Decision Analysis in the UK Energy Supply Chain Risk Management: Tools Development and Application

by

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Abstract

Large infrastructures like electricity supply networks are widely presumed to be crucial for the functioning of societies as they create conditions for essential economic activities. There has always been a continuing concern and complexity around risks in the field of energy security and particularly power grids within energy supply chain. Drawing on this complexity and a need for useful tools, this research contributes to developing and utilising proper decision-making tools (i.e. methods and models) to deal with the risk identification and mitigation in the UK energy supply chain as a compound networked system.

This thesis is comprised of four study phases (Figure I.A.). It is aimed at developing decision-making tools for risk identification, risk interdependency analysis, risk prioritisation, and long-term risk mitigation strategy recommendations. The application of the tools has focused on the UK power supply chain. The five new tools which are introduced and applied in this thesis are: (1) Proposed Expert Selection Model (ESM) and its application under hesitant fuzzy environment (i.e. HESM), (2) Proposed Neutrosophic Revised Decision-Making Trial and Evaluation Laboratory (NR-DEMATEL) method, (3) Proposed hybrid Spanning Trees Enumeration and Best-Worst Method (STE-BWM), (4) Proposed Neutrosophic Enhanced BWM (NE-BWM), and (5) Proposed stratified model of game of chance involving risk.

In this thesis, the applied decision analysis tools not only are theoretically improved but also implemented in the UK power supply chain risk management to validate their effectiveness. The utilised tools can provide helpful models and methods to illuminate and solve managerial problems by enhancing decision making and policy setting.

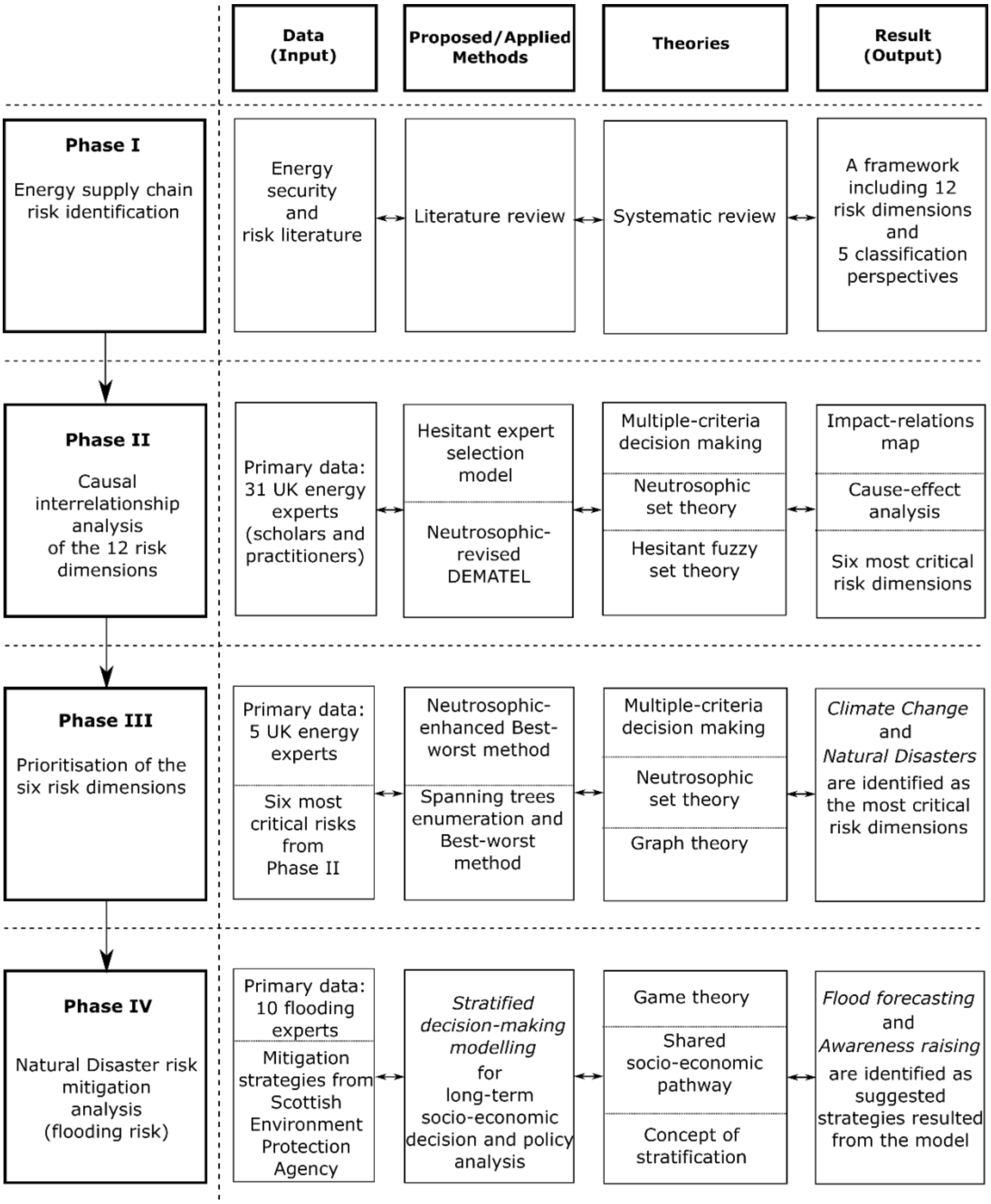

Figure I.A Phases of the research

Phases I and II:

