Decarbonising Future Power Systems by Demand Side Management in Smart Grid

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Abstract

Carbon emission reduction is an urgent global task. Renewable energy sources integration can promote the transformation of cleaner and greener power system. But the time-varying nature of these sources causes indeterminacy problems. Smart grid is a powerful tool that can deal with these problems in electricity aspect. One of the key smart grid technologies is demand side management. How to use demand side management to regulate and decarbonise the power system is the main point of this thesis.

In order to integrate renewable energy sources, a day-ahead electricity market scheme is proposed, involving the utility, the demand response aggregator and customers. This model leads to a multiobjective optimization problem, which is solved by an artificial immune algorithm. The simulation results confirm the feasibility and robustness of the proposed model. All participants can benefit from it, and the system power peak to average ratio can be reduced.

In order to realize the carbon emission reduction, a system model for annual fuel sources scheduling and operational policy making of electricity generation is established, considering the economic, environmental and social aspects. A minimum Manhattan distance approach is proposed to select the final solution. The impacts of carbon tax and renewable obligation on carbon emission, generation cost and electricity bill are examined. These can reveal the proper strategy for deciding renewable energy source and carbon emission related policies.

After that, a carbon emission flow model is introduced to facilitate the analysis and assessment of demand side management's impacts on carbon emission reduction. The time sensitivity of carbon emission in both generation side and customer side are obtained. The daily case and seasonal case are presented. The simulation results show that the load curtailment and load shift approaches can effectively reduce the carbon emission.

Declaration

The work in this thesis is based on research carried out at the Department of Engineering, Durham University, United Kingdom. No part of this thesis has been submitted elsewhere for any other degree or qualification and it is all my own work unless referenced to the contrary in the text.

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Publication List

- **Book Chapter**
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- **Journal Paper**
  - **Dan Li**, Hongjian Sun, Wei-Yu Chiu and Poor Vincent, *" Multiobjective Optimization for Demand Side Management in Smart Grid."*, IEEE Transactions on Industrial Informatics 14(4): 1482-1490.
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  - Weiqi Hua, **Dan Li**, Hongjian Sun and Peter Matthew, *"Stackelberg Game-theoretic Model for Low Carbon Energy Market Scheduling"*, IET Smart Grid, submitted in July 2018.
- **Conference Paper**
  - **Dan Li**, Hongjian Sun and Wei-Yu Chiu, *" A Layered Approach for Enabling Demand Side Management in Smart Grid."*, 2016 International

Conference on Control, Automation and Information Sciences (ICCAIS). Ansan, Korea, IEEE, 54-59.

- **Dan Li**, Weiqi Hua, Hongjian Sun and Wei-Yu Chiu, *" Multiobjective Optimization for Carbon Market Scheduling based on Behavior Learning"*, 2017 International Conference on Applied Energy. Cardiff, Energy Procedia 142 (2017): 2089-2094.
- **Dan Li**, Hongjian Sun and Wei-Yu Chiu, *" Achieving Low Carbon Emission using Smart Grid Technologies"*, 2017 IEEE 85th Vehicular Technology Conference (VTC2017). Sydney, IEEE, Piscataway, 1-5.
- Weiqi Hua, **Dan Li**, Hongjian Sun and Peter Matthew, *"Unit Commitment in Achieving Low Carbon Smart Grid Environment with Virtual Power Plant"*, 2017 IEEE International Smart Cities Conference (ISC2). Wuxi, China, IEEE, Piscataway, 1-6.

Contents

List of Figures

List of Tables

List of Symbols and Abbreviations

$:=$	Assignment operator.
α, β	Compensation coefficient.
γ	Additional operating cost coefficient.
μ	Bonus coefficient.
ω	Weight coefficient in the WS approach.
ψ	Wind turbine blade pitch angle.
ρ	Air density.
σ	Wind turbine performance coefficient.
τ	Wind turbine blade tip speed ratio.
θ	Mutate coefficient.
ε	Dissatisfactory coefficient.
ς	Wind turbine blade swept area.
$\mathbf{I_B}$	BCEF intensity.
$\mathbf{I_G}$	ECEF intensity.
$\mathbf{I_I}$	ICEF intensity.
$\mathbf{I_L}$	BCEL intensity.
$\mathbf{P_B^1}$	Branch active power inflow matrix.

$\mathbf{P_B}$ Branch active power outflow matrix.

$\mathbf{P_G}$ Active power ejection matrix.

$\mathbf{P_I}$ Active power injection matrix.

$\mathbf{P_N}$ Node power flow matrix.

$\mathbf{R_B}$ BCEF rate.

$\mathbf{R_G}$ ECEF rate.

$\mathbf{R_I}$ ICEF rate.

$\mathbf{R_L}$ BCEL rate.

$diag$ Diagonal matrix operator.

A Antibodies collection.

b_i Generation cost coefficient for source i.

c^0 Conventional generation cost without the DSM.

c^1 Conventional generation cost with the DSM.

c^{res} RESs generation cost.

d^0 Total electricity demand before the DSM.

d^1 Total electricity demand after the DSM.

e_i Carbon emission coefficient for source i.

$F(\cdot)$ Multiobjective problem.

$f_a(\cdot)$ Objective function for the aggregator.

$f_c(\cdot)$ Objective function for customers.

$f_p(\cdot)$ Objective function for the policy maker.

$f_u(\cdot)$ Objective function for the utility.

$f_{bas}(\cdot)$ Basic cost function of fuel sources for utilities.

$f_{bon}(\cdot)$ Bonus function for the aggregator.

$f_{com}(\cdot)$ Compensation function for customers.

$f_{ct}(\cdot)$ Carbon tax function for utilities.

$f_{dis}(\cdot)$ Dissatisfactory function for customers.

$f_e(\cdot)$ CEF function.

$f_{fit}(\cdot)$ Fitness function.

$f_{gene}(\cdot)$ Total generation cost function for utilities.

$f_{ope}(\cdot)$ Additional operating cost function for utilities.

$f_{ro}(\cdot)$ Extra generation cost function for utilities due to the Renewable Obligation.

g_i^0 Generation from source i before generation adjustment.

g_i^1 Generation from source i after generation adjustment.

g_t^c Power obtained from conventional generators at time slot t.

g_t^{res} Power obtained from RESs at time slot t.

g_t Expected power generation at time slot t.

g_{down} Power ramp down limit.

$g_{i,r}$ Generation from RESs.

g_{up} Power ramp up limit.

G Expected power generation from conventional generators.

h Price of the renewable energy certificate.

J Number of objectives.

l_t^0 Demand at time slot t without the DSM.

l_t^1 Demand at time slot t with the DSM.

L Total consumption of electricity in one day.

M Number of vectors in APS and APF.

m Carbon tax rate.

n_c Iteration number.

N_p Population size of antibodies.

p^* Selected Pareto optimal solution.

p The vector of decision variables.

q The price of per unit electricity.

R Minimum requirement for penetration of RESs.

r Clone rate.

s_i^0 Fuel usage of source i before generation adjustment.

s_i^1 Fuel usage of source i after generation adjustment.

$s_{i,r}$ Fuel usage of RESs.

S Spinning reserve requirement.

u_i Generation coefficient for source i .

v Wind speed.

w Wind turbine output power.

AIA Artificial immune algorithm

APF Approximate Pareto front

APS Approximate Pareto set

BCEF Branch carbon emission flow

BCEL Branch carbon emission loss

CEF Carbon emission flow

CPF Carbon price floor

D & C Divide & Conquer

DERs Distributed energy resources

DG Distributed generation

DR Demand response

DSM Demand side management

DSO Distribution system operator

ECEF Ejected carbon emission flow

ICEF Injected carbon emission flow

MCDM Multiple criteria decision making

MEF Marginal emission factor

MMD Minimum Manhattan distance

MOP Multiobjective optimization problem

Mtoe Million tons of oil equivalent

NIP Net improvement percentage

Ofgem Office of Gas and Electricity Markets

PAR Peak to average ratio

QoE Quality of experience

RESs Renewable energy sources

ToU Time-of-use

WS Weighted sum

Chapter 1

Introduction

1.1 Background

Climate change has posed a threat to the sustainable development, which brings the importance of carbon emission reduction. To reduce carbon emission, the U.K. government has made significant efforts since 1997, started from the Kyoto Protocol. The U.K. committed to reducing the carbon emission by all kinds of ways, such as improving the energy efficiency, utilizing renewable energy sources (RESs), enhancing the fuel standard, investing low-carbon technologies, and reducing the energy demand [1]. The U.K. was also the first country that sets a legally-binding limit on carbon emission amount. In 2008, the Climate Change Act was passed in the U.K., and the framework to develop an economically credible carbon emission reduction path was set up. It aimed to achieve at least 30% carbon emission reductions by 2020, and 80% by 2050 compared with the level of 1990 [2]. In December 2011, the U.K. government published the Carbon Plan. This plan set out how the country will transit to the decarbonization while ensuring energy security, and minimizing consumers' cost [3].

Overall, the electricity supply plays a significant role in achieving these targets [4]. It accounts for approximately one-third of the total emission in the U.K. for the past 15 years. The average carbon emission for electricity generation was 0.7 tonne/MWh in 1990, and decreased to 0.5 tonne/MWh in 2008. The anticipated aim is just 0.05 tonne/MWh by 2030 [5]. The monitor of fuel source usage in electricity supply is necessary during this transition process. Firstly, coal was the dominant source for almost half a century since 1950, contributed to 97% of the generation at 1950. Oil was generally used in the late 1950's, and came to a peak in the early 1970's, then impacted by the oil crisis at 1973. This gave an opportunity for the development of nuclear power. The electricity provided by it raised from 9% in 1970 to 28% in 1998. The natural gas was introduced in the 1990's, and had a rapid increase. It exceeded the use of coal in 1990, which accounted for 39% of the generation, while coal accounted for 28%. Recently, the use of RESs scaled up. Especially, wind and solar had a significant progress, provided 15.5% of the generation in 2017 [6]. The promotion of RESs impeded the use of fossil fuel. Coal, oil, and gas experienced gradually declines. The low carbon generation in generation mix is planned to reach 61% in 2020, compared to 47% in 2015 [7]. The detailed electricity generation mix by major fuel sources from 2000 to 2017 is shown in Fig. 1.1. The changes of generation mix and evolutions of technologies result in a carbon emission reduction. The emission from power generation was reduced by 57%, from 242.1 Mtons in 1990 to 110.9 Mtons in 2016. The emission mainly came from the combustion of coal and gas. It is projected to reduce another 52% of emission till 2020, based on the level of 2015 [8]. The detailed carbon emission from electricity generation by major fuel sources from 2000 to 2017 is shown in Fig. 1.2. In the U.K., the Department for Business, Energy & Industrial Strategy (BEIS) and Office of Gas and Electricity Markets (Ofgem) are primary regulators that are responsible for the carbon emission reduction.

As mentioned before, the utilization of RESs can help with the carbon emission issue [9]. More energy is expected to be supplied by RESs in the grid, such as wind, photovoltaic, and tidal energy. However, these RESs cause intermittent problems due to their inherent characteristics. The power provided by RESs varies with the external environment conditions, e.g., season, weather and time period. The management of RESs requires sophisticated planning and operation scheduling. Smart grid provides the ability for promoting the penetration of RESs. It is an intelligent power network that is composed of advanced generation, communication, control and computation technologies. It can improve the reliability, availability, and effi-

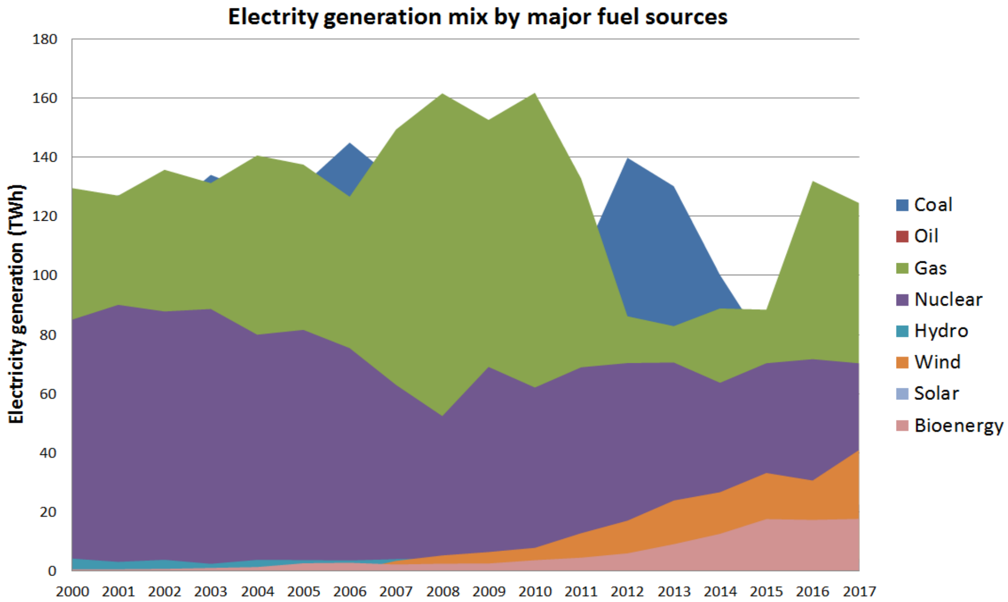


Figure 1.1: Electricity generation mix by major fuel sources in the U.K. from 2000 to 2017 [6].

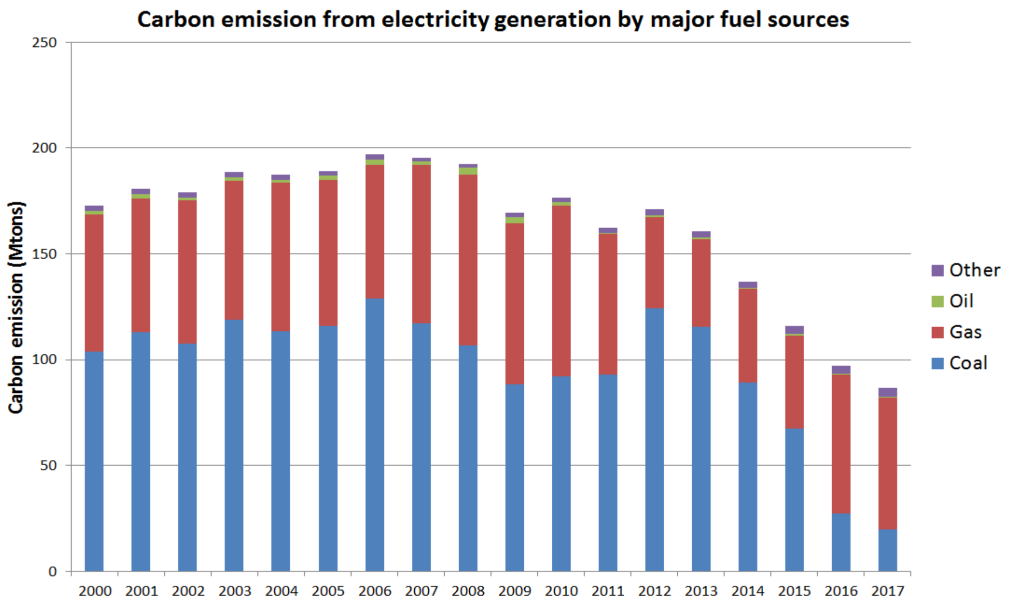


Figure 1.2: Carbon emission from electricity generation by major fuel sources in the U.K. from 2000 to 2017 [8].

ciency of the current system [10]. Demand side management (DSM) is one of the important technologies in smart grid. It can promote the interaction and responsiveness of customers, thus offer a wide range of potential benefits to the system and enhance the energy efficiency [11].

1.2 Research Motivations

Based on the background above, the motivations of this thesis can be summarized as follows:

- RESs are important for the electricity generation, but the inherent intermittent characteristic is the major impediment for their developments. It is a challenge to integrate RESs into the grid.

- The DSM is considered as one of the key smart grid technologies. It is a challenge to design a feasible scheme that can efficiently regulate energy generation and consumption.

- The fuel sources planning of electricity generation for the future plays a vital role for the sustainable development. It is a challenge to schedule the fuel sources that to meet both the environmental, economic and social requirements.

1.3 Research Objectives

In this thesis, a daily-based demand planning scheme is firstly proposed, which involving the utility, the demand response (DR) aggregator, and customers. Then, a system model for annual fuel sources scheduling and operational policy making of electricity generation is developed, which considering the economic, environmental, and social aspects. After that, a carbon emission flow model is introduced to assess the carbon emission caused by power generation. Specifically, the focus is placed on the following four research objectives in this thesis.

- The day-ahead demand planning with DR aggregators integrating RESs

- The fuel sources scheduling and operational policy making of electricity generation

- The effectivenesses of DSM approaches on the carbon emission reduction

- Multiobjective optimization problem (MOP)

1.4 Research Contributions

The main contributions of this thesis are summarised as follows:

- An advanced electricity market scheme is proposed. For the utility, the inherent intermittent problems of RESs can be addressed. For the DR aggregator, it is modelled as an independent participant. The role and the revenue of it are analysed. For customers, the social welfare is considered. All participants can benefit from the proposed design: the utility can reduce the generation cost and the power peak to average ratio (PAR); the DR aggregator can make profits by providing DR service; customers can save money on their bill. And even if there are perturbations to the system, the proposed approach can still work out an optimal solution.

- A novel system model for fuel sources scheduling and operational policy making of electricity generation is developed. Besides economic and environmental aspects of the electricity generation, the participation of consumers is introduced in the model. The minimum Manhattan distance (MMD) approach is proposed to select the final optimal solution. The generation plans for both short-term period and long-term period are presented. The system sensitivity to carbon tax and Renewable Obligation are analysed. These can give a hint for formulating carbon emission and RESs related mechanisms and policies.

- A carbon emission flow model is introduced to evaluate the carbon emission reduction caused by DSM. The time sensitivity of carbon emission in generation side and consumption side are obtained by applying the U.K. actual daily data of electricity generation and demand. The effectivenesses of load curtailment and load shift approaches for carbon emission reduction are quantified. These can indicate how to suggest different DSM programs to different consumers in the case of carbon emission reduction.

1.5 Thesis Outline

The remainder of this thesis is organized as follows:

Chapter 2

In this chapter, a review of smart grid technologies is presented. A brief history and basic concepts of DSM are introduced. A detailed classification of DR is discussed. The state-of-the-art models and methodologies are explained.

Chapter 3

In this chapter, a hierarchical day-ahead DSM model is proposed. The model involves three participants: the utility, the DR aggregator, and customers. This model leads to a MOP, which is solved by an artificial immune algorithm (AIA). The U.K. case study and system sensitivity analysis are presented.

Chapter 4

In this chapter, a system model for fuel usage scheduling and operational policy making of electricity generation, while considering carbon emission reduction is established. A MMD approach is proposed to process the multiple criteria decision making (MCDM). The proposed approach is compared with the weighted sum (WS) approach and the divide & conquer (D & C) approach. The case studies of short-term period and long-term period are given. The system sensitivity is analysed.

Chapter 5

In this chapter, a carbon emission flow model is introduced. The scope of the presented model is extended by involving DSM interventions. The time sensitivity of carbon emission is obtained. The effectivenesses of load curtailment and load shift approaches on the carbon emission reduction are examined.

Chapter 6

In this chapter, the thesis is summarised and potential research directions for the future are identified.

Chapter 2

Literature Review

2.1 Introduction

Smart grid technology is a powerful tool that facilitates the process of transforming conventional grids into green systems. It can offer a two-way flow of information and a two-way flow of electricity. DSM is a vital part of it. In this chapter, DSM is investigated from various perspectives. First, a general introduction of smart grid is presented. Second, a brief history and basic concepts of DSM are introduced. Next, a detailed classification of DR is discussed. Then, state-of-the-art models and methodologies are explained.

2.2 Smart Grid

Smart grid is defined by the European Technology Platform as [12]

> "an electricity network that can intelligently integrate the actions of all users connected to it - generators, consumers and those that do both - in order to efficiently deliver sustainable, economic and secure electricity supplies".

From 1998 to 2002, the EU's Fifth Framework Program funded the "renewable energy and distributed generation in the European power grid integration" project. Since then, smart grid has been gained great attention at the first time [13]. During

Table 2.1: Summary of the smart grid projects

Number	Budgets	Organizations	Implementation sites
Total: 950 projects in 50 countries	Total: € 4.97 billion	Total: 2900 organizations	Total: 800 sites in 36 countries
Average project duration: 30months	Average: € 5.75 million	Average: 6 partners per project	Average: 2.2 sites per project
Involved in more than one country: 324 projects	Largest investments: DE,UK, FR	Involved in more than one projects: 700 organizations	Most sites: DE (140) ES (95)

the past decades, there have been remarkable achievements in many countries. From 2002 to 2017, a total of 950 smart grid projects have been launched, amounting to €4.97 billion investments in 50 countries. These projects always involve more than one country (324 projects are multinational with an average of 14 countries per project). Among all, 642 projects have been completed with the budget of €2.82 billion, 308 projects are still ongoing with the budget of € 2.15 billion. Largest investments are from Germany, the U.K. and France. The U.K. government currently has 197 projects, in which 73 projects are national. The private investment takes up a large portion in the U.K., accounting for 83% of the total national investment [14]. The detailed information can be found in Table 2.1.

Smart grid is based on the integrated high-speed bidirectional communication network, on the basis of advanced sensor and measurement technologies, advanced equipment technologies, advanced control methods, and advanced decision support systems [12]. It is made up of several parts, divided into: smart power generation system, smart substation, smart power distribution network, smart interactive terminal, smart scheduling, smart building electricity, smart city power grid, smart meter, smart appliance, and the new type of energy storage system [15]. Compared to the conventional power grid, smart grid has following six advantages [16, 17]:

- Based on the strong power grid system and technical support system, it can tolerate different kinds of external disturbance and attacks, the stability of the grid is reinforced and ascended.

- It can obtain a panoramic view of the information, timely discover/foresee the possibility of failure. When a fault occurs, the grid can quickly isolate the fault, realize self-recovery to avoid the occurrence of blackouts.
- The control of the grid is more flexible, and can adapt to a large number of distributed power supplies, micro power grids, and electric vehicles.
- Through the modern management technologies, it can greatly improve the efficiency of power equipment, and reduce the loss of transmission, making the operation of the grid is more economical and efficient.
- The highly integrated real-time and non-real-time information sharing and utilization can show a comprehensive and complete grid operation state, therefore providing decision supports, control schemes and corresponding response plans.
- By means of the two-way interactive service mode, the electric power enterprise can obtain the user's electricity information in detail, to provide more value-added service; users can acknowledge the real-time status of the power supply ability, power quality, price and power outage information, thus can reasonably arrange the use of electric equipment.

2.3 Demand Side Management

One of the key smart grid technologies is DSM. Electricity demand always fluctuates dramatically during some short time frames. Generally, to meet the demand, a power system adjusts the supply by increasing/decreasing the generation or adding/curtailing additional resources (e.g., RESs and energy storages) [10]. The standby generators can incur additional costs on the budget and yield system instability, and there may still exist a power shortage during the peak period [18]. For these reasons, the idea of DSM has emerged.

2.3.1 Definition

The term "demand side management," also known as "energy demand management," stands for a variety of activities that are related to the energy consumption. It includes not only the control and modification of the energy usage, e.g., energy conservation, energy efficiency and energy storage, but also the behaviours that are involved in these processes, e.g., device installations, policies and regulation formulation, promotion, and education [10].

2.3.2 History

DSM was originated from the energy crises [19]. The first energy crisis (also called the "first oil shock") happened in October 1973. During the fourth Middle East War, the organization of petroleum exporting countries announced the oil embargo and exports suspension, causing a rise in oil prices. The crude oil prices increased almost four times from $3 per barrel to nearly $12, which caused the recession in western developed countries [20]. This situation brought the energy management into public consciousness. In response to that, the U.S. Congress legislated the National Energy Act of 1978. As part of it, the National Energy Conservation Policy Act and Power Plant and the Industrial Fuel Use Act were enacted, which took the energy demand management into consideration [21].

The second energy crisis in 1979 and the third energy crisis in 1990 speed up the development of DSM. The outbreak of Iranian revolution and the Iran−Iraq War caused a sharp drop in crude oil production. The crude oil price increased dramatically from about $15 in 1979 to $39 per barrel in 1981. Then, the Gulf War in 1990 also stimulated the international market [22]. To deal with this, the Energy Policy Act of 1992 was passed. It addressed the importance of energy efficiency, energy conservation and energy management, and also prompted the use of RESs.

The DSM became well-known to the public in the 1980's, popularized by the Electric Power Research Institute [23]. The California electricity crisis in 2001 has rung alarm bells to the world-wide, which proved the importance and emergency of the DSM, especially in the electricity market [24]. Since then, the DSM has become a hot issue, drawing more and more attention.

2.3.3 Advantages

DSM has an important role in power industry development, energy planning, and environmental protection. The introduction of DSM can bring the following advantages into the electricity market:

- It can promote an efficient operation of the market and effectively restrain the market power;
- It can realize instant information exchanges about the supply and demand, produce more reasonable and transparent transactions, and speed up and improve the formation of an electricity price mechanism;
- It can effectively relieve demand congestion during peak hours and improve the reliability of power system;
- It can effectively alleviate the investment pressure of power generation, transmission and distribution;
- It can facilitate opening up new prospects for the realization of energy conservation and emissions reduction.

2.4 Demand Response

2.4.1 Definition

DR mainly refers to the actions taken on the customer side that use the market price to influence the level and time of the electricity demand. According to the Federal Energy Regulatory Commission, DR is [25]:

> *"Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use*

at times of high wholesale market prices or when system reliability is jeopardized."

In general, the introduction of DR into power market requires a precondition: electricity market must achieve tentative liberalization or full liberalization, which means some kind of real-time market prices and effective market mechanism exist in the electricity market. Meanwhile, DR will accelerate the formation of the real-time market pricing mechanism. And with the high penetration of DR into the market, it can provide economic incentives to promote other projects like energy efficiency and energy storage in DSM. But DSM does not need this mechanism. Even without it, DSM can realize some of its projects. At the same time, DSM can fully boost and amplify the economic effectiveness of DR [26].

2.4.2 Services category

Typically speaking, DR can provide five services to the system: 1) Peak clipping; 2) Valley filling; 3) Load shifting; 4) Strategic conservation and 5) Strategic load growth [27, 28]. The first three can be grouped as load-shape change, and the last two can be grouped as load management. Load management is normally related to deliberate behaviours enforced by utilities. In contrast, the load-shape change can be both natural behaviors of customers and deliberate behaviors enforced by utilities [16].

Peak clipping

When the demand approaches the threshold of the supply capacity or the transmission system approaches the threshold of the thermal requirements, this peak load demand must be reduced. This can be realized by the direct load control in the residential sector, e.g., turn low the thermostat of heaters and turn up the temperature of refrigerators. This can also be achieved by the interruption in the industrial and commercial sectors. Fig. 2.1 shows a peak reduction from 12 MW to 10 MW during 18:00-20:00. This service can help to release the stress of system during the peak period. However, because it curtails the consumption of certain loads, it can cause dissatisfaction to customers.

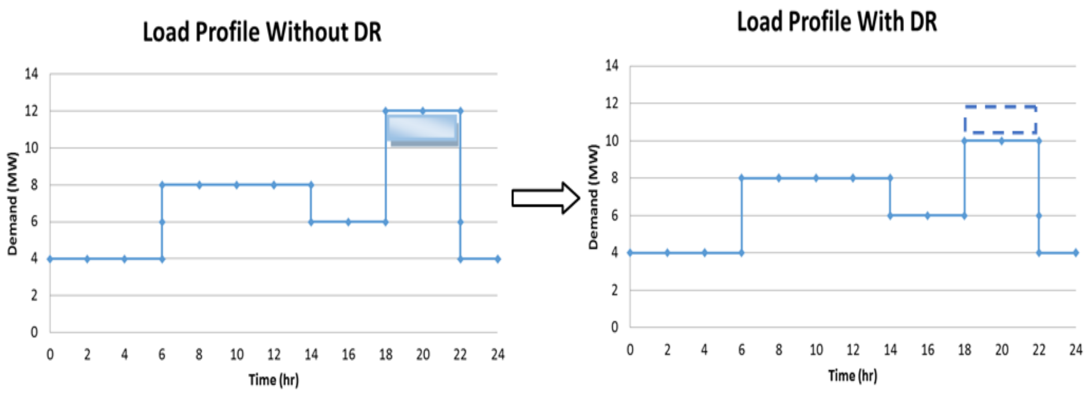


Figure 2.1: Demonstration of peak clipping.

Valley filling

When the demand is manifestly low at off-peak time, which is also not favorable for the system stability, the demand should be increased. The most common method is to add storage devices, e.g., the thermal storage for heaters and plug-in electric vehicles. Fig. 2.2 shows a valley filling from 4 MW to 6 MW during 2:00-6:00. This service increases the total power consumption of customers, but may not significantly increase the bill.

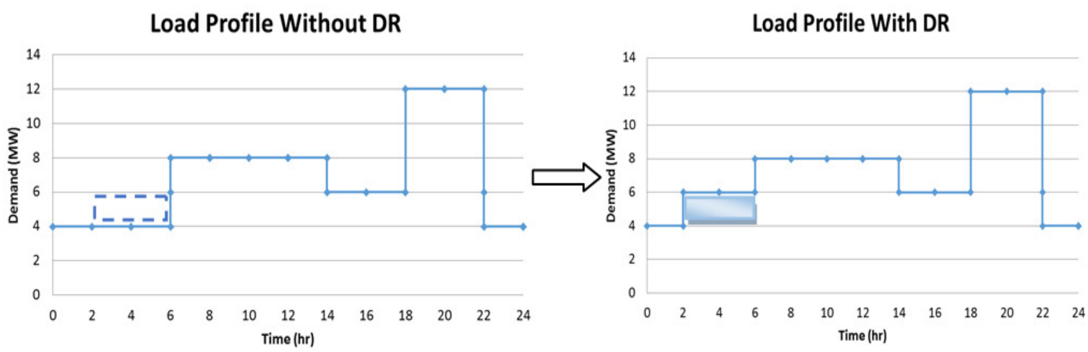


Figure 2.2: Demonstration of valley filling.

Load shifting

When the load is apparently higher than the average level in a certain period, a certain amount of load must be moved from that period to other periods. It primarily relies on the deferrable appliances, which can justify the time of usage, e.g., washing machines. In the short term, load shifting can be achieved on a daily basis from peak time to off-peak time. Fig. 2.3 shows a daily load shifting in which part of the peak demand is shifted from 18:00-20:00 to 2:00-6:00. It does not reduce the total consumption, but only changes the time of usage.

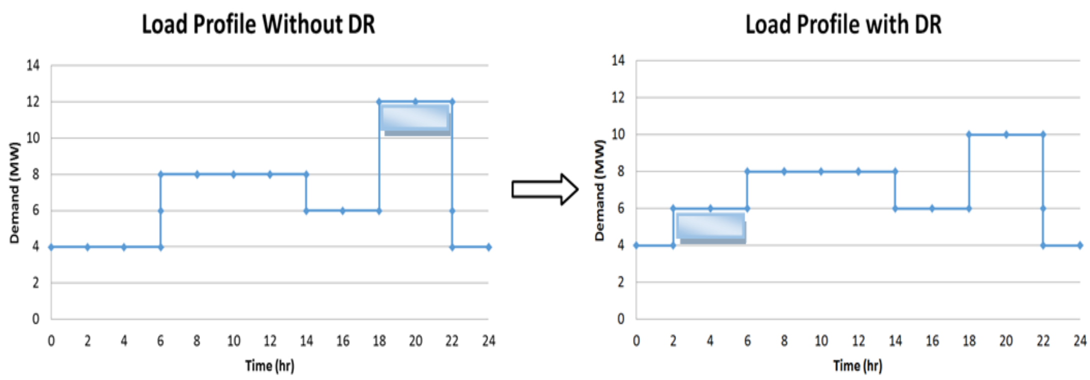


Figure 2.3: Demonstration of load shifting.

Strategic conservation

When the overall load exceeds the supply level, customers are encouraged to reduce the overall consumption. One basic method is to improve the energy efficiency. It can be applied at a small scale by replacing traditional devices with energy-efficient devices, e.g., changing filament lamps to fluorescent lamps. It also can be applied at a large scale, e.g., weatherization program, which is aimed to reduce the energy bill for low-income families by improving the energy efficiency of their house [29]. Besides the technical improvements, the information supports are also important. In general, providing consumption and cost details to customers can facilitate the power reduction. Fig. 2.4 shows strategic conservation from a high power level to a low level.

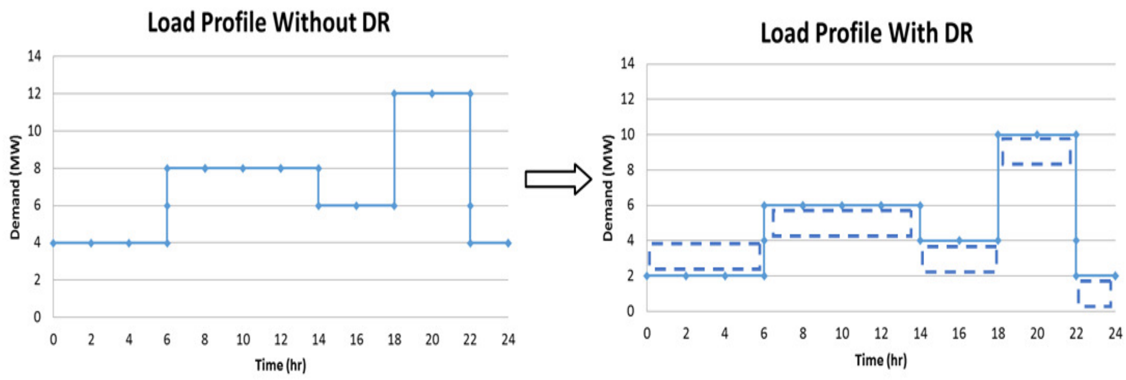


Figure 2.4: Demonstration of strategic conservation.

Strategic load growth

When the demand falls below the normal level of supply, customers are encouraged to increase the overall consumption. The electrification technology has the potential for this service, e.g., the popularization of electric vehicles. Fig. 2.5 shows strategic load growth from a low power level to a high level.

