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Optimal Generation Expansion Planning for a Low Carbon Future

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Optimal Generation Expansion Planning for a Low Carbon Future

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Abstract

Due to energy scarcity coupled with environment issues, it is likely to see the biggest shift in generation portfolio in the UK and world wide, stimulated by various governmental incentives policies for promoting renewable generation and reducing emission. The generation expansion in the future will be driven by not only peak demand growth but also emission reduction target. Thus, the traditional generation expansion planning (GEP) model has to be improved to reflect this change against the new environment. The policy makers need a better assessment tool to facilitate the new environment, so they can make appropriate policies for promoting renewable generation and emission reduction, and guide the generation mix to evolve appropriately over time. Since the expansion of new generation capacities is highly capital intensive, it makes the improvement of GEP quite urgent and important.

The thesis proposes the GEP modelling improvement works from the following aspects:

- Integrating short-term emission cost, unit commitment constraints in an emission target constrained GEP model.
- Including the network transmission constraints and generation location optimization in an emission constrained GEP.
- Investigating the impacts of multi-stage emission targets setting on an emission constrained GEP problem and its overall expansion cost.
- Incorporating the uncertain renewable generation expansion and short-term DSR into the GEP problem and find out its potential contributions to the GEP problem.

A real case study is made to determine the optimal generation mix of the Great Britain in 2020 in order to meet the 2020 emission reduction target. Different optimal generation mixes of the UK in 2020 are identified under a series of scenarios. The scenarios are constructed according to different GB network transmission capacity hypotheses and demand side response (DSR) level scenarios.

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Contents

List of Symbols

Bio	Biomass Power Plant
CC	Capital Cost
CCGT	Combined Cycle Gas Turbine Power Plant
COAL PF	Pulverized Fuel Coal Fired Power Plant
DECC	Department of Energy & Climate Change
EU-ETS	European Union Emission Trading Scheme
FC	Fuel Cost
FET	Final Emission Target
GB	Great Britain
GENCOs	Generation Companies
GEP	Generation Expansion Planning
GHG	Green House Gas
IGCC	Integrated Gasification Combined Cycle
LCPD	Large Combustion Plants Directive
MET	Mid-term Emission Target
MILP	Mixed Integer Linear Programming
NGET	National Grid Electricity Transmission plc.
OCGT	Open Cycle Gas Turbine
PS	Pumped Storage Power Plant
RO	Renewable Obligation
SHETL	Scottish Hydro-Transmission Ltd
SPT	Scottish Power Transmission Ltd
UNFCCC	Nations Framework Convention on Climate Change

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Chapter 1

Introduction

THIS chapter describes the background, motivation, objectives, and contributions of this work and the layout of this thesis.

1.1 Generation Expansion Planning

The big difference between the electricity and other commodities is that electricity cannot be stored in large quantity economically. Therefore, electricity has to be consumed at the time when it is produced. Almost every effort that the power system operator has made is to meet system demand with generation on a minute to minute basis. Traditionally, demand has very little flexibility to response to imbalance between generation and demand, so adjusting generation following the demand variance becomes the major way to keep demand/ supply in balance [1, 2].

This adjustment of generation should be made in different time scales in order to guarantee the system can run economically and securely from milliseconds to years and with a variety mixes of generation technologies. The hierarchy of the adjustment is shown in Table 1-1. This PhD research falls into the generation expansion planning (GEP) problem.

Table 1-1 Hierarchy of Generation Adjustment[1]

Time scale	Supply demand balancing activities
Milliseconds	Generator excitation control
Seconds-minutes	Generator AGC(Automatic Generation Control)
Minutes-Hours	Generation system’s Economic Dispatch
Hours-days	Generation system’s Unit commitment
Years	Generation expansion planning

There are many types of power generation technologies deployed in power industry. They can be classified by the primary energy source. For example, coal, oil, gas fired power plants, nuclear power, hydro, wind, solar, biomass and so on. They can be further classified by the specific technologies. For example, for gas fired power plant, there are combined cycle gas turbine (CCGT) and open cycle gas turbine (OCGT); for coal fired power plant, there are Pulverised Fuel (PF), Fluidised-bed (FB) combustion and integrated-gasification combined cycle (IGCC); for wind farm, there are on-shore and off-shore. Different generation technologies have different characteristics in plant size, operation cost, capital cost, emission factors, etc. An example showing these different characteristics is given in Table 1-2.

Table 1-2 Characteristics of different generation technologies[3]

Technology	Notional Size (MW)	Plant life (Year)	Capital cost (M €/MW)	Operation cost (k€/MW per annual)
Coal PF	1000	30	1.48	34.8
Coal IGCC	800	25	1.76	69.0
Coal FB	150	25	1.22	55.2
OCGT	110	20	0.52	36.0
CCGT	390	20	0.54	50.0
Wind(On-shore)	30	20	0.98	34.8
Wind(Off-shore)	30	20	1.03	54.2

The traditional GEP problem is to determine what type of generation technologies should be adopted, how many generation plants should be built, when the planned generation plants should be constructed and sometimes where they should be connected in the transmission network. The objective of the planning is to meet electricity demand in the future at the minimal cost, including both the generation capacity investment cost and the operational cost in the planning time horizon. For dynamic GEP problem, the decision variables are the numbers of generation units with different generation technologies to be constructed over the entire the planning horizon, where earlier investment will have an impact on the planning in later years [4]. Static GEP studies on the other hand focuses on finding the optimal types and numbers of different generation plants in a specific target year, for example, optimal generation mix in 2030 or 2050. In this case, dynamic interactions of the generation plant construction over time are neglected. This type of research is often named with optimal generation mix or portfolios [3, 5-9].

The GEP problem is very important because new generation capacity can not be increased overnight. It takes years and a huge amount of investment to construct a new power plant, and once it is constructed, it will be there for years to come. Therefore, it needs an appropriate planning to arrange the generation expansion process in advance, determining the right generation technologies, the proper capacity and the right time for constructing new plants. If the required system's total generation capacity in future is underestimated, then supply security will be compromised in the future. On the other hand, if it is overestimated, a huge amount of money will be wasted to build the costly but redundant power plants.

1.2 New Environment for Generation Expansion Planning

1.2.1 Emission Reduction and Emission Cost

Global warming presents the biggest threat to human living environment. Many countries have been or will be suffering from the problems caused by the rise of the sea level and extreme weather conditions. Among the factors accelerating global warming, the emission of Green House Gas[1] (GHG) is the main contributing factor. In order to slow the pace of global warming, many countries have developed ambitious emission control schemes or participated in the international or regional emission reduction programme. For example, the Kyoto Protocol was established in 1997 under the United Nations Framework Convention on Climate Change (UNFCCC), which has come into force since 16, February, 2005. The protocol proposed the GHG emission reduction obligations to developed countries, while developing countries were not subject to emission reduction commitments in the first Kyoto commitment period. By August 2011, 191 countries have signed up and ratified the protocol. In order to realise the emission reduction commitments in the Kyoto Protocol, the European Union Emission Trading Scheme (EU ETS) was launched in 2005 within the EU member states to cap the total the carbon emission of EU. Under the scheme, total EU emission allowance is allocated to each member state via the National Allocation Plans approved by European Commission, which is further allocated to different energy intensive industrial sectors in individual member state. Allowance trading can be made between the entities with surplus and lack of allowance via the emission allowance trading market. So far, a certain part of the emission allowance is granted to each sector mainly according to its historical emission data, so called grandfathering, and the other part is allocated by auctions. Outside Europe, in Japan, Canada, US, Australia and New Zealand, emission trading schemes has been also implemented either in nationwide or regional level. In the UK, the Climate Change Act 2008 set legally binding targets of at least 34% and 80% cut in greenhouse gas emissions by 2020 and 2050 respectively, both against a 1990 baseline .

[1] The six types GHG identified in Kyoto Protocol are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulphur hexafluoride (SF6), hydro fluorocarbons (HFCs) and perfluorocarbons (PFCs).

Apart from the carbon emission trading, carbon tax is another financial scheme to limit the emission. Unlike the emission trading, the carbon tax directly imposes the cost to carbon emitters. Carbon tax policies are usually made by the individual governments.

Among all the industrial sectors, the power generation industry takes up the biggest share of total carbon emission. In order to realise the emission reduction target, power generation industry has to contribute disproportionally to emission reduction over the other sectors. However, for a fixed generation mix, there is a limit to how much emission reduction the mix could achieve. This is because the fixed mix will naturally have limited low carbon content. Further, for renewable generation, it will require back up generators to balance its intermittency, which produce carbon emissions. The short-term emission control could exert financial pressure for power generation companies to move away from dirtier and cheaper generation plant, but it can not guarantee that emission produced throughout the year will meet the desired target desired, increasing emission price alone is not enough [10, 11]. In order to meet a predefined emission target, the current generation mix has to be assessed to see if it has enough clean generation capacity to realise the target. If not, the generation mix has to be restructured around the target alongside short-term emission control through financial incentives and/or taxes. Thus, an optimization is needed for restructuring the generation mix meeting the emission target at a minimum cost.

1.2.2 Generation Gap and Renewable Generation

By 2011, the UK power system had a peak demand for electricity at around 60GW and a total transmission connected generation capacity at around 80GW. However, this country will face a large generation gap in meeting projected electricity demand, since a number of large power stations are planned to retire in next decade. The EU's Large Combustion Plants Directive (LCPD) has required large electricity generators to meet more stringent air quality standards since 1 January 2008. This forces around 12 GW of coal and oil-fired power plants to close by 2016 in the UK [12, 13]. Additionally, 7.5GW nuclear power stations will come to the end of their asset lives by 2020 [13]. In order to fill the generation gap, new generation capacities will be required by 2020 [12].

Meanwhile, the UK government has committed to source 15% generation consumption from renewable energy by 2020 [14]. Due to the weak market competitiveness of renewable generation compared to the fossil fuel generation technologies, the renewable supporting mechanism, Renewable Obligation (RO), is applied across the UK. Under the RO, electricity suppliers are obliged to source a specified percentage of electricity sales from renewable generation or face penalty.

RO benefits the large scale transmission connected renewable generation, but for promoting the small scale distributed renewable generators up to 5MW, feed-in tariffs were announced in 2008 in the UK, supporting the renewable generator with eligible technologies.

In the traditional GEP problem, when making a capacity expansion decision for a conventional generation technology, planners know the conventional units can generate the expected amount of power at any time of the planning horizon. However, renewable generation emerges with new challenges in GEP problem. Take the wind generation as an example, in practice, the wind speed forecasting errors could be very large especially for a long term wind forecast. The output of a wind farm in the future quite depends on the volatile wind speed not the planners' expectation. These renewable supporting schemes in future will attract more and more renewable generation expansion, which will uncertainty caused by the renewable generation will increasingly challenge both the short-term economic operation and the long-term generation planning [15]. Hence, it requires more sophisticated treatment to handle the uncertainty in renewable generation expansion in a GEP problem.

1.2.3 Demand Side Response

Demand side response (DSR) refers to the modification of end-users' consumption from their original behaviours in response to certain types of demand side management programmes, such as price signal, incentives and education. The purpose of DSR is usually to motivate the users to move their consumption from peak time to off-peak times [16-19].

Due to the uncertain availability of the primary energy (wind, solar radiation, etc), the intermittent renewable generation is not a controllable and flexible generation source. It is not always available to provide as much output as people desire and acts almost like a volatile negative load. In short-term operation, this volatility has to be compensated by adjusting the outputs from other conventional, controllable and flexible generators. Therefore, with the rise of its penetration in the system, the traditional approach is to expand more and more flexible and expensive generation capacity, such as CCGT and OCGT, to cater for the increasing fluctuation from renewable source.

The flexibility desired for system demand supply balance could in part be provided by the use of demand side responses (DSR). However, electricity market is not extended to mass consumers, also there lacks of demand side management programmes and services that provide easy access for consumers to participate. However, with the development of smart grid technologies, such as the communication technologies, smart meters and real-time pricing programme, etc, the interface for customers to participate in the DSR could become a reality in the future. Furthermore, with increasing use of electric vehicles and other energy storage facilities, demand side has more and more flexibility in the electricity use. Therefore, DSR can potentially play a more and more important role in the future electricity market, thus its role in future generation mixes need to be carefully investigated.

1.3 Research Motivation

Due to energy scarcity coupled with environment issues, it is likely to see the biggest shift in generation portfolio in the UK and world wide, caused by various governmental incentives policies for promoting renewable generation and reducing emission. Thus, the traditional GEP model has to be modified to reflect this change against the new environment. The policy makers need a better assessment tool to facilitate the new environment, so they can make appropriate policies for promoting renewable generation and emission reduction, and guide the system generation mix to evolve appropriately over time.

Any improvement in modelling the GEP problem and the associated solutions will make the generation expansion plan closer to the real optimal plan, and make the estimated cost closer to the real case. Since the expansion of new generation capacities is highly capital intensive, it makes the improvement of GEP quite urgent and important. This is the major motivation of this research.

There have been plenty of works on improving the GEP modelling and solution. Some works focus on introducing new optimization theories and techniques to either improve the optimization accuracy or speed up the process for solving large scale GEP model. Some works focus on transforming the GEP from a centralised planning environment to a deregulated competitive market one. However, existing GEP problem formulations and solutions still have limitations in the following aspects:

- The previous GEP model over-simplified the assessment of production cost and emission in its operation model. The nonlinear and integer operational variables and constraints are often neglected or simplified to linear and continuous ones. The impacts of short-term emission pressure on long-term emission constrained GEP are seldom discussed.

- Most previous GEP researches did not consider transmission network limits (line flow limits). Although some other researchers considered the network, the generators can however only be able to expand at designated nodes. Few GEP models consider the optimization of the generation locations.

- Very few previous GEP researches include the renewable generation expansion appropriately in their GEP modelling. For an example, the wind generation is usually treated as either a controllable conventional generation technology or a known negative demand, similar to load profile. This treatment of renewable generation is not able to address the uncertain nature of renewable generation, because they all assume wind generation in the future is deterministic.

- Most previous GEP model made a lot of efforts to model the generation side, but treated the demand side simply as a fixed projected load profile. With increasing mature conditions for realising DSR in the near future, DSR will potentially play the role of traditional generators, as an alternative source, to provide the flexibility to maintain the demand supply balance. Therefore, DSR should be incorporated into the GEP problem. Short-term DSR implementation has been studied extensively in recent years, but very few of them took the DSR into account for long-term GEP problem.

The ambition of the research documented in this thesis is therefore to address the improvements of the above limitations in GEP problem modelling. The specific research purposes are listed as follows.

1.3.1 Impacts of Short-term Emission Cost on GEP

Different generation technologies emit air pollutants at different rates when generating electricity. Table 1-3 shows the emission factors of different types of air pollutants released after burning different types of primary fuel. The emission will be financially punished by the aforementioned emission policies, and then extra emission cost will be brought to the generation companies. Coupling with the economic characteristics shown in Table 1-2 , the original economic characteristics of different generation technologies will be biased by the additional emission cost. When the emission policies vary, for example the carbon tax is raised; the financial pressures added by emission will change the market competitiveness of the different generation technologies by different extents.

Table 1-3 Emission factors for different fuels [20]

Pollutant	Hard coal	Brown coal	Fuel oil	Other oil	Gas
CO2 (g/GJ)	94600	101000	77400	74100	56100
SO2 (g/GJ)	765	1361	1350	228	0.68
NOx (g/GJ)	292	183	195	129	93.3
CO (g/GJ)	89.1	89.1	15.7	15.7	14.5
Non methane organic compounds (g/GJ)	4.92	7.78	3.7	3.24	1.58
Particulate matter (g/GJ)	1203	3254	16	1.91	0.1
Flue gas volume total (m^3/GJ)	360	444	279	276	272

For example, One generation technology may have a very low capital cost but a high emission coefficient. Without considering the future short-term emission pressure, this generation technology will be considered to expand with higher priority in the future, since it has a very low capital cost and the long-term GEP problem aims to minimise the sum of the investment costs and short-term operation cost in the future. However, if the short-term emission pressure is considered, the high emission coefficient will lead to high short-term operation cost for this generation technology. With the increase of the short-term emission pressure, the priority of this technology in future generation expansion will drop, since its low capital cost will be offset by the increased the short-term operation cost. Therefore, from a long-term planning view, short-term emission cost will affect the optimal generation mix results.

1.3.2 Operational Constraints and Renewable Generation Expansion

As stated in Section 1.1, the objective of a generation expansion planning problem is to minimize the total of long-term capacity investment cost and short-term operational cost. However, the previous planning approaches over-simplified the assessment of production cost and emission in its operation model. Dynamic details were usually neglected, such as plant start-up cost, shut-down cost, minimum up/down time, ramping rates, and spinning reserve. Since, the dynamic process involves integer variables and non-linear constraints, the discreteness and nonlinearity make the GEP optimization very difficult. Historically, these dynamic factors can be neglected because the impacts of these factors on the generation cost were highly predictable. The unit costs of generation production from a generation technology and generation mix do not vary significantly from one year to another. That's why the previous researches simply use a linear operational cost multiplied by the power output to estimate the year round generation cost. However, this approximation would still stand if the demand profile can be accurately predicted based on the historical data and if all generation are controllable. In the near future, this case may not stand with the rise of the penetration of intermittent renewable generation and the deployment of DSR programme. Hence the tradition GEP model should be enhanced by considering a more detailed operational modelling.

Moreover, in traditional GEP problem, when making a capacity expansion decision for a conventional generation technology, planners know the conventional units can generate the expected amount of power at any time of the planning horizon. However, renewable generation emerges with new challenges in GEP problem. Take the wind generation as an example, in practice, the wind speed forecasting errors could be very large especially for a long term wind forecast. The output of a wind farm in the future quite depends on the volatile wind speed not the planners' expectation. Hence, it requires more sophisticated treatment for wind generation expansion in a GEP problem.

Very few previous GEP researches include the renewable generation expansion appropriately in their GEP modelling. Taking the wind generation as an example, the wind generation is usually either treated as a controllable conventional generation technology or as a known negative demand, similar to load profile. This treatment of renewable generation is not able to address the uncertain nature of renewable generation, because they all assume wind generation in the future is deterministic.

1.3.3 Network Constraints and Generation Location

An appropriate generation location can help make the most use of existing transmission network and future generation capacity and therefore save significant investment and operational cost when meeting future demand. On the other hand, in the potential DSR market in future, due to network constraints, DSR in different locations will have different contributions in providing the flexibility identified in Section 1.2.3. Hence it makes big sense to consider the generation location optimization in GEP under the new environment.

Most previous GEP researches did not consider transmission network limits (line flow limits). They tried to solve the GEP problem considering infinite network capacity [3, 5-8, 21-24]. Although some other researchers considered the network, the generators can however only be able to expand at designated nodes [9, 25]. However, in transmission system, when making a generation mix plan for an extra long-term horizon, when all the initial generation units will retire at the target year, such as 2050 target year, it is quite important to not only decide the generation type and size, but also allocate not a single but multiple power plants to appropriate locations.

1.3.4 Impacts of Multi-Phase Emission Targets on GEP

In order to fight the global warming, many governments have set various emission reduction targets at different time scales. Some of the emission control schemes are to be implemented in multiple phases, for example, the UK Climate Change Act 2008 set legally binding targets of at least 34% and 80% cut in greenhouse gas emissions by 2020 and 2050 respectively, both against a 1990 baseline. However, due to the generation plant is costly with a long time life span once it is built, the interim emission target setting will severely change the trajectory of system's generation mix evolvement to the final generation mix, which will have to meet the long-term emission reduction target. Therefore, inappropriate multiphase emission target settings will affect the generation mix planning and the related total investment dramatically. These impacts will be investigated and presented in this thesis.

1.3.5 Impacts of Demand Side Response on GEP

With increasing mature conditions for realising DSR in the near future, DSR will potentially play the role of traditional generators, as an alternative source, to provide the flexibility to maintain the demand supply balance. Therefore, DSR should be incorporated into the GEP problem.

DSR has been studied demand response level in recent years. Some researchers investigated the feasibility and effectiveness of the different DSR programmes, incentive based or pricing based [26-32]; some incorporated the DSR into short-term generation scheduling optimization [17, 28, 33-35]; some proposed the application of emerging smart grid facilities, like energy storage device [36-40]; but very few of them took the DSR into account for long-term GEP problem [6]. Most previous GEP model made major efforts to model the generation side, but treated the demand side simply as a fixed projected load profile. Although [6] innovatively proposed a GEP model considering demand side response by demand price elasticity modelling, it has the following limitations, which can be improved:

- This paper over simplified the generation side modelling. The discrete characteristic of GEP is neglected.

- Since this study did not consider the network constraints, the demand response levels are assumed the same for the whole system. However, in practice, the demand at different locations may have different response capabilities due to the composition of the load types (industrial, commercial and domestic). GEP model neglecting the network constraints and demand locations can not differentiate the impacts of DSR at different locations in the network.

Improving the above limitations is one of the motivations of this thesis.

1.4 Research Objectives and Contributions

This thesis presents the improved generation expansion planning modelling in the new environment indentified in previous sections. The major objectives and contributions of this research are as followed:

- To integrate short-term emission cost, unit commitment constraints, renewable generation expansion and network constraints in the GEP model. The enhanced model should reflect the impacts of the future new environment on the traditional GEP problem.

  In doing so, a novel GEP model is proposed. The model can take into account the emission cost, integer variables and nonlinearity at operational level with network constraints. The GEP model considers both renewable generation and conventional generation. The ratio of the two is constrained by a spinning reserve requirement at the operational level.

- To investigate the impacts of generation location on emission target constrained GEP model.

  In doing so, a novel mixed integer linear programming (MILP) based emission target constrained GEP model is developed, which can support generation location optimization constrained by network overloading limit. The generation location number (bus number) is used to index the decision variable. The generation at different locations is summed and linearly related to the line flow through generation shift factor and based on superposition theory.

- To investigate the impacts of multi-phase emission targets setting on the GEP problem and its overall expansion cost. To reveal how different interim emission targets will guide the generation mix to develop in different ways to meet a common final emission target

  In doing so, a MILP based two-phase GEP model is developed. The new GEP model is constrained by an interim and a final emission target respectively in two consecutive time horizons.

- To incorporate the renewable generation expansion and short-term DSR into the GEP problem and find out its potential contributions to the GEP total cost.

In doing so, a MILP GEP model is developed with renewable generation expansion and short-term DSR integrated. The renewable generation uncertainties are assessed by a two stage scholastic linear programming GEP model with Monte Carlo sampling technique.

- To determine the optimal generation mix of the Great Britain in 2020 in order to meet the 2020 emission reduction target.

  In doing so, a real case study is made based on a reduced Great Britain transmission network. Different optimal generation mixes of the UK in 2020 are identified under a series of scenarios. The scenarios are constructed according to different GB network transmission capacity hypotheses and demand side response (DSR) level scenarios.

1.5 Thesis Layout

The rest of the thesis is organized as follows:

In Chapter 2, a new generation expansion planning model is proposed, which takes account of the emission cost in operational level and explores its impacts on the long-term emission target oriented generation planning innovatively. Meanwhile, the model takes into account the integer variables and nonlinearity of the operational cost with network constraints and renewable generation expansion together in one long-term generation planning model. A case study on a modified IEEE 30 bus system is presented to demonstrate the application of this model and the value of considering short-term emission costs and the network constraints on the long-term generation expansion.

In Chapter 3, a novel GEP model based on mixed integer linear programming (MILP) is proposed, which can optimize generation locations as well as their technology and capacity in the transmission network. DC load flow is used to check the transmission line overloading. Comparative studies are made based on a five bus test system to show the difference between the GEP with and without network constraints and generation location optimization.

In Chapter 4, a MILP based two-phase GEP model is proposed, considering the generation expansion is constrained by different emission targets in two different time horizons, interim and final. It is test on a five bus test system. Comparative studies have been made to find out how different interim emission targets will guide the generation mix to develop in different ways to meet a common final emission target.

In Chapter 5, a MILP GEP model with renewable generation expansion and DSR integrated is proposed. It is test on a five bus test system. Comparative studies under different DSR level scenarios have been made to show how short-term DSR reduces the demand peak and fills the demand valley, and additionally save the total expansion cost and change the optimal generation mix.

In Chapter 6, a real case study is made based on a reduced Great Britain transmission network. Different optimal generation mixes of the UK in 2020 are identified under a series of scenarios, which are constructed according to different GB network transmission capacity hypotheses and demand side response (DSR) level scenarios.

In Chapter 7, major findings and contributions of this thesis are summarized, and the potential improvement future works of the research are proposed.

Chapter 2

Emission Constrained Generation Expansion

THIS chapter introduces an emission constrained GEP model, considering short-term emission cost, detailed operational modeling, renewable expansion and network constraint.

2.1 Introduction

Many countries have announced ambitious carbon emission control targets. For example, the UK has committed to reduce its carbon emission by 80% by 2050, relative to 1990 levels. The power industry, the biggest carbon emitter among all industrial sectors, has to take the largest decarbonisation responsibility. Hence, the ambitious long-term emission reduction target tends to drive the power system to restructure itself radically; for example a big share of clean and renewable generation technologies will penetrate into the generation mix. A huge amount of investment will be required for this evolution.

Having a comprehensive optimized generation mix as a reference would assist the policy makers in setting the emission reduction target and estimating its total cost required.

A number of previous works have been carried out on the optimal generation mix problem to meet forecasted load growth. Morris innovatively employed a dynamic programming model for solving the generation mix problem [41]. Masse and Gibrat applied the linear programming (LP) to the generation investment optimization problem [42]. In [43], three different decomposition approaches were compared to tackle the generation planning problem considering the demand uncertainty. More uncertain factors, such as renewable generation intermittency, regulatory policy uncertainties and fuel price volatility were considered in [44]. In [45], the authors proposed a generation expansion planning model in deregulated environment, which was to maximize the payoff of the privatized generation companies. A generation mix optimization model considering the short-term demand side response was proposed in [6]. However, these researches oversimplified the operational modelling: integer variable related costs and constraints were neglected, such as unit start-up cost, and minimum up time, and the nonlinear fuel cost was simplified to a linear one. These simplifications cannot better differentiate the performance (cost and flexibility) of different generation technologies. Additionally, these researches consider neither the system network constraints nor an interface for renewable generation planning. Therefore, these simplifications will bias the generation planning results. Besides, all the aforementioned studies did not consider the emission problem.

Since Gent and Lamont [46] did the early research on minimum emission dispatch, the optimization of the emission reduction has been considered more and more by successive researchers, but they mainly concentrated on the area of short-term power generation operation [47-50]. Some recent works have been carried out in the area of generation expansion planning, which consider the emission. A new efficient GA-Bender's approach, solving the power generation expansion planning problems with emission constraints, was given in [24]. However, the operational problem was still modelled in the aforementioned simplified manner and did not consider renewable generation and network constraints in the optimization. In [21], the author proposed a low carbon power generation expansion (LCPGE) model, which integrates a comprehensive set of low carbon factors. However, the whole problem was only formulated as a linear programming model. The integer characteristic of generation capacity was even ignored. The simplified linear programming model is also applied to [3, 11]. Both [24] and [21] did not explore the impacts of the short-term emission cost on the long-term optimal generation mix. Doherty made a trend analysis of the generation portfolio in the Ireland, considering the impact of emission costs to the optimal generation investment portfolios [3, 11]. Unfortunately, the study only formulated the emission cost in the objective function without setting an emission target as a constraint.

In summary, most of the previous researches on optimal generation mix planning have one or more of the following limitations:

- Integer variable cost and the nonlinearity of the operational level are neglected [3, 6, 11, 21, 24, 43-45, 50, 51]. Discrete characteristic of generation unit size in the investment level is ignored as well [3, 11, 21].

- There is only limited discussion of the impact of short-term emission cost on the long-term investment cost [3, 11].

- Network constraints and renewable generation expansion are seldom considered in the emission target oriented generation planning [3, 11, 21, 24].

The contribution of this chapter is that it proposes a static generation expansion planning model, which takes account of the emission cost in operational level and explores its impact on the long-term emission target oriented generation planning innovatively. Meanwhile, the model proposed in this chapter takes into account the integer variables and the nonlinearity of operational cost with network constraints and renewable generation expansion together into one long-term generation planning model.

This model attempts to determine the required generation mix which can meet a predefined emission target for a given power network at a minimum societal cost, overcoming the aforementioned limitations. The methodology developed takes the emission target settings, current generation mix, network data and load profiles in the target year as inputs. It considers typical thermal generation units and renewable wind units, and provides the optimized generation mix and the total cost and emission under this mix as outputs. The model proposed in this chapter is a centralized generation planning model. It aims to provide a low carbon generation mix assessment tool for policy makers when devising emission reduction targets and estimating the related cost. The government or other related authorities can use this assessment model to ensure long-term emission target could be achieved at a minimum societal cost. Since this formulation, taking into account detailed system operation constraints, such as unit commitment and network constraints, has a large problem size, an innovative index, emission reduction cost (ERC) has been developed to speed up the process of searching for the optimal generation technology. A case study based on IEEE 30 bus system is provided to verify the effectiveness of this formulation. Optimization results show the total cost (including investment) variation with different emission prices. Comparative study between optimizations with and without network constraints has been made to indicate the importance of network constraints in a generation expansion study.

2.2 Prerequisites

2.2.1 Operational Cost Modelling

There are many types of operational costs for running a conventional power station, such as fuel cost, maintenance cost, crew cost. Among these costs, the fuel cost takes the largest share and is related to how much electricity is generated by a power plant.

While the other costs are relatively fixed, not varying with the amount of electricity generation. There are various generation technologies. To generate the same amount of electricity, different technologies consume different amounts of primary energy source. Normally, burning per unit of coal, oil and gas will generate different amounts of heat.

For a thermal generator, the relationship between the amount of heat consumed by the boiler and the power output from the generator can be represented by an input-output heat rate curve. In practice, the steam pipes in some power plants may have multiple valves to adjust the steam output pressure. As introduced in [52] by A. J. Wood and B. F. Woolenberg, for a thermal generator with four valves, the input-output heat rate curve is shown in Fig 2-1. Due to the valves operation, the heat rate curve is not smooth and not convex, and this will make the problem intractable. In order to simplify the problem for mathematical study, the heat rate curve is often modelled by a quadratic function or a piece-wise linear curve or even simply a linear function, depending on how precisely the researchers want their analysis implemented. Different fossil fuels and generation technologies shape the curves in different ways [52].

Referring to the cost (£/kg, £/m^3) and the heat conversion rate (kg/Btu, m^3/Btu) of the fossil fuel, generators' input-output cost rate curve can be derived. Fig 2-2 shows the input-output cost rate in a quadratic curve. In this chapter, quadratic modelling is adopted.

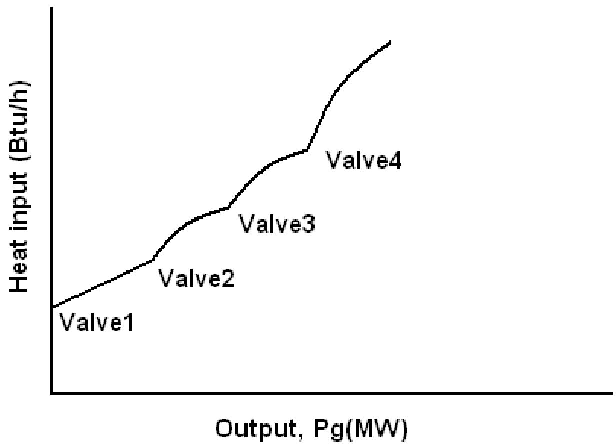

Fig 2-1 Input-output heat rate curve with valve operations

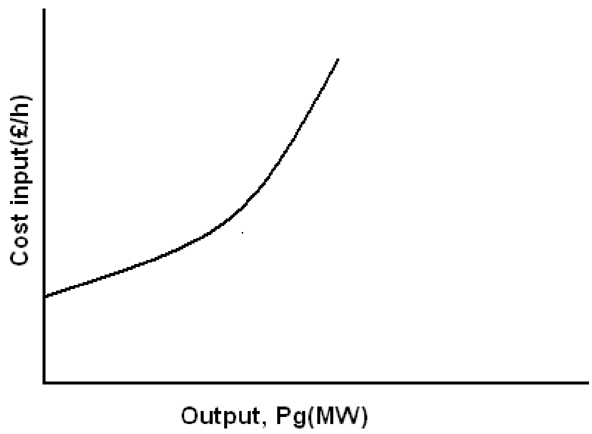

Fig 2-2 Quadratic input-output cost rate curve

Apart from the fuel cost, there are other two types of costs related to generation operation, which are unit's start-up cost and shut-down cost. These costs are dynamic and appear when generators are turned on or shut down. These costs will be introduced later in Section 2.2.3.

2.2.2 Emission Modelling

It is a chemical problem to determine precisely how much carbon emission is released after burning a unit of fossil fuel. The relation between emission and power output of a generation plant could be very complicated when expressed in a mathematical function precisely. However, for researches in power generation area, only several simple mathematical functions are commonly used to express the relation. They are quadratic or cubic polynomials[47, 53], or a combination of polynomial and exponential terms[46] or simply a linear function. Although, these functions can not represent the emission variation with power output very precisely, they are indeed good estimations for power engineering study, according to the historical statistic data from all kinds of fossil fuel fired power plants. Four commonly used modelling functions are listed below:

$$E = A_1 + A_2P + A_3e^{A_4P} + A_5e^{A_6P} \qquad \textbf{2-1}$$

$$E = A_1 + A_2P + A_3e^{A_4P} \qquad \textbf{2-2}$$

$$E = A_1P^2 + A_2P + A_3 \qquad \textbf{2-3}$$

$$E = A_1P + A_2 \qquad \textbf{2-4}$$

where, E is emission; P is the power output; A1, A2, A3, A4, A5 and A6 are shaping factors, whose values depend on the fuels and generation technologies. With the variation of the generation and carbon capture technologies, the shaping parameters vary.

2.2.3 Economic Dispatch (ED) and Unit Commitment (UC)

Given the mathematical representation of the individual generator, in order to evaluate total operational cost of generation system, modelling of system operation is required. Solving the ED and UC problem is a good way to estimate this cost.

ED is an important process of power system operation. It can help save a huge amount of cost by determining the optimal power output allocation among the committed generation units that can supply a given load at minimum cost. However, ED is only a sub-problem of UC. ED only attempts to optimize the output of the units which have already connected to the grid and committed to generate power. The UC problem is even more sophisticated. Given a series of forecasted load for a planning horizon (one day, one week, etc), the UC selects a subset of the complete set of N available generation units to serve the load for each scheduling block (usually hourly or half hourly) through to the end the of the planning horizon, which finally leads to a minimum operation cost for the entire planning horizon. Thus, ED optimizes the single block operation, while UC optimizes the operation through the entire time horizon [52].

The additional costs and constraints appear in UC process are units' start-up cost, shut-down cost, minimum up time, minimum down time and ramping rates. Their definitions are:

- Start-up/shut down costs: the cost required to turn on/off a unit for the transition from off/on state in last scheduling block.
- Minimum up/down time: the minimum time needed before the unit can be turned off/on, once it is turned on/off.
- Ramping rate: the maximum power output variance during unit time.

With the development of mathematics and computing technologies, the solution methods for ED and UC have been developing fast. In next section, important solution method for ED and UC, dynamic programming, is introduced, which is adopted for this study.

2.2.4 Dynamic Programming

Dynamic programming (DP) is a very powerful optimization algorithm, which breaks down a sophisticated problem into a sequence of simpler sub-problems, tackles them one by one and finally traces back to find the optimal solution for the whole problem. It has been developed since the late 1950s and the study was originally led by Richard Bellman[54, 55]. DP is not usually used to solve the ED problem on its own, unless the units' input-output characteristics are modelled by a non-convex function such as a piece-wise linear function. It is often used to optimize the entire system UC process, when there are integer variables varying from one state to another, such as variables representing units' on/off status. Pang and Chen made the early research to apply the dynamic programming algorithm to solve the thermal UC problem [56]. The basic principle of DP in UC solution works as Fig 2-3 shows. There are two units waiting to be scheduled hourly for 4 hours labelled by T. Two units can form 4 on/off combinations. DP will save the combinations' transition path of the lowest total cost including operational cost and start-up cost for each hour until the end hour of the scheduling. Then, it traces back from the saved feasible paths to find the path of the lowest total cost as the UC problem solution. In the case of Fig 2-3, the path depicted bold black is the UC solution duo to its lowest total cost, $190.

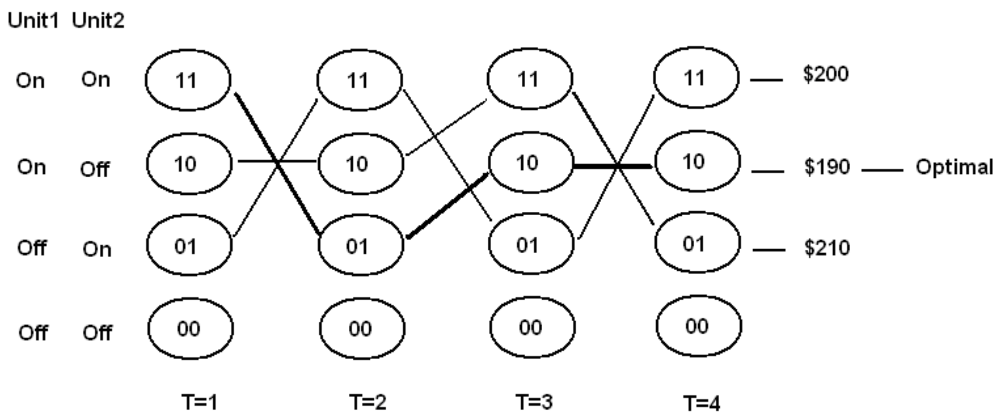

Fig 2-3 Dynamic programming for unit commitment solution

The dynamic programming method is able to find the global optimal solution and is easy to add constraints, but it suffers from the curse of dimensionality. When it is applied to a large system with a great number of units, it will consume a lot of PC memory and take a very long time to find the optimal solution.

The rest of the chapter is organized as follows: Section II gives the problem formulation; the solution method is presented in Section III; Section IV provides a case study to verify the effectiveness of the solution method; conclusions are drawn in Section V.

2.3 Problem Formulation

The proposed formulation in this chapter is to determine the optimal generation mix to meet a given carbon emission target at a minimum cost considering nonlinear and integer operational cost and short-term emission cost, under the constraints of network transmission capacity limit. The formulation follows the way that based on an initial generation mix, the candidate generators will be added into the mix stage by stage in a trial way.

The detailed structure of the problem is shown in Table 2-1, where the whole generation mix optimization problem is split into levels. The master problem is to determine the optimal new generators to be expanded, while the sub-problem is to determine the optimal power output and unit commitment status, so as to simulate the generation system operation and provide the yearly operation cost and emission for a given generation mix. The cost and emission results from the sub-problem will be used as performance index by the master problem to determine which new generators should be introduced in the optimal generation mix.

Table 2-1 Problem Decomposition

Hierarchy	**Sub -problem**	**Master problem**
Division	Operational modelling	Generation mix optimization
Decision variables	Optimal power outputs Optimal unit commitment status	Optimal new generator to be built
Solution method	Unit commitment (Dynamic programming)/ Economic Dispatch (Lagrange multiplier)	Heuristic discrete gradient search
Correlations	Assess the cost and emission performances for a given generation mix	Based on the assessment of operational problem, determining the optimal generation mix

2.3.1 Operational Sub-problem

In order to assess the performance of a potential generation mix after introducing a candidate generator in terms of cost and carbon emission, the operational sub problem is modelled first. The operational sub-problem includes two important parts, unit commitment (UC) and economic dispatch (ED). UC determines the optimal unit combination transition path from one scheduling block to another, while ED determines the optimal power output for each committed unit in each scheduling block.

- **Economic dispatch optimization**

In this research, a quadratic function is used to model the fuel cost of a generator unit. For a system with *N* generation units at a time horizon of *T*, the fuel cost ($FC_i(P_{it})$) of unit *i* at interval *t* is:

$$FC_i(P_{it}) = a_i P_{it}^2 + b_i P_{it} + c_i \qquad \textbf{2-5}$$

where, *i* is the generation unit index, *t* is the scheduling time interval index and P_{it} is power output of unit *i* at interval *t*. a_i, b_i and c_i are the fuel cost function coefficients of unit *i*.

The carbon emission (E_i) of unit *i* at interval *t* is modelled linearly by:

$$E_i(P_{it}) = \beta_i P_{it} + \gamma_i \qquad \textbf{2-6}$$

where, β_i and γ_i are the emission function coefficients of unit *i*.

In order to take the financial pressure of emission into account in the power dispatch [53], the emission is monetized and incorporated with the fuel cost by a weighting factor λ. In this study, emission price (EP) is uniformly used to call the factor λ in the rest of this chapter. The objective of the ED is to minimize the summation of fuel cost and weighted emission cost (SC_t):

$$\text{Minimize} \qquad \mathrm{SC}_{\mathrm{t}} = \sum_{i=1}^{N} (FC_i(P_{it}) + \lambda E_i(P_{it})) \qquad \textbf{2-7}$$

Subject to the following constraints:

$$P_{i\min} \leq P_{it} \leq P_{i\max} \qquad \forall t \in T; \qquad \textbf{2-8}$$

$$\sum_{i=1}^{N} P_{it} = D_t \qquad \forall t \in T; \qquad \textbf{2-9}$$

$$\sum_{i=1}^{N} sr_{it} \geq SR_t \qquad \forall t \in T; \qquad \textbf{2-10}$$

$$SR_t = DSR \times D_t + WSR(\sum_{n=1}^{NW} P_{wn}) \quad \forall t \in T \qquad \textbf{2-11}$$

$$-Lim_b <= L_{bt} <= Lim_b \qquad \forall b \in B, \forall t \in T \qquad \textbf{2-12}$$

where, the weighting factor λ is the emission penalty factor, reflecting the extent of impact on the power production cost from units' carbon emissions. In practice, its forms can be emission trading price or emission tax depending on which economic scheme is implemented for emission control. A higher emission price will exert larger pressure to emission reduction during the dispatch, and therefore power is more likely to be dispatched from clean but expensive units, vice versa. P_{imin} and P_{imax} are the minimum and maximum power output of unit *i*. D_t is the system total demand at the interval *t*. sr_{it} is the spinning reserve provided by unit *i* at interval *t*, while SR_t is the system spinning reserve requirement at interval *t*. SR_t at each interval is determined by two parts. DSR is a coefficient determining system spinning reserve requirement due to demand forecasting errors. *WSR* is a coefficient determining the spinning reserve requirement due to the wind power intermittency. *NW* is the number of the wind farms, and P_{wn} is the notional installed capacity of wind farm *n* [51]. L_{bt} is the power flow of line *b* at time *t* and Lim_b is the line flow limit of the line *b*.

The ED problem is solved by Lambda-Iteration method which is also known as Lagrange multiplier method [52, 57].

For each dispatch result in each interval, there is an interface to conduct line flow overloading check by load flow calculation to determine if the dispatch results are static operational and feasible.

- **Unit commitment optimization**

ED handles the nonlinear fuel cost, while the integer variable cost and constraints such as the unit's start-up cost, shut-down cost, unit's, minimum up time (MUT), minimum down time (MDT) and ramping rate will be dealt in UC. Dynamic programming algorithm is adopted here to solve the UC optimization in this research. The UC optimization aims to minimize the aggregated operational cost (C_a) through the whole UC horizon T.

$$C_{aT} = \sum_{t=1}^{T} SC_t + \sum_{i=1}^{N}\sum_{t=1}^{T}(ST_{it} + SD_{it} + MC_{it}) \quad \textbf{2-13}$$

where, ST_{it} is start-up cost of unit i, SD_{it} is shut-down cost of unit i, MC_{it} is maintenance cost of unit i.

2.3.2 Generation Mix Optimization

The operational sub-problem in Section A essentially acts as an performance evaluator for a given generation mix, network data and load profile, evaluating the total generation costs and emissions for a desired time period.

In order to restructure the generation mix, the capacities of some generation technologies will be expanded or contracted. So, the investment cost C_c for power plant is included in the total cost C_{total}. Since the wind generation expansion is considered in this research, a high level of wind power penetration will decrease the reliability of power supply, and loss of load probability will increase, which leads to social cost. This form of cost is taken into account through augmentation of spinning reserve requirements. The parameter, reserve price (RP) represents the price per MW spinning reserve capacity from the conventional generation plants. For a simplification, the reserve price is assumed to be equal for different conventional generation technologies. Therefore, the optimization objective is extended as well:

$$\text{minimise } C_{total} = C_a + C_c + RP\sum_{t=1}^{T}\sum_{i=1}^{N} sr_{it} \quad \textbf{2-14}$$

$$\text{subject to: } \sum_{i=1}^{N}\sum_{t=1}^{T} E_i(P_{it}) <= E_{Target} \quad \textbf{2-15}$$

where, E_{target} is emission limit in the target year.

In order to reduce the calculation burden and focus on the main problem, the following assumptions are made:

- The load in the target year is assumed to be well forecasted. Since the electricity load growth in a long term is hard to be accurately forecasted, it deserves another big research based on stochastic analysis.
- The network topology in the target year is the same as those given in the initial state.
- The newly added plant is assumed to be connected to the node where the units of the same technology are located initially.
- No unit is retired from the initial generation mix in the target year. Because: 1) the proposed model is static, and therefore the dynamic process is neglected; 2)conventional generation capacity has to be expanded accordingly to provide backup for increased wind capacity. It offsets some units' retirement.

2.3.3 Wind Power Modelling

In this chapter, the wind generation technology is used to stand for the renewable generation. The power output of a wind turbine can be described by Equation 2-16 [51, 58]:

$$P_w = \begin{cases} P_{wr} \dfrac{v_w - v_{ci}}{v_r - v_{ci}}, & (v_{ci} < v_w < v_r) \\ 0, & (v_w < v_{ci} \ or \ v_w > v_{co}) \\ P_{wr}, & (v_r < v_w < v_{co}) \end{cases} \qquad \textbf{2-16}$$

where, P_w is the instantaneous output of the wind turbine; P_{wr} is the rated output of the wind turbine. v_w, v_{ci}, v_r and v_{co} are instantaneous wind speed, cut-in speed, rated speed and cut-out speed.

Wind speed probability distribution in this research is modelled by Weibull probability function 2-17 .

$$f(v_w) = \frac{k}{\eta}\left(\frac{v_w}{\eta}\right)^{k-1} \cdot \exp[-(\frac{v_w}{\eta})^k] \quad \textbf{2-17}$$

where k is the shaping factor and η is the scaling factor. A set of random numbers are generated following the Weibull distribution for the operation scheduling horizon by MATLAB, representing the output of a wind farm in each scheduling interval. Wind farm output power is taken as negative load and used to mitigate the block total power demand in each scheduling block.

In this wind speed sampling process, the wind speed correlation between consecutive hours is neglected for simplicity.

2.4 Solution Methodology

Notably, the model proposed is a mix-integer nonlinear programming (MINLP) problem. It is hard to be solved directly by a single optimization algorithm, but can be tackled by types of decomposition techniques. Bender's Decomposition is a popular one of them. It divides the problem into a relaxed integer linear programming (master problem) and a non-integer programming (sub problem). The two problems are solved alternately and coupled by Benders' cuts. In the case of its application in generation planning, most previous researches [24, 43] neglected the integer variables in the operational level (unit commitment status and associated start up cost, etc.) and only considered the integer variables in the capacity investment level (number of new units to be built). With this simplification, the original planning problem can be easily divided into a mixed integer linear programming based investment master problem and a non-integer programming operational sub problem, where Benders' decomposition fits quite well. This chapter, however, has taken account of the integer variables and nonlinearity in the operational level, so it is hardly to decompose the problem into an integer problem and a non-integer problem. Therefore, this chapter proposes an innovative method to solve the MINLP problem. The flow chart of the proposed optimization process is shown in Fig.1. It first examines the initial generation mix by conducting a UC for a horizon of T, and checks whether the resultant emission meets the target or not. If yes, that means the current generation mix can already meet the emission target, otherwise, the optimization begins.