In Phase I, a framework is proposed containing 12 risk dimensions, and 5 classification perspectives. The 12 risk dimensions include Climate Change (CC), Natural Disasters (ND), Environmental and Health Safety (EHS), Technical Reliability (TR), Operational Safety (OS), Disease Outbreak (DO), Political Instability (PI), Industrial Action (IA), Sabotage and Terrorism (ST), Resource Availability (RA), Market Failure (MF), and Affordability (AF). The five classification perspectives are context-based, position-based, temporal, origin-based, and hybrid classification. Then, in Phase II, the NR-DEMATEL has been applied in order to analyse the 12 identified risk dimensions based on the causal interrelationships and interdependencies among them, which has been missing in the current electricity risk management practices. Additionally, a novel Hesitant Expert Selection Model (HESM) to systematically assist researchers with the expert selection process is also proposed. The proposed HESM along with scenario analysis would provide a basis for the expert selection and weight assignment process. Findings have suggested the six most significant risk dimensions are ND, CC, IA, AF, PI and ST.

Phase III:

Besides the interrelationships between risks, it is important to know the ranking of identified risks which motivated the development and application of the BWM, by highlighting some weaknesses in the original BWM and contributing to the theoretical development. The NE-BWM and STE-BWM are introduced to enhance the efficiency of the original BWM in dealing with uncertainty in experts' subjective judgements. The application results have highlighted that CC and ND are two most critical risk dimensions.

Phase IV:

A novel generic stratified decision-making model is introduced. It is based on Concept of Stratification (CST), game theory and Shared Socio-economic Pathway (SSP) to deal with long-term risk mitigation planning for the most critical identified risks (i.e. CC, and ND). The model is applied in the region of Highland and Argyll in Scotland based on the primary data obtained from experts to prioritise flooding risk mitigation strategies which were recommended by the Scottish Environment Protection Agency (SEPA). The model takes into account both UK socio-economic situations and flooding risk impacts for the long-term decision making (5 to 20-year time frame). The findings indicate that the most important strategies which can provide long-term benefit in mitigating flooding risk impact in the area of Highland and Argyll in Scotland are flood forecasting, awareness raising, emergency plans/response, planning policies, maintenance, and self help, respectively.

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Dissemination of Results

Part of the results of this thesis are disseminated via presentation at conferences and publication as a journal paper in *Annals of Operations Research* journal. The details are as follows:

Journal Article:

Vafadarnikjoo, A., Tavana, M., Botelho, T., Chalvatzis, K. (2020). "A Neutrosophic Enhanced Best-Worst Method for Considering Decision-Makers' Confidence in the Best and Worst Criteria." *Annals of Operations Research*, 289(2), 391-418. https://doi.org/10.1007/s10479-020-03603-x

This paper is mainly based on part of the Chapter 6 regarding the proposed method NE-BWM in Section 6.3. Other co-authors' contributions included guidance for improvement and minor editing the text, figures and tables.

Conference Presentations:

1. Vafadarnikjoo, A. (2019). "Modified Best-worst Method with Decision Maker's Uncertain Confidence about the Best and Worst Criteria." *OR61 Annual Conference*, 3rd September, University of Kent, Canterbury, UK. (Oral Presentation)

2. Vafadarnikjoo, A. (2018). "UK Energy Supply Chain Risk Identification and Evaluation." *OR60 Annual Conference*, 13th September, Lancaster University, Lancaster, UK. (Oral Presentation)

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Chapter 1 Introduction

Energy security is generally associated with various concepts and realms of studies such as political science, economics and engineering but its fundamental characteristic is indubitably risk management. Efficiently assessing risks of an energy supply chain cannot be achieved without thoroughly identifying risks via reliable methods. Knowing that the disruption concern is quite substantial in electric power network particularly with growing global demand for electricity. Risk identification by considering all levels of the power supply chain from upstream to downstream prior to risk mitigation phase is a highly important task. Hence, risks have to be identified first. In this study, this goal can be achieved by introducing an all-inclusive risk identification framework and then using proper quantitative methods to assess risks. An overview on the energy security literature led this study to comprehend a need of a framework for identifying risks in energy supply chain and then their analysis based on their interrelationships. The reason is that, risks usually act in close interconnection to each other and barely act independently; that means there would be causal relations among them that occurrence of one risk would cause the other one. Thus, it is surmised that analysing these interrelationships can provide insightful understanding about the links and relations between risks that can guide to find out what risks are key factors in leading to other risks. This helps also with the risk mitigation strategy suggestion to focus more on these vital risks especially via a proactive perspective which looks more into future status of the system. In subsequent studies, identified risks are prioritised by proposed quantitative tools and risk mitigation analysis for the most critical ones are discussed. In this chapter, an overview of the research including some definitions, aims and objectives, as well as the structure of thesis are explained.