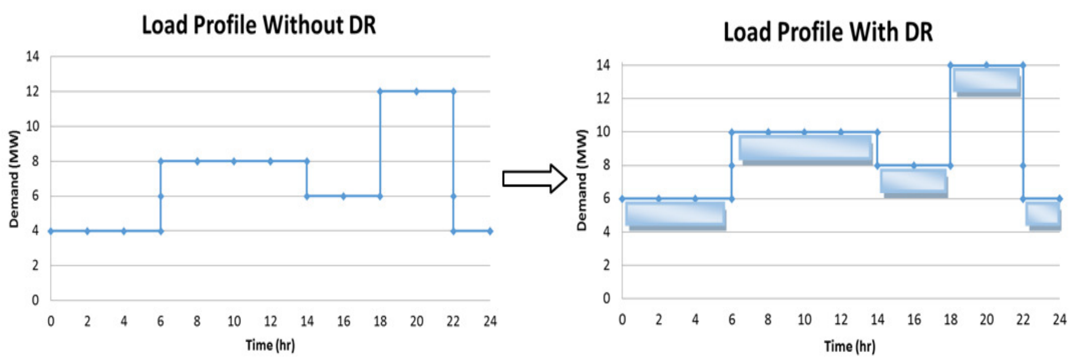


Figure 2.5: Demonstration of strategic load growth.

2.4.3 Customers category

DR is primarily focused on the Customers side. Detailed analysis of customers can facilitate the understanding and design of it. Generally, customers can be classified into four sectors: 1) Industrial sector; 2) Residential sector; 3) Commercial sector and 4) Transportation sector [30]. Fig. 2.6 shows the portion of electricity consumption about each sector in the U.K. in 2017. As for the DR, industrial sector, residential sector and commercial sector are mainly concerned.

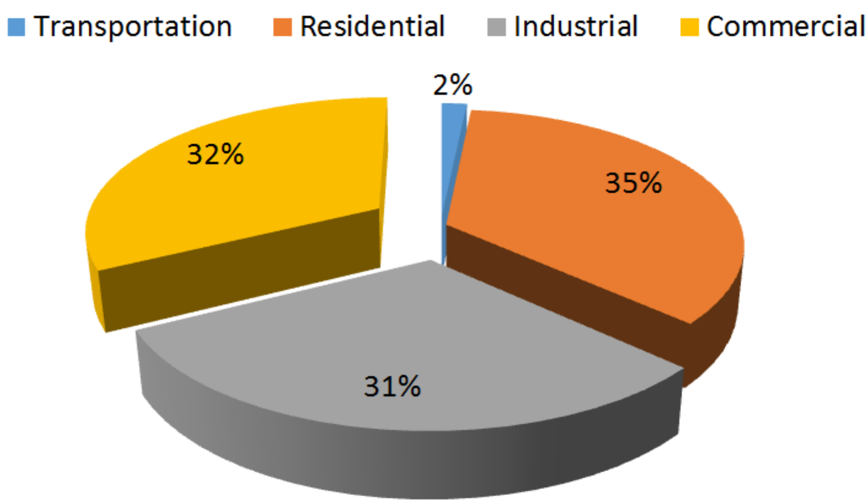


Figure 2.6: The electricity market share by sectors in the U.K. in 2017 [29].

Residential sector

The usage patterns in the residential sector are more complicated than the other two. Firstly, the quantity of customers is much higher. The distribution of customers is wide and scattered. Secondly, the types of appliances used by customers are diverse. Even for the same type of appliances, the power consumption of different brands can vary. Thirdly, every customer has his or her own personal preference of usage. That means each customer needs to be treated specifically rather identically [31].

Customers can be divided into five types based on the rationality [32]: 1) Long-range customers: their elasticity of electricity is relatively high. They are able to modify the usage in a wide range of time. 2) Real world-postponing customers: they consider the current and future electricity prices, and give certain responses to utilities. 3) Real world-advancing customers: they focus on the past and future electricity prices, and also give certain responses to utilities. 4) Real world-mixed customers: they are a combination of both postponing customers and advancing customers. 5) Short-range customers: they only pay attention to the current electricity price. Therefore, they are not willing to change their consumption pattern.

Industrial sector

It has a high electricity consumption, especially at a high voltage level. In addition, the peak load of it is significant. However, the adaption of DR in this sector is challenging [33]. Firstly, the information of the usage pattern and the operation of the appliances is confidential in some cases. To some extent, It can reflect the process of the manufacture, which is classified in a few industries. Therefore, the access to this information is limited. Secondly, even if there is sufficient information, the modification of electricity usage is still tough because many procedures are time-sensitive. They require a precise order and duration, which means they are less likely to be shifted. In this situation, a proper choice for industries is to improve the energy efficiency.

Commercial sector

The usage pattern in the commercial sector is quite typical and identical. The common and main loads for commercial customers come from the use of heating, ventilation, air-conditioning systems and lighting systems. The modification of these systems is relatively easy. Firstly, in general, these systems are autonomously controlled according to the preset requirements. This makes the systems able to quickly respond to the DR signals. Secondly, the effect of the external factors, e.g., temperature, humidity, and illumination, to these systems are predictable. For example, a light system consumes more electricity in winter than in summer [34].

Among these three sectors, the commercial sector and the industrial sector are relatively easier to realize the DR programs. Commercial and industrial customers are distributed regionally and intensively, and the power consumption of these customers is relatively high. What's more, the appliances and control systems for these customers are more advanced. In addition, in case of the emergency, most of these customers are equipped with the backup on-site generator. These appliances also can be used as auxiliary facilities of the DR programs [35]. Furthermore, the commercial and industrial sectors have a larger capacity of potential peak load reduction [36].

2.4.4 Loads category

Based on the operation characteristics of appliances, the loads can be classified by two standards: 1) whether the occupied time duration of appliances can be modified or not; 2) whether the total electricity consumption of appliances can be modified or not. For the first standard, loads can be divided into deferrable loads and non-deferrable loads [37]. For the second standard, loads can be divided into adjustable loads and nonadjustable loads [38].

Deferrable loads and non-deferrable loads

The activation time of deferrable loads can be stopped, re-started, and shifted to other time slots, e.g., washing machine and electric vehicles. Generally, most of the wet loads belong to the deferrable loads. These loads can be scheduled by a DR program. Based on the electricity price or the monetary incentive, they can be shifted from peak-hour to off-peak hours, therefore reducing the peak load demand [32]. The modification of these loads needs to abide by the predefined requirements, e.g., deadlines and operation times. On the contrary, the non-deferrable loads need to finish the schedule at specified time, e.g., lighting systems and kitchen systems [39]. These loads do not allow the time shift and interruption. As such, these loads are not suitable for the DR program.

Adjustable loads and nonadjustable loads

For the adjustable loads, the consumption can be adjusted to a lower level, e.g., in winter heaters can be set at 23^{o}C rather than 25^{o}C [40]. Normally, most of the thermal loads are part of the adjustable loads. These loads can be involved in the DR program. The total consumption can be brought down on the base of electricity price or the monetary incentive. However, reducing the consumption can affect customers' comfortability described by the quality of experience (QoE) [41]. QoE refers to the valuation of customers' experiences or satisfaction degree during a service. When a DR program is designed, this QoE must be taken into consideration to make sure that the DR program is executable theoretically and practically [42]. In contrast, for the nonadjustable loads, the total consumption is settled, e.g., TVs and computers [43]. Same as the non-deferrable loads, nonadjustable loads cannot be scheduled by a DR program either.

2.4.5 Approaches category

There are a number of motivation methods that encourage customers to participate in a DR program. These methods can be divided into two groups: time-based DR and incentive-based DR [44, 45].

Incentive-based DR

In these methods, incentives are offered to customers depending on their behaviour in the DR programs. Normally, customers are voluntary to change their consumption. However, in some cases, the failure of meeting the requirements will result in a penalty for customers. Generally, there are five types of incentive-based DR [46]: 1) Direct load control; 2) Interruptible/Curtailable service; 3) Demand bidding; 4) Capacity market program and 5) Ancillary service market .

- Direct load control: According to the advanced agreement between customers and utilities, utilities can remotely control some customers' appliances, e.g., air-conditioners and water heaters. The notices of the operation are normally announced at a short time ahead. To participate in this method, customers need to be equipped with a remote control switch system so that utilities can shift, turn on or turn off the appliances [47]. Direct load control is primarily applied to the residential sector or small-scale commercial sector. It is not suitable for the industrial sector because the industrial sector needs a precise process.

- Interruptible/Curtailable service: Compare to the direct load control, this method is normally applied to the industrial sector and large-scale commercial sector. When the system is congested, customers are asked to reduce some loads to a certain level. By participating in it, customers can receive a rate discount or bill discount. However, if customers failed to respond in the predefined time period, they could receive a penalty [48]. In this method, the operation frequency and the duration are limited.

- Demand bidding: Instead of being asked by the utilities to take part in the DR programs, customers can make decisions by themselves in this method. Based on the generation and demand situation, utilities announce the total amount of electricity that must be curtailed. Customers can bid for the amount based on their own situation and wholesale market. Once the bid is accepted, they must provide the specified curtailment, otherwise, they will get the penalty [49]. This method is also suitable for large-scale customers. For small-scale customers, they can be integrated by aggregators and involved in as a unity.

- Capacity market program: When the system is short of the reserve, customers are required to reduce the pre-defined consumption. The announcement is normally released one day ahead. These curtailments are treated as system capacity to replace the conventional generation and delivery resources. By proving the ability for the curtailment, customers can get reservation payment. And by providing the reduction, customers can get an incentive. In contrast, if they failed to provide it, they could receive a penalty [46].

- Ancillary service market: Similar to the demand bidding, customers also bid for the electricity curtailments. These bids are offered to independent system operator/regional transmission organization [46]. These curtailments are used as the operational reservation. If the bid was accepted, customers need to abide by a standby standard. In this situation, they are paid by the market price. Once the curtailments are really called, customers are paid by the spot price.

Time-based DR

In these methods, electricity prices vary according to the cost of generation and demand of electricity. Based on these prices and other information, customers can decide their consumption. Generally, there are four types of pricing schemes [35]:

1) Flat pricing; 2) Time-of-use (ToU) pricing; 3) Critical peak pricing and 4) Real time pricing .

- Flat pricing: This is the most traditional and widely used price scheme. The electricity price is constant all the time. In this situation, the only way to reduce the bill is to reduce the total consumption. The prices can be designed seasonally. Within a season, it is fixed. And for another season, a different price is used.

- ToU pricing: It is an improvement from flat pricing. The prices are different in different time slots. Within each slot, a flat price is applied. Fig. 2.7 shows an example of ToU pricing. Usually, prices are pre-defined for one day [35]. In this scheme, customers tend to shift their demand to a lower price period. In this way, the ability to reduce the total electricity demand is narrowed. For example, in the U.K., an Economy 7 tariff is applied in some area. It offers a cheap electricity price for the off-peak time, typically the night. This off-peak time lasts 7 hours in total, as the "7" implied, normally from 0:00 to 07:00. The price for day-time is higher, around 13-16p per kWh, while the price for night-time is lower, around 5-7p per kWh. This tariff was first introduced in 1978. To apply for the Economy 7, customers need to be equipped with a particular meter that can show two different readings: one for day-time electricity consumption and the other for night-time electricity consumption.

- Critical peak pricing: This scheme is derived from the ToU pricing scheme. The extreme peak demand period is picked out. During this period, a much higher electricity price is announced [31]. Fig. 2.8 shows an example of critical peak pricing. This scheme can effectively bring down the peak demand [31]. The critical peak price can be designed by the demand level or the time of the day. Three types of pricing are considered: fixed-period critical peak pricing, variable-period critical peak pricing and variable critical peak pricing. For fixed-period critical peak pricing, a specific period in one day is selected and a fixed high electricity price is applied based on the experience accumulation. For variable-period critical peak pricing, the application period is not fixed. The

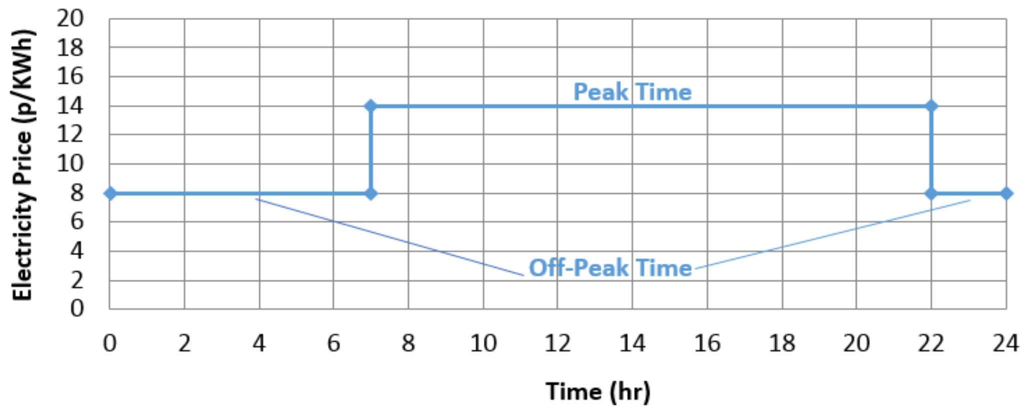


Figure 2.7: Demonstration of ToU pricing.

utilities can choose to trigger the critical peak pricing based on the pre-defined criteria. In this situation, the operation frequency and duration are limited. For variable critical peak pricing, the period is fixed, but the electricity price can vary on the basis of the current demand situation [50].

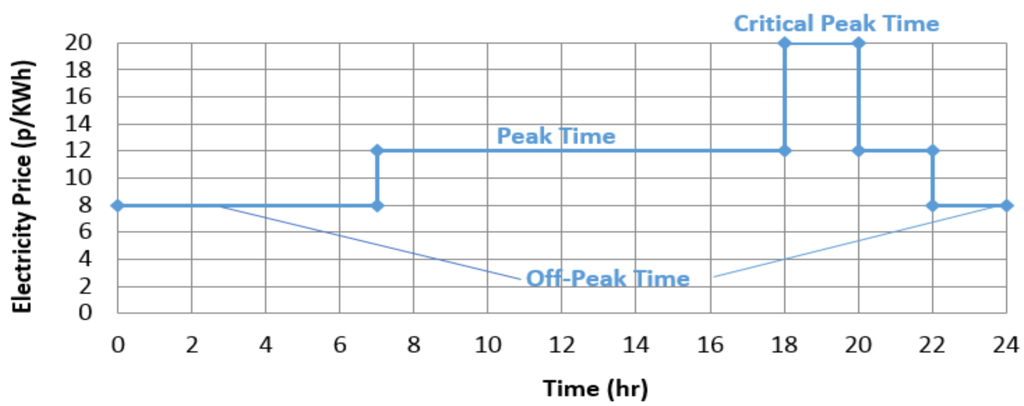


Figure 2.8: Demonstration of critical peak pricing.

- Real time pricing: The electricity price fluctuates frequently, normally by hours. Fig. 2.9 shows an example of real time pricing. The change of price can indicate the relationship between supply and demand in the wholesale market [51]. It requires effective two-way communication between utilities and customers. Sometimes, market aggregators also take part in this scheme to deal with the data collection and speed up the efficiency. Customers are involved mostly in this scheme and notified of these prices in a day-ahead manner, hour-ahead manner or 15-minutes ahead manner. Based on the price and the own situation, customers can decide their consumption pattern. Based on the total generation situation, total demand situation and customers reactions for the former price, utilities can decide the prices for the next period. This scheme is more acceptable by the industrial and commercial sectors than by the residential sector. There are two main difficulties for the application of this scheme. Firstly, it relies on continuous real-time data exchange, which is not favorable for customers [35]. Secondly, the large-scale data processing increases the complexity of the whole system [44].

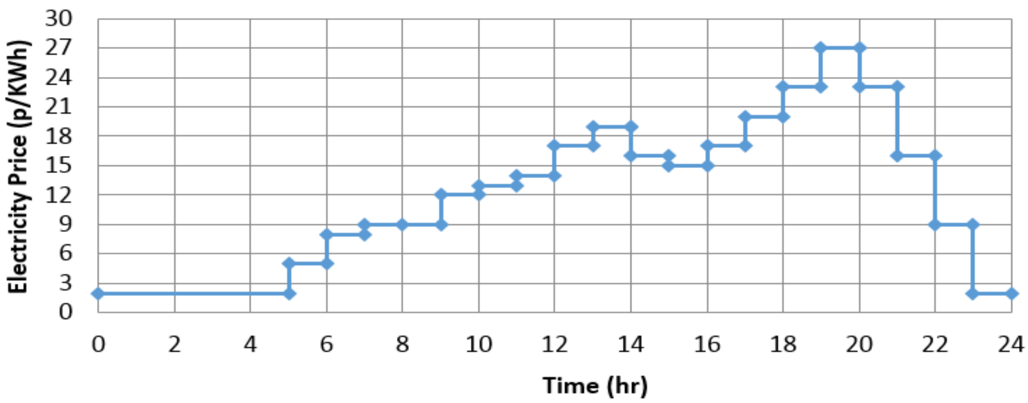


Figure 2.9: Demonstration of real time pricing.

2.5 Review of the Existing Theories, Models, and Methodologies

In this section, state-of-the-art models and methodologies are reviewed. The role of DR aggregator in electricity market is introduced at first. Then, the economic and environmental scheduling of electricity generation is presented. After that, the carbon emission tracing in power system is provided.

2.5.1 Demand response aggregator in electricity market

Although the development of DSM has a great future, the application of it is still a challenging task. If the generation side directly communicates with customers, there will be numerous information exchanges, which can delay the system response time. Meanwhile, the generation side is designed for large scale. The effect of individual's pattern is almost negligible to the system. The generation side is not able to negotiate directly with each customer. In this context, an intermediary/ representative is needed [52, 53].

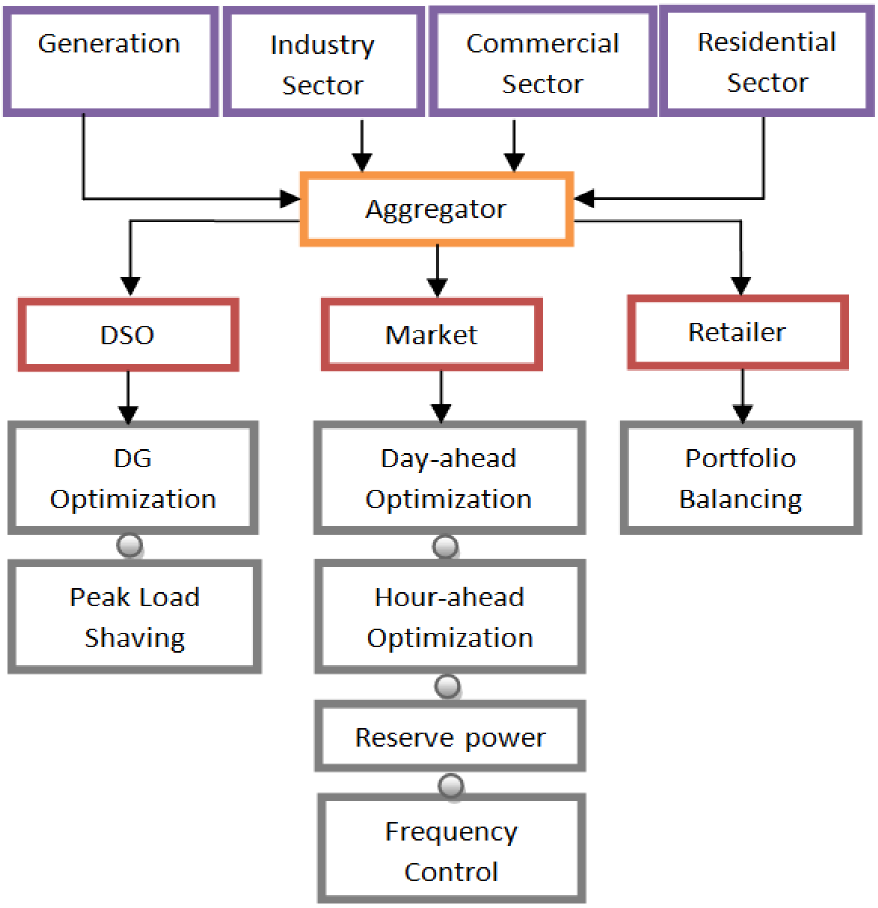


Figure 2.10: Functionality of the DR aggregator in a power grid [54].

Aggregator, as the name implies, bundle a group of customers into a cluster, therefore becomes an important aspect to the grid and occupies a certain weight in the trade [54]. As shown in Fig. 2.10, DR aggregator can bring several benefits into the system [55]. For distribution system operators (DSOs), it can achieve peak-load shaving and distributed generation (DG) supply optimization; For retailers, it can help with the internal portfolio balancing; For the market, it can deliver day-ahead/hour-ahead optimization, frequency control and power reservation [56,57]. In the U.K., DR aggregator is a booming entity. It is allowed and supported by the government in the power network. There are already many DR aggregators exist in the market from different companies, e.g., U.K. Power Reserve Ltd; KiWi Power Ltd; Npower Ltd; ESP Response Ltd [58].

The interactions between the generation side and the DR aggregator can be categorised into two different types:

- Mutual interaction: The network information is provided by the generation side in advance, DR aggregator then acts as a retailer buying electricity energy in the day-ahead market biding on the bulk and price of it.

- Directed interaction: The generation side announces that power adjustment requirement in the particular time slot, DR aggregator then attempts to achieve the goal, and if so, being rewarded by the generation side.

To introduce the aggregator into the system, a two-stage market model was proposed in [59]. For the first stage, the utility acted as the leader, setting the price for buying a certain power capacity from aggregators at particular time slot. Aggregators acted as followers, determining the supply capacity. The tatonnement process was used to achieve the equilibrium. For the second stage, aggregators acted as leaders, setting the price for buying power capacity from customers. Customers acted as followers, determining the supply capacity. The supply function bidding was used to maximize aggregators' profit. This work was designed for a certain time period and mainly focus on the aggregators' side.

In [60–63], the time horizon was extended. The dynamic electricity price over time was implemented in [60, 61]. The aggregator would give rewards to customers if they schedule their appliances according to the signal. The appliances were categorized into shiftable loads, thermal loads and interruptible loads. A mixed integer linear programming and a heuristic allocation algorithm were proposed to maximize aggregators' profit [60], and minimize the overall energy cost while considering customers' QoE [61]. The critical peak pricing was applied in [62]. The aggregator decided the time to employ the critical peak price. The regulatory, economic and technical perspectives of critical peak price were examined. In [63], the aggregator coordinated the regulation service on supply side and the DR service on consumer side. The regulation service could have a frequent control but a relatively slow update, while the DR service could have a quick response but could not change the control repeatedly. A multi-rate model predictive control approach was used to the capture the imbalance. When the imbalance occurred, an indirect signal was given, and then the DR aggregator solved a quadratic problem at each time slot.

In [52, 64, 65], a layered settlement mechanism was proposed. In [64], the independent system operator was at the first layer, announcing the power curtailment requirement in advance. The aggregator was at the second layer, committing to achieve the target. Customers were at the third layer, bidding their ancillary services to the aggregator. With the precondition of meeting the curtailment requirement, the mechanism aimed at minimizing customers' supply function, that is the incurred disutility minus the compensation. The model in [52] included the utility, DR aggregators, and customers. The utility provided rewards to aggregators for providing DR services, and customers can receive monetary compensation from DR aggregators for their demand adjustment. In [65], the aggregator was an agent, communicating with transmission system operator and residential storage space heating. It helped customers to minimize the electricity payment and maximize the bonus.

In [66, 67], the concept of virtual power plant was mentioned, which gathering distributed energy resources (DERs) to make them more manageable when participating in the real-time operating system. In [66], a direct load control approach was applied to schedule thermostatically controlled appliances in the virtual power plant, for the purpose of minimizing the demand. The aggregator bided the load reduction capability to electricity market, assisting the reduction of congestion and deviation between generation and demand. In [67], the aggregator provided services to the primary and secondary reserve markets. It could continuously modify the operation schedule of appliances to maximize the portfolio. This could solve the restriction issues of energy limitations and inaccurate baselines information in the virtual power plant.

In [68], the aggregator provided variety of DR strategies for consumers and DR service punchers. The aim of the aggregator was to maximize its profit. For customers, the aggregator implemented a ToU electricity price and a stepwise reward price for the load reduction. For DR service purchasers, the aggregator offered a fixed DR contract and an optional DR agreement. In fixed DR contract, the aggregator would provide a certain amount of load curtailment for a given time period. In optional DR agreement, the aggregator would provide the service only if it is profitable. The case study on the Australian national electricity market showed that the uncertainty on power consumption had a significant effect on the strategy, and should be considered. Therefore, the research in [69] took this uncertainty into consideration, a wind power offering strategy was proposed. A bi-level problem was formulated. The decision maker for the upper-level problem was wind power producer, setting its DR price. The decision maker for the lower-level problem was the DR aggregator, determining its market share. This problem is then linearised into a single level problem and be solved. And in [70], uncertainties were detailed classified, that caused by power demand, customers preferences, external environmental conditions, house thermal requirements and wholesale market. The Monte Carlo simulation method was applied to model these uncertainties. The DR aggregator represented customers to bid energy in the market. Customers were willing to modify their consumption profile according to the electricity price, in which the distribution locational marginal price in a real-time distribution market was used.

In [71–73], multiple utilities were involved, and the role of DR aggregator that balances the generation and demand was studied. Utilities aimed to maximize the profit, while customers aimed to maximize their individual welfare. A Stackelberg game was established based on that to solve the problem. In [73], utilities were divided into two types, fossil-fuel based and RESs based. The uncertainty of supply was considered. A utility selection program which can minimize customers' costs was proposed.

Research Challenges

In [61,64,65], only the objective for customers was considered. In [62,63,67,70], the role of the DR aggregator was involved, but the utility function was not explicit. Only benefits for the generation side and the customer side were considered, while the benefit for the DR aggregator was neglected. In [52,60,64,70], only the conventional generation was considered. In [66, 71–73], the inconvenience caused by DR program for customers was not detailed. A day-ahead demand planning with DR aggregators integrating RESs is proposed in Chapter 3 to address these challenges.

2.5.2 Economic/Environment scheduling of electricity generation

The fuel source scheduling of electricity supply plays an important role in the sustainable development. The analysis of fuel sources usage of electricity generation can elementally mitigate the carbon emission from the very beginning. A great number of researches were carried out on that [74–76]. Fig 2.11 illustrates the general structure of fuel source scheduling problems [77, 78].

In the beginning, only the economic scheduling of generation was considered. It was used to dispatch the committed generators' outputs so as to meet the load demand most economically. It mainly focused on minimizing the generation cost or maximizing the generation profit under variety system operation constraints. Amount of approaches were introduced, such as non-linear programming [79], sequential quadratic programming [80], hierarchical decentralized method [81], particle swarms algorithm [82] and genetic algorithm [83].

However, with the rising concerns of climate change and air pollution, the simplex consideration of economic scheduling was not enough. Utilities were requested to gradually reduce the carbon emission from power plants [84, 85]. Diverse strategies were proposed and discussed for the environmental protection, such as installing post combustion cleaning equipment, switching to low emission fuels, replacing the aged fuel burners with cleaner ones, and emission dispatching [86]. The most direct way to quantify and regulate the carbon emission in electricity generation was the

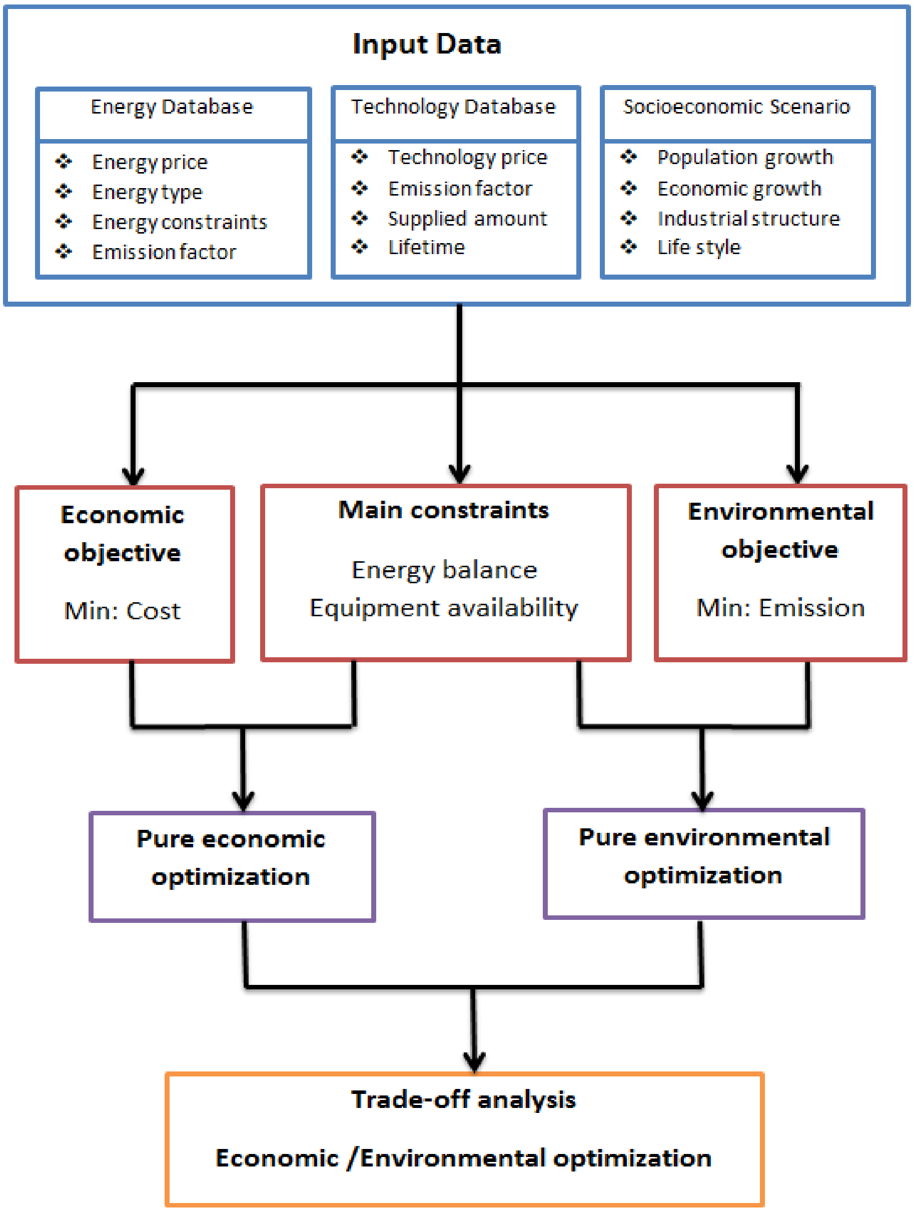


Figure 2.11: Structure of fuel source scheduling problems [76,77].

last strategy. The pure emission scheduling was similar to the economic scheduling, with the objective to be minimized being emission instead of generation cost. But still, this approach was onefold for the system.

The basic way to take both economic and environmental aspects into consideration was to set the carbon emission as a constraint for the scheduling problem, which leads to an emission constrained economic scheduling problem [87–89]. In [87], the total generation cost was minimized with a pre-specified carbon emission limit. In [88], two scenarios were analysed. The first scenario modelled cost function in a quadratic form. And the second scenario modelled cost functions in the form of quadratic summed with a sine term, in order to incorporate the valve-point effect for actual power system operation. The second scenario showed a higher cost than the first one. In [89], the total generation profit was maximized while fulfilling electricity demands and carbon emission mitigation. The financial risk of uncertainties, i.e. carbon emission mitigation operating costs, carbon credit prices and electricity prices, were imposed to the objective function by a penalty factor. The case study suggested replacing petroleum-fired power plants with coal-fired ones in Korea. And nuclear plants showed a great potential for the future market. But these work only took the carbon emission as a constraint, therefore can not reveal the relationship between generation cost and carbon emission.

Another simple way to involve both economic and environmental aspects was to combine these two objectives into one single objective, which brings the concept of environmental/economic scheduling. In [90–92], these two objectives were linearly combined. In [92], the emission constrained economic scheduling problem was compared with the economic emission scheduling problem. In the second problem, the total carbon emission was taken as an individual objective. For the first problem, as the total carbon emission allowance increased, the total power generation and profit were increased. For the second problem, an emission control cost factor was introduced to assign the weight between emission function and fuel costs function. As the importance of carbon emission increased, the total power generation and profit were decreased. However, in these approaches, the priori weight/preference need to be given between the generation cost and carbon emission.

The multi-objective optimization can treat these two objectives separately and competitively [78,93–98]. Several approaches were implemented to acquire the trade-off curve, such as the differential evolution algorithm [93], artificial bee colony algorithm [94], nondominating sorting genetic algorithm [95], and strength pareto evolutionary algorithm [96]. In [99], the influence of energy price on the economic/environmental scheduling was studied. In [100], instead of taking the total emission as one objective, different types of emission were modelled individually. In this case, four objectives were considered: minimization of fuel cost, minimization of nitrogen emission, minimization of carbon emission and minimization of sulphur emission. This model could provide the targeted schedule for specific emission requirement. In [101], three power plants, i.e., gas-fired power plant, petroleum-fired power plant, and coal-fired power plant, were considered as major carbon emission sources. In each power plant, two mitigations methods, i.e., carbon capture and storage and carbon emission trading, were used to reduce the amount of carbon emission. The environmental aspect of generation was represented by an emission cost function, which is the sum of emission trading cost and facility cost. The model can determine where and how much electricity to be generated and distributed in the Korea. In [97], a small autonomous hybrid power system was examined. The life cycle analysis of system's components was used to calculate the carbon emission. Two energy storage technologies, i.e., lead-acid batteries and hydrogen tanks, were considered. It showed that large sizes of biodiesel-fuelled generators would lead to less carbon emission and higher cost, while large sizes of diesel-fuelled generators would lead to vice verse. Natural gas was not recommended due to its high cost and high carbon emission. Lead-acid batteries were preferred than hydrogen tanks for both economic and environmental aspects.

Besides, the smart grid innervations and RESs supported policies can benefit the carbon emission reduction. The policy about RESs and carbon emission reduction was presented in [102]. The importance of DSM for carbon emission reduction was demonstrated in several aspects [78, 103–105]. In [103], a unit commitment model was presented, considering the electric vehicle, DR, DG as well as carbon emission trading. The impacts of DR and carbon emission trading were analysed in the model. The total cost and the total emission decreased obviously by applying DR. Generators with low emission intensity and DR approaches were more likely to be dispatched if carbon emission trading was carried out. In [78], compromise programming was used to provide the possible operational strategy for the distributed energy system while considering both objectives. The effects of electricity buy-back, carbon tax and fuel switching were analysed as well. The consideration of environmental aspect suggested a larger share of DERs, and resulted in a lower carbon emission and higher generation cost. When the electricity buy-back was introduced to the system, the share of DERs was increased. While the introduction of carbon tax had marginal impact on the system, unless it is extremely high. Moreover, switching from gas to bio source brought a great effect on environmental. In [104], the price-based and quantity-based measures considering RESs utilization and carbon mitigation were studied. The quantity-based measure could effectively reduce demand and stimulate energy efficiency, while the price-based measure was highly influenced by the price of carbon certificate or carbon allowance. And in both cases, nuclear was the suggested source to meet both RESs and carbon emission requirement. In [105], three DR resources, i.e., schedulable load, electric vehicle batteries and autonomous microgrid were involved in the power system. Carbon emission trading was used to encourage customers to participate in carbon emission quotas. Carbon emission would reduce in quantity with the application of DR resources and carbon emission trading. Generation side, power system operator and demand side were all benefited from it.

