Sustainability Assessment of Electricity Production and Consumption: DEA Systems Modelling of Complex Internal Structures

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I would like to dedicate this thesis to my brother - Felix Turkson.
May you continue to rest in peace.

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Abstract

Sustainability and sustainable development research have become a very important part in the development of energy policy. This has resulted in growing research interest in the assessment of the sustainable performance of energy systems using methodological tools such as Data Envelopment Analysis (DEA). However, existing sustainability evaluation has tended to either focus on production and environmental impacts at the electricity generation phase or focussed on the use of electricity for some economic or social benefits given the environmental impacts. Assessing the production and use phases separately ignores the interlinkages between energy security, clean energy and energy equity policies, the so-called energy trilemma. This limitation with existing energy research is due to the differences in the electricity generation portfolios of different countries, the complex interrelationships between policy variables and the weaknesses of existing quantitative techniques to handle such complex sustainability problems.

To address this shortcoming, this thesis draws on advances in network and non-homogenous DEA and Multi-Attribute Utility Theory to examine the application of DEA in sustainable energy research. European Union (EU) states are used as case studies to demonstrate the applications of these techniques. Specifically, DEA optimisation models are developed to allow for the integration of the generation and consumption phases of the energy system by adopting a systems approach to modelling while recognising the differences in the generation portfolios of the different EU states and allowing for cross-country comparison. Additionally, given the varying theoretical perspectives on sustainability in the literature, some of these divergent views are incorporated in the sustainable portfolio generation and energy consumption evaluations. Consequently, this thesis contributes to existing energy sustainability research by proposing novel approaches for handling non-homogeneity in electricity generation portfolios, developing models to provide holistic decision support and developing models to evaluate the incorporation of sustainability in electricity portfolio mix decisions.

These are achieved by addressing three main research objectives. The first objective pertains to the generation phase of the energy system. Specifically, DEA optimisation models are developed to assess sustainability and resource efficiency in electricity production. In the production phase, since units have different portfolios of generation sources, there exist non-homogeneity in the sub-processes of units under investigation. This sub-process non-homogeneity problem has not yet been addressed in the literature. Consequently, two approaches for addressing these non-homogeneities are proposed. The distinction between the two proposed approaches is whether the non-existent sub-processes are included in the model to determine optimal multipliers or not. A comparison of the proposed approaches with a traditional network DEA reveals differences in the overall scores and rankings of units under investigation. This underscores the need to ensure appropriate model correction where there exists such non-homogeneity within sub-processes, especially in the presence of shared inputs/outputs in parallel network DEA. Empirical assessment of resource efficient and sustainable production of the European electricity generation systems revealed average scores of between 0.4 and 0.6, over the study period, without a clear pattern towards performance improvement.

The second objective is to develop models for a holistic assessment of the energy system by integrating electricity production and consumption phases. While the production phase is composed of eleven parallel sub-processes, the consumption phase comprises three multi-stage serial sub-systems representing social development, economic development and environmental performance. Therefore, the integrated model is a mixed structure network problem that can provide decision support for both the generation and the consumption phases, as well as provide recommendations for the entire system. In addressing this objective, improvements to existing assessments are made. This includes incorporating electricity as a vital input and employment as a vital output in social development assessment; linking employment as an intermediate factor between social and economic development assessments; and determining environmental performance from emissions and bio-capacity. In the empirical application it was observed that, higher performers in the generation phase are not necessarily higher performers in the consumption phase. While higher performers in the generation phase include Estonia, Poland and Greece, higher performers in the consumption phase include Malta, Luxembourg and Cyprus. An integrated assessment, therefore, provides policy makers with a good understanding of the entire system which may not be evident in the phased assessments.

The final objective examines the implication of sustainability in energy portfolio mix planning. Awareness of environmental and social impacts of energy generation

has resulted in the incorporation of sustainability as a relevant consideration in energy mix planning decisions using portfolio optimisation. Current approaches for portfolio analyses has tended to add external (social) and environmental costs dimensions to operational (economic) costs to cater for sustainability in energy mix planning. It is shown that attempting to combine the various sustainability associated cost dimensions by adding the respective cost from the various dimensions has the potential to negate the relevance of some of the dimensions, thereby, making some dimensions more important than others. The result is optimal portfolios which may be inconsistent with expectations on sustainability. Relying on Multi-Attribute Utility Theory, the impact of the interactions and other relationships between the various components on technology ranking and optimal portfolios are explored. DEA is employed to examine the impact of the relationship between the cost dimensions on the technology ranking. The mean-variance framework is then used to construct optimal portfolios based on the different dimension relationships. It is found that portfolios constructed using multiplicative pooling of dimensions best conform to the expectations of sustainability while achieving lower emission potential and use of higher renewable energy sources given a cost minimisation objective. For example, additive pooling results in higher rankings for gas and coal powered power plants when compared to hydro, solar and biomass even though gas and coal under-perform renewable sources in two out of the three sustainability dimensions. It is, therefore, recommended that when constructing sustainable portfolio of generation sources, multiplicative pooling of cost dimensions along the sustainability objectives should be preferred.

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List of Abbreviations

AHP ..... Analytic Hierarchy Process
BCC ..... Banker, Charnes and Cooper
CCR ..... Charnes, Cooper and Rhodes
CRS ..... Constant Returns to Scale
DDF ..... Directional Distance Function
DEA ..... Data Envelopment Analysis
DMU ..... Decision-Making Units
EBED ..... Energy-Based Economic Development
EDI ..... Energy Development Index
EEA ..... European Environment Agency
EU ..... European Union
GDP ..... Gross Domestic Product
GEP ..... Gross Electricity Production
GHG ..... Greenhouse Gas
GWP ..... Global Warming Potential
HDI ..... Human Development Indicator
IAEA ..... International Atomic Energy Agency
IEA ..... International Energy Agency
KWh ..... Kilowatt Hour
LCA ..... Lifecycle Analysis
LP ..... Linear programming
MCDM ..... Multi-Criteria Decision-Making
MW ..... Megawatts
NDEA ..... Network Data Envelopment Analysis
NSBM ..... Network Slacks-Based Measure
O&M ..... Operation and maintenance
OR ..... Operational Research
PPS ..... Production Possibility Set

PV . . . . . Photovoltaic
SBM . . . . . Slack-Based Measure
SDG . . . . . Sustainable Development Goals
SSM . . . . . Soft Systems Methodology
TFEE . . . . . Total Factor Energy Efficiency
TFPI . . . . . Total Factor Energy Productivity Index
UN . . . . . United Nations
UNDESA . . . . . United Nations Department of Economic and Social Affairs
UNDP . . . . . United Nations Development Programme
VRS . . . . . Variable Returns to Scale
YMK . . . . . Yang, Ma and Koike

Research Declaration

This is an outline of the major research contributions made by this thesis. This comprises presentations at conferences, published articles, submissions under review and draft manuscripts that will soon be submitted based on research conducted in this thesis.

Workshops and Conferences

1. Turkson, C., Liu, W. & Acquaye, A. (2018) Sustainability in Energy and Environment. Paper presented at *the International Workshop on DEA Evaluation for Sustainable Energy Production 2018*, Business School, Hunan University, Changsha, China.

2. Turkson, C., Liu, W. & Acquaye, A. Reconceptualising Sustainable Energy Portfolio Diversification in Energy Mix Planning. Paper presented at *OR61 Conference 2019*, Operational Research Society at the University of Kent, UK.

3. Turkson, C., Liu, W. & Acquaye, (2019) A. Reconceptualising Sustainable Energy Portfolio Diversification in Energy Mix Planning. Paper presented at *Kent Business School PhD Conference 2019*, University of Kent Business School, UK.

Journal Articles

1. Turkson, C., Acquaye, A., Liu, W. & Papadopoulos, T. (2020) Sustainability Assessment of Energy Production: A Critical Review of Methods, Measures and Issues. *Journal of Environmental Management* **264(15)** 110464. Based on Chapter 2 of the thesis.

2. Turkson, C., Liu, W. & Acquaye, A. Reconceptualising Sustainable Energy Portfolio Diversification in Energy Mix Planning. To be submitted to Journal of Environmental Management. Based on Chapter 7 of the thesis.

3. Turkson, C., Liu, W. & Acquaye, A. Dealing with Sub-Process Non-Homogeneity in Parallel Network Data Envelopment Analysis Models. To be submitted to Expert Systems with Applications. Based on Chapter 5 of the thesis.

4. Turkson, C., Liu, W. & Acquaye, A. Resource Efficiency and Sustainable Electricity Production among EU States: Non-Homogeneous Parallel Network Data Envelopment Analysis. To be submitted to Omega: The International Journal of Management Science. Based on Chapters 2, 4 and 5 of the thesis.

5. Turkson, C., Acquaye, A. & Liu, W. Social Development Assessment of EU States: A Revised Energy Development Index. To be submitted to Journal of Development Studies. Based on Chapters 2, and 6 of the thesis.

6. Turkson, C., Liu, W. & Acquaye, A. Electricity Use and Economy-Society and Environment. A Multistage Network Data Envelopment Analysis. To be submitted to Global Environmental Change. Based on Chapter 6 of the thesis.

7. Turkson, C., Liu, W. & Acquaye, A. An Integrated Assessment of Sustainability in Electricity Generation and Use of EU States. To be submitted to Journal of Environmental Management. Based on Chapters 5 and 6 of the thesis.

Chapter 1

Introduction

1.1 Background of the study

Over the past few decades, policy discussions on sustainability and sustainable development have become mainstream at corporate, national and international levels of governance. Corporations are under increasing ethical and legal pressure to take into account their social and environmental impacts (Haugh and Talwar, 2010; Vigneau et al., 2015; Wolf, 2014). Governmental organisations have had the responsibility of ensuring the protection and preservation of resources that support welfare and economic development (Van Huijstee et al., 2007). Internationally, academic contribution and advocacy by various non-governmental organisations have driven intergovernmental organisations to develop policies with sustainability in mind. Sustainability policy aims to balance economic, social and environmental issues (Atilgan and Azapagic, 2016; Khan, 2015). This growing interest in 'sustainability' in research and policy has resulted in an increased focus on the generation and use of energy, since the secure, clean and affordable supply of energy is essential for economic and social development, as well as improvement of quality of life (Jovanović et al., 2010; Mondal and Denich, 2010).

This thesis extends Data Envelopment Analysis (DEA) and Network DEA (NDEA) methodologies in the assessment of the sustainability of electricity supply and use. Specifically, novel methods for handling differences in the portfolio of sub-processes in parallel NDEA models as well as incorporating sustainability into portfolio selection are proposed. Performance assessment models that incorporate differences in the electricity generation portfolios of different countries and integrate production efficiency, social sustainability assessment, energy utilisation ef-

ficiency, and environmental performance assessments into a single holistic assessment procedure for comprehensive energy policy decision support are developed.

Additionally, the thesis proposes approaches for incorporating sustainability in sustainable energy mix planning. This thesis argues that effective decision support for sustainable energy policy should provide cross-country evaluation that integrates both the supply and demand-side issues of the energy system while incorporating differences in generation portfolios of different countries. NDEA handles performance evaluation problems of complex system structures. Empirical evaluation of electricity demand and supply systems of countries in the European Union (EU) is conducted, thereby providing real-world examples of the internal generation systems and its implications on the society, environment, and economy.

Research in this area has been motivated by the crucial nature of secure, sufficient and accessible energy for modern societies (Varun et al., 2009) due to a growing world population, increased energy use per person, and increased urbanisation and industrialisation rates (Jovanović et al., 2010; Koroneos and Nanaki, 2007; Onat and Bayar, 2010). Additionally, securing a sustainable provision of energy has become one of the central political challenges in modern times (Gallego Carrera and Mack, 2010). As an example, one of the aims of the United Nations Sustainable Development Goals (SDGs) is ensuring access to affordable, reliable and modern energy for all (United Nations, 2015; Volkart et al., 2018). Achievement of this SDG goal is not only important for energy policy but also to fulfilling wider sustainable development objectives for both developed and developing countries. The electricity sector is important for sustainable development since it affects various environmental, economic and social issues across supply chains (Atilgan and Azapagic, 2016). As such, efforts to transition to sustainable energy systems are progressively becoming an issue of paramount importance for decision-makers at various levels (Štreimikienė et al., 2012).

As noted by Štreimikienė et al. (2012, pg. 3302), "efficient production, distribution, and use of energy resources coupled with the provision of equitable and affordable access to energy simultaneously ensuring the security of energy supply and environmental sustainability constitute the main energy policy objectives for a sustainable energy system". The policy objective for clean, secure and affordable energy is often termed the "energy trilemma", which must be balanced in policy and assessment (Jovanović et al., 2010). This has generated great interest among researchers to develop tools and techniques that can be used to measure sustainability as a prerequisite for identifying unsustainable processes and monitoring impact of energy generation and use on society (Afgan and Carvalho, 2004). In

this regard, various multi-criteria decision-making (MCDM) approaches have seen extensive application and methodological extension to handle the integration of multiple dimensions of operation and multiple indicators in sustainability research (Afgan and Darwish, 2011; Diaz-Balteiro et al., 2017; Doukas et al., 2010). DEA, originally introduced by Charnes et al. (1978), although popular for sustainability research has seen limited use in sustainable energy research.

DEA has an advantage over other MCDM approaches as it does not have challenges with normalisation, dimension weighting and aggregation when incorporating economic, social and environmental impacts as occurs with other MCDM approaches (Cinelli et al., 2014; Sueyoshi et al., 2017; Wang et al., 2009). DEA allows for cross-country assessment and benchmarking of energy systems in line with the regional and global nature with which sustainability policy is addressed. The limited application of DEA in sustainability assessment in energy generation is probably due to the complexity in modelling the differences in electricity generation portfolios of different countries, since most DEA approaches require homogeneity in the production systems of units under investigation and treat the production system as a 'black-box' (Zhou, Yang, Chen and Zhu, 2018). However, advances in NDEA methodology together with nonhomogeneous evaluation approaches have provided a new opportunity for advancing DEA literature in sustainable energy generation and use. NDEA has not been extensively employed in sustainability issues although it can take into account the inner operational mechanisms of the different sub-systems in each unit under investigation (Zhou, Yang, Chen and Zhu, 2018). NDEA can handle production systems with series structure, parallel structure, or even a mixture of these (Kao, 2014c), for cooperative and non-cooperative relationships (Liang et al., 2008).

Therefore, this thesis examines the application of DEA in sustainability research of systems characterised by complex internal structures and its implications on other socio-economic and environmental systems. The thesis advances DEA research in handling sustainability research from a systems perspective, while simultaneously incorporating concepts in sustainability literature to develop new approaches in DEA modelling.

1.2 Problem statement

While research on the impact of the electricity system is critical for the electricity mix planning policy, current research has two major limitations:

First, impact assessment of energy systems tends to either (a) focus on economic, social and environmental impacts in producing electricity from some generation sources (Ewertowska et al., 2016; Malkawi et al., 2017; Stamford and Azapagic, 2011); or (b) focus on the use of electricity for economic production while sometimes catering for environmental impact (Lu and Lu, 2019; Pan et al., 2020), thereby treating the production and use phases as separate systems. Štreimikienė et al. (2016) for example, conducted a sustainability evaluation of the Lithuanian electricity mix by considering institutional, economic, social-ethics, technological and environmental criteria associated with electricity generation. On the other hand, Pan et al. (2020) examined energy utilisation efficiency and economic development. Focussing on one thematic area provides decision support for one aspect of energy policy while ignoring the interlinkages between energy security, clean energy, and energy utilisation efficiency, which are important components of energy policy. Both Narula, Reddy and Pachauri (2017) and Narula, Reddy, Pachauri and Dev (2017) posit that energy demand by various sectors triggers energy supply, with supply dynamically responding to energy demand, hence the need to consider both themes concurrently. At the policy level, the European Council in 2007, for example, adopted energy and climate change goals of a 20% reduction in greenhouse gas emissions (GHG), a 20% share of renewable sources in energy consumption and a 20% improvement in energy efficiency by the year 2020 (EEA, 2017; Hadian and Madani, 2015; Kazagic et al., 2014). This requires a look at GHG minimisation in energy production, greater efficiency in energy consumption for economic activities and increased renewable energy sources in the portfolio of both produced and consumed energy.

Second, despite the plethora of Operational Research (OR) methods and techniques for multi-objective or multidimensional problems, application of such approaches for sustainability evaluation needs careful reconsideration since some assumptions of traditional approaches may be inconsistent with some theoretical views in sustainability literature. Kuhlman and Farrington (2010) observe that there have been two major developments in sustainability literature that have served as the building blocks for sustainability assessment: the triple bottom line of sustainability by Elkington (1997) and concepts of 'strong' and 'weak' sustainability coined by Pearce and Atkinson (1992) and extended by Turner (1993). While the triple bottom line emphasises the need to achieve economic, social and environmental objectives, the debate on strong and weak sustainability concerns whether there can be substitution or compensation between natural (environmental), social and manufactured (economic) capital over time. This relationship between the dimensions raises important issues of preference and trade-off, which are not adequately discussed in the

literature (Rowley et al., 2012). Approaches that construct composite indices based on weights that allow for compensation in the aggregation, for example, allow for disadvantages on some criteria to be offset by large advantages on other criteria (Hacatoglu et al., 2015a,b; Rowley et al., 2012) may be inconsistent with some views on sustainability. On the other side, most energy sustainability research is silent on their assumptions on such substitution. The few that do include Duan et al. (2011), Moreira et al. (2015), Myllyviita et al. (2013) and Rogner (2010) who explicitly indicate the capital substitution assumption made in their modelling. Myllyviita et al. (2013), for example, state that because compensation between the dimensions of sustainability is allowed in the framework developed, their framework should be considered to support the concept of weak sustainability. There is little consideration for the arguments of strong sustainability in the energy literature and it is uncertain whether performance evaluation based on the ideas of strong sustainability will yield significantly different results to that based on a weak form of sustainability. Theoretical views on weak and strong sustainability regarding capital substitution thereby provide interesting modelling considerations that can be incorporated into traditional approaches to be better suited for sustainability evaluation.

Although several definitions of sustainability exist, there is a recognition that sustainability assessment should provide global to a local integrated evaluation of economy-nature-society systems in short and long-term perspectives to assist in arriving at actions to make society sustainable (Kates et al., 2001; Singh et al., 2009). In this regard, sustainability assessment of the energy system should go beyond environmental impact and resource efficiency to consider the system's capacity to continue to support society in its use of different sources of energy (Afgan and Carvalho, 2008). This calls for a systems perspective towards sustainability assessment of energy. Such evaluation should not only include the energy system in a local context but also its global effects on economic, social and environmental systems. This is particularly important since little consideration is given in current research to the interactions between the energy system and some social, ecological and economic systems (Sala et al., 2015). For example, though ample research establishes the link between energy use and social development (Martínez and Ebenhack, 2008; Ouedraogo, 2013), assessments of social developments ignore energy use as an essential input (Despotis, 2005a,b).

Additionally, current research either evaluates the sustainability of energy technologies in one country/region while ignoring the global implications of the energy system (Maxim, 2014; Santoyo-Castelazo and Azapagic, 2014) or considers a global perspective that ignores the internal structural differences in energy systems of

different countries (Gómez-Calvet et al., 2014; Song et al., 2013). Consequently, this work provides new insights into the modelling of systems with sustainability considerations. Though sustainability has become an integral part of national and business discourse, modelling approaches employed in such decision support frameworks do not seem to have incorporated the various views espoused in sustainability literature. Neither have they been able to incorporate the production and use phases of the energy system in one assessment procedure. Advances in DEA literature provide the opportunity to incorporate interrelated systems in the same assessment, consider preference relationships between different dimensions and conduct cross-country evaluation in sustainability assessment of the electricity system. This study, therefore, explores how DEA modelling can be informed by sustainability in order to show how DEA can be used for sustainability assessment of complex systems.

1.3 Purpose and objectives

From the preceding arguments, the primary research question is how to provide a holistic sustainability assessment of the electricity system that incorporates the production and consumption phases of the system which allows for cross-country benchmarking of performance and caters for differences in generation portfolios. The thesis aims to develop DEA-based systems assessment models for integrated evaluation of the sustainability of energy systems that allow for differences in internal generation structures of different countries while allowing for cross-country comparison and benchmarking and interactions of the energy system with other systems. This is achieved by developing new DEA-based assessment models that integrate production and use phases of the energy system in the same assessment framework to evaluate the complex relationships in the entire system. Finally, it provides an empirical assessment and benchmarking of the energy mixes of members of the EU. Specifically, the study aims to:

a. explore DEA optimisation models that cater for differences in production portfolios and the assessment of sustainability and resource efficiency in electricity production of EU countries.

b. integrate electricity production and use evaluations, economic development, social development and environmental assessments into a single holistic assessment procedure that caters for alternative views on sustainability.

c. examine the implication of sustainability in portfolio optimisation models aimed at selecting an optimal mix of energy generation sources that aim to ensure affordable but clean energy system.

1.4 Research contributions

Unlike the existing literature, which has treated electricity production efficiency, environmental performance, and energy efficiency evaluation as separate, this study shows the utility of an integrated evaluation while recognising the interconnectedness of supply and consumption of electricity. Additionally, by formulating the evaluation models according to different views on sustainability, this work contributes to the DEA literature on sustainability and provides a basis for comparing prescriptions from different sustainability perspectives. Finally, the regional focus of the empirical application of this work contributes directly to the European Commission's Secure, Clean and Efficient Energy policy on a single, smart European electricity grid. This is because the decomposition of the internal generation systems of individual countries provides an understanding of the strengths and weaknesses of individual countries in generating electricity by generation source. This provides a good basis for future European plans for an integrated electricity generation grid.

To summarise, the following research and practical contributions are claimed in this thesis:

a. A model is introduced to examine the performance of the electricity generation systems of different European countries while recognising the differences in the generation portfolio. Novel methods for dealing with non-homogeneity in the production portfolio of units under investigation are proposed. The aim is to allow cross-country benchmarking and overview of the capabilities of different countries in generation using different sources in line with planned transition unto a single, smart European electricity grid.

b. In the consumption phase of the assessment, an extension to current eco-efficiency, social development assessment and environmental performance literature is provided. Unlike previous studies that mostly treat these assessments as separate, a concurrent assessment that shows the interrelationships and complementarities between these assessments in policy is proposed. As such, it is shown that decisions on economic development have implications on social development, environmental performance and even electricity generation.

c. A holistic model is formulated that extends the previous model to integrate the production of electricity with the consumption phase. This model, therefore, allows energy production and transmission processes to be understood in one assessment framework. Since this is a serial structure, it provides the ability to examine for each country, the source of poor performance in the entire energy system.

d. Additionally, novel approaches for social and environmental performance assessments are also proposed to examine the impact of electricity production and consumption on the human development and environmental systems of the countries under evaluation. For the social development assessment, for the first time, a DEA evaluation of the Energy Development Index (EDI) is conducted which incorporates energy as an important input to social development and employment as an output that links with economic development assessment. On the environmental performance phase, unlike previous studies, a direct link between emissions and the biological capacity of countries is proposed.

e. Finally, the study shows the weaknesses of traditional energy portfolio optimisation in constructing optimal technology portfolios when sustainability objectives are to be considered. It is shown that combining the various sustainability dimensions using an additive relationship negates the relevance of some of the dimensions, therefore, making some dimensions more important than others and resulting in optimal portfolios which are inconsistent with sustainability.

As such, this thesis provides an assessment of the security of supply of energy, the production and consumption of clean energy and decision support for incorporating environmental and social factors when generating an affordable energy system.

1.5 Outline of the thesis

Subsequent chapters of the thesis are organised as follows:

Chapter 2 provides a review of the literature on sustainable energy systems that relate to the current study. The chapter begins with a general overview of sustainability and sustainable development, highlighting definitional and other important concepts in the general sustainability literature. This is followed by sections on energy and economic, social and environmental development and sustainability

assessment in energy research. Subsequent sub-sections review methods in sustainability assessment with extended focus on DEA applications in energy sustainability literature.

Chapter 3 provides a methodological review of NDEA and related concepts. The chapter presents DEA models for parallel, series and mixed production structures. Additionally, the literature on modelling considerations on interlinking outputs or inputs, dealing with undesirable outputs and non-homogeneity is also presented. Critiques of current models are discussed and solutions to those critiques are proposed in subsequent sections.

Chapter 4 is the problem structuring chapter. The chapter begins with causal loop diagrams that provide a systematic framework of the problem. These causal loop diagrams, developed from careful studying of the literature, are then transformed into network structures to be assessed in subsequent sections.

Chapter 5 is the first empirical chapter of the study. This chapter examines the sustainability and resource efficiency in electricity production of EU countries. As such, it is aimed at addressing the first objective which focusses on the production phase of the sustainable energy system. As electricity is generated concurrently from different generation sources, parallel network models are constructed to provide empirical answers to issues under consideration. This chapter provides insights on the overall production performance as well as the component (technology-wise) performance of each EU country compared to its peers.

Chapter 6 combines the generation phase with the use phase of the energy system. The chapter further provides an empirical evaluation of the sustainability of the energy systems of various EU countries while integrating electricity production evaluation, energy use efficiency and environmental assessment into a single holistic assessment procedure. Consequently, the parallel network structures constructed in Chapter 5 are extended to incorporate series relationships with the environmental, social and economic systems. This chapter provides insights on the overall system, production and use, as well as sub-system performance of each country.

Chapter 7 moves on from discussions concerning energy security and energy efficiency issues, covered in previous chapters, to addressing issues of clean and affordable energy. In this chapter, the impact of interaction and other relationships between various cost components on the technology ranking and the optimal portfolio is explored. Here, how a truly sustainable optimal portfolio of generation sources can be constructed consistently with the ideal principles of sustainability is demonstrated.

Finally, Chapter 8 provides a summary of findings, conclusions on both model formulation and empirical assessment, as well as recommendations for practice, policy

and further research. The interrelationships and flow of the thesis are summarised in Figure 1.1.

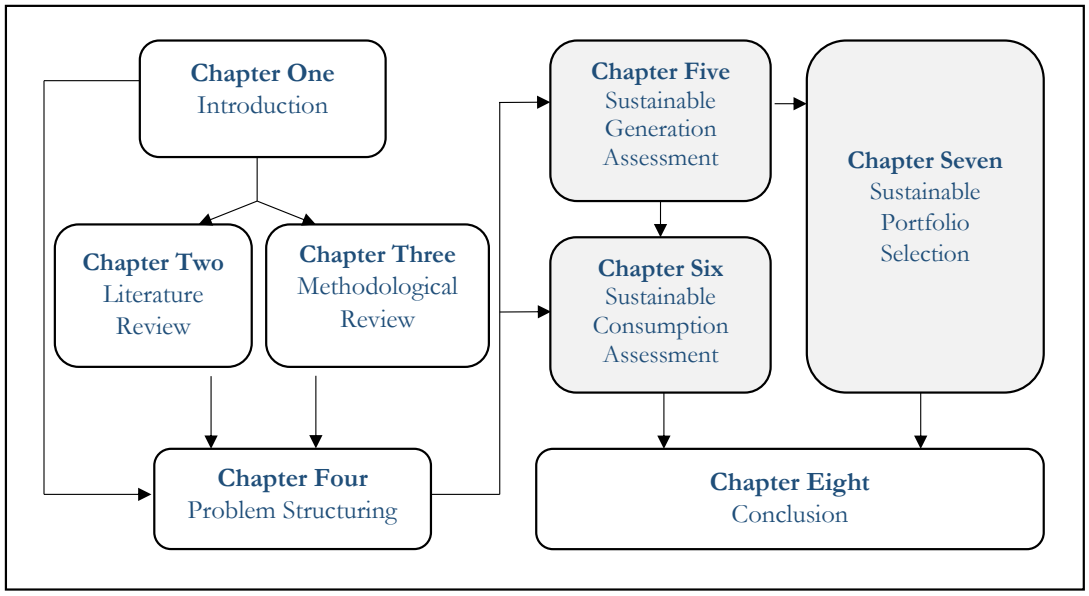

Figure 1.1 Overview of the thesis structure.

Arrows show the relationship between chapters and the research objectives in shaded boxes.

It is worth pointing out that Chapters 5 and 6 focus on the clean and secure energy aspects of the energy trilemma, while Chapter 7 addresses affordable energy through the minimisation of the cost of energy supply. Since the generation mix decision is related to how energy is produced, Chapter 7 is directly linked with Chapter 5, which looks at energy production. While Chapter 7 examines how countries select the portfolio of the generation sources, Chapter 5 looks at the sustainable and resource efficient electricity produced from the selected generation sources.

Chapter 2

Literature Review of Sustainable Energy System

2.1 Introduction

This chapter is divided into four main sections. Section 2.2 presents a general overview of sustainability and sustainable development, highlighting definitional and ethical issues as well as important concepts surrounding the dimensions of sustainability. Subsequent sections are dedicated to energy and sustainable development. While Sections 2.3 presents conceptual issues surrounding the relationship between energy, environment, social development and economic development, Section 2.4 presents empirical research on sustainability assessment in energy research. Section 2.5 reviews systems thinking and sustainability as it relates to energy research. Finally, Section 2.6 presents a summary of the chapter.

2.2 Sustainability and sustainable development

2.2.1 Towards a definition

Although the term 'sustainability' seems ubiquitous in policy and literature, there is little consensus on its meaning. It is a difficult concept to define because it is an evolving one and its meaning is both abstract (Martens, 2006) and contextual (Kajikawa et al., 2007; Young and Dhanda, 2013). The definition of sustainability depends on the context in which it is used, as such, 'sustainability economics' (Baumgärtner and Quaas, 2010), 'sustainability science' (Kajikawa et al., 2007), 'sustainable system', 'sustainable ecology', 'sustainable production' (Glavič and

Lukman, 2007) among others are used in different fields of study, each with a slightly different meaning. To be sustainable as a normative concept is analogous to terms like 'viability', 'survival', 'feasibility', 'persistence', 'unceasing' and 'continual'. However, its use in policy-oriented research is not as clear as its normative meanings.

A number of historical key works such as Tragedy of the Commons in 1968 (Hardin, 1968), A Blueprint for Survival in 1972 (Goldsmith and Allen, 1972) and Limits to Growth also in 1972 (Meadows et al., 1972), highlighted some of the key sustainable development principles even before the publication of the Brundtland Report in 1987 (Brundtland, 1987). Following the Brundtland Report, definitions in the literature have gone on to re-emphasize human or ecological underpinnings of sustainable development. Table 2.1 provides some definitions of sustainability from the literature. Shaker (2015) sees sustainability as humanity's target goal for human and ecosystem equilibrium (homeostasis). Finkbeiner et al. (2010) observe that sustainability should not focus on environmental impact alone but there should be a balance or even an optimum in environmental, economic and social well-being dimensions of society. Similarly, McMichael et al. (2003) believe that sustainability means transforming human ways of living to maximise chances that environmental and social conditions can support human security, well-being and health indefinitely. Kahle and Gurel-Atay (2013) believe that "sustainability implies the use of resources in a manner that can continue indefinitely."

All of these definitions though different, share some similarities. They all stress the impact of human activity on the environment or the use of resources by humans. Additionally, they strive for maintenance or maximisation of a level of quality of life in the long-term. The definition by Kahle and Gurel-Atay (2013), for example, advocates that sustainability should last indefinitely. Finally, several of these definitions see sustainability as an end-goal that can be attained. McMichael et al. (2003), for example, believe that sustainability can be attained through interactive inter-disciplinary efforts. It must be noted that the view that sustainability can be "attained" as an end-goal is disputed by some such as Kahle and Gurel-Atay (2013) who have suggested that sustainability is infinite and that because of the principle of continuous improvement used in sustainability, "ideal" sustainability can never be achieved.

Table 2.1 Definitions of sustainability.

Definition	Source
"Sustainability is defined as a requirement of our generation to manage the resource base such that the average quality of life that we ensure ourselves can potentially be shared by all future generations."	Asheim (1994)
"Sustainability is "the capacity for continuance more or less indefinitely into the future."	Ekins and Newby (1998) in Bonevac (2010)
"Sustainability means transforming our ways of living to maximize the chances that environmental and social conditions will indefinitely support human security, well-being and health."	McMichael et al. (2003)
"I define sustainability as the possibility that humans and other life will flourish on the Earth forever"	Ehrenfeld (2008) in Bonevac (2010)
"Sustainability does not only focus on the environmental impact, it rather consists of the three dimensions "environment", "economy" and "social well-being", for which society needs to find a balance or even an optimum"	Finkbeiner et al. (2010)
"Sustainability is a normative notion about the way how humans should act towards nature, and how they are responsible towards one another and future generations"	Baumgärtner and Quaas (2010)
"Sustainability may then be defined as maintaining well-being over a long, perhaps even an indefinite period"	Kuhlman and Farrington (2010)
"Sustainability can now loosely be defined as a state of affairs where the sum of natural and man-made resources remains at least constant for the foreseeable future, in order that the well-being of future generations does not decline"	Kuhlman and Farrington (2010)

Continued...

Continuation of Table 2.1

Definition	Source
"Sustainability implies the use of resources in a manner that can continue indefinitely. This ideal often remains elusive, but it is always the long-term goal, even if unstated."	Kahle and Gurel-Atay (2013)
"'Sustainability' should be viewed as humanity's target goal of human-ecosystem equilibrium (homeostasis)"	Shaker (2015)
"Sustainability is lexically defined as the ability to maintain something undiminished over some time period"	Lélé and Norgaard (1996)
"Sustainability refers to the ability of a society, ecosystem, or any such ongoing system to continue functioning into the indefinite future without being forced into decline through exhaustion or overloading of key resources on which that system depends"	Gilman (1992) in Foley et al. (2003)
"Sustainability is the principle of ensuring that our actions today do not limit the range of economic, social, and environmental options open to future generations."	Elkington (1997)
"Sustainability is a process involving people, institutions, natural resources, and the environment"	Munier (2005)

This shows the existence of different schools of thought about what constitutes sustainability. On the issue of human activities and implications for the environment, Kajikawa et al. (2007) assert that sustainability does not connote human exploitation of nature. In their view, the human-nature dynamic should rather relate to an alternative term 'sustainable development'. Regarding the term limits of sustainability policy, Bonevac (2010) believes that for the concept of sustainability to have real use and not be seen only as rhetoric, it must be restricted to a period about which reasonable claims of survival can be made. Expecting a resource to exist indefinitely is unreasonable since there are time limits to every natural system, including the universe (Bonevac, 2010). Finally, while Kuhlman and Farrington (2010), McMichael et al. (2003) and Shaker (2015) see sustainability as a goal to be achieved, Kajikawa et al. (2007) see sustainability not as a goal but rather a constraint on the achievement of other goals. Kahle and Gurel-Atay (2013) believe

that sustainability should last indefinitely and therefore should not be viewed as an end-goal to be achieved.

The problem becomes confounded when the meaning of sustainable development is explored. Some of such definitions are provided in Table 2.2. Critics believe 'sustainable development' is vague and can be an oxymoron (Bonevac, 2010; Kajikawa et al., 2007). Additionally, authors like Bonevac (2010) and Büyüközkan and Karabulut (2018) do not make a distinction between sustainability and sustainable development. Giovannoni and Fabietti (2013) use the terms sustainability and sustainable development as analogues but observe that whereas sustainability refers to a 'state', sustainable development refers to the processes required to reach that state. However, there is disagreement about these terms. Gallopín (2003) asserts that the two concepts are quite different in that the word "development" points to the idea of a progressive change which may not necessarily be quantitative. Shaker (2015) sees sustainable development as the holistic approach and temporal processes that lead us to the end point of sustainability.

Table 2.2 Definitions of sustainable development.

Definition	Source
"Development that meets the needs of the present without compromising that ability of future generations to meet their own needs"	Brundtland (1987)
"Development is sustainable if it involves a non-decreasing average quality of life."	Asheim (1994)
"'Sustainable development' refers to the holistic approach and temporal processes that lead us to the end point of sustainability"	Shaker (2015)
"Sustainable development as "development that lasts."	Giles Atkinson et al. (1997) in Bonevac (2010)
"Sustainable development is a strategy by which communities seek economic development approaches that also benefit the local environment and quality of life." The United States Department of Energy	Mawhinney in Bonevac (2010)

Perhaps, the most widely cited definition of sustainable development is the one outlined in the Brundtland Report that sustainable development is "*development that meets the needs of the present without compromising that ability of future generations to meet their own needs*" (Brundtland, 1987, p. 43). This definition has two implications - first, it stresses the ability to meet today's needs (intra-generational justice) while second, not compromising the needs of future generations (inter-generational justice) (Baumgärtner and Quaas, 2010; Kuhlman and Farrington, 2010; Schlör et al., 2012). These ethical perspectives on sustainable development are explored in Section 2.2.2.

There is no unanimity regarding the theoretical and conceptual foundations of sustainability and sustainable development (Shaker, 2015). Despite its vagueness and ambiguity, the Brundtland Report's definition has been highly instrumental and spurred research interest concerning the future of the planet (Mebratu, 1998). Some even believe that the absence of a rigorous definition of the terms provides an opportunity for more debate about the issues in search of common ground (Lélé, 1991). However, modern discussions of both sustainability and sustainable development believe that life on earth has environmental limits, which humans, through interconnected consideration of the economy, environment and society, have a responsibility to preserve (Young and Dhanda, 2013). These environmental limits are highlighted in the concept of the planetary boundaries (Rockström et al., 2009). Gallopín (2003) advocates that due to the ambiguity and lack of strong theoretical background to the field, sustainability can be viewed from a system's perspective, where careful consideration of the aspect of the system to be sustained are emphasised. Although there is no unanimity in terms of the theoretical foundations of sustainability, its ethical foundations are well understood. These are discussed in the next sub-section.

2.2.2 Ethical foundations

Discussions of sustainability are grounded within certain ethical considerations that provide the basis on which sustainability-related policy and measurement approaches should be focussed. The core meaning of the modern concept of sustainability is based on continuity with a long-term perspective which hinges on three fundamental relationships of human beings (Becker, 2012):

1. Relationship between humans and contemporaries (intra-generational justice);
2. Relationship between current and future human generations (inter-generational justice); and

3. Relationship between humans and nature.

The first two relationships are directly referenced in the famous Brundtland definition that sustainable development is, "*development that meets the needs of the present without compromising that ability of future generations to meet their own needs*" (Brundtland, 1987, p. 43). The first part of the definition "meeting the needs of the present" is a requirement for ensuring that the needs of current generations are met equitably or fairly without disadvantaging contemporaries. Intra-generational considerations in the sustainability of the energy system may include issues of reducing energy poverty, improving access to energy and ensuring energy security. The second part of the definition, "... without compromising the ability of future generations to meet their own needs", presents a requirement for current generations to ensure that resources necessary for future human generations can be met. In energy systems sustainability, objectives relating to the use of renewable energy sources and reducing negative externalities have some inter-generational underpinnings. These two perspectives carry an 'anthropocentric' notion of justice that reflects the view that nature exists to satisfy current and future human needs (Baumgärtner and Quaas, 2010).

However, the modern concept of sustainability also requires the need for some justice between human and nature interactions. This is indirectly captured in the Brundtland Report (Becker, 2012) since intra- and inter-generational justice will require that the quality or stock of nature is not depleted for the needs of current and future generations. There is, therefore, the requirement to recognise the importance of the environment as a key stakeholder (Hart, 1995) for both present and future generations and that there is an inescapable biological dependency of human life on nature (Becker, 2006). This view, termed as 'physio-centric ethics' by Baumgärtner and Quaas (2010), requires long-term justice for nature. It emphasises that the setting of human-nature relationships is central to the concept of sustainability. It moves from the 'bio-centric or eco-centric viewpoints' that sees the environment as the ethical precondition for sustainability even at the point of excluding humans or increasing human poverty (Gallopín, 2003). Justice towards current and future human society and environment shows the multidimensional nature of sustainability. Major dimensions in sustainability literature are discussed in subsequent sub-sections.

2.2.3 Dimensions of sustainability

Since the Brundtland Report, there have been two major developments in sustainability literature (Kuhlman and Farrington, 2010): a) the 'three dimensions of

sustainability' and; b) the distinction between 'strong' and 'weak' sustainability. While the three dimensions assessment of sustainability pioneered by Elkington (1997) is a framework which emphasises the need to consider economic, social and environmental objectives in sustainability assessment, the distinction between 'strong' and 'weak' sustainability coined by Pearce and Atkinson (1992) and further refined by Turner (1993), presents different perspectives on the relationship between nature and society. These have served as the building blocks for subsequent developments in sustainability assessments.

It must be noted that there exist other theoretical frameworks used in sustainability research. Chang et al. (2017) identifies corporate social responsibility (Carroll, 1999; Lee, 2008), stakeholder theory (Freeman, 1984) and corporate sustainability (Elkington, 1997) as the major theories used in sustainability research. However, these theories focus on the role of corporate entities in the sustainability. In this research, the focus is on sustainability of a national system. The three dimensions and the concepts of weak and strong sustainability provide a framework for studying sustainability at the national level. Consequently, the next two sub-sections discuss these two major developments in the sustainability literature.

Three dimensions of sustainability

Sustainability is widely considered a multidimensional undertaking that considers economic, social and environmental impacts as interdependent components relevant to achieving higher quality of life (Kuhlman and Farrington, 2010). Although there have been arguments to include other dimensions like technological and institutional dimensions to sustainability (International Atomic Energy Agency, 2005; Maxim, 2014), the three dimensions remain the basis of most sustainability assessment. The three dimensions consist of "environment", "economy" and "social well-being", for which society (or the system under consideration) needs to find a balance (Finkbeiner et al., 2010). This idea was pioneered by Elkington (1997) who coined the term "triple bottom line" while presenting a conceptual accounting framework which emphasises the need to find a balance in the dynamic interactions between economic, social and environmental dimensions within any system or decision-making process. This is a three-pronged model that proposes economic prosperity, environmental quality and social justice as the obligations to which businesses and economies should be held accountable in terms of performance instead of the traditional profit-based single bottom line focus (Elkington, 1997). The triple bottom line Venn diagram as

presented in Figure 2.1, shows sustainability as the point of intersection between social, environmental and economic objectives.

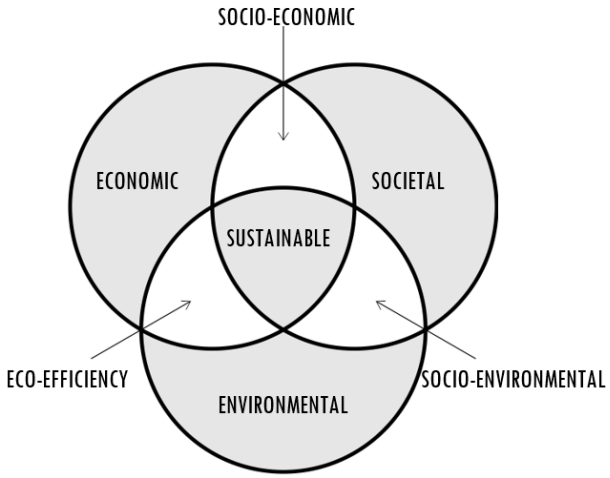

Figure 2.1 Triple bottom line Venn diagram.

The economic or profits dimension of sustainability is the more traditional ideas of cost and profit concerns of corporations and governments. It aims at an organisation remaining a going-concern or economic prosperity of citizens in the case of governments. Contemporary thinking of core drivers of a business case for sustainability now extends beyond cost and profit to include qualitative factors such as risk and risk reduction, reputation and brand value, the attractiveness of an employer and innovative capabilities (Schaltegger et al., 2012). From this perspective, sustainability is seen as the capability of a corporation to survive in terms of profitability, productivity and long-term financial performance (Giovannoni and Fabietti, 2013). This involves meeting the needs of stakeholders, effective and efficient management of resources and conformity to regulations. When it comes to public policy perspective, profit maximisation is usually not an appropriate goal, rather maximising the nation's wealth usually expressed as gross domestic product (GDP) is usually seen as the economic dimension (Kuhlman and Farrington, 2010). The International Atomic Energy Agency (IAEA), United Nations Department of Economic and Social Affairs (UNDESA), International Energy Agency (IEA), EUROSTAT and the European Environment Agency (EEA) all consider use and production patterns and energy security as critical economic themes for sustainable development of energy systems (International Atomic Energy Agency, 2005).

The social or people's dimension captures the impact of corporations, systems, products or processes on society (Kuhlman and Farrington, 2010). Social equity,

social justice, health and safety, distributive justice and equality of conditions, as well as the notion of social responsibility of corporations are usually discussed in the context of the social dimension of sustainability (Giovannoni and Fabietti, 2013; Glavič and Lukman, 2007). This perspective of sustainability requires that organisations, products and processes are delivered in a manner that will meet the objectives and values of society. The social dimension is often difficult to measure or quantify in practice (Kuhlman and Farrington, 2010). Important social themes for sustainable development in energy systems include equity, which includes accessibility and affordability, and health and safety (International Atomic Energy Agency, 2005).

The environmental or planet dimension considers the ecological impacts of human and corporate activities. Prior to the multidimensional perspective of sustainability, sustainability was often compartmentalised as an environmental issue alone (Giovannoni and Fabietti, 2013) relating to issues such as pollution control, clean production, eco-design, life cycle assessment and zero waste (Glavič and Lukman, 2007). This dimension recognises nature as a source of resources for human social and economic activities that generate waste which may be harmful to nature. There is, therefore, the need to consider the ecological impacts of human activities since this has an impact on the ability to meet current human needs and those of future generations. In energy systems, the atmosphere, water and land are important themes considered in environmental policy initiatives (International Atomic Energy Agency, 2005).

These three dimensions have been the primary focus of most studies on sustainability. The modern concept of sustainability is based on the idea of harmony in these three pillars of sustainability (Finkbeiner et al., 2010). There are other, less ambitious dimensions, such as those which are not environmentally damaging and support society but come at a high cost (bearable socio-environmental projects), economically viable projects which support society but have high environmental implications (equitable socio-economic projects) and those that are economically profitable, do not burden the environment but do not provide sufficient support from society (viable eco-efficiency activities) (Sykes and Trench, 2014). This idea of interconnectedness and dynamic interactions of natural, social and economic systems is fundamental to a holistic and system-wide sustainability thinking (Gallopín, 2003; Schoolman et al., 2012).

There have been other views on the dimensions of sustainability. Kuhlman and Farrington (2010), argue that the re-interpreting of the essence of sustainability to encompass the three dimensions obscures the real contradiction between welfare

and environmental conservation, diminishes the importance of the environmental dimension and separates the social dimension from economic dimension, which in reality are the same. They propose the replacement of the social and economic dimensions with a single dimension called 'well-being', which is to be balanced with another called sustainability, which primarily focusses on environmental or ecological aspects (Kuhlman and Farrington, 2010). There have been other proposals to include other dimensions like technological and institutional dimensions (International Atomic Energy Agency, 2005; Maxim, 2014), however, these have not been as popular in the literature.

Weak versus strong sustainability

Kuhlman and Farrington (2010) assert that the next most important development in the sustainability literature is the distinction between 'strong' and 'weak' sustainability, which was coined by Pearce and Atkinson (1992) and was further developed by Turner (1993) into 'very strong', 'strong', 'weak' and 'very weak' sustainability. This discussion of weak and strong sustainability moves the debate from how development must be measured to a focus on what must be done to secure the desired development (Pearce and Atkinson, 1998). This idea of sustainability is based on economic growth theory and equates sustainable development as that which ensures non-declining per capita well-being over some time (Pearce and Atkinson, 1998). Based on economic growth theory, the concept of capital (K) is defined to comprise manufactured capital (K_m), skills and knowledge of humans, otherwise called human capital (K_h) and natural resources and stock of environmental assets together known as natural capital (K_n) (Pearce and Atkinson, 1998).

The initial idea of weak sustainability is based on the belief that the next human generation should inherit a stock of wealth that is not less than the stock inherited by the current generation (Kuhlman and Farrington, 2010). Therefore, weak sustainability is to ensure that aggregate capital is non-declining, even to the detriment of other types of capital. This is expressed by Pearce and Atkinson (1998) as:

$$\frac{dK}{dt} \geq 0, \quad \text{where } K = K_m + K_h + K_n \tag{2.1}$$

In other words, the change in aggregate capital K over a change in time t should not fall. Weak sustainability, therefore, implicitly allows for the substitution of one form of capital for other forms of capital. This means that the stock of natural capital could be reduced as far as the proceeds received are reinvested in

other forms of capital such as social capital. This is the perspective of classical economists who relegate nature as the provider and sink (for wastes) of human consumption (Gallopín, 2003). Weak sustainability was later re-categorised as 'very weak' sustainability by Turner (1993).

Due to the capital substitution condition, the idea of weak (or very weak) sustainability is seen by environmentalists to be unsuitable for promoting sustainability goals (Bonevac, 2010). Strong sustainability (very strong by Turner (1993)), on the other hand, advocates that the next generation should inherit a stock of environmental assets which is not less than the stock inherited by the current generation (Kuhlman and Farrington, 2010).

$$\frac{dK}{dt} \geq 0 \quad \text{and} \quad \frac{dK_n}{dt} \geq 0 \tag{2.2}$$

This, therefore, imposes an additional constraint on weak sustainability, as proponents of this school of thought believe that natural capital has no substitute. Therefore, in addition to the non-declining requirement on aggregate capital stock, there is the requirement that natural capital should also be non-declining even if it means a reduction in human and manufactured capital (Pearce and Atkinson, 1998). Pursuance of ecological sustainability irrespective of human and economic concerns is not acceptable to critics (Gallopín, 2003). Bonevac (2010) also observes that the lack of substitution between natural and manufactured capital will mean that economic capital cannot be used to increase the stock of natural capital when in decline.

The divide between the tenets of strong and weak sustainability has led to several intermediate positions which allow for limited trade-offs between the various forms of capital (Bonevac, 2010). Whereas Bonevac (2010) views these intermediate schools as 'sensible sustainability', Gallopín (2003) sees the ideas of what Turner (1993) calls weak and strong sustainability as that which allows for the sustainability of the whole socio-ecological system. While Turner's (1993) view of strong sustainability holds that different forms of capital are not necessarily fungible and a minimum amount of these different capitals must be maintained independently, the weak view of sustainability places emphasis on preserving some critical natural capital which is considered irrecoverable if lost (Gallopín, 2003). Table 2.3 provides a summary of the various views discussed.

These views on substitution and non-substitution of various forms of capital in the OR literature is closely linked with the aggregation of overall sustainability indices across the dimensions (De Mare et al., 2015). The choice of a multidimensional

Table 2.3 The spectrum of sustainable development.

Classification		**Characteristics**
Pearce and Atkinson	Turner	
Weak sustainability	Very Weak sustainability	a. The overall stock of capital assets remains stable over time b. Complete substitution between human and natural capital
	Weak sustainability	a. Some natural capital is critical (non-substitutable) b. Trade-offs still possible
Strong sustainability	Very Strong sustainability	a. All natural and other forms of capital should be independently kept intact over time b. No capital substitution
	Strong sustainability	a. Minimum amounts of different capitals must be maintained independently b. No capital substitution

Adapted from Gibbs et al. (1998)

assessment approach may be characterised by a higher or lower level of compensation between the sustainability dimensions (De Mare et al., 2015; Figge and Hahn, 2004). If the method allows poor performance on one dimension to be compensated by excellent performance on other dimensions, then it can be argued that the dimensions are compensable, which is akin to the idea of weak sustainability (Rowley et al., 2012). This is because the approach allows for trade-off in the various dimensions (Hacatoglu et al., 2015a) and hence the aggregate performance is being maximised even at the expense of individual dimensions. If the approach does not allow for trade-off, however, then it is akin to strong sustainability (Rowley et al., 2012).

2.2.4 Sustainability of a system

The core ideas of modern thinking around sustainability and sustainable development are based on interaction and inter-dependency between different dimensions of the system or entity under study. This is because industrial, social and ecological systems are closely linked when making effective decisions regarding global sustainability (Fiksel, 2006; Finkbeiner et al., 2010). There are complex relationships within and between the various systems that need to be integrated in sustainability assessment.

Additionally, there is a need to understand the dynamic behaviour of the entity or system under study to develop a more integrated and resilient solution to sustainability objectives (Fiksel, 2006). There is also little unanimity and theoretical grounding around sustainability (Shaker, 2015), which makes sound and robust assessment for policy difficult.

Systems thinking can offer a useful perspective, compared to other analytical approaches, when thinking about sustainability since it is a way of thinking in terms of connectedness, relationships and contexts, which are key underlining principles in sustainability (Gallopín, 2003). This provides a more robust and conceptually sound framework for sustainability analysis. Indeed, the idea of the system view of sustainability is gradually becoming mainstream in sustainability literature. A survey of 96 papers, published from 1990 to 2015, on systems thinking in sustainability analysis by Williams et al. (2017) found that 67 out of the 96 papers published using systems thinking were published from 2010 onward. This shows a growing acceptance of the ability of systems thinking in enhancing understanding of the dynamic interactions within and across interconnected systems (Whiteman et al., 2013; Williams et al., 2017). Systems thinking of sustainability is very useful when considering the complexity, dynamic interactions and nonlinear interdependencies of related systems (Fiksel, 2006).

A system is considered as a set of interrelated elements which may include several other sub-systems or components (Gallopín, 2003). These interconnected elements are characterised by hierarchical structures, communication, emergent structures and control (Clayton and Radcliffe, 1997). Since all physically extant systems are open, the behaviour of a system depends on the system's internal interactions, how the external elements or variables from the environment affect it and outputs of the system into the environment (Gallopín, 2003). There is, therefore, the need to always determine the boundaries of the system being studied and the adjacent systems that interact with the system under consideration (Foley et al., 2003). Figure 2.2 is a general system, which represents the interaction between energy generation system, ecology and society.

The state variables internal to the boundary of the system under study at a given point in time are determined by the state of the system and the inputs received previously in time (Gallopín, 2003). Given Foley et al.'s (2003) definition of a state, changes in a state variable x_j over time can be expressed as:

$$x_j(t_2) = x_j(t_1) + \Delta x_j^A(t_1) + \Delta x_j^I(t_1) - \Delta x_j^B(t_1) - \Delta x_j^E(t_1) - \Delta x_j^L(t_1) \qquad (2.3)$$

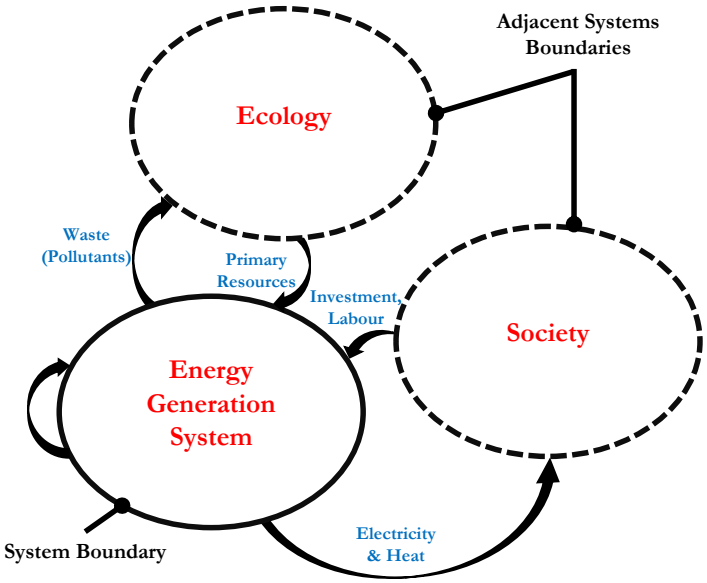

Figure 2.2 A sample representation of a system.

Adapted from Foley et al. (2003)

The new state $x_j(t_2)$ depends on the prior state $x_j(t_1)$, imports of the resource $\Delta x_j^I(t_1)$, inflows from adjacent systems $\Delta x_j^A(t_1)$, the exports $\Delta x_j^E(t_1)$, losses due to consumption $\Delta x_j^L(t_1)$, and outflows to adjacent systems $\Delta x_j^B(t_1)$. Based on this, the sustainability of a system could be defined as a system for which the net worth of outputs produced is non-decreasing over time (Gallopín, 2003):

$$x_j(t_2) \geq x_j(t_1) \tag{2.4}$$

Other definitions of sustainability can be explored. For example, a resource variable in the system may be required to operate indefinitely not less than a requirement $x_j^R(t_1)$ (Foley et al., 2003).

$$x_j(t_1) \geq x_j^R(t_1) \tag{2.5}$$

The systems approach can be used as the basis for understanding the meaning of sustainability by considering the need for continuing management of system resources over time, understanding the significance of interactions among systems, understanding the importance of planning and designing the system, appreciating the need to re-evaluate the system sustainability at regular intervals and examining issues related to the resilience of the system (Fiksel, 2006; Foley et al., 2003).

2.3 Energy and sustainable development

At the national level, electricity systems are powered by a mix of energy from three main sources, fossil fuels (coal, gas, petroleum which are non-renewable), nuclear power and renewables (wind, hydro, geothermal, solar etc.) (Varun et al., 2009), each with their own sub-processes and production requirements, cost and availability constraints and environmental impacts. The need to assess the implications of energy generation and use has resulted in attempts to define a set of energy indicators for assessing sustainable development. The IAEA, together with UNDESA, IEA, EUROSTAT and EEA, for example, have developed the 'Energy Indicators for Sustainable Development: Guidelines and Methodologies' (International Atomic Energy Agency, 2005). Energy indicators, developed by these bodies and in research, have been defined based on a combination of economic, environmental, social and technological characteristics of energy production and consumption (Jovanović et al., 2010), thus recognising the multidimensional nature of the sustainability problem in energy.

Sustainable development of energy systems has become important for policy since three of the main global policy objectives include economic growth, energy security and climate change mitigation (Santoyo-Castelazo and Azapagic, 2014). Activities related to the sustainable development of energy systems include a reduction in emissions and pollutant gases, increased safety of energy supply, use of renewable energy sources, improved energy efficiency and improved quality of life (Jovanović et al., 2009). Energy, therefore, has implications for the environment, economic development and social welfare. In the following sub-sections, the implications of energy production and consumption on the environment, society and the economy are discussed.

2.3.1 Energy and the environment

Ensuring that affordable and reliable energy is derived from environmentally appropriate supply sources is critical for sustainable development (Afgan et al., 2007). This is because of the substantial environmental impacts from the production of various forms of energy. Apart from its contribution to social and economic development, energy consumption is also recognised as a major source of greenhouse gas (GHG) emissions (Lu et al., 2016). A significant proportion of global carbon dioxide (CO_2) emissions and air pollution is a result of fossil fuel combustion to satisfy energy demand (Rafaj et al., 2006). Coal, for example, has the highest CO_2 emissions per

kWh but continues to dominate the market due to low cost and high availability (Evans et al., 2009; Varun et al., 2009).

Direct GHG emissions in the energy sector is mainly due to activities like transport, electricity generation, manufacturing, construction and consumption in the residential, commercial and institutional sub-sectors (Varun et al., 2009). Such emissions that are noxious to health and the environment include CO_2, carbon monoxide, methane, nitrogen oxides, sulfur oxides and particulate matter emissions (Genoud and Lesourd, 2009; Orecchini, 2007; Sahabmanesh and Saboohi, 2017). Among these, CO_2 has been of primary importance in research for several reasons. Although CO_2 is not directly dangerous to human health, it is seen as the major driver of climate change, with the scientific community nearly unanimous in this view (Orecchini, 2007) and related risks to human development as a whole (Filho et al., 2016). The World Commission on Environment and Development, in the Brundtland Report, identified CO_2 as the most important GHG since it is unlike other air pollutants whose cost of removal from the fuel combustion process is lower than the cost of damage (Brundtland, 1987). As a result of its global effect, reduction of CO_2 emissions has become of paramount interest in the design and construction of new power plants with the inclusion of features related to low emissions per unit of energy produced (Afgan and Carvalho, 2004).

Although fossil fuel is widely seen to have a higher environmental impact, no single technology shows the best performance on every type of environmental impact. Nuclear energy, for example, has marginal global warming potential but high ionising impact (Ewertowska et al., 2016, 2017). Nuclear also has contentious issues with its end of life waste storage and disposal and risk of large scale accidents (Stamford and Azapagic, 2011). Even renewable energy sources have environmental impacts when emissions are examined throughout their lifecycle (Peng et al., 2013; Varun et al., 2009). This notwithstanding, renewable generation sources, like solar photovoltaic (PV) systems and wind, have been seen to be relatively more environmentally friendly and continue to receive policy attention, investment in technology development and production capacity expansion. Renewable generation sources have become an attractive source of energy due to the threat of climate change, depletion of primary fossil fuels and the growing energy demand (Stougie et al., 2018). However, the cost of generation from renewable sources, coupled with the intermittent nature of some renewable sources have made total reliance on these sources challenging.

Apart from its pollution potential, generation of electricity, especially from non-renewable sources, comes with concerns about the depletion of primary energy resources. European countries, for example, have limited capacity to supply primary

energy resource in the case of conventional fossil fuels (Afgan and Carvalho, 2008). Due to the realisation of the limited primary resource capacity and the need to ensure future generations have relevant resources for their survival, sustainable development, therefore, also requires a balance between bio-capacity and ecological footprint (Hadian and Madani, 2015). Whereas ecological footprint is the demand that humans place on a bio-productive area to produce resources, bio-capacity is the planet's capacity to provide resources and ecosystem services annually consumed by humans (Mancini et al., 2016; Niccolucci et al., 2012). Therefore, environmental sustainability of the energy system should ensure a balance, resilience, and interconnectedness by allowing human society to satisfy its energy needs while not exceeding the capacity of its supporting ecosystems to continue to regenerate primary resources necessary to meet those needs or through its actions diminish biological diversity due to pollution (Khan, 2015; Morelli, 2011).

2.3.2 Energy and the society

The role of energy sustainability is indispensable in social development, as highlighted by the UN Sustainable Development Goal (SDG) of Affordable and Clean Energy (SDG7) on other SDGs such as Good Health and Well-being (SDG3), Decent Work and Economic Growth (SDG8), Reduced Inequality (SDG10) and Climate Action (SDG13). This is because the availability of energy is one of the driving forces that facilitate the development of vital social systems such as education, health and employment, among others. Principles such as good quality of life, human well-being, equitable opportunities for all, diversity and even democratic civil society are central themes that form the backbone of a socially sustainable society (Khan, 2015). Globally, evidence shows the importance of electricity consumption and development in various aspects of society. Figure 2.3 reveals a strong positive association between electric power consumption and Gross National Income, labour force, life expectancy at birth and literacy rate. As such, countries with higher electricity consumption are more likely to have better levels of wealth, employment, health and education. This is because access to modern energy services is essential to fulfilling basic social needs which are required to support economic growth and human development (Gaye, 2007).

As such, both the production and use phases of the energy system have implications on social development. There are implications in terms of health concerns from emissions during electricity production and social acceptance of some generation sources (European Commission, 2007) at the consumption phase, and implications

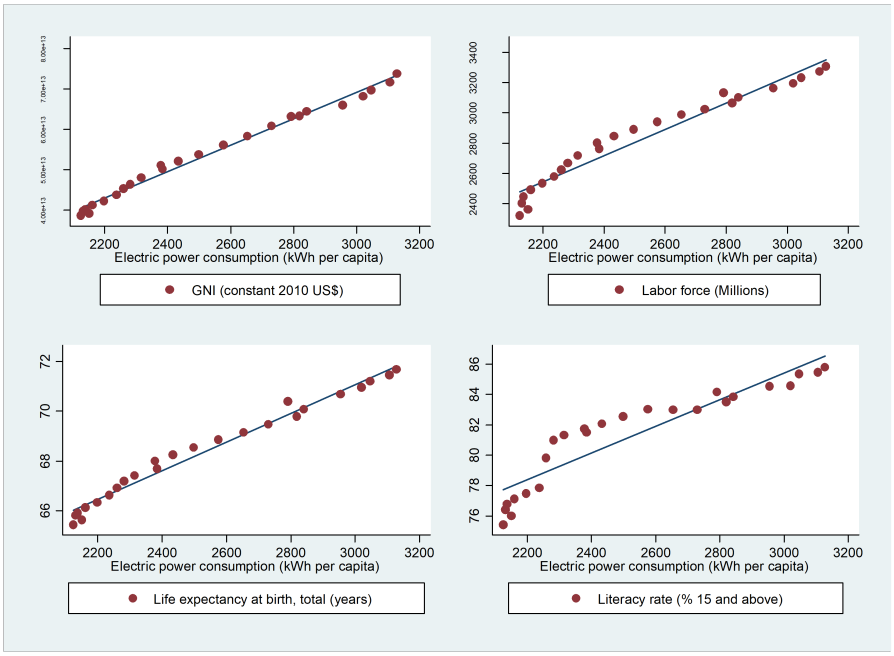

Figure 2.3 Global electricity power consumption and social indicators (1990-2017). Data from World Bank (2019) Development Indicators

of energy services needed to support the quality of life and human development (Dias et al., 2006; Ouedraogo, 2013). An indicator of social development is the Human Development Indicator (HDI), which emphasises measuring development using people and the capabilities rather than economic growth alone (do Carvalhal Monteiro et al., 2018; United Nations Development Programme, 2018). The HDI, a standard measure of well-being, is a composite measure of health, education and income and is a widely accepted alternative to GDP for assessing countries' progress (Freire et al., 2018; Ouedraogo, 2013). HDI is a measure of the average development of a country in terms of life expectancy, education level and economic performance (Dias et al., 2006). While HDI allows for analytic comparison between different countries and different periods (Freire et al., 2018; Hou et al., 2015), it does not consider all aspects of human development since it does not reflect inequalities, poverty, human security, empowerment and energy use (Dias et al., 2006; United Nations Development Programme, 2018).

Dias et al. (2006) argue the importance of seeking alternative development models for human development, natural resource conservation and the environment through rational concepts on energy use. Martínez and Ebenhack (2008) show that tremendous human development gains are possible, even for the world's poorest countries, with small incremental access to energy. Ouedraogo (2013) observe a

long-term positive correlation between electricity consumption and HDI - revealing that limited access to modern energy services could hamper economic and human development. It is, therefore, not surprising that attempts have been made to incorporate aspects of energy use in the assessment of human development. The EDI was developed by the IEA to track the progress of countries in the use of modern energy and better understand the role energy plays in human development (Johansson et al., 2012). The EDI incorporates per capita commercial energy consumption, per capita electricity consumption in residential sector, share of modern fuels in total residential energy use and the proportion of people with access to electricity supply (He, Jiao and Yang, 2018; International Energy Agency, 2011). The EDI focusses on a country's transition to using modern fuels without reference to whether the transition is sustainable given the country's economic, social and environmental conditions (Iddrisu and Bhattacharyya, 2015). In addition, although EDI is modelled to mirror the HDI, it does not include the components of HDI in its computation, raising concerns of its relevance as an indicator of human development. Energy is a key input to the development and human well-being cannot be advanced without access to electricity (Johansson et al., 2012).

The source of energy generation is particularly concerning as it not only makes the implementation of social programmes possible but also has an impact on the environment and human the health. Non-renewable energy sources, such as coal, gas and oil plants, have been shown to have negatively impact health (Orecchini, 2007). This makes a good case for renewable energy. However, there are still issues surrounding public perceptions towards renewable sources, especially in terms of land use. Nuclear energy presents a different level of scepticism regarding uncertainties related to disaster risk and the disposal of radioactive waste.

2.3.3 Energy and the economy

As development in any society is closely linked with the level of energy consumption, energy is a critical input for national economic development (Mondal and Denich, 2010). It is one of the major pillars of economic development for countries globally (Shaaban and Scheffran, 2017). Electricity demand is a major component of both economic and social development, as countries that lack an adequate supply of electric energy find it difficult to ensure growth of industrial production, national income, health and education (Onat and Bayar, 2010). Access to affordable energy is essential for economic development and poverty reduction, on the other hand,

expansion of energy-related infrastructure is critical for energy security (Fouquet, 2016).

Economic development may have an impact on the nature of the technology adopted in the energy system. More developed countries can better afford to invest in renewable technology sources and advances in even conventional generation technologies that have less impact on society. Furuoka (2017), for example, show that in Baltic countries, economic development has led to the expansion of renewable electricity consumption. This can also translate to increased private-investor interest in the country, with a positive impact on employment, taxation, and other economic services. On the other hand, the energy sector positively impact the economy. Availability of reliable power means more economic activity is possible and hence better economic development. At the supply side, economic development and growth have an impact on the energy system in terms of technology investment and capacity development in various sources of energy. However, at the consumption/use phase, energy security fosters economic activity and development. This cycle that links energy production to economic development: growth in economic development makes room for more efficient ways of energy production and subsequently a boost in the economy, can also be a vicious one as unsustainable energy production can have a detrimental effect on the environment and society and a fall in economic activity.