The relation of the cost and emission performance with a generation mix can be represented as follows:

$$C_{total} = f(P_1, P_2, ..., P_n) \qquad \textbf{2-18}$$

$$E_{total} = g(P_1, P_2, ..., P_n) \qquad \textbf{2-19}$$

In order to speed up the search for optimal generation mix, a new term named Emission Reduction Cost (ERC) is defined to represent the ratio between the cost increase due to a candidate generator introduction and the resultant emission reduction, given by the following numerical differentiation:

$$ERC\Big|_{\Delta P_n} = \frac{\Delta C_{total}\Big|_{\Delta P_n}}{\Delta E_{total}\Big|_{\Delta P_n}} = \frac{f(P_1, P_2, ..., P_n + \Delta P_n) - f(P_1, P_2, ..., P_n)}{g(P_1, P_2, ..., P_n + \Delta P_n) - g(P_1, P_2, ..., P_n)} \qquad \textbf{2-20}$$

$$ERC_m = \begin{bmatrix} ERC_m\big|_{\Delta P_1} \\ ERC_m\big|_{\Delta P_2} \\ \cdots \\ ERC_m\big|_{\Delta P_n} \end{bmatrix} = \begin{bmatrix} \dfrac{f_m(P_1 + \Delta P_1, P_2, ..., P_n) - f_{m-1}(P_1, P_2, ..., P_n)}{g_m(P_1 + \Delta P_1, P_2, ..., P_n) - g_{m-1}(P_1, P_2, ..., P_n)} \\ \dfrac{f_m(P_1, P_2 + \Delta P_2, ..., P_n) - f_{m-1}(P_1, P_2, ..., P_n)}{g_m(P_1, P_2 + \Delta P_2, ..., P_n) - g_{m-1}(P_1, P_2, ..., P_n)} \\ \cdots \\ \dfrac{f_m(P_1, P_2, ..., P_n + \Delta P_n) - f_{m-1}(P_1, P_2, ..., P_n)}{g_m(P_1, P_2, ..., P_n + \Delta P_n) - g_{m-1}(P_1, P_2, ..., P_n)} \end{bmatrix} \qquad \textbf{2-21}$$

The search is essentially based on gradient search using ERC as the goodness measure. Based on an initial generation mix, assuming M units are added to form the final optimal mix, which meets the emission target, the optimization will be divided into M cycles. In each cycle, denoted by m, the program will add one unit ΔP from each candidate generation technology respectively to evaluate the ERCs under different expanding strategies. The unit whose technology has the lowest ERC will be chosen to add into the generation mix for the m^{th} cycle. The decision making for the next cycle, the $(m+1)^{th}$ cycle, will be repeated based on the optimal mix determined by the m^{th} cycle. The process will iterate M times until no further optimal mix can be found. Fig 2-4 shows the flow chart for implementing the ERC based gradient search generation mix optimization algorithm. Following the algorithm of the flow chart, a programme written in C++ is developed to solve the case study model in next section.

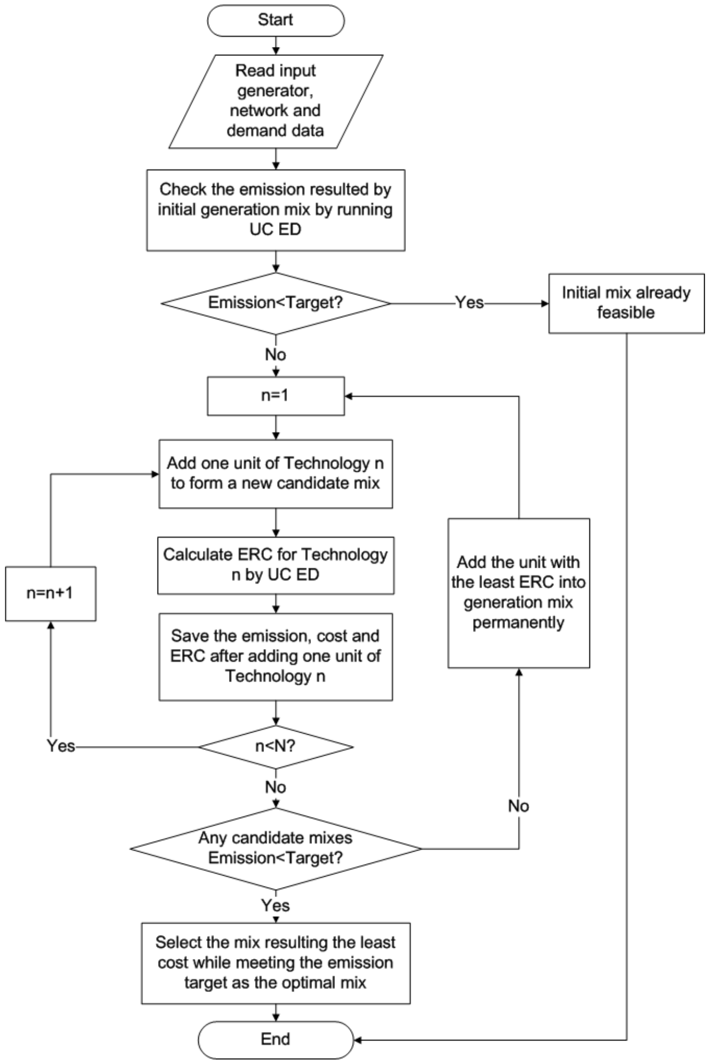

Fig 2-4 Flow chart of the generation mix optimization algorithm

The terminating conditions for the iteration are:

- In the m^{th} cycle, after evaluating the ERCs of N technologies, record the candidate technologies which meet the emission target into the set S. From the set, only the technology with the least ERC is added into the generation mix, and move on to the next cycle;

- In the final cycle, after evaluating the ERCs of N technologies, if E_{total} from all N technologies are below the emission target, terminate the iteration and trace back to find the solution with the least C_{total} from set S.

It should be noted that ERCs for the same technology may vary in different cycles. This is due to that generation mixes at different cycles are different, resulting in different impacts on the costs and emissions from the same technology intervention.

In operational sub-problem, Equation 2-10 and Equation 2-11 indicate the system minimum spinning reserve requirement. So during the iteration, there is a conventional capacity margin check, before adding a new wind unit into the mix each time. If, after the new wind unit is added, the total conventional capacity can not afford the peak demand plus the peak reserve requirement as Equation 2-22 indicates, the wind capacity expansion will not be considered for this cycle.

$$Total\ Conventional\ Capacity < D_{peak} + DSR \times D_{peak} + WSR(\sum_{n=1}^{NW} P_{wn}) \quad \textbf{2-22}$$

2.5 Case study

In this section, a case study is presented to demonstrate the application procedures of the proposed method for determining optimal energy mix to meet a given emission target. Sensitivity analysis is conducted to show the impacts of the short-term emission financial pressure to generation mix optimization. Comparative study between optimizations with and without network constraints is made to indicate the importance of considering network constraints in a generation expansion study.

Table 2-2 Generator Data Part 1

Technologies	a (£/(MW)^2)	b (£/MW)	c (£)	β (tonne/MW)	γ (tonne)	Cc (£/MW)
CCGT[2]1	0.024	6	300	0.38	0.03	483760
CCGT2	0.022	6.4	296	0.39	0.02	481880
COAl PF[3]1	0.032	4.06	630	0.84	0.03	1109175
COAl PF2	0.035	3.64	595	0.82	0.04	1101075
IGCC[4]1	0.014	4.06	756	0.6	0.02	1585200
IGCC2	0.017	3.78	777	0.62	0.01	1573200
OGCT[5]1	0.03	5	706	0.47	0.02	466580
OGCT2	0.034	4.6	720	0.45	0.04	465380
WIND1	0	0	0	0	0	885041
WIND2	0	0	0	0	0	886340

2 CCGT: combined cycle gas turbine generation technology

3 COAL PF: pulverized fuel coal fired generation technology

4 IGCC: integrated gasification combined cycle generation technology

5 OGCC: open cycle gas turbine generation technology

Table 2-3 Generator Data Part 2

Technologies	Notional capacity (MW)	Pmin (MW)	Pmax (MW)	Bus No.	Initial Units installed
CCGT1	300	100	300	11	1
CCGT2	350	100	350	5	1
COAl PF1	300	100	600	2	2
COAl PF2	300	50	300	1	1
IGCC1	200	80	400	19	2
IGCC2	250	10	250	14	1
OGCT1	100	20	200	8	2
OGCT2	150	50	300	13	2
WIND1	50	0	150	27	3
WIND2	40	0	200	24	5

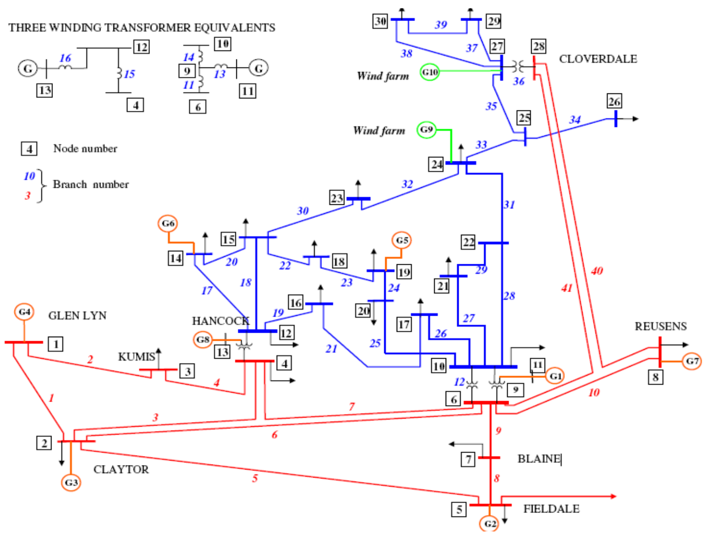

Fig 2-5 **IEEE 30 bus test system [59]**

2.5.1 Test Input

An IEEE 30 bus test system [60] was adopted in this research, which is shown in Fig 2-5. There are comparative studies subsequently between the cases of whether or not considering network constraints. For the case of considering the network constraints, the thermal ratings of all 41 transmission lines are set to 100MW evenly. For the other case, the thermal ratings are set to infinite. Of the 20 units connected to the grid, there are 10 different generation technologies, of which 8 technologies are conventional fossil fuel fired power plants with different performance on fuel cost, emission, and capital cost, and the others are 2 different wind farms which have zero fuel cost and emission output. The details of the 10 generation technologies are given in Table 2-2 and Table 2-3, where a, b and c are the fuel cost function coefficients; β and γ are the emission function coefficients; and Cc is capital cost. The wind turbines' speed parameters are assumed to be the same, as v_{ci} = 5m/s, v_{co}=45m/s, and v_r=15m/s. Since the turbines have been connected to two different locations, the wind speed Weibull distribution parameters for the two locations are differentiated. They are η =10.2, k=1.5 for WIND1, and η=8.6, k=1.5 for WIND2. These parameters are set to give a capacity factor of around 40% for WIND1 and 30% for WIND2. The load profile in this research is derived according to the IEEE Reliability Test System 1996 [61] with a total demand of annual aggregated peak demand of 2830 MW scaled base on the demand data provided in the IEEE 30 bus test system. The specific load profiling data in the IEEE Reliability Test System 1996 can be found in Appendix A. The hourly load is determined by the multiplication of annual peak demand and the coefficients of weekly peak demand in percentage of the annual peak, daily peak demand in percentage of the week peak and hourly peak demand in percentage of the daily peak. Although this model allows any long planning horizon, in order to reduce the calculation burden, this research only takes four days as the samples to estimate the yearly total operation cost. The four days are the first day of each season. The DSR and WSR are set to 5% and 80%, and the reserve price (RP) is assumed to be 5 £/MW/h. A sensitive analysis is provided to investigate the impacts of different emission prices (λ) on the generation planning.

Table 2-4 Emission Reduction Target Scenarios

Reduction	Reduction Target (tonne)			
percentage	EP=5	EP=10	EP=20	EP=30
current	8.95E+06	8.85E+06	8.67E+06	8.51E+06
9.9%	8.06E+06	7.98E+06	7.81E+06	7.67E+06
14.2%	7.68E+06	7.68E+06	7.44E+06	7.30E+06
18.5%	7.29E+06	7.29E+06	7.07E+06	6.93E+06
22.8%	6.91E+06	6.91E+06	6.69E+06	6.57E+06

2.5.2 Implementation

The relationship between emission target and the corresponding optimized generation mix and its year-round performance in terms of total cost and emission is investigated. Based on the emission of the current generation mix, 4 emission reduction targets are assumed for 4 different emission prices in the current and target year. The 16 scenarios are listed in Table 2-4. Because the emission price can influence the emission results, in order to illustrate the emission reduction achieved entirely by restructuring the generation mix, it is assumed that the target year and current year have the same emission price for all scenarios.

For the 16 scenarios, 16 optimal generation mixes have been found that meet the different levels of emission target. The generation mixes under various targets are shown in Fig 2-6 and the corresponding total cost and emission for each optimized generation mix are listed in Table 2-5 and depicted in Fig 2-8. In order to reflect the difference between optimizations with and without considering network constraints, the same evaluation has been made without considering the network constraints and the resultant generation mixes are shown in Fig 2-7 and the corresponding total cost and emission for each optimized generation mix are listed in Table 2-6 and depicted in Fig 2-9.

2.6 Results and Discussion

The Fig 2-6 shows optimal generation mix results under 16 scenarios considering the network constraints. There are 4 stack bar charts categorized by the four different emission prices, 5, 10, 20 and 30. Each bar chart has 5 to 6 stack bars. The first and last bars are the initial generation mix and the optimal generation mix which can realize the maximum emission reduction target respectively. Each stack bar has 10 components, representing the capacities of the 10 generation technologies in the generation mix. It can be seen that for the same reduction target, the resulting optimal generation mixes are different with different emission prices. Moreover, if emission prices in target year are £5/tonne, £10/tonne and £20/tonne, there will be no generation mixes which can meet the 22.8% reduction target. Additionally, the maximum reduction that could be achieved by restructuring the generation mix increases with the rise of emission price. For example, when the emission price is set at £5/tonne, the maximum emission reduction is around 20.0%, but when the emission price rises to £30/tonne, the maximum emission reduction can reach 27.1%. Therefore, there is a reduction limitation. Finally, it is important to note that the least cost to meet the more stringent emission target can only be achieved by a combination of long-term generation expansion and short-term emission control, as shown by the italic cost figures in Table 2-5.

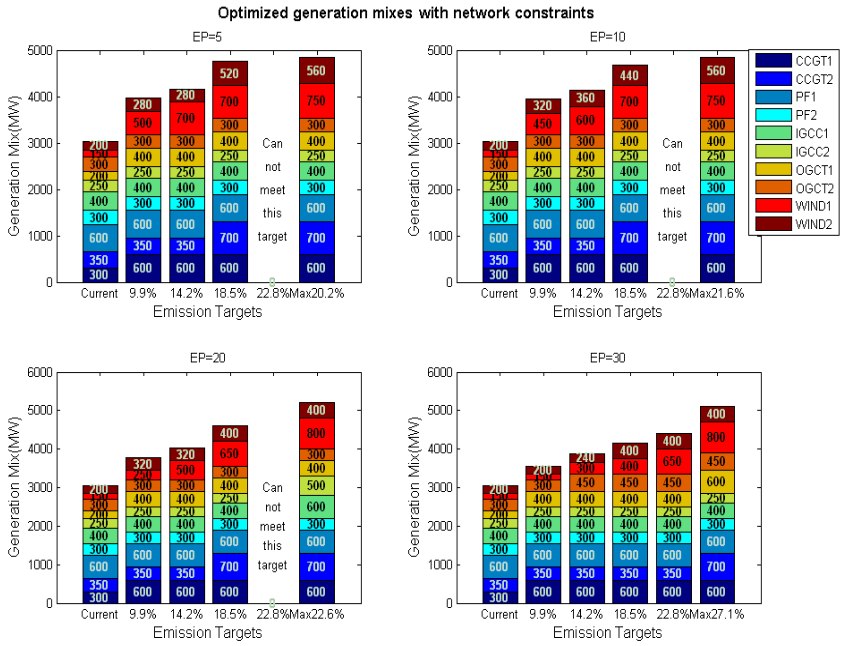

Fig 2-6 Optimized Mixes under Different Emission Targets with Network Constraints

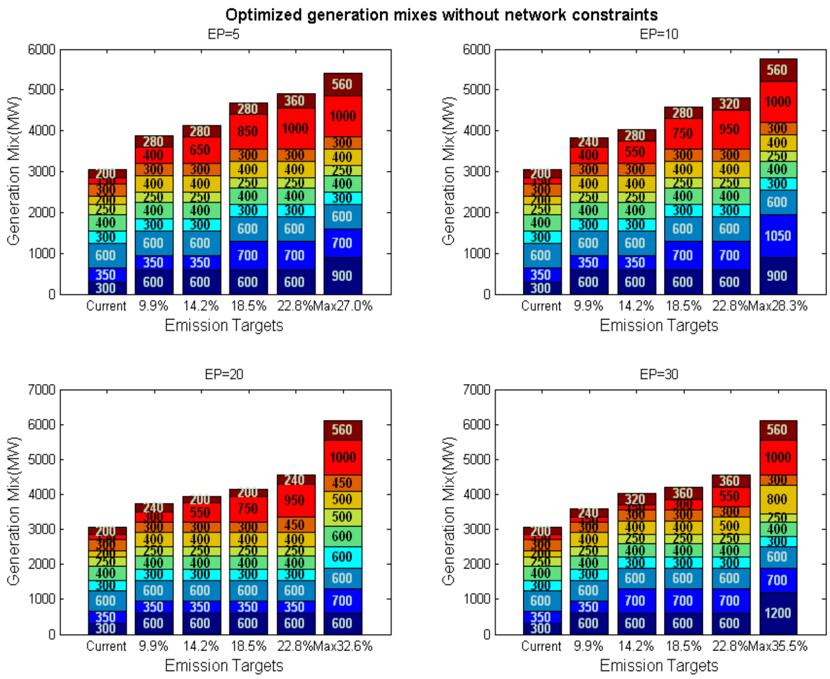

Fig 2-7 Optimized Mixes under Different Emission Targets without Network Constraints

Table 2-5 Cost and Emission Results of Optimization with Network Constraints

Reduction percentage	Total cost (billion £)				Total emission (million tonne)			
	EP=5	EP=10	EP=20	EP=30	EP=5	EP=10	EP=20	EP=30
current	*3.14*	3.19	3.27	3.36	8.95	8.85	8.67	8.51
9.9%	3.76	3.79	3.69	*3.58*	8.04	7.95	7.77	7.65
14.2%	3.93	3.95	3.90	*3.81*	7.66	7.59	7.39	7.28
18.5%	4.31	4.27	4.27	*4.03*	7.25	7.16	6.96	6.92
22.8%	N/A	N/A	N/A	4.23	N/A	N/A	N/A	6.52

Table 2-6 Cost and Emission Results of Optimization without Network Constraints

Reduction percentage	Total cost (billion £)				Total emission (million tonne)			
	EP=5	EP=10	EP=20	EP=30	EP=5	EP=10	EP=20	EP=30
current	3.14	3.19	3.27	3.36	8.95	8.85	8.67	8.51
9.9%	3.66	3.67	3.66	3.51	8.01	7.89	7.77	7.64
14.2%	3.88	3.83	3.84	3.75	7.63	7.58	7.32	7.28
18.5%	4.22	4.17	4.01	4.00	7.25	7.16	6.92	6.92
22.8%	4.42	4.38	4.28	4.16	6.87	6.79	6.64	6.57

The same calculation has been made without considering network constraints. The generation mix optimization results are shown in the Fig 2-7 and the corresponding cost and emission results are listed in Table 2-6. It can be seen that after removing these constraints, the 22.8% reduction target can be realized even for those modest emission prices, £5/tonne, £10/tonne and £20/tonne, which previously are not able to achieve the targets. Besides, the maximum reduction could be achieved rises to 27%, 28.3%, 32.6% and 35.5% for the emission price equal to £5/tonne, £10/tonne, £20/tonne and £30/tonne respectively. Compared to the situation with those constraints, the optimization without them can reduce more emission.

2.6.1 Effect of Network Constraints

From Table 2-5, Table 2-6, Fig 2-8 and Fig 2-9, it can be found that in order to reach the same emission reduction target, the optimization with network constraints always realizes the target at higher or equal total cost compared to the one without network constraints. Besides, the optimization with network constraints can not reach 22.8% emission reduction target when emission price is set to £5/tonne, £10/tonne, and £20/tonne, while it can be reached in the same cases of the optimization without network constraints. The cost differences in percentage between the optimization with and without network constraints are listed in Table 2-7. The differences vary from 0.74% to 6.09%, while the biggest difference is the optimization with constraints which could not achieve the 22.8% reduction target when emission price is equal to £5/tonne,

£10/tonne, and £20/tonne. This shows the importance of taking network constraints into account to avoid underestimating the cost for generation investment.

2.6.2 Effect of Emission Price

From Fig 2-8 and Fig 2-9, it can be observed clearly that with emission target becoming stricter, the total emission drops almost at the same rate for different emission price cases, while the total cost is rising at different rates of change. Generally for the same emission reduction target, a higher emission price can help find the optimal mix to meet the target at a lower total cost. For example, in order to meet the 18.5% reduction target with network constraints, raising EP from £5/tonne to £30/tonne can help reduce the total cost from £ 4.31 billion to £4.03 billion, saving 6.5%. This is because a higher emission price can make the clean technologies more cost efficient during the expansion process. It can avoid the capacity expansion from the technologies that are less clean but expensive.

The reason behind this observation is that the operation costs of the different technologies consist of both fuel cost and emission cost. Increasing the emission price will raise the emission cost and change the operation cost order in economic dispatch. Units with high fuel cost but low emission rate will be put at more prioritised position in the economic dispatch process. Therefore, increasing the emission price in short term can help fully use the existing clean generation capacity, and save the unnecessary generation capacity expansion. Thus, the large capital cost could be saved. This can be verified from Fig 2-6 that in order to meet the 18.5% reduction target, when emission price is set to £30/tonne, 350 MW CCGT1 Plant, 50 MW Wind1 farm and 120 MW can be saved compared with the case when emission price is set to £5/tonne. This shows the importance of considering the short-term financial pressure when optimizing the generation investment.

2.6.3 Emission Reduction Limit

For a fixed amount of demand, the system's total emission can not be reduced as much as desired merely by increasing the clean units' penetration. It has a reduction limit. If the network constraints are considered, the limit will be much tighter. That is because despite the wind energy is modelled as a zero emission generation source, the rise of wind energy penetration must rely on an increase of conventional generation capacity to provide sufficient spinning reserve to compensate the intermittency. Meanwhile, the conventional power plants have minimum output constraints once they are started up for providing the spinning reserve. Their minimum power output causes a certain amount of emission which is the aforementioned emission reduction limit. Only when the technologies are improved to diminish the constraints of the current generation and operation technologies, could the emission be further reduced.

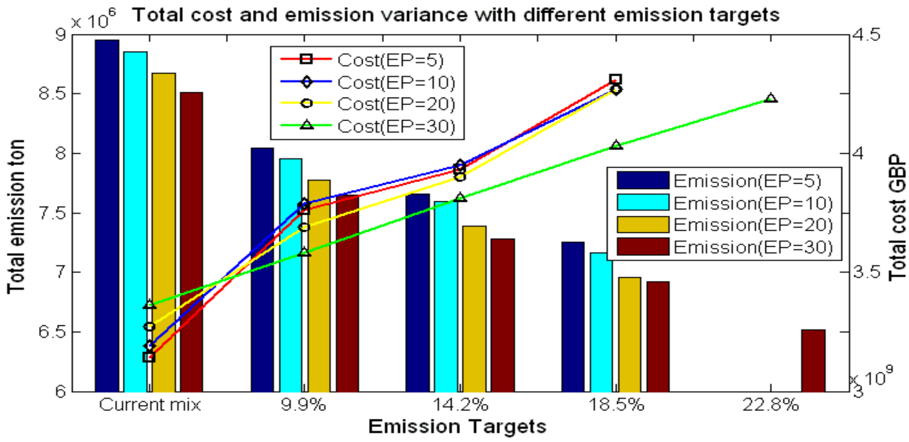

Fig 2-8 Cost and Emission Results with Network Constraints

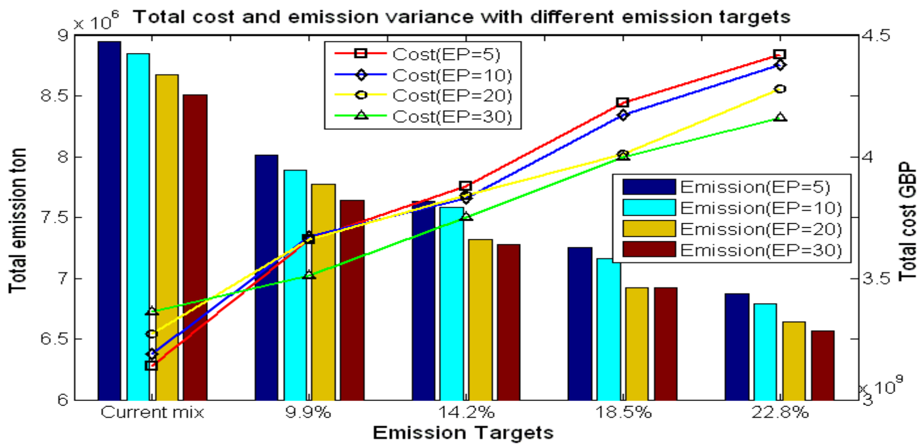

Fig 2-9 Cost and Emission Results without Network Constraints

Table 2-7 Cost Differences between Optimization with and without Network Constraints

Reduction percentage	Total cost difference (£)			
	EP=5	EP=10	EP=20	EP=30
9.90%	2.66%	3.17%	0.81%	1.96%
14.20%	1.27%	3.04%	1.54%	1.57%
18.50%	2.09%	2.34%	6.09%	0.74%
22.80%	N/A	N/A	N/A	1.65%

The case study has presented the application of this model under 16 different scenarios with different emission reduction targets ranging from 9.9% to 22.8% combined with different emission charge prices ranging from 5 £/tonne to 30£/tonne. It can be found that a more stringent emission target can be achieved more economically by a combination of long-run generation expansion and short-run emission control. The results also indicate a higher emission price can help find the optimal mix to meet the target at a lower total cost. They show the importance of including the emission financial pressure when optimizing the generation investment. Optimizations are conducted both with and without network constraints under the 16 scenarios. The comparison between the two optimizations indicates in order to reach the same emission reduction target, the optimization with network constraints always realizes the target at higher or equal total cost compared to the optimization without network constraints. The final cost differences between the two cases vary from 0.74% to 6.09%. It shows the importance of taking network constraints into account when optimizing the generation investment to avoid underestimating the cost. Besides, ignoring network constraints will make the realization of emission targets more possible than it should be. It is also found that the system total emission can not be reduced as much as expected by merely increasing the clean units' penetration. It is due to the necessity of increasing conventional generation capacity to compensate the rise of the wind generation penetration and the minimum output constraints of the conventional power plants.

2.7 Chapter Summary

This chapter proposes a new generation expansion planning model, which takes account of the emission cost in operational level and explores its impacts on the long-term emission target oriented generation planning innovatively. Meanwhile, the model proposed in this chapter takes into account the integer variables and nonlinearity of the operational cost with network constraints and renewable generation expansion together in one long-term generation planning model. The new concept Emission Reduction Cost is introduced in the generation expansion phase, which helps determine the most cost effective generation technologies to expand. The case study explores the impacts of the short-term emission cost on long-term generation planning. It also demonstrates the importance of including network constraints in the generation planning. Overall, this chapter presents a centralized assessment model to find the most economical generation mix pattern in order to meet a predefined emission target, which can assist policy makers in setting the emission reduction target and estimating its total cost required.

Chapter 3

GEP with Location Optimization

THIS chapter introduces a mixed integer linear programming GEP model, which can determine the optimal generation mix and the optimal locations for all candidate generators at the same time for a single target year.

3.1 Introduction

As the definition states, the GEP problem is to determine what type generation technologies should be adopted, how many generation plants should be built, when the planned generation plants should be constructed and sometimes where they should be connected in the transmission network. There have been massive research outcomes in the past to answer the 'what', 'how many' and 'when' questions under a number of scenarios with considering various constraints. Jin [22] developed a two-stage stochastic mixed integer linear programming GEP model, with focus on analysing the uncertainties coming from the GEP problem, such as load and renewable forecast uncertainty, fuel price uncertainty, emission control policy uncertainty, etc. Jonghe [6] proposed a GEP model considering the impacts of short-term price based demand side response on long-term generation mix. Careri [62] proposed mixed integer nonlinear programming GEP model, with focus on investigating the impacts of many types of renewable promotion and emission reduction incentive systems on GEP problem. Palmintier [23] investigated the impact of unit commitment constraints, such as unit ramping rate, operating reserve, etc, on GEP problem with renewable generation. Antonio [63] proposed a multi objective linear programming GEP model, considering total expansion cost, environmental impacts and environmental cost at different weighting in one objective function. However, these previous GEP researches [6, 22, 23, 62, 63] along with many more other literatures [3, 5, 7, 8, 21, 24, 64-71] did not consider transmission network limits (line flow limits) and generation location optimization. They tried to solve the GEP problem at only a single node in the network.

Kaymaz proposed a deregulated generation expansion model, which considered the transmission congestion [25]. However this paper did not consider the optimization of generation locations, as it was assumed that the generation companies may expand their capacity at the nodes where they initially owned generators. Yuan [9] developed an emission target constrained GEP model considering the impacts of short-term emission prices and unit commitment constraints. This paper took account of transmission network limits, but it is assumed that the generation capacity is expanding at their initial locations as well. The same assumption can be found in [72]. Kamalinia [72] proposed a security-constrained stochastic generation expansion model, considering the uncertainties of system component outage and forecast errors of wind and load. Although, this model considered the network transmission constraints, this model only attempted to determine the capacity of newly added fast response generators in given locations to cater for the wind volatility. Wang [45] proposed a strategic GEP model for privatised generation companies under a deregulated electricity market, where generation companies invest their own units for maximising their profit based on the incomplete investment information of other generation companies. Nevertheless, this model still assumed that each generation company invests its generators at a specified bus. The similar study with this assumption can also be found in [73]. Although these researches [9, 25, 45, 72, 73] along with the GEP model presented in Chapter 2 in this thesis considered the network constraints, the generators were assumed to be expanded at designated nodes. In other words, the generation location optimization was not considered.

Meza [74] proposed a model considering multi-period and multi-objective GEP, This model did consider the network flow constraints and generation location optimization. However, the proposed model is only a linear programme. The integer characteristic of generation capacity is neglected. Besides, the author did not mention any detail about the line flow calculation and how the line flow links to the generation outputs at different buses. The integer characteristic of generation expansion was considered in his later work [75] by employing heuristic evolutionary programme.

The generation location optimization was discussed a lot in the distribution generator (DG) siting problem [76-81]. However, due to the characteristics of distribution networks, the DG siting problem usually aims to minimise distribution active and reactive power loss, maintain voltage profiles or reduce the burden of heavily loaded feeders. It's not like the problem of the bulk transmission connected generation planning, which mainly aims to minimize the huge investment and operation cost.

Therefore, based on the literatures reviewed, there are not too many academic researches in GEP area well answering the 'where' question. Most of the previous GEP studies neglected network transmission constraints and generation location optimization. Some research considered the transmission constraints but assumed that the generators were to be expanded at designated nodes. Very few researches considered both transmission network constraints and generation location optimization at the same time.

This is possibly because the siting problem of large transmission connected power plants does not totally depend on power engineering academic analysis. The determination of the location a giant power plant involves too many political, environmental, and geographical factors. However, it is still of importance to well answer the 'where' question, since reasonable siting of new generators can fully take advantage of the existing transmission network capacity. Therefore, a huge amount of transmission network investment could be avoided and the societal cost can be saved potentially. Especially when making a generation mix plan for an extra long-term horizon, when all the initial generation units will retire at the target year, such as 2050 target year, it is quite important to not only decide the generation type and size, but also allocate not a single but multiple power plants to appropriate locations.

Additionally, among all the literatures reviewed above, only the GEP models [9, 23, 72] considered the short-term unit commitment constraints, such as unit's ramping up/down rates, minimum up/down time. The model introduced in Chapter 2 tackles the nonlinear, non-convex, discrete characteristics in both operational level and generation capacity expansion level. The operational level is solved by a dynamic programming algorithm, while the capacity expansion level is solved by an innovative heuristic search method. Although they can take account of many sophisticated details, such as nonlinear fuel cost, integer variables (units' on/off status, number of units expanded), integer constraints (minimum up/down time), spinning reserve and network constraints, it suffers from the curse of dimensionality. In this chapter, a more efficient model method, MILP is introduced.

Based on the aforementioned literature analysis, there is not a GEP model which can consider both generation location optimization and short-term unit commitment constraints simultaneously. This chapter will propose such a model by a mixed integer linear programming (MILP) modelling method.

The rest of this chapter will be organized as:

Section 3.2 introduces the preparation knowledge which will be employed by the developed GEP model. This includes the brief introduction of linear programming and mixed integer linear programming, DC power flow analysis and generation shift distribution factor. Section 3.3 introduces the problem formulation of the developed

GEP model. Section 3.5 presents a case study based on a five bus test system. The values of considering the generation location optimization and the short-term ramping rate constraint in GEP model are shown by comparative studies. Section 3.6 draws the conclusion.

3.2 Prerequisites

3.2.1 Linear Programming and Mixed Integer Linear Programming

- **Linear programming**

Linear programming (LP) is a type of optimization modelling method, whose objective function and equability or inequality constraints can all be expressed by linear polynomials. A standard mathematical expression of a linear programming model with N decision variables, p inequality constraints and q equality constraints is:

$$\text{Objective:} \quad \text{minimise} \;\; c_1 x_1 + c_2 x_2 + \cdots + c_N x_N \tag{3-1}$$

$$\begin{aligned}
\text{Contraints:} \quad & a_{11} x_1 + a_{12} x_2 + \cdots + a_{1N} x_N \le b_1 \\
& \ldots\ldots \\
& a_{p1} x_1 + a_{p2} x_2 + \cdots + a_{pN} x_N \le b_p \\
& aeq_{11} x_1 + aeq_{12} x_2 + \cdots + aeq_{1N} x_N = beq_1 \\
& \ldots\ldots \\
& aeq_{q1} x_1 + aeq_{q2} x_2 + \cdots + aeq_{qN} x_N = beq_q
\end{aligned} \tag{3-2}$$

where, x is the decision variable; c is objective function linear coefficient; a is the inequality constraint function coefficient; aeq is the equality constraint coefficient function.

For a LP problem with no more than three decision variables, it can be solved easily by visualizing the feasible region according to the constraints and finding the optimal point manually by observing along the edge of the feasible region. However, if the number of decision variables becomes large, the problem can not be visualized. In 1947, Dantzig developed the simplex method, which successfully solved the general LP problem and made the LP modelling widely adopted in practice [82-84].

- **Mixed Integer Linear Programming**

When some of the decision variables in the LP problem are required to be integers, then this original LP problem becomes a mixed integer linear programming problem (MILP). In GEP problem, decision variables like number of generation units to be expanded should be integer in practice, while the generation output variables in sub operational problem can be real numbers. The added integer constraints increase the difficulty of searching the optimal points. Many successive researchers have proposed the methods to solve the MILP problem, of which Branch and Bound method proposed by Land and Doig in 1960 is the most popular one [84-86].

Based on the solving methods mentioned above, there have been already various commercial modeling and optimization software packages that can tackle both LP and MILP problem, such as the optimization toolbox in Matlab, IBM ILGO CPLEX, GAMS, LINDO, Gurobi Optimizer, etc. There are also a few good open source optimization packages available, such as GNU Linear Programming Kit (GLPK), lpsolve, etc.

3.2.2 DC Power Flow

Solving AC power flow equations by Newton-Raphson method requires many iterations and modifications of the Jacobian matrix, hence it takes a lot of computation time, especially when the size of the problem becomes large. A GEP problem is usually with a large size since it considers both capacity variables in expansion problem and generators' operational variables in many scheduling blocks in sub operational problem. Therefore, time-efficient power flow analysis method is required when considering the network active power flow limit constraints in the GEP problem. DC power flow analysis meets this requirement very well, provided that only active power flow is of interest and bus voltage and reactive power flow can be neglected during the analysis [87, 88].

For an AC circuit, if the voltage magnitudes and phase angles are known for both sides of a transmission line, the active power flow on the line can be calculated by the function below:

$$P_{ij} = (V_i^2 - V_i V_j \cos\theta_{ij}) g_{ij} - V_i V_j \sin\theta_{ij} b_{ij} \quad \textbf{3-3}$$

where P_{ij} is the active power flow on the line from Bus i to Bus j ; V_i and V_j are the voltage magnitudes on Bus i and j; θ_{ij} is the voltage phase angle difference between Bus i and Bus j; g_{ij} and b_{ij} are conductance and susceptance of the line between Bus i and j.

For a power system under a steady state, the voltage magnitude on each bus is maintained around the rated voltage magnitude (1 per unit) and the voltage phase angle difference between the two sides of a transmission line is quite small. Besides, for a transmission line, the resistance is far less than the reactance. If it is assumed that:

$V_i=V_j=1$; $\sin\theta_{ij}=\theta_{ij}$; $\cos\theta_{ij}=1$; $r_{ij}=0$;

Then, Equation 3-3 can be approximated by:

$$P_{ij} = -\theta_{ij} b_{ij} = (\theta_i - \theta_j) / x_{ij} \quad \textbf{3-4}$$

where, x_{ij} is the reactance of the line from Bus i to Bus j; $x_{ij}= - b_{ij}$; Referring to Ohm's law in DC circuit, P_{ij} can be taken as DC current from Bus i to j; x_{ij} can be taken as the resistance; while θ_i and θ_j can be taken as the voltages at Bus i and j. That explains what the approximation of AC power flow by DC power flow is.

In order to derive the relationship between line active power flow P_{ij} from Bus i to j and active power inject P_i^{INJ} at Bus i, Kirchhoff's Current Law (KCL) is applied, mimicking the KCL in DC circuit:

$$P_i^{INJ} = \sum_{j=1, j\neq i}^{N} P_{ij} = \sum_{j=1, j\neq i}^{N} \frac{(\theta_i - \theta_j)}{x_{ij}} \qquad \text{for i= 1, 2, } \cdots \text{, N} \quad \textbf{3-5}$$

where, N=n-1, n is the number of buses in the network. Since the slack bus is the reference bus, the number of independent buses should be N. Rewrite the above set of equations in matrix style:

$$\boldsymbol{P^{INJ}}=\boldsymbol{B_0\theta} \tag{3-6}$$

where, $\boldsymbol{P^{INJ}}$ is the power injection vector, and $\boldsymbol{\theta}$ is the phase angle vector. They are all with a dimension of N. $\boldsymbol{B_0}$ is the 'admittance matrix', and components are:

$$B_0(i,i) = \sum_{j=1, j\neq i}^{N} \frac{1}{x_{ij}} \tag{3-7}$$

$$B_0(i,j) = \frac{1}{x_{ij}} \tag{3-8}$$

3.2.3 Generation Shift Distribution Factor

In GEP problem, the decision variables are generation capacity and generation output. Therefore when taking account of the transmission line flow limit constraints in the GEP problem, there should be a coefficient to link the generation output at each bus with the active power flow on each transmission line. However, Equation 3-6 describes the linear relationship between the voltage phase angle and active power injection at all buses. Thus, it is better to replace the voltage phase angle with line flow. Based on the DC power flow approximation, it can be derived from Equation 3-6 that:

$$\Delta\boldsymbol{\theta} = \mathbf{B}_0^{-1}\Delta\mathbf{P}^{\mathbf{INJ}} = \mathbf{X}\Delta\mathbf{P}^{\mathrm{INJ}} \tag{3-9}$$

where, $\Delta\boldsymbol{\theta}$ is the phase angle change vector; $\Delta\mathbf{P}^{\mathrm{INJ}}$ is the active power injection change vector; the X is the inverse matrix of B_0. If we only consider a change of injection, ΔP_i^{INJ}, appears at Bus i, then the corresponding phase angle change vector will be:

$$\Delta\boldsymbol{\theta} = \mathbf{X}_i \Delta P_i^{INJ} \tag{3-10}$$

where, $\mathbf{X}_i$ is the i^th^ column vector in matrix **X.** Note the change of power flow on Line k as ΔP_k^i. If the line flow is from Bus m to n, then:

$$\Delta P_k^i = \frac{\Delta(\theta_m - \theta_n)}{x_k} = \frac{\mathbf{M}_k \Delta\boldsymbol{\theta}}{x_k} = \frac{\mathbf{M_k X_i}}{x_k}\Delta P_i^{INJ} \tag{3-11}$$

where, $\mathbf{M}_k$ is Node-Branch Incidence Vector, describing the topology relationship between the nodes and branches in a matrix way. For a network with N nodes and K branches, The Node-Branch Incidence Vector for the k[th] branch from Node m to n is defined as:

$$\begin{array}{l} \mathbf{M_k} = [0 \ \cdots \ 0 \ 1 \ 0 \cdots 0 \ -1 \ 0 \ \cdots \ 0] \\ \qquad\quad 1 \qquad\quad m \qquad\quad n \qquad N \end{array} \tag{3-12}$$

Equation 3-11 linearly links the active power injection variance at Bus i with the active power flow on Line k by a constant factor. This factor is commonly called Generation Shift Distribution Factor (GSDF) in previous literatures. It equals to:

$$GSDF_{k-i} = \frac{\mathbf{M_k X_i}}{x_k} \tag{3-13}$$

The basic circuit analysis theorem, superposition theorem, states that in a linear electric system, one stimulation source can exert the response (current) in a branch independently from other sources. If more than one stimulation sources apply to a circuit, the response (current) in one branch is equal to algebraic sum of the response exerted by applying the every stimulation source individually to the circuit.

Based on the superposition theorem, the injections from all buses will be linearly and respectively distributed on the transmission lines at a rate of GSDF. Then a GSDF matrix can be constructed by identifying the factors relating Bus 1 to N and Line 1 to K. GSDF matrix will have a dimension of $K \times N$ [87, 88].

3.3 Problem Formulation

3.3.1 The Basic MILP GEP Model

Following the MILP modelling method introduced in Section 3.2, the basic MILP model of GEP problem with a total emission limit can be expressed as follows:

$$Min \quad C = \sum_{g=1}^{G}\sum_{t=1}^{T}(FC_g \cdot P_{gt} + EP \cdot E_g P_{gt}) + \sum_{g=1}^{G} CC_g \cdot RCap_g \cdot Np_g \tag{3-14}$$

$$s.t. \qquad \sum_{g=1}^{G} P_{gt} = D_t \qquad \forall t \in T \tag{3-15}$$

$$\sum_{t=1}^{T}\sum_{g=1}^{G} E_g \cdot P_{gt} \leq E_{\text{target}} \qquad \textbf{3-16}$$

$$0 \leq P_{gt} \leq RCap_g \cdot Np_g \qquad \forall t \in T, \forall g \in G \qquad \textbf{3-17}$$

$$NMin_g \leq Np_g \leq NMax_g \qquad \forall g \in G \qquad \textbf{3-18}$$

where, C is the total expansion cost, including generation capacity investment and sub operational cost; g is the unit technology index; t is the index of the sub operational scheduling block; P_{gt} is the generation output of technology g at time t; Np_g is the number of units of technology g to be expanded; FC_g is the operational cost for unit technology g; $CC_g \cdot$ is the capacity investment cost for technology g; $RCap_g$ is the unit nameplate capacity of technology g; D_t is the system demand at time t; EP is the emission price for penalising emission; E_t is the emission factor of generation technology g; E_{target} is the emission target in the target year. $NMin_g$ and $NMax_g$ are the minimum and maximum number of plants limitation for technology g. T is the operational scheduling time horizon; G is the total number of candidate generation technologies.

Equation 3-14 describes the objective which is to minimise the sum of generation capacity investment and the operational cost. Constraint 3-15 guarantees the total generation outputs from all generators equals to the demand in each sub operational scheduling time block. Constraint 3-16 limits the total emission from all generators throughout the sub operation horizon by an emission target. Constraint 3-17 gives the output limits for all types of generation technologies, which is the maximum nameplate capacity multiplied by the number of units to be installed. Constraint 3-18 sets the maximum number of units allowed to be expanded for all candidate technologies.

3.3.2 Inclusion of DC Load Flow Constraints

In the model proposed in Chapter 2, network transmission capacity limits were considered through an AC power flow check for the results from each economic dispatch. However, in the GEP model proposed in the Chapter 2, only active power overloading check is considered as network constraints. Both objective and constraints did not involve any voltage or reactive power analysis. Therefore, it wastes quite a big computation effort in running full AC power flow calculation. In this section, a DC power flow constraint is constructed to improve the computation efficiency. Based on the basic MILP GEP model in Section 3.3.1, the linear active power flow constraints can be added as follows:

$$-Lim_k \le L_{kt} \le Lim_k \qquad \forall k \in K, \forall t \in T \tag{3-19}$$

$$L_{kt} = \sum_{i=1}^{I} GSDF_{k-i} \times \sum_{g=1}^{G} (P_{git} - D_{it}) \qquad \forall k,t \in K,T \tag{3-20}$$

$$\sum_{i=1}^{I} (GSDF_{k-i} \times \sum_{g=1}^{G} P_{git}) \le Lim_k + \sum_{i=1}^{I} (GSDF_{k-i} \times D_{it}) \qquad \forall k,t \in K,T \tag{3-21}$$

$$-\sum_{i=1}^{I} (GSDF_{k-i} \times \sum_{g=1}^{G} P_{git}) \le Lim_k - \sum_{i=1}^{I} (GSDF_{k-i} \times D_{it}) \qquad \forall k,t \in K,T \tag{3-22}$$

where, k is the index of transmission line; K is the transmission line set; i is the bus index; I is the bus set; Lim_k is the active power flow limit of Line k; L_{kt} is the active power flow on Line b at time t; The generation output, P_{gt} in Equation 3-14 is extended to P_{git} with location index i, representing the generation output of technology g at time t at Bus i; Similarly, the system demand D_t is differentiated by location of index i, D_{it} is the demand at Bus i, at time t; $GSDF_{k-i}$ is the generation shift distribution factor from Bus i to Line k, whose definition and derivation have been introduced in Section 3.2.3.

Inequality constraint 3-19 sets the active power flow limits of Line k. It is assumed that the flow limits on Line k are all Lim_k for both directions; Equation 3-20 linearly links the generation at different buses to the line flow through the GSDF. Inequations 3-21 and 3-22 can be obtained by substituting Equation 3-20 to inequality constraint 3-19 and moving the polynomials with the decision variables P_{git} to the left hand side and the rest constant part to the right hand side, which makes the inequation follow the standard form of a MILP model introduced in Section 3.2.

3.3.3 GEP with Unit Location Optimization

Similar to the limitation identified for literatures [9, 25, 45, 72, 73], the GEP proposed in Chapter 2, takes account of transmission capacity limit, which were seldom considered by other GEP studies, but all the candidate generators were only allowed to be expanded at fixed locations, as the assumption in Section 2.3.2 in Chapter 2 states that a newly added plant is assumed to be connected to the node where the units of the same technology are located initially. This will make the generation technologies bound with initial generation locations. This assumption will not affect the GEP optimization results, provided that there are enough transmission capacities throughout the network. However, this is not the real case. In practice, if a competitive technology, which should be expanded to better approach the object, was initially connected at a congested generation bus, the transmission congestion will stop this technology from expanding. This inappropriate constraint will misguide the optimization to expand the right generation technology. In order to correct this issue, an innovative MILP GEP model with generation location optimization has been developed. The developed model can determine both the optimal generation mix and the optimal generation locations for all generators at the same time. Based on the basic GEP model in Section 3.3.1, the decision variables vectors P_{gt} and Np_g are augmented to P_{git} and Np_{gi} respectively, by including the bus index i. The new model can be obtained by augmenting the Equations 3-14 to 3-18 and combining the Equations 3-21 to 3-22 as follows:

$$Min \quad C = \sum_{i=1}^{I} \sum_{g=1}^{G} \sum_{t=1}^{T} (FC_g \cdot P_{git} + EP \cdot E_g P_{git}) + \sum_{i=1}^{I} \sum_{g=1}^{G} CC_g \cdot RCap_g \cdot Np_{gi} \qquad \textbf{3-23}$$

$$s.t. \qquad \sum_{i=1}^{I} \sum_{g=1}^{G} P_{git} = \sum_{i=1}^{I} D_{it} \qquad \forall t \in T \qquad \textbf{3-24}$$

$$\sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{g=1}^{G} E_g \cdot P_{git} \le E_{\text{target}} \qquad \textbf{3-25}$$

$$0 \le P_{git} \le RCap_g \cdot Np_{gi} \qquad \forall t \in T, \forall g \in G \qquad \textbf{3-26}$$

$$NMin_{gi} \le Np_{gi} \le NMax_{gi} \qquad \forall g \in G, \forall i \in I \qquad \textbf{3-27}$$

$$\sum_{i=1}^{I} (GSDF_{k-i} \times \sum_{g=1}^{G} P_{git}) \le Lim_k + \sum_{i=1}^{I} (GSDF_{k-i} \times D_{it}) \qquad \forall k,t \in K,T \qquad \textbf{3-28}$$

$$-\sum_{i=1}^{I} (GSDF_{k-i} \times \sum_{g=1}^{G} P_{git}) \le Lim_k - \sum_{i=1}^{I} (GSDF_{k-i} \times D_{it}) \qquad \forall k,t \in K,T \qquad \textbf{3-29}$$

The core of this model is the application of Superposition Theorem in a linear system. As introduced in Section 3.2.3, in a linear system, the stimulation source can exert its own influence independently from other stimulation sources. Therefore, in a DC load flow approximated power system, the generators with different generation technologies at different locations can independently exert their own influence in terms of load flow on each transmission line. The sum of these influences is the actual load flow across each transmission line.

3.3.4 Inclusion of UC constraints

The candidate generation technologies in above GEP models are only differentiated by four factors: operational cost, emission coefficient, capital cost and nameplate capacity size. These factors only describe the static characteristics of the different generation technologies. However, generation technologies also have their own dynamic characteristics, such as output ramping rate, minimum up and down time. These parameters can indicate how flexible the generation technologies are and are often considered during short-term UC scheduling problems. For example, if the ramping rate is very large, the unit can change its power output to a large extent between two consecutive scheduling intervals, which makes this unit quite flexible.