Research Challenges

These articles mainly focused on the performance of the generation side. Even if DSM approaches were mentioned, the consumers' involvement and the QoE on demand side were not included. The consumers' behaviour is pivotal to the power supply, and need to be considered as well. A fuel sources scheduling scheme, which considering the economic, environmental, and social aspects, is proposed in Chapter 4 to address these challenges.

2.5.3 Carbon emission flow in power network

The carbon footprint from generation to consumption varies spatially and temporally. Hence, it presents a challenge to accurately estimate the carbon intensity from the electricity aspect. The assessment of carbon emission has an important impact on both evaluating the potential of smart grid technologies and formulating policies for carbon emission reduction [85].

The common carbon emission quantification methods were production-based. One basic method was to calculate emission factors [9,106]. These factors depended on the type of fossil fuel used and can be derived from historical data or experiments. Another method was to use life cycle assessment, which traces the whole lifetime of carbon emission from raw materials to final combustion [107,108]. A few of research paper explored the carbon emission assessment based on these methods, while considering smart grid intervention. In [109], the major low-carbon technologies in power systems were investigated, including DSM, low-carbon generation technologies, utilization of low-carbon energy and low-carbon power scheduling. These factors were subsequently evaluated quantitatively through an assessment model. In [110], energy conservation and carbon reduction performance are investigated, by dividing the power value chain into upstream, midstream and downstream. The upstream was related to energy supply, the midstream was related to energy conservation and the downstream is related to energy utilization. In [111] the electricity grid carbon factor was calculated based on historical data. And the ensemble based closed-loop optimization scheme was applied to estimate the carbon savings in smart grids.

Even though the majority of the carbon emission is produced at generation side, the electricity demand is the key that affects the supply. The understanding of the relationship between consumption and carbon emission is important. Therefore, consumption-based emission analysis was proposed. Marginal emission factor (MEF) was an effective tool for estimating incremental changes in carbon emission as a result of the change in demand [112, 113]. In [112], the linear regression coefficients of change in total emission rate versus the change in total system demand were calculated to estimate the MEF. The effect of demand-side interventions was studied based on the U.K. case. In [113], a method to estimate MEF in power systems based on merit order dispatch was illustrated. It revealed how MEF estimation would change with different fuel price. In [114], the concept of consumption mix was put forward. It can provide a more accurate information of demand in life cycle assessment. A transportation linear programming model was implemented, to provide further analysis of carbon emissions estimation considering interstate electricity exchange. In [115], the comparison of three different methods for accounting carbon emissions intensity was presented, that is measuring carbon at the sites of electricity production, electricity consumption and integrated approach. However, these methods were based on either the observed historical utilization factor of generators or a set of possible criteria for activation of each plant in the system.

Based on this, in [116–118] a carbon emission flow (CEF) model to quantify the carbon emission accompanying the power delivery process was proposed. It can virtually allocate the emission from generation side to consumption side, specific to each component in the network. Hence, the transmission characteristic of electricity supply and locational energy mix was clearly reflected.

Research Challenges

These articles mainly considers the conventional generation process rather than the contributions of smart grid intervention. Therefore, there are still obstacles in the investigation of the carbon flow tracing method considering smart grid intervention. The effectiveness of DSM approaches on the carbon emission reduction by using carbon flow tracing method is analysed in Chapter 5 to address these challenges.

2.6 Chapter Summary

This chapter gave a brief introduction of the smart grid and DSM at first. Next, the DR was explained in detail on the basis of the services category, customers category, loads category, and control category. Then, existing system models were introduced, focusing on the DR aggregator, economic/environmental scheduling and carbon emission tracing.

Chapter 3

Day-ahead Demand Planning with Demand Response Aggregators

3.1 Introduction

DSM plays an important role in smart grids. In this chapter, a hierarchical day-ahead DSM model is proposed. The model involves three participants: the utility, including RESs, the DR aggregator, and customers. The utility seeks to minimize the operation cost and gives part of the revenue to the DR aggregator as a bonus. The DR aggregator acts as an intermediary, receiving the bonus from the utility and giving compensation to customers for modifying their energy usage pattern. The aim of the DR aggregator is maximizing its net benefit. Customers desire to maximize their social welfare, i.e., the received compensation minus the dissatisfactory level. To achieve these objectives, a MOP is formulated. An AIA is used to solve this problem, leading to an optimal solution set. Using a selection criterion, the solution which does not favour any particular participant can be selected, to ensure the overall fairness. Simulation results confirm the feasibility of the proposed method: the utility can reduce the operation cost and the power PAR; the DR aggregator can make a profit for providing DSM services; and customers can reduce their bills. After that, the system sensitivities are examined. Both the sensitivity to perturbation of optimal variables and system coefficients are analysed. It shows that even there are perturbations to the system, the proposed method can still work out an optimal solution. With different system coefficients, the system performance would change accordingly. Overall, the main contributions of this chapter can be summarized as below:

- A novel DSM scheme is proposed. For utility, the inherent intermittent problems of RESs can be addressed. For the DR aggregator, it is modelled as an independent participant. The role and the revenue of it are analysed. For customers, the social welfare is considered, i.e., the received compensation minus the dissatisfactory level caused by the DSM.
- The U.K. actual daily data of electricity generation and demand from Grid Watch are applied to prove the feasibility and effectiveness of the proposed model.
- The system sensitivity to perturbations and coefficients are examined.

The chapter is organized as follows. Section 3.2 introduces a hierarchical model for the day-ahead market, which includes the utility, the DR aggregator and customers. Section 3.3 formulates a MOP, and proposes the AIA and selection criterion. It can work out a Pareto optimal set and select an optimal solution. Section 3.4 provides a practical case study. Section 3.5 presents the system sensitivity analysis. Finally, Section 3.6 concludes this chapter.

3.2 System Model

In this chapter, the day-ahead market is considered and a hierarchical framework is introduced. This framework can help to define the specific role and goal of each participant, and make the system transparent. The system operation model is shown in Fig. 3.1. The utility is at the upper layer to supply electricity; the DR aggregator is at the middle layer to communicate with both the utility and customers; customers are at the lower layer to consume electricity provided from the utility [52, 61].

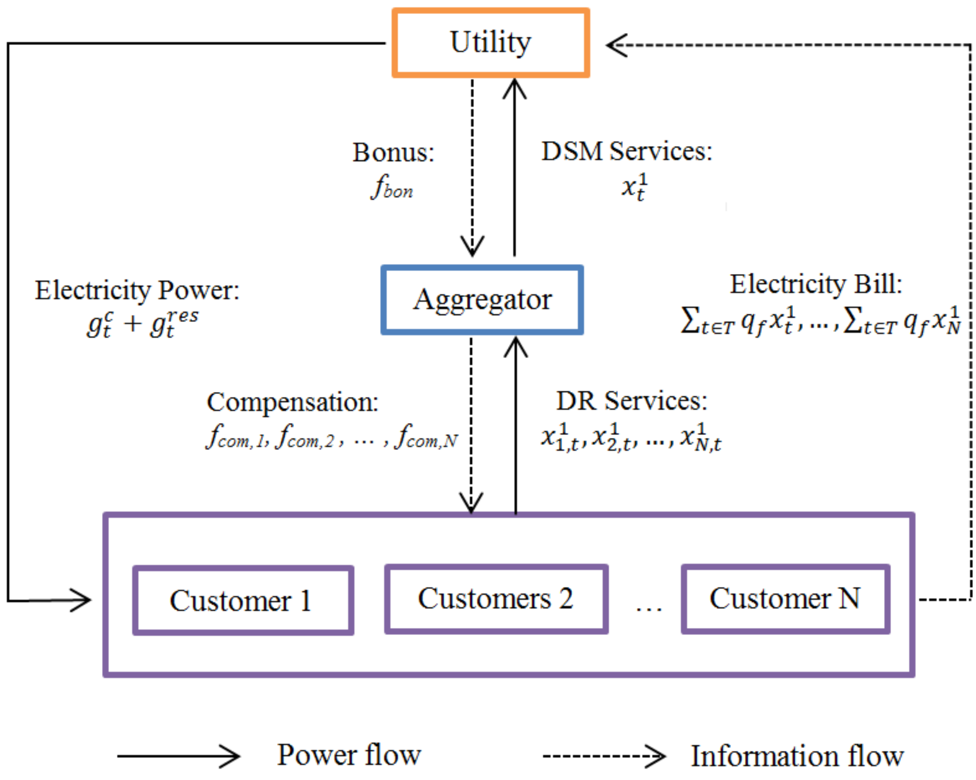


Figure 3.1: System operation model.

3.2.1 The role of the utility

In the electricity market, the daily demand of electricity fluctuates with the time according to customers' behaviour. What's more, the time-varying nature of RESs causes indeterminacy problems to the electricity supply. In order to balance the demand and the supply, generation side needs to adjust the production, activate the standby power plants, or even purchase power from third parties [119,120]. The term PAR is introduced to describe the stability of the system [121]:

$$PAR = \frac{Peak\ Load}{Average\ Load}. \tag{3.2.1}$$

The cost of generation consists of two parts: conventional generation cost and maintenance cost of RESs. For the conventional generators, the cost function $c(\cdot)$ should follow the listed three assumptions based on practical situation [71, 73, 122, 123]. A quadratic equation, which satisfies all assumptions, is considered to present the cost function in this chapter.

- *Assumption 1:* The total generation cost should correspondingly increase as the total supplied electricity increased. Therefore, the cost function should be monotonically increasing,

$$\frac{\partial c(x)}{\partial x} > 0. \tag{3.2.2}$$

- *Assumption 2:* The marginal cost should be positive to the total supplied electricity. The marginal cost means the incremental cost of each new unit of production. Therefore, the cost function should be strictly convex,

$$\frac{\partial c^2(x)}{\partial x^2} > 0. \tag{3.2.3}$$

- *Assumption 3:* There exists a differentiable function $f(x)$ with $x \in [0 + \infty)$, in which, $f(x) \geq 0$ holds true for all x and as $x \to \infty$, $f(x) \to \infty$. And the function $c(x)$ can be expressed as

$$c(x) = \int_0^x f(z)dz. \tag{3.2.4}$$

For RESs, as there is no expense for resources, the marginal cost is nearly zero [124]. The generation cost is mainly caused by the maintenance. Thus the cost function $c^{res}(\cdot)$ is simplified as a constant value and independent of supplied electricity [125]. (Note: The installation of conventional generators and RESs generators are not considered.)

Let q denotes the selling price of per unit electricity. For the day-ahead market, the daily generation vectors are $g^c = \{g_t^c : t \in T\}$ for conventional generators and $g^{res} = \{g_t^{res} : t \in T\}$ for RESs. The utility aims to maximize the net revenue. Without the use of DSM, the objective of the utility can be given by

$$\max_{g^c, g^{res}} : \quad \sum_{t \in T} q l_t^0 - [\sum_{t \in T} c^0(g_t^c) + \sum_{t \in T} c^{res}(g_t^{res})] \tag{3.2.5}$$

where l_t^0 denotes the aggregated consumption at time slot t without the DSM, c^0 and c^{res} denote the generation cost for conventional generators and RESs without the DSM, respectively. There are four general constrains for power system that need to be considered.

- Power balance constraint: the power generated should be able to cover the demand requirement and the real power loss in the transmission,

$$g_t^{res} + g_t^c = l_t + loss_t. \tag{3.2.6}$$

- Power capacity constraint: the power generated by each method must be restricted in certain limits,

$$g_{t,min}^{res} \leqslant g_t^{res} \leqslant g_{t,max}^{res}, \quad g_{t,min}^{c} \leqslant g_t^{c} \leqslant g_{t,max}^{c} \tag{3.2.7}$$

where $g_{t,max}^{res}$ and $g_{t,max}^{con}$ denote the maximum power can be provided from RESs and conventional generators, $g_{t,min}^{res}$ and $g_{t,min}^{con}$ denote the minimum initial power from RESs and conventional generators, respectively.

- Ramp rate constraint: if the generator remains operated in successive time, change of power generation should be restrained in a proper range, either the ramp up rate or the ramp down rate [113].

$$\begin{aligned} g_t^c - g_{t-1}^c \leqslant g_{up}, &\quad \text{as generation increases} \\ g_{t-1}^c - g_t^c \leqslant g_{down}, &\quad \text{as generation decreases} \end{aligned} \tag{3.2.8}$$

where g_t denotes the generation output for the current time slot, g_{t-1} denotes the generation output for the previous time slot, g_{down} and g_{up} denote the power ramp down limit and power ramp up limit, respectively.

- Spinning reserve constraint: in case of the emergency situation, the power system requires an operating reserve capacity,

$$g_{t,max}^{res} + g_{t,max}^{c} \geq l_t + S \tag{3.2.9}$$

where S is the spinning reserve requirement.

When the DSM is applied to customers, the peak demand and the total generation cost could be reduced to a certain degree. In this chapter, the DR aggregator is considered as the operator to implement the DSM. The utility will be willing to share part of the saved cost as a bonus to the DR aggregator as an incentive. The bonus can be calculated as [52]

$$f_{bon}(g_t^c) = \Delta c(g_t^c) = \mu \sum_{t \in T} [c^0(g_t^c) - c^1(g_t^c)] \tag{3.2.10}$$

where c^1 denotes the generation cost for conventional generators with the DSM, and $\mu \in (0, 1]$ denotes the bonus coefficient.

In order to ensure the basic needs, there is no curtailment in demand. The flat price is chosen in this chapter, therefore the total revenue from customers is fixed. The aim of the utility can be defined as minimizing the operational cost. Hence, the objective function of utility becomes

$$\min_{g^c} : \quad f_u(g^c) = \sum_{t\in T} \left[c^1(g_t^c) + \Delta c(g_t^c)\right] \tag{3.2.11}$$

$$\begin{aligned} s.t.: \quad & g_t^{res} + g_t^c \geqslant l_t, \quad g_{t,min}^{res} \leqslant g_t^{res} \leqslant g_{t,max}^{res}, \quad g_{t,min}^c \leqslant g_t^c \leqslant g_{t,max}^c, \\ & g_{t,max}^{res} + g_{t,max}^c \geq l_t + S, \quad g_t^c - g_{t-1}^c \leqslant g_{up} \text{ or } g_{t-1}^c - g_t^c \leqslant g_{down}. \end{aligned} \tag{3.2.12}$$

The first term of (3.2.11) corresponds to the generation cost for conventional generators, and the second term corresponds to the bonus given to the DR aggregator.

3.2.2 The role of the demand response aggregator

As stated before, it is difficult for the utility to give full consideration of each customer. On this occasion, the DR aggregator can group a number of individual customers into a cluster for the purpose of carrying more weight in the market. The DR aggregator acts as a mediator between the utility and customers. It undertakes dual responsibilities: on the one hand, ensuring the DSM service can be provided to the utility, therefore obtaining the bonus; on the other hand, guaranteeing there will be a reduction in the electricity bill for customers, encouraging customers to actively participate in the DSM program. By performing the duty, DR aggregator can help with the security and efficiency of the supply.

The DR aggregator tries to adjust customers' consumption pattern to smooth the peak and follow the generation pattern. The ideal scenario is the demand completely following the generation. Because of the participation of DSM, customers can receive compensation from the DR aggregator for the inconvenience it may cause. The compensation scheme depends on the difference between the aggregated consumption vector $l^1 = \{l_t^1 : t \in T\}$ and the generation expectation vector $g = \{g_t : t \in T\}$. Suppose the expected power from conventional generators is a constant value G at each time slot, and the generated power from RESs is time-varying represented by $g^{res} = \{g_t^{res} : t \in T\}$. Thus, the expected generation vector is $g = \{g_t = G + g_t^{res} : t \in T\}$. To make demand follow supply, the difference between generation and consumption should be reduced. A compensation function $f_{com}(\cdot)$ is introduced at that point to promote the DSM. There are four assumptions for the compensation function that need to be considered [52, 122].

- *Assumption 1:* The compensation should always be nonnegative,

$$f_{com}(x) \geq 0. \tag{3.2.13}$$

- *Assumption 2:* The total compensation should correspondingly increase as the total difference between generation and consumption decreased. Therefore, the compensation function should be monotonically decreasing,

$$\frac{\partial f_{com}(x)}{\partial x} < 0. \tag{3.2.14}$$

- *Assumption 3:* The marginal compensation should be negative to the total difference between generation and consumption. Therefore, the compensation function should be strictly concave,

$$\frac{\partial f_{com}^2(x)}{\partial x^2} < 0. \tag{3.2.15}$$

- *Assumption 4:* When the consumption totally follows generation, the compensation should be maximum,

$$\text{if} \quad l_t = g_t, \quad f_{com} = f_{com}^{max}. \tag{3.2.16}$$

A quadratic equation, which satisfies all assumptions, is modelled as the compensation in this chapter [52].

$$f_{com}(l_t^1) = \sum_{t \in T} \left[-\alpha \left(l_t^1 - g_t \right)^2 + \beta \right] \tag{3.2.17}$$

$$s.t.: \quad \alpha > 0, \quad \beta > 0, \tag{3.2.18}$$

where α and β are compensation coefficients.

The objective of the DR aggregator is to maximize its net payoff. Since the aggregator receives the bonus from the utility and provides compensations to customers, the objective function can be given by

$$\max_{g^c, l^1} : f_a(g^c, l^1) = \sum_{t \in T} \{\mu \Delta c(g_t^c) - [-\alpha(l_t^1 - g_t)^2 + \beta]\} \tag{3.2.19}$$

$$s.t. : \quad \alpha > 0, \quad \beta > 0, \quad l_t^1 > 0 \quad \forall t \in T, \quad l_{t,min} \leqslant l_t^1 \leqslant l_{t,max}. \tag{3.2.20}$$

The first term of (3.2.19) corresponds to the received bonus from the utility, and the second term corresponds to the compensation to customers.

3.2.3 The role of customers

Typically, customers intend to consume electricity on the basis of their most convenience, causing a peak demand around 17:00 to 22:00 and a valley demand around 0:00 to 6:00 [126]. As explained before, a single customer's behaviour is trivial to the system, a group of customers is organized as a cluster. The reference aggregated electricity demand at the time slot t is defined as $l^0 = \{l_t^0 : t \in T\}$, and the total demand for one day is $\sum_{t \in T} l_t^0 = L$.

Smart meters can provide customers with detailed information about their electricity consumption. By equipping them, customers can have a comprehensive understanding of their usage. And customers are assumed to be price-sensitive. With the financial incentive, they are willing to modify their consumption pattern by adjusting deferrable appliances to some extent. After the negotiation with the DR aggregator, the aggregated consumption vector becomes $l^1 = \{l_t^1 : t \in T\}$, and $\sum_{t \in T} l_t^1 \geq L$. (Note: The energy conservation approach is not considered.)

Clearly, DSM would cause inconvenience on customers' daily life. The incurred discomfort should be considered. It depends on the difference between the actual consumption and the reference consumption. There are three assumptions that need to be satisfied for the dissatisfactory function $f_{dis}(\cdot)$ [52].

- *Assumption 1:* The dissatisfactory level should correspondingly increase as the difference between the actual consumption and the reference consumption increased. Therefore, the dissatisfactory function should be monotonically increasing,

$$\frac{\partial f_{dis}(x)}{\partial x} > 0. \tag{3.2.21}$$

- *Assumption 2:* The marginal dissatisfactory level should be positive to the total incurred difference. Therefore, the dissatisfactory function should be strictly convex,

$$\frac{\partial f_{dis}^2(x)}{\partial x^2} > 0. \tag{3.2.22}$$

- *Assumption 3:* When the actual consumption is same as the reference consumption is zero, there is no dissatisfactory caused for customers,

$$\text{if} \;\; l_t^1 = l_t^0, \quad f_{dis} = 0. \tag{3.2.23}$$

Hence the dissatisfactory function should be increasing convex and can be modelled by a quadratic equation [52]

$$f_{dis}(l_t^1) = \varepsilon \left(l_t^1 - l_t^0\right)^2, \tag{3.2.24}$$

$$s.t.: \quad \varepsilon > 0, \quad l_{t,min} \leqslant l_t^1 \leqslant l_{t,max}, \tag{3.2.25}$$

where ε is the inelasticity coefficient of demand. For different customers, ε is different as a matter of the appliance used and personal preference. A relatively small ε illustrates the demand-insensitive that consumption modify will cause an insignificant discomfort; Otherwise, a relatively large ε characterizes the consumption modification will result in a greatly dissatisfactory. The objective of customers is to maximize their social welfare. The problem thus can be formulated as

$$\max_{l^1}: f_c(l^1) = \sum_{t \in T} \{[-\alpha(l_t^1 - g_t)^2 + \beta] - \varepsilon(l_t^1 - l_t^0)^2\} \tag{3.2.26}$$

$$s.t.: \quad \alpha > 0, \quad \beta > 0, \quad \varepsilon > 0, \quad l_{t,min} \leqslant l_t^1 \leqslant l_{t,max}, \quad \sum_{t \in T} l_t^1 \geqslant L. \tag{3.2.27}$$

The first term of (3.2.27) corresponds to the received compensation from the DR aggregator, and the second term corresponds to the dissatisfactory level.

3.3 Methodology - Artificial Immune Algorithm

In this section, a MOP is formulated for maximizing the benefits of all participants. An AIA is then proposed to solve the problem. To stabilize the normal operations of the electricity market, it is important to maintain the fairness among all participants.

3.3.1 Problem formulation

To maintain fairness, three objectives are considered. The objective of utility is to minimize the operation cost, i.e., the generation cost plus the bonus to the DR aggregator. The objective of the DR aggregator is to maximize the net income, i.e., the bonus from the utility minus the compensation to customers. The objective of customers is to maximize the social welfare, i.e., the compensation from the DR aggregator minus the dissatisfactory level. By considering the day-ahead market, the resultant MOP can be formulated as

$$\min_{g^c}: \quad f_u(g^c) = \sum_{t\in T} \left[c^1(g_t^c) + \mu\Delta c(g_t^c)\right] \tag{3.3.28}$$

$$\min_{g^c,l^1}: \ -f_a(g^c, l^1) = \sum_{t\in T}[-\mu\Delta c(g_t^c) - \alpha\left(l_t^1 - g_t\right)^2 + \beta] \tag{3.3.29}$$

$$\min_{l^1}; \ -f_c(l^1) = \sum_{t\in T} \left[\alpha\left(l_t^1 - g_t\right)^2 - \beta + \varepsilon\left(l_t^1 - l_t^0\right)^2\right] \tag{3.3.30}$$

$$\begin{aligned} s.t.: \quad & g_t^{res} + g_t^c \geqslant l_t, \quad g_{t,min}^{res} \leqslant g_t^{res} \leqslant g_{t,max}^{res}, \quad g_{t,min}^c \leqslant g_t^c \leqslant g_{t,max}^c, \\ & g_{t,max}^{res} + g_{t,max}^c \geq l_t + S, \quad g_t^c - g_{t-1}^c \leqslant g_{up} \ \text{ or } \ g_{t-1}^c - g_t^c \leqslant g_{down}, \\ & l_{t,min} \leqslant l_t^1 \leqslant l_{t,max}, \quad \sum_{t\in T} l_t^1 \geqslant L, \quad f_a(g^c, l^1) > 0, \quad f_c(l^1) > 0, \end{aligned} \tag{3.3.31}$$

which is solved hourly. An additional function $f_r(x)$ is introduced to simplify several constraints in (3.3.31).

$$\begin{aligned} f_r(g^c, g^{res}, l^1) = \sum[&\max(-f_a(g^c, l^1), 0) + \max(L - \sum_{t\in T} l_t^1, 0) \\ &+ \max\left(-f_c(l^1), 0\right) + \max\left(l_t^1 - g_t^{res} - g_t^c, 0\right)] \end{aligned} \tag{3.3.32}$$

The constraints hold true if and only if $f_r(x) = 0$. Using (3.3.32), the resulting MOP can be written as:

$$\min_{g^c, l^1} : F(g^c, l^1) = \left[f_u(g^c),\ -f_a(g^c, l^1),\ -f_c(l^1)\right] \tag{3.3.33}$$

$$\begin{aligned} s.t.: \quad & f_r(g^c, g^{res}, l^1) = 0, \quad g^{res}_{t,min} \leqslant g^{res}_t \leqslant g^{res}_{t,max}, \quad g^c_{t,min} \leqslant g^c_t \leqslant g^c_{t,max}, \\ & g^c_t - g^c_{t-1} \leqslant g_{up} \text{ or } g^c_{t-1} - g^c_t \leqslant g_{down}, \quad l_{t,min} \leqslant l^1_t \leqslant l_{t,max}. \end{aligned} \tag{3.3.34}$$

If the MOP is feasible, there should be a possible consumption schedule satisfying all the requirements. To address the process, Pareto optimality is used [127].

Definition 1 (Pareto optimality): A state of allocation procedure, in which it is impossible to improve one participant's situation without making at least one participant's situation worse.

Definition 2 (Pareto dominance): For a strategy set with H as the minimum objective function, each vector in the set means a possible strategy. For two different vectors u and k, k is Pareto dominated by u if $H(u)_i \leq H(k)_i$ holds true for all i and at least one inequality exists, where i is the ith element of objective vector. It means the strategy u can make at least one participant better without making anyone worse than the strategy k .

Definition 3 (Pareto optimal solution): A strategy u is a Pareto optimal solution if u is feasible and there are no other strategies dominate it.

Definition 4 (Pareto set): The collection of Pareto optimal solutions is termed a Pareto Set.

Definition 5 (Pareto front): When plotted in the objective space, the image of Pareto set is termed Pareto Front.

Fig. 3.2 shows an example of a Pareto set and a Pareto front. Every point in the decision variable space can map to a point in the objective function space. The Pareto set is in the decision variable space, and the Pareto front is in the objective function space. Fig. 3.3 shows an example of Pareto optimality of a minimization problem. In Fig. 3.3, all points are assumed to be feasible. Point N is dominated by point P and point Q. With the same objective value of f_1, point P can provide a smaller objective value of f_2 than point N. Similarly, with the same objective value

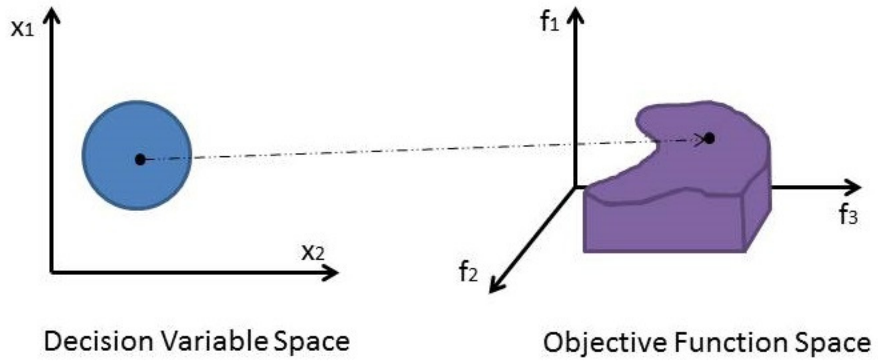


Figure 3.2: Example of a Pareto front.

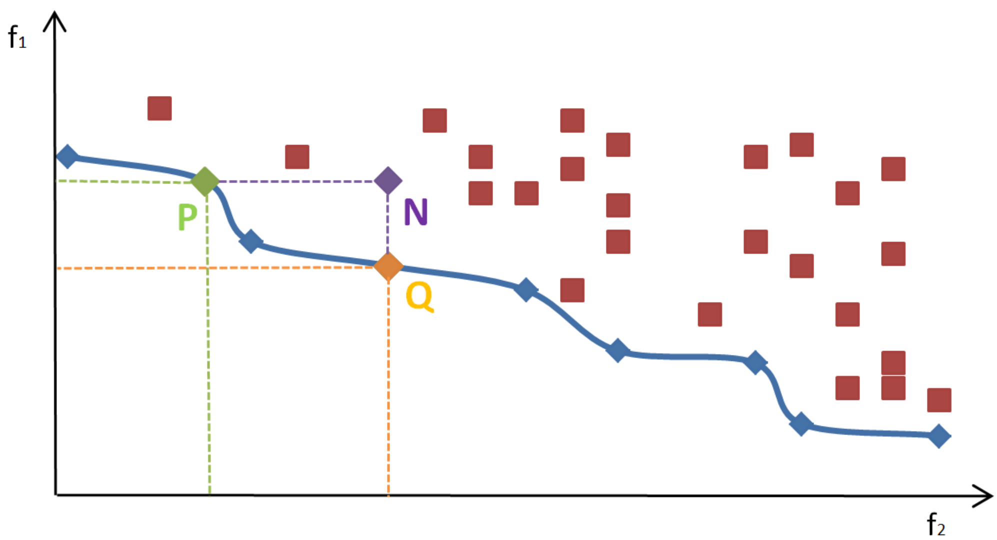


Figure 3.3: Example of a Pareto optimality.

of f_2, point Q can provide a smaller objective value of f_1 than point N. For points P and Q, they are not dominated by others. A Pareto front can then be obtained by collecting all nondominated points.

3.3.2 Algorithm

To attain the Pareto set for the proposed problem, the AIA can be used [127–129]. The AIA is originated from the theory of immunity system in biology, which is an efficient self-defense system to prevent foreign antigens or pathogens [130]. The AIA is a global search method that uses an iterative process. It has been approved that the AIA is abele to generate a well-distributed set of solutions, and can be effectively used to solve MOP [131, 132]. It is globally convergent, thus can avoid catching the local optimal [133]. Compared to traditional search algorithms, AIA is easy to use, robust, fast and suitable for parallel processing. In using the AIA, the terminology antibody is used to describe the point in the decision variable space.

Fig. 3.4 shows a flowchart of the AIA algorithm used to solve the MOP in (3.3.33). The antibody p represents the decision variables g^c and l^1 in the MOP. A group of antibodies are first randomly generated over the interval $[P_{min}, P_{max}]$ following the uniform distribution, where P_{min} and P_{max} are the minimum and maximum values of the decision variables, respectively. Dominated antibodies are removed gradually. Next, gene operation is applied to the nondominated antibodies. The antibodies then mutate in order to produce a diversified population. The dominated antibodies are removed as well. After that, the condition $f_r(p) = 0$ is used to eliminate the infeasible antibodies. If the population size is still too large, the antibody population update operation will be adopted till the population size reduces to N_{nom}. The above process repeats until the maximum number of iteration is reached. At this stage, a Pareto optimal set is obtained. According to the selection criterion, the fittest antibody is chosen as the output, which can maximize the minimum improvement in all dimensions. This solution can maintain the fairness, and does not favour any particular participants. Detailed search steps are described as follows.

- Step 1: Generate the initial population of antibodies randomly at the nominal

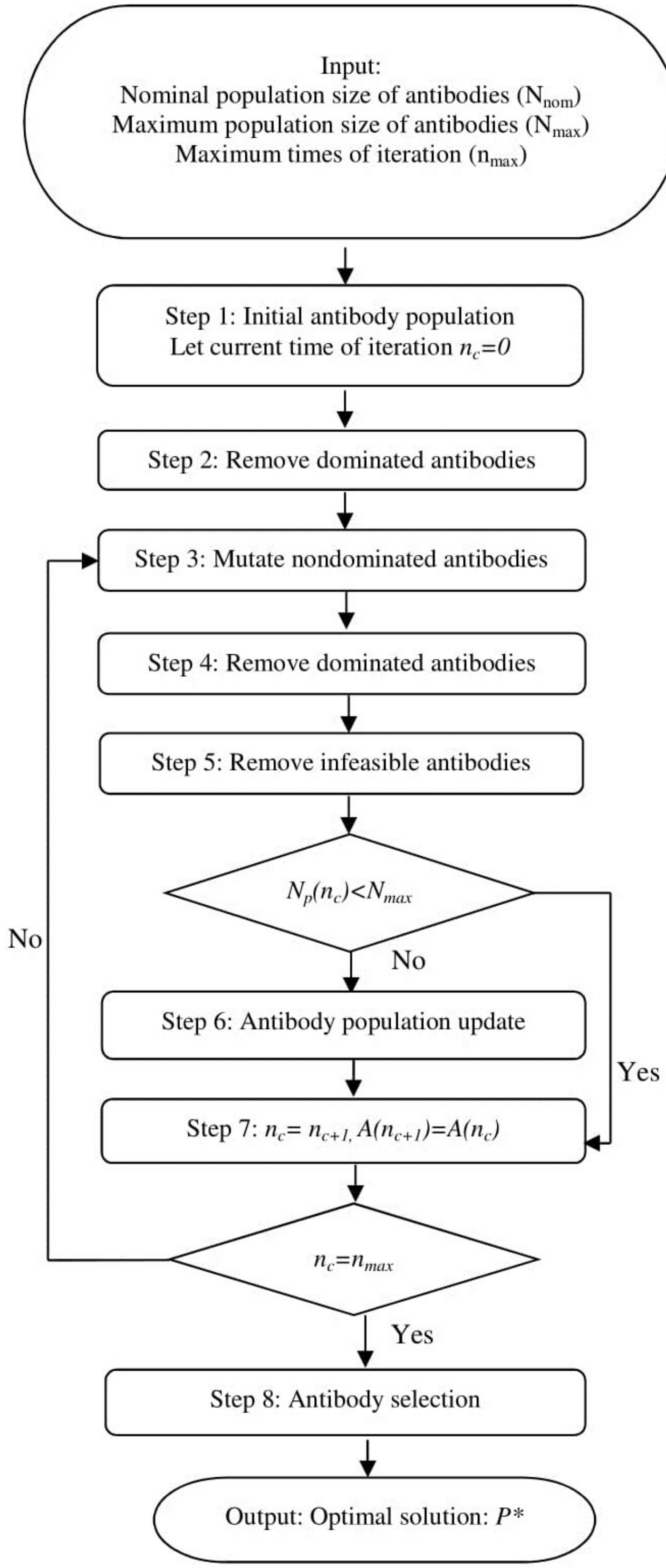


Figure 3.4: Flowchart of the AIA algorithm.

size. Let $n_c = 0$ and

$$A(0) = \{p_1, p_2, p_3, ...p_{nom}\} \tag{3.3.35}$$

where n_c denotes the iteration time, N_{nom} denotes the nominal population size, $A(.)$ denotes the antibody set, and p_i is a random vector from $[P_{min}, P_{max}]$.

- Step 2: Remove dominated antibodies and maintain the nondominated antibodies.