1.1 Background

1.1.1 Energy tri-lemma

The notion of energy tri-lemma balances between the demands for low emissions, affordable and secure energy supply (Figure 1.1) (Winzer, 2012). It requires that a sustainable energy system should be able to balance between three factors of emissions, cost and security. Design of an energy system which balances all the three elements is a challenging task. It is believed that the security aspect of a sustainable energy system is not isolated from cost and environmental issues. In other words, there would be an interrelationship between energy security and emissions. For instance, emissions can be stabilised by handling energy risks such as environmental health safety risk, via effective risk mitigation process. The same thing can happen for the cost side by mitigating the risks of market failures as an example. Thus, security is a crucial factor of a sustainable system with mutual relations with emissions and cost (Figure 1.1).

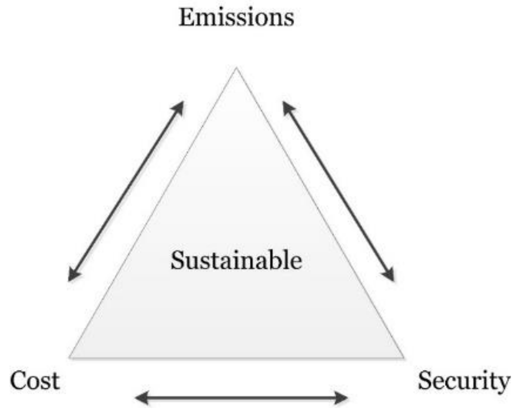


Figure 1.1 Sustainable energy system tri-lemma (Winzer, 2012)

Thus, under the spectrum of energy security, risk analysis in energy systems exploring the whole energy supply chain from upstream to downstream would be of paramount importance. This risk assessment cannot be reached successfully without thoroughly addressing and identifying risks ideally based on a compelling framework.

1.1.2 Energy supply chain

Supply chain vulnerability is a critical issue because a single disruption can lead to the collapse of the entire supply chain (Habermann et al., 2015; Kern et al., 2012). Furthermore, it is crucial for supply chain managers to know where networks are most vulnerable to allocate necessary resources (Chopra and Sodhi, 2004). Globalisation and outsourcing have raised the severity and frequency of supply chain disruptions (Zhao and Freeman, 2019). Potential severe repercussions resulting from supply chain risk uncertainty have led to growing interest in supply chain risk research (Hult et al., 2010; Kumar and Park, 2019; Yildiz et al., 2016). Basole and Bellamy (2014) indicated that supply chain risk identification and mitigation is a complicated task due to supply chains' progressively global, complex and intertwined nature. Klinke and Renn (1999) suggested that to deal with risks rationally one should be able to characterise them as well as to recognise the tools for designing proper responses. It has been realised that an integrated risk management approach in supply chains is necessary which takes into account multiple characteristics of supply chain risks noting that supply chain management has a multidisciplinary nature (Heckmann et al., 2015; Sanders et al., 2013).

Energy supply chain can be separated technically into three levels. In the upstream of the energy supply chain, the generation or supply of energy sources is considered. It can be either primary such as oil, gas and solid fuels or secondary such as electricity. Midstream or network, manages distribution and transmission of the energy sources. Downstream or demand side of the energy supply chain is where energy is delivered to consumers that can be in transport, domestic, service or industrial sectors. In Figure 1.2 adapted from Hammond and Waldron (2008) a simplified illustration of the UK energy supply chain is depicted to show various elements of this socio-technical energy system.