It must be noted that views about the relationship between energy, electricity consumption and economic growth (development) are by no means unanimous, as there exist some intellectual disagreements. Karanfil and Li (2015) highlight that four causal hypotheses have been presented and tested in the literature: (a) growth hypothesis – that electricity is a necessary factor for economic growth; (b) conservative hypothesis – economic growth leads to electricity consumption; (c) feedback hypothesis – interdependence between electricity consumption and economic growth; and (d) neutrality hypothesis – no causal link. Ang (2008) found strong evidence of causality running from economic growth to energy consumption growth in both the short and long run. On the other hand, Shahbaz et al. (2013) show evidence of the positive effect of energy use on economic growth in the long run. This shows that the nature and direction of the effect depend to a large extent on the context and period under investigation, which varies among countries (Bekhet et al., 2017; Karanfil and Li, 2015). The independence and neutrality hypotheses may be due to possible rebound effects, where gains in reducing energy consumption may be offset by behavioural changes of economic agents (Galvin, 2014; Zhang et al., 2017). Other hypotheses, such as the environmental Kuznets curve and pollution haven hypothesis, have also been explored when discussing energy consumption,

carbon emissions and economic development (Sarkodie and Strezov, 2019; Zaman and Moemen, 2017).

Irrespective of the hypothesised or observed relationship, there is evidence of a growing convergence between energy and economic planning in the literature. Convergence in the fields of economic development and energy policy and planning has resulted in the emergence of the field of energy-based economic development (EBED) aimed at integrating both economic development and energy planning approaches. EBED focusses on increasing energy efficiency or diversifying energy resources in ways that contribute to job creation, job retention and wealth creation (Carley et al., 2011). Energy efficiency and diversification of energy supply into renewable sources have become the pillars of sustainable energy policy (Prindle et al., 2007). This is because of regulatory emphasis on the importance of enhancing energy efficiency, which is the economic output per unit of energy consumption (Zaim et al., 2017). National and international policies in response to climate change promote energy efficiency (Shove, 2018). The EU, as an example, has a 20% energy efficiency improvement target (EEA, 2017). Energy efficiency has become an attractive policy dimension since it provides a cost-effective means of ensuring sustainable energy supply and reduction in emissions. As such, there has been research interest in the analysis of energy efficiency and energy savings potential (Feng and Wang, 2017; Honma and Hu, 2008). This notwithstanding, energy efficiency is a demand-side policy focussing on energy consumption reduction to achieve a given level of economic development. It does not incorporate the effect of economic development and renewable sources capacity investment which is a separate dimension of EBED.

2.4 Sustainability assessment of electricity systems

In this section, empirical research on sustainability assessment of electricity/energy systems is reviewed to present the current state of the literature. Specifically, methodological choices in these studies are analysed to understand the strengths and weaknesses of existing literature. The section is divided into two sub-sections covering the production and the consumption phases.

2.4.1 Sustainable production assessment

Studies reviewed here focussed on the performance of electricity production systems considering their economic, social and environmental implications. The study of sustainability issues often requires the integration of multiple dimensions of

operations involving multiple indicators (Diaz-Balteiro et al., 2017). The result is the reliance on composite indices to study and quantify the level of sustainability of units under investigation. Methods used to measure sustainability in these studies include Multi-Criteria Decision-Making (MCDM) approaches (Afgan and Darwish, 2011; Doukas et al., 2010; Khan, 2020; Yilan et al., 2020), exergy analysis (Koroneos and Nanaki, 2007; Lo Prete et al., 2012), lifecycle analysis (LCA) (Barros et al., 2020; Burkhardt et al., 2011; Evans et al., 2009; Rehl et al., 2012), and other optimisation based approaches such as multi-objective optimisation and tax/subsidy optimisation (Mondal and Denich, 2010; Resnier et al., 2007; Zhang et al., 2012). There have been other studies that have been descriptive without the need to form composite indices (Gallego Carrera and Mack, 2010; Tsoutsos et al., 2005).

The most widely used approach for sustainability assessment in the literature reviewed is MCDM approaches. This is mainly due to the multi-dimensionality of the problem of sustainability, which requires that different objectives and indicators are considered or integrated simultaneously (Brandenburg et al., 2014). Indeed Janeiro and Patel (2015) believe sustainability is inherently an MCDM problem. The review of the literature shows the use of a wide variety of MCDM approaches such as a) distance functions like TOPSIS (Brand and Missaoui, 2014; Štreimikienė et al., 2012), b) outranking approaches like PROMETHEE (Buchholz et al., 2009; Troldborg et al., 2014) and NAIADE (Browne et al., 2010; Giampietro et al., 2006), c) hierarchical techniques like Analytic Hierarchy Process (AHP) (Chatzimouratidis and Pilavachi, 2009; Karger and Hennings, 2009), Analytic Network Process (ANP) (Zhao and Li, 2015), and Multi-level MCDM (Joseph and Prasad, 2020), d) ranking and classification methods like Data Envelopment Analysis (DEA) (Ewertowska et al., 2016) and e) optimising averages approaches such as MAUT/MAVT (Phdungsilp, 2010; Santoyo-Castelazo and Azapagic, 2014), ASPID (Vučićević et al., 2014) and weighted average (Frangopoulos and Keramioti, 2010; Klein and Whalley, 2015). Approaches have been classified according to Diaz-Balteiro et al. (2017).

These approaches are sometimes used in combination with other approaches or even with crisp and fuzzy indicators. In their assessment of the sustainability of urban energy systems in Serbia, Jovanović et al. (2010), for example, used fuzzy set theory together with the ASPID approach. The problem with most MCDM approaches is usually with dimension weighting, which may rely on different expert opinions or equal weighting across dimensions. Additionally, the additive nature of most approaches means that poor performance on one dimension can be compensated by higher performance on other dimensions, which seem to be at odds with some views of sustainability. These approaches tend to be compensatory and must be

interpreted in terms of the trade-off between the dimensions (Hacatoglu et al., 2015a).

Another well-used approach is the LCA method. This is an analytical approach, which allows for the examination of organisational impact across the supply chain. Rehl et al. (2012) used attributional and consequential LCA approaches to analyse biogas system environmental impacts in the German electricity mix. They observed that the calculated environmental performance is affected by the methodology selected. Some other studies have also used LCA to estimate 'cradle-to-grave' impact of energy systems. The LCA approach is often used together with other MCDM or other aggregating approaches. Hacatoglu et al. (2015b), Roldán et al. (2014) and von Doderer and Kleynhans (2014) all used LCA results together with other MCDM techniques to arrive at a composite sustainability index. The literature on LCA tends to mainly focus on the environmental dimension of the operation with little, or no, emphasis on the economic and social aspects of the sustainability triad. Additionally, there are significant variations in the nature of system boundaries examined in the various papers. For example, some papers have focussed on 'cradle-to-gate' thinking (Hammond et al., 2013; Mahmud et al., 2020; Quek et al., 2018). This examines impact until the product leaves the gates of the entity. Barros et al. (2020) provide a review of LCA studies in sustainable energy generation.

Exergy analysis is another method observed in the review. Exergy analysis includes the quality of the output in the modelling process, thereby following the first and second laws of thermodynamics (Koroneos and Nanaki, 2007). The differences in the quality of output are important when comparing different energy conversion processes (Lo Prete et al., 2012). Outside these major approaches, there have been other optimisation and descriptive-based approaches used to understand the sustainability of energy generation systems. Studies that use descriptive statistics, such as Gallego Carrera and Mack (2010) and Tsoutsos et al. (2005), do not attempt to derive composite indices, but primarily focus on discussing the sustainability of these generating technologies across several indicators.

Dimensions of sustainability

Generally, in the sustainability literature, the triple bottom line concept first put forward by Elkington (1997), which requires consideration for social, economic and environmental objectives, is well accepted as the holistic dimensions of sustainability. This has, therefore, been translated into the sustainability literature of energy generation systems. It is important to note that almost every paper has attempted

to examine the impact of the system under investigation based on clearly defined dimensions. Even the few studies, like Browne et al. (2010), that do not identify specifically the dimensions being studied, consider the environmental, economic and social implications of the indicators used.

Another observation from the literature is the prevalence of studies that consider a fourth dimension. Afgan and Darwish (2011), Chatzimouratidis and Pilavachi (2009), Duan et al. (2011), Frangopoulos and Keramioti (2010), Pilavachi et al. (2006) and Rovere et al. (2010) all included a "technical" or "technological" dimension in addition to the economic, social and environmental dimensions which are widely studied. This fourth dimension is often defined to account for factors that relate directly to the operation of the generation technology that cannot be considered environmental, social or economic. Maxim (2014) defines it to include the ability to respond to demand, efficiency and capacity factor. The separation of the technical aspect is central to the idea of the systems approach to technology sustainability assessment of Musango and Brent (2011), which integrates the ideas of technology development, sustainable development and systems dynamics. From a systems perspective, the separation or decoupling of the technical dimension from the other dimensions allows for the modelling of the impact of other systems on the technology dimension and vice versa.

Weighting of dimensions

Multi-criteria analysis is by definition an assessment of multiple dimensions of a problem which might have different levels of importance. Weighting is, therefore, important in any multi-criteria analysis. Dimension and indicator weighting has been one of the critical issues in the sustainability literature. This is mirrored in the energy generation sustainability literature as well. Different papers have different approaches to dimension weighting. These include equal weighting (Evans et al., 2009; Varun et al., 2009), unequal weighting (Doukas et al., 2010; Jovanović et al., 2009) or even both (Klein and Whalley, 2015; Mahlooji et al., 2020; Malkawi et al., 2017). There are studies which do not even attempt to weight the dimensions in their assessment. Studies that do not weight dimensions either tend to focus on one specific dimension or provide a descriptive assessment of the sustainable operation of the energy generation systems. As there is no consensus on the importance of the various dimensions of sustainability, studies tend to be subjective in their weighting of dimensions. Most studies, however, conduct some form of scenario or sensitivity analysis to determine the robustness of their ranking to changes in

dimension weighting (Atilgan and Azapagic, 2016; Lipošćak et al., 2006; Rafaj et al., 2006).

On how weights are determined, many papers have relied on some form of expert or stakeholder opinions (Dombi et al., 2014; Gallego Carrera and Mack, 2010; Grafakos and Flamos, 2017), using approaches like AHP to determine the individual weights of each dimension, or have relied on estimation techniques that determine the dimension weights without the need for some direct weight input (Ewertowska et al., 2016, 2017). Evaluation approaches like DEA allow the units under investigation to choose the most favourable weights that maximise performance, hence requiring no need to specify dimension weights (Yang et al., 2014). Others have tended to use weights based on researcher perspectives. Moreira et al. (2015), for example, assigned a 60% weight to the environmental dimension emphasising an 'eco-centric' view.

Modelling weak and strong sustainability

The idea of capital substitution, which is captured in the debate between weak and strong sustainability (Gallopín, 2003; Turner, 1993), is another modelling dimension that is considered important in this review. Whereas arguments for a weak form of sustainability support the idea of non-declining aggregate capital even at the expense of individual components of aggregate capital (Pearce and Atkinson, 1998), arguments for the strong form of sustainability do not support the idea of capital substitution or compensation between various forms of capital (Kuhlman and Farrington, 2010). Papers surveyed were examined on whether they explicitly assumed or conducted their analysis from the perspective of strong or weak sustainability concerning the relationship between the various forms of capital. Indeed, only, Duan et al. (2011), Moreira et al. (2015), Myllyviita et al. (2013) and Rogner (2010) explicitly indicated the capital substitution assumption made in their modelling. Myllyviita et al. (2013), for example, state that, because compensation between the dimensions of sustainability is allowed in their study, their framework should be considered to support the concept of weak sustainability. Most studies are silent on the issue of factor substitutability, although the nature of their modelling seems to suggest weak sustainability. There is little consideration for the arguments of strong sustainability in the literature. The study by Giampietro et al. (2006) was one of the few exceptions, since their modelling of the post-normal science paradigm in sustainability did not allow for compensation between social and technical dimensions.

Systems modelling

Another issue considered as a basis for this review is the evaluation of the extent to which the literature includes systems thinking in the sustainability assessment of energy generation systems. Most studies do not consider sustainability as a systems problem. There are a few studies that considered some form of the systems approach in the modelling. However, a look at these papers, like Rehl et al. (2012), Roldán et al. (2014) and von Doderer and Kleynhans (2014), that incorporate some systems thinking in the assessment reveal that these are mainly LCA-based papers. LCA is a systemic analytical model (Acquaye et al., 2011; Brandenburg et al., 2014) which requires an assessment of the impact across the life cycle of the unit under investigation. Azapagic et al. (2016), for example, conducted an LCA assessment of UK's energy sector from the extraction of primary resources, through construction, operation, decommissioning, waste treatment and disposal phases of the life cycle. There is little evidence of systems thinking outside the LCA literature especially in the energy generation performance evaluation literature.

Energy sources and research context

Papers reviewed have studied a broad range of energy generation technologies, from renewables alone (Tsoutsos et al., 2005; Varun et al., 2009), non-renewable sources alone (Frangopoulos and Keramioti, 2010) to a combination of renewable and non-renewable sources (Ewertowska et al., 2016; Shmelev and van den Bergh, 2016). It is important, especially at national level energy planning to conduct an assessment that combines both renewable and non-renewable sources to understand the social, environmental and economic impacts of the system. Some papers even treat the energy sector as a black-box and consider sustainability issues from the total energy generated rather than at the technology level (Giampietro et al., 2006; Koroneos and Nanaki, 2007).

At the contextual level, though these studies span a broad range of countries, including both developed and developing nations, it is evident that such sustainability assessment is primarily done at the single state level. Most papers surveyed considered energy generation sustainability in a single country (Assefa and Frostell, 2007; Lipošćak et al., 2006). Very few studies consider such sustainability issues at the multi-state level or the regional level (Begić and Afgan, 2007; Gallego Carrera and Mack, 2010). Regional level assessment is particularly important since energy and sustainability policies are now being set at the intergovernmental level rather than the state level. The Economic Community of West African States and the EU,

for instance, have region-level energy policies and directives that are supposed to ensure sustainability in energy generation of member states. Indeed the EU has clear country-specific targets for climate and energy in its renewable energy directives (EEA, 2017).

As contemporary energy policies are formulated at the intergovernmental level, sustainability assessment must be conducted at the intergovernmental level as well. The impact of a nation's energy generation decisions has global implication as ecological systems are shared by all nations. The Paris Agreement, a universal legally binding global climate deal comprising 195 countries in 2015 (European Commission, 2018), is an example of the recognition given to the need for regional and international cooperation to build resilience and decrease vulnerability to the harmful effects on the environment. Greater regional focus, with country-level assessment and benchmarking, is imperative if the impact of sustainable energy policies will be effective.

DEA application in energy production assessment

The application of DEA in the literature of sustainable energy production has been in two main strands – performance evaluation at the generation technology level (plant level) and performance comparison between different technologies (national level).

The first strand is studies that conduct performance evaluation on one type of energy generation technology, usually incorporating undesirable outputs, such as emissions, in the production process. There is a large body of research in this area of DEA evaluation such as Yang and Pollitt (2009) who examined approaches for incorporating both undesirable outputs and uncontrollable variables into DEA in their performance evaluation of Chinese coal-fired power plants and Liu, Lin and Lewis (2010) who evaluated thermal power plants in Taiwan using radial DEA measurement. Sueyoshi and Goto (2012b) also conducted an environmental assessment of coal power plants in the U.S. using radial DEA measurement under managerial and natural disposability, which followed an earlier study on performance analysis of the U.S coal-fired power plants (Sueyoshi et al., 2010). Sueyoshi and Goto (2012a) have also conducted a methodological comparison of radial and non-radial models in the evaluation of U.S coal-fired power plants. Meanwhile, Bi et al. (2014) conducted an energy efficiency evaluation of China's thermal power generation. Similarly, Liu et al. (2017) conducted a DEA cross efficiency evaluation of coal-fired power plants in China. There have been other studies like Sueyoshi and Goto (2012c)

who focussed on the total power generation of the electricity system without the need to consider differences in the generation portfolio.

Recent research interest in this strand has focussed on decomposing the operations at the plant level to examine efficiency improvement potential in various sub-units of the plant. This has seen the application of various network DEA and hierarchical structure models. Starting from the earlier works of Cook et al. (1998) and Cook and Green (2005), recent studies include Xie et al. (2012) who decomposed the power plant operation into generation and grid operations in the two-stage network DEA evaluation and Bi et al. (2018) who considered a two-stage problem with power generation and pollutant abatement as the sub-units under investigation. Others include the two-stage evaluation of fossil fuel power plants by Tajbakhsh and Hassini (2018) with stages considering financial and sustainability objectives of the power plants. Xie et al. (2018) also conducted a dynamic network slacks-based evaluation of provincial power systems in China evaluating multiple operations of power plants – generation, transmission and distribution. Extensive reviews of studies in this strand of research have been conducted by Sueyoshi et al. (2017), Zhou et al. (2008) and Zhou et al. (2018).

These studies tend to focus on a type of production plant or examine the energy system as a composite without incorporating the differences in the production portfolios and hence focus on the power plant level, not the system-level. As such, policy recommendations are aimed at the plant level, not the national level which is relevant for sustainable energy policy. Due to the requirement for homogeneity in traditional DEA evaluation, studies are usually restricted to one type of generation technology ignoring the relevance of a system perspective. Countries produce power from different sources, therefore evaluation focussing on one or a few sources may lead to limited policy relevance. Additionally, it is important to consider the generation and use phases of the energy system for comprehensive decision support. All these studies in this strand focus on the generation phase of the energy system.

The second strand of DEA literature in the production phase are studies that conduct performance comparison between different technologies. The focus here is usually some multi-criteria evaluation of several sources along some sustainability dimensions to identify sustainable and less sustainable technologies. These studies are quite limited in the literature. Some identified studies in this strand have been summarised in Table 2.4 based on the main research issue, the nature of the portfolio of technologies studied, the context and the temporal nature of the models applied. It is worth noting that it seems DEA applications in this strand are relatively recent with application papers covering the period from 2010 to 2018.

The focus of most of the identified studies have been on efficiency in energy production (Vazhayil and Balasubramanian, 2013; Zurano-Cervelló et al., 2018). Such studies mainly focus on the social, economic and environmental factors that constrain the production of energy. The system boundary for such research usually ends in the power production plants. Other studies like Sueyoshi and Goto (2013) and Ewertowska et al. (2017) focus on only the environmental dimension and treats the production process as a 'black-box' without considering the internal differences in the structure in the energy generation portfolio. As such, the system boundary of such environmental performance studies rather begins from the output of the power plant. None of the studies combines the production phase with the consumption phase in the same assessment.

Table 2.4 DEA energy production technology studies.

Authors	Main Issue	Technology Portfolio	Decision-Making Units	Context	Time
Rovere et al. (2010)	Sustainable production expansion	Renewables + Non-renewables	Generation sources	Brazil	Static
Sueyoshi and Goto (2013)	Environmental efficiency	Renewables + Non-renewables	Countries	OECD (10)	Dynamic
Vazhayil and Balasubramanian (2013)	Production efficiency	Renewables + Non-renewables		India	Static
Ewertowska et al. (2016)	Environmental performance	Renewables + Non-renewables (does not differentiate between sources)	Countries	Europe (27)	Static
Galán-Martín et al. (2016)	Production	Renewables + Non-renewables	Generation sources	United Kingdom	Static
Li, Geng and Li (2016)	Production	Renewables + Non-renewables	Countries	G20 (23)	Static
Ewertowska et al. (2017)	Environmental performance	Renewables + Non-renewables	Generation sources	Unspecified	Static
Feng et al. (2017)	Production performance	Non-renewable	Cities	China	Static
Sartori et al. (2017)	Production	Renewables + Non-renewables	Power companies	Brazil	Static
Keshavarz and Toloo (2018)	Production	Renewables + Non-renewables	Generation sources	United Kingdom	Static
Zurano-Cervelló et al. (2018)	Production	Renewables + Non-renewables	Countries	EU (28)	Static

A majority of the papers make efforts to combine both renewable and non-renewable generation sources in their assessment. While this is appropriate since the energy supply of countries comes from both renewable and non-renewable sources, the requirement of homogeneity of decision-making units (DMUs) mean studies either select units with the same portfolio structure (Sueyoshi and Goto, 2013) or focus on one country while comparing different technologies and assuming the production process across technologies are essentially the same (Rovere et al., 2010; Vazhayil and Balasubramanian, 2013). There are significant differences in the production structures of different countries and significant differences in the production processes of different generation sources. This must be reflected in such studies. It is also evident in Table 2.4 that most studies tend to use static models that consider production at only one point in time or mainly focus on production in a single country. Since the real-world is constantly changing, a dynamic assessment may be more apt. Additionally, evaluation mostly focusses on a single country, however, energy policy and environmental impact go beyond one country. Therefore, there is a need for regional or global assessment.

Since the introduction of the traditional radial – CCR DEA model by Charnes et al. (1978) and radial BCC DEA model by Banker et al. (1984), there have been several advances in the methodology. There have been advances catering for nonhomogeneous DMUs (Cook et al., 2013), differences in production structures (Kao, 2014c) and treatment of undesirable outputs (Seiford and Zhu, 2002). To understand the extent of DEA application in sustainable energy production assessment, Table 2.5 summarises the 11 studies found in the literature in terms of the nature of DEA models used.

From looking at the table, it is evident that although the DEA literature is well advanced, its application in this strand of sustainable energy production literature is still growing. There is the prevalence of mainly traditional models, which measure performance improvement targets on a radial basis, which suffer from an inability to detect non-proportional performance improvement targets. Non-radial approaches employed are limited to Directional Distance Function, which does not distinguish input improvements from output improvement. All of these studies have also been single objective problems mainly focussing on input minimisation.

Table 2.5 Nature of DEA models.

Authors	DEA Approach	Objective	Target-setting	Environmental Output
Rovere et al. (2010)	CCR/BCC	Input Minimisation	Radial	Undesirable Output
Sueyoshi and Goto (2013)	Directional Distance Function, Malmquist Index	Range Adjustment (Maximisation and Minimisation)	Non-radial	Undesirable Output
Vazhayil and Balasubramanian (2013)	Stochastic DEA, Weight Restriction	Input Minimisation	Radial	Output Reciprocal
Ewertowska et al. (2016)	CCR, without Explicit Output	Input Minimisation	Radial	Inputs
Galán-Martín et al. (2016)	CCR, without Explicit Output, Order of Efficiency Preference	Input Minimisation	Radial	Inputs
Li, Geng and Li (2016)	Super Efficiency	Input Minimisation	Radial	Inputs
Ewertowska et al. (2017)	BCC, without Explicit Output, Stochastic and Deterministic	Input Minimisation	Radial	Inputs
Feng et al. (2017)	CCR/BCC	Input Minimisation	Radial	Inputs
Sartori et al. (2017)	Directional Distance Function, Weight Restriction	Range Adjustment (Maximisation and Minimisation)	Non-radial	Inputs
Keshavarz and Toloo (2018)	BCC, Cross Efficiency	Input Minimisation	Radial	Inputs
Zurano-Cervelló et al. (2018)	CCR/BCC	Input Minimisation	Radial	Inputs

2.4.2 Sustainable consumption assessment

In the consumption phase, the focus is on how energy is transformed into other social and economic services and its impacts on the environment. Therefore, the review here focusses on how energy interfaces with the economy, through energy and eco-efficiency assessments, and how energy affects the environment as captured by studies on environmental performance assessment.

Energy efficiency

As energy is the main intermediate resource for socio-economic development, energy efficiency constitutes the most important goal for contemporary energy policy (Štreimikienė et al., 2012). Energy efficiency is the ratio of energy services output to energy input (Herring, 2006). The focus is on using the energy input to gain the most output as possible. As such, it broadly defined as a simple ratio of the useful output of a process divided by energy input into a process (Patterson, 1996). Patterson (1996) defined various measures of energy efficiency and highlighted their strengths and weaknesses. These were grouped into four main groups: thermodynamic measures, physical-thermodynamic measures, economy-thermodynamic measures and economic measures of energy efficiency (Patterson, 1996). The differences between the various approaches pertain to the nature of variables in the efficiency measurement framework, such as monetary values and energy units. Whereas thermodynamic measures are calculations based on the science of thermodynamics, physical-thermodynamic measures rely on energy inputs measured in thermodynamic units but with outputs measured in physical units. Economic-thermodynamic measures rely on energy inputs in thermodynamic units and outputs measured in market prices. An example is the energy-GDP ratio of energy intensity. Finally, economic measures of energy efficiency rely purely on monetary terms (Patterson, 1996).

Hu and Wang (2006), observed that energy alone cannot be used to produce any output, as such, a multi-input model is necessary for effective energy efficiency assessment. As such, the focus has moved from using single-input and single-output measurements as highlighted by Patterson (1996) to a total factor energy efficiency (TFEE) measurement. In this regard, DEA has found utility in this context since it allows for multi-input, multi-output assessment. The DEA approach allows for the computation of energy consumption targets which is then divided by actual energy consumption to generate a TFEE measure (Zhang et al., 2011). This TFEE measure can be interpreted as energy-saving potential, as the target energy consumption is

the minimum possible energy consumption an entity under assessment could have achieved to generate a given level of output when benchmarked against its peers.

The TFEE has been used for energy efficiency examination of industrial sectors (Wang et al., 2012; Xiaoli et al., 2014), regions/provinces (Honma and Hu, 2008; Hu and Wang, 2006), and countries (Hu and Kao, 2007; Zhang et al., 2011). Wang et al. (2012) examined the regional total factor efficiency of industrial enterprises in 30 Chinese provinces from 2005 to 2009. Their assessment into the overall efficiency, pure technical efficiency and scale efficiency identified considerable regional divide in terms of energy efficiency. Honma and Hu (2008) examined the TFEE of 47 prefectures in Japan covering the period from 1993 to 2003 relying on 14 inputs of which 11 were energy sources. Their study allowed for the examination of energy efficiencies in the consumption of energy from various sources such as residential electric power, commercial and industrial electric use, and some primary energy sources. At the country-level analysis, Zhang et al. (2011) examined the TFEE in 23 developing countries over the period from 1980 to 2005 using DEA window analysis, which allows for the examination of both cross-sectional and time-varying data. Chang and Hu (2010) later extended the TFEE by taking into effect the dynamic energy productivity changes. Their measure of total factor energy productivity index (TFPI) allows for the decomposition of the TFPI into changes in energy efficiency and shift in the energy use technology.

Since these early works, there has been considerable interest in the DEA literature in the application and model development for energy efficiency assessment of various units due to the policy relevance of the approach. Recent studies have examined energy efficiency while taking into consideration environmental pollution (Guo et al., 2018; Yang and Wei, 2019b). Yang and Wei (2019b), for example, examined the urban energy efficiency of 26 Chinese cities from 2005 to 2015 while incorporating water waste, SO_2, and smoke and dust as undesirable outputs. Considerable attention has also been dedicated to second stage examination using some form of regression approaches after the estimation of the energy efficiency measures (Borozan, 2018; He, Liao and Zhou, 2018; Xiong et al., 2019; Yang and Wei, 2019b). Other recent studies include Khodadadipour et al. (2021), who examined the energy efficiency of thermal power plants using stochastic DEA cross-efficiency analysis, Li et al. (2021), who conducted an efficiency assessment of coal and non-coal energy using dynamic DEA models, and Mishra et al. (2021) who examined the energy efficiency of Indian power utilities using DEA.

Amidst all this research on energy efficiency is also growing scepticism of the practical implication of 'the gospel of energy efficiency' (Herring, 2006). Focus on

energy conversation policy has revealed an energy efficiency gap between actual energy consumption and optimal energy consumption (Jaffe and Stavins, 1994). Herring (2006), for example, argues against the belief that improving efficiency in energy use will allow for the reduction in natural emissions due to the reduction in energy consumption. Herring's (2006) view is hinged on the supposed 'rebound effect' as a result of a reduction in the implicit price of energy as a result of energy efficiency. The result is more affordable energy for households leading to greater use of energy. Consequently, more energy efficiency has the potential of increasing energy consumption rather than reducing energy consumption as policy implies (Galvin, 2014; Zhang et al., 2017). Energy efficiency is, therefore, not necessarily a goal in itself but a means of achieving energy conservation policy objectives in energy resource allocation (Jaffe and Stavins, 1994). More effective energy policy will be to shift to non-fossil energy generation sources through funding from carbon tax on renewable sources (Herring, 2006) while using energy efficiency assessment as decision support on the progress of energy policy initiatives. As such energy efficiency and energy conservation policies in the consumption of energy are still considered as key means of achieving reductions in GHG and other energy-related policies (Gillingham et al., 2009). Mardani et al. (2017) provide a comprehensive review of DEA applications in energy efficiency sampling articles published between 2006 and 2015. While they see great potential for DEA evaluation in the future, they find environmental efficiency assessment as an essential direction for further studies. Environmental efficiency research is reviewed is the next section of this chapter.

Environmental performance assessment

The policy needs to monitor and evaluate the environmental impacts of various units has resulted in the development of methods for environmental performance assessment. Various environmental performance indexes have been developed based on conventional productive efficiency measures (Coelli et al., 2007; Reinhard et al., 2000). These indices incorporate measures of environmental pollution in standard productive efficiency analysis to capture environmental performance (Coelli et al., 2007). Environmental efficiency evaluation is useful in providing an understanding of the differences in the environmental performance of different units under investigation as well as serving as an objective reference point for future environmental performance improvement (Song et al., 2012).

Reinhard et al. (2000) define environmental efficiency as "the ratio of minimum feasible to observed use of multiple environmentally detrimental inputs, conditional on observed levels of output and the conventional inputs." Reinhard et al. (2000) treat environmentally detrimental variables as inputs thereby implying that reduction in waste should result in reduced outputs. Zofío and Prieto (2001) characterise environmental efficiency in terms of expansion of desirable productions and reduction in undesirable production. Consequently, their definition implies environmental efficiency gain is achieved when the increase in desirable production is achieved along with a reduction in waste or pollutant.

It is clear from this that the handling of environmental impacts, or undesirable outputs, is fundamental to such environmental efficiency assessment. Literature is replete with various approaches for modelling such undesirable environmental impacts. Wang et al. (2018) highlight five ways of dealing with such environmental pollutants, which are often by-products of useful production - freely disposable[1] inputs (Reinhard et al., 2000); data transformation (Seiford and Zhu, 2002); weakly disposable outputs (Färe et al., 1989, 1996); using different production technologies (Murty et al., 2012); and using the materials balance (Coelli et al., 2007). As it is characteristic of most scientific literature, there have been debates on these methods for dealing with undesirable outputs. Wang et al. (2018) believe that treating undesirable outputs as inputs does not reflect the real production process and does not satisfy physical laws; also data transformation approaches results in inconsistent results. They further argue that weak disposability of undesirable outputs violates the monotonicity in the production of undesirable output and may lead to an inappropriate shadow price for pollution. Consequently, such weak disposability based approaches may evaluate strongly dominated DMU as efficient which may be used as a target for benchmarking and is inconsistent with the laws of thermodynamics (Wang et al., 2018).

The origins of environmental evaluation trace to the early works of Edmonds and Reilly (1983), Harvey (1989) and Reister (1984) who focussed on carbon emissions (Song et al., 2012). However, in the DEA literature, the early work of Färe et al. (1989) brought light into the modelling of environmental effects. They made modifications to the standard Farrell efficiency approach by relaxing the strong disposability assumption of outputs so that environmental variables could be in joint production with desirable outputs. The implication of this was that reduction in environmental outputs could only be achieved at the cost of desirable outputs

[1]disposability is the ability to discard unwanted inputs or outputs. This can be achieved at a cost (weakly disposable) or without cost (freely disposable) to the other inputs and outputs

when examining the technical efficiency of units under investigation. Although their work was broadly similar to Pittman (1981, 1983), Färe et al. (1989) established the nonparametric measurement of technical efficiency considering undesirable outputs. Färe et al. (1996) later provided an analysis of the environmental performance of fossil fuel-fired electric utility firms along the same concepts of weak disposability.

Recent contributions to environmental efficiency assessment in energy research include Wu et al.'s (2016) two-stage system evaluation of environmental efficiency and Wang et al.'s (2018) DEA evaluation using the materials balance approach, among others. Wang et al. (2018), for example, examined the environmental efficiency and abatement efficiency measurements of China's thermal power industry through a DEA-based materials balance approach. The materials balance condition, which essentially implies 'what goes in must come out', was incorporated into DEA measurement by Coelli et al. (2007) in a similar manner as price information is usually incorporated into DEA measurement. In contrast to traditional approaches that either threat pollutants as either undesirable outputs or environmentally determined inputs in the production process, Wang et al. (2018) argue that these approaches do not satisfy the physical laws that regulate economic and environmental processes. As such, their approach, which combines DEA with materials balance principle, can account for the laws of thermodynamics in the joint evaluation of environmental and abatement efficiency. Additionally, the overall environmental efficiency is decomposed into technical efficiency, polluting inputs allocative efficiency and polluting and non-polluting inputs allocative efficiency. This shows the recent interest of two-stage (network) DEA modelling in environmental efficiency assessment. Other recent environmental performance studies include Lin and Chen (2020) who examined environmental regulation and energy-environmental performance, and Koçak et al. (2021) who conducted and environmental efficiency of OECD countries using a bootstrap DEA approach.

Outside the theoretical applications of DEA in environmental efficiency, there have been several empirical policy-related studies. Zofío and Prieto (2001) examined the environmental efficiency of the manufacturing industries of OECD countries under different regulatory scenarios. Taskin and Zaim (2000) explored the search for theoretical Kuznets curves in environmental efficiencies of high and low-income countries. The same authors also provided empirical evidence of Kuznets curves in the environmental efficiency of OECD countries (Zaim and Taskin, 2000). Halkos and Tzeremes (2009) also explored the existence of Kuznets curves in the environmental efficiencies of 17 OECD countries by allowing for dynamic effects. Environmental efficiency evaluation cuts across industries, with applications in agriculture (Reinhard

et al., 2002, 1999), transportation (Chang et al., 2013; Liu et al., 2019), construction (Mandal and Madheswaran, 2010), oil and gas (Bevilacqua and Braglia, 2002), energy (Bi et al., 2014; Halkos and Polemis, 2018), trade (Yang et al., 2019), hospitality (Giama et al., 2018), among others. Song et al. (2012) provide a survey on DEA applications in environmental efficiency evaluation.

Outside the frontier-based evaluation of environmental efficiency, there have been other approaches employed for environmental efficiency assessment. Knight and Rosa (2011), for example, conducted a cross-national environmental efficiency analysis of 105 countries using maximum likelihood estimations. Their evaluation of the environmental efficiency of well-being combines the ecological footprint measure of environmental consumption with the average life satisfaction measure of subjective well-being to study the benefits societies derive from their environmental demands. Yang et al. (2019) employed input-output models in studying the environmental efficiency embodied in China's inter-regional trade.

Eco-efficiency

At its basic, eco-efficiency is a ratio that relates the economic value of goods and services to the environmental costs/value or impacts involved in the production process (Huppes and Ishikawa, 2005). Camarero et al. (2014) define eco-efficiency as "the ability to produce more goods and services with less impact on the environment and less consumption of natural resources." Eco-efficiency, therefore, integrates the environmental efficiency analysis with economic considerations. Essentially, eco-efficiency is the monetary impacts of environmental efficiency (Burritt and Saka, 2006). The triple bottom line Venn diagram, as depicted in Figure 2.1, shows eco-efficiency as the point where economic and environmental objectives are simultaneously considered. Although eco-efficiency does not consider the social dimension, the management philosophy of eco-efficiency guarantees economic and environmental benefits for society's welfare (Rybaczewska-Błażejowska and Masternak-Janus, 2018). The relevance of eco-efficiency as a concept in sustainable development policy planning is highlighted by the establishment of international standard to govern its use. The ISO 14045:2012 standard of the International Organization for Standardization (ISO) is an environmental management standard primarily focussed on the principles, requirements and guidelines for eco-efficiency assessments of product systems (International Organization for Standardization, 2019).

Eco-efficiency can be assessed from the regional (Rybaczewska-Błażejowska and Masternak-Janus, 2018), national (Camarero et al., 2014, 2013), industrial

(Wursthorn et al., 2011) and product-level (Caiado et al., 2017). Although the initial ideas of eco-efficiency were mainly focussed on product systems of companies, it has been adapted for policy strategies and macroeconomic evaluations (Wursthorn et al., 2011). Rybaczewska-Błażejowska and Masternak-Janus (2018) examined the eco-efficiency of regions in Poland intending to promote the sustainable transformation of such regions by combining LCA and DEA. LCA approaches were used to quantify the lifecycle emissions. Using input-oriented BCC DEA estimation revealed only a few of the Polish regions were eco-efficient relative to the other regions.

Wursthorn et al. (2011) also used environmental intensity, which is the environmental impact per unit of economic performance, to monitor the eco-efficiency of sectors in European countries. Their approach relied on lifecycle impact assessment to disaggregate the eco-efficiency levels for various industry classes. Camarero et al. (2014) examined whether there was convergence in the eco-efficiency in GHG emissions among EU countries. Using DEA-based directional distance functions for the eco-efficiency quantification and econometric approaches for the convergence, they found the existence of convergence groups, meaning there are at least four clear groups of EU countries in terms of their eco-efficiency and GHG emissions. Camarero et al. (2013) also examined eco-efficiency convergence among 22 OECD countries in an earlier study.

Rashidi and Saen (2015) divided the inputs in the eco-efficiency analysis into energy and non-energy inputs and the outputs into desirable and undesirable outputs. Their analysis of selected members of the OECD was based on a bounded adjusted DEA measure, which allowed for the calculation of energy-saving potential and undesirable output abatement potential. Robaina-Alves et al. (2015) used a stochastic frontier model to evaluate the resource and environmental eco-efficiency of European countries. They examined the eco-efficiency of two distinct periods – before the Kyoto Protocol in 2005 and after the Kyoto Protocol. To deal with potential misspecification errors of the distributional assumptions associated with the stochastic model, a maximum entropy approach, which combines DEA and stochastic frontier approach, was used.

Caiado et al. (2017), provide a systematic literature review of eco-efficiency that highlights the thematic developments in the field. They identify the need to consider sectoral energy and CO_2 emissions and its influence on energy efficiency as an important area of further research in the eco-efficiency literature. They also see the need to consider social aspects in the transition towards sustainable development.

2.5 Systems thinking in sustainable energy research

The literature on systems thinking in sustainable energy research is mostly based on the lifecycle assessment (Onat et al., 2017). However, there exist studies that rely on causal loop diagrams and system dynamics. Tejeda and Ferreira (2014) applied systems thinking to analyse wind energy sustainability. Specifically, causal loop models were developed to highlight the key factors in the sustainability of wind energy systems and the relationships between these factors. The causal model that was developed and presented in Figure 2.4 was based on a previously developed renewable energy causal model from the literature. Sustainability concerns are limited in scope to factors of installation, operation and maintenance phases of onshore wind energy generation projects within a country.

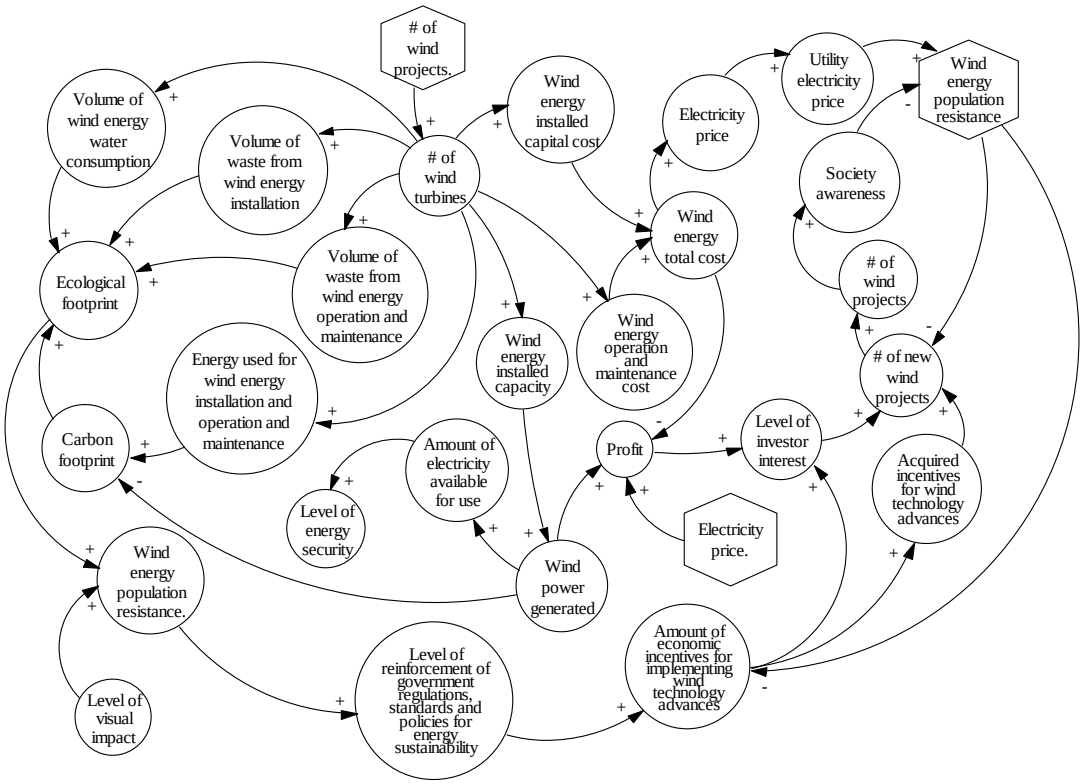

Figure 2.4 Reproduction of a subset of the wind energy sustainability causal model of Tejeda and Ferreira (2014, pg. 216).

The causal model highlights the economic, social and environmental dimensions of sustainability. For example, it is seen that an increase in wind energy installed capacity is likely to result in more wind power generation. This increased wind power generation should make an investment in wind energy profitable leading to more investor interest and more investment in wind projects. Investments in wind

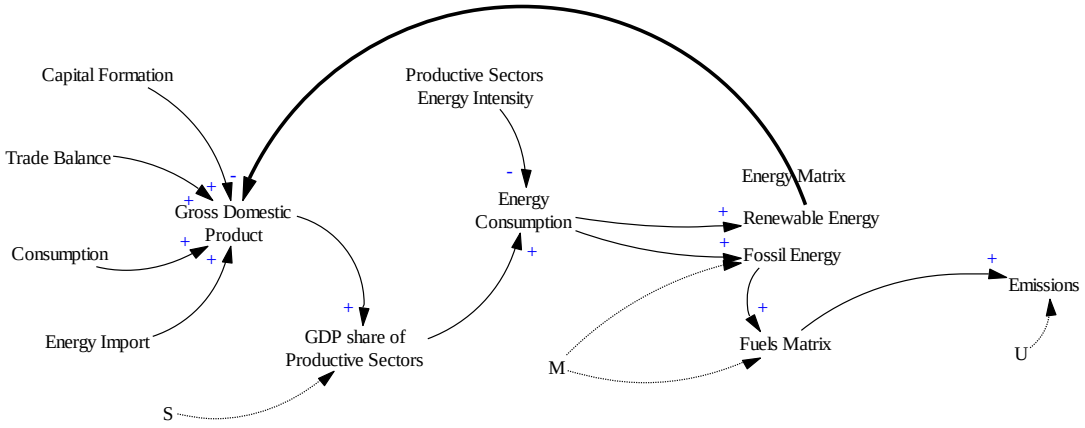

Figure 2.5 Reproduction of the causal model of Robalino-López et al. (2014, pg. 15).

projects come with the need to ensure more social awareness campaigns, which can help reduce social resistance towards wind energy production. This highlights part of the economic and social implications of wind energy generation. On the environmental dimension, the causal model of Tejeda and Ferreira (2014) show that increased wind energy installed capacity will lead to more wind power generation, which should reduce its carbon footprint and ecological footprint as a result of reliance on such renewable sources. In all, Tejeda and Ferreira (2014) identify seven major feedback loops in their causal model developed. Tejeda and Ferreira (2014) later conducted a system dynamics simulation of energy sustainability incorporating social development, economic development and environmental protection using the same causal relationships.

Robalino-López et al. (2014) also examined the use of system dynamics for renewable energy and CO_2 emissions in the case of Ecuador. Unlike Tejeda and Ferreira (2014), whose model considers the investor's perspective, Robalino-López et al. (2014) tackle the problem from the national perspective by studying the way changes to energy and GDP will affect carbon emissions of Ecuador. The effects of a reduction in non-renewable energy share of the energy generation sources and energy efficiency improvements are incorporated into the causal relationships studied. Their causal model is presented in Figure 2.5. They find that there is potential to control carbon emissions even under scenarios of persistent increment of GDP if it comes with an increase in the renewable energy share of the generation mix and improvement in fossil fuel technology.

Mutingi et al. (2017) provided a taxonomic analysis of system dynamics approaches for energy policy and simulation. They provided a causal loop analysis and system dynamics simulation of various archetypes. Mutingi et al. (2017), therefore,

developed several generic models to describe behavioural patterns and gain a deeper insight into the underlying structures in the system. These models include ones for energy-economy-environment, energy-demand-supply management, new product innovation, capacity management, energy pricing and hybrid energy management problems. In Figure 2.6, the energy-economy-environment problem developed is presented.

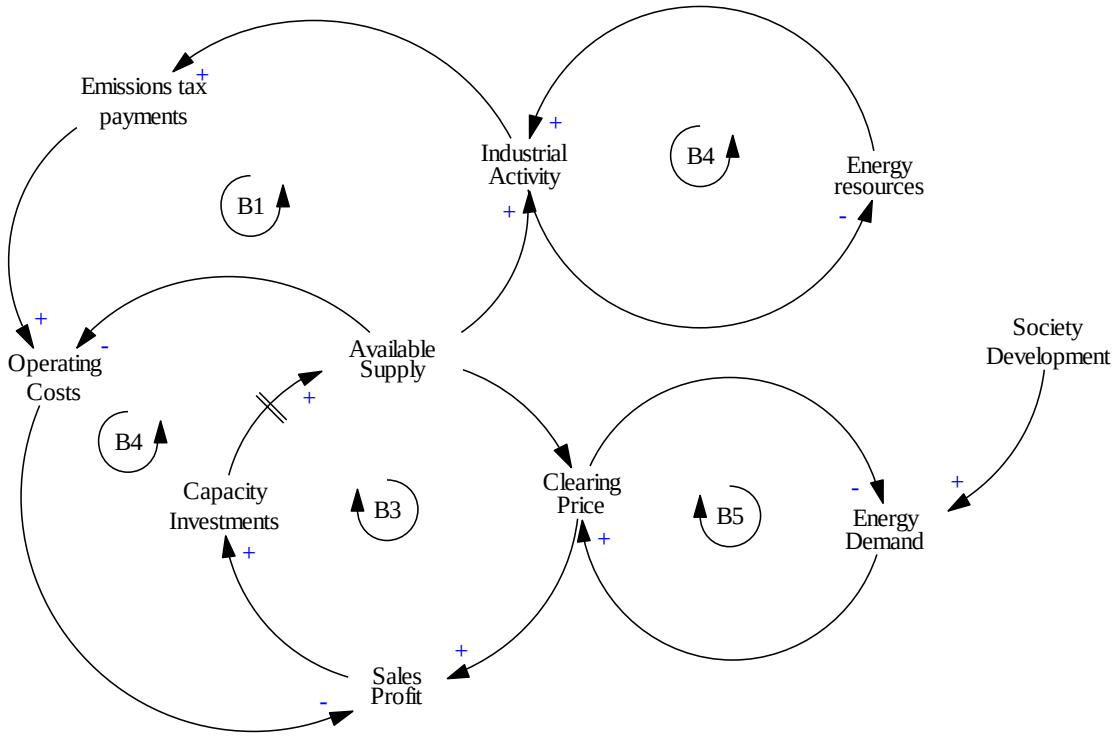

Figure 2.6 Reproduction of energy, economy and environmental causal model of Mutingi et al. (2017, pg. 538).

This model seeks the triple-sided objectives of economic profits, sustainable energy supply and environmental health (Mutingi et al., 2017). Capacity investments in energy are expected to lead to energy security over time. This increased supply is expected to push down the equilibrium price (clear price) of the energy supplied, which affects sales and profits of energy companies and hence their investment in capacity improvement. Their model also brings in the energy demand phase of the system through a clearing price. A higher equilibrium price should lead to a reduction in the quantity of energy demanded. On the other hand, a fall in the energy demand should lead to a fall in the equilibrium price and sales and capacity investments.

Other studies include Ford (2011), who conducted system dynamics modelling of environment, energy and climate change and Brent et al. (2011), who conducted a systems dynamic modelling of the sustainability of renewable energy generation technologies in South Africa, among others. These studies have tended to mostly focus on renewable sources without considering both renewable and non-renewable generation sources. Additionally, system modelling seems to be limited mostly to problem structuring and causal loop diagrams. Very few of these studies have conducted analysis of the static or dynamic behaviour of the system. Systems thinking provides a basis for understanding the complex interaction and relationships in the energy generation and consumption systems. This thesis, therefore, draws from it to aid in effective problems structuring that better addresses all policy dimensions in sustainable energy policy.

2.6 Chapter summary

This chapter provided an extensive review of sustainability literature as it relates to energy systems. Based on general sustainability definitions, concepts and dimensions, a specific review of energy and sustainable development were conducted to present the extant literature in this research area. Conceptual issues and methodological applications concerning the relationship between energy, environment, social development and economic development were identified in an empirical review of the literature. This also included a review of the literature on systems thinking and sustainability as it relates to energy research.

In this review, a number of key gaps in the literature were identified. First, whereas there has been increasing interest in the sustainable operation of energy production systems, this has not been equally translated to the assessment literature. The dominant method used in most sustainability assessment is MCDM though other approaches exist. A variety of MCDM approaches have been employed. However, the use of DEA is mostly limited to traditional approaches that treat the production system as a *black-box*. The means that the interconnection between sub-systems of the energy system is ignored in the performance assessment. Also dominant are LCA-based evaluations, which tend to focus on the environmental dimension while neglecting of other dimensions.

Second, with multi-criteria approaches, methodological problems associated with indicator selection and weighting of dimensions can lead to a variety of outcomes due to its subjectivity. Although different schools of thought on the substitution of natural, economic and social resources have emerged over the years, the consideration

of this has been limited in the assessment literature. Other gaps identified include the limited use of a systems approach outside LCA research when it comes to the sustainable operation of energy production systems and the restriction of most studies to national rather than multi-national basis.

Chapter 3

DEA Modelling of Complex Internal Structures

3.1 Introduction

In this chapter, a methodological review of the DEA models and concepts that are relied upon for building models and empirical assessment are presented and discussed. Specifically, it provides a methodological review of network DEA and associated concepts. The chapter presents NDEA models for parallel, series and mixed production structures. Additionally, the literature on modelling considerations on interlinking outputs or inputs, dealing with undesirable outputs and non-homogeneity are also presented. It also highlights modelling choices that is relied upon in subsequent chapters.

DEA is a performance measurement technique, introduced by Charnes et al. (1978), Charnes et al. (1981) and Banker et al. (1984) for the relative performance evaluation of DMUs with multiple inputs and outputs. The technique is based on earlier works of Debreu (1951), Koopmans (1951), Shephard (1953) and Farrell (1957), among others. The original estimation approaches were nonparametric frontier techniques that employ mathematical programming to evaluate the relative efficiency of homogeneous DMUs that use multiple inputs to generate multiple outputs, relative to an empirically generated efficient, or a "best-practice", frontier which envelopes the observed DMUs (Cooper et al., 2011). However, there has been a notable increase in DEA techniques and applications resulting in advances in both basic and advanced DEA models and techniques beyond the axiomatic restrictions of the original techniques (Cook and Zhu, 2007). One such extension

is the network DEA approach, pioneered by Färe and Whittaker (1995), which considers the intermediate products in the production system.

In presenting the methodological review, the rest of the chapter is organised as follows; Section 3.2 presents the basic/traditional DEA model. Since this basic model does not incorporate the internal structure of the DMU in the efficiency modelling, models that consider the internal structures are presented in section 3.3. Section 3.4 deals with non-homogenous DMU models. Section 3.5 presents undesirability in the DEA modelling specifically in the context of network models. Section 3.6 presents alternative DEA approaches for dealing with network problems and undesirable outputs. Finally, Section 3.7 provides a chapter summary and discussion of modelling choices.

3.2 Basic DEA models (models with unknown internal structure)

To formulate the basic DEA model with unknown internal structure, it is important to define:

a. $X_j = \{X_{ij}, \ldots, X_{mj}\}$: the vector of inputs for DMU j

b. $Y_j = \{Y_{rj}, \ldots, Y_{sj}\}$: the vector of outputs for DMU j

The basic DEA CCR model maximises the engineering efficiency ratio of each of the n DMUs ($j = 1, \ldots, n$) with s outputs ($r = 1, \ldots, s$) and m inputs ($i = 1, \ldots, m$) defined as the ratio of its weighted outputs to its weighted inputs:

$$\max \quad \frac{\sum_{r=1}^{s} u_r Y_{ro}}{\sum_{i=1}^{m} v_i X_{io}} \tag{3.1a}$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1 \quad j = 1, 2, ..., n \tag{3.1b}$$

$$u_r, v_i \geq \varepsilon > 0, \ \ \forall r, i \tag{3.1c}$$

In (3.1), Y_{ro} and X_{io} are the observed non-negative outputs and inputs respectively of DMU o under evaluation. u_r and v_i are unknown output and input multipliers to

be determined by solving the model. The objective function (3.1a) is to be maximised under the condition (3.1b) that the same ratio for all DMUs does not exceed the maximum efficiency score of unity for the specific multipliers selected by the DMU under investigation. To ensure that no DMU ignores a particular input or output in the selection of multipliers, the multipliers are expected to according to (3.1c) be at least ε, a small non-Archimedean infinitesimal (Alirezaee, 2005; Cook and Zhu, 2014a; Mehrabian et al., 2000). Model (3.1) can be transformed into a linear programming (LP) problem using the Charnes and Cooper (1973) transformation. The resulting LP problem is as follows:

$$E_0 = \max \sum_{r=1}^{s} \mu_r Y_{ro} \tag{3.2a}$$

$$\text{s.t.} \quad \sum_{i=1}^{m} \nu_i X_{io} = 1 \tag{3.2b}$$

$$\sum_{r=1}^{s} \mu_r Y_{rj} - \sum_{i=1}^{m} \nu_i X_{ij} \leq 0 \quad j = 1, 2, ..., n \tag{3.2c}$$

$$\mu_r, \nu_i \geq \varepsilon > 0, \;\; r = 1, ..., s, \quad i = 1, ..., m \tag{3.2d}$$

The model (3.2) expresses the DEA problem as an LP problem by setting the value of the denominator of the objective function in 3.1 to unity and imposing it as a constraint. For this problem, while a score of unity shows an efficient DMU, any score lower than unity shows inefficiency for a particular DMU. It is often common to see the dual form of model (3.2) in the literature. This dual version, also known as the envelopment model, is expressed as:

$$E_0 = \min_{\lambda, s_i, s_r, \phi} \; \phi - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \tag{3.3a}$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_j X_{ij} + s_i^- = \phi X_{io} \qquad i = 1, 2, ..., m \tag{3.3b}$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ = Y_{ro} \qquad r = 1, 2, ..., s \tag{3.3c}$$

$$\lambda_j, s_i^-, s_r^+ \geq 0, \quad j = 1, 2, ..., n \tag{3.3d}$$

Here $\boldsymbol{\lambda}$ is the intensity vector, while s_i^- and s_r^+ are slack variables. Model (3.3) is an input minimisation problem which finds the maximum possible radial contraction of all inputs necessary to make a DMU efficient under a constant returns to scale (CRS) assumption. Where variable returns to scale (VRS) is preferred, an additional convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$ can be added to model in 3.3. Such a model which allows for VRS constraint is often referred to as the Banker, Charnes and Cooper (BCC) model after Banker et al. (1984). On the other hand, the CRS model is often referred to as the Charnes, Cooper and Rhodes (CCR) model after Charnes et al. (1978). Both the CCR and the BCC models can also be formulated for the output-oriented case, which captures simultaneous radial output expansion. In such a case, the objective function becomes a maximisation problem, while ϕ will be attached to Y_{ro} in the second constraint instead of X_{io}. These models have been formulated using radial measurement approaches; several non-radial alternatives can be employed. Some of these are presented in Section 3.6 of the chapter.

The basic CCR and BCC models presented do not consider the internal structure of the DMU when measuring the efficiency, thereby treating the system as a black-box (Castelli et al., 2010; Kao, 2014c). Hence, the basic model assumes homogeneity in inputs and outputs of all DMUs and DMU independence (i.e. constraints do not bind inputs/outputs of a DMU to inputs/outputs of other DMUs) (Castelli et al., 2010). The black-box structure, which considers just the inputs consumed and the outputs produced by the overall system, is depicted in Figure 3.1.

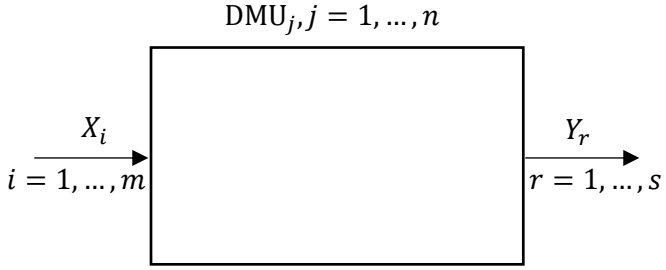

Figure 3.1 Basic 'black-box' structure.

Source: Kao (2014b, pg. 56)

In practice units under investigation are composed of several sub-units that are linked or operate independently to achieve overall goals (Tone and Tsutsui, 2009). Aggregating the outputs of the overall system, while ignoring the internal linking activities, does not allow for the assessment of the division-specific inefficiencies and their impact on the overall efficiency of the system under investigation (Tone and Tsutsui, 2009). Additionally, as a DEA model maximises the efficiency ratio by

determining optimal multipliers, the black-box approach may lead to inappropriate multipliers for input and output combinations since, DMUs do not have the opportunity to allocate inputs and outputs among sub-units (Castelli et al., 2010; Cook et al., 2000). Consequently, the black-box model may assign unreasonable efficiency scores to DMUs (Tone and Tsutsui, 2009).

The consequence of using the black-box approach is that some sub-unit inefficiency information is not available to system managers when diagnosing performance improvement potential. It is more informative to consider the internal structure of the system under investigation. By considering the internal structure, it is possible to identify specific under-performing sub-units that may require performance improvement. Examining the internal structure of DMUs may help explain the source of the overall performance measured under the 'black-box' approaches (Kao and Hwang, 2008).

3.3 Models with known internal structure

If the internal structures of the DMUs are ignored, the efficiency scores estimated using the black-box approach will sometimes be misleading (Kao, 2014a). Consequently, when the internal structure is known, it is important to incorporate this into the performance modelling. DMUs with known internal structures will have some sub-processes/sub-systems/sub-units. A sub-process p ($p = 1, \ldots, q$), as illustrated in Figure 3.2, can be defined to have:

a. $X_i^{(p)}$, $i \in I^{(p)}$: exogenous inputs from outside the system consumed by sub-process p

b. $Y_r^{(p)}$, $r \in O^{(p)}$: final outputs produced by sub-process p

c. $Z_f^{(p)}$, $f \in M_I^{(p)}$: intermediate inputs consumed by sub-process p produced by other sub-processes

d. $Z_g^{(p)}$, $g \in M_O^{(p)}$: intermediate outputs produced by sub-process p to be consumed by other sub-processes

For a DMU j the total inputs of the system is the sum of the inputs of all sub-processes such that $\sum_{p=1}^{q} X_{ij}^{(p)} = X_{ij}, i = 1, \ldots, m$ and total outputs of the system should be the sum of the outputs of the sub-processes $\sum_{p=1}^{q} Y_{rj}^{(p)} = Y_{rj}, r = 1, \ldots, s$. It is expected that all intermediate products produced in the system are consumed in the system (Kao, 2014a).

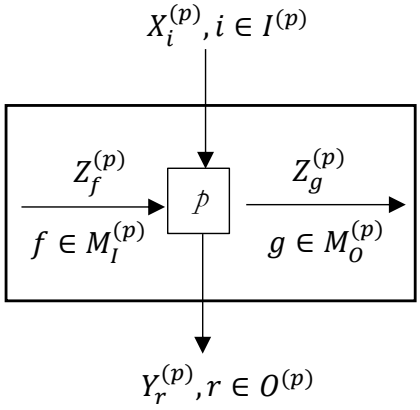

Figure 3.2 General structure of a sub-process.

Source: Adapted from Kao (2014c)

In typical practical applications, each DMU under evaluation will have some interrelated processes arranged in a variety of structures. Various mathematical models have been developed to evaluate DMUs with different internal structures. In the next sub-sections, models developed for series, parallel and mixed network structures are presented.

3.3.1 Series network structure

There exists a series network structure if some or all outputs of one sub-process are directly consumed by another sub-process in the DMU under consideration as depicted in Figure 3.3.

In this series structure, each sub-process may have exogenous inputs $X_i^{(p)}$ which do not come from other sub-processes and may produce exogenous outputs $Y_r^{(p)}$ to be consumed by other entities outside the system. There also exist intermediate product $Z_f^{(p)}$ produced in the system and consumed by units in the system. A generalised series structure efficiency model is presented in Section 3.3.1, however, a specialised type of series structure – the two-stage network, is first reviewed.

Two-stage networks

A special case of the series structure is the two-stage network structure which has been widely studied in the literature (Cook, Liang and Zhu, 2010). Such models have two sub-processes, where all outputs of the first sub-process are consumed by

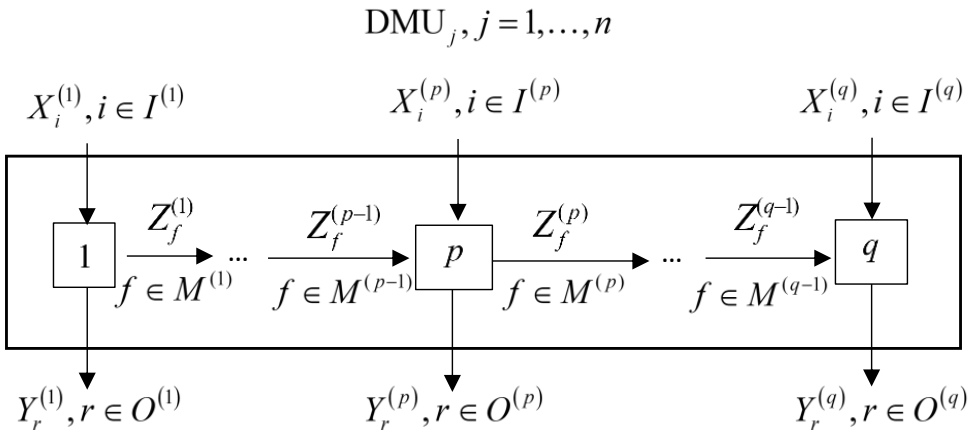

Figure 3.3 The general structure of the multi-stage series system.

Source: Kao (2014a, pg. 7)

the second sub-process (Cook and Zhu, 2014b). This is shown in Figure 3.4. A recent application of the two-stage model includes the joint analysis of eco-efficiency and eco-innovation of OECD countries by Mavi et al. (2019). In their paper, the first stage was the eco-efficiency assessment, which used labour, energy and land area as inputs used in generating economic output (GDP) and undesirable GHG emissions. In the second stage, the eco-efficiency outputs were the inputs in the eco-innovation analysis, which examined environmentally-related technology innovations.

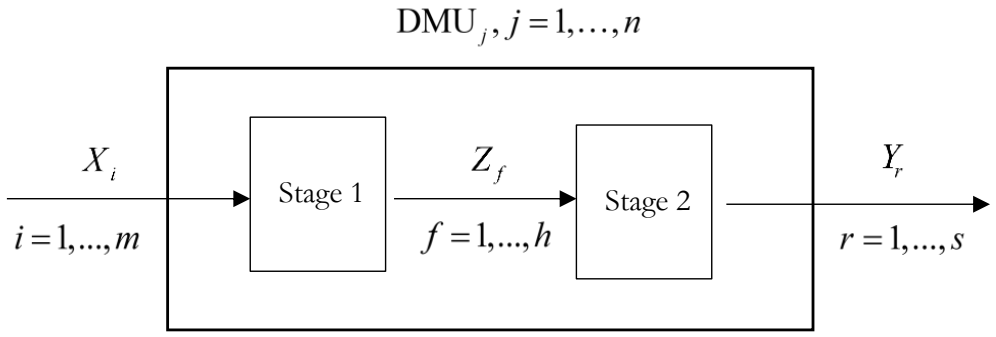

Figure 3.4 Two-stage series structure.

Source: Adapted from Kao (2014c)

Denoting the efficiency of stage 1 and stage 2 as $E_j^{(1)}$ and $E_j^{(2)}$ respectively, the CCR ratio for the two stages can be expressed as:

$$E_j^{(1)} = \frac{\sum_{f=1}^{h} \widehat{w}_f Z_{fj}}{\sum_{i=1}^{m} v_i X_{ij}}, \quad \text{and} \quad E_j^{(2)} = \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{f=1}^{h} \widetilde{w}_f Z_{fj}} \tag{3.4}$$

In (3.4), the unknown multipliers $\widehat{w}_f$ and $\widetilde{w}_f$ can be defined to be equal. The problem with the two-stage model is that the intermediate product Z_f is an output in the first stage but an input in the second stage. Consequently, while the input in the first stage may have to be reduced to maximise the stage 2 efficiency, it may come at the cost of a reduction in the output of stage 1, therefore, reducing stage 1 efficiency. Cook, Liang and Zhu (2010), identified four approaches in the literature for dealing with the problem of the intermediate products, namely standard DEA methodology, efficiency decomposition methodology, network DEA and game-theoretic approaches.

The standard DEA approach treats the two systems as independent, therefore, solving separate unrelated basic efficiency models for stage 1 ($E_j^{(1)}$) and stage 2 ($E_j^{(2)}$) (Seiford and Zhu, 1999; Zhu, 2000). This approach does not treat the sub-processes in a coordinated manner, therefore, efficiency improvement in one stage may lead to inefficiency in the other stage (Cook, Liang and Zhu, 2010). The efficiency decomposition approach determines the overall efficiency of the system before decomposing that overall efficiency among the sub-processes. Kao and Hwang (2008) developed a relational model which has the overall efficiency as a product of the sub-process efficiencies such that $E_j = E_j^{(1)} \times E_j^{(2)}$. In this case, the multiplier of the intermediate product remains the same whether it is an output or an input (i.e. $\widehat{w}_f = \widetilde{w}_f$). It is also plausible to define the overall efficiency as some form of average of the sub-processes (e.g. $E_j = (E_j^{(1)} + E_j^{(2)})/2$) (Cook, Liang and Zhu, 2010). Chen et al. (2009) introduced the additive decomposition of the two-stage DEA by defining the overall system efficiency as a weighted sum of the sub-process efficiencies.

There may be other outputs of the first stage that are not input to stage 2 or other inputs for stage 2 which are not outputs of stage 1. Where such exogenous inputs and outputs exist, then the problem can be seen as a network DEA approach. Despotis, Koronakos and Sotiros (2016) and Despotis, Sotiros and Koronakos (2016), for example, provide network DEA models for various types of series structures using their efficiency composition approach based on multi-objective programming. Tone and Tsutsui (2009) conduct network modelling of various systems using the slack-based measure of efficiency. Finally, the game-theoretic approach pioneered by Liang et al. (2008) models the two-stage problem using concepts in cooperative

and Stackelberg (leader-follower) game theory concepts. Zhou et al. (2013) later developed a two-stage efficiency decomposition in the centralised (cooperative) model using Nash bargaining game concepts. Game-theoretic approaches are presented in subsequent sections.

Although there are a number of such two-stage models, Cook, Liang and Zhu (2010) show that all existing approaches can be categorised as either a non-cooperative or cooperative game problem. Consequently, the centralised and the leader-follower approaches are presented in the next sub-sections. However, since these approaches are based on the multiplicative or additive efficiency decomposition, these decomposition approaches are first presented.

