *system coefficient of performance*, stands for the overall energy efficiency of the HVAC system and α stands for that ratio of the demand of HVAC terminal units to that of the HVAC system. According to the reference, the two parameters are 2.02 and 38.4% respectively. Fig. 7.1 shows the annual profile of the predicted cooling demand and the predicted electricity demand of buildings in this district.

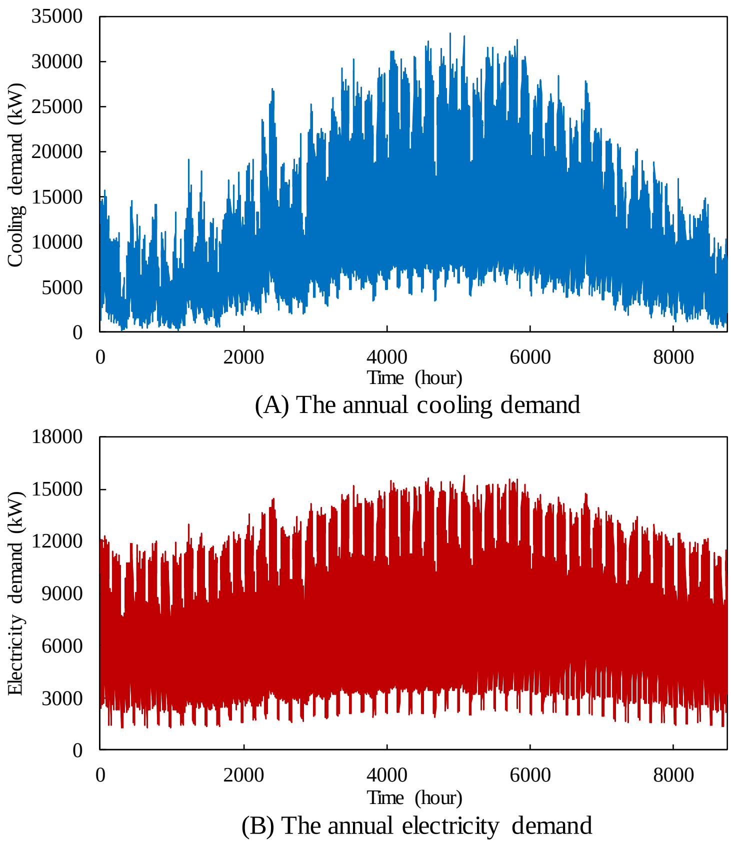
In addition, the certain price of natural gas ($Cost_f$) equals the current price in Hong Kong, 0.057 USD/kWh, while the electricity price ($Cost_e$) and the feed-in tariff ($Cost_{e,sell}$) can be deduced by the correlation equations. The penalty price of cooling demand dissatisfaction (Pen^C) equals the ratio of electricity price to the *SCOP*.

$$E_{building} = E_{lighting} + E_{equipment} + E_{PAU} + E_{AHU} + E_{CHWP} \tag{7-1}$$

$$E_{PAU} + E_{AHU} + E_{CHWP} = C_d \cdot \alpha / SCOP \tag{7-2}$$

Table 7.1 Specifications of building structure and demand density

Building	Area (m^2)	Window-wall ratio (%)	Occupant Density (m^2/person)	Outdoor Air (L/s/person)	Lighting power density (W/m^2)	Equipment Power Density (W/m^2)
Phase 1	55,251	55	5	8	16.4	17
Phase 2	24,419	50	4	10	16	14
Phase 3A	16,782	50	5	8	17	14
Phase 3B	23,400	55	4	10	17	17
Phase 4	19,330	60	4	12	16	16
Phase 5	10,078	50	4	12	16	14
Phase 6	12,307	65	5	8	17	25
Phase 7	25,000	65	4	12	16	20
Phase 8	44,000	55	4	10	17	25
JCIT	15,318	65	3	10	19.3	13
PCD	10,196	55	4	8	16	14
JCA	4,800	45	5	8	25	10



(A) The annual cooling demand

(B) The annual electricity demand

Figure 7.1 Profiles of the predicted annual energy demands

7.2.2 *Implementation of uncertain design inputs*

The trend factors of changes and the uncertainties probability distribution functions (PDFs) associated to the energy demands and gas price are assumed as presented in Table 7.2. It is assumed that the electricity demand will increase by an annual rate of 1.1% in the future according to the annual report of energy end-use data in Hong Kong published by the department of Electrical and Mechanical Services Department of the SAR government (EMSD Hong Kong, 2017). The uncertainty of electricity demand is assumed to follow a triangle distribution. The cooling demand will increase due to the rise of outdoor air temperature caused by global warming (Yang et al., 2014). It is assumed that the annual rate of such increase is 0.17% according to a forecasting study on the energy use of buildings in Hong Kong (Lam et al., 2010). The uncertainty of cooling demand, which is mainly caused by the weather and climate uncertainties, is assumed to follow a normal distribution as confirmed as shown in Fig. 7.2 (Gang et al., 2015). The gas price is assumed to increase by an annual rate of 4% in the future based on the prediction of The World Bank Group (World Bank Group, 2017). The range of gas price is deduced from statistic data in a report of historic gas price (U. S. Energy Information Administration, 2017). It is assumed that uncertainty of this range follows a uniform distribution. Therefore, the uncertain design inputs can be generated by these quantified uncertainty models.

Table 7.2 Uncertainty models of energy demands and prices

Parameter	**Trend factor F_{trend}**	**PDF of uncertainty**
Electricity demand	1+1.1%	**T** (0.3, 1.2, 0.9)
Cooling demand	1+0.17%	**N** (0.82, 0.205^2)
Gas price	1+4.0%	**U** [0.65, 1.35]

Note: For the triangle distribution **T**(a, b, c), a, b and c are the lower limit, upper limit, and mode respectively; for the normal distribution **N**(d, e), d is the mean and e is the variance; for the uniform distribution **U**(f, g), f and g are the lower limit and upper limit.

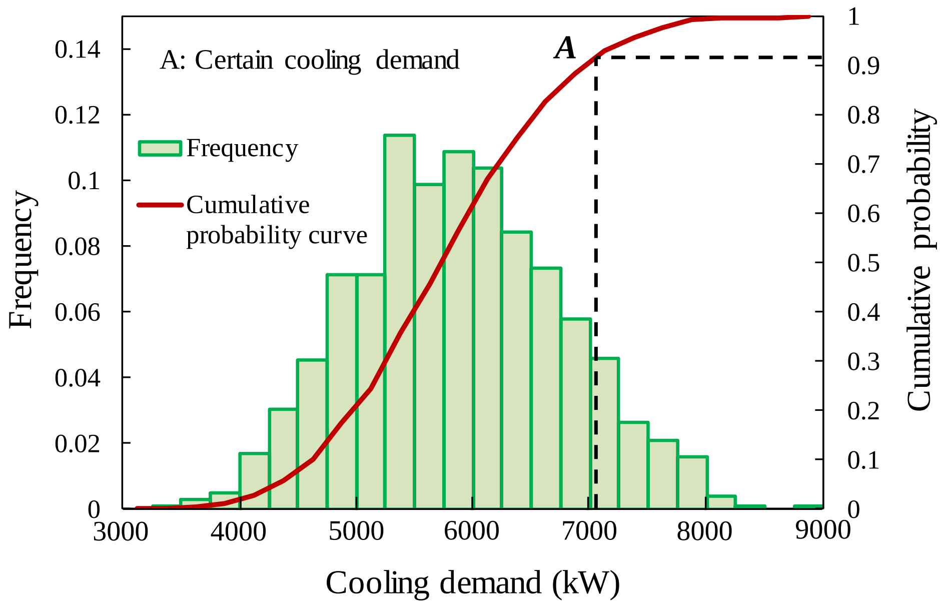


Figure 7.2 Distribution of uncertain cooling demand of a building in a typical hour