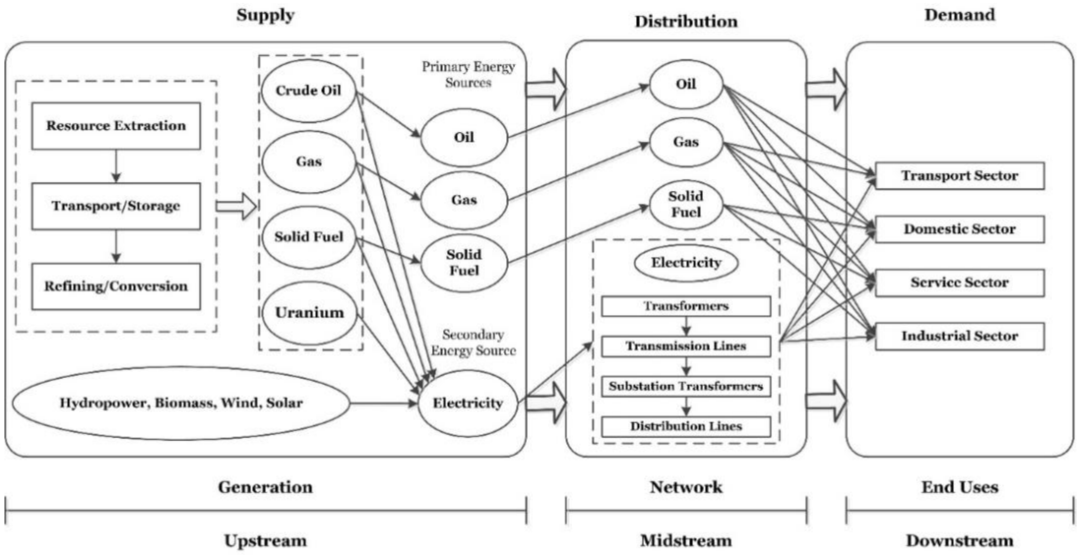


Figure 1.2 Simplified UK energy supply chain (adapted from Hammond and Waldron, 2008)

1.1.3 Risks, accidents, and incidents

To get an idea about what it is meant by risk, it should be referred to the Perrow's (1999) work where he introduced the Normal Accident Theory (NAT). He divided each system like an energy system into four levels:

1) *Part:* It is defined as the smallest and easily identifiable element of a system; an example of this can be a valve.

2*) Unit:* It is defined as a collection of parts which are functionally linked to each other; a steam generator can be an example for a Unit.

3) *Subsystem:* It constitutes a number of units. The secondary cooling system can be an example which includes condensate polishers and associate motors, pumps, and piping.

4) *System:* like a whole nuclear plant as an example.

Beyond these four levels, the environment is positioned. The disruptions to the third and fourth levels are named as *accidents*, while disruptions to the first and second levels are called *incidents*. In this study, all the potential incidents and accidents in an energy system are named risks. For complex systems such as nuclear plants which lie within the energy supply chain, accidents can cause disruption to the whole supply chain.

In the supply chain literature, risks or disruptions are unplanned and unforeseen events which disrupt the normal flow of goods within a supply chain. Subsequently, they impose operational and financial risks on stakeholders within the supply chain and can have both short-term and long-term effects. Supply chain risks can be grouped into two levels: operational risks and disruption risks. Operational risks are linked to the daily management of supply chains whereas on the other hand, disruption risks are basically associated with natural or man-made catastrophes like floods, terrorism and so on (Blackhurst et al., 2011; Craighead et al., 2007; Hendricks and Singhal, 2003; Kleindorfer and Saad, 2009; Kouvelis et al., 2009; Sodhi et al., 2012; Stauffer, 2003). Bhattacharya et al. (2013) defined *excursion event* as an unpredictable event with large negative impact on the performance of at least one component of a system for a comparatively long timescale.

1.2 Aims and Objectives

Large infrastructures like electricity supply networks are widely presumed to be crucial for the functioning of societies as they create conditions for essential economic activities. Electric power outages have been recognised as a national security issue by many governments like the US and more than 20 other countries including the UK (Brunner and Suter, 2008; Silvast, 2017). Aware of the importance of disruptions, the UK Government has been publishing National Risk Registers (UK Cabinet Office, 2017) that outline significant risks ranging from coastal flooding to widespread electricity failure, pandemic influenza, and attacks on infrastructures. The 2017 edition of this governmental publication has highlighted that widespread electricity supply failure has been classified with a severity of high impact and with a moderate likelihood of occurrence in the next five years, which confirms its importance. As declared by UK government report (UK Cabinet Office, 2017), the high impact severity of electricity supply failure in the UK, coupled with moderate likelihood of its occurrence between 2017-2022 exist. Thus, it is an interesting topic which is worth exploring within a broader context of energy supply chain. Furthermore, there is a need for a framework that clearly deals with the identification and classification of risks surrounding energy supply chain risks. Drawing on the complexity within the energy supply chain and a need for useful tools, this research contributes to the risk management body of knowledge (i.e. risk identification and mitigation) in energy supply chains as a compound networked system by proposing proper decision-making tools. Hence, this study's research aim is to develop decision-making tools (i.e. methods and models) based on various theories and methods. Theories such as game theory, graph theory, uncertainty theories, Concept of Stratification (CST), Shared Socio-economic Pathway (SSP) and methods such as Multiple Criteria Decision Making (MCDM) methods including Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Best-Worst Method (BWM) which are used in order to show their applications for dealing with risks in the UK power supply chain. This research intends to have significant theoretical contribution to the MCDM and decision analysis realms by developing quantitative tools as well as providing valuable information for policy and decision makers in the UK power supply chain.

1.2.1 Research questions

This thesis aimes to answer the following Research Questions (RQs):

RQ 1. What are the critical risks in the UK power supply chain?

RQ 2. What are the causal relationships among the critical risks?

RQ 3. How are these risks ranked and prioritised?

RQ 4. How can policy makers deal with mitigating the most critical risks in the longer timeframe by taking into account socio-economic situations?