- Step 3: Mutate the remaining nondominated antibodies. The current population size is

$$N_p(n_c) = \|A(n_c)\|. \tag{3.3.36}$$

Define the clone rate as

$$r(n_c) = \lfloor \frac{N_{max}}{N_p(n_c)} \rfloor \tag{3.3.37}$$

where $r(n_c)$ denotes the current clone rate, and $\lfloor . \rfloor$ is a floor function. The clone and mutation operation is implemented to each element p in the set $A(n_c)$, according to the equation

$$p_i^j = \theta p_i + (1-\theta)p_i^{'} \tag{3.3.38}$$

where p_i^j denotes the mutated antibody, θ is randomly chosen from $[0, 1]$, and $p_i^{'}$ is a random vector belonging to $[P_{min}, P_{max}]$. Through the mutation, a new set of antibodies is produced

$$\begin{aligned} C = &\left\{p_1^1, p_1^2, ..., p_1^{r(n_c)-1}\right\} \cup \left\{p_2^1, p_2^2, ..., p_2^{r(n_c)-1}\right\} \\ &\cup ... \cup \left\{p_{N_p(n_c)}^1, p_{N_p(n_c)}^2, ..., p_{N_p(n_c)}^{r(n_c)-1}\right\}. \end{aligned} \tag{3.3.39}$$

Let $A(n_c) := A(n_c) \cup C$.

- Step 4: Repeat Step 2, and remove the dominated antibodies from the new population.

- Step 5: The remaining antibodies are all nondominated, but not all of them are feasible. The antibodies with $f_r(p) > 0$ are not applicable for the MOP formulated in this paper. The antibodies with the largest $f_r(p)$ will be removed first. If $f_r(p_1) > f_r(p_2) > 0$, then p_1 is removed first. The process continues until the condition $f_r(p) = 0$ holds true for all antibodies.

- Step 6: After Step 4 and Step 5, if the population size is still larger than the nominal size, the antibody population update procedure needs to be applied to normalize the antibodies. For a crowded region, a fitness value is allocated to antibodies

$$f_{fit}(p_n) = \sum_{j=1}^{J} \frac{F(p_n)_j - F(p_{n-1})_j}{F_j^{n_c,up} - F_j^{n_c,low}} \tag{3.3.40}$$

where J is the number of objectives, $F_j^{n_c,up} = \max_{p\in A(n_c)} F(p)_j$ and $F_j^{n_c,low} = \min_{p\in A(n_c)} F(p)_j$ [127]. The antibody with the smallest fitness value will be removed first. If $f_{fit}(p_1) > f_{fit}(p_2)$, then p_2 is removed first. The procedure stops when the current population size is no large than the nominal size. It is noted that this procedure will not be carried out for extreme vectors in $F(P)$, where extreme vector means at least one element in this vector reaches its extreme value, i.e, $F(p')$ is an extreme vector if there exists j such that $F(p')_j = \max_{p\in A(n_c)} F(p)_j$ or $\min_{p\in A(n_c)} F(p)_j$.

- Step 7: Let $n_c = n_c + 1$ and $A(n_c + 1) = A(n_c)$. Repeat Step 3 to Step 7, until $n_c = n_{max}$.

- Step 8: As the iteration counter n_c increases gradually, $A(n_c)$ forms an approximate Pareto optimal set (APS). All vectors in it are possible solutions to $F(P)$. A solution that can maximize the minimum improvement in all dimensions is selected as the output [127]. This output can guarantee the fairness among all participants rather than give advantage to one particular participant. The criterion can be written as

$$p^\star = arg \max_{p\in A(n_{max})} \min_{j=1\ldots J} \frac{F_j^{up} - F(p)_j}{F_j^{up} - F_j^{low}} \tag{3.3.41}$$

where $F_j^{up} = \max_{p\in A(n_{max})} F(p)_j$ and $F_j^{low} = \min_{p\in A(n_{max})} F(p)_j$. The denominator $F_j^{up} - F_j^{low}$ means the objective domain of jth objective. The numerator $F_j^{up} - F(p)_j$ means the improvement of jth objective that the solution p can provide. The equation $\min_{j=1,\ldots,J} \frac{F_j^{up} - F(p)_j}{F_j^{up} - F_j^{low}}$ means the minimum improvement of J

objectives that solution p can provide. Therefore, the selected p^* represents the solution that can maximize the minimum improvement in all dimensions among all possible solutions.

3.4 Simulation Results

In this section, the practical case studies are presented. The simulation is conducted by using the software MATLAB. The modelled system consists of one utility, one DR aggregator and one cluster of customers. The utility manages 2500 wind turbines with the rating of 2.75MW, which is simplified by considering the average wind turbine output rate and the total wind generation capacity in the U.K. [6]. In the day-ahead market, a calendar day is equally divided into 24 time slots, i.e., $T = 24\ hours$. The U.K. actual electricity generation and demand daily data from Grid Watch, and the wind speed data from Wind Finder is fed into the model. The U.K. average electricity price 0.13 £/kWh is applied.

For conventional generators, the cost function is given as [134]

$$c(g_t^c) = 1.2(g_t^c)^2 + 3g_t^c + 2 \quad M£/GWh. \tag{3.4.42}$$

For RESs, wind power is considered. The wind speed v in m/s can be predicted in advance. The output power w in MW can be calculated based on v by the equation below

$$w = \sigma(\tau, \psi)\frac{\rho\varsigma}{2}v^3 \tag{3.4.43}$$

where the performance coefficient $\sigma(\tau, \psi)$ can be calculated from experiential arithmetic, based on the blade tip speed ratio τ and blade pitch angle ψ. The air density and swept area are set as $\rho = 1.225\ kg/m^3$ and $\varsigma = 1257\ m^3$ [135].

Fig. 3.5 shows the relationship between the output power and wind speed. The rated wind speed and maximum wind speed are specified as: $v_{rate} = 15\ m/s$ and $v_{max} = 30\ m/s$. When $v_t > v_{max}$, $v_t = 0$, since the extremely fast speed will produce an undesirable large moment on the blade, which may damage the wind turbine, so the turbine will be forced to stop for safety. When $v_{rate} < v_t < v_{max}$, $v_t = v_{rate}$, since the turbine is already fully operated when the wind speed reaches the rated speed. Even with a faster wind speed, the turbine is not able to generate more power.

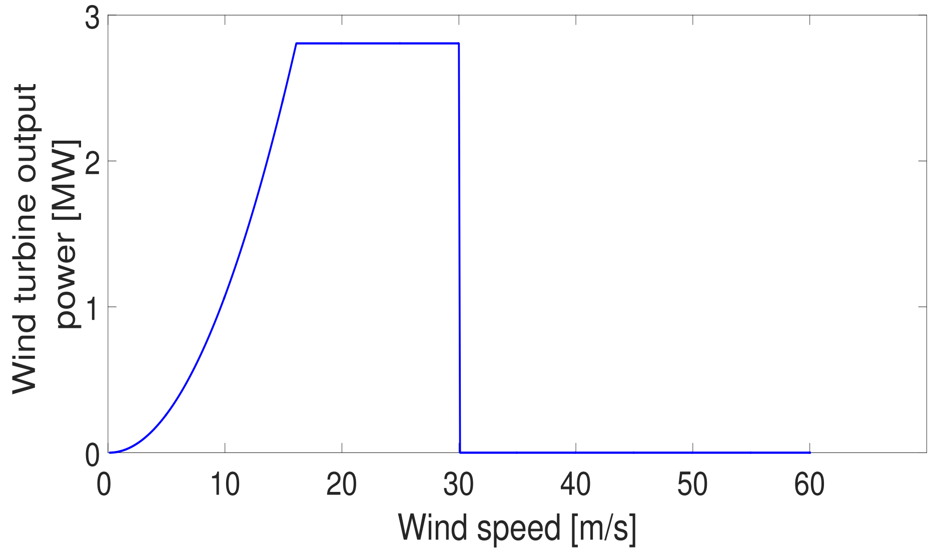


Figure 3.5: The wind turbine output performance [130].

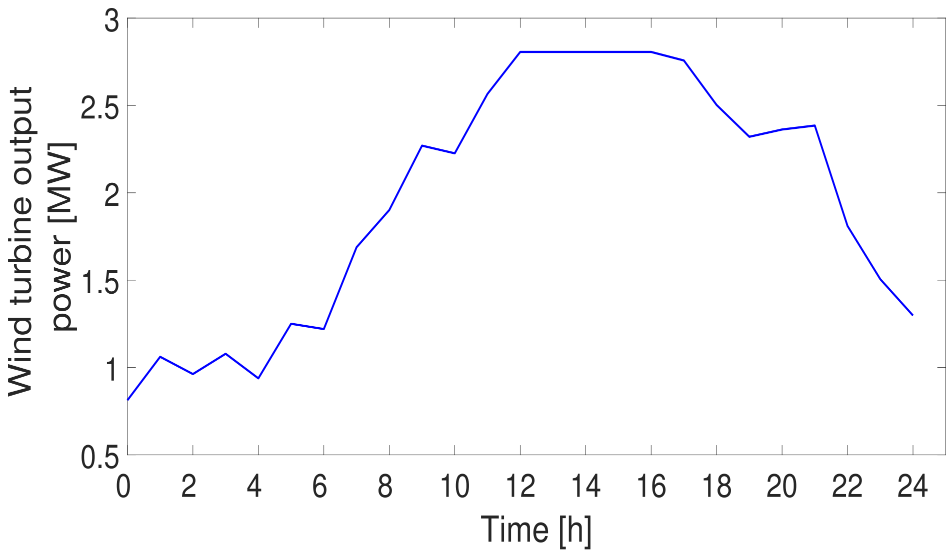


Figure 3.6: The wind turbine output for the selected day.

Fig. 3.6 shows the predicted wind power output g_{res} for the day-ahead market. It fluctuates dramatically during one day. A number of factors, e.g., air pressure, temperature, jet streams, humidity, Rossby waves, weather and season, can influence the wind speed and, therefore, influence the output power. The electricity generated from wind turbines will be consumed first. The remaining electricity demand will be satisfied by the conventional power generators.

For the utility, the bonus coefficient $\mu = 0.7$ in (3.2.10) has been set, indicating 70% of the DSM gain will be given to the DR aggregator.

For the DR aggregator, the compensation strategy is defined as [52]

$$f_{com} = \sum_{t \in T} [-2(l_t^1 - g_t)^2 + 80]. \tag{3.4.44}$$

For customers, it is assumed 10% of the load profile can be deferred with $l_{t,max} = 1.1l_t$ and $l_{t,min} = 0.9l_t$. The dissatisfactory function is assumed as

$$f_{dis} = 3(l_t^1 - l_t^0)^2. \tag{3.4.45}$$

Using the AIA, the approximate Pareto front (APF) and the APS for the day-ahead market model can be generated. Fig. 3.7 gives an example of the APF. It illustrates the trade-off between three objectives. These benefits of three participants are mutually associated, interacted and restricted. For a solution p, if an arbitrary element yields an extreme objective value $F(p)_j = F_j^{up}$ or $F(p)_j = F(p)_j^{low}$, it means this solution advantages a particular participant, and is not favoured by the market. To ensure the fairness, an optimal solution p^* can be chosen by using (3.3.41), which can maximize the minimum improvement in all dimensions. As shown in Fig. 3.7, the selected optimal solution p^* is located in the centre of the APF graphically. This means all objectives can be balanced improved. It proves that through the proposed multiobjective approach, a fair design can be obtained.

Fig. 3.8 shows the optimized load profile and the reference load profile in the U.K. for the selected day, 5th May 2017. The optimized load profile is more gentle than the referenced one. It is clearly shown that after the optimization, during the off-peak time (i.e., 0:00-5:00), the demand increases. While during the peak-time (i.e., 16:00-21:00), the demand decreases. That is, part of the demand is shifted from peak time to the off-peak time.

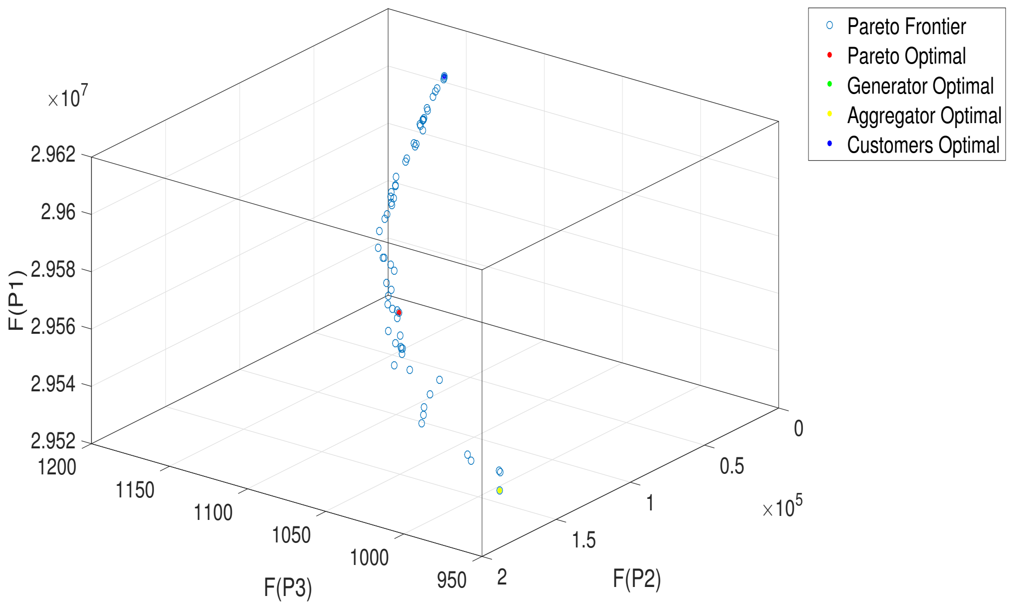


Figure 3.7: The APF for the proposed MOP.

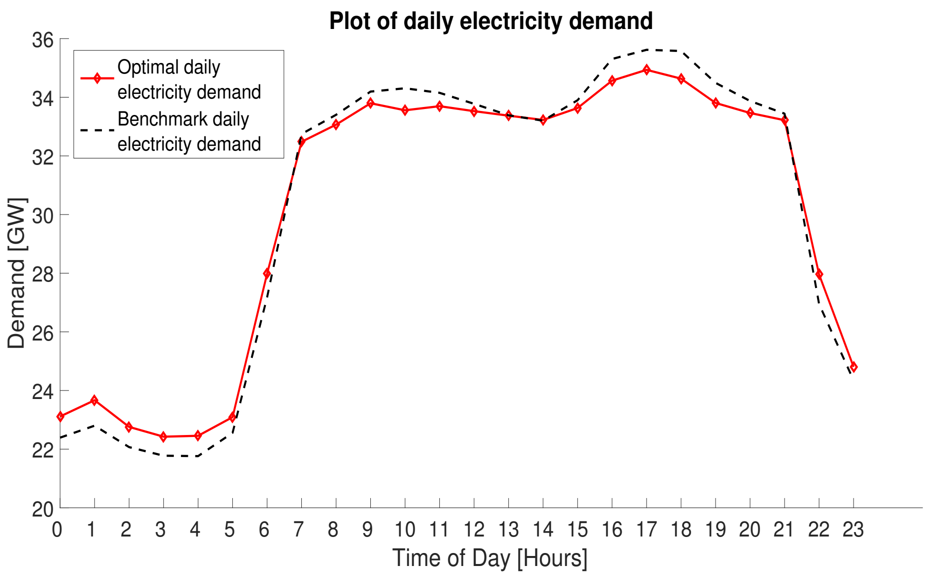


Figure 3.8: The optimized usage pattern for the day-ahead market.

Fig. 3.9 shows the net conventional generation in the U.K. for the selected day, 5th May 2017. The net conventional generation becomes flatter after the optimization. Because the peak demand is decreased, the peak generation is also reduced from 30.21 GW to 29.22 GW, about 3.3%; while the valley generation is increased from 19.46 GW to 20.13 GW, about 3.4%. This can indicate a more stable generation system. And the generation cost can be accordingly saved.

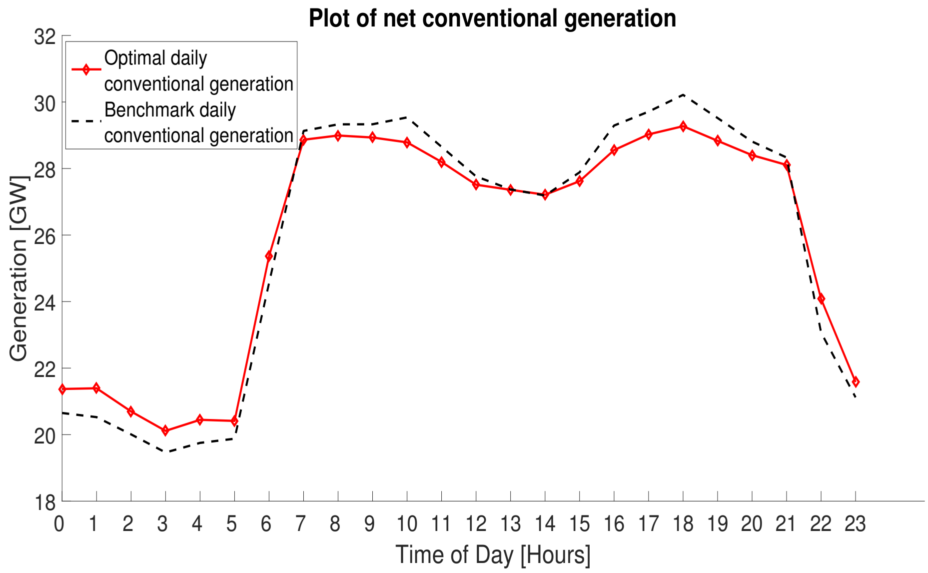


Figure 3.9: The net conventional generation for the day-ahead market.

The utility, the DR aggregator, and customers can benefit from using the proposed approach. The detailed information can be found in Table. 3.1 below. For that day, the utility can save £ 44418 for the generation cost, about 0.15% of the total generation cost. The PAR is reduced about 1.7%, from 1.182 to 1.162. By providing the DSM, the DR aggregator can make a profit of £ 96893. For customers, the electricity bill can be cut down by £ 1098 in total.

3.5 Sensitivity Analysis Results

A feasible approach should be general and robust when dealing with various situations. In this section, sensitivities of the approach are analysed. The system performances are studied for two kinds of scenarios, one scenario is when there are perturbations to variables, and the other one is when system coefficients change.

Table 3.1: Comparison of the reference and the optimal system performance

System performance	Referenced profile	Optimized profile	Improvement or Difference
Total generation(GWh)	723.193	723.235	0.01%
Average generation(GW)	30.133	30.135	0.01%
PAR	1.182	1.162	1.7%
Generation cost (M£)	29.609	29.565	0.15%
Bonus to DR aggregator (£)	–	96893	–
Compensation to customers (£)	–	1098	–

3.5.1 Sensitivity to perturbations

Firstly, the sensitivity of the optimal solution to perturbations of the variables is examined. It provides how robust the optimal strategy is when the consumption vector deviates from the suggested. Four case studies are conducted. The first two cases consider situations when there are deviations between the estimated and actual benchmark consumption vector. The remaining two cases consider situations when the optimal solution cannot be fully operated as designed.

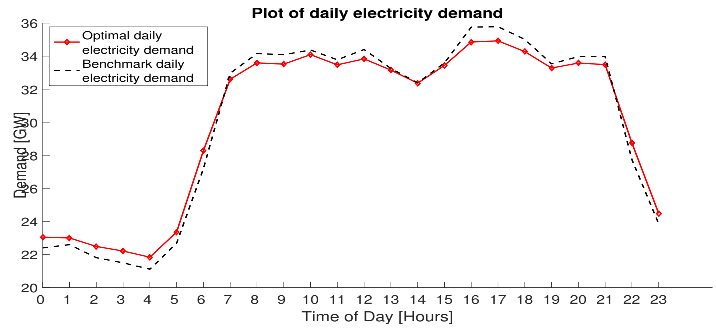
- Case 1 A normal distribution perturbation with the mean of 0 and the standard deviation of 0.5, in the unit of GW, is added to the benchmark consumption vector l^0. The optimized usage pattern is shown in Fig. 3.10, and detailed system information is listed in Table. 3.2.

- Case 2 A normal distribution perturbation with the mean of 0 and the standard deviation of 1, in the unit of GW, is added to the benchmark consumption vector l^0. The optimized usage pattern is shown in Fig. 3.11, and detailed system information is listed in Table. 3.2.

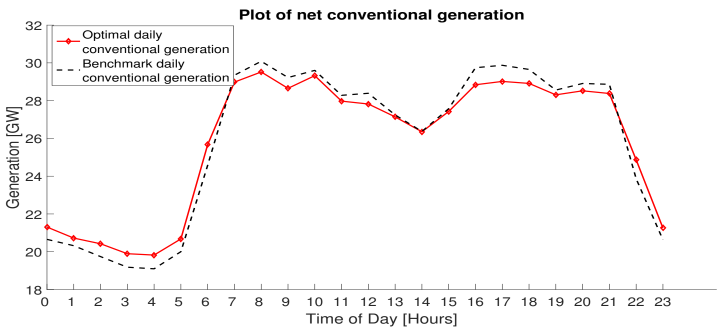
- Case 3 A normal distribution perturbation with the mean of 0 and the standard deviation of 0.5, in the unit of GW, is added to the optimized consumption vector l^1. The original optimal usage pattern and disturbed optimal usage pattern are shown in Fig. 3.12, and detailed system information is listed in

Table. 3.3.

- Case 4 A normal distribution perturbation with the mean of 0 and the standard deviation of 1, in the unit of GW, is added to the optimized consumption vector l^1. The original optimal usage pattern and disturbed optimal usage pattern are shown in Fig. 3.12, and detailed system information is listed in Table. 3.3.



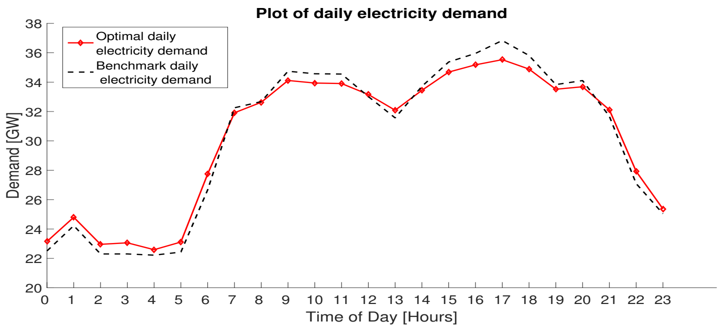
(a) The optimized usage pattern for the day-ahead market in Case 1.



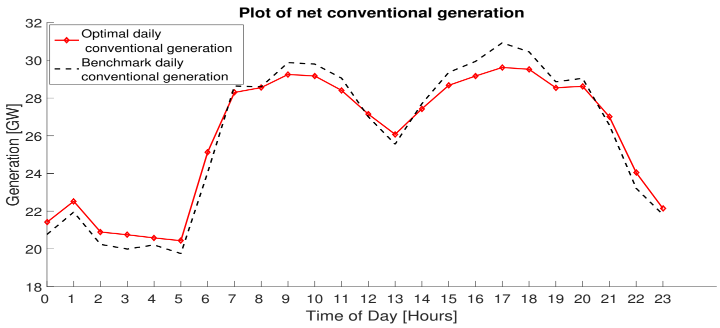
(b) The net conventional generation for the day-ahead market in Case 1.

Figure 3.10: The comparison of optimization results and benchmark in Case 1.

In Case 1, the utility can save £ 43911 for the generation cost. The PAR is reduced about 1.4%, from 1.175 to 1.159. The DR aggregator can make a profit of £ 97407. For customers, the electricity bill can be cut down by £ 1055 in total. In Case 2, the utility can save £ 42833 for the generation cost. The PAR is reduced about 2.9%, from 1.219 to 1.183. The DR aggregator can make a profit of £ 97338. For customers, the electricity bill can be cut down by £ 1091 in total. Case 1 and Case 2 prove if the system cannot have accurate information of the benchmark load profile l^0, the optimal strategy can still find a solution. All participants can still benefit from it and the power system can still have a better performance.



(a) The optimized usage pattern for the day-ahead market in Case 2.



(b) The net conventional generation for the day-ahead market in Case 2.

Figure 3.11: The comparison of optimization results and benchmark in Case 2.

Table 3.2: Results of the system performance in Case 1 and Case 2

	Case1		Case 2	
Load profile	Referenced	Optimized	Referenced	Optimized
Total generation (GWh)	723.479	725.503	725.761	725.770
Average generation (GW)	30.145	30.229	30.240	30.240
PAR	1.175	1.159	1.219	1.183
Generation cost (M£)	29.609	29.565	29.609	29.566
Bonus to DR aggregator (£)	–	97407	–	97338
Compensation to customers (£)	–	1055	–	1091

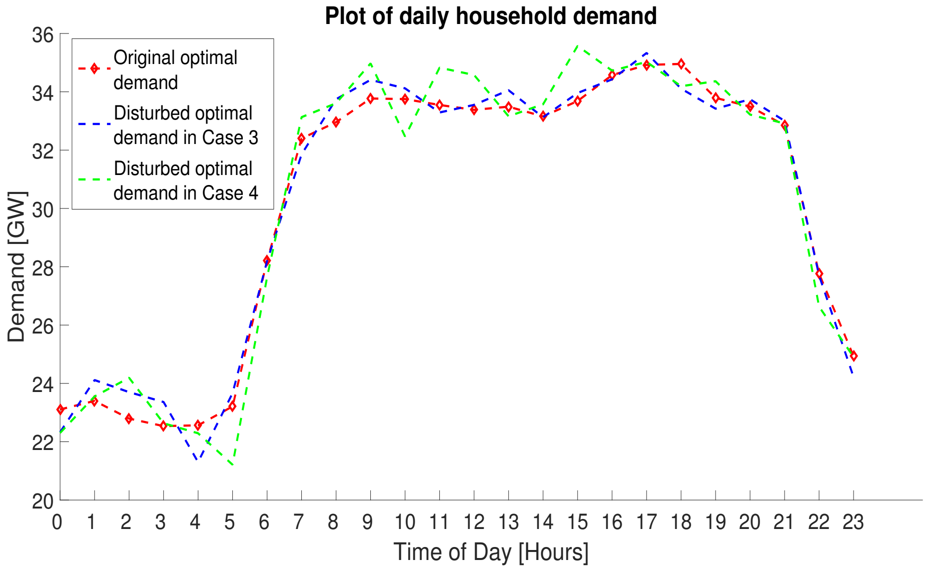


Figure 3.12: The comparison of original optimal and disturbed optimal results in Case 3 and Case 4.

Table 3.3: Results of the original optimal and disturbed optimal system performance in Case 3 and Case 4

Optimal Strategy	Original	Case 3	Case 4
Total Generation (GWh)	723.235	724.723	725.618
Average Generation(GW)	30.135	30.197	30.234
PAR	1.162	1.170	1.176
Generation Saving (£)	43282	40523	38702
Bonus to DR aggregator (£)	96893	96372	94758
Compensation to Customers (£)	1098	1088	1087

In Case 3, the utility can save £ 40523 for the generation cost. The PAR is reduced about 1.0%, from 1.182 to 1.170. The DR aggregator can make a profit of £ 96372. For customers, the electricity bill can be cut down by £ 1088 in total. In Case 4, the utility can save £ 38702 for the generation cost. The PAR is reduced about 0.51%, from 1.182 to 1.176. The DR aggregator can make a profit of £ 94758. For customers, the electricity bill can be cut down by £ 1087 in total. Case 3 and Case 4 prove if the actual consumption deviates from the optimal l^1, the system can still have a better performance than the benchmark. But compared to the original optimal solution, the disturbed solutions have slightly worse levels of performance in all aspects. And the larger the disturbance, the more deterioration of the system performance. This encourage all participants to follow the original optimal plan as close as possible.

3.5.2 Sensitivity to coefficients

Secondly, the sensitivity of the system performance to system coefficients is examined. It reveals interactions of three objective functions. Three system coefficients, which relates to optimization variables, are analysed in a certain range: the bonus coefficient μ, the compensation coefficient α, and the inelasticity coefficient of demand ε.

Sensitivity to bonus coefficient μ

The bonus coefficient μ indicates how would utility share the cost saving with the DR aggregator, where $\mu \in (0, 1]$. When $\mu = 0$, it means there is no bonus to the DR aggregator, therefore indicates no DSM is implemented in the system. When $\mu = 1$, it means the utility does not focus on the cost saving from DSM, but concerns the improvement of power system. To analyse it, the bonus coefficient μ is increased from 10% to 100% by the step of 10%, and other coefficients remain the same as stated in Section 3.4.

Table 3.4 shows the detailed beneficial of three participants. It is clear that, as μ increases, the utility's saving decreases, while the DR aggregator's profit increases. However, the bill reduction for customers does not change apparently with μ, which

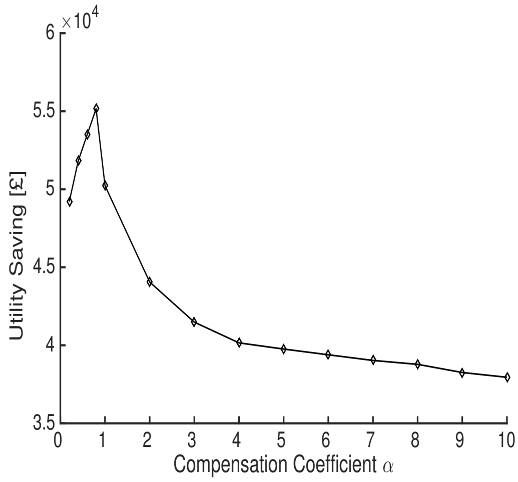
Table 3.4: The system performance with the change of bonus coefficient μ

μ	Utility's Saving(£)	Aggregator's profit(£)	Bill Reduction(£)
10%	133257	8057	1098
20%	118471	22873	1096
30%	103025	37628	1100
40%	88845	52075	1098
50%	73992	67271	1101
60%	59227	82087	1097
70%	44418	96893	1098
80%	29631	111785	1100
90%	14813	125848	1096
100%	0	141328	1099

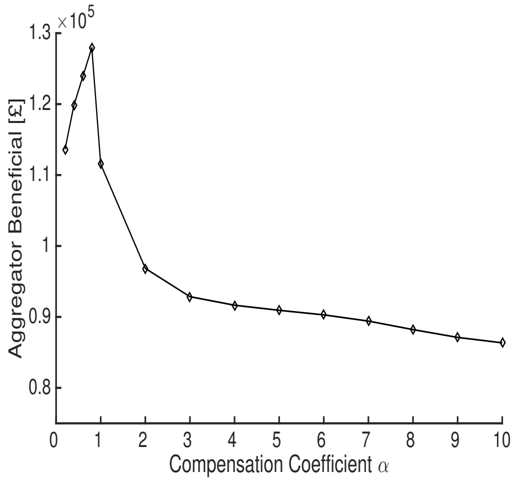
means the bonus coefficient would not influence customers' behaviour. Therefore the demand profile would not change apparently with μ, neither does the generation schedule. So μ only reflects the interaction between the utility and the DR aggregator, while the power system would not respond to it. If μ increases, it simply implies the utility is willing to share more of the cost saving to the DR aggregator. Even if the utility gives out all the cost saving, it could not boost the market and result in an improvement of the power system.

Sensitivity to compensation coefficient α

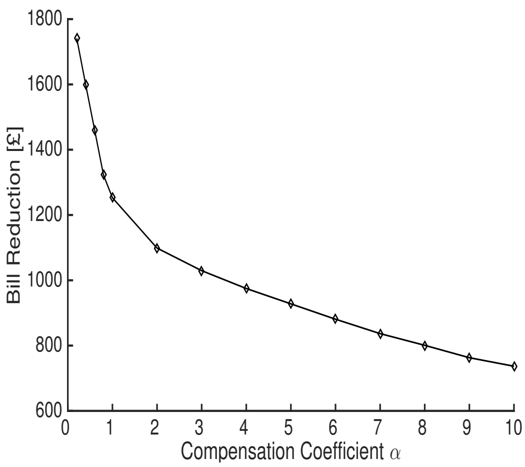
The compensation coefficient α indicates how would the DR aggregator encourage customers to involve in the DSM, where $\alpha > 0$. To analyse it, the compensation coefficient α is increased from 0 to 10, and other coefficients remain the same as stated in Section 3.4. Between the range of 0 to 1, the coefficient is increased by the step of 0.2, while between the range of 1 to 10, the coefficient is increased by the step of 1.



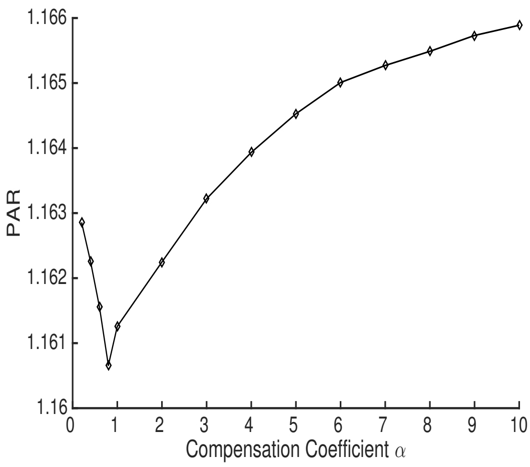
(a) Utility's Saving VS α



(b) Aggregator's Profit VS α



(c) Bill reduction VS α



(d) PAR VS α

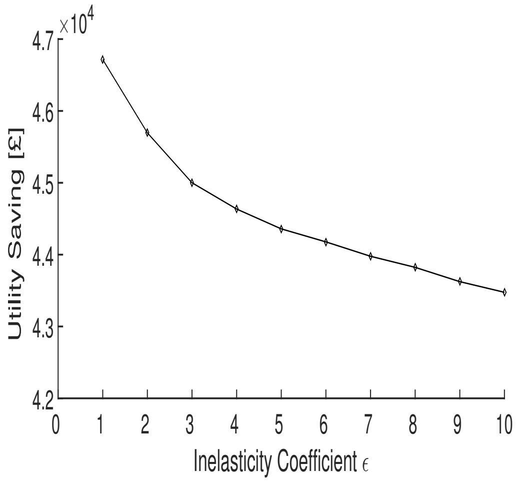
Figure 3.13: The system performance with the change of compensation coefficient α

Fig. 3.13 shows the detailed beneficial of three participants and the power system PAR. At the same level of demand adjustment, a larger α means a less compensation would be paid to customers. At the same amount of compensation, a larger α means a higher level of demand adjustment from customers is needed. As α increases, customers' bill reduction decreases. Between the range of 0.2 to 1, the utility's saving and the DR aggregator's profit increases, while the power PAR decreases. The dropping of PAR indicates the extent of demand shift from peak time to off-peak time is raising. Between the range of 1 to 10, the utility's saving and the DR aggregator's profit decreases, while the power PAR increases. The raising of PAR indicates the extent of demand shift from peak time to off-peak time is dropping. Based on simulation results, paying less to customers would not help the DR aggregator to increase its net profit. To promote the normal operation of the market, a suitable compensation rate should be designed.