7.3 Identification of alternative DES schemes based on the uncertain cooling demand

For the uncertain cooling demand profile of a year, 100 samples were generated using the Latin Hypercube Sampling method. Totally 2000 samples (i.e., 100 times for 20 years of DES service life) of uncertain cooling demand profiles in the DES life-cycle are obtained. The peak cooling demand of these samples can be identified and presented by a probability distribution as shown in Fig. 7.3. Seven DES cooling capacities and their corresponding probabilities of demand satisfaction are therefore selected as shown in Table 7.3. For instance, if the expected probability for a DES to meet the peak cooling demand in its life-cycle is 33%, the required cooling capacity of DES should be 30.9 MW. These seven cooling capacities are used to determine the alternative DES schemes as described in Section 5.3. Based on the method of obtaining a scheme matrix described in Section 5.3, the equipment capacities of alternative DES schemes are determined and listed in Table 7.4.

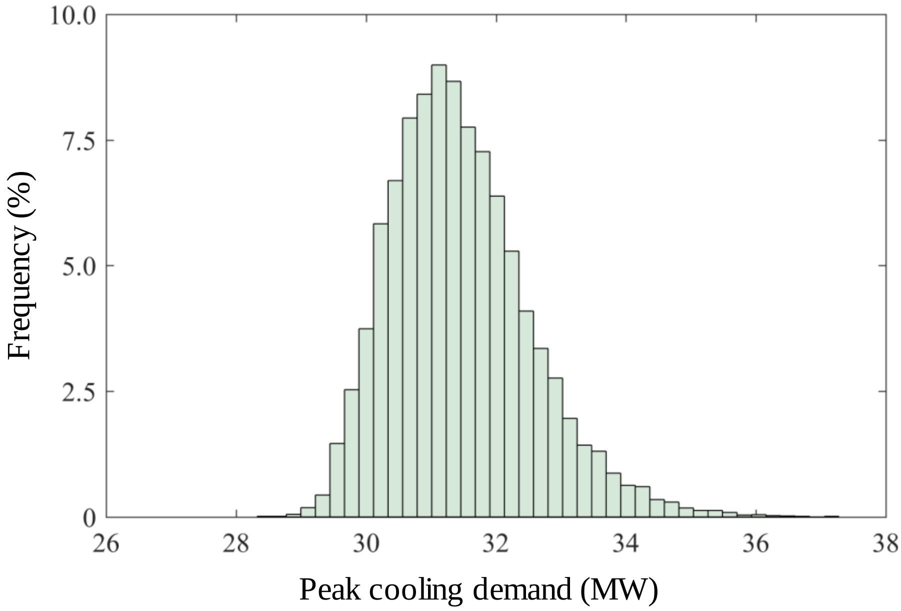


Figure 7.3 Distribution of peak cooling demand in the DES lifetime

Table 7.3 Seven thresholds and their corresponding cooling capacities

Thresholds	**Cumulative probability**	**Cooling capacity of DES (MW)**
β_1	0 %	$C_{CAP,1}$ =28.3
β_2	17 %	$C_{CAP,2}$ =30.4
β_3	33 %	$C_{CAP,3}$ =30.9
β_4	50 %	$C_{CAP,4}$ =31.3
β_5	67 %	$C_{CAP,5}$ =31.8
β_6	83 %	$C_{CAP,6}$ =32.4
β_7	100 %	$C_{CAP,7}$ =37.3

Table 7.4 Capacities of equipment (kW) for each DES scheme

Schemes		S_{A1}	S_{A2}	S_{A3}	S_{A4}	S_{A5}	S_{A6}	S_{A7}
S_{E1}	DGs	6087	7270	7540	7782	8057	8410	11270
	Absorption chillers	2110	2461	2540	2611	2691	2793	3602
	Electric chillers	2110	2110	2110	2110	2110	2110	2110
S_{E2}	DGs	6087	7270	7540	7782	8057	8410	11270
	Absorption chillers	2110	2461	2540	2611	2691	2793	3602
	Electric chillers	2461	2461	2461	2461	2461	2461	2461
S_{E3}	DGs	6087	7270	7540	7782	8057	8410	11270
	Absorption chillers	2110	2461	2540	2611	2691	2793	3602
	Electric chillers	2540	2540	2540	2540	2540	2540	2540
S_{E4}	DGs	6087	7270	7540	7782	8057	8410	11270
	Absorption chillers	2110	2461	2540	2611	2691	2793	3602
	Electric chillers	2611	2611	2611	2611	2611	2611	2611
S_{E5}	DGs	6087	7270	7540	7782	8057	8410	11270
	Absorption chillers	2110	2461	2540	2611	2691	2793	3602
	Electric chillers	2691	2691	2691	2691	2691	2691	2691
S_{E6}	DGs	6087	7270	7540	7782	8057	8410	11270
	Absorption chillers	2110	2461	2540	2611	2691	2793	3602
	Electric chillers	2793	2793	2793	2793	2793	2793	2793
S_{E7}	DGs	6087	7270	7540	7782	8057	8410	11270
	Absorption chillers	2110	2461	2540	2611	2691	2793	3602
	Electric chillers	3602	3602	3602	3602	3602	3602	3602

7.4 Life-cycle performance of the optimum DES and its robustness

7.4.1 Life-cycle performance of the optimum DES

The life-cycle total costs of all the alternative DES schemes are compared in Fig. 7.4. Scheme $S_{E6\ A4}$, which has two DGs of 7782 kW (each), six absorption chillers of 2611 kW (each) and six electric chillers of 2793 kW (each), is identified as the optimum DES scheme with a minimum life-cycle total cost as USD 363.9 million. Comparisons show that improper non-optimum capacities could result in a much higher life-cycle total cost of the DES. For example, the life-cycle total cost of the DES scheme $S_{E1\ A1}$, which has a small capacity with low rated efficiency, is USD 422.9 million, which is 16.2% higher than that of the optimum DES. One of the reasons is that this DES consumes more primary energy than other schemes in the process of energy production due to the low energy efficiency. Another reason is that this DES should pay the penalty for the dissatisfaction of cooling supply due to the insufficient cooling capacity of this DES. The oversized DES has higher rated efficiency and larger capacity to cover the cooling demand. However, it may operate in part load with lower practical efficiency so that consume more primary energy. For example, the life-cycle total cost of the DES scheme $S_{E7\ A7}$, which has the largest capacity, is USD 376.5 million, 3.5% higher than that of the optimum DES.