RQ 5. What are the most appropriate risk mitigation strategies in response to the most critical risks?

1.2.2 Research objectives

The Research Objectives (ROs) are listed as follows:

1. To provide a comprehensive framework for risk identification focusing on the UK energy supply chain. A risk identification framework will be proposed by scrutinising energy supply chain risks in the energy security literature. It is tried to incorporate all three aspects of a sustainable energy system (security, cost and emissions) in the power supply chain (Figure 1.1) (Chapter 5).

2. To analyse causal interrelationships between identified risks by proposing Neutrosophic Revised Decision-Making Trial and Evaluation Laboratory (NR-DEMATEL). Knowing that risks usually act in close interconnection to each other and barely act independently that means there would be causal relations among them that occurrence of one risk cause the other one. Hence, it is absolutely vital to take advantage of a method to analyse this type of interrelationships as well as dealing effectively with subjective judgements of experts in the UK energy supply chain (Chapter 5).

3. To develop and apply two extensions of the Best-Worst Method (BWM) to prioritise the most significant energy risks obtained from the interrelationship analysis. The two extensions of the BWM are Neutrosophic Enhanced BWM (NE-BWM) and hybrid Spanning Trees Enumeration and BWM (STE-BWM) (Chapter 6).

4. To introduce a novel stratified decision-making model in order to deal with long-term risk mitigation planning for the most critical identified risks (Chapter 7).

1.3 Thesis Structure and Summary

In this part, I will explain briefly the thesis structure and summary of each chapter in order to make the comprehension of the studies easier for the reader. The thesis is structured in eight chapters and the research is carried out in four phases (Phases I to IV as shown in Figure I.A).

Chapter 1: "Introduction": In this chapter, the background of energy supply chain, definition of risks, aims and objectives including research objectives, and research questions are provided.

Chapter 2: "Literature Review": This chapter consists of a number of subsections including the literature discussion of decision analysis methods in energy and risk (Section 2.2), energy security (Section 2.3), twelve identified energy supply chain risks (Section 2.4), various classifications of energy supply chain risks (Section 2.5). The knowledge gap is also discussed at the end of this chapter (Section 2.6).

Chapter 3: "Theories and Preliminaries": This chapter explains all necessary theories, concepts or logics which are used in this thesis and helps readers understand the methodology and analysis parts in the later chapters. MCDM and weighting methods are described in Section 3.2, and Section 3.3, respectively. Uncertainty theories including fuzzy logic (Fuzzy Set (FS), Hesitant Fuzzy Set (HFS), and Intuitionistic Fuzzy Set (IFS)), grey systems, and neutrosophic logic (Neutrosophic Set Theory (NST)), are explained in Section 3.4 and Appendix A. In addition, graph theory, Concept of Stratification (CST), and game theory are described in Section 3.5 and Appendix B, Section 3.6, and Section 3.7, respectively.

Chapter 4: "Proposed Decision-Making Tools": In this chapter all the novel applied tools including methods and models in the thesis are presented. The five new methods which are introduced and applied are as follows:

1) Proposed Expert Selection Model (ESM) (Section 4.2). The ESM provides a basis for the expert selection process in the similar decision-making problems where subject expert selection is necessary. In fact, it offers a reliable model that helps decision makers decide who can be an expert based on their credentials and experience as well as assigning each expert a relative importance weight. Chapter 5 illustrates an application of the proposed ESM as Hesitant Expert Selection Model (HESM).

2) Proposed NR-DEMATEL method (Section 4.3). The Battelle Memorial Institute launched a DEMATEL method project between 1972 and 1976 through its Geneva Research Centre in order to deal with complex issues. The original DEMATEL was utilised to solve fragmented and antagonistic issues of world societies. In this section, the revised-DEMATEL (Lee et al., 2013) is developed and enhanced under NST in order to capture uncertainty of Decision Makers' (DMs) subjective judgements. The method then is applied to understand the interrelationships between energy supply chain risks as presented in Chapter 5.

3) Proposed hybrid STE-BWM (Section 4.4). In the original BWM, DMs are required to offer with certainty the best and worst criteria. However, in real-world decision-making settings it would be simplistic to regard that DMs are able to choose one criterion as either the best or the worst with full confidence. In other words, there might be a set of best and a set of worst criteria instead of just one single best or worst criterion. The original BWM does not suggest any solution in this case and expect a DM to offer only one criterion. The STE-BWM deals with this issue and its applicability is verified and discussed within the energy supply chain risk prioritisation in Chapter 6.

4) Proposed NE-BWM (Section 4.5). In the original BWM, the degree of a DM's confidence on the best-to-others preferences and others-to-worst preferences has been overlooked by giving equal importance to them. This issue generated the motivation to improve the BWM by introducing the NE-BWM. The application of the proposed NE-BWM is presented in the energy supply chain risk prioritisation in Chapter 6.