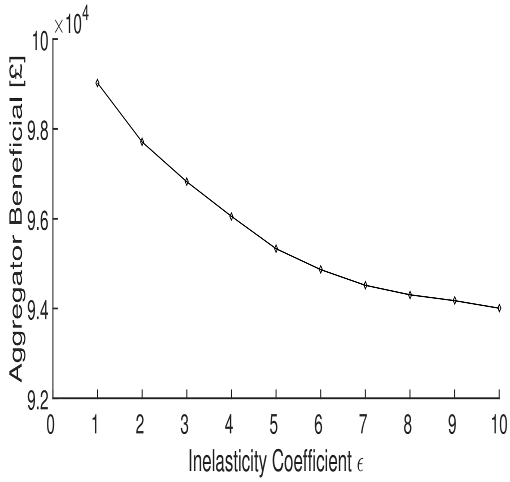
Sensitivity to inelasticity coefficient ε

The inelasticity coefficient ε indicates how would customers react to the inconvenience that caused by the DSM, where $\varepsilon > 0$. The inelasticity coefficient is related to customers' preference and the installed appliance. To analyse it, the compensation coefficient μ is increased from 1 to 10 by the step of 1, and other coefficients remain the same as stated in Section 3.4.

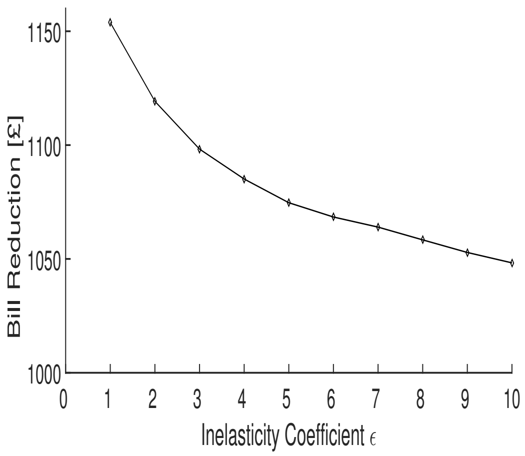
Fig. 3.14 shows the detailed beneficial of three participants and the power system PAR. At the same level of demand adjustment, a larger ε means customers are more sensitive, that a higher level of inconvenience would be caused. The inelasticity coefficient varies for customers. For the extreme case, some customers are mainly focused on the QoE and would resist to the demand adjustment. As ε increases, the utility's saving, the DR aggregator's profit and bill reduction decrease, while PAR increases. When the inconvenience caused by the DSM is significant, customers are reluctant to take part in the market, thus the DSM is hard to implement. In this situation, the adjustable ability of demand is restricted, and the system improvement is limited.



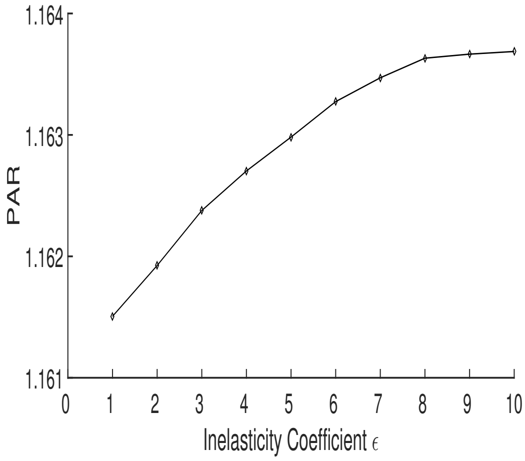
(a) Utility's Saving VS ε



(b) Aggregator's Profit VS ε



(c) Bill reduction VS ε



(d) PAR VS ε

Figure 3.14: The system performance with the change of inelasticity coefficient ε

3.6 Chapter Summary

This chapter proposed a hierarchical framework for the electricity market. The framework consisted of the utility, the DR aggregator, and customers. The role of the DR aggregator was defined as an intermediary communicating with both the utility and customers. The modelled system led to a MOP, which can be solved by the AIA. Through the proposed AIA, the APS was obtained. After that, a Pareto optimal solution was selected that maximizes the minimum improvement in all dimensions. The simulation results showed that all participants can benefit from the proposed design: the utility can reduce the generation cost and the power PAR; the DR aggregator can make a profit by providing DSM service; customers can save money on their bill. Even if there were perturbations to the system, the proposed approach can still work out an optimal solution. As the bonus coefficient μ increased, the DR aggregator's net income also increased, while the utility's generation cost saving decreased. As the compensation coefficient α increased, customers' bill reduction decreased. When the power PAR decreased, the utility's saving and the DR aggregator's profit increased, and vice verse. As the inelasticity coefficient ε increased, the utility's saving, the DR aggregator's profit and customers' bill reduction decreased, while the power PAR increased.

Chapter 4

Power Generation Scheduling and Operational Policy Making

4.1 Introduction

To effectively achieve the carbon emission reduction, a system model is established in this chapter, which consists of policy makers, utilities and consumers. Policy makers aim for minimizing the carbon emission, and making sure a certain penetration of RESs is reached. Utilities try to maximize the net profit of electricity supply, on the premise of system stability. Consumers seek to minimize the electricity bill, and receive an acceptable quality of electricity service. This model leads to a MOP. After obtaining the APF, a MMD approach is proposed to select the final solution. This proposed method is then compared with existing approaches, i.e., the WS approach and D & C approach. The case studies of short-term period and long-term period are presented. These case studies prove that these three approaches can work out a same solution. But the proposed MMD approach does not require priority information before selection, and does not need to differentiate objective functions, which make it can be widely used. The selected solution in short-term period case study suggests reductions in the use of coal and gas, while raises in nuclear and wind. For long-term period case study, the use of wind, nuclear and bioenergy are suggested to take the dominant status, while the use of coal, oil and gas are negligible. Then, system sensitivities to several coefficients are analysed. Overall, the main contributions of this chapter can be summarized as below:

- Besides economic and environmental aspects of the electricity generation, the participation of consumers is introduced in the system model.
- A MMD approach is proposed to process the MCDM, compared with D & C approach and WS approach.
- The practical U.K. case studies are conducted to illustrate the proposed model and approach. The generation plans for both short-term period and long-term period are presented.
- The impact of carbon tax and Renewable Obligation on carbon emission, generation cost and electricity bill are examined. These can reveal the proper strategy for deciding RESs and carbon emission related policies.

The chapter is organized as follows. Section 4.2 introduces a system model, which includes policy makers, utilities and customers. Section 4.3 illustrates the proposed MMD approach for MCDM, compared with D & C approach and WS approach. Section 4.4 provides the comparative analysis among three approaches. Section 4.5 presents the simulation results. Section 4.6 tests the system sensitivity. Finally, Section 4.7 concludes this chapter.

4.2 System Model

In this section, the system operational model is introduced. The framework is presented in Fig. 4.1. Policy makers set the carbon allowance and the RESs requirement. Utilities provide the electricity to consumers, and carry out the carbon emission reduction. They also encourage consumers to participate in DSM programs. Consumers use the electricity and are involved in the energy market [52].

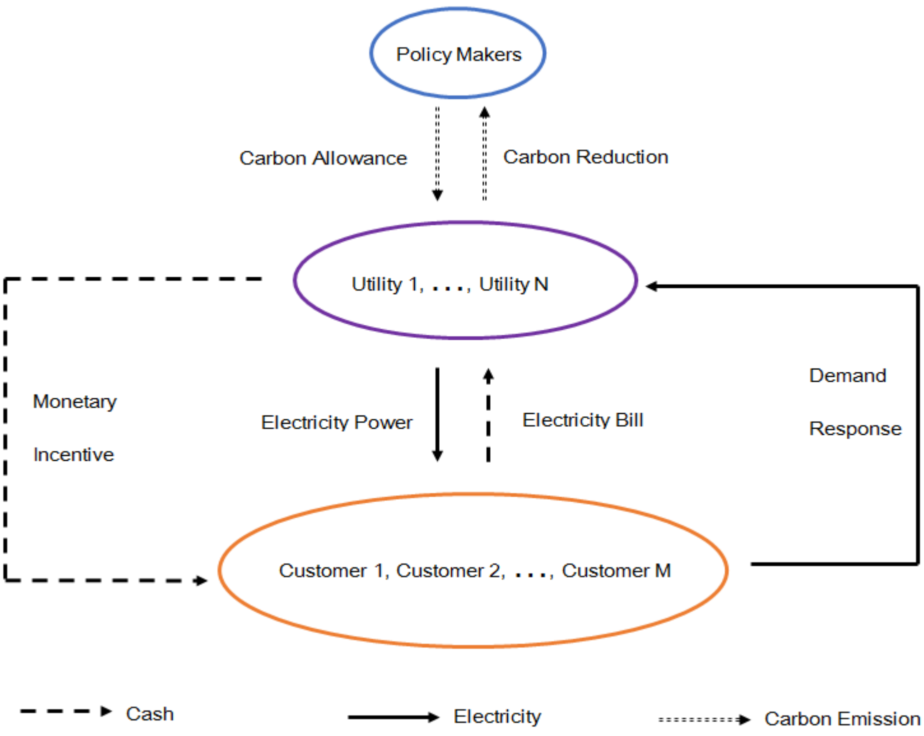


Figure 4.1: The system operation model.

4.2.1 The role of policy makers

The role of policy makers is to ensure the carbon emission reduction and stable the energy market. They support all kinds of emission reduction approaches, and enact a series of obligations. The Renewable Obligation for utilities is one of them, for the sake of promoting the utilization of RESs [136]. It sets the minimum penetration requirement of RESs, defined as R. If utilities can not meet the requirement, they need to pay for the substandard part. The extra generation cost f_{ro}, due to the Renewable Obligation, can be calculated as

$$f_{ro}(g_i, g_{i,r}) = \begin{cases} 0 & \frac{\sum_{i=1}^{n} g_{i,r}}{\sum_{i=1}^{n} g_i} \geqslant R \\ h\sum_{i=1}^{n}(Rg_i - g_{i,r}) & \frac{\sum_{i=1}^{n} g_{i,r}}{\sum_{i=1}^{n} g_i} < R \end{cases} \tag{4.2.1}$$

where g_i denotes the generation from source i, $g_{i,r}$ denotes the generation from RESs, and h denotes the price for each unit of the generation that does not meet the Renewable Obligation, which also known as the renewable energy certificate [136].

Besides the Renewable Obligation, policy makers also have the right to formulate the carbon tax. The carbon tax is imposed on the total amount of carbon emission. The total carbon tax levied from utilities can be calculated as

$$f_{ct}(s_i) = m\sum_{i=1}^{n} s_i e_i \tag{4.2.2}$$

$$s.t.: \qquad s_{min} \le s_i \le s_{max} \tag{4.2.3}$$

where e_i denotes the coefficient that transfers the fuel usage into the carbon emission, s_i denotes the fuel usage of source i, m denotes the carbon tax rate, s_{min} and s_{max} denote the minimum and the maximum capacity for source i, respectively.

Clearly, the aim of policy makers is to minimize the carbon emission rather than maximize the tax collection. By adjusting the fuel sources used for generation, the total carbon emission can be reduced. Hence, the objective function of policy makers can be defined as

$$\max_{s_i^1}: \qquad f_p(s_i^1) = \sum_{i=1}^{n} s_i^0 e_i - \sum_{i=1}^{n} s_i^1 e_i \tag{4.2.4}$$

$$s.t. \qquad s_{min} \le s_i^0, s_i^1 \le s_{max} \tag{4.2.5}$$

where s_i^0 and s_i^1 denote the fuel usage before and after generation adjustment, respectively. The first term corresponds to the benchmark carbon emission, and the second term corresponds to the carbon emission after generation adjustment.

4.2.2 The role of consumers

As stated in Chapter 3, consumers are assumed to be price-sensitive and would participate in the DSM. The total electricity demand before and after the DSM is defined as d^0 and d^1, respectively. According to the extent of carbon emission reduction owing to the DSM program, consumers can receive compensation as an incentive. The compensation can be calculated as

$$f_{com}(d^1) = \alpha(f_e(d^0) - f_e(d^1))^2 \tag{4.2.6}$$

$$s.t.: \quad \alpha > 0,\ d_{min} \le d^0, d^1 \le d_{max} \tag{4.2.7}$$

where α denotes the compensation coefficient, d_{min} denotes the minimum demand that need to be met, d_{max} denotes the maximum demand that can be provided, and $f_e(\cdot)$ denotes the CEF function which will be introduced in next chapter. The CEF function can virtually allocate the carbon emission that caused by generation to specific consumers.

Also as stated Chapter 3, the inconvenience caused by the DSM can be described as a dissatisfactory function. The incurred dissatisfactory depends on the level of demand change [52]. The dissatisfactory function can be modelled by a convex quadratic equation as

$$f_{dis}(d^1) = \varepsilon(d^0 - d^1)^2 \tag{4.2.8}$$

$$s.t.: \quad \varepsilon > 0,\ d_{min} \le d^0, d^1 \le d_{max} \tag{4.2.9}$$

where ε denotes the dissatisfactory inelasticity coefficient, which represents consumers' personal favour.

The aim of consumers is to maximize their bill reduction, thus paying least. Hence, the objective function of consumers can be defined as

$$\max_{d^1}: f_c(d^1) = d^0 q - [d^1 q - \alpha(f_e(d^0) - f_e(d^1)) + \varepsilon(d^0 - d^1)^2] \tag{4.2.10}$$

$$s.t.: \quad \alpha, \beta > 0,\ d_{min} \le d^0, d^1 \le d_{max} \tag{4.2.11}$$

where q denotes the price of per unit electricity. The first term corresponds to the original electricity bill, and the second term corresponds to the current electricity bill.

4.2.3 The role of utilities

The basic responsibility of utilities is to provide electricity to consumers. Due to the restriction of carbon emission allowance, utilities are suggested to adjust their generation method from preference method. Therefore, the generation cost is constituted of two parts: the basic cost of fuel sources $f_{bas}(\cdot)$ and the additional operating cost $f_{ope}(\cdot)$ because of generation adjustment. These two costs can be calculated as

$$f_{bas}(g_i) = \sum_{i=1}^{n} b_i g_i, \quad g_i = u_i s_i \tag{4.2.12}$$

$$f_{ope}(g_i) = \sum_{i=1}^{n} \gamma (g_i^0 - g_i^1)^2 \tag{4.2.13}$$

$$s.t.: \quad \gamma > 0, \ g_{i,min} \leq g_i^0, g_i^1 \leq g_{i,max} \tag{4.2.14}$$

where b_i denotes the basic cost of source i, u_i denotes the coefficient that transfers the fuel usage s_i into the electricity generation g_i, γ denotes the additional operating cost coefficient, $g_{i,min}$ and $g_{i,max}$ denote the minimum and maximum generation capacity for source i, respectively. Except these two costs, the aforementioned carbon tax and extra cost due to the Renewable obligation should be included. Thus, the total generation cost f_{gene} before and after adjustment can be calculated as

$$f_{gene}(g_i^0) = \sum_{i=1}^{n} (b_i g_i^0 + m s_i^0 e_i) + f_{ro}(g_i^0, g_{i,r}^0) \tag{4.2.15}$$

$$f_{gene}(g_i^1) = \sum_{i=1}^{n} [b_i g_i^1 + \gamma (g_i^0 - g_i^1)^2 + m s_i^1 e_i] + f_{ro}(g_i^1, g_{i,r}^1) \tag{4.2.16}$$

$$s.t.: \quad \gamma > 0, \ g_{i,min} \leq g_i^0, g_i^1 \leq g_{i,max}. \tag{4.2.17}$$

On the condition of securing an adequate supply, the aim of utilities is to maximize their net profit. The net profit can be described as the difference between received electricity bill from consumers and total generation cost. Hence, the objective function of utilities can be defined as

$$\max_{g_i^1}: \quad f_u(g_i^1) = [d^1 q - f_{gene}(g_i^1)] - [d^0 q - f_{gene}(g_i^0)] \tag{4.2.18}$$

$$s.t.: \gamma > 0, \ g_{i,min} \leq g_i^0, g_i^1 \leq g_{i,max}, \sum_{i=1}^{n} g_i^1 \geqslant d^1. \tag{4.2.19}$$

The first term corresponds to the net profit after generation adjustment, and the second term corresponds to the original net profit.

4.2.4 Problem formulation

Based on the described model, a MOP can be formulated. Three objectives are considered here. Firstly, policy makers try to maximize the carbon emission reduction. Secondly, consumers try to maximize their bill reduction while considering the QoE. Thirdly, utilities aim to maximize the net profit increment. These objectives result in a MOP as below

$$\min_{s_i^1}: \quad -f_p(s_i^1) = \sum_{i=1}^{n}(s_i^1 e_i - s_i^0 e_i) \tag{4.2.20}$$

$$\min_{d^1}: \quad -f_c(d^1) = [d^1 q - \alpha(f_e(d^0) - f_e(d^1)) + \varepsilon(d^0 - d^1)^2] - d^0 q \tag{4.2.21}$$

$$\min_{g_i^1}: \quad -f_u(g_i^1) = [d^0 p - f_{gene}(g_i^0)] - [d^1 p - f_{gene}(g_i^1)] \tag{4.2.22}$$

$$\begin{aligned} s.t.: \quad & \alpha,\ \varepsilon,\ \gamma > 0, \quad d_{min} \leq d^0, d^1 \leq d_{max}, \quad g_{i,min} \leq g_i^0, g_i^1 \leq g_{i,max}, \\ & f_p(s_i^1) > 0, \quad f_c(d^1) > 0, \quad f_u(g_i^1) > 0, \quad \sum_{i=1}^{n} g_i^1 \geqslant d^1. \end{aligned} \tag{4.2.23}$$

A forth function is proposed to simplify constraints in (4.2.23). It can ensure all constraints are strictly satisfied, if and only if $f_r = 0$ holds true.

$$\begin{aligned} f_r(d^1, s_i^1, g_i^1) = \sum [&\max(d^1 - \sum_{i=1}^{n} g_i^1, 0) + \max(-f_p(s_i^1), 0) + \max(-f_u(g_i^1), 0) \\ &+ \max(-f_c(d^1), 0)] \end{aligned} \tag{4.2.24}$$

The resultant MOP can be summarized as

$$\min_{g_i^1, s_i^1, d^1}: f(g_i^1, s_i^1, d^1) = \left[-f_p(s_i^1),\ -f_c(d^1),\ -f_u(g_i^1)\right)] \tag{4.2.25}$$

$$s.t. \quad f_v(g_i^1, d^1, s_i^1) = 0. \tag{4.2.26}$$

4.3 Multiple Criteria Decision Making Process

The AIA introduced in Section 3.3.2 is used here to proceed the Pareto optimization. Every vector in APS represents a Pareto optimal solution for the MOP. The selection of a final solution is proceeded by the MCDM. The MMD approach is proposed for MCDM, because of its advantageous properties [137]. The WS approach [138] and D & C approach [139], which are two of the most basic and simplest MCDM approaches [140, 141], are also presented for comparison. he detailed explanations are presented in the following sections.

Generally, there are three types of MCDM: before, during, and after the optimization process [142, 143]. In this chapter, the third type is applied and the MMD approach is proposed [137].

For a MOP $f(x)$ in (4.3.27), the APS in (4.3.28) and APF in (4.3.29) can be available by using AIA.

$$\underset{x}{min} \quad f(x) = \{f_j(x);\ n = 1, 2, ..., J\} \tag{4.3.27}$$

$$APS = \{x_m;\ m = 1, 2, ..., M\} \tag{4.3.28}$$

$$APF = \{f\left(x_m\right); m = 1, 2, ..., M\} \tag{4.3.29}$$

where J denotes the number of objectives, x denotes the vector of decision variables, and M denotes the number of vectors in APS and APF.

The vector lies in the knee region of the APF is considered as the final solution. To simplify the explanation, a MOP with two minimum objective functions and eight vectors in APS, i.e., $J = 2$, $M = 8$, is shown in Fig. 4.2. Comparing x_1 with x_2, it can be seen that x_1 provides a smaller value of $f_2(x)$ and a larger value of $f_1(x)$ than x_2. The difference of $f_1(x)$ between x_1 and x_2 is significant, while the difference of $f_2(x)$ between x_1 and x_2 is insignificant. This means x_2 can give a remarkable improvement in $f_1(x)$ while a unremarkable regression in $f_2(x)$ than x_1. Therefore, between the trade of two objectives, x_2 is preferred to the MOP. By evaluating the performance of all vectors from x_1 to x_8, x_5 is selected as the final solution, which is also known as the knee solution. The process of finding the knee solution by aforementioned approaches is detailed explained in following sections.

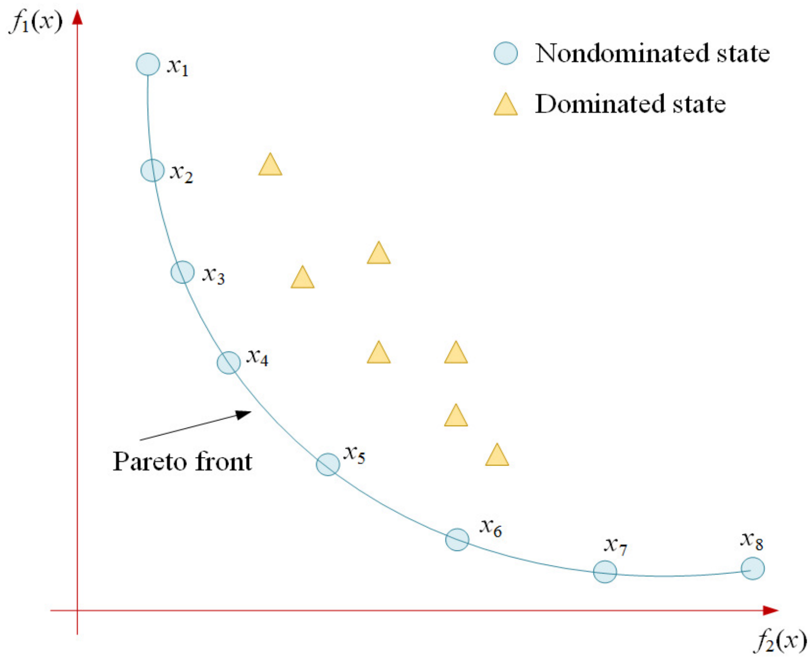


Figure 4.2: An example of the knee solution.

4.3.1 Minimum Manhattan distance approach

Firstly, the MMD approach is introduced. The MMD approach is able to find the solution which can minimize the Manhattan distance from a normalized ideal vector. The normalized ideal vector I is defined as

$$I = \{i_j;\ j = 1, 2, ..., J\} \tag{4.3.30}$$
$$i_j = \frac{\min f_j(x)}{\max f_j(x) - \min f_j(x)}.$$

The MOP $f(x)$ in (4.3.27) can also be normalized as a new MOP $g(x)$ in (4.3.31)

$$min\ g(x) = \{g_j(x);\ j = 1, 2, ..., J\} \tag{4.3.31}$$
$$g_j(x) = \frac{f_j(x)}{\max f_j(x) - \min f_j(x)}.$$

The vector x^* in (4.3.32) has the MMD to the normalized ideal vector

$$x^* = \arg \min_{x \in APS} \|g(x) - I\|_1 \tag{4.3.32}$$

$$\|g(x) - I\|_1 := \sum_{j=i}^{J} |g_j(x) - i_j| \tag{4.3.33}$$

where $\| \ \|_1$ denotes the Manhattan norm/Taxicab norm, := denotes the assignment operator.

In the geometric way, the process for a problem with two objectives can be presented in Fig. 4.3. A parameter r is defined as

$$r = \|g(x) - I\|_1. \tag{4.3.34}$$

A rhombus with centre in I and radius of r is inserted. The r is enlarged until there is a nonempty intersection with the normalized APF, the minimum value of r can be achieved and the solution x^* can be obtained

$$r_{min} = \min_{x \in APS} \|g(x) - I\|_1 . \tag{4.3.35}$$

Generally, the MMD approach has following advantages [137]:

- First, it does not require underlying information before selection, thus the heuristic subjective priority can be avoided.

- Second, it does not need to differentiate objective functions, thus can be widely used in various cases.

- Third, it has a rich geometric and algebraic interpretation.

4.3.2 Weighted sum approach

Secondly, the WS approach is introduced. According to the importance of each objective, the decision maker gives each objective function a corresponding weight coefficient. Then objectives are linearly combined into a new objective that can be used to solve the MOP.

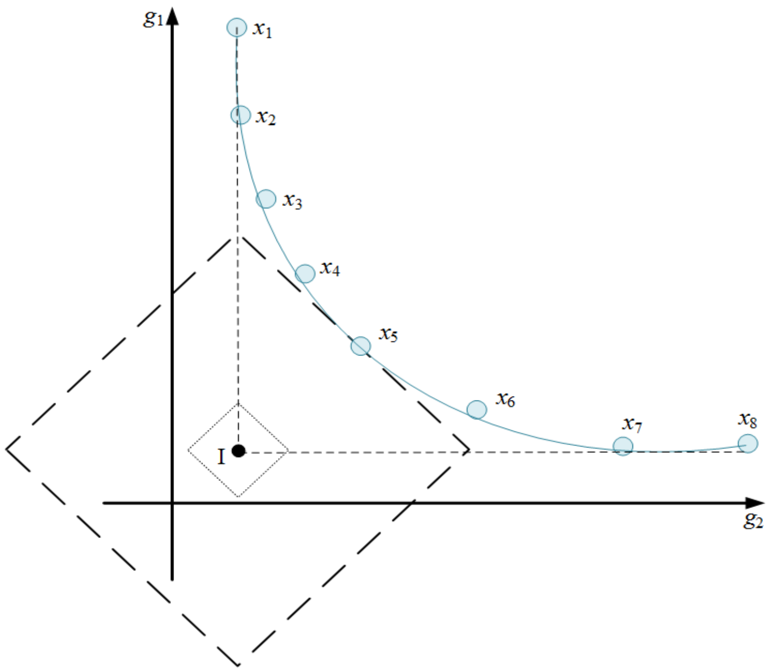


Figure 4.3: Demonstration of MMD approach to MCDM.

For the MOP $f(x)$ in (4.3.27), a coefficient ω_j is assigned to each objective function, then a new problem $h(x)$ in (4.3.36) is formulated. The solution x^{**} in (4.3.38) is the solution for the new problem $h(x)$, which is also the solution for $f(x)$.

$$min \quad h(x) = \sum_{j=1}^{J} \omega_j f_j(x) \tag{4.3.36}$$

$$s.t. \quad \omega_n \geq 0, \ \sum_{j=1}^{J} \omega_j = 1 \tag{4.3.37}$$

$$x^{**} = \arg \min_{x \in APS} h(x) \tag{4.3.38}$$

In the geometric way, the process for a problem with two objectives can be presented in Fig. 4.4. A parameter b is defined as

$$b = \sum_{j=1}^{J} \omega_j f_j(x). \tag{4.3.39}$$

A line is inserted and moved in a direction of decreasing value of b. When there is no nonempty intersection with the APF, the minimum value of b can be achieved and the solution x^{**} can be obtained

$$b_{min} = \min_{x \in APS} \sum_{j=1}^{J} \omega_j f_j(x). \tag{4.3.40}$$

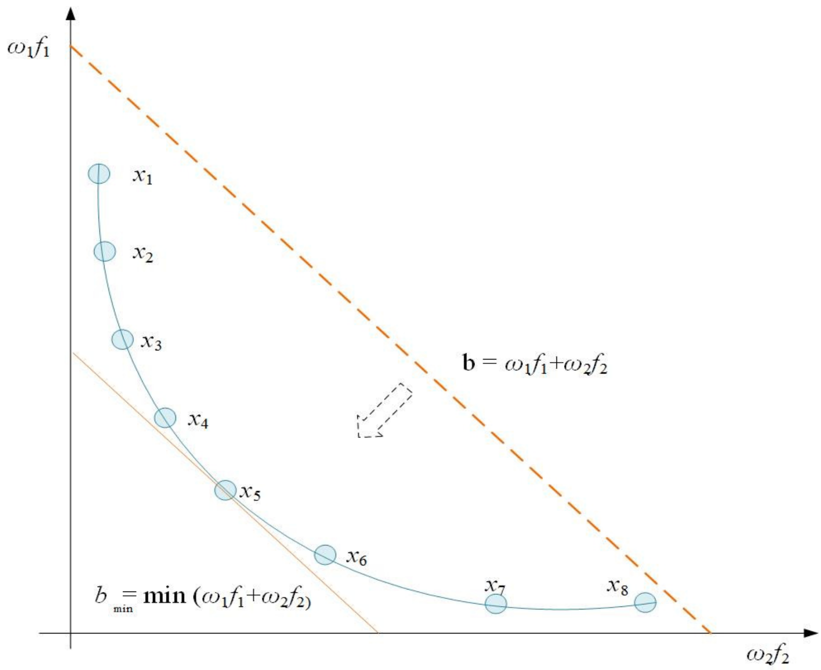


Figure 4.4: Demonstration of WS approach to MCDM.

4.3.3 Divide & Conquer approach

Thirdly, the D & C approach is introduced. The basic idea of D & C approach is recursively decomposing a problem of size J into smaller sub-problems in the size of K, which are independent and identical to the original problem. By solving the sub-problems, the solution to the original problem can be obtained. Generally, there are three steps to realize the approach.

- Step 1: Divide the original problem into sub-problems recursively.
- Step 2: Work out the solution for lowest-level sub-problems.
- Step 3: Combine solutions suitably for the original problem.

The concept of net improvement percentage (NIP) is used to illustrate this process. For a MOP demonstrated in Fig. 4.2, the NIP of objectives when moving from solution x_a to x_b can be expressed as

$$NIP(x_a \to x_b) = \sum_{j=1}^{J} \frac{f_j(x_a) - f_j(x_b)}{\max f_j(x) - \min f_j(x)} \tag{4.3.41}$$

where $x_a \to x_b$ denotes the process that moves from solution x_a to solution x_b.

As described before, solution x_2 is preferred to the MOP than solution x_1. The NIP from solution x_1 to solution x_2 is positive. It can be expanded as solution x_b is preferred to the MOP than solution x_a if the NIP for process $x_a \to x_b$ is positive. That is

$$x_b \text{ is preferred than } x_a, \text{ if } NIP(x_a \to x_b) > 0. \tag{4.3.42}$$

This preference strategy is not affected by the direction of movement. The NIP from solution x_a to solution x_b is opposite to the NIP from solution x_b to solution x_a

$$\begin{aligned} NIP(x_b \to x_a) &= \sum_{j=1}^{J} \frac{f_j(x_b) - f_j(x_a)}{\max f_j(x) - \min f_j(x)} \\ &= -\sum_{j=1}^{J} \frac{f_j(x_a) - f_j(x_b)}{\max f_j(x) - \min f_j(x)} = -NIP(x_a \to x_b). \end{aligned} \tag{4.3.43}$$

Therefore, for the situation stated in (4.3.42), the following preference strategy is equivalent

$$x_b \text{ is preferred than } x_a, \text{ if } NIP(x_b \to x_a) < 0. \tag{4.3.44}$$

Based on the statements before, the process of D & C approach can be simplified as iterations of pairwise comparisons. The process is presented in Fig. 4.5. The vectors in APS are divided into pairs for comparing till one final solution is left. For each iteration of pairwise comparison, the number of vectors is decreased by half. Three iterations are conducted for the demonstrated problem. Normally, for a MOP problem with M vectors in the APF, $log_2 M$ time of iterations is needed.

4.4 Comparative Analysis

In this section, the U.K. practical case is presented to demonstrate these approaches. The simulation is conducted by using the software MATLAB. Eight fuel sources are considered: coal, oil, gas, nuclear, hydro, wind, bioenergy and solar. The U.K. annual data of fuel usage for electricity generation and electricity consumption in 2017

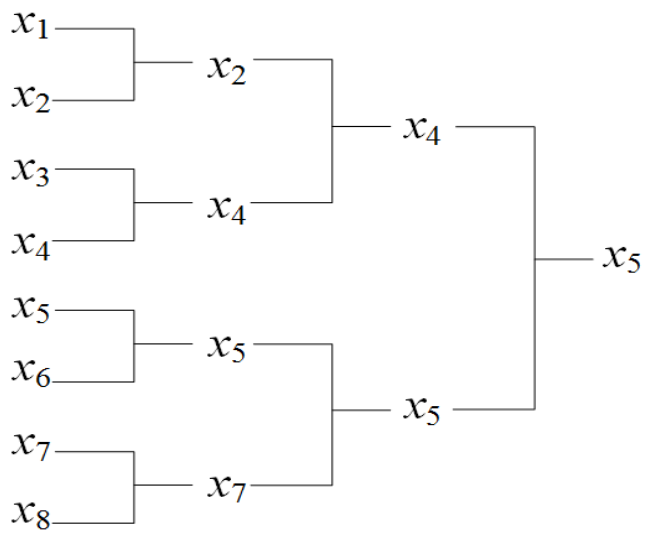


Figure 4.5: Demonstration of D & C approach to MCDM.

is selected as a benchmark. The unit Mtoe means the million tons of oil equivalent. The current U.K. carbon tax £18 for per tonne of carbon emission and average electricity price £0.13/kWh are used [144]. And according to Ofgem, the current U.K. Renewable Obligation 34.8% is used as the minimum penetration requirement of RESs. If the requirement is not met, £44.77/MWh need to be paid for substandard part [136]. The additional operating coefficient, compensation coefficient and dissatisfactory inelasticity coefficient are set as 0.2, 1 and 3, respectively. The basic generation cost coefficient b_i in equation (4.2.12), the carbon emission coefficient e_i in equation (4.2.2), and the fuel source generation coefficient u_i in equation (4.2.12) are listed in Table 4.1. These data are obtained from [8, 145]. As for the carbon emission coefficients, BEIS considers the life-cycle assessment of fuel sources, therefore they are not zero for RESs. As for the generation coefficients, BEIS takes the fuel used in tonnes, multiplies by the calorific values for the fuel and the conversion factor to oil equivalent. The high calorific values and conversion factors of RESs result in high generation coefficients. The detailed information can be found from [8] and Annex A in [145].

