PERFORMANCE MODELLING AND DECISION ANALYSIS OF DECENTRALIZED ENERGY SYSTEMS AND THEIR IMPACT ASSESSMENT

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Table of Contents

TABLE OF CONTENTS 2

LIST OF FIGURES 5

LIST OF TABLES 6

ABSTRACT 7

DECLARATION 9

COPYRIGHT STATEMENT 10

ACKNOWLEDGEMENT 11

CHAPTER 1 | INTRODUCTION 12

- 1.1 Research Background 12
- 1.2 Research Motivation 15
- 1.3 Research Objectives 18
- 1.4 Contributions of the Thesis 19
- 1.5 Structure of the Thesis 19

CHAPTER 2 | LITERATURE REVIEW 22

- 2.1 Development of decentralized energy systems 22
  - 2.1.1 Introduction of decentralized energy systems 22
  - 2.1.2 Development of micro-grid technology to overcome DE system challenges 26
  - 2.1.3 Global development status of DE systems 29
    - 2.1.3.1 Distributed energy development status and planning in US 29
    - 2.1.3.2 Distributed energy development status and planning in Japan 30
    - 2.1.3.3 Distributed energy development status and planning in Europe 31
  - 2.1.4 Distributed energy development status and planning in China 33
- 2.2 Literature review of decision analysis in renewable energy systems 34
  - 2.2.1 MCDA in renewable energy planning and policy 35
  - 2.2.2 MCDA in renewable energy evaluation and assessment 37
  - 2.2.3 MCDA in project selection and allocation 38
  - 2.2.4 MCDA in environmental impact assessment 40
- 2.3 MCDA model for performance analysis of renewable energy systems 42
  - 2.3.1 Performance criteria of renewable energy systems 42
  - 2.3.2 MCDA models for performance analysis in renewable energy systems 44
  - 2.3.3 Overview of relevant MCDA methods 46
  - 2.3.4 Typical MCDA methods used for performance analysis of DE systems 47
- 2.5 Summary 49

CHAPTER 3 | THE ASSESSMENT OF ENERGY EFFICIENCY WITH DATA ENVELOPMENT ANALYSIS (DEA) METHOD 51

3.1 EVALUATION OF ENERGY EFFICIENCY 51
3.2 DEA METHOD AND ITS APPLICATIONS IN ENERGY EFFICIENCY 53
3.2.1 Introduction to DEA method 53
3.2.2 Research status of energy and environmental efficiency based on DEA 54
3.3 ASSESSMENT OF THE ENERGY EFFICIENCY OF 39 COUNTRIES BASED ON DEA 60
3.3.1 DEA methodology and models applied in this case 60
3.3.2 Data collection 67
3.3.3 The results of energy efficiency..70
3.3.4 The improvement of energy efficiency...77
3.4 SUMMARY 81

CHAPTER 4 | THE PROPOSED MCDA MODEL BASED ON THE ER APPROACH WITH A CASE STUDY 82

4.1 HIERARCHY ASSESSMENT FRAMEWORK..82
4.2 SELECTION OF THE CRITERIA 83
4.3 DESCRIPTION AND ASSESSMENT GRADE OF EACH CRITERION......................................86
4.3.1 Technical criteria 86
4.3.2 Economic criteria...89
4.3.3 Social criteria 90
4.3.4 Environmental criteria 91
4.4 THE EVIDENTIAL REASONING METHOD 92
4.5 A CASE STUDY OF A MICRO-GRID PROJECT IN AN INDUSTRIAL PARK 95
4.5.1 Introduction of the case study...95
4.5.2 Data collection 97
4.5.3 Weight elicitation of assessment criteria 97
4.5.4 Data processing..99
4.5.5 Results and sensitivity analysis 100
4.6 CONCLUSION AND DISCUSSION 103

CHAPTER 5 | A CASE STUDY ON A MICRO-GRID CLUSTER...................... 105

5.1 INTRODUCTION OF THE CASE STUDY 107
5.1.1 Overview of power market development in planning regions..........................107
5.1.2 Electricity consumption forecast of the whole society in the planned area.......109
5.1.3 The installed capacity and planning of micro-grid 111
5.2 DATA COLLECTION AND ANALYSIS OF DIFFERENT CRITERIA 112
5.2.1 Data collection and analysis of technical aspect...112
5.2.2 Data collection and analysis of environmental aspect 115
5.2.3 Data collection and analysis of social aspect..118
5.2.4 Data collection and analysis of economic aspect 119

5.3 The Case study based on IDS 122
5.3.1 Data processing and weight elicitation 122
5.3.2 Result and sensitivity analysis 125
5.4 Conclusion and discussion 128
CHAPTER 6 | CONCLUSIONS AND FUTURE WORK 130
6.1 Research conclusions 130
6.2 Research limitations and future work 132
REFERENCES 134
APPENDIX I | LIST OF ABBREVIATIONS 160
APPENDIX II | QUESTIONNAIRE OF WEIGHT ELICITATION 163
APPENDIX III | DEA SOLUTION USING EXCEL 167
APPENDIX IV | PAPERS PUBLISHED IN JOURNALS OR CONFERENCE PROCEEDINGS 170

Word Count: around 32,000

List of Figures

Figure 1-1 Illustration of energy trilemma 13
Figure 1-2 Illustrative comparison between centralised power and clean & local power ... 14
Figure 2-1 Structure of micro-grids 27
Figure 3-1 The comparison between the three countries with worse performance and the average of 39 countries (TFEE) 75
Figure 3-2 The comparison between the three countries with worse performance and the average of 39 countries (PFEE) 78
Figure 3-3 An example of energy efficiency using BCC input-oriented dual model 78
Figure 3-4 Using BCC input-oriented dual model to evaluate the energy efficiency 79
Figure 4-1 Hierarchical assessment framework for DE systems 83
Figure 4-2 Stakeholder analysis for environmental impact assessment 85
Figure 4-3 Modelling structure and graphic interpretation of ER approach 95
Figure 4-4 The ranking of four alternatives on overall performance 101
Figure 4-5 The ranking of four alternatives in each top level criteria 102
Figure 4-6 Sensitivity analysis of changing the weight of economic criteria 102
Figure 4-7 Trade-off analysis between economic criteria & reliability, technical criteria and payback period 103
Figure 5-1 The architecture of the micro-grid cluster 107
Figure 5-2 Assessment framework of micro-grids in Inner Mongolia 107
Figure 5-3 The overall performance ranking of different alternatives 107
Figure 5-4 The performance on each top level criteria of different alternatives 107
Figure 5-5 Sensitivity analysis of changing the weight of technical criteria 107
Figure 5-6 Trade-off analysis between economic criteria & environmental criteria 107
Figure 5-7 Trade-off analysis between safety & CO2 emission reduction 107
Figure AIII-1 DEA solution of Energy efficiency in 2018 using BCC input oriented primal model (TFEE) 167
Figure AIII-2 DEA solution of Energy efficiency in 2018 using BCC output oriented primal model (TFEE) 167
Figure AIII-3 DEA solution of Energy efficiency in 2018 using BCC input oriented dual model (TFEE) 168
Figure AIII-4 DEA solution of Energy efficiency in 2018 using BCC output oriented dual model (TFEE) 168
Figure AIII-5 DEA solution of Energy efficiency in 2018 using BCC input oriented primal model (PFEE) 169

List of Tables

Table 3-1 Summary for the research samples during 2009–2018......................................68
Table 3-2 Total-factor energy efficiency of 39 countries during 2009-2018.......................72
Table 3-3 Efficiency score of three countries and average of 39 sample countries (TFEE)73
Table 3-4 Particular-factor energy efficiency of 39 countries during 2009-2018................76
Table 3-5 Efficiency score of three countries and average of 39 sample countries (PFEE)77
Table 4-1 Data information for all criteria in four alternatives...97
Table 4-2 Weights of different levels of criteria...99
Table 5-1 Total electricity consumption of in each planning region in 2015....................108
Table 5-2 Industrial structure and electricity consumption in each region in 2015 (%)....108
Table 5-3 Forecast of total electricity consumption growth of each region in 2020 109
Table 5-4 Statistics on the maximum load utilization hours in the planning area and the maximum electricity load forecast..110
Table 5-5 The capacity and planning of each area by 2022..111
Table 5-6 The installed capacity of county and five cities..119
Table 5-7 The key financial indexes of the county and each city.....................................121
Table 5-8 Data collection of the county and sub cities...123
Table 5-9 Weights of different levels of criteria...124

Abstract

Renewable energy contributes to attaining the general goal of energy security, affordability and sustainability in a balanced way, and the development trend of future energy should also aim to transfer centralized energy systems to clean and decentralized energy systems while using more renewable energy. Decentralized energy (DE), also called distributed energy, is usually produced close to where it is consumed, in contrast to centralised energy, which is produced at large power plants and transported through the national grid. DE is regarded to be central to the world's future energy strategies, and it plays an increasingly important role in the renewable energy development and economic strategies in many countries.

In this thesis, a comprehensive literature review is first conducted on decentralized energy systems and micro-grids, their development status, benefits and challenges, the performance assessment of DE systems, the applications of multiple criteria decision analysis (MCDA) in renewable energy, existing MCDA methods in the performance assessment of DE systems and their merits and limitations.

Second, a set of data envelopment analysis (DEA) models are constructed to evaluate the energy efficiency on the country level which takes into account not only energy input and economic output but also non-energy input and undesirable output. The use of DEA models can help decision maker evaluate the efficiency objectively and take effective measures to improve the energy and environmental efficiency of enterprises, industries or regions, and promote energy conservation and achievement of emission reduction goals.

Third, a performance modelling and decision analysis model is developed for decentralized renewable energy systems, and this requires the systematic and consistent handling of multiple factors of both a quantitative and qualitative nature under uncertainty. Among alternative MCDA methods, the evidential reasoning (ER) approach is a generic evidence-based MCDA approach and uses a belief structure or so called an extended probability

distribution to represent the assessment of an alternative on each attribute as a piece of evidence, regardless whether it is qualitative or quantitative. The aggregation of multiple criteria in the ER approach is through the combination of the extended probability distributions. The weights and reliabilities of assessment information collected from multiple sources can be taken into account consistently. In this way, the ER approach can deal with various types of uncertainty, form a solid basis for sensitivity analysis and provide a panoramic view for informative decision analysis. Thus in this research the ER approach is implemented systematically in the context of analysing the performance and impact of DE systems.

Furthermore, two real case studies are conducted respectively to validate the practicality of the proposed performance modelling and decision analysis methods. One is a small-scale micro-grid in an industrial park, which includes different kinds of renewable energies. The other one is a large micro-grid cluster project in Inner Mongolia, located at the northwest of China. The key findings are discussed from the systematic performance modelling and impact analysis of DE systems on the above case studies.

It is believed that multiple stakeholders can potentially benefit from these research findings, including policy makers, energy suppliers and consumers, energy network owners, and DE investors and stakeholders in local communities, who have direct interests in the generation, transition and consumption of renewable energy. In the future work, this research can be linked closely with specific decision contexts in order to support informed decision-making from multiple dimensional renewable energy performance evaluation. In addition, more detailed and comprehensive evidence combination rules can be developed to better characterise various types of uncertain data and information in the evaluation of various DE systems.

Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright Statement

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Chapter 1 | Introduction

1.1 Research Background

Since the beginning of the 21st century, energy security and environmental protection issues facing the world have become increasingly serious (Twidell & Weir, 2015). Renewable energy has become an important part of the energy strategies of many countries and the core and mainstream development area of energy transformation (Ahmad & Tahar, 2014).

'Energy trilemma' is often mentioned in energy industry, which is an encompassing term representing the integrated challenges in energy security, social impact (e.g., energy affordability) and environmental sensitivity (e.g., CO_2 emission) as illustrated in Figure 1-1. To solve the energy trilemma, sustainable generation and consumption of energy becomes essential in facilitating the world economy while maintaining the current and future generations' welfare, which can contribute in a balanced and holistic way to attaining the overarching goal of energy security from affordable energy supply to environmental protection (Mourmouris & Potolias, 2013). On one hand, the traditional model of centralised electricity generation, transmission and distribution has become increasingly difficult to justify its efficiency and sustainability, even though it delivers economies of scale, safety and reliability. For example, the most advanced centralised power station in the UK is estimated to achieve only an energy efficiency of 50% and a further energy loss of 9% can be incurred from the power transmission through the distribution network (Carson et al., 2008). On the other hand, the curtailment of solar and wind energy has also been observed in western China due to insufficient capacity and local congestion of transmission as well as excessive supply during the periods of low demand.

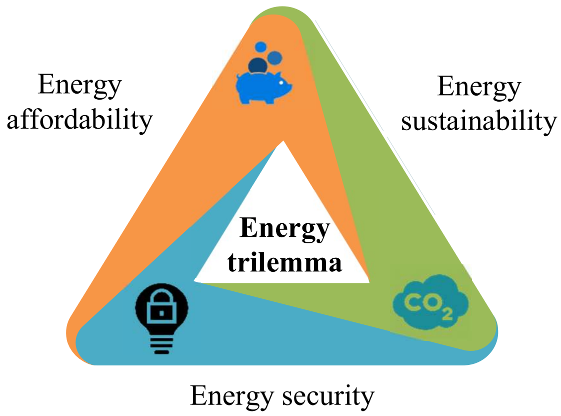


Figure 1-1 Illustration of energy trilemma

To achieve energy sustainability, the requirements for future energy include long-term supply, stable prices, continuous technology improvement and simple installation and maintenance (Omer, 2008). Essentially, sustainable energy development should consider not only cost saving, but also efficiency in energy systems and flexibility of replacing fossil fuels by various renewable energy sources (Lund, 2007). Often, decentralized energy (DE, also called distributed energy) and small-scale power grids can be a reliable and cost-effective alternative to large grids, which are more likely to cause failures and inefficiencies. Promoting the use of DE to individual households and local communities can lead to lower energy bills for households, businesses and even industry. In the recent decades, the costs of solar panels and battery storage have been reduced significantly, which provides a basis for producing and consuming energy in a very different way in the future in combination with smart meters and other fast-developing demand side response measures. As a consequence, the trend of future energy development is concerned with not only developing more renewable energies but also transferring from centralised power to clean and decentralized power as illustrated in Figure 1-2.

Currently, Europe has made a steady progress in making a transition from centralised and largely fossil-fuel or nuclear-based systems delivering electricity to more decentralized energy systems (DG Energy, 2008; EU ITRE, 2010), which mostly use renewable energy sources, such as small hydro, wind power, solar power, biomass, biogas and geothermal power. In China, the most polluted cities are mainly caused by the continued use of fossil fuel for heating, industry and transportation, and it is anticipated that the pollution can be reduced considerably by the widespread deployment of DE systems.

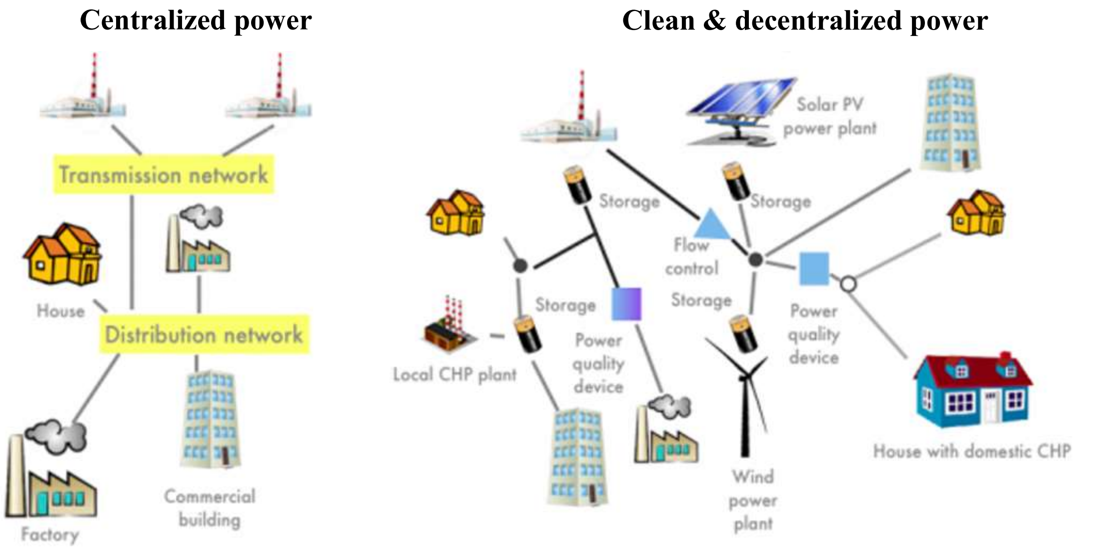


Figure 1-2 Illustrative comparison between centralised power and clean & local power

(Source: https://ilsr.org/challenge-reconciling-centralized-v-decentralized-electricity-system/)

DE is usually produced close to where it is consumed, in contrast to centralised energy which is produced at a large plant elsewhere and sent through the national grid (Alstone et al., 2015). DE is regarded to be central to the world's future energy and economic strategies. Our future production, distribution and consumption of energy will drive progress towards a more sustainable future (Narula et al., 2012).

There are a series of advantages to deploy DE systems. First of all, the decentralized generation of green energy reduces transmission losses and lowers carbon emissions (EU ITRE, 2010; Alstone, 2015). It is extremely helpful to combat climate change through reducing greenhouse gas (GHG) emissions in energy sectors. Secondly, the DE system can improve the efficiency of power generation and distribution compared to the traditional centralised electricity generation and facilitate the increasing contributions from renewable energies. Thirdly, the DE system can improve the security of energy supply, as the widespread consumption of energy does not have to heavily rely on relatively few, large and remote power stations (Olanrewaju & Jimoh, 2014). Finally, the DE system provides a cost-effective way of achieving carbon targets, and consumers can be fully involved in promoting locally generated, sustainable, competitive and smarter energy choices (UK BTSCP, 2008).

Despite the above benefits, there are also many challenges and barriers for implementing DE systems widely. For example, there are technological issues of grid connection and reverse-metering in real implementation. New technologies suitable for specific implementation environments, such as fuel cells, are mostly at the early stage of commercialisation. Economically, large up-front capital costs as well as long payback periods can hinder the wide adoption of DE systems without government subsidies in the business context. From the environmental perspective, the property leasing and management arrangements in the development of DE systems is often focussed primarily on short-term cost savings and security of energy supply rather than carbon emissions and energy efficiency. In addition, the acceptance of local community and their approval of generation capacity is also a prerequisite for developing small-scale DE systems, and it is often challenging to form new disciplines between suppliers and users to achieve the real-time matching of supply and demand.

1.2 Research Motivation

With the energy revolution and the development of renewable energy, policy making in the energy sector should take into account the performance of different DE systems and make an informed choice for a more efficient, more reliable, cleaner and economically efficient future of electricity (Olanrewaju & Jimoh, 2014; Omer, 2008). However, as discussed above, there are many challenges on the development of DE systems for real-world deployment. On the other hand, relevant policy, legislation and mechanism are not sufficiently comprehensive, since the deployment of DE systems involves a variety of aspects, such as economic incentives, energy trading management, environment protection and demand side management. The research in existing literature is mainly focussed on a single renewable energy sector or centralised power network, and DE systems and their potential impact have not been widely studied. Nevertheless, how to evaluate the performance and impact of DE systems including different sources of renewable energy is a key problem in energy policy making and involves different factors (Carsonet al., 2008). There are a series of research about the performance assessment of renewable energy systems, and normally different criteria from technical, economic, social and environmental aspects are identified in the context of multiple criteria decision analysis (Rimal & Tugrul, 2013; Stein, 2013). However, there is lack of details about the definition, assessment grades and the relationship among all the criteria in the existing research.

Performance assessment of DE systems can be viewed as a multiple criteria decision-making problem with correlating criteria and alternatives (Topcu & Ulengin, 2004). This task should take into consideration several conflicting aspects because of the increasing complexity of the social, technological, environmental, and economic factors. Traditional single criteria decision-making approaches cannot handle the complexity of current systems and this problem (Tsoutsos et al., 2009). Multi-criteria methods provide a flexible tool that is able to handle and bring together a wide range of variables appraised in different ways and thus offer useful assistance to the decision maker in mapping out the problem.

In the recent decades, many multiple criteria decision analysis (MCDA) methods have been developed, such as Analytical Hierarchy Process (AHP) and Multiple Attribute Utility Theory (MAUT). In these methods, MCDA problems are modelled using decision matrices, in which an alternative is assessed on each criterion by a single real number. While in many decision-making situations, it can be very difficult and even unacceptable to use a single number to represent the subjective judgement of the decision maker. Subjective judgement, probability distributions or incomplete pieces of information need to be included in the process of aggregation.

The evidential reasoning (ER) approach has been developed as a generic evidence-based MCDA approach for aggregating both qualitative and quantitative information as well as dealing with various types of uncertainty, including ignorance and randomness (Yang, 2001; Xu, 2006). Under a unified belief structure, both quantitative and qualitative criteria can be formulated to a belief decision matrix for further aggregation and analysis (Yang & Xu, 2013). In addition, the weights and reliabilities of assessment information collected from multiple sources can also be taken into account in the generalised ER rule.

A software package, namely Intelligent Decision System (IDS), has been developed for ER method-based decision analysis, which would greatly simplify the workload for the researchers so that much time could be saved for more important decision analysis tasks like sensitivity analysis. Different types of uncertainty can be handled using this software package including probability uncertainty, missing data, subjective judgements, interval data, and combinations of these. Belief functions are used to deal with problem modelling while the evidential reasoning approach is implemented for attribute aggregation. The results of the software include not only the ranking order of alternatives based on average scores, but also the aggregated performance distribution of each alternative, which would be a great help in decision making.

1.3 Research Objectives

The main aim of this research is to build a systematic framework of modelling and assessing performance, cost-effectiveness, societal and environmental impact of DE systems. In order to achieve this aim which requires multi-disciplinary knowledge, the following research will be conducted successively.

- Investigate important issues about DE systems and their contributions to green economy, which are of common and widespread interests to many countries.

- Construct DEA models to evaluate energy efficiency and environmental impact with considering the desirable output and undesirable output.

- Develop a hierarchical framework of evaluating the performance of DE systems from technical, economic, social and environmental aspects.

- Investigate the key issues relative to the above four aspects and conduct the detailed technical, economic, social and environmental assessment for alternative DE solutions.

- Develop MCDA methods to support the above performance assessment models. These require the systematic and consistent handling of multiple factors of both a quantitative and qualitative nature under uncertainty, and the method under study in this research is based on multiple criteria decision theory and evidence-based reasoning with both numerical data and expert knowledge.

- Collect data from different sources, conduct empirical study and validate the framework of modelling and assessing the performance, cost-effectiveness, social and environmental impacts of DE systems.

1.4 Contributions of the Thesis

The main contributions of the research are summarised as follows.

- Development of DEA models to analyse the energy efficiency and environmental impact in consideration of the desirable output and undesirable output and non-renewable and renewable energy consumption inputs. The proposed framework provides a comprehensive evaluation for energy efficiency and policy makers can benefit from the findings from data analysis to construct more reasonable, effective and environmental-friendly energy policies for local regions and countries.

- Identification and structuring of assessment criteria which include the definition, assessment grades and the utility independency among each criterion in detail and can be applied to measure the performance of different kinds of renewable energy systems. The ER approach and the Intelligent Decision System (IDS) are applied to develop an MCDM assessment solution for two case studies so as to provide informed decision support in development of DE systems. Multiple stakeholders including policy makers, energy suppliers and consumers, energy network owners, and DE investors and stakeholders in local communities can apply the criteria hierarchy for the assessment of multi-vector DE systems.

1.5 Structure of the Thesis

The structure of this thesis is as follows.

Chapter 1 briefly introduces the research background, motivation, objectives, questions, and contributions of this thesis.

Chapter 2 provides a comprehensive literature review on DE systems and micro-grids, their development status, benefits and challenges, the performance assessment of DE systems, MCDA applications in renewable energy, existing MCDA methods in the assessment of DE systems and their merits and limitations.

Chapter 3 briefly discusses the assessment of energy efficiency and then applies Data Envelopment Analysis (DEA) to evaluate the energy efficiency of 39 countries from 2009-2018 while considering the capital, labour force, energy consumption as inputs and GDP and CO2 emission as outputs. Furthermore, the energy consumption is split as renewable energy and non-renewable energy and analyse their effects on the energy efficiency and environmental aspects. All of the data are collected from open data sources. Capital, labour force and GDP values are extracted from The World Bank Open Data (2020), while the total primary energy consumption is collected from the IEA (International Energy Agency) data, and the proportions of renewable energy consumption is collected from the Enerdata Yearbook 2019.

Chapter 4 proposes a performance assessment model of DE systems from technical, economic, social and environmental aspects, including the definition, description and assessment grades of each criterion in the framework of multiple criteria decision analysis. The evidential reasoning approach, with the use of the Intelligent Decision System (IDS) software package, is applied to aggregate assessment information on a case study. The case study is mainly concerned with a hybrid multi-vector DE system which includes solar panels, wind turbines, storage and diesel backup. All of the data are collected from the open project report of an industry partner during the fieldwork in China. Sensitivity and trade-off analyses are conducted to validate the decision making process, which demonstrates how a robust MCDA model can be developed to support informed performance assessment and decision analysis of DE systems.

Chapter 5 conducts another case study using the proposed assessment model to evaluate and analyse a large micro-grid cluster. Based on the characteristics of the project itself, the implementation of the performance assessment model produces a series of results, which can be helpful for decision makers to make informed decision on the selection and development of alternative multi-vector decentralized energy systems. Most of the data are collected from the government statistics and reports such as local geography and environment status, industrial structure, related energy policies, and some project related data are extracted from the feasibility and planning reports which were provided by a collaborating research institute in China.

Finally, Chapter 6 concludes the thesis and summarises the limitations and directions for future research.

Chapter 2 | Literature review

The trend of future energy development is not only developing more renewable energies but also transferring from centralized power to clean and decentralized power. Decentralized energy (DE) is regarded to be central to the world's future energy and economic strategies, and it can drive the progress of energy distribution and consumption towards a more sustainable future. This chapter aims to investigate the concept, development status and trends, benefits and challenges of DE systems, and conduct literature review of performance modelling and decision analysis models and methods for DE systems.

2.1 Development of decentralized energy systems

2.1.1 Introduction of decentralized energy systems

Decentralized or distributed energy is usually produced close to where it is consumed, in contrast to centralised energy that is produced at large power plants elsewhere and transmitted through the national grid (Alstone et al., 2015). DE involves a range of technologies that utilise various sources of renewable energy, such as small hydro, wind, solar (including solar photovoltaic and solar thermal) and biomass. In practice, there are different definitions of DE (DTI, 2006), which broadly take into account: (1) electricity generating plants connected to a distribution network rather than a large-scale transmission network; (2) small-scale plants which supply electricity within a local area and can even sell any surplus back to a distribution network; (3) small-scale installations of solar panels, wind turbines or other renewable energies for local consumption and surplus selling; (4) combined heat and power (CHP) plants where the electricity output is primarily used to serve local consumption or feed into a transmission network, while the heat is often used locally on household, small-scale building or community level; (5) non-gas heat sources such as biomass, solar thermal panels or geothermal energy, for the supply of heat to just one household, a building or a local community. Obviously, different sources of renewable energy can be deployed at a range of different scales from household and building to local community level in accompany with demand-side measures for reducing or shifting energy consumption (Aiken, 2012).

DE has now been regarded as one of the central parts of the world's future energy and economic strategies. The main drivers for developing DE systems involve a range of considerations, such as increasing the use of green energy sources, reducing carbon emissions, improving energy efficiency, exploring new energy generation capacities, and improving the security of power generation and supply (EU ITRE, 2010). Specifically, there are a series of tangible benefits to deploy DE systems. (1) Decentralized generation of green energy can reduce transmission losses and lowers carbon emissions (EU ITRE, 2010; Alstone, 2015). It is extremely helpful to combat climate change by reducing carbon emissions in energy sectors. (2) DE can improve the efficiency of power generation and distribution compared to the traditional centralised electricity generation and facilitate the increasing contributions from renewable energies. (3) DE can improve the security of energy supply, as the widespread consumption of energy doesn't heavily rely on relatively few, large and remote power stations. (4) DE can provide a cost-effective way of achieving carbon targets, and consumers can be fully involved in promoting locally generated, sustainable, competitive and smarter energy choices (UK BTSCP, 2008). For example, it was estimated that the increased use of DE in the UK could approximately reduce as much as 30% of the greenhouse gas emissions associated with heat and power generation (UK BTSCP, 2008).

In the face of increasing power demand, especially in those rapidly rising developing countries, DE can provide a key balance between energy consumption and economic development. However, in many developed countries, the motivation to deploy distributed energy is often less intense due to the relatively stable demand for energy, including renewable energy. Nevertheless, distributed energy is still regarded as an effective way to increase energy efficiency and reduce the environmental impact of existing energy systems.

For example, CHP systems provide an effective and easy-to-implement solution for distributed energy technologies, and they have many different configurations and adopt multiple technologies. Simply speaking, CHP is an effective integrated energy system that can generate electrical energy and heat simultaneously. Often, CHP captures the heat generated during power generation and delivers it to thermal applications, such as space heating and industrial processes. By converting the heat loss during power generation into useful heat, CHP can provide energy producers and consumers and the entire society with multiple advantages.

Using distributed CHP systems to improve power supply efficiency can provide huge economic and environmental benefits. The average efficiency of fossil fuel power generation is about 35-37%, since waste heat is generated during power generation and approximately 2/3 of the input fuel energy is lost with the waste heat. However, through deploying CHP systems, the waste heat can be used to meet the heating needs of households, businesses, and local communities. By recovering heat and putting it into use, CHP systems can achieve a total energy efficiency of 90% (Soroudi et al., 2011).

After decades of technological advancements, distributed energy is now showing a steady growth trend globally. Technological innovation has not only reduced the cost of distributed energy technology but also improved its flexibility and performance. Digital transmission and the "Industrial Internet" can further enhance the applicability and capabilities of distributed energy systems, which overcomes at the same time the obstacles that constrain the construction of large power plants.

Photovoltaic (PV) is another typical distributed energy technology and can provide electricity in almost any place in the world (Charron & Athienitis, 2006). In fact, the concepts of solar energy and distributed energy are often interchangeable. Photovoltaic systems have unique advantages in distributed energy applications, particularly, it does not emit pollutants during power generation, nor does it require a fuel source for power generation (Murray, et al., 2018). Contrary to these advantages, solar energy is intermittent and can only be used when there is sufficient sunlight. However, in remote areas where fuel availability is limited, a photovoltaic system combined with battery energy storage can be a good choice to meet local power needs in some regional areas or countries.

It is evidenced that distributed energy technology has a series of advantages, which can bring us tangible or intangible benefits to use distributed energy to replace existing centralized power stations or to facilitate their expansion.

First of all, they can be installed quickly, e.g., within a few days or weeks, while centralized power plants normally require years to complete the installation. This rapid deployment feature will become especially applicable when there is unmet energy demand and supply must be increased quickly. In the situation of natural disasters requiring the restoration of power supply, or in the context of long-term unreliable energy systems, the rapid construction of distributed energy sources can become very important and suitable.

Secondly, due to its scalability, distributed energy technologies have lower requirements for procurement, construction, and operating costs. In the regions with limited financial support, there is no need to secure large amounts of capital to deploy distributed energy, while it normally requires significant funding support to develop critical infrastructure for large centralized power plants (Khailly, 2016).

Thirdly, due to its small size, distributed energy enables energy suppliers to achieve accurate supply and can gradually increase supply as demand increases. In contrast, centralized power plants require large-scale capital investment, and the scale of these power plants often does not match the required supply level. Recently, the gradual development of distributed energy has been adopted by many regions of the world as a suitable development mode.

Finally, distributed energy is deployed at or near the point of demand, which facilitates local control, operation, and maintenance, which cannot be achieved at centralized power stations. Therefore, system owners and operators can monitor and customize distributed energy solutions to meet their specific needs.

Despite the above benefits, there are also many challenges and barriers for implementing distributed energy systems, such as (1) new disciplines on energy suppliers and users to achieve supply and demand matching; (2) relatively long payback period on large up-front capital costs, which is generally beyond 3 years; (3) technological complexity for companies who don't see themselves as power generators; (4) property leasing and management arrangements that focus on short-term cost savings and security of energy supply rather than carbon emission reduction and energy efficiency improvement; (5) issues around the technology and economics of grid connection and reverse-metering; (6) local community acceptance and approval of generation capacity; and (7) selection of new technology, which is most suited to the deployment environment. For example, fuel cells can be useful in some rural communities, but there are mostly at pre-commercial stage (Ezbakhe and Perez-Foguet 2020; UK BTSCP, 2008).

2.1.2 Development of micro-grid technology to overcome DE system challenges

DE can supply users with green power generated from locally available renewable energy resources (Ruppert-Winkel & Hauber, 2014). However, many interconnected DE systems in a large-scale power network may also give rise to security issues of operation. Micro-grid technology provides an interface to the interconnection of multiple DE systems at different levels (Hatziargyriou, 2015), and can maintain an efficient, safe, reliable, and optimal operation of various DE systems through effective management. Simply speaking, micro-grids can integrate generation, storage, demand-side response and system control together and provide an infrastructure for addressing power security, affordability and sustainability. It is generally featured with a dispersed, locally controlled, independent energy system, which can optimise the real-time matching of supply and demand, can alleviate pressure on the national grid, and is fully compatible with renewable energies. An illustrative structure of micro-grids is shown in Figure 2-1.