5) Proposed stratified decision-making model (Section 4.6). A novel model is proposed based on the integration of CST (Section 3.6) and game theory (game of chance involving risk) (Section 3.7) for long-term decision-making planning. The novelty lies within the fact that in some games like games of chance (i.e. one-player game against nature), the dynamic change of various states of a system in a long-term decision-making time frame is overlooked. In the games of chance, the current state of the system has been considered unchanged during the decision-making timescale. This feature of fixed state of the game, makes the obtained decision useful in a longer time frame if only the current state at the time of arriving a decision persists which

barely occurs. The reason for this shortcoming might be due to lack of a proper theory to formulate dynamic change of states throughout a longer decision-making period. This encouraged the development of the proposed stratified decision-making model. The application of the model is verified in risk mitigation strategy selection in Chapter 7.

The other five applied tools which are already introduced in previous studies in the literature are explained in Appendices C, D, and H as follows:

1) Maximum Mean De-Entropy (MMDE) algorithm (Appendix D),

2) BWM (Appendix E),

3) Gray code algorithm for generating all spanning trees (Appendix C),

4) Enumerating All Spanning Trees (EAST) (Appendix H),

5) Geometric Mean of All Spanning Trees (GMAST) (Appendix H).

Chapter 5: "Risk Analysis by NR-DEMATEL": Energy supply chain risk identification (phase *I*) and causal interrelationship analysis of the 12 risk dimensions (phase *II*) are both presented in this chapter. This study proposes a comprehensive framework for risk identification focusing on the UK power supply chain. It is based on scrutinising energy supply chain risks in the energy security literature via consolidating information from various fields such as engineering, social sciences and natural sciences. The framework helps identify the most significant risks to the UK power supply chain. The 12 risk dimensions are identified and then by incorporating their interdependencies and causal influences, the most significant risks can be dealt with. The NR-DEMATEL is tailored and used in this chapter which makes it possible to analyse interrelationships between risks as well as dealing effectively with subjective judgements of experts.

Chapter 6: *"Prioritisation of Risks"*: Prioritisation of the six risk dimensions obtained from phase *II* is explored in Chapter 6 (phase *III*). The applications of STE-BWM and NE-BWM are shown in evaluating identified energy supply chain risk dimensions from NR-DEMATEL. Additionally, in two case studies from the literature the applicability of the proposed NE-BWM are also verified.

Chapter 7: "Risk Mitigation Analysis": In Chapter 7 (i.e. phase *IV*) the flooding risk mitigation strategies are evaluated in the Highland and Argyll in Scotland. The aim is to deal with the most significant climate change risk to UK infrastructure (i.e. flooding) for the long-term policy making (between 5 to 20 years) with reference to the UK socio-economic status.

Chapter 8: "Conclusions": Conclusions obtained from all analyses (Chapter 5, Chapter 6, and Chapter 7) are provided in this chapter. Moreover, research contributions, implications, limitations of the studies as well as suggestions for future research directions are discussed.

At the end, Glossary of Terms, Appendices A to I, and References are provided.

Chapter 2 Literature Review

2.1 Introduction

Understanding energy supply chain risks from supply, network, and demand sides necessitates a review of the related literature from transdisciplinary fields such as energy security and supply chain mangement. This would then help systematically identify risks within a comprehensive framework which is one of the aims of this thesis. Futrthermore, it is of paramount importance to recognise what similar decision-making methods are already in place in order to highlight the research gaps.

In this chapter the related literature is reviewed. First, in Section 2.2, applications of decision analysis methods such as MCDM in energy planning and risk management literature are reviewed. In Section 2.3, the related research on energy security literature is explored. In Section 2.4, energy supply chain risks containing 12 subsections that each one is discussing one of the identified energy risk dimensions via a systematic literature review. Five identified energy supply chain risk classification perspectives are described by providing literature support in Section 2.5. Finally, knowledge gap is discussed in Section 2.6.

2.2 Decision Analysis Methods in Energy Planning and Risk Management

In this section, literature on application of decision analysis methods mainly MCDM and game theory in energy planning and risk management is summarised. Energy planning is comprised of broad application areas, such as renewable energy planning, energy resource allocation, transportation energy systems, and electric utility planning. MCDM is one of the common methodologies in decision analysis. There are a number of studies that reviewed the literature on energy and MCDM which are briefly explained from the oldest to the most recent ones in the following paragraphs.