The proposed model leads to a 3-D problem. For MMD approach, a regular octahedron is needed instead of a rhombus, while for WS approach, a hyperplane is needed instead of a line. To clearly show the process of MCDM, the size of APS

Table 4.1: Coefficients for the proposed model

Fuel type	**Basic generation cost b_i (M£/TWh)**	**Carbon emission e_i (Mton/Mtoe)**	**Fuel source generation u_i (TWh/Mtoe)**
Coal	141	3.66	4.16
Oil	91	2.49	3.39
Gas	113	2.26	5.41
Nuclear	93	0.11	4.45
Hydro	96	0.34	11.63
Wind	82	0.30	11.57
Solar	80	0.99	11.63
Bioenergy	87	0.16	3.50

is set as 16, i.e., $M = 16$. Fig. 4.6 - Fig. 4.8 present the principles of these three approaches. It can be seen that all three approaches yield the same final solution.

Fig. 4.6 shows the process of MMD approach. The radius of a regular octahedron, which is centered at normalized ideal vector y_{opt}, is increased until nonempty intersection with the normalized APF. The intersection is labelled by $y(x_6)$, the solution x_6 is selected as final optimal solution.

Fig. 4.7 shows the process of WS approach. A hyperplane is moved in a decreasing direction till there is no nonempty intersection with the APF, thus the minimum WS is achieved. The intersection is labelled by $y(x_6)$, the solution x_6 is selected as final optimal solution.

Fig. 4.8 shows the process of D & C approach. Solutions are randomly allocated into pairs for comparison till only one solution is selected. $NIP = NIP(x_a \to x_b)$, where x_a and x_b denote the upper and lower solution, respectively. When $NIP > 0$, the lower solution is preferred. While when $NIP < 0$, the upper solution is preferred. As shown in the figure, two random comparing orders result in the same solution. The solution x_6 is selected as final optimal solution for both situations. It proves that the comparing order would not affect the result.

Table 4.2 summarizes the computation time for WS, D & C and MMD approaches, in the unit of second. Note that, this computation time is only for MCDM.

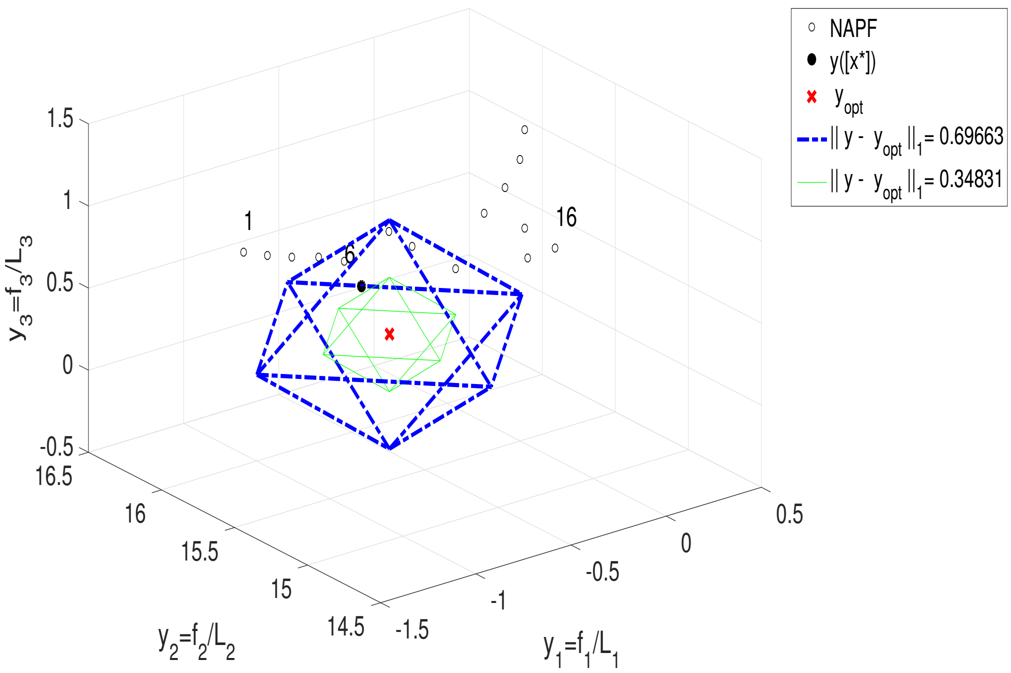


Figure 4.6: The MMD approach for a 3-D MOP.

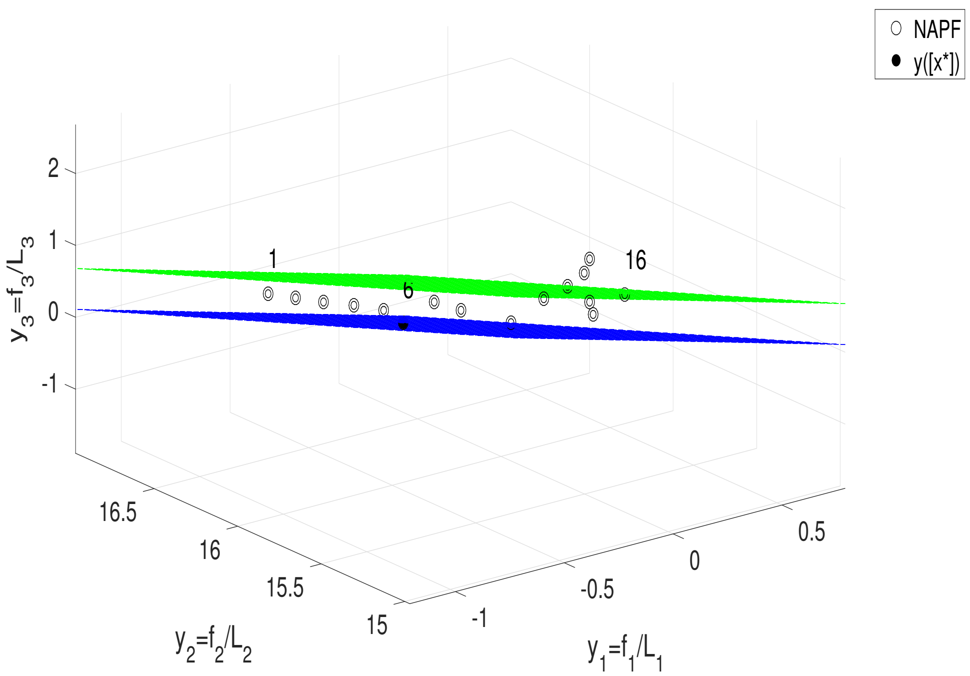
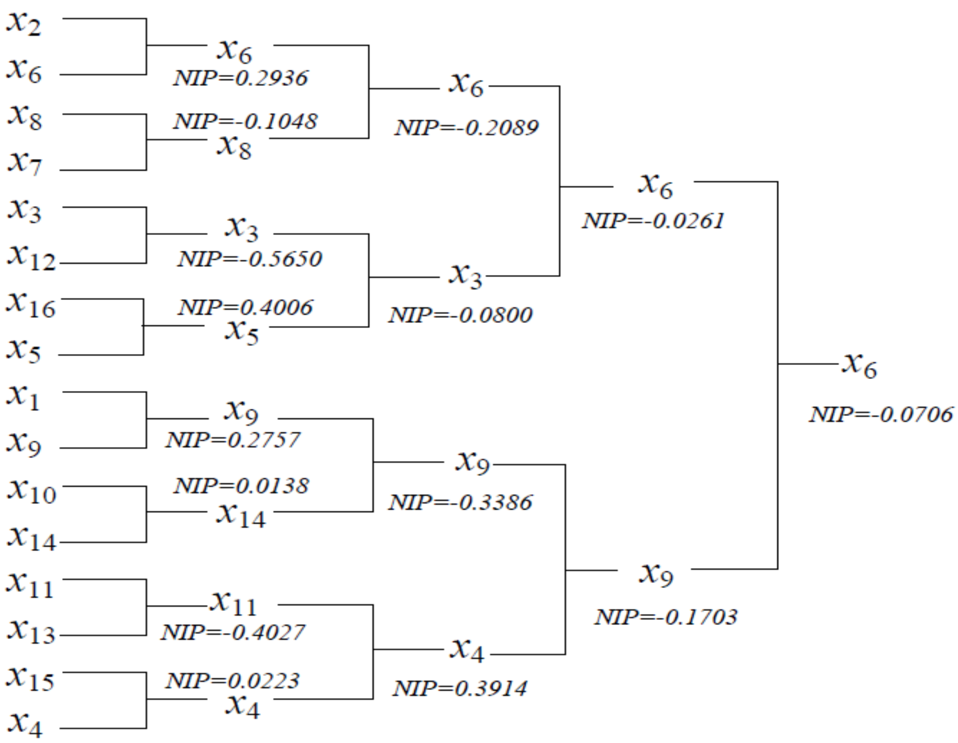
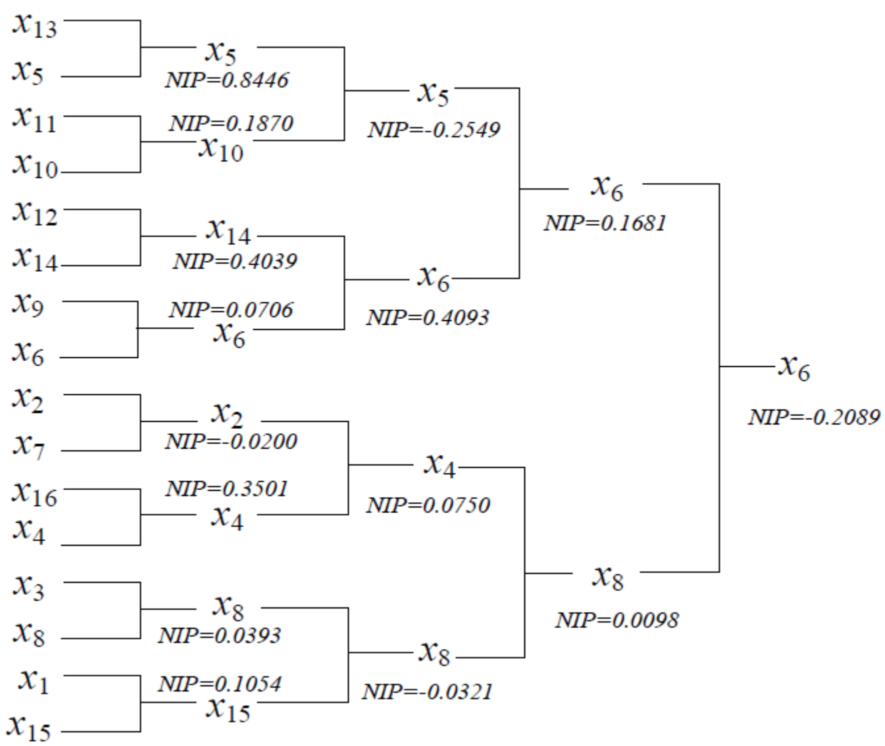


Figure 4.7: The WS approach for a 3-D MOP.



(a)



(b)

Figure 4.8: The D & C approach in two random comparing orders for the MOP.

Table 4.2: Computation time for WS, D & C and MMD approaches

Approach		WS		D & C		MMD	
Number of solutions	Number of simulation	Total time	Average time	Total time	Average time	Total time	Average time
50	100	0.0073	7.3221e-05	0.0525	5.2523e-04	0.0066	6.6116e-05
50	500	0.0280	5.5946e-05	0.1111	2.2220e-04	0.0126	2.5282e-05
50	1000	0.0300	3.0026e-05	0.2269	2.2687e-04	0.0248	2.4786e-05
50	2000	0.0537	2.6830e-05	0.4283	2.1413e-04	0.0430	2.1516e-05
50	3000	0.0775	2.5826e-05	0.5722	1.9072e-04	0.0625	2.0833e-05
50	4000	0.1006	2.5156e-05	0.6926	1.7316e-04	0.0773	1.9328e-05
100	2000	0.0620	3.0986e-05	0.4764	2.3821e-04	0.0433	2.1638e-05
200	2000	0.0628	3.1396e-05	0.5462	2.7311e-04	0.0454	2.2697e-05
500	2000	0.0656	3.2810e-05	0.9367	4.6833e-04	0.0467	2.3358e-05

The time spent on finding APF is not included, therefore the number of iteration for each simulation run would not affect the result. When solution size is set as 50, 2000 simulation runs can lead to a relatively stable average computation time. Obviously, D & C approach takes much longer than the other two. The average time for WS approach is a little bit higher than MMD approach. So, MMD approach is the most computational efficient one among these three approaches. When the solution size increases, the computation time for D & C approach increases significantly than the other two, because D & C approach needs iterations of pairwise comparisons. Increasing number of solutions would directly increase the number of comparisons, thus would apparently increase the computation time.

4.5 Case Studies

In this section, the system performance is examined. Two scenarios are introduced: the generation adjustment plan for short-term period and long-term period. The detailed fuel usage suggestions are presented.

4.5.1 Case study for short-term period

For the short-term period, the fuel usage of each source can not have a dramatic change. The adjustable range is set at 20% of the benchmark. The size of APS is set as 500. Other system coefficients remain the same as stated in previous section.

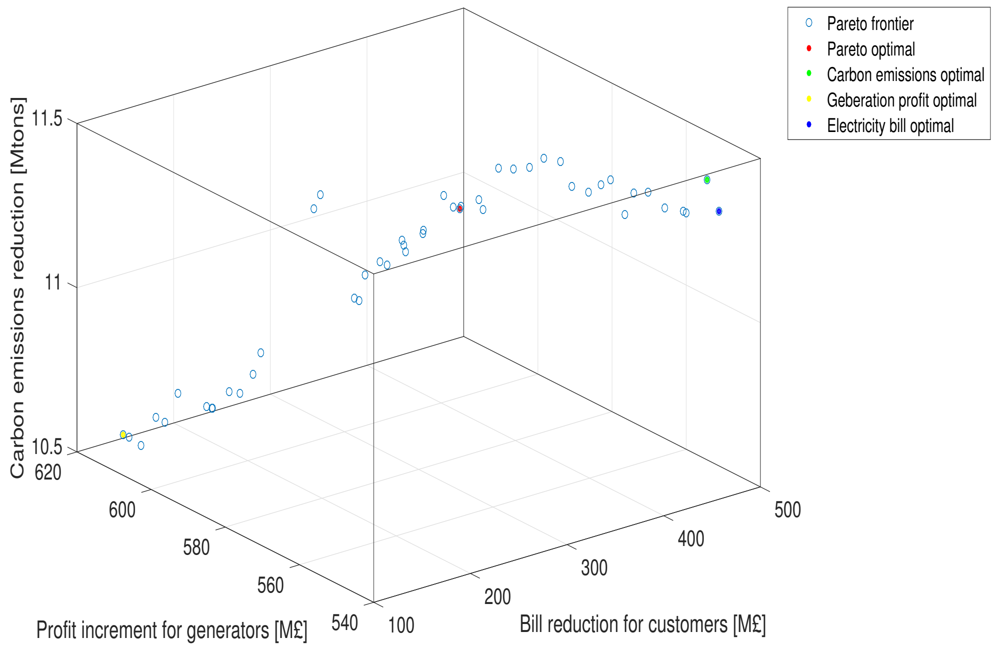


Figure 4.9: The APF for the proposed MOP.

Table 4.3: System performance for different solutions

	Carbon Emission (Mtons)	Generation Profit (M£)	Electricity Bill (M£)
Benchmark	74.16	5871	35576
Selected	62.89	6449	35237
Carbon Opt	62.71	6415	35115
Utilities Opt	63.61	6486	35445
Consumer Opt	62.79	6412	35115

Fig.4.9 and Table 4.3 illustrate the system performance. Four representative solutions are marked in Fig.4.9: consumers optimal, utilities optimal, policy makers

optimal and selected optimal solution. The detailed information of three objectives is listed in Table 4.3. It can be seen that the selected solution fairly distribute benefits to three participants. For the selected one, the total electricity generated is 273.5 TWh. 11.27 Mtons of carbon emission can be reduced. Utilities can increase £578M for the net profit. Customers can have a bill reduction of £339M.

Fig. 4.10 and Fig. 4.11 present the fuel usage and accordingly electricity generation of the benchmark, selected solution, carbon emission optimal solution and utilities optimal solution. Firstly, the benchmark and selected solution are compared. With the boundary limit, changes of fuel usage in oil, hydro and solar are insignificant. The use of coal and gas decrease noticeably from 5.441 Mtoe to 4.473 Mtoe, and from 22.152 Mote to 18.690 Mtoe, respectively. And the accordingly electricity generation from coal and gas decrease from 22.641 TWh to 18.617 TWh, and from 119.920 TWh to 101.190 TWh, respectively. The reduced part is mainly replenished by nuclear and wind. The use of nuclear and wind increase from 15.124 Mtoe to 18.077 Mtoe, and from 3.511 Mtoe to 4.118 Mtoe, respectively. And the accordingly electricity generation from nuclear and wind increase from 67.329 TWh to 80.497 TWh, and from 40.593 TWh to 47.630 TWh, respectively.

Secondly, the selected solution and carbon emission optimal solution are compared. Among these eight sources, nuclear has the lowest emission rate for per unit electricity generation, that is 0.0247 Mton/TWh. Wind ranks the second lowest place with the emission rate as 0.0259 Mton/TWh. While coal has the highest emission rate for per unit electricity generation, that is 0.879 Mton/TWh. Oil is following by, which has the emission rate as 0.733 Mton/TWh. To minimize the carbon emission, the low emission sources are favoured. The use of nuclear and wind in carbon emission optimal solution are a little bit higher than in the selected solution, which are 18.111 Mtoe and 4.207 Mtoe. Oppositely, the use of coal and oil are relatively lower, which are 4.423 Mtoe and 0.132 Mtoe.

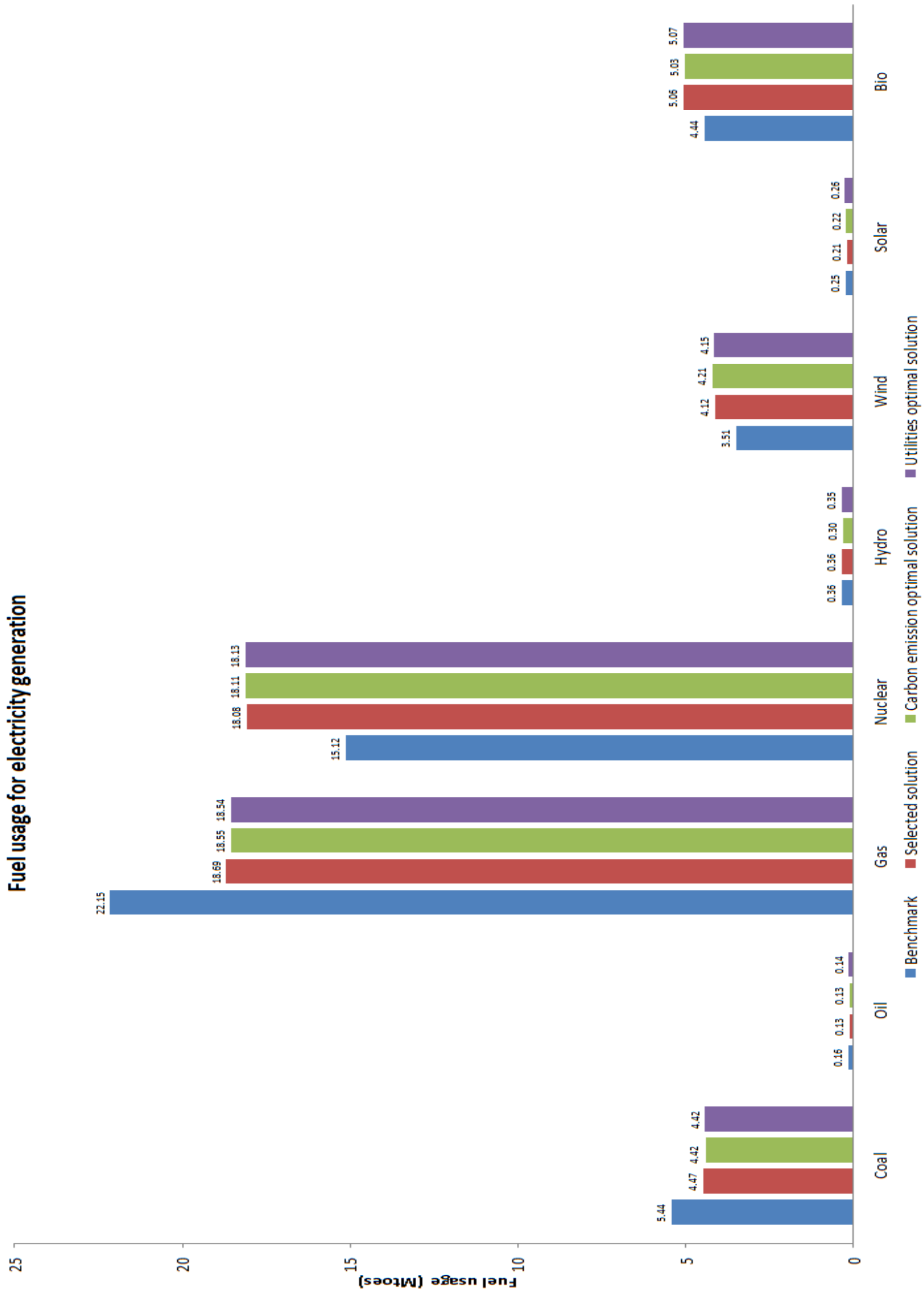


Figure 4.10: Comparison of the fuel usage plan for electricity generation in short-term period.

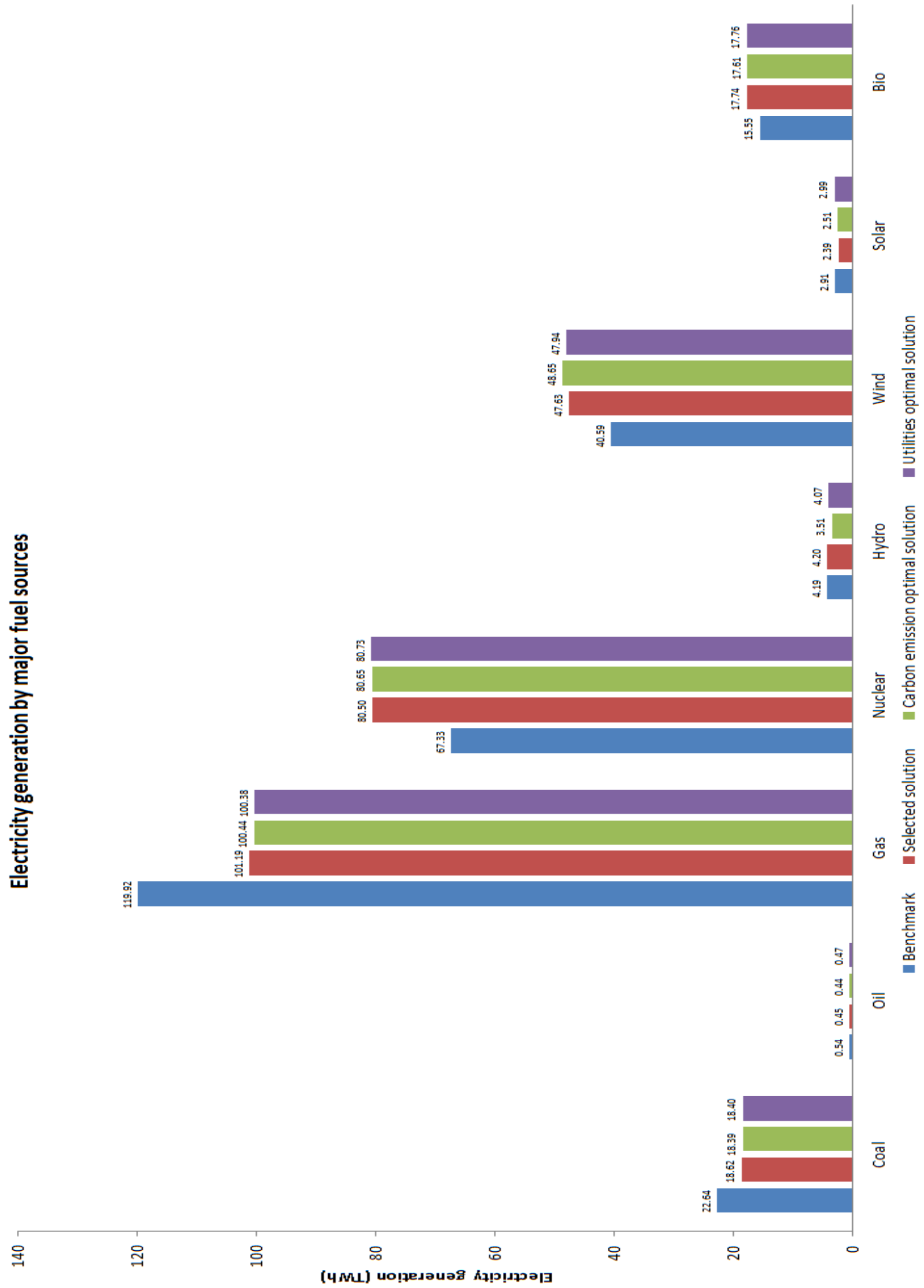


Figure 4.11: Comparison of the electricity generation by major fuel sources in short-term period.

Thirdly, the selected solution and utilities optimal solution are compared. For utilities, to minimize the generation cost, the source expenditure should be as low as possible. Besides, the total carbon emission amount also needs to be considered because of the carbon tax. By taking both the basic source cost and the corresponding carbon tax into account, coal is the most expensive source for per unit electricity generation, that is 156.837 M£/TWh. Gas ranks the second highest place with the cost as 120.519 M£/TWh. While solar is the cheapest source for per unit electricity generation, that is 81.532 M£/TWh. Wind is following by, for which the cost is 82.467 M£/TWh. Therefore, the use of solar and wind in utilities optimal solution are relatively higher than in the selected solution, which are 0.257 Mtoe and 4.154 Mtoe. Oppositely, the use of coal and gas become lower, which are 4.419 Mtoe and 18.542 Mtoe.

For customers, they mainly care about whether the total electricity generation amount can meet their demand and how much do they need to pay for it. Therefore, they do not have a specific preference on fuel sources that be used for electricity generation.

In a word, compared to the benchmark, all of the selected optimal solution, carbon emission optimal solution, utilities optimal solution and customers optimal solution can improve the performance of the system. But only the selected optimal solution can balance improvements among three participants. Compared to the selected optimal solution, carbon emission optimal solution and utilities optimal solution have different preferences on fuel sources, because of the priority for their own interests.

4.5.2 Case study for long-term period

For the long-term period, it is assumed there is no up boundary limit for each source. This gives a pointing plan for the future. Except for the range of eight sources, other system coefficients remain the same as stated in the previous section.

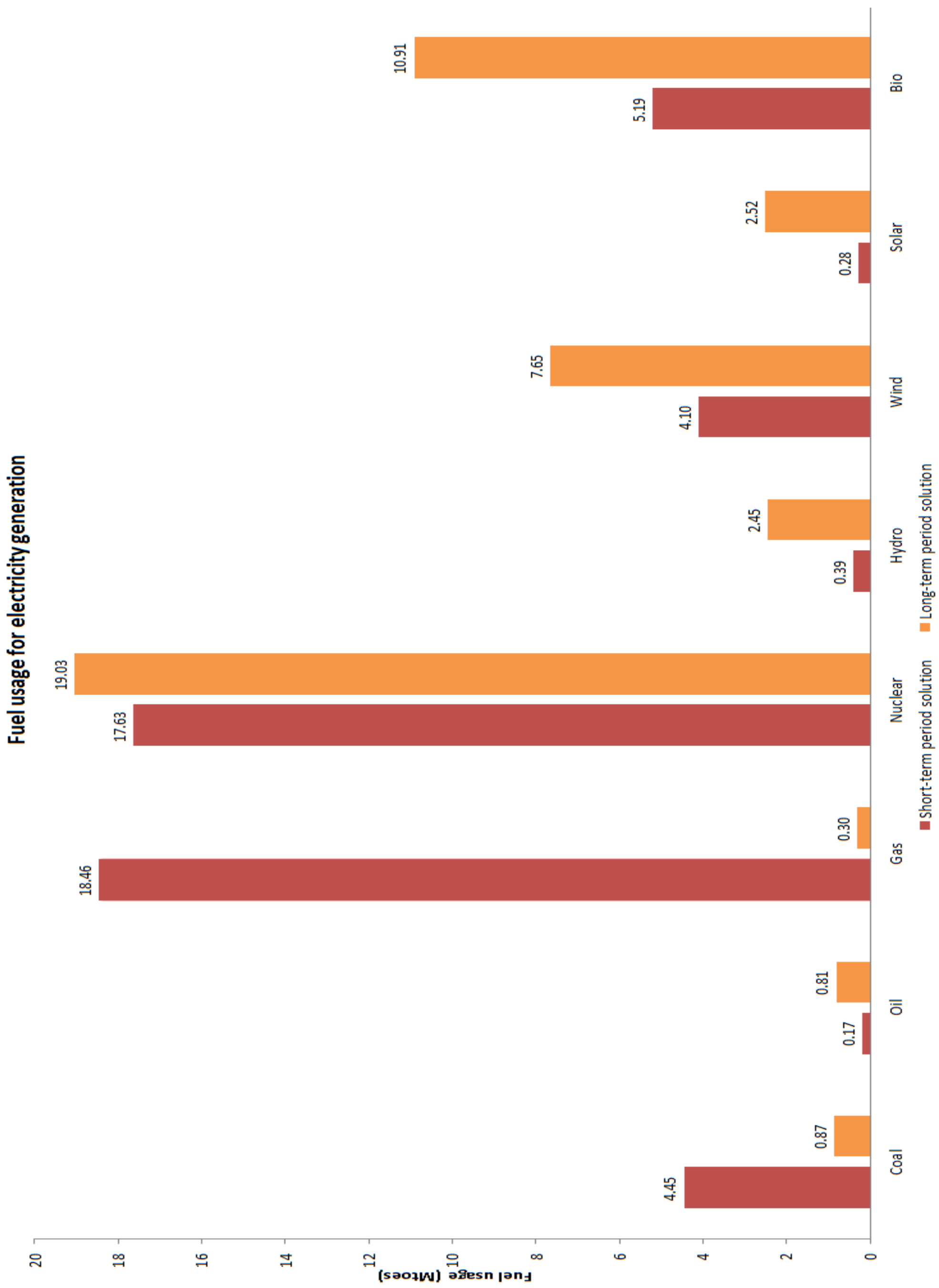


Figure 4.12: Comparison of the fuel usage plan for electricity generation in the short-term period and long-term period.

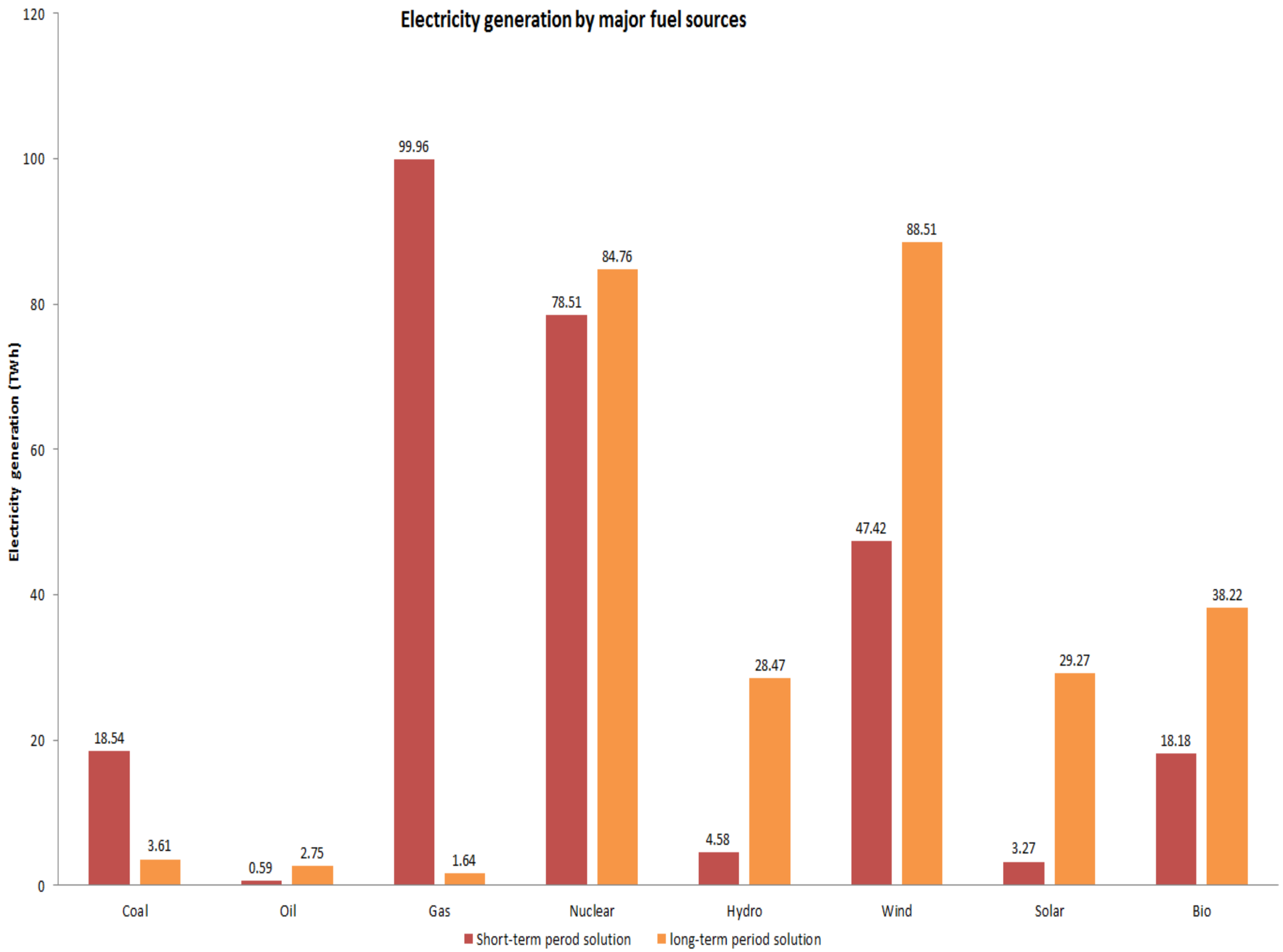


Figure 4.13: Comparison of the electricity generation by major fuel sources in the short-term period and long-term period.

Fig. 4.12 and Fig. 4.13 present fuel usage and accordingly electricity generation in the long-term period. Without the boundary limit, the use of nuclear, bioenergy and wind begin to predominate. The generation from wind ranks first, that is 32% of the total amount. The use of wind takes 17% of the total fuel usage. Nuclear is suggested to account for 43% of the total fuel usage, and contribute to 31% of the total electricity generation. The generation from bio, solar and hydro are relatively low, occupying 14%, 10% and 10%, respectively. The use of traditional fuel sources, i.e., coal, oil and gas, experience a dramatic decline. The total amount of electricity generated from these sources only holds 3%. This trend do follow the U.K.'s target.