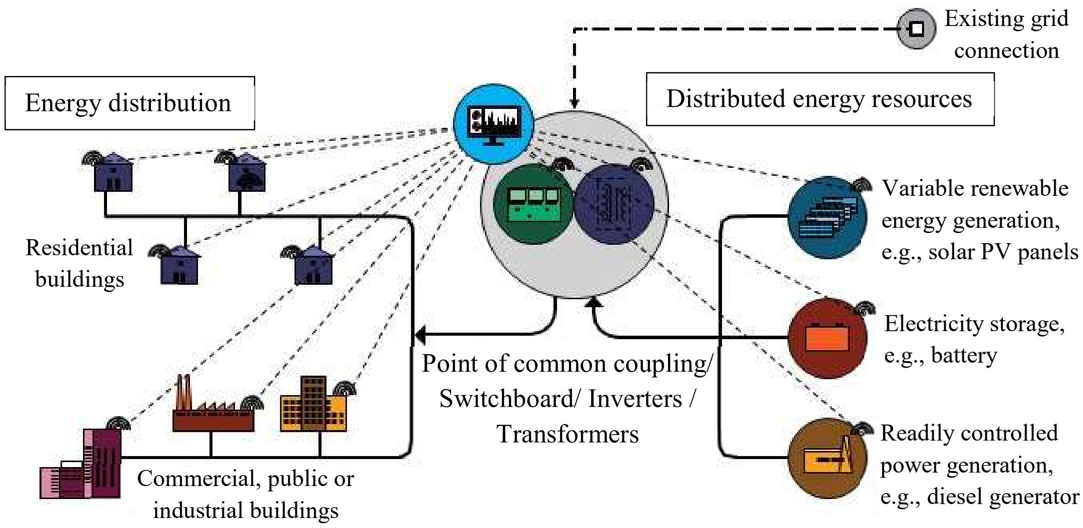


Figure 2-1 Illustrative structure of micro-grids

As a small-scale distributed system of power generation and distribution, micro-grids can also integrate energy storage, energy conversion, related load monitoring and protection device (Siraganyan et al., 2019). It can be not only connected to external grids in parallel but also operated in an isolated environment. In the microscopic aspect, micro-grids generally have the fully-configured functionality of power transmission and distribution, which enables local power balance and energy optimisation (Hassan et al., 2019; Kuznetsova et al., 2019). The key feature differentiating from a distributed power generation system with load is that micro-grids have the capabilities of both grid-connected and independent operation. In the macroscopic aspect, micro-grids can be thought of as a "virtual" power source or load in the distribution network. Existing research and practice has demonstrated that micro-grids is one of the most effective ways to facilitate DE supply and is of great significance in terms of various social and economic benefits (Katre et al., 2018; Oyedepo et al., 2019): (1) significantly increasing the utilisation of distributed power; (2) assisting to continuously supply power to critical loads during grid disasters; (3) avoiding the direct impact of intermittent power supply on the power quality of surrounding users; (4) contributing to the optimal use of renewable energy and the energy saving from transmission losses in the centralised power grid. Currently, micro-grid laboratories and demonstration projects with different characteristics have been launched widely in the United States of America, Europe, Japan and other countries (Piñas et al., 2019).

There are also challenging issues to be addressed for the operation of micro-grids despite the above benefits. In general, there are multiple energy inputs (e.g., photovoltaic, wind, hydrogen, natural gas) in micro-grids, multiple energy outputs (e.g., electricity and heat), multiple energy conversion units (e.g., optical/electrical, thermal/electric, wind/electric, AC alternating current /DC – direct current /AC) and a variety of operating conditions (e.g., grid, independent), which makes the dynamic characteristics of micro-grids more complex than a single distributed energy generation system (Evans et al., 2010; Zavadskas & Turskis, 2011). In addition to the dynamic characteristics of each distributed generation unit, the network structure and the type of network (e.g., DC or AC) also affect the dynamic characteristics of micro-grids. Therefore, further research should be conducted extensively to address the issues of distributed energy and micro-grids in the renewable energy industry. On the other hand, the characteristics of centralized energy systems are different from DE systems, which makes the hierarchical assessment model for DE systems much more comprehensive and complicated than centralized energy systems. It will be described in the following sectors and chapters.

2.1.3 Global development status of DE systems

In recent years, many countries have been actively seeking the development of renewable and distributed energy for environmental protection and sustainable development. According to the market research of global distributed energy generation, the annual installation capacity of new distributed energy along with the rapid development of the DE industry was more than 130 GW in 2015-2017, and the capacity is expected to increase to more than 500 GW by 2026 (Global DER Deployment Database 3Q20, 2020).

2.1.3.1 Distributed energy development status and planning in US

Distributed energy stations began to develop in the US in the late 1970s. Since distributed energy captures excess heat and uses it for factories and businesses while saving costs and improving the environment, the US Environmental Protection Agency (EPA) has made many efforts to promote the development of distributed energy for energy conservation and environmental protection. The EPA has established the CHP partnership to promote that distributed energy is an economically viable clean energy solution and it is considered one of the country's top priorities (Nomura & Akai, 2014).

From 2001 to 2015, the EPA's distributed energy collaboration group assisted in the completion of 1,047 distributed energy projects with a total installed capacity of 7,600 Megawatts (MW) and cumulative reductions in carbon dioxide emissions of 170 million tons. As of 2016, the installed capacity of distributed energy in the US was approximately 82.5 Gigawatts (GW) according to International Energy Agency (IEA).

In addition, in order to promote the development of CHP as a long-term development plan, it was proposed that CHP should contribute 50% of the energy for new office buildings or commercial buildings in 2020, and 15% of the energy supply for existing buildings needs to be converted into CHP. By 2035, the commercial distributed generation capacity will increase to at least 6.8 million kilowatts, ideally to achieve an increase of 9.8 million kilowatts.

Distributed energy in the US is mainly installed in the west coast, east coast and south coast of the US. In addition, distributed energy is mainly based on natural gas and CHP which account for 71% of the energy supply and is distributed in more than 3,700 industrial and commercial projects. Among the applications of distributed energy projects in the US, only 15% are used for cooling and heat in hospitals, schools, hotels and office complexes, and most are concentrated in the industrial and manufacturing sectors, where the chemical industry reached 29%, and the petroleum refining industry reached 18% (US EIA, 2018).

2.1.3.2 Distributed energy development status and planning in Japan

Due to the scarcity of natural resources, Japan has started relatively early to promote energy-saving and emission reduction technologies in order to maximise energy efficiency. Since 1980, with the operation of the first thermal power unit of the Tokyo National Arena, Japan has vigorously developed natural gas distributed energy, with an average annual installed capacity of 300 MW. The annual installed capacity added is 400 to 500 MW from the 1990s to 2007. Although the domestic investment enthusiasm declined and distributed energy development was affected by the rising fuel prices and the international financial crisis around 2008, Japan's distributed energy installed capacity reached 9.4 million kilowatts in 2011. Since then, Japan's distributed energy development has slowed down, and the installed capacity exceeded 10 million kilowatts in 2016, of which civilian use accounted for 21% (Narula et al., 2012).

In Japan's strategic energy plan, the goal of developing and popularising distributed energies is elaborated systematically, which includes CHP, solar power, wind power, biomass and waste-to-energy. Japan's distributed generation is mainly based on CHP and solar photovoltaic power generation, and its distributed power generation projects are developed widely in both commercial environments (such as hospitals, restaurants and public recreation facilities) and industrial sectors (such as chemical, manufacturing, steel and other industries). According to the Ministry of Economy, Trade and Industry (METI) of Japan, their CHP capacity will reach 16.3 million kilowatts by 2030, including thousands of commercial and industrial distributed power generation projects. Japan aims to generate 20% of the total electricity supply by distributed energy systems by 2030. Photovoltaic power generation is widely used not only for residential rooftop photovoltaic and public facilities such as parks, schools, hospitals and, exhibition halls (Goto et al., 2014).

Japan is also the market leader in development of micro-grids. The new energy and industrial technology development organization in Japan have facilitated R&D and demonstration for many micro-grid projects globally.

2.1.3.3 Distributed energy development status and planning in Europe

In Europe, Denmark is one of the countries which have achieved very high energy efficiency (European Commission, 2009). The growth of GDP has not led to increased energy consumption in Denmark, while the pollution emissions have even fallen considerably. The main measure is to develop distributed energy vigorously. In Denmark, around half of electricity is generated by decentralized energy systems, more than 80% of the district heating energy is produced by CHP, and the distributed power generation exceeds 50% of the total generated power. For example, the total installed capacity of wind power distributed to their low-voltage distribution network exceeds 3 million kilowatts. The development direction of energy in Denmark is to promote large-scale use of CHP plants with heat storage capacity and to change the fuel of regional district heating plants from coal to natural gas, garbage and biomass. In addition, the Danish government actively supports to build district heating and CHP projects, especially by companies and remote areas. In addition, more and more CHP projects in densely populated areas use natural gas as fuel, and their thermal efficiency indicators are slightly higher than coal-fired technologies.

Germany is one of the most successful countries in promoting distributed photovoltaic power generation. In terms of distributed energy development, the installed capacity of photovoltaic power generation in Germany reached 41.7GW by the end of 2017, and the main application form was the rooftop photovoltaic power system.

The "Energy Statistics Report" issued by the Department of Energy and Climate Change (DECC) in 2008, a British government agency, pointed out that the total installed capacity of gas-fired generator sets in the United Kingdom reached 5.47GW, accounting for 7% of the country's total power generation. In 2012, the total installed capacity of electricity generation in the UK was 89.2GW, of which gas generating units accounted for 28% of the total installed capacity. Vigorously promoting the decentralized energy system through the United Kingdom, in the past 20 years, more than 1,000 projects of distributed energy systems have been installed in public places such as commercial centres, hospitals, schools, airports, and office buildings, including the office buildings of British government agencies. Therefore, the efficiency of comprehensive energy utilization is improved. The UK's Energy Production Outlook Report issued by the Department of Business Energy and Industrial Strategy (BEIS) in 2016 indicated that natural gas power generation has accounted for 45% of the total power generation. The UK aims to cancel all coal-fired power plants by 2025.

The UK has implemented a climate change tax on April 10, 2001. The initial tax rate would increase electricity bills by 0.43p/KWh and coal and gas charges by 0.15p/KWh. There is no need to pay climate change taxes, and it is expected to save 20% of energy costs. It is stipulated that decentralized energy projects represented by combined heat and power are allowed to directly sell a certain amount of electricity.

2.1.4 Distributed energy development status and planning in China

According to the development summary of distributed energy in China in 2017, the growth rates of gas-fired power, wind power, small hydropower and photovoltaic power generation vary considerably. The cumulative installed capacity of gas-fired power generation reached 87.93 million kilowatts with an annual increase of 13.99%, the cumulative installed capacity of wind power was 188 million kilowatts with an annual increase of 11.7%, and the photovoltaic power generation was the fastest growing renewable energy. According to the '13th Five-Year Plan for Power Development', the total installed capacity of gas-fired power generation in China would reach 110 million kilowatts in 2020, of which the CHP supply would reach 15 million kilowatts (RE100 China Analysis, 2015). The '13th Five-Year Plan for Photovoltaic Development' proposes that the total installed capacity of photovoltaic would be 150 million kilowatts by the end of 2020. So far, China has built a series of micro-grid demonstration zones, where solar energy and wind energy dominate primarily the power generation, and pushed construction of 100 new energy demonstration cities. As of the end of 2016, the installed capacity of distributed power supplies reached 10.32 million kilowatts and there were more than 90 pilot projects for micro-network trials under planning and construction (Zhao & Guo, 2015).

With the continuous strengthening of China's environmental protection policy and the optimisation and upgrading of energy consumption structure, the prospect of distributed energy is relatively broad in China (Zou, 2020). Recycling energy grids for residential buildings and public buildings, energy centres with high load density and energy centres for industrial parks can all adopt the scheme of distributed energy in order to achieve the economies of scale of distributed energy and the social benefits of energy conservation and emission reduction.

In summary, on account of lower costs, better energy policy and increasing attention to renewable energy, global distributed generation is expected to show a rapid growth trend in the next few years (Baumann et al., 2019). In the US, Europe and many other developed countries, distributed power generation has already contributed to a high proportion of the total energy generation (Ardente et al., 2008). Although the growth rate of distributed energy development is expected to slow down in these developed countries in the future, the new investment boom of distributed energy will appear in emerging markets such as Asia Pacific and South America.

2.2 Literature review of decision analysis in renewable energy systems

In order to stride over the challenges and barriers and to support making informed and insightful decisions for developing renewable energy systems, there is a great necessity to model and assess the performance, cost-effectiveness, societal and environmental impact of alternative renewable energy system systemically (Brand & Missaoui, 2014; Mahdy & Bahaj, 2018; Rabe et al., 2019). How to evaluate the performance and impact of different sources of renewable energy is a key problem in energy policy making and involves different factors (Bauwens et al., 2016). Renewable energy decision making cannot be solved by traditional single criteria decision analysis approach, and it needs to be considered as a multiple criteria decision analysis problem with a variety of decision criteria and multiple alternatives so as to justify its choices clearly and consistently (Chang et al., 2008; Akella et al., 2009). In existing literature, many researchers have developed a spectrum of MCDA applications for the performance modelling and impact assessment of renewable energy systems and beyond. As discussed in the following sections, most of the applications can be classified into four areas: (1) renewable energy planning and policy-making, (2) renewable energy evaluation and assessment, (3) energy project selection and allocation, and (4) environmental impaction assessment.

2.2.1 MCDA in renewable energy planning and policy

There are several main tasks in this application area, such as adoption of renewable energy to reach a certain national target, decision factors, national planning, and system indicators. Usually, one of the key objectives is cost minimization when choosing among alternative energy sources (Fthenakis & Kim, 2011). However, it is widely recognized now that energy planning is a much more complicated decision problem involving many factors. Pohekar and Ramachandran (2004) reviewed systematically the applications of multi-criteria decision making to sustainable energy planning. Wang et al. (2009) presented a literature review on sustainable energy decision-making and discussed the applicability of MCDA methods under the multi-dimensionality of the sustainability goal and the complexity of socio-economic and biophysical systems. Beccali et al. (1998) utilized the ELECTRE (ELimination Et Choix Traduisant la REalité) method and fuzzy set theory in regional energy problems by analysing actor's reaction and results. Both methods were applied to the development of a renewable energy diffusion strategic planning and described advantages and disadvantage of each methodology. Georgopoulou et al. (1997) utilized ELECTRE III to reach a compromise in the choice among alternative energy policies. They defined a set of sustainability indicators and elements that are used in the analysis and assessment of the relationship between an energy system and its environment, and determined the weight of each criteria of each alternative and presented the effect of the priority. Diakoulaki et al. (2007) used MCDA to explore the relative contribution of different factors and characteristics of expected level of energy efficiency and further exploited them in energy policy making. Kowalski (2009) conducted a participatory multi-criteria analysis (PMCA) to analyse energy policy-making corresponding to public and stakeholder inputs. Lee et al. (2008) utilized the fuzzy theory and AHP to support decision analysis in national energy policy and analysed the competitiveness of Korea. Hobbs and Horn (2002) used different MCDA methods to develop a set of recommendations in energy planning and policy making through group discussions and interview processes among stakeholders (Huttunen et al., 2014). Instead of monetizing all criteria, Anagnostopoulos and Papantonis (2007) demonstrated the difference between applying MCDA for evaluation of criteria and alternatives, and they concluded that no single method is the best and a reasonable solution is to apply a combination of two or more MCDA methods. Enzensberger (2002) considered that all of stakeholder groups are important in the criteria evaluation process and they can help policy makers to anticipate possible problems at an early stage. Afgan and Carvalho (2002) proposed multi-criteria evaluation of energy systems and compared the hydro power plant option with other renewable energy power plant options, such as wind farms. Köne and Büke (2007) conducted a multi-criteria analysis using an analytical network process (ANP) to decide the best alternative technology for electricity generation in Turkey. Topcu and Ulengin (2004) developed a multi-attribute decision-making tool and supplied an integrated decision aid framework for the selection of the most suitable electricity generation alternative in Turkey. Önüt et al. (2008) also utilized ANP to evaluate alternative energy resources for the manufacturing industry in Turkey. Hamalainen and Karjalainen (1992) utilized AHP and value trees to analyse the relative weights of the evaluation criteria of Finland’s energy policies. Kablan (2004) utilized AHP framework to manage the prioritization process of different energy conservation policies in Jordan. Cristóbal (2011) applied a compromise ranking method, also known as the VIKOR method, to the assessment of several renewable energy alternatives to help the Spanish government to reach the target of achieving 12% renewable energy in 2010. Zhao et al. (2009) utilized an AHP model to evaluate alternative power technology according to the criteria of environmental cost and energy security and applied it to a real case study for planning the best choice of power plant in Guangdong province of China.

2.2.2 MCDA in renewable energy evaluation and assessment

Burton and Hubacek (2007) investigated a local study of renewable energy provision in Yorkshire, UK and applied a MCDA methodology to compare the small-scale schemes implemented in Kirklees with large-scale alternatives. It considered energy targets in the most socially, economically and environmentally effective way. Chatzimouratidis and Pilavachi (2009) utilized multi-criteria analysis based on hierarchically structured criteria to take the overall assessment of power plants according to the technological, economic and sustainability aspects which evaluated ten types of power plant using nine end node criteria properly structured under the Analytical Hierarchy Process. They also presented sensitivity analysis by comparing the original criteria weights with four alternative scenarios, changing each criteria weight at each scenario. Stefan et al. (2008) had an evaluation of sustainability of current and future electricity supply options of interest for a major Swiss utility company, and the results of MCDA-applications involving elicitation of preferences from a relatively homogeneous stakeholder group which involved a set of criteria and the associated indicators, In total 75 indicators were quantified, including 11 environmental, 33 social and 31 economic indicators. Haralambopoulos and Polatidis (2003) built an applicable group decision-making framework for renewable energy projects utilizing the PROMETHEE

(Preference Ranking Organization METHod for Enrichment of Evaluations) II outranking method, and they tested the proposed framework in a case study concerning the exploitation of a geothermal resource in Greece. Kahraman et al. (2010) suggested axiomatic design (AD) methodology for the selection among renewable energy alternatives in Turkey under fuzziness which evaluates the alternatives based on objective or subjective criteria with respect to the functional requirements obtained from experts. Cavallaro and Ciraolo (2005) made a preliminary assessment regarding the feasibility of installing some wind energy turbines in a site on the island of Salina in Italy. Nigim et al. (2004) analysed four wind turbine configurations by the comparison against a family of criteria and calculations using an MCDA algorithm to rank the solutions, from the best to worst. They used AHP and sequential interactive model for urban sustainability to make a decision to assist communities in prioritizing their renewable energy alternatives. Pilavachi et al. (2006) evaluated nine types of electrical energy generation options with regard to seven criteria using AHP in 19 different scenarios. Lin et al. (2009) presented a MCDA method in analysing alternative-fuel buses for public transportation in Taiwan. Experts from different decision-making groups performed the multiple attribute evaluation of alternative vehicles, and AHP was applied to determine the relative weights of evaluation criteria, TOPSIS (Technique of Order Preference Similarity to the Ideal Solution) and VIKOR are compared and applied to determine the best compromise alternative fuel mode. Oberschmidt (2010) elaborated a multi-criteria methodology for the performance assessment of energy supply technologies, which also took into account the dynamics of technological change.

2.2.3 MCDA in project selection and allocation

In this application area, MCDA can provide a systematic approach to rank a set of resources in an optimal manner and select the most suitable technology or project. It involves a set of available opportunities and an evaluation of the options in consideration of multiple aspects, in the format of both qualitative and quantitative, and under certainty and uncertainty. Aragonés-Beltrán et al. (2010) used ANP to select photovoltaic (PV) solar power projects. They constructed one hierarchy model and one network-based model, and then concluded that the single network model can manage all the information of the real world problem. Begic and Afgan (2007) used MCDA method to perform sustainability assessment of various options of energy power system in Bosnia. The assessment methodology comprises a system of stochastic models of uncertainty, enabling decision makers to evaluate options and select the optimal new power plant capacity. Cavallaro (2009) utilized MCDA to make a preliminary assessment of different solar thermal technologies, offered useful assistance to the decision maker in mapping out the problem, and further proposed fuzzy TOPSIS method to compare different heat transfer fluids in order to investigate the feasibility of utilizing a molten salt. Aras et al. (2004) evaluated the locations of wind-power plants and determined the most convenient location for a wind observation station to be built on the campus of a university using AHP. Kaya and Kahraman (2010) used an integrated fuzzy VIKOR & AHP methodology to the selection of the best energy policy and production site in Istanbul, both classical VIKOR and classical AHP procedures are extended under fuzzy environment. Goumas et al. (1999) considered the evaluation of alternative exploitation schemes for optimum development of a low enthalpy geothermal field using a multi-criteria decision-making procedure. Goletsis et al. (2003) made a project ranking in the Armenian energy sector using a multi-criteria method for groups. They took into account several decision parameters apart from purely economic ones, and a hybrid of ELECTRE III, PROMETHEE methods and MURAME (MUlticriteria RAnking MEthod) have been specially developed and constitutes the main part of an integrated project ranking methodology for groups. Goumas (2000) extended PROMETHEE to deal with fuzzy input data to rank alternative energy projects. Stein (2013) developed a model for decision-makers to rank various renewable and non-renewable electricity production technologies according to multiple criteria. The model was built using AHP with empirical data from government and academic sources. Latinopoulos and Kechagia (2015) implemented geographic information systems (GIS) and spatial multi-criteria decision analysis to provide a decision tool for wind-farm development projects. Wątróbski et al. (2015) presented a methodological decision support framework for the process of selecting the location of renewable energy sources. Ribeiro et al. (2013) implemented the MCDA method in a user-friendly Excel worksheet and used information obtained from a mixed integer optimization model to produce a set of optimal schemes under different assumptions and applied it to evaluate future scenarios for the power generation sector in a Portuguese case.

2.2.4 MCDA in environmental impact assessment

In the environmental planning and decision processes, several alternatives need to be analysed in terms of multiple non-commensurate criteria, and many different stakeholders with conflicting preferences are usually involved (Rosso-Cerón et al., 2019). MCDA methods can be used successfully in such processes and different multi-criteria methods have been applied to assess renewable energies from an environmental aspect. Huang et al. (1995) identified 95 publications in the survey of MCDA in energy and environmental modelling, and Zhou et al. (2006) further updated the survey and almost tripled the number of relevant publications to 252. It was emphasised that the importance of MCDA methods on energy-related environmental studies and the number of publications has increased substantially since 1995.

Greening and Bernow (2003) used MCDA methods in an integrated assessment framework based on a wide range of attributes associated with multi-pollutant reduction and energy system development strategies, and a diversity of stakeholder preferences incorporated into the analysis. Chatzimouratidis and Pilavachi (2007) evaluated the impact of non-radioactive emission with the AHP by synthesizing objective and subjective criteria. Zhao et al. (2009) presented an alternative power supply evaluation model to determine the optimal type of power supply from a sustainable development perspective and the AHP is applied to decide the priority of different types of power supply. Patlitzianas et al. (2007) presented an integrated approach of qualitative judgments for assessing the renewable energy producers' operational environment of the fourteen different member states of the EU accession. The approach is based on a MCDA methodology of quantifying multiple qualitative judgments and takes into account the many opportunities and threats which involve the energy market's new parameters as the continuously growing tendency to deregulate the energy market and the climate change. Chatzimouratidis and Pilavachi (2009) evaluated 10 types of power plants with regard to their overall impact on the living standard of local communities. Both positive and negative impacts of power plant operation were considered using the AHP. Linkov et al. (2011) presented a model based on MCDA for prioritizing research on impact of nanomaterials on the environment and human health. Myllyviita et al. (2012) applied MCDA to develop weighting tools in LCA (life cycle assessment) in order to describe a process of assessing environmental impacts of two alternative raw materials in biomass production chains. Wanderer and Herle (2015) developed a web-based spatial decision support system (SDSS) based on an MCDA approach that was implemented for identifying preferable locations for solar power plants based on user preferences. The designated areas serve for the input scenario development for a subsequent integrated environmental impact assessment. This methodology and the implemented SDSS are applicable for other renewable technologies as well (Bhat et al., 2009).

2.3 MCDA model for performance analysis of renewable energy systems

2.3.1 Performance criteria of renewable energy systems

Many researchers have developed a spectrum of different criteria, techniques and models for performance modelling and impact analysis of renewable energy systems. Generally, the performance and impact of a renewable energy system can be assessed from four main aspects, namely technical, financial, environmental and social (Wang et al., 2009; Seddiki & Bennadji, 2019). It requires the overall consideration of the geological and environmental conditions, the capacities of the energy networks, and also the economic and social limitations, which may lead to a small number of alternative solutions. There are some typical evaluation criteria for each aspect. For example, in the technical aspect, the criteria include energy efficiency, primary energy ratio, safety, reliability, maturity and others. In the economic aspect, the criteria include investment cost, operation and maintenance cost, fuel cost, electric cost, net present value (NPV), payback period, service life and equivalent annual cost (EAC). In the environmental aspect, the criteria include NOx emission, CO2 emission, CO emission, SO2 emission, particles emission, non-methane volatile organic compounds (NMVOCs), land use and noise (Bergmann et al., 2006). In the social aspect, the criteria include social acceptability, job creation and social benefits. In order to analyse the performance and impact systematically, relevant contributing factors need to be identified from all the technical, economic, environmental and social aspects.

(1) Technical

The fundamental criterion for the performance analysis of renewable energy systems should be attributed to technical feasibility and effectiveness (Michael & Gard, 2015). Thermodynamics can be used to assess how effective and efficient a renewable energy system works. A range of technical factors should be considered, including technical efficiency, safety and reliability.

Technical efficiency refers to how much useful energy can be produced from raw energy sources (Wang et al., 2009). It is one of the most widely used technical criteria to evaluate renewable energy systems, and can be measured by the ratio of output to input energy in a quantitative way (Doukas et al., 2007; Afgan and Carvalho; 2002; Mamlook et al., 2001; Pilavachi et al., 2006; Lo, 2014). Safety of renewable energy systems is vital to local residents and community. Safety-related issues can be assessed by the combination of occurrence likelihood and potential consequences, such as fatality rate, in the context of risk analysis (Wang et al., 2009; Madlener et al., 2007; Twidell and Weir, 2015). Reliability is concerned with the capacity of renewable energy systems to perform as designed, and it is among the most important technical criteria (Amjady, N., 2004; Wang et al., 2009; Chatzimouratidis, 2008)

In addition, other technical factors, such as maturity and availability, should also be considered (Cavallaro and Ciraolo, 2005). To some extent, the degree of maturity also decides how widely the technology can be adopted within its safety level (Wang et al., 2009).

(2) Environmental

The environmental impact can be assessed by the formal environmental impact assessment (EIA) method according to the EIA Directives (EC, 2003; 2009; Lawrence, 2007). In the context of conducting a systematic EIA, the stakeholder mapping approach (Mitchell et al., 1997) can usually be used to categorize the key stakeholders in terms of their interests and power for expressing environmental concerns. In the context of environmental impact analysis for renewable energy systems, typical factors, such as emissions, land use, noises, exposure to electromagnetic field and visual impact, should be considered (Lawrence, 2007; Wang et al., 2009; Haralambopoulos and Polatidis, 2003; Løken, 2009).

(3) Economic

In order to maintain economic sustainability and opportunities, it is necessary to consider the affordability and accessibility of renewable energy systems. In general, there are key attributes to be considered in the economic category which involve initial investment, construction time, operation and maintenance costs, payback time and cycle of service life (Doukas; 2007; Wang et al., 2009; Karakosta et al., 2013; Ahmad and Tahar, 2014)

(4) Social

As most distributed energy systems are located near to residential communities, the development of renewable energy systems during the construction and local consumption period plays an important role in shaping the society and involves every aspect of human participation and activities. For example, it creates technical and managerial job positions for launching a renewable energy system. While introducing some new technologies, the criteria of social acceptance and benefit are widely considered (Wang et al., 2009; Mourmouris and Potolias, 2013; Zhao and Guo, 2015).

It is worth noting that factors should be identified to analyse the performance and impact of various renewable energy systems in a consistent and systematic way. Furthermore, the relative importance of each category and its impact factors need to be taken into consideration in the decision making process.

2.3.2 MCDA models for performance analysis in renewable energy systems

The performance modelling and impact assessment of renewable energy systems can be easily formulated as a multiple criteria decision analysis (MCDA) problem. MCDA can be used to perform multi-criteria performance modelling and impact assessment among alternative renewable energy solutions, where no single attribute can capture and measure the overall (Yang, 2001). Thus, MCDA models have widely applied to perform energy-related environmental studies as discussed above, such as sustainable energy planning (Pohekar and Ramachandran, 2004), renewable energy comparison (Mendoza and Prabhu, 2005), assessment of traditional and renewable energy power plants (Chatzimouratidis and Pilavachi, 2009), evaluation of residential heating solutions (Browne et al., 2010).

Furthermore, Myllyviita et al. (2012) discussed that the utilization of multiple criteria decision analysis can incorporate new perspectives into traditional LCA in the context of environmental impact assessment of biomass production chains. Dong et al. (2014) pointed out that both LCA and MCDA can be introduced into impact assessment for different kinds of green energy applications in terms of energy, environment and economy.

Among the advances of MCDA models, it worth emphasising that the evidential reasoning (ER) approach has been developed as a generic evidence-based MCDA approach for aggregating both qualitative and quantitative information as well as dealing with various types of uncertainty, including ignorance and randomness (Yang, 2001). Under a unified belief structure, both quantitative and qualitative criteria can be formulated to a belief decision matrix for further aggregation and analysis. In addition, the weights and reliabilities of assessment information collected from multiple sources can also be taken into account in the generalised ER rule (Yang and Xu, 2013). Thus in this research, the ER approach will be chosen to conduct multiple criteria performance modelling and impact assessment, but certainly other relevant techniques reviewed above will also be discussed for comparative analysis.

2.3.3 Overview of relevant MCDA methods

Yang (2001) stated that MCDA can be used to perform multi-attribute performance assessment among alternatives, where there is no single attribute measuring the overall performance. The development of MCDA helps the comparison in a group of choices under uncertain environment. Also, the evidential reasoning (ER) approach can be used to model and aggregate the decision maker's preference logically into the assessment. Dong et al. (2014) pointed out that both LCA and MCDA can be introduced into assessment, so that the three aspects of energy, environment and economy can be judged together for different kinds of green energy applications.

The normalized MCDA model is $\max_{A \in A_r} F(A)$. Here, A is an alternative solution (decision variables) and it has a set of alternatives $A_r = \{A_1, A_2, \cdots, A_m\}$, in which every element is a controlled variable and has to satisfy certain constraint conditions. The attribute vector function $F(A)$ consists of attribute function $f_j(A)(j = 1,2,\cdots,n)$, f_j is the attribute value of A solution under the attributes $(C_1, C_2, \cdots, C_n)$, it can be noted as a vector function $F(A) = [f_1(A), f_2(A), \cdots, f_n(A)]^T$. An MCDA problem can also be expressed by a matrix $D = (f_{ij})_{m \times n}$, f_{ij} is the evaluation value of alternative A_i under j_{th} attribute, which can be either quantitative or qualitative (such as description of good, bad, high, low), $i \in I = \{1,2,\cdots,m\}$ is the set of alternative indicators $j \in J = \{1,2,\cdots,n\}$is the set of attribute indicators. Therefore, the row vector $f_i = (f_{i1}, f_{i2}, \cdots, f_{in})$ is the value of alternative A_i under every attribute, the column vector $f_j = \left(f_{1j}, f_{2j}, \cdots, f_{mj}\right)$is the value of every alternative over attribute j.

Generally speaking, the aim of MCDA is to find the best alternative or rank all alternatives. Since the performance of every alternative is different under different attributes, there is no absolutely best alternative (Belton & Stewart, 2002). A preferred structure should be determined by the decision maker according to the attributes, and the decision maker needs to assess the performance of every alternative under every attribute comprehensively, then many models and methods of decision analysis are presented (Baruah & Enweremadu, 2019). The MCDA methodologies have been successfully applied in many real-life problems in engineering, finances, market analysis, management and others. Decision is usually made under uncertain conditions from available alternatives. That is, these alternatives should be compared, ranked or chosen. However, with the development of economy, environment, technology and society, MCDA problems have become more and more complex, for which the decision maker can not only employ his knowledge and experience. Zhou et al. (2006) discussed multiple criteria energy-related environmental studies since 1995. Pohekar and Ramachandran (2004) reviewed the applications of multi-criteria decision making to sustainable energy planning. Mendoza and Prabhu (2005) used MCDA to compare renewable energy with conventional resources. Chatzimouratidis and Pilavachi (2009) applied MCDA to assess different power plants which were made from traditional and renewable energy. Browne et al. (2010) introduced MCDA to evaluate six kinds of residential heating solutions and domestic electricity consumption in an Irish city region.

2.3.4 Typical MCDA methods used for performance analysis of DE systems

In the applications of renewable energy evaluation and assessment, typical MCDA methods can be categorised to the following three categories. (1) Methods based on functional model. The multi-attribute utility theory (MAUT) can be used to support different approaches for MCDA problems. For example, weights are no longer constant but depend on the attribute-values; Weights are determined by sensitivity analysis; Alternatively, the multiplication of weights and attribute-values is considered as a whole to construct a programming model to solve multi-attribute decision making problems with incomplete information. Simple weighted average (SWA) is one of the simplest and most popular methods for MCDA problems. Analytical hierarchy process (AHP) proposed by T. L. Saaty in 1970s is another popular approach and requires the pairwise comparison analysis of the essence of an MCDA problem, e.g. the hierarchy of factors and their internal relationship. (2) Methods based on relational model under the concepts of outranking, for example, the ELECTRE method and PROMETHEE. The ELECTRE method proposed by Roy in 1971 is a relation model based on outranking relation. The PROMETHEE method proposed by Brans in 1984 uses preference function to discriminate the superiority-inferiority of alternatives under some criterion. (3) Methods based on fuzzy set or rough set theory. In this type of approach, decision rules are extracted from past decision examples by utilizing fuzzy set or rough set theory, to form a set of rules. The extracted rules are then used to solve MCDA problems.