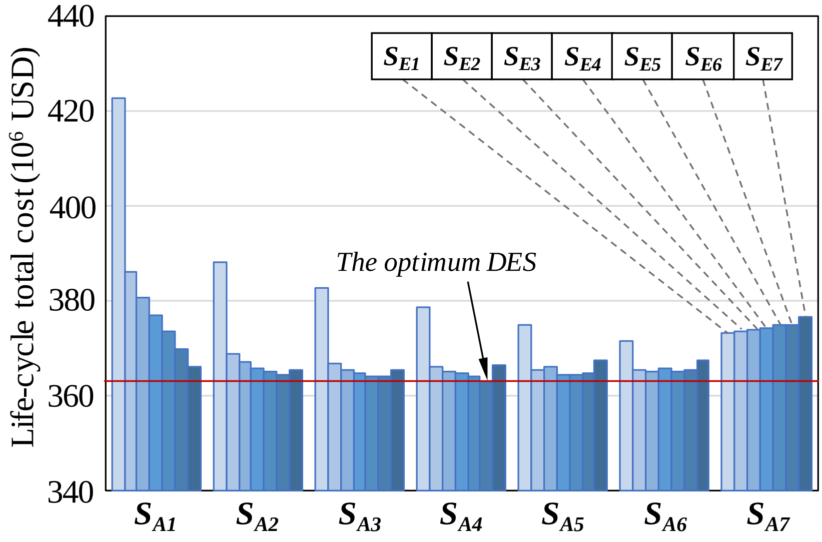


Figure 7.4 Life-cycle total costs of alternative DES schemes

Note: $\boldsymbol{S_{E(i)}}$ stands for the group of DESs which have the same capacities of electric chiller; $\boldsymbol{S_{A(j)}}$ stands for the group of DESs which have the same capacities of absorption chillers as well as DGs. ($i, j \in 1, 2, \cdots$, n).

7.4.2 Performance robustness of the DES

The robustness of performance can be interpreted as the ability of the DES to keep performance stable when operating condition changes. The less variation of the DES performance denotes that the DES has a higher robustness. A sensitivity study is conducted to show the variation of DES performance under different electricity prices and the results are shown in Fig. 7.5. The operating costs of the first operating year of three different DES schemes are assessed and presented, including the optimum DES identified by the proposed design method (marked as The optimum DES), scheme $S_{E1\,A1}$ which has the smallest capacity (marked as DES scheme A) and scheme $S_{E4\,A6}$ which has the same cooling capacity with the optimum DES (marked as DES scheme B). It can be seen that the operating costs of the DESs increase with the increase in the electricity price. The operation cost of DES scheme A is the highest of those three and it rises rapidly. The operation cost of DES scheme B is less compared with that of the optimum DES when the electricity price is low. When the price increases, however, the cost of DES scheme B increases and exceeds that of the optimum DES. The optimum DES has the minimal operation cost variation when electricity price changes. It indicates that the performance of the DES designed by the proposed method has high robustness and has less impacts from the variations of operating conditions.

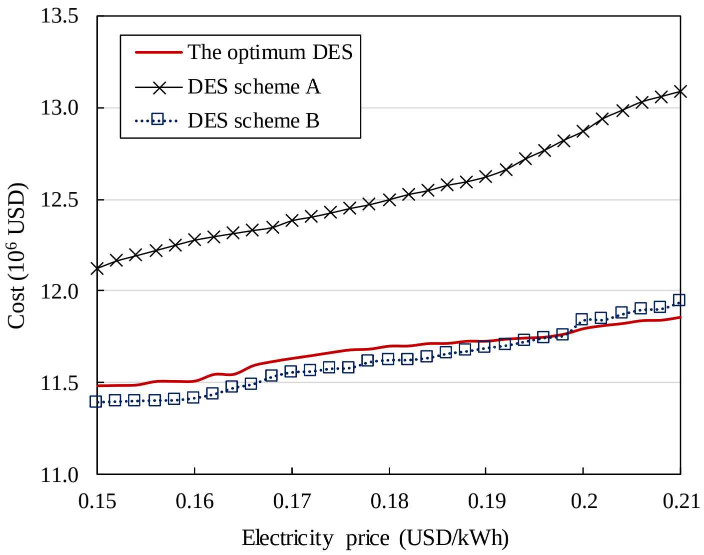


Figure 7.5 Annual operating costs of the DESs at different electricity prices

7.5 Comparison with performance of the DES achieved by uncertainty-based optimal design method

7.5.1 Economic performance of DESs over their life-cycle

The uncertainty-based optimal method for DES design is the method that only considers the uncertainties and does not consider the life-cycle performance. In this method, the DES performance in the first operating year is assessed and is regarded as the optimization objective. Using the uncertainty-based method, the DES scheme S_{E3A1} (marked as DES_1), which has two DGs of 6087kW (each), six absorption chillers of 2110 kW (each) and six electric chillers of 2540 kW (each) is identified as the optimum one. The annual total costs of the DES_1 and the DES identified by the proposed robust optimal design method (marked as DES_2) in their life-cycle are assessed and compared in Fig. 7.6. A lower annual total cost denotes that the DES has better economic performance. It can be seen that due to the combined impacts of the equipment degradation as well as the increase of energy demands and prices, the annual total costs of DESs increase with the increase of the operating year. In the first seven years, the annual total costs of DESs are almost the same which indicates that the economic performance of these two DESs is similar at the initial stages of their life-cycle. The annual total cost of DES_2 is lower than that of DES_1 in the eighth year, and such cost saving increases when the operating year increases. For example, the cost saving of DES_2 is USD 0.5 million in the eighth year, and increases to USD 2.5 million in the twentieth year. This indicates that the DES identified by the proposed design method is able to maintain higher economic performance in the later phase of its life-cycle. It also suggests that it is necessary to use the life-cycle performance as the optimization objective in the DES design.

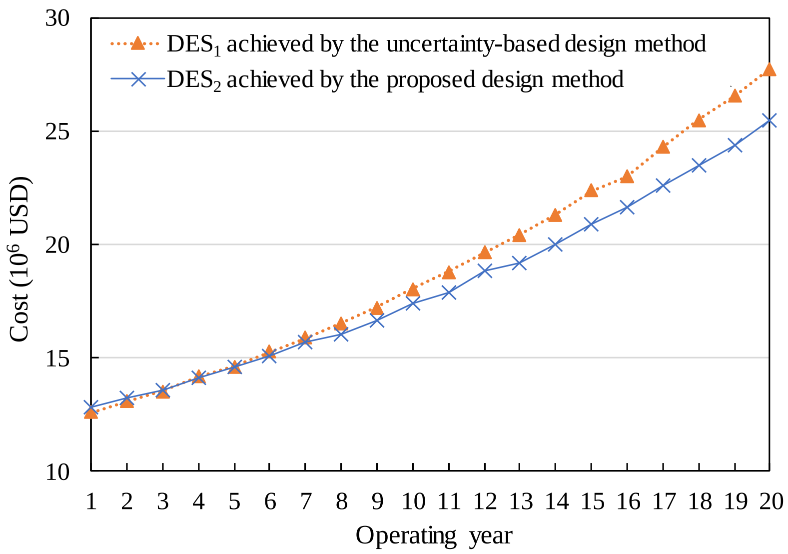


Figure 7.6 Comparison between annual total costs of DESs achieved by uncertainty-based and proposed optimal design methods

7.5.2 Energy performance of DESs over their life-cycle

The total system energy efficiency is used to evaluate the energy performance of DESs. The total system energy efficiency is the ratio of total energy output (i.e., the sum of the net useful power and thermal outputs) to the total fuel input (U.S. Environmental Protection Agency, 2015b). It indicates the percentage of the primary energy being effectively used in the DES. The annual total system energy efficiency (ATSE) can be calculated by dividing the annual total energy outputs (electricity as E_{DG} and E_{grid}, and recovered heat as $Q_{r.AC}$) by the annual primary energy consumption as shown in Eq. (7-3). Fig. 7.7 compares the annual total system energy efficiency of DES_1 and DES_2 in their life-cycle. It can be seen that the energy efficiency of DES_2 is much higher than that of DES_1. It means that the DES identified by the proposed design method can achieve superior energy performance in its life-cycle. The efficiency curve in Fig. 7.7 also reveals the impacts of the variations of operating conditions on the DES energy performance. Taking DES_2 as an example, the efficiency of DES increases due to the increase of the energy demands in the first several operating years. When the energy demands increase to some levels, such as the demand level in the fifth year, the energy efficiency of DES will no longer increase. On the contrary, the energy efficiency will reduce due to the effects of the equipment degradation. From the fifth year to the twentieth year, the DES energy efficiency reduces from 86.7% to 85.1%. It indicates that the equipment degradation has seriously negative effects on the DES energy performance. Some measures, like regular maintenance, should be performed to alleviate the equipment degradation in the DES life-cycle.