Arroyo innovatively proposed a linear UC model in [89], which successively linearises the ramping rates, minimum unit up/down time constraints along with the relationship between commitment status, start-up status and shut-down status. There were also successive researches based on this linear UC model [90, 91]. However, they all focused on short-term operation scheduling, but in this section, the linear UC model is augmented by introducing generation expansion decision variables and location optimization. The specified modelling is introduced as follows.

For the ramping up/down constraints, it can be modelled as Inequations 3-30 and 3-31.

$$0 \le P_{git} - P_{gi(t-1)} \le Ru_g \cdot Rcap_g \cdot Np_{gi} \qquad \forall g \in G, \forall i \in I, \forall t \in [2,T] \tag{3-30}$$

$$0 \le P_{gi(t-1)} - P_{git} \le Rd_g \cdot RCap_g \cdot Np_{gi} \qquad \forall g \in G, \forall i \in I, \forall t \in [2,T] \tag{3-31}$$

where, Ru_g and Rd_g are the ramping up and down rates of technology g. In order to reduce the dimension of the decision variables, the generators with the same technology g installed at the same bus i are assumed aggregated to a whole generator with a maximum output of $RCap_g \cdot Np_{gi}$. The aggregated generator could ramp up and down at the rates of $Ru_g \times Np_{gi}$ and $Rd_g \times Np_{gi}$ respectively. The aggregation assumption also applies to the modelling equations from 3-14 to 3-29.

However, if considering the commitment, start-up and shut-down state variables, the aggregated generators of same generation technology has to be disaggregated into individual units, so they can commit, start up and shut down individually. The reason for this is that for the aggregated generators, their output can be constrained by Inequation 3-26, which is the aggregated maximum output, $RCap_g \cdot Np_{gi}$. However, if the unit commitment status is considered, it will also constrain the generation output. These two constraints can be expressed by a linear inequation. Therefore, the units of the same generation technology should be index individually. In order to include UC details in the GEP model, Inequation 3-26 should be replaced by the following:

$$P_{gin(i)t} \le x_{gi(n)t} \; RCap_g \qquad \forall g \in G, \forall i \in I, \forall n(i) \in N(i), \forall t \in T \qquad \textbf{3-32}$$

where, n(i) indexes the n[th] unit of the generation technology g; $x_{gi(n)t}$ is the commitment status. Then the unit minimum up time (MUT), minimum down time (MDT), the logic relationship between commitment, start-up and shut-down states can be formulated as follows:

MUT limit:

$$\sum_{t=k}^{k+UT_g-1} x_{gin(i)t} \ge UT_g \cdot u_{gin(i)k} \qquad \forall g \in G, \forall i \in I, \forall n(i) \in N(i), \forall k \in [1, T-UT_g+1] \qquad \textbf{3-33}$$

$$\sum_{t=k}^{T} (x_{gin(i)t} - u_{gin(i)t}) \ge 0 \qquad \forall g \in G, \forall i \in I, \forall n(i) \in N(i), \forall k \in [T-UT_g+2, T] \qquad \textbf{3-34}$$

MDT limit:

$$\sum_{t=k}^{k+DT_g-1} (1 - x_{gin(i)t}) \ge DT_g \cdot v_{gin(i)k} \qquad \forall g \in G, \forall i \in I, \forall n(i) \in N(i), \forall k \in [1, T-DT_g+1] \qquad \textbf{3-35}$$

$$\sum_{t=k}^{T} (1 - x_{gin(i)t} - v_{gin(i)t}) \ge 0 \qquad \forall g \in G, \forall i \in I, \forall n(i) \in N(i), \forall k \in [T-UT_g+2, T] \qquad \textbf{3-36}$$

Logic relationships between unit commitment, start-up and shut-down states:

$$u_{gin(i)t} - v_{gin(i)t} = x_{gin(i)t} - x_{gin(i)(t-1)} \qquad \forall g \in G, \forall i \in I, \forall n(i) \in N(i), \forall t \in [2, T] \qquad \textbf{3-37}$$

$$u_{gin(i)t} + v_{gin(i)t} \le 1 \qquad \forall g \in G, \forall i \in I, \forall n(i) \in N(i), \forall t \in T \qquad \textbf{3-38}$$

Unit commitment status, start-up status and shut-down status integer limits:

$$x_{gin(i)t}, u_{gin(i)t}, v_{gin(i)t} \in \{0,1\} \qquad \forall g \in G, \forall i \in I, \forall n(i) \in N(i), \forall t \in T \qquad \textbf{3-39}$$

where, $u_{gin(i)t}$ is the start-up state; $v_{gin(i)t}$ is the shut-down state; UT_g is the MUT requirement for technology g; DT_g is the MDT requirement for technology g.

3.3.5 Model Demonstration

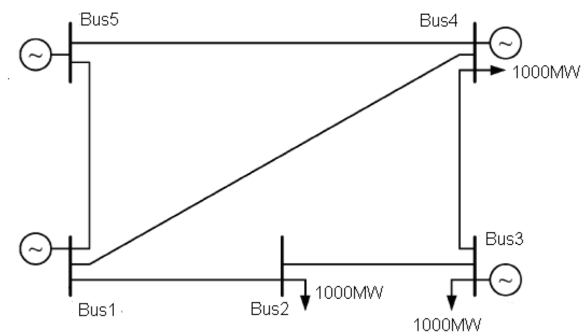

Fig 3-1 Five Bus Test System

In this section, the detailed MILP modelling is demonstrated by showing how the Constraints 3-28 and 3-29 can be constructed to the standard MILP form. For a system with 5 buses and 6 lines as shown in Fig 3-1, Bus 3, 4 and 5 are generator buses, where the candidate generators can be connected to; Bus 2, 3 and 4 are load buses; Bus 1 is selected to be the slack bus. There are five types of candidate generation technologies for selection. The GSDF for three generation buses and six lines can be collected as a matrix and noted as $GSDF_G$. Similarly GSDF for three load buses and six lines can be collected as a matrix and noted as $GSDF_D$. $GSDF_G$ and $GSDF_D$ are defined by Equations 3-40 and 3-41.

$$\mathbf{GSDF_G} = \begin{bmatrix} GSDF_{1-3} & GSDF_{1-4} & GSDF_{1-5} \\ GSDF_{2-3} & GSDF_{2-4} & GSDF_{2-5} \\ GSDF_{3-3} & GSDF_{3-4} & GSDF_{3-5} \\ GSDF_{4-3} & GSDF_{4-4} & GSDF_{4-5} \\ GSDF_{5-3} & GSDF_{5-4} & GSDF_{5-5} \\ GSDF_{6-3} & GSDF_{6-4} & GSDF_{6-5} \end{bmatrix} \qquad \textbf{3-40}$$

$$\mathbf{GSDF_D} = \begin{bmatrix} GSDF_{1-2} & GSDF_{1-3} & GSDF_{1-4} \\ GSDF_{2-2} & GSDF_{2-3} & GSDF_{2-4} \\ GSDF_{3-2} & GSDF_{3-3} & GSDF_{3-4} \\ GSDF_{4-2} & GSDF_{4-3} & GSDF_{4-4} \\ GSDF_{5-2} & GSDF_{5-3} & GSDF_{5-4} \\ GSDF_{6-2} & GSDF_{6-3} & GSDF_{6-4} \end{bmatrix} \tag{3-41}$$

For a single scheduling time block, the generation output decision variables from 5 generation technologies and 3 generation buses can be written in a vector **Pgi,** as is shown in Equation 3-42. The demands at three demand buses are collected in vector **Di** (Equation 3-43). The transmission limits for 6 lines are collected in vector **Limk** (Equation 3-44). Then, Constraints 3-28 and 3-29 can be expressed by a matrix operation, as shown Inequations 3-45 and 3-46. They contribute 12 inequations in the MILP model, ensuring the transmission line not overloaded in both directions for the 6 lines.

$$\mathbf{Pgi} = [P_{11}\ P_{12}\ P_{13}\ P_{21}\ P_{22}\ P_{23}\ P_{31}\ P_{32}\ P_{33}\ P_{41}\ P_{42}\ P_{43}\ P_{51}\ P_{52}\ P_{53}\ ] \tag{3-42}$$

$$\mathbf{Di} = [D_1\ D_2\ D_3\ \ ] \tag{3-43}$$

$$\mathbf{Limk} = [Lim_1\ Lim_2\ Lim_3\ Lim_4\ Lim_5\ Lim_6\ \ ] \tag{3-44}$$

$$[\mathbf{GSDF_G}\ \mathbf{GSDF_G}\ \mathbf{GSDF_G}\ \mathbf{GSDF_G}\ \mathbf{GSDF_G}\ \ ]\times \mathbf{Pgi}^T \le \mathbf{Limk}^T + \mathbf{GSDF}_D \times \mathbf{Di}^T \tag{3-45}$$

$$-[\mathbf{GSDF_G}\ \mathbf{GSDF_G}\ \mathbf{GSDF_G}\ \mathbf{GSDF_G}\ \mathbf{GSDF_G}\ \ ]\times \mathbf{Pgi}^T \le \mathbf{Limk}^T - \mathbf{GSDF}_D \times \mathbf{Di}^T \tag{3-46}$$

3.4 Solution Method

The proposed MILP GEP model in Section 3.3 is solved by an open source MILP solver software package, LPSOLVE. The MILP solver in this software is based on the branch and bound algorithm. The software provides a toolbox for Matlab users. The specification of LPSOLVE and its usage in Matlab can be found in [92].

3.4.1 Introduction of LPSOLVE

For a generic MILP problem as follows:

Maximise v = f’·x

a·x <= b

vlb <= x <= vub

x(int) are integer

The function used to call the MILP solver in Matlab is defined by LPSOLVE as:

[obj, x, duals] = lp_solve (f, a b, e, vlb, vub, xint, scalemode, keep)

Where:

Input Parameters

f: n vector of coefficients for a linear objective function.

a: m by n matrix representing linear constraints.

b: m vector of right sides for the inequality constraints.

e: m vector that determines the sense of the inequalities:

e(i) = -1 ==> Less Than

e(i) = 0 ==> Equals

e(i) = 1 ==> Greater Than

vlb: n vector of lower bounds. If empty or omitted, then the lower bounds are set to zero.

vub: n vector of upper bounds. May be omitted or empty.

xint: vector of integer variables. May be omitted or empty.

scalemode: scale flag. Off when 0 or omitted.

keep: Flag for keeping the lp problem after it's been solved. If omitted, the lp will be deleted when solved.

Output values:

obj: Optimal value of the objective function.

x: Optimal value of the decision variables.

duals: solution of the dual problem

Once the input parameters are fed into the LPSOLVE function, the optimization results can be obtained, in terms of optimal values of decision variables x and maximum objective value.

3.4.2 Building Objective and Constraint Matrix

The programme developed in this chapter is coded in Matlab and calls the LPSOLVE function to tackle the MILP solution. The major difficulties and efforts are to build the input parameter matrix (f, a, b) according to the mathematical model equations in Section 3.3 to fit the objective and constraints into LPSOLVE function.

The objective function coefficient vector, f is relatively easy to build, since it is only a vector. Table 3-1 shows the construction f corresponding to each decision variable. The generator output decision variables in operational sub-problem are associated with the sum of fuel cost and emission cost, while the unit decision variables are associated with capital cost.

Table 3-1 Construction of Objective Function Coefficient Vector

Dimension		GxIxT	GxI
Decision variable vector	x	P_{git}	Np_{gi}
Objective function coefficient vector	f	$-FC_g-EP\cdot E_g$	$-Cc_g\cdot RCap_g$

It should be noted that the default configuration of the LPSOLVE function is to maximise the objective function. Therefore, if the users want to minimise an objective, the coefficient vectors of the original objective function should be multiplied by -1.

The construction of linear constraint matrix, a and b, is relatively complex. The detailed structures of matrix a and b are provided in Appendix D. In Appendix D, Table. D1 shows the constraint matrix for line flow limits. Table. D2 shows the constraint matrix for generator output upper limits. Table. D3 shows the constraint matrix for generation/ demand balance limits. Table. D4 shows the constraint matrix for total emission limits. Table. D5 shows the constraint matrix for generator ramping up/down limits.

Each of the above five constraints matrixes has the same column width, which is the number of decision variables, but has different row width. The five matrixes can be assembled in column direct to form the entire constraint matrix a, so as to b.

Input parameter e is an index vector to indicate whether the rows in constraint matrix a are equations or inequations and direction of the inequations. xint is an index factor to indicate which decision variables are integer variables. In this case, it should index the variables of Np_{gi}.

After feeding the prepared input parameter vectors and matrixes in the LPSOLVE function, optimal decision variables and the associated minimum total cost can be obtained.

3.5 Case Study

In this section, a case study is presented to demonstrate the application of the proposed method for solving the GEP problem with the aim to optimize generation locations. In order to demonstrate the value of network constraints and location optimization in GEP problem, three different GEP models are solved respectively based on the same test input. They are:

1. Basic GEP as introduced in Section 3.3.1 , which does not consider network constraints and generation location;

2. GEP with network constraints, but the generation locations are fixed, which simulates the way of treating the network constraints and locations in the model proposed in Chapter 2.

3. GEP with network constraints and location optimization for all candidate generators, which represents the MILP GEP model proposed in this Chapter.

The results have been compared to show the impacts of network constraints and generation location optimization on GEP problem. In order to show the impacts of the UC constraints on the GEP problem, the same calculation has been made twice to compare the GEP results without and with considering the UC constraints, ramping up/down rates. Although, the MUT, MDT constraints can be formulated in the way as proposed in Section 3.3.4, it increases the problem size too much due to the introduction of three sets of state integer variables. Hence the ramping rate limits can already reflect the dynamic characteristic of a generation technology, so the MUT and MDT constraints are neglected for this case study.

3.5.1 Test Input

A modified PJM five bus test system was adopted for this case study, which is shown in Fig 3-1 as the model demonstration used [93]. Bus3, 4 and 5 are selected to be the generation buses, where all candidate generators could be connected. Bus 1 is selected to be the slack bus. The parameters of the 6 lines are given in Table 3-2. The transmission capacity of each line can be set in two modes, unconstrained and constrained.

There are five types of candidate generation technologies for selection. They have different performance indexes in terms of nameplate capacity, operational cost, capital cost, emission coefficient, and ramping rate. The details of generation technologies are listed in Table 3-3, which are gathered from [65]. Since the impacts of the different emission price on GEP results have been investigated in Chapter 2, in this study emission price (EP) is set to be 10 £/tonne without analysing its impacts. In this case study, we only investigate the carbon emission. Therefore, the emission coefficient provided in Table 3-3 refers to carbon emission coefficient, and the word 'emission' will be used to refer to carbon emission for short for the rest of this chapter.

Bus 2, 3 and 4 are load buses, each of which has 1000MW annual peak load evenly in the planning target year. The load profile in this research is determined according to the IEEE Reliability Test System 1996 [61] . The specific load data can be found in Appendix A. The hourly load is determined by the multiplication of annual peak demand and the coefficients of weekly peak demand in percentage of the annual peak, daily peak demand in percentage of the week peak and hourly peak demand in percentage of the daily peak. In order to save calculation time and put more efforts on investigating the impacts of network constraints and generation locations, this research only takes four days as the samples to estimate the yearly total operation cost. The four typical days are the first day of each season specified by IEEE Reliability Test System 1996. Therefore the scheduling horizon T is 24x4 for this study case. The related operation cost and emission results will be scaled up by 91 (52x7/4), since the scheduling year has 52 weeks.

Table 3-2 Line Data of Five Bus Test System

Line		1-2	1-4	1-5	2-3	3-4	4-5
X (%)		2.81	3.04	0.64	0.08	2.97	2.97
Transmission capacity(MW)	Unconstrained	9999	9999	9999	9999	9999	9999
	Constrained	500	500	300	500	300	500

Table 3-3 Candidate Generation Technology Parameters

Plant type	Nameplate Capacity (MW)	Operation Cost (£/MWh)	Emission Coefficient (tonne/MWh)	Capital Cost (M£/MW)	Ramping Rate (MW/h)
CCGT1	300	6	0.38	0.484	10
CCGT2	350	6.4	0.39	0.482	50
COAl PF	300	3.64	0.84	1.109	20
IGCC1	200	4.06	0.6	1.585	10
OGCT	100	5	0.47	0.467	20

3.5.2 Experiment Implementation

In order to show the generation expansion under different levels of emission limits, the GEP problems are solved respectively under six different emission target ranging from 9.5E+06 tonnes to 7.0E+06 tonnes.

The case study is executed through the following four steps:

1. For the basic GEP problem neglecting network constraints and location optimization, the objective and constraints from Equations 3-14 to 3-18 are used to construct the input matrix. The GEP model is solved six times under six different emission targets. The generation expansion decision results are given in Table 3-5, and the related optimal objective values are given in Table 3-8. Step 1 presents a very basic GEP case as a contrast.

2. For the GEP problem with network constraints but at fixed locations, the objective and constraints from Equations 3-14 to 3-22 are used to construct the input matrix. In this evaluation, the transmission lines are set at the constrained mode, while CCGT1 and CCGT2 units are set to be connected only at Bus 3; Peat FB and IGCC units are to set to be connected only at Bus 4; OCGT units are set to be connected only at Bus 5. This is to simulate the way of treating the generation location in the model proposed in Chapter 2. The GEP model is also solved six times under six different emission targets. The generation expansion decision results are given in Table 3-6, and the related optimal objective values

are given in Table 3-9. Step 2 presents a MILP GEP simulating the GEP model proposed in Chapter 2 as a contrast. For short, we call this model, Model 1, from here onwards.

3. For the GEP problem considering network constraints and location optimization, the objective and constraints from Equations 3-23 to 3-29 are used to construct the input matrix. In this evaluation, the transmission lines are set at the constrained mode, while five generation technologies can be freely located in any of the three generation buses, Bus 3, 4 and 5. The GEP model is solved six times under six different emission targets. The generation expansion decision results are given in Table 3-7 and the related optimal objective values are given in Table 3-10. Step 3 presents a newly developed MILP GEP model with generation location optimization. For short, we call this model, Model 2, from here onwards.

4. Include the Equations 3-30 and 3-31 into the above three models respectively for considering ramp rate limits in GEP problem, repeat the above three steps. The corresponding results are given in Table 3-11 to Table 3-16. Step 4 attempts to show the importance of considering the generators' dynamic characteristics in GEP problem. It is shown by comparing the GEP cases with and without including ramping rate constraints. For short, we call this model proposed in this study, Model 3, from here onwards.

In a real GEP problem, it should be consider that some old units may not be retired in the target year, or some kind of units must be built in the target year due to political or environmental reasons. These units will definitely appear in the generation mix in the target year. Hence there should be a lower boundary for the number of the generation units of each generation technology. Table 3-4 shows these limits. For the Step 1 and 2, since there is not location optimization, the total mix applies as the low bound, as the $NMin_g$ in Inequation 3-18. There is no upper boundary for Step 1 and 2. For Step 3, the location optimization is considered; therefore, the low bound is given for different technologies at different buses respectively. Besides, for the upper bound, maximum 2 units of the same generation technologies are allowed to be built at each bus. This setting is due to the constraints of resource, space, and land availability.

Table 3-4 Minimum Number of Units to Appear in the Target Year

Plant type	Bus 3	Bus 4	Bus 5	Total Mix
CCGT1	2	0	0	2
CCGT2	1	0	0	1
COAl PF	0	1	0	1
IGCC	0	1	0	1
OGCT	0	0	1	1

3.5.3 Results and Analysis

3.5.3.1 GEP without Ramping Constraints

Table 3-5, Table 3-6 and Table 3-7 show the number of units to appear in the target year from the first three steps respectively stated in Section 3.5.2. The top row in each table labels the emission targets under which the GEP is executed. The optimized numbers of generators of different generation technologies are listed in columns corresponding to each emission target.

Table 3-8, Table 3-9 and Table 3-10 show the GEP optimization results in terms of total cost (including capital, operational and emission cost) and total emission. The results in these three tables are related to the generation mix results in Table 3-5, Table 3-6 and Table 3-7 respectively.

- Comparison between Model 2 and Model 1

Comparing Table 3-5 and Table 3-8 to Table 3-6 and Table 3-9, it can be found that even though in Step 2, the network constraint is added, the generation mix, the total cost and emission results are still the same when ET equals to 9.5E+06 tonnes, 9.0E+06 tonnes and 8.5E+06 tonnes. However, when the ET becomes more stringent, less than 8.5E+06 tonnes, the results begin to differ. In Table 3-5, more and more IGCC units are replaced mainly by CCGT1 and CCGT2, which have the first two lowest emission coefficients. This exactly reflects the ET pressure on the GEP. However, surprisingly, in Table 3-6, more and more IGCC units are replaced mainly by OCGT, which have the third lowest emission coefficient. This is because in the Step 2, the GEP model includes network constraints, but generation location selection is bounded with generation technologies. CCGT1 and CCGT2 units are allowed to expand at Bus 3, while OCGT are allowed to expand at Bus 5. Due to the transmission capacity limits, when the generation capacity in Bus 3 reaches a saturated level, over expanded capacity will be wasted. Therefore, even CCGT1 and CCGT2 have the lowest emission coefficients, but it can not play a bigger role even when ET becomes more stringent due to their saturated location. However, although OCGT unit has the third lowest emission coefficient, it penetrates a lot in the target year due to its connecting to a less crowed location. Besides, for Model 2, the total cost increases compared to the results from the Model 1 when ET equals to 8.0E+06 tonnes and 7.5E+06 tonnes. It is of more interest in Table 3-6 that when ET reaches 7.0E+06 tonnes, there is not a feasible mix solution for realising the low emission target. These all shows the from Model 1 to Model 2, the optimal generation mix varies; the total cost increases; and the feasibility drops due to more constraints added.

- Comparison between Model 3, Model 2 and Model 1

Comparing Table 3-6 and Table 3-9 to Table 3-7 and Table 3-10, it can be found that after including the generation location optimization in Model 3, the generation mix, the total cost and emission results are totally different from that in Model 2, for all ET scenarios. For the generation mix results in Model 3, when ET becomes more stringent, the IGCC units are replaced mainly by CCGT1 and CCGT2, rather than OCGT. This is more similar to the results in Model 1. Additionally, the infeasible scenario, when ET equals to 7.0E+06 tonnes in Model 2, however, can be realised in Model 3.

There is another interesting observation that for loose ET scenarios, when ET equals to 9.5E+06 tonnes, 9.0E+06 tonnes and 8.5E+06 tonnes, the total cost in Model 3 is greater than that in Model 1 and 2. But for tight ET scenarios, when ET equals to 8.0E+06 tonnes, 7.5E+06 tonnes and 7.5E+06 tonnes, the total cost in Model 3 is greater than that in Model 2 but less than that in Model 1. These are because in Model 3, there is an upper boundary, which is maximum 2 units of the same generation technologies are allowed to be built at each bus, due to the constraints of resource, space, and land availability. But there are no such upper boundaries for Model 1 and Model 2. Therefore, when ET is loose, the cost efficient generation technologies will be expanded with priority, but the upper boundaries in Model 3 stops it to expand immoderately. For example, when ET equals to 9.5E+06 tonnes, 6 IGCC units appear in the optimal generation mix of Model 1 and 2, but only 4 appear in that of Model 3 along with one more CCGT1 unit, which has a bit higher operational cost and capital cost compared to IGCC. Therefore, when ET equals to 9.5E+06 tonnes, 9.0E+06 tonnes and 8.5E+06 tonnes, the total cost of Model 3 is higher, which reflects the results closer to the real practice. Similarly, when ET becomes tighter, more and more emission efficient generation technologies will be expanded with priority. Model 1 allows the emission efficient units to expand immoderately, while Model 2 over constrains this immoderate expansion by bounding the generation technologies with the expansion location. Only Model 3 appropriately constrains the immoderate expansion by optimizing generation location to better use the available network transmission capacity and capping the maximum number of units at each bus for each generation technology. That is why when ET equals to 8.0E+06 tonnes, 7.5E+06 tonnes and 7.5E+06 tonnes, the total cost in Model 3 is greater than that in Model 2 but less than that in Model 1.

Table 3-5 Optimal Generation Mix without Network Constraint

Emission target(tonne)		9.5E+06	9.0E+06	8.5E+06	8.0E+06	7.5E+06	7.0E+06
Number of Installed Units	CCGT1	2	2	2	3	3	5
	CCGT2	1	1	1	1	2	1
	COAl PF	1	1	1	1	1	1
	IGCC	6	6	6	4	3	1
	OGCT	1	1	2	2	1	3

Table 3-6 Optimal Generation Mix with Constrained Network and Fixed Location

Emission target (tonne)		9.5E+06	9.0E+06	8.5E+06	8.0E+06	7.5E+06	7.0E+06
Number of Installed Units	CCGT1	2	2	2	3	2	Not Feasible
	CCGT2	1	1	1	1	2	
	COAl PF	1	1	1	1	1	
	IGCC	6	6	6	4	2	
	OGCT	1	1	2	3	7	

It can be concluded from these observations that Model 3 can better utilise the available resources than Model 2 does. Compared to Model 1, Model 3 improves a lot by taking account of network constraints and deciding the generation mix and its optimal location simultaneously. Additionally, Model 3 is more close to the real GEP problem. Therefore its results are more close to the real optimal generation mix and required total cost. In a word, compared to Model 1 and Model 2, Model 3 can avoid the overestimation or underestimation of optimal capacities of different generation technologies and required total cost, subject to various ETs.

Table 3-7 Optimal Generation Mix with Constrained Network and Optimized Location

Emission target(tonne)		9.5E+06	9.0E+06	8.5E+06	8.0E+06	7.5E+06	7.0E+06
Number of Installed Units	CCGT1	3	3	3	3	3	3
	CCGT2	1	1	1	1	2	3
	COAl PF	1	1	1	1	1	1
	IGCC	4	4	4	4	3	1
	OGCT	1	1	1	2	1	2

Table 3-8 Optimal GEP Results without Network Constraint

Emission Target (tonne)	Total Cost £	Total Emission(tonne)
9.5E+06	1203746414	8925363
9.0E+06	1203746414	8925363
8.5E+06	1249929997	8500000
8.0E+06	1331392430	8000000
7.5E+06	1422341839	7500000
7.0E+06	1571150045	7000000

Table 3-9 Optimal GEP Results with Constrained Network and Fixed Location

Emission Target (tonne)	Total Cost £	Total Emission(tonne)
9.5E+06	1203746414	8925363
9.0E+06	1203746414	8925363
8.5E+06	1249929997	8500000
8.0E+06	1377351936	8000000
7.5E+06	1524288203	7500000
7.0E+06	Not feasible	

Table 3-10 Optimal GEP Results with Constrained Network and Optimized Location

Emission Target (tonne)	Total Cost £	Total Emission(tonne)
9.5E+06	1285692636	8433461
9.0E+06	1285692636	8433461
8.5E+06	1285692636	8433461
8.0E+06	1331392430	8000000
7.5E+06	1422341839	7500000
7.0E+06	1574516289	7000000

3.5.3.2 GEP with Ramping Constraints

As Step 4 states, the first three steps are executed again by adding the unit's ramping rate constraints. The corresponding results are shown in Table 3-11 to Table 3-16. The table structure is exactly the same as Table 3-5 to Table 3-10. The difference between Models 1, 2 and 3 found in Section 3.5.3.1 still applies. Therefore, it will not be repeated in this section. The key point in this section is to investigate the impacts of ramping rate constraints on GEP problem.

Compared Table 3-11 to Table 3-16 with Table 3-5 to Table 3-10, it can be found that after adding the ramping rate constraints, the generation mix results of Models 1, 2 and 3 all changes under some ET scenarios. Especially, it can be seen from Table 3-12 that it even can not realise the 7.5E+06 tonnes emission target after considering ramping rate constraint. It is more notable that the total costs of Models 1, 2 and 3 with ramping rate constraint are all higher then that without ramping rate constraint, no matter under which emission targets. This is because ramping rate constraints can reflect the unit's output flexibility, which is also an important characteristic of a generation technology. If a GEP problem neglects ramping rate constraints, it equals to make an assumption that each generation technology can ramp up or down its output immoderately. But if the ramping rate constraints are considered, the cost efficient generator may not be able to provide as much as cheap power output whenever it is needed. That is why the total cost is underestimated.

It can be concluded that solving a GEP problem without considering the ramping rate constraints may lead to sub optimal generation mix results and will definitely underestimate the total cost required. The findings demonstrate the value of the GEP model developed in this research.

Table 3-11 Optimal Generation Mix without Network Constraint

Emission target(tonne)		9.5E+06	9.0E+06	8.5E+06	8.0E+06	7.5E+06	7.0E+06
Number of Installed Units	CCGT1	2	2	2	2	4	2
	CCGT2	1	1	1	2	1	4
	COAl PF	1	1	1	1	1	1
	IGCC	6	6	6	5	3	1
	OGCT	1	1	2	1	2	2

Table 3-12 Optimal Generation Mix with Constrained Network and Fixed Location

Emission target (tonne)		9.5E+06	9.0E+06	8.5E+06	8.0E+06	7.5E+06	7.0E+06
Number of Installed Units	CCGT1	2	2	2	3	Not Feasible	
	CCGT2	1	1	1	1		
	COAl PF	1	1	1	1		
	IGCC	5	5	6	4		
	OGCT	2	2	2	3		

Table 3-13 Optimal Generation Mix with Constrained Network and Optimized Location

Emission target(tonne)		9.5E+06	9.0E+06	8.5E+06	8.0E+06	7.5E+06	7.0E+06
Number of Installed Units	CCGT1	3	3	3	2	4	3
	CCGT2	1	1	1	2	1	3
	COAl PF	1	1	1	1	1	1
	IGCC	4	4	4	4	3	1
	OGCT	1	1	1	2	2	3

Table 3-14 Optimal GEP Results without Network Constraint

Emission Target (tonne)	Total Cost £	Total Emission(tonne)
9.5E+06	1204337757	8916827
9.0E+06	1204337757	8916827
8.5E+06	1249986763	8500000
8.0E+06	1341135203	8000000
7.5E+06	1443660987	7500000
7.0E+06	1599175956	7000000

Table 3-15 Optimal GEP Results with Constrained Network and Fixed Location

Emission Target (tonne)	Total Cost £	Total Emission(tonne)
9.5E+06	1220417392	8977613
9.0E+06	1220417392	8977613
8.5E+06	1249986763	8500000
8.0E+06	1377896582	8000000
7.5E+06	Not feasible	
7.0E+06		

Table 3-16 Optimal GEP Results with Constrained Network and Optimized Location

Emission Target (tonne)	Total Cost £	Total Emission(tonne)
9.5E+06	1286815472	8513333
9.0E+06	1286815472	8513333
8.5E+06	1286830709	8500000
8.0E+06	1356192809	8000000
7.5E+06	1443660987	7500000
7.0E+06	1620607641	7000000

3.5.3.3 Generation Location Optimization Results

The above tables do not provide the optimal generation locational distribution results in Model 3. These results are shown in Fig 3-2 to Fig 3-5. In each figure, there are two sub figures. The figure on the left hand side shows the generator locational distribution result in Model 3 without ramping rate constraint, while the figure on the right hand side shows the generator locational distribution result in Model 3 with ramping rate constraint. The horizontal axis labels the three generation buses, while the vertical axis labels the integer number of the generation units to appear in the target year. Different generation technologies are differentiated by different colours, with a legend at the top right showing the corresponding relation.

Fig 3-2 shows the generator distribution when ET equals to 9.5E+06 tonnes, 9.0E+06 tonnes and 8.5E+06 tonnes respectively. It can be seen that the generation mix and location allocation results are the same when ET equals to 9.5E+06 tonnes, 9.0E+06 tonnes and 8.5E+06 tonnes and for whether or not considering generators' ramping rate constraint. This indicates that the GEP will not be constrained by the emission targets more than 8.5E+06 tonnes. This is because even without emission constraints, any mix of the five candidate technologies found by the GEP model for the least cost solution will produce an emission less than 8.5E+06 tonnes. Besides, the unit ramping rate constraints will not affect either the generation mix or the locational distribution.

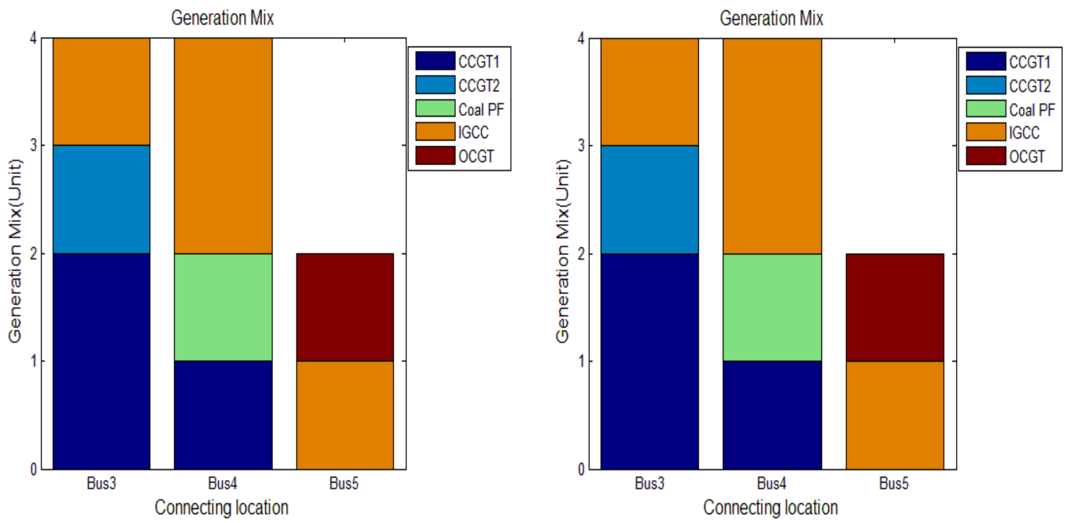

Fig 3-2 Generator Distribution, Emission Target =9.5E+06 tonnes, 9.0E+06 tonnes and 8.5E+06 tonnes

However, when emission target becomes more stringent, the situation changes as more low emission units will be penetrating in the mixes. This can be observed from Fig 3-3, Fig 3-4 and Fig 3-5.

Ramping rate constraints will not only affect the generation mix results, but also affect the optimal generation locational distribution. In Fig 3-3, if the ramping rate constraints are neglected, there will be a CCGT1 unit connecting at Bus4, but if they are included, the CCGT1 unit will be replaced by CCGT2 unit. In Fig 3-4, if the ramping rate constraints are neglected, there will be one CCGT1 unit and one CCGT2 unit connecting at Bus4, but if they are included, the CCGT2 unit will be replaced by CCGT1 unit. Additionally, one more OCGT unit will be connected at Bus4. In Fig 3-5, compared with the case neglecting the ramping rate constraints, there will be one more OCGT unit connecting at Bus4 in the case including the ramping rate constraints. This indicates under the stringent emission target constraints, a small difference in unit's ramping characteristic can significantly affect the generation technologies competitiveness in a long-term view.

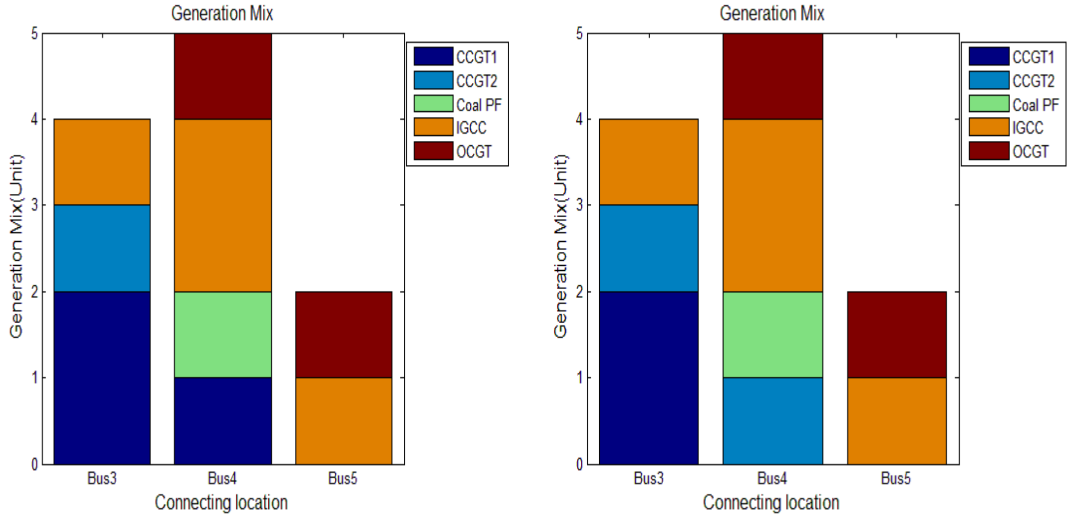

Fig 3-3 Generator Distribution, Emission Target =8.0E+06 tonnes

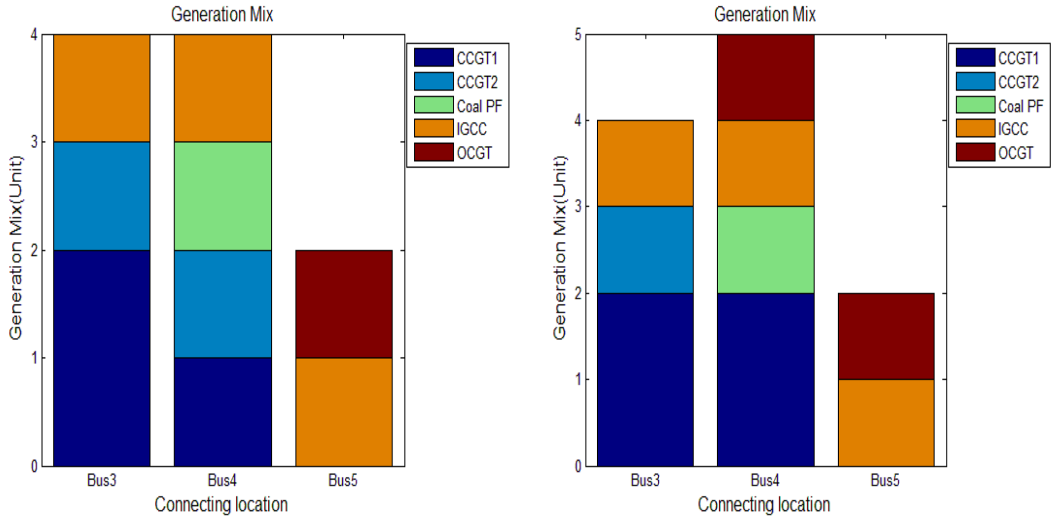

Fig 3-4 Generator Distribution, Emission Target =7.5E+06 tonnes

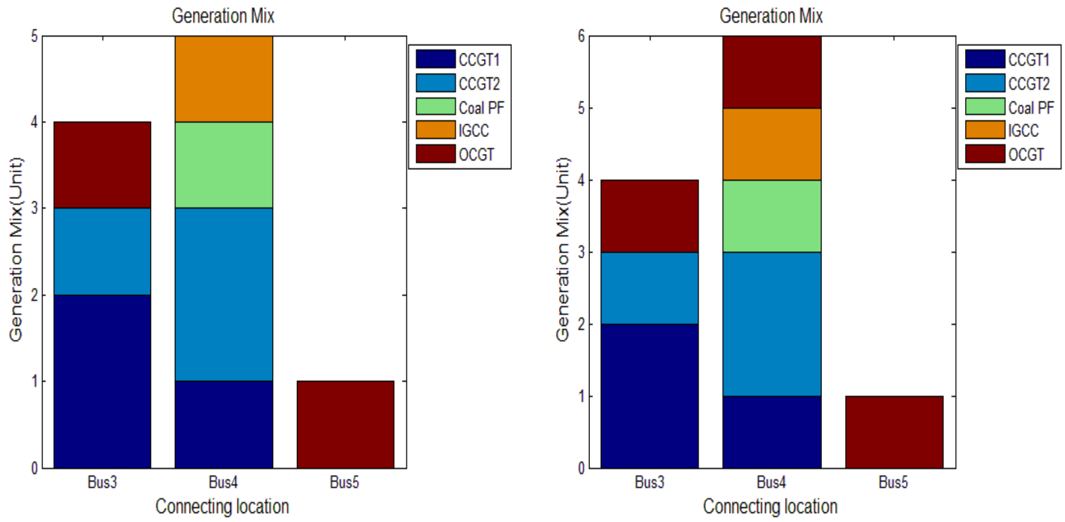

Fig 3-5 Generator Distribution, Emission Target =7.0E+06 tonnes

From the above observations, it can be concluded that for loose emission target constraints the ramping rate constraints may affect the long-term generation mix and generation locational distribution. However, when the emission target becomes stringent, the ramping rate constraints will significantly affect not only the long-term generation mix but also the generation locational distribution. Besides, neglecting ramping rate constraint will definitely underestimate the total cost for the generation expansion. In essence, unit's flexibility (ramping rate), like nameplate size, operational cost efficiency, capital cost efficiency and emission efficiency plays a significant role in the GEP problem.

3.6 Chapter Summary

This chapter proposes a new MILP GEP model. Compared to the previous GEP model, the values of this model are that it can deal with generation location optimization and the short-term unit commitment constraints together in one GEP model. The network constraints and generation location optimization are achieved by employing the generation shift distribution factor (GSDF) under the DC load flow approximation. The decision variables, generation outputs at different buses, are linearly linked to the load flow on each transmission line by GSDF. The unit commitment constraints are also expressed linearly and augmented by bus indexes in order to integrate with the MILP GEP model.

A case study is provided to show the effectiveness of the proposed model. The case study implemented a GEP problem solution based on a five bus test system. Comparison has been made between three different GEP models, which are basic GEP model without network constraint, GEP model with network constraint but at fixed locations, and the new GEP model with network constraint and location optimization. The three models are solved under various emission target constraints, so as to find the difference of the three models under different emission reduction pressures. The results show that the GEP model with location optimization can better utilises the available resources than the second GEP model. Because it can model the GEP problem more close to the real case, it generates a more real generation mix and related cost outputs than the other two simpler models. Therefore, the new GEP model can avoid the overestimation or underestimation of optimal capacities of different generation technologies and required total cost, subject to various emission targets.

The above three GEP models are augmented by including the ramping rate constraints afterwards. The same experiments are executed again to demonstrate the importance to take account of ramping rate constraints in GEP model. The results show that solving a GEP problem without considering the ramping rate constraints may lead to sub optimal generation mix results for some certain levels of emission target pressures. It can be concluded from the results that for loose emission target constraints the ramping rate constraints may affect the long-term generation mix and generation locational distribution. However, when the emission target becomes stringent, the ramping rate constraints will significantly affect not only the long-term generation mix but also the generation locational distribution. Besides, neglecting ramping rate constraints will definitely underestimate the total cost for the generation expansion. In essence, unit's flexibility characteristics (ramping rate), like unit nameplate size, operational cost efficiency, capital cost efficiency and emission efficiency play a significant role in the GEP problem.

In summary, the new GEP model can determine not only the optimal generation mix but also the optimal location of each generation unit in the mix. Since this model takes account of network constraints, location optimization and unit dynamic characteristics, it can provide a more accurate generation mix and related total cost results.

Chapter 4

GEP with Multi-Phase Emission Targets

THIS chapter proposes a multi-phase emission targets constrained GEP model, simultaneously considering generation location optimization at multi phases.

4.1 Introduction

4.1.1 Multi-Phase Emission Targets Setting

In order to fight the global warming, many governments have enforced various green house gas (GHG) emission reduction schemes. Most of these schemes tend to realise the emission reduction target step by step in a multi phase way. METs may be set to approach the final emission reduction target gradually. For example, the European Union enforced the world's biggest emission cap and trade policy, European Union Emission Trading Scheme (EU-ETS) in 2005. EU-ETS was initially designed to be implemented through three phases, covering the period from 2005 to 2020. It now has entered into the Phase III (2013-2050) [94]. Emission caps are specified for each member state for the first three phases. Additional operational phases and related GHG reduction specifications are waiting to be conceived and implemented in the future potentially by European Commission, in order to realise the even long term GHG reduction target in 2050.

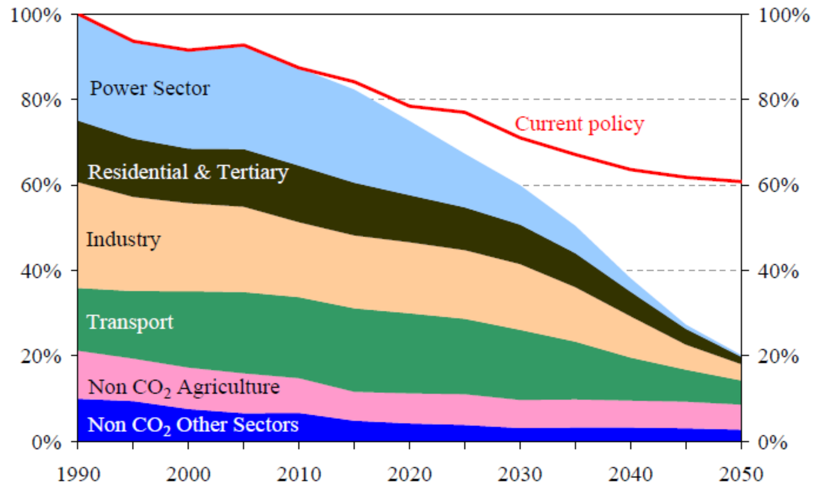

Fig 4-1 EU GHG emissions towards an 80% domestic reduction (100% =1990)[95]

Fig 4-1 illustrates a pathway towards an 80% GHG reduction by 2050 relative to the 1990 level, shown in 5 year steps. The upper "reference" projection shows how domestic greenhouse gas emissions would develop under current policies. A scenario consistent with an 80% GHG reduction then shows how overall and sectoral emissions could evolve, if additional policies are put in place, taking into account technological options available overtime. It can be seen the GHG from power sector will be reduced step by step as those from other sectors [95]. Following the EU-ETS, UK government enforced the Climate Change Act 2008, setting legally binding emission reduction targets of the UK, which are at least 34% and 80% cut in GHG emission by 2020 and 2050 respectively, both against a 1990 baseline.

However, in power industry, the generation plant investment and operation require a very huge amount of money, and usually a generation plant has a long time life, spanning tens of years, once it has been built. Setting emission reduction targets for the whole power industry will push the generation mix to include more low emission generators and exclude more high emission generators. During the evolvement to a final emission reduction target year, new generators will be constructed while the old generators may retire. If there are METs, the settings of these targets may severely change the trajectory of system's generation mix evolvement to the final optimal generation mix, which tends to meet a long-term final emission reduction target. It can be imagined that over stringent METs may lead to excessive clean generation capacity expansion in the mid-term periods, and this excessively expanded clean generation capacity may be not necessary in the FET year. Therefore, inappropriate multiphase emission target settings may affect the GEP in terms of total societal cost dramatically. This chapter investigates these effects.

4.1.2 Literature Reviews

Massive researches have been done in the GEP area, but all the previous GEP models can be categorised into two groups according to their planning time horizons:

One is the single period GEP model, which only attempts to find the optimal generation mix in a single period (target year). For example, in the very early GEP researches [8, 96-98], the authors considered many factors to improve the GEP modelling, such as introducing new solving algorithm, considering uncertainties, multi-objectives, existing units and so on. However, they only solved the optimal generation mix in a single period. There are also a lot of recent single period GEP researches. Doherty performed a generation portfolio analysis considering carbon emission constraints, fuel price uncertainties and wind penetration in [3, 65]. Yuan [9] developed an emission target constrained GEP model considering the impacts of short-term emission price and unit commitment constraints. Jonghe [6] proposed a GEP model considering the impacts of short-term price based demand side response on long-term generation mix. GEP models considering deregulated electricity market environment were presented in [99-102]. The above models are all single period GEP models. Obviously, these models are not able to investigate the impacts of the multiphase emission target settings on the total societal cost.

The other category is multi-period GEP model, which attempts to find the optimal generation mixes for more than one period, gapped by a certain time length (one year, five years, etc). For example, Sepasian proposed a multi-year security constrained combined generation-transmission expansion planning model [103]. Sirikum proposed a GA-Benders' decomposition GEP model to tackle the mixed integer nonlinear programming GEP model in [24]. GEP models considering multi-period and multi-objective GEP can be found in [74, 104]. In [21], the author proposed a low carbon power generation expansion (LCPGE) model, which integrates a comprehensive set of low carbon factors. Jin [22] developed a two-stage stochastic mixed integer linear programming GEP model, with focus on analysing the uncertainties coming from the GEP problem, such as load and renewable forecast uncertainty, fuel price uncertainty, emission control policy uncertainty, etc. Careri [62] proposed mixed integer nonlinear programming GEP model, with focus on investigating the impacts of many types of renewable promotion and emission reduction incentive systems on GEP problem. Kamalinia investigated the fast-response generation unit planning to accommodating the uncertain wind generation in [51, 72]. Multi-period GEP models considering deregulated electricity market environment were presented in [73, 105-107].

Among all the above multi-period GEP researches, only [21, 24, 51, 62, 72, 104] provide the functional interfaces for considering emission targets constraints in each planning period. However, none of them made the numerical analysis for the impacts of the multiphase emission target settings on the total societal cost. Furthermore, there is no previous numerical analysis for the impacts of the multiphase emission target settings on the total societal cost, particularly considering the network constraints and generation location optimization. The study in this chapter fills this blank.