Based on the principles of probabilistic inference and evidence-based decision making, in the past decades, the evidential reasoning (ER) approach has been developed for dealing with MCDA problems with various types of uncertainty, including ignorance and randomness (Yang, 2001). It uses a belief structure to represent both quantitative and qualitative criteria, a belief decision matrix to formulate a MCDA problem under uncertainty, and the evidential reasoning algorithm to enable probabilistic inference for aggregating multiple criteria to generate overall distributed assessments. The further development of the evidential reasoning rule provides a unique method for combining multiple pieces of independent evidence conjunctively with weights and reliabilities (Yang and Xu, 2013).

In summary, the performance modelling and impact analysis of different renewable energy systems is considered as a complex multi-dimensional problem, which involves technical, economic, environmental, and social related criteria. MCDA can provide comprehensive and reliable analyses for alternative renewable energy systems. The MCDA framework can be used to incorporate multiple-dimensional information in the decision making process of renewable energy selection and planning, along with their traditional benefit-cost analysis

(Benini & Toffolo, 2002). However, different MCDA methods can lead to different results even on the same problem and with the same data, and it is usually difficult to determine which method provides the most appropriate solution. This literature review can provide us with some insightful knowledge about the research progress and the development trend. It is evident in literature that AHP is widely used in relevant applications due to its simplicity, however, new advances of MCDA methods, such as the ER approach, can facilitate the application of performance modelling and impact analysis of renewable energy systems within a specific region and under certain situations.

On the other hand, from most MCDA applications in DE systems, it can be observed that the focus is mainly concerned with a single renewable energy sector. However, DE systems usually include multi-vectors renewable energies such as solar, wind, storage and so on. Researchers have used some existing methods such as AHP, TOPSIS and MAUT to support the analysis of MCDA problems in the energy field, but have rarely analysed relationships among criteria, and tested whether the conditions or assumptions can be satisfied so that a MCDA method can be applied to deal with a particular MCDA problem. In this research, the ER approach is tailored to construct a specific MCDA evaluation model by taking into account the characteristics of multi-vector DE systems and specific problems and analysing the relationships among these characteristics.

2.5 Summary

DE has already been regarded to be one of the most effective solutions for solving the energy trilemma problem and it is thus very important to model and assess the performance of alternative DE systems systemically. In general, the assessment of DE systems is considered as a complex MCDA problem, which can involve technical, environmental, economic and social aspects. Thus, the literature review provides a holistic overview on the trend of future energy development in the situation of energy trilemma, the importance of DE systems, in particular decentralized renewable energy systems, and the challenges and difficulties in the performance assessment of these DE systems. On the other land, this chapter develops an overview of MCDA methods in the context of their applications in assessment of renewable energy systems and their benefits and limitations. According to the specific nature and characteristics of DE systems and specific MCDA methods, it is useful to construct the performance modelling and multiple criteria decision analysis models for decentralized renewable energy systems.

Chapter 3 | The assessment of energy efficiency with Data Envelopment Analysis (DEA) method

Promoting economic development, ensuring energy security and protecting ecological environment are the fundamental goals of energy and environmental strategies. The coordinated development of energy, environment and economy involves evaluation and analysis of energy, environment and economic efficiency, clean production, energy-saving technologies, and energy and environmental policies. Among them, evaluation of energy environment and economic efficiency is a key issue. Effective and reasonable evaluation can provide accurate information for the formulation and implementation of energy and environmental policies and energy conservation and emission reduction programs. This chapter utilises data envelopment analysis (DEA) to perform energy and environmental efficiency evaluation. At first, the significance of energy and environmental efficiency research is highlighted. And then the DEA theory is briefly introduced along with the review of the current status and limitations of energy and environmental efficiency research. Finally, the CCR (Charnes, Cooper and Rhodes) and BCC (Banker, Charnes and Cooper) DEA models are developed to evaluate the energy efficiency of 39 countries and the efficiency analysis results are discussed in detail.

3.1 Evaluation of energy efficiency

Sustainable development aims to overcome a series of economic energy and environmental problems, especially the global environmental pollution and the unbalanced relationship between economy, energy and environment (Xie et al., 2012). The key to sustainable development is how to operate this new strategy to help decision makers identify the main issues affecting the coordination of the economy, energy and environment, and design effective strategies (Chandel et al., 2016). In order to better analyse the coordination among economy, energy and environment strategies, the International Energy Agency (IEA) officially published the first energy efficiency report in 1997, and the report has been updated annually. Generally speaking, energy efficiency is defined as the ratio of economic output to energy input. This indicator can be used to assess the energy efficiency of economic activities at different levels, including at the micro-enterprise, meso-industry and macro-national economy level (Suzuki et al., 2015). Decision makers can increase energy consumption according to the growth of economic output, or reduce energy consumption according to the reduction of economic output to improve energy efficiency. This means that energy efficiency must be improved in order to achieve coordinated development of economy, energy and environment.

In the process of industrialization, when people first evaluate the production activities of an enterprise, industry or region, they mainly consider economic indicators such as capital, labour, and economic output. However, sustainable development requires that various departments must coordinate the relationship between economy, energy and environment when carrying out production activities (Balitskiy et al., 2016). In addition, with the advancement of energy efficiency policies and the intensification of the environmental protection situation, the requirements for energy and environmental efficiency evaluation are becoming higher and higher. These problems put forward new requirements for efficiency evaluation, and provide new directions for the formulation of relevant energy policies (Banaeian et al., 2012).

Therefore, when analysing the efficiency of an enterprise, industry or region, it is necessary to consider its economic output, energy input, non-energy input, and pollutant emissions. In practice, it must also consider coping strategies, uncertainties, and energy-saving technology levels, energy consumption structure and other factors. This can help decision maker objectively describe the efficiency and take effective measures to improve the energy and environmental efficiency of specific enterprise, industry or region, and promote energy conservation and achievement of emission reduction goals.

3.2 DEA method and its applications in energy efficiency

3.2.1 Introduction to DEA method

DEA is a mathematical method using linear programming techniques to convert inputs to outputs with the purpose of evaluating the performance of comparable organizations or products which is suitable for performance measurement activities. In DEA methods, each decision making unit (DMU) has the flexibility to choose any combination of inputs and outputs in order to maximize its relative efficiency. The relative efficiency or so-called the efficiency score is the ratio of the total weighed output to the total weighed input which is estimated by linear programming and allocated to a DMU as a result of the DEA. This relative efficiency is a non-negative value calculated based on linear relations between the inputs and outputs of the DMUs under analysis. In other words, it determines how efficient a DMU is in producing a certain level of output, based on the amount of input it uses, compared to similar DMUs.

The DEA method is mainly used to evaluate the relative efficiency among homogeneous DMUs with multiple inputs and outputs (Chen et al., 2016). The DEA method has several advantages for performance evaluation. First, it does not need to estimate the production function in advance. Secondly, it does not need to make assumptions about the relevant weights and parameters, thereby avoiding the influence of the subjective judgements from decision makers. In addition, it can portray the frontier of effective production and provide a benchmark for the efficiency improvement of ineffective DMUs. Based on these advantages, DEA has become an important evaluation and analysis tool in the field of performance assessment (Xie et al., 2014).

In the 1990s, DEA has been widely used to evaluate the efficiency of power plants (Dincer, 1999). Since then, a large number of related studies have appeared, and the research perspective has also expanded from a single country to the international scope (Jamasb and Pollitt, 2003; Chen et al., 2015).

3.2.2 Research status of energy and environmental efficiency based on DEA

The key advantages in efficiency evaluation have facilitated the use of DEA methods to evaluate the energy efficiency and assess the impact of environmental policies. Existing research mainly covers the following three aspects.

(1) The application of DEA methods to evaluate company-level environmental efficiency, such as Boyd et al. (2002), Sueyoshi et al. (2010), Sueyoshi and Goto (2013), Bi et al. (2014) and Wu et al. (2015).

(2) The application of DEA methods to evaluate the environmental efficiency at the macro level, which has become a popular research topic, especially in the research of regional or national carbon emissions, such as Zaim and Taskin (2000), Zofio and Prieto (2001), Fare et al. (2004); Zhou et al. (2006), Wu et al. (2014) and Zhao et al. (2016).

(3) The international community's continuous attention to the problem of climate change caused by carbon emissions has further promoted the application of the DEA method in energy and environmental efficiency research (Lenzet al., 2018). Energy efficiency evaluation is an important issue in the study of energy and environmental problems. Boyd and Pang (2000) analysed the relationship between energy efficiency and productivity. Hu and Wang (2006) used a DEA method to put forward an effective energy efficiency index

that is total factor energy efficiency. Zhang et al. (2011) applied a framework of full factors to evaluate the energy efficiency of 23 developing countries. Azadeh et al. (2007) combined DEA and principal component analysis (PCA) to study the energy efficiency evaluation of energy-intensive manufacturing. Shi et al. (2010) studied the energy efficiency of Chinese industries considering fixed-sum and non-energy inputs in a fixed-sum DEA model. Wu et al. (2012) combined the Malmquist Productivity Index (MPI) with the DEA method to analyse the dynamic energy efficiency of industries in China. Zhou et al. (2012) used a parametric frontier approach to assess the energy efficiency of OECD countries at the economic level. Wang et al. (2013) used the non-radial method distance function to study China's energy efficiency and production efficiency under three development strategies. Lin and Wang (2014) used a stochastic frontier approach to discuss the energy efficiency of Chinese steel industry. Zhao et al. (2016) analysed the uncertainty of carbon emission estimation and proposed an energy efficiency evaluation model that takes into account uncertain carbon emissions.

In addition to the above three application areas, DEA is also used to evaluate the production efficiency of specific energy sectors, such as district heating plants (Agrell and Bogetoft, 2005; Munksgaard et al., 2005; Seifert et al. 2016; Zou, 2020), oil and gas industries (Hawdon, 2003; Kashani, 2005; Sueyosshi and Goto, 2012; Zhu et al., 2014).

It can be seen from related DEA literatures that the existing research mainly analyses the efficiency in a general sense. With the intensification of energy and environmental problems, the related efficiency evaluation is also more complicated, which puts new requirements on existing research methods.

(1) Considering the impact of corresponding strategies on DMU efficiency evaluation

To tackle the intensification of energy and environmental issues, regional or national governments have made some energy-saving and emission-reduction policies, and some of those policies are made stricter (Borozan, 2015; Halkos et al., 2015.). In the face of this strict energy and environmental regulation, in order to ensure the smooth operation of production activities, the decision making unit must adapt corresponding strategies according to its own situation (Fallahi et al., 2011; Khoshnevisan et al., 2013). For example, a factory may reduce production output to reduce the pollutant emissions and alternatively it may reduce capital emissions by increasing capital investment to improve production technology without affecting product quality (Apergis et al., 2015). These two different strategies have a significant impact on the factory's expected and undesired output, which have an effect on its efficiency. The existing efficiency evaluation model is not suitable for this situation, and a reasonable efficiency evaluation model needs to be constructed to better describe the impact of the conversion between different strategies on the efficiency of DMUs.

(2) Considering the influence of uncertain factors on DMU efficiency evaluation

Existing energy efficiency studies often use carbon emissions as a deterministic variable. In reality, the production process of carbon dioxide is variable in space and time. In this context, it is difficult to design an appropriate estimation model, and therefore, it is difficult to obtain accurate emission data (Monni et al., 2004). For example, the data of carbon emissions in some Chinese cities, regions, or provinces cannot be directly collected in official databases or statistics yearbooks. Since carbon dioxide is mainly generated from the consumption of mineral energy, the carbon emission of each mineral energy can be estimated by the product of its consumption and its carbon emission coefficient (Liu et al., 2010; Li et al., 2012). This estimation method is often used to obtain carbon emissions from various regions in China, and the underlying assumption of this method is that the carbon emission factor for a given mineral energy in all regions is identical. However, this assumption may not be suitable for production gaps or clean technology gaps between regions. In the literature, a large number of studies have analysed the uncertainties in the carbon emission estimation process (Rypdal and Winiwarter, 2001; Monni et al., 2004). In addition, uncertain estimates of national greenhouse gas inventories have become part of the guidance of the Intergovernmental Panel on Climate Change (IPCC). In the context of DEA, studying the impact of uncertain carbon emissions on energy and environmental efficiency has great practical significance.

(3) Considering the achievability of energy saving and emission reduction goals based on efficiency evaluation

Existing research usually assumes that an inefficient DMU can be flexibly pushed to an effective frontier by adjusting its energy consumption and carbon emissions. However, this may not be the case in reality (Ederer, 2015; Vazhayil & Balasubramanian, 2013). In the short term, a DMU cannot change its production structure significantly, and rapidly changing policies may encounter resistance during implementation (Yu et al., 2013). For example, the Chinese government announced that the proportion of non-mineral energy consumption to total energy consumption would increase to 15% by 2020, and the carbon emissions per unit of GDP would drop to 40-45% (Makridou, et al., 2016). In order to achieve these goals, it is necessary to keep adjusting the industrial structure for a long time, promote the development of new energy technologies, balance the energy structure, and implement strict energy efficiency standards. At present, the improvement of energy efficiency and the reduction of carbon emissions in China are mainly achieved through energy-saving technological progress and energy structure adjustment (Bian et al., 2013). Then, the progress of energy-saving technology is a gradual process, and the energy consumption structure is limited by the supply capacity of mineral energy and non-mineral energy. Balancing the energy structure also requires a long-term process (Pawlak, 2010). Therefore, it is difficult for a decision-making unit to achieve its energy-saving and emission-reduction goals in a short period of time (Brissimis and Zervopoulos, 2012; Begona & Hanley, 2002). This requires to propose effective energy-saving and emission-reduction paths on the basis of energy and environmental efficiency evaluation to help decision-makers meet their own realistic goals.

In recent years, a number of scholars have measured and reviewed the energy efficiency issues in different countries, sectors, economies or projects (Cicea et al., 2014; Ebrahimi & Salehi, 2015), and many DEA models and methods have been widely used in macro and micro energy or environment efficiency research. Mardani (2018) reviewed 145 papers which used DEA for assessing energy and environment not only in regions and countries but also in different sectors or industries. Zurano-Cervelló et al. (2017) combined DEA and input-output (IO) analysis to evaluate the eco-efficiency of manufacturing sectors in the USA and European Union, where the environmental impacts are formulated as inputs while the economic factor as a single output. Yeh et al. (2010) utilized DEA to guide a comparative study of energy utilization efficiency between Taiwan and China considering the labour force, real capital stock and energy consumption as three inputs and GDP, CO2, SO2 emissions as three outputs. Wang et al. (2012) considered the undesirable outputs and conducted a comparative analysis of China's regional energy and emission performance during the period of 2000–2009 in which the three inputs and outputs are the same as in the Yeh's (2010) paper. Wang et al. (2013) had an assessment of the energy and environmental efficiency of 29 administrative regions of China during the period of 2000–2008 based on an improved DEA models. Wang and Wei (2014) evaluated the regional energy and emission efficiencies as well as the energy saving and emission reduction potentials of the industrial sector of 30 major Chinese cities during 2006–2010 considering capital, labour, and total energy consumption as inputs and value-added, CO2 emissions, and SO2 emissions as outputs. Bian et al. (2013) employed an extended non-radial DEA approach to estimate the potential energy saving and CO2 emission reduction in China. Hong et al. (2013) applied the super-

SBM (slacks-based measure) DEA model with undesirable outputs (waste) to analyse the regional environmental efficiency in China over the period of 1991–2001. Zhang and Choi (2013) used a non-oriented slacks-based measure analysis to assess the environmental energy efficiency of China's regional economies under considering three undesirable outputs (i.e., carbon dioxide, sulfur dioxide, and chemical oxygen demand). Song et al. (2013) applied a super SBM and bootstrap-DEA approach in their pilot research to analyse the energy efficiency in China only considering GDP as the single output. Apergis et al. (2015) used a slack based model with undesirable outputs to evaluate the energy efficiency of selected OECD countries. Yang and Wei (2019) conducted the measurement and influences of China's urban total factor energy efficiency under environmental pollution which is based on the game cross-efficiency DEA approach. Lin and Du (2013) utilized an improved non-radial DEA to evaluate the energy and CO2 emission performance of China regionally during the period of 1997–2009. Rui et al. (2015) selected 87 countries and used non-parametric method of production economic to construct the directional distance function of slack-based measurement in the total-factor energy efficiency from 2004 to 2010. Liu and Liu (2016) applied a three-stage DEA method to do the measurement of low carbon economy efficiency measurement of low carbon economy efficiency and a comparison of the largest twenty CO2 emitting countries. Zhou et al. (2017) employed the two-stage DEA method to analyse the energy efficiency and congestion of APEC countries during the period of 1995–2012. Recently, Chen and Jia (2017) applied DEA method to support the environmental efficiency analysis of China's regional industry. Wang et al. (2017) employed a DEA-SBM model to evaluate the energy efficiency of 17 countries during 2010–2015. Yaser (2017) used a network DEA approach to carry out a study on the energy and CO2 emission efficiency of major economies. Those study results found that none of the economies was efficient overall and that China was the worst country, whereas the United States were the most efficient country in terms of energy. Cucchiella et al. (2018) employed a ZSG (zero sum game)-DEA model to compare EU countries based on energy consumption and GHG emissions and economic performance. Wang et al. (2019) applied a DEA-SBM model to measure the energy efficiency of 25 countries with CO2 emissions as well as their energy efficiency improvement.

On one hand, much research on energy efficiency in relation to the environment has never been excessive or has been considered unnecessary (Woo et al., 2015). On the other hand, it was found that there is limited research concerning the difference between results with and without the existence of undesired output. Moreover, not much research addressing energy improvement is found in the literature (Nabavi-Pelesaraei et al., 2016). Very few papers considered the impact of different strategies on efficiency in the face of environmental regulation. There are two strategies for reducing undesired output, namely natural domination and management domination. In the case of natural domination, a decision-making unit reduces undesired output by reducing inputs. In the case of management domination, a decision-making unit increases the capital input for promoting technological progress to reduce undesired output.

3.3 Assessment of the energy efficiency of 39 Countries based on DEA

3.3.1 DEA methodology and models applied in this case

In general, there are multi-dimensional inputs and outputs in energy efficiency assessment. Therefore, when evaluating the efficiency of DMUs, it is necessary to integrate inputs and outputs and assign appropriate weights to various inputs and outputs. Generally, the DEA model has two basic forms: fractional programming and linear programming. The basic DEA models are described as follows.

(1) The basic CCR Model

The CCR model, which is one of the basic DEA models, was developed by Charnes, Cooper and Rhodes in 1978. Suppose there are n DMUs, for each DMU, the virtual input and output (yet unknown) can be formed by two sets of weights (v_i) and (u_r), and DMU j has

$$m\ inputs: (x_{1j}, x_{2j}, x_{3j}, \dots \dots, x_{mj})$$

$$s\ outputs: (y_{1j}, y_{2j}, y_{3j}, \dots \dots, y_{sj})$$

For each DMU j, the ratio of virtual output to virtual input should be maximised to determine the weight by using linear programming,

$$r(DMU\ j) = \frac{virtual\ output}{virtual\ input} = \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}}$$

The optimal weights may and generally vary from one DMU to another. Thus, the "weights" in DEA models are derived from data instead of being fixed in advance. Each DMU is assigned a best set of weights.

The fractional programming model for DMU_0 is formulated as follows

$$(FP_0)\ \max \theta = \frac{u_1 y_{1j0} + u_2 y_{2j0} + \cdots + u_s y_{sj0}}{v_1 x_{1j0} + v_2 x_{2j0} + \cdots + v_m x_{mj0}}$$

$$s.t. \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}} \leq 1\ (j = 1, 2, \dots, n)$$

$$v_1, v_2, \dots, v_m \geq 0$$

$$u_1, u_2, \dots, u_s \geq 0$$

The optimisation problem is to obtain a set of weights (v_i) and (u_r) that maximises the ratio for DMU$_0$ as the DMU being evaluated. The fist constraint ensures that the ratio of "virtual output" and "virtual input" should not exceed 1 for every DMU.

The fractional program (FP$_0$) can be transformed equivalently to a linear program (LP$_0$)

$$(LP_0)\ Max\ \theta = u_1 y_{1j0} + u_2 y_{2j0} + \cdots + u_s y_{sj0}$$

$$s.t.\ \ v_1 x_{1j0} + v_2 x_{2j0} + \cdots + v_m x_{mj0} = 1$$

$$u_1 y_{1j} + u_2 y_{2j} + \cdots + u_s y_{sj} \leq v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}\ (j = 1, 2, \ldots, n)$$

$$v_1, v_2, \ldots, v_m \geq 0,\ u_1, u_2, \ldots, u_s \geq 0$$

The objective is to maximise the virtual output, while normalising the virtual input for the DMU being evaluated. The virtual output should be no more than the virtual input for every DMU. Suppose the optimal solution of (*LP*$_0$) is represented by (θ^*, v^*, u^*). There is $0 \leq \theta^* \leq 1$.

DMU$_0$ is efficient if $\theta^* = 1$ and there exists at least one optimal (v^*, u^*) with $v^* > 0$ and $u^* > 0$; if only $\theta^* = 1$, DMU$_0$ is technically efficient; Otherwise, DMU$_0$ is inefficient. The efficiency score for the DMU0 is given by,

$$\theta^* = u_1^* y_{1j_0} + \cdots + u_s^* y_{sj_0}$$

(v^*, u^*) is the set of the most favourable weights for the DMU$_0$ with the objective of maximising the ratio scale θ. u_r^* is the optimal weight for the r^{th} output and its magnitude expresses how highly the r^{th} output is evaluated. v_i^* is the optimal weight for the i^{th} input and its magnitude expresses how highly the i^{th} input is evaluated.

If DMU_0 is inefficient or $\theta^* < 1$, there must be at least one constraint (or DMU) in the LP_0 model, for which the weight (v^*, u^*) produces equality between the left and right sides. This is because, otherwise, θ^* could be enlarged. Let the set of such DMUs $j \in \{1, \dots, n\}$ be,

$$E_0' = \left\{j \middle| \sum_{r=1}^{s} u_r^* y_{rj} = \sum_{i=1}^{m} v_i^* x_{ij}\right\}$$

The subset E_0 of the above set, composed of efficient DMUs, is called the reference set to the DMU_0. The convex set spanned by E_0 is called the efficient frontier of DMU_0.

(2) Dual CCR model

According to the above primal CCR model, the dual CCR model can also be constructed in order to identify the reference set for inefficient DMUs.

$$(LP_0)\ Min\ \theta$$

$$s.t.\ \theta x_{ij} \ - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \quad i = 1, 2, \dots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj0}, \quad r = 1, 2, \dots, s; \quad \lambda_j \geq 0 \text{ for all } j$$

λ_j: Proportion of DMU j used to construct a composite DMU

$\sum_{j=1}^{n} \lambda_j x_{ij}$ is the i^{th} input of the composite DMU

$\sum_{j=1}^{n} \lambda_j y_{rj}$ is the r^{th} output of the composite DMU

The objective is to minimise the proportion of input, so called input-oriented, while the two main constraints ensure respectively that the composite input is no larger than a proportion of the input of the assessed DMU and the composite output is no less than the output of the assessed DMU.

The LP has a feasible solution $\theta = 1, \lambda_0 = 1, \lambda_j = 0\ (j \neq 0)$. Hence, the optimal θ, denoted by θ^*, is not greater than 1. DMU_0 is efficient if $\theta^* = 1$ and there exists no slack in any of the constraints for DMU_0, or all binding; if only $\theta^* = 1$, DMU_0 is technically efficient; Otherwise, DMU_0 is inefficient.

(3) Output-oriented CCR models

The output-oriented primal CCR model can be formulated in a similar way from the fractional programming model.

$$(LP_0)\ Min\, h = v_1 x_{1j0} + v_2 x_{2j0} + \cdots + v_m x_{mj0}$$

$$s.t.\ \ u_1 y_{1j0} + u_2 y_{2j0} + \cdots + u_s x_{sj0} = 1$$

$$u_1 y_{1j} + u_2 y_{2j} + \cdots + u_s x_{sj} \le v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}\ \ (j = 1, 2, \dots, n)$$

$$v_1, v_2, \dots, v_m \ge 0,\ u_1, u_2, \dots, u_s \ge 0$$

The objective is to minimise the virtual input of DMU_0, while normalising the virtual output for the DMU being evaluated. The virtual output should be no more than the virtual input for every DMU.

The output-oriented dual CCR model can then be constructed as follows,

$$Max\ h_0 = \theta$$

$$s.t.\quad \theta y_{rj0} - \sum_{j=1}^{n} \lambda_j y_{rj} \le 0,\quad r = 1, 2, \dots, s$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{ij0},\quad i = 1, 2, \dots, m;\quad \lambda_j \ge 0 \text{ for all } j$$

λ_j: Proportion of DMU *j* used to construct a composite DMU

$\sum_{j=1}^{n} \lambda_j x_{ij}$ is the i^{th} input of the composite DMU

$\sum_{j=1}^{n} \lambda_j y_{rj}$ is the r^{th} output of the composite DMU

The objective is to maximise the proportion of the output of DMU_0, while the two main constraints ensures respectively that the output of the composite DMU is no less than a proportion of the output of the assessed DMU and the composite input is no more than the input of the assessed DMU. The LP has a feasible solution $\theta = 1, \lambda_0 = 1, \lambda_j = 0 \; (j \neq 0)$. Hence, the optimal θ, denoted by θ^*, is greater than or equal to 1.

(4) The basic BCC model

The basic CCR DEA model assumes a constant return to scale, but the assumption of a constant return to scale can be accepted only if the DMUs operate under the condition of their optimal size. The CCR model assumes that there is perfect competition (but in real world this situation is unreal). Imperfect competition, financial constraints, control steps and other factors can cause DMUs not to operate at their optimal size. A DEA model, namely BCC model (Banker, Charnes & Cooper, 1982), which allows for calculations with a variable return to scale has been developed to overcome this problem. In practice, people often apply both models to the same data to determine the scale efficiency. The overall technical efficiency (CCR) can be decomposed into the pure technical efficiency (BCC) and scale efficiency (SE). The value of scale efficiency indicates whether the DMU operates under increasing or decreasing return to scale. DEA models, including both CCR model and BCC model, can be based on inputs or outputs. The input-oriented models make recommendations of how inefficient units can achieve efficiency in the form of reductions on the inputs side. Output-oriented models require an increase on the outputs side to achieve efficiency.

The BCC model distinguishes between technical and scale inefficiencies by estimating pure technical efficiency at the given scale of operation and identifying whether increasing decreasing, or constant returns to scale possibilities are present for further exploitation.

- *Constant returns to scale*: Increase in input(s) (keeping the input mix constant for multiple inputs) results in a proportionate increase in output.
- *Increasing returns to scale*: Increase in input(s) results in a larger than proportionate increase in output.
- *Decreasing returns to scale*: Increase in input(s) results in a less than proportionate increase in output.

Input-oriented BCC dual model for variable returns of scale (VRS) is based on the input-oriented CCR dual model and the dual variables are added to one to account for VRS.

$$Min\ \theta$$

$$s.t.\ \theta x_{ij} \ - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \quad i = 1, 2, \dots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj0}, \quad r = 1, 2, \dots, s; \quad \lambda_j \geq 0$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

As to the output-oriented BCC dual model for variable returns of scale, it can be constructed in a similar way as the input-oriented BCC model.

$$Max\ h_0 = \theta$$

$$s.t.\quad \theta y_{rj} - \sum_{j=1}^{n} \lambda_j y_{rj} \leq 0, \quad r = 1, 2, \dots, s$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ij0}, \quad i = 1, 2, \dots, m; \quad \lambda_j \geq 0$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

In the following sections, the above described DEA methodology is used to measure energy efficiency and evaluate efficiency changes during 2009–2018.

3.3.2 Data collection

According to the data obtained from the World Bank Open Data (2020), the top 40 countries or regions in average total GDP during the period of 2009-2018 are selected since the latest year the data was available during data collection is 2018. These countries or regions include United States, China, Japan, Germany, France, United Kingdom, Italy, Brazil, India, Canada, Russian Federation, Spain, Australia, Mexico, Korea, Rep., Netherlands, Turkey, Indonesia, Switzerland, Saudi Arabia, Sweden, Belgium, Poland, Norway, Austria, Argentina, South Africa, Nigeria, Thailand, Denmark, United Arab Emirates, Colombia, Greece, Malaysia, Finland, Ireland, Israel, Portugal, Singapore and Hong Kong SAR China. However, this study excluded Hong Kong due to limited data availability, which leads to a selection of 39 countries. Based on related literature review and sustainable development consideration, four inputs (including capital, labour force, no-renewable energy consumption and renewable energy consumption) and two outputs (including GDP and CO2 emission) were selected respectively.

In this study, the energy efficiency refers to using energy resources to promote the growth of GDP and reduce greenhouse gas (GHG) emissions, and what's more, in order to find the effect of sustainable economy and energy policy, the total energy consumption has been split as non-renewable energy and renewable energy. At the same time, the other two economic indicators, capital and labour force were also selected as inputs, while GDP and CO2 emission were selected as desirable output and undesirable output respectively.

Data regarding labour force, as well as capital, GDP values, were collected from The World Bank Open Data (2020), while the total primary energy consumption was collected from the IEA data, the proportions of renewable energy consumption was collected from the Enerdata Yearbook 2019. From these two data sources, the relevant data have been pre-processed to obtain the non-renewable energy consumption and renewable energy consumption respectively for each country. As to the CO2 emissions, it was also collected from the Enerdata Yearbook 2019. A summary of inputs and outputs regarding the maximum, minimum and average of each indicator is presented in Table 3-1.

Table 3-1 Summary for the research samples during 2009–2018

Years	Variables	Input criteria				Output criteria	
		Labour force	Gross capital	Non-renewable Energy	Renewable Energy	GDP	CO2
2009	Max	774.94	2543.9	2006.09	319.52	14617	7220.97
	Min	2.210	39.8	12.41	0.01	209.4	30.33
	Average	58.22	335.9	218.05	37.20	1452.77	621.16
2010	Max	775.35	2904.6	2209.63	326.80	14992	7762.56
	Min	2.274	38.3	12.93	0.01	222.1	30.09
	Average	58.51	370.3	230.46	38.87	1514.62	655.81
2011	Max	777.89	3188.8	2483.18	318.44	15225	8490.94

	Min	2.253	39.6	11.58	0.01	222.9	29.43
	Average	58.84	392.7	234.02	39.27	1561.58	674.35
2012	Max	780.28	3429.5	2483.18	337.61	15567	8753.73
	Min	2.245	30.3	11.58	0.01	223.4	31.11
	Average	59.26	404.6	236.76	40.74	1598.98	684.44
2013	Max	782.22	3756.3	2567.05	344.69	15854	9167.20
	Min	2.264	27.3	12.04	0.01	222.3	31.08
	Average	59.59	419.5	239.87	41.86	1640.39	698.83
2014	Max	783.68	4037.1	2602.61	362.44	16243	9081.57
	Min	2.267	29.1	11.16	0.01	224.0	32.09
	Average	59.98	437.8	241.90	43.06	1686.84	699.29
2015	Max	784.60	4289.9	2622.26	371.64	16710	9061.26
	Min	2.283	25.5	10.69	0.01	228.1	31.65
	Average	60.41	453.0	242.17	43.40	1735.56	695.92
2016	Max	784.95	4563.0	2595.13	369.49	16972	9003.33
	Min	2.322	27.0	10.99	0.01	232.7	31.16
	Average	60.81	460.7	241.82	44.44	1777.61	692.75
2017	Max	784.64	4792.3	2662.15	388.45	17348	9178.94
	Min	2.344	29.7	10.49	0.01	240.8	31
	Average	61.26	480.9	247.20	45.12	1833.78	707.49
2018	Max	783.42	5020.4	2764.98	399.10	17857	9466.50
	Min	2.386	30.3	10.17	0.01	246.7	31.12
	Average	61.66	497.5	252.50	46.52	1888.96	722.02

In Table 3-1, it is shown that the average GDP of all 39 selected countries has a growth in the past 10 years. Among the 39 samples, the country with the highest GDP is the United States, followed by China and Japan, and the country with the lowest GDP average is Portugal. The average CO2 emission has also an increasing trend during this period, but there was a slight decrease in 2015. The three countries with the highest CO2 emissions are China, the United States and India, whereas the countries with the lowest CO2 emissions are Ireland, Denmark and New Zealand. Relative to the GDP and CO2 emissions growth trends, the average labour force has hardly increased in this period. China, the United States, and India are the top three countries in labour force, whereas Ireland has the lowest amount of labour force. As to the non-renewable energy consumption, the top three countries are China, the United States and Russia and the last country is Denmark. The three countries that consumed the most renewable energy are China, India and the United States whereas Saudi Arabia consumed the least renewable energy. However, Nigeria, Norway and Sweden have the highest proportion of renewable energy in total energy consumption whereas Saudi Arabia has the lowest proportion.

3.3.3 The results of energy efficiency

Firstly, since some of the factors have large values and different dimensions, the following pre-processing tasks have been performed on the data: (1) the respective GDP has been divided by the maximum value in all 39 countries; (2) the CO2 emission is the undesirable output, so it has been subtracted from 10000 for obtaining a non-negative desirable output and then divided by the maximum value; (3) the input factors of capital, labour force, renewable energy consumption and non-renewable energy consumption have been pre-processed in the same way as the GDP and been divided by their respective maximum values for all 39 countries.

Secondly, in this research a set of eight DEA models have been developed to evaluate the energy efficiency in all 39 sample countries, and they include BCC input oriented primal and dual model, BCC output oriented primal and dual model, CCR input oriented primal and dual model, CCR output oriented primal and dual model. As discussed above, GDP and CO2 emission are selected as desirable output and undesirable output respectively and the energy efficiency refers to using economic and energy resources to promote the growth of GDP while reducing greenhouse gas emissions. The eight DEA models are further solved in the form of the linear programming models to get the same result of energy efficiency. The total factor energy efficiency (TFEE) and particular factor energy efficiency (PFEE) are used respectively to conduct an insightful analysis of different results. TFEE means that all of the input and output factors will be considered in the DEA model while PFEE means that only some particular input or output factors will be considered in order to analyse some specific relationship among them. The energy efficiency of 39 countries with TFEE over the ten years period of 2009-2018 is shown in Table 3-2. The results show that 9 countries were efficient in this period by using the multiple inputs to produce GDP and CO2 emissions as the corresponding efficiency score are "1". It means that the 9 countries utilized the capital, labour force and energy consumption more effectively than the other countries, and it also indicates that they have a more balanced development between GDP growth and CO2 emissions.