4.6 Sensitivity Analysis Results

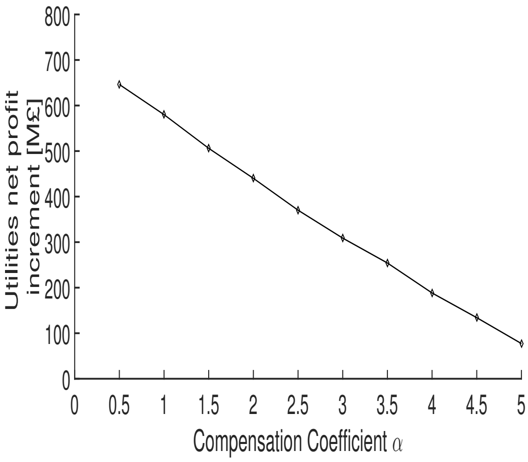
In this section, sensitivities of the model to several system coefficients are analysed. The system performance varies with the change of coefficients. These can give a suggestion that how to appropriately design the compensation mechanism and RESs related policies.

4.6.1 Sensitivity to compensation coefficient

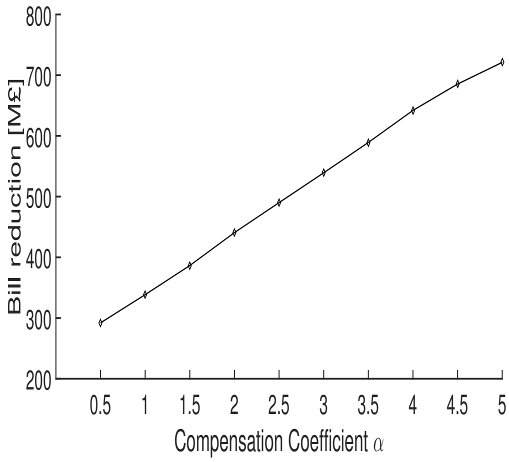
Firstly, the sensitivity to compensation coefficient α is examined. The compensation coefficient α indicates how would utilities encourage customers to involve in the market, where $\alpha > 0$. To analyse it, the compensation coefficient α is increased from 0.5 to 5 by the step of 0.5, and other coefficients remain the same as stated in Section 4.5.1.

Fig. 4.14 shows the detailed system performance. As α increases, the utilities' net profit and customers' bill reduction have a reciprocal relationship, and the carbon emission reduction decreases in a quadratic way. At the same level of carbon emission reduction, a larger α means more compensation would be paid to customers. Therefore, the increase in α is conducive to customers. Customers bill reduction is increased as compensation coefficient α increases. Because this compensation directly comes from utilities, utilities net profit decreases correspondingly.

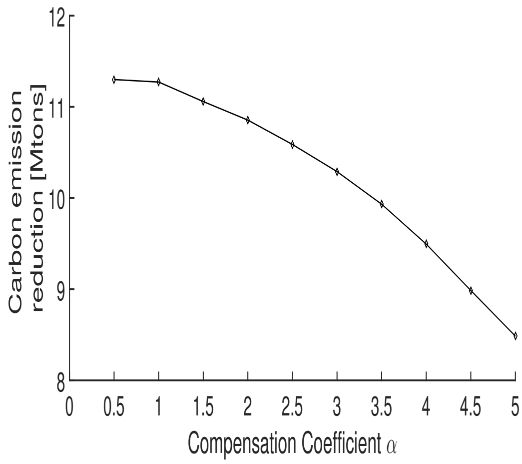
With regard to the carbon emission reduction, for the same amount of compensation, a larger α means a less level of carbon emission reduction is required. Therefore, the increases in α would result more carbon emission. Based on simulation results, paying more to customers could not guarantee to achieve a better carbon emission reduction. But paying too little to customers could not persuade them to positively participant in the market. To promote the normal operation of the market, a suitable compensation rate should be designed.



(a) Utilities' net profit increment VS α



(b) Bill reduction VS α

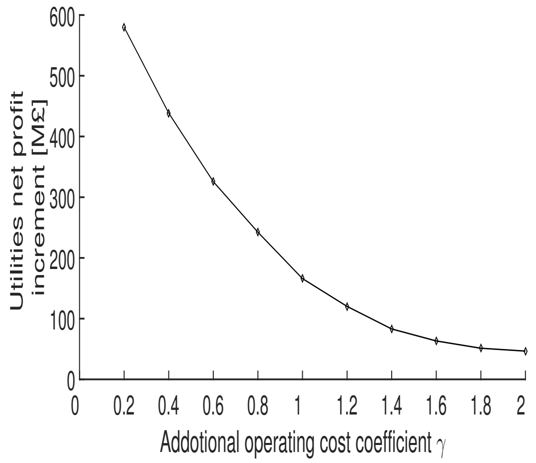


(c) Carbon emission reduction VS α

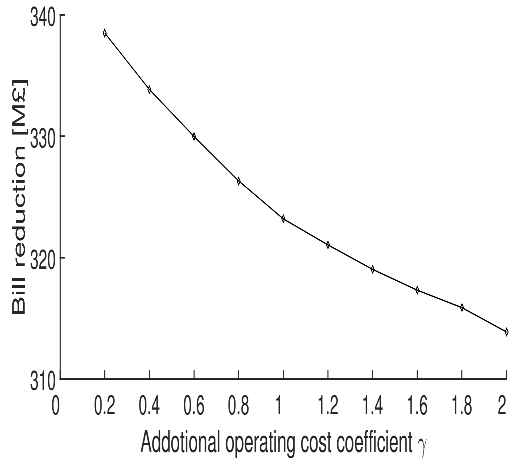
Figure 4.14: The system performance with the change of compensation coefficient α.

4.6.2 Sensitivity to additional operating cost coefficient

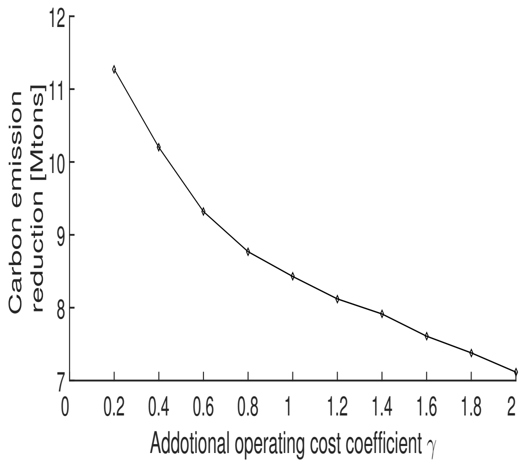
Secondly, the sensitivity to additional operating cost coefficient γ is examined. The additional operating cost coefficient γ indicates how the change of fuel source would affect the generation cost, where $\gamma > 0$. To analyse it, the additional operating cost coefficient γ is increased from 0.2 to 2 by the step of 0.2, and other coefficients remain the same as stated in Section 4.5.1.



(a) Utilities' net profit increment VS γ



(b) Bill reduction VS γ



(c) Carbon emission reduction VS γ

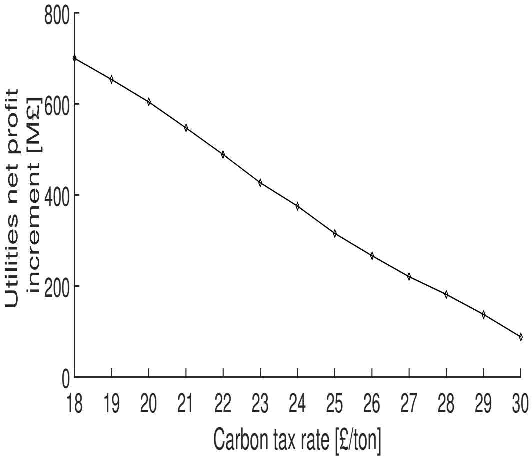
Figure 4.15: The system performance with the change of additional operating cost coefficient γ.

Fig. 4.15 shows the detailed system performance. As γ increases, the utilities' net profit, customers' bill reduction and the carbon emission reduction all decrease in a quadratic way. At the same level of generation change for a certain source, a larger γ means more additional cost would be caused. To avoid raising the total cost, utilities would adjust the usage of fuel source on a smaller scale. Therefore, the increase in γ urges utilities to stick to the original plan. In this case, policy makers can not have carbon emission reduction for full-scale implementation effort. And customers would be required less involvement and receive less compensation from utilities. The bill reduction for customers would consequently be less. In a word, the increase in γ would have a negative effect on the whole system. However, to be noticed, with the progress of science and technology, the additional operating cost should be reduced gradually.

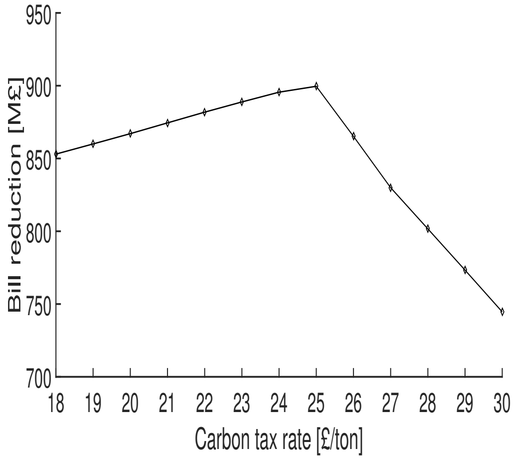
4.6.3 Sensitivity to carbon tax rate

Thirdly, the sensitivity to carbon tax rate m is examined. The particular policy about carbon tax in the U.K. is called carbon price floor (CPF) [144]. When it was first introduced in 2013, the government projected to increase the carbon tax every year till £30/ton in 2020. But in 2014, the government declared to maintain a cap price at £18/ton until 2020. This is because the U.K. had a higher carbon price than other E.U. countries at that time due to the CPF. This price frozen can help to restrict competitive disadvantages for energy-intensive industries [144]. And this period was prolonged to 2021 in 2016. For short-term, the carbon tax rate would remain the same. And for long-term, RESs would dominate the fuel mix, and the carbon emission should be effectively reduced. The carbon tax would have a limit effect on the generation cost at that time. Given that, the sensitivity to carbon tax rate m is analysed at mid-term. The adjustable range of fuel source is set at 50% of the benchmark. The carbon tax rate m is increased from 18 to 30 by the step of 1, and other coefficients remain the same as stated in Section 4.5.1.

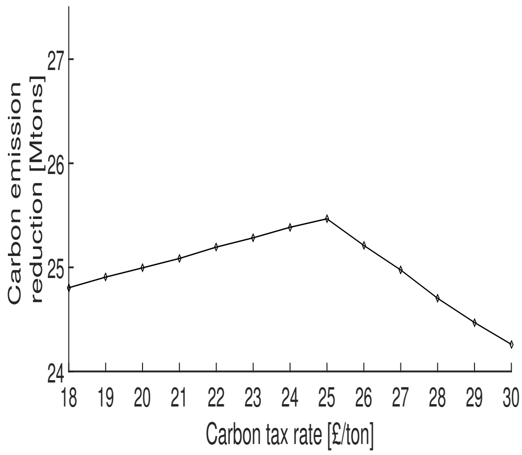
Fig. 4.16 shows the detailed system performance. As m increases, the utilities' net profit drops dramatically. Between the range of £18/ton to £25/ton, customers bill reduction and carbon emission reduction increase, while between the range of



(a) Utilities' net profit increment VS m



(b) Bill reduction VS m



(c) Carbon emission reduction VS m

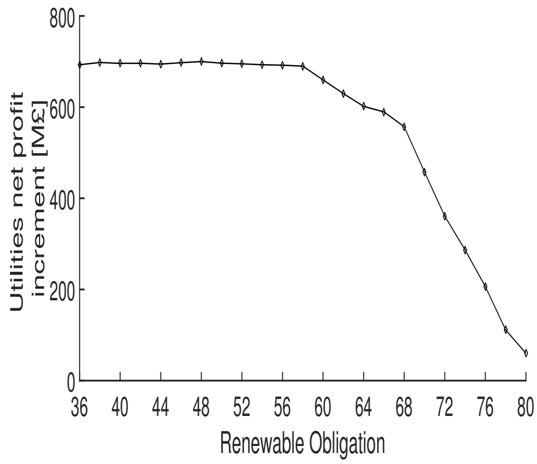
Figure 4.16: The system performance with the change of carbon tax rate m.

£25/ton to £30/ton, customers bill reduction and carbon emission reduction decrease. Comparing three objectives, the carbon tax has a significantly effect on utilities' net profit than the other two. The carbon emission could be further reduced in a small scale with the carbon tax increased in a certain range. The carbon tax should be deliberately set by policy makers that can both facilitate the carbon emission reduction and maintain the market stability.

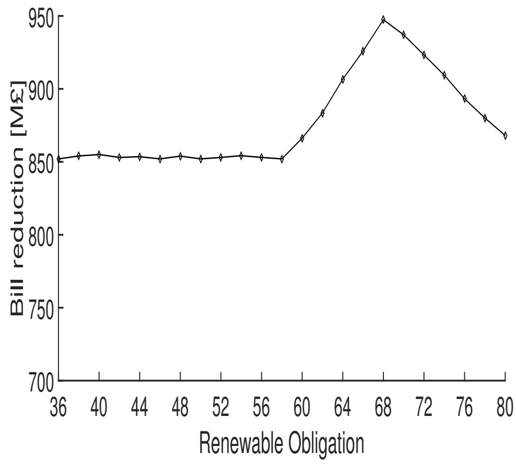
4.6.4 Sensitivity to Renewable Obligation

Fourthly, the sensitivity to Renewable Obligation R is examined. For short-term, fuel usage of each source can not have a dramatic change and generation from RESs cannot experience an enormous increase. And for long-term, the penetration of RESs should reach a relatively high level. Because of these, the sensitivity to Renewable Obligation R is also analysed at mid-term. The adjustable range of fuel source is also set at 50% of the benchmark. The Renewable Obligation R is increased from 36% to 80% by the step of 2%. And other coefficients remain the same as stated in Section 4.5.1.

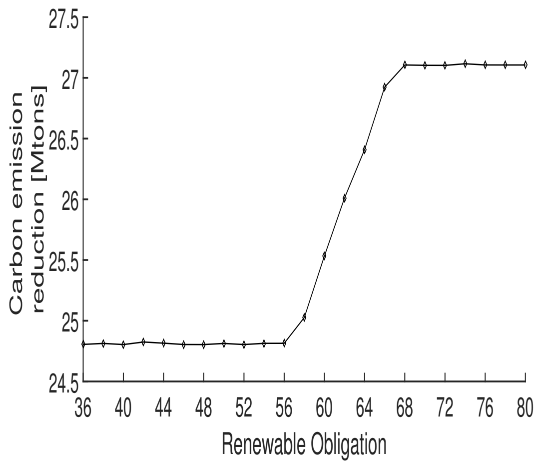
Fig. 4.17 shows the detailed system performance. Between the range of 36% to 56%, the system performance does not change. This means at that time the penetration of RESs is higher than the Renewable Obligation. Therefore the change of Renewable Obligation would not influence utilities. Between the range of 56% to 68%, the carbon emission reduction increases obviously, while the utilities' net profit decreases. This indicates utilities would use more RESs to reach the Obligation. Between the range of 68% to 80%, the carbon emission reduction remains the same, while utilities net profit decreases at a more rapid rate. With the limit of each fuel source, utilities could not adjust the usage any more at that time. The carbon emission reduction is maximized at that situation. Because the Renewable Obligation is not achieved, utilities need to pay extra for it. Hence the generation cost is raised and the net profit is accordingly reduced.



(a) Utilities' net profit increment VS R



(b) Bill reduction VS R



(c) Carbon emission reduction VS R

Figure 4.17: The system performance with the change of Renewable Obligation R.

4.7 Chapter Summary

This chapter introduced a system model that consists of consumers, utilities, and policy makers. Consumers aimed to minimize the bill, utilities aimed to maximize the net profit, and policy makers aimed to minimize the carbon emission. This model formed a MOP. The MMD approach for MCDM was proposed to select the final solution, compared with WS approach and D & C approach. Simulation results showed that these three approaches can yield a same solution. But MMD was more efficient in computational time. Both the short-term period and long-term period case studies suggested a larger portion of RESs, especially nuclear, wind and bioenergy, and a less portion of traditional sources. Compared to the selected optimal solution, carbon emission optimal solution preferred nuclear and wind, and utilities optimal solution preferred solar and wind. After that, the system sensitivity was examined. As the compensation coefficient α increased, utilities' profit and customers' bill decreased, while the carbon emission increased. As the additional operating cost coefficient γ increased, the whole system had a worse performance. As the carbon tax rate m increased, the utilities' net profit decreased significantly. As the Renewable Obligation R increased in a certain range, the carbon emission can be effectively reduced.

Chapter 5

Assessment of the Demand Side Management's Impacts on Carbon Emission Reduction

5.1 Introduction

This chapter introduces a CEF model to facilitate the analysis and assessment of carbon emissions in power networks [117, 118]. It can virtually allocate the carbon emission from the generation side to the consumption side. This enables a sensible measure to mitigate the carbon emission according to network's specific information. This chapter extends the scope of presented model by considering smart grid technologies intervention. Using CEF model, the impacts of DSM approaches on carbon emission can be precisely obtained. The IEEE 30-bus system is used to demonstrate the framework of CEF, involving the U.K. actual daily data of electricity generation and demand. Three levels of load curtailment (5%, 10%, and 15%) and load shift approach proposed in Chapter 3 are examined by the model, for the purpose of evaluating carbon emission. Simulation results confirm the effectiveness of load curtailment and load shift approaches for the carbon emission reduction. In the case of load curtailment, a higher level of curtailment can result in a higher carbon emission reduction. In the case of load shift, the carbon emission can be effectively reduced, particularly during the peak time. In addition, winter day shows a better carbon emission reduction than summer day with proposed DSM approaches. Compared with existing researches, the main contributions of this chapter can be summarised as follows:

- The time sensitivity of carbon emission can be obtained by applying the U.K. actual daily data of electricity generation and demand to the model.
- The effectiveness of load curtailment and load shift approaches for carbon emission reduction can be precisely quantified.
- The typical winter day and summer day are selected to extend the analysis of carbon emission reduction with DSM approaches.

The chapter is organized as follows. Section 5.2 introduces the CEF model, including two concepts and four types of the CEF. Section 5.3 presents the static case study, which is based on the IEEE 30-bus system. Section 5.4 provides the daily case study. The effectiveness of several DSM approaches is analysed. Section 5.5 gives the seasonal case. Finally, Section 5.6 concludes this chapter.

5.2 Carbon Emission Flow Model

This section defines two concepts and four types of the CEF, and then explains how to calculate the CEF from power flow. The CEF is defined as a virtual network flow that describes the carbon emission from power network [117]. The CEF concepts and types are explained as follows.

5.2.1 Definition

In power flow model, the node that is connected with power generators can be defined as an outflow node. The transmission line between two nodes can be defined as a branch. And the node that is connected with consumers can be defined as an inflow node. These definitions are used to explain the CEF model.

- Ejected CEF (ECEF): The ECEF is the carbon emission outflow produced from generators to node because of the combustion of fossil fuel. It can be analogous to the power generation in the power flow.

- Branch CEF (BCEF): The BCEF is the CEF through the branch. It can be analogous to the power transmission in the power flow.

- Injected CEF (ICEF): The ICEF is the carbon emission inflow obtained from branches to the node. It can be analogous to the power consumption at node in the power flow.

- Branch carbon emission loss (BCEL): The BCEL is the carbon emission caused by the power offset due to transmission loss. It can be analogous to the branch loss in the power flow.

- CEF rate: The CEF rate describes the amount of CEF in the network for per unit of time.

- CEF intensity: The CEF intensity describes the amount of CEF in the network for per unit of active power.

A typical IEEE 5-bus system is presented here to demonstrate four types of the CEF. It consists of 2 generators, 4 loads and 5 buses.

5.2.2 Calculation Model

In this section, the CEF calculation model proposed from [117] is briefly presented based on aforesaid definitions. The calculation for the CEF rate and intensity are illustrated at first. Both the CEF rate and intensity can be applied to four types of the CEF. Suppose the network consists of G generators, L loads and B buses. And generators can be classified according to the used fuel source.

CEF rate

The CEF rate indicates the velocity of CEF that come across the node/branch. It is denoted by R and can be expressed as

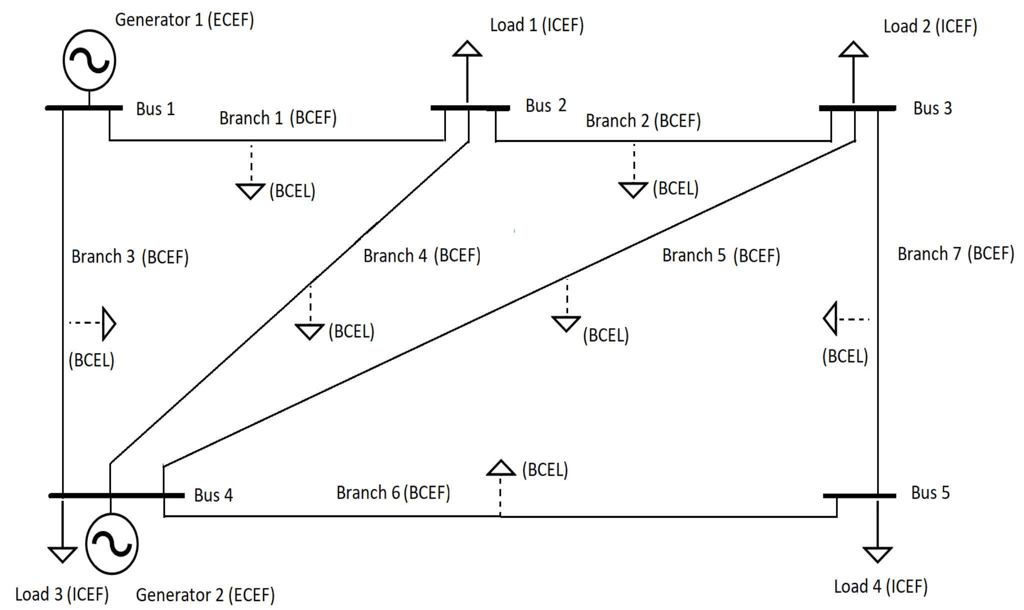


Figure 5.1: Demonstration of the CEF model by an IEEE 5-bus system.

$$R = \frac{dE}{dt} \tag{5.2.1}$$

in the unit of tonne of CO_2 per hour (tCO_2/h), where E is the CEF in the unit of tonne of CO_2 (tCO_2), and t is the time index.

CEF intensity

The CEF intensity indicates the relationship between CEF and active power. It is denoted by I and can be expressed as

$$I = \frac{R}{P} \tag{5.2.2}$$

in the unit of tonne of CO_2 per MWh (tCO_2/MWh), where P is the active power flow.

ECEF

The intensity of ECEF is determined by the type of generators and can be obtained directly. If the node only connects to one type of generators, the ECEF of this outflow node is equal to the generation carbon emission intensity. It depends on the type of used fuel source, and can be easily calculated based on the carbon emission coefficient and generation coefficient that introduced in Section 4.2, as below

$$I_G = \frac{e_n}{u_n} \tag{5.2.3}$$

where e_n denotes the coefficient that transfers the fuel usage into the carbon emission, u_i denotes the coefficient that transfers the fuel usage into the electricity generation. If the node connects to more than one type of generators, the ECEF of this outflow node depends on all operated generators and can be calculated as

$$I_G = \frac{\sum_{n=1}^{N_f} e_n s_n}{\sum_{n=1}^{N_f} u_n s_n} \tag{5.2.4}$$

$$P = \sum_{n=1}^{N_f} u_n s_n \tag{5.2.5}$$

where N_f denotes the types of fuel sources that connected generators used, and s_n denotes the fuel usage of source n.

Once the ECEF intensity is available, the ECEF rate can be calculated as

$$\mathbf{R_G} = \mathbf{P_G} \cdot \mathbf{I_G} \tag{5.2.6}$$

where $\mathbf{R_G}$ is a B dimensional column vector of ECEF rate, $\mathbf{I_G}$ is a G dimensional column vector of ECEF intensity composed by I_G, and $\mathbf{P_G}$ is a $B \times G$ active power ejection matrix. The matrix $\mathbf{P_G}$ can reveal the position of generators. When the ath node is connected with the bth generator/genrators at capacity P, $P_G(a, b) = P$; otherwise $P_G(a, b) = 0$.

BCEF

The proportional sharing principle for electricity is used here for tracing the CEF mix from node to different branches [146]. It is an assumption that can build a physical link between inflow power and outflow power. The node is assumed to be a perfect "mixer" to distribute the power flow. At any node, the inflow power is shared proportionally by the outflow power. Fig. 5.2 is presented here to demonstrate the principle.

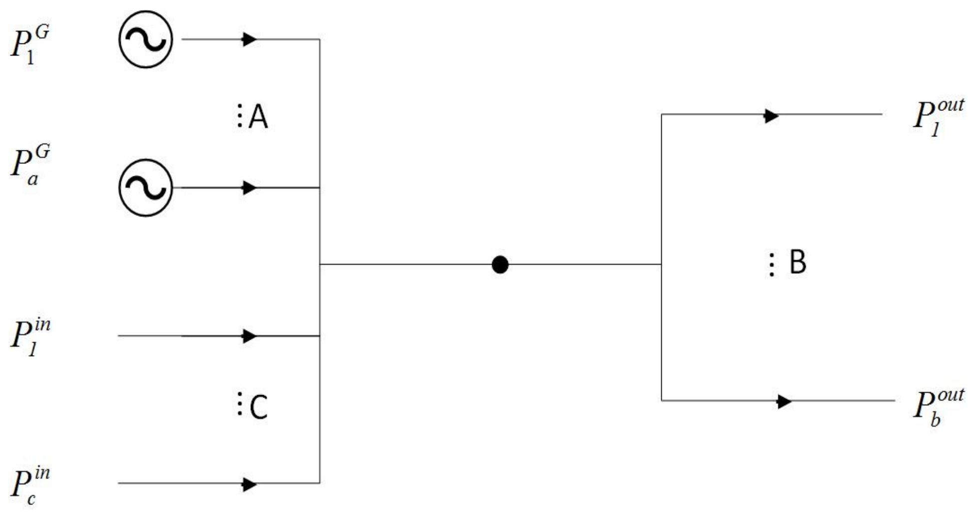


Figure 5.2: Demonstration of proportional sharing principle.

The power provided from generators into the node is defined as $P^G = \left\{P_a^G : a \in A\right\}$, the power flow from branches into the node is defined as $P^{in} = \{P_c^{in} : c \in C\}$, the power flow out of the node is defined as $P^{out} = \{P_b^{out} : b \in B\}$. The power lost/consumed at the node is also regarded as the outflow power. The proportional sharing principle can be expressed as

$$\frac{P_{b,a}^{out}}{P_b^{out}} = \frac{P_a^G}{\sum_{a=1}^{A} P_a^G + \sum_{c=1}^{C} P_c^{in}} \tag{5.2.7}$$

$$\frac{P_{b,c}^{out}}{P_b^{out}} = \frac{P_c^{in}}{\sum_{a=1}^{A} P_a^G + \sum_{c=1}^{C} P_c^{in}} \tag{5.2.8}$$

where $P_{b,a}^{out}$ is the share of power in the bth branch that comes from the ath generator, and $P_{b,c}^{out}$ is the share of power in the bth branch that comes from the cth branch.

Abiding by the principle, the power flow in the bth branch can be regarded as a hybrid of power that comes from branches in C and generators in B. Therefore, the CEF rate for the bth branch can be expressed as

$$R_b = \sum_{a=1}^{A} P_{b,a}^{out} \cdot I_G + \sum_{c=1}^{C} P_{b,c}^{out} \cdot I_c \tag{5.2.9}$$

where I_G is the ECEF intensities for generators, and I_c is the CEF rate for the cth branch. The CEF intensity for the bth branch can be then obtained as

$$\begin{aligned} I_b =& \frac{R_b}{P_b^{out}} = \frac{\sum_{a=1}^{A} P_{b,a}^{out} \cdot I_G + \sum_{c=1}^{C} P_{b,c}^{out} \cdot I_c}{P_b^{out}} \\ =& \frac{\sum_{a=1}^{A} \big(\frac{P_a^G}{\sum_{a=1}^{A} P_a^G + \sum_{c=1}^{C} P_c^{in}} \cdot P_b^{out}\big) \cdot I_a + \sum_{c=1}^{C} \big(\frac{P_c^{in}}{\sum_{a=1}^{A} P_a^G + \sum_{c=1}^{C} P_c^{in}} \cdot P_b^{out}\big) \cdot I_c}{P_b^{out}} \\ =& \frac{\sum_{a=1}^{A} P_a^G \cdot I_a + \sum_{c=1}^{C} P_c^{in} \cdot I_c}{\sum_{a=1}^{A} P_a^G + \sum_{c=1}^{C} P_c^{in}} = \frac{R_G + R_C}{P^G + P^{in}} \end{aligned} \tag{5.2.10}$$

According to the equation (5.2.10), the BCEF intensity for the bth outflow branch is independent of itself, but dependent on branches in C and generators in A. Therefore, the BCEF intensity is the same for every branch in B.

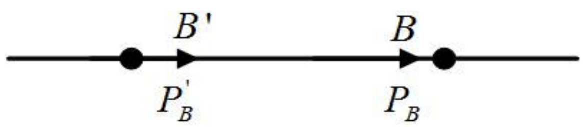


Figure 5.3: Relationship between branch power flow and node power flow.

It is noted that the node inflow power is the branch outflow power as shown in Fig. 5.3. Expanding the equation (5.2.10) to the whole network, the following equation can be obtained

$$\mathbf{I_B} = \frac{\mathbf{R_G} + \mathbf{P_B^T} \cdot \mathbf{I_B}}{\mathbf{P_N}} \tag{5.2.11}$$

where $\mathbf{I_B}$ is a B dimensional column vector of BCEF intensity, $\mathbf{P_N}$ is a $B \times B$ node power flow diagonal matrix, and $\mathbf{P_B}$ is a $B \times B$ branch active power outflow distribution matrix. For matrix $\mathbf{P_N}$, the ath diagonal element is the total inflow power at the ath node. For matrix $\mathbf{P_B}$, it reveals the power transmission between nodes. When there is power straightly flowing from the ath node to the bth node at the quantity of P, the power outflow for this branch is P, that is $P_B(a,b) = P$; otherwise $P_B(a,b) = 0$.

Thus, the BCEF intensity vector is derived. It is related to the branch power outflow and the node active power inflow. It can be calculated as

$$\mathbf{I_N} = (\mathbf{P}_N - \mathbf{P_B}^{\mathbf{T}})^{-1} \cdot \mathbf{R_G} \tag{5.2.12}$$

The BCEF rate can be calculated on the basis of BCEF intensity as

$$\mathbf{R_B} = diag(\mathbf{I_N}) \cdot \mathbf{P_B} \tag{5.2.13}$$

where *diag* denotes the diagonal matrix operator, and $\mathbf{R_B}$ is a $B \times B$ BCEF rate matrix.

ICEF

The ICEF for a given node should be the total of BCEF that flows from connected branches into the connected load, as the equation (5.2.14) expressed.

$$E_{ICEF} = \sum_{n \in B} E_{BCEF,n} - \sum_{n \in B'} E_{BCEF,n} \tag{5.2.14}$$

where B represents inflow branches, and B' represents outflow branches.

The ICEF rate should also abide this rule, and can be expressed as

$$R_I = \sum_{n \in B} R_{B,n} - \sum_{n \in B'} R_{B,n} \tag{5.2.15}$$

In the power system, the power load at node can be regarded as an outflow branch. And according to the previous section, the BCEF intensity is the same for every outflow branch that connected to a given node. Therefore, the ICEF intensity should be the same as the BCEF intensity and can be also calculated as

$$\mathbf{I_I} = (\mathbf{P}_N - \mathbf{P_B}^{\mathbf{T}})^{-1} \cdot \mathbf{R_G} \tag{5.2.16}$$

where $\mathbf{I_I}$ is a B dimensional column vector of ICEF rate.

The ICEF intensity can be used to calculate the ICEF rate. It can be expressed as

$$\mathbf{R_I} = diag(\mathbf{I_I}) \cdot \mathbf{P_I} \tag{5.2.17}$$

where $\mathbf{R_I}$ is a $B \times L$ ICEF rate matrix, and $\mathbf{P_I}$ is a $B \times L$ injection power distribution matrix. The matrix $\mathbf{P_I}$ can reveal the position of loads. When the ath node is connected with the bth load/loads at capacity P, $P_I(a, b) = P$; otherwise $P_I(a, b) = 0$.

BCEL

Same as the load, the branch loss can also be regarded as an outflow branch. The BCEL intensity has the same value as the BCEF intensity and can be used to calculate the BCEL rate. It can be expressed as

$$\mathbf{I_L} = (\mathbf{P}_N - \mathbf{P_B}^{\mathbf{T}})^{-1} \cdot \mathbf{R_G} \tag{5.2.18}$$

$$\mathbf{R_L} = diag(\mathbf{I_B}) \cdot (\mathbf{P_B^1} - \mathbf{P_B}) \tag{5.2.19}$$

where $\mathbf{I_L}$ is a B dimensional column vector of BCEL rate, $\mathbf{R_L}$ is a $B \times B$ BCEL rate matrix, and $\mathbf{P}_B^1$ is a $B \times B$ branch active power inflow distribution matrix.

Analogous to the power conservation, the CEF also leads to the emission conservation, and can be expressed as

$$\sum_{n \in G} E_{ECEF,n} = \sum_{n \in L} E_{ICEF,n} + \sum_{n \in B} E_{BCEL,n} \tag{5.2.20}$$

Procedure

According to the presentation above, the process to calculate the CEF for power network can be divided into 5 steps as below.

- <u>Step 1:</u> Carry out the power flow analysis. Obtain the power ejection matrix $\mathbf{P_G}$, power injection matrix $\mathbf{P_I}$, node power flow matrix $\mathbf{P_N}$, branch power outflow matrix $\mathbf{P_B}$ and branch power inflow matrix $\mathbf{P_B^1}$.

- <u>Step 2:</u> Find out nodes that connect with generators, known as ejection nodes. Calculate the ECEF intensity $\mathbf{I_G}$ based on carbon emission coefficients and generation coefficients. Derive the ECEF rate $\mathbf{R_G}$ from the ECEF intensity.