The rest of this chapter will be organized as:

Section 4.2 introduces a multi phase GEP problem formulation extended from the GEP model proposed in Chapter 3, where the objective functions, constraints and solution method are specified; Section 4.3 provides a numerical case study to investigate the impacts of multi phase emission target setting on the total societal cost assessment, especially under the GEP modelling considering generation location optimization in each planning period; conclusions are drawn in Section 4.4.

4.2 Problem formulation

In order to address the problem more clearly, a two phase emission targets constrained GEP model is proposed in this section. It should be noted that although only two phase emission targets are considered in the mathematical formulation, there is no obstacle to extend the current model to a multi phase emission targets constrained GEP model. It's quite straight forward. The problem is formulated by a Mixed Integer Linear Programming (MILP) model [89], which extends the GEP model proposed in Chapter 3 by introducing the two-phase emission targets constraints. The two-phase emission targets are set for two separate target years in future, namely mid-term emission target (MET) and final emission target (FET).

The model attempts to find the optimal generation mixes in both target years at the minimum total cost, including the total generation capacity investment and the total operational cost for both phases. The structure of the proposed model is shown in Fig 4-2.

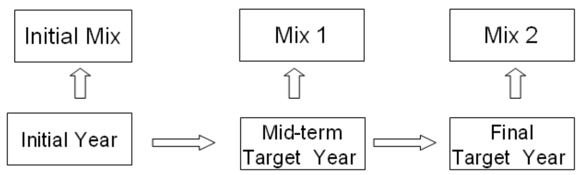

Fig 4-2 Structure of the Two Phase Emission Targets GEP Model

The detailed mathematical MILP formulation is presented as follows:

The objective function combines the short-term operational and emission cost with long-term capital cost:

$$
\begin{aligned}
Min \quad & \sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{i=1}^{I}(FC_g \cdot P1_{git} + EP \cdot E_g \cdot P1_{git}) \\
& + \sum_{g=1}^{G}\sum_{i=1}^{I} CC_g \cdot Rcap_g . Np1_{gi} \\
& + \sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{i=1}^{I}(FC_g \cdot P2_{git} + EP \cdot E_g \cdot P2_{git}) \\
& + \sum_{g=1}^{G}\sum_{i=1}^{I} CC_g \cdot Rcap_g . Np2_{gi} \\
& Np1_{gi}, Np2_{gi} \in Non-negative\ Integer
\end{aligned}
\tag{4-1}
$$

where,

g	Index of generation technology type;
t	Index of scheduling time interval for sub-operational problem;
i	Index of bus;
G	Total number of candidate generation technologies;
T	Scheduling time horizon for sub-operational problem;
I	Total number of buses;
$P1_{git}$	Real power output of unit of generation technology g at bus i at time t in the MET year;
$P2_{git}$	Real power output of unit of generation technology g at bus i at time t in the FET year;
$Np1_{gi}$	Integer decision variable for number of unit of generation technology g to be built at bus i in the MET year;
$Np2_{gi}$	Integer decision variable for number of unit of generation technology g to be built at bus i in the FET year;
$Rcap_g$	Nameplate capacity of generation technology g;
FC_g	Operational cost of generation technology g;
E_g	Emission rate of generation technology g;
EP	Emission price;
CC_g	Capital cost of generation technology g;

The decision variables are $P1_{git}$, $P2_{git}$, $Np1_{gi}$ and $Np2_{gi}$ in Equation 4-1. The constraints include the following:

Supply demand balance in both target years:

$$\sum_{i=1}^{I}\sum_{g=1}^{G} P1_{git} = \sum_{i=1}^{I} D1_{it} \qquad \forall t \in T \tag{4-2}$$

$$\sum_{i=1}^{I}\sum_{g=1}^{G} P2_{git} = \sum_{i=1}^{I} D2_{it} \qquad \forall t \in T \tag{4-3}$$

Transmission capacity limits in both target years:

$$-Lim1_k \le L1_{kt} \le Lim1_k \qquad \forall k \in K, \forall t \in T \tag{4-4}$$

$$L1_{kt} = \sum_{i=1}^{I} GSDF1_{k-i} \times \sum_{g=1}^{G} (P1_{git} - D1_{it}) \qquad \forall k,t \in K,T \tag{4-5}$$

$$-Lim2_k \le L2_{kt} \le Lim2_k \qquad \forall k \in K, \forall t \in T \tag{4-6}$$

$$L2_{kt} = \sum_{i=1}^{I} GSDF2_{k-i} \times \sum_{g=1}^{G} (P2_{git} - D2_{it}) \qquad \forall k,t \in K,T \tag{4-7}$$

Unit power output limits in both target years:

$$0 \le P1_{git} \le RCap_g \cdot Np1_{gi} \qquad \forall t \in T, \forall g \in G \tag{4-8}$$

$$0 \le P2_{git} \le RCap_g \cdot Np2_{gi} \qquad \forall t \in T, \forall g \in G \tag{4-9}$$

Emission target limits in both target years:

$$\sum_{t=1}^{T} \sum_{i=1}^{I}\sum_{g=1}^{G} (E_g \cdot P1_{git}) \le Et1 \tag{4-10}$$

$$\sum_{t=1}^{T} \sum_{i=1}^{I}\sum_{g=1}^{G} (E_g \cdot P2_{git}) \le Et2 \tag{4-11}$$

Ramping up/down constraints in both target years:

$$0 \le P1_{git} - P1_{gi(t-1)} \le Ru_g \cdot RCap_g \cdot Np1_{gi} \qquad \forall g \in G, \forall i \in I, \forall t \in [2,T] \tag{4-12}$$

$$0 \le P1_{gi(t-1)} - P1_{git} \le Rd_g . RCap_g \cdot Np1_{gi} \qquad \forall g \in G, \forall i \in I, \forall t \in [2,T] \tag{4-13}$$

$$0 \le P2_{git} - P2_{gi(t-1)} \le Ru_g \cdot RCap_g \cdot Np2_{gi} \qquad \forall g \in G, \forall i \in I, \forall t \in [2,T] \tag{4-14}$$

$$0 \le P2_{gi(t-1)} - P2_{git} \le Rd_g \cdot RCap_g \cdot Np2_{gi} \qquad \forall g \in G, \forall i \in I, \forall t \in [2,T] \tag{4-15}$$

Relationships of unit service status between initial year and MET year and FET year:

$$\sum_{i=1}^{I} Np1_{gi} \ge PS10_g \sum_{i=1}^{I} Np0_{gi} \qquad \forall g \in G \tag{4-16}$$

$$\sum_{i=1}^{I} Np2_{gi} \geq PS21_g (\sum_{i=1}^{I} Np1_{gi} - \sum_{i=1}^{I} Np0_{gi}) + PS20_g (\sum_{i=1}^{I} Np2_{gi} - \sum_{i=1}^{I} Np0_{gi}) \quad \forall g \in G \tag{4-17}$$

where,

$D1_{it}$	Demand at bus i in time t in MET year;
$D2_{it}$	Demand at bus i in time t in FET year;
k	Index of transmission line;
K	Total number of transmission lines;
$Lim1_k$	Transmission capacity limit of line k in MET year;
$Lim2_k$	Transmission capacity limit of line k in FET year;
$L1_{kt}$	Active power flow on line k at time t in MET year;
$L2_{kt}$	Active power flow on line k at time t in FET year;
$GSDF1_{k-i}$	Generation shift distribution factor from bus i to line k in MET year;
$GSDF2_{k-i}$	Generation shift distribution factor from bus i to line k in FET year;
Ru_g	Ramping rates of generation technology g;
$Et1$	Emission target in MET year;
$Et2$	Emission target in FET year;
$PS10_g$	Binary parameters indicating the service status in MET year of generation technology g built in initial year;
$PS21_g$	Binary parameters indicating the service status in FET year of generation technology g in MET year;
$PS20_g$	Binary parameters indicating the service status in FET year of generation technology g built in initial year;
$Np0_{gi}$	Integer parameter specifying the number of unit of generation technology g at bus i in initial year;

It should be noted that $PS10_g$, $PS21_g$ and $PS20_g$ are binary parameters to indicate whether the generators' life time can cover the time gaps from initial year to MET year, from MET year to FET year and from initial year to FET year. They can be calculated simply by subtracting the time gaps from the life times of different generation technologies. If the difference is positive, that means units with this technology won't retire in next target year. Otherwise, if the difference is zero or negative, it means the units with this technology will retire in or before next target year. For the values of $PS10_g$, $PS21_g$ and $PS20_g$, 1 is used to describe the corresponding in-service generation technology g and 0 is used to describe the retirement generation technology g.

$PS10_g$, $PS21_g$ and $PS20_g$ place constraints that once a generator is built in the previous planning periods; it may stay though to the next planning periods. Therefore, Equation 4-16 and Equation 4-17 respectively describe which generators in the initial year will be still in service in MET year and which generators in initial year and MET year will be still in service in FET year.

Same with Chapter 3, the problem formulated above is also coded in Matlab and solved by the open source MILP solver, 'lpsolve' [92]. The specific method of construction of the objective and constraint matrix has been introduced in Section 3.4.

4.3 Case Study

In order to verify the effectiveness of the method proposed in this study, a case study is presented. Comparative studies have been made to find out the impacts of MET settings on the results of a multi phase emission target constrained GEP problem and the importance of considering generation location distribution on the multi phase emission targets constrained GEP model.

4.3.1 Test System

The GEP model with multi-phase emission targets is tested based on the modified PJM 5 bus test system shown in Fig 3-1 [93], which is also used in Chapter 3. Same as the case study in Chapter 3, Bus3, 4 and 5 are selected to be the generation buses, where all candidate generators will be connected. Bus 1 is selected to be the slack bus. The parameters of six transmission lines are given in Table 4-1. In order to find the impacts on total generation expansion cost purely brought by multiphase emission targets setting, it is assumed that the transmission network parameters stay the same in both MET year and FET year. That means the line parameters in the MET year, $Lim1_k$ and $GSDF1_{k-i}$ equal to those in the FET year, $Lim2_k$ and $GSDF2_{k-i}$.

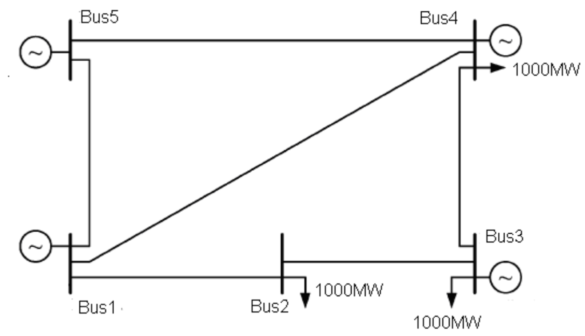

Fig 4-3 Five Bus Test System

Table 4-1 Line Data of Five Bus Test System

Line	1-2	1-4	1-5	2-3	3-4	4-5
X (%)	2.81	3.04	0.64	0.08	2.97	2.97
Transmission capacity(MW)	500	500	300	500	300	500

Table 4-2 Candidate Generation Technology Parameters

Plant Type	Nameplate Capacity (MW)	FC (£/MWh)	Emission Coefficient (tonne /MWh)	CC (M£/MW)	Plant Life (Years)	Ramping Rate (MW/h)
CCGT1	300	6.00	0.38	0.48	30	10
CCGT2	350	6.40	0.05	0.69	20	50
COAl PF	300	3.64	0.84	1.11	20	20
IGCC	200	4.06	0.60	1.59	25	10
OGCT	100	5.00	0.47	0.47	30	20

Five different candidate generation technologies are to be connected to the grid. They have different performances in terms of nameplate capacity, operational cost, capital cost, emission coefficient, plant life and ramping rate. The details of generation technologies are listed in Table 4-2, which are gathered from [65]. Compared to the generator data used in Chapter 3, the technology CCGT2 in this case study is assumed to be equipped with carbon capture and storage (CCS) facility. Therefore, CCGT2 has a very low emission coefficient, but a bit higher investment cost against CCGT1. The reason of introducing the low emission generation technology is to differentiate the emission characteristics of the candidate generation technologies and allow the GEP planning to achieve an even lower emission targets compared to the case in Chapter 3. The generation mix in the initial year is shown in Table 4-3. In order to simplify the calculation of the parameters $PS1_g$ and $PS2_g$ in Equation 4-16 and Equation 4-17, it is assumed that all the units in the initial year are newly built, and they will last for their individual plant life times. Emission price (EP) is set to be 10 £/tonne in this case study.

Table 4-3 Generation Mix in the Initial Year

Plant type	Bus 3	Bus 4	Bus 5	Total Mix
CCGT1	2	0	0	2
CCGT2	1	0	0	1
COAl PF	0	1	0	1
IGCC	0	1	0	1
OGCT	0	0	1	1

Bus2, 3 and 4 are load buses, which have 1000MW annual peak load evenly in the initial year. This case study sets the time gaps evenly between initial year, MET year and FET year to 15 years. It means the MET year is 15 years after the initial year, and the FET year is 15 years after the MET year. It is assumed that there is load growth from the initial year to the MET year and to the FET year. The load growth rate scenarios are shown in Table 4-4 and Table 4-5. It should be noted that for both scenarios, the total load growth is equal.

Table 4-4 Load Growth Scenario 1

Demand Bus		Bus 2	Bus3	Bus4
Load Growth Rate	Initial Year to MET Year	0.05	0.08	0.01
	MET Year to FET Year	0.05	0.08	0.01

Table 4-5 Load Growth Scenario 2

Demand Bus		Bus 2	Bus3	Bus4
Load Growth Rate	Initial Year to MET Year	0.01	0.05	0.08
	MET Year to FET Year	0.01	0.05	0.08

For the MET year, the total demand is equal for both scenarios as shown in the below calculation.

$$
\begin{aligned}
&1000MW\times(1+0.05)+1000MW\times(1+0.08)+1000MW\times(1+0.01)\\
&=1000MW\times(1+0.05)+1000MW\times(1+0.05)+1000MW\times(1+0.08)
\end{aligned}
$$

And also for the FET year:

$$
\begin{aligned}
&1000MW\times(1+0.05)\times(1+0.05)+1000MW\times(1+0.08)\times(1+0.08)\\
&+1000MW\times(1+0.01)\times(1+0.01)\\
&=1000MW\times(1+0.01)\times(1+0.01)+1000MW\times(1+0.05)\times(1+0.05)\\
&+1000MW\times(1+0.08)\times(1+0.08)
\end{aligned}
$$

However, the load growth rates in individual buses are different in each scenario. These two load growth rate scenarios are used to make the comparative study to show the importance of considering generation location optimization in a multi phase emission targets constrained GEP model.

The load profile in this research is determined according to the IEEE Reliability Test System 1996 [61]. The specific load data can be found in Appendix A. The hourly load is determined by the multiplication of annual peak demand and the coefficients of weekly peak demand in percentage of the annual peak, daily peak demand in percentage of the week peak and hourly peak demand in percentage of the daily peak. In order to speed up the calculation, and put more efforts on investigating the impacts of the multiphase emission target settings on the total generation expansion cost. This research only takes one day as a sample to estimate the yearly total operation cost. The day is the first day of a year specified by IEEE Reliability Test System 1996. Therefore the scheduling horizon T is 24 for this study case. The related operation cost and emission results will be scaled up by 364 (52x7/1), since the scheduling year has 52 weeks.

4.3.2 Experiment Implementation

The case study mainly aims to investigate two impacts. The numerical experiment is implemented in two steps:

Step 1:

The first step is to investigate the impact of multi phase emission targets setting on the total cost of generation expansion. In order to do so, the GEP model proposed in Section 4.2 is solved six times under six different emission target settings as are shown in Table 4-6. The six settings have the common final year emission target, but different METs.

Table 4-6 Six Emission Target Settings

MET(tonne)	7.5E+06	7.0E+06	6.5E+06	6.0E+06	5.5E+06	5.0E+06
FET(tonne)	4.0E+06	4.0E+06	4.0E+06	4.0E+06	4.0E+06	4.0E+06

After the calculation, the optimal generation mix results in the MET year are shown in Table 4-7, and those in the FET year are shown in Table 4-8. The total expansion cost and the total emission results under the six settings are shown in Table 4-9. The optimized generation locational distribution results under the six settings are shown in Fig 4-5 through to Fig 4-10. In the first step, load growth scenario 1 shown in Table 4-4 is adopted to decide the forecasted demand in MET year and FET year.

Step 2:

The second step is to investigate the impact of generation location distribution on the multi phase emission targets constrained GEP model. In order to do so, the numerical experiment in the first step is repeated by modifying the load growth rate to the load growth scenarios 2 shown in Table 4-5.

After the calculation, the optimal generation mix results in the MET year are shown in Table 4-10, and those in the FET year are shown in Table 4-11. The total expansion cost and the total emission results under the six settings are shown in Table 4-12. The optimized generation locational distribution results under the six settings are shown in Fig 4-11 through to Fig 4-16.

4.3.3 Results and Discussion

4.3.3.1 Impacts of Multi Phase Emission Target Setting

Table 4-7 shows the number of units to appear in the MET year, and Table 4-8 shows that in the FET year. They are both from the numerical results in Step 1. The top row in each table labels the MET settings under which the GEP is executed. Since the FET is common for all six Emission Target Settings, it is not listed in the tables. The optimized numbers of generators of different generation technologies are listed in columns corresponding to each MET.

It can be seen clearly in Table 4-7 that optimal mid-term generation mixes are the same when METs are set to 7.5E+06 tonnes and 7.0E+06 tonnes. However, when MET becomes more stringent, the optimal mid-term generation mix becomes (5, 1, 1, 1, 3) when MET=6.5E+06 tonnes, (3, 2, 1, 1, 5) when MET=6.0E+06 tonnes, and (2, 3, 1, 1, 4) when MET=5.5E+06 tonnes and 5.0E+06 tonnes respectively. This is as expected that METs becoming more stringent, the optimal generation mix in MET year tends to include more low emission but expensive units.

Table 4-7 MET Year Generation Mix under Six Emission Target Settings

MET(tonne)		7.5E+06	7.0E+06	6.5E+06	6.0E+06	5.5E+06	5.0E+06
Number of Installed Units	CCGT1	4	4	5	3	2	2
	CCGT2	1	1	1	2	3	3
	COAl PF	1	1	1	1	1	1
	IGCC	1	1	1	1	1	1
	OGCT	5	5	3	5	4	4

For the optimal generation mix in the FET year, it can be seen from Table 4-8 that optimal generation mixes in FET year are all the same (2, 4, 0, 0, 7) except that when MET is set to 6.5E+06 tonnes (3, 4, 0, 0, 4). This is an interesting finding because the FET is 4.0E+06 tonnes in all six emission target settings, but when MET is set to 6.5E+06 tonnes, the GEP model generates an optimal generation mix in FET year which is different from those when MET is set to other values.

Table 4-8 FET Year Generation Mix Under Six Emission Target Settings

MET(tonne)		7.5E+06	7.0E+06	6.5E+06	6.0E+06	5.5E+06	5.0E+06
Number of Installed Units	CCGT1	2	2	3	2	2	2
	CCGT2	4	4	4	4	4	4
	COAl PF	0	0	0	0	0	0
	IGCC	0	0	0	0	0	0
	OGCT	7	7	4	7	7	7

More interesting findings can be obtained from Table 4-9. The total cost (including the generation investment and operational cost in both MET year and FET year) tends to increase with the MET becoming more stringent, despite of the same FET. In other words, in order to realise the same final target, extra total cost will be required if stringent mid-term targets are imposed. This is quite similar to the geometry fact that the shortest path between two points is the straight line between the two points. Travelling between the two points via a third point that not in the straight line between the two will lead to longer distance. This shows the importance of setting the multi phase emission targets appropriately, otherwise, a huge amount of unnecessary cost could occur.

Table 4-9 Total Expansion Cost and Emission under Six Emission Target Settings

MET(tonne)	FET(tonne)	Total Cost £	Mid-term Emission (tonne)	Final Emission (tonne)
7.50E+06	4.00E+06	3.615E+09	6.91E+06	3.67E+06
7.00E+06	4.00E+06	3.615E+09	6.91E+06	3.67E+06
6.50E+06	4.00E+06	3.671E+09	6.50E+06	3.51E+06
6.00E+06	4.00E+06	3.703E+09	5.78E+06	3.67E+06
5.50E+06	4.00E+06	3.745E+09	4.81E+06	3.67E+06
5.00E+06	4.00E+06	3.745E+09	4.81E+06	3.67E+06

Table 4-7 and Table 4-8 show the optimal generation mixes in an aggregated way. The optimal generation locational distribution results under the six settings are shown in Fig 4-5 through to Fig 4-10. In each figure, there are two sub stack bar charts. The one on the left hand side shows the optimal generator locational distribution result in MET year, while that on the right hand side shows the optimal generator locational distribution result in FET year. The horizontal axis labels the three generation buses, while the vertical axis labels the integer number of the generation units to appear in the target year. Different generation technologies are differentiated by different colours, with a legend at the top right showing the corresponding relation.

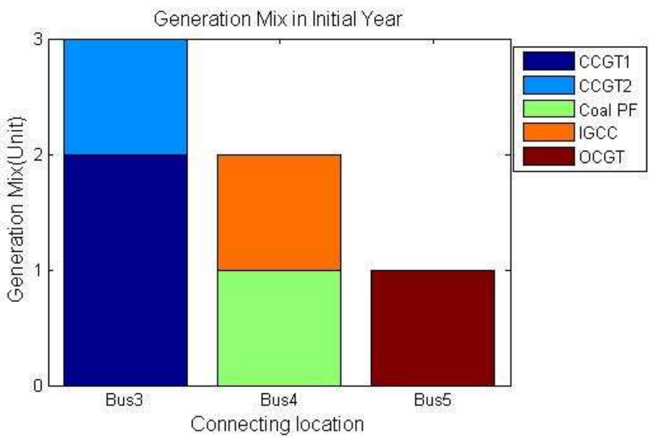

Fig 4-4 Generation Mix in Initial Year

Although, as Table 4-8 shows, the aggregated generation mixes in FET year is the same when MET equals 7.5E+06 tonnes, 7.0E+06 tonnes, 6.0E+06 tonnes, 5.5E+06 tonnes, and 5.0E+06 tonnes, their locational distributions are different, which can be clearly observed from Fig 4-5 through to Fig 4-10. This can be explained that since the MET year and initial year are gapped by 15 years, which is less than plant life of all technologies, all the units in initial year will still be in service in the MET year.

However, in FET year, all the plants in initial year will retire, but the plants built in MET year will still stay.

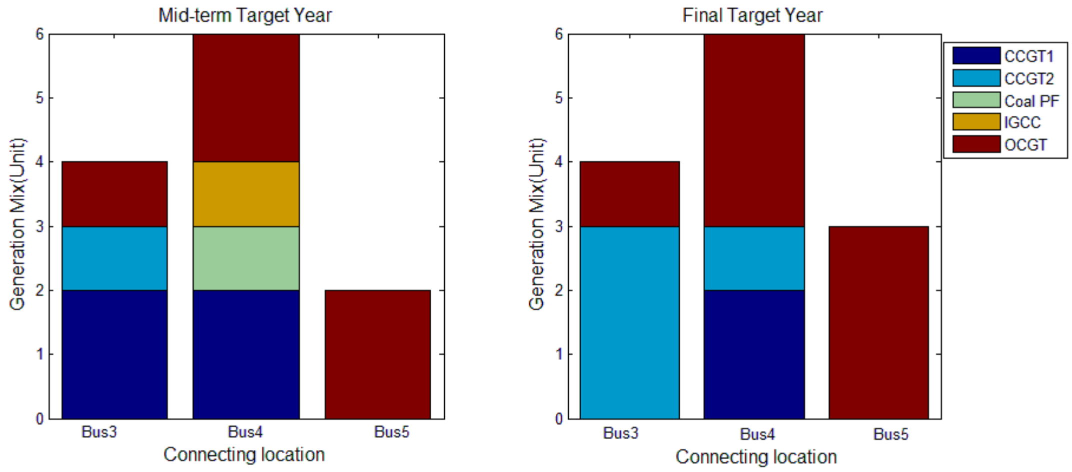

Fig 4-5 Optimal Generator Location in Step 1 when MET=7.5E06 tonnes, FET=4.0E06 tonnes

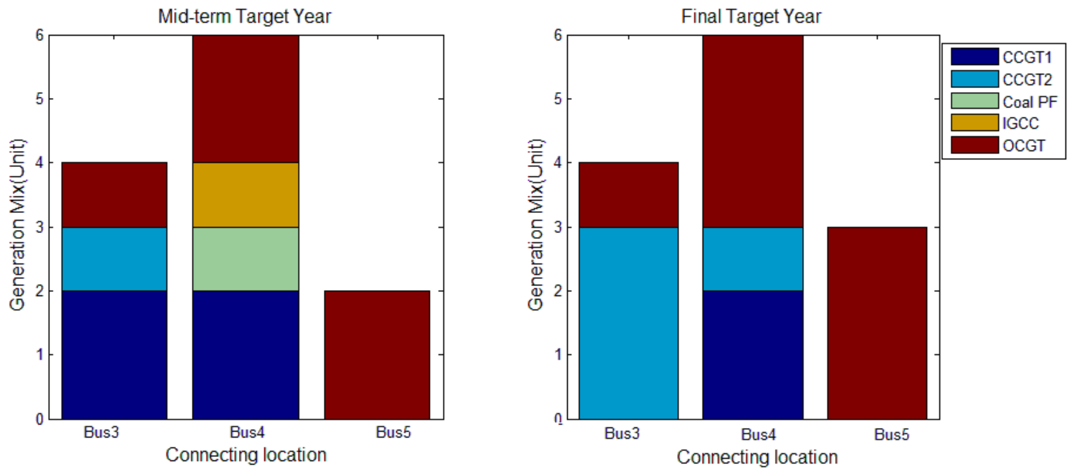

Fig 4-6 Optimal Generator Location in Step 1 when MET=7.0E06 tonnes, FET=4.0E06 tonnes

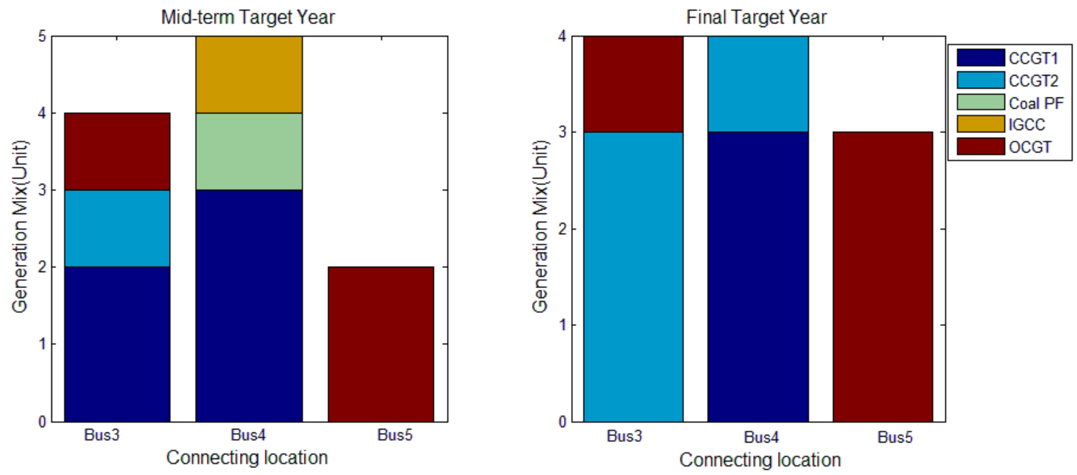

Fig 4-7 Optimal Generator Location in Step 1 when MET=6.5E06 tonnes, FET=4.0E06 tonnes

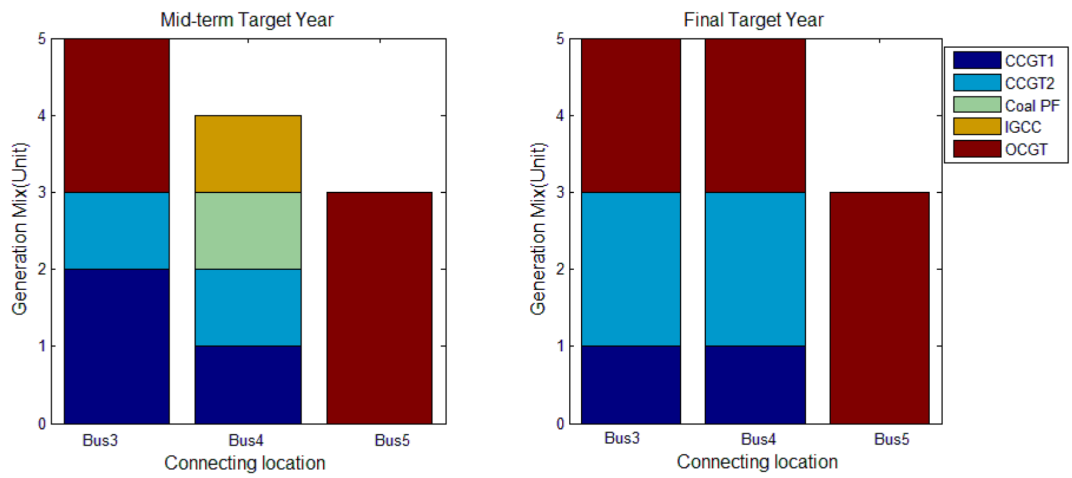

Fig 4-8 Optimal Generator Location in Step 1 when MET=6.0E06 tonnes, FET=4.0E06 tonnes

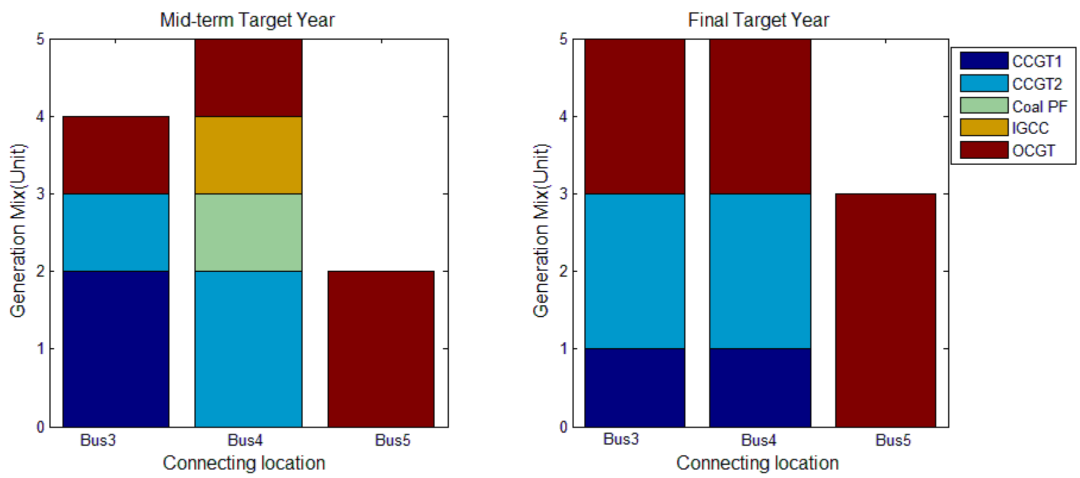

Fig 4-9 Optimal Generator Location in Step 1 when MET=5.5E06 tonnes, FET=4.0E06 tonnes

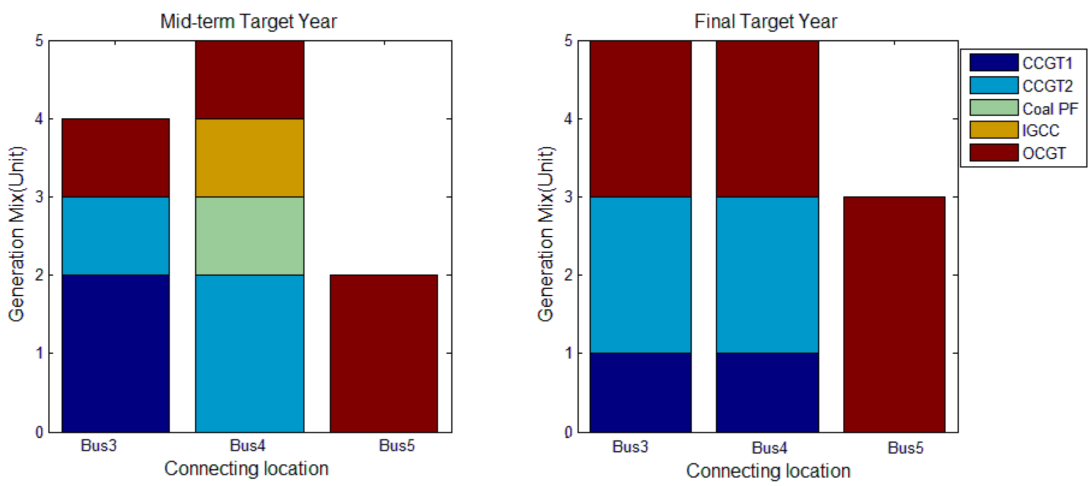

Fig 4-10 Optimal Generator Location in Step 1 when MET=5.0E06 tonnes, FET=4.0E06 tonnes

- **Comparison between the cases when MET is set to 7.5E06 tonnes and 6.5E06 tonnes**

When MET is set to 7.5E06 tonnes and 6.5E06 tonnes, the optimal generation mixes in FET year are different as Table 4-8 shows. Contrasting to Fig 4-4 showing the generation mix in initial year, when MET is set to 7.5E06 tonnes, one OCGT unit is expanded at Bus 3; two OCGT units and two CCGT1 units are expanded at Bus 4; one OCGT unit is expanded at Bus 5 in the MET year. But when MET is set to 6.5E06 tonnes, one OCGT unit is expanded at Bus 3; none OCGT units and three CCGT1 units are expanded at Bus 4; one OCGT unit is expanded at Bus 5 in the MET year. These MET settings will lead:

1. There are at least **two** CCGT1 units connecting at Bus 4 in FET year, when MET is set to 7.5E06 tonnes.

2. There are at least **three** CCGT1 units connecting at Bus 4 in FET year, when MET is set to 6.5E06 tonnes.

The generation mix in FET year in Fig 4-5 is sufficient to realise the FET when MET is set to 7.5E06 tonnes, but if MET is set to 6.5E06 tonnes, one more CCGT1 will be forced to connected at Bus 4, which is unnecessary and therefore leads to a sub optimal GEP result compared to that when MET is set to 7.5E06 tonnes. In essence, over stringent METs will require more clean but expansive units to be built in MET year, and these units may be unnecessary for realising the FET, hence, extra total cost arises. This explains why the total cost in Table 4-9 tends to increase with the MET becoming more stringent, despite of the same FET.

- **Comparison between the cases when MET is set to 7.5E06 tonnes and 6.0E06 tonnes**

When MET is set to 7.5E06 tonnes and 6.0E06 tonnes, the optimal generation mixes in FET year are the same in aggregated statistics as Table 4-8 shows but different in the locational distribution as Fig 4-5 and Fig 4-8 show. The same incremental analysis can be made as above. It can be found that in essence, over stringent METs will require more clean but expansive units to be built in MET year, and these early constructed units may be placed at less optimal locations for realising the FET (due to transmission congestion), hence, extra total cost arises. This also explains why the total cost in Table 4-9 tends to increase with the MET becoming more stringent, despite of the same FET.

4.3.3.2 Impacts of Generation Location Optimization on a Multi Phase Emission Target Constrained GEP model

In order to demonstrate the importance of considering network constraints and the optimization of generation location in a multi phase emission targets constrained GEP problem, the second load growth scenario (Table 4-5) is used to execute the Step 2 specified in Section 3.5.2. The results follow the presenting style of the results from Step 1 and are listed from Table 4-9 to Fig 4-16.

Table 4-10 MET Year Generation Mix under Six Emission Target Settings in Step 2

MET(tonne)		7.5E+06	7.0E+06	6.5E+06	6.0E+06	5.5E+06	5.0E+06
Number of Installed Units	CCGT1	3	4	5	2	4	2
	CCGT2	1	1	1	2	2	3
	COAl PF	1	1	1	1	1	1
	IGCC	1	1	1	1	1	1
	OGCT	8	5	3	8	2	4

Table 4-11 FET Year Generation Mix under Six Emission Target Settings in Step 2

MET(tonne)		7.5E+06	7.0E+06	6.5E+06	6.0E+06	5.5E+06	5.0E+06
Number of Installed Units	CCGT1	2	2	3	2	2	2
	CCGT2	4	4	4	4	4	4
	COAl PF	0	0	0	0	0	0
	IGCC	0	0	0	0	0	0
	OGCT	7	7	4	7	7	7

Table 4-12 Total Expansion Cost and Emission under Six Emission Target Settings in Step 2

MET(tonne)	FET(tonne)	Total Cost £	Mid-term Emission (tonne)	Final Emission (tonne)
7.50E+06	4.00E+06	3.610E+09	7.15E+06	3.67E+06
7.00E+06	4.00E+06	3.615E+09	6.91E+06	3.67E+06
6.50E+06	4.00E+06	3.671E+09	6.50E+06	3.51E+06
6.00E+06	4.00E+06	3.697E+09	6.00E+06	3.67E+06
5.50E+06	4.00E+06	3.708E+09	5.50E+06	3.67E+06
5.00E+06	4.00E+06	3.745E+09	4.81E+06	3.67E+06

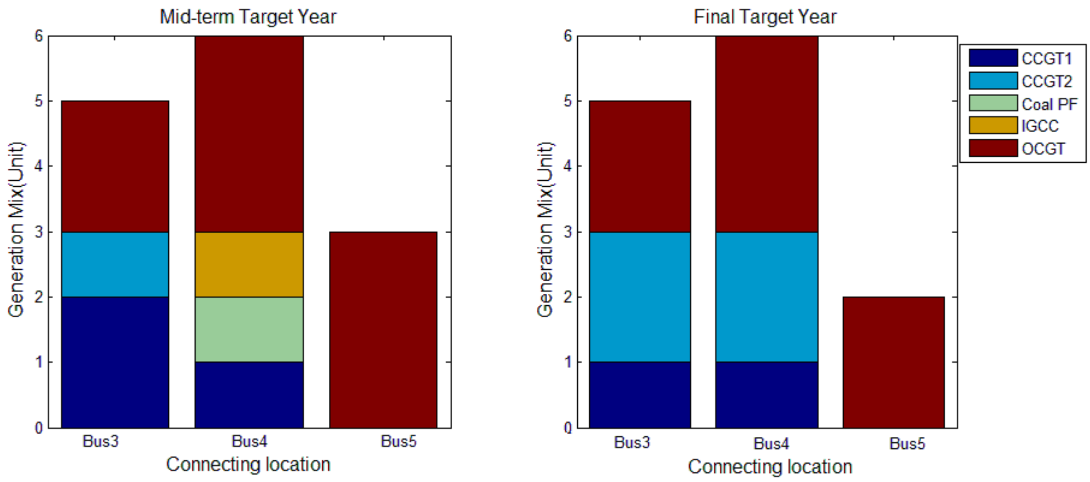

Fig 4-11 Optimal Generator Location in Step 2 when MET=7.5E06 tonnes, FET=4.0E06 tonnes

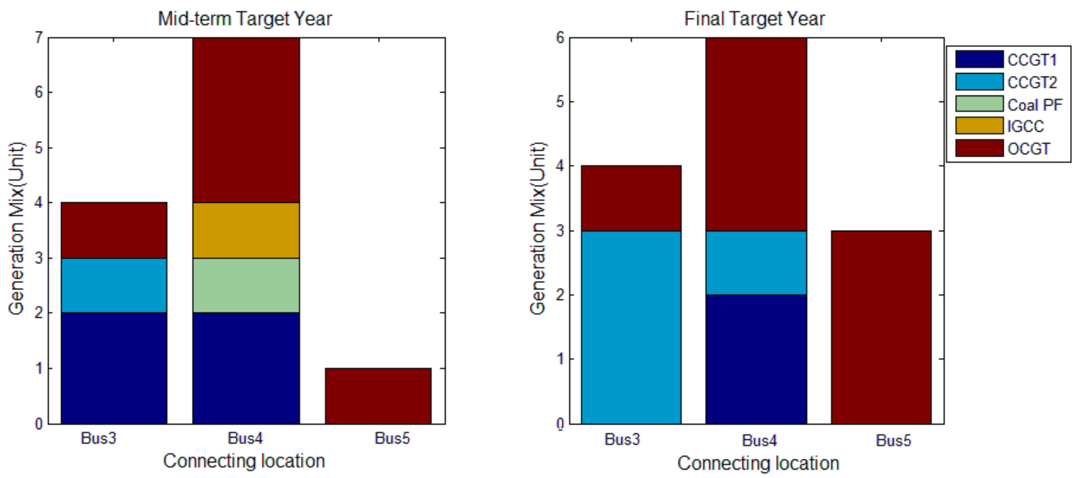

Fig 4-12 Optimal Generator Location in Step 2 when MET=7.0E06 tonnes, FET=4.0E06 tonnes

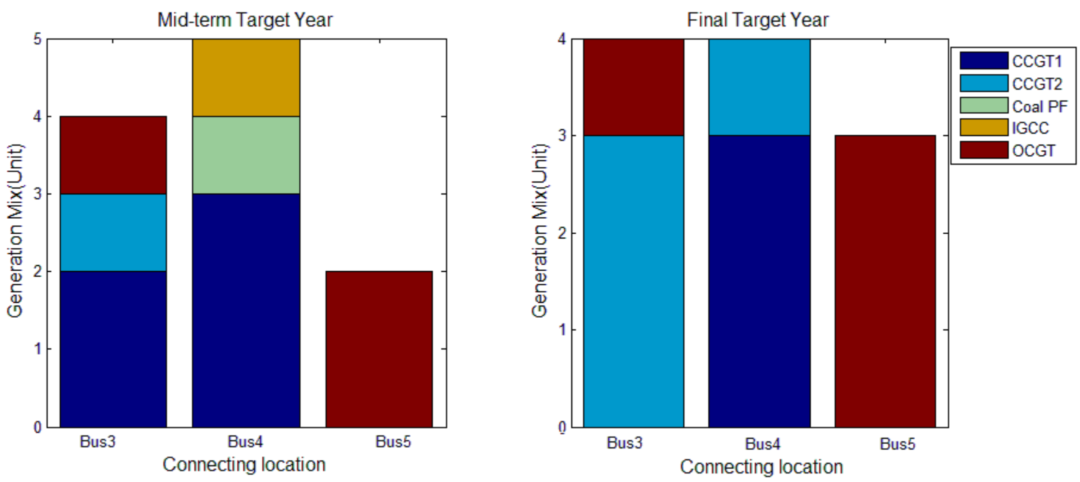

Fig 4-13 Optimal Generator Location in Step 2 when MET=6.5E06 tonnes, FET=4.0E06 tonnes

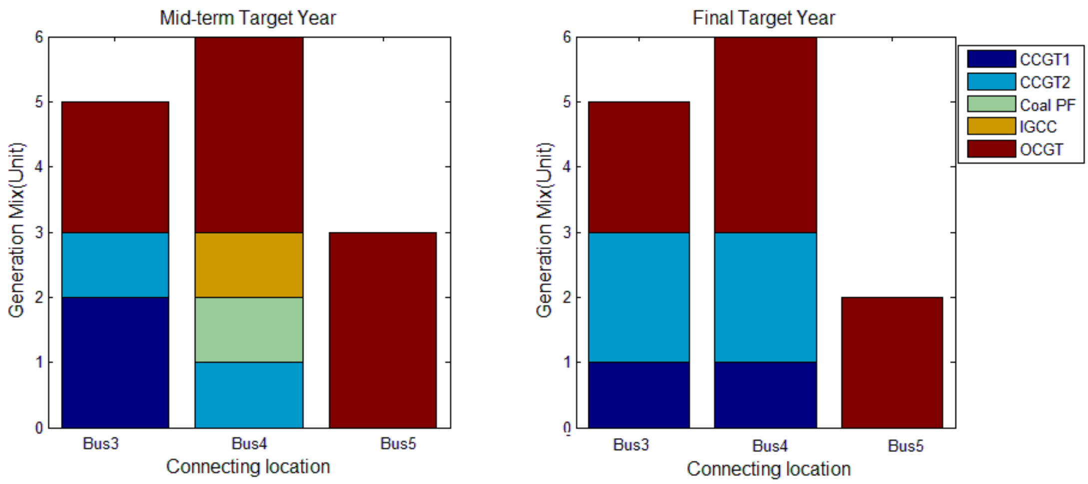

Fig 4-14 Optimal Generator Location in Step 2 when MET=6.0E06 tonnes, FET=4.0E06 tonnes

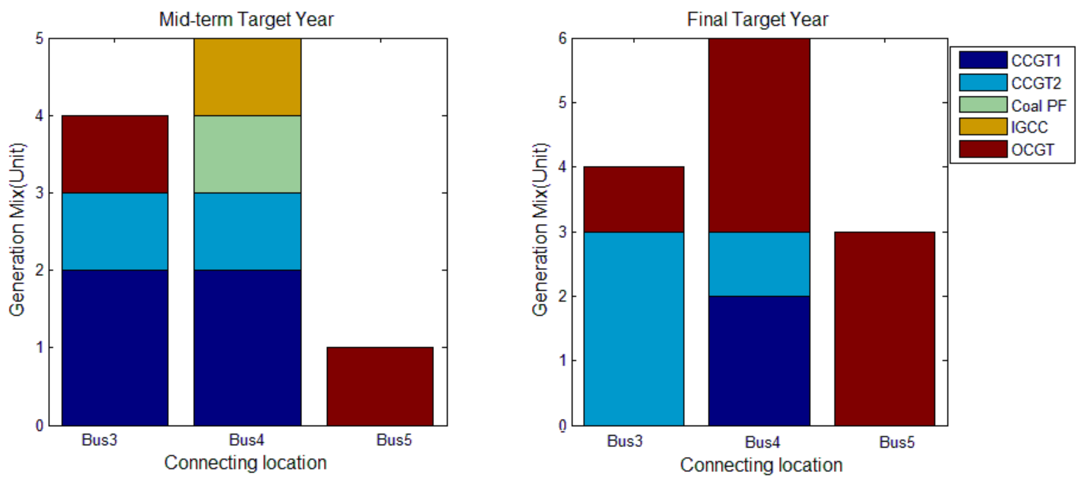

Fig 4-15 Optimal Generator Location in Step 2 when MET=5.5E06 tonnes, FET=4.0E06 tonnes

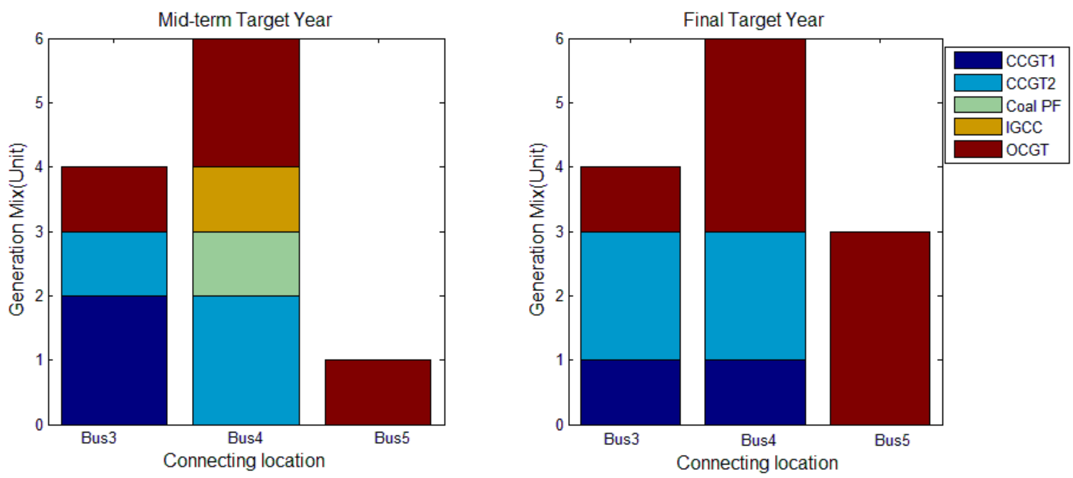

Fig 4-16 Optimal Generator Location in Step 2 when MET=5.0E06 tonnes, FET=4.0E06 tonnes

It can be observed that all the findings summarised in last section still stand in this new case that optimal generation mixes and their locational distribution in MET and FET year vary with different settings of MET, and the total cost tends to increase with the MET becoming more stringent, despite of the same FET.

However, comparing the results obtained from Step 1 and Step 2. More important findings that can be found:

1. Comparing Table 4-10 to Table 4-7, it can be found that if the load growth distribution changes; it can severely affect the optimal generation mixes in MET year.

2. Comparing Table 4-12 to Table 4-9, it can be found that if the load growth distribution changes; it can severely affect the total cost of the whole GEP.

3. Comparing Table 4-11 to Table 4-8, it can be found that although the changes of the load growth distribution do not affect the optimal aggregated generation mix in FET year. But it severely changes the optimal generation location in FET year, which can be found by comparing the generation locational distribution results from Step 2 (Fig 4-11 to Fig 4-16) and Step 1 (Fig 4-5 to Fig 4-10).