Multiplicative decomposition

Given the two-stage system depicted in Figure 3.4, the CCR efficiency ratios for the first and second stages can be expressed as:

$$E_o^{(1)} = \max \quad \frac{\sum_{f=1}^{h} \widehat{w}_f Z_{fo}}{\sum_{i=1}^{m} v_i X_{io}} \tag{3.5a}$$

$$\text{s.t.} \quad \frac{\sum_{f=1}^{h} \widehat{w}_f Z_{fj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1 \quad j = 1, 2, ..., n \tag{3.5b}$$

$$\widehat{w}_f, v_i \geq \varepsilon > 0, \;\; f = 1, \ldots, h, \;\; i = 1, \ldots, m \tag{3.5c}$$

$$E_o^{(2)} = \max \quad \frac{\sum_{r=1}^{s} u_r Y_{ro}}{\sum_{f=1}^{h} \widetilde{w}_f Z_{fo}} \tag{3.6a}$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{f=1}^{h} \widetilde{w}_f Z_{fj}} \leq 1 \quad j = 1, 2, ..., n \tag{3.6b}$$

$$\widetilde{w}_f, u_r \geq \varepsilon > 0, \;\; f = 1, \ldots, h, \;\; r = 1, \ldots, s \tag{3.6c}$$

The approach by Kao and Hwang (2008) defines the overall efficiency of the system as a product of the sub-system efficiencies, therefore, it requires the multipliers for the intermediate product to remain the same in both models (i.e. $\widehat{w}_f = \widetilde{w}_f = w_f$) . If this condition is not introduced, models (3.5) and (3.6) become independent models with no linking relationship. The overall efficiency ratio under the multiplicative model becomes:

$$E_o = \max \left(\frac{\sum_{f=1}^{h} w_f Z_{fo}}{\sum_{i=1}^{m} v_i X_{io}} \times \frac{\sum_{r=1}^{s} u_r Y_{ro}}{\sum_{f=1}^{h} w_f Z_{fo}} \right) = \frac{\sum_{r=1}^{s} u_r Y_{ro}}{\sum_{i=1}^{m} v_i X_{io}} \tag{3.7a}$$

$$\text{s.t.} \quad \frac{\sum_{f=1}^{h} w_f Z_{fj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1 \quad j = 1, 2, ..., n \tag{3.7b}$$

$$\frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{f=1}^{h} w_f Z_{fj}} \leq 1 \quad j = 1, 2, ..., n \tag{3.7c}$$

$$w_f, u_r, v_i \geq \varepsilon > 0, \;\; f = 1, \ldots, h, \;\; i = 1, \ldots, m, r = 1, \ldots, s \tag{3.7d}$$

Model (3.7) introduces the sub-process constraints in (3.4) into the CCR model (3.1). The overall constraint $\sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \leq 1$ becomes redundant in (3.7) since it is implied by (3.7b) and (3.7c).

Additive decomposition

The multiplicative model is a rational assumption for efficiency decomposition but can be restricted to the CCR model. Chen et al. (2009) developed a weighted additive model that avoids possible nonlinearity in the multiplicative model in the

case of a BCC model. The additive model, therefore, allows for decomposing of the overall efficiency for both the CCR and BCC models. This model becomes:

$$E_o = \max \ \omega_1 \left(\frac{\sum_{f=1}^{h} w_f Z_{fo}}{\sum_{i=1}^{m} v_i X_{io}} \right) + \omega_2 \left(\frac{\sum_{r=1}^{s} u_r Y_{ro}}{\sum_{f=1}^{h} w_f Z_{fo}} \right) \tag{3.8a}$$

$$\text{s.t.} \quad \frac{\sum_{f=1}^{h} w_f Z_{fj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1 \quad j = 1, 2, ..., n \tag{3.8b}$$

$$\frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{f=1}^{h} w_f Z_{fj}} \leq 1 \quad j = 1, 2, ..., n \tag{3.8c}$$

$$w_f, u_r, v_i \geq \varepsilon > 0, \ f = 1, \ldots, h, \ i = 1, \ldots, m, \ r = 1, \ldots, s \tag{3.8d}$$

Note that for the weights $\omega_1 + \omega_2 = 1$ and it is a measure of the relative importance of the sub-unit which could be exogenously determined outside model (3.8). However, as the weight is a measure of the relative importance of the sub-process, Chen et al. (2009) propose that if the size of a unit reflects its importance, then the use of the total system resources that are dedicated to the sub-process under consideration may be used. Subsequently, if $\sum_{i=1}^{m} v_i X_{io} + \sum_{f=1}^{h} w_f Z_{fo}$ is the total size of resources used in the system, then the sizes of the two stages could be determined as:

$$\omega_1 = \frac{\sum_{i=1}^{m} v_i X_{io}}{\sum_{i=1}^{m} v_i X_{io} + \sum_{f=1}^{h} w_f Z_{fo}} \tag{3.9a}$$

$$\omega_2 = \frac{\sum_{f=1}^{h} w_f Z_{fo}}{\sum_{i=1}^{m} v_i X_{io} + \sum_{f=1}^{h} w_f Z_{fo}} \tag{3.9b}$$

If these weights are introduced into (3.8), then the new model becomes:

$$E_o = \max \quad \frac{\sum_{f=1}^{h} w_f Z_{fo} + \sum_{r=1}^{s} u_r Y_{ro}}{\sum_{i=1}^{m} v_i X_{io} + \sum_{f=1}^{h} w_f Z_{fo}} \tag{3.10a}$$

$$\text{s.t.} \quad \frac{\sum_{f=1}^{h} w_f Z_{fj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1 \quad j = 1, 2, ..., n \tag{3.10b}$$

$$\frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{f=1}^{h} w_f Z_{fj}} \leq 1 \quad j = 1, 2, ..., n \tag{3.10c}$$

$$w_f, u_r, v_i \geq \varepsilon > 0, \;\; f = 1, \ldots, h, \;\; i = 1, \ldots, m, \; r = 1, \ldots, s \tag{3.10d}$$

Model (3.10) can be linearised using the Charnes and Cooper (1973) transformation. The optimal solution to models (3.7) and (3.10) may not be unique, since there may exist multiple optimal solutions (Chen et al., 2009; Kao and Hwang, 2008). Kao and Hwang (2008) have proposed a procedure to determine if multipliers are uniquely determined.

As earlier indicated, Cook, Liang and Zhu (2010) observe that all two-stage DEA problems can be categorised as either a cooperative or non-cooperative game theory problem. Liang et al. (2008) developed two perspectives for modelling two-stage problems. While in the cooperative (or centralised) model both sub-processes work together to achieve the highest overall efficiency possible, the non-cooperative model uses Stackelberg duopoly (i.e. leader-follower competition) where one sub-process (the follower) optimises its efficiency subject to the optimal multipliers of the other sub-process (leader) (Liang et al., 2008). For both models, the overall efficiencies are defined as a product of the sub-processes. The next sub-sections present the cooperative and non-cooperative two-stage models.

Cooperative model

Considering the two-stage model depicted in Figure 3.4, the cooperative model is essentially Kao and Hwang's (2008) multiplicative model presented in (3.7). The linearised model to the overall model is, therefore:

$$E_o^{\text{centralised}} = \max \quad \sum_{r=1}^{s} u_r Y_{ro} \tag{3.11a}$$

$$\text{s.t.} \quad \sum_{f=1}^{h} w_f Z_{fj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \quad j = 1, 2, ..., n \tag{3.11b}$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{f=1}^{h} w_f Z_{fj} \leq 0 \quad j = 1, 2, ..., n \tag{3.11c}$$

$$\sum_{i=1}^{m} v_i X_{io} = 1 \tag{3.11d}$$

$$w_f, u_r, v_i \geq \varepsilon > 0, \;\; f = 1, \ldots, h, \;\; i = 1, \ldots, m, \; r = 1, \ldots, s \tag{3.11e}$$

Assuming the optimal multipliers u_r^*, v_i^* and w_f^* of (3.11) are uniquely determined, then the overall efficiency of the centralised model could be decomposed into the sub-process efficiencies:

$$E_o^{(1),\text{centralised}} = \frac{\sum_{f=1}^{h} w_f^* Z_{fo}}{\sum_{i=1}^{m} v_i^* X_{io}} = \sum_{f=1}^{h} w_f^* Z_{fo} \tag{3.12a}$$

$$E_o^{(2),\text{centralised}} = \frac{\sum_{r=1}^{s} u_r^* Y_{ro}}{\sum_{f=1}^{h} w_f^* Z_{fo}} \tag{3.12b}$$

As the optimal multipliers in (3.12) may not be uniquely determined, there exist a test for uniqueness and an alternative decomposition approach in Liang et al. (2008).

Non-cooperative model

Unlike the cooperative model, for the non-cooperative model, a clear leader must be determined *a priori*. This can be either of the stages. The leader's efficiency will be determined using CCR model (3.1). The follower's efficiency is then computed

while maintaining the efficiency of the first stage. Assuming stage 1 is the leader, its efficiency of the stage will be:

$$
\begin{aligned}
E_o^{(1)} = \quad & \max \quad \sum_{f=1}^{h} w_f Z_{fo} && \text{(3.13a)}\\
& \text{s.t.} \quad \sum_{f=1}^{h} w_f Z_{fj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \qquad j = 1, 2, ..., n && \text{(3.13b)}\\
& \qquad \sum_{i=1}^{m} v_i X_{io} = 1 && \text{(3.13c)}\\
& \qquad w_f, v_i \geq \varepsilon > 0, \;\; f = 1, \ldots, h, \;\; i = 1, \ldots, m, \; r = 1, \ldots, s && \text{(3.13d)}
\end{aligned}
$$

After determining the optimal efficiency of that stage, the follower's efficiency is determined by solving for the optimal multipliers in stage 2 that ensures the optimal efficiency of the leader's model will remain optimal.

$$
\begin{aligned}
E_o^{(2)} = \quad & \max \quad \left(\sum_{r=1}^{s} u_r Y_{ro} \right) / E_o^{(1)*} && \text{(3.14a)}\\
& \text{s.t.} \quad \sum_{r=1}^{s} u_r Y_{rj} - \sum_{f=1}^{h} w_f Z_{fj} \leq 0 \qquad j = 1, 2, ..., n && \text{(3.14b)}\\
& \qquad \sum_{f=1}^{h} w_f Z_{fj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \qquad j = 1, 2, ..., n && \text{(3.14c)}\\
& \qquad \sum_{i=1}^{m} v_i X_{io} = 1 && \text{(3.14d)}\\
& \qquad \sum_{f=1}^{h} w_f Z_{fo} = E_o^{(1)*} && \text{(3.14e)}\\
& \qquad w_f, v_i, u_r \geq \varepsilon > 0, \;\; f = 1, \ldots, h, \;\; i = 1, \ldots, m, \; r = 1, \ldots, s && \text{(3.14f)}
\end{aligned}
$$

Note that $E_o^{(1)*}$ is determined in model (3.13), therefore, model (3.14) is linear. It is also possible to make stage 2 the leader. The overall system efficiency is still the product of the sub-system efficiencies.

$$E_o^* = E_o^{(1)*} \cdot E_o^{(2)*} \tag{3.15a}$$

$$= \left(\sum_{f=1}^{h} w_f^* Z_{fo}\right) \left(\left(\sum_{r=1}^{s} u_r^* Y_{ro}\right) / \sum_{f=1}^{h} w_f^* Z_{fo}\right) \tag{3.15b}$$

$$= \sum_{r=1}^{s} u_r^* Y_{ro} \tag{3.15c}$$

Note that $\sum_{i=1}^{m} v_i^* X_{io} = 1$. Unlike the centralised model, the efficiency decomposition in the Stackelberg model is unique (Liang et al., 2008).

Basic series networks

While the two-stage structure models systems with two sub-processes, the basic series network models involves q sub-processes ($q \geq 2$) where only the first sub-process has exogenous inputs while only the final sub-process produces the final or exogenous output. Each of the remaining p sub-processes consume and produce $Z_f^{(p)}$ intermediate products. This is shown in Figure 3.5.

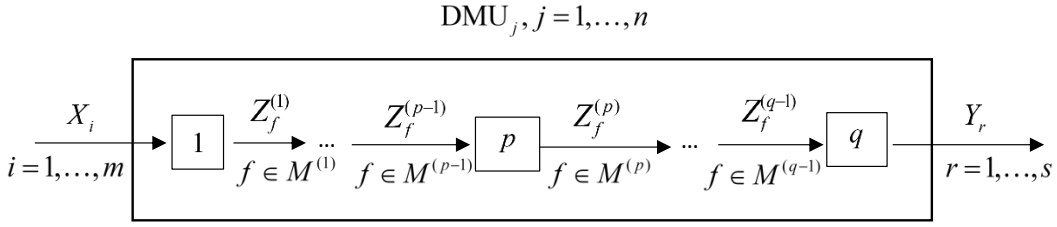

Figure 3.5 Basic series structure.

Source: Kao (2014a, pg. 119)

Using the relational model of Kao and Hwang (2008), the system efficiency can be formulated as:

$$E_0 = \max \sum_{r=1}^{s} u_r Y_{ro} \tag{3.16a}$$

$$\text{s.t.} \sum_{i=1}^{m} v_i X_{io} = 1 \tag{3.16b}$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \qquad j = 1, 2, ..., n \tag{3.16c}$$

$$\sum_{f \in M^{(1)}} w_f Z_{fj}^{(1)} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \qquad j = 1, 2, \ldots, n \tag{3.16d}$$

$$\sum_{f \in M^{(p)}} w_f Z_{fj}^{(p)} - \sum_{f \in M^{(p-1)}} w_f Z_{fj}^{(p-1)} \leq 0$$

$$p = 2, \ldots, q-1, \;\; j = 1, 2, \ldots, n \tag{3.16e}$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{f \in M^{(q-1)}} w_f Z_{fj}^{(q-1)} \leq 0 \qquad j = 1, 2, \ldots, n \tag{3.16f}$$

$$u_r, v_i, w_f \geq \varepsilon, \;\; r = 1, ..., s, \quad i = 1, ..., m, \;\; f = 1, \ldots, h \tag{3.16g}$$

Given the optimal solution u_r^*, v_i^* and w_f^*, the efficiencies for the system and sub-process for each DMU can be estimated as:

$$E_o = \frac{\sum_{r=1}^{s} u_r^* Y_{ro}}{\sum_{i=1}^{m} v_i^* X_{io}} = \sum_{r=1}^{s} u_r^* Y_{ro} \tag{3.17a}$$

$$E_o^{(1)} = \frac{\sum_{f \in M^{(1)}} w_f^* Z_{fo}^{(1)}}{\sum_{i=1}^{m} v_i^* X_{io}} \tag{3.17b}$$

$$E_o^{(p)} = \frac{\sum_{f \in M^{(p)}} w_f^* Z_{fo}^{(p)}}{\sum_{f \in M^{(p-1)}} w_f^* Z_{fo}^{(p-1)}}, \qquad p = 2, \ldots, q-1, \tag{3.17c}$$

$$E_o^{(q)} = \frac{\sum_{r=1}^{s} u_r^* Y_{ro}}{\sum_{f \in M^{(q-1)}} w_f^* Z_{fo}^{(q-1)}} \tag{3.17d}$$

For the relational series structure model, the product of all the sub-process efficiencies is the system efficiency (Kao, 2014a). Subsequently, a system is overall efficient if all sub-processes are efficient.

$$\prod_{p=1}^{q} E_o^{(p)} = \left(\frac{\sum\limits_{f \in M^{(1)}} w_f^* Z_{fo}^{(1)}}{\sum\limits_{i=1}^{m} v_i^* X_{io}} \right) \left(\prod_{p=2}^{q-1} \frac{\sum\limits_{f \in M^{(p)}} w_f^* Z_{fo}^{(p)}}{\sum\limits_{f \in M^{(p-1)}} w_f^* Z_{fo}^{(p-1)}} \right) \left(\frac{\sum\limits_{r=1}^{s} u_r^* Y_{ro}}{\sum\limits_{f \in M^{(q-1)}} w_f^* Z_{fo}^{(q-1)}} \right) \tag{3.18a}$$

$$= \frac{\sum\limits_{r=1}^{s} u_r^* Y_{ro}}{\sum\limits_{i=1}^{m} v_i^* X_{io}} \tag{3.18b}$$

General multi-stage series networks

While two-stage network and the basic series structures model systems with two or more sub-processes without other exogenous inputs and outputs, it is possible that sub-systems will have such exogenous products. This is depicted in Figure 3.3 where the system has q sub-processes. The multi-stage series structure network model can be seen as an extension or generalisation of the two-stage and basic series models to capture more than two stages of interlinked sub-processes. Given q sub-processes,

using multiplicative decomposition in a centralised model, the efficiency of the system can be determined using (Kao, 2014a):

$$E_0 = \max \sum_{r=1}^{s} u_r Y_{ro} \tag{3.19a}$$

$$\text{s.t.} \sum_{i=1}^{m} v_i X_{io} = 1 \tag{3.19b}$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \qquad j = 1, 2, ..., n \tag{3.19c}$$

$$\left(\sum_{r \in O^{(1)}} u_r Y_{rj}^{(1)} + \sum_{f \in M^{(1)}} w_f Z_{fj}^{(1)} \right) - \sum_{i \in I^{(1)}} v_i X_{ij}^{(1)} \leq 0$$

$$j = 1, 2, \ldots, n \tag{3.19d}$$

$$\left(\sum_{r \in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fj}^{(p)} \right) - \left(\sum_{i \in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fj}^{(p-1)} \right) \leq 0$$

$$p = 2, \ldots, q-1, \;\; j = 1, 2, \ldots, n \tag{3.19e}$$

$$\sum_{r \in O^{(q)}} u_r Y_{rj}^{(q)} - \left(\sum_{i \in I^{(q)}} v_i X_{ij}^{(q)} + \sum_{f \in M^{(q-1)}} w_f Z_{fj}^{(q-1)} \right) \leq 0$$

$$j = 1, 2, \ldots, n \tag{3.19f}$$

$$u_r, v_i, w_f \geq \varepsilon, \;\; r = 1, ..., s, \;\; i = 1, ..., m, \;\; f = 1, \ldots, h \tag{3.19g}$$

Where $X_{ij} = \sum_{p=1}^{q} X_{ij}^{(p)}, i = 1, \ldots, m$, $Y_{rj} = \sum_{p=1}^{q} Y_{rj}^{(p)}, r = 1, \ldots, s$ and w_f is the multiplier of the fth intermediate product. The overall model constraint (3.19c) is redundant and can be eliminated from (3.19). Given the optimal solution

u_r^*, v_i^* and w_f^*, the efficiencies for the system and sub-process for each DMU can be estimated as:

$$E_o = \frac{\sum_{r=1}^{s} u_r^* Y_{ro}}{\sum_{i=1}^{m} v_i^* X_{io}} = \sum_{r=1}^{s} u_r^* Y_{ro} \tag{3.20a}$$

$$E_o^{(1)} = \frac{\sum_{r \in O^{(1)}} u_r^* Y_{ro}^{(1)} + \sum_{f \in M^{(1)}} w_f^* Z_{fo}^{(1)}}{\sum_{i=1}^{m} v_i^* X_{io}^{(1)}} \tag{3.20b}$$

$$E_o^{(p)} = \frac{\sum_{r \in O^{(p)}} u_r^* Y_{ro}^{(p)} + \sum_{f \in M^{(p)}} w_f^* Z_{fo}^{(p)}}{\sum_{i \in I^{(p)}} v_i^* X_{io}^{(p)} + \sum_{f \in M^{(p-1)}} w_f^* Z_{fo}^{(p-1)}}, \qquad p = 2, \ldots, q-1 \tag{3.20c}$$

$$E_o^{(q)} = \frac{\sum_{r \in O^{(q)}} u_r^* Y_{ro}^{(q)}}{\sum_{i \in I^{(q)}} v_i^* X_{io}^{(q)} + \sum_{f \in M_I^{(q-1)}} w_f^* Z_{fo}^{(q-1)}} \tag{3.20d}$$

Cook, Zhu, Bi and Yang (2010) also proposed an extension of their additive two-stage decomposition in Chen et al. (2009). They define the overall system efficiency as a weighted additive average of the sub-process efficiencies such that

$E_o = \sum_{p=1}^{q} \omega^{(p)} E_o^{(p)}$ and $\sum_{p=1}^{q} \omega^{(p)} = 1$. Where the weights are determined by the relative resource consumption, their model can be expressed as:

$$E_0 = \max \quad \sum_{r=1}^{s} u_r Y_{ro} + \sum_{f=1}^{h} w_f Z_{fo} \tag{3.21a}$$

$$\text{s.t.} \quad \sum_{i=1}^{m} v_i X_{io} + \sum_{f=1}^{h} w_f Z_{fo} = 1 \tag{3.21b}$$

$$\left(\sum_{r=1}^{s} u_r Y_{rj} + \sum_{f=1}^{h} w_f Z_{fj} \right) - \left(\sum_{i=1}^{m} v_i X_{ij} + \sum_{f=1}^{h} w_f Z_{fj} \right) \leq 0$$

$$j = 1, 2, ..., n \tag{3.21c}$$

$$\left(\sum_{r \in O^{(1)}} u_r Y_{rj}^{(1)} + \sum_{f \in M^{(1)}} w_f Z_{fj}^{(1)} \right) - \sum_{i \in I^{(1)}} v_i X_{ij}^{(1)} \leq 0 \qquad j = 1, 2, \ldots, n \tag{3.21d}$$

$$\left(\sum_{r \in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fj}^{(p)} \right) - \left(\sum_{i \in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fj}^{(p-1)} \right) \leq 0$$

$$p = 2, \ldots, q-1, \;\; j = 1, 2, \ldots, n \tag{3.21e}$$

$$\sum_{r \in O^{(q)}} u_r Y_{rj}^{(q)} - \left(\sum_{i \in I^{(q)}} v_i X_{ij}^{(q)} + \sum_{f \in M^{(q-1)}} w_f Z_{fj}^{(q-1)} \right) \leq 0$$

$$j = 1, 2, \ldots, n \tag{3.21f}$$

$$u_r, v_i, w_f \geq \varepsilon, \;\; r = 1, ..., s, \;\; i = 1, ..., m, \;\; f = 1, \ldots, h \tag{3.21g}$$

Sub-process efficiency decomposition can then be made using (3.20).

3.3.2 Parallel network structure

Unlike series network structures, for parallel networks, the output of one sub-process is not directly consumed by another sub-process (Castelli et al., 2010). Sub-processes operate independently as depicted in Figure 3.6. In subsequent sections, various parallel network models are presented.

Yang, Ma and Koike (YMK) model

Yang et al. (2000) developed a DEA model for measurement of the overall efficiencies of independent production systems where the overall efficiency is equal to the maximum efficiency among all the sub-systems under CCR model. This model,

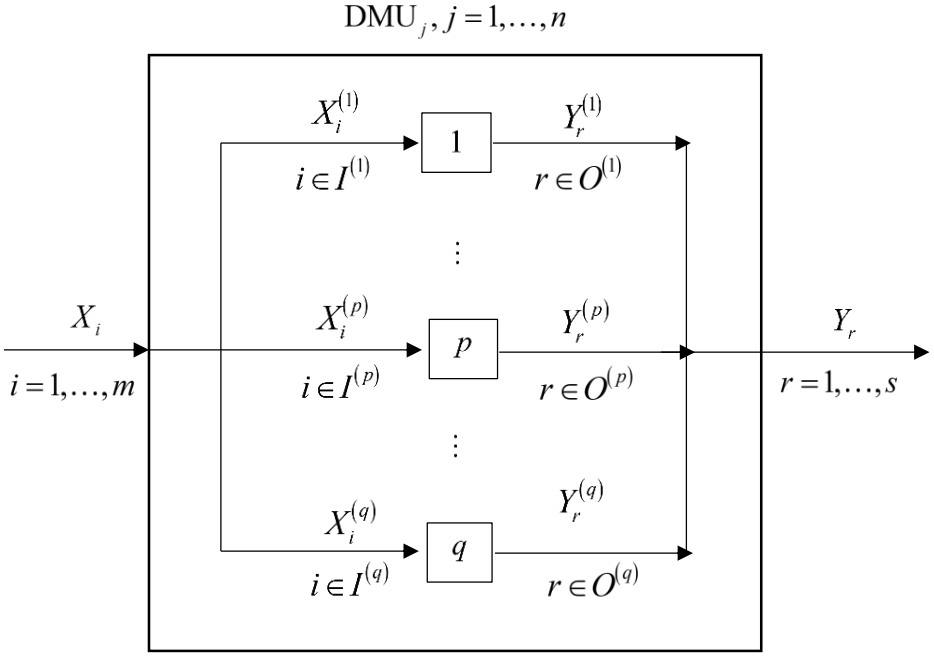

Figure 3.6 General structure of parallel sub-processes.

Source: Kao (2014a, pg. 120)

therefore, uses Pareto order for system aggregation (Shen et al., 2018). The YMK model to determine the overall efficiency of the system is defined as:

$$E_0 = \max \sum_{p=1}^{q} \sum_{r\in O^{(p)}} u_r^{(p)} Y_{ro}^{(p)} \tag{3.22a}$$

$$\text{s.t.} \sum_{p=1}^{q} \sum_{i\in I^{(p)}} v_i^{(p)} X_{io}^{(p)} = 1 \tag{3.22b}$$

$$\sum_{r\in O^{(p)}} u_r^{(p)} Y_{rj}^{(p)} - \sum_{i\in I^{(p)}} v_i^{(p)} X_{ij}^{(p)} \leq 0 \quad p=1,\ldots,q, \;\; j=1,2,\ldots,n \tag{3.22c}$$

$$u_r^{(p)}, v_i^{(p)} \geq \varepsilon, \quad r=1,...,s, \quad i=1,...,m \tag{3.22d}$$

For the YMK model, the sub-process efficiencies are computed as using the CCR model similar to the one in (3.2) for each sub-system independently. The dual version of the YMK model is presented in (3.23).

$$E_0 = \min_{\lambda,\theta} \ \theta \tag{3.23a}$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_j^{(p)} X_{ij}^{(p)} \leq \theta X_{io}^{(p)} \quad i = 1, 2, ..., m, \ p = 1, \ldots, q \tag{3.23b}$$

$$\sum_{j=1}^{n} \lambda_j^{(p)} Y_{rj}^{(p)} \geq Y_{ro}^{(p)} \qquad r = 1, 2, ..., s, \ p = 1, \ldots, q \tag{3.23c}$$

$$\lambda_j^{(p)} \geq 0, \ j = 1, 2, ..., n \tag{3.23d}$$

Since the overall efficiency is the maximum of the efficiencies of sub-processes, it implies that the system is efficient if any of the sub-processes are efficient. This can be a challenging condition to justify in practice.

Kao model

Unlike the YMK model, Kao (2009b) developed the relational model which attaches the same input and output multipliers to the same type of inputs and outputs irrespective of the production system. The rationale behind this is that the price of the factor, on the market, remains the same irrespective of how it is used in the system (Kao, 2012). For the parallel network of Kao (2009b) the system input is the sum of all the sub-process inputs such that $\sum_{p=1}^{q} X_{ij}^{(p)} = X_{ij}, i = 1, \ldots, m$. Similarly, the sum of the sub-process outputs is the overall system output $\sum_{p=1}^{q} Y_{rj}^{(p)} = Y_{rj}, r = 1, \ldots, s.$. Therefore, where possible, a system can reallocate resources to the different independent sub-units in a way that maximises the overall efficiency of the system

(Kao, 2009b). The model to assess the efficiency of the system shown in Figure 3.6 is as follows:

$$E_0 = \max \sum_{r=1}^{s} u_r Y_{ro} \tag{3.24a}$$

$$\text{s.t.} \sum_{i=1}^{m} v_i X_{io} = 1 \tag{3.24b}$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \qquad j = 1, 2, ..., n \tag{3.24c}$$

$$\sum_{r \in O^{(p)}} u_r Y_{rj}^{(p)} - \sum_{i \in I^{(p)}} v_i X_{ij}^{(p)} \leq 0 \quad p = 1, \ldots, q, \;\; j = 1, 2, \ldots, n \tag{3.24d}$$

$$u_r, v_i \geq \varepsilon, \;\; r = 1, ..., s, \quad i = 1, ..., m \tag{3.24e}$$

From the optimal solution u_r^* and v_i^*, the efficiencies for the system and sub-process for each DMU can be computed as:

$$E_o = \frac{\sum\limits_{r=1}^{s} u_r^* Y_{ro}}{\sum\limits_{i=1}^{m} v_i^* X_{io}} = \sum_{r=1}^{s} u_r^* Y_{ro} \tag{3.25a}$$

$$E_o^{(p)} = \frac{\sum\limits_{r \in O^{(p)}} u_r^* Y_{ro}^{(p)}}{\sum\limits_{i \in I^{(p)}} v_i^* X_{io}^{(p)}}, \qquad p = 1, \ldots, q \tag{3.25b}$$

Kao (2012) and Kao (2014a) show that the system efficiency is a weighted sum of the sub-process efficiencies. That is, where the importance of a sub-process is defined as a proportion of resources dedicated to the sub-process to the overall

resources, $w^{(p)} = \sum_{i \in I^{(p)}} v_i X_{io}^{(p)} / \sum_{i=1}^{m} v_i X_{io}$, where $\sum_{p=1}^{q} \sum_{i \in I^{(p)}} v_i X_{io}^{(p)} = \sum_{i=1}^{m} v_i X_{io}$ then the weighted average of all sub-process efficiencies becomes:

$$\sum_{p=1}^{q} w^{(p)} E_o^{(p)} = \sum_{p=1}^{q} \left[\left(\frac{\sum_{i \in I^{(p)}} v_i X_{io}^{(p)}}{\sum_{i=1}^{m} v_i X_{io}} \right) \left(\frac{\sum_{r \in O^{(p)}} u_r Y_{ro}^{(p)}}{\sum_{i \in I^{(p)}} v_i X_{io}^{(p)}} \right) \right] \tag{3.26a}$$

$$= \frac{\sum_{r=1}^{s} u_r Y_{ro}}{\sum_{i=1}^{m} v_i X_{io}} \tag{3.26b}$$

Consequently, a system is only efficient if all of its sub-processes are efficient and the total slacks for the system efficiency are the sum of the slacks of the sub-processes (Kao, 2012). The dual version (envelopment model) of Kao's parallel network model in 3.24 is:

$$E_0 = \min_{\lambda, \theta} \ \theta \tag{3.27a}$$

$$\text{s.t.} \ \sum_{p=1}^{q} \sum_{j=1}^{n} \lambda_j^{(p)} X_{ij}^{(p)} \leq \theta X_{io} \quad i = 1, 2, ..., m \tag{3.27b}$$

$$\sum_{p=1}^{q} \sum_{j=1}^{n} \lambda_j^{(p)} Y_{rj}^{(p)} \geq Y_{ro} \qquad r = 1, 2, ..., s \tag{3.27c}$$

$$\lambda_j^{(p)} \geq 0, \quad j = 1, 2, ..., n \tag{3.27d}$$

Kao's model therefore uses the average order for overall system aggregation (Shen et al., 2018).

General parallel network model

While YMK model attaches different importance (multipliers) to the same factors for different sub-processes, Kao's model attaches the same importance to these factors irrespective of the sub-process. It is reasonable for some decision-makers to attach the same importance to some particular factors while other factors may have different importance for different sub-processes. Therefore, to capture the advantages of both the YMK and Kao's models, Shen et al. (2018) developed a general parallel model that combines the Pareto and average orders. Their idea is

based on the observation that the YMK model can be transformed into a form of Kao's model. In the general model, the input bundles $I^{(p)}$ and output bundles $O^{(p)}$ can be defined as a union of factors which are compensable across sub-units in Kao's model $\left(I_k^{(p)}, O_k^{(p)}\right)$ and factors that have different importance as in YMK $\left(I_y^{(p)}, O_y^{(p)}\right)$ such that $\left(I^{(p)}, O^{(p)}\right) = \left(I_k^{(p)} \cup I_y^{(p)}, O_k^{(p)} \cup O_y^{(p)}\right)$. The general parallel model and its dual are formulated as follows:

$$E_0 = \max \quad \sum_{r \in O_k^{(p)}} u_r Y_{ro} + \sum_{p=1}^{q} \sum_{r \in O_y^{(p)}} u_r^{(p)} Y_{ro}^{(p)} \tag{3.28a}$$

$$\text{s.t.} \quad \sum_{i \in I_k^{(p)}} v_i X_{io} + \sum_{p=1}^{q} \sum_{i \in I_y^{(p)}} v_i^{(p)} X_{io}^{(p)} = 1 \tag{3.28b}$$

$$\left(\sum_{r \in O_k^{(p)}} u_r Y_{rj}^{(p)} + \sum_{r \in O_y^{(p)}} u_r^{(p)} Y_{rj}^{(p)} \right) - \left(\sum_{i \in I_k^{(p)}} v_i X_{ij}^{(p)} + \sum_{i \in I_y^{(p)}} v_i^{(p)} X_{ij}^{(p)} \right) \leq 0$$

$$p = 1, \ldots, q, \;\; j = 1, 2, \ldots, n \tag{3.28c}$$

$$u_r, u_r^{(p)}, v_i, v_i^{(p)} \geq \varepsilon, \;\; r = 1, ..., s, \quad i = 1, ..., m \tag{3.28d}$$

$$E_0 = \min_{\lambda, \theta} \; \theta \tag{3.29a}$$

$$\text{s.t.} \; \sum_{p=1}^{q} \sum_{j=1}^{n} \lambda_j^{(p)} X_{ij}^{(p)} \leq \theta X_{io} \quad i \in I_k^{(p)} \tag{3.29b}$$

$$\sum_{j=1}^{n} \lambda_j^{(p)} X_{ij}^{(p)} \leq \theta X_{io}^{(p)} \qquad i \in I_y^{(p)}, \; p = 1, \ldots, q \tag{3.29c}$$

$$\sum_{p=1}^{q} \sum_{j=1}^{n} \lambda_j^{(p)} Y_{rj}^{(p)} \geq Y_{ro} \qquad r \in O_k^{(p)} \tag{3.29d}$$

$$\sum_{j=1}^{n} \lambda_j^{(p)} Y_{rj}^{(p)} \geq Y_{ro}^{(p)} \qquad r \in O_y^{(p)}, \; p = 1, \ldots, q \tag{3.29e}$$

$$\lambda_j^{(p)} \geq 0, \; j = 1, 2, ..., n \tag{3.29f}$$

3.3.3 Mixed network structure

It is also possible to have complex internal structures that have both series and parallel sub-processes. Under such conditions, while some sub-processes share intermediate factors, other sub-processes are independent of the remaining sub-processes. An example of a mixed network structure is shown in Figure 3.7.

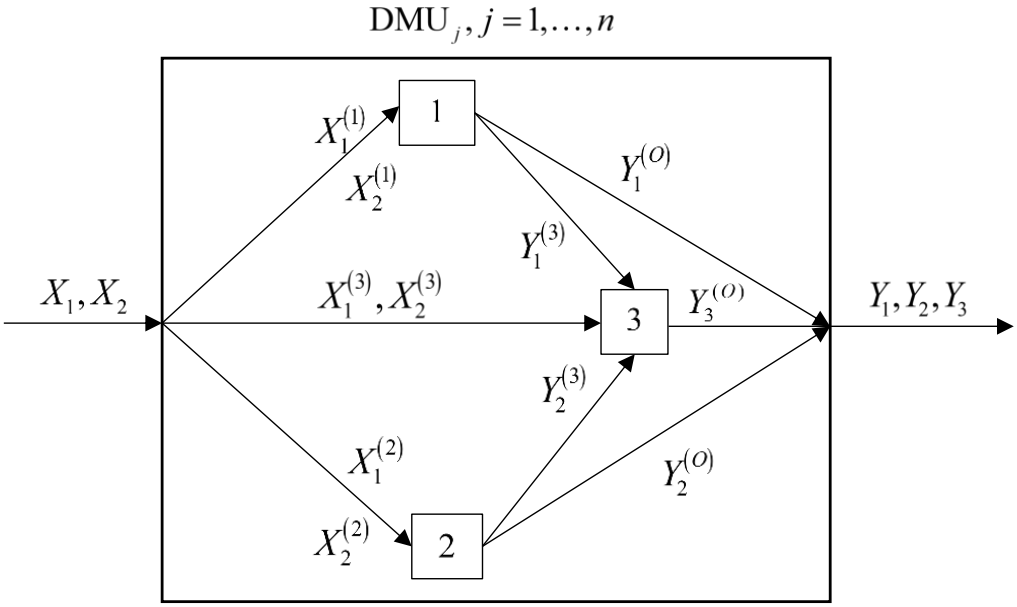

Figure 3.7 General structure of mixed sub-processes.

Source: Adapted from Kao (2009a)

In the example in Figure 3.7, the system has two inputs and three outputs. All inputs are consumed by all three sub-processes in differing but known quantities. For the outputs Y_1, Y_2 and Y_3 are exclusively produced by sub-process 1, sub-process 2 and sub-process 3 respectively. However, part of the outputs Y_1 and Y_2 are consumed by sub-process 3 for further production of Y_3. In this case, therefore, sub-process 1 and sub-process 2 operate independently (parallel) of one another. However, sub-process 3 consumes intermediate products from the two other sub-processes making it in a serial structure to sub-processes 1 and 2. $Y_r^{(O)}$ is the part of output r

which is not consumed by other sub-processes. The model, as formulated by Kao (2009a), to assess the efficiency of the system shown in Figure 3.7 is as follows:

$$E_0 = \max \quad u_1 Y_{1o}^{(O)} + u_2 Y_{2o}^{(O)} + u_3 Y_{3o} \tag{3.30a}$$

$$\text{s.t.} \quad v_1 X_{1o} + v_2 X_{2o} = 1 \tag{3.30b}$$

$$\left(u_1 Y_{1j}^{(O)} + u_2 Y_{2j}^{(O)} + u_3 Y_{3j}\right) - (v_1 X_{1j} + v_2 X_{2j}) \leq 0 \qquad j = 1, 2, ..., n \tag{3.30c}$$

$$\left(u_1 Y_{1j}^{(O)} + u_1 Y_{1j}^{(3)}\right) - \left(v_1 X_{1j}^{(1)} + v_2 X_{2j}^{(1)}\right) \leq 0 \qquad j = 1, 2, ..., n \tag{3.30d}$$

$$\left(u_2 Y_{2j}^{(O)} + u_2 Y_{2j}^{(3)}\right) - \left(v_1 X_{1j}^{(2)} + v_2 X_{2j}^{(2)}\right) \leq 0 \qquad j = 1, 2, ..., n \tag{3.30e}$$

$$u_3 Y_{3j} - \left(v_1 X_{1j}^{(3)} + v_2 X_{2j}^{(3)} + u_1 Y_{1j}^{(3)} + u_2 Y_{2j}^{(3)}\right) \leq 0 \qquad j = 1, 2, ..., n \tag{3.30f}$$

$$u_1, u_2, u_3, v_1, v_2 \geq \varepsilon \tag{3.30g}$$

From the optimal multipliers $u_1^*, u_2^*, u_3^*, v_1^*$ and v_2^*, the efficiencies for the system and sub-process for each DMU can be estimated as:

$$E_o = \left(u_1^* Y_{1o}^{(O)} + u_2^* Y_{2o}^{(O)} + u_3^* Y_{3o}\right)/(v_1^* X_{1o} + v_2^* X_{2o}) \;=\; u_1^* Y_{1o}^{(O)} + u_2^* Y_{2o}^{(O)} + u_3^* Y_{3o} \tag{3.31a}$$

$$E_o^{(1)} = \left(u_1^* Y_{1o}^{(O)} + u_1^* Y_{1o}^{(3)}\right)/\left(v_1^* X_{1o}^{(1)} + v_2^* X_{2o}^{(1)}\right) \tag{3.31b}$$

$$E_o^{(2)} = \left(u_2^* Y_{2o}^{(O)} + u_2^* Y_{2o}^{(3)}\right)/\left(v_1^* X_{1o}^{(2)} + v_2^* X_{2o}^{(2)}\right) \tag{3.31c}$$

$$E_o^{(3)} = u_3^* Y_{3o}/\left(v_1^* X_{1o}^{(3)} + v_2^* X_{2o}^{(3)} + u_1^* Y_{1o}^{(3)} + u_2^* Y_{2o}^{(3)}\right) \tag{3.31d}$$

An alternative approach to structuring such mixed system structures is shown in Figure 3.8 where the sub-processes are shown as a series of parallel networks. In this way, it is possible to compute the overall efficiency of the different series (of parallel networks). This is useful in this study where production and consumption phases of the electricity system are to be assessed.

This is done by introducing dummy sub-process alongside sub-processes 1 and 2 to absorb the inputs for sub-process 3. Also, a dummy sub-process is introduced alongside sub-process 3 to absorb the final output not consumed by sub-process 3.

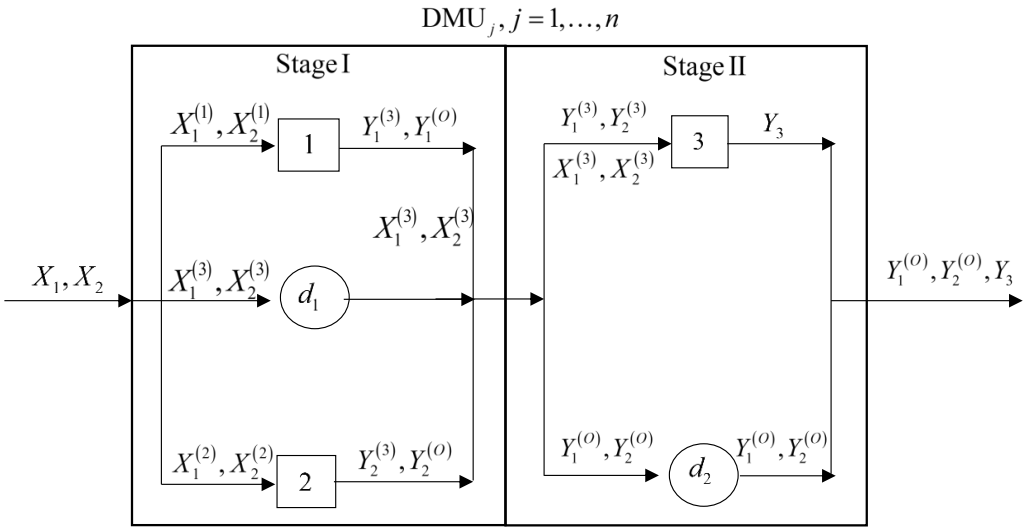

Figure 3.8 Alternative structure of mixed sub-processes.

Source: Adapted from Kao (2009a)

For each dummy sub-process, its outputs are the same as inputs to make that sub-process redundant in the optimal solution. The redundant constraints for dummy sub-processes d_1 and d_2 that can be introduced into model (3.30) are:

$$\left(v_1 X_{1j}^{(3)} + v_2 X_{2j}^{(3)}\right) - \left(v_1 X_{1j}^{(3)} + v_2 X_{2j}^{(3)}\right) \leq 0 \qquad j = 1, 2, ..., n \qquad (3.32a)$$

$$\left(u_1 Y_{1j}^{(O)} + u_2 Y_{2j}^{(O)}\right) - \left(u_1 Y_{1j}^{(O)} + u_2 Y_{2j}^{(O)}\right) \leq 0 \qquad j = 1, 2, ..., n \qquad (3.32b)$$

The model associated with these constraints will, therefore, be the same as the model in (3.30). As shown in (3.32), the system efficiency of a series structure is the product of the sub-process efficiencies. Therefore, the structure in Figure 3.8 can be viewed in one way as two series, i.e. stage I and stage II. Therefore, the overall efficiency E_o is a product of stage I and stage II efficiencies: $E_o = E_o^I \times E_o^{II}$

(Kao, 2009a). From the optimal multipliers the stage I and stage II efficiencies can, therefore, be estimated as:

$$\begin{aligned} E_o^I &= \frac{\left(\left(u_1^* Y_{1o}^{(O)} + u_1^* Y_{1o}^{(3)}\right) + \left(v_1^* X_{1o}^{(3)} + v_2^* X_{2o}^{(3)}\right) + \left(u_2^* Y_{2o}^{(O)} + u_2^* Y_{2o}^{(3)}\right)\right)}{\left(\left(v_1^* X_{1o}^{(1)} + v_2^* X_{2o}^{(1)}\right) + \left(v_1^* X_{1o}^{(2)} + v_2^* X_{2o}^{(2)}\right) + \left(v_1^* X_{1o}^{(3)} + v_2^* X_{2o}^{(3)}\right)\right)} \\ &= \frac{u_1^* Y_{1o} + \left(v_1^* X_{1o}^{(3)} + v_2^* X_{2o}^{(3)}\right) + u_2^* Y_{2o}}{(v_1^* X_{1o} + v_2^* X_{2o})} \end{aligned} \tag{3.33a}$$

$$\begin{aligned} E_o^{II} &= \frac{u_1^* Y_{1o}^{(O)} + u_2^* Y_{2o}^{(O)} + u_3^* Y_{3o}}{\left(\left(u_1^* Y_{1o}^{(O)} + u_1^* Y_{1o}^{(3)}\right) + \left(v_1^* X_{1o}^{(3)} + v_2^* X_{2o}^{(3)}\right) + \left(\left(u_2^* Y_{2o}^{(O)} + u_2^* Y_{2o}^{(3)}\right)\right)\right)} \\ &= \frac{u_1^* Y_{1o}^{(O)} + u_2^* Y_{2o}^{(O)} + u_3^* Y_{3o}}{u_1^* Y_{1o} + \left(v_1^* X_{1o}^{(3)} + v_2^* X_{2o}^{(3)}\right) + u_2^* Y_{2o}} \end{aligned} \tag{3.33b}$$

$$\begin{aligned} E_o &= E_o^I \times E_o^{II} \\ &= \left(\frac{u_1^* Y_{1o} + \left(v_1^* X_{1o}^{(3)} + v_2^* X_{2o}^{(3)}\right) + u_2^* Y_{2o}}{(v_1^* X_{1o} + v_2^* X_{2o})}\right)\left(\frac{u_1^* Y_{1o}^{(O)} + u_2^* Y_{2o}^{(O)} + u_3^* Y_{3o}}{u_1^* Y_{1o} + \left(v_1^* X_{1o}^{(3)} + v_2^* X_{2o}^{(3)}\right) + u_2^* Y_{2o}}\right) \\ &= \frac{u_1^* Y_{1o}^{(O)} + u_2^* Y_{2o}^{(O)} + u_3^* Y_{3o}}{(v_1^* X_{1o} + v_2^* X_{2o})} = u_1^* Y_{1o}^{(O)} + u_2^* Y_{2o}^{(O)} + u_3^* Y_{3o} \end{aligned} \tag{3.33c}$$

Notice the system efficiency defined in (3.33) is the same as that defined in (3.31). For all the network models defined in the sections above, if the sub-process constraints are ignored, the model becomes the traditional CCR model. This means that the network models impose additional restrictions on the model, therefore, the efficiency scores on the network models are more restrictive than the traditional CCR models (Kao, 2009a,b, 2014a).

3.3.4 Shared-flow models

Models discussed in previous sections assume that the input and output quantities used by sub-processes are empirically known. However, different sub-processes may have to compete over inputs to be consumed in producing outputs. On the other hand, different sub-processes may be required to produce different proportions of output to meet or maximise the overall output levels of the DMU under consideration. In such situations, the sub-processes are sharing the flow of inputs and/or outputs

in a shared-flow or multi-activity model (Castelli et al., 2010; Shen et al., 2018). In shared-flow models, the allocation of input/outputs among sub-processes is considered a decision variable to be determined to maximise the overall efficiency of the DMU (Castelli et al., 2010). Early works on shared-flow models include Beasley (1995), who looked at teaching and research efficiencies of UK universities by considering how resources are shared among activities. Castelli et al. (2010) presented an example of a shared-flow model similar to that presented in Figure 3.9.

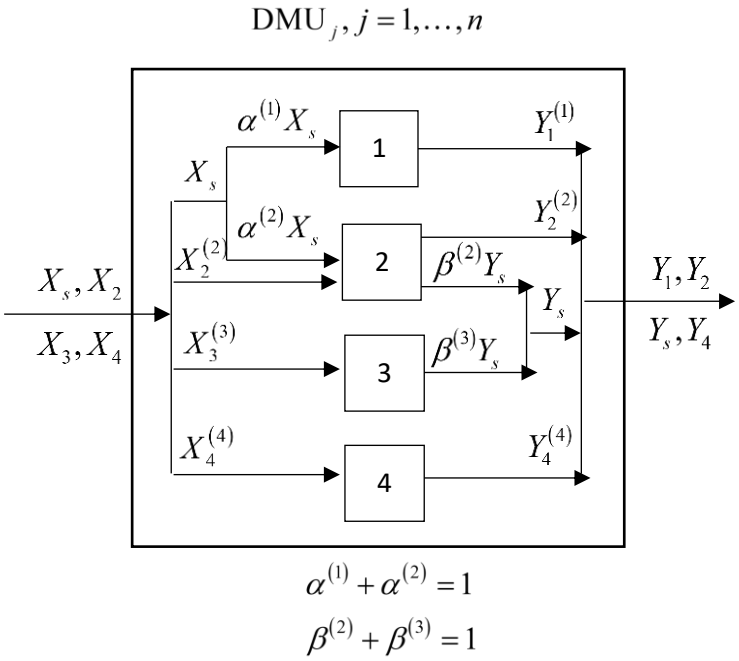

Figure 3.9 Shared flow model.

Source: Adapted from Castelli et al. (2010)

As depicted in Figure 3.9, each DMU has 4 sub-processes that together consume four inputs to produce four outputs. Inputs X_2, X_3 and X_4 are unique inputs to sub-processes 2, 3 and 4 respectively. Input X_s is shared by sub-processes 1 and 2 only. Outputs Y_1, Y_2 and Y_4 are unique outputs produced by sub-processes 1, 2 and 4. The output Y_s is a shared output jointly produced by sub-units 2 and 3 only. Weights α and β are apportionment factors that determine the proportion of input

and output, respectively, that should be allocated to each sharing sub-process. For such a problem, the efficiency model can be formulated as:

$$E_0 = \max \ \frac{u_1 Y_{1o} + u_2 Y_{2o} + u_s Y_{so} + u_4 Y_{4o}}{v_1 X_{so} + v_2 X_{2o} + v_3 X_{3o} + v_4 X_{4o}} \tag{3.34a}$$

$$\text{s.t.} \ \frac{u_1 Y_{1j} + u_2 Y_{2j} + u_s Y_{sj} + u_4 Y_{4j}}{v_s X_{sj} + v_2 X_{2j} + v_3 X_{3j} + v_4 X_{4j}} \leq 1 \qquad j = 1, 2, ..., n \tag{3.34b}$$

$$\frac{u_1 Y_{1j}^{(1)}}{v_s \alpha^{(1)} X_{sj}} \leq 1 \qquad j = 1, 2, ..., n \tag{3.34c}$$

$$\frac{u_2 Y_{2j}^{(2)} + u_s \beta^{(2)} Y_{sj}}{v_s \alpha^{(2)} X_{sj} + v_2 X_{2j}^{(2)}} \leq 1 \qquad j = 1, 2, ..., n \tag{3.34d}$$

$$\frac{u_s \beta^{(3)} Y_{sj}}{v_3 X_{3j}^{(3)}} \leq 1 \qquad j = 1, 2, ..., n \tag{3.34e}$$

$$\frac{u_4 Y_{4j}^{(4)}}{v_4 X_{4j}^{(4)}} \leq 0 \qquad j = 1, 2, ..., n \tag{3.34f}$$

$$\beta^{(2)} + \beta^{(3)} = 1 \qquad j = 1, 2, ..., n \tag{3.34g}$$

$$\alpha^{(1)} + \alpha^{(2)} = 1 \qquad j = 1, 2, ..., n \tag{3.34h}$$

$$u_1, u_2, u_s, u_4, v_s, v_2, v_3, v_4 \geq \varepsilon \tag{3.34i}$$

Model in (3.34) is nonlinear but can be transformed into an LP problem using the Charnes and Cooper transformation. Shen et al. (2018) presented shared-flow models based on their generalised parallel network problem and a linear version based using the Charnes and Cooper (1973) transformation. The shared-flow problem contains first the objective to determine the most appropriate allocation of resources and

second obtaining the best efficiency scores (Shen et al., 2018). This model and the linearised version can be formulated as:

$$E_0 = \max_{(\alpha,\beta)} \max_{(u_r,v_i)} \sum_{r\in O_k^{(p)}} u_r Y_{ro} + \sum_{p=1}^{q} \sum_{r\in O_y^{(p)}} u_r^{(p)} Y_{ro}^{(p)} \tag{3.35a}$$

$$\text{s.t.} \sum_{i\in I_k^{(p)}} v_i X_{io} + \sum_{p=1}^{q} \sum_{i\in I_y^{(p)}} v_i^{(p)} X_{io}^{(p)} = 1 \tag{3.35b}$$

$$\left(\sum_{r\in O_k^{(p)}} u_r \beta_r^{(p)} Y_{rj} + \sum_{r\in O_y^{(p)}} u_r^{(p)} Y_{rj}^{(p)} \right) - \left(\sum_{i\in I_k^{(p)}} v_i \alpha_i^{(p)} X_{ij} + \sum_{i\in I_y^{(p)}} v_i^{(p)} X_{ij}^{(p)} \right) \leq 0$$

$$p = 1, \ldots, q, \;\; j = 1, 2, \ldots, n \tag{3.35c}$$

$$\sum_{p=1}^{q} \alpha_i^{(p)} = 1, \qquad \forall i \in I_k^{(p)} \tag{3.35d}$$

$$\sum_{p=1}^{q} \beta_r^{(p)} = 1, \qquad \forall r \in O_k^{(p)} \tag{3.35e}$$

$$u_r, u_r^{(p)}, v_i, v_i^{(p)}, \alpha_i^{(p)}, \beta_r^{(p)} \geq 0, \;\; r = 1, ..., s, \quad i = 1, ..., m \tag{3.35f}$$

$$E_0 = \max \sum_{r\in O_k^{(p)}} \mu_r Y_{ro} + \sum_{p=1}^{q} \sum_{r\in O_y^{(p)}} \mu_r^{(p)} Y_{ro}^{(p)} \tag{3.36a}$$

$$\text{s.t.} \sum_{i\in I_k^{(p)}} \nu_i X_{io} + \sum_{p=1}^{q} \sum_{i\in I_y^{(p)}} \nu_i^{(p)} X_{io}^{(p)} = 1 \tag{3.36b}$$

$$\left(\sum_{r\in O_k^{(p)}} \omega_r^{(p)} Y_{rj} + \sum_{r\in O_y^{(p)}} \mu_r^{(p)} Y_{rj}^{(p)} \right) - \left(\sum_{i\in I_k^{(p)}} \gamma_i^{(p)} X_{ij} + \sum_{i\in I_y^{(p)}} \nu_i^{(p)} X_{ij}^{(p)} \right) \leq 0$$

$$p = 1, \ldots, q, \;\; j = 1, 2, \ldots, n \tag{3.36c}$$

$$\sum_{p=1}^{q} \gamma_i^{(p)} = \nu_i \qquad \forall i \in I_k^{(p)} \tag{3.36d}$$

$$\sum_{p=1}^{q} \omega_r^{(p)} = \mu_r \qquad \forall r \in O_k^{(p)} \tag{3.36e}$$

$$\mu_r, \mu_r^{(p)}, \nu_i, \nu_i^{(p)}, \gamma_i^{(p)}, \omega_r^{(p)} \geq 0, \;\; r = 1, ..., s, \quad i = 1, ..., m \tag{3.36f}$$

This model in (3.36) is akin to Du et al.'s (2015) non-homogenous parallel DEA model with disjoint outputs and non-separable inputs. Du et al. (2015) developed various parallel network models that handle problems with various degrees of non-homogeneity in the input/output sets of the sub-units.

3.4 Non-homogeneous DMUs

While the original DEA model was based on the assumption that DMUs are homogenous in their input and outputs, in practice there is potential for non-homogeneity in inputs and/or outputs of various DMUs. DMUs may use the same inputs to produce a slightly different set of outputs. One way for handling non-homogeneity is by breaking the DMUs into multiple groups where in each group all members produce the same outputs. Separate DEA analysis is then conducted for each group in a way that DMUs are compared to their true peers (Cook et al., 2013). However, as Cook et al. (2013) point out, this may result in small sample problems which may mean DMUs will be assigned artificially large efficiencies as the partial peers may be the best-practice alternatives.

There has been some work on modelling non-homogenous DMUs. Cook et al. (2012) and Cook et al. (2013) have systematically studied the problem of non-homogeneity in DEA and developed methods for handling DMUs with non-homogenous outputs. Li, Liang, Cook and Zhu (2016) looked at the problem of non-homogeneity of inputs. Shen et al. (2018) showed that some previous non-homogeneity models could also be transformed into the form of their general parallel DEA model. Additionally, whiles Du et al. (2015) examine non-homogeneity in parallel network problems, Barat et al. (2019) examine non-homogeneity in mixed network DEA problems.

With the approach by Cook et al. (2013), the N DMUs are grouped into q $(p = 1, \ldots, q)$ mutually exclusive categories, such that all firms in a category p share the same output set. Each p category has N_p members that belong exclusively to that DMU set. The two group case in Cook et al. (2013) as presented in Figure 3.10 show that DMUs in N_1 all produce the four outputs y_1, y_2, y_3 and y_4. DMUs in N_2 produce the same subset of outputs y_1, y_2 and y_3. In both cases, the same inputs are used for the production of the identified outputs. Their approach involves conducting separate DEA analysis for each output sub-group $O_k(k = 1, \ldots, K)$. In the two-groups case, the mutually exclusive output groups are $O_1 = y_1, y_2, y_3$ and $O_2 = y_4$ However, for DMUs in N_1 their inputs must be split in a way that while $\alpha\%$ are used for producing outputs in set O_1, the remaining $1 - \alpha\%$ are dedicated

to the production of the output in O_2. In order to cater for the split, they propose a three step process involving 1) deciding the split of inputs across output groups and 2) deriving the efficiencies of DMUs in each output sub-group using the splits derived in step 1. For DMUs that belong to more than one output sub-group (N_1 for example), 3) their final scores are a weighted average of the efficiencies of the sub-processes.

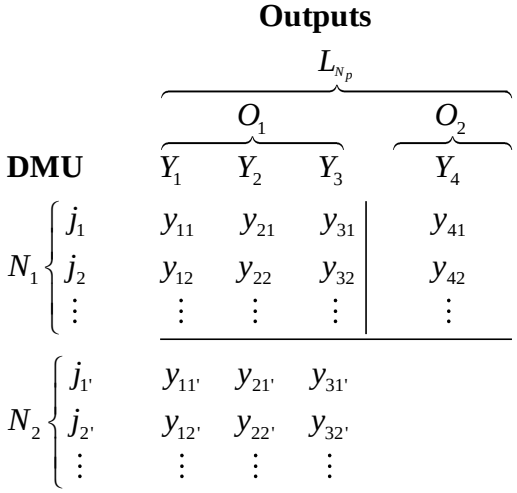

Figure 3.10 Sample setting for two-groups.

Source: Adapted from Cook et al. (2013)

The generalised non-homogenous output DEA model developed by Cook et al. (2013) can be expressed as:

$$E_0 = \max \sum_{O_k \in L_{N_{po}}} \sum_{r \in O_k} u_r Y_{ro} \tag{3.37a}$$

$$\text{s.t.} \sum_i v_i X_{io} = 1 \tag{3.37b}$$

$$\sum_{r \in O_k} u_r Y_{rj} - \sum_i v_i \alpha_{iO_k p} X_{ij} \leq 0$$

$$\forall j \in N_p, O_k \in L_{N_p}, p = 1, \ldots, q, \tag{3.37c}$$

$$\sum_{O_k \in L_{N_p}} \alpha_{iO_k p} = 1 \qquad \forall i, p = 1, \ldots, q, \tag{3.37d}$$

$$a_{iO_k p} \leq \alpha_{iO_k p} \leq b_{iO_k p} \qquad \forall i, O_k \in L_{N_p}, p = 1, \ldots, q \tag{3.37e}$$

$$u_r, v_i, \alpha_{iO_k p} \geq 0 \qquad \forall i, r, O_k \in L_{N_p}, p = 1, \ldots, q \tag{3.37f}$$

Where L_{N_p} denotes the full output set for any DMU in N_p and a_{iO_kp} and b_{iO_kp} set the lower and upper bounds for the split proportions. Model (3.37) can be linearised using the Charnes and Cooper (1973) transformation. As pointed out by Li, Liang, Cook and Zhu (2016) this model is similar to the parallel network approach of Kao (2009b). It is in this regard that Shen et al. (2018) extended the non-homogenous model into a general DEA framework following the parallel network approach. Unlike Cook et al.'s models where sub-groups are data-driven, Shen et al. (2018) categorise output groups based on the internal structure of the operational properties of the DMUs. Additionally, dummy sub-process k is introduced to make the model a parallel problem. For such dummy sub-processes $a_{ip}^{(k)} = 0\,(\forall i \in I_o)$, $\beta_{rp}^{(k)} = 0\,(\forall r \in O_o)$, $Y_{rj}^{(k)} = 0\,\forall r \in O^{(k)})$, and $X_{ij}^{(k)} = 0\,(\forall i \in I^{(k)})$. Their model can be expressed as:

$$E_0 = \max \sum_{r\in O_o} u_r Y_{ro} + \sum_k \sum_{r\in O_k} u_r^{(k)} Y_{ro}^{(k)} \tag{3.38a}$$

$$\text{s.t.} \sum_{i\in I_o} v_i X_{io} + \sum_k \sum_{i\in I_k} v_i^{(k)} X_{io}^{(k)} = 1 \tag{3.38b}$$

$$\left(\sum_{r\in O_o} u_r \beta_{rp}^{(k)} Y_{rj} + \sum_{r\in O_k} u_r^{(k)} Y_{rj}^{(k)}\right) - \left(\sum_{i\in I_o} v_i \alpha_{ip}^{(k)} X_{ij} + \sum_{i\in I_k} v_i^k X_{ij}^k\right) \leq 0$$

$$\forall j, \forall k, \forall p \tag{3.38c}$$

$$\sum_k \alpha_{ip}^{(k)} = 1, \qquad \forall i \in I_o, \forall p \tag{3.38d}$$

$$\sum_k \beta_{rp}^{(k)} = 1, \qquad \forall r \in O_k, \forall p \tag{3.38e}$$

$$u_r, u_r^{(k)}, v_i, v_i^{(k)}, \alpha_{ip}^{(k)}, \beta_{rp}^{(k)} \geq 0, \;\; \forall i, r, k, \forall p \tag{3.38f}$$

This could also be transformed into a linear model using the Charnes and Cooper (1973) transformation. The models presented deal with DMUs with non-homogenous inputs or outputs. These DMUs are categorised into sub-processes then efficiency analysis could be conducted for the sub-processes independently.

In parallel network DEA, DMUs may have a similar configuration of sub-processes although the inputs and outputs of each sub-process may be different. This kind of non-homogeneity is studied by Du et al. (2015). However, there are applications where DMUs also differ in terms of sub-processes. For example, different countries

may have different energy generation sources which means that DMUs differ in terms of the sub-processes not necessarily the inputs and outputs. This type of non-homogeneity problem is studied in subsequent chapters of this thesis.

3.5 Undesirable factors

In all models presented in previous sections, outputs satisfy the "more is better" condition, while inputs satisfy the "less is better condition". In practice, however, there is the potential for some outputs, like pollution, to be undesirable. In such cases, less of those outputs will be required to be efficient. While output desirability is determined by the decision-maker, input desirability is determined by the system (Liu, Zhou, Ma, Liu and Shen, 2015). This is so because while undesirable outputs are outputs the decision-maker will want less of, undesirable inputs are inputs whose increase will reduce desirable outputs (Liu, Zhou, Ma, Liu and Shen, 2015). In this study, the focus is on handling undesirable emissions as a result of the production of energy and economic outputs, therefore, approaches for handling undesirable outputs are reviewed in the sub-section.

Modelling such undesirable factors in the DEA literature could be traced to the early work of Färe et al. (1989). There have been several approaches for dealing with such undesirable factors in the literature. As earlier mention in the second chapter, Wang et al. (2018) highlight five ways of dealing with such environmental pollutants, which are often by-products of useful production – data transformation (Seiford and Zhu, 2002); freely disposable inputs (Reinhard et al., 2000); weakly disposable outputs (Färe et al., 1989, 1996); under different production technologies (Murty et al., 2012); and using the materials balance (Coelli et al., 2007).

The data transformation approach converts, by some mathematical operation, an undesirable output into a desirable output. Seiford and Zhu (2002) for example suggested a translation of the undesirable output y_j^u, by using the constant w, to the desirable form $\bar{y}_j^u$ where $\bar{y}_j^u = w - y_j^u > 0$. The translated outputs are then included in the DEA model in the nature previously discussed. However, data transformation may affect not only the scores but also the rankings of the DMUs depending on the choice of the transformation vector (Liu, Meng, Li and Zhang, 2010). Other approaches that avoid such data transformation include treating the undesirable output as a desirable input (strong/freely disposable inputs), treating the undesirable outputs using weak disposability, and using DDF (Färe and Grosskopf, 2004; Liu, Meng, Li and Zhang, 2010). The material balance approach does not necessarily require the inclusion of undesirable variables in the production model as it examines

pollution potential from price information or the unit mass bound in the inputs and outputs (Coelli et al., 2007; Wang et al., 2018). Subsequent sub-sections will summarise the strong and weak disposability approaches, while the DDF approach is presented in section 3.6.1.

For the n DMUs ($n = 1, \ldots, j$), given $P(X)$ which is the set of desirable outputs $Y^D \in \Re^s_+$ and undesirable outputs $Y^U \in \Re^l_+$ which can be produced from the input vector $X \in \Re^m_+$, where sets are closed and bounded with inputs freely disposable.

3.5.1 Strong/Free disposability

Outputs are strongly disposable if $\left(Y^D, Y^U\right) \in P\left(X\right)$ then $\left(Z^D, Z^U\right) \in P\left(X\right)$ if $\left(Z^D, Z^U\right) \leq \left(Y^D, Y^U\right)$. Under this condition, desirable outputs and undesirable outputs can be independently and freely varied by the decision-maker without a cost to the other outputs. This means that undesirable outputs could be freely reduced without affecting the number of desirable outputs produced. The production possibility set (PPS) under such a condition will be:

$$P_1 = \left\{ \left(X, Y^D, Y^U\right) \middle| \; X \geq \sum_{j=1}^{n} \lambda_j X_j, Y^D \leq \sum_{j=1}^{n} \lambda_j Y_j^D, Y^U \geq \sum_{j=1}^{n} \lambda_j Y_j^U, \lambda_j \geq 0 \right\} \tag{3.39}$$

The problem with this approach to handling undesirable outputs is that it implicitly treats such outputs as inputs, which does not reflect the real production process (Wang et al., 2018). To give a theoretical basis for free disposability of undesirable outputs, Liu, Meng, Li and Zhang (2010) proposed the extended strong disposability assumption to cater for situations where undesirable outputs, to some extent, are freely disposable and not in a joint production with desirable outputs. Where one introduces desirable inputs and undesirable inputs into the PPS, the extended strong disposability holds if: $(X, Y) = \left(X^D, X^U, Y^D, Y^U\right) \in P$, then if $W^D \geq X^D, W^U \leq X^U, Z^D \leq Y^D$ and $Z^U \geq Y^U$ then $\left(W^D, W^U, Z^D, Z^U\right) \in P$. Note than $\left(W^D, W^U, Z^D, Z^U\right)$ are less desirable set of inputs and outputs compared with $\left(X^D, X^U, Y^D, Y^U\right)$. The CCR input-oriented envelopment DEA model with

strongly disposable inputs and outputs (3.40) and its multiplier version (3.41) can be formulated as in::

$$E_0 = \quad \min \phi \tag{3.40a}$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_j X_{ij} \leq \phi X_{io} \qquad i = 1, 2, ..., m \tag{3.40b}$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj}^D \geq Y_{ro}^D \qquad r = 1, 2, ..., s \tag{3.40c}$$

$$\sum_{j=1}^{n} \lambda_j Y_{kj}^U \leq Y_{ko}^U \qquad k = 1, 2, ..., l \tag{3.40d}$$

$$\lambda_j \geq 0, \ j = 1, 2, ..., n \tag{3.40e}$$

$$E_0 = \max \sum_{r=1}^{s} u_r Y_{ro}^D - \sum_{k=1}^{l} c_k Y_{ko}^U \tag{3.41a}$$

$$\text{s.t.} \sum_{i=1}^{m} v_i X_{io} = 1 \tag{3.41b}$$

$$\left(\sum_{r=1}^{s} u_r Y_{rj}^D - \sum_{k=1}^{l} c_k Y_{kj}^U \right) - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \quad j = 1, 2, ..., n \tag{3.41c}$$

$$u_r, c_k, v_i \geq 0, \ \ r = 1, ..., s, \ \ k = 1, ..., l, \quad i = 1, ..., m \tag{3.41d}$$

The coefficient of the undesirable factor is (3.41) can be interpreted as a cost that reduces the gains made producing the desirable outputs (Coelli et al., 2007).