$$ATSE = \frac{\sum(E_{DG}+E_{grid}+Q_{r.AC})}{\sum(F_{DG}+F_{grid})} \tag{7-3}$$

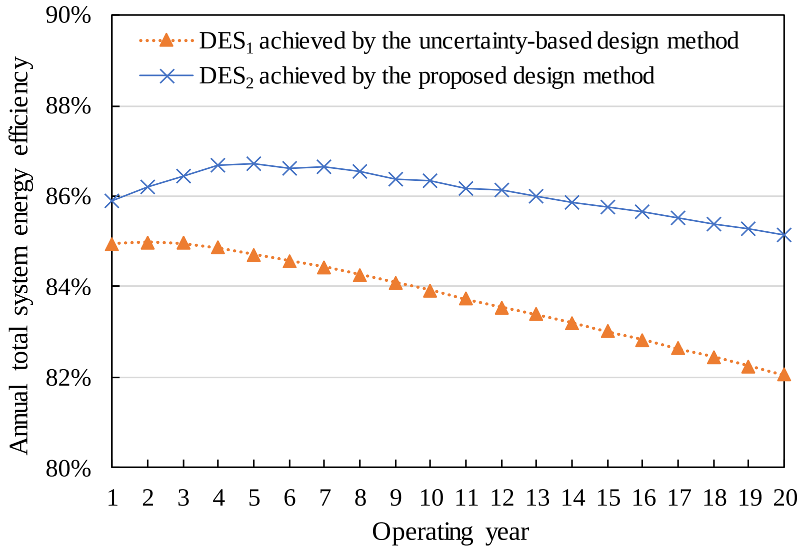


Figure 7.7 Comparison between annual total system energy efficiencies of DESs achieved by uncertainty-based and proposed optimal design methods

7.6 Summary

In this case study, the robust optimal method for distributed energy systems (DESs) design based on life-cycle performance analysis is tested. The uncertain design inputs, i.e., energy demands and energy prices, are obtained by Building Simulation tools and uncertainty models. The alternative DES schemes are determined based on the probability distribution of uncertain cooling demand, and the proposed design method is performed to identify the optimum DES from those alternative schemes. Through the case study, it can be seen that this method is able to identify the optimum DES, which has the best life-cycle performance and robustness of performance. Compared with the DES that identified by the uncertainty-based optimal design without considering the life-cycle performance, this DES could achieve economic benefits and higher energy efficiency in the late phase of its life-cycle. More detailed conclusive remarks can be drawn as follows:

- The proposed robust optimal design method can achieve the expected design optimization objectives. This new DES design method is able to identify the DES with the lowest life-cycle total cost for new DES developments and it can be also used to effectively assess the realistic life-cycle performance of DESs. Results denote that this method can prevent problems of undersize or oversize in DES design. The designed DES achieves the least total cost by to balancing the operating cost and the investment cost.
- In the DES design, it is important and very helpful to take a full consideration of the variations of operating conditions in the DES life-cycle, as what adopted in the proposed optimal design method. Considering the impacts of energy demand and energy price increases as well as the equipment performance degradation, selecting a slightly and properly larger capacity is beneficial for the better performance of DES at its life-cycle. Investors can use this method to identify the best DES according to the different scenarios of variations in local energy demands and energy prices.
- Even the annual total system energy efficiency of the optimum DES reduces in later years of the life-cycle, it can still maintain a high level, i.e., above 85.1%. Such a high efficiency indicates that the DES will consume less primary energy in the process of energy supply. It demonstrates that the DES of proper and optimized design can be a very energy efficiency and eco-friendly technology for high density districts in subtropical regions.

CHAPTER 8 IMPACTS OF UNCERTAINTIES ON DES PERFORMANCE ROBUSTNESS

Monte Carlo simulation is implemented to sample the inputs with uncertainties according to their probability distributions, which are then propagated to the outputs by repeated stochastic modelling. By analysing those stochastic outputs generated by stochastic modelling and Monte Carlo simulation, the impacts of uncertainties of model inputs on outputs can be evaluated. In this chapter, the impacts of uncertainties on DES performance robustness, i.e., the ability of a DES to maintain a stable performance, are comprehensively studied. Section 8.1 elaborates a quantification approach of DES performance robustness and analyses the variation of DES performance robustness in life-cycle using this approach. Section 8.2 compares the impacts of different uncertainties on DES performance robustness and identifies the factors for achieving high performance robustness. Section 8.3 elaborates the probability distribution of DES performance based on the outputs of stochastic modelling. Conclusive remarks of this study are given in Section 8.4.

8.1 Quantification of the DES performance robustness

8.1.1 Robustness index

Robustness of DES performance indicates the ability of the DES to maintain stable performance when operating conditions deviate from the design conditions (i.e., considering uncertainties of energy demands and prices). In the process of the robust optimal design, Monte Carlo simulation and stochastic modelling generate sufficient samples of DES performance. By analysing these samples, the DES performance robustness can be quantified and presented. A robustness index, Rob_{index}, is proposed to quantify the performance robustness as shown in Eq. (8-1). Where, C_i is the performance of sample i (there are n samples), C_{exp} is the expectation of all samples. The index indicates the ratio of the average difference between samples and the expectation to that expectation. It is obvious that a smaller Rob_{index} (i.e., closer to 0) means the DES performance has higher robustness and is less affected by uncertainties. For a better representation, the index is presented in form of a percentage.

$$Rob_{index} = \frac{1}{n}\sum_{i=1}^{n}\frac{|C_i - C_{exp}|}{C_{exp}} \times 100\% \tag{8-1}$$

Fig. 8.1 compares the variation of life-cycle total cost for two DESs, i.e., the DES (referred to as the optimum DES) identified by the proposed robust optimal design method and the DES (referred to as DES_1) identified by uncertainty-based optimal design method, under the impacts of uncertainties. It can be seen that the DES life-cycle total cost varies within a range around its expectation (marked by "×" symbol). For the optimum DES. i.e., the DES identified by the proposed method, its life-cycle total cost varies in a range between USD 358.8 million and 370.0 million due to the uncertainties concerned in this thesis. For DES_1, its life-cycle total cost varies in a range between USD 371.6 million and 388.5 million. The robustness index of the optimum DES and DES_1 are 0.63% and 0.64%, respectively. It indicates that the DES life-cycle performance has a high robustness and is less affected by the uncertainty. The main reason is that the operation of DES is optimized in the process of the robust optimal design method, which enables the DES to operate with stable life-cycle performance. Results denote that the robustness index is an effective measure to quantify and compare the performance robustness of DESs of different capacities.