The above foundlings indicate the importance of the considering transmission constraints and generation location optimization in the multi phase emission targets constrained GEP problem. Since the two load growth scenarios used in this case study both have a common total load grow rate, but after allocating the total growth to load buses in different percentages, different optimal GEP results will be achieved. Optimization without transmission constraints and generation location optimization is not able to differentiate these differences.

4.3.3.3 Optimal MET Setting

Based on the findings in previous two sections, policy makers may wonder how the MET should be set that can lead a minimum total cost through multi GEP planning horizons. In order to give the implication to policy makers about the optimal MET setting based on the work in Section 4.3.3.2, more METs are chosen to perform a broad sensitive study. The results are shown in Table 4-13. Compared with Table 4-12, more relaxed METs are examined, which are 1.00E+07 tonnes, 9.50E+06 tonnes, 9.00E+06 tonnes, 8.50E+06 tonnes and 8.00E+06 tonnes.

Table 4-13 Total GEP Cost and Emission under Different MET Settings in Step 2

MET(tonne)	FET(tonne)	Total Cost £	Mid-term Emission (tonne)	Final Emission (tonne)
1.00E+07	4.00E+06	3.610E+09	7.15E+06	3.67E+06
9.50E+06	4.00E+06	3.610E+09	7.15E+06	3.67E+06
9.00E+06	4.00E+06	3.610E+09	7.15E+06	3.67E+06
8.00E+06	4.00E+06	3.610E+09	7.15E+06	3.67E+06
7.50E+06	4.00E+06	3.610E+09	7.15E+06	3.67E+06
7.00E+06	4.00E+06	3.615E+09	6.91E+06	3.67E+06
6.50E+06	4.00E+06	3.671E+09	6.50E+06	3.51E+06
6.00E+06	4.00E+06	3.697E+09	6.00E+06	3.67E+06
5.50E+06	4.00E+06	3.708E+09	5.50E+06	3.67E+06
5.00E+06	4.00E+06	3.745E+09	4.81E+06	3.67E+06

It can be found that when the METs are set above 7.50E+06 tonnes. The METs will not constrain the mid-term emission, since the system's nature emission is only 7.15E+06 tonnes. The impacts of the different MET settings on the total GEP cost are depicted in Fig 4-17. It can be clearly seen that when MET is set at 7.50E+06 tonnes or above will give the minimum total GEP cost, while if the MET is set at more stringent values, below 7.50E+06 tonnes, the total GEP cost tends to increase. This also verifies that METs below 7.50E+06 tonnes tend to constrain the optimization of total GEP cost. The findings indicate that the policy makers may need to set the MET to around 7.50E+06 tonnes in this case, which can force the system generation mix in the mid-term to achieve appropriate amount of emission reduction without bringing extra the total GEP cost for realising the FET.

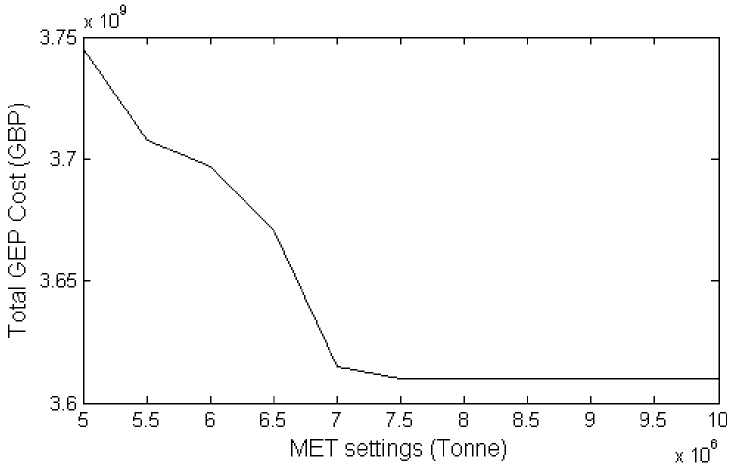

Fig 4-17 Total GEP Cost Variation with Different MET Settings

4.4 Chapter Summary

In this chapter, based on the MILP GEP model proposed in Chapter 3, a multi phase emission targets constrained GEP model is proposed. This model inherits the advantages of the model proposed in Chapter 3 that it can deal with generation location optimization and the short-term unit commitment constraints together in one GEP model. It also extends the previous model by introducing multi-phase emission targets constraints.

A case study is provided based on a five bus test system. The proposed GEP model is solved for twelve times with six different emission target settings and two different load growth scenarios. In order to find out the impacts of MET settings on the results of a multi phase emission target constrained GEP problem, the six different emission target settings have the same FET but different METs. In order to investigate the impact of generation location distribution on the multi phase emission targets constrained GEP model, the two different load growth scenarios have the same total load growth, but different load growth distributions at load buses.

Comparative studies between different MET settings show that the total cost tends to increase with the MET becoming more stringent, despite of the same FET. This is because over stringent METs require more clean but expensive units to be built in MET year, and these early constructed units may be unnecessary or placed at less optimal locations for realising the FET.

Comparative studies between different load growth scenarios clearly demonstrate the importance of the considering transmission constraints and generation location optimization in the multi phase emission targets constrained GEP problem. Since the two load growth scenarios used in this case study both have a common total load grow rate, but after allocating the total growth to load buses in different percentages, different optimal GEP results will be achieved. GEP model without transmission constraints and generation location optimization is not able to differentiate these differences.

Chapter 5

GEP with Renewable Generation and Demand Response

THIS chapter proposes a new GEP model, which considers both stochastic renewable generation expansion and demand side response simultaneously with network constraints and generation location optimization.

5.1 Introduction

Due to conventional energy source scarcity coupled with environment issues, the renewable generation technology is increasingly accepted as the most feasible energy supply solution in the future. Many governments have enforced renewable energy promotion polices. For example, the UK government has committed to raise the percentage of renewable generation out of total generation to 15% by 2020, while the current (2011) UK renewable penetration is around 9.4% [108]. However, due to the intermittent and volatile availability of the primary energy (wind, solar radiation, etc), the renewable generation is not a controllable and flexible generation source as the conventional fossil fuel fired power generation technologies. It is not able to be available at any time to provide as much power output as people desire. Therefore, the renewable generation acts almost like a volatile negative load. In short-term operation, this volatility has to be compensated by adjusting the outputs from other conventional, controllable and flexible generators. Therefore, with the rise of its penetration in the system, more and more flexible and expansive generation capacity has to be expanded as well to cater for the increasing fluctuation from renewable source.

However, it is likely to see that the desire of the precious flexibility can also be met by demand side response (DSR) in the near future, provided that the demand side can be appropriately stimulated to adjust its demand according to the requirement for the system demand supply balance. In the past, the demand side in electricity market could hardly response, due to the lack of demand side management programmes and facilities. However, with the development of smart grid technologies, such as the communication between system operators and demand side, smart metering and real-time pricing programme, etc, the interface for customers to participate in the DSR will become mature gradually in the future. Besides, with increasing use of electric vehicles and other energy storage facilities, demand side has more and more flexibility in the electricity sector. Therefore, DSR can potentially play a more and more important role in the future electricity market.

5.1.1 Literature Review

In traditional GEP problem, when making a capacity expansion decision for a conventional generation technology, planners know the conventional units can generate the expected amount of power at any time of the planning horizon. However, renewable generation emerges with new challenges in GEP problem. The output of a wind farm in the future quite depends on the volatile wind speed rather that the planners' expectation. Hence, it requires more sophisticated treatment for wind generation expansion in a GEP problem. Not too many GEP researches include the renewable generation expansion appropriately in their GEP modelling. In [21, 22, 74, 75, 104, 109], the wind generation is simply treated as a controllable conventional generation technology. In [62], renewable generation is treated specially by introducing renewable generation supporting incentives. In [6, 72], hourly wind generation forecast data is used in planning horizon. The wind generation is treated as a known negative demand, similar to load profile. However, these treatment of renewable generation is not able to address the uncertain nature of renewable generation, because they all assume either the renewable generation controllable [21, 22, 62, 74, 75, 104, 109] or the future power output from renewable generation is deterministic [6, 72]. Kamalinia proposed a stochastic wind thermal GEP planning model to handle the uncertainty of wind generation in [51], in which a set of possible wind generation scenarios in the planning horizon are generated following a Weibull distribution to perform a Monte Carlo simulation. However, it did not consider the impacts of DSR on the GEP problem. Additionally, the transmission network constraints and generation location optimization were not involved in these researches.

In addition, with increasing mature conditions for realising DSR in the near future, DSR will potentially play the role of traditional generators, as an alternative source, to provide the flexibility to maintain the demand supply balance. Therefore, DSR should be incorporated into the GEP problem. Short-term DSR implementation has been studied extensively in recent years. Some researches investigated the feasibility and effectiveness of the different DSR programmes, incentive based or pricing based [26-32]; some incorporated the DSR into short-term generation scheduling optimization [17, 28, 33-35]; some proposed the application of emerging smart grid facilities, like energy storage device [36-40]; but very few of them took the DSR into account for long-tern

GEP problem [6]. Most previous GEP model made a lot of efforts to model the generation side, but treated the demand side simply as a fixed projected load profile [3, 9, 21, 22, 51, 62, 65, 72, 74, 75, 101, 104, 109].

Martins proposed a multi-objective linear programming GEP model considering the demand side management (DSM) [63]. DSM is also included in a GA-Benders' decomposition method GEP model in [24]. In these two papers, the demand side management is assumed to be realised by direct load control, which is taken as equivalent generator and treated as other conventional generator. The same way of treating DSM in a GEP problem can also be found in [110]. However, these papers did not consider renewable generation expansion. Although paper [6] innovatively proposed a GEP model considering both renewable generation expansion and demand side response by demand price elasticity modelling, the discrete characteristic of GEP is neglected, and the wind generation is simply modelled by a set of historical wind output data. The uncertainty of wind generation is not investigated. Additionally, the transmission network constraints and generation location optimization were not included.

The review of the aforementioned literatures indicates that there have been no researches on GEP problem that consider both renewable generation expansion and DSR simultaneously with network constraints and generation location optimization. The GEP model proposed in this chapter will fill this gap.

The rest of this chapter will be organized as:

Section 5.2 introduces techniques of stochastic programming and Monte Carlo simulation, preparing for the mathematical formulation of uncertain wind generation expansion; Section 5.3 proposes the GEP model considering the both renewable generation expansion and DSR simultaneously with network constraints and generation location optimization; Section 4.3 provides a numerical case study to show the effectiveness of the proposed model and investigate the impacts of stochastic wind expansion and DSR on GEP problem; Conclusions are drawn in Section 5.5.

5.2 Prerequisites

Prior to describing the mathematical problem formulation of the GEP model considering uncertain wind expansion, knowledge about the stochastic programming and Monte Carlo simulation techniques will be introduced first, in order to help readers better understand the stochastic wind modelling in the rest of the chapter.

5.2.1 Stochastic Programming

A mathematical programming problem, also known as optimization problem is the selection of best decisions to achieve an optimal target, subject to various constraints. If the constraints are all known and deterministic before making the optimal decisions, it is a deterministic programming problem. However, if constraints involve some uncertain parameters, the problem becomes stochastic. For example, if a factory aims to manufacture as many as cars, subject to a certain amount of available budget. This is a deterministic programming problem, since the constraint of the available budget is known before making the decision that how many cars should be manufactured. However, if the factory aims to make as many as profits, also subject to a certain amount of available budget, but an uncertain amount of sales, this becomes a stochastic programming. Since the objective, making the most profits, depends on not only how many cars are manufactured but also how many cars can be sold, but the amount of car sale is uncertain and can not be known before making the decision that how many cars should be manufactured.

In GEP problem, there are also some uncertain parameters when making the optimal generation expansion decision, such as the demand, fuel prices, investment discount rate, components outage, and wind speed profiles in the future target year. However, compared to the wind speed profile in the future, the uncertainties of the other aforementioned parameters would not be very large and are more predictable. For example, due to the relatively fixed custom of people's electricity usage, the demand profile will nearly stay same. Therefore, the demand at the peak time in the future could be reasonably predicted. However, wind speed distribution across time is much more random, it is very hard to predict what the wind speed will be at the peak time in the target year. Hence, a stochastic programming is required to model the uncertainty of the wind in a GEP problem.

5.2.2 Two-Stage Stochastic Linear Programming

The most widely applied stochastic programming model is two-stage linear programming, which was first studied by Dantzig [111]. In a stochastic programming problem, some of the decision variables are constrained by uncertain parameters, which will be revealed in the future. However, these decisions have to be made now based on the currently available parameters. The two-stage linear stochastic programming is designed to convert the stochastic programming to an equivalent deterministic programming. Equation 5-1 shows such a two-stage linear stochastic programming model. X denotes the first stage decision variable vector. Coefficients A and b only constrain the first stage decision variables. While Y denotes the second stage decision variable vector, which are constrained jointly by B, D and d. c and f are the objective function coefficients. Among these parameters, B and d couple the first and second stage variables, which are not deterministic at the first stage, but have Ω possible realizations at the second stage. These possible realizations are indexed by ω. E represents the expectation of the objective of second stage problem [112-114] .

$$
\begin{aligned}
&Objective: && \text{minimise} \quad cX + E(fY^{\omega}) \\
&Subject\ to: && AX \leq b \\
& && -B^{\omega}X + DY^{\omega} \leq d^{\omega} \\
& && X, \quad Y^{\omega} \geq 0, \ \omega \in \Omega
\end{aligned}
\qquad \textbf{5-1}
$$

If the ω^{th} possible realization of the second stage parameters follows a discrete probability distribution, and has a corresponding probability of p^{ω}, then Equation 5-1 can be rewritten as Equation 5-2 provided that there are K possible realizations of the second stage constraints. It can be seen that the two-stage stochastic linear programming tackles the uncertainty by making a first stage decision X that can meet all the possible second stage constraints and generate a minimum expected objective value of the second stage problem.

$$
\begin{array}{llllllll}
\textit{Objective}: & \text{minimise} & cX + p^1 fY^1 + p^2 fY^2 + \cdots + p^K fY^K) & & & & & \\
\textit{Subject to}: & & AX & & & & & \leq b \\
 & & -B^1 X + & DY^1 & & & & \leq d^1 \\
 & & -B^2 X + & & DY^2 & & & \leq d^2 \\
 & & \vdots & & & \ddots & & \vdots \\
 & & -B^K X + & & & & DY^K & \leq d^K \\
 & & X, & Y^1 & Y^2 & \cdots & Y^K & \geq 0
\end{array} \quad \textbf{5-2}
$$

It should be noted that in the above mathematical formulation, all the constraints are expressed in a way that the left hand side is less or equal than the right hand side. However, the direction of the inequalities can be simply changed as required by multiplying by minus one for both sides. And it should be noted that the equality constraints may also appear in the optimization problem, but it is not written particularly in the above mathematical formulation. This is because the equality constraint can all be transformed to equivalent inequality constraints:

$$
a_1 x_1 + a_2 x_2 + \cdots + a_n x_n = b \quad \Leftrightarrow \quad \begin{cases} a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \leq b \\ -a_1 x_1 - a_2 x_2 - \cdots - a_n x_n \leq -b \end{cases} \quad \textbf{5-3}
$$

5.2.3 Monte Carlo Simulation

Solving the above model is only tractable if K is small. However, the above model can hardly be solved when K is very large, or even infinite if the ω^{th} possible realization of the second stage parameters follows a continuous probability distribution. Under this background, Monte Carlo simulation technique can be used to reduce the number of scenarios to a manageable size.

Monte Carlo simulation can be defined as a method to randomly generate a set of sample data following a known probability distribution for numerical experiments and to investigate the characteristics of the whole sample space by the sample data. This technique is a numerical method that makes use of random numbers to solve mathematical problems which is difficult to be solved by an analytical method. The name of Monte Carlo technique was firstly appeared in the article “The Monte Carlo Method” by Metropolis and Ulam in 1949 [112, 115-117].

Monte Carlo simulation is very simple in concept. The difficulties exist in applying the algorithm to various problems. For the two-stage stochastic programming model proposed in last section, if the second stage random realizations are with a continuous probability distribution, then a set of N independent samples could be generated following the same probability distribution function. This can be easily done by computers. Since they are generated independently following the same probability distribution, each sample has the same probability, 1/N. Based on the sample average approximation method [112, 118, 119], the original expected minimum objective value for the second stage problem can be approximated as follows:

$$E(fY^{\omega}) \approx \frac{1}{N}\sum_{j=1}^{N} fY^{j} \qquad \textbf{5-4}$$

Therefore, the model 5-4 can be reformulated by using the N Monte Carlo samples, which is shown in Equation 5-5.

$$\begin{array}{llllllll}
\textit{Objective}: & \text{minimise} & cX+\frac{1}{N}fY^{1}+\frac{1}{N}fY^{2}+\cdots+\frac{1}{N}fY^{N}) & & & & & \\
\textit{Subject to}: & & AX & & & & \le b & \\
 & & -B^{1}X+ & DY^{1} & & & \le d^{1} & \\
 & & -B^{2}X+ & & DY^{2} & & \le d^{2} & \textbf{5-5} \\
 & & \vdots & & & \ddots & \vdots & \\
 & & -B^{N}X+ & & & DY^{N} & \le d^{N} & \\
 & & X, & Y^{1} & Y^{2} \quad \cdots & Y^{N} & \ge 0 &
\end{array}$$

The advantage of Monte Carlo simulation is that it can tackle the stochastic problems with very large or even infinite number of uncertainty scenarios, which can not be practically solved by analytical method. However, it is indeed an approximation, hence the accuracy is sacrificed. Generally, the standard error of the approximation is decreasing with the sample size (N). More details about the evaluating the quality of approximation by Monte Carlo simulation can be found in [112]. In order to increase the approximation accuracy without increasing the number of samples, mathematicians on operation research areas have already proposed some scenario reduction methods [120, 121]. These methods aim to keep the same approximation accuracy of the stochastic problem by using minimum number of scenarios. However, realization of these scenario reduction methods requires either expansive commercial software packages or sophisticated statistic knowledge and coding work. In order to focus on integrating the stochastic renewable generation expansion and demand side response in the GEP problem with generation location optimization, the model developed in this chapter will employ the basic Monte Carlo simulation technique to tackle the uncertainty of renewable generation without considering the scenario reduction method.

5.3 Problem Formulation

The model proposed in this chapter extends the GEP model introduced in Chapter 3, by including the stochastic renewable generation expansion and demand side response.

The renewable generation technology in the mathematical formulation is represented as wind generation. The uncertainty of wind generation is modelled by Monte Carlo simulation. A number of wind output scenarios are generated following a Weibull Distribution. And these wind output scenarios are taken as the negative load and used to formulate a two-stage stochastic GEP programming model.

The demand side response modelling is realized by setting the demands at different locations at different time intervals as decision variables. The demands are allowed to deviate from their forecasted amount up or down within a pair of certain lower and upper bounds. The range between the lower and upper bounds represents the flexibility of the demand. Since the load type composition (industrial, commercial and domestic) varies for different load buses, the flexibilities on different load buses may be different. The fact can also be taken account by the model proposed in this chapter. The demand side response is also constrained by a rule that the total demand in a single day after DSR should be equal to the total forecasted demand in that day. This constraint models the real life case that the demand can only be shifted from one time to another, but can not disappear.

For the DSR market structure, it is assumed that, in the future, there will be a new market participant, DSR provider, who is responsible for organize the demand side to response following the system total demand variation. However, this chapter will not consider the DSR market implementation details and the cost required for realizing the demand side response, since they involve too many operational modelling efforts, such as the balancing the profit of DSR provider and the custom surplus, analysing electricity demand elasticity, forecasting electricity whole sale price, etc. This chapter puts more focus on how the short term demand side response can impacts on the long-term generation expansion planning from a centralized planning view, hence to reveal the potential contribution of DSR to the savings of the total societal cost.

5.3.1 GEP with DSR and Stochastic Wind Generation

The detailed mathematical MILP formulation is presented as follows:

The objective function combines the short-term operational and emission cost with the long-term capital cost:

$$\begin{aligned} Min \quad & \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{i=1}^{I}(FC_g \cdot P_{ngit} + EP \cdot E_g \cdot P_{ngit}) \\ & + \sum_{g=1}^{G}\sum_{i=1}^{I} CC_g \cdot Rcap_g . Np_{gi} \\ & + \sum_{w=1}^{W}\sum_{i=1}^{I} CCW_w \cdot RWcap_w . Nwp_{wi} \\ & Np_{gi}, Nwp_{wi} \in Non-negative\ Integer \end{aligned} \qquad \textbf{5-6}$$

where,

n	Wind output scenario index;
g	Index of conventional generation technology type;
w	Index of wind generation technology type;
t	Index of scheduling time interval for sub-operational problem;
i	Index of bus;
N	Total number of wind output scenarios generated for Monte Carlo simulation;
G	Total number of candidate conventional generation technologies;
W	Total number of candidate wind generation technologies;
T	Scheduling time horizon for sub-operational problem;
I	Total number of buses;
P_{ngit}	Active power output of unit of conventional generation technology g at bus i at time t for scenario n in the target year;
Np_{gi}	Integer decision variable for number of unit of conventional generation technology g to be built at bus i in the target year;

Nwp_{gi}	Integer decision variable for number of unit of wind generation technology w to be built at bus i in the target year;
$Rcap_g$	Nameplate capacity of conventional generation technology g;
$RWcap_w$	Nameplate capacity of wind generation technology w;
FC_g	Operational cost of conventional generation technology g;
E_g	Emission rate of conventional generation technology g;
EP	Emission price;
CC_g	Capital cost of conventional generation technology g;

Under the two-stage stochastic programming environment, Np_{gi} and Nwp_{wi} are the first stage decision variables, and P_{ngit} is the second stage decision variables. That's because it needs to determine how many conventional and wind generation plants should be built first before determining the optimal power output from each constructed plants. Since the wind generation output is not completely controllable, its power output can only follow the wind speed rather than load variation. Therefore, the wind power output can only be taken as negative load instead of decision variables. The Monte Carlo simulation will generate N wind output scenarios, which will affect the optimal power outputs from conventional generators; hence there are N sets of second stage decision variables to be decided. In addition to Np_{gi} and Nwp_{wi}, there is one more first stage decision variable associated with the DSR modelling, which is D_{it}, the demand at each load bus at each scheduling time interval. It is invisible in the objective function because as is stated before that this chapter will not consider the DSR market implementation details and the costs required for realizing the demand side response. But D_{it} along with the other two first stage variables, Np_{gi} and Nwp_{wi} and the second stage variables P_{ngit} are limited by the following constraints:

Supply demand balance in the target year:

$$\sum_{i=1}^{I}\sum_{g=1}^{G} P_{ngit} + \sum_{i=1}^{I}\sum_{w=1}^{W} P_{nwit} = \sum_{i=1}^{I} D_{it} \qquad \forall t \in T, \forall n \in N \qquad \textbf{5-7}$$

Transmission capacity limits in the target year:

$$-Lim_k \le L_{nkt} \le Lim_k \qquad \forall k \in K, \forall t \in T, \forall n \in N \qquad \textbf{5-8}$$

$$L_{nkt} = \sum_{i=1}^{I} GSDF_{k-i} \times (\sum_{g=1}^{G} P_{ngit} + \sum_{w=1}^{W} P_{nwit} - D_{it}) \quad \forall k \in K, \forall t \in T, \forall n \in N \qquad \textbf{5-9}$$

Unit power output limits:

$$0 \le P_{ngit} \le RCap_g \cdot Np_{gi} \quad \forall t \in T, \forall g \in G, \forall n \in N \qquad \textbf{5-10}$$

Capacity expansion limits:

$$NMin_{gi} \le Np_{gi} \le NMax_{gi} \quad \forall g \in G, \forall i \in I \qquad \textbf{5-11}$$

$$NWMin_{wi} \le Nwp_{wi} \le NWMax_{wi} \quad \forall w \in W, \forall i \in I \qquad \textbf{5-12}$$

It is assumed wind generation is emission free. Therefore, the emission target limits in the target year only constrain the conventional generation:

$$\sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{g=1}^{G} (E_g \cdot P_{ngit}) \le Et \qquad \forall n \in N \qquad \textbf{5-13}$$

Ramping up/down constraints for conventional generators:

$$0 \le P_{ngit} - P_{ngi(t-1)} \le Ru_g \cdot RCap_g \cdot Np_{gi} \qquad \forall g \in G, \forall i \in I, \forall t \in [2,T], \forall n \in N \qquad \textbf{5-14}$$

$$0 \le P_{ngi(t-1)} - P_{ngit} \le Rd_g \cdot RCap_g \cdot Np_{gi} \qquad \forall g \in G, \forall i \in I, \forall t \in [2,T], \forall n \in N \qquad \textbf{5-15}$$

Demand response lower and upper boundaries: the demand is assumed to be able to response around the forecasted demand up and down within a certain flexibility range. The boundaries are modelled as follows:

$$DL_{it} \le D_{it} \le DU_{it} \qquad \forall i \in I, \forall t \in T \qquad \textbf{5-16}$$

$$DL_{it} = (1-f) \times D0_{it} \qquad \forall i \in I, \forall t \in T \qquad \textbf{5-17}$$

$$DU_{it} = (1+f) \times D0_{it} \qquad \forall i \in I, \forall t \in T \qquad \textbf{5-18}$$

In real life case the electricity users normally would not reduce their net demand but move it from one time to another. Therefore, the following constraint is applied to simulate this demand conservation rule in real life that the total demand after response should equal to the total forecasted demand within each day during the sub operational scheduling horizon:

$$\sum_{t=(day-1)\times 24+1}^{day\times 24} D_{it} = \sum_{t=(day-1)\times 24+1}^{day\times 24} D0_{it} \qquad \forall i \in I, \forall day \in [1,2,...,364] \qquad \textbf{5-19}$$

Wind energy is an intermittent energy source. Excessive penetration of wind generation will jeopardize the system power supply reliability. Due to this reason, wind capacity penetration limit is introduced to guarantee that the increased uncertainty from intermittent wind source will be compensated by certain amount of conventional generation capacity [109]. The constraint is as follows:

$$\sum_{w=1}^{W}\sum_{i=1}^{I} RWcap_w.Nwp_{wi} \le wc \times \sum_{g=i}^{G}\sum_{i=1}^{I} RCap_g \cdot Np_{gi} \qquad \textbf{5-20}$$

where,

D_{it}	Demand at bus i in time t in the target year;
P_{nwit}	Active power output of unit of wind generation technology w at bus i at time t for scenario n in the target year;
k	Index of transmission line;
K	Total number of transmission lines;
Lim_k	Transmission capacity limit of line k in the target year;
L_{nkt}	Active power flow on line k at time t for scenario n in the target year;
$GSDF_{k-i}$	Generation shift distribution factor from bus i to line k in the target year;
$NMin_{gi}$	Minimum number of plants required from conventional generation technology g at bus i;
$NMax_{gi}$	Maximum number of plants allowed from conventional generation technology g at bus i;
$NWMin_{wi}$	Minimum number of plants required from wind generation technology g at bus i;
$NWMax_{wi}$	Maximum number of plants allowed from wind generation technology g at bus i;
Ru_g	Ramping rates of generation technology g;
Et	Emission target in the target year;

DL_{it}	Lower boundary for DSR load at bus i at time t;
DU_{it}	Upper boundary for DSR load at bus i at time t;
f	Demand flexibility coefficient indicating the percentage of the demand deviation from its forecasted level;
$D0_{it}$	Forecasted demand at bus i at time t;
wc	The ratio between wind generation capacity and conventional generation capacity;

Referring to Equation 5-5, it can be seen that the two stage stochastic linear programming tackles the uncertainty by making first stage decisions, which are the capacities of different generation technologies to be expanded. The first stage expansion decisions can meet all possible second stage constraints and generate a minimum expected operational cost of the second stage generation operation problem.

Same with Chapter 3 and 4, the formulated problem in this section is also coded in Matlab and solved by the open source MILP solver, 'lpsolve' [92].

5.3.2 Wind Power Output Scenarios Construction

In this chapter, the wind generation technology is used to stand for the renewable generation. The power output of a wind turbine can be described by Equation 2-16 [51, 58]:

$$P_w = \begin{cases} RWcap_w \dfrac{v_w - v_{ci}}{v_r - v_{ci}}, & (v_{ci} < v_w < v_r) \\ 0, & (v_w < v_{ci} \ or \ v_w > v_{co}) \\ RWcap_w, & (v_r < v_w < v_{co}) \end{cases} \tag{5-21}$$

where, P_w is the instantaneous output of the wind turbine; $RWcap_w$ is the rated output of the wind turbine of technology g. v_w, v_{ci}, v_r and v_{co} are instantaneous wind speed, cut-in speed, rated speed and cut-out speed respectively.

It is assumed in this study that the wind power is subject to a Weibull distribution which is adopted by many previous researches [51, 58, 72, 122, 123]. The detailed modelling of wind generation uncertainty with a Weibull distribution is shown below:

Wind speed probability distribution in this research is modelled by Weibull probability Equation 2-17.

$$f(v_w) = \frac{q}{\eta}\left(\frac{v_w}{\eta}\right)^{q-1} \cdot \exp[-(\frac{v_w}{\eta})^q] \qquad \textbf{5-22}$$

where, q is the shaping factor and η is the scaling factor. Different values of q and η will set the Weibull distribution with different expected values and variances. A set of random numbers are generated following the Weibull distribution for the sub operation scheduling horizon T, representing the output of a wind farm in each scheduling interval. Wind farm output power is taken as negative load and used to mitigate the interval total power demand in each scheduling time interval. One set of T Weibull random wind speed values will be used as one wind scenario.

The generation of random scenarios of wind speed subject to a Weibull probability distribution can be easily realised by calling the 'wblrnd' function in MATLAB.

Same with Chapter 3, the problem formulated above is also coded in Matlab and solved by the open source MILP solver, 'lpsolve' [92]. The specific method of construction of the objective and constraint matrix has been introduced in Section 3.4.

5.4 Case Study

In order to verify the effectiveness of the method proposed in this study, a case study is presented. Comparisons have been made to find out the impacts of considering DSR and stochastic natures of wind capacity expansion in a GEP with generation location optimization.

5.4.1 Test System

The proposed model is tested based on the modified PJM 5-bus test system shown in Fig 3-1 [93]. Same as the case study in Chapter 3 and 4, Bus3, 4 and 5 are selected to be the generation buses, where all conventional candidate generators will be connected. Bus 3 is selected to connect all the candidate wind farms. Bus 1 is selected as a slack bus. The parameters of six transmission lines are given in Table 3-2.

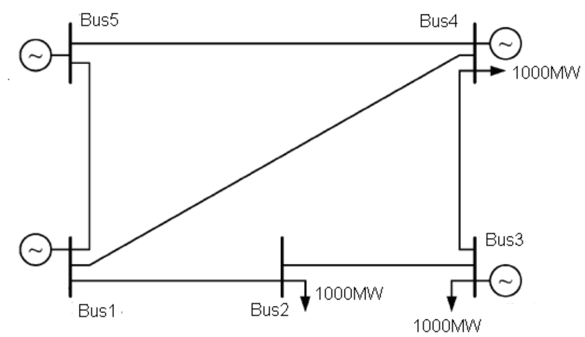

Fig 5-1 5-Bus Test System

Table 5-1 Line Data of 5-Bus Test System

Line	1-2	1-4	1-5	2-3	3-4	4-5
X (%)	2.81	3.04	0.64	0.08	2.97	2.97
Transmission capacity(MW)	500	400	400	400	400	400

Table 5-2 Candidate Generation Technology Parameters

Plant Type	Nameplate Capacity (MW)	FC (£/MWh)	Emission Coefficient (tonne/MWh)	CC (M£/MW)	Ramping Rate (MW/h)
CCGT1	300	6.00	0.38	0.484	10
CCGT2	350	6.40	0.22	0.883	50
COAl PF	300	3.64	0.84	1.109	20
IGCC	200	4.06	0.60	1.585	10
OGCT	100	5.00	0.47	0.467	20
Wind	30	0	0	0.914	N/A

Six different candidate generation technologies including wind are to be connected to the grid. They have different performances in terms of nameplate capacity, operational cost, capital cost, emission coefficient, and ramping rate. The details of generation technologies are listed in Table 5-2, which are gathered from [65]. The wind generation is assumed to have negligible operational cost and emission. It should be noted that normally, a single wind turbine has rated capacity ranging from hundreds of kW to several MW, but a wind farm often includes several to tens of wind turbines. In this case study, the rated capacity ($RWcap_w$) refers to a wind farm's total wind installed capacity rather than a single wind turbine. In this case study, the ratio between wind generation capacity and conventional generation capacity (wc) is set to 20%, which means the wind capacity is not allowed to expand to more than 20% of the conventional generation capacity.

It is assumed that some of the generation units in the initial year will still be in service in the target year. These units are listed in Table 3-4. This assumption can not only make the GEP model comply with the real life case, but also accelerate the solution speed, since they provide an initial condition of the decision variables, Np_{gi} and reduce the size of the searching space. Emission price (EP) is set to be 10 £/tonne in this case study. The emission target is set to be 4.0E+06 tonnes in the target year. Since the sensitivity analysis about the impacts of different emission targets on the GEP results has been made in Chapter 2, 3 and 4, this chapter will not repeat this work.

Table 5-3 Minimum Number of Units to Appear in the Target Year

Plant type	Bus 3	Bus 4	Bus 5	Total Mix
CCGT1	2	0	0	2
CCGT2	1	0	0	1
COAl PF	0	1	0	1
IGCC	0	1	0	1
OGCT	0	0	1	1

Bus2, 3 and 4 are load buses, each of which has 1000MW annual peak load evenly in the initial year. There is a peak demand growth forecast for the target year. The forecasted load growth rate is shown in Table 4-4.

Table 5-4 Load Growth from Initial Year to the Target Year

Demand Bus	Bus 2	Bus3	Bus4
Load Growth Rate	0.05	0.05	0.03

The forecasted load profile for the target year ($D0_{it}$) in this research is determined according to the IEEE Reliability Test System 1996 [61]. The specific load data can be found in Appendix A. The hourly load is determined by the multiplication of annual peak demand and the coefficients of weekly peak demand in percentage of the annual peak, daily peak demand in percentage of the week peak and hourly peak demand in percentage of the daily peak. In order to speed up the calculation, this research only takes one day as a sample to estimate the yearly total operation cost. The day is the first day of a year specified by IEEE Reliability Test System 1996. Therefore the scheduling horizon T is 24 for this study case. The related operation cost and emission results will be scaled up by 364 (52x7/1), since the scheduling year has 52 weeks.

The forecasted demand profile reflects the regular pattern of the electricity consumption. Based on the forecasted demand profile, the demand side could be guided to response via various DSR programs in order to achieve a minimum total GEP cost. Four scenarios of demand flexibility coefficients (f in Equation 5-17 and Equation 5-18) are used to demonstrate the impacts of different DSR levels on the optimal GEP results. The corresponding DSR upper and lower bounds (DL_{it} and DU_{it}) can be calculated following Equation 5-17 and Equation 5-18. For scenarios DR1 and DR3, the DSR level is relatively low. Averagely, demand side can response within 2% up and down of the forecasted level. For scenarios DR2 and DR4, the DSR level is relatively high. Averagely, demand side can response within 10% up and down of the forecasted level. The four scenarios are differentiated by not only DSR levels, but also locational distribution. For example, although the average DSR levels of DR1 and DR3 are the same, in DR1, the most flexible load is at Bus 2, while in DR3, it is at Bus 3.

Table 5-5 DSR Flexibility Scenarios

Demand Bus			Bus 2	Bus3	Bus4
DSR Flexibility Scenarios	DR1	Low	0.03	0.02	0.01
	DR2	High	0.10	0.15	0.05
	DR3	Low	0.01	0.03	0.02
	DR4	High	0.15	0.05	0.10

In this case study, one wind generation technology is considered. The wind turbines' speed parameters are assumed that v_{ci} = 5m/s, v_{co}=45m/s, and v_r=15m/s. The Weibull distribution parameter for wind speed distribution at Bus 3 are set that η =10.2, k=1.5. These parameters are set to give a capacity factor of around 40% for this wind generation technology at Bus 3. Ten sets of 24-hour wind output scenarios are generated following the specified Weibull distribution to implement the Monte Carlo simulation of the wind generation uncertainty. They are listed in Table 5-6, in which the decimals indicated the wind farm power output in percentage of its rated capacity ($RWcap_w$), which is 30MW in this case as listed in Table 5-2 .

Table 5-6 Wind Output Scenarios in Percentage of Rated Capacity

Hour	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
1	0.100	0.068	0.811	0.957	0.000	0.094	0.000	0.000	0.097	0.000
2	0.000	0.242	1.000	0.436	0.126	0.000	1.000	0.234	1.000	0.876
3	1.000	0.000	0.590	0.000	0.013	0.300	0.000	0.322	0.000	0.482
4	1.000	0.000	0.187	0.117	0.000	0.411	1.000	0.392	0.322	1.000
5	0.000	0.599	1.000	1.000	0.375	0.000	0.388	0.115	1.000	0.644
6	0.986	0.000	0.000	0.455	0.972	1.000	0.162	1.000	0.706	0.000
7	1.000	0.398	0.594	0.650	0.128	0.154	0.101	0.233	1.000	0.038
8	0.628	0.163	0.317	1.000	0.271	0.842	0.249	0.875	1.000	0.000
9	0.000	1.000	0.408	0.635	0.526	0.465	0.876	0.721	0.815	1.000
10	0.807	0.614	0.743	1.000	0.000	0.652	0.049	0.672	0.000	0.307
11	0.170	0.121	0.000	0.399	0.000	0.105	0.788	0.000	0.000	0.410
12	0.000	0.000	0.000	0.045	0.616	0.000	0.000	0.442	0.020	0.562
13	0.593	0.000	0.000	0.000	0.158	1.000	0.462	0.258	0.492	0.000
14	0.885	1.000	0.375	0.000	0.000	0.000	0.473	0.000	0.330	1.000
15	0.526	1.000	0.589	1.000	1.000	0.025	0.442	0.499	0.000	0.484
16	0.000	0.457	1.000	0.221	0.000	0.000	1.000	0.097	0.000	0.000
17	0.000	1.000	1.000	0.261	0.037	1.000	0.000	0.981	0.445	1.000
18	0.091	0.669	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.619
19	0.000	0.042	0.091	0.391	0.000	0.000	0.000	0.524	0.910	1.000
20	0.351	0.000	0.608	1.000	0.483	0.000	0.106	0.000	0.254	1.000
21	0.813	0.463	1.000	0.000	0.343	0.742	1.000	0.569	0.292	1.000
22	0.617	0.000	0.543	1.000	1.000	0.008	0.106	0.000	0.325	1.000
23	0.000	1.000	0.000	0.221	0.000	0.662	0.000	1.000	0.502	0.250
24	0.103	0.000	0.657	0.000	0.043	1.000	0.000	1.000	0.269	0.000

5.4.2 Experiment Implementation

The case study includes two parts. The first part is to show the effectiveness of the integration of DSR in a GEP model and further investigate the impacts of DSR levels and location distribution on the GEP optimization results. The second part is to show the effectiveness of using two-stage stochastic programming and Monte Carlo simulation to analyse the uncertainty of wind generation in a GEP problem.

Part 1:

In this part, the proposed GEP model in Section 5.3.1 is solved five times under five different load flexibility scenarios. The first scenario is that there is no DSR in the system. The optimal power flow in sub operational problem only needs to guarantee the total power output meeting the system total forecasted load. This is the way how the

GEP models proposed in Chapter 2, 3 and 4 deal with the demand side. The other four are the four different DSR scenarios listed in Table 5-5.

After the calculation, the optimal generation mix results under the five load Flexibility scenarios are shown in Table 5-7. The associated total expansion cost and the total emission results are shown in Table 5-8. The associated optimized generation locational distribution results are shown in Fig 5-2 through to Fig 5-4. The optimal load profiles at three load buses after four response scenarios are shown in Fig 5-5 through to Fig 5-8. The associated system total load profiles aggregating of the three load buses are shown in Fig 5-9 through to Fig 5-12.

Part 2:

In order to show the effectiveness of using two-stage stochastic programming and Monte Carlo simulation to analyse the uncertainty of wind generation in a GEP problem, in this part, the proposed GEP model in Section 5.3.1 is solved ten times with each of ten wind output scenarios in Table 5-6 individually without demand side response. The results are compared with the case with the GEP considering 10 wind output scenarios in the two-stage stochastic programming. The associated optimal generation mix results under the ten different wind output scenarios are shown in Table 5-9. The associated total expansion cost and the total emission results are shown in Table 5-10. The associated optimized generation locational distribution results are shown in Fig 5-13and Fig 5-14.

The above assessment is executed again under DR2 load flexibility scenario. The corresponding results are shown in Table 5-11, Table 5-12, Fig 5-15 and Fig 5-16 respectively.

5.4.3 Results and Discussion

5.4.3.1 Impacts of DSR Levels and Location Distribution on GEP

Table 5-7 shows the optimized number of units of each candidate generation technology to appear in the target year in Part 1. The top row labels demand side flexibility scenarios under which the GEP is executed, where No DSR stands for the case that demand is inflexible, and DR1 to DR4 stand for the four DSR scenarios in Table 5-5.

The optimized numbers of generators of different generation technologies are listed in columns corresponding to each scenario.

It can be seen clearly in Table 5-7 that optimal generation mixes are affected by the demand flexibility scenarios. Compared to the case without DSR, the optimal generation mix under scenarios DR1 requires one less OCGT unit and three less Wind farms; that under scenario DR2 requires one less CCGT1 unit and eight less wind farms; that under scenario DR3 requires one less OCGT unit and two less wind farms; while that under scenario DR4 requires one less CCGT1 unit, one less OCGT unit and nine less wind farms. It can be found that in order to meet a fixed load growth and emission target, with the increase of demand flexibility, more and more generation capacity investment could be avoided.

Table 5-7 Optimal Generation Mix under Five Load Flexibility Scenarios

DSR Scenarios		No DSR	DR1	DR2	DR3	DR4
Number of Installed Units	CCGT1	3	3	2	3	2
	CCGT2	6	6	6	6	6
	COAl PF	1	1	1	1	1
	IGCC	1	1	1	1	1
	OGCT	2	1	2	1	1
	Wind	24	21	16	22	15

More interesting findings can be found from Table 5-8. The total cost (including the generation investment and operational cost in the target year) tends to decrease with the increase of demand flexibility. This is just as expected, since the DSR saves the generation capacity investment, as Table 5-7 shows.

Table 5-8 Optimal GEP Cost and Emission Results under Five Load Flexibility Scenarios

DSR Scenarios	Total Cost £	Total Emission (tonnes)
No DSR	3.826E+09	3.79E+06
DR1	3.699E+09	3.78E+06
DR2	3.468E+09	3.85E+06
DR3	3.726E+09	3.78E+06
DR4	3.394E+09	3.83E+06

As mentioned in Section 5.4.1, the demand flexibility scenarios DR1 and DR3 have similar average demand flexibility, but the different location allocation. The DR2 and DR4 are arranged in the same way. However, it can be seen that the optimal generation mix and total cost results between DR1 and DR3 are different, so are those between DR2 and DR4. These can be explained that in optimal power dispatch process, the system will first fully load the cheapest generation units to meet the demand. However, some units may partially loaded, which are also called marginal units. They are partially loaded because either they are expensive units or located at a congested bus even though they may be cheaper than the other fully loaded units. In this chapter, we give the location where the expansive marginal unit (EMU) stay a name as expansive marginal bus (EMB) and give the location where the congested marginal unit (CMU) stay a name as congestion marginal bus (CMB). When the EMU has to start up to supply the load at peak load time, if the demand at EMB is more flexible, more demand could be moved to off-peak time to save the output from EMU, hence total generation cost is reduced. On the other hand, when there is one or more transmission lines are overloaded, the units connected may become CMUs, which has to be partially loaded even they are very cheap. The short of supply has to be provided by more expensive units. However, as introduced in Chapter 3, according to the network's generation shift distribution factor (GSDF), power injections at some buses are more sensitive to the congested lines than those at other ones. Hence, if the demand at these sensitive buses is more flexible, more demand could be moved from the congestion time and further alleviate the corresponding line overloading. Therefore, the cheap CMU could contribute more, and total generation cost is reduced.

That is to say the demand response can contribute more at EMB or the most sensitive bus to congestion lines compared with that at other locations. The findings explain why the demand flexibility scenarios DR1 and DR3 have similar average demand flexibility, but results in different generation mix plans and costs, and so DR2 and DR4 do.

Table 5-7 shows the optimal generation mixes in an aggregated way. Fig 5-2 shows the optimal conventional generation location results when the GEP model is solved without considering DSR. Those when the GEP model is solved under DR1, DR2, DR3 and DR4 are shown in Fig 5-3 and Fig 5-4. The horizontal axis labels the three generation buses, while the vertical axis labels the integer number of the generation units to appear in the target year. Different generation technologies are differentiated by different colours, with a legend at the top right showing the corresponding relation. From these figures, it can be seen not only the generation mix variance due to different DSR scenarios, but also the location where the variance takes place, compared with Table 5-7.

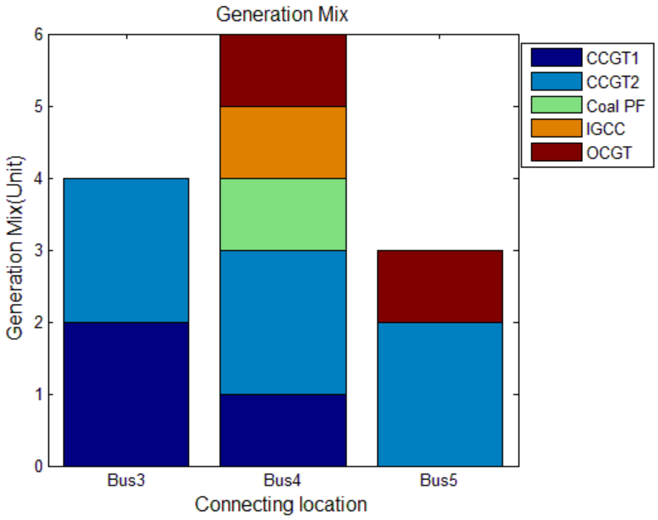

Fig 5-2 Optimal Generation Location Distribution without DSR

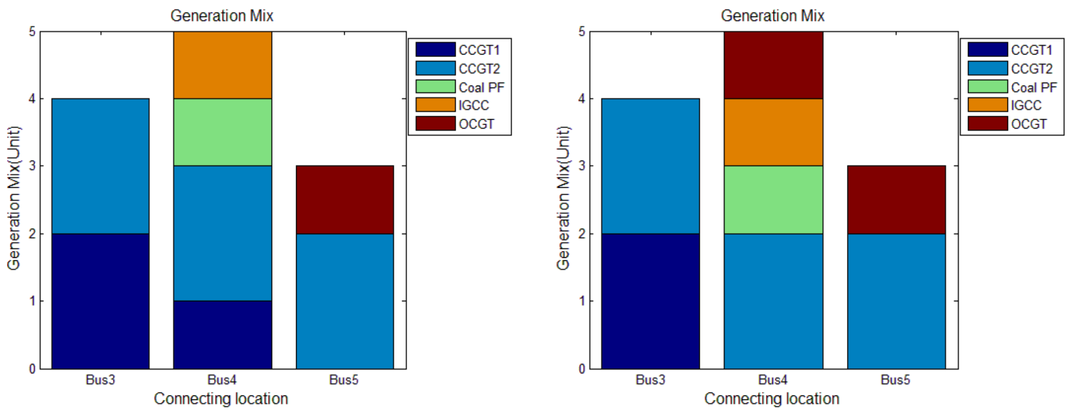

Fig 5-3 Optimal Generation Location Distribution for DR 1 and DR2

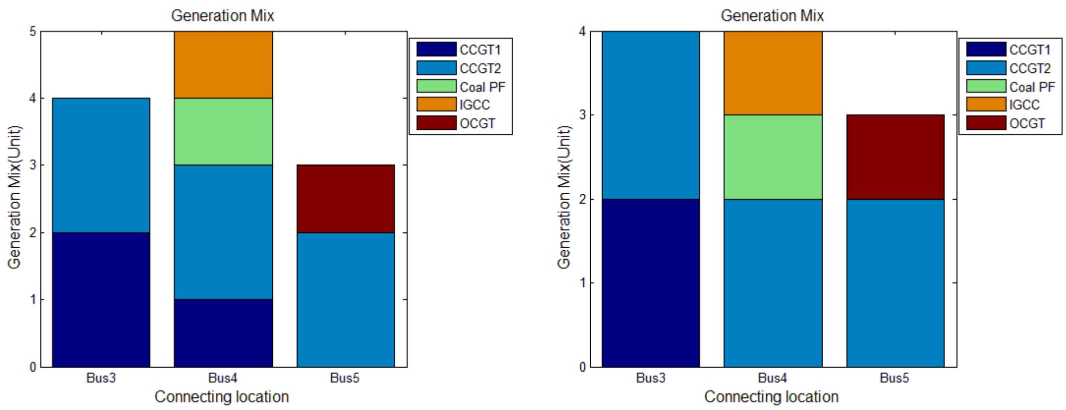

Fig 5-4 Optimal Generation Location Distribution for DR 3 and DR4

As mentioned in problem formulation, in this GEP model, the demand at each bus at each scheduling interval becomes a decision variable. The optimal demand response results under DSR scenarios DR1, 2, 3 and 4 are shown from Fig 5-5 through to Fig 5-8 respectively. In each figure, the black solid line represents the original forecasted load profiles; the optimized DSR load profiles at three load buses are depicted by dash lines in different colours as the legend indicates. The horizontal axis labels the 24 hours in the sample day for the sub operational problem. The vertical axis labels the hourly demand in the percentage of the annual peak demand at corresponding buses. For readers who are interested in how the curves are depicted, the experiment results data for original and DSR load profiles are provided in Appendix B.