3.5.2 Weak disposability

In many practical cases, such as in electricity production, the undesirable outputs are in a joint production with the desirable outputs. In such cases, it is not possible to reduce the production of undesirable outputs without affecting the production of desirable outputs. It is also the case that if desirable outputs are not produced then undesirable bad products will not be produced. Formally, if $\left(Y^D, Y^U\right) \in P(X)$ and $0 \leq \theta \leq 1$ then $\left(\theta Y^D, \theta Y^U\right) \in P(X)$. This requires proportional abatement between the desirable and undesirable outputs. For the null-joint condition for $\left(Y^D, Y^U\right) \in P(X)$, if $Y^U = 0$ then $Y^D = 0$. The PPS that

imposes free disposability on desirable inputs and outputs and weak disposability of such undesirable outputs can be expressed as:

$$P_2 = \left\{ \left(X, Y^D, Y^U\right) \middle| \; X \geq \sum_{j=1}^{n} \lambda_j X_j, Y^D \leq \sum_{j=1}^{n} \lambda_j Y_j^D, Y^U = \sum_{j=1}^{n} \lambda_j Y_j^U, \lambda_j \geq 0 \right\} \tag{3.42}$$

Based on this PPS, it is possible to develop performance measures. The CCR input-oriented envelopment DEA model with strongly disposable desirable inputs and outputs but weakly disposable undesirable outputs (3.43) and its multiplier version (3.44) can be formulated as in:

$$\begin{aligned}
E_0 = \quad & \min \; \phi && \text{(3.43a)} \\
& \text{s.t.} \; \sum_{j=1}^{n} \lambda_j X_{ij} \leq \phi X_{io} \qquad i = 1, 2, ..., m && \text{(3.43b)} \\
& \sum_{j=1}^{n} \lambda_j Y_{rj}^D \geq Y_{ro}^D \qquad r = 1, 2, ..., s && \text{(3.43c)} \\
& \sum_{j=1}^{n} \lambda_j Y_{kj}^U = Y_{ko}^U \qquad k = 1, 2, ..., l && \text{(3.43d)} \\
& \lambda_j \geq 0, \; j = 1, 2, ..., n && \text{(3.43e)}
\end{aligned}$$

$$\begin{aligned}
E_0 = \max \; & \sum_{r=1}^{s} u_r Y_{ro}^D + \sum_{k=1}^{l} c_k Y_{ko}^U && \text{(3.44a)} \\
\text{s.t.} \; & \sum_{i=1}^{m} v_i X_{io} = 1 && \text{(3.44b)} \\
& \left(\sum_{r=1}^{s} u_r Y_{rj}^D + \sum_{k=1}^{l} c_k Y_{kj}^U \right) - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \quad j = 1, 2, ..., n && \text{(3.44c)} \\
& u_r, v_i \geq 0, \; c_k \text{ urs}, \; r = 1, ..., s, \; k = 1, ..., l, \; i = 1, ..., m && \text{(3.44d)}
\end{aligned}$$

Note that c_k is unrestricted in sign for model (3.44). This means that the shadow price of the undesirable output can be positive or negative in the multiplier model (Hailu, 2003; Kuosmanen and Matin, 2011; Leleu, 2013). There has been considerable debate in the literature concerning the economic interpretation of an unrestricted shadow price of undesirable factors (Hailu, 2003; Leleu, 2013; Murty

et al., 2012). Various approaches have been provided in the literature to handle the unexpected sign in the shadow price, however, any restricting of the shadow price to only non-positive or non-negative values implicitly assumes undesirable factors are inputs in the primal model (Barat et al., 2019; Leleu, 2013). Kuosmanen and Matin (2011) reformulate the dual models to provide useful interpretations of the duality of weakly disposable technologies.

The approaches for dealing with undesirable outputs discussed in sections 3.5.1 and 3.5.2 have been based on the basic DEA model with unknown internal structure. Considering undesirable outputs in the network structure may introduce additional considerations. For example, an undesirable output in one stage may be a desirable input in the subsequent stage. Liu, Zhou, Ma, Liu and Shen (2015) systematically studied undesirable input-intermediate outputs for two-stage DEA models. They develop various PPSs based on the free disposability axioms. Outside this study, there have been several network DEA model-based papers that consider undesirable outputs, however, these are particularly in the domain of series network or two-stage DEA applications (Iftikhar et al., 2018; Lozano, 2015; Mirhedayatian et al., 2014).

3.6 Alternative measurement of efficiency

DEA models presented in previous sections of this chapter have been based on the CCR and BCC radial models. These are radial performance merit functions used in assessing performance difference between DMUs based on the formulated production possibility set. There are other radial and non-radial approaches in the literature that are used for network-based performance assessment. This section reviews two of these approaches: the directional distance function (DDF) and the slack-based measure (SBM) methods of network DEA assessment.

3.6.1 Directional distance function

The DDF, introduced by Chambers et al. (1998), allows for concurrent output expansion and input contraction at the same time. Färe and Grosskopf (2000) show that the Shephard distance functions, which the CCR models are based on, can be special cases of the DDF. In the undesirable output context, Färe and Grosskopf (2004) proposed the DDF approach in assessing the expansion of desirable outputs and contraction of undesirable outputs under weak disposability. Based on the PPS

in (3.42), and given the directional vector $g = (-g_i, g_r, -g_k)$, the inefficiency score of a DMU o can be assessed using the LP problem:

$$\begin{aligned}
\overrightarrow{D}_0\left(X, Y^D, Y^U; g\right) = \quad & \max \delta && (3.45a)\\
& \text{s.t.} \sum_{j=1}^{n} \lambda_j X_{ij} \leq X_{io} - \delta g_i \qquad i = 1, 2, ..., m && (3.45b)\\
& \sum_{j=1}^{n} \lambda_j Y^D_{rj} \geq Y^D_{ro} + \delta g_r \qquad r = 1, 2, ..., s && (3.45c)\\
& \sum_{j=1}^{n} \lambda_j Y^U_{kj} = Y^U_{ko} - \delta g_k \qquad k = 1, 2, ..., l && (3.45d)\\
& \lambda_j \geq 0, \ \delta \text{ urs}, \ j = 1, 2, ..., n && (3.45e)
\end{aligned}$$

Here, a DMU is efficient if $\overrightarrow{D}_0\left(X, Y^D, Y^U; g\right) = 0$. If the directional vector g is set to the observed data $g = \left(0, Y^D_{ro}, Y^U_{ko}\right)$ then the problem in (3.45) is equivalent to the traditional problem, however, if $g = (0, 1, -1)$ then the solution is the net improvement of performance for feasible desirable output increases and feasible undesirable output decreases (Färe and Grosskopf, 2004). The dual of (3.45) is formulated as:

$$\begin{aligned}
\overrightarrow{D}_0\left(X, Y^D, Y^U; g\right) = \min \ & \sum_{i=1}^{m} v_i X_{io} - \sum_{r=1}^{s} u_r Y^D_{ro} + \sum_{k=1}^{l} c_k Y^U_{ko} && (3.46a)\\
& \text{s.t.} \ \sum_{i=1}^{m} v_i X_{ij} - \sum_{r=1}^{s} u_r Y^D_{rj} + \sum_{k=1}^{l} c_k Y^U_{kj} \geq 0 \quad j = 1, 2, ..., n && (3.46b)\\
& \sum_{i=1}^{m} v_i g_i + \sum_{r=1}^{s} u_r g_r + \sum_{k=1}^{l} c_k g_k = 1 && (3.46c)\\
& u_r, v_i \geq 0, \ c_k \text{ urs}, \ r = 1, ..., s, \ \ k = 1, ..., l, \ \ i = 1, ..., m && (3.46d)
\end{aligned}$$

Since the DDF in Chambers et al. (1998) and Färe and Grosskopf (2004) assumes that all factors are adjusted at the same rate, it may be considered as a radial measure (Zhou et al., 2012). Zhou et al. (2012), therefore, proposed a non-radial DDF to allow for differing factor adjustments. Given the normalised weight vector

$\omega = (\omega_i, \omega_r, \omega_k)$, the directional vector $g = (-g_i, g_r, -g_k)$ and the vector of scaling factors $\delta = (\delta_i, \delta_r, \delta_k)$ the non-radial DDF can be estimated using the model:

$$\overrightarrow{D}_0\left(X, Y^D, Y^U; g\right) = \max \sum_{i=1}^{m} \omega_i \delta_i + \sum_{r=1}^{s} \omega_r \delta_r + \sum_{k=1}^{l} \omega_k \delta_k \tag{3.47a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j X_{ij} \leq X_{io} - \beta_i \delta_i \qquad i = 1, 2, ..., m \tag{3.47b}$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj}^D \geq Y_{ro}^D + \beta_r \delta_r \qquad r = 1, 2, ..., s \tag{3.47c}$$

$$\sum_{j=1}^{n} \lambda_j Y_{kj}^U = Y_{ko}^U - \beta_k \delta_k \qquad k = 1, 2, ..., l \tag{3.47d}$$

$$\lambda_j \geq 0,\ \delta_i, \delta_r,\ \delta_k \text{ urs},\ j = 1, 2, ..., n \tag{3.47e}$$

Kuosmanen and Matin (2011) systematically studied duality of weak disposable technologies based mainly on DDF. In the network DEA context, Fukuyama and Weber (2014) show how to measure performance in two-stage problems using non-radial approaches including the DDF. For the two-stage series structure in Figure 3.4, the primal and dual network DDF of the system are formulated as:

$$N\overrightarrow{D}_0\left(X, Y; g\right) = \max_{\lambda_j^{(1)}, \lambda_j^{(2)}, \delta, \widehat{z}_f} \delta \tag{3.48a}$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_j^{(1)} X_{ij} \leq X_{io} - \delta g_i \qquad i = 1, 2, ..., m \tag{3.48b}$$

$$\sum_{j=1}^{n} \lambda_j^{(1)} Z_{fj} \geq \widehat{z}_f \qquad f = 1, \ldots, h \tag{3.48c}$$

$$\sum_{j=1}^{n} \lambda_j^{(2)} Z_{fj} \leq \widehat{z}_f \qquad f = 1, \ldots, h \tag{3.48d}$$

$$\sum_{j=1}^{n} \lambda_j^{(2)} Y_{rj} \geq Y_{ro} + \delta g_r \qquad r = 1, 2, ..., s \tag{3.48e}$$

$$\lambda_j^{(2)} \geq 0,\ \lambda_j^{(2)} \geq 0,\ \widehat{z}_f \geq 0,\ \delta \text{ urs}, \qquad j = 1, 2, ..., n \tag{3.48f}$$

$$N\overrightarrow{D}_0\left(X,Y;g\right)=\min\ \sum_{i=1}^{m}v_iX_{io}-\sum_{r=1}^{s}u_rY_{ro} \tag{3.49a}$$

$$\text{s.t.}\ \sum_{i=1}^{m}v_iX_{ij}-\sum_{f=1}^{h}w_fZ_{fj}\geq 0\quad j=1,2,...,n \tag{3.49b}$$

$$\sum_{f=1}^{h}w_fZ_{fj}-\sum_{r=1}^{s}u_rY_{rj}\geq 0\quad j=1,2,...,n \tag{3.49c}$$

$$\sum_{i=1}^{m}v_ig_i\ +\ \sum_{r=1}^{s}u_rg_r\ =\ 1 \tag{3.49d}$$

$$w_f,u_r,v_i\geq 0,\ \ f=1,\ldots,h,\ i=1,\ldots,m,\ r=1,\ldots,s \tag{3.49e}$$

3.6.2 Slacks-based measure (SBM)

Tone and Tsutsui (2009) introduced the Network slacks-based measure (NSBM) which relies on SBM, a non-radial measure of performance, for evaluating the network efficiency of the DMUs. Using the notations in Section 3.3 and Figure 3.2, the PPS set can be defined as:

$$P_3=\{\left(X,Y,Z\right)|\ X^{(p)}\geq\sum_{j=1}^{n}\lambda_j^{(p)}X_j^{(p)}\quad(p=1,\ldots,q)\ , \tag{3.50a}$$

$$Y^{(p)}\leq\sum_{j=1}^{n}\lambda_j^{(p)}Y_j^{(p)}\quad(p=1,\ldots,q)\,, \tag{3.50b}$$

$$Z^{(p)}=\sum_{j=1}^{n}\lambda_j^{(p)}Z_j^{(p)}, \tag{3.50c}$$

$$Z^{(p)}=\sum_{j=1}^{n}\lambda_j^{(h)}Z_j^{(p)}, \tag{3.50d}$$

$$\lambda_j^{(h)}\geq 0,\ \ \forall j,p\Big\} \tag{3.50e}$$

The inequalities in the PPS could be transformed into equalities by introducing input (s^-) and output (s^+) slacks as follows:

$$X^{(p)} = \sum_{j=1}^{n} \lambda_j^{(p)} X_j^{(p)} + s^{(p)-} \quad (p = 1, \ldots, q) \ , \tag{3.51a}$$

$$Y^{(p)} = \sum_{j=1}^{n} \lambda_j^{(p)} Y_j^{(p)} - s^{(p)+} \quad (p = 1, \ldots, q) \, , \tag{3.51b}$$

$$\lambda_j^{(p)} \geq 0, \ \ s^{(p)-} \geq 0, \ \ s^{(p)+} \geq 0, \forall p \tag{3.51c}$$

Tone and Tsutsui (2009) proposed two possible cases for handling intermediate factors (called links in the Tone and Tsutsui model). If linking activities can be freely determined by the model (discretionary) then the linking factors can be modelled as:

$$\sum_{j=1}^{n} \lambda_j^{(p)} Z_j^{(p)} = \sum_{j=1}^{n} \lambda_j^{(h)} Z_j^{(p)}, \ \ \forall p \tag{3.52}$$

In this case, the value of the intermediate factor can be optimised in the LP solution. However, if the decision-maker has no discretion over the intermediate factors such that they must remain unchanged in the optimal solution then the links can be modelled as:

$$Z_o^{(p)} = \sum_{j=1}^{n} \lambda_j^{(p)} Z_j^{(p)} \qquad \forall p, \tag{3.53a}$$

$$Z_o^{(p)} = \sum_{j=1}^{n} \lambda_j^{(h)} Z_j^{(p)} \qquad \forall p \tag{3.53b}$$

The non-oriented NSBM model can, therefore, be formulated as:

$$\rho_o = \min_{\lambda^{(p)}, s^{(p)-}, s^{(p)+}} \frac{\sum\limits_{p=1}^{q} w^{(p)} \left[1 - \frac{1}{m_p} \left(\sum\limits_{i \in I^{(p)}} \frac{s_i^{(p)-}}{X_{i0}^{(p)}} \right) \right]}{\sum\limits_{p=1}^{q} w^{(p)} \left[1 + \frac{1}{s_p} \left(\sum\limits_{r \in O^{(p)}} \frac{s_r^{(p)+}}{Y_{r0}^{(p)}} \right) \right]} \tag{3.54}$$

s.t. (3.51) and (3.52) or (3.53)

Note that the weights are exogenously determined to reflect the importance of a sub-process p to the overall system efficiency. Also, this is a nonlinear problem which could be linearised using the Charnes and Cooper (1973) transformation as shown in Tone (2001). From the optimal solution $\left(s^{(p)-*}, s^{(p)+*}\right)$, the divisional or sub-process efficiencies can be computed as:

$$\rho_o^{(p)} = \frac{1 - \frac{1}{m_p}\left(\sum_{i \in I^{(p)}} \frac{s_i^{(p)-*}}{X_{i0}^{(p)}}\right)}{1 + \frac{1}{s_p}\left(\sum_{r \in O^{(p)}} \frac{s_r^{(p)+*}}{Y_{r0}^{(p)}}\right)} \quad (p = 1, \ldots, q). \tag{3.55}$$

There are extensions for the output-oriented case, the input-oriented case, undesirable outputs as well as frontier projections. Indeed, Färe and Grosskopf (2010) proposed an SBM model based on the DDF.

3.7 Chapter summary

In this chapter, a methodological review of development in the DEA literature on modelling internal structures of production systems, undesirable outputs and non-homogeneity have been conducted. The chapter focussed on different modelling perspectives required for model building. Section 3.2 presented the basic/traditional DEA model, which does not consider the internal structure of the production system. Since this thesis provides a system-wide assessment of the energy system, the internal generation and consumption structures of the countries under investigation must be considered. Consequently, in Section 3.3, models that consider the internal structures were presented. These include a series structure, parallel structure and generalised network structure. Since different countries generate electricity using different portfolios of energy sources and some generation sources result in environmental emissions, separate sub-sections are dedicated to handling such non-homogeneity and undesirable outputs. Section 3.4 deals with non-homogenous DMU models, while Section 3.5 presents models for undesirable outputs. Finally, in Section 3.6, alternative DEA approaches for performance measurement are presented.

All models presented in this chapter have been based on the CRS assumption. This is because the CRS assumption is adopted in the thesis for the sustainability assessment of electricity generation and use among EU countries. The CRS assumption is justified because all member countries are developed economies and operate under a similar policy/regulatory environment (EEA, 2019; European Commission, 2010; United Nations, 2019). Additionally, the assessment is confined to the use of

radial evaluation techniques, although assessments could be extended to non-radial measurement approaches. Input orientation is chosen for performance assessment. This means that DMU performance is determined by the DMU's ability to consume fewer resources to achieve a given output level. As shown in Table 2.5, which is a summary of some DEA studies on energy production, input minimisation has been the primary orientation for such performance evaluation.

Finally, with regard to handling of the undesirable factors, the choice between strong disposability and weak disposability depends on the practical application the model must be applied (Liu, Meng, Li and Zhang, 2010). If the desirable and undesirable outputs are in joint production, then weak disposability may be appropriate, otherwise (extended) strong disposability may be applied. In this thesis, undesirable outputs, are in a joint production with the desirable outputs therefore weak disposability is used. As earlier indicated, there are other approaches for handling undesirable outputs in DEA (Wang et al., 2018), however, the use of strong and weak disposability have been widely accepted in the literature for empirical evaluation of environmental outputs. The assessment is confined to strong and weak disposability for which literature on network DEA has been established.

Chapter 4

Problem Conceptualisation

4.1 Introduction

Systems methodology or systems thinking is gaining increasing relevance in sustainability research (Williams et al., 2017) since it allows for the understanding of the interactions of the complexity of economic, social and environmental systems (Holling, 2001). The objective of systems thinking is to better understand the structure of a complex system (Tejeda and Ferreira, 2014). It provides a solution to linear or 'silos' approach to problems, as it offers a more holistic lens to study the behaviour of actors and actions within social-ecological systems (Williams et al., 2017). The general approach to systems thinking is systems dynamics developed by Forrester (1961). System dynamics is a systems thinking methodology that analyses complex systems which change over time (Ford, 2011). However, system thinking goes beyond the confines of systems dynamics since approaches such as soft systems methodology (SSM), interactive planning, systems intervention strategy, cognitive mapping, viable systems diagnosis, critical systems thinking, lifecycle analysis, complex adaptive systems, are all systems thinking approaches (Holland, 2006; Ison et al., 1997; Paucar-Caceres and Pagano, 2009).

In the DEA literature, network DEA provides a systems perspective of evaluation of the production system. DEA aids in assessing useful attributes of the system (Smith and Shaw, 2019). In practice, systems are composed of several related sub-systems. Network DEA provides a means of both static and dynamic evaluation of the efficiency of production and consumption systems and its sub-systems (Kao, 2012). There is evidence of the increasing use of DEA in systems thinking literature, usually in combination with other approaches (Mingers and White, 2010). Mingers et al. (2009), for example, use SSM as a means of defining the problem and identifying

the inputs and outputs to be used in DEA evaluation. In this thesis, causal loop diagrams are used to define the problem structure, while performance evaluation is conducted by DEA. Irrespective of the chosen systems approach, much of systems thinking rely on causal loops diagrams to structure the factors and relationships in the complex system under study (Forrester, 1994). Consequently, this chapter uses causal loop diagrams to provide a systematic framework to conceptually present the nature of sustainable energy generation and consumption problem.

To conceptualise the research problem, the remainder of the chapter is divided into two main sections. Section 4.2 conceptualises the sustainable energy system by developing causal structures based on literature. This section first examines the sustainability problem in the generation phase before examining the consumption phase. Section 4.3 then conceptualises the sustainable energy problem in a network framework. The final section is the chapter summary.

4.2 Sustainable energy system

As it has been earlier highlighted, systems modelling of sustainable energy systems has been primarily used in LCA studies where environmental impacts of the energy generation system are assessed from raw material stage to disposal. In Section 2.5 of the literature review chapter, various studies using causal diagrams to highlight the interrelationships between social, economic, environmental and other systems and the energy generation system were discussed. Causal loop diagrams provide the basis for developing actions and implementing policies as it simplifies complex conceptual linkages (Cavana and Mares, 2004). This is usually the qualitative aspect of systems modelling where the relationship between various pairs of system elements are revealed (Shire et al., 2018). In this study, this qualitative approach is used to conceptualise the relevant variables and their relationships to determine the inputs, outputs and sub-systems in the network analysis.

4.2.1 Sustainable electricity generation

Sustainable electricity generation assessment involves examining the social, environmental and economic implications of electricity generation. The causal loop diagram in Figure 4.1 presents the causal relationships between electricity generation and social, economic and environmental aspects of sustainability.

The environmental dimension highlights the resource consumption and the emissions potential of energy generation systems. Electricity can be generated from

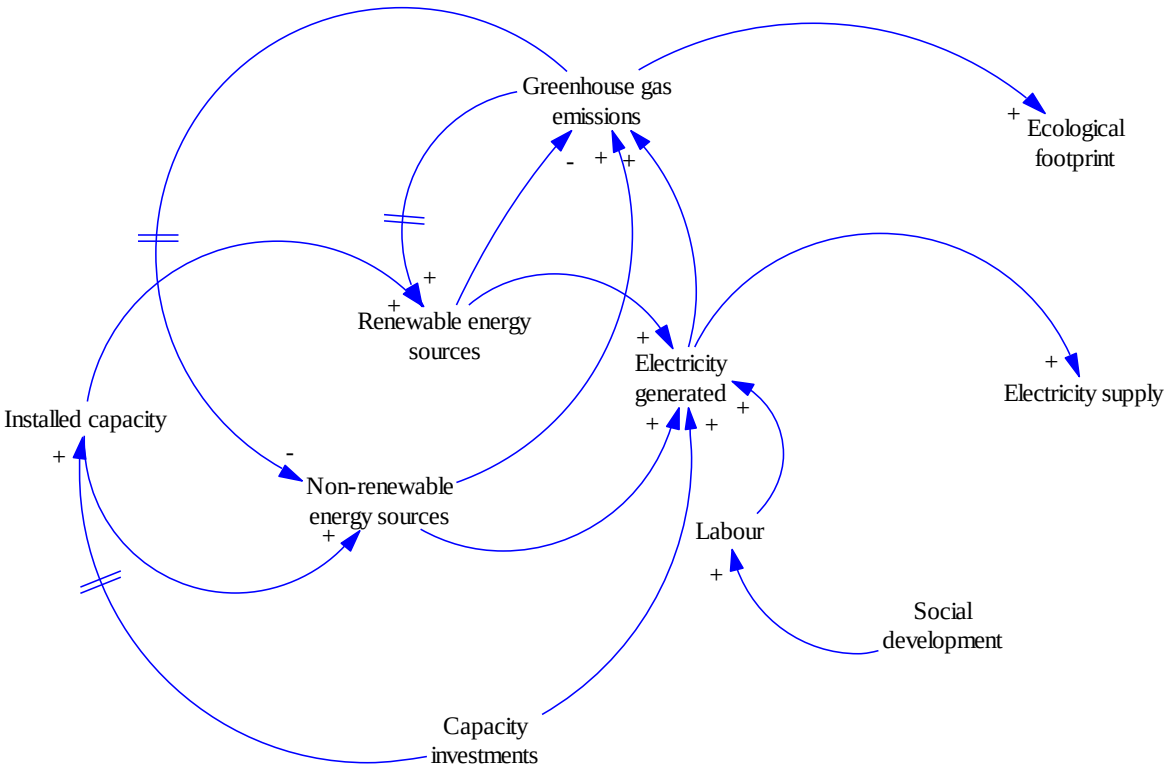

Figure 4.1 Causal loop representation of sustainable energy generation.

a plethora of sources which are either renewable or non-renewable. Reliance on non-renewable sources generally increases the environmental impact of energy generation. Fossil fuel combustion is a major source of global carbon dioxide (CO_2) and other greenhouse gas emissions (Evans et al., 2009; Lu et al., 2016; Rafaj et al., 2006; Varun et al., 2009). That is why the polarity between non-renewable sources and greenhouse emissions is positive. It should also be noted that greenhouse emissions in energy generation generally causes an increase in ecological footprint (Mancini et al., 2016). Increasingly, energy policy aimed at managing carbon emissions and decarbonising the generation mix is targeted at reducing non-renewable sources, carbon capture and investment in nuclear and renewable energy capacity (Gerbaulet et al., 2019). Consequently, while increased greenhouse gas emissions will lead to policies for non-renewable energy reduction, the renewable energy source component of the generation mix is expected to rise with time.

Higher capacity investments in renewable sources result in relatively less environmental impact. Investments in the capacity of renewable or non-renewable sources depend on economic considerations of profitability, economic development or government policy interventions (Agnew et al., 2018; Furuoka, 2017). This usually

requires long-term planning of the generation mix. Consequently, there is a time delay for capacity investment to be available in installed capacity (Mutingi et al., 2017).

On the social dimension of sustainability, there is a link with society as the source of skilled personnel to manage and operate power generation plants (Onat et al., 2017). Well-developed societies tend to have better-educated citizens and are expected to lead to better-skilled employees for the power generation system. There is a link between energy supply and societal welfare which subsequently leads to energy demand. However, as this is the use of energy, it is better discussed in the energy consumption phase of the problem conceptualisation.

4.2.2 Sustainable electricity consumption

The consumption phase of sustainable energy policy tends to focus on eco-efficiency, energy efficiency and social development (Feng and Wang, 2017; Honma and Hu, 2008). Figure 4.2 shows the interrelationships between the electricity system and these policy dimensions. Elements from the production phase that remain in Figure 4.2 are in blue while the links in the consumption phase are in red.

Energy generation and consumption are related but are not the same concept. Various factors account for the difference between generation and consumption. Distribution losses in the transmission of power from plants to households and export of electricity tend to reduce the amount of power available for domestic supply. On the other hand, where local demand outweighs generation, electricity imports can supplement the demand. This recognition of the difference between generation and consumption is visible in the policy. The EU's requirement for increased renewable energy consumption by member countries targets the consumption phase, rather than the production phase (EEA, 2016).

In the consumption phase, electricity supply enhances both economic development and social development. Access to modern energy services is essential in meeting basic social needs, of health, education, employment which is required to fuel economic growth and human development (Gaye, 2007). Human well-being cannot be advanced without access to electricity (Johansson et al., 2012). As energy is a critical input for national economic development, availability of secure and affordable power is expected to boost economic activities. This increased economic development will come at the cost of increased environmental impact on the environment, but may over time lead to expansion of both renewable and non-renewable energy-related infrastructure critical for energy security (Fouquet, 2016).

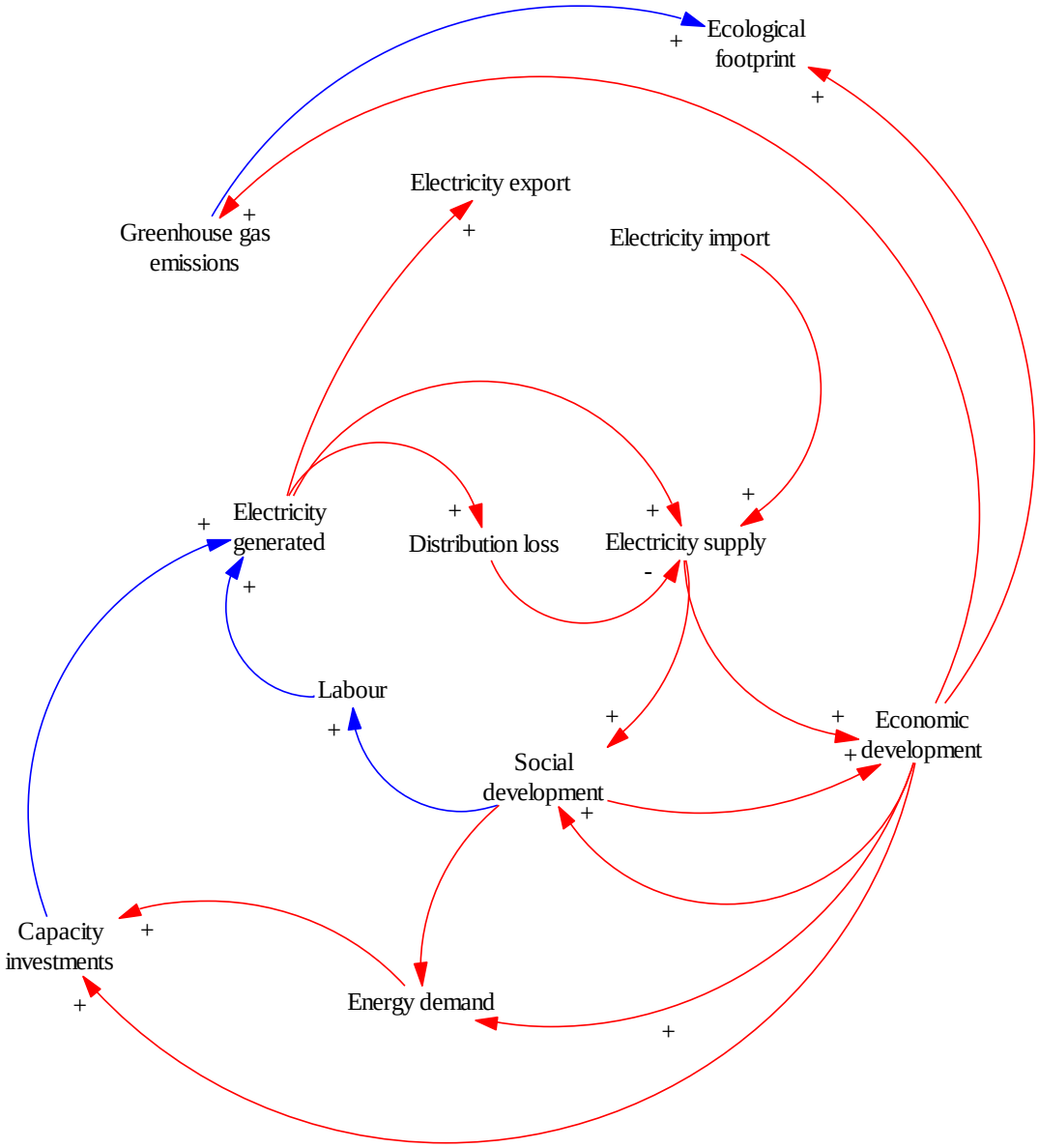

Figure 4.2 Causal loop representation of sustainable energy consumption.

Karanfil and Li (2015) propose various causal hypotheses for the nature of the relationship between energy and economic development. First, the growth hypothesis lays the foundation of electricity consumption and economic growth as seen in eco-efficiency analysis. Their conservative hypothesis proposes that economic growth leads to electricity consumption. This can be explained by increased energy demand as a result of social development from economic development. In that case, higher economic development will mean society can afford more power for development.

Finally, while the feedback hypothesis proposes interdependence between electricity consumption and economic growth, the neutrality hypothesis proposes no causal link probably due to rebound effects. This is where gains in reducing energy consumption may be offset by behavioural changes of economic agents, therefore, leading to increased energy demand (Galvin, 2014; Zhang et al., 2017).

This shows that economic development will have an impact on social welfare and development. Similarly, social development will also enhance economic development and increased energy demand. Reliable power supply will enhance education attainment, health and standard of lives of citizens which will result in skilled personnel available for employment in the power and all other economic sectors. Consequently, energy efficiency and diversification of energy supply into renewable sources are the pillars of sustainable energy policy (Prindle et al., 2007).

4.2.3 Sustainable energy system

The previous sub-sections presented and discussed the relevant interrelationships between electricity and sustainability considerations in both the generation and consumption phases. These two are important and complementary subsets of policy on the sustainable energy system. In Figure 4.3 the production and consumption phases of sustainable energy policy are combined.

From Figure 4.3, it is possible to trace the expected behaviour of power generation along the sustainability dimensions. There exists a number of feedback loops in terms of these policy and assessment variables. In the social dimension, more electricity generation will make power available for household consumption, which should foster social development and increase both energy demand and skilled labour required for more electricity generation. This is, therefore, a reinforcing loop. When traced along the environmental dimensions, electricity generation will lead to emissions, which will lead to a policy response of decarbonisation, which may mean higher electricity production from renewable sources. If emissions are examined, from the technology perspective, a balancing loop is revealed. Increased generation from non-renewable sources will result in more emissions, which will lead to a policy response aimed at reducing such non-renewable sources.

These notwithstanding, since the purpose of this thesis is not to examine the dynamics of relationships over time, further discussion and analysis of these loops will not be required. The purpose of the causal loop diagram was to structure the sustainable energy policy from which network models could be developed and performance assessment and cross-country benchmarking conducted. The next

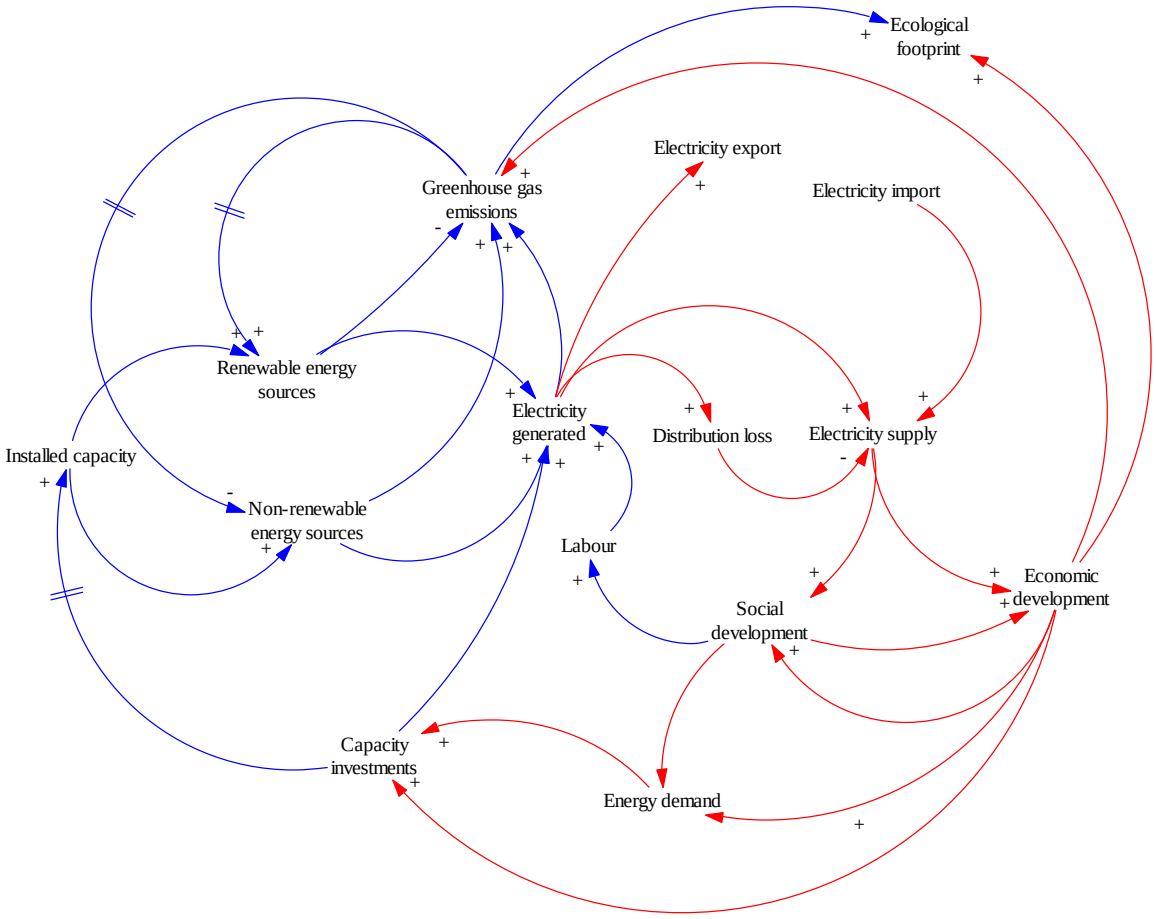

Figure 4.3 Causal loop representation of sustainable energy generation and consumption.

section converts these causal loop diagrams into network diagrams, highlighting the inputs and outputs required for the performance assessment.

4.3 Network structure of sustainable energy system

The causal loop diagrams presented provide an overview of important variables and relationships that must be modelled in sustainable energy policy decision support. However, as this thesis is focussed on cross-country performance assessment and benchmarking of energy systems, it is important to translate the causal loops into production structures. Sub-sections provide network representations of the electricity generation system, the consumption system and a combined structure.

4.3.1 Electricity generation network structure

The causal loop diagram for the sustainable electricity generation system is presented in Figure 4.1. Generally, electricity is generated from renewable and non-renewable sources. A by-product of the electricity generated is greenhouse gas emissions. Consequently, there are two outputs in the generation phase of the system. The electricity generation and greenhouse gas emissions, which are jointly produced with the useful output. The generation sources are the technologies for producing electricity. As countries operate with different power generation plants (and sources) concurrently and independently, it is possible to represent the production system as a parallel network structure as depicted in Figure 4.4.

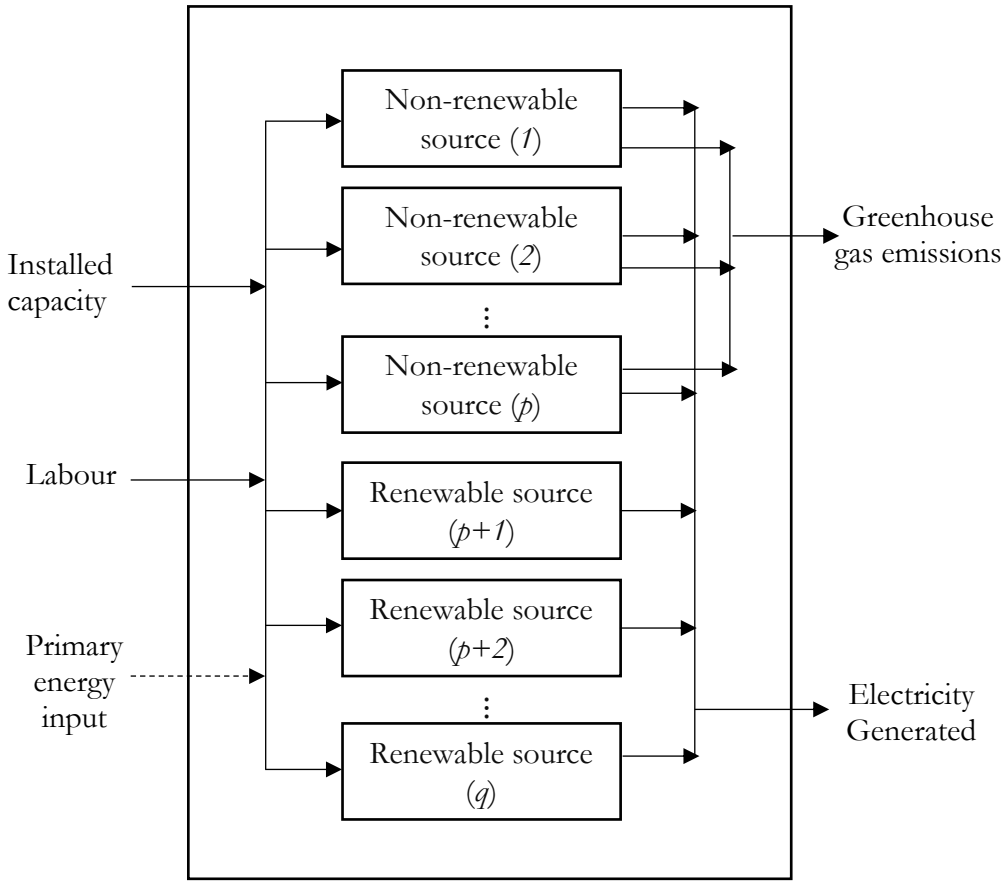

Figure 4.4 Parallel network representation of sustainable energy generation.

These power generation plants require some inputs to generate electricity. From the causal loop diagram, it is evident that the operation of such power generation sources is directly linked with the installed capacity and investment in such capacity. Consequently, the installed capacity of a source at a point in time is a relevant input.

Additionally, labour is another important input in traditional production systems. Finally, both renewable and non-renewable sources require some raw materials to convert into electricity. For example, primary oil resources will be required for oil-based power plants. Therefore, the primary energy input is also selected as a necessary input.

There are many differences between the causal loop diagram in Figure 4.1 and the parallel network structure in Figure 4.4. First, the feedback loop between greenhouse gas emissions and renewable and non-renewable sources are not modelled since such policy responses will require time and may not occur in the same period within which the performance assessment is being conducted. Additionally, while both renewable and non-renewable sources have a link with greenhouse emissions, in the parallel network, only the non-renewable sources are directly linked with such greenhouse emissions. This is since the emissions modelled are those directly produced as a result of fuel combustion. As such, direct emissions are modelled in the parallel network, not the lifecycle emissions. Capacity investments are also not represented directly in the parallel network. It is possible to include investment in the sector as an input, however, since such capacity investment may be correlated with installed capacity as well as the time lag for such investment to translate into installed capacity, only the installed capacity is included as an input. Finally, ecological footprint, electricity supply and social development variables are discussed in the consumption phase and are not directly represented in the generation network.

From the structure presented in Figure 4.4, it is possible to assess the performance of each decision-making unit in terms of each of the generation sources as well as the entire production system. These inputs and outputs have been variously used in performance assessment of the sustainability of electricity generation systems. Sueyoshi and Goto (2013) had electricity and CO_2 as the outputs. While electricity was the desirable output, the CO_2 was the undesirable output. Similarly, Mahmoudi et al. (2019) had electricity generation, carbon emissions together with revenues as outputs in their assessment of the performance of Iranian thermal power plants. Labour, generation/installed capacity and primary energy (fuel) consumption has been used as inputs in Mahmoudi et al. (2019). Other studies that rely on these inputs and outputs include Mou (2014), Sueyoshi and Goto (2015), Yadav et al. (2014), Yang and Pollitt (2009), among many others.

4.3.2 Electricity consumption network structure

Electricity generated in an economy is mainly consumed by economic units to satisfy social needs or generate other economic activities. Consequently, the uses of electricity, and energy in general, have been a matter of relevance to policy and research on eco-efficiency, environmental performance and energy efficiency. The causal loop diagram of the consumption phase is depicted in Figure 4.2, while its network representation is presented in Figure 4.5. In the consumption phase, the network starts from the electricity supply which is consumed by either households or other economic sectors like manufacturing, transportation, other services and agriculture. Therefore, some proportion of the electricity generated serves as an input to both the economic sub-system and the social sub-system. In the social sub-system, electricity is an essential input which has implication on social welfare and development. While social development will mean higher levels of employment, such labour provided by the society serves as an important input in the economic sub-system. The economic sub-system uses electricity, capital and labour to generate economic productivity. However, such economic production also results in some environmental impact. Therefore, environmental performance assessment can be an assessment from both the electricity generation phase and the economic productivity stage.

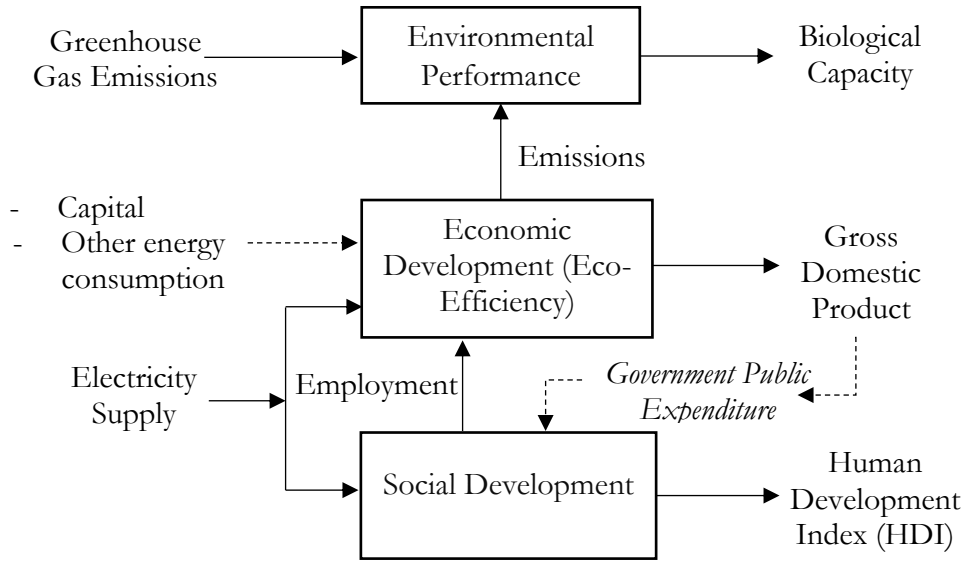

Figure 4.5 Series network representation of sustainable energy consumption.

There are several differences between the causal loop diagram and the network diagram. First, while the link between social development and economic development

is captured in the network diagram, the link between economic development and social development is not directly represented. This is because government public expenditure, which forms part of the GDP, is captured as an input in the social development sub-system. However, it is not directly an output in the economic development sub-system since it is part of GDP. Therefore, this link is implicit in one of the outputs in the economic development sub-system. Consequently, the link is represented by a dashed arrow. Second, the link between economic development and capacity investment, as well as social development and capacity development as a result of increased energy demand is not represented in the network diagram. This is because such capacity investment takes time and will not be captured in a particular assessment year. Also, capital stock is a relevant variable in eco-efficiency assessment and is therefore included as an input at this phase. This can be thought of as the value of previous years' economic activity as an important stock for future production (Feenstra et al., 2015). Also, in the environmental performance sub-system, the output used is the bio-capacity which is a measure of the planet's capacity to replenish resources and ecosystem services annually consumed by humans and absorb waste (Mancini et al., 2016; Niccolucci et al., 2012). Greenhouse emissions increase the ecological footprint which affects the bio-capacity. Finally, the link between electricity generation and electricity supply and the factors that play a role in the difference are discussed in Section 4.3.3.

This series network structure, therefore, allows for the assessment of social development performance, eco-efficiency and environmental performance in one conceptual model. Additionally, the optimal weights in the economic development assessment can be used for energy efficiency assessment of countries under study. Together, the system efficiency value will, therefore, provide an assessment of the performance in energy use. Variables in the economic development sub-system are not new as there are a plethora of studies that use capital, labour and energy as input and GDP and emissions are outputs in the literature (Lu and Lu, 2019; Mardani et al., 2017; Mavi et al., 2019; Robaina-Alves et al., 2015; Yang and Wei, 2019a,b).

On the social development sub-system, HDI and its components have been widely used proxies for social development and social sustainability assessment (Ülengin et al., 2011; Mariano et al., 2015). This study proposes the inclusion of electricity supply as an input in this phase due to the extant literature linking secured power supply to higher levels of social development (Martínez and Ebenhack, 2008; Ouedraogo, 2013). HDI is a measure of the average development of a country concerning longevity, education level and economic performance (Dias et al., 2006).

However, an essential part of social development is employment which is not captured in the HDI. Therefore, employment is included in the social development assessment and linked to economic development as an input in that sub-system.

In the environmental phase, environmental performance in the literature is typically assessed as a by-product in eco-efficiency assessment (Mavi et al., 2019; Sueyoshi and Goto, 2015). This approach does not link environmental performance to the available resource endowment of the state. However, with the realisation of the limited capacity of primary resources and the requirement to ensure future generations have relevant resources for their survival, sustainable development requires a balance between bio-capacity and ecological footprint (Hadian and Madani, 2015). Whereas the ecological footprint is a measure of human impact on the environment, the bio-capacity is the natural capital's bio-productivity or capacity to contain these human impacts (Siche et al., 2008). An important input in the assessment of the ecological footprint is carbon emissions (DiMaria, 2019; Geng et al., 2014). Therefore, increased emissions from electricity generation and economic production increase the ecological footprint. However, for sustainable development, the ecological footprint is compared to the bio-capacity to examine the ecological deficit (DiMaria, 2019; Geng et al., 2014). The objective is to have higher bio-capacity and lower ecological footprint as an indication of sustainable development. This study proposes to use greenhouse gas emissions as inputs and bio-capacity as output in the environmental performance assessment. In the DEA framework, it is possible to construct models that minimise the ecological footprint (emissions) at a given level of bio-capacity in a country.

4.3.3 Electricity generation and consumption network structure

Previous sub-sections have discussed independent conceptual approaches for performance assessment of electricity generation and consumption. However, in this thesis, the production and consumption phases are combined in one assessment framework. Therefore, decision support for sustainable energy policy is based on one systematic assessment. In Figure 4.6 the assessment frameworks in the generation and consumption phases are combined. The environmental performance assessment system is linked by emissions from electricity production and other emissions from other economic activities. For the economic development and the social development assessment, there is a link between the electricity generated in the first phase and the electricity supplied in the second phase. The difference between these two concepts

is due to trade and distribution losses. Therefore, the difference between the two may be treated as an additional exogenous output in the first phase or by including a dummy sub-system to take electricity generated as inputs and electricity supply as output. This accounts for imports, exports and distribution loss links in the causal loop diagram in Figure 4.3.

The overall network structure is, therefore, a mixed network with parallel generation phase and serial consumption phase. In the assessment, therefore, the overall performance score of each decision-making unit can be decomposed into the generation and consumption phases to identify the source of inefficiency.

4.4 Chapter summary

In this chapter, conceptual frameworks for model development and performance evaluation are presented. This was presented in two major sections the first of which employed causal loop diagrams to conceptually map relevant variables and interrelationships in sustainability policy at the electricity generation and consumption phases. These causal loop diagrams were developed based on literature review and existing causal loops used for systems analysis of electricity production and use. From the causal loop diagrams, different network diagrams that reasonably capture the important elements of the system diagrams were developed. The electricity generation phase is described by a parallel network structure since electricity production is characterised by the existence of various plants operating independently to meet national energy demands. The consumption phase, however, had a series structure which recognises the interrelationships between social development, economic development and environmental performance. While the generation and consumption phases could be treated independently, there is utility in combining these in a single assessment model, thus emphasising a systems approach to modelling. Consequently, the chapter also showed how the generation and consumption phases could be combined to allow for holistic assessment of the sustainability performance in electricity generation and use.

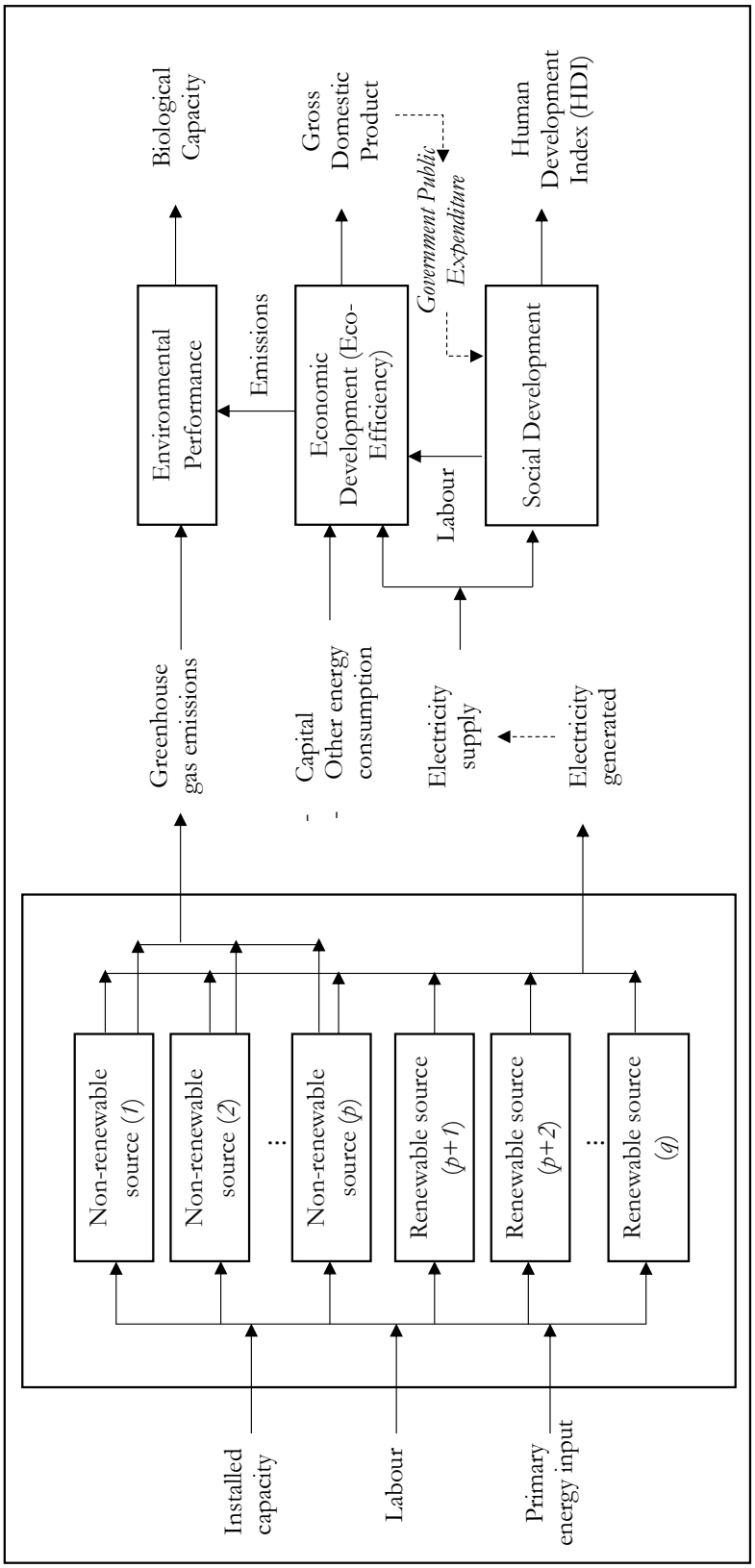

Figure 4.6 Conceptual framework: mixed network representation of sustainable energy generation and consumption.

Chapter 5

Sustainable and Resource Efficient Electricity Generation

5.1 Introduction

Electricity generation globally comes from a variety of generation sources with varying environmental consequences and primary energy resource requirement. Generation sources may include renewable and non-renewable sources. As different countries may have different combinations of generation sources, cross-country performance benchmarking of sustainability of electricity production should incorporate such portfolio differences. Unfortunately, the existing literature either conducts performance assessment at the plant level, usually in one country (Liu, Lin and Lewis, 2010; Sueyoshi et al., 2010; Yang and Pollitt, 2009), or compares the total generation at the national level without providing performance assessment at the generation source-level (Li, Geng and Li, 2016; Sueyoshi and Goto, 2013).

Research at the plant level compares the operational efficiency of various generation plants of similar generation sources sometimes with process decomposition. Xie et al. (2012), for example, decomposed the Chinese thermal power plant operation into generation and grid operations in the two-stage network DEA evaluation. Similarly, Bi et al. (2018) considered a two-stage problem with power generation and pollutant abatement as the sub-units under investigation. Other sub-process decompositions include financial objective and sustainability objectives of the fossil fuel power plants (Tajbakhsh and Hassini, 2018) and generation, transmission and distribution (Xie et al., 2018). Apart from the single country evaluation prominent in these studies, these studies fail to consider other generation sources in the

same assessment. Hardly do such decomposition incorporate both renewable and non-renewable sources in the same DEA performance assessment.

On the other hand, national level assessment has tended to focus on the social, economic and environmental factors that constrain the production of energy (Vazhayil and Balasubramanian, 2013; Zurano-Cervelló et al., 2018). These studies, like Sueyoshi and Goto (2013) and Ewertowska et al. (2017), have treated the production system of the country as a 'black-box' without providing an assessment of the performance at the individual source-level as part of the performance assessment.

In the EU, there is focus on the transition towards a Sustainable Smart European Grid, where it may be possible for decentralised electricity generation and transmission in different countries (Crispim et al., 2014; IqtiyaniIlham et al., 2017). Therefore, there is the need to conduct a country-specific analysis of electricity generation performance for each technology and the overall system. Comparing the performance of different plants producing electricity from a similar source does not allow for the determination of which countries are higher performers for that particular source. Also, the cross-country performance assessment that examines the total electricity generated and environmental outputs fail to provide an assessment of the sub-systems (different sources) that account for the overall generation performance.

To aid in decision support, the European Environment Agency (EEA) produces annually an "Overview of electricity production and use in Europe" as a means of monitoring the performance of countries. This report monitors: CO_2 emission intensity; gross electricity production by fuel; the contribution of fuels to total electricity production; whether electricity production in Europe is becoming less carbon-intensive; whether electricity production in Europe is increasing; and whether power plants are becoming more efficient (EEA, 2019). The report provides some descriptive summary of resource efficiency and emissions from the various generation sources without in-depth assessment and cross-country performance benchmarking in electricity generation and use. There is, therefore, the need for performance assessment to conduct cross-country assessment that compares the performance of how resources are efficiently consumed for power generation at the technology level, as well as provides an assessment of the overall system while incorporating environmental outputs.

This chapter, therefore, develops DEA optimisation models that provide cross-country performance assessment in gross electricity production and emissions reduction and also decomposes the overall performance to generation source-level performances. In this process, new optimisation models are developed into handle non-homogeneity in the production processes. Additionally, models developed incor-

porate emissions as undesirable outputs in the performance assessment. The chapter is organised as follows: Section 5.2 provides an overview of the European electricity generation system from which models are formulated in Sections 5.3 and 5.4 and empirical analyses conducted in Section 5.5. Finally, in Section 5.6 conclusions are drawn about the models developed and the empirical assessment conducted.

5.2 The European electricity generation system

The EU has been a leader in promoting sustainable development in the international arena by way of campaigns, networks and regulations (Afgan and Carvalho, 2008; Gallego Carrera and Mack, 2010). While Europe has limited capacity in the supply of primary energy sources of fossil fuel, its capacity in terms of renewable energies is not yet fully developed (Afgan and Carvalho, 2008). There is potential for hydro, solar, geothermal and biomass to contribute a large proportion of the total energy supply. Due to the increasingly integrated economies and energy sectors, the EU is the world's second-largest energy consumer behind the USA (Koroneos and Nanaki, 2007). It is not surprising that low-carbon energy sources (renewables and nuclear) currently dominate the electricity mix of EU countries (EEA, 2019). Figure 5.1 presents the 2017 generation mixes of the 28 EU countries.

On average, 53 per cent of gross electricity production (GEP) in 2017 came from such low-carbon sources. EU countries have a wide range of renewable source integration in their production mixes. From 87 per cent renewable energy generation by Luxembourg to as low as 9 per cent for Cyprus (European Commission, 2020). Together with Luxembourg, Lithuania, Austria, Latvia, Denmark, Croatia and Sweden, they have all managed over 50 per cent electricity generation from renewable sources (European Commission, 2020). Other countries like Slovakia, Belgium and France with relatively low renewable generation source content had very large GEP from nuclear, taking their total low-carbon generation source composition over the 50 per cent mark. Overall, 16 of these 28 countries had over 50 per cent of GEP from low-carbon sources. However, to achieve the EU's objective of reducing greenhouse gas emissions by 80-95% by 2050 compared to 1990 levels, there will be a need for full decarbonisation of the electricity sector (EEA, 2017). From Figure 5.2 it is evident that gains in decarbonisation crossed the 50 per cent mark in 2012.

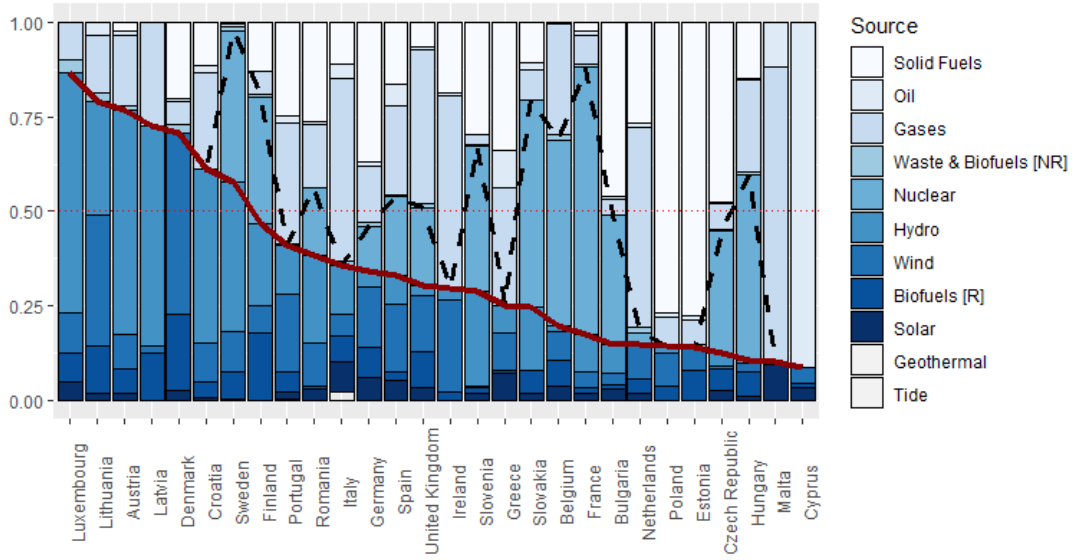

Figure 5.1 Electricity generation mixes of EU countries (2017).

Source: Data from European Commission (2020)
Solid line shows the percentage of renewables in generation mix while the dashed-lines show percentage of low-carbon energy sources in the generation mix.

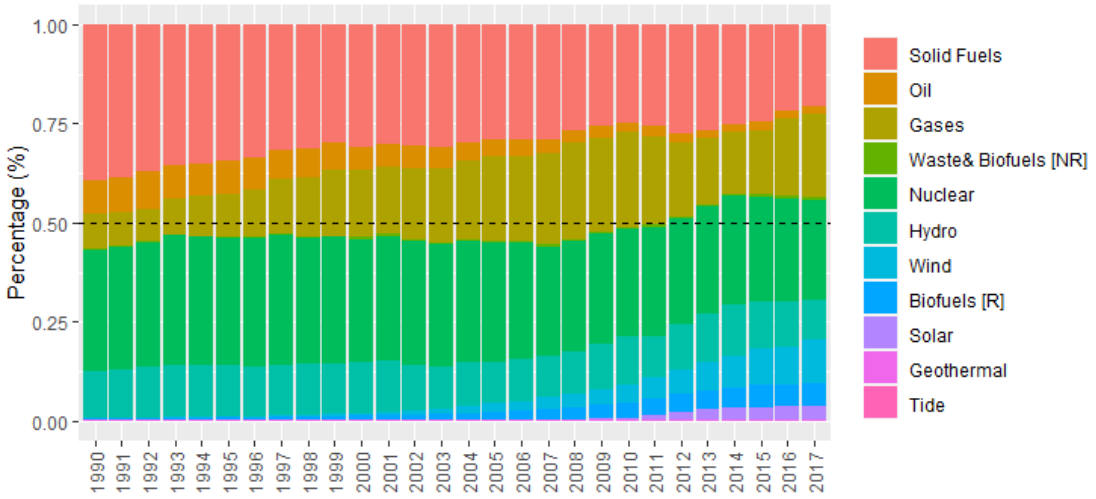

Figure 5.2 Combined gross generation mix of all 28 EU countries (1990-2017).

Source: Data from European Commission (2020)

The GEP covers electricity generation from all types of power plants (main transformers) and private producers (auto-producers) using coal and lignite (solid fuels), oil, natural and derived gas (gases), non-renewable biomass and waste (waste

& biofuels [NR]), nuclear and renewable sources comprising hydro, wind, renewable biofuels (Biofuels [R]), solar photovoltaics, geothermal, tide and other fuels (EEA, 2016; Eurostat, 2019a). It must be noted that Directive 2001/77/EC which requires an increased share of renewable sources in energy consumption by the year 2020 (EEA, 2017; Hadian and Madani, 2015; Kazagic et al., 2014) does not directly apply to the GEP since consumption is affected by distribution losses and trade among other factors (EEA, 2016).

In the policy context, several directives, projections and guidelines exist to aid countries in the transformation towards reducing GHG emissions from the electricity sector. A binding target of 40 per cent GHG emission reductions until 2030 based on 1990 levels have been set by the EU for the low-carbon energy transformation objective (Gerbaulet et al., 2019). Additionally, there is the objective for decarbonisation of at least 80 per cent of the 1990 levels by 2050 (European Commission, 2011). This is to be ensured through carbon capture and capacity investments in nuclear and renewable sources (Gerbaulet et al., 2019). Also, while Directive 2009/28/EC promotes the use of renewable sources, Directive 2009/29/EC focuses on improvement in GHG through trading schemes (EEA, 2019). Finally, COM[2010]-639 sets out strategies for competitive, sustainable and secure energy by setting new priority areas (European Commission, 2010). There is, therefore, efforts at capacity improvements, energy security and emissions reductions. Performance assessment models developed in subsequent sections reflect this policy environment.

5.3 Methods and modelling

5.3.1 Inputs and outputs

Although the source of energy may be different, sources are homogenous in terms of electricity produced. The by-product of the power generated is GHG emissions that are generated from fuel combustion in the production of non-renewable sources (excluding nuclear). Since this undesirable by-product is in joint production with the desirable power generated, GHG emissions is modelled as a weakly disposable output while GEP is modelled as freely disposable output. It must be noted that, this study focusses on direct GHG emissions since the EU's emissions reduction policy relates to direct emissions from electricity production. In reality, there may be other sources of environmental impact for even renewable sources. Output generation is subject to capacity restrictions, primary energy consumption and labour conditions. Since an increase in these factors will reasonably increase the desirable outputs, these

factors are modelled as freely disposable desirable inputs. The general structure of the system and variables is presented in Figure 5.3.

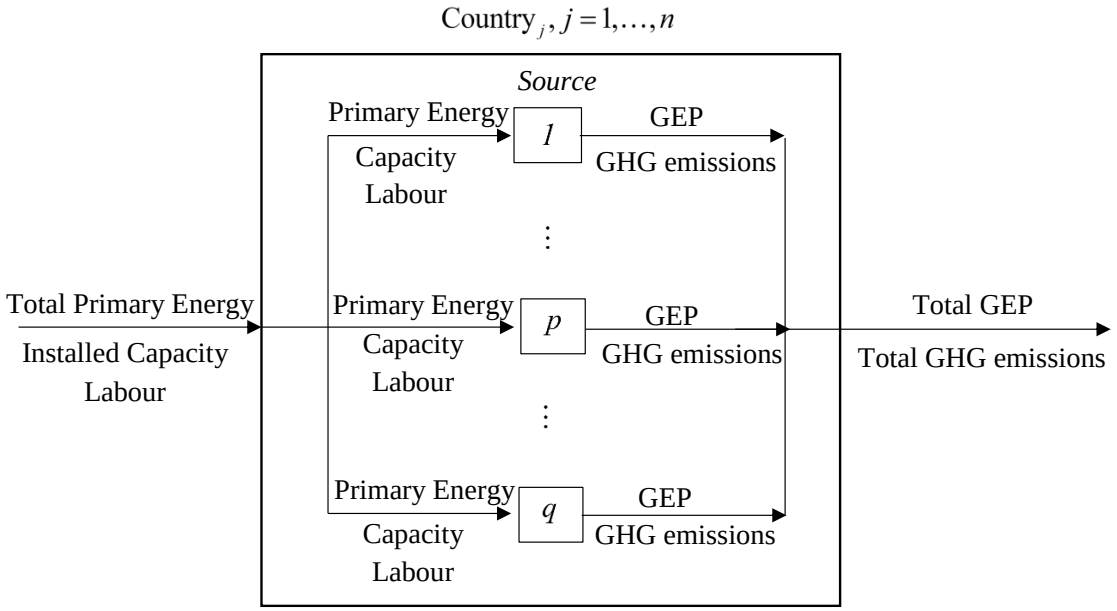

Figure 5.3 General structure of electricity generation system.