From the results in Table 3-2, based on the Human Development Index (HDI) in 2018, most of these 9 countries, including United Arab Emirates, Singapore, Denmark, Switzerland, Nigeria, Norway, United Kingdom, Saudi Arabia and Ireland are developed countries (HDI: Human Development Index > 0.9), and in the total 39 sample countries, most developed countries showed a better performance of energy efficiency than that in developing countries (HDI: Human Development Index < 0.9). The 10 countries with the lowest average energy efficiency over the 10 years are Russia, Mexico, Poland, South Korea, South Africa, Turkey, Thailand, Indonesia, India and China, in which most countries are developing countries and the HDIs are less than 0.9. Among them, China has the lowest performance of energy efficiency with the most labour force and largest amount of CO2 emissions, whereas India also has very poor performance of energy efficiency with the third largest amount of CO2 emissions and the second largest labour force.

In Table 3-3, the 3 countries whose average efficiency score is less than 0.5 are chosen to compare with the average of these 39 countries as shown in Figure 3-1. It can be observed from the results that there is a decreasing trend on the average efficiency score of all sample countries, and more specifically it decreased from 0.8499 in 2009 to the bottom 0.8012 in 2013 and then continually increased up to 0.8231 in the four consecutive years from 2013 to 2017, then decreased to 0.8166 again in 2018. Meanwhile, the efficiency scores of these 3 countries have the same fluctuating over the ten years period where the score increased from the value of 2009 to the top in 2010 or 2011 and then have a decreasing trend in the following years.

Table 3-2 Total-factor energy efficiency of 39 countries during 2009-2018

Country Name	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Average
United Arab Emirates	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Singapore	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Denmark	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Switzerland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Nigeria	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Norway	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
United Kingdom	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Saudi Arabia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Ireland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Greece	0.9501	0.9920	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9942
Nethelands	0.9804	0.9657	0.9570	1.0000	0.9854	1.0000	0.9641	1.0000	1.0000	0.9902	0.9843
Israel	1.0000	0.9128	0.8439	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9757
Portugal	0.9000	0.8189	0.9121	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9631
United States	0.9886	0.9368	0.9611	0.9391	0.9289	0.9325	0.9508	0.9565	0.9484	0.9299	0.9473
Italy	0.8840	0.8538	0.8506	0.9610	0.9995	1.0000	1.0000	0.9791	0.9497	0.9365	0.9414
Finland	0.9329	0.8645	0.8533	0.8912	0.8875	0.9591	1.0000	1.0000	1.0000	1.0000	0.9389
Japan	0.9060	0.8689	0.9008	0.9470	0.9348	0.9421	0.9510	0.9887	0.9714	0.9000	0.9311

Germany	0.8831	0.8527	0.8480	0.9177	0.9207	0.9277	0.9573	0.9450	0.9250	0.8997	0.9077
Belgium	0.9487	0.8828	0.8937	0.9009	0.8742	0.8732	0.8894	0.8794	0.8923	0.8322	0.8867
Australia	0.8843	0.8315	0.8667	0.8681	0.8637	0.8475	0.8607	0.8930	0.9002	0.8595	0.8675
France	0.8538	0.8291	0.8426	0.8647	0.8610	0.8595	0.8763	0.8708	0.8569	0.8483	0.8563
Sweden	0.8830	0.8467	0.8341	0.8658	0.8580	0.8527	0.8591	0.8497	0.8368	0.8059	0.8492
Austria	0.8232	0.8181	0.8178	0.8233	0.8330	0.8459	0.8450	0.8467	0.8420	0.8342	0.8329
Canada	0.8300	0.7724	0.7856	0.7752	0.7762	0.8051	0.8630	0.8991	0.8744	0.8762	0.8257
Brazil	0.8688	0.8105	0.7937	0.7709	0.7309	0.7449	0.7800	0.8162	0.8662	0.8398	0.8022
Spain	0.7323	0.7730	0.7703	0.8318	0.8298	0.8324	0.8102	0.8246	0.8108	0.7944	0.8010
Argentina	1.0000	0.9394	0.7944	0.7266	0.6973	0.7098	0.7136	0.6944	0.6850	0.7014	0.7662
Colombia	0.8799	0.8053	0.7666	0.7347	0.6568	0.6461	0.6538	0.6541	0.7098	0.7019	0.7209
Malaysia	0.8569	0.7296	0.7382	0.6375	0.6098	0.6406	0.6323	0.6232	0.6348	0.6740	0.6777
Russia	0.7969	0.7135	0.6061	0.5436	0.5829	0.6609	0.7197	0.6839	0.6993	0.6955	0.6702
Mexico	0.6536	0.7123	0.6809	0.5919	0.6176	0.6520	0.6734	0.6719	0.7018	0.7222	0.6678
Poland	0.7560	0.7764	0.6891	0.5943	0.6115	0.6107	0.5999	0.5989	0.6087	0.5880	0.6434
South Korea	0.6634	0.6381	0.6263	0.6397	0.6533	0.6363	0.6313	0.6464	0.6025	0.6361	0.6373
South Africa	0.7622	0.8558	0.7746	0.5832	0.5230	0.5742	0.4870	0.5653	0.6018	0.6232	0.6350
Turkey	0.6584	0.6117	0.5924	0.6053	0.5850	0.6062	0.5968	0.5770	0.5668	0.6051	0.6005
Thailand	0.7494	0.6620	0.6445	0.4495	0.4177	0.5055	0.4480	0.5302	0.5234	0.4656	0.5396
Indonesia	0.4155	0.4969	0.4868	0.4353	0.4215	0.4222	0.4189	0.4281	0.4395	0.4309	0.4395
India	0.3831	0.4008	0.4039	0.3276	0.3184	0.3324	0.3179	0.3381	0.3531	0.3481	0.3523
China	0.3232	0.3372	0.3453	0.2686	0.2676	0.2797	0.2828	0.2866	0.3002	0.3080	0.2999

Table 3-3 Efficiency score of three countries and average of 39 sample countries (TFEE)

Country Name	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
All 39 countries	0.8499	0.8284	0.8174	0.8075	0.8012	0.8128	0.8149	0.8217	0.8231	0.8166
Indonesia	0.4155	0.4969	0.4868	0.4353	0.4215	0.4222	0.4189	0.4281	0.4395	0.4309
India	0.3831	0.4008	0.4039	0.3276	0.3184	0.3324	0.3179	0.3381	0.3531	0.3481
China	0.3232	0.3372	0.3453	0.2686	0.2676	0.2797	0.2828	0.2866	0.3002	0.3080

Although there was an insignificant decline, the mean efficiency scores of these three countries after 2012 were quite stable. In addition, it was found that the lowest efficiency score was in 2013 for both the countries with better performance and those with worse performance. That was probably due to the fact that the increase on the amount of CO2 emissions was faster in that year than other years, while the share of GDP was decreased.

Before using the PFEE to conduct the efficiency analysis, the energy consumption is regarded as the input to produce GDP and CO2 emissions. The renewable energy consumption has been replaced by the ratio of non-renewable energy consumption to the total energy consumption since it is expected to use less energy consumption especially non-renewable energy consumption to produce more GDP and less CO2 emission. The BCC input-oriented model is used to conduct the energy efficiency which is shown in Table 3-4. The result indicates that there are 6 different countries with the average efficiency score being “1”. They are Ireland, United States, Japan, Switzerland, Norway, Nigeria and Denmark. Among of them, Ireland, Switzerland, Norway, Nigeria and Denmark are the countries with the best performance of energy efficiency. The reason was probably the high ratio of renewable energy. For example, the hydropower in Nigeria accounts for 80% of total energy production. It was discussed in the literature review in Chapter 2 that Denmark is one of the countries with the highest energy efficiency and less CO2 emissions. The countries with the worse performance are also different from the result of TFEE. There are ten countries with the average score being less than 0.5, and they include Poland, Argentina, Thailand, United Arab Emirates, Malaysia, South Korea, South Africa, India, Saudi Arabia and Russia. India is still one of the countries with relatively low energy efficiency, however, China has risen to be among the countries with middle energy efficiency, and has the average score 0.5234. What’s more, China’s energy efficiency has been increasing since 2009, and it is attributed to the key development of renewable energy projects in China in recent years.

From the results in Figure 3-2, it shows that the average efficiency score of all 39 countries are stable over the ten years period. Initially, it was expected that the efficiency score would become higher on average since without considering capital and labour force as inputs and more DMU would be efficient. However, the results in Table 3-4 and Table 3-5 are opposite to the initial expectation. The results imply the effective utilisation of joining economic and energy resources to grow GDP and reduce CO_2 emissions. Additionally, the average efficiency score of all 39 countries in PFEE have the same decline during this period as the results in TFEE. This indicates that the decrease in energy efficiency of these countries is largely due to the slower growth of GDP in recent years in comparison to previous years. However, the energy efficiency of the three countries with worse performance has a slight increasing trend in PFEE during this period, and this implies that the ratio of renewable energy has been greater than before. Moreover, as shown in Figure 3-1 and Figure 3-2, there is a similar big gap in efficiency score between the best performance and the worst performance group, which implies that the sample developed countries had a better performance in terms of energy efficiency than the developing countries.

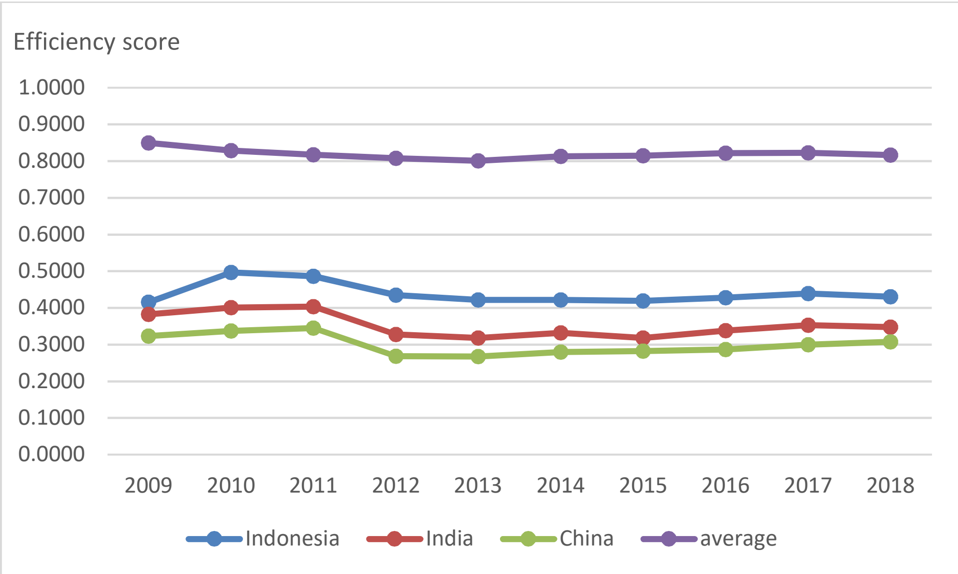


Figure 3-1 The comparison between the three countries with worse performance and the average of 39 countries (TFEE)

In Table 3-4, it indicates that Russia is the country that has the poorest performance with considering the energy consumption and the ratio of non-renewable energy consumption as inputs to produce GDP and CO_2 emission, followed by Saudi Arabia and India. India accounts for about 18% of the global population and more than 25% of the world demand for primary energy as well as one-third of the world's CO_2 emissions. However, although

India had a rapid increase of their GDP over this period, its energy consumption and CO2 emissions continued to grow, leading it to be the least-performing countries in terms of energy efficiency. Meanwhile, China has a great development of renewable energy in recent years to decrease the ratio of non-renewable energy which leads to an improvement of energy efficiency in China. The average energy efficiency of all 39 countries and 3 countries in terms of TFEE and PFEE are shown in Figure 3-1 and Figure 3-2.

Table 3-4 Particular-factor energy efficiency of 39 countries during 2009-2018

Country Name	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Average
Ireland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
United States	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Japan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Switzerland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Norway	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Nigeria	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Denmark	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
U.K.	0.9901	0.9753	0.9905	0.9514	0.9723	1.0000	0.9990	1.0000	1.0000	1.0000	0.9879
Italy	0.9811	0.9746	0.9057	0.9248	0.9297	0.9363	0.8903	0.8906	0.8751	0.8627	0.9171
Portugal	0.9156	0.9434	0.9013	0.8929	0.9293	0.9045	0.8457	0.8548	0.8405	0.8243	0.8852
Germany	0.8934	0.8925	0.8977	0.8788	0.8534	0.8719	0.8589	0.8576	0.8604	0.8849	0.8749
Sweden	0.8133	0.7939	0.7897	0.8099	0.8097	0.8332	0.8910	0.8877	0.9037	0.8994	0.8431
Brazil	0.8971	0.8911	0.8799	0.8407	0.8187	0.7872	0.7761	0.7684	0.7730	0.7593	0.8192
France	0.8523	0.8469	0.8221	0.8091	0.8030	0.8114	0.7882	0.7939	0.7999	0.8022	0.8129
Finland	0.8215	0.7485	0.7299	0.7638	0.7945	0.7910	0.8241	0.7921	0.8230	0.8200	0.7908
Spain	0.8489	0.8463	0.7673	0.7600	0.7878	0.7829	0.7652	0.7681	0.7526	0.7590	0.7838
Austria	0.8252	0.7769	0.7410	0.7646	0.7732	0.7806	0.7539	0.7467	0.7549	0.7498	0.7667
Greece	0.7580	0.7754	0.7476	0.7392	0.8122	0.7786	0.7656	0.7714	0.7392	0.7327	0.7620
Israel	0.8540	0.8406	0.8021	0.7410	0.7606	0.7237	0.6929	0.7136	0.7055	0.7007	0.7535
Colombia	0.8384	0.8057	0.7494	0.7388	0.6626	0.6536	0.6463	0.6230	0.6404	0.6396	0.6998
Nethelands	0.7266	0.6851	0.6763	0.6685	0.6735	0.6834	0.6746	0.6651	0.6693	0.6786	0.6801
Singapore	0.7725	0.8030	0.8151	0.7216	0.6986	0.6515	0.6134	0.5882	0.5603	0.5426	0.6767
Australia	0.6796	0.6843	0.6678	0.6658	0.6800	0.6771	0.6724	0.6562	0.6563	0.6562	0.6696
Canada	0.5936	0.6069	0.6000	0.5932	0.5923	0.5841	0.5754	0.5765	0.5770	0.5646	0.5864

Turkey	0.5604	0.5616	0.5587	0.5407	0.5850	0.5741	0.5680	0.5466	0.5523	0.5504	0.5598
Belgium	0.5515	0.5241	0.5132	0.5302	0.5292	0.5443	0.5378	0.5137	0.5270	0.5400	0.5311
Indonesia	0.4957	0.5150	0.5494	0.5294	0.5344	0.5241	0.5255	0.5370	0.5362	0.5358	0.5283
China	0.4154	0.4360	0.4805	0.4803	0.5063	0.5323	0.5546	0.5829	0.6146	0.6314	0.5234
Mexico	0.5017	0.5211	0.5113	0.4936	0.4979	0.5063	0.5063	0.5099	0.5099	0.5167	0.5075
Poland	0.4416	0.4430	0.4455	0.4392	0.4475	0.4575	0.4559	0.4545	0.4561	0.4573	0.4498
Argentina	0.4530	0.4525	0.4508	0.4368	0.4445	0.4473	0.4371	0.4371	0.4424	0.4442	0.4446
Thailand	0.4550	0.4542	0.4573	0.4399	0.4356	0.4455	0.4368	0.4370	0.4374	0.4417	0.4440
United Arab Emirates	0.4671	0.4647	0.4348	0.4235	0.4211	0.4160	0.4089	0.4100	0.4119	0.4135	0.4272
Malaysia	0.4410	0.4358	0.4275	0.4153	0.4127	0.4158	0.4167	0.4142	0.4149	0.4150	0.4209
South Korea	0.4294	0.4312	0.4243	0.4154	0.4207	0.4224	0.4169	0.4127	0.4153	0.4117	0.4200
South Africa	0.3748	0.4040	0.4052	0.3996	0.4040	0.4024	0.4077	0.4057	0.4136	0.4114	0.4028
India	0.3692	0.3903	0.3999	0.3825	0.3895	0.3838	0.3930	0.4031	0.4117	0.4144	0.3937
Saudi Arabia	0.3544	0.3541	0.3732	0.3512	0.3607	0.3504	0.3453	0.3524	0.3519	0.3540	0.3548
Russia	0.2899	0.2980	0.3020	0.2968	0.3008	0.2948	0.2893	0.2827	0.2796	0.2722	0.2906

Table 3-5 Efficiency score of three countries and average of 39 sample countries (PFEE)

Country Name	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
All 39 countries	0.7093	0.7071	0.6979	0.6882	0.6934	0.6915	0.6854	0.6834	0.6848	0.6843
India	0.3692	0.3903	0.3999	0.3825	0.3895	0.3838	0.3930	0.4031	0.4117	0.4144
Saudi Arabia	0.3544	0.3541	0.3732	0.3512	0.3607	0.3504	0.3453	0.3524	0.3519	0.3540
Russia	0.2899	0.2980	0.3020	0.2968	0.3008	0.2948	0.2893	0.2827	0.2796	0.2722

3.3.4 The improvement of energy efficiency

The BCC input-oriented and input-oriented dual models are further used to evaluate the energy efficiency considering the undesirable output as well as energy efficiency improvement of all 39 countries. The input oriented dual model is minimising the proportion of the input of each DMU and the input of composite DMU is not larger than a proportion of the input of the DMU. Figure 3-3 provides an example of using BCC input-oriented dual model with TFEE to get the energy efficiency score and reference set for each DMU (Some rows and columns of some original data have been hidden to emphasise the model results).

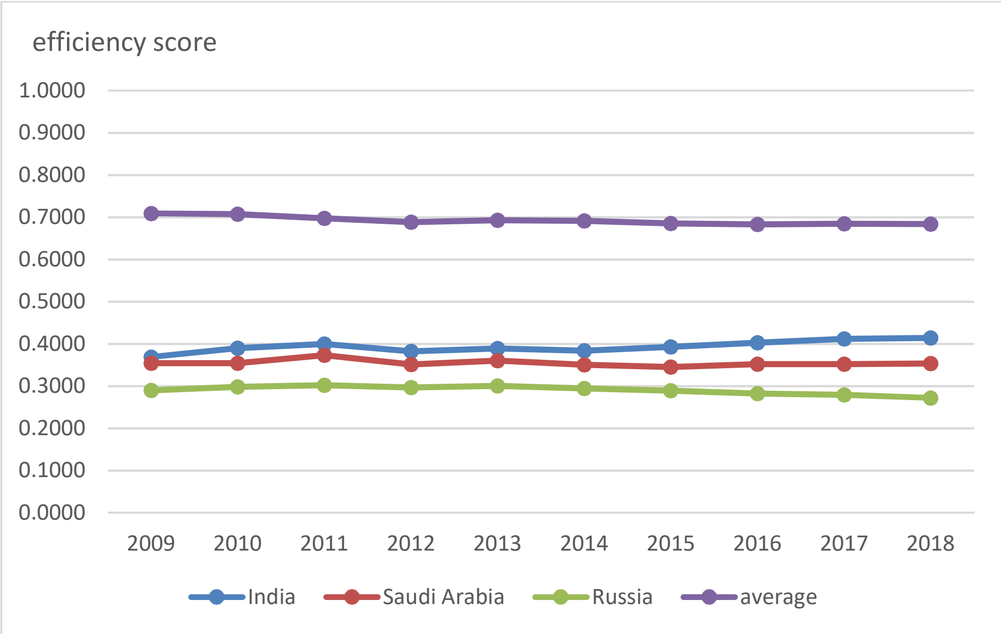
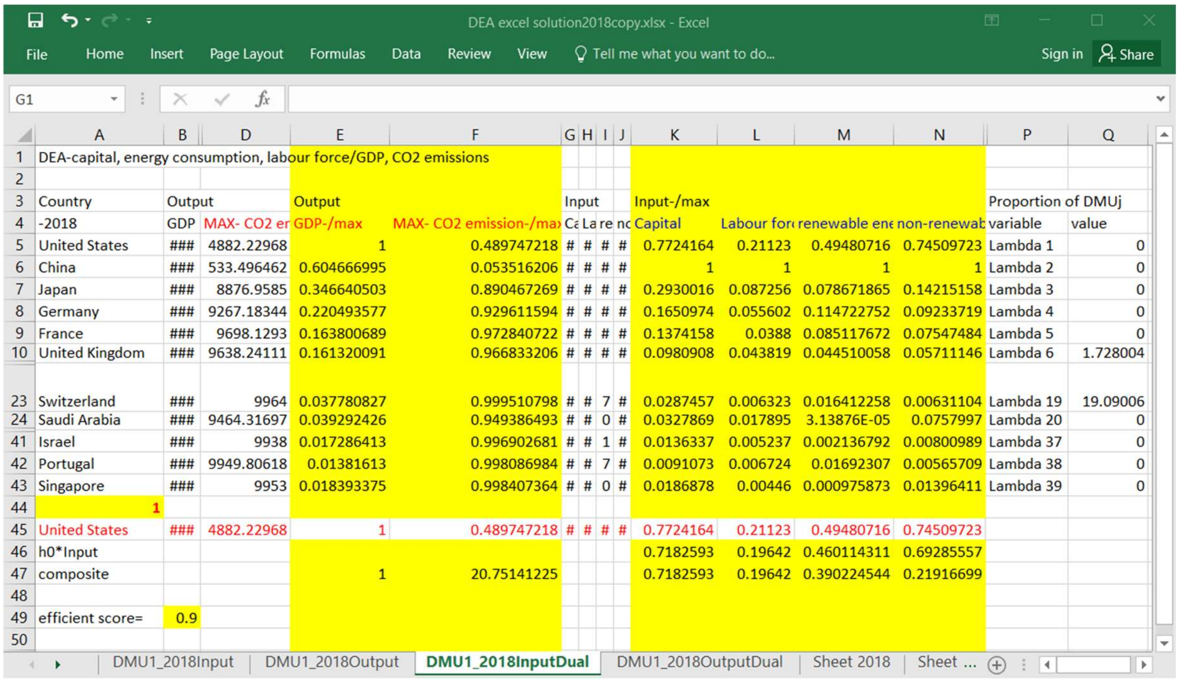


Figure 3-2 The comparison between the three countries with worse performance and the average of 39 countries (PFEE)



DEA excel solution2018copy.xlsx - Excel

	A	B	D	E	F	G	H	I	J	K	L	M	N	P	Q
1	DEA-capital, energy consumption, labour force/GDP, CO2 emissions														
2															
3	Country	Output		Output		Input				Input-/max				Proportion of DMUj	
4	-2018	GDP	MAX- CO2 er	GDP-/max	MAX- CO2 emission-/ma	Ca	La	re	nc	Capital	Labour for	renewable ene	non-renewab	variable	value
5	United States	###	4882.22968	1	0.489747218	#	#	#	#	0.7724164	0.21123	0.49480716	0.74509723	Lambda 1	0
6	China	###	533.496462	0.604666995	0.053516206	#	#	#	#	1	1	1	1	Lambda 2	0
7	Japan	###	8876.9585	0.346640503	0.890467269	#	#	#	#	0.2930016	0.087256	0.078671865	0.14215158	Lambda 3	0
8	Germany	###	9267.18344	0.220493577	0.929611594	#	#	#	#	0.1650974	0.055602	0.114722752	0.09233719	Lambda 4	0
9	France	###	9698.1293	0.163800689	0.972840722	#	#	#	#	0.1374158	0.0388	0.085117672	0.07547484	Lambda 5	0
10	United Kingdom	###	9638.24111	0.161320091	0.966833206	#	#	#	#	0.0980908	0.043819	0.044510058	0.05711146	Lambda 6	1.728004
23	Switzerland	###	9964	0.037780827	0.999510798	#	#	7	#	0.0287457	0.006323	0.016412258	0.00631104	Lambda 19	19.09006
24	Saudi Arabia	###	9464.31697	0.039292426	0.949386493	#	#	0	#	0.0327869	0.017895	3.13876E-05	0.0757997	Lambda 20	0
41	Israel	###	9938	0.017286413	0.996902681	#	#	1	#	0.0136337	0.005237	0.002136792	0.00800989	Lambda 37	0
42	Portugal	###	9949.80618	0.01381613	0.998086984	#	#	7	#	0.0091073	0.006724	0.01692307	0.00565709	Lambda 38	0
43	Singapore	###	9953	0.018393375	0.998407364	#	#	0	#	0.0186878	0.00446	0.000975873	0.01396411	Lambda 39	0
44	1														
45	United States	###	4882.22968	1	0.489747218	#	#	#	#	0.7724164	0.21123	0.49480716	0.74509723		
46	h0*Input									0.7182593	0.19642	0.460114311	0.69285557		
47	composite			1	20.75141225					0.7182593	0.19642	0.390224544	0.21916699		
48															
49	efficient score=	0.9													
50															

DMU1_2018Input | DMU1_2018Output | DMU1_2018InputDual | DMU1_2018OutputDual | Sheet 2018 | Sheet ...

Figure 3-3 An example of energy efficiency using BCC input-oriented dual model

The efficiency score of the United States in 2018 is 0.9298, the reference set for this country is United Kingdom and Switzerland ($Lambda\ 6 = 1.7280, Lambda\ 19 = 19.0900$) which means the U.S. energy efficiency could be improved in accordance with the United Kingdom and Switzerland and the efficiency score of these two countries is “1”. On the other hand, this input-oriented dual model is minimizing the total input without increasing output to improve the efficiency. The other output-oriented dual model is maximizing the total output without increasing the input to improve the efficiency. The Figure 3-4 shows how to use BCC input-oriented dual model and linear programming to get the energy efficiency.

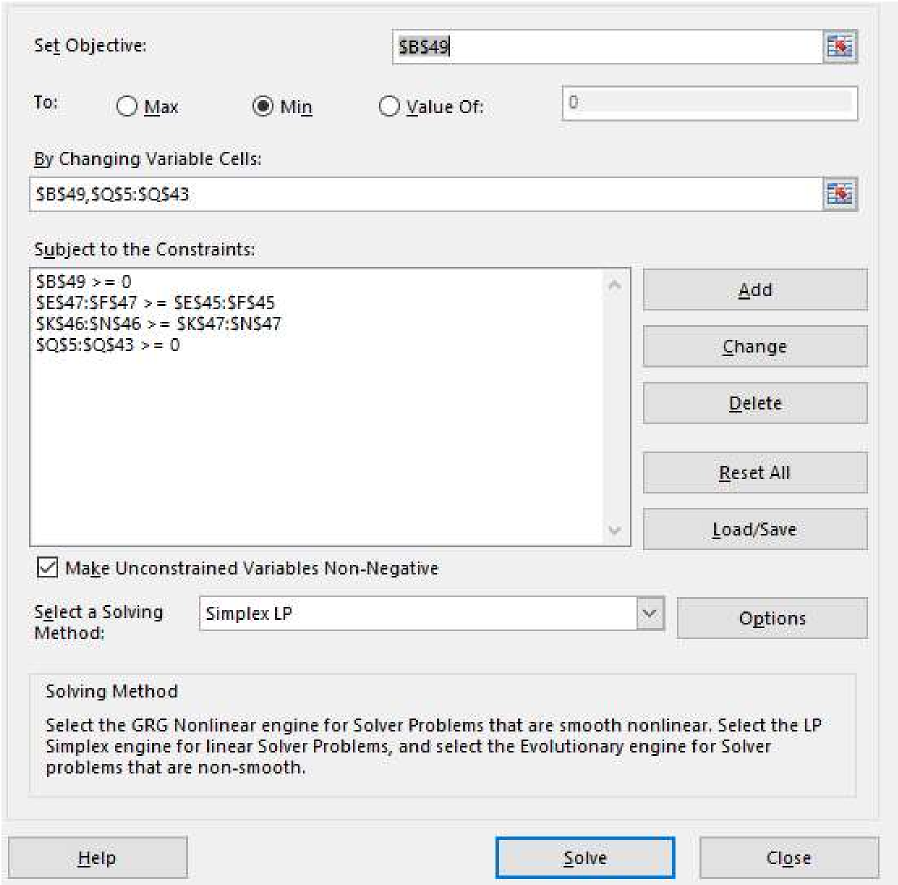


Figure 3-4 Using BCC input-oriented dual model to evaluate the energy efficiency

The result also provides implications on some important policy making. By measuring the efficiency with and without capital and labour force, the results of our study reveal the increasing trend of the efficiency score in some developing countries, caused mostly by the increase of the ratio of renewable energy consumption during the period of 2009–2018, which implies that these countries should continue to develop the renewable energy and pay more attention to effectively utilizing economic to promote GDP growth as well. Moreover, especially China, India, Iran, Indonesia, and Russia which have lower efficiency scores indicate that more efforts should be made to improve their energy efficiency. India experienced an improvement in both TFEE and PFEE, which indicated that India achieved a better balance between GDP growth and CO2 emission during the period. On the other hand, China witnessed the rapid improvement of more than 100% only in PFEE, indicating that China performed well in terms of using energy to promote the growth of GDP. However; using a large amount of energy also costs the country a huge quantity of greenhouse gas emissions, which significantly affects the TFEE. According to the reference set that is obtained by the dual DEA model, the solution for enhancing energy efficiency is attempting not to increase input resources while maintaining GDP growth. A tax policy for CO2 emission can possibly be applied to reach the energy efficiency targets. On the other hand, in order to improve the energy efficiency, it is also possible to reduce the inputs while decreasing the outputs. For example, for the countries with low energy efficiency, they need to reconsider their energy resources and relevant policies and make a great development of renewable energy thereby not only reducing the use of fossil fuels to reduce the total energy consumption but also decreasing the proportion of non-renewable energy and reducing the CO2 emission. Furthermore, the results demonstrate that most developed countries generally showed rather higher energy efficiency than most developing countries in these 39 samples and the gap between them is notable. Therefore, the inefficient countries should learn from the efficient ones in terms of experiences, policies, and new renewable energy technologies which can be useful for improving their energy efficiency.

3.4 Summary

This chapter reviews some basic theories of DEA and the current research status and limitation on DEA-based energy and environmental efficiency research. A framework featuring with multiple factors has been developed for the evaluation of 39 sample countries selected with the GDP production. The framework considers gross capital and labour force as two no-energy inputs, renewable energy consumption and non-renewable energy consumption as two energy inputs to produce two outputs which are the GDP as the desirable output and CO2 emissions as the undesirable output. Eight DEA models are developed for evaluating the energy efficiency in TFEE and PFEE respectively, then the different results have been compared and analysed to find the difference and inherent reasons for the changes. Furthermore, the implications of some policy making from the result are also discussed. It provides a technical route and guidance for the countries with relatively low energy efficiency.

In addition, there are some external environmental or economic factors affecting the gap of energy efficiency between developed and developing countries. Therefore, it is one of the limitations of this research and some external factors can be considered to evaluate the energy efficiency in the future. Moreover, there are different results from TFEE and PFEE robustness which can be tested quantitatively. Therefore, it is useful to conduct a sensitivity analysis in order to evaluate the robustness of the energy efficiency score in the future research.

Chapter 4 | The proposed MCDA model based on the ER approach with a case study

This chapter is mainly concerned with developing a performance assessment model based on multiple criteria decision analysis (MCDA), including the definition, description and assessment grades of each criterion. The evidential reasoning approach, which is implemented in the Intelligent Decision System (IDS), is applied to aggregate assessment information on a real case study. Sensitivity and trade-off analyses are conducted to validate the decision making process, which demonstrates how a robust MCDA model can be developed to support informed performance assessment of DE systems.

4.1 Hierarchy assessment framework

In the performance modelling and assessment of renewable energy systems, multiple criteria can be identified and weighted in order to provide a systematic way to produce informative assessment results. It can not only provide in-depth understanding of key advantages and inherent impact but also facilitate an informed decision making process. Papadopoulos and Karagiannidis (2008) adopted an interdisciplinary comprehensive approach which analyses technical, economic, environmental and social factors for implementation of renewable energy systems. Wang et al. (2009) summarised and classified different criteria of assessing energy supply systems. Akella et al. (2009) analysed the social, economic and environmental impacts of renewable energy systems systematically. Ezbakhe and Pérez-Foguet (2020) formulated the evaluation model of renewable energy resources in terms of technological, technical, economic, environmental, and socio-politic criteria. On the basis of the previous research, a hierarchical assessment framework is formulated for multiple criteria performance modelling of decentralized energy system, which breaks down to technical, economic, environmental and social dimensions, as illustrated in Figure 4-1.