For the weak DSR scenarios DR1 and DR3, very slight valley filling and peak clipping effect can be observed compared with the forecasted load profile. Just as expected, the green dash curve shows the biggest deviation from the black curve in Fig 5-6 as in DR2, the demand at Bus 3 has the biggest flexibility at 0.15. While the red dash curve shows the biggest deviation from the black curve in Fig 5-8 as in DR4, the demand at Bus 4 has the biggest flexibility at 0.15. A very interesting observation can be found in Fig 5-6 that at Hour 17 quit close to the peak time, the demand at Bus 3 chooses to increase to a very high level surprisingly, which is even much higher than the forecasted peak. However, at this time the demands at Bus 2 and 4 choose to drop below the forecasted value. The same effect can also be found in Fig 5-8. The implication of the effect will be addressed next by comparing with Fig 5-9 to Fig 5-12.

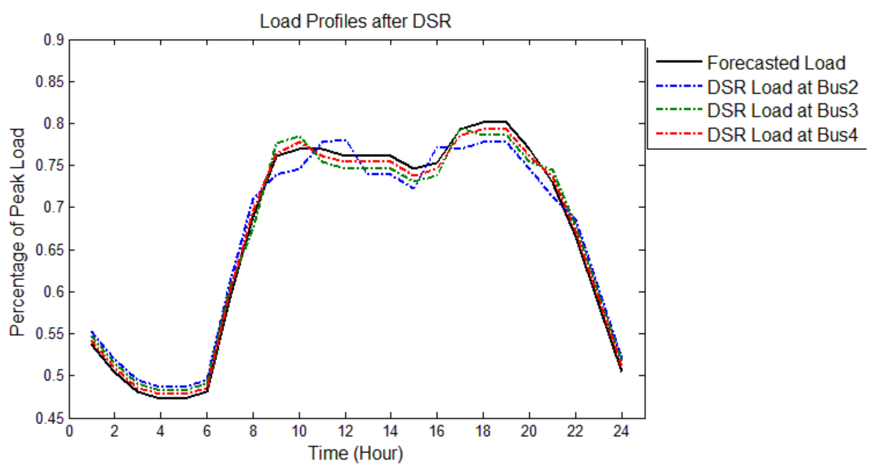

Fig 5-5 Optimized Load Profiles under DR1

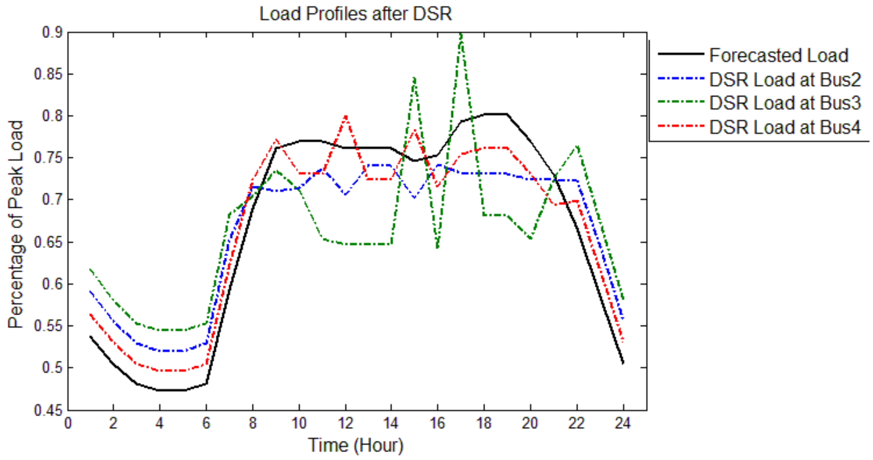

Fig 5-6 Optimized Load Profiles under DR 2

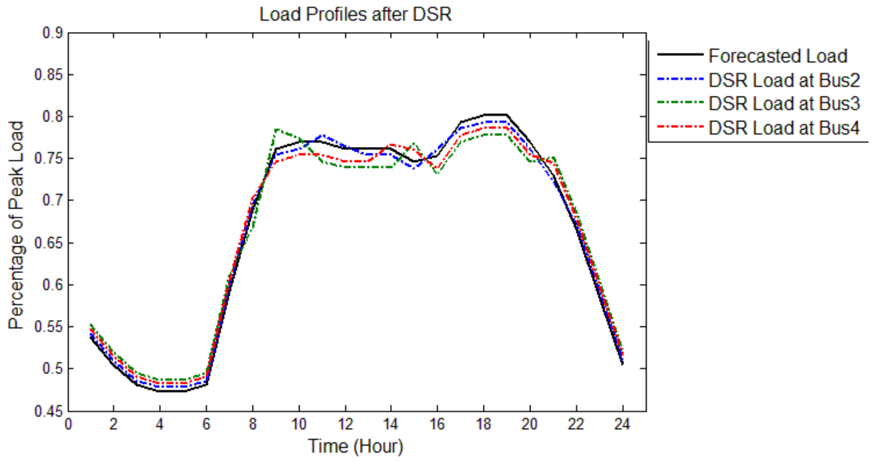

Fig 5-7 Optimized Load Profiles under DR 3

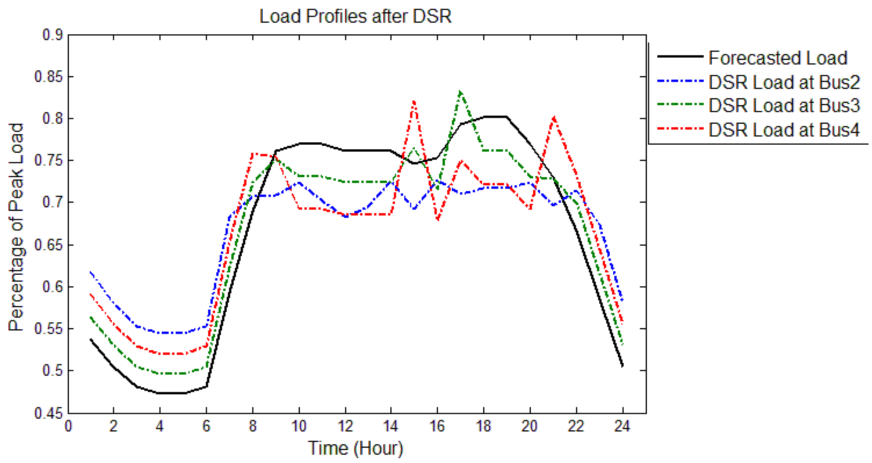

Fig 5-8 Optimized Load Profiles under DR 4

Fig 5-9 to Fig 5-12 show the aggregated optimized load profiles of load Bus 2, 3 and 4 under demand flexibility scenarios DR1, 2, 3 and 4. In these four figures, the vertical axis labels the specific demand rather than percentage. Although there are load spikes that exceed the forecasted peak load at individual buses as the aforementioned interesting observation in Fig 5-6 and Fig 5-8, the aggregated load profiles give very good demand responses. The demand valley is well filled and the demand peak is well clipped, no matter for which demand flexibility scenario. This indicates the raised demand at Bus 3 at Hour 17 is dragged down by the dropped demand at Bus 2 and 4, which leads to a net reduced total demand. It is out of expectation that the demands at three buses choose to response in this way, rather than drop evenly all. The reason is that the raised demand could make better use of the lightly loaded transmission line, while the dropped demand could alleviate the corresponding line congestion or directly reduce the load level of the EMU. It can be concluded that the coordinated demand and generation response at different buses can make better use of the transmission capacity and cheap generation and avoid drawing power from EMU.

From the long term GEP view, it can take full advantage of the current network by allocating the expanded generation units at smart locations and more importantly save expensive peak unit investment. All the above results and analysis demonstrate the value of considering DSR simultaneously with the network constraints and generation location optimization in a GEP problem.

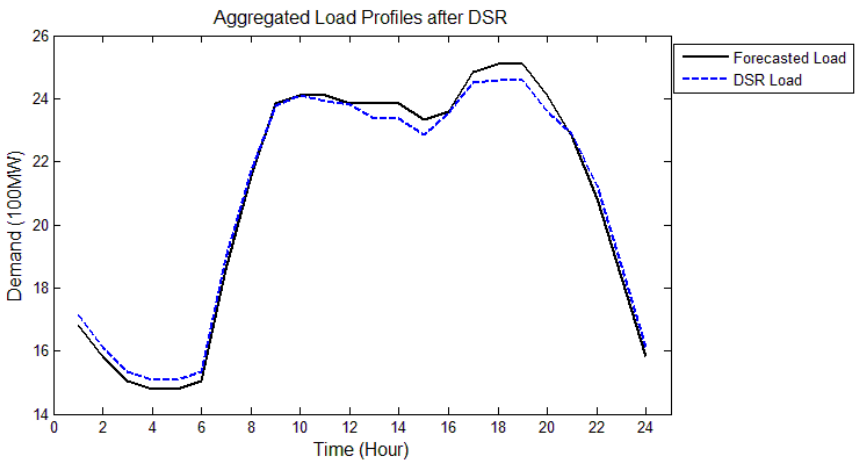

Fig 5-9 Aggregated Optimized Load Profiles of Bus 2, 3 and 4 under DR 1

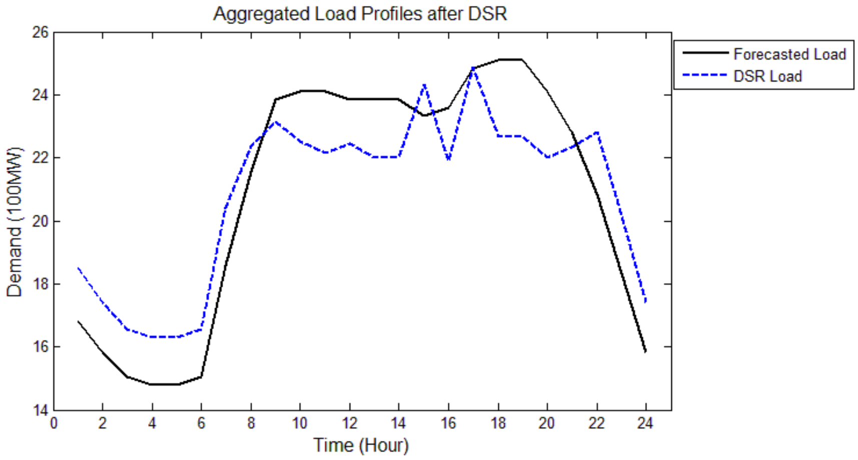

Fig 5-10 Aggregated Optimized Load Profiles of Bus 2, 3 and 4 under DR 2

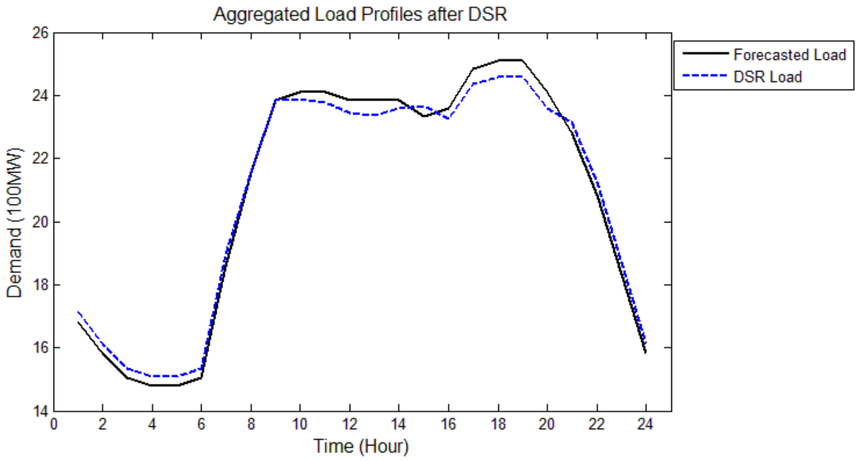

Fig 5-11 Aggregated Optimized Load Profiles of Bus 2, 3 and 4 under DR 3

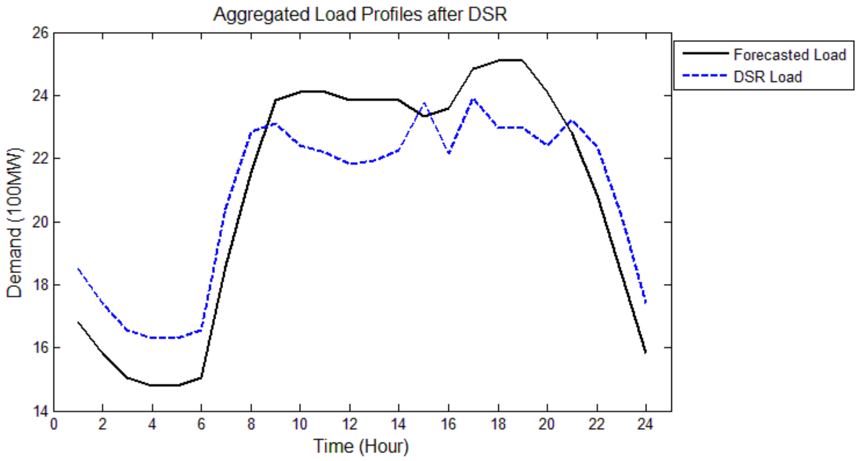

Fig 5-12 Aggregated Optimized Load Profiles of Bus 2, 3 and 4 under DR 4

5.4.3.2 Importance of Considering Wind Uncertainty in GEP

In order to address the difference between deterministic and stochastic treatment of wind generation, GEP model is solved under each individual wind output scenario (S1 to S10) listed in Table 5-6. The deterministic treatment of wind generation is assumed that the wind farm will precisely generate the predicted amount of power at the forecasted time, which was adopted in literatures [3, 9, 21, 22, 51, 62, 65, 72, 74, 75, 101, 104, 109].

- **Comparison between Deterministic and Stochastic GEP Model without DSR**

In the first step, the GEP model is solved without considering DSR. The optimal generation mix results are shown in Table 5-9. It can be seen that all the ten scenarios except S5, have the same optimal conventional generation mix. S5 requires one more CCGT2 unit compared with other nine scenarios. However, the ten scenarios require very different numbers of optimal wind farms ranging from 13 to 19. The conventional generators' locational distribution for S5 is shown in Fig 5-13, while for S1 to S4 and S6 to S10, they have the same conventional generators' locational distribution as is shown in Fig 5-14.

The optimal generation mix obtained from the GEP model proposed in this chapter is shown in the last column of Table 5-9 in bold, which is just copied from Table 5-7. Compared with deterministic GEP model, the stochastic one gives a very different mix solution with more units included especially wind farms. Since the more units are expended, the generators' locational distribution for the stochastic GEP model is different from that for the deterministic one. This can be seen by comparing Fig 5-2 to Fig 5-13 and Fig 5-14.

Table 5-9 Optimal Generation Mixes for 10 Wind Output Scenarios

Wind Scenarios		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	**MC**
Number of Installed Units	CCGT1	2	2	2	2	2	2	2	2	2	2	**3**
	CCGT2	5	5	5	5	6	5	5	5	5	5	**6**
	COAl PF	1	1	1	1	1	1	1	1	1	1	**1**
	IGCC	1	1	1	1	1	1	1	1	1	1	**1**
	OGCT	1	1	1	1	1	1	1	1	1	1	**2**
	Wind	19	19	16	16	16	19	18	18	19	13	**24**

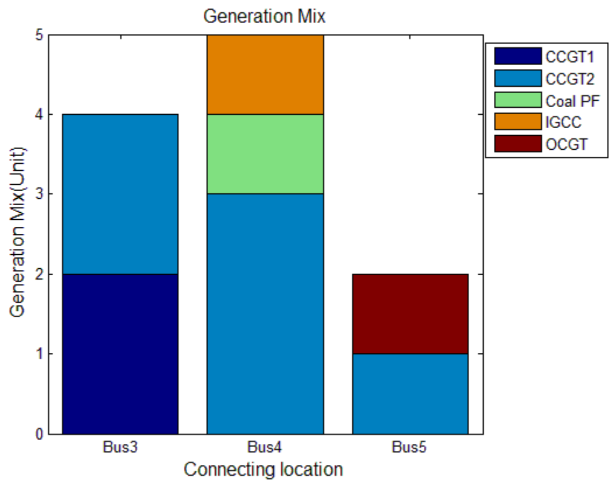

Fig 5-13 Optimal Generation Location Distribution for S5 without DSR

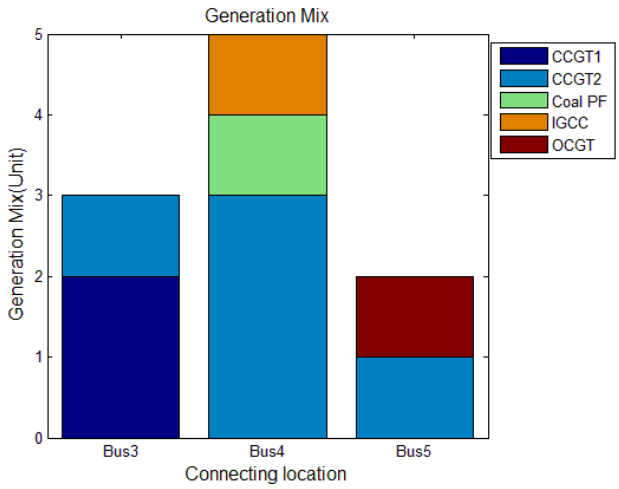

Fig 5-14 Optimal Generation Location Distribution for S1-S4, S6-S10 without DSR

Table 5-10 Optimal GEP Results for 10 Wind Output Scenarios

Wind Scenarios	Total Cost £	Total Emission(tonnes)
S1	3.194E+09	3.996E+06
S2	3.195E+09	3.992E+06
S3	3.111E+09	3.992E+06
S4	3.112E+09	4.000E+06
S5	3.427E+09	3.992E+06
S6	3.194E+09	3.994E+06
S7	3.168E+09	4.000E+06
S8	3.167E+09	4.000E+06
S9	3.194E+09	4.000E+06
S10	3.031E+09	4.000E+06
MC	**3.826E+09**	**3.79E+06**

Since more generation units are expanded, the total cost from the stochastic GEP model must be higher than that from each deterministic GEP model. The guess is verified by the data provided in Table 5-10, showing the cost results of the ten solutions for a deterministic GEP model. The last row in bold is the cost of the stochastic GEP model, also shown in Table 5-8. It can be seen the total expansion cost from stochastic model is indeed higher than those from the deterministic one. The reason of these differences is that the two stage stochastic linear programming GEP model can tackle the uncertainty of wind farm output by Monte Carlo simulation. The first stage decisions, capacities of different generation technologies to be expanded are made to meet all second stage constraint scenarios and generate a minimum expected operational cost of the second stage generation operation problem. In optimization theory, more second stage constraints added may narrow the feasible region and hence affect the value of optimal solution.

- **Comparison between Deterministic and Stochastic GEP Model with DSR**

In the second step, in order to investigate whether DSR will affect the observation in the first step experiment, the above assessment is made again, keeping all the input parameters the same except the demand flexibility scenario. In this assessment, the DR2 scenario is adopted. The optimal generation mix results are shown in Table 5-11. The optimal generation locational distribution results are shown in Fig 5-15 and Fig 5-16. The cost results of the ten solutions for a deterministic GEP model are shown in Table 5-12. All the observation of the first step results still exists. Therefore, no matter what demand flexibility level is, the stochastic GEP model with multi wind output scenarios will produce a solution with more generation capacity and more total cost, compared with the case with deterministic GEP model with only a single wind output scenario.

All the above comparison and analysis show the importance of considering the wind uncertainty in a GEP problem. The GEP model with a deterministic wind output profile may underestimate the optimal generation capacities and the required total cost.

Table 5-11 Optimal Generation Mixes for 10 Wind Output Scenarios

Wind Scenarios		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	**MC**
Number of Installed Units	CCGT1	2	2	2	2	2	2	2	2	2	2	**2**
	CCGT2	5	5	5	5	6	5	5	5	5	5	**6**
	COAl PF	1	1	1	1	1	1	1	1	1	1	**1**
	IGCC	1	1	1	1	1	1	1	1	1	1	**1**
	OGCT	1	1	1	1	1	1	1	1	1	1	**2**
	Wind	15	15	13	13	8	15	16	15	15	11	**16**

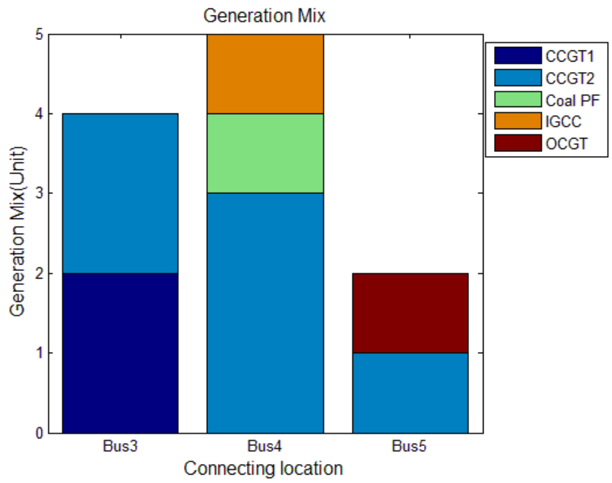

Fig 5-15 Optimal Generation Location Distribution for S5 and DR2

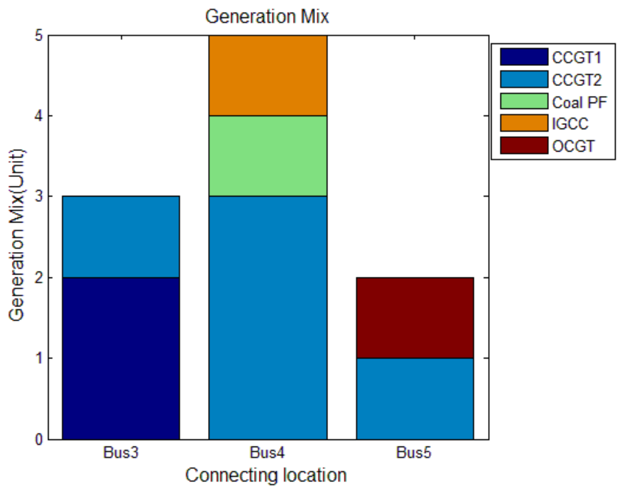

Fig 5-16 Optimal Generation Location Distribution for S1-S4, S6-S10 and DR2

Table 5-12 Optimal GEP Results for 10 Wind Output Scenarios

Wind Scenarios	Total Cost £	Total Emission(tonnes)
S1	3.087E+09	4.000E+06
S2	3.088E+09	4.000E+06
S3	3.032E+09	4.000E+06
S4	3.033E+09	4.000E+06
S5	3.211E+09	4.000E+06
S6	3.087E+09	4.000E+06
S7	3.114E+09	4.000E+06
S8	3.087E+09	4.000E+06
S9	3.087E+09	4.000E+06
S10	2.978E+09	4.000E+06
MC	**3.468E+09**	**3.85E+06**

5.5 Chapter Summary

In this chapter, a new GEP model is proposed, which considers both stochastic renewable generation expansion and demand side response simultaneously with network constraints and generation location optimization. This GEP model inherits the advantages of the model proposed in Chapter 3 which can deal with generation location optimization. Additionally, wind generation capacity expansion is included, whose uncertainty is taken account of by a two stage scholastic linear programming model. The uncertain wind output profile in the future is handled by Monte Carlo simulation technique, which generates a number of wind output scenarios following a given wind speed probability distribution. A basic introduction about the two-stage stochastic programming and Monte Carlo simulation technique is provided to help readers better understand the stochastic GEP in this chapter.

The demand side response modelling is realized by setting the demands at different locations at different time intervals as decision variables. The demands are allowed to deviate from their forecasted amount up or down within a pair of certain lower and upper bounds. The range between the lower and upper bounds represents the flexibility of the demand. Since the load type composition (industrial, commercial and domestic) varies for different load buses, the flexibilities on different load buses may be different. The demand side response is also constrained by a rule that the total demand in a single day after DSR should be equal to the total forecasted demand in that day. This constraint models the real life case that the demand can only be shifted from one time to another, but can not disappear.

A case study is provided based on a five bus test system to verify the effectiveness of the method proposed in this study. Five load flexibility scenarios are used to investigate the impacts of DSR on GEP problems. Ten wind output scenarios for two-stage stochastic programming are generated following a Weibull distribution.

Comparisons have been made to find out that with more flexible demand, the load valley can be better filled and the load peak could be better clipped. Therefore, more generation capacity expansion can be avoided and the huge cost could be saved. Moreover, the results also indicates that for the same flexibility level, demand response can contribute more if it is located at the bus where the system marginal units stay or the most sensitive bus to congestion lines (with biggest GSDF), compared with other locations. From the long term GEP view, raising the demand flexibility at the most sensitive locations by applying appropriate DSR programmes can help take full advantage of the current network and generation capacity and more importantly help save the future expensive peak unit investment.

In order to address the difference between the deterministic and stochastic treatment of wind generation, GEP model is solved under each of the 10 wind output scenarios individually. This deterministic treatment of wind generation is assumed the wind farm will precisely generate the predicted amount of power at the forecasted time, which was adopted in literatures [3, 9, 21, 22, 51, 62, 65, 72, 74, 75, 101, 104, 109]. Results show that no matter what demand flexibility level is, the two-stage stochastic GEP model with multi wind output scenarios will produce a solution requiring more generation capacity expansion and more total cost, compared with the results from the deterministic GEP model with only a single wind output scenario. The reason of these differences is that the two-stage stochastic linear programming GEP model can tackle the uncertainty of wind farm output by Monte Carlo simulation. The first stage decisions, capacities of different generation technologies to be expanded are made to meet all second stage constraint scenarios and generate a minimum expected operational cost of the second stage generation operation problem. In optimization theory, more second stage constraints added may narrow the feasible region and hence affect the value of optimal solution.

In summary, this chapter proposes a new GEP model, which considers both stochastic renewable generation expansion and demand side response simultaneously with network constraints and generation location optimization. The comparison and analysis of the results show the importance of considering DSR and the wind uncertainty in a GEP problem. The GEP model ignoring the potential impacts of DSR may overestimate the required optimal generation capacities and total cost; whereas those may be underestimated if the GEP model doesn't recognise the stochastic nature of the wind output and use a deterministic wind output profile instead.

Chapter 6

Optimal Generation Mix of Great Britain in 2020

THIS chapter presents a case study specifically for investigating the optimal generation mix of Great Britain (GB) in 2020.

6.1 Introduction

In Chapter 2, the GEP model has been enhanced by taking account of the emission cost in operational level. Meanwhile, the model proposed in this chapter takes into account the integer variables and nonlinearity of the operational cost with network constraints and renewable generation expansion together in one long-term generation planning model. Dynamic programming and a heuristic gradient search method are employed to tackle the short-term operational optimization and long-term expansion optimization respectively.

Although the GEP model in Chapter 2 considers the network constraints, the new generation capacities are assumed to be expanded at designated locations. The generation location optimization is ignored. In order to include the location optimization in the GEP problem, the dimension of the decision variable has to be augmented to represent the location index. The combined dynamic programming and heuristic gradient search method is hard to cope with the new optimization problem with the increased the search space for generation location decision. Hence, in Chapter 3, the research direction is switched to a mixed integer linear programming (MILP) based GEP modelling method, which can handle the optimization problem with much larger dimension. However, in a MILP model, all the objective and constraint should be expressed linearly respect to the decision variable. Compared with the modelling method in Chapter 2, nonlinear operation cost function has to be approximated by a linear one in a MILP GEP model. However, as a trade-off, the optimal generation location can be decided in the new MILP GEP model.

Lately, the MILP GEP model proposed in Chapter 3 is enhanced by taking account of multi-phase emission targets in Chapter 4. In addition, it is enhanced by incorporating stochastic renewable generation and demand side response in Chapter 5.

In Chapter 2, 3, 4 and 5, the proposed models are all tested by case studies. However, the case studies in previous chapters are all based on test systems. In order the show the practical effectiveness of the proposed modelling methods and answer the question specified by the thesis title, this chapter will propose a case study specifically for investigating the optimal generation mix for Great Britain (GB).

6.2 Reduced GB Network Model

The GEP model proposed in Chapter 5 is adopted to assess the optimal generation mix of GB, which considers the generation location optimization simultaneously with stochastic wind generation and demand side response. However, before introducing the specific assessment detail, a slight modification of the adopted GEP model shall be explained.

The modification is made to accommodate the GB network data. Therefore, the GB network data will be introduced firstly, which can help the readers better understand the reasons and details of the modification to the GEP model.

In this chapter, the real case study is made based on a reduced Great Britain (GB) transmission network, whose data is obtained from the Seven Year Statement (SYS), which is the yearly published UK power system report by National Grid (UK) [12]. In the SYS, the UK transmission network is simulated by 17 study zones and 17 transmission boundaries. The 17 zones represent 17 different areas of the Great Britain, in each of which, the power plants and demands from different buses are aggregated. The transmission network inside a zone is neglected. However, the transmission capabilities between zones are constrained by 17 transmission boundaries. A boundary can be linked to multiple zones. The total flow across the boundary will be the sum of the difference between generation and demand in all the zones affecting that boundary. The geographic zone division map is shown in Fig 6-1. The 17 study zones are listed in Table 6-1. The 17 study boundaries are listed in Table 6-2, where the zones affecting the each boundary are listed in the last column. As is stated in SYS report, “the 17 boundaries have historically reflected some of the main weaknesses on the interconnected system. Such weaknesses can lead to the need to restrict power flows across the system; possibly through the potentially uneconomic constrained operation of generating plant. Alternatively, weaknesses in transmission may be removed by transmission reinforcement. Although the most critical boundaries may not be precisely the same as those studied, the 17 boundaries which have been used remain relevant for illustrating system trends and limitations.” [12]

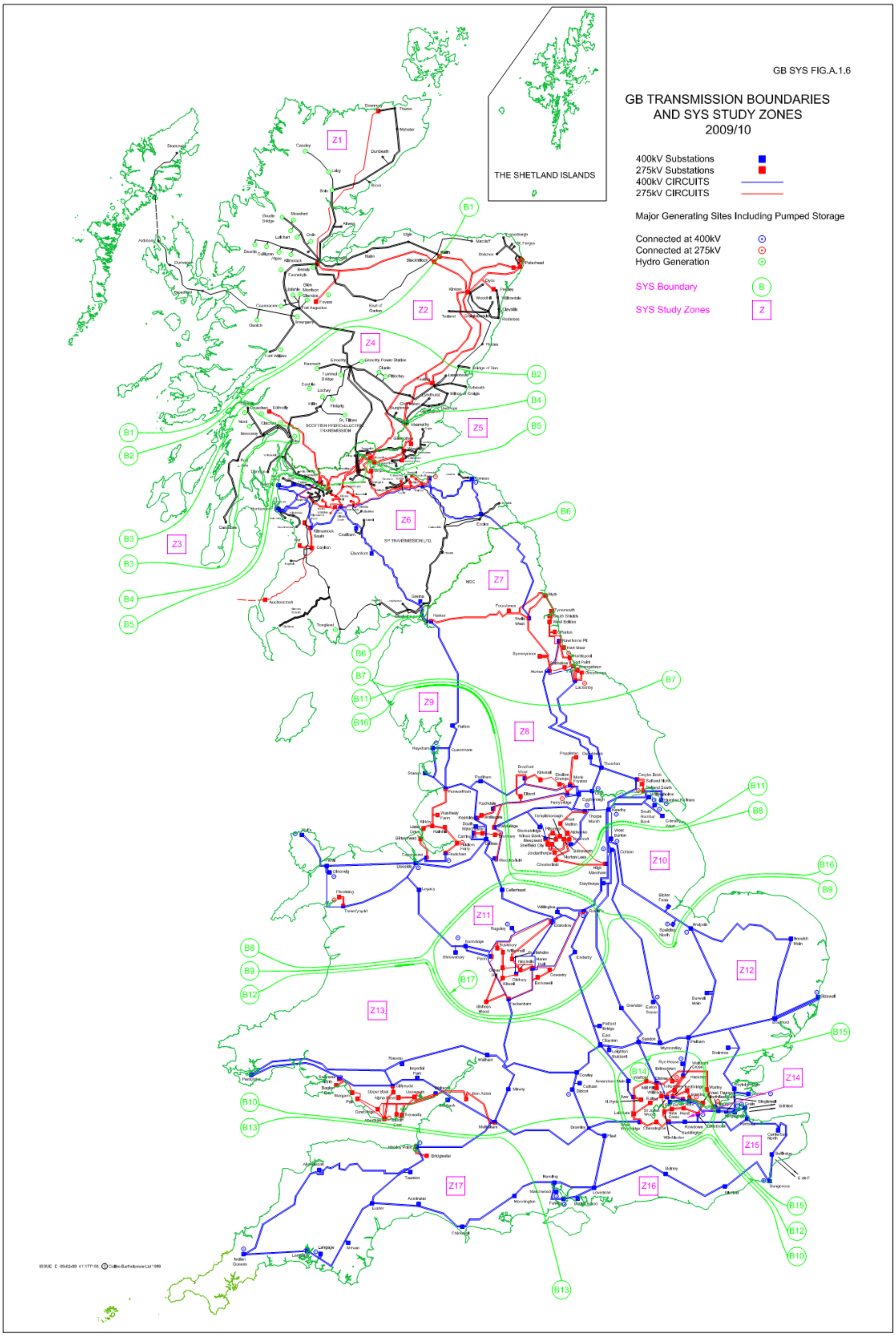

Fig 6-1 GB Transmission Boundaries and SYS Study Zones

Table 6-1 SYS Study Zones

Zone Number	Zone Name	Licensee
Z1	North West (SHETL)	SHETL[6]
Z2	North (SHETL)	SHETL
Z3	Sloy (SHETL)	SHETL
Z4	South (SHETL)	SHETL
Z5	North (SPT)	SPT[7]
Z6	South (SPT)	SPT
Z7	North & NE England	NGET[8]
Z8	Yorkshire	NGET
Z9	NW England & N Wales	NGET
Z10	Trent	NGET
Z11	Midlands	NGET
Z12	Anglia & Bucks	NGET
Z13	S Wales & Central England	NGET
Z14	London	NGET
Z15	Thames Estuary	NGET
Z16	Central S Coast	NGET
Z17	South West England	NGET

Table 6-2 Boundary to Zone Mapping Table

Boundary Number	Boundary Name	Zone Numbers
B1	North West	Z1
B2	North-South	Z1, Z2
B3	South West	Z3
B4	SHETL-SPT	Z1, Z2, Z3, Z4
B5	North-South	Z1, Z2, Z3, Z4, Z5
B6	SPT-NGET	Z1, Z2, Z3, Z4, Z5, Z6
B7	Upper North-North	Z1, Z2, Z3, Z4, Z5, Z6, Z7
B8	North to Midlands	Z1, Z2, Z3, Z4, Z5, Z6, Z7, Z8, Z9
B9	Midlands to South	Z1, Z2, Z3, Z4, Z5, Z6, Z7, Z8, Z9, Z10, Z11
B10	South Coast	Z16, Z17
B11	North East & Yorkshire	Z1, Z2, Z3, Z4, Z5, Z6, Z7, Z8
B12	South & South West	Z13, Z16, Z17
B13	South West	Z17
B14	London	Z14
B15	Thames Estuary	Z15
B16	North East, Trent & Yorkshire	Z1, Z2, Z3, Z4, Z5, Z6, Z7,Z8, Z10
B17	West Midlands	Z11

[6] SHETL: Scottish Hydro-Transmission Ltd.
[7] SPT: Scottish Power Transmission Ltd
[8] NGET: National Grid Electricity Transmission plc.

Compared with the topology of the traditional power system network model, the zones act like the buses (nodes), and the boundaries act like lines (branches). As introduced in Chapter 3, the DC power flow over a line can be expressed linearly by the power injections at all nodes multiplied by their corresponding generation shift distribution factors (GSDF).

For the reduce GB network obtained from SYS by Nation Grid, the 17 boundaries are not given a reactance data. Therefore, it is not feasible to calculate the GSDF between zones and boundaries. It is not necessary either, since the zones that affecting the boundary flow have been identified already, which is shown in third column of Table 6-2. Base on the linking relation between zones and boundaries, a zone to boundary incidence matrix (ZB) is developed, showing in Table 6-3. In ZB matrix, zones are indexed by Z1 to Z17 and boundaries are indexed by B1 to B17. The value “1” means the power-demand imbalance in the zone will contribute to the power flow on the boundary, and “0” means the reverse. For example, B1 will affected by Z1, while B12 will be affected by Z13, Z16 and Z17 together.

Table 6-3 Zones to Boundaries Incidence Matrix

	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11	Z12	Z13	Z14	Z15	Z16	Z17
B1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
B5	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B6	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
B7	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
B8	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
B9	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
B10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
B11	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
B12	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
B13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
B14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
B15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
B16	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0
B17	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0

In order to accommodate difference in network power flow modelling, the transmission capacity constraints used in the GEP model in Chapter 3, 4 and 5 should be modified slightly. Firstly, all the bus indexes refer to zone indexes, and all the line indexes refer to boundary indexes in this chapter. Secondly, in the previous GEP model the power injection at nodes are linked to the power flow linearly by GSDF, which are shown as in Equation 6-2, and flow is constrained by transmission limits Lim_k bidirectionally as Equation 6-1 shows:

$$-Lim_k \le L_{nkt} \le Lim_k \qquad \forall k \in K, \forall t \in T, \forall n \in N \tag{6-1}$$

$$L_{nkt} = \sum_{i=1}^{I} GSDF_{k-i} \times (\sum_{g=1}^{G} P_{ngit} + \sum_{w=1}^{W} P_{nwit} - D_{it}) \quad \forall k \in K, \forall t \in T, \forall n \in N \tag{6-2}$$

In the reduced GB zone boundary model, Equation 6-2,

$$L_{nkt} = \sum_{i=1}^{I} ZB_{k-i} \times (\sum_{g=1}^{G} P_{ngit} + \sum_{w=1}^{W} P_{nwit} - D_{it}) \quad \forall k \in K, \forall t \in T, \forall n \in N \tag{6-3}$$

where, *ZB* is the zone to boundary incidence matrix, ZB_{k-i} reflects whether Zone i will affect the power flow on Boundary k. Lim_k is used to index the transmission capacity of Boundary k.

All the other modelling details are still kept the same as the GEP model proposed in Section 5.3 in Chapter 5. Therefore, they are not repeated here.

6.3 GB Case Study

6.3.1 Test Inputs

6.3.1.1 Generation Mix in 2011

The generation mix subtotalled by plant type and SYS study zone in 2011 can be found in [12], which is listed Table.C1 in Appendix C. This table lists 25 different plant types. However, some plants have a zero or very small capacities such as thermal, tidal, wave and woodchip plant. Some plants have similar characteristic, such as five nuclear power plants, named Nuclear AGR, Nuclear APR, Nuclear EPR, Nuclear Magnox and Nuclear PWR, which are just operated by different companies. In order to simplify the calculation burden, the large unit coal power plant and large unit coal +AGT plant in Table. C1 in Appendix C are aggregated as simply coal plant. The five nuclear power plants are aggregated as simply nuclear power plant. Plant types with zero or relatively small penetration are discarded from the generation expansion planning in this chapter, which are CHP, clean coal, IGCC, medium and small unit coal, OCGT, oil, thermal, tidal, wave and woodchip.

Finally, eight generation technologies are selected to perform the case study. The selected candidate generation technologies are nuclear, coal, CCGT, pumped storage hydro plant (PS), hydro, biomass (bio), on-shore wind and off-shore wind. Table 6-4 shows the GB generation mix by the selected eight generation technologies in 2011. In practice, by the time of doing this case study, there have been already a certain amount of planned new generation capacity under construction or will be constructed between 2011 and 2020. On the other hand, some of the existing units have be planned to close or will be closed sometime between 2011 and 2020. These actions are planned by individual generation companies and long time before this research. This case study will not consider these previous planned actions and will purely calculate the optimal generation mix made by the GEP model proposed in the thesis. Therefore, assumption is made that the generation mix listed in Table 6-4 will be the minimum capacities of different power plants to appear in the 2020 target year. In other words, the previous planned unit construction and closure is neglected between 2011 and 2020.

Table 6-4 Minimum Capacities of Different Power Plants to Appear in the 2020 Target Year

Plant Type	Nuclear	Coal	CCGT	PS	Hydro	Bio	Wind On-shore	Wind Off-shore
Z1	0	0	0	300	577	0	651	0
Z2	0	0	1,180	0	18	0	0	0
Z3	0	0	0	0	230	0	172	0
Z4	0	0	0	0	259	0	103	0
Z5	0	2,284	0	440	0	0	35	0
Z6	2,289	0	20	0	33	45	1,327	0
Z7	1,207	0	1,974	0	0	0	0	0
Z8	0	7,832	4,945	0	0	0	0	0
Z9	3,368	1,987	2,934	2,004	0	0	0	182
Z10	0	3,987	2,975	0	0	0	0	0
Z11	0	4,003	0	0	0	0	0	0
Z12	1,207	0	3,050	0	0	0	0	815
Z13	430	3,723	4,431	0	0	0	0	0
Z14	0	0	2,123	0	0	0	0	0
Z15	1,081	1,966	3,165	0	0	0	0	201
Z16	0	0	1,320	0	0	0	0	0
Z17	1,261	0	905	0	0	0	0	0
Sub total	10,843	25,782	29,022	2,744	1,117	45	2,288	1,198
Penetration	14.8%	35.3%	39.7%	3.8%	1.5%	0.1%	3.1%	1.6%

6.3.1.2 Candidate Generation Data

The characteristics of the selected eight candidate generation technologies are shown in Table 6-5, which are gathered from [62]. They have different performances in terms of nameplate capacity, operational cost, capital cost, and emission coefficient. The wind generation is assumed to have negligible operational cost and emission. It should be noted that normally, a single wind turbine has rated capacity ranging from hundreds of kW to several MW, but a wind farm often includes several to tens of wind turbines. In this case study, the rated capacity refers to a wind farm's total wind installed capacity rather than a single wind turbine. In this case study, the ratio between wind generation capacity and conventional generation capacity (wc) is set to 20% for reliability reasons, which means the wind capacity is not allowed to expand to more than 20% of the conventional generation capacity. Emission price (EP) is set to be 10 £/tonne in this case study.

Table 6-5 Candidate Generation Technology Data

Plant Type	Nameplate Capacity (MW)	FC (£/MWh)	Emission Coefficient (tonne/MWh)	CC (M£/MW)
Nuclear	1,200	14	0	2.50
Coal	600	34	0.92	1.00
CCGT	400	72	0.47	0.47
Pumped Storage	300	50	0	1.70
Hydro	10	20	0	3.00
Biomass	20	147	0.22	2.35
Wind On-shore	100	N/A	0	1.20
Wind Off-shore	100	N/A	0	2.80

It should be noted that in this case study, hydro and nuclear technologies are considered in sub operational problem but they are not included in the generation capacity expansion level. Since their expansion plans are almost set by the government. It is not realistic to incorporate too many changes on them. For coal, CCGT and biomass power plants, they are allowed to be expanded at any of the 17 study zones. However, due to the wind speed distribution characteristics in the Great Britain, they should be expanded at the zones with rich wind source. Referring to the locations the planned wind farm construction between 2011 and 2017 in SYS 2011, the wind zones are identified for this case study. For candidate on-shore wind farms, they can be expanded freely in Z1 Z2 Z3 Z4 Z5 Z6 Z9 and Z13. For off-shore wind farms, they can be expanded freely in Z1 Z4 Z5 Z8 Z9 Z12 Z13 and Z14.

6.3.1.3 Boundary Capacity

The transmission capacities of the 17 boundaries are shown in Table 6-6, which is collected from SYS 2011 [12]. There are two columns of transmission capacity. One is for the year 2011. The other is for the year 2017, which considers the planned transmission reinforcement and expansion. The capacities of the boundaries (B1 to B7) in the northern Great Britain will be expanded a lot. In the case study, the optimal GB generation mix is calculated under two boundary capacity scenarios. The first one is based on the capacity in 2011, which represents the existing transmission capability. The second one is based on the capacity in 2017, which represents the transmission capability in the 2020 target year. (Boundary capacity variance between 2017 and 2020 is neglected due to lack of data.)

Table 6-6 SYS Boundary Capacity (MW)

Boundary Number	Year 2011	Year 2017
B1	450	2,300
B2	1,600	3,400
B3	350	500
B4	1,700	3,650
B5	3,050	5,350
B6	2,700	8,050
B7	3,691	6,600
B8	10,669	11,035
B9	10,889	10,985
B10	6,051	6,167
B11	10,218	9,556
B12	4,338	4,804
B13	2,201	3,264
B14	9,633	9,849
B15	5,817	6,121
B16	15,264	16,909
B17	5,049	5,706

6.3.1.4 Demand Data

The forecasted zonal peak demand of the 17 zones in 2017 are shown in Table 6-7, which is also collected from SYS 2011 [12]. In the case study, the forecasted demand in 2017 is used to represent the forecasted peak demand in the 2020 target year. The demand growth between 2017 and 2020 is neglected due to lack of data.

Table 6-7 Zonal Peak Demand (MW)

Zone Number	Year 2017
Z1	506
Z2	609
Z3	67
Z4	545
Z5	1,169
Z6	3,131
Z7	3,303
Z8	5,094
Z9	7,625
Z10	828
Z11	7,325
Z12	5,127
Z13	5,083
Z14	10,205
Z15	2,322
Z16	4,237
Z17	3,053
All	60,229

In SYS 2011, the half hourly annual load duration curve is provided, which records the GB system total demands for 17520 half hourly intervals in 2011, which is shown as Fig 6-2. The 17520 demand levels are sorted in descending order. The vertical axis labels the demand value in percentage of the annual peak demand, which is 59,132MW in 2011. The horizontal axis labels the percentage of time in the year against the proportion of the year's peak. For example, demand exceeded 50% of the annual peak for 78% of the time.

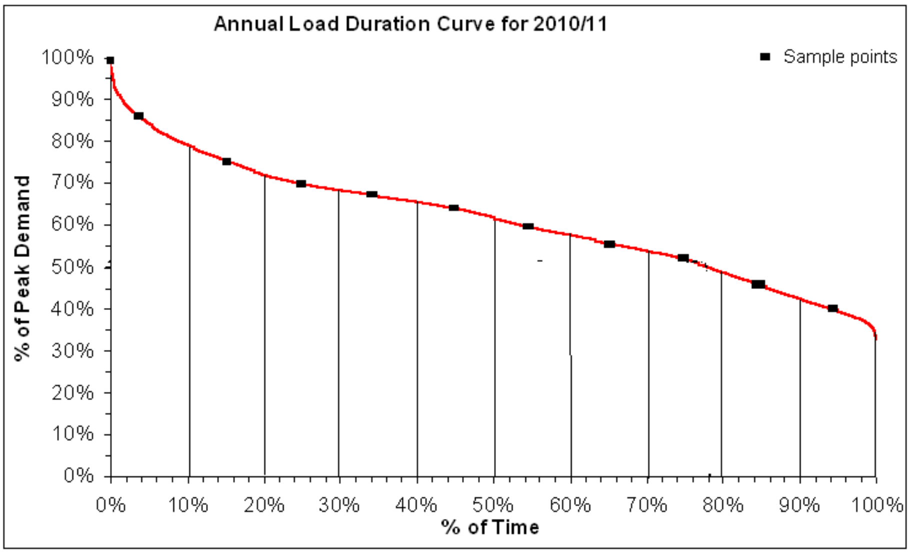

Fig 6-2 GB Annual Load Duration Curve

The demand profile used in this chapter is sampled from this curve. The sampling principle is:

1. Divide the load duration curve into 10 sections evenly by time.

2. Get the average demand in each section as the sample demand for the corresponding section. Therefore, each sample demand represents 876 hours of a year in the sub operational problem of the master GEP problem. (A year has 8760 hours.) In addition, the related operation cost and emission results will be scaled up by 876.

3. The annual peak demand is also sampled to reflect the demand intense at peak time, which is critical for generation capacity expansion. However, it only represents 1 hour of a year in the sub operational problem of the master GEP problem.

Therefore the scheduling horizon for the sub operational problem is 11 hours for this study case. The sample load profile is shown in Table 6-8. It is assumed that the demands in the 17 study zones are all following this load profile.