- Step 3: Calculate the BCEF intensity $\mathbf{I_B}$ by following the proportional sharing principle. Derive the BCEF rate $\mathbf{R_B}$ from the BCEF intensity.
- Step 4: Derive the ICEF intensity $\mathbf{I_I}$ from the BCEF intensity. Find out nodes that connect with loads. Calculate the ICEF rate $\mathbf{R_I}$ by considering power consumption.
- Step 5: Derive the BCEL intensity $\mathbf{I_B}$ from the BCEF intensity. Calculate the BCEL rate $\mathbf{R_I}$ by considering power loss.

5.3 Static Case

A typical IEEE 30-bus system is used to demonstrate the model. The simulation is conducted by using the software MATLAB and MATPOWER. The system consists of 6 generators, 21 loads, 30 buses and 41 branches. The static case is first presented.

The default optimal power flow data from MATPOWER and the emission factor from [134] are applied to testify the calculation model and analysis four types of the CEF. For one hour, the total power generation of 6 generators is 191.75MW, the total consumption of 21 loads is 189.30MW, and the total power loss of 41 branches is 2.45MW. As for the carbon emission, the total ECEF is 177.715 tCO_2, the total ICEF is 175.542 tCO_2, and the total BCEL is 2.173 tCO_2. These results obey the principle described in (5.2.20).

Table I presents the ECEF rates and intensities. The ECEF intensities depend on the types of generators and can be calculated straightforward. By considering the generation capacity of each generator, the corresponding ECEF rate can be calculated according to equation (5.2.6).

The remaining CEF rates and intensities can be obtained on the basis of ECEF rate and power flow data. Fig. 5.4 shows the IEEE 30-bus system model. The BCEF rates (tCO_2/h) between each bus are marked to illustrate the CEF distribution. The simulation results from bus 21 to bus 24 are selected in Table II and Table III to demonstrate the model. The ”→” symbol in Table III indicates the direction of power flow. Several investigations can be obtained from it.

Table 5.1: ECEF calculation for generators

Node	Generator	Generation [MW]	ECEF intensity [tCO_2/MWh]	ECEF rate [tCO_2/h]
Bus 1	G1	26.077	1.186	30.927
Bus 2	G2	60.970	1.186	72.310
Bus 22	G3	21.590	1.186	25.606
Bus 27	G4	26.910	0.434	11.679
Bus 23	G5	19.200	0.434	8.333
Bus 13	G6	37.000	0.78	28.860

Table 5.2: ICEF results for buses

Node	Load Capacity [MW]	ICEF intensity [tCO_2/MWh]	ICEF rate [tCO_2/h]
Bus 21	17.45	1.119	19.527
Bus 22	0	1.119	0
Bus 23	3.20	0.434	1.389
Bus 24	8.70	0.430	3.741

Table 5.3: BCEF & BCEL results for branches

Branch	BCEF/BCEL intensity [tCO_2/MWh]	BCEF rate [tCO_2/h]	Power loss [MW]	BCEL rate [tCO_2/h]
Bus 22 → Bus 21	1.119	22.140	0.093	0.104
Bus 23 → Bus 24	0.434	3.047	0.066	0.029
Bus 24 → Bus 22	0.430	0.914	0.078	0.034
Bus 21 → Bus 10	1.119	2.506	0.044	0.049

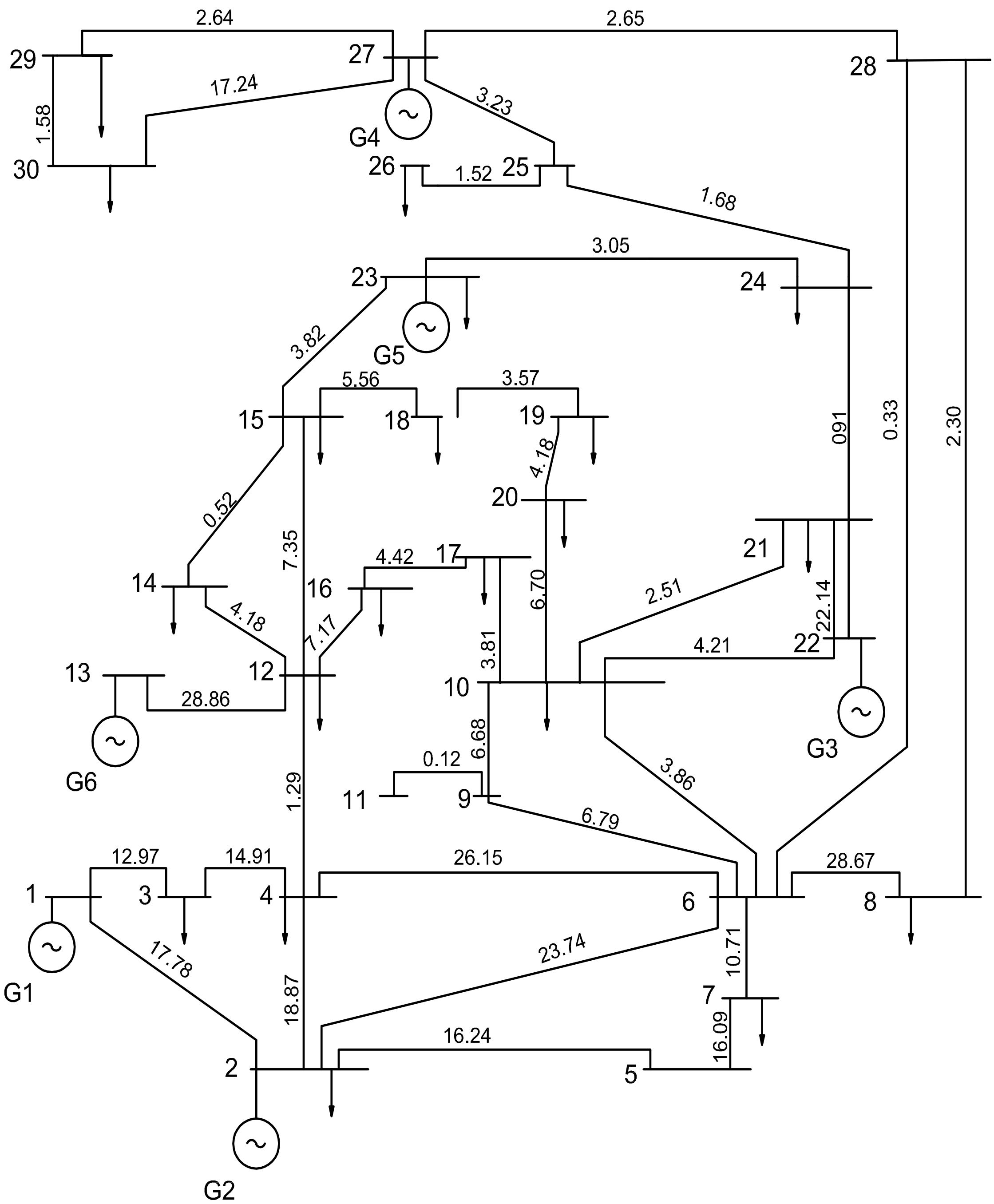


Figure 5.4: The CEF model of an IEEE 30-bus system.

- For bus 21, the inflow power only comes from bus 22. Therefore, it has the same ICEF intensity as bus 22.
- For bus 22, the inflow power comes from G3 and bus 24. The ICEF intensity of bus 22 is a little bit lower than that of G3, because bus 24 has a relatively lower intensity. If the inflow power from bus 24 reduces, the ICEF intensity of bus 22 increases, but cannot be higher than that of G3. The ICEF rate of bus 22 is 0 because there is no load connected to it.
- For the branch that connects bus 22 and bus 21, the high BCEF intensity, large power transmission, and large power loss result in a high BCEF rate and a high BCEL rate.
- For any given node, the emission conversation also holds true. Bus 21 gets power from bus 22, then consumes part of the power and transfers the remaining part to bus 10. The BCEF rate of the branch that connects bus 22 and bus 21 subtracts the BCEL of it equals to the sum of ICEF rate of bus 21 and BCEF rate of the branch that connects bus 21 and bus 10.

5.4 Daily Case of the U.K. Data

In this section, the U.K. actual daily (5th May 2017) fuel sources usage, electricity generation and demand data from the Grid Watch are fed into the IEEE 30-bus system. These data cover an entire day with 24 time slots. Generators of IEEE 30-bus system and fuel sources of the U.K. actual data are ranked by their generation capacity. Then each generator represents one fuel source by the corresponding order. The detailed ECEF intensity and daily ECEF for 6 generators can be found in Table 5.4. For one day, the total ECEF is 141.162 $ktCO_2$, the total ICEF is 137.693 $ktCO_2$, and the total BCEL is 3.469 $ktCO_2$. With the high ECEF intensity and large power generation, gas turbines contribute to most of the carbon emission.

The simulation results of bus 3 and bus 30 are selected, which have the similar level of power consumption. The ICEF rate and power load of these two buses are presented in Fig. 5.5. It can be seen that the ICEF rates fluctuate with time, which

Table 5.4: ECEF calculation for generators

Generator	Source Type	ECEF intensity [tCO_2/GWh]	Daily generation [GWh]	ECEF [tCO_2]
G1	Bioenergy	45.69	62.574	2859.006
G2	Gas	417.74	307.261	128355.210
G3	Coal	879.38	2.018	1774.589
G4	Wind	25.94	142.503	3696.527
G5	Hydro	29.25	3.580	104.715
G6	Nuclear	24.70	177.019	4372.369

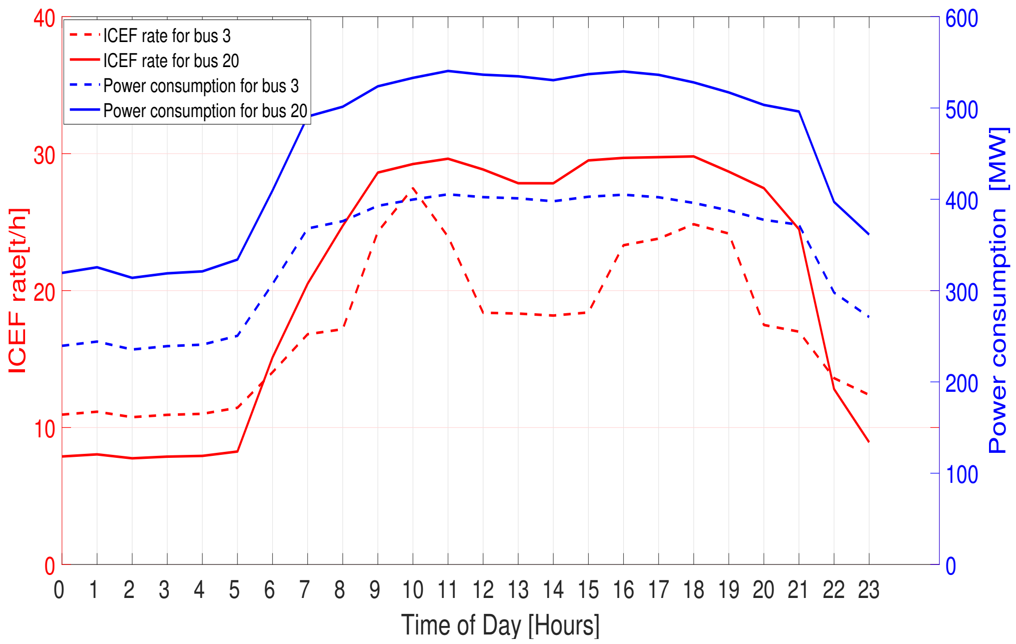


Figure 5.5: Daily ICEF for bus 3 and bus 20.

means a different amount of carbon emission for each time period. For bus 20, the trend of its ICEF rate is consistent with its power consumption. For consumers at bus 20, there are high carbon emission periods, that is 09:00 - 12:00 and 15:00 - 18:00. While during 0:00 - 6:00, when the power consumption is low, the carbon emission is insignificant. However, for bus 3, the trend of its ICEF rate is inconsistent with its power consumption. For consumers at bus 3, the normal demand during 9:00 - 11:00 results in a significant level of carbon emission. But with the similar demand during 12:00 - 15:00, the carbon emission is markedly low. Comparing the carbon emission for both buses during 0:00 - 6:00, bus 20 has higher power consumption, but a lower carbon emission. These bring the importance of CEF model. For different consumers, a higher demand does not necessarily mean a higher carbon emission. With the CEF information available, consumers could know exactly how would their consumptions give rise to the carbon emission for each time period. These also indicate how to suggest DSM programs to different consumers in case of the carbon emission reduction.

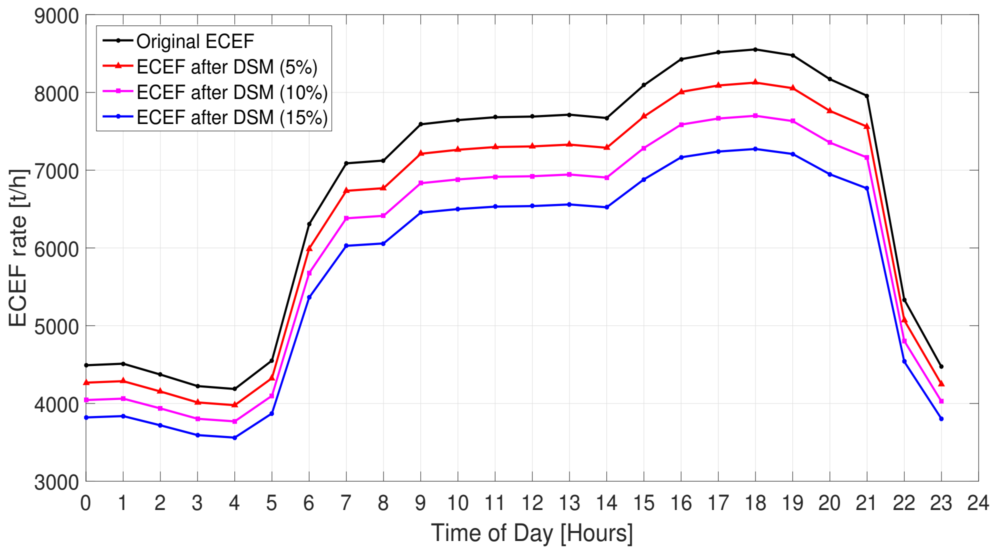
Taking the whole system into consideration, three scenarios are examined here to analysis the effectiveness of DSM for carbon emission reduction.

- S1: Three levels of load curtailments, 5%, 10%, and 15%, are applied to each hour of the day. This scenario indicates how would load conservation approach influence the carbon emission.

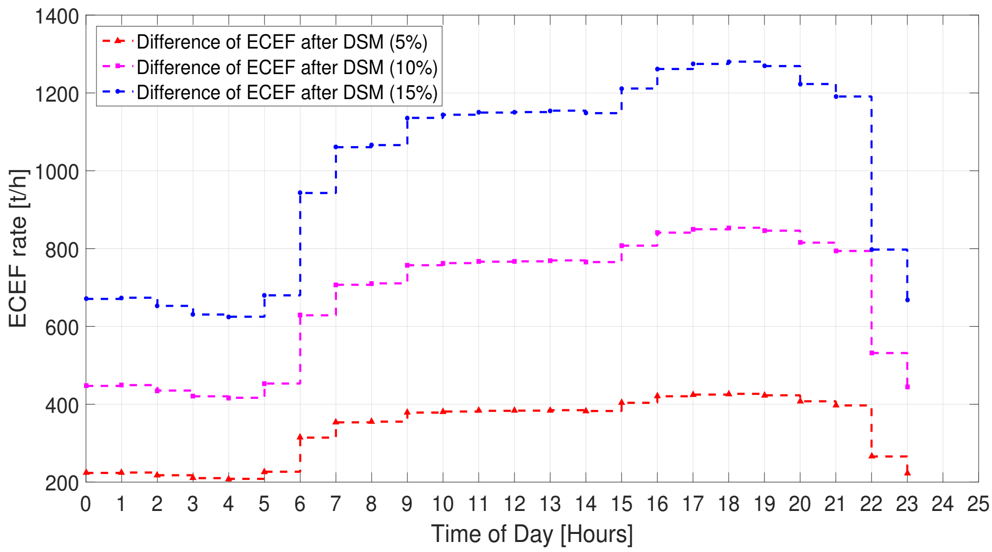
- S2: The optimized load profile proposed at Section 3.4.1 is applied to the model. This scenario indicates how would load shift approach influence the carbon emission.

- S3: Both the load shift proposed at S2 and 5% of load curtailment are applied to the model. This scenario indicates how would load shift approach and load curtailment worked together to influence the carbon emission.

Table 5.5 provides the detailed system performance for these three scenarios. Fig. 5.6 shows the daily ECEF rate with respect to various levels of load curtailment for the selected day. The ECEF patterns have a similar trend as electricity

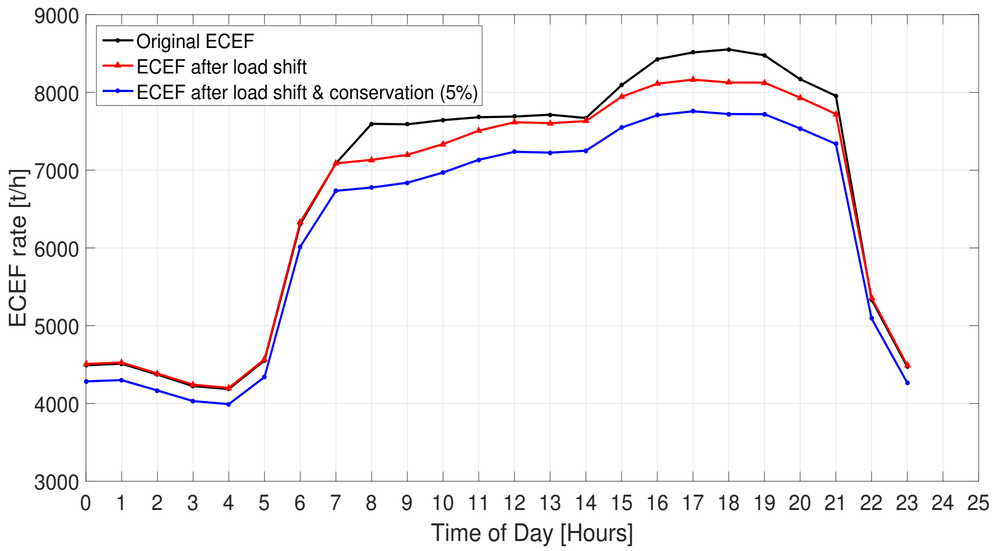


(a) Daily ECEF with respect to various level of load curtailment.

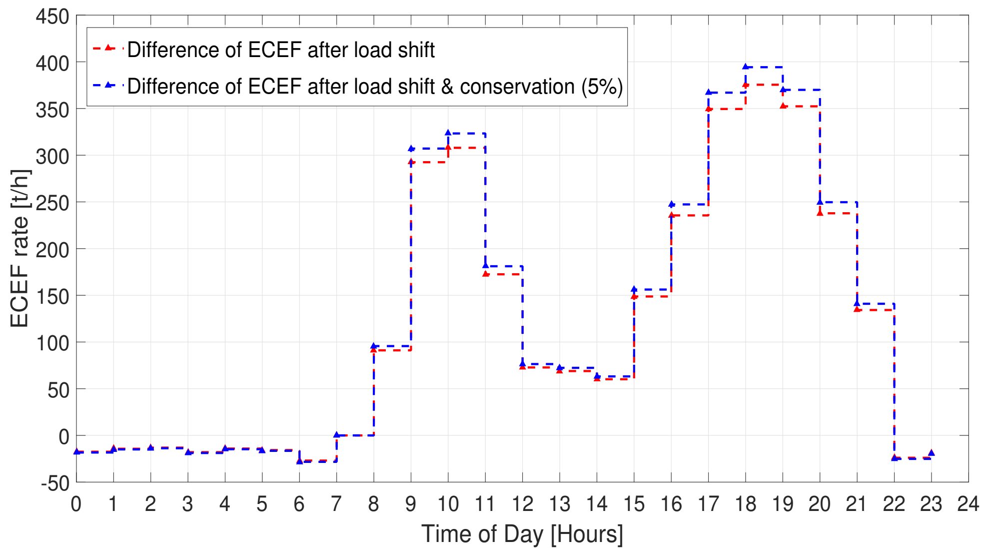


(b) Difference of daily ECEF with respect to various level of load curtailment.

Figure 5.6: Daily ECEF performance with respect to load curtailments on 5th May. 2017.



(a) Daily ECEF with respect to load shift and curtailment.



(b) Difference of daily ECEF with respect to load shift and curtailment.

Figure 5.7: Daily ECEF performance with respect to load shift and curtailment on 5th May. 2017.

Table 5.5: CEF performance on 5th May. 2017

Scenario	Original	S1 (5%)	S1 (10%)	S1 (15%)	S2	S3
ECEF [tCO_2]	160842	152821	144801	136781	157855	149983
ICEF [tCO_2]	157406	149419	141429	133439	154467	146628
BCEL [tCO_2]	3436	3402	3372	3342	3388	3355

demand. There is a peak emission period during 16:00 - 20:00, and a valley emission period during 0:00 - 6:00. As the penetration of load curtailment increases, the ECEF decreases accordingly. The total ICEF are reduced of 7988 tCO_2, 15977 tCO_2 and 23967 tCO_2 for 5%, 10%, and 15% load curtailment, respectively. And the corresponding total ECEF reductions are 8021 tCO_2, 16041 tCO_2, and 24061 tCO_2, respectively. The ICEF reduction and ECEF reduction are proportional to the level of load curtailment.

Fig. 5.7 shows the daily ECEF with load shift and load curtailment. For scenario 2, the total ICEF is reduced of 2939 tCO_2, and the corresponding total ECEF is reduced of 2987 tCO_2. During the period of 0:00 - 8:00, the carbon emission is increased in a small scale. This is because the ECEF intensity is relatively lower during that period, when the demand is shifted to these time slots, the occurred ECEF is unapparent. While during the period of 09:00 - 12:00 and 17:00 - 20:00, the carbon emission reduction is markedly. During these periods, the ECEF intensity is relatively higher. The load shift from these periods can effectively mitigate carbon emission. For scenario 3, the trend of ECEF is the same as in scenario 2. With the load curtailment, the carbon emission can be further reduced.

5.5 Seasonal Case of the U.K. Data

To extend the analysis, the U.K. actual power generation and demand data on 14th Jan. 2017 (typical winter day) and 14th Jul. 2017 (typical summer day) is fed into the IEEE 30-bus system. The proposed CEF model and scenario 3 are applied to the system. Fig. 5.8 and Fig. 5.9 show the daily ECEF performance for the

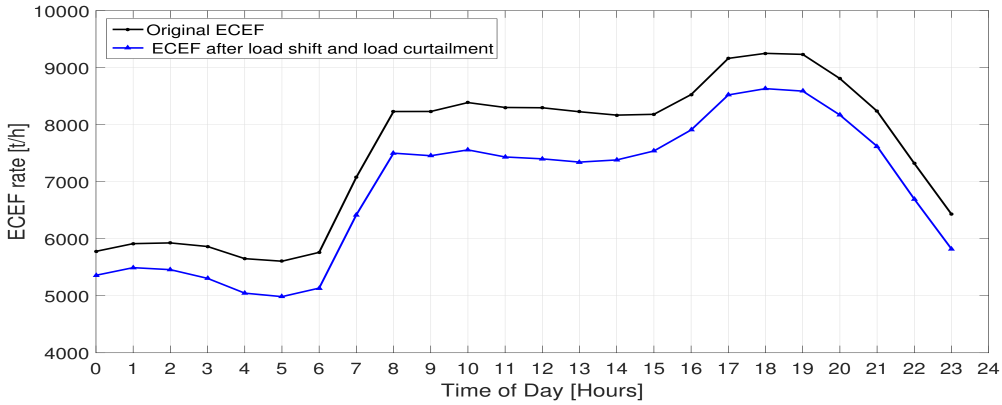


Figure 5.8: Daily ECEF performance on 14th Jan. 2017.

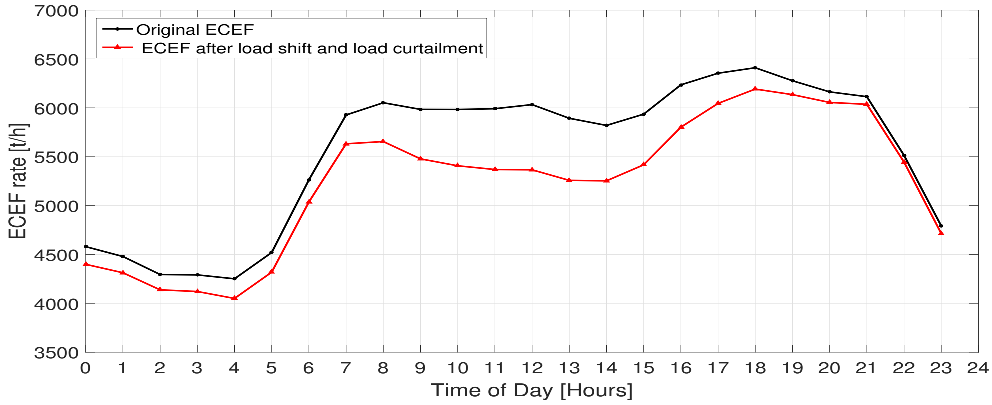


Figure 5.9: Daily ECEF performance on 14th Jun. 2017.

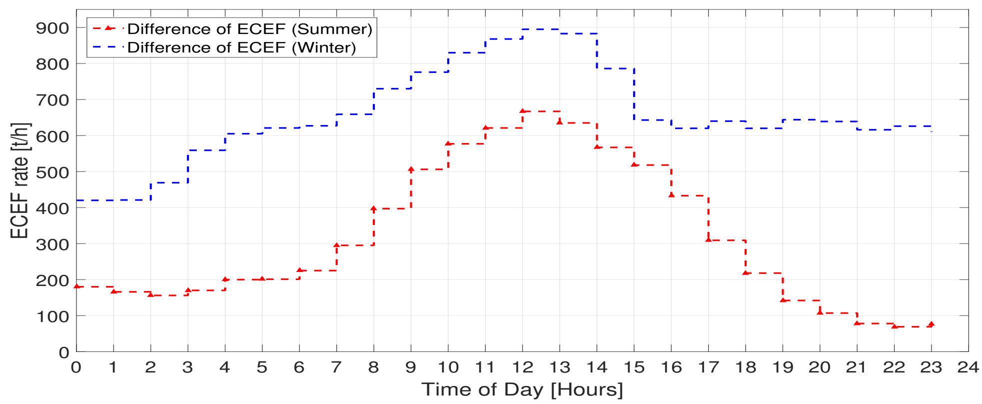


Figure 5.10: Difference of daily ECEF on 14th Jan. 2017 and 14th Jun. 2017.

selected days. For 14th Jan. 2017, the total original ECEF is 180582 tCO_2, the total ECEF after DSM is 165252 tCO_2. For 14th Jul. 2017, the total original ECEF is 133156 tCO_2, the total ECEF after DSM is 125642 tCO_2. And Fig. 5.10 shows the difference of ECEF between the original ECEF and ECEF after DSM for both days. For 14th Jan. 2017, the total ECEF is reduced of 15330 tCO_2, 8.5% of the original. For 14th Jun. 2017, the total ECEF is reduced of 7514 tCO_2, 5.6% of the original.

In comparison with the selected two days, the DSM has a better level of performance on Jan. 14th than on Jul. 14th. These results correspond to situations in summer season and winter season. Firstly, the electricity demands are generally higher on winter days than summer days, 19% higher on average [147]. Therefore, with the same penetration of load curtailment, the electricity demand would reduce more on winter days, subsequently influencing the ECEF. Secondly, the peak demands on summer days are much lower than that on winter days. This is because more lighting and heating are needed for winter days during the night. As such, the DSM could have a larger effect during the peak time on winter days. Thirdly, among all the RESs used for electricity generation, wind energy has the largest share around 50%, while solar energy has a lower share around 10% [148]. From 2002 to 2017, the wind speeds in winter season and summer season are 10.3 knots and 7.7 knots on average, respectively [149]. Even though winter days have less solar energy because of the shorter sunshine duration, they still have more RESs available because of the faster wind speed. Therefore, winter days lead to a better carbon emission reduction performance than summer days.

5.6 Chapter Summary

This chapter used a CEF model to calculate carbon emission derived from power flow. Two concepts, CEF intensity and rate, and four CEF types, ECEF, BCEF, BCEL, and ICEF, were introduced. This model can accurately quantify and assess the carbon emissions for each component in power networks. The IEEE 30-bus system with default data was applied to illustrate the framework of this model.

Furthermore, to demonstrate the practical use of CEF model, real data in the U.K. was applied. The CEF rate fluctuated with time, which means a different amount of carbon emission for each time period. For the ECEF, gas turbines contributed to most of the carbon emission. For the ICEF, a higher demand does not necessarily mean a higher ICEF rate. Several DSM approaches were analysed for the purpose of carbon emission reduction, including three levels of load curtailment and load shift proposed in Chapter 3. In the load curtailment case, the carbon emission reduction had the similar trend as the electricity demand. With the increasing penetration of load curtailment, the carbon emission reduction increased accordingly. In the load shift case, with the load moved from peak time to off-peak time, the carbon emission can be effectively mitigated. What's more, with DSM approaches available, winter day can provide a better carbon emission reduction than summer day.

Chapter 6

Conclusions and Future Work

This thesis contributed to the application of DSM in the smart grid and the carbon emission reduction in electricity generation. In this concluding chapter, a summary of the key contributions from different chapters are given in Section 6.1. Several suggestions for future research areas are presented in Section 6.2.

6.1 Conclusion

In order to integrate RESs, chapter 3 proposed a hierarchical DSM model for day-ahead electricity market. The utility was in the upper layer, seeking to minimize the generation cost. The DR aggregator was in the middle layer, communicating with both the utility and customers. Customers were in the lower layer, aiming to maximize their social welfare. This model formulated a MOP, which can be solved by the AIA. A Pareto optimal solution that maximizes the minimum improvement in all dimensions was selected. This solution can fairly improve the performance of all participants: the utility can reduce the power PAR and save generation cost; the DR aggregator can make a profit by providing DSM service; customers can save money on their bill. The system sensitivity analysis proved the proposed model is robust against perturbations. If the system could not have accurate information of the load profile, the proposed model could still find out an optimal solution. If the optimal solution could not be fully operated as designed, the system could still have a better performance than the benchmark, but the system improvement would be deteriorated. Furthermore, the change of bonus coefficient would only influence the share of generation saving between the utility and the DR aggregator. Neither the demand profile nor the generation schedule would be affected. The increase of the compensation coefficient would raise customer's bill. And the increase of the inelasticity coefficient had an unfavourable impact on the whole system improvement.

In order to effectively achieve the carbon emission reduction, chapter 4 established a system model for power system scheduling, considering the economic, environmental and social aspects of power generation. Eight fuel sources were considered: coal, oil, gas, nuclear, hydro, wind, bioenergy and solar. For policy makers, to minimize the carbon emission, wind and nuclear were preferred. For utilities, to minimize the generation cost and carbon tax, solar and wind were preferred. For customers, they mainly focused on the electricity bill and did not have a specific preference on fuel sources. The optimal solution selected by MMD approach can balance these three objectives. The short-term case study suggested a higher use of nuclear and wind. And the long-term case study suggested a higher use of wind, nuclear and bioenergy. Moreover, as compensation increases, customers would pay less electricity bill, but utilities' net profit and carbon emission would increase. As the additional operating cost decreased, the whole system had a better performance. As the carbon tax rate increased, the utilities' net profit decreased significantly. As the Renewable Obligation increased in a certain range, the carbon emission could be effectively reduced.

In order to assess the impact of DSM on carbon emission, chapter 5 introduced a CEF model. It can accurately quantify the carbon emission from the generation side to the consumption side. The U.K. daily generation and demand data was applied to the model. Gas turbines contributed to the most of the carbon emission. The trend of daily carbon emission consisted with the electricity demand. The carbon emission was significant during the peak-time, and insignificant during the off-peak time. But for different customers, a higher demand did not necessarily result in a high carbon emission. Three levels of load curtailment were applied to the model. As the level of load curtailment increased, the total carbon emission decreased accordingly. With the load shifted from peak time to off-peak time, the carbon emission can be evidently reduced. The carbon emission reduction during the peak time was remarkable, while the carbon emission increment during the off-peak time was unapparent. What's more, the simulation results showed that winter days could have better carbon emission reductions than summer days with DSM intervention.

6.2 Future Work

As discussed in the previous section, the work introduced in this thesis brings some potential new research directions. Thus some future works are identified as follows.

6.2.1 Allocation mechanism

Customers agree to adjust the consumption pattern in order to reduce the bill. To weight more in the market, customers are aggregated as a cluster. Therefore, the actual consumption schedule is an aggregated number for the cluster. The next question is how to allocate the electricity power among all customers. Customers are assumed to be self-interested. Based on the signed contract, they need to provide the usage information about next-day consumption schedule, the percentage of deferrable load and the willingness of adjustment. According to the provided information, each customer can have a unique objective function.

6.2.2 Privacy protection

As stated in the above section, customers need to provide the required information to the DR aggregator. This brings the safety and privacy concerns. From the detailed electricity usage information, much other information can be derived, i.e. how many people live in the house, when will the people leave the house/come back to the house. Therefore, the detailed information exchange has potential security risks to the system. To avoid the unnecessary hazards and the exposure of private information, two methods may be used: 1) Coordination with neighbours. The customers can have an agreement with adjacent neighbours, sharing the usage patterns with each other. Then the small group provides joint information to the aggregator. 2)

Use of the storage device. With the auxiliary of the storage devices, the customers can buy the electricity at off-peak time and use it at peak time. Therefore, the customers are more flexible and the actual usage pattern is unknown to the aggregator. Both of these methods need to be tested in the model to verify their feasibility.

6.2.3 Market competition

In the proposed model, there is only one aggregator serves customers. In the real market, there are a group of aggregators that competing with each other to maximize their profits. When there are multiple aggregators join the market, the compensation rate set by them would be affected by others. The interaction between aggregators can be modelled by non-cooperative game theory to achieve a Nash equilibrium point.

6.2.4 Data exchange

Besides the day-ahead market, the proposed framework is capable of running within seconds, which means that has the potential to be applied in a real-time electricity market. On one hand, the real-time operation requires shorter time slot of dispatch, and more frequent decision-making from scheduling. On the other hand, a shorter time slot of framework operation requires a larger data storage capability and less communication delay. The distributed cloud storage system and higher bandwidth of 5G network provide the possibility for this issue.

6.2.5 Uncertainty prediction

From the aspect of macro-environment, the electricity market is influenced by a lot of uncertainties, such as the variation of fuel prices, electricity prices, population sizes and climate conditions. From the aspect of micro-environment, customers' electricity demand is also influenced by a lot of elements, such as the equipment of electric vehicles, the installation of self-production facilities like photovoltaic. The trend of electricity market development and the pattern of customer' consumption can be predicted by the behaviour learning.

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