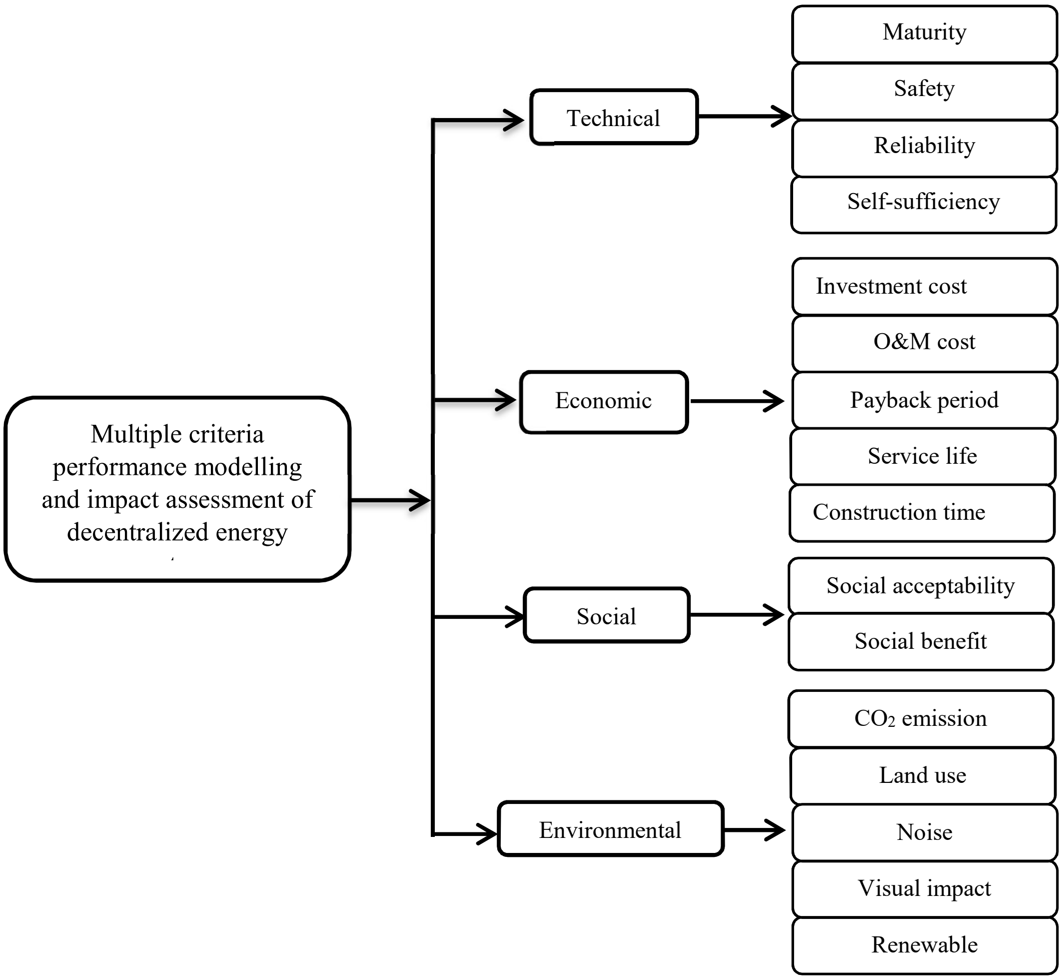


Figure 4-1 Hierarchical assessment framework for DE systems

4.2 Selection of the criteria

(1) Technical criteria.

Technical feasibility and effectiveness are the fundamental criteria for the assessment of renewable energy systems. Thermodynamics can possibly be used to assess how effective and efficient a renewable DE system works. Primarily, the technical criteria, such as technical maturity, safety, reliability and self-sufficiency should be considered

(Chatzimouratidis, 2008; Madlener et al., 2007; Mamlook et al., 2001; Twidell and Weir, 2015; Wang et al., 2009).

(2) Economic criteria.

In order to maintain economic sustainability and opportunities, it is necessary to consider the affordability and accessibility of renewable energy systems. In general, there are key attributes to be considered in the economic category, which involve initial investment, construction time, operation and maintenance costs, payback time and cycle of service life (Ahmad and Tahar, 2014; Doukas; 2007; Karakosta et al., 2013;Wang et al., 2009).

(3) Social criteria.

As most distributed energy systems are located near to local communities, the development of renewable energy systems during construction and local consumption period plays an important role in shaping the society and involves every aspect of human participation and activities. For example, it creates technical and managerial job positions for launching a renewable energy system. While introducing some new technologies, the criteria of social acceptance and benefit are widely considered (Chatzimouratidis et al., 2008; Mourmouris and Potolias, 2013; Wang et al., 2009; Zhao and Guo, 2015).

It is important that factors are identified to assess the performance and impact of various renewable energy systems in a consistent and systematic way. Furthermore, the relative importance of each category and its impact factors need to be taken into account. For example, the technical feasibility may be among the most important considerations.

(4) Environmental criteria.

Sustainable development aims to overcome a series of economic, energy and environmental problems, especially the global environmental pollution and the unbalanced relationship between economy, energy and environment. With the intensification of the environmental protection situation, the requirements for the environmental efficiency evaluation of energy are becoming higher and higher. These problems provide new directions for the relevant decision making problem (EC, 2003; 2009; Lawrence, 2007). The stakeholder mapping approach (Mitchell et al., 1997) as illustrated in Figure 4-2 can be used to analyse environmental impact assessment.

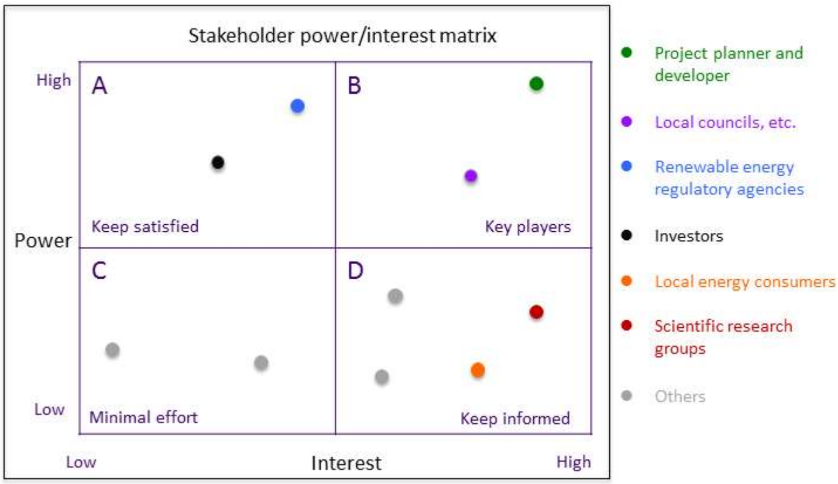


Figure 4-2 Stakeholder analysis for environmental impact assessment

Typical environmental impact factors should be considered for various renewable energy systems which include CO2 emissions, SO2 emissions, land use, noises, exposure to electromagnetic field and visual impact (Haralambopoulos and Polatidis, 2003; Lawrence, 2007; Løken, 2009; Wang et al., 2009).

All of the above criteria or factors which are used to assess the performance of various renewable energy systems should be identified in a consistent and systematic way. Furthermore, the relative importance of each category and its impact factors need to be taken into consideration.

4.3 Description and assessment grade of each criterion

4.3.1 Technical criteria

Maturity

Definition: Maturity is often used to evaluate the technology itself, and the degree of maturity can be approximated by whether this kind of technology has been widely adopted at regional, national and international level. This measure also indicates whether the technology has reached its theoretical efficiency limit or it can still be improved further. In practice, it can be considered whether the technology is only tested in the laboratory setting, performed in some private companies, used in a wide range yet with a potential of technology improvement, or has reached its maturity and theoretical efficiency limits (Beccali et al., 2003). The assessment grades can be defined as follows,

Assessment grade:

(1) Technologies only tested in laboratory (Immature);

(2) Technologies only performed in demonstration projects with the goal of experimenting the operating and technical conditions (Poorly mature);

(3) Technologies increasingly applied with the scope of further improvement (Mature);

(4) Technologies that are consolidated and close to the theoretical limit of efficiency (Sufficiently mature).

Safety

Definition: Safety is concerned with the very basis that people who work in the power plant can be guaranteed of safety and the infrastructure will not be damaged. There are two generic safety indicators. One is the specific power generation accidents, accounting for the proportion of total power accidents (PA), and the other is the proportion of casualties by accidents to the total number of casualties (PC) in the previous year. In a hybrid power system, an additive function can be used to calculate PA and PC, i.e., for a hybrid system which includes multiple types of energy resource. An illustrative set of assessment grades can be defined as follows,

Assessment grade:

(1) PA>0.4 or PC>0.4 (Low safety).

(2) 0.4<PA<0.2 and 0.4<PC<0.2 (Medium safety);

(3) PA<0.2 and PC<0.2 (High safety).

Reliability

Definition: The term of reliability has a range of different definitions. A generally reliable power system is able to provide uninterrupted power supply to meet the demand with acceptable quality standards. Power system reliability can be broken down into two basic aspects of system adequacy (or static reliability) and system security (or dynamic reliability). System adequacy relates to the existence of sufficient facilities within the system to generate sufficient energy to satisfy the consumer load demands and to meet the operation constraints of power transmission and distribution (Amjady, 2004). Adequacy is mainly concerned with the static conditions, while security relates to the ability of the system responding to dynamic or transient disturbances or faults arising within the system, which is associated with the conditions where both local and widespread disturbances and the abrupt loss of major generation or transmission facilities can potentially lead to dynamic, transient, or voltage instability of the system (Murray, 2018).

In practice, the static reliability can be measured by the unavailability duration of the system (UDTS), which represents the reliability of equipment based on the mean time to failure (MTTF) of each main component. For example, if UDTS is smaller than 8 days per year, the system will be considered as statically reliable. If UDTS is greater than 8 days per year, it will be considered as statically unreliable.

Assuming that the load level requires the normal reliability of power supply, there are two other reliability indicators: loss of load frequency (LOLF) and loss of load expectation (LOLE). In general, the LOLE of reliable energy system is from 0.1 to 5 days per year. Practical and theoretical research findings can be used as guides for the assessment of system reliability. For example,

(i) Wind and photovoltaic hybrid power generation have excellent complementary benefits;

(ii) If it is only powered by wind power or photovoltaic, the system reliability will deteriorate when the capacity is greater than 500MW;

(iii) When the installed capacity of the hybrid system is small, there is no obvious advantage. Reliability can be improved when the installed capacity reaches a certain level;

(iv) For the hybrid systems, which include wind power, photovoltaic and energy storage, when the proportion of photovoltaic is large, the change in energy storage capacity has a high impact on system reliability;

(v) When the installation capacity of a system is less than 400MW, the access to renewable energy can alleviate the insufficient power supply of the system, reduce the probability of extreme conditions, and improve the reliability of the system. When the capacity is more than 400MW, the impact on system reliability is related to the access point by which the DE system is connected to the national grids.

Self-sufficiency

Definition: The degree of self-sufficiency can be measured by the ratio between the total generation capacity of a system and the maximum load of consumption. Taking into account the characteristics of DE systems and micro-grids, the optimal situation is that the total power generation can meet demands and consumed by local load. Therefore, an ideal range of 0.8-1.0 is given on this criterion.

4.3.2 Economic criteria

Investment cost

Investment cost of DE systems comprises of all costs relating to the purchase and installations of mechanical equipment, engineering services, construction of roads and connections to the national grid (Wang et al., 2009). Further operation and maintenance costs are not normally counted into investment costs. Investment cost is the most commonly used economic criteria to evaluate DE systems.

Operation and maintenance cost

Operation cost includes employees' wages and the funds spent for energy, products and services associated with the operation of an energy system. Maintenance cost is used to prolong energy system life and avoid failures. Maintenance cost is much less than the financial losses incurred from the failure of an energy system and maintenance also increases the credibility and confidence index of an energy system.

Payback period

Payback period means the time period needed to repay the lump sum of investment back to the investors. This criterion is usually used to assess the profitability. From a financial perspective, investors always favour projects with short payback periods over those with longer ones.

Service life

Service life is the expected lifetime for a system that can be functional properly, i.e., how many years the system can be on its service. Normally, service life is featured as a U-curve. At the beginning period of the system, it is more likely to fail, before the system reaches a stable condition. Later in the life cycle, the system becomes more likely to fail again. Projects which have a long service life and a short payback period are undoubtedly more competitive in attracting investment.

Construction time

The construction time captures the time from the beginning to the end of constructing an energy system. The length of construction can be somehow considered as the degree of difficulty of implementing the energy system.

4.3.3 Social criteria

Social acceptability

Social acceptability measures the overall opinion related to an energy project primarily by the local population to be affected (Kaya and Kahraman, 2010). It is important since the opinions of the local population and pressure groups may heavily influence the amount of time needed to complete the energy project. The qualitative criterion of social acceptability can be evaluated from surveys or focus group meetings. For example, a rating between -2 and +2 can be used to reflect the population's expected attitude to the occurrence of new power plant technologies in the local region (Brand and Missaoui, 2014). A zero score can be given to technologies on which local population have no explicit preference or local reserved opinions are outweighed by a generally positive reputation of the technology in a wider community. A +2 score is given to the technologies which are widely regarded to have positive impact on the ecosystem and environment, and have no extra cost for the living and no negative effect on the property value.

Social benefit

Social benefit can take into account a range of things, like job creation, tax redemption and income generation, to be brought to the local region by introducing an energy project, especially in less developed regions. This criterion can be recapitulative in the assessment.

4.3.4 Environmental criteria

CO2 emission reduction

CO2 emission reduction is one of the most important considerations for the development of DE systems. It is a quantitative criterion and can be calculated approximately.

Land use (KM2/1000MW)

Every energy power plant needs to use land, which will lead to environmental and landscape change due to the land being occupied by the energy power plant. This criterion could be regarded broadly as a social impact criterion.

Noise

Noise pollution generated from energy power plants can be quite disturbing. Noise can be caused by aerodynamic and mechanical sources, and can be disruptive to animal life as well as human life. Noise pollution not only affects the environment, but also damages human physiological heath, as human can suffer from hearing loss if they are exposed to a very noisy environment for a long time. Noise may also cause operational accidents indirectly.

Sound pressure level can be used to measure noise levels in residential areas (Walker and Jenkins, 1997; Rabe, 2019). This criterion can be measured quantitatively in dB. In general, noise levels must be lower than 45 dB in proximity of residential areas.

Visual impact

Visual impact reflects the visual nuisance that may be caused by the development of an energy project in a specific area (Wang et al., 2009). It is often used to evaluate alternative solar and wind energy plants. The evaluation of the visual impact for alternative DE systems can involve the landscape of different sites, the distance from the nearest observers, the type and size of plants to be installed and the possibility to integrate them with their surroundings.

Renewable penetration

Renewable penetration refers to the percentage of electricity generated by a particular renewable resource (Wu et al., 2019). It can be quantified by the percentage relative to the total amount of electricity either generated or consumed.

4.4 The Evidential Reasoning method

Researchers have used some existing methods such as AHP, TOPSIS and MAUT to support the analysis of MCDA problems in the energy field, but have rarely analysed relationships among criteria, and tested whether the conditions or assumptions can be satisfied so that a MCDA method can be applied to deal with a particular MCDA problem. On the other hand, the information or data of DE system on some qualitative criteria, such as maturity, safety and social acceptability, is uncertain even missing, the above existing method cannot deal with the decision making under uncertain information. The evidential reasoning (ER) approach (Yang & Singh, 1994), a belief distribution-based information aggregation tool, is employed to formulate and aggregate the uncertain information for decision making in DE systems. The main strength of using the ER approach is its capability of describing subjective assessments and handling uncertainties by using the concept of the degrees of belief (Yang & Singh, 1994).

The benefits of using the ER approach compared with other MCDA methods include: a) it allows the quantification of subjective judgements with uncertainty (i.e., incompleteness and fuzziness) by using belief distributions (Yang & Singh, 1994; Yang & Sen, 1994); b) it improves the insightfulness and rationality of decision-making process by using a belief decision matrix for problems modelling and the evidential reasoning algorithm for criterion aggregation (Xu et al., 2006); c) it is developed on the basis of the evidence theory and enables values of qualitative and quantitative criteria be transformed and aggregated with rule-based techniques (Yang & Singh, 1994). Besides, as influence dissemination in the final stage of the proposed model is also mapped into belief spreading and updating, it is believed that the use of the ER approach can not only model both precise and imprecise information but also maintain good continuity (Usher et al., 2013).

Evidential Reasoning (ER) is an assessment distribution by a belief structure. For example, A qualitative assessment that the quality y_q of a product A is assessed to be "Good" or "Excellent" by an equal number (50%) of the customers surveyed, respectively, with no returned assessment below "Average", can be described as the following distribution,

$$S\left(y_q(A)\right) = \{(Bad, 0), (Average, 0), (Good, 0.5), (Excellent, 0.5)\}$$

which is termed as a belief distribution of assessment, with "Bad", "Average", "Good" and "Excellent" given as "assessment grade" and with 0 (0%) and 0.5 (50%) as "belief degree" (relative frequency to which "Good" or "Excellent" is ticked by the customers surveyed in this example).

In ER, a criterion is associated with either a qualitative attribute measured on an ordinal scale, or a quantitative attribute measured on a discrete cardinal scale, termed as a framework of discernment and defined by H as follows:

$$H = \{H_1, H_2, \cdots\cdots, H_N\}$$

Where H_n is an assessment grade on the scale. The assessment of an alternative A is described in terms of a belief distribution $S(A)$ on H, defined by,

$$S(A) = \{(H_1, \beta_1), (H_2, \beta_2), \cdots\cdots, (H_N, \beta_N)\}$$

with β_n defined as belief degree, $0 \leq \beta_n \leq 1$, and $\sum \beta_n = 1$.

β_n can be generated by using the following nonlinear evidential reasoning algorithm (through the use of the Intelligent Decision System – IDS Software in this research):

$$\beta_n = k\left[\prod_{i=1}^{m}\left(\omega_i\beta_{i,n} + 1 - \omega_i\right) - \prod_{i=1}^{m}(1 - \omega_i)\right]$$

$$k = \left[\sum_{n=1}^{N}\prod_{i=1}^{m}\left(\omega_i\beta_{i,n} + 1 - \omega_i\right) - N\prod_{i=1}^{m}(1 - \omega_i)\right]^{-1}$$

Here, ω_i is the weight of the criterion i, the marginal value $u_i(A)$ and overall value $u(A)$ of an alternative A can be calculated by the following expectation:

$$u_i(A) = \sum_{n=1}^{N}\beta_{i,n}u(H_n) \qquad u(A) = \sum_{n=1}^{N}\beta_n u(H_n)$$

Here, $u(H_n)$ is the utility of different assessment grade on the scale. $\beta_{i,n}$ is the belief degree of the criterion i on the assessment grade n on the scale for alternative A. According to the formula, we can get the utility or marginal value of each sub-criteria and top-criteria then the overall performance.

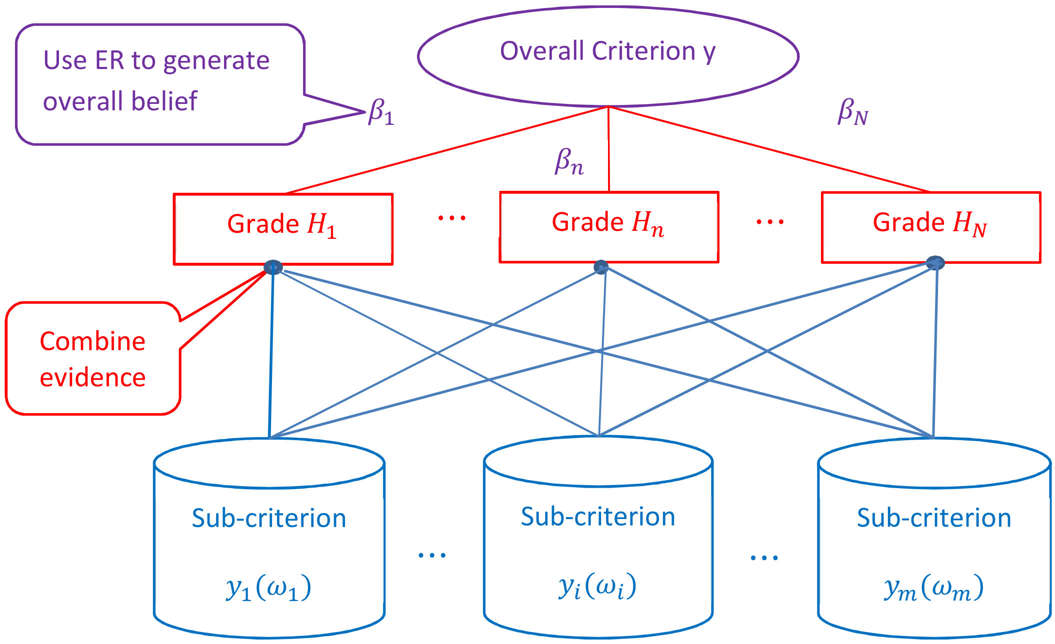


Figure 4-3 Modelling structure and graphic interpretation of ER approach

An alternative A is preferred to another alternative B if and only if $u(A) > u(B)$ (i.e., evidential ranking or preferential ranking). An alternative A is indifferent to another alternative B if and only if $u(A) = u(B)$. It can be shown that $u(A)$ is an strictly-increasing function of $u_i(A)$. The modelling structure of ER method is shown in Figure 4-3.

4.5 A case study of a micro-grid project in an industrial park

In this section, a case study is conducted on a big micro-grid project in Wuxi industrial park in Jiangsu province, China.

4.5.1 Introduction of the case study

It is a hybrid multi-vector renewable energy system which includes photovoltaic, wind, storage and diesel backup. There are four buildings in this area. All of the building roofs have been used to installed solar panels and wind turbines. Due to the intermittent power supply of renewable energy, the battery storage system has been introduced in this hybrid system. The whole system is an intelligent management platform of power utilization so that it cannot only coordinate and integrate multi-vector energies efficiently. On the other side, the distributed power generation can be consumed locally and then reduce the load at peak hours and improve the efficiency of final energy consumption. As to the aspect of future energy policy, it will promote the development of decentralized energy and accelerate the growing of micro gird technology.

The project was initially conducted mainly using experts' knowledge, rather than systematic performance modelling and impact analysis. Based on this case study, multiple stakeholders can directly benefit from these research findings, including policy makers, energy suppliers and consumers, energy network owners, and DE investors and stakeholders in local communities, who have direct interests in the generation, transition and consumption of renewable energy. The project was launched initially for demonstration purpose without performance modelling and decision analysis.

This hybrid distributed energy system includes 400KW roof photovoltaic, 100KW carport photovoltaic, 10KW wind energy, 450KW*2h Lithium-ion battery, 1500KW diesel generators for backup. In order to analyse the performance of different hybrid energy systems and then get the best choice, four different alternatives have been proposed: A1, A2, A3 and A4, where A1 has only 600KW photovoltaic, A2 is a combination system of 500KW photovoltaic and 10KW wind energy, A3 added energy storage into A2, and A4 added another diesel generator for backup.

4.5.2 Data collection

According to the survey data of this project and the assessment framework, the detailed information of each criterion in each alternative is shown in Table 4-1.

Table 4-1 Data information for all criteria in four alternatives

Top criteria	Lower criteria	Unit	A1 (PV)	A2	A3	A4
Technical	Maturity	Scale	[0, 0, 0, 1]	[0, 0, 0.3, 0.7]	[0.5,0.3,0.2, 0]	[0.6,0.3,0.1, 0]
	Safety	Scale	[0,0.1,0.9]	[0,0.2,0.8]	[0,0.3,0.7]	[0,0.3,0.7]
	Reliability	Score	-2	0	1.5	2
	Self-sufficiency		1	1	1	1
Social	Social acceptability	Scale	[0,0.2,0.8]	[0,0.3,0.7]	[0.4,0.6]	[0.35,0.65]
	Social benefit	Scale	[0,0.2,0.8]	[0,0.15,0.85]	[0,0.1,0.9]	[0,0.1,0.9]
Economic	Investment cost	Million £	0.48	0.52	0.93	1.29
	Service life	year	25	25	18	18
	Construction time	month	5	6	8	8
	Payback period	year	6	8	15	18
Environ-mental	Renewable penetration	/	1	1	1	0.95
	CO2 emission reduction	Ton/year	449	580	580	430
	Noise	dB	0	36.5	41.2	44.5
	Land use	0	0	0	0	0
	Visual impact	scale	[0.2,0.6,0.2]	[0.5,0.5,0]	[0.6,0.4,0]	[0.6,0.4,0]

4.5.3 Weight elicitation of assessment criteria

Weights of top-level criteria

There are four top level criteria which include technical, economic, social and environmental. We can use AHP or simple pairwise method to produce the weights. However, we have not got the importance information of each criterion from experts or questionnaire, so at first we directly assign the weights based on the consideration of decision makers and the characteristics of the project itself. Since it is a demonstration project, it aims to promote the development of hybrid multi-vector energy system technologies if it can be operated and managed successfully. Therefore, we will give the highest weight to the technical criterion. On the other hand, given the fact that this system includes renewable energy, with little pollution to the environment compared with those conventional energy sources, so the environmental criterion is regarded as the second important one. The other two criteria are given the same importance. After the assignments, the weights for technical, economic, environmental and social are set to be $W1$=0.45, $W2$=0.15, $W3$=0.15 and $W4$=0.25 respectively, and $W1+W2+W3+W4=1$.

Weights of lower-level criteria

Four top level criteria can be divided into 15 sub-criteria. Maturity, safety, reliability and self-sufficiency are used to support the assessment of the technical criterion. While the economic criterion is divided into four sub-criteria, namely investment cost, construction time, service life and payback period. Renewable energy penetration, noise, CO2 emission reduction, visual impact and land use are related to the environmental criterion. In the last top level social criterion, social benefit and social acceptability are used. In order to generate the weights for these sub-criteria, we also directly assign the weights based on the importance of each criterion according to the stakeholder's opinion. All the weights for different criteria are summarized in Table 4-2.

Table 4-2 Weights of different levels of criteria

Top criteria	Lower level criteria
Technical w_1=0.45	Maturity w_{11}=0.1
	Safety w_{12}=0.1
	Reliability w_{13}=0.5
	Self-sufficiency w_{14}=0.3
Social w_2=0.15	Social acceptability w_{21}=0.5
	Social benefit w_{22}=0.5
Economical w_3=0.15	Investment cost w_{31}=0.2
	Service life w_{32}=0.3
	Construction time w_{33}=0.2
	Payback period w_{34}=0.3
Environmental w_4=0.25	Renewable penetration w_{41}=0.35
	CO2 emission reduction w_{42}=0.35
	Noise w_{43}=0.1
	Land use w_{44}=0.1
	Visual impact w_{45}=0.1

4.5.4 Data processing

After the initial weights are generated, we proceed to the next part of modelling and analysis. MCDA models can be built using the IDS software, with all the weights and data information ready. Although the original data could be used in the IDS, it can be useful to standardize all the data if different software is used in the analysis of the performance of the energy alternatives.

For some qualitative data, they are already standardized within the utility function. For those quantitative data, the standard 0-1 transformation is applied. The idea is quite straightforward for some criteria, where the best value is converted to 1, the worst value to 0, and others to a value between 0 and 1. In other criteria, the utility function is given by piece-wise linear function or other complicated function according to the assessment standard of the criterion itself.

Two types of criteria, including benefit criterion and cost criterion are used in the model. For benefit criterion, a larger value is desirable. On the contrary, a smaller value is favourable for cost criterion. In the assessment of different renewable energy alternatives, there are 15 criteria in total regardless of their assessment levels. The criteria are categorized as follows,

Benefit criteria: maturity, safety, reliability, self-sufficiency, social benefit, social acceptability, service life, renewable energy penetration, CO2 emission reduction, visual impact.

Cost criteria: investment cost, construction time, payback period, noise, land use.

All the data are inputted in the model generated by IDS, and all the utility curves are set to be linear, which means that the marginal utility would be the same within the data range for every criterion.

4.5.5 Results and sensitivity analysis

The sensitivity analysis is widely acknowledged as a critical step in verifying the reliability and accuracy of the model and methodology. The sensitivity analysis here is performed with to determine data (inputs) that contribute most to the output uncertainty and to identify criteria that are most sensitive to the change of weight and have significant impact on the MCDA outcomes.

The assessment results are shown in Figure 4-4 and Figure 4-5, while the sensitivity and trade-off analysis are shown in Figure 4-6 and Figure 4-7. In Figure 4-4, it is shown that A4 is ranked the first which includes PV, wind, battery storage and diesel generator, while A3 is ranked the second which includes PV, wind and storage. From Figure 4-5, the single PV system A1 gets the best performance over the economic criteria. The reason for this is that A1 has the shortest construction time and payback period. However, it has the extremely poor performance in the technical criteria as it has a rather low reliability due to intermittent power generation.

Alternative A4 is a hybrid system and outperforms other systems in the top technical criteria. Given the fact that the weight of the technical criterion is relatively high, a change in the weight of the criterion leads to a change of overall ranking and performances. When the weight of the technical criterion keeps changing, a balance point is found during the process. Similarly, alternative A1 and A2 outperform A3 and A4 in the top economic criteria, but their overall performances are lower than the other two alternatives since the weight of the economic criterion is relatively low. As such a change in the weight of the economic criterion also leads to a change of overall ranking and performance as shown in Figure 4-6. Therefore, the weight of each criterion is very important for MCDA problem, and the generation method needs consider each alternative with specific preferences and judgments from different stake-holders. Different weights affect directly the results of energy system's alternatives.

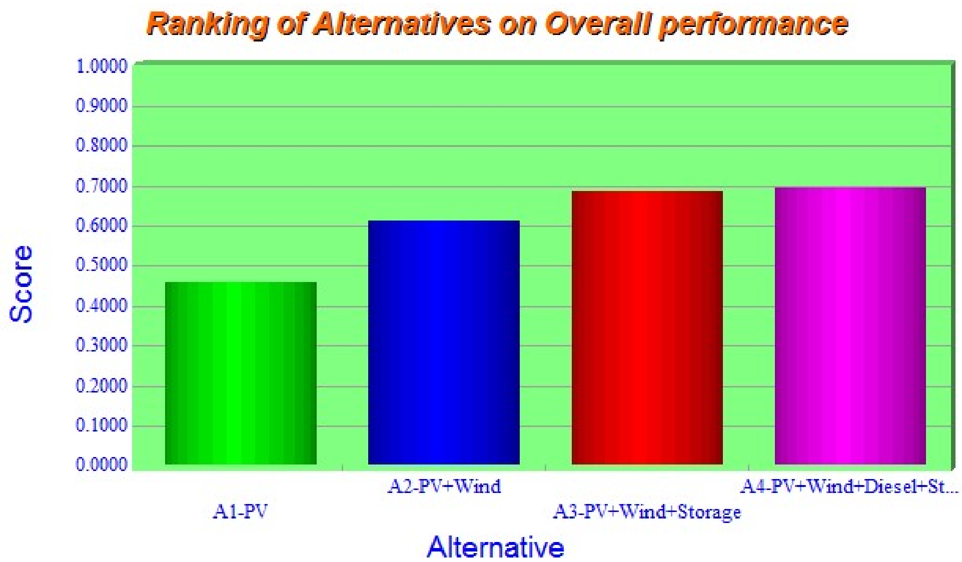


Figure 4-4 The ranking of four alternatives on overall performance

A trade-off is a decision that involves diminishing or losing quality, quantity or property of a criterion or design in return for gains in other aspects (Shackley & McLachlan 2006). In simple terms, a trade-off is where one thing increases and another must decrease. In this case study, a trade-off analysis is conducted between any two different top level criteria or lower level criteria. In Figure 4-7, reliability and economic criteria are selected, and it shows clearly that A1 has a quite high economic performance but rather low reliability, while A4 has very high reliability. Similarly, any other two criteria can be chosen to do trade-off analysis as well. The trade-off analysis is closely related to the preferences of stakeholders.