5.3.2 General model

For n DMUs ($n = 1, \ldots, j$), there is the input vector $X \in \Re_+^m$ which can be used to produce the output set $P(X)$ comprising the set of desirable outputs $Y^D \in \Re_+^s$ and undesirable outputs $Y^U \in \Re_+^l$. This set is closed and bounded with inputs freely disposable. The weak disposability of the undesirable outputs means that if there exists $\left(Y^D, Y^U\right) \in P(X)$ and $0 \leq \theta \leq 1$ then it should mean that $\left(\theta Y^D, \theta Y^U\right) \in P(X)$ (Färe et al., 1989). Consequently, there is proportional abatement between the desirable and undesirable outputs such that reduction in undesirable output will come at the expense of desirable outputs. However, desirable outputs can be freely disposable. There is also implied a null-joint condition that no undesirable output can be produced if no desirable output is produced - $\left(Y^D, Y^U\right) \in P(X)$, if $Y^D = 0$ then $Y^U = 0$. This means that direct emissions from fuel combustion are modelled rather than lifecycle emissions. If lifecycle emissions are rather modelled, then it should be possible to produce positive units of emissions even when no electricity has been generated. However, the focus is on modelling the direct emissions in this thesis. The PPS can be defined as:

$$P = \left\{ \left(X, Y^D, Y^U\right) \middle| \; X \geq \sum_{j=1}^{n} \lambda_j X_j, Y^D \leq \sum_{j=1}^{n} \lambda_j Y_j^D, Y^U = \sum_{j=1}^{n} \lambda_j Y_j^U, \lambda_j \geq 0 \right\} \tag{5.1}$$

Following the traditional CCR efficiency model, the input-oriented envelopment DEA model with strongly disposable desirable inputs and outputs but weakly disposable undesirable outputs (5.2) and its multiplier version (5.3) can be formulated as in:

$$E_0 = \quad \min \; \phi \tag{5.2a}$$

$$\text{s.t.} \; \sum_{j=1}^{n} \lambda_j X_{ij} \leq \phi X_{io} \qquad i = 1, 2, ..., m \tag{5.2b}$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj}^D \geq Y_{ro}^D \qquad r = 1, 2, ..., s \tag{5.2c}$$

$$\sum_{j=1}^{n} \lambda_j Y_{kj}^U = Y_{ko}^U \qquad k = 1, 2, ..., l \tag{5.2d}$$

$$\lambda_j \geq 0, \; j = 1, 2, ..., n \tag{5.2e}$$

$$E_0 = \max \; \sum_{r=1}^{s} u_r Y_{ro}^D + \sum_{k=1}^{l} c_k Y_{ko}^U \tag{5.3a}$$

$$\text{s.t.} \; \sum_{i=1}^{m} v_i X_{io} = 1 \tag{5.3b}$$

$$\left(\sum_{r=1}^{s} u_r Y_{rj}^D + \sum_{k=1}^{l} c_k Y_{kj}^U \right) - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \quad j = 1, 2, ..., n \tag{5.3c}$$

$$u_r, v_i \geq 0, \; c_k \, \text{urs}, \; r = 1, ..., s, \; \; k = 1, ..., l, \; \; i = 1, ..., m \tag{5.3d}$$

The models presented in (5.2) and (5.3) are based on the traditional 'black-box' DEA without sub-system integration. The model in (5.4) is based on Kao's (2009b) relational model and incorporates the weakly disposable undesirable outputs. Given that the overall system can be decomposed into q sub-processes ($p = 1, \ldots, q$). Each sub-process p has $X_i^{(p)}$, $i \in I^{(p)}$ inputs which are used in producing $Y_r^{D(p)}$, $r \in O^{D(p)}$ desirable outputs and $Y_k^{U(p)}$, $k \in O^{U(p)}$ undesirable outputs. It should be noted that

the total system inputs and outputs are a sum of those of all the sub-processes. $\sum_{p=1}^{q} X_{ij}^{(p)} = X_{ij}, i = 1, \ldots, m$, $\sum_{p=1}^{q} Y_{rj}^{D(p)} = Y_{rj}^{D}, r = 1, \ldots, s$ and $\sum_{p=1}^{q} Y_{kj}^{U(p)} = Y_{kj}^{U}, k = 1, \ldots, l$. The general parallel network model to estimate the overall and sub-system efficiencies of the network presented in Figure 5.4 is formulated as:

$$E_0 = \max \sum_{r=1}^{s} u_r Y_{ro}^{D} + \sum_{k=1}^{l} c_k Y_{ko}^{U} \tag{5.4a}$$

$$\text{s.t.} \sum_{i=1}^{m} v_i X_{io} = 1 \tag{5.4b}$$

$$\left(\sum_{r=1}^{s} u_r Y_{rj}^{D} + \sum_{k=1}^{l} c_k Y_{kj}^{U} \right) - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \qquad j = 1, 2, ..., n \tag{5.4c}$$

$$\left(\sum_{r \in O^{D(p)}} u_r Y_{rj}^{D(p)} + \sum_{k \in O^{U(p)}} c_k Y_{kj}^{U(p)} \right) - \sum_{i \in I^{(p)}} v_i X_{ij}^{(p)} \leq 0$$

$$p = 1, \ldots, q, \;\; j = 1, 2, \ldots, n \tag{5.4d}$$

$$u_r, v_i \geq 0, \; c_k \text{ urs}, \;\; r = 1, ..., s, \;\; k = 1, ..., l, \;\; i = 1, ..., m \tag{5.4e}$$

This model attaches the same input and output multipliers to the same type of inputs and outputs irrespective of the production system since the price of the factor on the market, is expected to remain the same irrespective of the sub-process (Kao, 2012). From the optimal solution (u_r^*, c_k^* and v_i^*), the efficiencies for the system and sub-processes for each DMU can be computed as:

$$E_o = \frac{\sum_{r=1}^{s} u_r^* Y_{ro}^{D} + \sum_{k=1}^{l} c_k^* Y_{ko}^{U}}{\sum_{i=1}^{m} v_i^* X_{io}} = \sum_{r=1}^{s} u_r^* Y_{ro}^{D} + \sum_{k=1}^{l} c_k^* Y_{ko}^{U} \tag{5.5a}$$

$$E_o^{(p)} = \frac{\sum_{r \in O^{D(p)}} u_r^* Y_{ro}^{D(p)} + \sum_{k \in O^{U(p)}} c_k^* Y_{ko}^{U(p)}}{\sum_{i \in I^{(p)}} v_i^* X_{io}^{(p)}}, \qquad p = 1, \ldots, q \tag{5.5b}$$

Where sub-processes are weighted by the proportion of inputs dedicated to the sub-process to the overall inputs in the system, Kao (2012, 2014a) show that the system efficiency is a weighted sum of the sub-process efficiencies. That is, if the

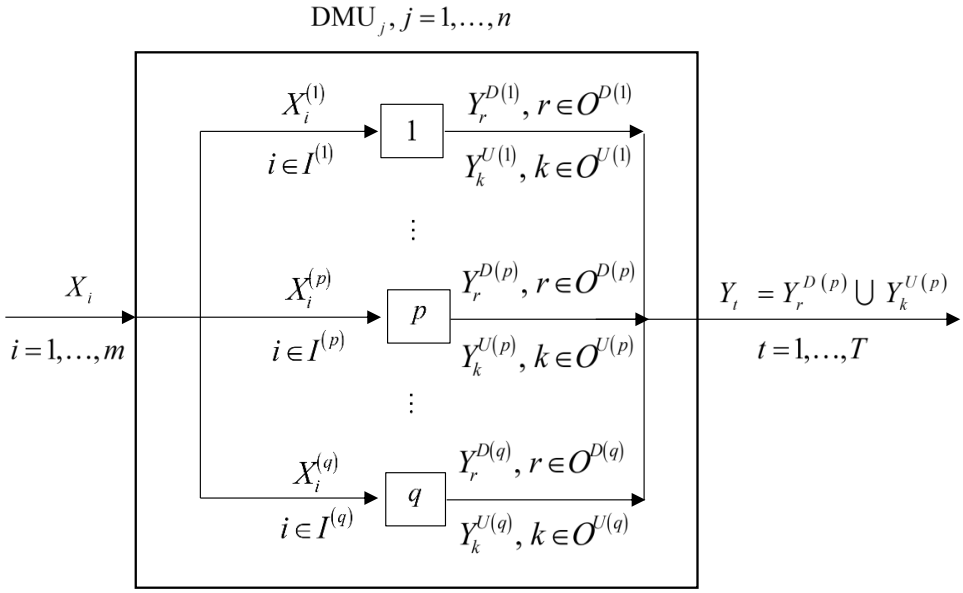

Figure 5.4 Schematic network structure.

importance of a sub-process is defined by the proportion of resources dedicated to the sub-process relative to the overall system resources, $w^{(p)} = \sum_{i\in I^{(p)}} v_i X_{io}^{(p)} / \sum_{i=1}^{m} v_i X_{io}$, where $\sum_{p=1}^{q} \sum_{i\in I^{(p)}} v_i X_{io}^{(p)} = \sum_{i=1}^{m} v_i X_{io}$, then the weighted average of all sub-process efficiencies becomes:

$$\sum_{p=1}^{q} w^{(p)} E_o^{(p)} = \sum_{p=1}^{q} \left[\left(\frac{\sum_{i\in I^{(p)}} v_i X_{io}^{(p)}}{\sum_{i=1}^{m} v_i X_{io}} \right) \left(\frac{\sum_{r=1}^{s} u_r Y_{ro}^{D} + \sum_{k=1}^{l} c_k Y_{ko}^{U}}{\sum_{i\in I^{(p)}} v_i X_{io}^{(p)}} \right) \right] \tag{5.6a}$$

$$= \frac{\sum_{r=1}^{s} u_r Y_{ro}^{D} + \sum_{k=1}^{l} c_k Y_{ko}^{U}}{\sum_{i=1}^{m} v_i X_{io}} \tag{5.6b}$$

5.3.3 Non-homogeneity in parallel processes

Cook et al. (2012) and Cook et al. (2013) show that non-homogeneity may exist in the 'black-box' model where some DMUs choose not to produce some of the outputs of other DMUs. Their solution is to regroup the DMUs into parallel sub-groups where all DMUs in each sub-group produce the same set of outputs. Since a DMU

may belong to more than one sub-group, their inputs must be reallocated across all sub-units they belong to. Li, Liang, Cook and Zhu (2016) looked at the problem from the inputs side where DMUs use different combinations of inputs to produce the same set of outputs. Cook et al. (2013) and Li, Liang, Cook and Zhu (2016) proposed a three-step process of splitting the outputs/inputs, deriving the efficiencies of DMUs in each sub-groups and determining the overall efficiencies as the weighted average of the efficiencies of the sub-groups. Shen et al. (2018) showed that this three-step process could be achieved in a step. They also determined the sub-groups based on the internal production structure as compared to Cook et al. (2013) and Li, Liang, Cook and Zhu (2016) whose grouping was data-driven.

Du et al. (2015) and Barat et al. (2019) have examined non-homogeneity in the network DEA literature where sub-processes have different combinations of inputs and outputs. Du et al. (2015) examined non-homogeneity in parallel network problems while Barat et al. (2019) examined non-homogeneity in mixed network DEA problems. These studies, however, assume that different DMUs have the same combination of sub-processes. In the electricity generation system, different countries have different portfolios of energy generation sources. As such, there is non-homogeneity in the combination of sub-processes used by each DMU as well as differences in the inputs/outputs of those sub-processes. This study, therefore, extends the work of Du et al. (2015) for conditions where DMUs have differences in the sub-processes.

Both Cook et al. (2013) and Shen et al. (2018) provide a way for dealing with situations where DMUs under investigation do not belong to some of the sub-groups in the black-box approach. These ideas could be extended for handling such non-homogeneity in parallel network problem. For Cook et al. (2013), where a DMU does not belong to a sub-group, its overall efficiency is defined as the weighted average of the efficiencies of only the sub-groups it belongs. Therefore, it is not assessed based on the other sub-groups in the system. As such, the other sub-groups are treated as non-existent and may be replaced with zero inputs, zero outputs and zero input/output apportionment. Shen et al. (2018) create a dummy sub-group where, $Y_{rj}^{(p)} = 0$ $(\forall r \in O^{(p)})$ and $X_{ij}^{(p)} = 0\,(\forall i \in I^{(p)})$ to make the problem a parallel problem while ensuring that no split inputs/outputs are assigned to the dummy sub-group.

From Figure 5.3, different sources have capacity, labour and primary energy as inputs and GEP and GHG as outputs. As some inputs (such as labour) and outputs (such as GHG) are shared, additional restrictions must be placed on the apportionment factors $\alpha_i^{(p)}$ and $\beta_r^{(p)}$ where the DMU does not produce electricity

using that source. Consequently, if no electricity is produced from that source, that DMU should get no GHG emissions assigned to the source. Additionally, it should not have any labour, primary energy resources or capacity allocated to the source if that variable is shared among the sources.

The problem can be illustrated in model (5.7) where outputs are divided into a set of shared outputs $Y_{r_s}^{(p)}$, $r_s \in O_k^{(p)}$ and dedicated outputs $Y_r^{(p)}$, $r \in O_y^{(p)}$. Similarly, inputs are divided into a set of shared inputs $X_{i_s}^{(p)}$, $i_s \in I_k^{(p)}$ and dedicated inputs $X_i^{(p)}$, $i \in I_y^{(p)}$. The parallel network DEA problem without any adjustment on the split input and outputs can be formulated as:

$$E_0 = \max \sum_{r_s \in O_k^{(p)}} u_{r_s} Y_{r_s o} + \sum_{p=1}^{q} \sum_{r \in O_y^{(p)}} u_r Y_{ro}^{(p)} \tag{5.7a}$$

$$\text{s.t.} \sum_{i_s \in I_k^{(p)}} v_{i_s} X_{i_s o} + \sum_{p=1}^{q} \sum_{i \in I_y^{(p)}} v_i X_{io}^{(p)} = 1 \tag{5.7b}$$

$$\left(\sum_{r_s \in O_k^{(p)}} u_{r_s} \beta_{r_s}^{(p)} Y_{r_s j} + \sum_{r \in O_y^{(p)}} u_r Y_{rj}^{(p)} \right) - \left(\sum_{i_s \in I_k^{(p)}} v_{i_s} \alpha_{i_s}^{(p)} X_{i_s j} + \sum_{i \in I_y^{(p)}} v_i X_{ij}^{(p)} \right) \leq 0 \quad p = 1, \ldots, q, \;\; j = 1, 2, \ldots, n \tag{5.7c}$$

$$\sum_{p=1}^{q} \alpha_{i_s}^{(p)} = 1, \qquad \forall i_s \in I_k^{(p)} \tag{5.7d}$$

$$\sum_{p=1}^{q} \beta_{r_s}^{(p)} = 1, \qquad \forall r_s \in O_k^{(p)} \tag{5.7e}$$

$$u_r, u_{r_s}, v_i, v_{i_s}, \alpha_{i_s}^{(p)}, \beta_{r_s}^{(p)} \geq 0,$$
$$r = 1, ..., s, \;\; r_s = 1, \ldots s, \;\; i = 1, ..., m, \;\; i_s = 1, ..., m \tag{5.7f}$$

The system input bundle $I^{(p)}$ and output bundle $O^{(p)}$ are defined as a union of the shared and dedicated sets such that $\left(I^{(p)}, O^{(p)}\right) = \left(I_k^{(p)} \cup I_y^{(p)}, O_k^{(p)} \cup O_y^{(p)}\right)$. In this problem, the dedicated output is the electricity generated by energy source p. It should be noted that if a country does not generate electricity from source p then it has no installed capacity and should not get any of the sharable inputs dedicated to that source. If that source is not a low-carbon energy source, then the null-joint condition should also apply to any sharable undesirable output. Consequently,

non-renewable energy sources (except nuclear) should not receive any sharable joint output if the good output for the source is zero.

Two approaches for handling the non-existing sub-processes are proposed in this study. First, L_n is defined as the set of all the parallel sub-processes in the system. Let, $L_n = \{1, \ldots, q\}$ with cardinality $|L_n| = q$. Given this, the parallel network model to assess the system efficiency with q sub-processes as presented in (5.7) can be reformulated as:

$$E_0 = \max \sum_{r_s \in O_k^{(p)}} u_{r_s} Y_{r_s o} + \sum_{p=1}^{|L_n|} \sum_{r \in O_y^{(p)}} u_r Y_{ro}^{(p)} \tag{5.8a}$$

$$\text{s.t.} \sum_{i_s \in I_k^{(p)}} v_{i_s} X_{i_s o} + \sum_{p=1}^{|L_n|} \sum_{i \in I_y^{(p)}} v_i X_{io}^{(p)} = 1 \tag{5.8b}$$

$$\left(\sum_{r_s \in O_k^{(p)}} u_{r_s} \beta_{r_s}^{(p)} Y_{r_s j} + \sum_{r \in O_y^{(p)}} u_r Y_{rj}^{(p)} \right) - \left(\sum_{i_s \in I_k^{(p)}} v_{i_s} \alpha_{i_s}^{(p)} X_{i_s j} + \sum_{i \in I_y^{(p)}} v_i X_{ij}^{(p)} \right) \leq 0$$

$$p \in L_n, \;\; j = 1, 2, \ldots, n \tag{5.8c}$$

$$\sum_{p=1}^{|L_n|} \alpha_{i_s}^{(p)} = 1, \qquad \forall i_s \in I_k^{(p)}, p \in L_n \tag{5.8d}$$

$$\sum_{p=1}^{|L_n|} \beta_{r_s}^{(p)} = 1, \qquad \forall r_s \in O_k^{(p)}, p \in L_n \tag{5.8e}$$

$$u_r, u_{r_s}, v_i, v_{i_s}, \alpha_{i_s}^{(p)}, \beta_{r_s}^{(p)} \geq 0,$$
$$r = 1, ..., s, \;\; r_s = 1, \ldots s, \;\; i = 1, ..., m, \;\; i_s = 1, ..., m \tag{5.8f}$$

The difference between (5.7) and (5.8) is that the latter uses the cardinality of L_n rather than q. This model will assign some non-negative values of the sharable output to process p of each DMU irrespective of whether the DMU operates with that sub-process. At least nothing in the model restricts a DMU from allocating sharable units to non-existing sub-processes.

A particular DMU j will have L_j set of sub-processes that it utilises in its production process, where $L_j \subseteq L_n$. It is reasonable to assume that if a DMU does not operate using a particular sub-process then its system efficiency should be unconstrained by that sub-process. Consequently, the non-existing sub-process, and all constraints associated with that, should be removed from the model examining

the system and sub-process efficiencies of the DMU. As such, for each DMU, if a sub-process produces zero dedicated output, then the sub-process will be ignored.

If the cardinality of the sub-process set of a DMU is smaller than the cardinality of the sub-process set for the entire system, i.e. $|L_j| < |L_n|$, then the system efficiency is calculated based on only the existing sub-processes of the DMU under consideration. The system efficiency for the DMU under this approach (approach 1) will be:

$$E_0 = \max \sum_{r_s \in O_k^{(p)}} u_{r_s} Y_{r_s o} + \sum_{p=1, p \in L_j}^{|L_j|} \sum_{r \in O_y^{(p)}} u_r Y_{ro}^{(p)} \tag{5.9a}$$

$$\text{s.t.} \sum_{i_s \in I_k^{(p)}} v_{i_s} X_{i_s o} + \sum_{p=1, p \in L_j}^{|L_j|} \sum_{i \in I_y^{(p)}} v_i X_{io}^{(p)} = 1 \tag{5.9b}$$

$$\left(\sum_{r_s \in O_k^{(p)}} u_{r_s} \beta_{r_s}^{(p)} Y_{r_s j} + \sum_{r \in O_y^{(p)}} u_r Y_{rj}^{(p)} \right) - \left(\sum_{i_s \in I_k^{(p)}} v_{i_s} \alpha_{i_s}^{(p)} X_{i_s j} + \sum_{i \in I_y^{(p)}} v_i X_{ij}^{(p)} \right) \leq 0$$

$$p \in L_j, \;\; j = 1, 2, \ldots, n \tag{5.9c}$$

$$\sum_{p=1, p \in L_j}^{|L_j|} \alpha_{i_s}^{(p)} = 1, \qquad \forall i_s \in I_k^{(p)}, p \in L_j \tag{5.9d}$$

$$\sum_{p=1, p \in L_j}^{|L_j|} \beta_{r_s}^{(p)} = 1, \qquad \forall r_s \in O_k^{(p)}, p \in L_j \tag{5.9e}$$

$$u_r, u_{r_s}, v_i, v_{i_s}, \alpha_{i_s}^{(p)}, \beta_{r_s}^{(p)} \geq 0,$$
$$r = 1, ..., s, \;\; r_s = 1, \ldots s, \;\; i = 1, ..., m, \;\; i_s = 1, ..., m \tag{5.9f}$$

For DMUs with sub-process cardinality the same as the system's (equinumerous), they are assessed based on all sub-processes. However, the model as formulated remains the same since $|L_j| = |L_n|$. The system efficiency of DMU j is, therefore, a weighted average of the efficiencies of only its existing sub-processes.

An alternative way for dealing with such non-existent sub-processes is to ensure that where a DMU does not have the particular sub-process, all split factors for the sub-process will be zero. i.e. $\beta_r^{(p)} = 0$ and $\alpha_i^{(p)} = 0$ if the DMU does not have dedicated outputs and inputs for the sub-process. However, the optimal multipliers for the dedicated factors will still be constrained by the inputs and outputs of other DMUs that operate using the non-existent sub-process. This approach maintains all

the sub-processes of the system in the assessment of each DMU. However, it imposes restrictions on the split variables such that nothing is allocated to non-existing sub-processes. Therefore, unlike the first approach that restricts multipliers to the existing sub-processes, approach two restricts the multipliers using all sub-processes. However, if a DMU does not operate with that sub-process no factors are dedicated. For a DMU with $|L_j| < |L_n|$, then the split values for all processes belonging to the set-theoretic difference of L_n and L_j ($L_n \backslash L_j$) are set to zero. The model to examine the system efficiency will therefore be:

$$E_0 = \max \sum_{r_s \in O_k^{(p)}} u_{r_s} Y_{r_s o} + \sum_{p=1}^{|L_n|} \sum_{r \in O_y^{(p)}} u_r Y_{ro}^{(p)} \tag{5.10a}$$

$$\text{s.t.} \sum_{i_s \in I_k^{(p)}} v_{i_s} X_{i_s o} + \sum_{p=1}^{|L_n|} \sum_{i \in I_y^{(p)}} v_i X_{io}^{(p)} = 1 \tag{5.10b}$$

$$\left(\sum_{r_s \in O_k^{(p)}} u_{r_s} \beta_{r_s}^{(p)} Y_{r_s j} + \sum_{r \in O_y^{(p)}} u_r Y_{rj}^{(p)} \right) - \left(\sum_{i_s \in I_k^{(p)}} v_{i_s} \alpha_{i_s}^{(p)} X_{i_s j} + \sum_{i \in I_y^{(p)}} v_i X_{ij}^{(p)} \right) \leq 0$$

$$p \in L_n, \;\; j = 1, 2, \ldots, n \tag{5.10c}$$

$$\sum_{p=1}^{|L_n|} \alpha_{i_s}^{(p)} = 1, \qquad \forall i_s \in I_k^{(p)}, p \in L_n \tag{5.10d}$$

$$\sum_{p=1}^{|L_n|} \beta_{r_s}^{(p)} = 1, \qquad \forall r_s \in O_k^{(p)}, p \in L_n \tag{5.10e}$$

$$\alpha_{i_s}^{(p)} = 0, \qquad p \in L_n \backslash L_j \tag{5.10f}$$

$$\beta_{r_s}^{(p)} = 0, \qquad p \in L_n \backslash L_j \tag{5.10g}$$

$$u_r, u_{r_s}, v_i, v_{i_s}, \alpha_{i_s}^{(p)}, \beta_{r_s}^{(p)} \geq 0,$$
$$r = 1, ..., s, \;\; r_s = 1, \ldots s, \;\; i = 1, ..., m, \;\; i_s = 1, ..., m \tag{5.10h}$$

If $|L_j| = |L_n|$ then the relative complement will be a null set (i.e. $L_n \backslash L_j = \varnothing$) and will not require any restriction on the split variables.

It can be seen that in approach one shown in (5.9), the multipliers for the DMU under consideration are determined subject to constraints relating to only the sub-processes the DMU currently has. This follows the idea of Cook et al. (2013) where the DMU's overall efficiency is determined from a weighted average of sub-group efficiencies. Since the multipliers are unconstrained in approach one by non-existing sub-processes, this approach implicitly assumes that the price of the inputs and

outputs reflects the DMU's internal operational structure rather than the industry's operating structure. Approach one may, therefore, be useful where the DMUs under evaluation have some form of price control such that the price of inputs and outputs can be freely determined depending on mostly the DMU's internal cost assessment.

On the other hand, since constraints relating to even the non-existing sub-processes remain in the model for approach two, its multipliers reflect the entire industry information. This approach follows the ideas of Shen et al. (2018) where dummy units with zero inputs and outputs are created for a DMU when it does not belong to the specific sub-group. Similar to Shen et al. (2018), split variables for non-existing sub-processes are set to zero. Since the optimal multipliers reflect all the sub-processes in the industry, it is argued that approach two may be useful where the DMU is a price-taker or where the DMU would want to consider the entire industry policy environment in determining factor prices. In the next section, an empirical assessment using the models developed is conducted. This includes an empirical comparison of the results from models (5.8), (5.9) and (5.10).

5.4 Empirical assessments

The sustainability and resource efficiency of the electricity generation systems of EU countries are assessed in this section. Data for assessment is sourced from the EU's Energy datasheets which are based on energy balance statistics from the Eurostat database. Eurostat's energy balance dataset provides uniform data across countries that allow for studying domestic energy and conducting an impact assessment of energy policy (Eurostat, 2019a). Data analysed in this study cover the 10 years from 2008 to 2017. As earlier indicated, three inputs and two outputs are used in the assessment model. These include:

1. *Installed capacity* (X_1): Megawatts (MW) of installed electricity capacity.
2. *Transformation inputs* (X_2): Millions of tonnes of oil equivalent (Mtoe) of primary energy resources.
3. *Labour* (X_3): Thousands of persons aged from 15 to 64 years employed in electricity, gas and air conditioning supply.
4. *Gross electricity production* (Y_1): Terawatt hour (TWh) of gross electricity generated.

5. *Greenhouse gas emissions* (Y_2): Million tonnes of CO_2 (Mt CO_2) of greenhouse gas emissions.

In the European case, there are 28 member countries[1] whose electricity production has been categorised into 11 generation sources. These sources comprise 6 renewable sources (hydro, wind, renewable biomass, solar, geothermal and tidal energy), nuclear and 4 non-renewable sources (solid fuels, oil, gases, and non-renewable biofuels and waste). There is an additional category, called 'other', which includes electricity produced from pumped hydro storage and other fuels not accounted for elsewhere such as industrial wastes not classed as renewable (EEA, 2016). However, although there exists installed capacity for such a source in some countries, gross electricity production from the 'other' category for most countries is zero. Consequently, this source is eliminated from the assessment.

5.4.1 System description

The evaluation framework for this chapter is depicted in Figure 5.5. Starting with the GEP, each energy source has separate production quantities in the dataset. However, for the GHG the dataset reports a composite value for all combustible fuel sources. Consequently, this undesirable output is modelled in a shared-flow problem with allocations to solid fuels, oil, gases and waste and other biofuel sub-processes. For the inputs, each input has some level of sharing between the sub-processes. Installed capacity for renewable sources (except renewable biomass) and nuclear are known and dedicated to the sub-processes without the need for sharing. Note, only the composite installed capacity for combustible fuels is reported. Consequently, this must be optimally allocated between solid fuels, oil, gas, renewable biomass and waste and non-renewable biofuels.

Transformation input for non-renewable energy sources are known and dedicated, however, for renewable sources, the transformation input must be optimally allocated between these sources to maximise efficiency. Finally, the labour variable is a composite score for the entire industry. As such, the exact number of people employed in each sub-process is unknown. This variable must, therefore, be allocated across all sub-processes.

[1] 28 member countries in the study period (2008 to 2017)

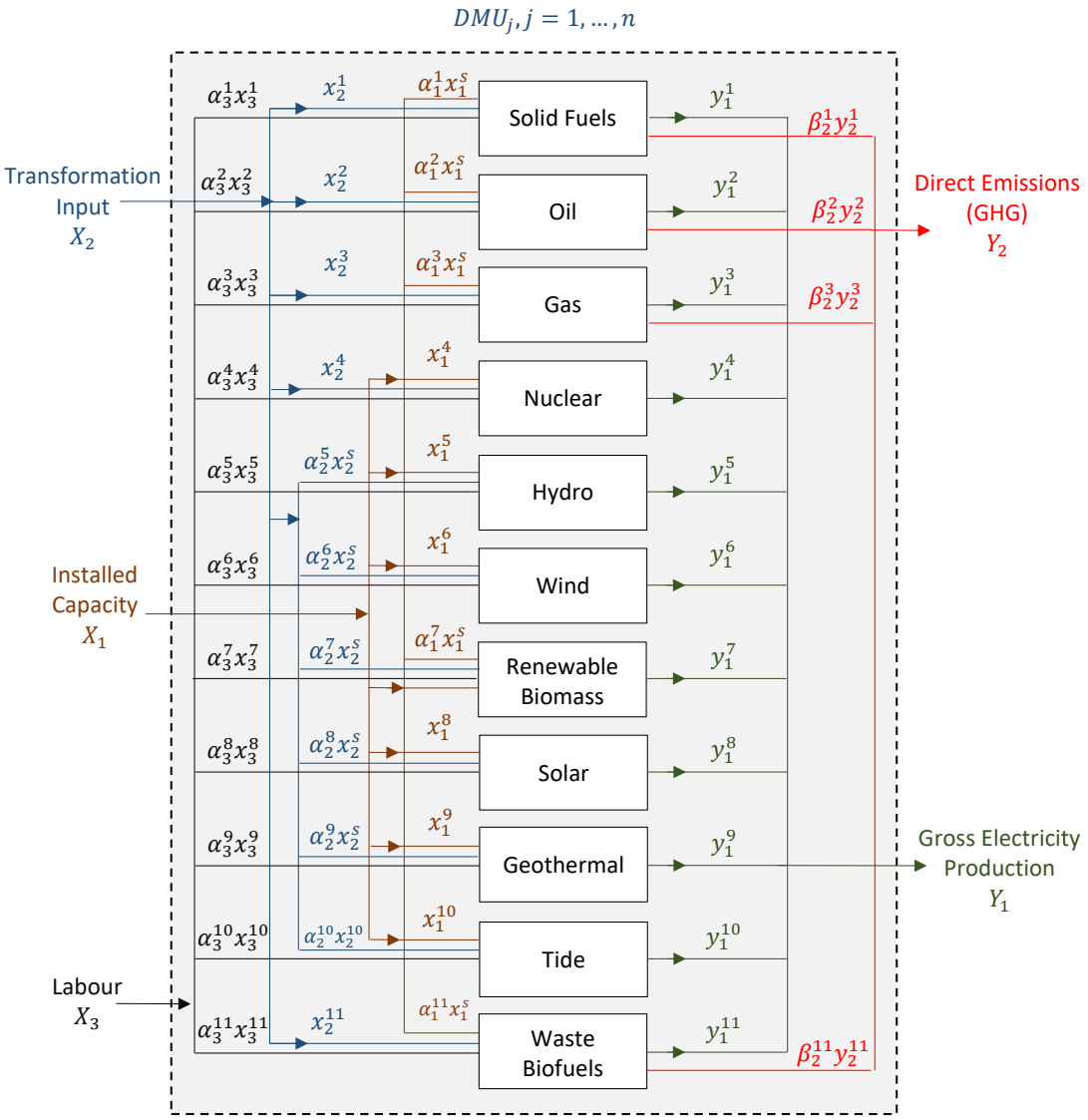

Figure 5.5 Evaluation framework of the production system.

5.4.2 Model formulation

System description in the previous sub-section shows that the system is characterised by a parallel network of 11 sources with shared-flows in both inputs and some output variables. Additionally, the existence of an undesirable output which is in joint production with the desirable output requires that the empirical model must capture weak disposability. This is formulated as follows:

$$E_0 = \max \;\; u_1 Y_{1o} + u_2 Y_{2o} \tag{5.11a}$$

subject to:

$$v_1 X_{1o} + v_2 X_{2o} + v_3 X_{3o} = 1 \tag{5.11b}$$

$$u_1 Y_{1j} + u_2 Y_{2j} - (v_1 X_{1j} + v_2 X_{2j} + v_3 X_{3j}) \leq 0 \tag{5.11c}$$

$$\left(u_1 Y_{1j}^{(1)} + u_2 \beta_2^{(1)} Y_{2j}\right) - \left(v_1 \alpha_1^{(1)} X_{1j}^s + v_2 X_{2j}^{(1)} + v_3 \alpha_3^{(1)} X_{3j}\right) \leq 0 \tag{5.11d}$$

$$\left(u_1 Y_{1j}^{(2)} + u_2 \beta_2^{(2)} Y_{2j}\right) - \left(v_1 \alpha_1^{(2)} X_{1j}^s + v_2 X_{2j}^{(2)} + v_3 \alpha_3^{(2)} X_{3j}\right) \leq 0 \tag{5.11e}$$

$$\left(u_1 Y_{1j}^{(3)} + u_2 \beta_2^{(3)} Y_{2j}\right) - \left(v_1 \alpha_1^{(3)} X_{1j}^s + v_2 X_{2j}^{(3)} + v_3 \alpha_3^{(3)} X_{3j}\right) \leq 0 \tag{5.11f}$$

$$u_1 Y_{1j}^{(4)} - \left(v_1 X_{1j}^{(4)} + v_2 X_{2j}^{(4)} + v_3 \alpha_3^{(4)} X_{3j}\right) \leq 0 \tag{5.11g}$$

$$u_1 Y_{1j}^{(5)} - \left(v_1 X_{1j}^{(5)} + v_2 \alpha_2^{(5)} X_{2j}^s + v_3 \alpha_3^{(5)} X_{3j}\right) \leq 0 \tag{5.11h}$$

$$u_1 Y_{1j}^{(6)} - \left(v_1 X_{1j}^{(6)} + v_2 \alpha_2^{(6)} X_{2j}^s + v_3 \alpha_3^{(6)} X_{3j}\right) \leq 0 \tag{5.11i}$$

$$u_1 Y_{1j}^{(7)} - \left(v_1 \alpha_1^{(7)} X_{1j}^s + v_2 \alpha_2^{(7)} X_{2j}^s + v_3 \alpha_3^{(7)} X_{3j}\right) \leq 0 \tag{5.11j}$$

$$u_1 Y_{1j}^{(8)} - \left(v_1 X_{1j}^{(8)} + v_2 \alpha_2^{(8)} X_{2j}^s + v_3 \alpha_3^{(8)} X_{3j}\right) \leq 0 \tag{5.11k}$$

$$u_1 Y_{1j}^{(9)} - \left(v_1 X_{1j}^{(9)} + v_2 \alpha_2^{(9)} X_{2j}^s + v_3 \alpha_3^{(9)} X_{3j}\right) \leq 0 \tag{5.11l}$$

$$u_1 Y_{1j}^{(10)} - \left(v_1 X_{1j}^{(10)} + v_2 \alpha_2^{(10)} X_{2j}^s + v_3 \alpha_3^{(10)} X_{3j}\right) \leq 0 \tag{5.11m}$$

$$\left(u_1 Y_{1j}^{(11)} + u_2 \beta_2^{(11)} Y_{2j}\right) - \left(v_1 \alpha_1^{(11)} X_{1j}^s + v_2 X_{2j}^{(11)} + v_3 \alpha_3^{(11)} X_{3j}\right) \leq 0 \tag{5.11n}$$

$$\beta_2^{(1)} + \beta_2^{(2)} + \beta_2^{(3)} + \beta_2^{(11)} = 1 \tag{5.11o}$$

$$\alpha_1^{(1)} + \alpha_1^{(2)} + \alpha_1^{(3)} + \alpha_1^{(7)} + \alpha_1^{(11)} = 1 \tag{5.11p}$$

$$\alpha_2^{(5)} + \alpha_2^{(6)} + \alpha_1^{(7)} + \alpha_2^{(8)} + \alpha_2^{(9)} + \alpha_2^{(10)} = 1 \tag{5.11q}$$

$$\alpha_3^{(1)} + \alpha_3^{(2)} + \alpha_3^{(3)} + \alpha_3^{(4)} + \alpha_3^{(5)} + \alpha_3^{(6)} + \alpha_3^{(7)} + \alpha_3^{(8)} + \alpha_3^{(9)} + \alpha_3^{(10)} + \alpha_3^{(11)} = 1 \tag{5.11r}$$

$$a_i^{(p)} \leq \alpha_i^{(p)} \leq b_i^{(p)} \tag{5.11s}$$

$$a_r^{(p)} \leq \beta_r^{(p)} \leq b_r^{(p)} \tag{5.11t}$$

$$u_1, v_i \geq \varepsilon,\; u_2 \,\text{urs}, \;\; r = 1, ..., s, \quad i = 1, ..., m, \;\; j = 1, 2, \ldots, n \tag{5.11u}$$

Since the model in (5.11) is nonlinear, it must be transformed into an LP problem. Both the shared inputs and outputs must be apportioned across the relevant sub-processes. While the sharing proportions for the inputs are determined in the efficiency model, that of the output (GHG) is externally determined. For the jth country ($j = 1, 2, \ldots, n$), the emissions output variable of the pth technology ($p = 1, 2, \ldots, q$) for time t ($t = 1, 2, \ldots, T$) is determined by the contribution of

the technology to the production mix and the global warming potential (GWP) attributable to the technology using the formula:

$$\mathrm{GHG}_{pjt} = \left(R_{pjt}\mathrm{GWP}_{pj} / \sum_{p=1}^{q} R_{pjt}\mathrm{GWP}_{pj} \right) \times \mathrm{GHG}_{jt} \tag{5.12}$$

Where R_{pjt} represents the contribution of the generation source to the total non-renewable and non-nuclear generation at time t. Consequently, the sum of the contributions across all the sources is unity, $\sum_{p=1}^{q} R_{pjt} = 1$. GWP_{pj} is the emissions factor represented by the 100 year GWP for source p and country j. The term in the brackets is, therefore, a generation mix adjusted proportion which satisfies the null-joint condition. Therefore, if a country has no electricity generated from a particular source, then no GHG is assigned to the source, given that $\mathrm{GHG}_{pj} = \beta_2^{(p)} Y_{2j}$. Such decomposition is done in the literature in the absence of sub-process emissions information (Mandal and Madheswaran, 2010). The 100 year GWP is sourced from the ecoinvent database (version 3) by Wernet et al. (2016).

To linearise the remainder of model (5.11), first set $k_i^{(p)} = v_i \alpha_i^{(p)}$. Since $\sum_{p=1}^{q} \alpha_i^{(p)} = 1$, therefore, $v_i \sum_{p=1}^{q} \alpha_i^{(p)} = v_i = \sum_{p=1}^{q} k_i^{(p)}$. Using Charnes and Cooper (1973) transformation, $t = 1/(v_1 X_{1o} + v_2 X_{2o} + v_3 X_{3o})$ and define $\mu_r = t u_r$, $\nu_i = t v_i$ and $\gamma_i^{(p)} = t k_i^{(p)}$. The nonlinear programming problem above can, therefore, be reduced to the problem:

$$E_0 = \max \quad \mu_1 Y_{1o} + \mu_2 Y_{2o} \tag{5.13a}$$

$$\text{s.t.} \quad \nu_1 X_{1o} + \nu_2 X_{2o} + \nu_3 X_{3o} = 1 \tag{5.13b}$$

$$\mu_1 Y_{1j}^{(1)} + \mu_2 Y_{2j}^{(1)} - \gamma_1^{(1)} X_{1j} - \nu_2 X_{2j}^{(1)} - \gamma_3^{(1)} X_{3j} \leq 0 \tag{5.13c}$$

$$\mu_1 Y_{1j}^{(2)} + \mu_2 Y_{2j}^{(2)} - \gamma_1^{(2)} X_{1j} - \nu_2 X_{2j}^{(2)} - \gamma_3^{(2)} X_{3j} \leq 0 \tag{5.13d}$$

$$\mu_1 Y_{1j}^{(3)} + \mu_2 Y_{2j}^{(3)} - \gamma_1^{(3)} X_{1j} - \nu_2 X_{2j}^{(3)} - \gamma_3^{(3)} X_{3j} \leq 0 \tag{5.13e}$$

$$\mu_1 Y_{1j}^{(4)} - \nu_1 X_{1j}^{(4)} - \nu_2 X_{2j}^{(4)} - \gamma_3^{(4)} X_{3j} \leq 0 \tag{5.13f}$$

$$\mu_1 Y_{1j}^{(5)} - \nu_1 X_{1j}^{(5)} - \gamma_2^{(5)} X_{2j} - \gamma_3^{(5)} X_{3j} \leq 0 \tag{5.13g}$$

$$\mu_1 Y_{1j}^{(6)} - \nu_1 X_{1j}^{(6)} - \gamma_2^{(6)} X_{2j} - \gamma_3^{(6)} X_{3j} \leq 0 \tag{5.13h}$$

$$\mu_1 Y_{1j}^{(7)} - \gamma_1^{(7)} X_{1j} - \gamma_2^{(7)} X_{2j} - \gamma_3^{(7)} X_{3j} \leq 0 \tag{5.13i}$$

$$\mu_1 Y_{1j}^{(8)} - \nu_1 X_{1j}^{(8)} - \gamma_2^{(8)} X_{2j} - \gamma_3^{(8)} X_{3j} \leq 0 \tag{5.13j}$$

$$\mu_1 Y_{1j}^{(9)} - \nu_1 X_{1j}^{(9)} - \gamma_2^{(9)} X_{2j} - \gamma_3^{(9)} X_{3j} \leq 0 \tag{5.13k}$$

$$\mu_1 Y_{1j}^{(10)} - \nu_1 X_{1j}^{(10)} - \gamma_2^{(10)} X_{2j} - \gamma_3^{(10)} X_{3j} \leq 0 \tag{5.13l}$$

$$\mu_1 Y_{1j}^{(11)} + \mu_2 Y_{2j}^{(11)} - \gamma_1^{(11)} X_{1j} - \nu_2 X_{2j}^{(11)} - \gamma_3^{(11)} X_{3j} \leq 0 \tag{5.13m}$$

$$\gamma_1^{(1)} + \gamma_1^{(2)} + \gamma_1^{(3)} + \gamma_1^{(7)} + \gamma_1^{(11)} = \nu_1 \tag{5.13n}$$

$$\gamma_2^{(5)} + \gamma_2^{(6)} + \gamma_2^{(7)} + \gamma_2^{(8)} + \gamma_2^{(9)} + \gamma_2^{(10)} = \nu_2 \tag{5.13o}$$

$$\gamma_3^{(1)} + \gamma_3^{(2)} + \gamma_3^{(3)} + \gamma_3^{(4)} + \gamma_3^{(5)} + \gamma_3^{(6)} + \gamma_3^{(7)} + \gamma_3^{(8)} + \gamma_3^{(9)} + \gamma_3^{(10)} + \gamma_3^{(11)} = \nu_3 \tag{5.13p}$$

$$\nu_i a_i^{(p)} \leq \gamma_i^{(p)} \leq \nu_i b_i^{(p)} \tag{5.13q}$$

$$\mu_1, \nu_i, \gamma_i^{(p)} \geq \varepsilon, \mu_2 \text{ urs}, \ r = 1, ..., s, \quad i = 1, ..., m, \quad p = 1, ..., q, \tag{5.13r}$$

$$j = 1, 2, \ldots, n \tag{5.13s}$$

Note that for the second output, $Y_{2j}^{(p)}$ is determined using (5.12). From the optimal solution $\left(\mu_r^*, \nu_i^*, \gamma_i^{*(p)}\right)$, the system and sub-process efficiencies can be estimated as:

$$E_0 = \frac{\mu_1^* Y_{1o} + \mu_2^* Y_{2o}}{\nu_1^* X_{1o} + \nu_2^* X_{2o} + \nu_3^* X_{3o}} \qquad E_0^{(6)} = \frac{\mu_1^* Y_{1o}^{(6)}}{\nu_1^* X_{1o}^{(6)} + \gamma_2^{*(6)} X_{2o}^s + \gamma_3^{*(6)} X_{3o}}$$

$$E_0^{(1)} = \frac{\mu_1^* Y_{1o}^{(1)} + \mu_2^* Y_{2o}^{(1)}}{\gamma_1^{*(1)} X_{1o}^s + \nu_2^* X_{2o}^{(1)} + \gamma_3^{*(1)} X_{3o}} \qquad E_0^{(7)} = \frac{\mu_1^* Y_{1j}^{(7)}}{\gamma_1^{*(7)} X_{1o}^s + \gamma_2^{*(7)} X_{2o}^s + \gamma_3^{*(7)} X_{3o}}$$

$$E_0^{(2)} = \frac{\mu_1^* Y_{1o}^{(2)} + \mu_2^* Y_{2o}^{(2)}}{\gamma_1^{*(2)} X_{1o}^s + \nu_2^* X_{2o}^{(2)} + \gamma_3^{*(2)} X_{3o}} \qquad E_0^{(8)} = \frac{\mu_1^* Y_{1o}^{(8)}}{\nu_1^* X_{1o}^{(8)} + \gamma_2^{*(8)} X_{2o}^s + \gamma_3^{*(8)} X_{3o}}$$

$$E_0^{(3)} = \frac{\mu_1^* Y_{1o}^{(3)} + \mu_2^* Y_{2o}^{(3)}}{\gamma_1^{*(3)} X_{1o}^s + \nu_2^* X_{2o}^{(3)} + \gamma_3^{*(3)} X_{3o}} \qquad E_0^{(9)} = \frac{\mu_1^* Y_{1o}^{(9)}}{\nu_1^* X_{1o}^{(9)} + \gamma_2^{*(9)} X_{2o}^s + \gamma_3^{*(9)} X_{3o}}$$

$$E_0^{(4)} = \frac{\mu_1^* Y_{1o}^{(4)}}{\nu_1^* X_{1o}^{(4)} + \nu_2^* X_{2o}^{(4)} + \gamma_3^{*(4)} X_{3o}} \qquad E_0^{(10)} = \frac{\mu_1^* Y_{1o}^{(10)}}{\nu_1^* X_{1o}^{(10)} + \gamma_2^{*(10)} X_{2o}^s + \gamma_3^{*(10)} X_{3o}}$$

$$E_0^{(5)} = \frac{\mu_1^* Y_{1o}^{(5)}}{\nu_1^* X_{1o}^{(5)} + \gamma_2^{*(5)} X_{2o}^s + \gamma_3^{*(5)} X_{3o}} \qquad E_0^{(11)} = \frac{\mu_1^* Y_{1o}^{(11)} + \mu_2^* Y_{2o}^{(11)}}{\gamma_1^{*(11)} X_{1o}^s + \nu_2^* X_{2o}^{(11)} + \gamma_3^{*(11)} X_{3o}} \tag{5.14}$$

It is possible to determine the optimal values of the apportioning factors $\alpha_i^{(p)}$. Note that since $v_i \sum_{p=1}^q \alpha_i^{(p)} = v_i$ and $\sum_{p=1}^q \gamma_i^{(p)} = v_i$, the optimal input allocations to sub-process p can be determined using:

$$\alpha_i^{(p)} = \gamma_i^{*(p)} / v_i^* \,, \qquad p = 1, \ldots, q \tag{5.15}$$

In the next section, the models proposed and developed are empirically tested and applied to the European context. R/R studio is used to solve all models and generate graphs in subsequent sections.

5.5 Findings and discussions

This section is dedicated to the empirical assessment of the sustainability and resource efficiency in the electricity generation systems of the 28 EU countries examined. After the data description in the next sub-section is presented, the various approaches for handling non-homogenous sub-processes are first examined before the empirical assessment of the production systems.

5.5.1 Data and description

This study uses a total of five variables, comprising two outputs and three inputs, for the empirical assessment. One of the outputs (GHG) is an undesirable output modelled as weakly disposable and in joint production with the desirable output in some of the sub-processes. The summary statistics of the variables used are presented in Table 5.1.

Table 5.1 Descriptive statistics of inputs and outputs (2008-2017).

variables	n	mean	sd	min	max
Outputs:					
Gross electricity production (TWh)[a]	280	117.25	162.79	0.86	652.04
Greenhouse gas emissions (mt CO_2)[b]	280	41.4	65.95	0.24	336.72
Inputs:					
Installed capacity (MW)	280	33340	45756.16	571	215142
Transformation inputs (Mtoe)	280	23.92	34.35	0.16	137.94
Labour (Thousand)	280	57.06	76.84	0.8	374.5

[a] *Desirable output*
[b] *Undesirable output*

The summary statistics are based on the 10-year dataset for all 28 EU countries. As such the dataset is a balanced panel with 280 observations. On average, gross electricity production for the 10 years stands at an average of 117.25 TWh per country with high variation among countries. Malta, for example, had the lowest GEP in 2016 of about 0.86 TWh with power mainly generated from oil combustion power plants (0.72 TWh) and Solar (0.13 TWh). On the other spectrum is Germany with about 652 TWh in 2017 with reliance on solid fuel based power plants. This variation among the EU countries is observed across all the variables with even higher variations, relative to the means, in emissions and transformation inputs.

Nearly all the countries, 27 out of the 28 countries, had complete data for all variables for the entire study period. The only exception was Malta, which had

missing employment data in the electricity, gas, steam and air conditioning supply industrial sector from 2014 to 2017. However, as there was complete data from 2008 to 2014 and complete employment data across all industries for the entire study period, the average proportion of the industry data to the national level for 2008 to 2014 was used for estimating reasonable employment figures for the missing period. Consequently, 1.072% (sd = 0.00102) of the national employment figures for 2014 to 2017 were used as estimates of the industry employment values for the missing periods.

5.5.2 Non-homogeneous sub-systems

This sub-section examines the three approaches for dealing with non-homogeneity in parallel network DEA models. Where DMUs operate with a different combination of sub-processes together with the existence of split variables, it is important to consider how this affects the shared variable apportioning and the efficiency scores. In this study, three approaches have been discussed in section 5.3.3. The first approach presented in models (5.7) and (5.8) is to apply the usual parallel network model without any specific treatment for the non-existing sub-processes for the DMUs. The next approach presented in model (5.9), and akin to Cook et al.'s (2013) approach for dealing with non-homogeneity in black-box DEA models, assesses DMU's efficiency based on only the existing sub-processes. The third approach presented in model (5.10), and akin to Shen et al.'s (2018) approach for handling non-homogeneity in black-box models, is to keep all sub-processes but assign zero values to all inputs, outputs and split variables for the DMU for non-existent sub-process.

To empirically examine the differences in the efficiency scores from the three approaches, the dataset for the year 2008 is used. The empirical model and the structure of the network model is shown in equation (5.13) and Figure 5.5 except that necessary adjustments are made depending on the specific approach adopted for solving the network problem. As can be seen in Figure 5.5, each of the three inputs must be split across some specific sub-processes. Installed capacity for renewable sources is jointly provided, therefore optimal apportionment must be made across the renewable sources (hydro, wind, renewable biomass, solar and geothermal). The transformation input for solid fuels, oil, gases, renewable biomass and waste are jointly reported as combustible fuels. This must also be optimally apportioned across relevant sub-processes. Finally, the labour variable is reported at the industry level, therefore, there is no specific sub-process allocation at the data source. This labour variable must, therefore, be optimally allocated across all the eleven sub-

processes. Although in Figure 5.5 the emissions variable is to be also shared across four sub-processes, this apportionment has been done using (5.12). Therefore, no split factors are considered for the output side. The optimal proportions using the traditional parallel network model as shown in model (5.8) and other characteristics of the solution have been presented in Table 5.2.

Table 5.2 Parallel network model characteristics based on equation (5.7) or (5.8).

Country	Existing Sources (Out of 11)	Non-existent sources	Split Factor Proportions[a]		
			Installed Capacity	Transformation Input	Labour
Austria	9	Nuclear	n.a	n.a	0.002
		Tide	n.a	0.002	0.002
Belgium	9	Geothermal	n.a	0.002	0.6808
		Tide	n.a	0.002	0.002
Bulgaria	8	Geothermal	n.a	0.0597	0.0909
		Tide	n.a	0.002	0.0909
		Waste & Biofuels [NR]	0.0035	n.a	0.0909
Croatia	6	Nuclear	n.a	n.a	0.002
		Solar	n.a	0.002	0.002
		Geothermal	n.a	0.0689	0.002
		Tide	n.a	0.002	0.002
		Waste & Biofuels [NR]	0.002	n.a	0.002
Cyprus	4	Solid Fuels	0.6649	n.a	0.002
		Gas	0.3291	n.a	0.002
		Nuclear	n.a	n.a	0.002
		Hydro	n.a	0.4627	0.002
		Geothermal	n.a	0.0462	0.002
		Tide	n.a	0.002	0.002
		Waste & Biofuels [NR]	0.002	n.a	0.002
Czech Republic	9	Geothermal	n.a	0.062	0.002
		Tide	n.a	0.002	0.002
Denmark	8	Nuclear	n.a	n.a	0.002
		Geothermal	n.a	0.002	0.0336
		Tide	n.a	0.002	0.002
Estonia	6	Nuclear	n.a	n.a	0.002
		Solar	n.a	0.0127	0.002
		Geothermal	n.a	0.0127	0.002
		Tide	n.a	0.002	0.002

Continued...

Continuation of Table 5.2.

Country	Existing Sources (Out of 11)	Non-existent sources	Split Factor Proportions		
			Installed Capacity	Transformation Input	Labour
		Waste & Biofuels [NR]	0.2	n.a	0.002
Finland	9	Geothermal	n.a	0.002	0.2093
		Tide	n.a	0.002	0.002
France	10	Geothermal	n.a	0.002	0.7034
Germany	10	Tide	n.a	0.002	0.002
Greece	8	Nuclear	n.a	n.a	0.002
		Geothermal	n.a	0.0463	0.002
		Tide	n.a	0.002	0.002
Hungary	9	Geothermal	n.a	0.0702	0.0909
		Tide	n.a	0.002	0.0909
Ireland	6	Nuclear	n.a	n.a	0.002
		Solar	n.a	0.002	0.002
		Geothermal	n.a	0.002	0.2254
		Tide	n.a	0.002	0.002
		Waste & Biofuels [NR]	0.002	n.a	0.002
Italy	9	Nuclear	n.a	n.a	0.002
		Tide	n.a	0.002	0.002
Latvia	6	Nuclear	n.a	n.a	0.0909
		Solar	n.a	0.002	0.0909
		Geothermal	n.a	0.0498	0.0909
		Tide	n.a	0.002	0.0909
		Waste & Biofuels [NR]	0.002	n.a	0.0909
Lithuania	7	Solar	n.a	0.002	0.002
		Geothermal	n.a	0.1039	0.002
		Tide	n.a	0.002	0.002
		Waste & Biofuels [NR]	0.0028	n.a	0.002
Luxembourg	7	Solid Fuels	0.002	n.a	0.0101
		Nuclear	n.a	n.a	0.002
		Geothermal	n.a	0.002	0.0439
		Tide	n.a	0.002	0.002
Malta	1	Solid Fuels	0.6649	n.a	0.002
		Gas	0.3291	n.a	0.002
		Nuclear	n.a	n.a	0.002
		Hydro	n.a	0.4627	0.002

Continued...

Continuation of Table 5.2.

Country	Existing Sources (Out of 11)	Non-existent sources	Split Factor Proportions		
			Installed Capacity	Transformation Input	Labour
		Wind	n.a	0.0448	0.002
		Biomass [R]	0.002	0.4423	0.002
		Solar	n.a	0.002	0.002
		Geothermal	n.a	0.0462	0.002
		Tide	n.a	0.002	0.002
		Waste & Biofuels [NR]	0.002	n.a	0.002
Netherlands	9	Geothermal	n.a	0.002	0.2149
		Tide	n.a	0.002	0.002
Poland	7	Nuclear	n.a	n.a	0.002
		Solar	n.a	0.002	0.002
		Geothermal	n.a	0.0466	0.002
		Tide	n.a	0.002	0.002
Portugal	9	Nuclear	n.a	n.a	0.002
		Tide	n.a	0.002	0.002
Romania	8	Geothermal	n.a	0.0577	0.0909
		Tide	n.a	0.002	0.0909
		Waste & Biofuels [NR]	0.0056	n.a	0.0909
Slovakia	8	Solar	n.a	0.002	0.002
		Geothermal	n.a	0.1047	0.002
		Tide	n.a	0.002	0.002
Slovenia	8	Wind	n.a	0.002	0.002
		Geothermal	n.a	0.0896	0.002
		Tide	n.a	0.002	0.002
Spain	9	Geothermal	n.a	0.002	0.1378
		Tide	n.a	0.002	0.002
Sweden	9	Geothermal	n.a	0.002	0.0194
		Tide	n.a	0.002	0.002
United Kingdom	10	Geothermal	n.a	0.002	0.249

n.a: not applicable

[a] *minimum bound is 0.002*

From Table 5.2, it is evident that not a single country operated using all the eleven sub-processes in 2008. The highest included France, Germany and the United Kingdom, which operated 10 of the 11 generations sources. Whiles France produced

no power from tidal energy, both the UK and Germany did not have production from geothermal energy. On the other end is Malta, which only produced electricity using oil-based power plants.

When the optimal split variables, using the traditional parallel network model without adjustment, are considered across the countries, it is evident that all countries saw some allocation to at least one non-existing sub-process. For example, 68.08% of the labour for Belgium in 2008 was allocated to the non-existent geothermal power sub-process. For France, as much as 70.34% of labour was allocated to geothermal power. Similar observations can be made for installed capacity and transformation inputs as well. For example, whereas 66.49% of the combustible installed capacity is allocated to the non-existing solid fuels sub-process of Malta, 46.27% of the transformation input for renewable energy for the same country was allocated to the hydro energy sub-process. The implications of these allocations to non-existing sub-processes are twofold. First, allocating inputs to non-existing sub-processes deprive the actual operational sub-processes the relevant inputs. This understating of the inputs may, therefore, mean overestimation of the efficiencies since the DMUs are assigned artificially smaller inputs. The second implication is that when coupled with output variables that must be apportioned in the model, then the assignment of inputs and outputs to the non-existing sub-process will mean the DMU will have efficiency scores for non-existing sub-process. This will affect the efficiency decomposition across the other sub-processes. It is important to note that a minimum allocation of 0.2% for the split variable is enforced such that every sub-process will receive some allocation. In Appendix A, the optimal allocations where the minimum bound constraint is relaxed is presented. The results without the minimum bound constraint are generally similar to that reported in Table 5.2.

As earlier indicated, two approaches are proposed for handling such non-homogenous sub-processes. Table 5.3 compares the system-level efficiency scores from these two approaches with that from the traditional parallel network model. From the table, it seems the system efficiency scores from approach 1 are closer, on average, to the traditional parallel network model than that of approach 2. This can be explained by the fact that approach 2 puts more restrictions on the multipliers than approach 1. With approach 1 the non-existing sub-units are ignored in the assessment, consequently, the optimal multipliers chosen by the model is unconstrained by the constraints attributable to the other DMUs that operate using those non-existing sub-process. As such, the price paid for a unit of the output is determined by only the generation sources a DMU currently operates. Approach 2, however, considers all the other sources in determining the optimal multipliers, except that it ensures

no allocation is made for the non-existing sub-processes in terms of the split factors. The price of the outputs is therefore determined by all the possible generation sources available on the market.

Table 5.3 System efficiency comparison across models (2008).

Country		Traditional Parallel NDEA (5.8)		Approach 1 (5.9)		Approach 2 (5.10)	
		Score	Rank	Score	Rank	Score	Rank
Austria	AT	0.8208	6	0.8215	8	0.8003	3
Belgium	BE	0.7281	14	0.7353	15	0.4973	18
Bulgaria	BG	0.6782	21	0.6823	21	0.4879	19
Croatia	HR	0.7134	19	0.7206	17	0.4245	23
Cyprus	CY	0.7508	10	0.9573	1	0.5354	12
Czech Republic	CZ	0.6569	23	0.6605	22	0.5565	10
Denmark	DK	0.6905	20	0.6955	20	0.5973	8
Estonia	EE	0.9296	1	0.9303	2	0.9000	1
Finland	FI	0.7652	8	0.7695	10	0.4982	17
France	FR	0.7314	13	0.7362	14	0.5066	16
Germany	DE	0.7170	17	0.7172	18	0.7172	5
Greece	EL	0.8763	2	0.8784	3	0.7851	4
Hungary	HU	0.6434	24	0.6475	24	0.4799	21
Ireland	IE	0.8319	5	0.8411	7	0.5247	14
Italy	IT	0.6581	22	0.6585	23	0.6489	7
Latvia	LV	0.6155	27	0.6224	27	0.3613	26
Lithuania	LT	0.5145	28	0.5221	28	0.2093	28
Luxembourg	LU	0.7765	7	0.8115	9	0.3467	27
Malta	MT	0.7206	16	0.8759	4	0.5368	11
Netherlands	NL	0.7580	9	0.7638	11	0.5579	9
Poland	PL	0.8557	3	0.8564	6	0.8222	2
Portugal	PT	0.7136	18	0.7141	19	0.6896	6
Romania	RO	0.6382	25	0.6426	25	0.4594	22
Slovakia	SK	0.6262	26	0.6341	26	0.3963	25
Slovenia	SI	0.7420	12	0.7511	13	0.5286	13
Spain	ES	0.7240	15	0.7289	16	0.4017	24
Sweden	SE	0.8523	4	0.8578	5	0.4831	20
United Kingdom	UK	0.7477	11	0.7543	12	0.5240	15
Geometric Mean		0.7259		0.7428		0.5233	

Another point to note is that if a DMU assigns fewer units of the split variable to non-existing units in the traditional parallel NDEA, the efficiency scores for the three models are relatively closer compared to a DMU that assigns more units

to non-existing units. An example is Italy which from Table 5.2 assigns only the minimum allowable proportions of the split variables to the non-existent DMU (a total of only 0.6%). Consequently, Italy's system efficiency scores presented in Table 5.3 are 0.6581, 0.6585 and 0.6489 for the traditional NDEA, approach 1 and approach 2 respectively. A similar observation can be made for Germany, Austria and Portugal. Countries with large variation in the overall scores across the three models have very large split variable allocations across sub-processes. Cyprus, for example, assigns a total of 99.6% of combustible fuel installed capacity and 51.09% of renewable energy transformation input to non-existing sub-processes. It is, therefore, not surprising that there is high variation in the overall efficiency scores from the traditional NDEA (0.7508), approach 1 (0.9573) and approach 2 (0.5354).

Finally, differences in the ranking of countries based on the approach selected for handling this non-homogeneity underscores the importance of correcting non-homogeneity in the sub-processes. Since approach 2 uses the entire market data in estimating the system and sub-process efficiencies, subsequent sub-sections of this chapter are based on parallel network models using this approach. This is because the price of factors must reflect the entire industrial production possibilities when assessing the resource efficiency and sustainability in the electricity system.

5.5.3 Efficiency assessment

This section presents and discusses the results of the assessment of the sustainability and resource efficiency in electricity generation among the EU countries. Results presented in this section aim at providing an overview of the performance of individual countries in minimising resource use in generating electricity from different production sources and minimising emissions. First, the system efficiency scores, which looks at the overall industry level data across all generation sources, are presented. This is followed by a decomposition of the system efficiencies at the country-level.

System efficiency

System-level efficiency scores in the traditional 'black-box' DEA sense do not incorporate any information about the composition of generation sources. As such the country-level total inputs and total outputs are used in the efficiency assessment as shown in (3.2). There is, therefore, no need to split any inputs across sub-processes. However, such aggregation, which ignores the internal sub-divisions have the tendency of overestimating the actual efficiency of the DMUs (Castelli et al., 2010;

Cook et al., 2000; Tone and Tsutsui, 2009). This is shown in Figure 5.6 where the system efficiencies based on the black-box approach and the parallel network model (approach two) are compared.

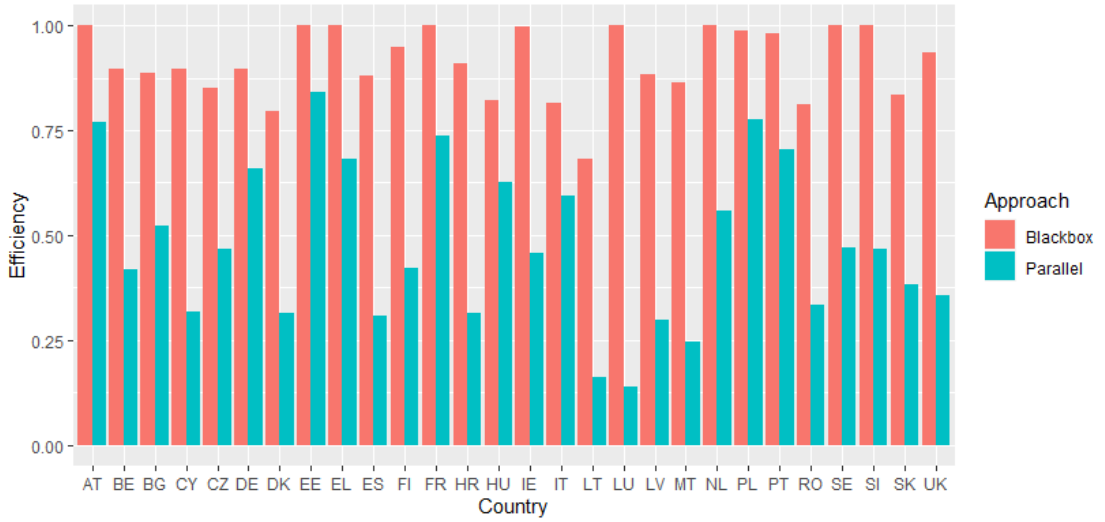

Figure 5.6 System efficiencies from 'black-box' DEA model and parallel network model (2017).

For each country, the black-box approach shows a higher efficiency score than the parallel network approach. As a result, the parallel network approach is more discriminatory than the black-box approach. Additionally, it allows for the decomposition of the system efficiency to provide additional information on which specific sub-processes require performance improvement (Kao and Hwang, 2008).

Since all countries were examined over 10 years from 2008 to 2017, a summary of the individual country performance is presented in Figure 5.7 and Figure 5.8 . Figure 5.7 is a boxplot with jitters that is ordered according to the median overall system efficiencies. As such, countries on the far right of Figure 5.7 had relatively higher resource efficiency and sustainable electricity generation on average over the study period. As can be seen in the figure, over the 10 years, higher performers on average have included Estonia (EE), Poland (PL), Greece (EL) and Austria (AT). Other countries with average system-level efficiency higher than 50% include France (FR), Portugal (PT), Germany (DE), Italy (IT), Netherlands and others. Half of the EU countries have median system efficiency below 50% on average over the 10 years. Luxembourg (LU), Latvia (LV) and Lithuania (LT) are at the lower levels of sustainability in electricity generation. This is generally, similar to the 2017 distributions shown in Figure 5.6.

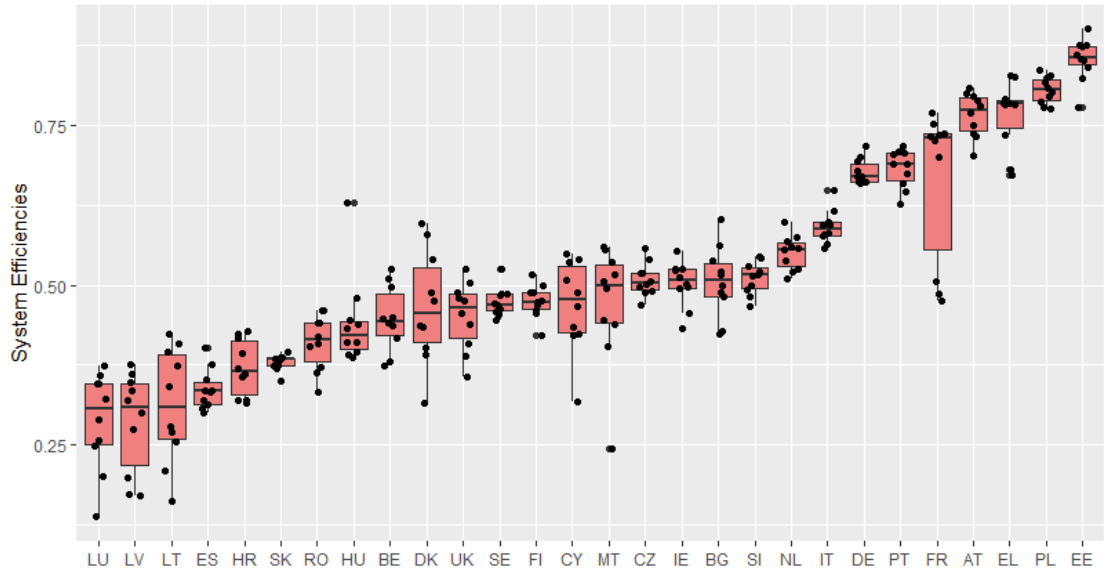

Figure 5.7 Boxplot with jitters of yearly system efficiencies across countries (2008-2017).