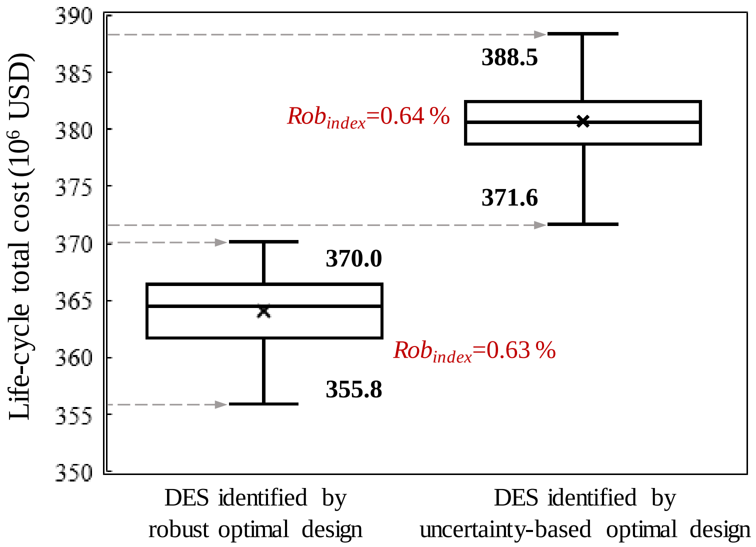


Figure 8.1 Variations of DESs life-cycle total costs

8.1.2 Performance robustness in the DES life-cycle

Robustness of the DES performance in life-cycle can be evaluated and analysed by estimating the corresponding robustness index. Fig. 8.2 and 8.3 present the annual total cost of the optimal DES and its corresponding robustness index, respectively. It can be found that for each operating year, the DES annual total cost varies within a range due to the impacts of uncertainties. Robustness index (Rob_{index}) indicates that this economic performance maintains a stable robustness in the DES life-cycle even the index fluctuates between 2.5% and 3.5%. Comparing the robustness index, it can be found that uncertainties have greater impacts on annual total cost (Rob_{index} is around 3.0%) than life-cycle total cost (Rob_{index} is 0.63%) of a DES. The impacts of uncertainties on the DES annual total cost of particular years will offset each other to a great extent so that those uncertainties will not have significant impacts on the DES life-cycle total cost.

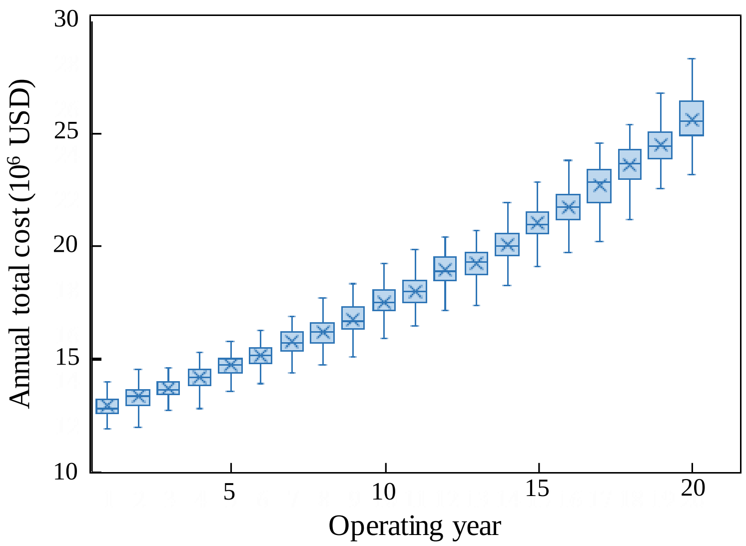


Figure 8.2 Variation of DES annual total cost *vs* operating year

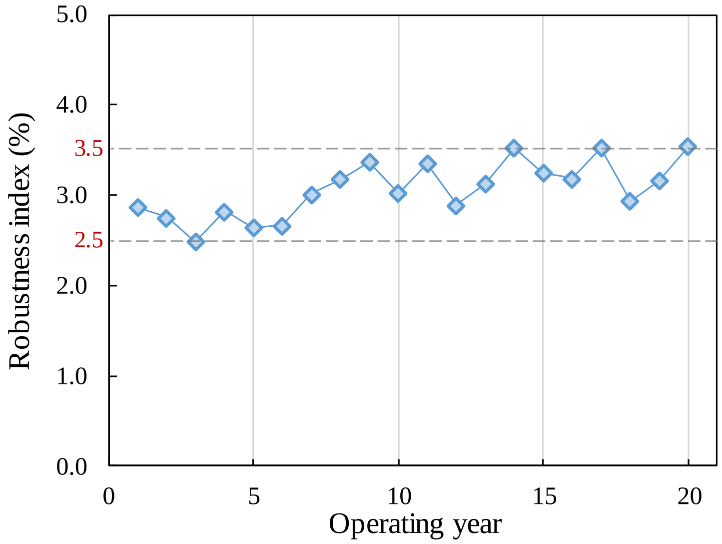


Figure 8.3 Robustness index of DES annual total cost *vs* operating year

Fig. 8.4 and 8.5 present the annual system energy efficiency of the optimal DES and its corresponding robustness index, respectively. It can be found that the DES energy performance is less affected by the uncertainties than the economic performance (i.e., the annual total cost). Fig. 8.5 presents that the robustness index is smaller than 0.73%, which means that the DES can operate with robust energy performance in its life-cycle. Reduced data in Fig. 8.5 denotes that the robustness of energy performance is improved in the late phase of life-cycle. The reason can be deduced as: a large amount of electricity needs to be imported from the centralized power plants when the energy demand increases in the late phase of life-cycle; the efficiency of power plants is not affected by the demand uncertainty so that the variation of overall energy efficiency of DES is reduced and the performance robustness is enhanced.

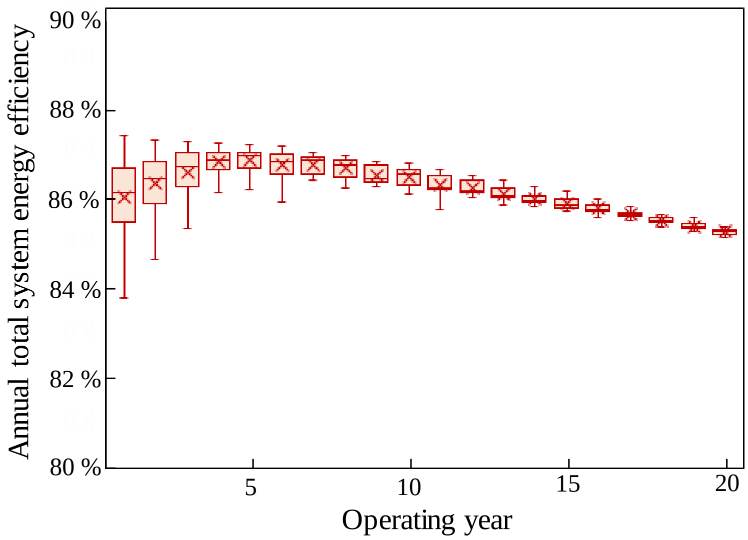


Figure 8.4 Variation of DES annual total system energy efficiency *vs* operating year

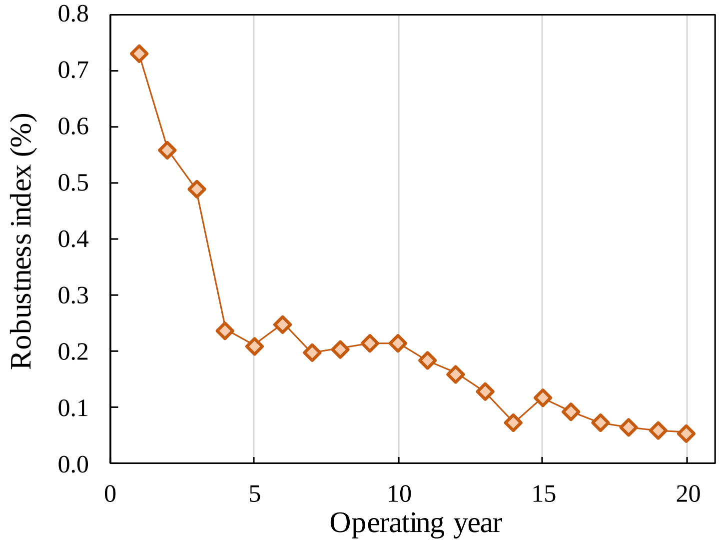


Figure 8.5 Robustness index of DES annual total system energy efficiency *vs* operating year

8.2 Impacts of different uncertainties on DES performance robustness

Both uncertainties of energy demand and energy price are considered when investigating the DES performance robustness. In fact, a situation that some kinds of uncertainties (e.g., price uncertainty) can be ignored may exist, then the DES performance robustness may be improved or reduced in this situation. It is essential to analyse the impacts of different uncertainties on DES performance robustness and to identify factors to achieve high performance robustness for DESs based on the results. A study including three cases is therefore organized as follows.