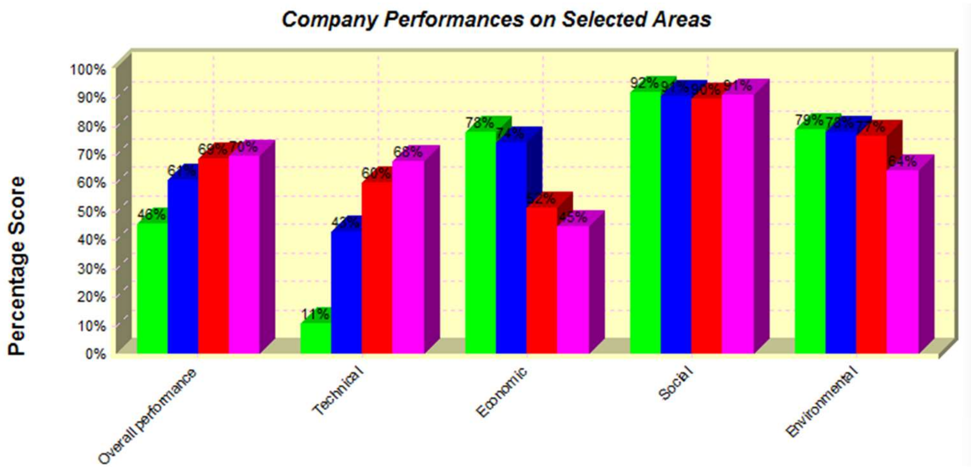


Figure 4-5 The ranking of four alternatives in each top level criteria

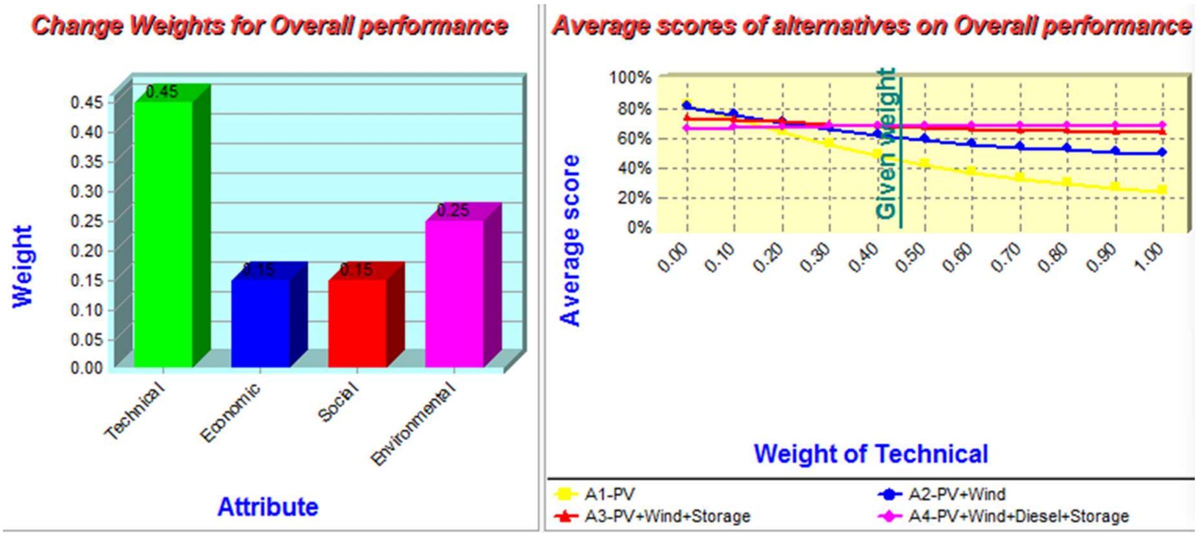


Figure 4-6 Sensitivity analysis of changing the weight of economic criteria

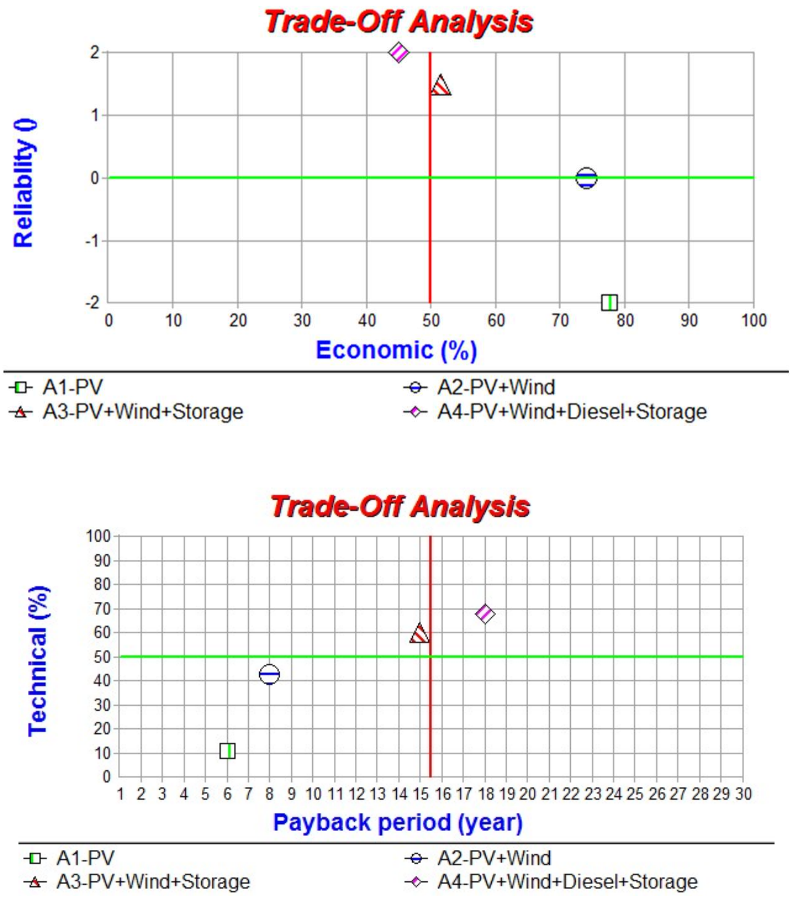


Figure 4-7 Trade-off analysis between economic criteria & reliability, technical criteria and payback period

4.6 Conclusion and discussion

According to the specific nature and characteristics of DE systems, a performance modelling and multiple criteria decision analysis model is presented for multi-vector decentralized renewable energy systems in this chapter. The model was applied to the case study of selecting alternative micro-grid energy systems in an industrial park in China, sensitivity and trade-off analysis was also conducted to validate the decision making process. It also demonstrates how a comprehensive MCDA model can be developed to support informed decision making on the multi-vector decentralized energy system. On the other hand, in most MCDA applications in renewable energy area, the novelty of research is that they just use special methods as mentioned in this thesis to solve MCDA problems. However, the relationships among criteria that govern the conditions or assumptions about whether a specific method can be applied for robust performance analysis are not analysed. In future research, more attention should be paid to investigating how criteria are defined in a comprehensive way, what value or utility functions can be generated and how relationships and dependence among criteria are explained. In addition, more case studies in different decentralized renewable energy systems for a specific region are also needed to justify the proposed assessment model.

Chapter 5 | A Case Study on a Micro-grid Cluster

In recent years, the renewable energies have a fast and efficient development in China. Many large power plants have been built in many areas which have very rich renewable energy resources such as solar, wind and tidy. At the same time, the Chinese government has also transferred the focus of energy strategy on the distributed renewable energy and micro-grid systems.

This large micro-grid cluster project is developed in Inner Mongolia, located at the northwest of China, where is rich in wind and solar energy resources. At the same time, the planning area has vast land resources, which makes it suitable for the development and construction of a large cluster of micro-grid power supply. The cluster of 7 micro-grid projects are planned with a total installation capacity of 2.535 GW. Among them, the installed capacity of wind power is 1.82 GW, photovoltaic is 565MW, and solar heat is 150MW, the energy storage facilities are 160MW. At the beginning of construction, the cumulative power generation units are mostly wind power and photovoltaic, supplemented by appropriate solar thermal and energy storage facilities, and the power supply is constructed according to the principle of distributed power construction. In the later stage of construction, the proportion of solar thermal and energy storage will be further increased, the stability and controllability of power supply will be improved, and a power system suitable for micro-grid operation will be constructed.

In order to further adjust the power supply and demand balance in the micro-grid cluster according to the load characteristics, the micro-grid project after construction will adjust the power load change characteristic curve and integrate the surplus electricity from micro-grid to be consumed through heating. In the plan, the total power consumption of the "one county and five cities” wind power heating system is expected to be 2.133 GWh, the total heat supply is about 768,000 GJ, and the achievable heating area is about 1.33 million square meters.

The plan is divided into three stages. The first stage to 2018 is the micro-grid training period. At this stage, according to the local load growth, renewable energy cluster power supplies are planned and constructed in a distributed form, and a relatively stable supply and consumption matching operation mode is formed; the second stage will be the construction period of the micro-grid from 2020. It is required to configure the equipment and facilities required for its operation, and establish and improve the micro-grid operation mode; The third phase to 2022 is the joint operation period of the cluster micro-grid, through the construction of the connection line to realize the network operation of each cluster micro-grid, and explore the super large renewable energy micro-grid construction and operation mode.

The wind energy and solar energy resources of each city in the planned area are rich. Among them, the average wind speed at a height of 70m is between 7.2 and 8.3m/s, and the wind power density is between 384 and 528W/m^2. The resource level is between 3 and 4 levels, the total solar horizontal radiation is between 1600 and 1698kWh/m^2, and the sunshine hours are between 2907 and 3341h annually. The solar radiation level is "very rich". When constructing a solar thermal project, the source of water resources needs to be considered. In the region with abundant surface water resources, the abundant surface water can be used as the source of the solar thermal project. In the region where the surface water is relatively scarce, the project will consider selecting the wastewater from the sewage treatment plant as a water source as a water source for solar thermal projects.

Recently, individual DE system has been constructed for each area of one county and five cities before connected to a big energy network. Every individual DE system is a hybrid system which includes various types of multi-vector energy including solar, wind and storage unit. The entire energy network covering the five regions is a complex hybrid system which includes energy generation, energy transmission and trading.

The research objective in this case study is using the proposed assessment model to analysing the performance of micro-grids in the selected county and cities and giving an example to analyse or improve the performance of other micro-grids and total grid cluster in different criteria and aspects.

5.1 Introduction of the case study

5.1.1 Overview of power market development in planning regions

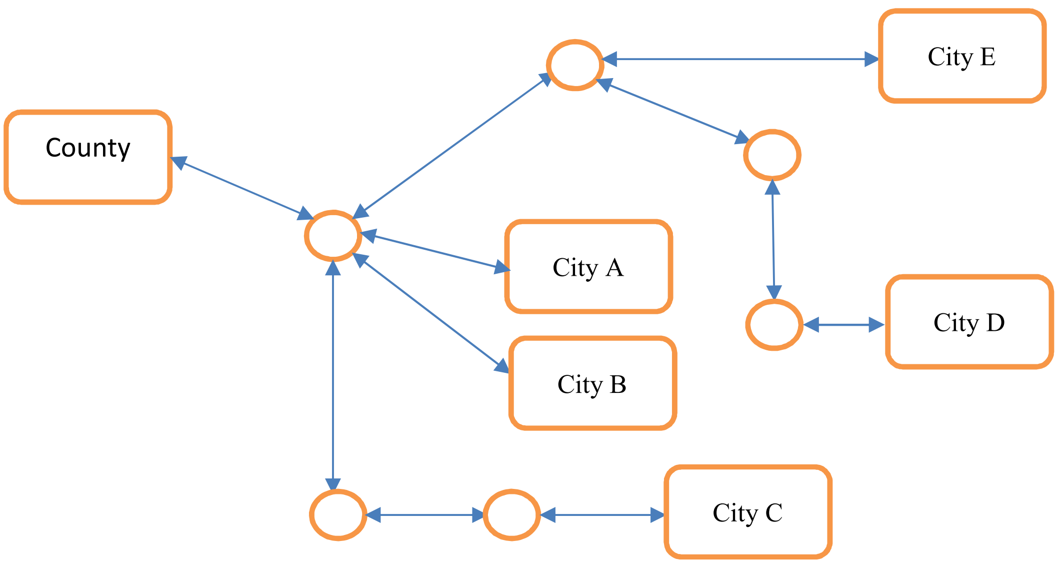


Figure 5-1 The architecture of the micro-grid cluster

By the end of 2015, the total installed capacity of grid-connected power in the planned area was1163.5MW, of which 1073.5 MW for wind power and 90MW for photovoltaic. In 2015, the total electricity consumption of the whole society in the planned area was 1.65954 trillion kwh, an increase of 8.19% compared with 2014, keeping pace with the growth of the entire society's electricity consumption in the autonomous region. The architecture of the micro-grid cluster is shown in Figure 5-1. The electricity consumption of the whole society in each planning region in 2015 is shown in Table 5-1. The comparison of industrial structure and electricity consumption structure in each region in 2015 is shown in Table 5-2.

Table 5-1 Total electricity consumption of in each planning region in 2015

Planning region	total electricity consumption in 2015 (MWh)
The county	326220
City A	637660
City B	111740
City C	231770
City D	174800
City E	177350

Table 5-2 Industrial structure and electricity consumption in each region in 2015 (%)

Planning region	Industrial structure (1/2/3) (%)	Electricity consumption (%)
The county	0.6/39.3/60.1	0.36/47.49/18.04/34.11
City A	9.1/67.2/23.6	0.14/88.66/6.88/4.33
City B	12.4/68/19.6	1.42/76.87/11.75/9.87
City C	6.7/76.9/16.4	0.34/89.39/7.19/4.59
City D	17.5/51.8/30.7	0.74/81.22/8.78/9.15
City E	12.5/73.2/14.3	0.08/87.58/3.64/8.57

(1: primary industry; 2: second industry; 3: tertiary industry)

5.1.2 Electricity consumption forecast of the whole society in the planned area

The load demand forecast of North Inner Mongolia Power Grid mainly adopts the elasticity coefficient of electricity and the time series method. In this planning process, due to the lack of data samples, the electricity market demand forecast mainly adopts the elasticity coefficient of electricity. The elasticity coefficient reflects the relative amounts of economic growth and electricity consumption growth. Elasticity coefficient of electricity consumption is the ratio of annual growth rate of electricity consumption to the GDP growth rate.

According to the local economic development speed and elasticity coefficient of electricity, the total social power consumption in the planned area will reach 5775140MWh by 2020. The average growth rate from 2015 to 2020 is from 9.5% to 19.5%, and the growth rate of the total social power consumption in each region is from 10% to 36%. The forecast of total electricity consumption growth in 2020 is shown in the Table 5-3.

Table 5-3 Forecast of total electricity consumption growth of each region in 2020

Region	Elasticity coefficient	Average annual growth rate of GDP (%)	Electricity consumption growth (%)	Total electricity consumption in 2020 (MWh)
County	1.3	13	17	960098
City A	1.5	12	18	2028636
City B	1.2	30	36	969992
City C	1.0	10	10	466181
City D	1.2	15	18	571214
City E	1.4	17	24	779019

In addition to the natural growth of small and medium-sized industrial projects, the load of newly added large industrial power projects accounted for more than 44% of the maximum power load in 2020. The planned area belongs to the post-development area, and the base of power load is small, the load of large industrial projects is an important component of electricity load. The maximum utilization hours will be in an upward trend, with an average annual increase of 1% to 9%.

Table 5-4 Statistics on the maximum load utilization hours in the planning area and the maximum electricity load forecast

Region	Total electricity consumption in 2020 (MWh)	Maximum load utilization hours in 2015 (h)	Maximum load utilization hours in 2020 (h)	Maximum electricity load (MW)
County	960098	4660	6300	152
City A	2028636	4568	7100	286
City B	969992	4139	6950	140
City C	466181	5038	7400	63
City D	571214	4772	6800	84
City E	779019	4158	7600	103

The electricity load of each region in this plan has its common characteristics and also shows considerable differences between regions. Among them, the electricity load of industrial production has local characteristics due to the economic structure and industrial characteristics of each region. According to the load status, power consumption status of the whole society, GDP, industrial structure status and forecast provided by the district, the planning situation of industrial park enterprises under the jurisdiction of each city, the power elasticity coefficient method is used to predict and analyse the load characteristics of each area planned. Combine the load forecasting of the "one district and five cities" in the planned area in 2022, the load forecasting of the joint operation shows that the time period of 0: 00 ~ 6: 00 is the period of low power load. The load gradually rises at 7:00, 11: 00 ~ 12: 00 and

14: 00 ~ 15: 00 is the peak period of electricity load, and it shows a slow downward trend from 18: 00 ~ 23: 00.

5.1.3 The installed capacity and planning of micro-grid

According to the load forecast and the simulation of wind power, photovoltaic, solar thermal and energy storage facilities, by 2022 the integrated development and construction of renewable energy system has the capacity of 2.535 million kW in total, of which wind power is 1.82 million kW, photovoltaic power is 565,000 kW, and solar thermal power is 15 million kW, 10,000 kW, supporting energy storage facilities of 160,000 kW, cluster micro-grid power. The capacity and planning of each area by 2022 is shown in Table 5-5.

Table 5-5 The capacity and planning of each area by 2022

Region	Wind energy (MW)	Photovoltaic (MW)	Solar thermal (MW)	Energy storage (MW)	In total (MW)
County	280	90	50	30	420
City A	720	110	100	40	930
City B	280	125	0	40	405
City C	140	40	0	20	180
City D	170	50	0	30	220
City E	230	150	0	0	380
In total	1820	565	150	160	2535

According to the planning area, each city has different capacities of wind power, photovoltaic, solar thermal and energy storage. By analysing the technical characteristics of ratios among different renewable energies, it can be determined the best capacity of each city. According to the optimal ratio of distributed energies, economic feasibility and benefit balance and evaluation of all criteria, the most optimal construction of big cluster distributed energy systems can be identified.

According to the current technology maturity and investment profile of wind power, photovoltaic, solar thermal and energy storage projects, the unit kilowatt investment of wind power is $1100, which is the lowest. The highest investment of solar thermal is $3500/kW, and the investment per kilowatt of photovoltaic projects is in the middle at $1400/kW, energy storage depends on different power sources, and its unit kilowatt investment is about $1100. The difference in energy storage investment and the price of solar thermal power has reproducible energy storage and solar thermal projects for each region. Through comparative analysis of the regulations, the economic evaluation conclusions of distributed power projects in each cluster in the planned area, the best energy storage investment and solar thermal power prices are balanced for the economic benefits and the financial internal rate of return of capital is over 11%. The economic benefit analysis of each banner city in the specific planning area will be considered with other criteria in our assessment model.

5.2 Data collection and analysis of different criteria

5.2.1 Data collection and analysis of technical aspect

By 2022, the installed capacity of clustered micro-grid power supply will reach 2.535 million kW, and the energy storage capacity will reach 160,000 kW. The local electricity load and clustered micro-grid power supply will reach a certain scale. According to the power supply and load situation in each area, the construction of relatively complete regional distributed power sources will be as a priority strengthened and transformed in accordance with the requirements of the micro-grid, and then establish and improve the micro-grid operation mode.

This clustered micro-grid is a grid-connected micro-grid, which can be not only connected to the external power grid but also can be run as a pre-designed island. It can be operated independently when the external power grid fails or is disconnected from the external grid when needed. The integrated control network distributes power generation and energy storage system to maintain the power supply of all or part of the important electrical loads. The micro-grid is generally connected to the upper-level grid at a Common Connection Point (PCC), and the demarcation point can be set at the connection line breaker at the outlet of the micro-grid.

Distributed power generations connected to the micro-grid mainly include renewable energy systems such as photovoltaic, solar thermal, and wind energy. As an important part of the micro-grid, the energy storage system can play an important role in regulating grid fluctuations and increasing system inertia. Energy storage systems with different characteristics and different scales can be planned and constructed on the distributed power supply side, the appropriate location of the micro-grid, and the load side. Considering the maintainability of the system, a flow battery energy storage system suitable for large-scale energy storage applications is recommended. The solar thermal power generation system has energy storage characteristics, and an appropriate proportion of energy storage facilities should be configured according to the local electricity load.

For the micro-grid group, a dedicated control system will be configured. Different from the traditional power monitoring system, the micro-grid control system should also include new energy generation forecasting functions, load forecasting functions, and micro-grid energy management systems. It will comprehensively dispatch distributed power generation, energy storage, and controllable loads in the micro-grid, adjust the energy exchange capacity with the superior grid, and ensure safe, reliable, and economical power supply in the micro-grid.

In the normal operation mode, the regional micro-grid group is connected to the main network to accept the predetermined order from it and control the exchange power with the main network. The concentrated solar power (CSP) system of the main micro-grid is used as the standard voltage source for the integrated micro-grid in the entire area to realize the voltage support for the micro-grid, and cooperate with the energy storage to instantly compensate the power difference, so that it can maintain the system power balance and seamlessly transfer to the isolated network operation mode.

The sub micro-grid and the upper-level micro-grid, the main micro-grid and the main network interface are all connected through a fast PCC switch that can be quickly inserted. The internal loop configuration of the micro-grid can realize the self-adaptive microcomputer protection when operated as the grid-connected mode or isolated network. When there is an internal or external fault in the micro-grid, the PCC switch isolates quickly to avoid the mutual influence between the main grid and the micro-grid in the event of a failure. At the same time, it can achieve rapid isolation and avoid the change of the fault characteristics of the main network so that the relay protection configuration and the overall delimitation of the fixed value of the main network are not affected by the micro-grid access, and the configuration can be maintained without any change resulting from the reception of the micro-grid.

Micro-grid group joint operation mode: As the power load and power supply in micro-grid group reach a certain scale, in order to improve the utilization rate of renewable energy in each cluster and the reliability of the system and achieve mutual aid between cluster power supplies and load areas, the integrated system can realize the network operation of each cluster micro-grid through the connection line at the right time, and explore the construction and operation mode of the ultra-large renewable energy micro-grid. By comparing and analysing the output characteristics and load characteristics of each distributed micro-grid power supply, those distributed systems with close geographical locations and complementary power output and load can be networked to make the internal power supply to realize integrated operation with the load in a larger range, and smoothly connect to the main network through coordinated control or operate independently and autonomously to further meet the user's requirements for power quality, power supply reliability and safety.

5.2.2 Data collection and analysis of environmental aspect

The impact of project development on the ecological environment is mainly during the construction period. The disturbance of the ground surface and the destruction of surface vegetation caused by construction activities will make soil erosion and further aggravate the deterioration of the local ecological environment. The construction period of the project is relatively short, and water and soil conservation and ecological protection are adopted during the construction process with strict implementation of construction environmental supervision, the impact on the ecological environment should be controlled within the acceptable level.

The ecological impacts during the operation period mainly include the operation of wind turbines in wind power, possible light pollution in photovoltaic power generation, and the impact of transmission lines on birds. The reflection of solar panels on sunlight is mainly scattering and its total reflectivity is only about 25%, so the light pollution has little effect on birds. The construction area is not on the bird migration channel, therefore, the construction of a solar-wind-storage joint power generation project in this area has also little impact on bird populations and habitats.

Sprinkle water on the construction site can suppress dust. Sprinkling water 4 to 5 times a day can effectively control construction dust and reduce the TSP pollution distance to the range of 20-50 meters. In addition, in order to control the impact of vehicles loaded with goods on the outside of the construction site, water can be sprayed on the corresponding parts of the vehicle body to remove sludge and dust when the vehicle leaves the construction site to reduce the impact of dust on the outside world. Another case of construction dust is the open-air stacking and mixing of building materials. The main feature of this type of dust is affected by the wind speed during operation. Therefore, prohibiting such operations on windy days and reducing open-air stacking of building materials are effective means to suppress such dust. In addition, in the process of transportation, loading and unloading building materials, civilized construction and civilized management should be carried out to avoid or reduce the generation of dust as much as possible to prevent dust pollution in the regional ambient air. After the prevention and control measures of construction dust are taken, dust pollution can be effectively reduced and the working environment of the construction site can be improved. The construction period is short, and dust hazards can be minimized by taking preventive measures.

During the construction period, the acoustic environment impact time and scope are limited, there are no environmentally sensitive points around the construction area, and construction noise has little impact on the acoustic environment. During the operation period, the contribution of the fan operating noise and the operating noise of the booster station's main transformer is small, and will not have a significant impact on the surrounding acoustic environment.

Minimizing construction noise and strengthening the management of construction units can effectively reduce the impact of construction noise. The wind turbine can be selected as soundproof and shockproof type, the variable speed gearbox is of noise reduction type, and the blades are decelerating blades. The transformer in the booster station is of low noise and low loss equipment. Such measures above can effectively reduce operating noise.

The direct discharge of waste and sewage during construction and operation will have an impact on the water environment and ecological environment. After reasonable sewage treatment measures are taken, it can be discharged or recycled up to the standard to reduce the impact on the water environment and ecological environment. Collect and treat construction production wastewater and domestic sewage separately and set up domestic sewage treatment facilities during the operation period of the wind-solar storage joint power generation and power supply project to ensure compliance with discharge. Solar panel mirror flushing drainage needs to consider the source of flushing water and the corresponding disposal measures.

The wind, solar, and storage joint power generation and supply project uses clean energy to generate electricity, does not produce smoke pollutants and solid waste, reduces environmental pollution, and has significant environmental benefits. The main impact of the project on the environment is on the ecological environment. The ecological environment of the construction area is fragile. In addition to the large area of the project, construction activities should trigger and aggravate soil erosion and accelerate the degradation of the ecological environment. Reasonable and effective environmental protection measures must be taken to ensure that the project construction brings eco-environmental impacts are within acceptable levels of the environment and will not have a major impact on the integrity of the ecological environment and biodiversity. On this basis, preliminary analysis from the perspective of environmental protection shows that the construction of the project is feasible. The planning and construction of the project have avoided the environmentally sensitive areas which include nature reserves, scenic spots, natural heritage sites, drinking water source protection areas, basic grasslands, important wetlands and collected the construction views to protect photovoltaic from some relevant departments.

The planned installed capacity of this project is 2.535 million kilowatts, and the total annual power generation is 5935500MWh. Based on the 330g standard coal consumption per kWh of thermal power, 1958715t standard coal can be saved annually. The development and utilization of renewable energy can not only reduce coal consumption, but also reduce many environmental problems caused by the development of non-renewable energy. In accordance with the emission standards of various exhaust gas and waste residues of thermal power plants: smoke and dust is 0.4g/kWh, SO2 is 2.3g/kWh, CO2 is 822g/kWh, and ash is 119.45g/kWh, this project can reduce annually the emission of smoke and dust is about 2374.2t, SO2 is about 13651.65t, CO2 is about 4878981t, and ash is about 708995.48t, which can also save a lot of water resources and avoid noise impact.

5.2.3 Data collection and analysis of social aspect

This planned project not only has obvious environmental and energy-saving benefits, but also with the construction of the project, a new human landscape will appear in this area, which will improve the appearance of the area, beautify the environment, and will have a positive effect on soil and water conservation enhancement.

Since solar energy and wind energy are renewable energy sources that do not consume fossil fuels, the use of solar and wind power generation is equivalent to saving the same amount of fossil fuels required for electricity, which can reduce the amount of primary energy such as coal, oil, and natural gas, while saving a lot of water resources. In addition, the production process of solar and wind power plants is the process of converting local energy resources into electrical energy. During the entire process, no air, water, solid waste and pollutants are generated, and no loud noise pollution is generated. Therefore, solar and wind power generation projects can not only bring considerable economic benefits, but also social and environmental benefits, coupled with the country's strong support for the development of renewable resources and preferential policies, the solar energy utilization industry has huge potential and optimistic development prospects. Therefore, after the completion of the project, it will not only provide electricity, reduce pollution and save resources, but also has positive social and environmental significance. It also has the ability to pay debts as the financial internal rate of return of capital is relatively good. The project has economic, social and environmental benefits to be possibly constructed.

5.2.4 Data collection and analysis of economic aspect

The planned investment level is 2015. Among them, the static investment per kilowatt for wind power is $1100/kW, the static investment per kilowatt for photovoltaic projects is $1400/kW, and the static investment per kilowatt for solar thermal projects is $3400/kW. The static investment per kilowatt of energy storage is $1100/kW, and the static investment per kilowatt of the wind power heating project is $300/kW.

Table 5-6 The installed capacity of county and five cities

Area	solar thermal	Photovoltaic	wind power	Storage	wind heating
County	50	90	280	30	20
City A	100	110	720	40	40
City B	0	125	280	40	30
City C	0	40	140	20	20
City D	0	50	170	30	25
City E	0	150	230	0	28
In total	150	565	1820	160	163

The planned installed capacity in the area is 1820MW for wind power, 565MW for photovoltaic power, and150MW, energy storage 160MW, and wind power heating 163MW. Installed capacity of county and each city is shown in Table 5-6.

The total static investment of this plan is $3509.4 million, among them , the investment for solar thermal is $510 million, photovoltaic is $510 million, wind power is $1950 million, energy storage is $180 million and wind heating is $46.6 million respectively.

The operation period of wind power projects is 20 years, and the on-grid price is $0.07 /kWh; The operation period of photovoltaic is 25 years, the on-grid price is $0.13/kWh for the first 20 years, and 5 years after this period is $0.043/kWh; the operating period of the solar thermal project is 25 years, and there is no specific electricity price for this. The price $0.14/kWh is calculated as economic benefits. The operating period of the energy storage project is 20. In 2015, the on-grid electricity price was $0.07/kWh, and the operation period of the wind power heating project was 20 years and the electricity price is $0.06 /kWh, and the heat-sale equivalent electricity price is $0.01/kWh. The financial index of the county and each city are shown in Table 5-7.

The planning area has rich wind and solar resources. The wind resources are all above level 3, and the equivalent utilization time is more than 2362h per year. The solar resources are all rich and stable in distribution. The service life of photovoltaic projects are 25 years and the average equivalent utilization hours are more than 1400h, and the average annual equivalent utilization hours of solar thermal projects are about 2500h, which is suitable for large-scale development and construction of wind power and solar projects.

The site selection of this planning project does not involve land types such as overlying minerals, culture protection, basic farmland, forest land, and meets the construction land requirements of various renewable energy power sources in the renewable energy cluster power source. At the same time, it is relatively far from the load concentrated area, it is conducive to the local consumption of renewable energy power supply, while improving its economy.

Table 5-7 The key financial indexes of the county and each city

Area	IRR for investment (after tax %)	Payback period (year)	Payback period for equity (year)	Rate of Return (%)	Net profit ratio (%)
County	7.31	11.52	13.88	5.17	14.11
City A	7.02	11.53	13.89	5.08	13.75
City B	7.45	11.01	11.92	5.32	14.70
City C	7.61	10.89	11.47	5.42	15.08
City D	7.67	10.86	11.29	5.52	15.50
City E	7.75	10.80	11.12	5.57	15.67

According to the distribution of wind energy and solar energy resources in each region and its load forecast, the renewable energy cluster power will reach 2.535 million kW by 2020, and energy storage facilities will reach 160,000 kW, of which wind power is 1820,000 kW, photovoltaic 565,000 kW and solar thermal 150,000 kW.

Through the economic evaluation of the renewable energy cluster power supply in each planned area, the sensitivity analysis of solar thermal power price and energy storage investment, it can be obtained that when the solar thermal power price is $0.18/kWh and the energy storage investment is $1140/kW, the economics of renewable energy cluster projects are basically balanced, and the internal rate of return of capital has reached more than 11%, and the economy is good.

5.3 The Case study based on IDS

5.3.1 Data processing and weight elicitation

The assessment model for the two cases in Chapter 4 and Chapter 5 is identical, but the data collection of each criterion and the weights are different which were collected from different decision makers and experts.

According to the different renewable energy resources, one county and 3 sub-cities (city A, city D and city E) have been chosen to represent different micro-grid systems. The constructed assessment framework is shown in Figure 5-2, and the data collected on each criterion is represented in Table 5-8.

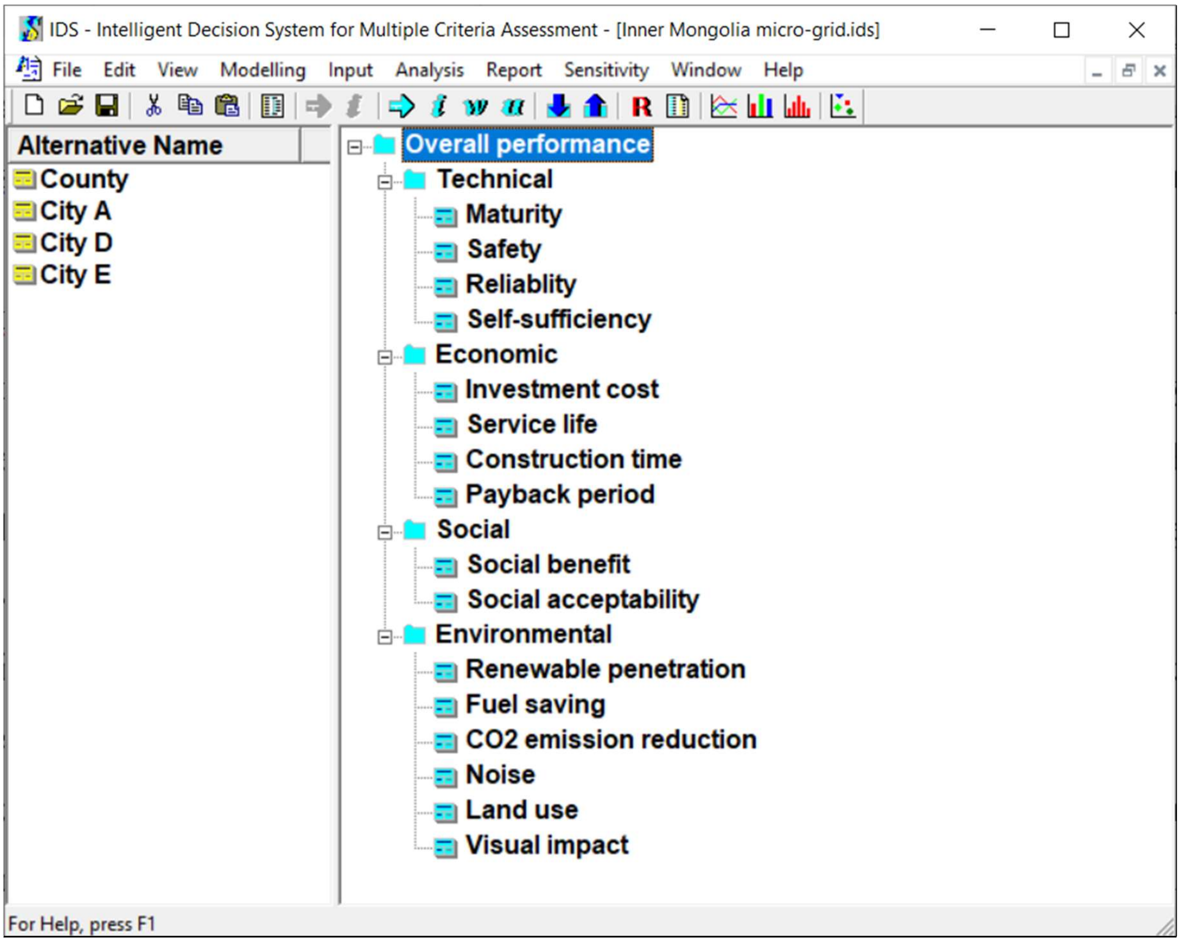


Figure 5-2 Assessment framework of micro-grids in Inner Mongolia

Table 5-8 Data collection of the county and sub cities

Top criteria	Lower criteria	Unit or grades	County	City A	City D	City E
Technical	Maturity	[worst, poor, average, good]	[0,0.2,0.2,0.6]	[0, 0.2, 0.2, 0.6]	[0,0,0.2,0.8]	[0,0,0,1]
	Safety	[low, medium, high]	[0,0.1,0.9]	[0,0.2,0.8]	[0,0.3,0.7]	[0,0.3,0.7]
	Reliability	[low, medium, high]	[0,0,1]	[0,0,1]	[0,1,0]	[0,1,0]
	Self-sufficiency	[0,1]	0.3	0.2	0.25	0.35
Social	Social acceptability	[low, medium, high]	[0,0.2,0.8]	[0,0.3,0.7]	[0, 0.4,0.6]	[0.35,0.65]
	Social benefit	[low, medium, high]	[0,0.2,0.8]	[0,0.15,0.85]	[0,0.1,0.9]	[0,0.1,0.9]
Economic	Investment cost	Million £	487.6	505.7	400.5	349.9
	Service life	Year [18,25]	20	20	22	23
	Construction time	Month [36,60]	60	60	48	36
	Payback period	Year [10,12]	11.74	10.89	10.86	11.01
Environmental	Renewable penetration	[0,1]	1	1	1	0.95
	CO_2 emission reduction	Ton/year	808206	885178	904422	779342
	Noise	dB	50	48.5	49	44.5
	Land use	Km^2	130	126	80	104
	Visual impact	[negative, neutral, positive]	[0.2,0.6,0.2]	[0.2,0.6,0.2]	[0.6,0.3,0.1]	[0.6,0.4,0]

There are four top-level criteria, which include technical, economic, social and environmental dimensions. At first, we designed a questionnaire to collect the information about criteria and their weights from 20 corresponding experts and decision makers. The questionnaire has been attached in the Appendix I. The weights of top criteria and sub criteria are calculated as the average score of each criterion. After the data processing of surveys, the weights for technical, economic, environmental and social criteria are set to be $W1$=0.45, $W2$=0.15, $W3$=0.15 and $W4$=0.25 respectively, and $W1+W2+W3+W4=1$.