Huang et al. (1995) reviewed the literature on decision analysis in energy modelling and identified that energy planning and policy analysis was the most popular application field. They also realised that decision-making under uncertainty was the most common practised methodology. In another review of more than 90 articles on application of MCDM techniques to sustainable energy planning in seven application areas by Pohekar and Ramachandran (2004), it was identified that Analytic Hierarchy Process (AHP), Preference Ranking Organisation Method for

Enrichment Evaluations (PROMETHEE), and Elimination and Choice Expressing Reality (ELECTRE) were the most favoured methods. Loken (2007) reviewed energy planning literature. It is indicated that energy planning is a suitable field for the Multi Criteria Decision Analysis (MCDA) applications. His findings revealed that more research is required on local energy systems with multiple energy carriers (i.e. electricity, hydrogen, and natural gas). Wang et al. (2009) reviewed MCDA methods corresponding to each decision-making stage for sustainable energy and recognised that AHP is the most favoured method. They also summarised evaluation criteria for energy supply systems from technical, economic, environmental, and social perspectives. The results revealed that investment cost followed by carbon-dioxide emission are the most critical criteria. Suganthi et al. (2015) reviewed applications of fuzzy-based models in Renewable Energy (RE) systems and found out that site assessment for installing PV/wind farms was among popular application areas. Elena Arce et al. (2015) reviewed the energy systems literature which applied Grey Relational Analysis (GRA). They realised that technical criterion and energy systems' efficiency have been the most-utilised criterion and sub-criterion, respectively. Strantzali and Aravossis (2016) provided a review on decision-making methods applied in RE literature. Ioannou et al. (2017) provided a review of risk-based quantitative and semi-quantitative methods for sustainable energy system planning. Kumar et al. (2017) reviewed the applied MCDM methods in RE applications. Leimeister and Kolios (2018) reviewed the literature of risk and reliability analysis methods in the offshore wind industry. Kaya et al. (2018) reviewed the literature on both RE and non-RE energy alternatives spanning from 1986 to 2017.

Apart from literature review papers, in other research, Ali et al. (2019) evaluated renewable energy technologies (i.e. solar, wind, biomass, biogas, solar-wind battery hybrid) in southern region of Bangladesh considering economic, technical, environmental, and socio-political criteria by Evaluation based on Distance from Average Solution (EDAS) method. Lin et al. (2018) identified risk elements of the New Energy Power System (NEPS) in China and analysed their internal influence relations based on D numbers and DEMATEL. Wu et al. (2018) evaluated RE power sources in China applying a fuzzy AHP method and a cumulative prospect theory. Okoro and Kolios (2018) developed and applied a multiple criteria risk assessment framework in a complex oil and gas support structure. Okoro et al. (2017) introduced a new multiple criteria risk assessment framework based on Technique for Order

Preference by Similarity to Ideal Solution (TOPSIS) and showed its applicability in an offshore wave energy converter case study. Kolios et al. (2016) utilised TOPSIS and weighted sum methods in order to rank risks in tidal energy developments. Bolsover (2015) employed Bayesian Network (BN) in order to monitor risks in real-time which would lead to a more efficient decision making in an offshore drilling rig. Chou and Ongkowijoyo (2014) proposed a risk-based approach to compare alternative RE schemes. They applied a hybrid graphical matrix approach with Monte Carlo simulation. Maxim (2014) prioritised 13 power generation technologies considering 10 criteria using a weighted sum multi-attribute utility approach. Bhattacharya et al. (2013) proposed stochastic dynamic decision-making tools in order to design a resilient shock absorber for disrupted supply chain networks. Aplak and Sogut (2013) used game theory to evaluate decision-making process of the industry and the environment as two players by the scope of energy management. The strategies were analysed using MCDM methods to calculate performance efficiency values. Ren et al. (2009) studied the causal interrelationships between risk elements in offshore installation operations using a Fuzzy Bayesian Network (FBN). Afgan and Carvalho (2002) assessed new and renewable energy power plants using multi-criteria evaluation considering analysis of parameters based on the information deficiency method. Matos (1999) showed the application of Fuzzy Filtering Method (FFM) in a planning problem in the field of power distribution systems.

After reviewing the applied decision analysis methods in the literature, in the next section, the literature on the the energy security and its relation to energy risk is discussed. The reason is that energy risk and energy security are closely connected, so it is beneficial to understand energy risks which is the application context of the current thesis from the lens of energy security.

2.3 Energy Security

The energy security literature is characterised by continuing concerns about risks. Although there is no universally accepted definition of energy security, there appears to be a consensus on security's connection to risks (Chalvatzis and Ioannidis, 2017a; Chalvatzis and Rubel, 2015; Rutherford et al., 2007; Wright, 2005).

Sustainable production and use of energy at affordable prices have been considered as a country's objective for energy security which focuses on three pillars:

efficiency, diversification of supplies, and price volatility (The World Bank Group, 2005). In another definition, four A's of energy security have been realised as: (1) Availability (geological elements); (2) Accessibility (geopolitical elements); (3) Affordability (economic elements); and (4) Acceptability (environmental and societal elements). There is a complex interplay between these categories and they are by no means isolated (Asia Pacific Energy Research Centre, 2007; Kruyt et al., 2009). Based on the International Energy Agency (IEA) the security definition of energy supply is when it is adequate, affordable and reliable. Energy security is context-dependent such as a country's level of economic development, risk perceptions, energy system's robustness and prevailing geopolitical issues (Ang et al., 2015). It is indicated that there are three distinct perspectives on energy security as sovereignty (intentional actions by malevolent agents), robustness (predictable natural and technical factors) and resilience (diverse and partially unpredictable factors) perspectives. These perspectives have their roots in political science, natural science, and engineering and economics/complex systems analysis, respectively (Cherp and Jewell, 2014, 2011). Energy security has been linked to securing of access to oil supplies considering impending fossil fuel depletion. On the other hand, with a rise in natural gas use, the security concept has widened to cover other fuels and primary energy supply (Chalvatzis and Ioannidis, 2017a) such as gas or even electricity (Chalvatzis and Rubel, 2015) and is not limited to oil anymore.