Case 1: Both uncertainties of demand and price are considered. It is also the common case used in this thesis.

Case 2: Only demand uncertainty is considered. Energy prices are constant, or their uncertainties can be ignored in this case.

Case 3: Only price uncertainty is considered. Uncertainty of energy demand is ignored in this case. However, demand uncertainty is inevitable in the real case. Case 3 is a hypothetical situation where the energy demand does not deviate or less deviates from the predicted value.

Stochastic modelling for the DES operation in the above three cases is performed respectively. The variation range and the corresponding robustness index (Rob_{index}) of the DES performance under different cases are compared in Fig. 8.6. Fig. 8.6(a) presents that annual total cost has lower robustness in Case 1 and Case 3, while higher robustness in Case 2. It indicates that the price uncertainty enables DES annual total cost varies in a large range, while the demand uncertainty does not affect this performance obviously. Fig. 8.6(b) presents that the robustness of DES energy performance, i.e., annual total system energy efficiency, is significantly improved in Case 2 and Case 3. It indicates that the improvement of DES energy performance robustness can be achieved by reducing price uncertainty or demand uncertainty. The impacts of different uncertainties on the DES income are presented in Fig. 8.6(c). Like the annual total cost, the impacts of price uncertainty are greater than the impacts of demand uncertainty on the DES income. When both uncertainties are inevitable (i.e., in Case 1), the robustness of DES income will be reduced to an obviously low level (Rob_{index} equals 12% means that the average deviation between the practical DES income and its expectation is 12%). Based on the above analysis, it can be seen that the price uncertainty is the main cause of the variation of DES performance, while demand uncertainty has little effect on the DES performance, especially economic performance. The pricing organization in the energy markets is suggested to alleviate or avoid frequent and large variations of energy price so that the robustness of DES performance can be improved significantly.

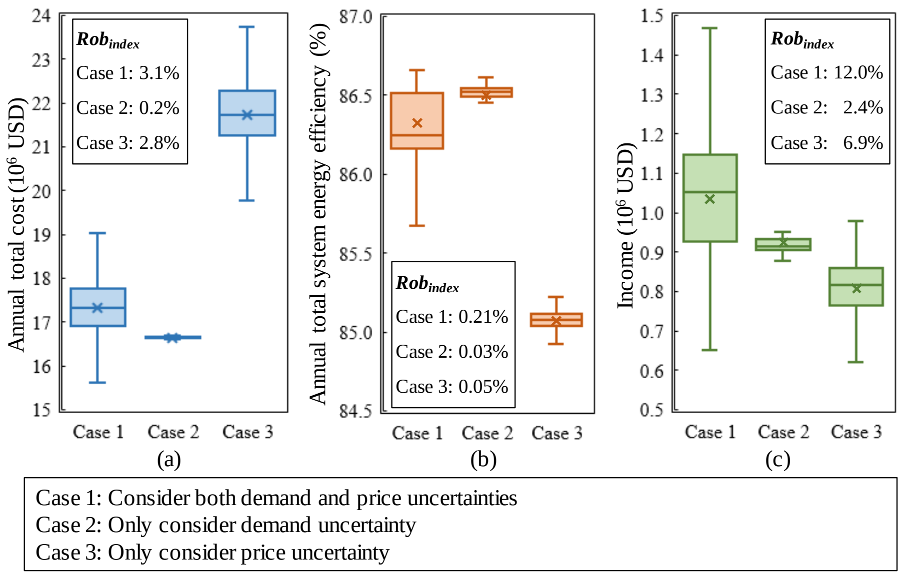


Figure 8.6 Comparison of DES performance robustness under impacts of different uncertainties

8.3 Probability distributions of DES performance

Due to the impacts of uncertainties, the DES performance will vary stochastically and cannot be predicted as an individual value. Probability distribution can elaborate characteristics of the variations of stochastic DES performance and can be used for the probabilistic prediction of DES performance (i.e., predict the probability of the DES performance within a certain range). Take the 10th operating year of the optimum DES as an example, the stochastic annual total cost that generated by stochastic modelling and Monte Carlo simulation can be drawn as a probability distribution as seen in Fig. 8.7. Where, the bar presents the frequency of performance and the line presents its cumulative probability. It can be seen that the annual total cost of DES varies between USD 15.18 and 19.13 million with a probability similar to a normal distribution. Points in the cumulative probability curve present the probability of the DES performance within a certain range. For example, the marked point in Fig. 8.7 indicates that the probability of the annual total cost of DES between USD 15.18 and 18.12 million is 90%.

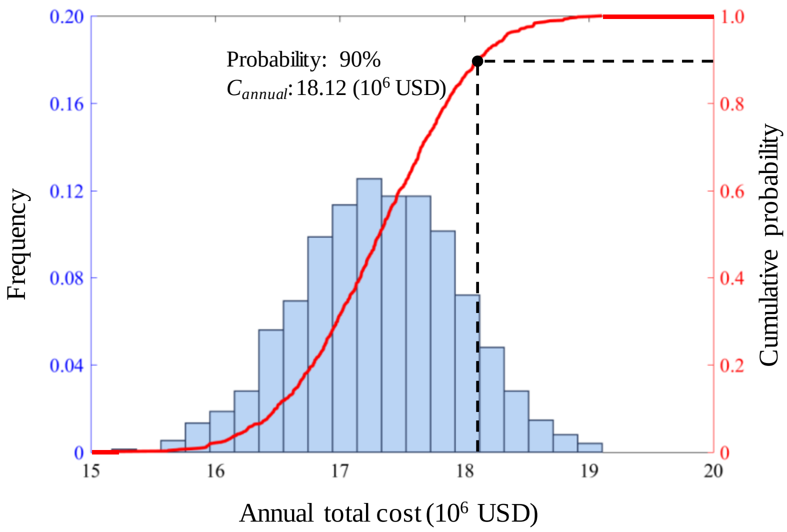


Figure 8.7 Probability distribution of annual total cost of the optimum DES

The probability distribution of the DES annual total system energy efficiency (ATSE) is shown in Fig. 8.8. Even the minimum value of this energy performance is 85.53%, it has a significantly high probability (96%) to be within a small range, i.e., between 86% and 86.6%. It further indicates that the impacts of uncertainties on the DES energy performance can be negated. Fig. 8.9 shows the probability distribution of the income which the DES earns by selling generated electricity. The DES income varies within USD 0.66 and 1.48 million and is expected to be USD 1.04 million, which accounts for 6.0% of the DES total cost. It is worth noting that the amount of selling electricity reduces when the energy demands increase in the DES life-cycle. It can be foreseen that the DES can earn much as the income in the first installation. Exporting electricity to the grid is an effective policy to promote the development of DES by creating considerable economic benefits.