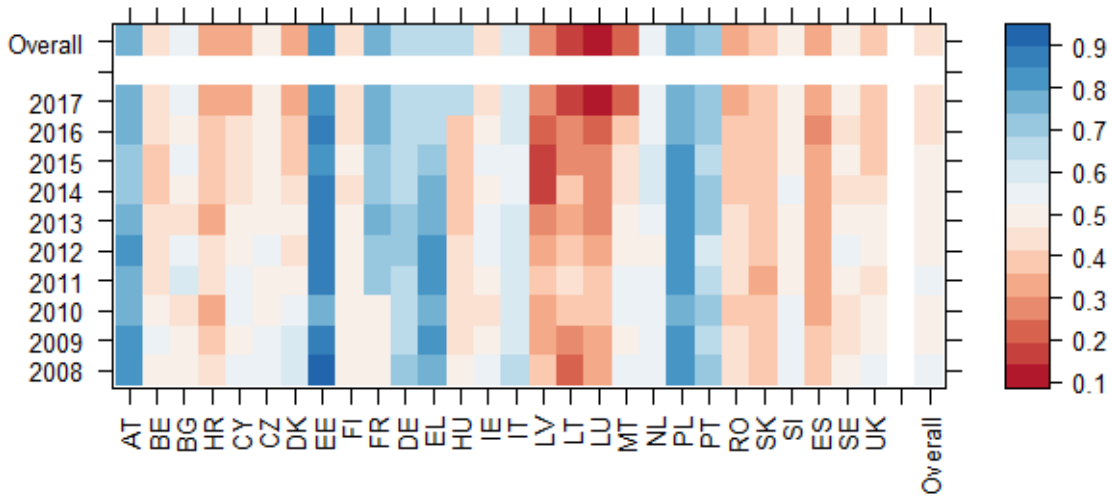

Figure 5.8 The level plot of yearly system efficiencies across countries (2008-2017).

A review at the jitters in Figure 5.7 shows that the performance of most countries differs yearly. Hungary, for example, had an average efficiency of 0.4223. However, Hungary saw system efficiency as high as 0.6281 in 2017, which shows large improvement over the previous years' scores. To trace the yearly progress in resource efficiency and sustainable electricity generation, in Figure 5.8, a level plot of the individual country and EU-wide (average) system efficiencies over time is presented. From the level plot, it is evident that countries like Austria, Estonia and Poland

have maintained higher efficiency scores in the 0.7 to 1 range. Other countries like Latvia, Lithuania and Luxembourg have had scores in the lower end of the scale over the years. When scores of the 28 countries are averaged, it can be observed that resource efficiency and sustainable electricity generation in the EU have been within the 0.4 to 0.6 range with no clear pattern towards performance improvement.

Sub-process efficiency

To understand the source of the system efficiencies, it is important to decompose the system efficiencies. Decomposition is done from the optimal multipliers using the equations in (5.14). The decomposition of the 2017 system efficiencies is presented in Table 5.4. Each country's system efficiency is decomposed into the sub-system efficiencies. It is important to remember that the system efficiency is a weighted average of the sub-system efficiencies where the weights are the ratio of the resource consumption in a specific sub-process to the overall system-wide resource consumption (Kao, 2012, 2014a,c).

From Table 5.4 Lithuania, for example, has a very low system efficiency of 0.1620. However, a closer look at the decomposition shows clearly that the country's sustainable production problem has nothing to do with its oil-fuelled power plants as it is a leader in this technology (1.0000). It also has a relative advantage in generating power from renewable biomass (0.4148). Its lower efficiency in generating power using hydroelectricity and solar is the primary cause of the lower 2017 performance levels. The implication is that other countries use lower units of inputs to generate higher levels of clean electricity using these technologies than Lithuania does. For hydroelectricity as an example, Austria is the leader in sustainable and resource efficient production. It is also possible to examine at the technology level which other countries are higher performers.

Table 5.4 Decomposition of system efficiencies (2017).

Country	System	Decomposition										
		Solid Fuels	Oil	Gas	Nuclear	Hydro	Wind	Ren. Biomass	Solar	Geo thermal	Tide	Waste & NR Bio
AT	0.7684	0.4901	0.3769	0.7719	n.a.	0.9271	0.7019	0.4811	0.4145	0.0001	n.a.	0.6064
BE	0.4173	0.0030	0.0071	1.0000	0.7905	0.1172	0.2770	0.5439	0.1087	n.a.	n.a.	0.3267
BG	0.5217	0.9847	0.3243	0.2948	0.2481	0.1052	0.2566	0.2213	0.1615	n.a.	n.a.	n.a.
HR	0.3148	0.5843	0.2518	0.5054	n.a.	0.0372	0.2356	0.2461	0.0996	n.a.	n.a.	n.a.
CY	0.3175	n.a.	0.3302	n.a.	n.a.	n.a.	0.0001	0.0052	0.0374	n.a.	n.a.	n.a.
CZ	0.4685	0.7270	0.0397	0.3696	0.2406	0.1600	0.2256	0.2650	0.1263	n.a.	n.a.	0.1330
DK	0.3155	0.9934	0.4876	0.5195	n.a.	0.0009	0.2220	0.0007	0.0269	n.a.	n.a.	0.0147
EE	0.8415	1.0000	0.5034	0.5683	n.a.	0.0002	0.2456	0.8716	n.a.	n.a.	n.a.	0.1876
FI	0.4204	0.2414	0.0078	0.1327	0.8932	0.5390	0.2800	1.0000	0.0695	n.a.	n.a.	0.2738
FR	0.7371	0.5804	0.3941	0.7268	0.8336	0.6249	0.6826	0.2699	0.4144	0.0271	0.3130	0.4734
DE	0.6605	0.9265	0.2124	0.6027	0.5774	0.3115	0.7295	0.7051	0.3892	0.0252	n.a.	0.2882
EL	0.6805	0.7074	0.5867	1.0000	n.a.	0.0016	0.1890	0.0104	0.1369	n.a.	n.a.	n.a.
HU	0.6281	0.6474	0.0248	0.5563	0.8751	0.1464	0.8574	0.3888	0.3776	0.0055	n.a.	0.6556
IE	0.4561	0.5748	0.1489	0.5695	n.a.	0.0744	0.2104	0.0002	0.0014	n.a.	n.a.	0.0953
IT	0.5945	0.7261	0.3498	0.8639	n.a.	0.4098	0.5639	0.2847	0.5180	1.0000	n.a.	0.3766
LV	0.2994	0.0001	0.0029	0.8183	n.a.	0.2399	0.2271	0.4115	0.0213	n.a.	n.a.	n.a.
LT	0.1620	n.a.	1.0000	0.2226	n.a.	0.0064	0.2903	0.4148	0.0694	n.a.	n.a.	0.2253
LU	0.1375	n.a.	0.0003	0.2843	n.a.	0.1219	0.2339	0.6112	0.1010	n.a.	n.a.	0.3232
MT	0.2451	n.a.	0.2970	0.2483	n.a.	n.a.	0*	0.0018	0.0327	n.a.	n.a.	n.a.
NL	0.5589	0.3292	0.1847	1.0000	0.0278	0.0191	0.2777	0.0113	0.0811	n.a.	n.a.	0.0044
PL	0.7759	0.9165	0.2699	0.4867	n.a.	0.1436	0.3022	0.0145	0.0470	n.a.	n.a.	0.0799
PT	0.7060	0.9312	0.8704	0.8708	n.a.	0.3521	0.9268	0.3389	0.6338	0.2884	0*	0.1582
RO	0.3323	0.4508	0.1888	0.4578	0.2514	0.2648	0.2913	0.0202	0.1605	n.a.	n.a.	0.0000
SK	0.3841	0.2878	0.0644	0.2903	0.7877	0.2188	0.1712	0.5296	0.1144	n.a.	n.a.	0.0224
SI	0.4672	0.8017	0.0073	0.1875	0.6629	0.3671	0.1268	0.2461	0.1371	n.a.	n.a.	0.0102
ES	0.3078	0.3141	0.4275	0.6789	0.2761	0.1252	0.2537	0.0546	0.2437	n.a.	n.a.	0.0920
SE	0.4688	0*	0.0030	0.0220	0.8189	0.4716	0.3180	1.0000	0.1116	n.a.	n.a.	0.4843
UK	0.3566	0.1285	0.0180	0.8139	0.6049	0.2270	0.3009	0.8956	0.1076	n.a.	0.0036	0.1277
Geomean	0.4351	0.2080	0.0911	0.4454	0.4357	0.0888	0.1344	0.1079	0.1046	0.0205	0.0031	0.0891

n.a. the country does not produce electricity using this sub-process
** near-zero value*

5.6 Chapter summary

This chapter presents optimisation models used to empirically examine cross-country performance assessment in gross electricity production and emissions reduction. It also presents the results of the decomposition of the overall performance to generation source-level performances of 28 EU countries. It is shown in this chapter that where there exists non-homogeneity in the combination of sub-processes across DMUs in a parallel network DEA model, there is potential for inaccuracies in the system and process efficiency scores. DEA-based optimisation models that provide a cross-country performance assessment of electricity production in the presence of different country-specific portfolio of generation sources are developed. Specifically, two new optimisation approaches for handling sub-process non-homogeneity are developed and compared with the parallel network model without such corrections. These novel models allow for a better allocation of split factors across sub-processes, therefore, correcting the potential overestimation of efficiencies as a result of artificially smaller inputs from allocation of inputs to non-existing sub-processes. Additionally, the potential for non-existing sub-processes to be assigned efficiency scores have been solved.

An empirical application of the models is conducted using data on the 28 EU countries as of the end of 2017. Previous studies have either conducted a country-wide assessment of sustainable and resource efficient electricity production without considering the sub-systems in the country or conducted sub-system assessment of one type of production technology in a single country or across countries. However, this empirical assessment incorporates multiple production technologies and multiple countries in one performance assessment framework.

Chapter 6

Sustainable Electricity Consumption

6.1 Introduction

The demand-side of the energy system has been long at the forefront of policy on energy and the environment. Perhaps the most widely known energy policy is energy efficiency, which is the need to ensure less energy consumption in generating economic outputs (Feng and Wang, 2017; Honma and Hu, 2008; Zaim et al., 2017). Energy efficiency, together with the diversification of energy supply into renewable sources, are the main strategies driving sustainable energy policy (Prindle et al., 2007). There is a wide range of policies and directives aimed at ensuring access to clean and cheap energy required to ensure both economic and social development (EEA, 2017; Hadian and Madani, 2015; Kazagic et al., 2014; United Nations, 2015; Volkart et al., 2018). Consequently, the aim of assessment at the use phase of the energy system aims at examining how energy is used for both economic and social purposes while minimising the impact on the environment.

This chapter examines the performance of the EU countries in consuming energy and ensuring economic productivity and social development while minimising environmental impact. In this regard, the assessment integrates eco-efficiency assessment, social development assessment and environmental impact assessment in a single assessment framework. This is achieved using a multi-stage network assessment approach which links these three policy areas in a manner that shows their close relationship and complementarity.

The first stage of the assessment is dedicated to social development where countries are benchmarked on their ability to ensure better welfare for citizens.

At this stage, this thesis differs from existing research in two main ways. First, electricity consumption at the household level is modelled as an input required for higher human development and welfare. There is a plethora of evidence to support the fact that countries with a secure supply of power tend to have higher social performance in terms of health, literacy, employment, income, among others (Dias et al., 2006; European Commission, 2007; Gaye, 2007; Johansson et al., 2012; Ouedraogo, 2013). However, existing research does not incorporate energy as an input in social development assessment (Freire et al., 2018; Hou et al., 2015; Ülengin et al., 2011; Mariano et al., 2015). Consequently, an electricity/energy development index is proposed as a measure of social development. Second, while the HDI has been widely used for such assessment, it only measures education attainment, income and health (Freire et al., 2018; Hou et al., 2015). This study, therefore, proposes the inclusion of employment as an important factor to be maximised in social development assessment.

The second stage of the assessment pertains to economic development assessment. Here factors of production, namely labour, capital and energy, are consumed in generating economic outputs. However, environmental emissions are a by-product of increased economic productivity. While assessment in this phase has been widely studied in the literature (Lu and Lu, 2019; Mavi et al., 2019; Robaina-Alves et al., 2015), the novel contribution of this thesis is how this assessment is linked to social development phase and environmental performance assessment together with the electricity generation phase. Specifically, while the labour input in the economic development phase is an important output in the social development phase, the environmental emissions output which is in a joint production with economic outputs is an input in the environmental performance assessment. Finally, energy is separated into electric energy and other primary fuels. The link between the electricity generation system and the energy input for economic productivity is also studied.

The final stage of the multi-stage assessment is dedicated to environmental performance analysis. Environmental performance studies in the literature are based on the modelling of environmental output in the economic development phase (Mavi et al., 2019; Sueyoshi and Goto, 2015) or the abatement of some environmental factors in the second stage of eco-efficiency assessment (Wang et al., 2018). However, this study proposes the use of the relationship between ecological footprint and bio-capacity for studying the performance of countries in terms of their environmental performance. Specifically, emissions from economic productivity together with emissions from electricity production are modelled as undesirable inputs in this

phase. The output considered is bio-capacity, which is nature's bio-productivity or capacity to contain the human impact on the environment (Siche et al., 2008). Sustainability implies minimising the ecological footprint and maximising the bio-capacity of countries (DiMaria, 2019; Geng et al., 2014). As emissions, specifically carbon footprint, is an important component of the ecological footprint (DiMaria, 2019; Geng et al., 2014), the environment performance assessment aims at minimising such emissions given the bio-capacity of countries under investigation.

It is important to note that the three stages highlighted above are the three dimensions of Elkington's (1997) triple bottom line of sustainability – social, economic and environmental objectives. Therefore, the overall score that incorporates all three stages can be seen as a measure of sustainable use of electricity. Generating an aggregate measure across these three phases also provides an opportunity to study the difference in aggregation based on a weaker form of sustainability, where dimensions are allowed to be compensated when they reduce in stock or a stronger form of sustainability which does not allow for compensation between dimensions (Bonevac, 2010; Gallopín, 2003; Kuhlman and Farrington, 2010; Pearce and Atkinson, 1998; Turner, 1993). Specifically, the use of the additive and multiplicative composition of the overall system performance measures across the three phases provide another interesting area of assessment.

Finally, this sustainability assessment in the use phase of the energy system is combined with the sustainability assessment in the generation phase captured in the previous chapter. As a result, an integrated model that provides a cross-country holistic performance assessment of the generation and consumption phases of the energy system, which incorporates differences in generating portfolio of countries at the generation phase, and eco-socio-environmental interrelationships at the use phase is proposed and empirically applied. This assessment, therefore, captures policy issues relating to energy security and clean energy, which are essential components of the energy trilemma- clean, secure and affordable energy (Jovanović et al., 2010).

In addressing these issues, the remainder of the chapter is organised as follows: Section 6.2 provides a brief overview of policy considerations and extant literature on energy and economic, social and environmental performance. This is then followed by Section 6.3 which provides an overview of methods and models to be used for the development of empirical models that integrates the three sustainability phases. Section 6.4 is dedicated to the analysis of empirical data and the presentation of findings and discussions. This section is divided into two main sub-sections. Sub-section 6.4.1 integrates the social, economic and environmental assessment in a single framework. Here the concepts of weak and strong sustainability are explored

while aggregating of the three dimensions. Sub-section 6.4.2 then integrates the generation and consumption phases of the energy system in one assessment. Finally, Section 6.5 provides conclusions and chapter summary.

6.2 Sustainability and electricity consumption

Policy on sustainable development has always had close links with the energy sector. Although there is a clear SDG on access to affordable, reliable, sustainable and modern energy for all (SDG 7) (United Nations, 2015; Volkart et al., 2018), several remaining SDGs including climate action (SDG 13), responsible consumption and production (SDG 12), good health and well-being (SDG 3), among others have a clear link with sustainable energy system (United Nations, 2015). Therefore, the main energy policy objectives for sustainable energy include demand-side issues like provision of equitable and affordable access, which ensures the security of energy supply and environmental sustainability (Štreimikienė et al., 2012). In this section, a brief overview of energy and the economy, society and environment is presented.

6.2.1 Energy and economic development

Energy is a critical input for economic development (Mondal and Denich, 2010; Shaaban and Scheffran, 2017) as access to reliable power ensures poverty reduction and industrial productivity (Fouquet, 2016). Karanfil and Li (2015), for example, show the various causal mechanisms that explain the relationship between energy and economic development. Environmental Kuznets curve and pollution haven hypothesis have also explored energy consumption, carbon emissions and economic development (Sarkodie and Strezov, 2019; Zaman and Moemen, 2017). In the performance assessment literature, research linking energy and the environment have been based on TFEE assessment (Hu and Wang, 2006; Zhang et al., 2011) or eco-efficiency assessment (Camarero et al., 2014, 2013; Rybaczewska-Błażejowska and Masternak-Janus, 2018). Although these streams of literature use similar variables, their focuses are slightly different. While TFEE examines the energy-saving potential in generating economic outputs (Zhang et al., 2011), eco-efficiency assessment measures the ability to produce more economic outputs while minimising resource use and environmental impacts (Camarero et al., 2014; Huppes and Ishikawa, 2005).

6.2.2 Energy and social development

The availability of reliable energy fosters the development of social systems and expectations such as health, education, employment and quality of life. Empirical evidence, based on UN data, provided in Figure 2.3 in Chapter 2, shows a strong positive association between electricity consumption and income, employment, health and literacy. Policy and performance assessment linking society and energy have primarily been towards social acceptance of generation sources and social impact of energy generation (Afgan and Darwish, 2011; Chatzimouratidis and Pilavachi, 2009; Duan et al., 2011; European Commission, 2007; Frangopoulos and Keramioti, 2010; Pilavachi et al., 2006; Rovere et al., 2010). There is a separate stream of literature which assesses social development using social indicators such as the HDI (Freire et al., 2018; Ülengin et al., 2011; Mariano et al., 2015; Ouedraogo, 2013). However, such literature does not consider energy consumption as a relevant input, although there is empirical evidence of an association between energy consumption and social development. Another stream of energy research that is based on the HDI is the EDI developed by the IEA as a measure to track the progress of countries in the use of modern energy and better understand the role energy plays in human development (Johansson et al., 2012). However, this measure does not include any measure of social development inspite of being created to mirror the HDI. As energy is a key input to development and human well-being cannot be advanced without access to electricity (Johansson et al., 2012), energy must be incorporated in the assessment of social development.

6.2.3 Energy and environmental performance

The relationship between the energy system and the environment is well understood in the literature. Energy-related activities require resource consumption from the environment and also produce negative externalities harmful to the environment (Lu et al., 2016; Varun et al., 2009). Consequently, sustainable development requires that affordable and reliable energy is derived from environmentally appropriate supply sources (Afgan et al., 2007). This requires continuous monitoring of emissions given the capacity of the environment to absorb such emissions. In the performance assessment literature, such environment performance assessment are usually conducted within the traditional productive efficiency analysis (Coelli et al., 2007) where environmental factors are captured as undesirable outputs as a by-product of other desirable factors (Bevilacqua and Braglia, 2002; Bi et al., 2014; Chang et al., 2013). Such analysis, therefore, looks at environmental efficiency as ensuring

minimum feasible environmental outputs from the use of multiple environmentally detrimental inputs (Reinhard et al., 2000). However, sustainable development from the environmental point of view is discussed as a relationship between ecological footprint and bio-capacity. Countries with a higher biological capacity to contain pollution are seen to be more sustainable than those with higher ecological footprint relative to their biological capacity (DiMaria, 2019; Geng et al., 2014). It is possible, therefore, to conduct a separate environmental performance assessment that uses emissions from various economic and industrial sources as inputs to be minimised given the bio-capacity of the countries in question. This is the approach adopted in this thesis.

6.3 Methods and modelling

6.3.1 Multi-stage network DEA

As earlier indicated, there exist links between the sub-systems studied in this chapter in the form of intermediate inputs and outputs. Where outputs of one sub-process are consumed by other sub-processes, there exist a series or a multi-stage network problem. The general multi-stage series structure shown in Figure 3.3 is replicated as follows:

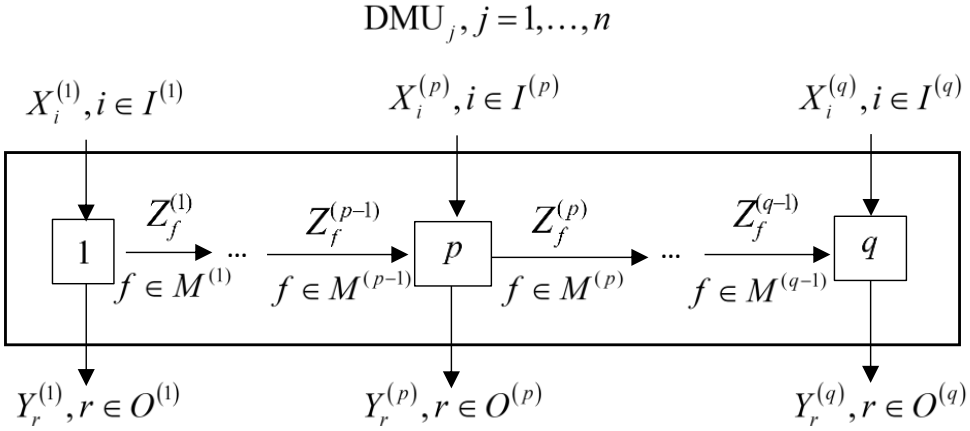

Figure 6.1 General multi-stage series structure.

Source: Kao (2014a, pg. 7)

Here, $X_i^{(p)}, i \in I^{(p)}$ represents exogenous inputs from outside the system under investigation but are consumed by sub-processes p. $Y_r^{(p)}, r \in O^{(p)}$ are outputs produced by sub-process p but are not consumed by other sub-processes. Finally,

$Z_f^{(p)}, f \in M^{(p)}$ are intermediate factors produced (consumed) by sub-processes and consumed (produced) by sub-process p. Given these factors, the efficiency of a sub-process p can be computed as:

$$E_o^{(p)} = \max \ \frac{\sum_{r \in O^{(p)}} u_r Y_{ro}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fo}^{(p)}}{\sum_{i \in I^{(p)}} v_i X_{io}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fo}^{(p-1)}} \tag{6.1a}$$

$$\text{s.t.} \quad \frac{\sum_{r \in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fj}^{(p)}}{\sum_{i \in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fj}^{(p-1)}} \leq 1\,, \quad j = 1, 2, \ldots, n \tag{6.1b}$$

$$u_r, v_i, w_f \geq \varepsilon, \ \ r = 1, ..., s, \quad i = 1, ..., m, \ \ f = 1, \ldots, h$$

Each sub-process will have a similar model as a measure of its efficiency, except that sub-system 1 will have no intermediate input and sub-system q will have no intermediate output. Note that the multiplier for an intermediate measure is assumed to be the same whether it is used as an input or output (Kao and Hwang, 2008) since the price of the factor, on the market, remains the same irrespective of how it is used in the system (Kao, 2012). The sub-process efficiencies must then be combined in a way that characterise the efficiency of the system. Various series structure models were reviewed in Section 3.3.1 of this thesis.

In this chapter, the centralised or cooperative model (Liang et al., 2008) is used since no leader-follower relationship is assumed to exist between social, economic and environmental aspects of sustainability. An 'anthropocentric' assessment may give preference to economic and social sub-processes since it assumes nature exists to satisfy human needs (Baumgärtner and Quaas, 2010). On the other hand, 'bio-centric or eco-centric viewpoints' see the environment as the ethical precondition for sustainability even at the point of excluding humans or increasing human poverty and may give preference to the environmental sub-system (Gallopín, 2003). As nature and humans have inescapable biological interdependence (Becker, 2006), the centralised model which requires no *a priori* preference for a particular sub-process is employed. Two approaches for combining or decomposing the system efficiencies are employed in this study. These are presented in the next sub-sections.

Additive decomposition

The additive decomposition approach proposed by Chen et al. (2009) and Cook, Zhu, Bi and Yang (2010) define the system efficiency as a weighted additive average of the sub-system efficiencies. Therefore, system efficiency is a linear convex combination of the q sub-system efficiencies $E_o = \sum_{p=1}^{q} \omega^{(p)} E_o^{(p)}$ given that $\sum_{p=1}^{q} \omega^{(p)} = 1$. The weight of the sub-system could be exogenously determined, however, Cook, Zhu, Bi and Yang (2010) suggest weighting the sub-processes by the proportion of their resource consumption to the system's resource consumption. In that case, the weight of sub-systems will be determined as:

$$\omega^{(1)} = \sum_{i \in I^{(1)}} v_i X_{io}^{(1)} \Big/ \left(\sum_{i \in I^{(1)}} v_i X_{io}^{(1)} + \sum_{p=2}^{q-1} \left(\sum_{i \in I^{(p)}} v_i X_{io}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fo}^{(p-1)} \right) + \sum_{i \in I^{(q)}} v_i X_{io}^{(q)} + \sum_{f \in M^{(q-1)}} w_f Z_{fo}^{(q-1)} \right) \tag{6.2a}$$

$$\omega^{(p)} = \left(\sum_{i \in I^{(p)}} v_i X_{io}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fo}^{(p-1)} \right) \Big/ \left(\sum_{i \in I^{(1)}} v_i X_{io}^{(1)} + \sum_{p=2}^{q-1} \left(\sum_{i \in I^{(p)}} v_i X_{io}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fo}^{(p-1)} \right) + \sum_{i \in I^{(q)}} v_i X_{io}^{(q)} + \sum_{f \in M^{(q-1)}} w_f Z_{fo}^{(q-1)} \right) \quad p = 2, ..., q-1 \tag{6.2b}$$

$$\omega^{(q)} = \left(\sum_{i \in I^{(q)}} v_i X_{io}^{(q)} + \sum_{f \in M^{(q-1)}} w_f Z_{fo}^{(q-1)} \right) \Big/ \left(\sum_{i \in I^{(1)}} v_i X_{io}^{(1)} + \sum_{p=2}^{q-1} \left(\sum_{i \in I^{(p)}} v_i X_{io}^{(p)} + \sum_{f \in M^{(p)}} w_f Z_{fo}^{(p-1)} \right) + \sum_{i \in I^{(q)}} v_i X_{io}^{(q)} + \sum_{f \in M^{(q-1)}} w_f Z_{fo}^{(q-1)} \right) \tag{6.2c}$$

If these weights are applied on the sub-system efficiency ratios as shown in (6.1), then the additive system efficiency of a DMU can be expressed as:

$$E_0 = \max \quad \sum_{r\in O^{(1)}} u_r Y_{ro}^{(1)} + \sum_{f\in M^{(1)}} w_f Z_{fo}^{(1)} + \sum_{p=2}^{q-1} \left(\sum_{r\in O^{(p)}} u_r Y_{ro}^{(p)} + \sum_{f\in M^{(p)}} w_f Z_{fo}^{(p)} \right) + \sum_{r\in O^{(q)}} u_r Y_{ro}^{(q)} \tag{6.3a}$$

$$\text{s.t.} \quad \sum_{i\in I^{(1)}} v_i X_{io}^{(1)} + \sum_{p=2}^{q-1} \left(\sum_{i\in I^{(p)}} v_i X_{io}^{(p)} + \sum_{f\in M^{(p)}} w_f Z_{fo}^{(p-1)} \right) + \sum_{i\in I^{(q)}} v_i X_{io}^{(q)} + \sum_{f\in M^{(q-1)}} w_f Z_{fo}^{(q-1)} = 1 \tag{6.3b}$$

$$\left(\sum_{r\in O^{(1)}} u_r Y_{rj}^{(1)} + \sum_{f\in M^{(1)}} w_f Z_{fj}^{(1)} \right) - \sum_{i\in I^{(1)}} v_i X_{ij}^{(1)} \le 0 \qquad j = 1, 2, \ldots, n \tag{6.3c}$$

$$\left(\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{f\in M^{(p)}} w_f Z_{fj}^{(p)} \right) - \left(\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{f\in M^{(p)}} w_f Z_{fj}^{(p-1)} \right) \le 0 \quad p = 2, \ldots, q-1, \;\; j = 1, 2, \ldots, n \tag{6.3d}$$

$$\sum_{r\in O^{(q)}} u_r Y_{rj}^{(q)} - \left(\sum_{i\in I^{(q)}} v_i X_{ij}^{(q)} + \sum_{f\in M^{(q-1)}} w_f Z_{fj}^{(q-1)} \right) \le 0 \quad j = 1, 2, \ldots, n \tag{6.3e}$$

$$u_r, v_i, w_f \ge \varepsilon, \;\; r = 1, ..., s, \;\; i = 1, ..., m, \;\; f = 1, \ldots, h \tag{6.3f}$$

The objective can be replaced by $\sum_{r=1}^{s} u_r Y_{ro} + \sum_{f=1}^{h} w_f Z_{fo}$, while the left-hand side of the first constraint could be: $\sum_{i=1}^{m} v_i X_{io} + \sum_{f=1}^{h} w_f Z_{fo}$. As this decomposition of the system efficiency is additive, the system efficiency measure allows compensation between sustainability dimensions akin to the idea of weak sustainability. The sub-process efficiencies can be computed from the optimal multipliers u_r^*, v_i^* and w_f^*, as:

$$E_o^{(a1)*} = \frac{\sum_{r\in O^{(1)}} u_r^* Y_{ro}^{(1)} + \sum_{f\in M^{(1)}} w_f^* Z_{fo}^{(1)}}{\sum_{i=1}^{m} v_i^* X_{io}^{(1)}} \tag{6.4a}$$

$$E_o^{(ap)*} = \frac{\sum\limits_{r\in O^{(p)}} u_r^* Y_{ro}^{(p)} + \sum\limits_{f\in M^{(p)}} w_f^* Z_{fo}^{(p)}}{\sum\limits_{i\in I^{(p)}} v_i^* X_{io}^{(p)} + \sum\limits_{f\in M^{(p-1)}} w_f^* Z_{fo}^{(p-1)}}, \qquad p = 2, \ldots, q-1 \tag{6.4b}$$

$$E_o^{(aq)*} = \frac{\sum\limits_{r\in O^{(q)}} u_r^* Y_{ro}^{(q)}}{\sum\limits_{i\in I^{(q)}} v_i^* X_{io}^{(q)} + \sum\limits_{f\in M_I^{(q-1)}} w_f^* Z_{fo}^{(q-1)}} \tag{6.4c}$$

Multiplicative decomposition

Kao and Hwang (2008) proposed a multiplicative decomposition of the system efficiency in the two-stage serial network structure as a product of the sub-system efficiencies. Their system was based on the closed system two-stage structure where stage two only consumes the outputs of stage one, while stage one produces no exogenous outputs (Cook, Zhu, Bi and Yang, 2010). They later proposed a relational model for multi-stage serial networks as presented in Figure 6.1, which is an extension of their multiplicative decomposition (Kao, 2014a).

This is achieved by transforming the multi-stage network into a series of parallel structures where the product of the modified stage efficiencies represents the system efficiency. The transformed multi-stage network for Figure 6.1 is shown in Figure 6.2. This is achieved by introducing a dummy parallel sub-process for each of the stages in Figure 6.1 to capture the inputs and outputs of the intermediate processes (Kao, 2009a).

In Figure 6.2, the dummy sub-processes are represented by the shaded nodes. Dummy sub-process p' captures all exogenous inputs yet to be consumed by subsequent sub-processes and exogenous outputs already produced by previous sub-processes. These inputs and outputs are not attributable to sub-process p. For example at p', from Figure (6.2), exogenous inputs to be consumed by subsequent sub-processes include the inputs for sub-processes $p+1$ and all subsequent sub-processes until the final sub-process q. Outputs produced by previous sub-processes, which are not attributable to sub-process p, include outputs produced by sub-process 1 until sub-process $p-1$. For the dummy sub-process, the inputs are the same as the outputs and consequently, the constraints for these sub-processes are redundant.

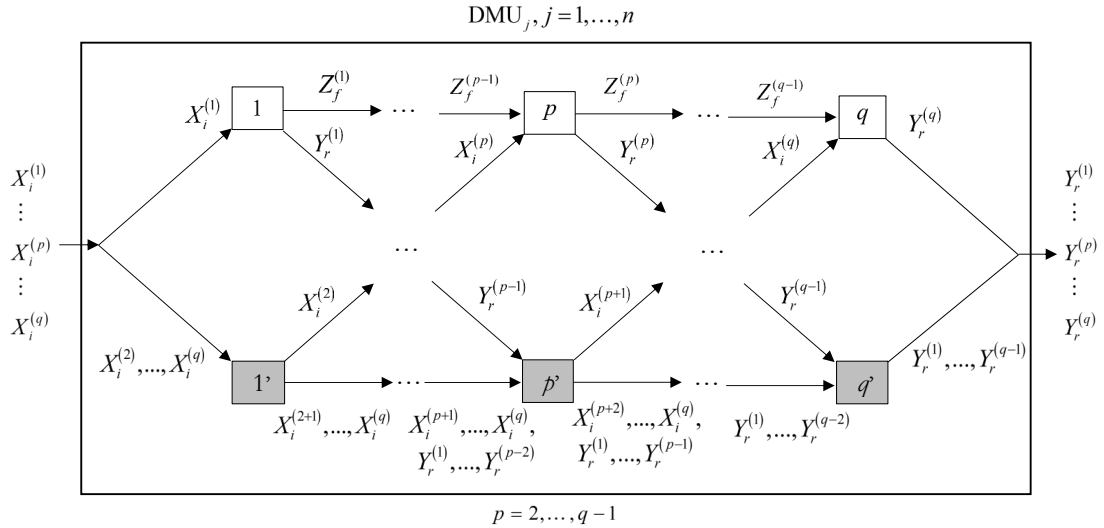

Figure 6.2 Transformation of the multi-stage network in Figure 6.1 to a series of parallel networks.

Model (6.5) shows the constraints for the dummy sub-processes $1'$, p' and q'. Note that $j = 1,\ldots,n$ and $p = 1,\ldots,q$.

$$\sum_{p=2}^{q-1}\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{i\in I^{(q)}} v_i X_{ij}^{(q)} \le \sum_{p=2}^{q-1}\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{i\in I^{(q)}} v_i X_{ij}^{(q)} \tag{6.5a}$$

$$\sum_{p=1}^{p-1}\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{p+1}^{q}\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)} \le \sum_{p=1}^{p-1}\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{p+1}^{q}\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)} \tag{6.5b}$$

$$\sum_{p=1}^{q-1}\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)} \le \sum_{p=1}^{q-1}\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)} \tag{6.5c}$$

For each parallel sub-process, the efficiency of the dummy sub-process will be unity since inputs are the same as the outputs. In parallel network models, the efficiency of the system is a weighted average of the sub-process efficiencies (Kao, 2009b, 2012), so the efficiency of each of the new parallel system will be a weighted average of the real and the dummy sub-processes efficiencies (Kao, 2014a).

Constraints must be imposed to ensure that sub-system efficiency are not greater than one:

$$\left(\sum_{r\in O^{(1)}} u_r Y_{rj}^{(1)} + \sum_{f\in M^{(1)}} w_f Z_{fj}^{(1)} + \sum_{p=2}^{q-1}\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{i\in I^{(q)}} v_i X_{ij}^{(q)}\right) - \left(\sum_{i\in I^{(1)}} v_i X_{ij}^{(1)} + \sum_{p=2}^{q-1}\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{i\in I^{(q)}} v_i X_{ij}^{(q)}\right) \leq 0 \qquad j = 1, 2, \ldots, n \tag{6.6a}$$

$$\left(\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{f\in M^{(p)}} w_f Z_{fj}^{(p)} + \sum_{p=1}^{p-1}\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{p+1}^{q}\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)}\right) - \left(\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{f\in M^{(p)}} w_f Z_{fj}^{(p-1)} + \sum_{p=1}^{p-1}\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{p+1}^{q}\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)}\right) \leq 0$$
$$p = 2, \ldots, q-1, \; j = 1, 2, \ldots, n \tag{6.6b}$$

$$\left(\sum_{r\in O^{(q)}} u_r Y_{rj}^{(q)} + \sum_{p=1}^{q-1}\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)}\right) - \left(\sum_{i\in I^{(q)}} v_i X_{ij}^{(q)} + \sum_{f\in M^{(q-1)}} w_f Z_{fj}^{(q-1)} + \sum_{p=1}^{q-1}\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)}\right) \leq 0 \qquad j = 1, 2, \ldots, n \tag{6.6c}$$

If identical elements are removed from each of the constraints in (6.6) and the redundant constraints in (6.5) are removed, system efficiency using the multiplicative decomposition can be computed using the LP model:

$$E_0 = \max \quad \sum_{r\in O^{(1)}} u_r Y_{ro}^{(1)} + \sum_{r\in O^{(p)}} u_r Y_{ro}^{(p)} + \sum_{r\in O^{(q)}} u_r Y_{ro}^{(q)} \tag{6.7a}$$

$$\text{s.t.} \quad \sum_{i\in I^{(1)}} v_i X_{io}^{(1)} + \sum_{i\in I^{(p)}} v_i X_{io}^{(p)} + \sum_{i\in I^{(p)}} v_i X_{io}^{(q)} = 1 \tag{6.7b}$$

$$\left(\sum_{r\in O^{(1)}} u_r Y_{rj}^{(1)} + \sum_{f\in M^{(1)}} w_f Z_{fj}^{(1)}\right) - \sum_{i\in I^{(1)}} v_i X_{ij}^{(1)} \le 0 \quad j = 1, 2, \ldots, n \tag{6.7c}$$

$$\left(\sum_{r\in O^{(p)}} u_r Y_{rj}^{(p)} + \sum_{f\in M^{(p)}} w_f Z_{fj}^{(p)}\right) - \left(\sum_{i\in I^{(p)}} v_i X_{ij}^{(p)} + \sum_{f\in M^{(p)}} w_f Z_{fj}^{(p-1)}\right) \le 0$$
$$p = 2, \ldots, q-1, \;\; j = 1, 2, \ldots, n \tag{6.7d}$$

$$\sum_{r\in O^{(q)}} u_r Y_{rj}^{(q)} - \left(\sum_{i\in I^{(q)}} v_i X_{ij}^{(q)} + \sum_{f\in M^{(q-1)}} w_f Z_{fj}^{(q-1)}\right) \le 0$$
$$j = 1, 2, \ldots, n \tag{6.7e}$$

$$u_r, v_i, w_f \ge \varepsilon, \;\; r = 1, ..., s, \;\; i = 1, ..., m, \;\; f = 1, \ldots, h \tag{6.7f}$$

The objective function can be replaced by $\sum_{r=1}^{s} u_r Y_{ro}$, while the left-hand side of the first constraint could be: $\sum_{i=1}^{m} v_i X_{io}$. From this, the efficiency ratio of each of the new parallel sub-systems can be determined as:

$$E_o^{(m1)*} = \frac{\sum_{r\in O^{(1)}} u_r^* Y_{ro}^{(1)} + \sum_{f\in M^{(1)}} w_f^* Z_{fo}^{(1)} + \sum_{p=1}^{q-1} \sum_{i\in I^{(p)}} v_i^* X_{io}^{(p)} + \sum_{i\in I^{(q)}} v_i^* X_{io}^{(q)}}{\sum_{i\in I^{(1)}} v_i^* X_{io}^{(1)} + \sum_{p=1}^{q-1} \sum_{i\in I^{(p)}} v_i^* X_{io}^{(p)} + \sum_{i\in I^{(q)}} v_i^* X_{io}^{(q)}} \tag{6.8a}$$

$$E_o^{(mp)*} = \frac{\sum_{r\in O^{(p)}} u_r^* Y_{ro}^{(p)} + \sum_{f\in M^{(p)}} w_f^* Z_{fo}^{(p)} + \sum_{i\in I^{(q)}} v_i^* X_{io}^{(q)} + \sum_{r\in O^{(1)}} u_r^* Y_{ro}^{(1)}}{\sum_{i\in I^{(p)}} v_i^* X_{io}^{(p)} + \sum_{f\in M^{(p)}} w_f^* Z_{fo}^{(p-1)} + \sum_{i\in I^{(q)}} v_i^* X_{io}^{(q)} + \sum_{r\in O^{(1)}} u_r^* Y_{ro}^{(1)}} \quad p = 2, \ldots, q-1 \tag{6.8b}$$

$$E_o^{(mq)} = \frac{\sum_{r\in O^{(q)}} u_r^* Y_{ro}^{(q)} + \sum_{r\in O^{(p)}} u_r^* Y_{ro}^{(p)} + \sum_{r\in O^{(1)}} u_r^* Y_{ro}^{(1)}}{\sum_{i\in I^{(q)}} v_i^* X_{io}^{(q)} + \sum_{f\in M^{(q-1)}} w_f^* Z_{fo}^{(q-1)} + \sum_{r\in O^{(p)}} u_r^* Y_{ro}^{(p)} + \sum_{r\in O^{(1)}} u_r^* Y_{ro}^{(1)}} \tag{6.8c}$$

Since the efficiency of the parallel system is a weighted average of the actual sub-process and the dummy sub-process (with efficiency = 1), the efficiency of the actual sub-process in the parallel structure can be computed using (6.4). The multiplicative decomposition, therefore, treats the overall system efficiency as some form of a geometric average (Chen et al., 2009) thereby minimising the level of compensation between dimensions as required by strong sustainability advocates. R/R studio is used to solve all models and generate graphs in subsequent sections.

6.4 Empirical assessments

The empirical assessment is divided into two main sub-sections. The first concentrates the assessment on the consumption phase where social development, economic development and environmental performance assessments are conducted. The second section integrates the generation assessment in chapter 5 with the consumption assessment into a single assessment framework.

6.4.1 Social, economic and environmental performance assessment

System description – consumption system

The conceptual framework that serves as the basis for assessment in this chapter has been previously presented in Figure 4.5 of this thesis. This multi-stage network structure presented in Figure 4.5 was based on causal loop diagram developed from literature and presented in Figure 4.2. The empirical evaluation framework for this sub-section is presented in Figure 6.3.

Three sub-processes corresponding to the three dimensions of sustainability are assessed in a multi-stage network problem. For the three sub-processes, there are a total of six inputs, two intermediate factors and three outputs in the evaluation framework. Although electricity supply is depicted in Figure 4.5 as a shared input to be apportioned between social development and economic development sub-processes, in Figure 6.3, electricity consumption has been depicted as dedicated inputs to individual sub-processes. This is because in the social development sub-sector

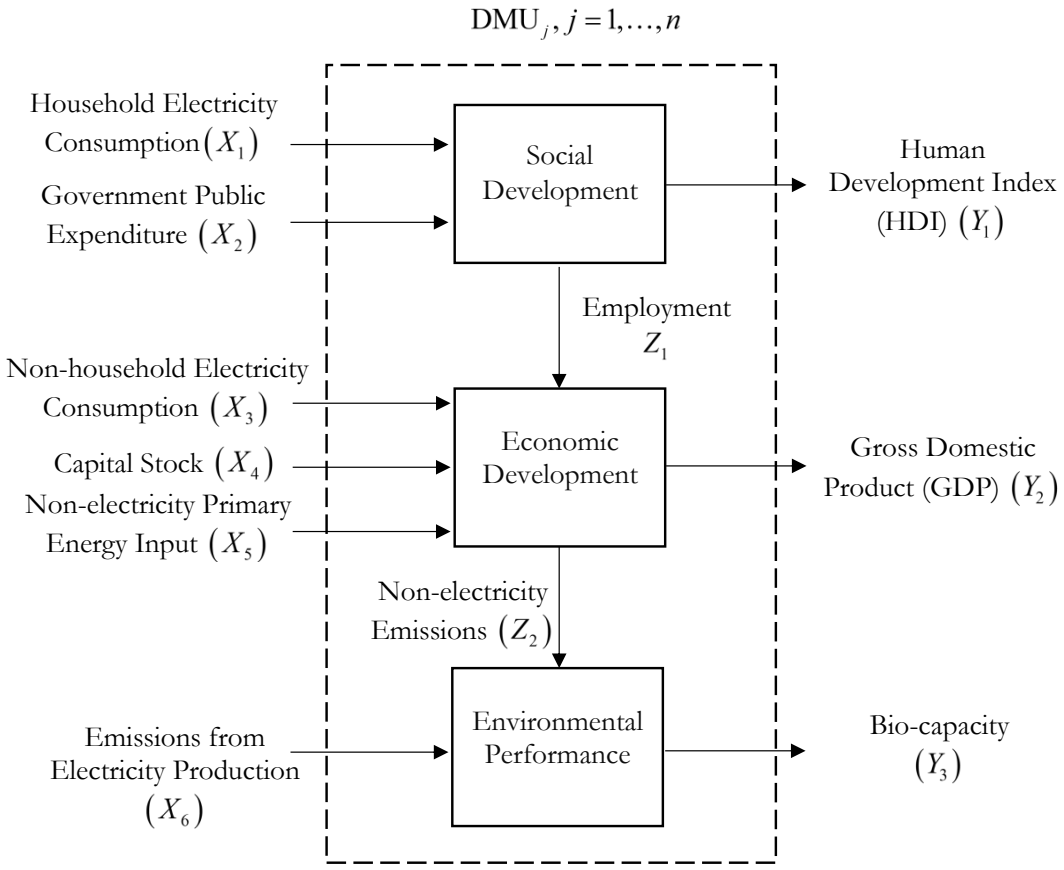

Figure 6.3 Evaluation framework of the consumption system.

only household electricity consumption is used. All other electricity consumption, including industry, transport, energy, commercial and public services, agriculture and forestry, and fishing (European Commission, 2020), have been assigned to the economic development sub-process.

Variables and data sources are summarised in Table (6.1). Household electricity consumption (X_1) and non-household electricity consumption (X_3) are measured in TWh. Government public expenditure (X_2) represents total general government expenditure on general public services, defence, public order and safety, economic affairs, environmental protection, housing and community amenities, health, recreation, culture and religion, education and social protection (Eurostat, 2019b). This variable is measured in trillions of euros. HDI (Y_1) is a standard measure of well-being, which is a composite measure comprising variables on health, education and income (Freire et al., 2018; Ouedraogo, 2013). Employment, measured in millions, represents the number of people aged 15 to 64 years employed in all economic sectors. GDP in trillions of euros is measured at 2010 exchange rates. Capital stock,

Table 6.1 Variables and data sources.

Variable	Unit	Source
Household electricity consumption (X_1)	TWh	European Commission (2020)
Government public expenditure (X_2)	Trillions of euros	Eurostat (2020)
Non-household electricity consumption (X_3)	TWh	European Commission (2020)
Capital stock (X_4)	Trillions of 2011 U.S. dollars	Penn World Tables Feenstra et al. (2015)
Non-electricity primary energy inputs (X_5)	MTOE	European Commission (2020)
Emissions from electricity production (X_6)	Mt CO_2	European Commission (2020)
Employment (Z_1)	Millions	Eurostat (2020)
Non-electricity emissions (Z_2)	Mt CO_2	European Commission (2020)
HDI (Y_1)	Unit-free	UNDP (2019)
GDP (Y_2)	Trillions of 2010 euros	European Commission (2020)
Bio-capacity (Y_2)	Global hectares	Global Footprint Network (2016)

on the other hand, is measured in trillions of dollars at 2011 U.S. dollar national prices. The non-electric primary energy inputs (X_5) represent all other primary energy inputs consumed in the country that was not used for electricity generation. These include those used in refineries, petroleum production and other relevant sectors (European Commission, 2020). Emissions data comprises that from public electricity and heat production (X_6) and that from other sectors like manufacturing and construction, transportation, agriculture and other sectors including even other non-electricity producing energy industries (Z_2). Finally, the bio-capacity, measured in global hectares, represents total productive capacity taking into consideration actual physical area, the yield factor and the appropriate equivalence factor (Global Footprint Network, 2016). For bio-capacity, since pollution affects the bio-capacity already available, the bio-capacity variable is lagged by one year. All variables except the electricity and emissions variables are normalised in the empirical assessment.

The electricity and energy consumption data, together with the emissions and GDP are sourced from the EU's 2020 energy statistics datasheets (European Com-

mission, 2020). Government public expenditure and employment data are sourced from the Eurostat database (Eurostat, 2020). HDI is sourced from the United Nations Development Programme (UNDP) database (UNDP, 2019). Finally, while the capital stock data is sourced from the Penn World Tables (Feenstra et al., 2015), bio-capacity data are sourced from the Global Footprint Network (Global Footprint Network, 2016).

Model formulation

From the system description in 6.4.1, the sub-process models for the social, economic and environmental models are formulated as follows:

$$
\begin{aligned}
E_o^{(\text{soc})} = \max \quad & u_1 Y_{1o} + w_1 Z_{1o} && \text{(6.9a)}\\
\text{s.t.} \quad & v_1 X_{1o} + v_2 X_{2o} = 1 && \text{(6.9b)}\\
& \left(u_1 Y_{1j} + w_1 Z_{1j}\right) - \left(v_1 X_{1j} + v_2 X_{2j}\right) \leq 0 \;\; j = 1, 2, \ldots, n && \text{(6.9c)}\\
& u_1, v_1, v_2, w_1 \geq \varepsilon && \text{(6.9d)}
\end{aligned}
$$

$$
\begin{aligned}
E_o^{(\text{econ})} = \max \quad & u_2 Y_{2o} + w_2 Z_{2o} && \text{(6.10a)}\\
\text{s.t.} \quad & v_3 X_{3o} + v_4 X_{4o} + v_5 X_{5o} + w_1 Z_{1o} = 1 && \text{(6.10b)}\\
& \left(u_2 Y_{2j} + w_2 Z_{2j}\right) - \left(v_3 X_{3j} + v_4 X_{4j}\right. && \text{(6.10c)}\\
& \qquad \left. + v_5 X_{5j} + w_1 Z_{1j}\right) \leq 0 \qquad j = 1, 2, \ldots, n && \text{(6.10d)}\\
& u_2, v_3, v_4, v_5, w_1 \geq \varepsilon, \;\; w_2 \text{ urs} && \text{(6.10e)}
\end{aligned}
$$

$$
\begin{aligned}
E_o^{(\text{env})} = \max \quad & u_3 Y_{3o} && \text{(6.11a)}\\
\text{s.t.} \quad & v_6 X_{6o} + w_2 Z_{2o} = 1 && \text{(6.11b)}\\
& u_3 Y_{3j} - \left(v_6 X_{6j} + w_2 Z_{2j}\right) \leq 0 \qquad j = 1, 2, \ldots, n && \text{(6.11c)}\\
& u_3 \geq \varepsilon, \;\; v_6, w_2 \text{ urs} && \text{(6.11d)}
\end{aligned}
$$

Non-electricity emission is a weakly disposable output in (6.10) as such is unrestricted in the multiplier version of the model. In the environmental sub-system

shown in (6.11), as an increase in emissions has the potential of reducing the desirable output (bio-capacity), therefore, both emissions variables are undesirable inputs in this stage as well Liu et al. (2015). As the emissions variable is an undesirable output in the economic (or electricity production) sub-system and an undesirable input in the environmental sub-system, these emissions variables satisfy the consistency condition in determining the desirability of intermediate input-output Liu et al. (2015). As these variables are weakly disposable in the primal envelopment model, they are unrestricted in the dual multiplier model.

These sub-process models, as formulated are independent of each other. It is important to link them to generate a system score and a sub-process decomposition based on optimal multipliers. Two decomposition approaches are used – multiplicative decomposition (6.12) and additive decomposition (6.15). The multiplicative model is as follows:

$$
\begin{aligned}
E_0 = \max\ & u_1 Y_{1o} + u_2 Y_{2o} + u_3 Y_{3o} && \text{(6.12a)}\\
\text{s.t.}\ & v_1 X_{1o} + v_2 X_{2o} + v_3 X_{3o} + v_4 X_{4o} + v_5 X_{5o} + v_6 X_{6o} = 1 && \text{(6.12b)}\\
& \left(u_1 Y_{1j} + w_1 Z_{1j}\right) - \left(v_1 X_{1j} + v_2 X_{2j}\right) \leq 0 \quad j = 1, 2, \ldots, n && \text{(6.12c)}\\
& \left(u_2 Y_{2j} + w_2 Z_{2j}\right) - \left(v_3 X_{3j} + v_4 X_{4j} + v_5 X_{5j} + w_1 Z_{1j}\right) \leq 0 \\
& \qquad j = 1, 2, \ldots, n && \text{(6.12d)}\\
& u_3 Y_{3j} - \left(v_6 X_{6j} + w_2 Z_{2j}\right) \leq 0 \ \ j = 1, 2, \ldots, n && \text{(6.12e)}\\
& u_1, u_2, u_3, v_1, v_2, v_3, v_4, v_5, w_1 \geq \varepsilon \ \ v_6, w_2 \text{ urs} && \text{(6.12f)}
\end{aligned}
$$

From the optimal multipliers, the efficiency decomposition based on the multiplicative decomposition is as follows:

$$
\begin{aligned}
E_o^{m(I)*} &= \frac{u_1^* Y_{1o} + w_1^* Z_{1o} + v_3^* X_{3o} + v_4^* X_{4o} + v_5^* X_{5o} + v_6^* X_{6o}}{v_1^* X_{1o} + v_2^* X_{2o} + v_3^* X_{3o} + v_4^* X_{4o} + v_5^* X_{5o} + v_6^* X_{6o}} && \text{(6.13a)}\\
E_o^{m(II)*} &= \frac{u_2^* Y_{2o} + w_2^* Z_{2o} + u_1^* Y_{1o} + v_6^* X_{6o}}{v_3^* X_{3o} + v_4^* X_{4o} + v_5^* X_{5o} + w_1^* Z_{1o} + u_1^* Y_{1o} + v_6^* X_{6o}} && \text{(6.13b)}\\
E_o^{m(III)*} &= \frac{u_3^* Y_{3o} + u_1^* Y_{1o} + u_2^* Y_{2o}}{v_6^* X_{6o} + w_2^* Z_{2o} + u_1^* Y_{1o} + u_2^* Y_{2o}} && \text{(6.13c)}
\end{aligned}
$$

This decomposition represents the efficiencies of the three parallel sub-systems with one actual sub-process and one dummy sub-processes. The efficiency of the

actual sub-processes can be determined as:

$$E_o^{m(\text{soc})*} = \frac{u_1^* Y_{1o} + w_1^* Z_{1o}}{v_1^* X_{1o} + v_2^* X_{2o}} \tag{6.14a}$$

$$E_o^{m(\text{econ})*} = \frac{u_2^* Y_{2o} + w_2^* Z_{2o}}{v_3^* X_{3o} + v_4^* X_{4o} + v_5^* X_{5o} + w_1^* Z_{1o}} \tag{6.14b}$$

$$E_o^{m(\text{env})*} = \frac{u_3^* Y_{3o}}{v_6^* X_{6o} + w_2^* Z_{2o}} \tag{6.14c}$$

Additive system efficiency is determined using:

$$E_0 = \max \; u_1 Y_{1o} + w_1 Z_{1o} + u_2 Y_{2o} + w_2 Z_{2o} + u_3 Y_{3o} \tag{6.15a}$$

$$\text{s.t.} \; v_1 X_{1o} + v_2 X_{2o} + v_3 X_{3o} + v_4 X_{4o} + v_5 X_{5o} + w_1 Z_{1o} + v_6 X_{6o} + w_2 Z_{2o} = 1 \tag{6.15b}$$

$$\left(u_1 Y_{1j} + w_1 Z_{1j}\right) - \left(v_1 X_{1j} + v_2 X_{2j}\right) \leq 0 \quad j = 1, 2, \ldots, n \tag{6.15c}$$

$$\left(u_2 Y_{2j} + w_2 Z_{2j}\right) - \left(v_3 X_{3j} + v_4 X_{4j} + v_5 X_{5j} + w_1 Z_{1j}\right) \leq 0 \quad j = 1, 2, \ldots, n \tag{6.15d}$$

$$u_3 Y_{3j} - \left(v_6 X_{6j} + w_2 Z_{2j}\right) \leq 0 \quad j = 1, 2, \ldots, n \tag{6.15e}$$

$$u_1, u_2, u_3, v_1, v_2, v_3, v_4, v_5, w_1 \geq \varepsilon \;\; v_6, w_2 \text{ urs} \tag{6.15f}$$

From the optimal multipliers, the sub-system efficiencies can be computed as follows:

$$E_o^{a(\text{soc})*} = \frac{u_1^* Y_{1o} + w_1^* Z_{1o}}{v_1^* X_{1o} + v_2^* X_{2o}} \tag{6.16a}$$

$$E_o^{a(\text{econ})*} = \frac{u_1^* Y_{2o} + w_2^* Z_{2o}}{v_3^* X_{3o} + v_4^* X_{4o} + v_5^* X_{5o} + w_1^* Z_{1o}} \tag{6.16b}$$

$$E_o^{a(\text{env})*} = \frac{u_3^* Y_{3o}}{v_6^* X_{6o} + w_2^* Z_{2o}} \tag{6.16c}$$

In the next section, a descriptions of the data and empirical findings and discussion are presented.

Data description

Input, output and intermediate factors employed in this section are summarised in Table 6.1. The summary is based on the pooled data from 2008 to 2017. The table lists the variables and descriptive statistics for each relevant sub-process.

Table 6.2 Summary statistics of variables used (2008-2017).

		mean	sd	min	max	sub-process(es)
Outputs						
HDI	Y_1	0.87	0.04	0.77	0.94	Soc
GDP	Y_2	473.94	710.64	6.37	2928.07	Econ
Bio-capacity	Y_3	3.8E+07	4.1E+07	2.6E+05	1.8E+08	Env
Inputs						
Household electricity consumption	X_1	29.16	40.94	0.57	166.13	Soc
Government public expenditure	X_2	236.13	358.93	2.57	1441.42	Soc
Non-household electricity consumption	X_3	73.68	98.32	1.14	405.69	Econ
Capital stock	X_4	2974.20	4197.55	35.69	15656.57	Econ
Non-electricity TPEI	X_5	31.16	39.19	0.00	167.11	Econ
GHG from electricity sector	X_6	41.40	65.95	0.24	336.72	Env
Intermediate Factors						
Employment	Z_1	7.68	9.92	0.16	40.48	Soc-Econ
GHG from non-electricity sectors	Z_2	125.87	165.17	1.25	671.32	Econ-Env

Soc. – social development, Econ. – economic development, Env. – environmental performance
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Average HDI of EU countries over the study period was 0.8703 (sd = 0.0391) showing countries under assessment have very high levels of health, education and income levels with low difference between countries. This is not particularly surprising as the countries are all developed economies (United Nations, 2019). However, there is considerable variation in GDP (m = 473.94, sd = 710.64) and the bio-capacity (m = 38,000,000, sd = 41,400,000). Due to the high difference in the scale of these variables, all outputs are normalised to have them in a similar range. For the inputs, more electricity is consumed for economic activities (m = 73.68, sd = 98.32) than household consumption (m = 29.16, sd = 40.94). Areas of non-household industrial consumption include industry, transport, agriculture and energy production (European Commission, 2020). Finally, when the emissions variables are compared, on average about 33% of GHG emissions are generated from electricity production. This is particularly high for a single industry as the remaining emissions

are from many industries including manufacturing, transportation, agriculture, among others.

Results and analysis

As has been indicated earlier, both the additive and multiplicative decomposition of system efficiency are conducted in the assessment. While additive decomposition defines the system (consumption system) efficiency as a weighted average of the sub-system efficiencies, multiplicative decomposition defines the system efficiency from the product of the series of parallel sub-systems.

It is argued that both the additive and multiplicative approaches provide insights into different views of sustainability. This is because additive and multiplicative decomposition allow for an alternative perspective on overall (sustainability) performance based on whether compensation should be allowed between the sustainability dimensions (Hacatoglu et al., 2015a; Kuhlman and Farrington, 2010). Consequently, while additive decomposition allows for some considerable compensation between dimensions, which aligns with the views of weak sustainability (Kuhlman and Farrington, 2010; Pomerol and Barba-Romero, 2000), multiplicative decomposition limits the level of compensation between the dimensions, thus aligning with the view of strong sustainability (Kuhlman and Farrington, 2010). The difference between additive and multiplicative composition of measures is further discussed in the next chapter of this thesis. The 2017 system efficiencies and decompositions using the additive decomposition of Cook, Zhu, Bi and Yang (2010) and multiplicative decomposition of Kao (2014a) are presented in Table 6.3.

Table 6.3 shows the decomposition of the system efficiencies for each country. Note that the decomposition for the multiplicative model as presented in Table 6.3 represents the second stage of decomposition, where the efficiencies of the actual sub-processes in the parallel network are determined. Consequently, overall efficiency is not a product of the actual efficiencies. For both the additive and multiplicative models, higher overall performers in 2017 include Malta, Luxembourg, Cyprus, Ireland and Sweden. These countries are able to achieve higher social, economic and environmental outcomes given the use of energy and other resources. The difference with the decomposition approaches is more prominent when countries at the lower spectrum of overall performance is examined. For the additive model, the three countries with the lowest performance for 2017 included Portugal (0.4597), Greece (0.4888) and the Czech Republic (0.5174). On the other hand, the three least performers for the multiplicative decomposition were the Czech Republic (0.3952),

Table 6.3 System and sub-system efficiencies of the consumption phase (2017).

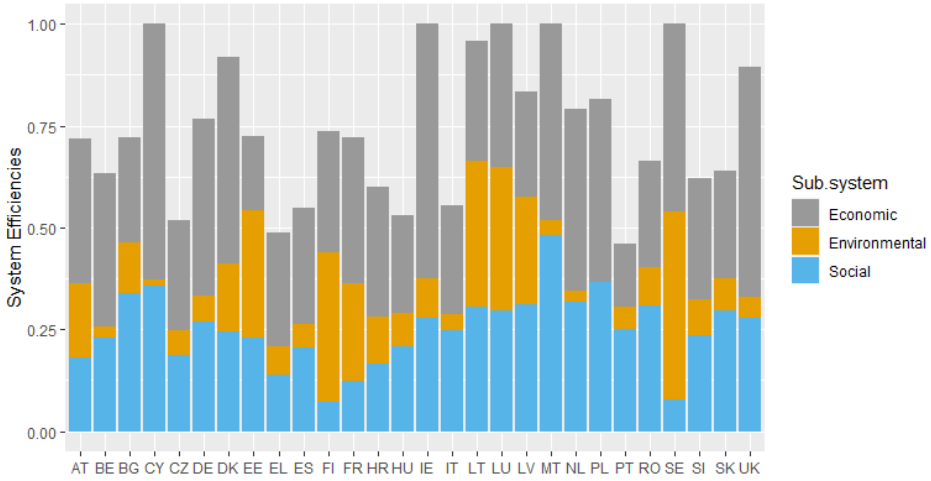
Country	Additive					Multiplicative				
	System	Rank	Sub-systems			System	Rank	Sub-systems [c]		
			Soc.	Econ.	Env.			Soc.	Econ.	Env.
AT	0.7198	*17*	0.3634	0.7198	0.3713	0.7198	*15*	0.3634	0.7198	0.2262
BE	0.6327	*20*	0.3835	0.6327	0.0444	0.6327	*16*	0.3835	0.6327	0.0396
BG	0.7213	*16*	1.0000	0.7625	0.3650	0.5164	*22*	0.4373	0.7012	0.3650
HR	0.5997	*22*	0.4359	0.8422	0.3079	0.4281	*24*	0.4359	0.4281	0.3319
CY	1.0000 [a]	*3*	0.5683	1.0000	0.0260	1.0000 [a]	*3*	0.5683	1.0000	0.0260
CZ	0.5174	*26*	0.5270	0.7602	0.1749	0.3952	*28*	0.5164	0.3952	0.1749
DK	0.9178	*7*	0.4428	0.9178	0.2997	0.9178	*7*	0.4428	0.9178	0.2997
EE	0.7242	*14*	0.7381	0.5854	1.0000	0.5299	*21*	0.7381	0.5854	1.0000
FI	0.7369	*13*	0.1750	0.7210	0.8785	0.7364	*13*	0.1750	0.7365	1.0000
FR	0.7223	*15*	0.2503	0.7224	0.4825	0.7223	*14*	0.2503	0.7224	0.3023
DE	0.7681	*12*	0.4743	0.7681	0.1084	0.7681	*12*	0.4743	0.7681	0.1039
EL	0.4888	*27*	0.2948	0.5988	0.1475	0.4793	*23*	0.2948	0.4793	0.1475
HU	0.5313	*25*	0.6028	0.7005	0.2404	0.4249	*25*	0.6028	0.4249	0.2404
IE	1.0000 [a]	*4*	0.4447	1.0000	0.1582	1.0000 [a]	*4*	0.4447	1.0000	0.1582
IT	0.5552	*23*	0.5148	0.5552	0.0810	0.5552	*19*	0.5148	0.5552	0.1649
LV	0.8332	*9*	0.9987	0.8228	0.8460	0.8037	*9*	0.9987	0.7786	0.8037
LT	0.9576	*6*	0.8143	0.7836	0.9576	0.9576	*6*	0.8143	0.7836	0.9576
LU	1.0000 [a]	*2*	0.8397	1.0000	1.0000	1.0000 [a]	*2*	0.8397	1.0000	1.0000
MT	1.0000 [a]	*1*	1.0000	1.0000	0.0737	1.0000 [a]	*1*	1.0000	1.0000	0.0737
NL	0.7903	*11*	0.5601	0.7904	0.0480	0.7903	*11*	0.5601	0.7904	0.0607
PL	0.8159	*10*	0.8186	1.0000	0.000 [b]	0.7971	*10*	0.8186	0.7971	0.1592
PT	0.4597	*28*	0.5553	0.3387	0.1229	0.4124	*26*	0.5552	0.4124	0.1229
RO	0.6648	*18*	1.0000	0.8556	0.3108	0.4050	*27*	1.0000	0.4050	0.3108
SK	0.6401	*19*	0.8242	0.7335	0.2183	0.6213	*17*	0.8242	0.6213	0.2152
SI	0.6200	*21*	0.5401	0.6780	0.1962	0.6145	*18*	0.5401	0.6146	0.1962
ES	0.5473	*24*	0.3928	0.5473	0.1155	0.5473	*20*	0.3873	0.5473	0.2126
SE	1.0000 [a]	*5*	0.1661	1.0000	1.0000	1.0000 [a]	*5*	0.1661	1.0000	1.0000
UK	0.8957	*8*	0.4390	0.8958	0.0862	0.8957	*8*	0.4390	0.8958	0.2303
Geometric Mean	0.7249		0.5200	0.7563	0.1388	0.6701		0.5042	0.6743	0.2327

[a] *the actual score is lower than 1, the value in the table is due to rounding up*

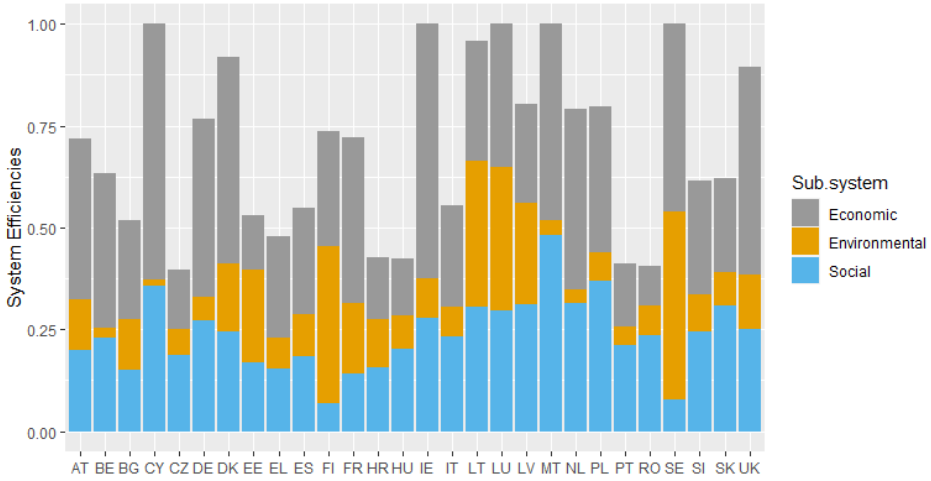
[b] *the actual score is near-zero. Value in the table is due to rounding up*

[c] *efficiency decomposition reported in the table is the efficiency of the actual sub-systems in the parallel networks. The system efficiency score is therefore not expected to be a product of these scores reported*

Romania (0.4050) and Portugal (0.4124). The difference in the rankings and scores is due to the assumptions made about how overall efficiency is characterised. The additive defines system efficiency as a weighted average while the multiplicative defines system efficiency in a geometric manner (Chen et al., 2009). It is believed that multiplicative decomposition better reflects the dimensions' importance in the overall system efficiency, since the additive decomposition allows for compensation across sustainability dimensions. Therefore, multiplicative decomposition is used in the subsequent sub-sections.