Table 5-9 Weights of different levels of criteria

Top criteria	Lower level criteria
Technical $\boldsymbol{W_1 = 0.4}$	Maturity $\boldsymbol{W_{11} = 0.1}$
	Safety $\boldsymbol{W_{12} = 0.1}$
	Reliability $\boldsymbol{W_{13} = 0.5}$
	Self-sufficiency $\boldsymbol{W_{14} = 0.3}$
Social $\boldsymbol{W_2 = 0.15}$	Social acceptability $\boldsymbol{W_{21} = 0.5}$
	Social benefit w_{22}=0.5 $\boldsymbol{W_{22} = 0.5}$
Economical $\boldsymbol{W_3 = 0.15}$	Investment cost $\boldsymbol{W_{31} = 0.2}$
	Service life $\boldsymbol{W_{32} = 0.3}$
	Construction time $\boldsymbol{W_{33} = 0.15}$
	Payback period $\boldsymbol{W_{34} = 0.35}$
Environmental $\boldsymbol{W_4 = 0.3}$	Renewable penetration $\boldsymbol{W_{41} = 0.4}$
	CO2 emission reduction $\boldsymbol{W_{42} = 0.3}$
	Noise $\boldsymbol{W_{43} = 0.1}$
	Land use $\boldsymbol{W_{44} = 0.1}$
	Visual impact $\boldsymbol{W_{45} = 0.1}$

Four top level criteria can be divided into 15 sub-criteria. Maturity, safety, reliability and self-sufficiency are from technical criteria. While in the economic criteria, it is divided into four criteria, namely investment cost, construction time, service life and payback period.

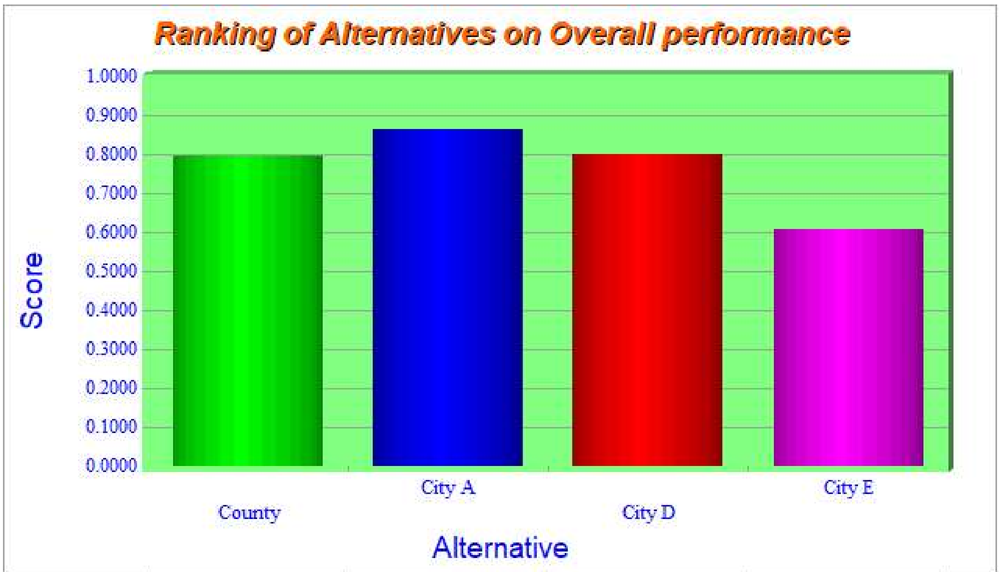
Renewable energy penetration, noise, CO2 emission reduction, visual impact and land use are belong to the environmental criteria. In the last top level social criteria, social benefit and social acceptability are used. In order to generate the weights for these sub-criteria, we also elicited the weights based on the importance of each criterion according to the stakeholder's opinion. All the weights for different criteria were summarized in Table 5-9. Although the size of the survey for weight production is small, but the importance of each criteria can be adjusted in IDS when it is needed to change in different situations. It indicates that this assessment model and software have a good versatility in system evaluations.

After the initial weights are generated, the next step is to perform modelling and analysis. A MCDA models can be built using the IDS software. Similar to the case study in Section 4.5, qualitative and quantitative data, and benefit and cost criteria should be transformed accordingly.

5.3.2 Result and sensitivity analysis

The assessment results are shown in Figure 5-3 and Figure 5-4. The sensitivity and trade-off analysis are shown in Figure 5-5, Figure 5-6 and Figure 5-7. In Figure 5-3, it is shown that City A is ranked the first which includes solar thermal, photovoltaic, wind, storage and wind heating while County and city D are nearly the same ranking but city D does not include solar thermal in the system. From Figure 5-4, City E gets the best performance over the economic criteria. The reason for this is that City E has the shortest construction time and investment cost. However, it has the extremely poor performance in the technical criteria as it has a rather low reliability and the technical criteria have more importance than the economic criteria. Therefore, the ranking of overall performance is affected by multiple factors which is also indicated by the following sensitivity analysis.

City A is a hybrid system and outperforms other systems in the top technical criteria. Given the fact that the weight of the technical criterion is relatively high, a change in the weight of the criterion leads to a change of overall ranking and performances. When the weight of the technical criterion keeps changing, a balance point is found during the process. Similarly, City D and City E outperform County and City A in the top economic criteria, but their overall performances are lower than the other two alternatives since the weight of the economic criterion is relatively low. As such a change in the weight of the economic criterion also leads to a change of overall ranking and performance as shown in Figure 5-5. Therefore, the weight of each criterion is very important for MCDA problem, and the generation method needs consider each alternative with specific preferences and judgments from different stake-holders. Different weights affect directly the results of energy system's alternatives. On the other hand, if you change the input data of different criteria, it will also has an effect on the result of ranking of overall performance and other performance in different aspects. However, the sensitivity analysis also provides a solution for us to improve the performance of the system in the future.



	County	City A	City D	City E
Average score	0.7930	0.8635	0.7990	0.6092

Figure 5-3 The overall performance ranking of different alternatives

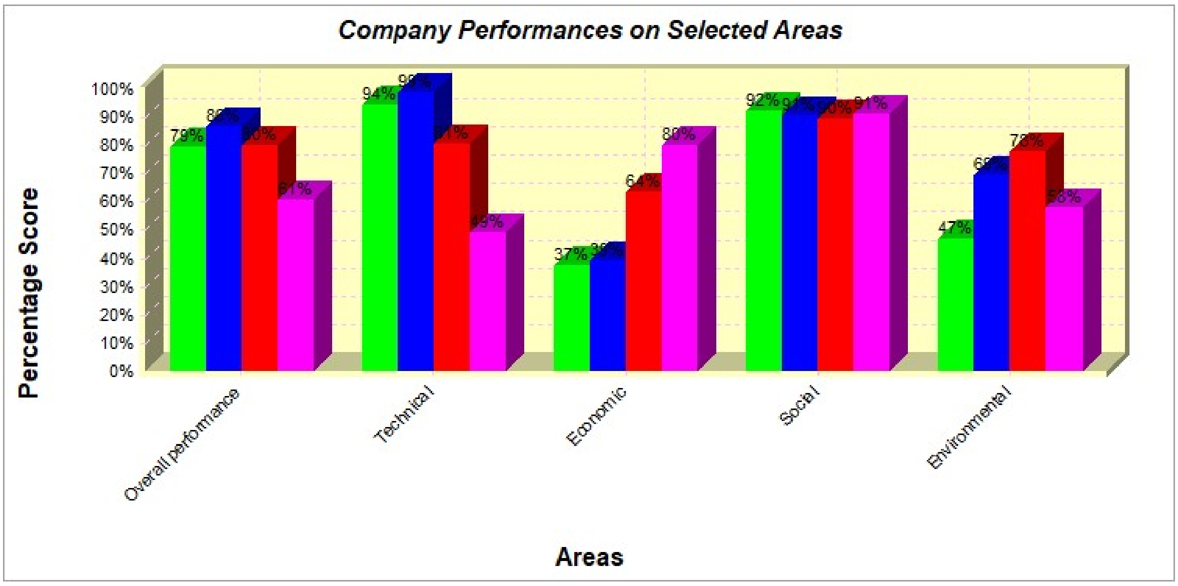


Figure 5-4 The performance on each top level criteria of different alternatives

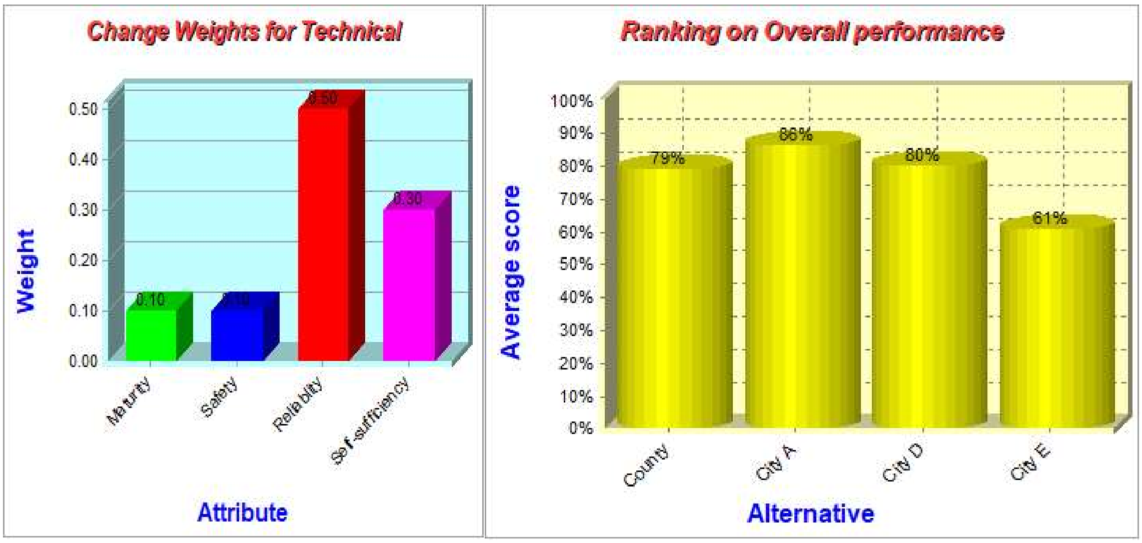


Figure 5-5 Sensitivity analysis of changing the weight of technical criteria

A trade-off is to analyse diminishing or losing quality, quantity or property of a criterion or design in return for gains in other aspects. In simple terms, a trade-off is where one thing increases and another must decrease. In this case study, a trade-off analysis can be conducted between any two different top level criteria or lower level criteria. In Figure 5-6, environmental and economic criteria are selected, and it shows clearly that City D has a quite high environmental performance but low economic performance, while the county has very high safety but rather low CO2 emission reduction. Similarly, any other two criteria can be chosen to do trade-off analysis as well. The trade-off analysis is closely related to the preferences of stakeholders.

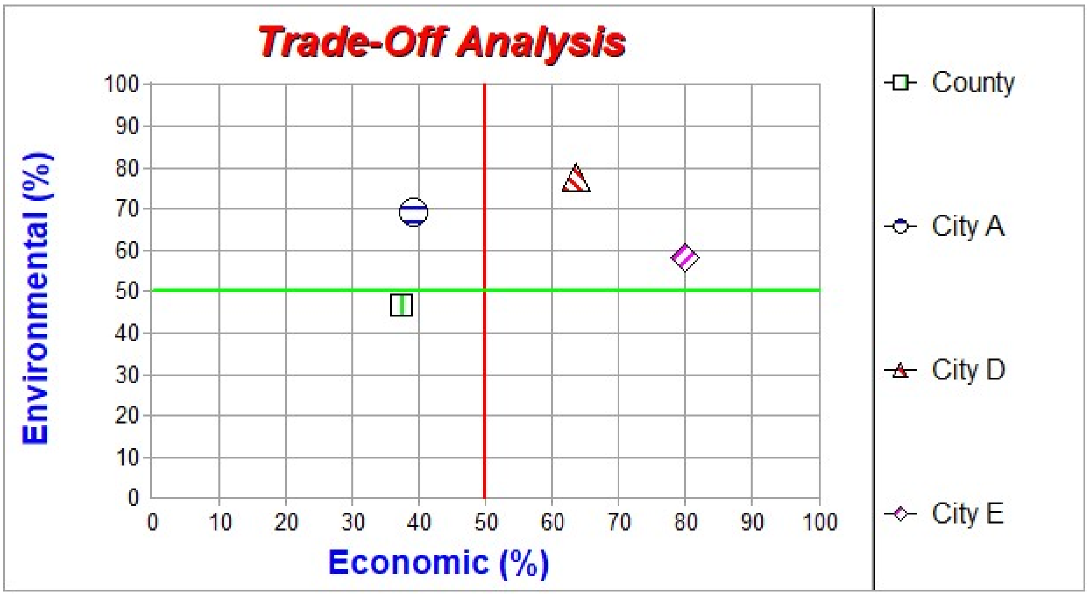


Figure 5-6 Trade-off analysis between economic criteria & environmental criteria

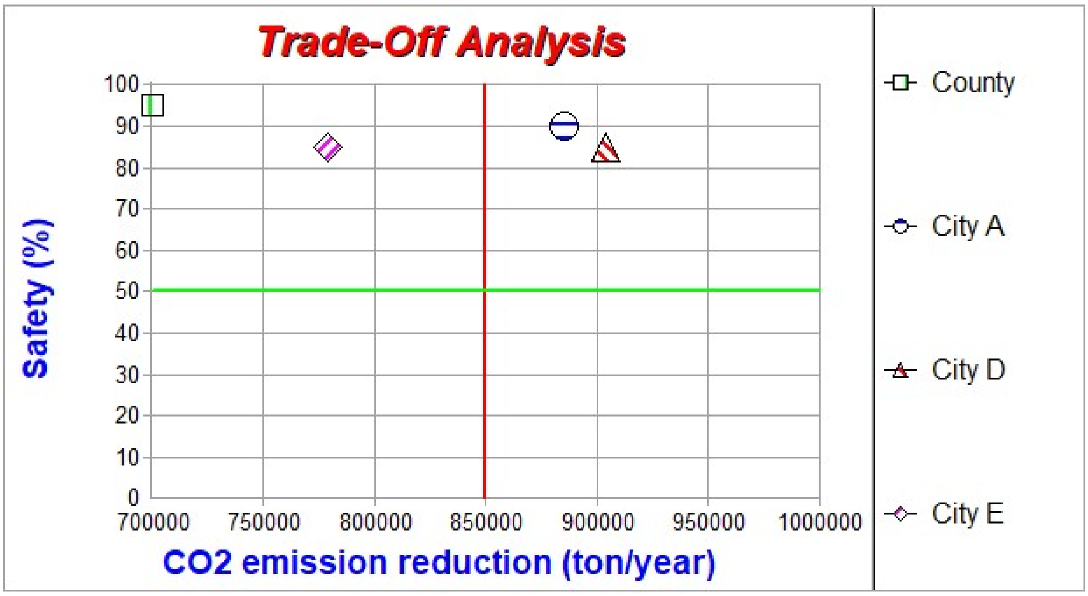


Figure 5-7 Trade-off analysis between safety & CO_2 emission reduction

5.4 Conclusion and discussion

In this chapter, based on the assessment MCDA model proposed in Chapter 3, a case study is conducted on a large micro-grid cluster project in Inner Mongolia, located at the northwest of China in which the DE system has been constructed for each area of one county and five cities before connected to a big energy network. Every individual DE system is a hybrid system, which includes various types of multi-vector energy including solar, wind and storage unit. The entire energy network covering the five regions is a complex hybrid system which includes energy generation, energy transmission and trading. The project was comparing some sub micro-grid energy systems in the big cluster of micro-grids groups, sensitivity and trade-off analysis was conducted to validate the decision making process. It further demonstrates how a comprehensive MCDA model can be developed to support informed decision making on the multi-vector decentralized energy system.

Chapter 6 | Conclusions and Future Work

This chapter provides a summary of the main research contributions of this thesis as well as research limitations and future work.

6.1 Research conclusions

Unlike the traditional centralized energy systems, the main barrier with renewable energy sources in a DE system is its high dependency on environmental conditions like wind speed and solar irradiance. Single renewable energy source in particular wind and solar does not provide continuous power supply due to its uncertain and intermittent nature. This makes it necessary to integrate different renewable energy sources to form a hybrid system for more reliable and environmentally friendly energy supply.

It can first be summarised from the literature review that the performance assessment of DE systems requires the systematic and consistent handling of multiple factors in both quantitative and qualitative nature under uncertainty, and the performance assessment in essence is a multiple criteria decision analysis (MCDA) problem but needs to make use of both numerical data and expert knowledge which involves technical, economic, environmental, and social related criteria.

In Chapter 3, a set of Data Envelopment Analysis (DEA) models are developed to evaluate the energy efficiency on the country level, which considered the gross capital, labour force, renewable energy consumption and non-renewable energy consumption as inputs while considering GDP and CO2 emission as desirable output and undesirable output separately. 8 different DEA models are constructed for solving the energy efficiency in TFEE and PFEE respectively, the different results have also been compared and analysed to find the difference and reasons for the changes. The results demonstrated that most developed countries showed rather higher energy efficiency than most developing countries among 39 selected countries and the gap between them is notable, therefore, the inefficient countries should learn from the efficient ones in terms of experiences, knowledge, and new technologies in order to improve their energy efficiency. Furthermore, the implications of some policy making from the results are also been discussed. It provides a technical route and guidance for the countries with relatively low energy efficiency.

In Chapters 4 and 5, according to the specific nature and characteristics of DE systems and survey data collection from experts and case studies, a performance modelling and decision analysis model is constructed for multi-vector decentralise energy systems with technical, economic, social and environmental aspects. A set of criteria, including maturity, safety, reliability and self-sufficiency as technical criteria, investment cost, O&M cost, payback period, service life and construction time as economic criteria, social acceptability and social benefit as social criteria while considering CO2 emission reduction, land used, noise, visual impact and renewable penetration as environmental criteria, are considered systematically. In the meantime, all the criteria are evaluated in details such as the definitions, assessment grades, independency and the method of weight production, which forms the basis for implementing the performance assessment model to two case studies.

From the MCDA application on the two case studies, it was proved that MCDA can provide comprehensive and reliable analyses for alternative DE systems. The MCDA framework can be used to incorporate multiple-dimensional information in the decision making process of renewable energy selection and planning. Based on the principles of probabilistic inference and evidence-based decision making, the evidential reasoning (ER) approach is suitable for dealing with MCDA problems with various types of uncertainty. It uses a belief structure to represent both quantitative and qualitative criteria, a belief decision matrix to formulate a

MCDA problem under uncertainty, and the ER algorithm to enable probabilistic inference for aggregating multiple criteria to generate overall distributed assessments. it is believed that many stakeholders can directly benefit from these research findings, including policy makers, energy suppliers and consumers, energy network owners, and DE investors and stakeholders in local communities, who have direct interests in the generation, transition and consumption of renewable energy.

6.2 Research limitations and future work

First of all, there is a big efficiency gap between the countries with better performance and those with poor performance from the results of energy efficiency based on DEA models, as only a few inputs and outputs which are widely studied in literature are considered in this thesis. Therefore, it is essential to investigate further whether the energy efficiency is affected by other factors, such as policy-making or environmental aspects. It can be regarded as one of the limitations of this research. Moreover, the energy efficiency score and changing trend are different from the TFEE and PFEE, and the robustness of these differences have not been tested systematically. Therefore, in order to test the robustness of the energy efficiency result, it is necessary to take a sensitivity analysis and other verification in the future research. On the other hand, in the future research, it would be useful to integrate the DEA results and MCDA results to conduct performance planning and improvement holistically and comprehensively.

Secondly, some of the criteria in the proposed performance assessment model might not be suitable for the assessment of some specific DE systems or scenarios. In the selection of criteria, how to choose suitable criteria and make appropriate definitions is a key and difficult issue in the assessment of DE systems. For example, there are many definitions and different evaluation standards for the criterion of reliability in technical aspect, and some of them are related to industrial standards and some others to civil standards. Therefore, it is not easy to make a generic definition and standard of reliability for different DE systems. What's more, the requirements on the criteria of reliability can be different for pre-project evaluation and post-project evaluation. It can also be an issue for some other criteria. Therefore, how to construct an appropriate assessment model for general DE systems with suitable criteria is one of the most important problems in the future research. Moreover, the determination of assessment grades in each criterion is another important issue when building the assessment framework. For example, the range of assessment values could be better defined with a global range for quantitative attributes. The definitions of assessment grades for the qualitative attributes should cover all different scenarios. In addition, different weight elicitation methods can be applied to obtain criterion weights from experts and stakeholders.

Thirdly, the conditions of using the ER approach should be validated rigorously in the research context. As discussed previously, most MCDA applications in renewable energy systems used difference MCDA methods such as AHP, TOPSIS and MAUT, but have not fully analysed the relationships among criteria for the validation of the conditions or assumptions where a specific MCDA method can be applied to deal with a particular MCDA problem.

Finally, the case studies focussed primarily on the pre-project evaluation stage where some data was estimated and might not be accurate. In the future research, the proposed performance assessment model and MCDA methods could also be developed for post-project evaluation, and it would be interesting to conduct a comparative analysis between the pre-project and post-project evaluation.

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Appendix I | List of Abbreviations

DE: Decentralized Energy

MCDA: Multi-Criteria Decision Analysis

DEA: Data Envelopment Analysis

ER: Evidential Reasoning

GHG: Greenhouse gas

IDS: Intelligent decision system

CHP: Combined heat and power

PV: Photovoltaic

AC: Alternating current

DC: Direct current

EPA: Environmental protection agency

IEA: International energy agency

METI: Ministry of economy, trade and industry

ELECTRE: ELimination Et Choix Traduisant la REalité

PMCA: Participatory Multi-Criteria Analysis

ANP: Analytical Network Process

AHP: Analytic Hierarchy Process

VIKOR: VIseKriterijumska Optimizacija I Kompromisno Resenje

PROMETHEE: Preference Ranking Organization METHod for Enrichment of Evaluations

AD: Axiomatic Design

TOPSIS: Technique of Order Preference Similarity to the Ideal Solution

MURAME: MUlti-criteria RAnking MEthod

GIS: Geographic Information System

SDSS: Spatial Decision Support System

NPV: Net Present Value

EAC: Equivalent Annual Cost

NMVOCs: Non-Methane Volatile Organic Compounds

EIA: Environment Impact Assessment

LCA: Life Circle Analysis

MAUT: Multi-Attribute Utility Theory

SWA: Simple Weighted Average

IEA: International Energy Agency

DMU: Decision Making Unit

PCA: Principle Component Analysis

MPI: Malmquist Productivity Index

OECD: Organisation for Economic Co-operation and Development

METI: Ministry of Economy, Trade and Industry

IPCC: Intergovernmental Panel on Climate Change

GDP: Gross Domestic Product

SBM: Slacks-Based Measure

APEC: Asia-Pacific Economic Cooperation

ZSG: Zero Sum Game

FP: Fractional Programming

LP: Linear Programming

CCR: Charnes, Cooper and Rhodes

BCC: Banker, Charnes&Cooper

SE: Scale Efficiency

VRS: Variable Return of Scale

TFEE: Total Factor Energy Efficiency

PFEE: Particular Factor Energy Efficiency

HDI: Human Development Index

UDTS: Unavailability Duration of The System

MTTF: Mean Time To Failure

LOLF: Loss Of Load Frequency

LOLE: Loss Of Load Expectation

CSP: Concentrated Solar Power

PCC: Point of Common Coupling

IRR: Internal Rate of Return

Appendix II | Questionnaire of weight elicitation

Questionnaire: Performance Modelling and Decision Analysis of Decentralized Energy Systems

The main problem with renewable energy sources in a decentralized system is its high dependency on environmental conditions like wind speed and solar irradiance. Single renewable energy source in particular wind and solar does not provide continuous power supply because of its uncertainty and intermittent nature. This makes it necessary to integrate different renewable energy sources, including wind, solar, hydro, biogas and storage unit, to form a hybrid system for more reliable and environmentally friendly energy supply. Given the novelty and relatively short development history of DE systems, their performances and potential impact on world economy have not yet been studied systematically, and there are also challenges and barriers to renewable energy generation, distribution and consumption, which involve technical, economic, cultural and financial aspects. There is an urgent need to systemically model, analyse and assess the cost-effectiveness and the societal and environmental impact of various DE solutions which are based on different types of renewable energy. This requires the systematic and consistent handling of multiple factors of both a quantitative and qualitative nature under uncertainty, which in essence is a multiple criteria decision analysis (MCDA) problem but needs to make use of both numerical data and expert knowledge.

In this project, we aim to develop a performance and impact assessment model of hybrid DE systems, primarily multi-vector renewable energy systems. The main renewable resources include PV, wind and storage unit. In order to build a comprehensive assessment framework, we would be grateful if you could spend up to 30 minutes to complete this questionnaire and provide your inputs.

General questions:

1. What type of role do you play in the renewable energy sector?

A. Renewable energy policy making ______

B. Renewable energy industrial manager ______

C. Users of green energy ______

Others, please specify ______

2. Can you provide an importance ranking on the following four aspects of the performance modelling of decentralized energy systems (1 most important – 4 least important)

A. Technical ______

B. Economic ______

C. Social ______

D. Environmental ______

3. Do you think which of the following criteria are relevant to the technical aspect of the performance assessment of DE systems? (√ multiple choices)

A. Maturity ______

B. Efficiency ______

C. Safety ______

D. Reliability ______

E. Self-sufficiency ______

F. Primary energy ratio ______

Others, please specify ______

4. Do you think which of the following criteria are relevant to the economic aspect of the performance assessment of DE systems? (√ multiple choices)

A. Investment cost ______

B. Construction time ______

C. Payback period ______

D. Service life ______

E. Net Present Value (NPV) ______

F. Equivalent annual cost (EAC) ______

Others, please specify ______

5. Do you think which of the following criteria are relevant to the social aspect of the performance assessment of DE systems? (√ multiple choices)

A. Social benefit ______

B. Social acceptability ______

C. Job creation ______

Others, please specify ______

6. Do you think which of the following criteria are relevant to the environmental aspect of the performance assessment of DE systems? (√ multiple choices)

A. Fuel cost saving ______

B. CO2 emission reduction ______

C. Visual impact ______

D. Noise ______

E. Land use ______

F. Renewable energy penetration ______

Others, please specify ______

Since we will focus on the hybrid DE system based on multi-vector renewable energy systems, especially in micro-grid assessment, there are some questions about the importance of each criterion.

7. Can you provide an importance score for the following criteria on the technical aspects of DE systems (10 most important – 0 least important)

A. Maturity ______

B. Efficiency ______

C. Safety ______

D. Reliability ______

E. Self-sufficiency ______

Others, please specify and give the importance score. ______

8. Can you provide an importance score for the following criteria on the economic aspect of DE systems (10 most important – 0 least important)

A. Investment cost ______

B. Construction time ______

C. Payback period ______

D. Service life ______

Others, please specify and give the importance score. ______

9. Can you provide an importance score for the following criteria on the social aspect of DE systems (10 most important – 0 least important)

A. Social benefit ______

B. Social acceptability ______

C. Job creation ______

Others, please specify and give the importance score. ______

10. Can you provide an importance score for the following criteria on the environmental aspect of DE systems (10 most important – 0 least important)

A. Fuel saving ______

B. CO2 emission reduction ______

C. Visual impact ______

D. Renewable energy penetration ______

E. Noise ______

F. Land use ______

Others, please specify and give the importance score. ______

Appendix III | DEA solution using Excel

U10 =MMULT(E43:F43,T5:T6)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	P	Q	S	T	U	V
4	-2018	GDP	CO2 emissior	MAX- CO2 em	GDP-/max	MAX- CO2 emis	Capital	Labour force	renewable ene	non-renewable (	Capital	Labour force	renewable ene	non-renewabl	Virtual outputs	Virtual inputs	Output Weights		Input Weights	
5	United State	1.786E+13	5117.77032	4882.229677	1	0.489747218	3.87785E+12	165483017	197.4758451	2060.181557	0.772416409	0.21123043	0.49480716	0.745097226	0.490528451	136.01229	u1=	0.0000	v1=	35.1229
6	China	1.08E+13	9466.50354	533.4964619	0.604667	0.053516206	5.02042E+12	783424134	399.0965798	2764.983529	1	1	1	1	0.053601574	249.95586	u2=	1.0016	v2=	0.0000
7	Japan	6.19E+12	1123.0415	8876.958495	0.3466405	0.890467269	1.47099E+12	68358370	31.39767222	393.0467865	0.293001564	0.08725589	0.078671865	0.142151583	0.891887722	27.847211			v3=	204.5173
8	Germany	3.937E+12	732.816556	9267.183444	0.2204936	0.929611594	8.28858E+11	43560137	45.78545777	255.3107997	0.165097389	0.05560224	0.114722752	0.092337186	0.931094489	30.214007			v4=	10.3156
9	France	2.925E+12	301.870697	9698.129303	0.1638007	0.972840722	6.89884E+11	30396906	33.97017183	208.6866987	0.137415793	0.038800063	0.085117672	0.075474843	0.974392575	23.013052				
10	United Kingc	2.881E+12	361.758886	9638.241114	0.1613201	0.966833206	4.92456E+11	34329233	17.76381177	157.9122577	0.098090767	0.043819473	0.044510058	0.057111464	0.968375476	13.137452	Efficiency score =		1	
11	Italy	2.141E+12	326.564672	9673.435328	0.1199113	0.970363615	4.02279E+11	26034264	27.71573441	126.9751489	0.080128589	0.033231379	0.069446184	0.04592257	0.971911517	17.491017				
12	Brazil	2.321E+12	419.502464	9580.497536	0.129973	0.961040821	4.02339E+11	105542232	124.2985624	166.1838678	0.080140503	0.134719148	0.311449831	0.060103023	0.962573851	67.131653				
13	India	2.842E+12	2276.95165	7723.048354	0.1591344	0.774716	9.8851E+11	487622021	325.5042845	603.9443774	0.196897961	0.622424048	0.815602792	0.218426031	0.775951809	175.97373				
14	Canada	1.905E+12	596.286673	9403.713327	0.106657	0.943307207	4.23811E+11	20344918	67.1260669	233.5457667	0.084417418	0.025969226	0.168195044	0.084465518	0.944811949	38.2351				
15	Russian Fed	1.722E+12	1754.59123	8245.408772	0.0964463	0.827115125	3.59719E+11	73826094	27.23564753	772.8178365	0.071651256	0.094235154	0.06824325	0.279501787	0.828434519	19.356762				
16	Spain	1.54E+12	254.986083	9745.013917	0.0862168	0.977543821	3.34125E+11	23064439	21.28243953	102.0647204	0.066553332	0.029440552	0.05332654	0.036913319	0.979103177	13.624532				
17	Australia	1.421E+12	403.107309	9596.892691	0.0795579	0.962685455	3.49996E+11	13254463	12.80853754	119.5041903	0.069714592	0.01691863	0.032093829	0.043220579	0.964221108	9.4581711				
18	Mexico	1.313E+12	429.924593	9570.075407	0.0735213	0.959995354	2.80869E+11	56253063	16.84189739	164.5421653	0.055945337	0.071804098	0.042200054	0.059509275	0.961526716	11.209481				
19	Korea, Rep.	1.382E+12	703.98904	9296.01096	0.077387	0.932503345	4.56027E+11	28272711	7.69299038	299.0814155	0.090834585	0.036088639	0.019276012	0.108167522	0.933990853	8.2484692				
20	Netherlands	9.481E+11	31.1232058	9968.876794	0.0530956	1	2.06553E+11	9227941	4.389933908	68.90434724	0.04114252	0.011778985	0.010999678	0.024920346	1.001595177	3.951739				
30	Argentina	4.469E+11	185.414434	9814.585566	0.0250263	0.984522707	81166163554	20551682	9.152345121	74.50652316	0.016167219	0.026233149	0.022932657	0.026946462	0.986093195	5.535935				
31	South Africa	4.295E+11	427.730568	9572.269432	0.0240535	0.960215441	82523883763	22947458	25.29088827	114.0517644	0.016437658	0.029291232	0.063370346	0.041248623	0.961747155	13.963177				
32	Nigeria	4.694E+11	99.377361	9900.622639	0.0262861	0.993153275	74579920258	58403811	136.3140458	19.23234432	0.014855327	0.074549415	0.341556537	0.006955681	0.99473753	70.447742				
33	Thailand	4.417E+11	268.217618	9731.782382	0.0247349	0.976216537	1.1359E+11	38907795	35.32183864	106.7436362	0.022625583	0.049663769	0.088504488	0.038605523	0.977773775	19.293617				
34	Denmark	3.703E+11	32	9968	0.0207377	0.999912047	83844813770	3014756	6.828947119	10.17105288	0.01670077	0.003848179	0.017111014	0.003678522	1.001507083	4.1240247				
35	United Arab	3.928E+11	188.499762	9811.500238	0.0219962	0.984213211	94876001975	6752973	0.105762906	71.78894906	0.018898036	0.008619817	0.000265006	0.025963608	0.985783205	0.9857832				
36	Colombia	3.819E+11	76.4886238	9923.511376	0.0213864	0.995449295	87212484004	26229069	9.520320043	29.23569062	0.017371565	0.033480037	0.023854677	0.01057355	0.997037213	5.5979074				
37	Greece	2.527E+11	62	9938	0.014153	0.996902681	30258566985	4803828	3.995110936	19.00488906	0.006027103	0.006131836	0.010010386	0.006873419	0.998492917	2.3298904				
38	Malaysia	3.821E+11	236.096759	9763.903241	0.0214	0.979438651	90838891746	15381536	5.435604227	86.78014213	0.018093897	0.019633728	0.013619772	0.03138541	0.981001029	3.7447496				
39	Finland	2.69E+11	43	9957	0.0150646	0.998808613	66740397101	2742737	15.71998928	18.28001072	0.013293798	0.003500961	0.039388935	0.006611255	1.000401889	8.5908356				
40	Ireland	3.731E+11	35	9965	0.0208967	0.99961111	89611922099	2385553	1.691395862	12.30860414	0.017849501	0.003045034	0.004238062	0.004451601	1.001205667	1.5396046				
41	Israel	3.087E+11	62	9938	0.0172864	0.996902681	68446789450	4102822	0.85278639	22.14721361	0.013633689	0.005237038	0.002136792	0.00800989	0.998492917	0.9984929				
42	Portugal	2.467E+11	50.1938248	9949.806175	0.0138161	0.998086984	45722562470	5267545	6.75393946	15.64176513	0.009107325	0.006723746	0.01692307	0.005657092	0.999679109	3.8392932				
43	Singapore	3.284E+11	47	9953	0.0183934	0.998407364	93820304799	3493801	0.389467766	38.61053223	0.018687755	0.004459655	0.000975873	0.013964109	1	1				