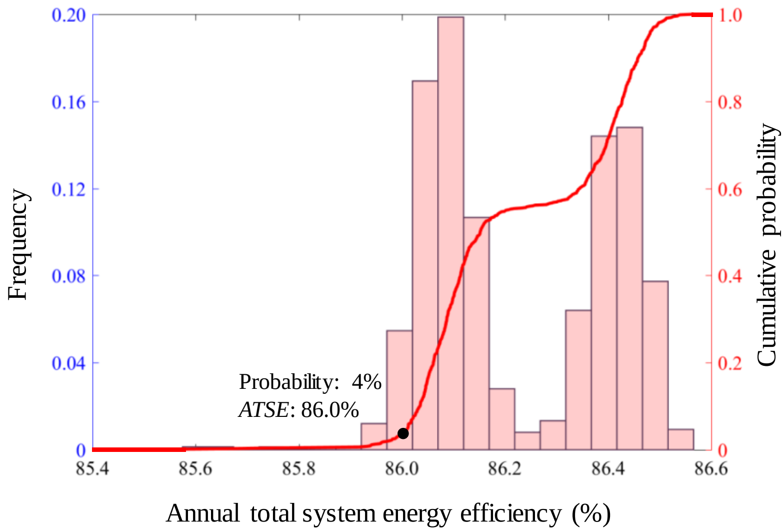


Figure 8.8 Probability distribution of annual total system energy efficiency of the optimum DES

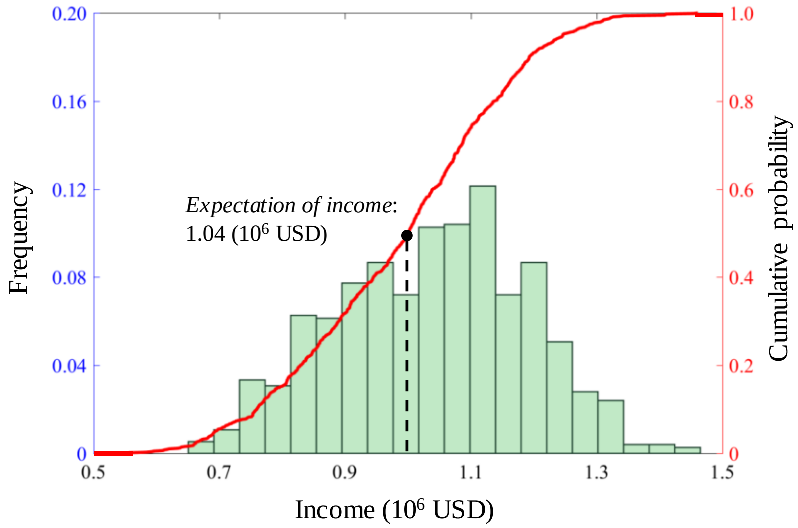


Figure 8.9 Probability distribution of income of the optimum DES

8.4 Summary

To investigate the impacts of uncertainties on the DES performance robustness, a quantitative approach, i.e., the robustness index, is developed to assess the robustness based on the stochastic performance data generated by stochastic modelling. Using this approach, the DES performance robustness at different phases of the life-cycle is quantified and assessed. Cases studies are organized to compare the impacts of different uncertainties on the DES performance, while measures to improve the performance robustness are identified by analysing the results. Further study shows that the DES performance varies with probabilities due to impacts of uncertainties. By analysing the probability distribution of DES performance, the DES performance can be predicted more accurately. More detailed conclusive remarks can be drawn as follows:

- The proposed robustness index is an effective measure to quantify the DES performance robustness, which is defined as the ability of a DES to maintain stable performance under uncertainties. By analysing the quantified robustness, impacts of uncertainties on the performance of different DESs can be compared. For a DES, uncertainties have greater impacts on the annual total cost of particular years than on the life-cycle total cost due to averaging effects, and have negligible impacts on the DES energy efficiency. The robustness of the DES economic performance remains stable in its life-cycle, while the robustness of the DES energy performance is improved.

- Results of the case study indicate that the uncertainty in the energy price has a greater impact on the DES performance, especially the economic performance, compared with the demand uncertainty. Maintaining stable energy prices is suggested if possible, so that the performance robustness of a DES can be enhanced.
- The probability distribution of DES performance can be used to predict the probability of the DES performance within certain range. When considering the impacts of uncertainties, stochastic modelling can be adopted to generate sufficient stochastic outputs, and the probabilistic DES performance can therefore be predicted.

CHAPTER 9 CONCLUSIONS AND RECOMMENDATIONS

This thesis presents a comprehensive study on the performance assessment and robust optimal design of distributed energy systems (DESs) in subtropical regions. Based on characteristics of energy demands in subtropical regions, the basic DES configuration and main equipment in the DES are determined, and the mathematic models for this system are developed. Performance assessment methods for the DES is developed and the main factors which significantly affect the application of DES in subtropical regions are identified. An optimal DES design method based on real-site measurements in energy system retrofitting cases is developed and is implemented and tested in an existing district in Hong Kong. A robust optimal design method is developed for DESs on the basis of life-cycle performance assessment. This method is implemented and tested in a new DES development case. In addition, a quantitative approach for the DES performance robustness is developed to assess the impacts of uncertainties on the DES performance in future operation. Furthermore, useful recommendations for DES design and application in subtropical regions are summarized.

This chapter is organized as follows: Section 9.1 presents a summary of the main contributions of the research presented in this thesis. The conclusions of studies presented in this thesis is presented in Section 9.2. Section 9.3 summarizes the recommendations on DES design and application in subtropical regions. The recommendations for future research are presented in Section 9.4.

9.1 Summary of main contributions

The main contributions in this thesis are summarized as follows:

i. The DES configurations suitable for applications in subtropical and high energy demand density regions are proposed. In the proposed DES, high-efficient gas engines and water-cooled centrifugal chillers are adopted to supply electricity and cooling for users. Mixed-stage absorption chillers with high stability and COP are adopted to recover and reuse the exhaust waste heat in the system. The models of the DES, including the energy models, economic models, are developed. Two basic operation strategies which are subject to energy policies are selected.

ii. Assessment criteria used for evaluating the DES performance are determined. Compared with the operating data of the CES, the DES energy and economic performance is quantified and evaluated using the assessment criteria. Main factors affecting the DES performance and the best situations for applying DES in subtropical regions are identified through organized case studies. Based on the experience and the results of the case studies, useful suggestions are provided for the development and applications of DESs in subtropical regions.

iii. An optimal design method for DES planning in energy system retrofitting is developed. This design method is able to identify the optimum DES which can achieve the maximum energy and cost savings compared with the existing energy system (i.e., CES). A DES design case study for retrofitting the existing CES in a district is conducted to test this method and evaluate the benefits of DES implementation.

iv. A robust optimal design method of DESs for new development projects is developed. Considering the impacts of uncertainties comprehensively, this method is able to identify the optimum DES for an application that can operate with high and stable performance throughout its life-cycle even when operating condition changes significantly. A DES design case study concerning in a new district development is conducted to test this method and analyse its advantages.

v. A quantitative approach is developed to assess the robustness of DES performance under the impacts of uncertainties. Using this approach, the impacts of different uncertainties on the DES performance robustness are evaluated and compared. The measures that enable the DES to achieve high robustness are therefore identified by the comparison studies.