(a) Additive decomposition



(b) Multiplicative decomposition

Figure 6.4 Source of system efficiencies (2017).

Generally, decomposition using either the additive or multiplicative models shows similar dimension rankings for each country, except in a few cases where the rankings of the dimension change depending on the model. Austria, for example, performs better on the environmental dimension (0.3713) than the social dimension (0.3634) on the additive model. However, this changes in when the multiplicative model is used resulting in higher social performance (0.3634) than the environmental dimension (0.2262). Bulgaria, Croatia, the Czech Republic and Hungary also experience such preference reversal due to model choice. When all countries are averaged, it is evident that consumption system efficiency is mostly driven by the economic dimension, followed by social and environmental performance. Environmental performance

for both approaches is very low compared to the other dimensions. The system efficiencies reflecting the percentage importance of the three dimensions for both the additive and multiplicative models are presented in Figure 6.4. It can be observed that economic and social sub-systems are the primary sources of efficiency among these EU countries. There is, therefore, more effort required for addressing the environmental dimension of sustainability in the consumption phase.

Overall performance of the countries is also summarised for the entire study period in Figure 6.5. Countries have also ordered based on their average system efficiency scores. The figure displays both the additive and the multiplicative system efficiency scores. As can be observed, the majority of EU states have overall efficiencies at or above a score of 0.5. This signifies considerable efforts to ensure social development, economic development and environmental performance in these countries.

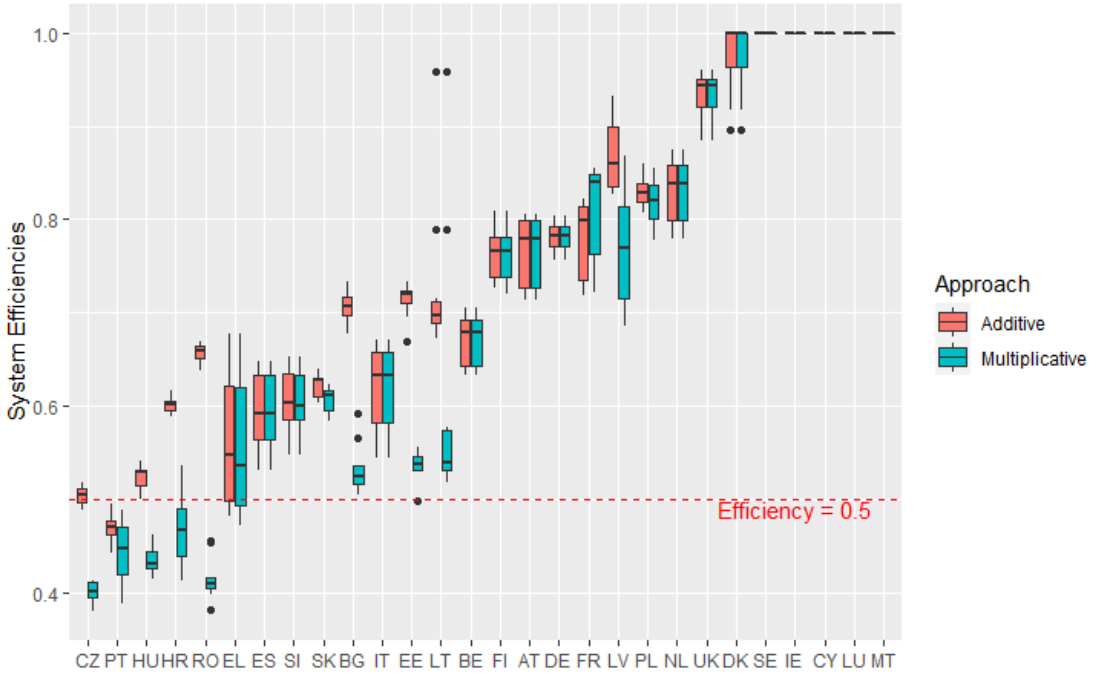


Figure 6.5 Boxplots of system efficiencies of EU countries (2008-2017).

When the additive and multiplicative models are compared, more countries have their multiplicative score below the 0.5 mark than the additive score. This shows the multiplicative model is more discriminatory and has a stronger requirement for sustainability than the additive measure. Finally, when the performance of countries in the consumption phase displayed in Figure 6.5 is compared to those from the generation phase as captured in Figure 5.7, it is clear that higher performance

in generating electricity does not necessarily result in higher performance in its consumption and use phase. Consequently, when performance assessment on the electricity system is being conducted for policy purposes, it is important to conduct both the generation and consumption phase assessment in a single assessment. The next section provides a holistic assessment of the generation and consumption phases in a single assessment framework.

6.4.2 Energy production and consumption

Since the main policy objectives for a sustainable energy system are, "efficient production, distribution, and use of energy resources coupled with the provision of equitable and affordable access to energy simultaneously ensuring the security of energy supply and environmental sustainability" (Štreimikienė et al., 2012), it is important that performance assessment of the energy system incorporates both the production and consumption phases of the system. The production systems of EU countries were assessed in Chapter 5 of this thesis. The consumption phase has also been examined in Section 6.4.1 of this chapter. Issues on affordable access to energy are examined in chapter 7 of the thesis.

In this section, an integrated assessment of both the production and consumption sub-systems of the energy system of the EU countries is conducted. This assessment essentially combines the parallel network structure presented in Chapter 5 and the multi-stage serial structure in previous sections of Chapter 6 in a holistic mixed structure network framework. This is a novel assessment not previously seen in the literature.

System description – the entire system

The conceptual framework which is the basis for assessment in this section has been previously presented in Figure 4.6 of this thesis. As has already been indicated, performance assessments of components of this system have been previously presented and discussed. The primary aim of this section is, therefore, to show how the production and consumption phases could be integrated. The empirical mixed network structure is presented in Figure 6.6.

The major difference between this schema and the previous ones is the inclusion of a new sub-process between the production and consumption phases. This is the transmission system, which in practice transfers electricity from production units to consumption units. This is introduced to capture the difference between the units of electricity generated and the units consumed. In practice, the difference between

electricity production and consumption is due to distribution losses, electricity imports to supplement domestic demands and exports of power to other countries among other factors (EEA, 2016). For the environmental aspect, it is important to note that the volume of emissions from electricity production captured as Y_2 in Chapter 5 is the same as variable X_6 in consumption analysis. The link between these variables, therefore, requires no special sub-process.

Note that for simplicity and consistency purposes, all variables in the consumption phase carry 'tilde' as an accent, while variables in the consumption phase carry a 'bar' as an accent. It is also important to note that some variables which were exogenous in previous assessments have become intermediate factors in Figure 6.6. There are therefore six exogenous inputs, three exogenous outputs and six intermediate factors. To solve this mixed network structure, the approach of Kao (2014a) is adopted by transforming the network into a series of five parallel networks. Here, parallel network I is the production phase and network II is the transmission stage. The remaining three stages are the three components of the consumption phase.

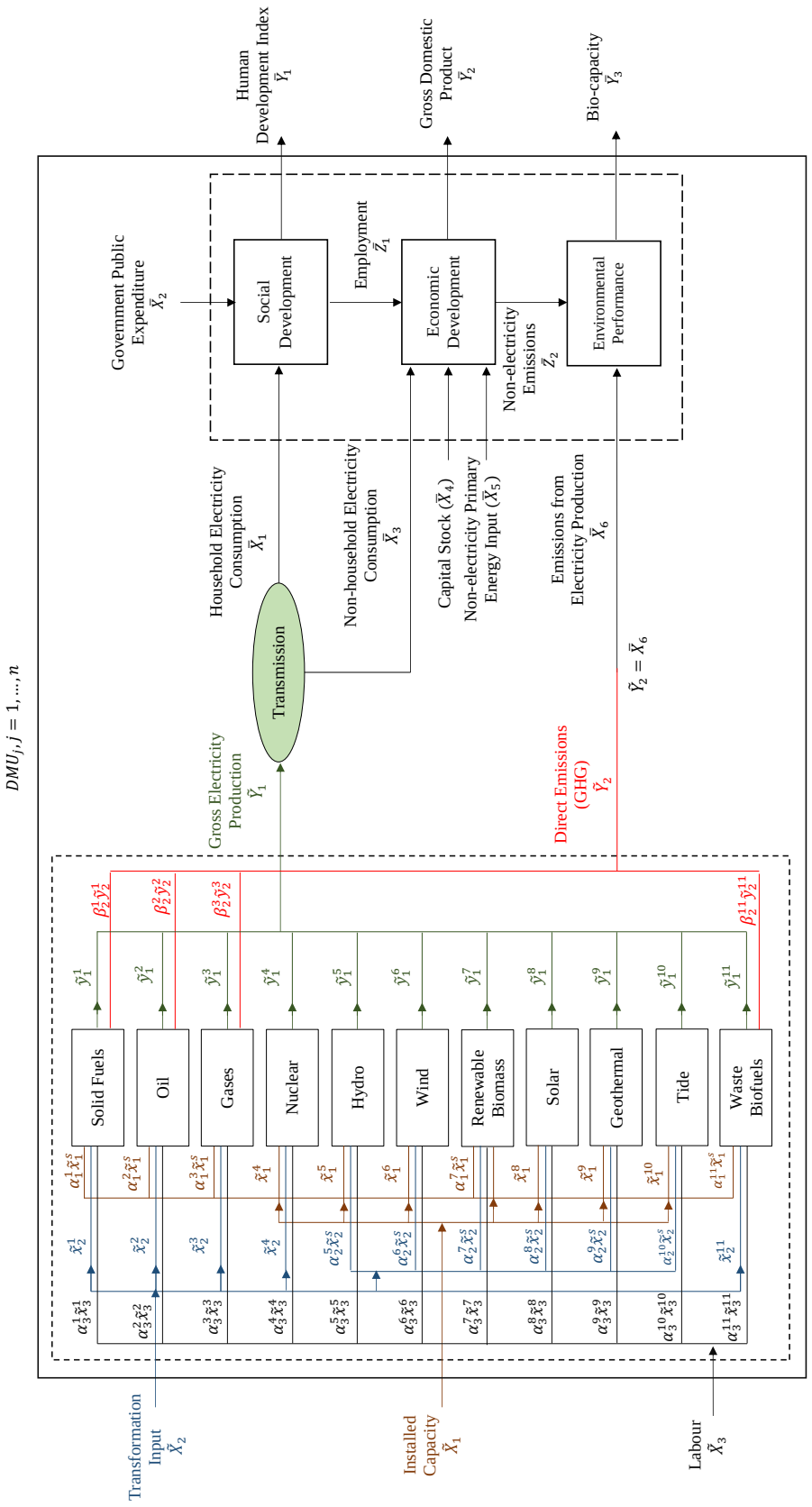


Figure 6.6 Evaluation framework of the entire energy system.

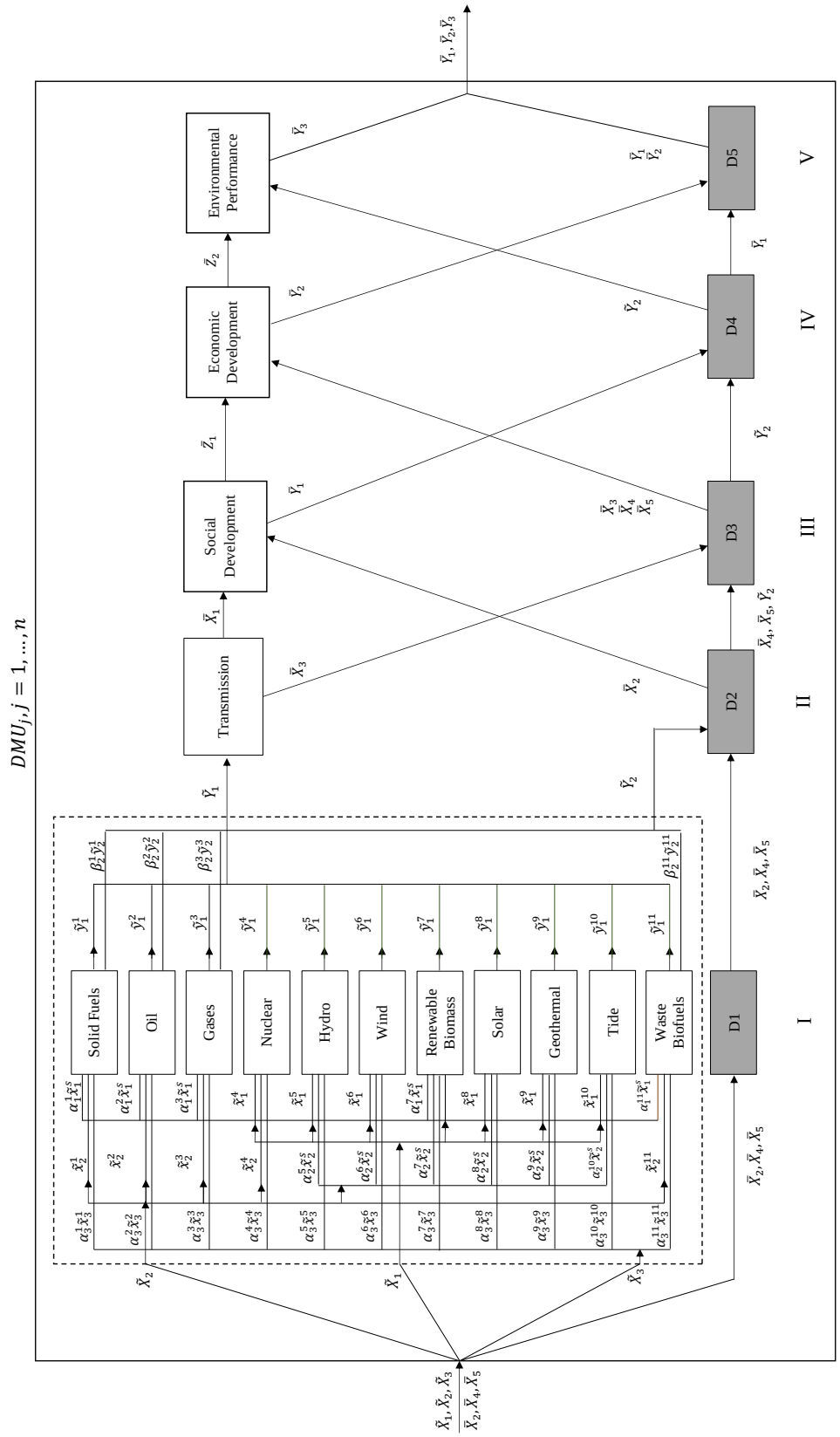


Figure 6.7 Transformation of the mixed network in Figure 6.6 into a series of parallel networks.

As depicted in Figure 6.7, for each phase, a dummy sub-process has been introduced to capture the inputs and outputs of the intermediate processes (Kao, 2009b). In the next sub-section performance models are formulated.

Model formulation

From the series of parallel networks presented in Figure 6.7, there are five stages in this assessment framework. First, the constraints for each of the five parallel networks are presented before they are combined into one framework.

Constraints of parallel sub-processes

Parallel network I – Electricity generation
Parallel network I has 12 sub-processes, 11 of which are actual generation sources. There are three inputs (labour, installed capacity and transformation inputs) and two outputs (gross electricity production and greenhouse emissions). Since there are shared inputs and outputs and non-homogeneity in terms of the sub-units, these are incorporated in the formulations. The constraints for the parallel network are presented in (6.17).

$$\left(\tilde{u}_1\widetilde{Y}_{1j}^{(1)} + \tilde{u}_2\beta_2^{(1)}\widetilde{Y}_{2j}\right) - \left(\tilde{v}_1\alpha_1^{(1)}\tilde{X}_{1j}^{s} + \tilde{v}_2\tilde{X}_{2j}^{(1)} + \tilde{v}_3\alpha_3^{(1)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17a}$$

$$\left(\tilde{u}_1\widetilde{Y}_{1j}^{(2)} + \tilde{u}_2\beta_2^{(2)}\widetilde{Y}_{2j}\right) - \left(\tilde{v}_1\alpha_1^{(2)}\tilde{X}_{1j}^{s} + \tilde{v}_2\tilde{X}_{2j}^{(2)} + \tilde{v}_3\alpha_3^{(2)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17b}$$

$$\left(\tilde{u}_1\widetilde{Y}_{1j}^{(3)} + \tilde{u}_2\beta_2^{(3)}\widetilde{Y}_{2j}\right) - \left(\tilde{v}_1\alpha_1^{(3)}\tilde{X}_{1j}^{s} + \tilde{v}_2\tilde{X}_{2j}^{(3)} + \tilde{v}_3\alpha_3^{(3)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17c}$$

$$\tilde{u}_1\widetilde{Y}_{1j}^{(4)} - \left(\tilde{v}_1\tilde{X}_{1j}^{(4)} + \tilde{v}_2\tilde{X}_{2j}^{(4)} + \tilde{v}_3\alpha_3^{(4)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17d}$$

$$\tilde{u}_1\widetilde{Y}_{1j}^{(5)} - \left(\tilde{v}_1\tilde{X}_{1j}^{(5)} + \tilde{v}_2\alpha_2^{(5)}\tilde{X}_{2j}^{s} + \tilde{v}_3\alpha_3^{(5)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17e}$$

$$\tilde{u}_1\widetilde{Y}_{1j}^{(6)} - \left(\tilde{v}_1\tilde{X}_{1j}^{(6)} + \tilde{v}_2\alpha_2^{(6)}\tilde{X}_{2j}^{s} + \tilde{v}_3\alpha_3^{(6)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17f}$$

$$\tilde{u}_1\widetilde{Y}_{1j}^{(7)} - \left(\tilde{v}_1\alpha_1^{(7)}\tilde{X}_{1j}^{s} + \tilde{v}_2\alpha_2^{(7)}\tilde{X}_{2j}^{s} + \tilde{v}_3\alpha_3^{(7)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17g}$$

$$\tilde{u}_1\widetilde{Y}_{1j}^{(8)} - \left(\tilde{v}_1\tilde{X}_{1j}^{(8)} + \tilde{v}_2\alpha_2^{(8)}\tilde{X}_{2j}^{s} + \tilde{v}_3\alpha_3^{(8)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17h}$$

$$\tilde{u}_1\widetilde{Y}_{1j}^{(9)} - \left(\tilde{v}_1\tilde{X}_{1j}^{(9)} + \tilde{v}_2\alpha_2^{(9)}\tilde{X}_{2j}^{s} + \tilde{v}_3\alpha_3^{(9)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17i}$$

$$\tilde{u}_1\widetilde{Y}_{1j}^{(10)} - \left(\tilde{v}_1\tilde{X}_{1j}^{(10)} + \tilde{v}_2\alpha_2^{(10)}\tilde{X}_{2j}^{s} + \tilde{v}_3\alpha_3^{(10)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17j}$$

$$\left(\tilde{u}_1\widetilde{Y}_{1j}^{(11)} + \tilde{u}_2\beta_2^{(11)}\widetilde{Y}_{2j}\right) - \left(\tilde{v}_1\alpha_1^{(11)}\tilde{X}_{1j}^{s} + \tilde{v}_2\tilde{X}_{2j}^{(11)} + \tilde{v}_3\alpha_3^{(11)}\tilde{X}_{3j}\right) \leq 0 \tag{6.17k}$$

$$\left(\bar{v}_2\bar{X}_{2j} + \bar{v}_4\bar{X}_{4j} + \bar{v}_5\bar{X}_{5j}\right) - \left(\bar{v}_2\bar{X}_{2j} + \bar{v}_4\bar{X}_{4j} + \bar{v}_5\bar{X}_{5j}\right) \leq 0 \tag{6.17l}$$

Note that the final constraint is redundant. There are additional constraints for the split factors. First, following approach two for dealing with non-homogeneity as presented in Section 5.3.3 of Chapter 5, L_n is defined as the set of all the sub-processes with shared factors. In parallel network I, these include all sub-process except the dummy sub-process. For each DMU j, L_j is defined as the set of sub-processes, out of the L_n, that specific DMU operates such that $L_j \subseteq L_n$. The first set of constraints for the split factors require that the sum of the split factors for existing sub-processes in the set will be one.

$$\beta_2^{(1)} + \beta_2^{(2)} + \beta_2^{(3)} + \beta_2^{(11)} = 1 \tag{6.18a}$$
$$\alpha_1^{(1)} + \alpha_1^{(2)} + \alpha_1^{(3)} + \alpha_1^{(7)} + \alpha_1^{(11)} = 1 \tag{6.18b}$$
$$\alpha_2^{(5)} + \alpha_2^{(6)} + \alpha_1^{(7)} + \alpha_2^{(8)} + \alpha_2^{(9)} + \alpha_2^{(10)} = 1 \tag{6.18c}$$
$$\alpha_3^{(1)} + \alpha_3^{(2)} + \alpha_3^{(3)} + \alpha_3^{(4)} + \alpha_3^{(5)} + \alpha_3^{(6)} + \alpha_3^{(7)} + \alpha_3^{(8)} + \alpha_3^{(9)} + \alpha_3^{(10)} + \alpha_3^{(11)} = 1 \tag{6.18d}$$

If a sub-process p is not the member of L_j but a member of L_n, then split factor for that particular sub-process will be zero. This will ensure no allocation is made to non-existing sub-processes for a particular DMU. Therefore, all elements in the set-theoretic difference of L_n and L_j ($L_n \backslash L_j$) are set to zero:

$$\alpha_i^{(p)} = 0, \qquad p \in L_n \backslash L_j \tag{6.19a}$$
$$\beta_r^{(p)} = 0, \qquad p \in L_n \backslash L_j \tag{6.19b}$$

Finally, upper and lower bounds are set for the split factors so that at least some units of the shared variable will be allocated to all existing sub-processes.

$$a_i^{(p)} \leq \alpha_i^{(p)} \leq b_i^{(p)} \qquad p \in L_j \tag{6.20a}$$
$$a_r^{(p)} \leq \beta_r^{(p)} \leq b_r^{(p)} \qquad p \in L_j \tag{6.20b}$$

Since elements in (6.17) will result in nonlinearity, the constraints are linearised using the Charnes-Cooper transformation. If redundant constraints are eliminated, then the constraints for this parallel network will be:

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(1)} + \tilde{\mu}_2\tilde{Y}_{2j}^{(1)} - \tilde{\gamma}_1^{(1)}\tilde{X}_{1j}^{s} - \tilde{\nu}_2\tilde{X}_{2j}^{(1)} - \tilde{\gamma}_3^{(1)}\tilde{X}_{3j} \leq 0 \tag{6.21a}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(2)} + \tilde{\mu}_2\tilde{Y}_{2j}^{(2)} - \tilde{\gamma}_1^{(2)}\tilde{X}_{1j}^{s} - \tilde{\nu}_2\tilde{X}_{2j}^{(2)} - \tilde{\gamma}_3^{(2)}\tilde{X}_{3j} \leq 0 \tag{6.21b}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(3)} + \tilde{\mu}_2\tilde{Y}_{2j}^{(3)} - \tilde{\gamma}_1^{(3)}\tilde{X}_{1j}^{s} - \tilde{\nu}_2\tilde{X}_{2j}^{(3)} - \tilde{\gamma}_3^{(3)}\tilde{X}_{3j} \leq 0 \tag{6.21c}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(4)} - \tilde{\nu}_1\tilde{X}_{1j}^{(4)} - \tilde{\nu}_2\tilde{X}_{2j}^{(4)} - \tilde{\gamma}_3^{(4)}\tilde{X}_{3j} \leq 0 \tag{6.21d}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(5)} - \tilde{\nu}_1\tilde{X}_{1j}^{(5)} - \tilde{\gamma}_2^{(5)}\tilde{X}_{2j}^{s} - \tilde{\gamma}_3^{(5)}\tilde{X}_{3j} \leq 0 \tag{6.21e}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(6)} - \tilde{\nu}_1\tilde{X}_{1j}^{(6)} - \tilde{\gamma}_2^{(6)}\tilde{X}_{2j}^{s} - \tilde{\gamma}_3^{(6)}\tilde{X}_{3j} \leq 0 \tag{6.21f}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(7)} - \tilde{\gamma}_1^{(7)}\tilde{X}_{1j}^{s} - \tilde{\gamma}_2^{(7)}\tilde{X}_{2j}^{s} - \tilde{\gamma}_3^{(7)}\tilde{X}_{3j} \leq 0 \tag{6.21g}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(8)} - \tilde{\nu}_1\tilde{X}_{1j}^{(8)} - \tilde{\gamma}_2^{(8)}\tilde{X}_{2j}^{s} - \tilde{\gamma}_3^{(8)}\tilde{X}_{3j} \leq 0 \tag{6.21h}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(9)} - \tilde{\nu}_1\tilde{X}_{1j}^{(9)} - \tilde{\gamma}_2^{(9)}\tilde{X}_{2j}^{s} - \tilde{\gamma}_3^{(9)}\tilde{X}_{3j} \leq 0 \tag{6.21i}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(10)} - \tilde{\nu}_1\tilde{X}_{1j}^{(10)} - \tilde{\gamma}_2^{(10)}\tilde{X}_{2j}^{s} - \tilde{\gamma}_3^{(10)}\tilde{X}_{3j} \leq 0 \tag{6.21j}$$

$$\tilde{\mu}_1\tilde{Y}_{1j}^{(11)} + \tilde{\mu}_2\tilde{Y}_{2j}^{(11)} - \tilde{\gamma}_1^{(11)}\tilde{X}_{1j}^{s} - \tilde{\nu}_2\tilde{X}_{2j}^{(11)} - \tilde{\gamma}_3^{(11)}\tilde{X}_{3j} \leq 0 \tag{6.21k}$$

$$\tilde{\gamma}_1^{(1)} + \tilde{\gamma}_1^{(2)} + \tilde{\gamma}_1^{(3)} + \tilde{\gamma}_1^{(7)} + \tilde{\gamma}_1^{(11)} = \tilde{\nu}_1 \tag{6.21l}$$

$$\tilde{\gamma}_2^{(5)} + \tilde{\gamma}_2^{(6)} + \tilde{\gamma}_2^{(7)} + \tilde{\gamma}_2^{(8)} + \tilde{\gamma}_2^{(9)} + \tilde{\gamma}_2^{(10)} = \tilde{\nu}_2 \tag{6.21m}$$

$$\tilde{\gamma}_3^{(1)} + \tilde{\gamma}_3^{(2)} + \tilde{\gamma}_3^{(3)} + \tilde{\gamma}_3^{(4)} + \tilde{\gamma}_3^{(5)} + \tilde{\gamma}_3^{(6)} + \tilde{\gamma}_3^{(7)} + \tilde{\gamma}_3^{(8)} + \tilde{\gamma}_3^{(9)} + \tilde{\gamma}_3^{(10)} + \tilde{\gamma}_3^{(11)} = \tilde{\nu}_3 \tag{6.21n}$$

$$\tilde{\gamma}_i^{(p)} = 0 \qquad p \in L_n \backslash L_j \tag{6.21o}$$

$$\tilde{\nu}_i a_i^{(p)} \leq \tilde{\gamma}_i^{(p)} \leq \tilde{\nu}_i b_i^{(p)} \qquad p \in L_j \tag{6.21p}$$

The split factor for the emissions variable ($\widetilde{Y}_{2j}$) is externally determined as discussed in Section 5.4.2 of Chapter 5. It is also important to note that since emissions are undesirable outputs in a joint production with the desirable outputs, it is modelled as a weakly disposable output. Consequently, $\tilde{\mu}_2$ is unrestricted in direction.

Parallel network II – Transmission

Unlike the previous parallel network, network II is simple in terms of the constraints. This comprises two sub-processes. For the actual sub-process, the input is the gross electricity produced by all generation sources, whiles the outputs are electricity consumption for households and non-households. Constraints are presented in (6.22).

Note that the final constraint is redundant.

$$\left(\bar{\nu}_1\bar{X}_{1j} + \bar{\nu}_3\bar{X}_{3j}\right) - \tilde{\mu}_1\tilde{Y}_{1j} \leq 0 \tag{6.22a}$$
$$\left(\bar{\nu}_2\bar{X}_{2j} + \bar{\nu}_4\bar{X}_{4j} + \bar{\nu}_5\bar{X}_{5j} + \tilde{\mu}_2\tilde{Y}_2\right) - \left(\bar{\nu}_2\bar{X}_{2j} + \bar{\nu}_4\bar{X}_{4j} + \bar{\nu}_5\bar{X}_{5j} + \tilde{\mu}_2\tilde{Y}_2\right) \leq 0 \tag{6.22b}$$

Parallel network III – Social development
In the social development phase (III), there are two sub-processes whose constraints are shown in (6.23). The actual sub-process consumes household electricity supply and government expenditure to generate human development (HDI) and employment. As with the previous parallel networks, the constraint for the dummy sub-process is redundant.

$$\left(\bar{\mu}_1\bar{Y}_{1j} + \bar{w}_1\bar{Z}_{1j}\right) - \left(\bar{\nu}_1\bar{X}_{1j} + \bar{\nu}_2\bar{X}_{2j}\right) \leq 0 \tag{6.23a}$$
$$\left(\bar{\nu}_3\bar{X}_{3j} + \bar{\nu}_4\bar{X}_{4j} + \bar{\nu}_5\bar{X}_{5j} + \tilde{\mu}_2\tilde{Y}_2\right) - \left(\bar{\nu}_3\bar{X}_{3j} + \bar{\nu}_4\bar{X}_{4j} + \bar{\nu}_5\bar{X}_{5j} + \tilde{\mu}_2\tilde{Y}_2\right) \leq 0 \tag{6.23b}$$

Parallel network IV – Economic development
This parallel network IV also has two sub-processes. The actual sub-process has three exogenous inputs and one intermediate input. The intermediate input is the non-household electricity supplied from the transmission system for economic activities. Two outputs are produced by this parallel network, GDP and emissions from other sources excluding electricity production. Constraints for this parallel network are as follows:

$$\left(\bar{\mu}_2\bar{Y}_{2j} + \bar{w}_2\bar{Z}_{2j}\right) - \left(\bar{\nu}_3\bar{X}_{3j} + \bar{\nu}_4\bar{X}_{4j} + \bar{\nu}_5\bar{X}_{5j} + \bar{w}_1\bar{Z}_{1j}\right) \leq 0 \tag{6.24a}$$
$$\left(\bar{\mu}_1\bar{Y}_{1j} + \tilde{\mu}_2\tilde{Y}_2\right) - \left(\bar{\mu}_1\bar{Y}_{1j} + \tilde{\mu}_2\tilde{Y}_2\right) \leq 0 \tag{6.24b}$$

Parallel network V – Environmental performance
The final parallel network has two weakly disposable inputs which are both intermediate factors from the economic and the electricity production sub-processes. The output is the bio-capacity of the country. Constraints for parallel network V are as follows:

$$\bar{\mu}_3\bar{Y}_{3j} - \left(\bar{w}_2\bar{Z}_{2j} + \tilde{\mu}_2\tilde{Y}_{2j}\right) \leq 0 \tag{6.25a}$$
$$\left(\bar{\mu}_1\bar{Y}_{1j} + \bar{\mu}_2\bar{Y}_{2j}\right) - \left(\bar{\mu}_1\bar{Y}_{1j} + \bar{\mu}_2\bar{Y}_{2j}\right) \leq 0 \tag{6.25b}$$

The full model

The objective function for the multiplicative decomposition considers only the exogenous variables. This is since the intermediate factors are consumed in the system. Additionally, the weighted sum of the exogenous inputs of the firm under consideration should also sum up to one. The fully integrated model for the system will, therefore, be as follows:

$$E_0 = \max \ \bar{\mu}_1\bar{Y}_{1o} + \bar{\mu}_2\bar{Y}_{2o} + \bar{\mu}_3\bar{Y}_{3o} \tag{6.26a}$$

$$\text{s.t.} \ \ \tilde{\nu}_1\tilde{X}_{1o} + \tilde{\nu}_2\tilde{X}_{2o} + \tilde{\nu}_3\tilde{X}_{3o} + \bar{\nu}_2\bar{X}_{2o} + \bar{\nu}_4\bar{X}_{4o} + \bar{\nu}_5\bar{X}_{5o} = 1 \tag{6.26b}$$

$$(6.21),(6.22),(6.23),(6.24) \text{ and } (6.25) \tag{6.26c}$$

$$\tilde{\mu}_1, \tilde{\gamma}_i^{(p)}, \tilde{\nu}_i, \bar{\mu}_r, \bar{\nu}_1, \bar{\nu}_2, \bar{\nu}_3, \bar{\nu}_4, \bar{\nu}_5, \bar{w}_1 \geq \varepsilon, \quad \tilde{\mu}_2, \bar{w}_2 \,\text{urs} \tag{6.26d}$$

$$r = 1, ..., s, \quad i = 1, ..., m, \quad p = 1, ..., q, \ \ j = 1, 2, \ldots, n \tag{6.26e}$$

Redundant constraints in (6.21),(6.22),(6.23),(6.24) and (6.25) are eliminated from the model in (6.26). The model in (6.26) computes the efficiency of the entire system. The next part of this sub-section shows the decompositions.

Efficiency decomposition

The efficiency score computed by (6.26) represents the overall system efficiency that incorporates the generation, transmission and consumption systems. It is important to decompose this efficiency to determine sub-system performance. It is possible to decompose the efficiency for each of the five parallel sub-processes as well as the individual sub-systems within the parallel networks using (6.8) and (6.4). Various levels of decomposition can be made. Three stages of efficiency decomposition of the overall system efficiency are defined.

Stage one decomposes the system efficiency into the efficiencies of the five parallel sub-systems. Stage two decomposes the parallel sub-system efficiencies into the efficiencies of the components of those parallel sub-systems. Finally, the third stage decomposes the overall efficiency into the generation and consumption phase efficiencies. The overall system efficiency of a series of parallel systems is a product of the parallel sub-systems efficiencies, while the efficiency of the parallel sub-system is a weighted average of the sub-process efficiencies (Kao, 2009b, 2012). These

efficiency decompositions are presented as follows:

Stage one decomposition – Parallel sub-systems
The efficiencies of the five parallel networks are determined from the optimal multipliers as follows:

$$E_o^{I*} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o} + \tilde{\mu}_2^*\tilde{Y}_{2o} + \bar{\nu}_2^*\bar{X}_{2o} + \bar{\nu}_4^*\bar{X}_{4o} + \bar{\nu}_5^*\bar{X}_{5o}}{\tilde{\nu}_1^*\tilde{X}_{1o} + \tilde{\nu}_2^*\tilde{X}_{2o} + \tilde{\nu}_3^*\tilde{X}_{3o} + \bar{\nu}_2^*\bar{X}_{2o} + \bar{\nu}_4^*\bar{X}_{4o} + \bar{\nu}_5^*\bar{X}_{5o}} \tag{6.27a}$$

$$E_o^{II*} = \frac{\bar{\nu}_1^*\bar{X}_{1o} + \bar{\nu}_3^*\bar{X}_{3o} + \bar{\nu}_2^*\bar{X}_{2o} + \bar{\nu}_4^*\bar{X}_{4o} + \bar{\nu}_5^*\bar{X}_{5o} + \tilde{\mu}_2^*\tilde{Y}_{2o}}{\tilde{\mu}_1^*\tilde{Y}_{1o} + \bar{\nu}_2^*\bar{X}_{2o} + \bar{\nu}_4^*\bar{X}_{4o} + \bar{\nu}_5^*\bar{X}_{5o} + \tilde{\mu}_2^*\tilde{Y}_{2o}} \tag{6.27b}$$

$$E_o^{III*} = \frac{\bar{\mu}_1^*\bar{Y}_{1o} + \bar{w}_1^*\bar{Z}_{1o} + \bar{\nu}_3^*\bar{X}_{3o} + \bar{\nu}_4^*\bar{X}_{4o} + \bar{\nu}_5^*\bar{X}_{5o} + \tilde{\mu}_2^*\tilde{Y}_{2o}}{\bar{\nu}_1^*\bar{X}_{1o} + \bar{\nu}_2^*\bar{X}_{2o} + \bar{\nu}_3^*\bar{X}_{3o} + \bar{\nu}_4^*\bar{X}_{4o} + \bar{\nu}_5^*\bar{X}_{5o} + \tilde{\mu}_2^*\tilde{Y}_{2o}} \tag{6.27c}$$

$$E_o^{IV*} = \frac{\bar{\mu}_2^*\bar{Y}_{2o} + \bar{w}_2^*\bar{Z}_{2o} + \bar{\mu}_1^*\bar{Y}_{1o} + \tilde{\mu}_2^*\tilde{Y}_{2o}}{\bar{\nu}_3^*\bar{X}_{3o} + \bar{\nu}_4^*\bar{X}_{4o} + \bar{\nu}_5^*\bar{X}_{5o} + \bar{w}_1^*\bar{Z}_{1o} + \bar{\mu}_1^*\bar{Y}_{1o} + \tilde{\mu}_2^*\tilde{Y}_{2o}} \tag{6.27d}$$

$$E_o^{V*} = \frac{\bar{\mu}_3^*\bar{Y}_{3o} + \bar{\mu}_1^*\bar{Y}_{1o} + \bar{\mu}_2^*\bar{Y}_{2o}}{\bar{w}_2^*\bar{Z}_{2o} + \tilde{\mu}_2^*\tilde{Y}_{2o} + \bar{\mu}_1^*\bar{Y}_{1o} + \bar{\mu}_2^*\bar{Y}_{2o}} \tag{6.27e}$$

These represent a weighted average of the efficiency of the actual sub-processes as well as the dummy sub-process. The efficiency of the dummy sub-process is 1 in each case while the weights are determined from the resource consumption.

Stage two decomposition – Actual sub-systems
Each parallel process comprises actual units as well as dummy units. Here, how the efficiencies of the actual units are determined is presented. Parallel network I is comprised of 11 actual sub-processes which efficiencies are determined as:

$$E_0^{(\text{solid})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o}^{(1)} + \tilde{\mu}_2^*\tilde{Y}_{2o}^{(1)}}{\tilde{\gamma}_1^{*(1)}\tilde{X}_{1o}^s + \tilde{\nu}_2^*\tilde{X}_{2o}^{(1)} + \tilde{\gamma}_3^{*(1)}\tilde{X}_{3o}} \qquad E_0^{(\text{biomass})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1j}^{(7)}}{\gamma_1^{*(7)}\tilde{X}_{1o}^s + \gamma_2^{*(7)}\tilde{X}_{2o}^s + \tilde{\gamma}_3^{*(7)}\tilde{X}_{3o}}$$

$$E_0^{(\text{oil})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o}^{(2)} + \tilde{\mu}_2^*\tilde{Y}_{2o}^{(2)}}{\tilde{\gamma}_1^{*(2)}\tilde{X}_{1o}^s + \tilde{\nu}_2^*\tilde{X}_{2o}^{(2)} + \tilde{\gamma}_3^{*(2)}\tilde{X}_{3o}} \qquad E_0^{(\text{solar})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o}^{(8)}}{\tilde{\nu}_1^*\tilde{X}_{1o}^{(8)} + \tilde{\gamma}_2^{*(8)}\tilde{X}_{2o}^s + \tilde{\gamma}_3^{*(8)}\tilde{X}_{3o}}$$

$$E_0^{(\text{gas})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o}^{(3)} + \mu_2^*\tilde{Y}_{2o}^{(3)}}{\tilde{\gamma}_1^{*(3)}\tilde{X}_{1o}^s + \tilde{\nu}_2^*\tilde{X}_{2o}^{(3)} + \tilde{\gamma}_3^{*(3)}\tilde{X}_{3o}} \qquad E_0^{(\text{geothermal})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o}^{(9)}}{\tilde{\nu}_1^*\tilde{X}_{1o}^{(9)} + \tilde{\gamma}_2^{*(9)}\tilde{X}_{2o}^s + \tilde{\gamma}_3^{*(9)}\tilde{X}_{3o}}$$

$$E_0^{(\text{nuclear})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o}^{(4)}}{\tilde{\nu}_1^*\tilde{X}_{1o}^{(4)} + \tilde{\nu}_2^*\tilde{X}_{2o}^{(4)} + \tilde{\gamma}_3^{*(4)}\tilde{X}_{3o}} \qquad E_0^{(\text{tide})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o}^{(10)}}{\tilde{\nu}_1^*\tilde{X}_{1o}^{(10)} + \tilde{\gamma}_2^{*(10)}\tilde{X}_{2o}^s + \tilde{\gamma}_3^{*(10)}\tilde{X}_{3o}}$$

$$E_0^{(\text{hydro})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o}^{(5)}}{\tilde{\nu}_1^*\tilde{X}_{1o}^{(5)} + \tilde{\gamma}_2^{*(5)}\tilde{X}_{2o}^s + \tilde{\gamma}_3^{*(5)}\tilde{X}_{3o}} \qquad E_0^{(\text{waste})} = \frac{\tilde{\mu}_1^*\tilde{Y}_{1o}^{(11)} + \tilde{\mu}_2^*\tilde{Y}_{2o}^{(11)}}{\tilde{\gamma}_1^{*(11)}\tilde{X}_{1o}^s + \tilde{\nu}_2^*\tilde{X}_{2o}^{(11)} + \tilde{\gamma}_3^{*(11)}\tilde{X}_{3o}}$$

$$E_0^{(\text{wind})} = \frac{\tilde{\mu}_1^* \tilde{Y}_{1o}^{(6)}}{\tilde{\nu}_1^* \tilde{X}_{1o}^{(6)} + \tilde{\gamma}_2^{*(6)} \tilde{X}_{2o}^{s} + \tilde{\gamma}_3^{*(6)} \tilde{X}_{3o}} \tag{6.28}$$

The remaining 4 parallel systems only have one actual sub-process each. Consequently, the efficiency decomposition for the transmission, social, economic and environmental sub-units in parallel networks II, III, IV and V respectively are as follows:

$$E_o^{\text{transmission}*} = \frac{\bar{\nu}_1^* \bar{X}_{1o} + \bar{\nu}_3^* \bar{X}_{3o}}{\tilde{\mu}_1^* \tilde{Y}_{1o}} \tag{6.29a}$$

$$E_o^{\text{social}*} = \frac{\bar{\mu}_1^* \bar{Y}_{1o} + \bar{w}_1^* \bar{Z}_{1o}}{\bar{v}_1^* \bar{X}_{1o} + \bar{\nu}_2^* \bar{X}_{2o}} \tag{6.29b}$$

$$E_o^{\text{economic}*} = \frac{\bar{\mu}_2^* \bar{Y}_{2o} + \bar{w}_2^* \bar{Z}_{2o}}{\bar{\nu}_3^* \bar{X}_{3o} + \bar{\nu}_4^* \bar{X}_{4o} + \bar{\nu}_5^* \bar{X}_{5o} + \bar{w}_1^* \bar{Z}_{1o}} \tag{6.29c}$$

$$E_o^{\text{environment}*} = \frac{\bar{\mu}_3^* \bar{Y}_{3o}}{\bar{w}_2^* \bar{Z}_{2o} + \tilde{\mu}_2^* \tilde{Y}_{2o}} \tag{6.29d}$$

Stage three decomposition – Generation and Consumption
The final stage of the decomposition provides a breakdown of the overall system efficiency into the generation and consumption phases. Since the multiplicative decomposition was used, the overall system efficiency is a product of the five parallel sub-systems such that:

$$E_o = E_o^I \times E_o^{II} \times E_o^{III} \times E_o^{IV} \times E_o^V \tag{6.30}$$

This E_o^I represents the efficiency of the generation phase of the system.

$$\text{Generation} = E_o^I \tag{6.31}$$

However, the consumption phase comprises the social, economic and environmental systems. Therefore, the efficiency of the consumption phase is estimated as follows:

$$\text{Consumption} = E_o^{III} \times E_o^{IV} \times E_o^V \tag{6.32}$$

The next sections of this chapter present the results, discussions and conclusions based on the models developed.

Findings and discussion

In this sub-section, empirical results based on the models developed in the previous sub-section are presented and discussed. Results encompass both the generation phase and the consumption phase of energy assessment relevant to energy policy. In Table 6.4 overall efficiency scores of the countries under study are presented. These scores are based on constraints about sustainable and resource efficient electricity generation and how well countries use electricity and other resources to ensure better social, economic and environmental outcomes for citizens.

From Table 6.4 higher performers include Malta, Cyprus, Luxembourg, Sweden and Ireland. All of these countries had relatively lower performance in the generation assessment (Figure 5.6) but had relatively higher performance in the consumption assessment (Figure 6.4). This is probably because in the holistic assessment, the focus is on how well countries use primary resources to generate favourable social, economic and environmental outcomes, while producing electricity in a way that meets their consumption needs. This is compared to the generation assessment, which focuses on how well countries use primary resources to generate electricity without considering electricity demand. Pure consumption assessment also focuses on how countries use electricity available to meet their needs without considering how efficiently electricity is produced. As these assessments answer different questions there is a utility in conducting both a phased assessment as well as a holistic assessment. However, since energy policy focuses on the system-wide consideration of energy production and use, the essence of a holistic assessment cannot be understated.

Table 6.4 Overall efficiency and stage one decomposition (2017).

Country	Overall	Stage One Decomposition				
		I	II	III	IV	V
Austria	0.70003	0.98916	0.99872	0.99999	0.70861	1.00000 [a]
Belgium	0.61367	0.99084	0.99854	0.99999	0.62025	1.00000[a]
Bulgaria	0.50387	0.99566	0.99990	0.99999	0.70116	0.72183
Croatia	0.40488	0.99802	0.99998	1.00000[a]	0.40569	0.99999
Cyprus	0.99961	0.99962	0.99999	1.00000[a]	1.00000	1.00000[a]
Czech Republic	0.37483	0.99041	0.99873	0.99999	0.37894	1.00000[a]
Denmark	0.82737	0.99352	0.99947	0.99999	0.83322	1.00000[a]
Estonia	0.47354	0.99898	0.99974	0.99997	0.49615	0.95570
Finland	0.73032	0.99299	0.99896	0.99998	0.73626	1.00000[a]
France	0.65082	0.94643	0.98864	0.99987	0.69565	1.00000
Germany	0.67919	0.90702	0.98691	0.99992	0.75881	1.00000[a]
Greece	0.45281	0.99415	0.99990	0.99999	0.45553	1.00000[a]
Hungary	0.41497	0.99616	0.99962	1.00000[a]	0.41673	1.00000[a]
Ireland	0.88900	0.99546	0.99943	1.00000[a]	0.89357	1.00000[a]
Italy	0.48529	0.94977	0.99491	0.99997	0.51359	1.00000[a]
Latvia	0.49455	0.99882	0.99996	1.00000[a]	0.58570	0.84541
Lithuania	0.53259	0.99866	1.00000[a]	1.00000[a]	0.53331	1.00000[a]
Luxembourg	0.99933	0.99933	1.00000	1.00000[a]	1.00000	1.00000[a]
Malta	0.99978	0.99978	1.00000[a]	1.00000	1.00000	1.00000[a]
Netherlands	0.75895	0.98654	0.99730	0.99999	0.77140	1.00000[a]
Poland	0.78031	0.98157	0.99772	0.99999	0.79678	1.00000[a]
Portugal	0.37493	0.99092	0.99889	0.99999	0.37878	1.00000[a]
Romania	0.37831	0.98932	0.99909	1.00000	0.38275	1.00000[a]
Slovakia	0.61896	0.99666	0.99966	1.00000[a]	0.62124	1.00000[a]
Slovenia	0.61348	0.99848	0.99979	0.99999	0.61455	1.00000[a]
Spain	0.48384	0.95448	0.99481	0.99995	0.50958	1.00000[a]
Sweden	0.93163	0.98401	0.99681	0.99996	0.94984	1.00000
United Kingdom	0.79152	0.95574	0.99351	0.99994	0.83363	1.00000[a]
Geometric Mean	0.61072	0.98449	0.99789	0.99998	0.63376	0.98093

[a] *The actual score is lower than 1, the value in the table is due to rounding*

Table 6.5 Stage two decomposition of the generation phase (2017).

Country	Solid Fuels	Oil	Gas	Nuclear	Hydro	Wind	Renewable Biomass	Solar	Geothermal	Tide	Waste & Non renewable Bio
AT	0.0566	0.0301	0.4846	n.a.	0.1466	0.1116	0.1714	0.0488	0.0006	n.a.	0.0279
BE	0.0023	0.0047	0.7242	0.3492	0.0479	0.1136	0.1656	0.0446	n.a.	n.a.	0.0357
BG	0.1949	0.0042	0.0167	0.0532	0.0074	0.0152	0.0030	0.0096	n.a.	n.a.	n.a.
HR	0.0229	0.0035	0.0482	n.a.	0.0177	0.0149	0.0070	0.0090	n.a.	n.a.	n.a.
CY	n.a.	0.0709	n.a.	n.a.	n.a.	0.0183	0.0010	0.0221	n.a.	n.a.	n.a.
CZ	0.5678	0.0016	0.0846	0.2422	0.0492	0.0683	0.0683	0.0388	n.a.	n.a.	0.0013
DK	0.1811	0.0086	0.0591	n.a.	0.0688	0.1312	0.1966	0.0405	n.a.	n.a.	0.0211
EE	0.8207	0.0097	0.0803	n.a.	0.1536	0.1204	0.1222	n.a.	n.a.	n.a.	0.0138
FI	0.2216	0.0050	0.1057	0.3957	0.2212	0.1149	0.3228	0.0274	n.a.	n.a.	0.0121
FR	0.1123	0.0822	0.4762	0.3094	0.1052	0.0897	0.0856	0.0544	0.1251	0.1005	0.0220
DE	0.5597	0.0143	0.2533	0.3443	0.1148	0.0930	0.1309	0.0456	0.0791	n.a.	0.0169
EL	0.0472	0.0143	0.8080	n.a.	0.0111	0.0199	0.0008	0.0145	n.a.	n.a.	n.a.
HU	0.1483	0.0026	0.2406	0.2950	0.1271	0.0832	0.0644	0.0367	0.0038	n.a.	0.0061
IE	0.2011	0.0052	0.5783	n.a.	0.0826	0.1100	0.0270	0.0285	n.a.	n.a.	0.0055
IT	0.1226	0.0461	0.5699	n.a.	0.0832	0.0892	0.0775	0.0607	0.3833	n.a.	0.0093
LV	0.0001	0.0003	0.3306	n.a.	0.0464	0.0336	0.0511	0.0019	n.a.	n.a.	n.a.
LT	n.a.	0.0021	0.0089	n.a.	0.0093	0.0187	0.0078	0.0063	n.a.	n.a.	0.0013
LU	n.a.	0.0012	0.2167	n.a.	0.1169	0.2334	0.6805	0.1008	n.a.	n.a.	0.1527
MT	n.a.	0.0090	0.0549	n.a.	n.a.	0.0002	0.0005	0.0131	n.a.	n.a.	n.a.
NL	0.3402	0.0151	0.7912	0.4618	0.0935	0.1675	0.0586	0.0505	n.a.	n.a.	0.0184
PL	0.6954	0.0108	0.0655	n.a.	0.0461	0.0947	0.0345	0.0191	n.a.	n.a.	0.0017
PT	0.4210	0.0394	0.5797	n.a.	0.0519	0.1174	0.0990	0.0836	0.3224	0.0001	0.0082
RO	0.2765	0.0104	0.1770	0.2962	0.0815	0.0895	0.0087	0.0491	n.a.	n.a.	0.0000 [a]
SK	0.2053	0.0302	0.1522	0.2846	0.0672	0.0209	0.1165	0.0348	n.a.	n.a.	0.0017
SI	0.6596	0.0020	0.0649	0.3347	0.1130	0.0307	0.0398	0.0420	n.a.	n.a.	0.0012
ES	0.2244	0.0830	0.3433	0.3985	0.0514	0.1043	0.0320	0.1002	n.a.	n.a.	0.0038
SE	0.0153	0.0095	0.0321	0.3575	0.1937	0.1305	0.3960	0.0448	n.a.	n.a.	0.0494
UK	0.0875	0.0069	0.5907	0.3670	0.0928	0.1236	0.1372	0.0442	n.a.	0.0035	0.0161
Average	0.2577	0.0187	0.2940	0.3207	0.0846	0.0842	0.1109	0.0397	0.1524	0.0347	0.0194

[a] *near-zero value*

n.a. the country does not produce electricity using this sub-process

It is important to note that, although the holistic assessment may answer a slightly different question from the pure phased assessment, it provides the necessary decompositions as observed in the pure phased assessment. For example, in Table 6.5 the generation source-specific decomposition of 2017 assessment is provided. When compared with phase-specific assessment in Table 5.4 it is seen that both show similar results. Austria, for example, has its best generation sources being gas and hydro and worst generation sources being geothermal and oil. Similarly, when compared to other countries, Italy is the leader in generating electricity from geothermal energy, while France is the leader in tidal energy in both the phased and holistic assessments.

Table 6.6 provides the second stage decomposition of the transmission, social, economic and environmental systems. Just like the results in the consumption phase assessment presented in Table 6.3, the main source of efficiency on average is the economic system. This is then followed by the social and environment sub-systems. The rankings for the dimensions for each country generally remains the same as the consumption phase-specific assessment earlier conducted. Unlike the phase-specific assessments, however, combining the generation and consumption phases also provides additional insights on how efficiently countries transmit electricity generated to consumption sectors. Higher performers include Luxembourg and Lithuania.

Table 6.6 Stage two decomposition of transmission and consumption phases (2017).

	Transmission		Social		Economic		Environmental	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Austria	0.2794	*17*	0.3634	*23*	0.7086	*12*	0.1665	*18*
Belgium	0.3158	*12*	0.3835	*22*	0.6203	*16*	0.0447	*26*
Bulgaria	0.2408	*23*	0.4373	*19*	0.7012	*13*	0.3418	*7*
Croatia	0.4791	*4*	0.4359	*20*	0.4057	*25*	0.3319	*8*
Cyprus	0.3176	*10*	0.5683	*9*	1.0000	*1*	0.0260	*28*
Czech Republic	0.2126	*28*	0.5164	*13*	0.3789	*27*	0.2881	*12*
Denmark	0.3047	*14*	0.4428	*17*	0.8332	*7*	0.3261	*9*
Estonia	0.2150	*27*	0.7381	*7*	0.4962	*22*	0.8381	*5*
Finland	0.3741	*5*	0.1750	*27*	0.7363	*11*	0.8785	*3*
France	0.2211	*26*	0.2503	*26*	0.6957	*14*	1.0000	*2*
Germany	0.2583	*19*	0.4743	*15*	0.7588	*10*	0.1039	*21*
Greece	0.3517	*7*	0.2948	*24*	0.4555	*23*	0.2495	*15*
Hungary	0.3671	*6*	0.6028	*8*	0.4167	*24*	0.2641	*13*
Ireland	0.2466	*22*	0.4447	*16*	0.8936	*5*	0.1704	*17*
Italy	0.3332	*8*	0.5064	*14*	0.5136	*20*	0.0937	*22*
Latvia	0.3091	*13*	0.9987	*3*	0.5857	*18*	0.8454	*4*
Lithuania	0.9728	*2*	0.2533	*25*	0.5333	*19*	0.3956	*6*
Luxembourg	1.0000	*1*	0.8397	*4*	1.0000	*1*	0.0281	*27*
Malta	0.4930	*3*	1.0000	*1*	1.0000	*3*	0.0737	*24*
Netherlands	0.3172	*11*	0.5601	*10*	0.7714	*9*	0.0535	*25*
Poland	0.2861	*16*	0.8186	*6*	0.7968	*8*	0.2976	*11*
Portugal	0.2475	*21*	0.5552	*11*	0.3788	*28*	0.1503	*19*
Romania	0.2376	*24*	1.0000	*1*	0.3827	*26*	0.3108	*10*
Slovakia	0.3321	*9*	0.8242	*5*	0.6212	*15*	0.2152	*16*
Slovenia	0.2987	*15*	0.5401	*12*	0.6146	*17*	0.2604	*14*
Spain	0.2678	*18*	0.3873	*21*	0.5096	*21*	0.1276	*20*
Sweden	0.2215	*25*	0.1661	*28*	0.9498	*4*	1.0000	*1*
United Kingdom	0.2537	*20*	0.4390	*18*	0.8336	*6*	0.0910	*23*
Geometric Mean	0.3183		0.4833		0.6338		0.2053	

The third stage decomposition compares the contribution of the generation and consumption phases to overall system sustainability. The consumption phase here represents the product of the social, economic and environmental parallel networks without considering the transmission system. This decomposition has been presented in a 100% stacked column graph in Figure 6.8. From the figure, it is clear that the generation phase is the major source of overall system efficiency for most of the countries under assessment. Some exceptions to this are Cyprus, Luxembourg and Malta, which are able to leverage performance in the consumption phase.

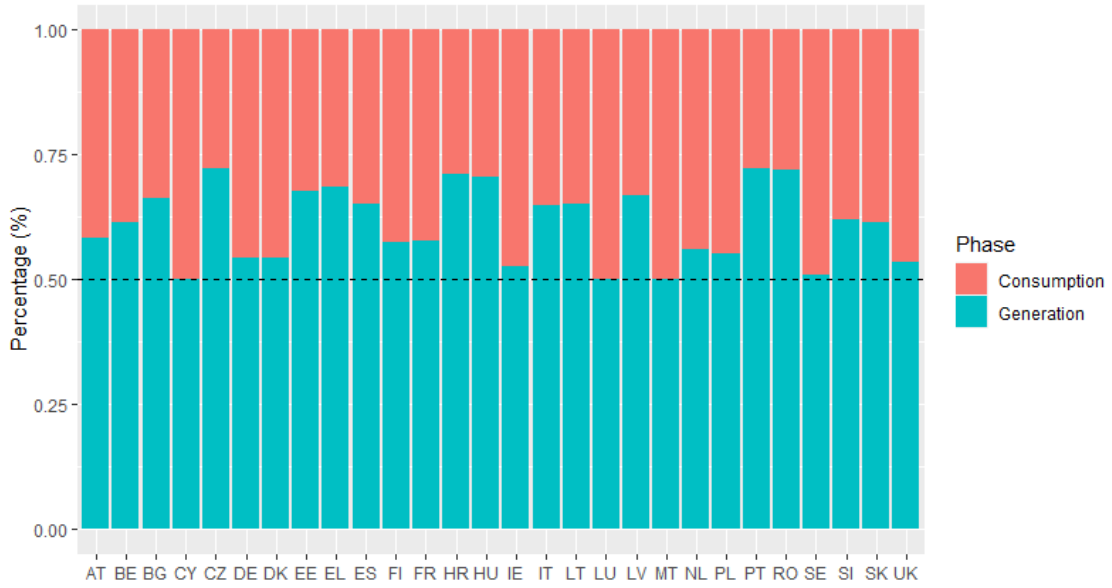


Figure 6.8 Stage three decomposition of the source of overall performance.

6.5 Chapter summary

The focus of the previous chapter, Chapter 5, was on the assessment of resource efficiency and sustainable generation of electricity. Chapter 6 was aimed at addressing the second objective of this thesis. That is to integrate electricity production evaluation, economic development, social development and environmental impact assessments into a single holistic assessment procedure that caters for alternative views on sustainability. To achieve this, performance models were first developed to assess the consumption phase of the electricity system. Specifically, a multi-stage serial network DEA was developed and empirically tested to provide insights on the social development, economic development and environmental performance of the countries under evaluation. Several contributions were introduced in the structure of the stages used for assessment. Finally, the consumption phase assessment was then integrated with the generation phase assessment which was earlier conducted in the fifth chapter.

In the consumption phase, two views on forming composite sustainability scores across the three dimensions studied were explored. The first is additive decomposition, which defines the overall (composite) efficiency as a weighted average of the efficiencies of the three dimensions. As this is an additive weighted average, it inherently allows compensation across dimensions and can, therefore, be considered to be consistent with the view of weak sustainability. The second approach,

multiplicative decomposition, evaluates the overall efficiency from a product of the dimensions in a series of parallel networks. With composite measures evaluated from the multiplication of sub-components, an overall score is susceptible to low scores on any dimension. Therefore, this measure limits the level of compensation across dimensions, which is viewed as consistent with views on strong sustainability. It is observed in the analyses that multiplicative decomposition is more discriminatory. However, the rankings of the dimensions for each DMU are generally similar for both additive or multiplicative decomposition. By this, it is possible to conduct an assessment from an anthropocentric perspective by giving more weights to the economic and social dimensions or from a bio-centric perspective where more weight is given to the environmental dimension or even a more neutral point of view by allowing the overall score to reflect all three dimensions without the assessor's input.

In the integrated assessment of the generation and consumption phases, it is shown that the objective of the integrated assessment is slightly different from separate phased assessments. The integrated assessment examines how resources are consumed to generate favourable social, economic and environmental outcomes given a country's generation capability and electricity demand. This is different from phased assessments, which either look at how resources are consumed to generate electricity without considering demand or how electricity and other resources are consumed to achieve favourable outcomes without considering efficiency in generating clean electricity. It is observed that since the phased and holistic assessment answer slightly different questions, it may be useful to conduct either a phased assessment or a holistic one. This will depend on the objective of the assessment is conducted. However, where policy is focussed on the entire electricity system, the utility of a holistic assessment is highest. It is shown that the results of the holistic assessment can be further decomposed in ways that are generally consistent with the results of a phased assessment. Consequently, the holistic assessment proposed can capture insights from the phased assessments and incorporate the complementarity between the generation and consumption phases, thereby providing further insights that cannot be achieved from a purely phased assessment.

Chapter 7

Sustainable Energy Portfolio Diversification

7.1 Introduction

This chapter moves the research from policy issues on energy security and eco-efficiency towards addressing policy concerns on clean and affordable energy mix planning. In order to incorporate sustainability concerns in affordable energy mix planning, the traditional approach has been to incorporate environmental and social cost indicators in the total generation cost for each available technology in a portfolio optimisation model. The impact of the cost configuration along sustainability dimensions on technology rankings and optimal portfolio are studied in this chapter. It is shown that combining the various cost dimensions using an additive relationship has the potential to erase the relevance of some of the dimensions, therefore, making some dimensions more important than others and resulting in optimal portfolios which may be inconsistent with sustainability. The use of a multiplicative relationship between the dimensions to assess how environmental and external (such as social) cost components in the generation cost, based on multilinear utility theory, is recommended. DEA is used to build models to examine how the internal structure of the cost of generation for each technology affects the optimal portfolios generated.

The remainder of the chapter is organised as follows: Section 7.2 provides background and highlights the problems with traditional energy mix planning. Section 7.3 presents the problem with summative technology costs in portfolio optimisation. Section 7.4 develops various optimisation models to examine the relationship between the dimensions of sustainability. Section 7.5 presents an

empirical analysis. The section first examines the impact of various configurations of cost composition on rankings of individual sources using DEA. This is then followed by an analysis of the impact of the cost configuration on the optimal portfolio selected using the mean-variance framework. Finally, concluding remarks and recommendations are made in Section 7.6.

7.2 Constructing a sustainable energy mix

Rapid economic development and increasing population growth globally have placed massive pressure on energy resources (Bazmi and Zahedi, 2011; Peng et al., 2013; Zhao et al., 2019). As such, the development and planning of energy generation sources have become a matter of priority for countries (Bazmi and Zahedi, 2011). However, due to awareness of the limits of non-renewable primary resources, environmental and social impacts of both renewable and non-renewable generation sources and increasing requirements of policy for clean, secure and affordable energy (the so-called "energy trilemma") (Jovanović et al., 2010), there has been growing research interest in constructing a sustainable mix of energy generation technologies/sources.

Markowitz (1952) first introduced a mean-variance framework for optimising a portfolio of investment assets by maximising expected returns and minimising associated risks, specifically return variance. Since then, this mean-variance framework has found relevance in several areas, including energy planning decisions. Early work of Bar-Lev and Katz (1976) and later Awerbuch and Berger (2003) laid the foundation for the application of this portfolio diversification theory in energy planning decisions to optimise the portfolio of generation technologies. Subsequently, there have been many other studies that have used the mean-variance framework in energy planning decisions (Arnesano et al., 2012; Bazilian and Roques, 2008; Roques et al., 2010; Westner and Madlener, 2011). Although there have been several approaches and applications of the mean-variance framework in energy portfolio planning (Westner and Madlener, 2011), at its foundation, the framework requires estimates for generation cost (or return) and risk, which form the building blocks for further assessment. The composition of the generation cost (or return) and risk have been the basis for some differences in literature, since it has direct implications on the nature of optimal portfolios generated.

On the one hand, there are studies that tackle portfolio optimisation problems without considering negative externalities borne by the environment and society (Allan et al., 2011; Delarue et al., 2011; Shakouri et al., 2015). For example, components of generation cost in Delarue et al. (2011) include investment costs, fuel

costs and fixed and variable operation and maintenance (O&M) costs. Similarly, Allan et al. (2011) considered private costs in estimating the levelised costs of the technology, thereby ignoring external costs such as the cost of emissions. Cost components considered included construction, storage, fuel and fuel delivery, pre-development, O&M costs and a waste and processing plant decommissioning cost for nuclear energy (Allan et al., 2011). Studies that do not consider environmental or societal dimensions provide portfolios aimed at optimising the generation cost in ensuring secure and affordable energy. However, such studies ignore the requirement for clean energy, which is an essential part of the sustainable energy policy. As such, optimal portfolios generated do not factor in emission-reduction potential, thereby, favouring non-renewable sources compared to renewable generation sources.

On the other hand, some studies include environmental or external impacts when estimating expected generation cost or return (Novacheck and Johnson, 2017; Stempien and Chan, 2017). The ambitious carbon emissions reduction targets and the need to raise energy efficiency has significantly influenced the structure of power generation (Westner and Madlener, 2010, 2011). Consequently, some studies have sort to consider the seemingly conflicting and competing priorities of energy security policies and sustainability/climate change policies (Stempien and Chan, 2017). The sustainability problem requires that different objectives or indicators, on economic, social and environmental dimensions, are considered or integrated simultaneously (Brandenburg et al., 2014). The solution adopted by studies in the literature, including Arnesano et al. (2012), Bhattacharya and Kojima (2012) and Marrero et al. (2015), is the addition of environmental and other external costs to the industrial cost used in the optimisation model. Arnesano et al. (2012), for example, defined total generation cost to be the sum of industrial cost, external costs and direct and indirect CO_2 costs. While the industrial cost component comprised construction, fuel and O&M costs per KWh, the external and CO_2 cost components captured the social and environmental impacts of the various generation technologies. Marrero et al. (2015), added the externality cost of CO_2 emissions to the levelised cost of energy in the sensitivity analysis to model the potential complementarity between renewable and non-renewable energy sources in reducing both portfolio risk/cost and CO_2 emission.

While the inclusion of external or environmental cost dimensions in the portfolio diversification problem is widely accepted in sustainable energy mix planning, it is argued in this chapter that merely adding such environmental and societal costs to other economic generation costs does not effectively capture the essence of sustainability and hence there is more emission-reduction potential for a truly

sustainable energy portfolio diversification. Relying on multi-attribute utility theory, it is shown that the preference relationships in an additive model fail to consider the joint effects in such multi-attribute problems (Keeney and Raiffa, 1993). This has implications for the optimal portfolios generated and the emissions reduction potential. This is because, for additive aggregation, there is the potential for poor performance on some dimensions of sustainability to be compensated by good performance on other dimensions of sustainability. Additionally, differences in the magnitude of the contributions of each of the dimensions towards total generation cost mean some dimensions may be disadvantaged in favour of dimensions with higher contribution magnitude.