Table 6-8 Sampled Load Profile

Index	Hours Represented	% of Peak
1	1	100.00%
2	876	84.92%
3	876	75.40%
4	876	69.85%
5	876	66.76%
6	876	63.74%
7	876	59.42%
8	876	55.62%
9	876	51.49%
10	876	45.40%
11	876	39.07%

The forecasted demand profile reflects the regular pattern of the electricity consumption. Based on the forecasted demand profile, the demand side could be guided to response via various DSR programs in order to achieve a minimum total GEP cost. In order to investigate the impacts of DSR on the optimal GB generation mix, Zone 8, Zone 11 and Zone 13 are assumed to have DSR programmes deployed by 2020. Two scenarios of demand flexibility coefficients are constructed to demonstrate the impacts of different DSR levels on the optimal GEP results, which is listed in Table 6-9. For scenarios DR1, the DSR level is relatively low. Averagely, demand side can response within 2% up and down of the forecasted level. For scenarios DR2, the DSR level is relatively high. Averagely, demand side can response within 10% up and down of the forecasted level.

Table 6-9 DSR Flexibility Scenarios

Demand Zone			Zone 8	Zone 11	Zone14
DSR Flexibility Scenarios	DR1	Low	0.03	0.02	0.01
	DR2	High	0.10	0.15	0.05

6.3.1.5 Wind Generation Data

In this case study, the wind speed distribution characteristics are differentiated by geographical condition. Off-shore wind farm places in Z1 Z4 Z5 Z8 Z9 Z12 Z13 and Z14 are assumed to have the largest wind speed expectation. Northern on-shore wind farm locations in Z1 Z2 Z3 Z4 Z5 and Z6 have medium wind speed expectation. Southern on-shore wind farm locations in Z9 and Z13 have the smallest wind speed expectation.

In this case study, it is assumed the on-shore and off-shore wind turbines have the same speed parameters which are cut-in speed = 5m/s, cut-out speed=45m/s, and rated speed=15m/s. The wind speeds are subject to the Weibull distribution. For off-shore wind zones, the Weibull parameters are set as η =12.8, k=1.5. These parameters are set to give an expected load factor of around 50% for off-shore wind units in off-shore wind zones. For northern on-shore wind zones, the Weibull parameters are set as η =10.2, k=1.5. These parameters are set to give an expected load factor of around 40% for northern on-shore wind units in northern on-shore wind zones. For southern on-shore wind zones, the Weibull parameters are set as η =8.6, k=1.5. These parameters are set to give an expected load factor of around 30% for southern on-shore wind units in southern on-shore wind zones. Ten sets of 11-hour wind output scenarios are generated following the specified Weibull distribution to implement the Monte Carlo simulation of the wind generation uncertainty. They are listed in Table C2 in Appendix C, in which the decimals indicated the wind farm power output in percentage of its nameplate capacity.

6.3.2 Case Study Implementation

UK government enforced Climate Change Act 2008, setting legally binding emission reduction targets of the UK, which are at least 34% and 80% cut in GHG emission by 2020 and 2050 respectively, both against a 1990 baseline. The UK carbon emission in 1990 from power industrial sector is around 200 million tons (Mt) according to the report from DECC [124]. However, there are no published documents specifying emission reduction targets for power industrial sector. Therefore, an emission reduction target at around 34% is set for power industry in 2020 for this case study. At the beginning, the GB GEP model with a 34% reduction target has been solved. Results show that the existing generation mix in 2011 shown in Table 6-4 can already realise the 34% target, no more clean generation units need to be expanded before 2020. In order to shows the effectiveness of the GEP model, 50% emission reduction target is set. That means maximum 100 Mt carbon emission is allowed from power industry in 2020. Under this target, some new clean generation capacities have to be expanded. The results are shown in next section.

In order to show the impacts of the boundary capacity on the optimal GB generation mix in 2020, the GB GEP model is solved under two boundary capacity scenarios. One is the existing boundary capacity scenario in 2011. The other is the expanded boundary capacity scenario in 2020. The two boundary scenarios are listed in Table 6-6.

For each boundary capacity scenario, the GB GEP model is solved under three DSR scenarios. The first one is No-DSR scenario, which totally neglects the demand flexibility. The other two are low and high DSR scenarios. The demand flexibility parameters for the two scenarios are shown in Table 6-9.

6.3.3 Results and Analysis

6.3.3.1 Optimal GB Generation Mix in 2020 with 2011 Boundary Capacity Scenario

Table 6-10 shows the optimized number of units to be expanded for realizing the 2020 emission target (50% reduction) under three different DSR scenarios with 2011 boundary capacity. For No DSR scenario, it requires one new CCGT unit built in Z11 and twenty two new on-shore wind farms built in Z2, Z3 and Z4. For DR1 scenario, two less wind farms are required in Z4, which is replaced by one more biomass unit in Z14. For DR2 scenario, only one CCGT and sixteen wind farms are required. It can be found that compared with the GEP without DSR, the low level DSR programme can help save investment by replacing the two 100 MW on-shore wind farms with a 20 MW biomass power plant. However, the high level DSR programme can help save investment for six 100MW on-shore wind farms.

Table 6-10 Optimal Number of Units to Be Expanded under 3 DSR Scenarios with 2011 Boundary Capacity

Demand Flexibility Scenarios	No DSR		DR1			DR2	
Expanded Plant Types	CCGT	Wind On-shore	CCGT	Bio	Wind On-shore	CCGT	Wind On-shore
Z1							2
Z2		7			7		5
Z3		1			1		3
Z4		14			12		6
Z11	1		1			1	
Z14				1			
Subtotal	1	22	1	1	20	1	16

Table 6-11 shows the related optimized GEP cost and emission results. It can be seen that in order to realise the common emission reduction target, the GEP without DSR will generate a total cost of 16.9 billion pounds including the new generation capacity investment and the annual generation operation cost in the target year. However, with a very low level (averagely 2%) DSR implemented in Z8, Z11 and Z14, the total cost can be saved by 0.11 billion pounds, which is around 0.7% of the No DSR case. If a bit higher level (averagely 10%) DSR implemented, it can be saved by 0.64 billion pounds, which is around 3.8% of the No DSR case. This reveals the import role of DSR in the GEP problem.

Table 6-11 Optimal GEP Cost and Emission Results under Three DSR Scenarios

DSR Scenarios	Total Cost £	Total Emission (tonne)
No DSR	1.690E+10	1.00E+08
DR1	1.679E+10	1.00E+08
DR2	1.626E+10	1.00E+08

Table 6-12 Optimal GB Generation Mix (MW) without DSR with 2011 Boundary Capacity

	Nuclear	Coal	CCGT	PS	Hydro	Bio	Wind On-shore	Wind Off-shore
Z1	0	0	0	300	577	0	651	0
Z2	0	0	1,180	0	18	0	700	0
Z3	0	0	0	0	230	0	272	0
Z4	0	0	0	0	259	0	1,503	0
Z5	0	2,284	0	440	0	0	35	0
Z6	2,289	0	20	0	33	45	1,327	0
Z7	1,207	0	1,974	0	0	0	0	0
Z8	0	7,832	4,945	0	0	0	0	0
Z9	3,368	1,987	2,934	2,004	0	0	0	182
Z10	0	3,987	2,975	0	0	0	0	0
Z11	0	4,003	400	0	0	0	0	0
Z12	1,207	0	3,050	0	0	0	0	815
Z13	430	3,723	4,431	0	0	0	0	0
Z14	0	0	2,123	0	0	0	0	0
Z15	1,081	1,966	3,165	0	0	0	0	201
Z16	0	0	1,320	0	0	0	0	0
Z17	1,261	0	905	0	0	0	0	0
Sub total	10,843	25,782	29,422	2,744	1,117	45	4,488	1,198
Penetration	14.3%	34.1%	38.9%	3.6%	1.5%	0.1%	5.9%	1.6%
Total	75,639							

Table 6-13 Optimal GB Generation Mix (MW) under DR1 with 2011 Boundary Capacity

	Nuclear	Coal	CCGT	PS	Hydro	Bio	Wind On-shore	Wind Off-shore
Z1	0	0	0	300	577	0	651	0
Z2	0	0	1,180	0	18	0	700	0
Z3	0	0	0	0	230	0	272	0
Z4	0	0	0	0	259	0	1,303	0
Z5	0	2,284	0	440	0	0	35	0
Z6	2,289	0	20	0	33	45	1,327	0
Z7	1,207	0	1,974	0	0	0	0	0
Z8	0	7,832	4,945	0	0	0	0	0
Z9	3,368	1,987	2,934	2,004	0	0	0	182
Z10	0	3,987	2,975	0	0	0	0	0
Z11	0	4,003	400	0	0	0	0	0
Z12	1,207	0	3,050	0	0	0	0	815
Z13	430	3,723	4,431	0	0	0	0	0
Z14	0	0	2,123	0	0	20	0	0
Z15	1,081	1,966	3,165	0	0	0	0	201
Z16	0	0	1,320	0	0	0	0	0
Z17	1,261	0	905	0	0	0	0	0
Sub total	10,843	25,782	29,422	2,744	1,117	65	4,288	1,198
Penetration	14.4%	34.2%	39.0%	3.6%	1.5%	0.1%	5.7%	1.6%
Total	75,459							

Table 6-14 Optimal GB Generation Mix (MW) under DR2 with 2011 Boundary Capacity

	Nuclear	Coal	CCGT	PS	Hydro	Bio	Wind On-shore	Wind Off-shore
Z1	0	0	0	300	577	0	851	0
Z2	0	0	1,180	0	18	0	500	0
Z3	0	0	0	0	230	0	472	0
Z4	0	0	0	0	259	0	703	0
Z5	0	2,284	0	440	0	0	35	0
Z6	2,289	0	20	0	33	45	1,327	0
Z7	1,207	0	1,974	0	0	0	0	0
Z8	0	7,832	4,945	0	0	0	0	0
Z9	3,368	1,987	2,934	2,004	0	0	0	182
Z10	0	3,987	2,975	0	0	0	0	0
Z11	0	4,003	0	0	0	0	0	0
Z12	1,207	0	3,050	0	0	0	0	815
Z13	430	3,723	4,431	0	0	0	0	0
Z14	0	0	2,123	0	0	0	0	0
Z15	1,081	1,966	3,165	0	0	0	0	201
Z16	0	0	1,320	0	0	0	0	0
Z17	1,261	0	905	0	0	0	0	0
Sub total	10,843	25,782	29,022	2,744	1,117	45	3,888	1,198
Penetration	14.5%	34.5%	38.9%	3.7%	1.5%	0.1%	5.2%	1.6%
Total	74,639							

The 2020 optimal GB generation mix results under three DSR scenarios with 2011 boundary capacity are listed in Table 6-12, Table 6-13 and Table 6-14 respectively. It can be found that with increasing of the demand flexibility in the three DSR zones, the optimal penetration of on-shore wind farms drops from 5.9% of the No DSR case to 5.7% (DR1) and 5.2% (DR2), and the total installed generation capacity drops from 75,639 MW of the No DSR case to 75,459 MW (DR1) and 74,639 MW (DR2).

The optimal demand response results under DSR scenarios DR1 and 2 are shown in Fig 6-3 and Fig 6-4 respectively. In each figure, the black solid line represents the original forecasted load profiles; the optimized DSR load profiles at three load zones are depicted by dash lines in different colours as the legend indicates. The horizontal axis labels the 11 sampled hours for the sub operational problem. The vertical axis labels the hourly demand in the percentage of the annual peak demand at corresponding zones. For both DSR scenarios DR1 and DR2, valley filling and peak clipping effect can be observed compared with the forecasted load profile.

For readers who are interested in how the curves are depicted, the experiment results data for original and DSR load profiles are provided in Table C3, Table C4 and Table

C5 in Appendix C. Aggregated Optimized Load Profiles of Zone 8, 11 and 14 under DR1 and DR2 are also provided in Fig C-1 and Fig C-2 in Appendix C.

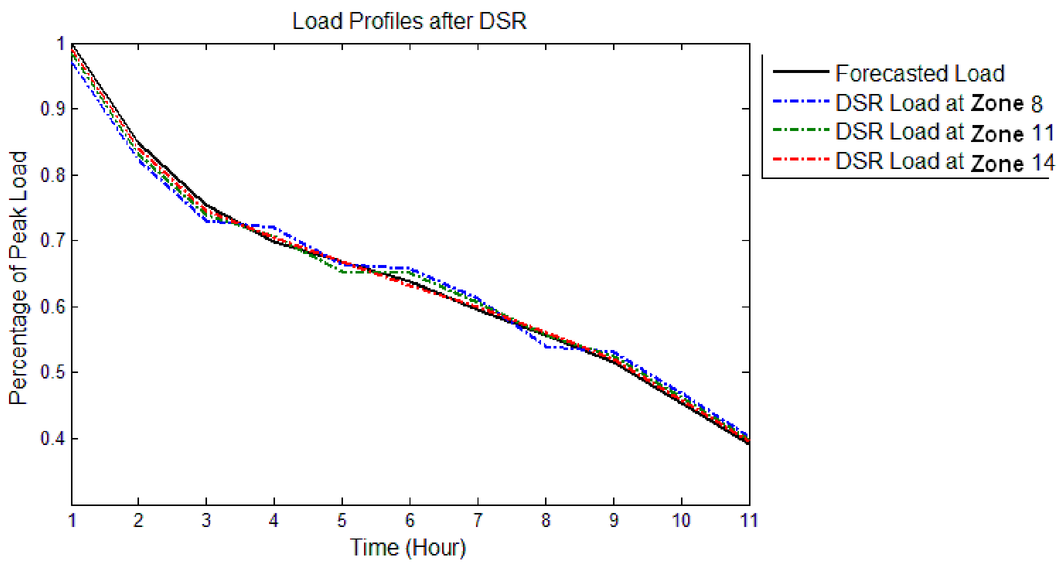

Fig 6-3 Optimized Load Profiles under DR1 with 2011 Boundary Capacity

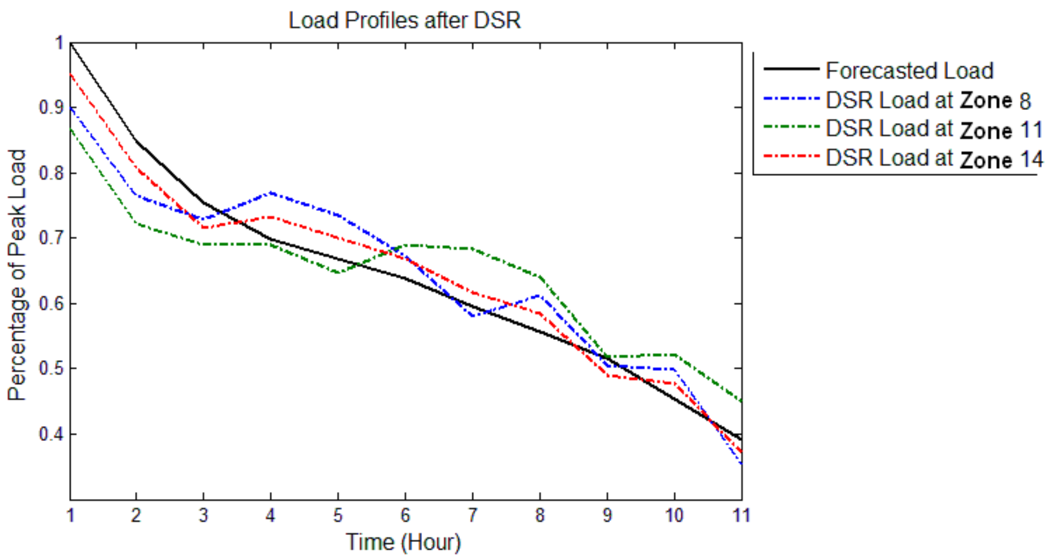

Fig 6-4 Optimized Load Profiles under DR2 with 2011 Boundary Capacity

6.3.3.2 Optimal GB Generation Mix in 2020 with 2020 Boundary Capacity Scenario

Similar to the results in Section 6.3.3.1, Table 6-15 shows the optimized number of units to be expanded for realizing the 2020 emission target (50% reduction) under three different DSR scenarios with 2020 boundary capacity. For No DSR scenario, it requires nineteen new on-shore wind farms built in Z1, Z2, Z3 and Z4. For DR1 scenario, two less wind farms are required. For DR2 scenario, only ten wind farms are required. It can be found that compared with the GEP without DSR, the low level DSR programme can help save investment for two 100 MW on-shore wind farms. However, the high level DSR programme can help save investment for nine 100MW on-shore wind farms.

Table 6-15 Optimal Number of Units to Be Expanded under 3 DSR Scenarios with 2020 Boundary Capacity

Demand Flexibility Scenarios	No DSR	DR1	DR2
Expanded Plant Types	Wind On-shore	Wind On-shore	Wind On-shore
Z1	5	2	1
Z2	5	6	5
Z3	2	1	1
Z4	7	8	3
Subtotal	19	17	10

However, compared with the results in Table 6-10, it can be found that after boundary capacity expansion, the generation capacity required to expand is obviously reduced for all the three DSR scenarios. For No DSR scenario, it requires one CCGT and twenty two on-shore wind farms if the boundary capacity is not expanded, but it only requires nineteen on-shore wind farms, if the boundary capacity is expanded. The differences are one CCGT unit and three on-shore wind farms. For DR1 scenario, the differences are one CCGT unit, one biomass unit and three on-shore wind farms. For DR2 scenario, they are one CCGT unit and six on-shore wind farms.

Table 6-16 shows the related optimized GEP cost and emission results. It can be seen that in order to realise the common emission reduction target, the GEP without DSR will generate a total cost of 16.9 billion pounds including the new generation capacity investment and the annual generation operation cost in the target year. However, with a very low level (averagely 2%) DSR implemented in Z8, Z11 and Z14, the total cost can be saved by 0.15 billion pounds, which is around 0.9% of the No DSR case. If a bit higher level (averagely 10%) DSR implemented, it can be saved by 0.68 billion pounds, which is around 4.5% of the No DSR case. This reveals the import role of DSR in the GEP problem.

Table 6-16 Optimal GEP Cost and Emission Results under Five Load Flexibility Scenarios

DSR Scenarios	Total Cost £	Total Emission (tonne)
No DSR	1.633E+10	1.00E+08
DR1	1.618E+10	1.00E+08
DR2	1.565E+10	1.00E+08

Compared with the results in Table 6-11, it can be found that after boundary capacity expansion, the total cost required is reduced as well for all the three DSR scenarios. For No DSR scenario, it is reduced from 16.90 billion to 16.33 billion, saving around 3.4%. For DR1 scenario, it is reduced from 16.79 billion to 16.18 billion, saving around 3.6%. For DR2 scenario, it is reduced from 16.26 billion to 15.65 billion, saving around 3.8%.

The 2020 optimal GB generation mix results under three DSR scenarios with 2020 boundary capacity are listed in Table 6-12, Table 6-13 and Table 6-14 respectively. It can be found that with increasing of the demand flexibility in the three DSR zones, the optimal penetration of on-shore wind farms drops from 5.6% of the No DSR case to 5.3% (DR1) and 4.4%(DR2), and the total installed generation capacity drops from 74,939 MW of the No DSR case to 74,739 MW (DR1) and 74,039 MW (DR2). Compared with the results in Table 6-12 to Table 6-14, the optimal total installed generation capacities are 75,639 MW for No DSR scenario, 75,459 MW for DR1 scenario and 74,639 MW DR2 scenarios respectively. After boundary capacity expansion, the optimal total generation capacities can be saved by 700MW, 720MW and 600MW for the three DSR scenarios respectively.

Table 6-17 Optimal GB Generation Mix (MW) without DSR with 2020 Boundary Capacity

	Nuclear	Coal	CCGT	PS	Hydro	Bio	Wind On-shore	Wind Off-shore
Z1	0	0	0	300	577	0	1,151	0
Z2	0	0	1,180	0	18	0	500	0
Z3	0	0	0	0	230	0	372	0
Z4	0	0	0	0	259	0	803	0
Z5	0	2,284	0	440	0	0	35	0
Z6	2,289	0	20	0	33	45	1,327	0
Z7	1,207	0	1,974	0	0	0	0	0
Z8	0	7,832	4,945	0	0	0	0	0
Z9	3,368	1,987	2,934	2,004	0	0	0	182
Z10	0	3,987	2,975	0	0	0	0	0
Z11	0	4,003	0	0	0	0	0	0
Z12	1,207	0	3,050	0	0	0	0	815
Z13	430	3,723	4,431	0	0	0	0	0
Z14	0	0	2,123	0	0	0	0	0
Z15	1,081	1,966	3,165	0	0	0	0	201
Z16	0	0	1,320	0	0	0	0	0
Z17	1,261	0	905	0	0	0	0	0
Sub total	10,843	25,782	29,022	2,744	1,117	45	4,188	1,198
Penetration	14.5%	34.4%	38.7%	3.7%	1.5%	0.1%	5.6%	1.6%
Total	74,939							

Table 6-18 Optimal GB Generation Mix (MW) under DR1 with 2020 Boundary Capacity

	Nuclear	Coal	CCGT	PS	Hydro	Bio	Wind On-shore	Wind Off-shore
Z1	0	0	0	300	577	0	851	0
Z2	0	0	1,180	0	18	0	600	0
Z3	0	0	0	0	230	0	272	0
Z4	0	0	0	0	259	0	903	0
Z5	0	2,284	0	440	0	0	35	0
Z6	2,289	0	20	0	33	45	1,327	0
Z7	1,207	0	1,974	0	0	0	0	0
Z8	0	7,832	4,945	0	0	0	0	0
Z9	3,368	1,987	2,934	2,004	0	0	0	182
Z10	0	3,987	2,975	0	0	0	0	0
Z11	0	4,003	0	0	0	0	0	0
Z12	1,207	0	3,050	0	0	0	0	815
Z13	430	3,723	4,431	0	0	0	0	0
Z14	0	0	2,123	0	0	0	0	0
Z15	1,081	1,966	3,165	0	0	0	0	201
Z16	0	0	1,320	0	0	0	0	0
Z17	1,261	0	905	0	0	0	0	0
Sub total	10,843	25,782	29,022	2,744	1,117	45	3,988	1,198
Penetration	14.5%	34.5%	38.8%	3.7%	1.5%	0.1%	5.3%	1.6%
Total	74,739							

Table 6-19 Optimal GB Generation Mix (MW) under DR2 with 2020 Boundary Capacity

	Nuclear	Coal	CCGT	PS	Hydro	Bio	Wind On-shore	Wind Off-shore
Z1	0	0	0	300	577	0	751	0
Z2	0	0	1,180	0	18	0	500	0
Z3	0	0	0	0	230	0	272	0
Z4	0	0	0	0	259	0	403	0
Z5	0	2,284	0	440	0	0	35	0
Z6	2,289	0	20	0	33	45	1,327	0
Z7	1,207	0	1,974	0	0	0	0	0
Z8	0	7,832	4,945	0	0	0	0	0
Z9	3,368	1,987	2,934	2,004	0	0	0	182
Z10	0	3,987	2,975	0	0	0	0	0
Z11	0	4,003	0	0	0	0	0	0
Z12	1,207	0	3,050	0	0	0	0	815
Z13	430	3,723	4,431	0	0	0	0	0
Z14	0	0	2,123	0	0	0	0	0
Z15	1,081	1,966	3,165	0	0	0	0	201
Z16	0	0	1,320	0	0	0	0	0
Z17	1,261	0	905	0	0	0	0	0
Sub total	10,843	25,782	29,022	2,744	1,117	45	3,288	1,198
Penetration	14.6%	34.8%	39.2%	3.7%	1.5%	0.1%	4.4%	1.6%
Total	74,039							

It may be hard to imagine that under the expanded boundary capacity scenario, the required wind capacities in north wind zones drops compared with the 2011 boundary capacity case. This is because according Table 6-6, the boundary capacities related to north wind zones are all expanded. Especially for B1 which is solely related to Zone 1, According to Table 6-7, the peak demand in Zone in 2020 is only 506 MW. Based on the load profile in Table 6-8, the valley demand is 506*39.7%=197 MW. However, the initial total installed capacity in 2011 is already 1,528 MW as shown in Table 6-4. Therefore, there is 1,528-506=1,022MW extra generation capacity need exporting even at peak load time. However, in 2011, the B1 has only a capacity of 450MW, which severely block the power exporting from Zone 1. The capacity of B1 in 2020 is massively expanded to 2,300MW, which radically releases the potential of generation capacity in Zone 1. The same situation also can be found for Zone 3, which also has generation exportation congestion under the 2011 boundary capacity. This explains why the 2020 boundary case requires less wind generation capacities, since the expanded boundary capacity in northern wind zones can help further take advantage of the existing generation capacities.

Similar to in Fig 6-3 and Fig 6-4 in Section 6.3.3.1, the optimal demand response results under DSR scenarios DR1 and DR2 are shown in Fig 6-5 and Fig 6-6 respectively. For readers who are interested in how the curves are depicted, the experiment results data for original and DSR load profiles are provided in Table C3, Table C6 and Table C7 in Appendix C. Aggregated Optimized Load Profiles of Zone 8, 11 and 14 under DR1 and DR2 are also provided in Fig C-3 and Fig C-4 in Appendix C.

The comparative analysis between results from different DSR scenarios shows that in order to realise the same emission reduction target, it can help save the future generation expansion cost by up to 0.68 billion pounds (4.5%) by raising the demand side flexibility by appropriate DSR programmes. Additionally, different levels of DSR at different locations will also affect the optimal generation type and location to be expanded.

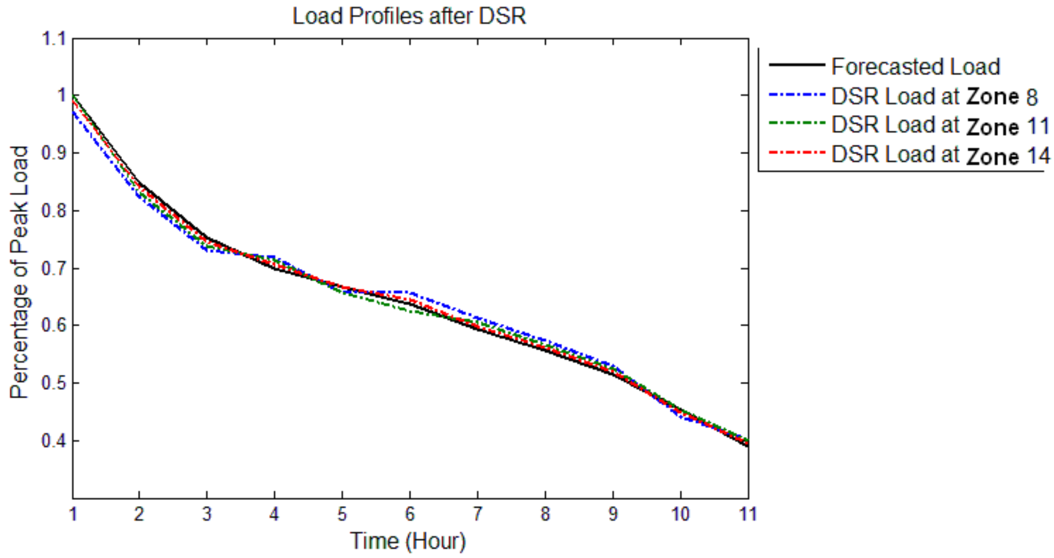

Fig 6-5 Optimized Load Profiles under DR1 with 2020 Boundary Capacity

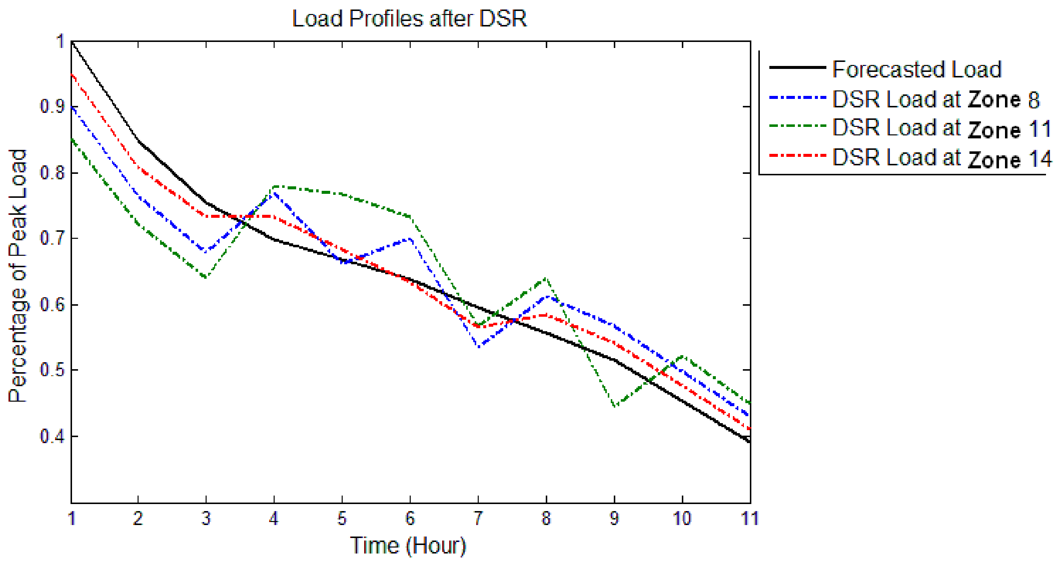

Fig 6-6 Optimized Load Profiles under DR2 with 2020 Boundary Capacity

Comparison of the GEP results between low and high boundary capacity scenarios indicates that in order to realise the same emission reduction target, increasing the transmission capacities can help fully use the existing generation capacity and also save the future generation expansion investment by up to 0.64 billion pound (3.8%).

Although the above results show the generation expansion cost can be saved by large amounts by raising DSR levels and expanding transmission capacities, there are also DSR implementation costs and transmission expansion costs associated. Therefore, a new question arises for the policy maker that how to optimize the combined generation investment, transmission investment and DSR deployment investment in one optimization problem. The combined optimization problem needs to be investigated in future works.

6.4 Chapter Summary

The case studies in previous chapters are all based on test systems. In order the show the practical effectiveness of the proposed modelling methods and answer the question specified by the thesis title, this chapter proposes a case study specifically for investigating the optimal generation mix for Great Britain (GB).

The GEP model proposed in Chapter 5 is adopted to assess the optimal generation mix of GB, which inherits the advantages of the model proposed in Chapter 3 that it can deal with generation location optimization and the short-term unit commitment constraints together in one GEP model. It also extends the previous model by incorporating stochastic renewable generation expansion and demand side response (DSR). In order to accommodate the boundary data, a slight modification is made that the generation shift distribution factor (GSDF) based transmission constraints in the GEP model in Chapter 5 is replaced by a boundary based one. This modification is due to the available GB network data format.

The real case study in this chapter is made based on a reduced Great Britain (GB) transmission network, whose data is obtained from the Seven Year Statement by National Grid (UK) in 2011. The UK transmission network is simulated by 17 study zones and 17 transmission boundaries. The 17 zones represent 17 different areas of the Great Britain, in each of which, the power plants and demands from different buses are aggregated. The transmission network inside a zone is neglected. However, the transmission capabilities between zones are constrained by 17 transmission boundaries. A boundary can be linked to multiple zones. The total flow across the boundary will be the sum of the generation less demand in all the zones affecting that boundary.

Based on the network data collected from the Seven Year Statement (2011) publish by National Grid (UK), different optimal GB generation mixes in 2020 are identified under a series of scenarios, which are constructed according to two boundary capacity hypotheses (2011 and 2020 boundary capacities) and three demand side response levels (No DSR, DR1(2%) and DR2 (10%)).

Results show that in order to meet a 50% emission reduction target for power industry in 2020, the GEP without DSR will lead to a total cost of 16.9 billion pounds including the new generation capacity investment and the annual generation operation cost in the target year. However, with a very low level (averagely 2%) DSR implemented in Z8, Z11 and Z14, the total cost can be saved by 0.11 billion pounds, which is 0.65%. If a bit higher level (averagely 10%) DSR implemented, it can be saved by 0.64 billion pounds, which is 3.79%. Therefore, in order to realise the same emission reduction target, it can help save the future generation expansion investment by raising the demand side flexibility by appropriate DSR programmes.

Comparison of the GEP results between low and high boundary capacity scenarios indicate that in order to realise the same emission reduction target, increasing the transmission capacities can help fully use the existing generation capacity and also save the future generation expansion investment. For example, for the same DR2 scenario and same 50% emission reduction target, optimal GEP results under the 2011 boundary capacity scenario require to expand one CCGT unit and sixteen on-shore wind farms, which lead a total cost of 16.26 billion pounds. However, those under expanded 2020 boundary capacity scenario, only 10 on-shore wind farms are required, which leads a total cost of 15.65 billion pounds, saving by 3.8%.

Chapter 7

Conclusions and Future Works

THIS chapter summaries the thesis and proposes the future works showing three major aspects where the research work can be improved.

7.1 Conclusions

7.1.1 Emission Constrained Generation Expansion in Chapter 2

Most of the previous researches on optimal generation mix planning have one or more of the following limitations:

- Integer variable cost and the nonlinearity of the operational level are neglected [3, 6, 11, 21, 24, 43-45, 50, 51]. Discrete characteristic of generation unit size in the investment level is ignored as well [3, 11, 21].

- There is only limited discussion of the impact of short-term emission cost on the long-term investment cost [3, 11].

- Network constraints and renewable generation expansion are seldom considered in the emission target oriented generation planning [3, 11, 21, 24].

The GEP model proposed in Chapter 2 attempts to determine the required generation mix which can meet a predefined emission target for a given power network at a minimum societal cost. The methodology developed takes the emission target settings, current generation mix, network data and load profiles in the target year as inputs. It considers typical thermal generation units and renewable wind units, and provides the optimized generation mix and the total cost and emission under this mix as outputs.

Compared with previous researches, this GEP model can take account of the emission cost in short-term operational level and explores its impacts on the long-term emission target oriented generation planning. In addition, the model proposed in this chapter takes into account the integer variables and the nonlinearity of operational cost with network constraints and renewable generation expansion together into one long-term generation planning model. Dynamic programming and a heuristic gradient search method are employed to tackle the short-term operational optimization and long-term expansion optimization respectively.

This GEP model is a centralized generation planning model. It aims to provide a low carbon generation mix assessment tool for policy makers when devising emission reduction targets and estimating the related cost. The government or other related authorities can use this assessment model to ensure long-term emission target could be achieved at a minimum societal cost. Since this formulation, taking into account detailed system operation constraints, such as unit commitment and network constraints, has a large problem size, an innovative performance index, emission reduction cost (ERC) has been developed to speed up the process of searching for the optimal generation technology.

The case study has presented the application of this model on the IEEE 30-bus system under 16 different scenarios with different emission reduction targets ranging from 9.9% to 22.8% combined with different emission charge prices ranging from 5 £/tonne to 30£/tonne. It can be found that a more stringent emission target can be achieved most economically by a combination of long-run generation expansion and short-run emission control. The results also indicate within a certain price range, a higher emission price can help find the optimal mix to a meet the target at a lower total cost. For example, in order to meet the 18.5% reduction target with network constraints, raising emission price from £5/tonne to £30/tonne can help reduce the total cost from £ 4.31 billion to £4.03 billion, saving 6.5%. These show the importance of including the emission financial pressure when optimizing the generation investment. Optimizations are conducted both with and without network constraints under the 16 scenarios The comparison between the optimizations with and without network constraints indicates in order to reach the same emission reduction target, the optimization with network constraints always realizes the target at higher or equal total cost compared to the optimization without network constraints. In the case of study, the final cost differences between optimization with and without network constraints vary from 0.74% to 6.09%. This shows the importance of taking network constraints into account when optimizing the generation investment to avoid underestimating the cost. In addition, ignoring network constraints will underestimate the difficulty and effort to realise the emission target. It also can be found that the system's total emission can not be reduced as much as people desired by merely increasing the clean units' penetration, which is caused by both the necessity of increasing conventional generation capacity to back up the rise of the wind generation penetration and the minimum output constraints of the conventional power plants.

7.1.2 GEP with Location Optimization and Unit Commitment Constraints in Chapter 3

Most of the previous GEP studies neglected network transmission constraints and generation location optimization. Some research considered the transmission constraints but assumed that the generators were to be expanded at designated nodes, such as the GEP model proposed in Chapter 2. Very few researches considered both transmission network constraints and generation location optimization at the same time.

Additionally, there is not a GEP model which can simultaneously consider both generation location optimization and short-term unit commitment constraints, such as unit's ramping up/down rates, minimum up/down time. Chapter 3 proposes such a GEP model by a mixed integer linear programming (MILP) modelling method.

Compared to the previous GEP model, the values of this model are that it can deal with generation location optimization and the short-term unit commitment constraints together in one GEP model.

Although the GEP model in Chapter 2 considers the network constraints, the new generation capacities are assumed to be expanded at designated locations. The generation location optimization is ignored. In order to include the location optimization in the GEP problem, the dimension of the decision variable has to be augmented to represent the location index. The combined dynamic programming and heuristic gradient search method is difficult to cope with the new optimization problem with the increased search space for generation location decision. Hence, in Chapter 3, the research direction is switched to a mixed integer linear programming (MILP) based GEP modelling method, which can handle the optimization problem with much larger dimension. However, in a MILP model, all the objective and constraint should be expressed linearly respect to the decision variable. Compared with the modelling method in Chapter 2, nonlinear operation cost function has to be approximated by a linear one in a MILP GEP model. However, as a trade-off, the optimal generation location can be decided in the new MILP GEP model.

The network constraints and generation location optimization are achieved by employing the generation shift distribution factor (GSDF) under the DC load flow approximation. The decision variable, generation at each bus is linked to the load flow on each transmission line by GSDF. The unit commitment constraints are also expressed linearly and augmented by bus index in order to integrate with the MILP GEP model.

The case study solves a GEP problem based on a 5-bus test system. Comparison has made between three different GEP models. The first one is a basic GEP model without network constraint. The second one is a GEP model with network constraint but at fixed locations, which represents the way of treating generation location in Chapter2. The third one is the new GEP model with network constraint and location optimization which is proposed in Chapter 3. The three models are solved under various emission target constraints, so as to find the difference of the three models under different emission reduction pressures. The results show that the GEP model with location optimization can model the GEP problem more close to the real case, it generates a more real generation mix and related cost outputs than the other two simpler models. For example, considering the ramping rate constraints, when emission target is set to 8 million tonnes, the total cost from the third model is 1.36 billion pounds total cost, while those from the first model and second model are 1.34 billion and 1.38 billion pounds respectively. Therefore, the new GEP model can avoid the overestimation or underestimation of optimal capacities of different generation technologies and required total cost, subject to various emission targets.

The above three GEP models are augmented by including the ramping rate constraint afterwards. The same experiments are executed again to demonstrate the importance to take account of ramping rate constraint in GEP model. The results show that solving a GEP problem without considering the ramping rate constraint may lead to sub optimal generation mix results for some certain levels of emission target pressures. It can be concluded from the results that for loose emission target constraints the ramping rate constraint may affect the long-term generation mix and generation locational distribution. However, when the emission target becomes stringent, the ramping rate constraint will significantly affect not only the long-term generation mix but also the generation locational distribution. Furthermore, neglecting ramping rate constraint will definitely underestimate the total cost for the generation expansion. For example, in order to meet the 7.0 million tonnes emission target, the third GEP model considering ramping rate constrains will cost 1.62 billion pounds, while the that without ramping rate constraints will cost 1.56 billion pounds, which underestimates the cost required by around 3%. In essence, unit's flexibility characteristic (ramping rate), like unit nameplate size, operational cost efficiency, capital cost efficiency and emission efficiency plays a significant role in the GEP problem.

7.1.3 GEP with Multi-Phase Emission Targets in Chapter 4

Many governments have enforced various green house gas (GHG) emission reduction schemes. Most of these schemes tend to set some mid-term emission reduction targets for realising a final reduction target. In order to consider the impacts of the multi-phase emission targets on GEP problem, Chapter 4 proposes a multi-phase emission targets constrained GEP mode. This model inherits the advantages of the model proposed in Chapter 3 that it can deal with generation location optimization and the short-term unit commitment constraints together in one GEP model. It also extends the previous model by introducing multi-phase emission targets constraints.

The case study is provided based on a 5-bus test system. The proposed GEP model is solved for twelve times with six different emission target settings and two different load growth scenarios. In order to find out the impacts of mid-term emission target (MET) settings on the results of a multi-phase emission target constrained GEP problem, the six different METs are set (ranging from 7.5 million tonnes to 5 million tonnes) to meet the common final emission target (FET) (4 million tonnes). In order to investigate the impact of generation location distribution on the multi-phase emission targets constrained GEP model, the two different load growth scenarios are set to have the same total load growth, but different load growth distributions at load buses. Load growth scenario 1 is 5%, 8% and 1% for Bus 2, 3 and 4, and Load growth scenario 2 is 1%, 5% and 8% for Bus 2, 3 and 4.

Comparative studies between different MET settings show that the total cost tends to increase with the MET becoming more stringent, despite of the same FET. For example, in order to meet the common FET (4 million tonnes), the total cost will be 3.615 billion pounds if the MET is set to 7.5 million tonnes. However, it will increase to 3.745 billion pounds if the MET is set to 5 million tonnes, which leads to 3.5% extra costs. This is because over stringent METs will require more clean but expansive units to be built in

MET year, and these early constructed units may be unnecessary or placed at less optimal locations for realising the FET.

Comparative studies between different load growth scenarios clearly demonstrate the importance of the considering transmission constraints and generation location optimization in the multi-phase emission targets constrained GEP problem. Since the two load growth scenarios used in this case study both have a common total load grow rate, but after allocating the total growth to load buses in different percentages, different optimal GEP results will be achieved. For example, for the same MET (5.5 million tonnes) and FET (4.0 million tonnes), the total cost will be 3.708 billion pounds if growth scenario 1 is selected. However, it will increase to 3.745 billion pounds if growth scenario 1 is selected, which leads to around 1% extra costs. GEP model without transmission constraints and generation location optimization is not able to differentiate these differences.

7.1.4 GEP with Renewable Generation and Demand Response in Chapter 5

In traditional GEP problem, when making a capacity expansion decision for a conventional generation technology, planners know the conventional units can generate the expected amount of power at any time of the planning horizon. However, renewable generation emerges with new challenges in GEP problem. Take the wind generation as an example, in practice, the wind speed forecasting errors could be very large especially for a long term wind forecast. The output of a wind farm in the future quite depends on the volatile wind speed not the planners' expectation. Hence, it requires more sophisticated treatment for wind generation expansion in a GEP problem.

Very few previous GEP researches include the renewable generation expansion appropriately in their GEP modelling. Take the wind generation as an example, the wind generation is usually either treated as a controllable conventional generation technology or as a known negative demand, similar to load profile. This treatment of renewable generation is not able to address the uncertain nature of renewable generation, because they all assume either the renewable generation controllable or the future power output from renewable generation is deterministic.

In addition, with increasing mature conditions for realising DSR in the near future, DSR will potentially play the role of traditional generators, as an alternative source, to provide the flexibility to maintain the demand supply balance. Therefore, DSR should be incorporated into the GEP problem. Short-term DSR implementation has been studied extensively in recent years, but very few of them took the DSR into account for long-tern GEP problem. Most previous GEP model made a lot of efforts to model the generation side, but treated the demand side simply as a fixed projected load profile.

Moreover, there have been no researches on GEP problem that consider both stochastic renewable generation expansion and DSR simultaneously with network constraints and generation location optimization.

In order to catch the impacts of stochastic renewable generation and demand side response on GEP problem, Chapter 5 proposes a new GEP model, which considers both stochastic renewable generation expansion and demand side response simultaneously with network constraints and generation location optimization. This GEP model also inherits the advantages of the model proposed in Chapter 3 that it can deal with generation location optimization. Additionally, wind generation capacity expansion is included, whose uncertainty is taken account by a two-stage scholastic linear programming model. The uncertain wind output profile in future is handled by Monte Carlo simulation technique, which generates a number of wind output scenarios following a given wind speed probability distribution. A basic introduction about the two-stage stochastic programming and Monte Carlo simulation technique is provided to help reader better under the stochastic GEP in this chapter.

The demand side response modelling is realized by setting the demands at different locations at different time intervals as decision variables. The demands are allowed to deviate from their forecasted amount up or down within a pair of certain lower and upper bounds. The range between the lower and upper bounds represents the flexibility of the demand. Since the load type composition (industrial, commercial and domestic) varies for different load buses, the flexibilities on different load buses may be different. The demand side response is also constrained by a rule that the total demand in a single day after DSR should be equal to the total forecasted demand in that day. This constraint models the real life practice that the demand can only be shifted from one time to another, but can not disappear.

A case study is provided based on a 5-bus test system to verify the effectiveness of the method proposed in this study. Five load flexibility scenarios are used to investigate the impacts of DSR on GEP problem, which are no DSR scenario and other four DSR scenarios, indexed by DR1, DR2, DR3 and DR4. DR1 and DR3 have relatively low demand response capability, averagely, responding within 2% up and down of the forecasted level. DR2 and DR4 have relatively high demand response capability, averagely, demand side can response within 10% up and down of the forecasted level. The four DSR scenarios are differentiated by not only DSR levels, but also locational distribution. For example, although the average DSR levels of DR1 and DR3 are the same, in DR1, the most flexible load is at Bus 2, while in DR3, it is at Bus 3. Ten wind output scenarios are generated following a Weibull distribution for two-stage stochastic programming.

Comparisons have been made to find out that with more flexible demand, the load valley can be better filled and the load peak could be better clipped. Therefore, more generation capacity expansion can be avoided and the huge cost could be saved. For example, the GEP costs for no DSR, DR1 and DR2 are 3.826, 3.699 and 3.468 billion pounds respectively. The results indicate that compared with no DSR scenario, a low DSR (2%) can help save the total cost by around 3.3%, while a higher DSR (10%) can help save the total cost by around 9.3%. Moreover, the results also indicates that for the same flexibility level, demand response can contribute more if it is located at the bus where the system marginal units stay or the most sensitive bus to congestion lines (with biggest GSDF), compared to other locations. For example, DR2 and DR4 have the same average demand response level (10%) but different locational distribution, the optimal generation mix results for DR2 requires one more OCGT unit and one more wind farm that that for DR4. From the long term GEP view, raising the demand flexibility at the most sensitive locations by appropriate DSR programmes can help take full advantage of the current network and generation capacity and more importantly help save the future expensive peak unit investment.

In order to address the difference between deterministic and stochastic treatment of wind generation, GEP model is solved under each of the 10 wind output scenarios individually. This deterministic treatment of wind generation is assumed that the wind farm will precisely generate the predicted amount of power at the forecasted time, which was adopted in literatures [3, 9, 21, 22, 51, 62, 65, 72, 74, 75, 101, 104, 109]. Results show that no matter what demand flexibility level is, the two-stage stochastic GEP model with multi wind output scenarios will produce a solution requiring more generation capacity expansion and more total cost, compared to the results from deterministic GEP model with only a single wind output scenario. For example, in the comparison under DR2, the deterministic wind GEP model will underestimate the total cost by 7.4% at least and by 14%.1 at most. The reason of these differences is that the two-stage stochastic linear programming GEP model can tackle the uncertainty of wind farm output by Monte Carlo simulation. The first stage decisions, capacities of different generation technologies to be expanded are made to meet all second stage constraint scenarios and generate a minimum expected operational cost of the second stage generation operation problem. In optimization theory, more second stage constraints added may narrow the feasible region and hence affect the value of optimal solution.

7.1.5 Optimal Generation Mix of GB in 2012 in Chapter 6

The case studies in previous chapters are all based on test systems. In order the show the practical effectiveness of the proposed modelling methods and answer the question specified by the thesis title, Chapter 6 proposes a case study specifically for investigating the optimal generation mix of Great Britain (GB) in 2020.

The GEP model proposed in Chapter 5 is adopted to assess the optimal generation mix of GB, which inherits the advantages of the model proposed in Chapter 3 that it can deal with generation location optimization and the short-term unit commitment constraints together in one GEP model. It also extends the previous model by incorporating stochastic renewable generation expansion and demand side response (DSR). In order to accommodate the boundary data, a slight modification is made that the generation shift distribution factor (GSDF) based transmission constraints in the GEP model in Chapter 5 is replaced by a boundary based one. This modification is due to the available GB network data format.

In Chapter 6, a real case study is made based on a reduced Great Britain (GB) transmission network, whose data is obtained from the Seven Year Statement by National Grid (UK). The UK transmission network is simulated by 17 study zones and 17 transmission boundaries. The 17 zones represent 17 different areas of the Great

Britain, in each of which, the power plants and demands from different buses are aggregated. The transmission network inside a zone is neglected. However, the transmission capabilities between zones are constrained by 17 transmission boundaries. A boundary can be linked to multiple zones. The total flow across the boundary will be the sum of the generation less demand in all the zones affecting that boundary.

Based on the network data collected from the Seven Year Statement (2011) publish by National Grid (UK), different optimal GB generation mixes in 2020 are identified under a series of scenarios, which are constructed according to two boundary capacity hypotheses (2011 and 2020 boundary capacities) and three demand side response levels (no DSR, 2% and 10%).

Results show that in order to meet a 50% emission reduction target for power industry in 2020, the GEP without DSR will lead to a total cost of 16.9 billion pounds including the new generation capacity investment and the annual generation operation cost in the target year. However, with a very low level (averagely 2%) DSR implemented in Z8, Z11 and Z14, the total cost can be saved by 0.11 billion pounds, which is 0.65%. If a bit higher level (averagely 10%) DSR implemented, it can be saved by 0.64 billion pounds, which is 3.79%. Therefore, in order to realise the same emission reduction target, it can help save the future generation expansion investment by raising the demand side flexibility by appropriate DSR programmes.