9.2 Conclusions

<u>Influential factors and their impacts on DES performance in subtropical regions</u>

Primary energy saving and payback period are major criteria for assessing the energy performance and the economic performance of DESs. By assessing and comparing the performance of DESs, the impacts of major design parameters and energy policies on DESs performance used in subtropical resigns are evaluated. Results indicate that the building level DESs can achieve substantial benefits (i.e., up to 13.55% of primary energy saving and 1.64 years of payback period) in subtropical regions under certain situations.

The scale and the function of buildings affect the benefits of using DESs significantly. The use of DESs is found to be beneficial only when a building scale is larger than 40,000 square meters. More benefits will be achieved by DESs when they are used in commercial buildings than other kinds of buildings. It is less for office buildings and even much less for public buildings like schools.

For a given building, both undersized and oversized distributed generations (DGs) will result in reduced DES performance. With proper design, DESs can achieve 6.54% primary energy saving and 1.98 years of payback period when selling electricity is not permitted. Permission for selling electricity to the grid can improve the benefits of using DES effectively. The primary energy saving of using DESs can be increased by 7.01% when selling electricity is permitted. Reasonably low gas price is a prerequisite for cost-effective operation and application of DESs. In addition, an incentive policy for energy saving enables the DES to achieve more economic benefits.

Optimal design of DES for energy system retrofitting

The proposed optimal design method uses the real-site monitored energy demands of existing centralized energy systems (CES) in a district to identify the best DES design option that can achieve maximum energy saving and economic benefits. The results of the case study indicate that the proposed district level DES is a cost-effective and energy-efficient technology in subtropical regions. The DES designed using the optimal design method can achieve 9.6% of primary energy saving and substantial economic benefits, i.e., the annual operating cost reduces greatly so that the extra capital cost can be recovered within 1.93 years.

The using of DES can reduce the annual electricity consumption, especially the electricity consumption of chillers, of the district significantly compared with the existing CES. When the DES is used in the districts of high cooling demand density, the pumps in chilled water networks only consumes a low proportion of electricity (2.5% of the overall consumption). It is one of the reasons that DESs are able to achieve benefits in such regions.

For the DES in Hong Kong climate condition, DGs can match the electricity demand of the district very well while absorption chillers can only match cooling demand well in transition months. In winter months, the absorption chillers may dump a substantial part of the recoverable heat (around 30%), and can only satisfy around 50% of cooling demand in summer months. Electric chillers in the DES can operate with higher efficiency than that in the CES due to the use of larger chillers and higher part load ration of operating chillers, and the efficiency can be improved significantly by using chillers with proper design.

<u>Robust optimal design of DES for a new development</u>

Considering the impacts of the uncertainties and the equipment degradations comprehensively, the proposed robust optimal design method can identify the optimum DES, which has the lowest life-cycle total cost and high robustness of performance, in the new development case concerned. Compared with the DES that identified by the uncertainty-based optimal design without considering the life-cycle performance, the DES identified by the robust optimal design method, considering both uncertainty and the life-cycle performance, could achieve economic benefits and higher energy efficiency in the late phase of its life-cycle. Even though the annual total system energy efficiency of the optimum DES reduces late phase of the life-cycle, it can still be maintained at a high level, i.e., above 85.1%. It demonstrates that the DES of proper and optimized design can be a very energy efficient technology for high density districts in subtropical regions.

In addition, this method can be also effectively used to assess the realistic life-cycle performance of DESs. The degradations of equipment performance and the increases of energy demand and energy price in the DES life-cycle have great impacts on the energy efficiency and the annual cost of the DES. In the DES design, it is important and very helpful to take a full consideration of the above factors and select a slightly and properly larger capacity so that the DES can achieve better life-cycle performance.

Impacts of uncertainties on the DES performance robustness

The proposed robustness index can be used to quantify and assess the DES performance robustness under the impacts of uncertainties. For a DES, uncertainties have greater impacts on the annual total cost of particular years than that on the life-cycle total cost due to the averaging effect, while their impacts on the DES energy efficiency are negligible. The robustness of the DES economic performance remains stable in its life-cycle, while the robustness of energy performance is improved. The impacts of different uncertainties on the DES performance can be compared using case studies. Results of these case studies indicate that the uncertainty of the energy price has greater impacts on the DES performance, especially on the economic performance, compared with the uncertainty of the energy demand. To improve the performance robustness of a DES, maintaining stable energy prices is therefore recommended if possible.

The probability distribution of DES performance can be used to predict the probability of the DES performance within certain range. When considering the impacts of uncertainties, stochastic modelling and Monte Carlo simulation can be adopted to generate relevant stochastic outputs, and the probabilistic DES performance can therefore be predicted.

9.3 Recommendations on DES application and design

Based on the experiences and the results of this study, recommendations on DES applications in practice and design of DESs of enhanced performance in subtropical regions are summarised as follows.

i. For DES applications, the prerequisites or favourable conditions, which allow that DESs to be profitable in subtropical regions, include: 1) the energy demands of users concerned are high; 2) the surplus electricity generated by DGs can be sold to the utility grid; and 3) the gas price is much lower than the electricity price. In addition, some incentive policies for DES application, for example, the economic incentive for energy saving, can be implemented to further reduce the operating cost and increase economic benefits of the DES in such regions. The district level DES is recommended for districts with high cooling demand density so that it can consume less electricity in delivering the chilled water from the chillers to the users.

ii. For DES design, the "two-level optimization", i.e., optimizing the DES operation and the DES capacity simultaneously, can be adopted to identify the DES option that can realize the potentials of DES for energy saving and cost reduction. In the DES design of energy system retrofitting projects, the energy demands of the users should be monitored in detail. The realistic performance of the DES options under consideration can be therefore evaluated using these measured energy demands. In the DES design of new development projects, it is essential for designers to comprehensively consider the impacts of uncertainties in power demands, price and equipment degradation on the DES performance. The robust optimal design method is an effective approach and tool to identify the DES that has good life-cycle energy and economic performance and a high robustness of the performance throughout its life-cycle.

9.4 Recommendations for future work

Major efforts of this PhD research project have been made on the investigation on the feasibility of the DES using in subtropical regions, and the development of optimal design methods for DESs considering uncertainties. It would be very desirable and valuable to make further efforts on the following aspects to improve the quality of the research and to study the feasibility of combining the DES with other technologies.

- In this study, the number of main equipment in a DES (i.e., the energy generators) is determined based on the recommendation of a commonly-used design guide. The energy efficiency and the economic benefits of DES could be improved by changing the number of equipment in the DES. In the future, the number of equipment should be optimized in DES design and the corresponding optimal design method should be developed. The impacts of the chilled water distribution network sizing on the DES performance should also be considered. The optimal configuration of the distribution networks in a DES needs to be identified.
- Based on the results of this study, a proper designed DES is able to reduce substantial energy consumption in subtropical regions under favourable conditions. However, thermal energy might be wasted in winter months. Thermal energy storages seem to be potential options for proper use of this part of energy, such as for domestic hot water production. In addition, batteries could be used to can store surplus electrical energy generated in DESs. In the future work, the form of energy storages and the coupling between the energy storages and the DESs in subtropical regions should be studied. The potentials and benefits of such

integration need to be identified. Meanwhile, the application of renewable energy is not considered in this PhD study. The integration of renewable and the DES should be studied and its potential to reduce greenhouse gas emission should be evaluated in future works.

- With the development of smart grid, new concepts are emerging such as smart energy hubs, demand respond and agent-based control. Buildings are required to be smarter, grid-friendly and grid-responsive due to that building energy systems contribute a large amount of the electric energy consumption. This results in the necessity to study the design and the control of the integration of DESs and smart grids. It is worthwhile to investigate the advantages and potential problems of this integration.

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