The need to ensure sustainability, security and affordability of energy is one of the most pressing concerns faced by many governments and international bodies in contemporary times (Stempien and Chan, 2017). As such, effective modelling of the problem is key for energy policy. This chapter examines the impact of the composition of the cost structure on the preference between alternative generation sources that should be optimised in a portfolio model. As such, the implications of various cost configurations on the preference between sources and the optimal portfolio of sources are presented to show the weaknesses of traditional approaches to constructing sustainable generation mixes. From this, recommendations are made on how to generate a more sustainable mix with higher emissions reduction potential and a more effective combination of renewable and non-renewable generation sources.

7.3 Portfolio diversification

The mean-variance framework of Markowitz (1952) used in portfolio optimisation requires estimates of the expected value of the portfolio of generation sources and associated risk. The portfolio expected return is defined from the generation cost (Mari, 2014; Park et al., 2016) or output perspectives (Roques et al., 2010). In energy mix planning, however, the inverse of expected generation cost (i.e. $1/C_j$) is usually used in a maximisation model (Delarue et al., 2011). The general portfolio expected return is defined as (Roques et al., 2010):

$$E(R_p) = \sum_{j=1}^{n} w_j E(R_j) \tag{7.1}$$

This expected annual value of the portfolio ($E(R_p)$) comprises the weighted sum of the returns ($E(R_j)$) of n technologies under investigation. The risk of the portfolio is estimated by the standard deviation of the technologies:

$$\sigma_p = \left(\sum_{j=1}^{n} w_j^2 \sigma_j^2 + \sum_{j=1}^{n} \sum_{\substack{k=1 \\ j \neq k}}^{n} w_j w_k \sigma_j \sigma_k \rho_{jk} \right)^{1/2} \tag{7.2}$$

Where the σ_j and σ_k represent the standard deviation of technology j and technology k, while ρ_{jk} is the correlation between technologies j and k. In the optimisation problem, the portfolio with the highest return can be found by maximising the portfolio expected return subject to the portfolio risk as a constraint. On the other hand, the minimum-variance portfolio can be estimated by minimising the portfolio risk subject to the expected return as a constraint. For both problems, there is a further requirement for the weights w_j to sum up to unity, such that: $\sum_{j=1}^{n} w_j = 1$. There may be other upper and lower bound requirements, as well as capacity constraints on the optimal weights to be estimated. This depends on the national and international policies on the generation mix (Rombauts et al., 2011; Santos-Alamillos et al., 2017). Sensitivity analysis is conducted to solve the maximisation and minimisation models for various values of return and risk.

7.3.1 Decomposing the expected return and risk

The focus of this chapter is to examine the internal structure of the return of technology from which the optimal portfolio is selected. The expected return, defined from the inverse of generation costs, comprises various generation cost types including (but not limited to) O&M costs, capital/investment cost, fuel costs, as well as emissions factor usually from carbon trading, as well as external costs such as costs on health damages (Delarue et al., 2011). These costs may be generally classified as private industrial costs incurred during the plant operation and CO_2 costs usually imposed by governments to check emissions and external costs that could be incurred as a result of the impact of the operation of the plant on society (Allan et al., 2011; Arnesano et al., 2012). Total cost should reflect the economic, social and environmental cost per unit of energy produced which should be minimised to achieve secure, affordable and clean energy. Consequently, the generation cost (and the risk) of a technology is the basis for determining preference between different generation sources to generate a sustainable mix.

Total cost is often defined as a sum or weighted sum of the various cost components for each technology (see Arnesano et al., 2012; Delarue et al., 2011). If the cost of generation is decomposed into the $r = 1, \ldots, s$ independent sustainability dimensions

(e.g. economic, social and environmental costs), the expected return and variance of a given technology j can be defined as:

$$E(R_j) = \sum_{r=1}^{s} E(r_r) \tag{7.3}$$

$$\text{var}(r_{1j} + \ldots + r_{sj}) = \sum_{r=1}^{s} \text{var}(r_r) \tag{7.4}$$

where $r_r = 1/c_r$. The covariance is zero since the components are independent. Summing the components may not provide a truly sustainable portfolio since disadvantages on some dimensions can be compensated by large advantages on other dimensions. Since the expected return is the basis for determining the overall sustainability and preference between technologies, it is possible to look at the problem from a utility maximisation perspective. If the preference between alternatives satisfy the Von Neumann and Morgenstern (1947) axioms of rational behaviour and the components are mutually utility independent, then it is possible to express the multi-attribute utility problem in multilinear form (Keeney and Raiffa, 1993; Stewart, 2005):

$$u(Y) = \sum_{r=1}^{s} k_r u_r(y_r) + \sum_{r=1}^{s} \sum_{t>r} k_{rt} u_r(y_r)\, u_t(y_t) + \ldots + k_{1,2,\ldots,s} u_1(y_1) u_2(y_2) \ldots u_s(y_s) \tag{7.5}$$

where k's are scaling constants that ensure consistency. The attribute y_r is utility independent of its complements if the preference for lotteries with different levels of that attribute y_r do not depend on fixed levels of the remaining attributes (Stewart, 2005). In this case, higher economic returns are preferred to low economic returns at the same level of social and environmental returns. If all subsets of all attributes are utility independent of their complements, then the attributes are mutually utility independent (Keeney and Raiffa, 1993; Stewart, 2005). The multilinear form is a generalisation of both the additive and multiplicative utility functions (Keeney and Raiffa, 1993). The additive expected return as expressed in (7.3) follows the first term of the multilinear utility model in (7.5). The additive aggregation is used if alternatives satisfy additive independence, meaning preferences between the lotteries depend only on the marginal probability distributions (Keeney and Raiffa, 1993). It ignores the joint probability distribution and hence does not allow for interaction between the attributes. Elkington (1997) shows sustainability as the point of intersection between social (people), environmental (planet) and economic (profit)

objectives. Therefore, the idea of sustainability-focussed planning decisions should require *both* economic efficiency and external considerations not *either* economic *or* external. This is seen in the triple bottom line theory, depicted in Figure 2.1, which shows sustainability as the point of intersection between economic, social and environmental dimensions. Sustainable development of energy system includes a reduction in emissions and pollutant gases, increased safety of energy supply, use of renewable energy sources, improved energy efficiency and improved quality of life (Jovanović et al., 2009).

An approach which constructs composite scores in a way that allows disadvantages on some criteria to be offset by large advantage on other criteria (Hacatoglu et al., 2015a,b; Rowley et al., 2012) is inconsistent with the idea of sustainability (Elkington, 1997). Additivity of the utility function across attributes with comparable scales allows for loss on one criterion to be compensated by gains of another (Pomerol and Barba-Romero, 2000). Additionally, the various dimensions may not have the same magnitude. Bhattacharya and Kojima (2012), show that CO_2 costs represent very little of the total generating cost breakdown in the Japanese case with economic costs (capital, fuel and O&M) accounting for about 75% of the total risk. Awerbuch and Yang (2007), showed that carbon costs play very little in the generating cost structure of fossil-based fuels and even no direct impact on the cost of generating non-fossil technologies. Examining these dimensions by the sum of the costs has the potential of reducing the weight of CO_2 and other external costs in the final analysis and so it can be at variance with the ideas of sustainability.

In the case of sustainability, it may be more appropriate to define the expected return of the technology as a product of its components. In that case, the joint probability distribution across attributes is of concern such that overall preference for a technology differs at different levels of some attributes. Consequently, the desirability of different amounts of an attribute may depend on the specific level of other attributes (Keeney and Raiffa, 1993). Such interaction is not captured in the additive utility function. In such a case, the multiplicative preference relation may be preferred for determining the expected return of a technology across the sustainability dimensions. This presents some complexity in the estimation of the risk attributable to the various components. When variables are interacting, variance depends on whether the interacting variables are independent random variables or are correlated. Since the economic, social and environmental cost components are independent, the covariance between the components is assumed to be zero.

$$E(R_j) = \prod_{r=1}^{s} E(r_r) \tag{7.6}$$

$$\text{var}(r_{1j} \cdot \ldots \cdot r_{sj}) = \prod_{r=1}^{s} \left(\text{var}\left(r_r\right) + \left(E\left[r_r\right]\right)^2\right) - \prod_{r=1}^{s} \left(E\left[r_r\right]\right)^2 \tag{7.7}$$

Although the multilinear function in (7.5) has different levels of interactions between the dimensions, since the definition of sustainability requires only the interaction among the three dimensions, this study focusses on the interaction of all the three dimensions simultaneously when determining the technology return. However, it may sometimes be useful to rely on pairwise interactions when a technology has zero costs/returns on some dimension. In Section 7.4, optimisation models to examine the different relationships between dimensions of sustainability are developed. These models are empirically tested in Section 7.5 to see how the relationship between dimensions influences the preference between technologies.

7.4 Modelling the relationship between dimensions

DEA is used as the basis for examining the impact of various cost configuration on the scores and rankings of the technologies. With DEA, it is possible to examine the dimensions from the individual to composite level which allows for the examination of the impact of the dimension configuration on the composite scores. Additionally, DEA has been widely used to tackle portfolio optimisation problems of financial assets (Basso and Funari, 2001; Edirisinghe and Zhang, 2007; Liu, Zhou, Liu and Xiao, 2015; Zhou, Xiao, Jin and Liu, 2018) and sustainability assessments of various nature (Thies et al., 2019; Zhou, Yang, Chen and Zhu, 2018).

7.4.1 Relationship between DEA and multilinear utility function

The multilinear utility function is presented in equation (7.5), with a set of $Y = (y_1, y_2, \ldots, y_s)$ mutually utility independent attributes. Here $u_r(y_r)$ is the utility of the rth attribute scaled by k_r where $0 \leq k_r \leq 1$. In practice, the procedure for constructing the utility $u(Y)$ in multi-attribute utility theory involves first an assessment of the partial utilities $u_r(y_r)$ then determination of an appropriate scaling using qualitative judgements or other approaches like AHP, Entropy method or Principal Component Analysis (Dyer, 2005; Yang et al., 2014). Yang et al. (2014)

have shown the relationship between the DEA approach and the multi-attribute utility theory in estimating the scaling factors. Since the attributes in (7.5) are all 'more is better', DEA Without Explicit Output (DEA-WEI), which uses index data of the form $y_{ir} = e_r/x_i$ where e_r and x_i are outputs and inputs respectively (Liu et al., 2011), can be used for the assessment of the scaling factors (Yang et al., 2014) in the model:

$$
\begin{aligned}
h = \text{Max} \quad & \sum_{r=1}^{s} w_r u_r(y_{ro}) + \sum_{r=1}^{s} \sum_{t>r} w_{rt} u_r(y_{ro})\, u_t(y_{to}) \\
& \qquad + \ldots + w_{1,2,\ldots,s} u_1(y_{1o}) u_2(y_{2o}) \ldots u_s(y_{so}) && \text{(7.8a)} \\
\text{s.t.} \quad & \sum_{r=1}^{s} w_r u_r(y_{rj}) + \sum_{r=1}^{s} \sum_{t>r} w_{rt} u_r(y_{rj})\, u_t(y_{tj}) \\
& \qquad + \ldots + w_{1,2,\ldots,s} u_1(y_{1j}) u_2(y_{2j}) \ldots u_s(y_{sj}) \leq 1 && \text{(7.8b)} \\
& w_r \geq 0,\ j = 1, \ldots, n,\ r = 1, \ldots, s,\ t = 1, \ldots, s && \text{(7.8c)}
\end{aligned}
$$

The objective in (7.9) determines the scaling factors that maximise the multilinear utility function of the alternative o under investigation subject to the restriction that for all the other j alternatives ($j = 1, \ldots, n$), the same function given the chosen scaling factors does not exceed unity. Alternatively, the dual form of the LP problem (7.8) may be preferred:

$$
\begin{aligned}
\text{Max} \quad & \theta && \text{(7.9a)} \\
\text{s.t.} \quad & \sum_{j=1}^{n} z_j u_r(y_{rj}) \geq \theta u_r(y_{ro}),\ \ r = 1, \ldots, s && \text{(7.9b)} \\
& \sum_{j=1}^{n} z_j u_r(y_{rj}) u_t(y_{tj}) \geq \theta u_r(y_{ro}) u_t(y_{to}),\ \ r = 1, \ldots, s, t = 1, \ldots, s && \text{(7.9c)} \\
& \ \vdots \\
& \sum_{j=1}^{n} z_j u_1(y_{1j}) u_2(y_{2j}) \ldots u_s(y_{sj}) \geq \theta u_1(y_{1o}) u_2(y_{2o}) \ldots u_s(y_{so}) && \text{(7.9d)} \\
& \sum_{j=1}^{n} z_j = 1 && \text{(7.9e)} \\
& \theta \geq 1 && \text{(7.9f)} \\
& z_j \geq 0,\ j = 1, \ldots, n && \text{(7.9g)}
\end{aligned}
$$

The optimal solution of (7.9) is the reciprocal of the optimal solution of (7.8). In a single-input case, as in the risk-return problem, the DEA-WEI can directly be converted into the CRS (i.e. CCR) DEA model (Liu et al., 2011):

$$\text{Max} \quad \theta \tag{7.10a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j e_{rj} \geq \theta e_{ro} \tag{7.10b}$$

$$\sum_{j=1}^{n} \lambda_j x_j \leq x_o \tag{7.10c}$$

$$\lambda_j \geq 0,\ j = 1, \ldots, n,\ r = 1, \ldots, s \tag{7.10d}$$

Note that (7.10) shows the CCR model corresponding to a DEA-WEI model with just the additive term in the multilinear function. It is possible to show a CCR model with the interacting terms. This will only require additional constraints. In the next sub-section, DEA models based on the CCR are developed to examine how the relationship between the sustainability dimensions influence the rankings of technologies.

7.4.2 DEA modelling of attribute relationships

DEA models using the CCR model are developed to examine how the modelling of the relationship between the sustainability dimensions (or attributes) influence the ordinal ranking of the technologies (or DMUs) ($j = 1, \ldots, n$). In this section, the expected return ($E(r)$) is modelled as the output to be maximised while risk (σ) is modelled as the input to be minimised. For each of the DEA models presented, the score may be interpreted as a risk-adjusted performance measure since returns are maximised at given levels of risks.

Additive modelling of sustainability dimensions (Model 1)

As a starting point, the DEA model with expected return and risk defined by (7.3) and (7.4) is presented for the performance ranking. This model uses technology returns as a sum of the returns of the various sustainability dimensions that make up the generation cost of the technology. This risk measure in (7.11) is the square

root of the variance in (7.4). This is the traditional way return is estimated for portfolio optimisation problems.

$$E_o^1 = \max_{z,\,\phi} \quad \phi \tag{7.11a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} z_j \sigma_j \leq \sigma_o \tag{7.11b}$$

$$\sum_{j=1}^{n} z_j E(r_j) \geq E(r_o)\phi \tag{7.11c}$$

$$z_j \geq 0,\ j = 1, 2, \ldots, n \tag{7.11d}$$

For technology o, the objective is to find the maximum Pareto-efficient proportional expansion in expected return given a specified risk level. As such, if the score ϕ is equal to unity, then there is no opportunity for expansion of return since no other technology has a more Pareto-efficient risk-return combination. The inverse of the score in (7.11) is bounded by zero and unity with unity as the most efficient score ($0 < 1/\phi \leq 1$). Also, z_j is a non-negative vector of weights for technology j and $E(r_j)$ is the additive expected return score for technology j. It is believed that the rankings in (7.11) are inconsistent with the idea of sustainability since the various dimensions are combined without the requirement for good performance on each of the sustainability dimensions, thereby, allowing compensation.

Separating the sustainability dimensions (Model 2)

To address the weakness of the additive model presented in (7.11), one solution is to define the various dimensions as separate outputs, thereby, allowing Pareto preference on each of the sustainability dimensions. Given the dimensions of sustainability - economic, environmental and social - the total return and risk are,

therefore, decomposed into the three dimensions treated as the separate/independent outputs/inputs in separate constraints in Model (7.12).

$$E_o^2 = \max_{z,\,\phi} \quad \phi \tag{7.12a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} z_j \sigma_{rj} \leq \sigma_{ro} \qquad r = 1, \ldots, s \tag{7.12b}$$

$$\sum_{j=1}^{n} z_j E(r_{rj}) \geq E(r_{ro})\phi \qquad r = 1, \ldots, s \tag{7.12c}$$

$$z_j \geq 0, \;\; j = 1, 2, \ldots, n \tag{7.12d}$$

The model in (7.12) will, therefore, have three risk constraints and three expected return constraints representing the risk and returns for the three sustainability dimensions. This model is preferred to that presented in (7.11) since it allows preference to be examined on each dimension independently. However, the model allows the technology to choose the sustainability dimension for which more emphasis will be placed in terms of the weighting. This is because the weights are local and differ between DMUs. A feature of DEA is that it allows the DMU (technology) under evaluation to choose the most favourable weights to maximise its scores in the assessment (Yang et al., 2014). Also, in such a model, the technology return and risk may be defined as a weighted average in the portfolio analysis. This will, therefore, present the same challenges as the additive model in forming a composite return and risk for the technologies since a weighted additive average is used.

Multiplicative modelling of sustainability dimensions (Model 3)

To handle this preference problem between the expected returns across sustainability dimensions, it may be more appropriate to interact the various dimensions under study since the idea of sustainability fundamentally requires interacting its dimensions. Here, only the joint probability distribution is explored. Yang et al. (2014) have shown that the DEA approach can be extended using the multi-attribute utility theory with variable weights to include interaction terms to reflect value judgements. To cater for the need for interactions between the dimensions, therefore, the three return dimensions are included as an interaction term as formulated in (7.13). This will require an estimation of a new risk variable defined as a product of the returns.

This new risk variable for each technology is incorporated in (7.13) as $\widehat{\sigma}_j$. Also, note that the expected return and risk are estimated as in (7.6) and (7.7) respectively.

$$E_o^3 = \max_{z,\,\phi} \quad \phi \tag{7.13a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} z_j \widehat{\sigma}_j \leq \widehat{\sigma}_o \tag{7.13b}$$

$$\sum_{j=1}^{n} z_j E\left(\prod_{r=1}^{s} r_{rj}\right) \geq E\left(\prod_{r=1}^{s} r_{ro}\right)\phi \tag{7.13c}$$

$$z_j \geq 0,\ j = 1, 2, \ldots, n \tag{7.13d}$$

It is believed that the rankings generated from model (7.13) is most consistent with the principles of sustainability and will ensure that economic, social and environmental considerations are comparably prioritised in the composition of different technologies.

Pairwise interaction of sustainability dimensions (Model 4)

The potential problem with (7.13) is the impact a zero score on any dimension can have on the final ranking. A zero value on any dimension may mean no performance assessment based on the other dimensions can be undertaken. A renewable technology may have no environmental cost, for example, if only direct emissions are considered. In such circumstances, it is possible to conduct pairwise interaction as a compromise solution.

$$E_o^4 = \max_{z,\,\phi} \quad \phi \tag{7.14a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} z_j \widetilde{\sigma}_{rtj} \leq \widetilde{\sigma}_{rto},\ r = 1, \ldots, h-1,\ t = h+1, \ldots, s \tag{7.14b}$$

$$\sum_{j=1}^{n} z_j E\left(r_{rj} \cdot r_{tj}\right) \geq E\left(r_{ro} \cdot r_{to}\right)\phi,\ r = 1, \ldots, h-1, \tag{7.14c}$$

$$t = h+1, \ldots, s$$

$$z_j \geq 0,\ j = 1, 2, \ldots, n \tag{7.14d}$$

Note that $\widetilde{\sigma}_{rtj}$ in (7.14) represents the standard deviations of the expected return for sustainability dimensions r and t estimated using pairwise interaction

for technology j. The variance is estimated like (7.7) except r is 2 in each case. The model presented in (7.14) retains the interactions between the dimensions as required by sustainability while catering for the possibility of zero scores on a dimension. In essence, this approach examines the other less desirable outcomes in the triple bottom line Venn diagram in Figure 2.1 such as technologies which are not environmentally damaging and support society but come at high cost (socio-environmental), economically viable technologies which support society but have high environmental implications (socio-economic) and those that are economically profitable, do not burden the environment but do not provide sufficient support for society (eco-efficiency) (Sykes and Trench, 2014). The overall technology expected return and risk under such evaluation is the an average of the pairwise interactions.

Multilinear assessment of sustainability dimensions (Model 5)

An alternative compromise solution that addresses the problem of zero data on the dimensions and which also captures the joint effects across dimensions is presented in (7.15). This approach captures both the marginal effects and the joint effects between the dimensions.

$$E_o^5 = \max_{z,\,\phi} \quad \phi \tag{7.15a}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} z_j \left(\sum_{r=1}^{s} \sigma_{rj} + \widehat{\sigma}_j \right) \leq \left(\sum_{r=1}^{s} \sigma_{ro} + \widehat{\sigma}_o \right),\ r = 1, \ldots, s \tag{7.15b}$$

$$\sum_{j=1}^{n} z_j E \left(\sum_{r=1}^{s} r_{rj} + \prod_{r=1}^{s} r_{rj} \right) \geq E \left(\sum_{r=1}^{s} r_{ro} + \prod_{r=1}^{s} r_{ro} \right) \phi \tag{7.15c}$$

$$z_j \geq 0,\ j = 1, 2, \ldots, n \tag{7.15d}$$

7.5 Empirical assessment

To test the arguments presented in this chapter empirical analysis of the models is conducted. Since energy mix planning is conducted at the national level, the data by Arnesano et al. (2012) on portfolio optimisation of the Italian electricity generation mix is used. In their assessment, generation cost comprised environmental (CO_2 cost), societal (external costs) and economic (industrial) dimensions. In their study, the relationship between these dimensions was modelled as a sum where the inverse

of the sum of generation costs, comprising industrial, external and direct and indirect CO_2 costs, was maximised given the risk associated with each generation technology.

7.5.1 DEA evaluation of sustainability dimensions

Arnesano et al. (2012)) examined the Italian context to verify whether a different energy mix could be identified that minimises financial costs and risks, while at the same time examining environmental sustainability. The environmental dimension, represented by CO_2 costs, was based on a lifecycle estimate of the environmental emissions of the technology, as such, even renewable energy sources like hydro, wind and solar PVs incur some environmental cost in the production due to embodied emissions. Assessment based on the lifecycle perspective does not limit the environmental impact to only the generation of the resources, but the environmental impacts from 'cradle-to-grave' lifecycle thinking perspective. The composition of total cost included an external cost dimension, which represents all other costs due to the production of energy that is not sustained by the power plants itself but by society. This external cost is used as the social dimension of sustainability in this chapter. A summary of the data from the paper for the 10 technologies comprising both renewable and non-renewable sources are presented in Table 7.1.

Table 7.1 Cost estimates for the Italian case from Arnesano et al. (2012).

Technology	CO_2 Cost (Environmental)	External Cost (Societal)	Industrial (Economic)	Total Cost	Risk
Gas (100-160)	0.423	2.500	9.893	12.816	11.020
Gas (660)	0.423	2.500	6.939	9.862	10.850
Coal (100-160)	0.816	5.850	5.487	12.154	15.480
Coal (320)	0.816	5.850	4.975	11.642	16.020
Hydro (>10)[a]	0.172	0.340	5.457	5.968	8.190
Hydro (<10)[a]	0.172	0.340	6.410	6.922	27.460
Wind (>0.1-2)[a]	0.041	0.150	13.293	13.484	3.750
PV (0.5-1)[a]	0.272	0.160	39.746	40.178	4.020
Biomass (<15)[a]	0.234	2.650	13.223	16.107	12.570
Nuclear (1100)	0.021	0.250	5.082	5.353	16.720

[a] *Renewable energy source*

A priori, it is expected based on values in Table 7.1 that renewable energy generation sources (hydro, solar (PV), wind and biomass) will outperform their

non-renewable counterparts (gas and coal) if the technologies are considered along environmental and social perspectives of sustainability. This is because renewable sources generally have relatively lower environmental and societal costs and have relatively lower risk levels compared to most non-renewable technologies. Non-renewable sources like coal and gas have a comparative advantage in terms of the economic (industrial) dimension. Nuclear energy is also expected to be a higher performer since it is also associated with lower costs, though the risk may be high. When cost is examined at the total level, it is seen that the high industrial costs associated with renewables erodes the gains it makes on the other cost dimensions. The industrial cost of PV, for an example, represents 98.9% of the total cost of generation. At the national level, sustainable generation mix planning implies an optimal mix that effectively caters for environmental and social objectives together with economic implications. In this section, therefore, the effect of the structure of the cost/return on the rankings of the various technologies and its implications on the portfolio generated are examined.

Table 7.2 shows the risk-adjusted performance scores and rankings of the technologies estimated by model 1 (equation (7.11)) where the costs are combined as a sum of the dimensions. As expected, due to the use of the additive composite score, poor performance on some sustainability dimensions is compensated by higher performance on the others. For example, PV is disadvantaged in terms of comparative performance due to high industrial (economic) costs, although it has a low environmental and social impact as well as risk. Additionally, gas (100-160) and gas (660) which are fossil fuel based technologies are among the higher performers although they are among the riskiest technologies in terms of environmental impact.

Table 7.2 Model 1 – Additive modelling of sustainability dimensions.

Technology	Return	Risk	Score	Rank
Gas (100-160)	*0.08*	*11.02*	*0.3459*	*5*
Gas (660)	*0.1*	*10.85*	*0.4567*	*4*
Coal (100-160)	0.08	15.48	0.2598	8
Coal (320)	0.09	16.02	0.2620	7
Hydro (>10)	0.17	8.19	1.0000	1
Hydro (<10)	*0.14*	*27.46*	*0.2571*	*9*
Wind (>0.1-2)	0.07	3.75	0.9669	2
PV (0.5-1)	*0.02*	*4.02*	*0.3027*	*6*
Biomass (<15)	*0.06*	*12.57*	*0.2414*	*10*
Nuclear (1100)	0.19	16.72	0.5459	3

Next, the total return is decomposed with the three dimensions treated as separate outputs and inputs in separate constraints as in the model 2 (7.12) with the results presented in Table 7.3. Arnesano et al. (2012) do not provide estimates for risk of the social (external) dimension due to unavailability of historical data. As such, no risk constraint for the social dimension is included.

Table 7.3 Model 2 – Separating the sustainability dimensions.

Technology	Return Env.	Return Soc.	Return Eco.	Risk Env.	Risk Eco.	Score	Rank
Gas (100-160)	2.36	0.4	0.1	0.86	10.99	0.4180	8
Gas (660)	*2.36*	*0.4*	*0.14*	*1.12*	*10.8*	*0.5936*	*5*
Coal (100-160)	1.23	0.17	0.18	1.75	15.38	0.5271	7
Coal (320)	*1.23*	*0.17*	*0.2*	*1.83*	*15.92*	*0.5616*	*6*
Hydro (>10)	5.81	2.94	0.18	0.75	8.15	1.0000	1
Hydro (<10)	*5.81*	*2.94*	*0.16*	*0.64*	*27.45*	*0.2821*	*10*
Wind (>0.1-2)	24.39	6.67	0.08	0.08	3.75	1.0000	1
PV (0.5-1)	3.68	6.25	0.03	0.18	4.02	0.8738	4
Biomass (<15)	*4.27*	*0.38*	*0.08*	*0.38*	*12.56*	*0.2954*	*9*
Nuclear (1100)	47.62	4.00	0.20	0.10	16.72	1.0000	1

From Table 7.3, the preference evaluation of the technologies is deemed relatively more consistent with sustainability than previously shown in Table 7.2 since dimensions are independently compared based on Pareto preference. However, in forming an overall score, since each dimension is compared across technologies, the model will be less discriminatory than the previous model. Additionally, technologies choose which dimension more emphasis is placed on in their weighting. That explains why gas (660) is among the better performers since it places more emphasis on its higher economic performance. Coal (320) also places more weight on its low industrial costs (high economic returns), though it has relatively poor performance on the environmental and societal dimensions. This, however, does not conform with the traditional idea of sustainability, since emphasis can be placed on one dimension to the neglect of other ones.

The next table explores how interacting the expected returns for the sustainability dimensions affect the scores and rankings. It is believed that these interactions align more with the idea of sustainability than the additive model. Due to the relatively higher risk scores on the economic dimension (see Table 7.3), the economic return variable is transformed and replaced with the square root of the returns in Table 7.3, for each technology. Risks are estimated, with respect to Equation (7.7).

Table 7.4 Model 3 – Multiplicative modelling of sustainability dimensions.

Technology	Return	Risk	Score	Rank
Gas (100-160)	0.30	0.1091	0.0060	7
Gas (660)	0.36	0.1694	0.0046	8
Coal (100-160)	0.09	0.1275	0.0015	9
Coal (320)	0.09	0.1398	0.0015	10
Hydro (>10)	7.32	0.9429	0.0170	6
Hydro (<10)	6.75	0.7491	0.0197	5
Wind (>0.1-2)	44.60	0.1474	0.6609	2
PV (0.5-1)	3.64	0.1754	0.0454	3
Biomass (<15)	0.44	0.0391	0.0248	4
Nuclear (1100)	84.49	0.1845	1.0000	1

Results, presented in Table 7.4, conform much better to *a priori* expectations of the rankings, with most renewables and nuclear among higher performers and fossil-based fuels among the lower performers. Among the top performers are wind, nuclear, hydro and PV. This interaction between the dimensions allows for better incorporation of all three dimensions of sustainability in the portfolio generation. However, it must be noted that zero value on any dimension will mean no performance score for that technology. A technology may have no environmental cost, for example, if only direct emissions are considered and not the whole lifecycle emissions which would account for embodied emissions.

To cater for the implication of a zero score on a dimension on the final score for such special occasions, it is reasonable to use compromise solutions. Ranks generally stay similar to those presented in Table 7.4 while catering for the possibility of zero scores on a dimension. Table 7.5 shows the rankings using the two compromise solutions that incorporate some level of interaction between the dimensions. For both compromise solutions, renewables outperform non-renewable sources, which is consistent with *a priori* expectations.

While pairwise interaction captures the joint effect between two dimensions at a time, multilinear form captures both the joint effect of the three dimensions and their marginal effects. Therefore, for pairwise interaction if there is a value of zero on any one dimension, the expected return will comprise only the interaction of the two remaining dimensions. Consequently, such a technology will not dominate another technology with non-zero values. In the multilinear model, the expected return of a technology comprises both the additive and multiplicative terms. Hence,

Table 7.5 Model 4 and Model 5 – Compromise solutions.

Technology	Pairwise Interaction		Multilinear	
	Score	Rank	Score	Rank
Gas (100-160)	0.0869	7	0.0139	8
Gas (660)	0.0798	8	0.0142	7
Coal (100-160)	0.0573	10	0.0051	9
Coal (320)	0.0576	9	0.0050	10
Hydro (>10)	0.1340	6	0.0866	4
Hydro (<10)	0.1436	5	0.0285	5
Wind (>0.1-2)	1.0000	1	1.0000	1
PV (0.5-1)	0.4274	3	0.1632	3
Biomass (<15)	0.1710	4	0.0209	6
Nuclear (1100)	1.0000	1	0.4204	2

if a technology has zero value on any dimension, its expected return will be lower since it will be made up of only the additive component.

7.5.2 Constructing optimal generation portfolios

It has been shown that the internal structure of the cost/return used for portfolio optimisation can impact preference between technologies and their rankings. The next question is whether changes in the internal structure of the cost/return affect the optimal portfolio of technologies generated using the Markowitz approach. Two portfolios, the maximum return and minimum risk portfolios are constructed for each of the cost configurations examined in this section. For the maximum return portfolio, the expected return of the portfolio of technologies is maximised given risk and capacity constraints. Minimum risk portfolio constructs the optimal portfolio that minimises the overall portfolio risk. The minimum risk portfolio is usually the most diversified portfolio while the maximum return portfolio is least diversified (Arnesano et al., 2012). For the Italian case, the minimum and maximum capacity constraints showing the lower and upper bounds for the different technologies considered are given in Appendix B.

In Figure 7.1, the optimal portfolios of technologies excluding nuclear energy are presented. The current generation mix of Italy, for the period under study, had no nuclear generation input, as such the portfolios presented in Figure 7.1 exclude the nuclear option. CO_2 emissions have been estimated based on the allocation of gas and coal options using the emission factors of 55.82 kg/GJ and 94.073 kg/GJ

respectively for an annual electricity demand of 314.57 TWh, which is consistent with Arnesano et al. (2012). Full portfolio characteristics are presented in Appendix B.

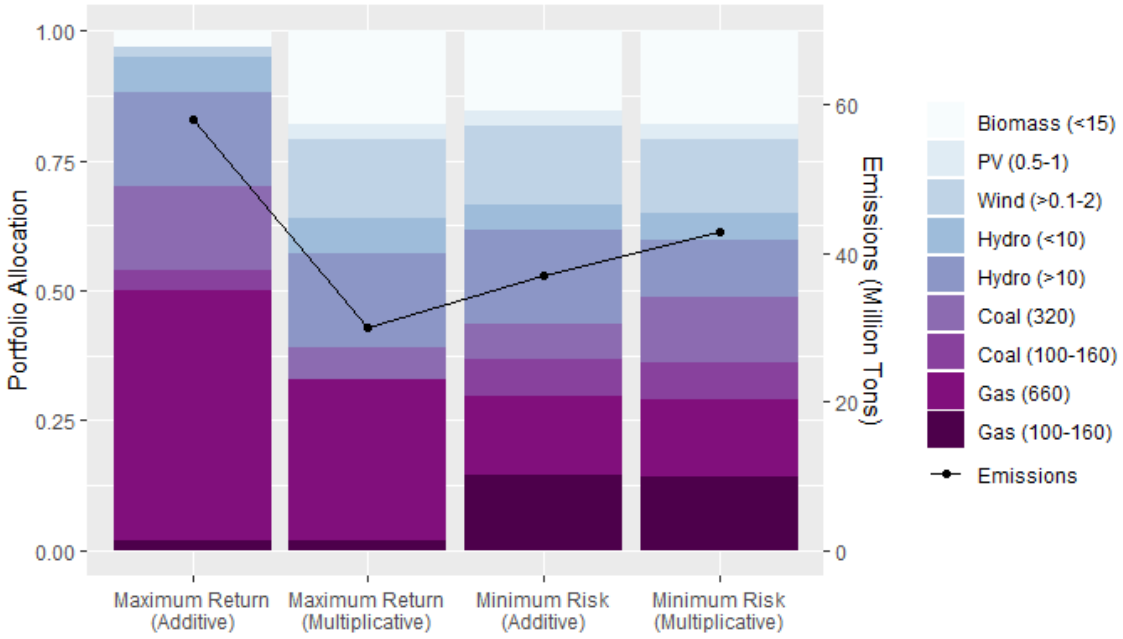


Figure 7.1 Optimal production mix and CO_2 emissions (without nuclear option).

Maximum return portfolios for the additive (model 1) and multiplicative (model 3) options show a clear difference. The optimal portfolio based on an addition of the sustainability dimensions has only 30% total allocation to renewable energy sources, although maximum capacity constraints allow for at most 61% allocation to renewable sources. PV even gets no allocation in the generation mix. The portfolio is, therefore, dominated by non-renewable sources with gas (660) receiving the highest allocation of about 48%. Compare that to the portfolio generated based on the interaction of the components (model 3) of the total return for the technologies. Here, 61% of the portfolio allocation has been given to renewable generation sources, thereby, ensuring a massive reduction in the CO_2 emissions based on the additive model (model 1). Evidently, this is a cleaner generation mix compared to the additive portfolio which allows for more non-renewable sources due to lower economic cost alone.

For the minimum risk portfolio, it is seen that the additive model slightly outperforms the multiplicative model, probably because no risk for the social dimension was captured in the original data, although the expected returns reflect the social dimension of sustainability. Note that discussions in the previous section

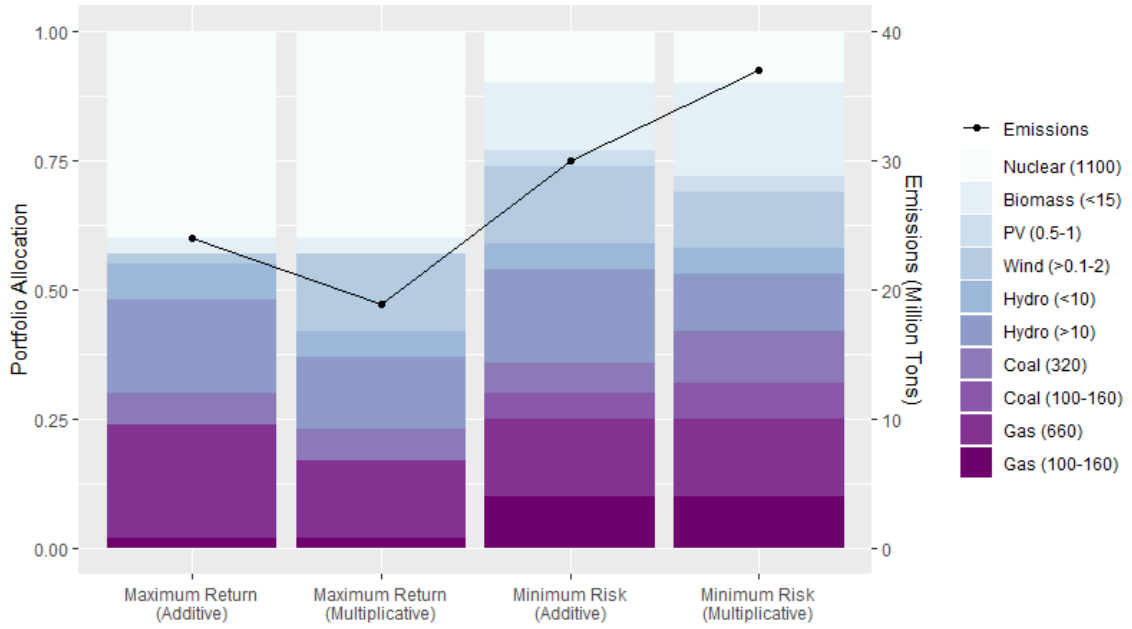


Figure 7.2 Optimal production mix and CO_2 emissions (with nuclear option).

were based on the maximisation of return and its implication on risk, however, the portfolio generated by the multiplicative model for the minimum risk portfolio does not seem very different from that generated by the additive model. Generally, the allocations for the minimum risk portfolios are identical with renewables comprising 56% of the additive model and 51% in the multiplicative model. Figure 7.2 shows the maximum return and minimum risk portfolios for the set of technologies including nuclear energy. Regardless, renewable content in the multiplicative model is higher than in the additive model. Observations made earlier for the minimum risk portfolio remains the same when nuclear energy is included in the optimal portfolio.

Finally, in the case of zero data on some dimensions, compromise solutions based on pairwise interaction and multilinear models are presented. The optimal portfolios using these approaches have been presented for nuclear and no nuclear cases in Figure 7.3 and Figure 7.4, respectively. In the figures, the optimal solutions are compared to the current Italian mix as well as the optimal solution in the multiplicative model. Evidently, while the maximum return portfolios give similar emission levels, the compromise solutions outperform even the multiplicative model in the minimum risk case.

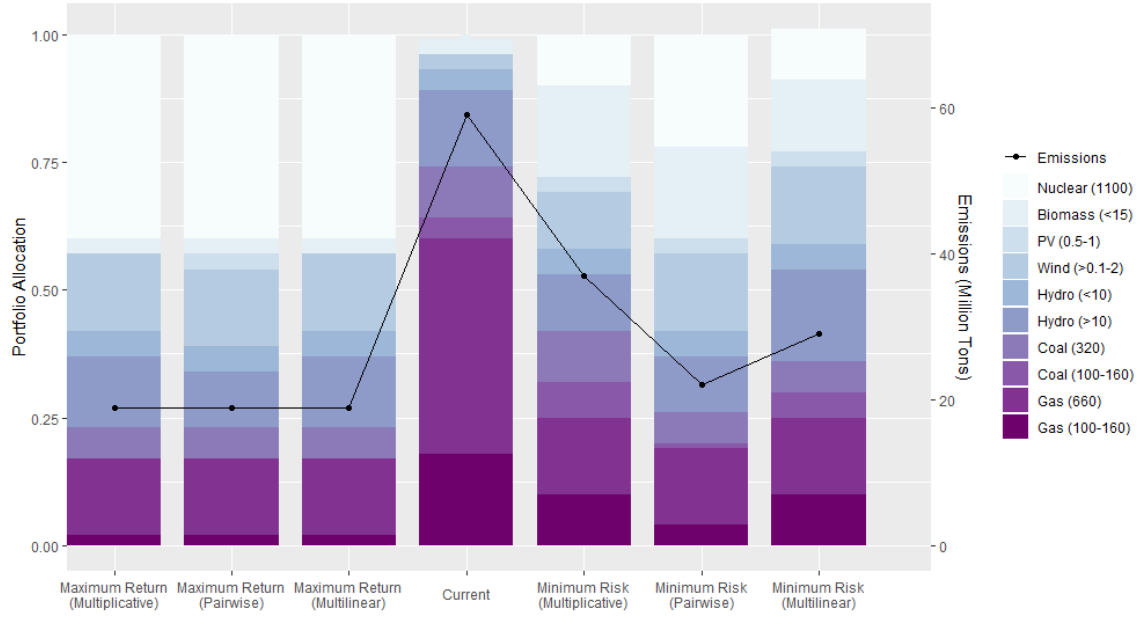


Figure 7.3 Comparison of compromise solution with other solutions (with nuclear).

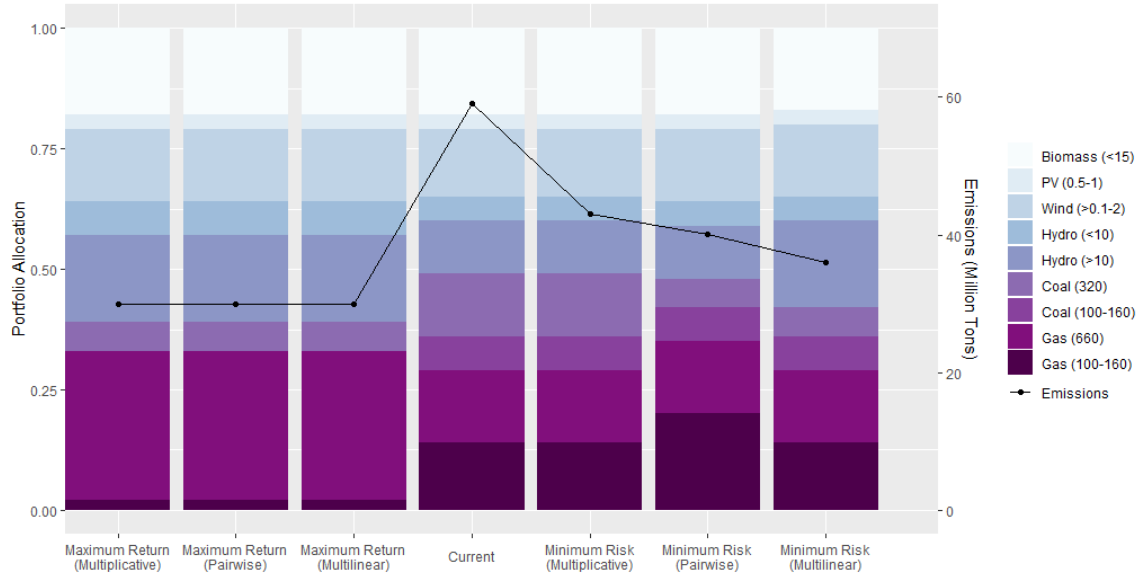


Figure 7.4 Comparison of compromise solution with other solutions (without nuclear).

7.6 Chapter summary

This chapter examines how environmental and social cost indicators are considered in the total generation cost for each available technology in a portfolio optimisation model. Traditional approaches to this objective have generally adopted the mean-variance analysis approach to incorporate external and environmental dimensions in the estimation of the expected returns of the technology. However, it is shown that the way in which these sustainability-oriented dimensions are incorporated into the expected returns has the potential to erase the relevance of some of the dimensions. This study, therefore, has significance in promoting the sustainability assessment of energy generation systems. Environmental and external cost components (such as social costs) in the generation cost can be combined with industrial (economic) costs by exploring interactions and other relationships between the various components.

The nature of the interaction between the dimensions has an impact on the performance score and rankings. It is shown that using an additive composite total costs/returns will have an impact on the nature of the portfolio selected. If the environmental and social impacts are to be appropriately modelled in terms of sustainability performance, then it is important to examine how the various dimensions interact with each other. The analyses show that current approaches used have the potential of disadvantaging renewable energy sources in the modelling and the optimal portfolio process especially based on maximum returns. It is not surprising that deLlano Paz et al. (2017) observe that portfolio optimisation has a limitation when it comes to assessing the impact of the inclusion of renewable technologies in the portfolio.

Chapter 8

Conclusions and Recommendations

This chapter provides a summary of the findings of the research conducted in this thesis. Additionally, further research opportunities, based on the findings and ideas from the thesis, are highlighted.

8.1 Summary and conclusions

The primary objective of the thesis was to develop DEA sustainability assessment models of electricity generation and consumption that can incorporate differences in generation portfolios, while providing a cross-country performance comparison in the European context. This was undertaken in the prior seven chapters.

The first chapter of the study provided the foundation upon which the entire study was based. It began with a brief background statement that provided an overview of the sustainability problem and its relevance in energy systems. This was followed by a problem statement that communicated the limitations with current literature. Problems highlighted included the seeming disconnect between the production and consumption assessment literature, the inherent limitations of some traditional OR techniques in handling sustainability problems, and the peculiar challenges in sustainability and performance assessment of energy systems. As a result of these key research gaps, three research objectives were presented. Specifically, to:

a. explore DEA optimisation models that cater for differences in production portfolios and the assessment of sustainability and resource efficiency in electricity production of EU countries.

b. integrate electricity production and use evaluations, economic development, social development and environmental impact assessments into a single holistic assessment procedure that caters for alternative views on sustainability.

c. examine the implication of sustainability in portfolio optimisation models aimed at selecting an optimal mix of energy generation sources that ensures affordable but clean energy system.

The chapter concluded with a discussion of the expected contributions of the thesis and an outline of the thesis.

The second chapter was a review of the extant literature on the sustainable energy system. The first section reviewed conceptual issues in the sustainability literature. This included definitions and dimensions of sustainability and sustainable development and systems thinking in sustainability. The second section provided some conceptual and empirical literature on energy and sustainable development. In this section, the relationship between energy and the three dimensions of sustainability, namely the economy, society and the environment, were discussed. The third section was dedicated to sustainability assessment literature. Methodological issues in the production and consumption assessment literature were then discussed. The chapter concluded with a section on systems thinking in sustainable energy research. The chapter, therefore, provided the conceptual and empirical background for model building and empirical assessment in subsequent chapters.

Since the thesis develops DEA models for sustainability assessment, it was important to provide some methodological review and determine the modelling choices. Consequently, a synthesis of the DEA literature that related to the assessments to be conducted in subsequent chapters was undertaken in Chapter 3. Specifically, the DEA literature on models with unknown internal structure, network DEA models, non-homogenous DEA, undesirable inputs/outputs, as well as alternative efficiency measurement approaches were extensively reviewed. The NDEA literature was essential in developing evaluation models that incorporate alternative generations sources in the generation phase, different policy objectives in the consumption phase and an integrated assessment that combines the generation and consumption phases. In the generation phase, since different countries generate electricity from different portfolios of energy sources, there were some non-homogeneity across countries. A review of the DEA non-homogeneity literature revealed the absence of approaches dealing with non-homogeneity in combination with sub-processes in a parallel NDEA structure. This absence of an approach to handle this type of non-homogeneity presented opportunity for model development in subsequent chapters.

Chapters 2 and 3 provided a foundation for the thesis by defining clear objectives and providing a discussion of conceptual, empirical and methodological literature to understand the strengths and weaknesses of existing literature. The fourth chapter brought together knowledge identified in previous chapters to structure the problem in a manner that would guide model development and empirical assessment to achieve the research objectives. This chapter employed causal loop diagrams to develop conceptual models that reflect the necessary policy variables in sustainable energy policy. This provided a systemic overview and a simplification of the complex interrelationships in sustainable energy as captured in literature. From these causal loop diagrams, NDEA conceptual frameworks were developed for the generation phase, the consumption phase and the integration of these two phases. While the generation phase resulted in a parallel network structure, the consumption phase was a multi-stage series network with three stages. This meant that the entire system was a mixed structure problem with parallel and multi-stage components.

Chapter 5 provided model development and empirical assessment of the consumption phase of the energy system. This was objective one of the thesis - to explore DEA optimisation models that cater for differences in the production portfolios and for sustainable and resource efficient electricity production of EU countries. As earlier indicated, due to differences in the generation portfolios of the countries, it was important to ensure that models developed recognise such non-homogeneity. It was shown that where there exists non-homogeneity in the sub-processes and there exist shared inputs or outputs, then using traditional parallel NDEA models could result in potential allocation to non-existing sub-processes. The consequences are artificially lower inputs and outputs to existing sub-processes and the potential for efficiency scores being computed for non-existing sub-processes. Two approaches for handling such non-homogeneity and factor allocation were, therefore, proposed. The first approach ensures that the optimal multipliers for each DMU are only determined for existing sub-processes. This is achieved by eliminating non-existing sub-processes in the evaluation of the DMU. The second approach maintains all sub-processes in the industry but ensures that no allocation is made to non-existing sub-processes. When both of these approaches were compared to a traditional NDEA, differences in the overall scores and rankings were observed, which underscored the need to correct such non-homogeneity problems.

The choice between the two proposed approaches depends on whether the DMU has price controls in determining their optimal multipliers. If price-taking exists or regulatory control determines prices, then approach two would be more appropriate. The subsequent empirical assessment was based on the second approach since it uses

the entire market data and DMUs have relatively similar regulatory environment due to membership of a regional block. In the empirical assessment of the electricity generation systems, evaluation models that employ transformation inputs, labour and installed capacity of 11 generation sources to produce electricity and GHG emissions for some sub-processes were developed. It was observed that half of EU countries have a score lower than 50% on average for the 10-year study period. Higher performers included Estonia, Poland, Greece and Austria. After averaging the system scores across the countries, it was observed that resource efficiency and sustainable electricity generation in the EU were within the 0.4 to 0.6 range over the study period without a clear pattern towards performance improvement. Country-specific decomposition of the overall efficiencies was also conducted and reported. The contribution of this chapter is, therefore, the introduction of models, which recognise differences in the generation portfolios of EU countries and the examination of the performance of electricity production systems in EU countries.

Chapter 6 addressed the second objective of the study. This objective was to integrate electricity production evaluation with policy areas in the consumption phase while catering for alternative views on sustainability. This chapter, therefore, addressed production and consumption sustainability in a single assessment. The chapter was divided into two main parts. The first part developed models for the consumption phase of the energy system. In this part, both the additive and multiplicative decomposition of overall efficiency were used for the multi-stage series network comprising social, economic and environmental sub-systems. It is believed that while the additive decomposition in the assessment is consistent with the weak sustainability viewpoint, the multiplicative decomposition is more consistent with the strong sustainability view of sustainability. This is because the level of compensation between the performance dimensions is higher in the additive model than the multiplicative model. Therefore, there is the potential for more substitution of low performance on one dimension for higher performance on other dimensions of sustainability performance with additive decomposition. For both the additive and multiplicative models, higher overall performers in the consumption phase included Malta, Luxembourg, Cyprus, Ireland and Sweden. There were differences, however, in the lower performing countries for the two models.

The second part of the assessment in Chapter 6 provided a holistic assessment comprising both the production and consumption phases. As evident in the preceding assessments, higher performers in the generation phase are not necessarily higher performers in the consumption phase. Therefore, it was important to combine these two phases to capture the interrelationship and complementarities in these two phases

of the energy system. Using the multiplicative decomposition, a series of parallel networks were used to characterise the system efficiency. This system efficiency was further decomposed into the efficiencies of the generation sources, the policy dimensions in the consumption phase and two-phase efficiencies. It was observed that higher performance on a phase-specific assessment does not necessarily mean higher performance on the system-wide assessment. This together with the differing objectives of the phased and holistic assessments mean there is a utility in sometimes conducted phased assessment. However, where decision support is required for system-wide considerations then the holistic assessment is best placed to do that. Decompositions of the holistic model revealed its results are generally consistent with the phased assessment while providing more information than available in the phased assessment. For example, it was observed that for most of the countries, system-wide efficiency was mostly influenced by the generation phase rather than the consumption phase.

Chapters 5 and 6 provided assessments pertaining to on secure and clean energy. Chapter 7, meanwhile, examined economic, environmental and social cost dimensions of sustainability. Renewable energy sources are characterised by high running costs per KWh, however, they have an advantage in terms of lower costs to the environment and society as well as lower risk in most cases. This shows that renewables outperform non-renewable generation sources in two of the three dimensions of sustainability. However, it was shown in Chapter 7 that additive pooling of the costs across dimensions when used in portfolio optimisation will disadvantage renewable generation sources in favour of non-renewable sources. Therefore, alternative pooling of the total cost per technology were examined to determine how economic, social and environmental dimensions could be incorporated in portfolio optimisation of energy mix planning in line with sustainability objectives. It was found that multiplicative pooling of the total cost best conforms with the expectations on technology rankings with a sustainability focus. Additionally, when technology costs determined through multiplicative pooling were used in portfolio analyses with an affordable energy focus, the resulting optimal portfolios achieved lower emissions and higher renewable energy content than additive pooling. This chapter, therefore, addressed the third objective of the study.

This thesis has, therefore, addressed all the dimensions of the energy trilemma in energy policy by providing an assessment of secure energy supply, the production and consumption of clean energy and the generation of an affordable energy system with a sustainability focus. In doing this, novel DEA models have been developed

and empirically implemented to examine the complex internal structures of units under investigation.

8.2 Suggestions for further research

Although a comprehensive assessment and model development has been conducted in this thesis, some opportunities for further research in different areas are highlighted below.

In Chapter 4, causal loop diagrams were developed as the basis for understanding the causal relationships studied in literature and structuring network models for DEA assessment. Although loop diagrams were developed, DEA was used for assessment since the focus was on the performance of the system in comparison with the same system of other countries. Network DEA was the chosen DEA systems assessment methodology. However, further research could explore the dynamic behaviour of the energy systems using these causal diagrams. Systems dynamics could also be used to explore the system behaviour of each country over time. In the DEA literature, dynamic DEA can be useful for studying the dynamic performance of the energy systems over time. This thesis did not specifically consider changes in performance over time.

Secondly, it was shown that where DMUs in a parallel NDEA have a different set of sub-processes, there is the potential of allocation to non-existing sub-processes. To cater to the non-homogeneity, two approaches were proposed for handling such non-homogeneity in parallel NDEA problems. Parallel NDEA was the focus of the non-homogeneity problem in this thesis since the differences between countries exist in the portfolio of concurrent electricity generation sources rather than the serial relationships with other sub-systems. It is reasonable to believe that such non-homogeneity may also exist in some serial problems. For example, countries can have differences in electricity transmission systems. In such cases, the existence of shared-flow factors in the model would present similar challenges as those discussed in the thesis. Consequently, further research could explore approaches for handling such non-homogeneity in serial and mixed structure network problems.

Some improvement can also be made to the empirical assessments in Chapters 5 and 6. Firstly, in the generation phase, no distinction about the importance of gross electricity production from renewable and non-renewable sources was made. Additionally, the weights of the sub-processes were determined using resource consumption. Where available, external weighting of the importance of electricity generation sources could be incorporated into an assessment of system sustainability

and resource efficiency. This external weighting could also be incorporated into the consumption phase as well as the integration of the phases. Secondly, while the literature on assurance regions for multiplier restriction in DEA is well advanced, multiplier restriction in this thesis was limited to minimum and maximum bounds. In a practical application, it is possible to more extensively define assurance regions to control the relative importance of optimal multipliers in a manner that is consistent with actual factor prices. It is important to also note that this study focussed on direct emissions from electricity production. Further research can explore indirect emissions that is embodied in resources used in establishment power plants. This can be achieved using lifecycle analysis.

Finally, in Chapter 7, various DEA models were developed to examine how the pooling of costs along the sustainability dimensions affects the technology rankings and the optimal portfolio. In the empirical assessment, data for the Italian case described previously in the literature was used. The choice of this data was informed by the existence of cost data on the three sustainability dimensions and the ability to compare the findings with existing literature. Reliance on existing research data resulted in some challenges with the determination of risks. The social (external) dimension, for example, did not have a risk in the original application. Further research could generate cost and risk data from historic data series or some forecasted values. While the focus was on the composition of costs, similar arguments could be made about the composition of risk, especially when it is considered that risk for an energy technology does not only come from fuel cost but it is an amalgamation of different dimensions, including CO_2 cost volatilities. Additionally, the assessment focussed on only the Italian case. It would be interesting to determine if there is the potential for an optimal EU-wide generation mix. In such an assessment, countries might choose to generate power from only sources they have sufficient cost, efficiency and other comparative advantages for their operation. This comprehensive portfolio optimisation might perhaps be useful in the EU's transition towards a unified, smart and decarbonised electricity grid. In the same chapter, new DEA models were also developed. Further research could extend network DEA using these DEA models developed based on multi-attribute utility theory.

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Appendix A

Optimal allocation of split variables

A.1 Split factors without minimum bound

Country	Existing Sources (Out of 11)	Non-existent sources	Split Factor Proportions[a]		
			Installed Capacity	Transformation Input	Labour
Austria	9	Nuclear	n.a	n.a	0*
		Tide	n.a	0*	0.0034
Belgium	9	Geothermal	n.a	0*	0.6933
		Tide	n.a	0*	0.0002
Bulgaria	8	Geothermal	n.a	0.0599	0.0909
		Tide	n.a	0*	0.0909
		Waste & Biofuels [NR]	0.0035	n.a	0.0909
Croatia	6	Nuclear	n.a	n.a	0.0001
		Solar	n.a	0*	0.0001
		Geothermal	n.a	0.069	0.0001
		Tide	n.a	0*	0.0001
		Waste & Biofuels [NR]	0.0009	n.a	0.0001
Cyprus	4	Solid Fuels	0.6449	n.a	0.5219
		Gases	0.3535	n.a	0*
		Nuclear	n.a	n.a	0*
		Hydro	n.a	0.4641	0*
		Geothermal	n.a	0.0466	0*
		Tide	n.a	0*	0*

Continued...

Continuation of Table

Country	Existing Sources (Out of 11)	Non-existent sources	Split Factor Proportions		
			Installed Capacity	Transformation Input	Labour
		Waste & Biofuels [NR]	0.0005	n.a	0*
Czech Republic	9	Geothermal	n.a	0.0623	0.0009
		Tide	n.a	0*	0.0009
Denmark	8	Nuclear	n.a	n.a	0*
		Geothermal	n.a	0*	0.0359
		Tide	n.a	0*	0.0017
Estonia	6	Nuclear	n.a	n.a	0*
		Solar	n.a	0.0292	0*
		Geothermal	n.a	0.013	0*
		Tide	n.a	0.0014	0*
		Waste & Biofuels [NR]	0.2	n.a	0*
Finland	9	Geothermal	n.a	0*	0.2032
		Tide	n.a	0*	0*
France	10	Geothermal	n.a	0*	0.7055
Germany	10	Tide	n.a	0*	0.0015
Greece	8	Nuclear	n.a	n.a	0*
		Geothermal	n.a	0.0466	0*
		Tide	n.a	0*	0*
Hungary	9	Geothermal	n.a	0.0703	0.0909
		Tide	n.a	0	0.0909
Ireland	6	Nuclear	n.a	n.a	0*
		Solar	n.a	0*	0*
		Geothermal	n.a	0*	0.2335
		Tide	n.a	0*	0.0017
		Waste & Biofuels [NR]	0.0022	n.a	0*
Italy	9	Nuclear	n.a	n.a	0.0002
		Tide	n.a	0*	0.0018
Latvia	6	Nuclear	n.a	n.a	0.0909
		Solar	n.a	0*	0.0909
		Geothermal	n.a	0.0499	0.0909
		Tide	n.a	0.0011	0.0909
		Waste & Biofuels [NR]	0.0007	n.a	0.0909
Lithuania	7	Solar	n.a	0*	0.0002
		Geothermal	n.a	0.1038	0.0002

Continued...

Continuation of Table

Country	Existing Sources (Out of 11)	Non-existent sources	Split Factor Proportions		
			Installed Capacity	Transformation Input	Labour
		Tide	n.a	0*	0.0002
		Waste & Biofuels [NR]	0.0028	n.a	0.0002
Luxembourg	7	Solid Fuels	0.0021	n.a	0.0102
		Nuclear	n.a	n.a	0*
		Geothermal	n.a	0*	0.0455
		Tide	n.a	0*	0.0026
Malta	1	Solid Fuels	0.668	n.a	0*
		Gases	0.33	n.a	0*
		Nuclear	n.a	n.a	0*
		Hydro	n.a	0.4632	0*
		Wind	n.a	0.0454	0*
		Biomass [R]	0.0014	0.4449	0*
		Solar	n.a	0*	0*
		Geothermal	n.a	0.0465	0*
		Tide	n.a	0*	0*
		Waste & Biofuels [NR]	0.0003	n.a	0*
Netherlands	9	Geothermal	n.a	0*	0.2303
		Tide	n.a	0*	0.0016
Poland	7	Nuclear	n.a	n.a	0.0005
		Solar	n.a	0*	0.0005
		Geothermal	n.a	0.0468	0.0005
		Tide	n.a	0*	0.0005
Portugal	9	Nuclear	n.a	n.a	0*
		Tide	n.a	0*	0.0055
Romania	8	Geothermal	n.a	0.0581	0.0909
		Tide	n.a	0*	0.0909
		Waste & Biofuels [NR]	0.0056	n.a	0.0909
Slovakia	8	Solar	n.a	0*	0.0004
		Geothermal	n.a	0.1048	0.0004
		Tide	n.a	0*	0.0004
Slovenia	8	Wind	n.a	0*	0.0001
		Geothermal	n.a	0.0899	0.0001
		Tide	n.a	0*	0.0001
Spain	9	Geothermal	n.a	0*	0.1405

Continued...

Continuation of Table

Country	Existing Sources (Out of 11)	Non-existent sources	Split Factor Proportions		
			Installed Capacity	Transformation Input	Labour
Sweden	9	Tide	n.a	0*	0.002
		Geothermal	n.a	0*	0.0199
		Tide	n.a	0*	0.0007
United Kingdom	10	Geothermal	n.a	0*	0.2546

n.a: not applicable

** near zero score, but not zero*

Appendix B

Portfolio optimisation

B.1 Correlations between technologies

	Source	1	2	3	4	5	6	7	8	9	10
1	Gas (100-160)	1.000	0.449	0.029	0.029	0.010	0.010	0.003	-0.006	0.031	-0.048
2	Gas (660)	0.449	1.000	0.029	0.029	0.010	0.010	0.003	-0.006	0.031	-0.048
3	Coal (100-160)	0.029	0.029	1.000	0.449	-0.003	-0.003	0.041	0.071	0.011	0.004
4	Coal (320)	0.029	0.029	0.449	1.000	-0.003	-0.003	0.000	0.071	0.011	0.004
5	Hydro (>10)	0.010	0.010	-0.003	-0.003	1.000	0.000	0.000	0.000	0.034	0.074
6	Hydro (<10)	0.010	0.010	-0.003	-0.003	0.000	1.000	0.000	0.000	0.034	0.074
7	Wind (>0.1-2)	0.003	0.003	0.041	0.000	0.000	0.000	1.000	0.000	0.034	0.015
8	PV (0.5-1)	-0.006	-0.006	0.071	0.071	0.000	0.000	0.000	1.000	-0.041	-0.059
9	Biomass (<15)	0.031	0.031	0.011	0.011	0.034	0.034	0.034	-0.041	1.000	-0.111
10	Nuclear (1100)	-0.048	-0.048	0.004	0.004	0.074	0.074	0.015	-0.059	-0.111	1.000

B.2 Capacity constraints

Source	Minimum	Maximum
Gas (100-160)	0.02	0.20
Gas (660)	0.15	0.48
Coal (100-160)	0.00	0.07
Coal (320)	0.06	0.16
Hydro (>10)	0.11	0.18
Hydro (<10)	0.05	0.07
Wind (>0.1-2)	0.02	0.15
PV (0.5-1)	0.00	0.03
Biomass (<15)	0.03	0.18
Nuclear (1100)	0.10	0.40

B.3 Emissions factors

	kg/GJ	kg/KW h
Gas (100-160)	55.8200	0.7030
Gas (660)	55.8200	0.7030
Coal (100-160)	94.0730	1.1850
Coal (320)	94.0730	1.1850

B.4 Optimal portfolios without nuclear option (weighted

		Current	Additive		Multiplicative		Pairwise		Multilinear	
	Source	Mix	Max Ret [a]	Min Risk [b]	Max Ret	Min Risk	Max Ret	Min Risk	Max Ret	Min Risk
	Portfolio Allocations									
1	Gas (100-160)	0.18	0.02	0.14	0.02	0.14	0.02	0.20	0.02	0.14
2	Gas (660)	0.42	0.48	0.15	0.31	0.15	0.31	0.15	0.31	0.15
3	Coal (100-160)	0.04	0.04	0.07	0.00	0.07	0.00	0.07	0.00	0.07
4	Coal (320)	0.10	0.16	0.07	0.06	0.13	0.06	0.06	0.06	0.07
5	Hydro (>10)	0.15	0.18	0.18	0.18	0.11	0.18	0.11	0.18	0.18
6	Hydro (<10)	0.04	0.07	0.05	0.07	0.05	0.07	0.05	0.07	0.05
7	Wind (>0.1-2)	0.03	0.02	0.15	0.15	0.14	0.15	0.15	0.15	0.15
8	PV (0.5-1)	0.003	0.00	0.03	0.03	0.03	0.03	0.03	0.03	0.03
9	Biomass (<15)	0.03	0.03	0.15	0.18	0.18	0.18	0.18	0.18	0.16
	Portfolio Characteristics									
	Portfolio Return	0.10	0.11	0.10	8.79	7.79	10.94	10.34	8.89	8.73
	Portfolio Risk	6.42	6.64	4.56	0.19	0.12	0.19	0.14	5.21	4.67
	% Renewables	0.26	0.30	0.56	0.61	0.51	0.61	0.52	0.61	0.57
	% Non-Renewables	0.74	0.70	0.44	0.39	0.49	0.39	0.48	0.39	0.43
	CO_2 Emissions [c]	58.94	58.33	36.99	30.04	43.35	30.04	39.65	30.04	36.93

[a] Maximum return portfolio
[b] Minimum risk portfolio
[c] Measured in million tons

B.5 Optimal portfolios with nuclear option (weighted)

		Current	Additive		Multiplicative		Pairwise		Multilinear	
	Source	Mix	Max Ret [a]	Min Risk [b]	Max Ret	Min Risk	Max Ret	Min Risk	Max Ret	Min Risk
	Portfolio Allocations									
1	Gas (100-160)	0.18	0.02	0.10	0.02	0.10	0.02	0.04	0.02	0.10
2	Gas (660)	0.42	0.22	0.15	0.15	0.15	0.15	0.15	0.15	0.15
3	Coal (100-160)	0.04	0.00	0.05	0.00	0.07	0.00	0.01	0.00	0.05
4	Coal (320)	0.10	0.06	0.06	0.06	0.10	0.06	0.06	0.06	0.06
5	Hydro (>10)	0.15	0.18	0.18	0.14	0.11	0.11	0.11	0.14	0.18
6	Hydro (<10)	0.04	0.07	0.05	0.05	0.05	0.05	0.05	0.05	0.05
7	Wind (>0.1-2)	0.03	0.02	0.15	0.15	0.11	0.15	0.15	0.15	0.15
8	PV (0.5-1)	0.003	0.00	0.03	0.00	0.03	0.03	0.03	0.00	0.03
9	Biomass (<15)	0.03	0.03	0.13	0.03	0.18	0.03	0.18	0.03	0.13
10	Nuclear (1100)	0.00	0.40	0.10	0.40	0.10	0.40	0.22	0.40	0.10
	Portfolio Characteristics									
	Portfolio Return	0.10	0.15	0.11	41.93	14.92	38.52	25.70	42.07	17.16
	Portfolio Risk	6.42	7.72	4.29	0.17	0.12	0.13	0.13	7.44	4.40
	% Renewables	0.26	0.70	0.64	0.77	0.58	0.77	0.74	0.77	0.64
	% Non-Renewables [d]	0.74	0.30	0.36	0.23	0.42	0.23	0.26	0.23	0.36
	CO_2 Emissions [c]	58.94	23.77	30.43	18.89	36.98	18.89	21.65	18.89	30.36

[a] Maximum return portfolio
[b] Minimum risk portfolio
[c] Measured in million tons
[d] Percentage of non-renewable sources and nuclear energy