Figure AIII-1 DEA solution of Energy efficiency in 2018 using BCC input oriented primal model (TFEE)

U11 =MMULT(K5:N5,V5:V8)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	P	Q	S	T	U	V
3	Country	Output			Output		Input				Input-/max									
4	-2018	GDP	CO2 emission	MAX- CO2 en	GDP-/max	MAX- CO2 emi	Capital	Labour force	renewable en	non-renewable	Capital	Labour force	renewable en	non-renewabl	Virtual outputs	Virtual inputs	Output Weights		Input Weights	
5	United State	1.7856E+13	5117.770323	4882.22968	1	0.489747218	3.87785E+12	165483017	197.4758451	2060.181557	0.772416409	0.21123043	0.49480716	0.745097226	1	1.075400498	u1=	1.0000	v1=	0.9940
6	China	1.0797E+13	9466.503538	533.496462	0.604667	0.053516206	5.02042E+12	783424134	399.0965798	2764.983529	1	1	1	1	0.604666995	2.450437222	u2=	0.0000	v2=	1.4565
7	Japan	6.1898E+12	1123.041505	8876.9585	0.3466405	0.890467269	1.47099E+12	68358370	31.39767222	393.0467865	0.293001564	0.08725589	0.078671865	0.142151583	0.346640503	0.418317015			v3=	0.0000
8	Germany	3.9372E+12	732.8165558	9267.18344	0.22049358	0.929611594	8.28858E+11	43560137	45.78545777	255.3107997	0.165097389	0.05560224	0.114722752	0.092337186	0.220493577	0.245083046			v4=	0.0000
9	France	2.9249E+12	301.8706971	9698.1293	0.16380069	0.972840722	6.89884E+11	30396906	33.97017183	208.6866987	0.137415793	0.03880006	0.085117672	0.075474843	0.163800689	0.193096713				
10	United Kingc	2.8806E+12	361.7588864	9638.24111	0.16132009	0.966833206	4.92456E+11	34329233	17.76381177	157.9122577	0.098090767	0.04381947	0.044510058	0.057111464	0.161320091	0.161320091	Efficiency score =		0.92989	
11	Italy	2.1412E+12	326.564672	9673.43533	0.11991125	0.970363615	4.02279E+11	26034264	27.71573441	126.9751489	0.080128589	0.03323138	0.069446184	0.04592257	0.119911255	0.128045122		h0=	1.0754	
12	Brazil	2.3209E+12	419.5024636	9580.49754	0.12997297	0.961040821	4.02339E+11	105542232	124.2985624	166.1838678	0.080140503	0.13471915	0.311449831	0.060103023	0.129972973	0.275872099				
13	India	2.8416E+12	2276.951646	7723.04835	0.15913439	0.774716	9.8851E+11	487622021	325.5042845	603.9443774	0.196897961	0.62242405	0.815602792	0.218426031	0.159134389	1.102257289				
14	Canada	1.9045E+12	596.2866727	9403.71333	0.10665698	0.943307207	4.23811E+11	20344918	67.1260669	233.5457667	0.084417418	0.02596923	0.168195044	0.084465518	0.106656981	0.121730827				
15	Russian Fedı	1.7222E+12	1754.591228	8245.40877	0.0964463	0.827115125	3.59719E+11	73826094	27.23564753	772.8178365	0.071651256	0.09423515	0.06824325	0.279501787	0.096446299	0.208469951				
16	Spain	1.5395E+12	254.9860827	9745.01392	0.08621678	0.977543821	3.34125E+11	23064439	21.28243953	102.0647204	0.066553332	0.02944055	0.05332654	0.036913319	0.086216783	0.109030657				
17	Australia	1.4206E+12	403.1073095	9596.89269	0.0795579	0.962685455	3.49996E+11	13254463	12.80853754	119.5041903	0.069714592	0.01691863	0.032093829	0.043220579	0.079557904	0.093934849				
18	Mexico	1.3128E+12	429.924593	9570.07541	0.07352128	0.959995354	2.80869E+11	56253063	16.84189739	164.5421653	0.055945337	0.0718041	0.042200054	0.059509275	0.073521276	0.160188539				
19	Korea, Rep.	1.3819E+12	703.98904	9296.01096	0.07738703	0.932503345	4.56027E+11	28272711	7.69299038	299.0814155	0.090834585	0.03608864	0.019276012	0.108167522	0.077387029	0.14284795				
20	Netherlands	9.481E+11	31.12320579	9968.87679	0.05309563	1	2.06553E+11	9227941	4.389933908	68.90434724	0.04114252	0.01177898	0.010999678	0.024920346	0.053095627	0.058049695				
30	Argentina	4.4688E+11	185.4144338	9814.58557	0.02502626	0.984522707	81166163554	20551682	9.152345121	74.50652316	0.016167219	0.02623315	0.022932657	0.026946462	0.025026264	0.054277603				
31	South Africa	4.2951E+11	427.7305682	9572.26943	0.02405354	0.960215441	82523883763	22947458	25.29088827	114.0517644	0.016437658	0.02929123	0.063370346	0.041248623	0.02405354	0.059000452				
32	Nigeria	4.6938E+11	99.37736097	9900.62264	0.02628608	0.993153275	74579920258	58403811	136.3140458	19.23234432	0.014855327	0.07454942	0.341556537	0.006955681	0.02628608	0.123345426				
33	Thailand	4.4168E+11	268.2176184	9731.78238	0.0247349	0.976216537	1.1359E+11	38907795	35.32183864	106.7436362	0.022625583	0.04966377	0.088504488	0.038605523	0.024734904	0.094823208				
34	Denmark	3.703E+11	32	9968	0.02073774	0.999912047	83844813770	3014756	6.828947119	10.17105288	0.01670077	0.00384818	0.017111014	0.003678522	0.020737739	0.022204617				
35	United Arab	3.9277E+11	188.4997618	9811.50024	0.02199617	0.984213211	94876001975	6752973	0.105762906	71.78894906	0.018898036	0.00861982	0.000265006	0.025963608	0.021996167	0.031338408				
36	Colombia	3.8189E+11	76.48862375	9923.51138	0.02138636	0.995449295	87212484004	26229069	9.520320043	29.23569062	0.017371565	0.03348004	0.023854677	0.01057355	0.021386361	0.066029633				
37	Greece	2.5272E+11	62	9938	0.01415303	0.996902681	30258566985	4803828	3.995110936	19.00488906	0.006027103	0.00613184	0.010010386	0.006873419	0.014153033	0.014921579				
38	Malaysia	3.8213E+11	236.0967594	9763.90324	0.02140003	0.979438651	90838891746	15381536	5.435604227	86.78014213	0.018093897	0.01963373	0.013619772	0.03138541	0.021400026	0.046580695				
39	Finland	2.69E+11	43	9957	0.01506455	0.998808613	66740397101	2742737	15.71998928	18.28001072	0.013293798	0.00350096	0.039388935	0.006611255	0.015064555	0.018312524				
40	Ireland	3.7314E+11	35	9965	0.0208967	0.99961111	89611922099	2385553	1.691395862	12.30860414	0.017849501	0.00304503	0.004238062	0.004451601	0.020896701	0.022176638				
41	Israel	3.0867E+11	62	9938	0.01728641	0.996902681	68446789450	4102822	0.85278639	22.14721361	0.013633689	0.00523704	0.002136792	0.00800989	0.017286413	0.021178926				
42	Portugal	2.4671E+11	50.19382483	9949.80618	0.01381613	0.998086984	45722562470	5267545	6.75393946	15.64176513	0.009107325	0.00672375	0.01692307	0.005657092	0.01381613	0.018845288				
43	Singapore	3.2844E+11	47	9953	0.01839338	0.998407364	93820304799	3493801	0.389467766	38.61053223	0.018687755	0.00445965	0.000975873	0.013964109	0.018393375	0.025070195				

Figure AIII-2 DEA solution of Energy efficiency in 2018 using BCC output oriented primal model (TFEE)

F47 =SUMPRODUCT(F5:F43,$Q$5:$Q$43)

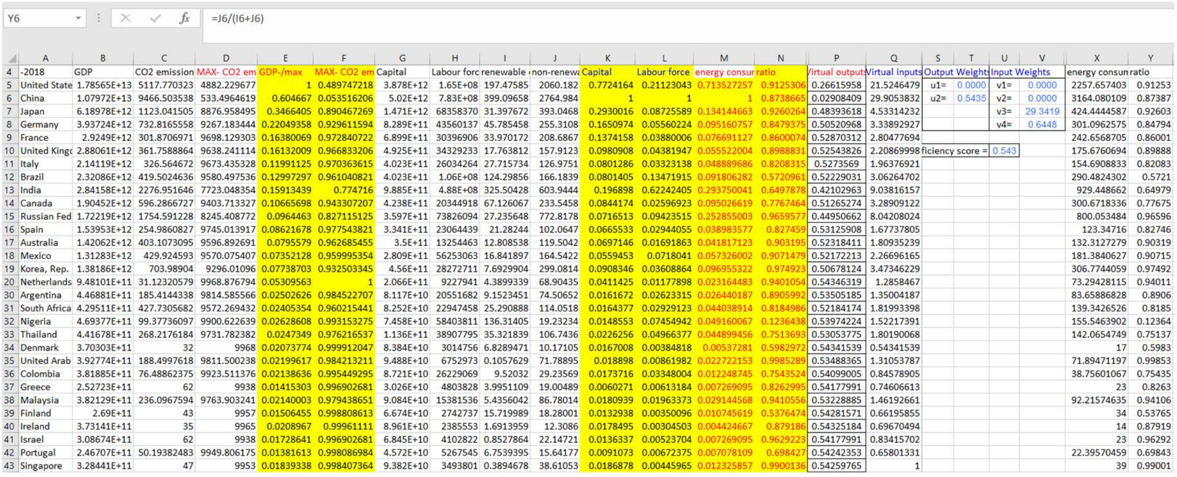
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	P	Q
1	DEA-capital, energy consumption, labour force/GDP, CO2 emissions															
3	Country	Output			Output		Input				Input-/max				Proportion of DMUj	
4	-2018	GDP	CO2 emission	MAX- CO2 emis:	GDP-/max	MAX- CO2 emissic	Capital	Labour force	renewable e	non-renewable	Capital	Labour force	renewable energ	non-renewable	variable	value
5	United States	1.78565E+13	5117.770323	4882.229677	1	0.489747218	3.87785E+12	165483017	197.47585	2060.181557	0.772416409	0.21123043	0.49480716	0.745097226	Lambda 1	0
6	China	1.07972E+13	9466.503538	533.4964619	0.604666995	0.053516206	5.02042E+12	783424134	399.09658	2764.983529	1	1	1	1	Lambda 2	0
7	Japan	6.18978E+12	1123.041505	8876.958495	0.346640503	0.890467269	1.47099E+12	68358370	31.397672	393.0467865	0.293001564	0.08725589	0.078671865	0.142151583	Lambda 3	0
8	Germany	3.93724E+12	732.8165558	9267.183444	0.220493577	0.929611594	8.28858E+11	43560137	45.785458	255.3107997	0.165097389	0.05560224	0.114722752	0.092337186	Lambda 4	0
9	France	2.9249E+12	301.8706971	9698.129303	0.163800689	0.972840722	6.89884E+11	30396906	33.970172	208.6866987	0.137415793	0.038800063	0.085117672	0.075474843	Lambda 5	0
10	United Kingdom	2.88061E+12	361.7588864	9638.241114	0.161320091	0.966833206	4.92456E+11	34329233	17.763812	157.9122577	0.098090767	0.043819473	0.044510058	0.057111464	Lambda 6	0.114132
11	Italy	2.14119E+12	326.564672	9673.435328	0.119911255	0.970363615	4.02279E+11	26034264	27.715734	126.9751489	0.080128589	0.033231379	0.069446184	0.04592257	Lambda 7	0
12	Brazil	2.32086E+12	419.5024636	9580.497536	0.129972973	0.961040821	4.02339E+11	105542232	124.29856	166.1838678	0.080140503	0.134719148	0.311449831	0.060103023	Lambda 8	0
13	India	2.84158E+12	2276.951646	7723.048354	0.159134389	0.774716	9.8851E+11	487622021	325.50428	603.9443774	0.196897961	0.622424048	0.815602792	0.218426031	Lambda 9	0
14	Canada	1.90452E+12	596.2866727	9403.713327	0.106656981	0.943307207	4.23811E+11	20344918	67.126067	233.5457667	0.084417418	0.025969226	0.168195044	0.084465518	Lambda 10	0
15	Russian Federation	1.72219E+12	1754.591228	8245.408772	0.096446299	0.827115125	3.59719E+11	73826094	27.235648	772.8178365	0.071651256	0.094235154	0.06824325	0.279501787	Lambda 11	0
30	Argentina	4.46881E+11	185.4144338	9814.585566	0.025026264	0.984522707	81166163554	20551682	9.1523451	74.50652316	0.016167219	0.026233149	0.022932657	0.026946462	Lambda 26	0
31	South Africa	4.29511E+11	427.7305682	9572.269432	0.02405354	0.960215441	82523883763	22947458	25.290888	114.0517644	0.016437658	0.029291232	0.063370346	0.041248623	Lambda 27	0
32	Nigeria	4.69377E+11	99.37736097	9900.622639	0.02628608	0.993153275	74579920258	58403811	136.31405	19.23234432	0.014855327	0.074549415	0.341556537	0.006955681	Lambda 28	0
33	Thailand	4.41678E+11	268.2176184	9731.782382	0.024734904	0.976216537	1.1359E+11	38907795	35.321839	106.7436362	0.022625583	0.049663769	0.088504488	0.038605523	Lambda 29	0
34	Denmark	3.70303E+11	32	9968	0.020737739	0.999912047	83844813770	3014756	6.8289471	10.17105288	0.01670077	0.003848179	0.017111014	0.003678522	Lambda 30	0
35	United Arab Emirates	3.92774E+11	188.4997618	9811.500238	0.021996167	0.984213211	94876001975	6752973	0.1057629	71.78894906	0.018898036	0.008619817	0.000265006	0.025963608	Lambda 31	0.044432
36	Colombia	3.81885E+11	76.48862375	9923.511376	0.021386361	0.995449295	87212484004	26229069	9.52032	29.23569062	0.017371565	0.033480037	0.023854677	0.01057355	Lambda 32	0
37	Greece	2.52723E+11	62	9938	0.014153033	0.996902681	30258566985	4803828	3.9951109	19.00488906	0.006027103	0.006131836	0.010010386	0.006873419	Lambda 33	0
38	Malaysia	3.82129E+11	236.0967594	9763.903241	0.021400026	0.979438651	90838891746	15381536	5.4356042	86.78014213	0.018093897	0.019633728	0.013619772	0.03138541	Lambda 34	0
39	Finland	2.69E+11	43	9957	0.015064555	0.998808613	66740397101	2742737	15.719989	18.28001072	0.013293798	0.003500961	0.039388935	0.006611255	Lambda 35	0
40	Ireland	3.73141E+11	35	9965	0.020896701	0.99961111	89611922099	2385553	1.6913959	12.30860414	0.017849501	0.003045034	0.004238062	0.004451601	Lambda 36	0
41	Israel	3.08674E+11	62	9938	0.017286413	0.996902681	68446789450	4102822	0.8527864	22.14721361	0.013633689	0.005237038	0.002136792	0.00800989	Lambda 37	3.355116
42	Portugal	2.46707E+11	50.19382483	9949.806175	0.01381613	0.998086984	45722562470	5267545	6.7539395	15.64176513	0.009107325	0.006723746	0.01692307	0.005657092	Lambda 38	0
43	Singapore	3.28441E+11	47	9953	0.018393375	0.998407364	93820304799	3493801	0.3894678	38.61053223	0.018687755	0.004459655	0.000975873	0.013964109	Lambda 39	0
44	15														sum=	3.513679
45	Korea, Rep.	1.38186E+12	703.98904	9296.01096	0.077387029	0.932503345	4.56027E+11	28272711	7.6929904	299.0814155	0.090834585	0.036088639	0.019276012	0.108167522		
46	h0*Input										0.05777757	0.022955066	0.012260981	0.068802611		
47	composite				0.077387029	3.498800615					0.05777757	0.022955066	0.012260981	0.034545962		
48																
49	efficient score=	0.63607458														

Figure AIII-3 DEA solution of Energy efficiency in 2018 using BCC input oriented dual model (TFEE)

F47 =SUMPRODUCT(F5:F43,$Q$5:$Q$43)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	P	Q
4	-2018	GDP	CO2 emission	MAX- CO2 emis	GDP-/max	MAX- CO2 emis	Capital	Labour force	renewable ene	non-renewable	Capital	Labour force	renewable ener	non-renewable	variable	value
5	United States	1.78565E+13	5117.770323	4882.229677	1	0.489747218	3.87785E+12	165483017	197.4758451	2060.181557	0.772416409	0.21123043	0.49480716	0.745097226	Lambda 1	0
6	China	1.07972E+13	9466.503538	533.4964619	0.604666995	0.053516206	5.02042E+12	783424134	399.0965798	2764.983529	1	1	1	1	Lambda 2	0
7	Japan	6.18978E+12	1123.041505	8876.958495	0.346640503	0.890467269	1.47099E+12	68358370	31.39767222	393.0467865	0.293001564	0.08725589	0.078671865	0.142151583	Lambda 3	0
8	Germany	3.93724E+12	732.8165558	9267.183444	0.220493577	0.929611594	8.28858E+11	43560137	45.78545777	255.3107997	0.165097389	0.05560224	0.114722752	0.092337186	Lambda 4	0
9	France	2.9249E+12	301.8706971	9698.129303	0.163800689	0.972840722	6.89884E+11	30396906	33.97017183	208.6866987	0.137415793	0.038800063	0.085117672	0.075474843	Lambda 5	0
10	United Kingdom	2.88061E+12	361.7588864	9638.241114	0.161320091	0.966833206	4.92456E+11	34329233	17.76381177	157.9122577	0.098090767	0.043819473	0.044510058	0.057111464	Lambda 6	1.85829644
11	Italy	2.14119E+12	326.564672	9673.435328	0.119911255	0.970363615	4.02279E+11	26034264	27.71573441	126.9751489	0.080128589	0.033231379	0.069446184	0.04592257	Lambda 7	0
12	Brazil	2.32086E+12	419.5024636	9580.497536	0.129972973	0.961040821	4.02339E+11	105542232	124.2985624	166.1838678	0.080140503	0.134719148	0.311449831	0.060103023	Lambda 8	0
13	India	2.84158E+12	2276.951646	7723.048354	0.159134389	0.774716	9.8851E+11	487622021	325.5042845	603.9443774	0.196897961	0.622424048	0.815602792	0.218426031	Lambda 9	0
14	Canada	1.90452E+12	596.2866727	9403.713327	0.106656981	0.943307207	4.23811E+11	20344918	67.1260669	233.5457667	0.084417418	0.025969226	0.168195044	0.084465518	Lambda 10	0
15	Russian Federatio	1.72219E+12	1754.591228	8245.408772	0.096446299	0.827115125	3.59719E+11	73826094	27.23564753	772.8178365	0.071651256	0.094235154	0.06824325	0.279501787	Lambda 11	0
30	Argentina	4.46881E+11	185.4144338	9814.585566	0.025026264	0.984522707	81166163554	20551682	9.152345121	74.50652316	0.016167219	0.026233149	0.022932657	0.026946462	Lambda 26	0
31	South Africa	4.29511E+11	427.7305682	9572.269432	0.02405354	0.960215441	82523883763	22947458	25.29088827	114.0517644	0.016437658	0.029291232	0.063370346	0.041248623	Lambda 27	0
32	Nigeria	4.69377E+11	99.37736097	9900.622639	0.02628608	0.993153275	74579920258	58403811	136.3140458	19.23234432	0.014855327	0.074549415	0.341556537	0.006955681	Lambda 28	0
33	Thailand	4.41678E+11	268.2176184	9731.782382	0.024734904	0.976216537	1.1359E+11	38907795	35.32183864	106.7436362	0.022625583	0.049663769	0.088504488	0.038605523	Lambda 29	0
34	Denmark	3.70303E+11	32	9968	0.020737739	0.999912047	83844813770	3014756	6.828947119	10.17105288	0.01670077	0.003848179	0.017111014	0.003678522	Lambda 30	0
35	United Arab Emira	3.92774E+11	188.4997618	9811.500238	0.021996167	0.984213211	94876001975	6752973	0.105762906	71.78894906	0.018898036	0.008619817	0.000265006	0.025963608	Lambda 31	0
36	Colombia	3.81885E+11	76.48862375	9923.511376	0.021386361	0.995449295	87212484004	26229069	9.520320043	29.23569062	0.017371565	0.033480037	0.023854677	0.01057355	Lambda 32	0
37	Greece	2.52723E+11	62	9938	0.014153033	0.996902681	30258566985	4803828	3.995110936	19.00488906	0.006027103	0.006131836	0.010010386	0.006873419	Lambda 33	0
38	Malaysia	3.82129E+11	236.0967594	9763.903241	0.021400026	0.979438651	90838891746	15381536	5.435604227	86.78014213	0.018093897	0.019633728	0.013619772	0.03138541	Lambda 34	0
39	Finland	2.69E+11	43	9957	0.015064555	0.998808613	66740397101	2742737	15.71998928	18.28001072	0.013293798	0.003500961	0.039388935	0.006611255	Lambda 35	0
40	Ireland	3.73141E+11	35	9965	0.020896701	0.99961111	89611922099	2385553	1.691395862	12.30860414	0.017849501	0.003045034	0.004238062	0.004451601	Lambda 36	0
41	Israel	3.08674E+11	62	9938	0.017286413	0.996902681	68446789450	4102822	0.85278639	22.14721361	0.013633689	0.005237038	0.002136792	0.00800989	Lambda 37	0
42	Portugal	2.46707E+11	50.19382483	9949.806175	0.01381613	0.998086984	45722562470	5267545	6.75393946	15.64176513	0.009107325	0.006723746	0.01692307	0.005657092	Lambda 38	0
43	Singapore	3.28441E+11	47	9953	0.018393375	0.998407364	93820304799	3493801	0.389467766	38.61053223	0.018687755	0.004459655	0.000975873	0.013964109	Lambda 39	0
44	1															
45	United States	1.78565E+13	5117.770323	4882.229677	1	0.489747218	3.87785E+12	165483017	197.4758451	2060.181557	0.772416409	0.21123043	0.49480716	0.745097226		
46	h0*Input				1.075400498	0.526674402										
47	composite				1.075400498	22.31607907					0.772416409	0.21123043	0.419647669	0.235692287		
48																
49	efficient score=	0.929886123														
50	h0 =	1.075400498														

Figure AIII-4 DEA solution of Energy efficiency in 2018 using BCC output oriented dual model (TFEE)



Y6 | =J6/(I6+J6)

	A	B	C	D	E	F	G	H	I	J
4	-2018	GDP	CO2 emission	MAX- CO2 em	GDP-/max	MAX- CO2 em	Capital	Labour forc	renewable (	non-renewa
5	United State	1.78565E+13	5117.770323	4882.229677	1	0.489747218	3.878E+12	1.65E+08	197.47585	2060.182
6	China	1.07972E+13	9466.503538	533.4964619	0.604667	0.053516206	5.02E+12	7.83E+08	399.09658	2764.984
7	Japan	6.18978E+12	1123.041505	8876.958495	0.3466405	0.890467269	1.471E+12	68358370	31.397672	393.0468
8	Germany	3.93724E+12	732.8165558	9267.183444	0.22049358	0.929611594	8.289E+11	43560137	45.785458	255.3108
9	France	2.9249E+12	301.8706971	9698.129303	0.16380069	0.972840722	6.899E+11	30396906	33.970172	208.6867
10	United Kingc	2.88061E+12	361.7588864	9638.241114	0.16132009	0.966833206	4.925E+11	34329233	17.763812	157.9123
11	Italy	2.14119E+12	326.564672	9673.435328	0.11991125	0.970363615	4.023E+11	26034264	27.715734	126.9751
12	Brazil	2.32086E+12	419.5024636	9580.497536	0.12997297	0.961040821	4.023E+11	1.06E+08	124.29856	166.1839
13	India	2.84158E+12	2276.951646	7723.048354	0.15913439	0.774716	9.885E+11	4.88E+08	325.50428	603.9444
14	Canada	1.90452E+12	596.2866727	9403.713327	0.10665698	0.943307207	4.238E+11	20344918	67.126067	233.5458
15	Russian Fed	1.72219E+12	1754.591228	8245.408772	0.0964463	0.827115125	3.597E+11	73826094	27.235648	772.8178
16	Spain	1.53953E+12	254.9860827	9745.013917	0.08621678	0.977543821	3.341E+11	23064439	21.28244	102.0647
17	Australia	1.42062E+12	403.1073095	9596.892691	0.0795579	0.962685455	3.5E+11	13254463	12.808538	119.5042
18	Mexico	1.31283E+12	429.924593	9570.075407	0.07352128	0.959995354	2.809E+11	56253063	16.841897	164.5422
19	Korea, Rep.	1.38186E+12	703.98904	9296.01096	0.07738703	0.932503345	4.56E+11	28272711	7.6929904	299.0814
20	Netherlands	9.48101E+11	31.12320579	9968.876794	0.05309563	1	2.066E+11	9227941	4.3899339	68.90435
30	Argentina	4.46881E+11	185.4144338	9814.585566	0.02502626	0.984522707	8.117E+10	20551682	9.1523451	74.50652
31	South Africa	4.29511E+11	427.7305682	9572.269432	0.02405354	0.960215441	8.252E+10	22947458	25.290888	114.0518
32	Nigeria	4.69377E+11	99.37736097	9900.622639	0.02628608	0.993153275	7.458E+10	58403811	136.31405	19.23234
33	Thailand	4.41678E+11	268.2176184	9731.782382	0.0247349	0.976216537	1.136E+11	38907795	35.321839	106.7436
34	Denmark	3.70303E+11	32	9968	0.02073774	0.999912047	8.384E+10	3014756	6.8289471	10.17105
35	United Arab	3.92774E+11	188.4997618	9811.500238	0.02199617	0.984213211	9.488E+10	6752973	0.1057629	71.78895
36	Colombia	3.81885E+11	76.48862375	9923.511376	0.02138636	0.995449295	8.721E+10	26229069	9.52032	29.23569
37	Greece	2.52723E+11	62	9938	0.01415303	0.996902681	3.026E+10	4803828	3.9951109	19.00489
38	Malaysia	3.82129E+11	236.0967594	9763.903241	0.02140003	0.979438651	9.084E+10	15381536	5.4356042	86.78014
39	Finland	2.69E+11	43	9957	0.01506455	0.998808613	6.674E+10	2742737	15.719989	18.28001
40	Ireland	3.73141E+11	35	9965	0.0208967	0.99961111	8.961E+10	2385553	1.6913959	12.3086
41	Israel	3.08674E+11	62	9938	0.01728641	0.996902681	6.845E+10	4102822	0.8527864	22.14721
42	Portugal	2.46707E+11	50.19382483	9949.806175	0.01381613	0.998086984	4.572E+10	5267545	6.7539395	15.64177
43	Singapore	3.28441E+11	47	9953	0.01839338	0.998407364	9.382E+10	3493801	0.3894678	38.61053

	A	K	L	M	N	P	Q	S	T	U	V	X	Y
4	-2018	Capital	Labour force	energy consur	ratio	/irtual output	Virtual inputs	Output Weight		Input Weights		energy consun	ratio
5	United State	0.7724164	0.21123043	0.713527257	0.9125306	0.26615958	21.5246479	u1=	0.0000	v1=	0.0000	2257.657403	0.91253
6	China	1	1	1	0.8738665	0.02908409	29.9053832	u2=	0.5435	v2=	0.0000	3164.080109	0.87387
7	Japan	0.2930016	0.08725589	0.134144663	0.9260264	0.48393618	4.53314232			v3=	29.3419	424.4444587	0.92603
8	Germany	0.1650974	0.05560224	0.095160757	0.8479375	0.50520968	3.33892927			v4=	0.6448	301.0962575	0.84794
9	France	0.1374158	0.03880006	0.076691127	0.8600074	0.52870312	2.80477694					242.6568705	0.86001
10	United Kingc	0.0980908	0.04381947	0.055522004	0.8988831	0.52543826	2.20869998	ficiency score =		0.543		175.6760694	0.89888
11	Italy	0.0801286	0.03323138	0.048889686	0.8208315	0.5273569	1.96376921					154.6908833	0.82083
12	Brazil	0.0801405	0.13471915	0.091806282	0.5720961	0.52229031	3.06264702					290.4824302	0.5721
13	India	0.196898	0.62242405	0.293750041	0.6497878	0.42102963	9.03816157					929.448662	0.64979
14	Canada	0.0844174	0.02596923	0.095026619	0.7767464	0.51265274	3.28909122					300.6718336	0.77675
15	Russian Fed	0.0716513	0.09423515	0.252855003	0.9659577	0.44950662	8.04208024					800.053484	0.96596
16	Spain	0.0665533	0.02944055	0.038983577	0.827459	0.53125908	1.67737805					123.34716	0.82746
17	Australia	0.0697146	0.01691863	0.041817123	0.903195	0.52318411	1.80935239					132.3127279	0.90319
18	Mexico	0.0559453	0.0718041	0.057326002	0.9071479	0.52172213	2.26696165					181.3840627	0.90715
19	Korea, Rep.	0.0908346	0.03608864	0.096955322	0.974923	0.50678124	3.47346229					306.7744059	0.97492
20	Netherlands	0.0411425	0.01177898	0.023164483	0.9401054	0.54346319	1.2858467					73.29428115	0.94011
30	Argentina	0.0161672	0.02623315	0.026440187	0.8905992	0.53505185	1.35004187					83.65886828	0.8906
31	South Africa	0.0164377	0.02929123	0.044038914	0.8184986	0.52184174	1.81993398					139.3426526	0.8185
32	Nigeria	0.0148553	0.07454942	0.049160067	0.1236438	0.53974224	1.52217391					155.5463902	0.12364
33	Thailand	0.0226256	0.04966377	0.044899456	0.7513693	0.53053775	1.80190068					142.0654749	0.75137
34	Denmark	0.0167008	0.00384818	0.00537281	0.5982972	0.54341539	0.54341539					17	0.5983
35	United Arab	0.018898	0.00861982	0.022722153	0.9985289	0.53488365	1.31053787					71.89471197	0.99853
36	Colombia	0.0173716	0.03348004	0.012248745	0.7543524	0.54099005	0.84578905					38.75601067	0.75435
37	Greece	0.0060271	0.00613184	0.007269095	0.8262995	0.54177991	0.74606613					23	0.8263
38	Malaysia	0.0180939	0.01963373	0.029144568	0.9410556	0.53228885	1.46192661					92.21574635	0.94106
39	Finland	0.0132938	0.00350096	0.010745619	0.5376474	0.54281571	0.66195855					34	0.53765
40	Ireland	0.0178495	0.00304503	0.004424667	0.879186	0.54325184	0.69670494					14	0.87919
41	Israel	0.0136337	0.00523704	0.007269095	0.9629223	0.54177991	0.83415702					23	0.96292
42	Portugal	0.0091073	0.00672375	0.007078109	0.698427	0.54242353	0.65801331					22.39570459	0.69843
43	Singapore	0.0186878	0.00445965	0.012325857	0.9900136	0.54259765	1					39	0.99001

Figure AIII-5 DEA solution of Energy efficiency in 2018 using BCC input oriented primal model (PFEE)

Appendix IV | Papers published in Journals or Conference Proceedings

Wu, T., Xu, D.L. and Yang, J.B., 2020. Decentralized energy and its performance assessment models. *Frontiers of Engineering Management*. Online. https://doi.org/10.1007/s42524-020-0148-7

Wu, T., Xu, D.L. and Yang, J.B., 2020, August. Decentralized energy system and its performance assessment framework based on MCDA. *In Developments of Artificial Intelligence Technologies in Computation and Robotics, Proceedings of the 14th International FLINS Conference* (FLINS 2020), Cologne, Germany (pp. 18-21).

Wu, T., Xu, D.L. and Yang, J.B., 2019, March. Multiple Criteria Performance Assessment for Decentralized Energy Systems: A Case Study. *In 2019 5th International Conference on Information Management* (ICIM) (pp. 257-261). IEEE.

Wu, T., Xu, D.L. and Yang, J.B., 2018. Multiple criteria performance modelling and impact assessment of renewable energy systems—a literature review. *In Renewable Energies* (pp. 1-15). Springer, Cham.

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