Comparison of the GEP results between low and high boundary capacity scenarios indicate that in order to realise the same emission reduction target, increasing the transmission capacities can help fully use the existing generation capacity and also save the future generation expansion investment. For example, for the same DR2 scenario and same 50% emission reduction target, optimal GEP results under the 2011 boundary capacity scenario require to expand one CCGT unit and 16 on-shore wind farms, which lead a total cost of 16.26 billion pounds. However, those under expanded 2020 boundary capacity scenario, only 10 on-shore wind farms are required, which leads a total cost of 15.65 billion pounds, saving by 3.8%.

7.2 Future Works

7.2.1 GEP under Deregulated Electricity Market Environment

The GEP models proposed in Chapter 2, 3, 4 and 5 are centralised planning models. It aims to provide a generation mix assessment tool for policy makers when devising emission reduction targets and estimating the related cost. The government or other related authorities can use this assessment model to ensure long-term emission target could be achieved at a minimum societal cost.

However, in deregulated electricity markets, such as the UK electricity, the generation capacity expansion decision is made by individual generation companies (GENCOs). Their decisions are made to maximise their own profits. The government or other related authorities can not directly force the GENCOs to implement the centralised optimal generation expansion plan. They can only disapprove or encourage some types of plants to be built somewhere. Therefore, in order to model the GEP more close to the real practice in deregulated electricity market, game theory and other similar techniques can be employed to simulating competition between different GENCOs in the future study.

In addition, the demand side response in Chapter 5 is modelled as a flexibility load with certain upper and lower limits. The cost for market implementation of the demand side response is neglected. In practice, the modification of electricity customers' behaviour requires extra cost to pay off their consumer surplus. The pay-off could be realised by price-based DSR programmes or incentive-based DSR programmes. The future GEP model can further incorporate the market implementation of the DSR in order to reflect the cost from realising DSR.

7.2.2 Stochastic Modelling of Wind Generation

The GEP model proposed in Chapter 5 employs two-stage stochastic programming method to make the stochastic GEP decisions. 10 wind output scenarios by Monte Carlo sampling are generated subject to Weibull distribution to simulate the wind generation uncertainty. However, the accuracy of the Monte Carlo simulation is decreasing with the sample size (number of wind output scenarios). The relationship between the sample size and the results accuracy is not discussed in Chapter 5. This could be done in the future work.

Additionally, in order to increase the approximation accuracy without raising the number of samples, mathematicians on operation research areas have already proposed some scenario reduction methods [120, 121], these methods could be employed in the future to keep the same approximation accuracy of the stochastic problem by using minimum number of scenarios..

7.2.3 Incorporating Reliability Assessment into GEP Model

The GEP models proposed in this thesis do not involve too much power system reliability assessment. The components in power system, such as generators and transmission lines, could come across faults subject to certain probabilities. The power supply could be suspended in some load buses due to either generation or transmission capacity shortages during some component outages.

In order to maintain a certainty reliability level, the in power system operators should reserve a certain amount transmission and generation capacity margin to cope with the component outages. Therefore, GEP models should take account of the generation capacity margin for maintaining the reliability. Otherwise, it would underestimate the generation capacity and investment. The power system reliability is typically indexed by Loss-of-Load Probability (LOLP), Loss-of-Load Expectation (LOLE), and Expected Energy not Supplied (EENS). The GEP model proposed in this thesis could be enhanced by taking account of component outages and the reliability indices can in future works.

Appendix. A

IEEE Reliability Test System 1996

Table.A1 Weekly Peak Load in Percent of Annual Peak Load profile

Week	Peak Load	Week	Peak Load
1	86.2	27	75.5
2	90	28	81.6
3	87.8	29	80.1
4	83.4	30	88
5	88	31	72.2
6	84.1	32	77.6
7	83.2	33	80
8	80.6	34	72.9
9	74	35	72.6
10	73.7	36	70.5
11	71.5	37	78
12	72.7	38	69.5
13	70.4	39	72.4
14	75	40	72.4
15	72.1	41	74.3
16	80	42	74.4
17	75.4	43	80
18	83.7	44	88.1
19	87	45	88.5
20	88	46	90.9
21	85.6	47	94
22	81.1	48	89
23	90	49	94.2
24	88.7	50	97
25	89.6	51	100
26	86.1	52	95.2

Table.A2 Daily load in Percent of Weekly Peak

Day	Peak Load
Monday	93
Tuesday	100
Wednesday	98
Thursday	96
Friday	94
Saturday	77
Sunday	75

Table.A3 Hourly Peak Load in Percent of Daily Peak

Hour	Winter Weeks 1 -8 & 44 - 52		Summer Weeks 18 -30		Spring/Fall Weeks 9-17 & 31 - 43	
	Week day	Week end	Week day	Week end	Week day	Week end
12-1 A.M	67	78	64	74	63	75
1-2	63	72	60	70	62	73
2-3	60	68	58	66	60	69
3-4	59	66	56	65	58	66
4-5	59	64	56	64	59	65
5-6	60	65	58	62	65	65
6-7	74	66	64	62	72	68
7-8	86	70	76	66	85	74
8-9	95	80	87	81	95	83
9-10	96	88	95	86	99	89
10-11	96	90	99	91	100	92
11-Noon	95	91	100	93	99	94
Noon-1 P.M	95	90	99	93	93	91
1-2	95	88	100	92	92	90
2-3	93	87	100	91	90	90
3-4	94	87	97	91	88	86
4-5	99	91	96	92	90	85
5-6	100	100	96	94	92	88
6-7	100	99	93	95	96	92
7-8	96	97	92	95	98	100
8-9	91	94	92	100	96	97
9-10	83	92	93	93	90	95
10-11	73	87	87	88	80	90
11-12	63	81	72	80	70	85

Appendix. B

Table.B1 Original Load Profile

Time	Bus2	Bus3	Bus4
1	0.537	0.537	0.537
2	0.505	0.505	0.505
3	0.481	0.481	0.481
4	0.473	0.473	0.473
5	0.473	0.473	0.473
6	0.481	0.481	0.481
7	0.593	0.593	0.593
8	0.689	0.689	0.689
9	0.762	0.762	0.762
10	0.770	0.770	0.770
11	0.770	0.770	0.770
12	0.762	0.762	0.762
13	0.762	0.762	0.762
14	0.762	0.762	0.762
15	0.746	0.746	0.746
16	0.754	0.754	0.754
17	0.794	0.794	0.794
18	0.802	0.802	0.802
19	0.802	0.802	0.802
20	0.770	0.770	0.770
21	0.730	0.730	0.730
22	0.665	0.665	0.665
23	0.585	0.585	0.585
24	0.505	0.505	0.505

Table.B2 Optimized Load Profile for DSR Scenario 1

Time	Bus2	Bus3	Bus4
1	0.553	0.548	0.542
2	0.520	0.515	0.510
3	0.495	0.491	0.486
4	0.487	0.482	0.478
5	0.487	0.482	0.478
6	0.495	0.491	0.486
7	0.611	0.605	0.599
8	0.710	0.676	0.696
9	0.739	0.777	0.764
10	0.747	0.785	0.777
11	0.778	0.754	0.762
12	0.780	0.746	0.754

13	0.739	0.746	0.754
14	0.739	0.746	0.754
15	0.723	0.731	0.738
16	0.772	0.738	0.746
17	0.770	0.794	0.786
18	0.778	0.786	0.794
19	0.778	0.786	0.794
20	0.747	0.754	0.762
21	0.713	0.744	0.737
22	0.685	0.679	0.672
23	0.603	0.597	0.591
24	0.520	0.515	0.510

Table.B3 Optimized Load Profile for DSR Scenario 2

Time	Bus2	Bus3	Bus4
1	0.591	0.618	0.564
2	0.556	0.581	0.530
3	0.529	0.553	0.505
4	0.520	0.544	0.497
5	0.520	0.544	0.497
6	0.529	0.553	0.505
7	0.653	0.682	0.623
8	0.716	0.704	0.724
9	0.710	0.736	0.772
10	0.714	0.712	0.731
11	0.738	0.654	0.731
12	0.706	0.647	0.800
13	0.740	0.647	0.723
14	0.740	0.647	0.723
15	0.702	0.846	0.783
16	0.742	0.641	0.716
17	0.732	0.898	0.754
18	0.731	0.681	0.762
19	0.731	0.681	0.762
20	0.724	0.654	0.731
21	0.724	0.726	0.693
22	0.722	0.765	0.699
23	0.644	0.673	0.614
24	0.556	0.581	0.530

Table.B4 Optimized Load Profile for DSR Scenario 3

Time	Bus2	Bus3	Bus4
1	0.542	0.553	0.548
2	0.510	0.520	0.515
3	0.486	0.495	0.491
4	0.478	0.487	0.482
5	0.478	0.487	0.482
6	0.486	0.495	0.491
7	0.599	0.611	0.605

8	0.696	0.669	0.703
9	0.754	0.784	0.746
10	0.762	0.773	0.754
11	0.777	0.747	0.754
12	0.763	0.739	0.746
13	0.754	0.739	0.746
14	0.754	0.739	0.767
15	0.738	0.768	0.760
16	0.761	0.731	0.738
17	0.786	0.770	0.778
18	0.794	0.778	0.786
19	0.794	0.778	0.786
20	0.762	0.747	0.754
21	0.722	0.751	0.744
22	0.672	0.685	0.679
23	0.591	0.603	0.597
24	0.510	0.520	0.515

Table.B5 Optimized Load Profile for DSR Scenario 4

Time	Bus2	Bus3	Bus4
1	0.618	0.564	0.591
2	0.581	0.530	0.556
3	0.553	0.505	0.529
4	0.544	0.497	0.520
5	0.544	0.497	0.520
6	0.553	0.505	0.529
7	0.682	0.623	0.653
8	0.708	0.724	0.758
9	0.709	0.752	0.754
10	0.724	0.731	0.693
11	0.701	0.731	0.693
12	0.682	0.723	0.685
13	0.694	0.723	0.685
14	0.725	0.723	0.685
15	0.692	0.766	0.820
16	0.727	0.716	0.678
17	0.710	0.833	0.750
18	0.717	0.762	0.721
19	0.717	0.762	0.721
20	0.724	0.731	0.693
21	0.697	0.727	0.802
22	0.714	0.699	0.732
23	0.673	0.614	0.644
24	0.581	0.530	0.556

Appendix. C

Table.C1 Subtotals of TEC (MW) by Plant Type and SYS Study Zone, 2010/11

Plant Type	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11	Z12	Z13	Z14	Z15	Z16	Z17
Biomass					0	45	0	0	0				0				
CCGT		1,180				20	1,974	4,945	2,934	2,975	0	3,050	4,431	2,123	3,165	1,320	905
CHP		12			139	120		1,218	365		228					158	
Clean Coal						0	0										
Hydro	577	18	230	259		33											
IGCC with CCS								0									
Large Unit Coal					2,284								2,058				
Large Unit Coal + AGT								7,832	1,987	3,987	4,003		1,665		1,966		
Medium Unit Coal						1,102											
Medium Unit Coal + AGT															1,131		
Nuclear AGR						2,289	1,207		2,408						1,081		1,261
Nuclear APR									0								
Nuclear EPR									0			0	0		0		0
Nuclear Magnox									960				430				
Nuclear PWR												1,207					
OCGT													100	144		195	140
Oil + AGT														1,245	1,355	1,036	
Pumped Storage	300				440				2,004								
Small Unit Coal							420						363				
Thermal						0											
Tidal	0		0														0
Wave	0																
Wind Offshore	0			0	0			0	182	0		815	0		201		
Wind Onshore	651	0	172	103	35	1,327			0				0				
Woodchip													0				

Table.C2 Wind Farm Output Scenarios for GB Case Study

Wind Scenario Index	Time	Off-shore Wind Farm Output Percentage								Northern On-shore Wind Farm Output Percentage						Southern On-shore Wind Farm Output Percentage	
		Zone 1	Zone 4	Zone 5	Zone 8	Zone 9	Zone 12	Zone 13	Zone 14	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 9	Zone 13
WS1	1	0.47	1.00	0.47	0.50	0.09	0.17	0.00	0.00	1.00	0.17	0.00	1.00	0.46	0.54	0.00	0.72
	2	0.00	0.00	1.00	0.35	1.00	0.77	0.15	0.98	0.00	0.06	0.61	1.00	0.21	0.30	0.08	1.00
	3	1.00	0.01	0.48	0.64	0.13	1.00	0.00	0.04	0.15	0.00	0.00	0.04	0.00	0.00	0.20	1.00
	4	0.50	0.00	0.53	0.67	0.47	0.36	1.00	0.00	0.73	0.00	0.00	0.48	0.16	0.00	1.00	0.00
	5	0.16	1.00	0.07	0.92	0.10	0.68	0.92	1.00	0.00	0.00	0.03	0.85	0.00	0.00	0.47	0.21
	6	0.00	0.13	0.54	0.77	0.00	1.00	0.00	0.00	0.00	0.42	0.00	0.00	0.60	0.25	0.00	0.60
	7	0.35	0.89	1.00	0.49	0.72	0.00	0.01	0.81	0.00	0.00	0.24	0.04	1.00	1.00	0.29	0.00
	8	0.00	0.31	0.52	1.00	0.00	1.00	1.00	0.13	0.46	0.31	0.99	0.16	0.87	1.00	0.39	0.00
	9	0.49	1.00	0.46	0.00	0.05	1.00	0.27	1.00	0.09	0.45	1.00	0.40	1.00	0.00	0.00	0.00
	10	0.00	0.35	0.00	0.45	0.00	0.58	0.64	1.00	0.69	0.16	0.56	0.67	0.14	0.00	0.99	0.00
	11	0.25	0.00	1.00	0.00	1.00	0.60	0.00	0.72	0.00	0.00	1.00	1.00	0.00	1.00	0.28	0.00
WS2	1	0.04	0.61	1.00	1.00	1.00	1.00	0.08	0.06	0.00	0.00	1.00	0.07	0.36	1.00	0.00	0.23
	2	0.00	0.37	0.24	0.60	0.49	0.00	0.00	1.00	0.62	0.00	0.00	0.00	0.60	0.00	0.00	0.52
	3	0.62	1.00	1.00	1.00	0.14	1.00	0.74	1.00	1.00	0.36	0.00	0.73	1.00	0.84	0.68	0.41
	4	0.87	0.36	0.12	0.00	1.00	0.85	0.14	0.96	1.00	0.70	0.46	0.00	0.01	0.27	0.62	0.91
	5	0.95	0.12	0.00	0.07	1.00	0.00	0.00	1.00	0.00	0.08	1.00	1.00	0.00	0.00	1.00	0.00
	6	1.00	0.73	0.21	0.87	0.35	0.00	0.34	0.94	0.83	0.94	0.12	1.00	0.00	0.06	0.00	0.14
	7	1.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.14	0.00	0.00	0.25	0.70	1.00	0.50	0.00
	8	0.00	0.87	0.09	0.18	1.00	0.23	0.00	0.00	0.32	0.33	0.00	0.00	1.00	1.00	0.09	0.27
	9	0.67	0.23	0.00	0.01	0.20	0.09	0.34	1.00	0.39	0.00	0.78	0.00	0.81	0.00	0.17	0.00
	10	0.00	1.00	0.55	0.63	0.26	0.00	0.48	0.03	0.33	0.00	0.39	0.03	0.53	1.00	0.53	0.00
	11	0.80	0.81	1.00	0.04	0.26	0.86	0.54	0.00	0.77	0.00	0.75	1.00	0.00	1.00	0.12	0.37
WS3	1	0.52	0.00	1.00	0.66	0.15	1.00	1.00	1.00	0.00	0.16	0.00	1.00	0.15	0.55	1.00	0.17
	2	0.00	0.36	0.00	0.41	0.00	0.69	0.32	1.00	0.26	0.00	0.00	0.00	0.16	1.00	0.00	0.19
	3	1.00	1.00	0.10	0.03	0.54	0.00	0.00	0.12	1.00	0.32	0.33	0.36	0.61	0.00	0.00	0.00
	4	1.00	0.72	0.00	1.00	0.34	0.87	0.21	0.84	0.00	0.00	0.48	0.18	0.00	0.04	0.00	1.00
	5	1.00	0.00	0.48	0.82	0.00	0.00	0.22	1.00	0.00	0.00	0.00	0.51	0.28	0.50	0.87	0.00
	6	0.35	0.75	0.60	0.35	1.00	0.16	0.06	0.22	1.00	0.44	0.00	0.26	0.46	0.00	0.65	0.00
	7	0.00	0.72	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.27	0.00	0.00	0.68	0.00	0.00	0.00
	8	0.06	0.34	1.00	0.82	0.11	0.00	1.00	0.60	1.00	0.42	0.00	0.59	0.32	0.00	0.26	0.17
	9	1.00	1.00	0.00	0.18	0.01	0.00	0.00	0.23	0.85	0.34	0.04	0.15	0.00	0.17	1.00	0.19
	10	0.26	0.00	1.00	1.00	1.00	0.55	0.01	1.00	0.00	0.22	0.00	0.43	0.71	0.17	0.00	0.78
	11	1.00	1.00	0.75	0.00	0.00	0.74	1.00	0.57	1.00	0.00	0.42	0.88	0.00	0.53	0.12	0.00
WS4	1	0.44	1.00	1.00	1.00	0.00	0.87	1.00	0.26	1.00	1.00	0.65	0.05	0.63	0.00	0.28	0.02
	2	0.29	0.36	0.00	0.62	0.00	1.00	0.16	1.00	1.00	0.19	0.96	1.00	0.14	1.00	0.00	0.00
	3	0.69	0.01	0.00	1.00	0.00	1.00	0.61	0.47	1.00	1.00	0.00	0.84	0.01	0.37	0.00	0.00
	4	0.68	0.97	0.29	0.38	1.00	0.77	0.80	0.70	0.41	0.00	0.00	0.00	0.00	0.61	0.71	0.62
	5	0.18	1.00	1.00	1.00	0.09	0.09	0.49	1.00	0.55	0.03	0.31	0.12	0.00	0.00	0.00	0.76
	6	0.00	0.41	0.30	0.08	0.00	0.78	1.00	0.81	0.00	1.00	0.00	0.69	0.99	0.00	0.00	0.00
	7	1.00	0.00	0.63	0.00	0.00	0.00	0.67	1.00	1.00	0.00	1.00	0.10	1.00	1.00	1.00	1.00
	8	0.00	0.59	0.64	0.00	1.00	0.50	0.00	1.00	0.56	0.72	0.39	0.20	1.00	0.00	0.29	0.37
	9	0.67	0.12	0.26	0.28	0.15	0.59	0.52	0.71	1.00	0.06	1.00	0.08	0.71	1.00	0.00	0.57
	10	1.00	0.87	0.32	0.40	0.12	0.36	0.12	0.00	0.00	0.00	1.00	0.21	0.82	0.00	0.59	0.61
	11	0.85	0.67	0.86	0.32	1.00	0.00	0.00	0.23	1.00	1.00	0.02	0.00	1.00	0.00	1.00	0.00

WS5	1	0.70	0.89	0.86	0.00	0.41	0.97	0.48	1.00	0.97	0.26	0.00	1.00	0.15	0.63	0.84	0.00
	2	0.51	0.00	1.00	0.26	0.00	0.00	0.78	1.00	0.07	1.00	0.00	0.00	0.83	1.00	0.42	0.00
	3	0.00	1.00	0.55	1.00	0.78	0.38	0.61	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.17	0.44
	4	0.45	0.00	0.00	0.00	0.68	0.95	0.87	1.00	0.03	0.42	0.00	0.23	0.00	0.48	0.37	0.22
	5	0.60	0.05	0.58	1.00	0.70	0.83	1.00	0.07	0.49	0.07	0.00	0.42	0.74	0.00	0.29	0.24
	6	0.00	0.94	0.45	1.00	0.44	0.00	1.00	0.00	0.45	0.00	0.00	0.00	0.06	1.00	0.10	0.00
	7	0.43	0.02	1.00	0.00	1.00	1.00	1.00	0.00	0.37	0.34	0.00	0.00	0.00	0.29	0.68	1.00
	8	0.16	0.22	1.00	0.19	0.00	0.00	0.00	0.49	0.00	0.05	0.20	0.11	0.00	0.60	0.43	0.09
	9	0.00	0.91	1.00	1.00	0.76	0.36	0.34	0.00	0.36	1.00	1.00	0.62	1.00	0.00	0.58	0.77
	10	0.04	0.23	0.00	1.00	1.00	1.00	0.20	0.70	0.58	0.02	0.09	0.65	0.00	0.00	0.55	1.00
	11	0.53	0.74	0.00	0.56	0.25	1.00	0.66	0.40	0.27	0.62	0.79	1.00	0.25	1.00	0.00	0.00
WS6	1	0.69	0.50	1.00	0.05	0.41	0.62	0.79	0.58	0.98	0.83	1.00	0.19	0.07	0.52	0.11	0.30
	2	1.00	1.00	0.98	0.29	0.00	0.00	1.00	0.83	0.00	0.00	0.20	0.84	0.00	0.00	1.00	0.65
	3	1.00	0.80	0.27	1.00	0.58	0.10	0.00	0.06	0.28	0.00	0.22	0.38	0.00	0.63	0.43	0.00
	4	0.00	0.00	1.00	0.94	0.36	0.59	1.00	1.00	0.09	0.30	0.00	0.22	0.00	0.54	1.00	0.00
	5	1.00	0.64	0.00	0.67	0.63	0.00	1.00	0.32	0.84	1.00	0.00	0.26	0.61	0.79	0.00	0.43
	6	1.00	0.00	1.00	0.23	1.00	0.26	1.00	0.31	0.00	0.00	0.09	0.70	0.16	0.14	0.67	0.70
	7	1.00	0.27	0.00	0.00	0.65	0.00	1.00	1.00	0.07	0.18	0.92	0.64	0.04	0.12	0.48	0.48
	8	0.58	0.31	0.00	0.78	1.00	1.00	1.00	0.69	0.20	0.00	0.80	0.10	0.01	0.86	0.26	0.00
	9	1.00	1.00	1.00	1.00	1.00	0.00	0.75	1.00	0.35	0.00	1.00	0.33	0.00	0.11	0.18	0.89
	10	0.91	0.57	1.00	0.00	0.00	0.00	1.00	0.09	0.00	0.00	0.62	1.00	0.00	0.05	0.00	1.00
	11	0.48	0.00	0.59	1.00	0.71	0.07	0.64	0.55	0.07	0.05	0.00	0.00	1.00	0.88	1.00	0.32
WS7	1	0.00	0.97	0.00	0.02	0.68	1.00	0.57	0.01	0.00	0.03	0.00	0.27	0.43	0.66	1.00	0.00
	2	1.00	0.70	1.00	0.54	0.01	1.00	1.00	0.11	0.19	0.04	0.47	0.00	1.00	1.00	0.12	0.00
	3	0.45	0.00	0.60	0.00	1.00	1.00	0.00	0.84	0.64	0.00	0.00	0.28	0.01	0.18	1.00	0.42
	4	0.72	0.94	0.00	0.80	1.00	1.00	0.27	0.00	0.60	0.00	0.13	0.84	0.00	0.13	0.00	0.73
	5	0.57	0.20	1.00	1.00	1.00	0.25	0.51	0.86	0.23	1.00	0.54	0.03	0.53	0.00	0.19	0.00
	6	1.00	0.02	0.56	0.00	0.52	0.00	0.36	1.00	0.70	0.83	0.73	0.00	0.50	0.04	0.00	0.00
	7	0.00	0.17	0.00	0.00	0.26	1.00	0.00	1.00	0.98	0.09	0.13	0.00	0.00	0.00	1.00	0.00
	8	0.66	0.08	1.00	0.00	0.00	0.46	1.00	0.02	0.00	0.00	0.94	0.06	0.00	0.00	0.04	0.22
	9	0.90	1.00	0.21	0.27	0.00	1.00	0.51	0.00	0.72	0.00	0.39	0.01	0.27	0.60	0.00	0.00
	10	0.04	0.16	0.46	0.00	0.00	0.07	1.00	0.35	0.09	0.96	1.00	1.00	1.00	0.00	0.30	0.35
	11	0.23	1.00	0.53	0.29	0.87	1.00	0.92	0.98	1.00	0.00	0.00	0.00	0.00	0.71	0.01	0.73
WS8	1	1.00	0.25	0.00	0.54	0.48	1.00	0.06	1.00	1.00	0.12	0.00	0.16	0.08	0.18	0.23	1.00
	2	0.00	1.00	0.26	0.12	0.14	0.00	1.00	1.00	0.04	0.77	0.62	0.00	1.00	1.00	1.00	0.00
	3	0.66	0.78	0.99	0.31	0.07	0.00	0.52	0.42	0.00	0.00	1.00	0.17	0.00	1.00	0.24	0.23
	4	0.31	0.81	0.21	0.15	0.94	1.00	0.16	0.03	0.09	0.35	1.00	1.00	0.00	0.37	0.47	0.00
	5	0.49	0.75	0.06	0.00	0.47	1.00	0.61	1.00	0.00	0.88	1.00	0.00	0.00	0.00	0.00	0.00
	6	1.00	0.59	1.00	0.93	0.59	0.94	1.00	1.00	0.49	0.00	0.82	0.59	0.09	0.01	0.17	0.00
	7	0.37	0.93	0.84	0.12	0.87	0.69	0.11	1.00	0.06	1.00	1.00	0.16	0.23	0.00	0.77	1.00
	8	0.29	0.13	0.00	1.00	0.46	0.64	1.00	1.00	0.00	0.00	0.42	1.00	0.03	0.53	0.03	0.16
	9	0.13	0.27	1.00	0.00	1.00	0.00	0.35	0.91	0.12	1.00	0.00	1.00	1.00	0.00	0.52	0.03
	10	0.87	0.16	0.08	0.12	0.00	0.80	1.00	0.00	1.00	1.00	0.84	0.21	0.30	0.30	0.00	0.00
	11	0.31	1.00	1.00	0.00	0.00	0.72	0.17	0.02	0.00	0.34	0.00	0.00	0.32	0.00	0.34	0.00
WS9	1	0.00	0.00	0.00	1.00	1.00	0.00	0.15	0.86	0.00	0.18	0.00	0.00	0.00	0.05	0.00	0.48
	2	0.01	1.00	0.00	1.00	0.00	0.27	1.00	0.84	0.32	0.00	0.41	0.58	0.43	0.00	0.00	1.00
	3	0.42	0.44	0.06	1.00	0.29	0.54	0.07	0.28	1.00	0.67	0.80	0.00	0.34	0.27	0.00	0.24
	4	0.31	0.00	0.39	0.91	0.30	0.00	0.97	0.40	0.00	1.00	0.00	1.00	0.64	0.72	0.00	0.66
	5	1.00	0.12	0.00	1.00	0.68	0.74	1.00	1.00	0.07	1.00	0.49	1.00	0.00	0.25	0.00	0.45
	6	1.00	1.00	1.00	1.00	0.76	1.00	1.00	0.53	0.97	0.57	0.30	0.08	0.34	0.25	0.96	0.00
	7	1.00	1.00	0.98	1.00	0.00	0.54	0.14	0.76	0.09	1.00	0.08	0.40	0.96	0.04	0.17	0.10
	8	0.02	1.00	0.00	0.80	0.70	0.86	1.00	1.00	0.33	0.69	1.00	0.29	0.73	0.27	0.15	0.00
	9	1.00	1.00	0.00	1.00	0.04	1.00	0.11	1.00	0.30	0.15	0.00	0.24	0.13	0.48	0.68	0.00

	10	1.00	0.89	0.00	0.36	1.00	0.56	0.00	0.00	0.77	1.00	0.98	0.12	0.00	0.29	0.00	0.00
	11	0.40	1.00	0.59	0.00	0.00	0.00	1.00	1.00	0.00	0.32	0.02	0.00	0.65	0.00	0.00	0.07
WS10	1	0.00	0.10	1.00	0.00	0.35	1.00	1.00	0.18	0.04	0.00	0.32	0.31	1.00	1.00	0.00	0.00
	2	0.00	1.00	0.45	0.83	0.30	0.00	1.00	0.00	0.51	0.04	1.00	1.00	0.31	0.66	0.00	0.68
	3	1.00	1.00	1.00	0.28	0.58	0.84	0.43	0.73	0.00	0.00	0.86	0.12	1.00	1.00	0.00	0.00
	4	1.00	0.00	0.00	0.37	1.00	0.00	0.00	1.00	0.00	1.00	1.00	0.06	0.74	0.62	0.00	0.00
	5	0.00	1.00	0.00	1.00	1.00	0.38	0.04	0.35	0.67	0.45	1.00	0.07	0.00	0.27	0.00	0.00
	6	0.00	1.00	0.81	0.00	0.44	0.00	0.68	0.22	1.00	0.44	0.61	0.59	0.34	0.00	0.00	0.98
	7	0.58	1.00	1.00	0.00	1.00	0.00	0.00	0.25	0.00	0.43	1.00	0.00	0.40	0.34	0.00	0.00
	8	0.39	0.00	0.00	1.00	0.41	0.75	1.00	1.00	0.75	0.15	0.00	1.00	0.00	0.00	0.00	0.25
	9	0.13	1.00	0.39	1.00	0.46	0.00	0.37	1.00	0.81	1.00	0.88	0.04	1.00	1.00	0.11	0.10
	10	0.58	0.52	0.54	0.91	0.00	0.83	0.06	1.00	0.00	0.00	0.23	0.00	0.00	0.79	0.00	0.41
	11	0.89	0.00	0.40	0.92	1.00	0.10	0.72	1.00	0.37	0.03	0.00	0.81	0.41	0.90	0.00	0.42
Average		**0.50**	**0.53**	**0.48**	**0.49**	**0.46**	**0.50**	**0.53**	**0.60**	**0.40**	**0.33**	**0.40**	**0.37**	**0.37**	**0.40**	**0.31**	**0.29**

Table.C3 Original Load Profile

Time	Bus8	Bus11	Bus14
1	1	1	1
2	0.849247	0.849247	0.849247
3	0.753957	0.753957	0.753957
4	0.698538	0.698538	0.698538
5	0.667585	0.667585	0.667585
6	0.637427	0.637427	0.637427
7	0.594174	0.594174	0.594174
8	0.556195	0.556195	0.556195
9	0.514896	0.514896	0.514896
10	0.454026	0.454026	0.454026
11	0.390688	0.390688	0.390688

Table.C4 Optimized Load Profile under DR1 with 2011 Boundary Capacity

Time	Bus8	Bus11	Bus14
1	0.97	0.983415	0.99
2	0.82377	0.832262	0.840755
3	0.731338	0.738878	0.746417
4	0.719494	0.707828	0.705523
5	0.663675	0.654233	0.667906
6	0.656549	0.650175	0.631052
7	0.611999	0.606057	0.600116
8	0.539509	0.557081	0.561757
9	0.530343	0.525194	0.520045
10	0.467647	0.463107	0.458567
11	0.402409	0.398502	0.394595

Table.C5 Optimized Load Profile under DR2 with 2011 Boundary Capacity

Time	Bus8	Bus11	Bus14
1	0.9	0.868903	0.9522
2	0.764322	0.72186	0.806785
3	0.72861	0.689283	0.716259
4	0.768392	0.689283	0.733465
5	0.734344	0.646049	0.700964
6	0.673114	0.689283	0.669298
7	0.580614	0.6833	0.616724
8	0.611814	0.639624	0.584005
9	0.504474	0.517727	0.489152
10	0.499429	0.52213	0.476728
11	0.351619	0.449291	0.371154

Table.C6 Optimized Load Profile under DR1 with 2020 Boundary Capacity

Time	Bus8	Bus11	Bus14
1	0.97	1.001059	0.99
2	0.82377	0.832262	0.840755
3	0.731338	0.738878	0.746417
4	0.719494	0.712509	0.705523
5	0.657545	0.657152	0.665663
6	0.656549	0.624678	0.643801
7	0.611999	0.606057	0.598691
8	0.572881	0.567319	0.561757
9	0.530343	0.525194	0.520045
10	0.440406	0.453123	0.449486
11	0.402409	0.398502	0.394595

Table.C7 Optimized Load Profile under DR2 with 2020 Boundary Capacity

Time	Bus8	Bus11	Bus14
1	0.9	0.850547	0.95
2	0.764322	0.72186	0.806785
3	0.678561	0.640863	0.733691
4	0.768392	0.778976	0.733465
5	0.662146	0.767723	0.683858
6	0.701169	0.73304	0.632874
7	0.534757	0.567205	0.564465
8	0.611814	0.639624	0.584005
9	0.566386	0.445472	0.540641
10	0.499429	0.52213	0.476728
11	0.429757	0.449291	0.410222

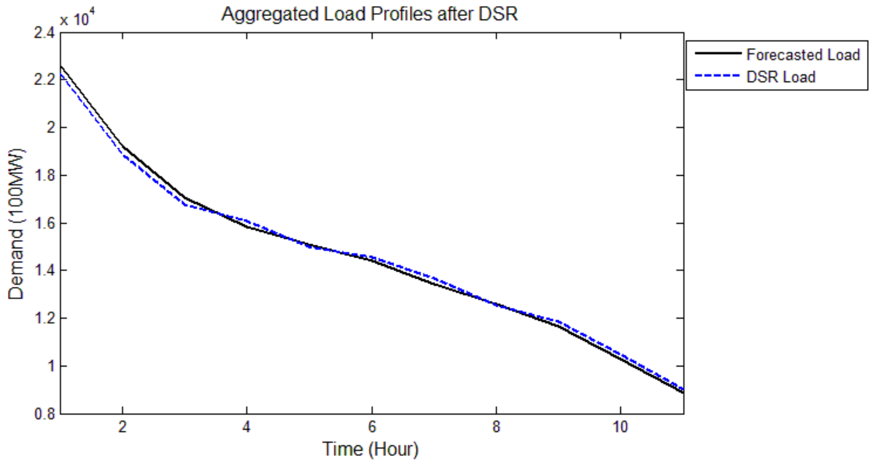

Fig C-1 Aggregated Optimized Load Profiles under DR1 with 2011 Boundary Capacity

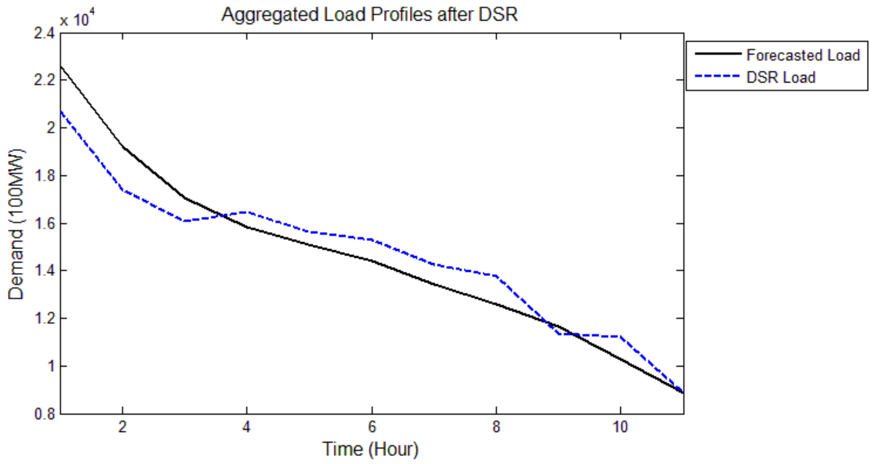

Fig C-2 Aggregated Optimized Load Profiles under DR2 with 2011 Boundary Capacity

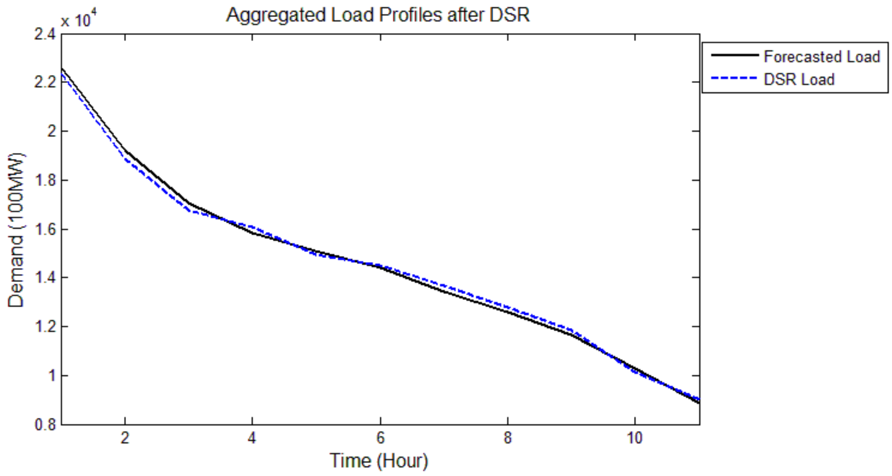

Fig C-3 Aggregated Optimized Load Profiles under DR1 with 2020 Boundary Capacity

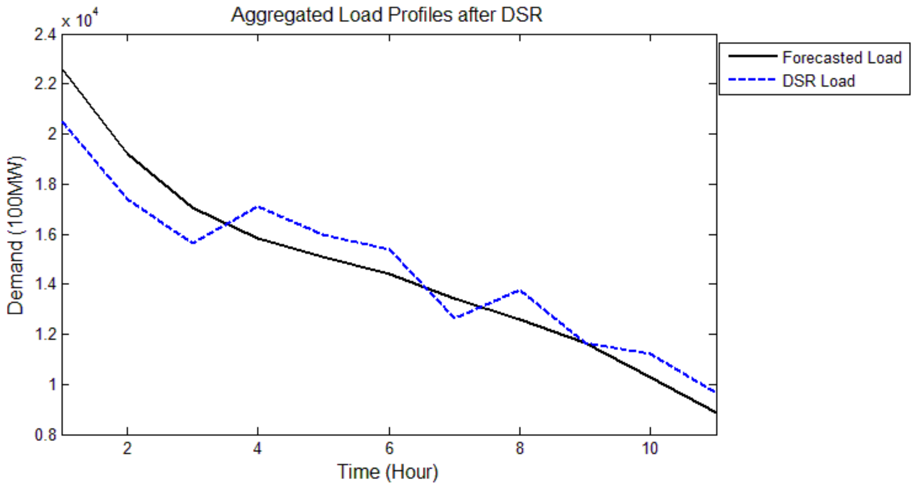

Fig C-4 Aggregated Optimized Load Profiles under DR2 with 2020 Boundary Capacity

Appendix. D

Table.D1 Linear Constraint Matrix for Line Flow Limits

LPSOLVE input parameters			**a**													**b**
	Dimension		GxIxT										GxI			column vector
			GxI			GxI			…	GxI			GxI			
			P_{111}-P_{I11}	P_{121}-$P_{I(G-1)1}$	P_{1G1}-P_{IG1}	P_{112}-P_{I12}	P_{121}-$P_{I(G-1)2}$	P_{1G2}-P_{IG2}	P_{113}-$P_{IG(T-1)}$	P_{11T}-P_{I1T}	P_{121}-$P_{I(G-1)T}$	P_{1GT}-P_{IGT}	Np_{11}-Np_{GI}			
			I	…	I	I	…	I		I	…	I	I	…	I	
Line flow Upper Limit	KxT	K	GSDF	…	GSDF											Lim+GSDF·D1
		K				GSDF	…	GSDF								Lim+GSDF·D2
		…							……							…
		K								GSDF	…	GSDF				Lim+GSDF·DT
Line flow Lower Limit	KxT	K	-GSDF	…	-GSDF											Lim-GSDF·D1
		K				-GSDF	…	-GSDF								Lim-GSDF·D2
		…							……							…
		K								-GSDF	…	-GSDF				Lim-GSDF·DT

*The annotations used in the above table are from the problem modelling in Chapter 3.

Table.D2 Linear Constraint Matrix for Generator Output Upper Limits

<table>
<tr><th colspan="3">LPSOLVE input parameters</th><th colspan="13">a</th><th>b</th></tr>
<tr><td rowspan="4"></td><td colspan="2" rowspan="4">Dimension</td><td colspan="10">GxIxT</td><td colspan="3">GxI</td><td rowspan="4">column vector</td></tr>
<tr><td colspan="3">GxI</td><td colspan="3">GxI</td><td>…</td><td colspan="3">GxI</td><td colspan="3">GxI</td></tr>
<tr><td>P_{111}-P_{I11}</td><td>P_{121}-$P_{I(G-1)1}$</td><td>P_{1G1}-P_{IG1}</td><td>P_{112}-P_{I12}</td><td>P_{121}-$P_{I(G-1)2}$</td><td>P_{1G2}-P_{IG2}</td><td>P_{113}-$P_{IG(T-1)}$</td><td>P_{11T}-P_{I1T}</td><td>P_{121}-$P_{I(G-1)T}$</td><td>P_{1GT}-P_{IGT}</td><td colspan="3">Np_{11}-Np_{GI}</td></tr>
<tr><td>I</td><td>…</td><td>I</td><td>I</td><td>…</td><td>I</td><td></td><td>I</td><td>…</td><td>I</td><td>I</td><td>…</td><td>I</td></tr>
<tr><td rowspan="4">Generator Output Upper Limit</td><td rowspan="4">GxIxT</td><td>GxI</td><td colspan="3">Eye(GxI)</td><td colspan="3"></td><td></td><td colspan="3"></td><td colspan="3">-Eye(GxI)·RCap</td><td>0</td></tr>
<tr><td>GxI</td><td colspan="3"></td><td colspan="3">Eye(GxI)</td><td></td><td colspan="3"></td><td colspan="3">-Eye(GxI)·RCap</td><td>0</td></tr>
<tr><td>…</td><td colspan="3"></td><td colspan="3"></td><td>……</td><td colspan="3"></td><td colspan="3">……</td><td>…</td></tr>
<tr><td>GxI</td><td colspan="3"></td><td colspan="3"></td><td></td><td colspan="3">Eye(GxI)</td><td colspan="3">-Eye(GxI)·RCap</td><td>0</td></tr>
</table>

*The annotations used in the above table are from the problem modelling in Chapter 3. Eye(GxI) is a function in Matlab to build a GxI by GxI identity (unit) matrix .

Table.D3 Linear Constraint Matrix for Generation Demand Balance Limits

<table>
<tr><th colspan="3">LPSOLVE input parameters</th><th colspan="13">a</th><th>b</th></tr>
<tr><td rowspan="4"></td><td colspan="2" rowspan="4">Dimension</td><td colspan="10">GxIxT</td><td colspan="3">GxI</td><td rowspan="4">column vector</td></tr>
<tr><td colspan="3">GxI</td><td colspan="3">GxI</td><td>…</td><td colspan="3">GxI</td><td colspan="3">GxI</td></tr>
<tr><td>P_{111}-P_{I11}</td><td>P_{121}-$P_{I(G-1)1}$</td><td>P_{1G1}-P_{IG1}</td><td>P_{112}-P_{I12}</td><td>P_{121}-$P_{I(G-1)2}$</td><td>P_{1G2}-P_{IG2}</td><td>P_{113}-$P_{IG(T-1)}$</td><td>P_{11T}-P_{I1T}</td><td>P_{121}-$P_{I(G-1)T}$</td><td>P_{1GT}-P_{IGT}</td><td colspan="3">Np_{11}-Np_{GI}</td></tr>
<tr><td>I</td><td>…</td><td>I</td><td>I</td><td>…</td><td>I</td><td></td><td>I</td><td>…</td><td>I</td><td>I</td><td>…</td><td>I</td></tr>
<tr><td rowspan="4">Generation /Demand Balance</td><td rowspan="4">T</td><td>1</td><td colspan="10">[1,1,1,1,1,…1]</td><td colspan="3"></td><td>D_1</td></tr>
<tr><td>1</td><td colspan="10">[1,1,1,1,1,…1]</td><td colspan="3"></td><td>D_2</td></tr>
<tr><td>…</td><td colspan="10">……</td><td colspan="3"></td><td>…</td></tr>
<tr><td>1</td><td colspan="10">[1,1,1,1,1,…1]</td><td colspan="3"></td><td>D_T</td></tr>
</table>

*The annotations used in the above table are from the problem modelling in Chapter 3.

Table.D4 Linear Constraint Matrix for Emission Target Limits

LPSOLVE input parameters		**a**													**b**
		GxIxT										GxI			column vector
		GxI			GxI			…	GxI			GxI			
	Dimension	P_{111}-P_{I11}	P_{121}-$P_{I(G-1)1}$	P_{1G1}-P_{IG1}	P_{112}-P_{I12}	P_{121}-$P_{I(G-1)2}$	P_{1G2}-P_{IG2}	P_{113}-$P_{IG(T-1)}$	P_{11T}-P_{I1T}	P_{121}-$P_{I(G-1)T}$	P_{1GT}-P_{IGT}	Np_{11}-Np_{GI}			
		I	…	I	I	…	I		I	…	I	I	…	I	
Emission Target	1	[E_1…E_1]	…	[E_G…E_G]	[E_1…E_1]	…	[E_G…E_G]	…	[E_1…E_1]	…	[E_G…E_G]				E_{target}

*The annotations used in the above table are from the problem modelling in Chapter 3.

Table.D5 Linear Constraint Matrix for Generator Ramping Rate Limits

<table>
<tr><th colspan="3">LPSOLVE input parameters</th><th colspan="13">a</th><th>b</th></tr>
<tr><td rowspan="4"></td><td colspan="2" rowspan="4">Dimension</td><td colspan="10">GxIxT</td><td colspan="3">GxI</td><td rowspan="4">column vector</td></tr>
<tr><td colspan="3">GxI</td><td colspan="3">GxI</td><td>…</td><td colspan="3">GxI</td><td colspan="3">GxI</td></tr>
<tr><td>P_{111}-
P_{I11}</td><td>P_{121}-
$P_{I(G-1)1}$</td><td>P_{1G1}-
P_{IG1}</td><td>P_{112}-
P_{I12}</td><td>P_{121}-
$P_{I(G-1)2}$</td><td>P_{1G2}-
P_{IG2}</td><td>P_{113}-
$P_{IG(T-1)}$</td><td>P_{11T}-
P_{I1T}</td><td>P_{121}-
$P_{I(G-1)T}$</td><td>P_{1GT}-
P_{IGT}</td><td colspan="3">Np_{11}-Np_{GI}</td></tr>
<tr><td>I</td><td>…</td><td>I</td><td>I</td><td>…</td><td>I</td><td></td><td>I</td><td>…</td><td>I</td><td>I</td><td>…</td><td>I</td></tr>
<tr><td rowspan="4">Ramping Down Rates</td><td rowspan="4">GxIxT</td><td>GxI</td><td colspan="3">Eye(GxI)</td><td colspan="3">-Eye(GxI)</td><td></td><td colspan="3"></td><td colspan="3">-Eye(GxI)·Rd·RCap</td><td>0</td></tr>
<tr><td>GxI</td><td colspan="3"></td><td colspan="3">Eye(GxI)</td><td></td><td colspan="3"></td><td colspan="3">-Eye(GxI)·Rd·RCap</td><td>0</td></tr>
<tr><td>…</td><td colspan="3"></td><td colspan="3"></td><td>……</td><td colspan="3"></td><td colspan="3"></td><td>…</td></tr>
<tr><td>GxI</td><td colspan="3"></td><td colspan="3"></td><td></td><td colspan="3">-Eye(GxI)</td><td colspan="3">-Eye(GxI)·Rd·RCap</td><td>0</td></tr>
<tr><td rowspan="4">Ramping Up Rates</td><td rowspan="4">GxIxT</td><td>GxI</td><td colspan="3">-Eye(GxI)</td><td colspan="3">Eye(GxI)</td><td></td><td colspan="3"></td><td colspan="3">-Eye(GxI)·Ru·RCap</td><td>0</td></tr>
<tr><td>GxI</td><td colspan="3"></td><td colspan="3">-Eye(GxI)</td><td></td><td colspan="3"></td><td colspan="3">-Eye(GxI)·Ru·RCap</td><td>0</td></tr>
<tr><td>…</td><td colspan="3"></td><td colspan="3"></td><td>……</td><td colspan="3"></td><td colspan="3"></td><td>…</td></tr>
<tr><td>GxI</td><td colspan="3"></td><td colspan="3"></td><td></td><td colspan="3">Eye(GxI)</td><td colspan="3">-Eye(GxI)·Ru·RCap</td><td>0</td></tr>
</table>

*The annotations used in the above table are from the problem modelling in Chapter 3. Eye(GxI) is a function in Matlab to build a GxI by GxI identity (unit) matrix .

Publications

C. Yuan, C. Gu, F. Li, and B. Kuri, “New Problem Formulation of Emission Constrained Generation Mix”, *IEEE Transactions on Power Systems*, 2013 (accepted and ready to appear, No.: TPWRS-01084-2012)

C. Gu, C. Yuan, and F. Li, “Risk Management in Use-of-System Tariffs for Network Users”, *IEEE Transactions on Power Systems*, 2013 ((Revised and Resubmitted))

J. Li, C. Yuan, and F. Li, “The Relationship of Constraints Cost and Load Factor: A Evaluation for the Improved ICRP Method”, *11th International Conference on the European Energy Market (EEM),* 2013, (accepted)

C. Yuan, F. Li, and B. Kuri, “Optimal Power Generation Mix towards an Emission Target”, *IEEE Power & Energy Society General Meeting,* 2011. PES '11.

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