Disruptions can happen at any position within the supply chain thus, energy conversion and transport are regarded in connection to energy security. The political instability of producer and transit countries is another subject of discussion in the energy sector that takes geopolitical elements into consideration (Kruyt et al., 2009). As a result, the energy security concept has widened and developed over time.

The IEA developed an exhaustive perspective on energy security to analyse all dimensions of energy system that goes beyond oil. The IEA Model of Short-term Energy Security (MOSES) has focused on short-term energy security dealing with vulnerabilities which can cause physical disruptions of few days or weeks (Jewell, 2011). Chevalier (2006) indicated dimensions of time, space, and social for Security of Supply (SOS). Chester (2010) presented a couple of aspects related to energy security such as energy security as risk management concept.

Energy security in comparison with SOS is considered as a broader concept which covers all elements of an energy supply chain including supply, network and demand sectors from upstream to downstream. Hence, SOS should be regarded as a subcategory of energy security.

2.4 Energy Supply Chain Risks

In previous studies, Bode and Macdonald (2017) applied the organisational information-processing viewpoint to empirically study the decision-making process leading to rapid responses in supply chain disruptions. The outcome contributed to a deeper realisation of the decision stages role in mitigating supply chain perturbations. It was also confirmed that information processing speed and positive cooperation between stages influence supply chain performance. Bode and Wagner (2015) explored the frequency of supply chain disruptions by focusing on an upstream supply chain. Hammond and Waldron (2008) identified and ranked major risks concerning the UK electricity sector by taking into account various stakeholder groups and quantifying risks by multiplication of the likelihood of each risk and its consequences. Silvast (2017) studied the electricity infrastructures and interruptions from the social science perspective and tried to answer how people and organisations react to these interruptions. Moreover, he explained how interruptions to the electricity infrastructures can be anticipated and how risks can be managed. Klinke and Renn (1999) suggested a set of eight criteria to evaluate risks in general terms, not exclusively in an energy context. The authors discussed various methodologies to analyse risks, identified six different risk types and for each type developed special risk management strategies. Hunt et al. (2013) proposed a decision support framework tool based on MCDA for complex prediction of decision-making processes in the UK energy sources. Bhattacharya et al. (2013) defined an "excursion event" as *"an unpredictable event that effectively shuts down or has a relatively large negative impact on the performance of at least one member of a system for a relatively long amount of time."* They classified excursion events in supply chain networks into two main groups: natural and forced disruptions. Natural disruptions such as natural calamities, infectious diseases, psychological panic among customers, market fluctuations, and economic recession. Forced disruptions included terrorism, organisational issues, contamination of raw materials, accidents due to negligence, and delivery failure. Staid and Guikema (2015) provided an overview of the risks encountered by an offshore wind farm in US where they put emphasis on this point that an integrated framework for risks is needed in this area of wind farm electricity generation. They considered their work as a preliminary starting point for such a framework within offshore windfarms.

As discussed in the research aims and objectives, this thesis intends to provide a comprehensive perspective towards macro-level energy risks including all energy sources through the entire UK energy supply chain. That is why it requires taking a thorough approach and avoiding a limited vision. For example, this overarching approach not only focuses on risks which are related to specific energy supply risk but also is aimed at including all risks from supply, demand, and network positions. More details about the protocol of the systematic literature review leading to the following energy supply chain risks is provided in Section 5.2 where the energy supply chain risk identification framework is described.

2.4.1 Climate change

Climate Change (CC) is a long-term alteration in the climate mainly driven by manmade Green-House Gas (GHG) emissions. These elements are expected to impact energy systems at all levels. Changes in power generation are resulted from changes in precipitation. A long-term alteration in the climate can change weather patterns and threaten renewable energy supply or capability for cooling thermal power stations. The transformation and transportation of electricity could be affected due to extreme weather events occurrence. Mideksa and Kallbekken (2010) stated that there is a surprisingly scant number of research on the effects of climate change on the energy sector. Intergovernmental Panel on Climate Change (IPCC) indicated that energy is *"an example of an industrial sector particularly sensitive to climate change"* (Intergovernmental Panel on Climate Change, 2007). Based on a scientific assessment, IPCC declared with very high confidence that humans are having a critical influence on the global warming. The policy response is likely to be the most significant challenge to climate change (Hammond and Waldron, 2008). Considine (2000) indicated that changes in weather have influence on electricity and natural gas demand. Wilbanks et al. (2008) in a review of US energy system indicated that for a 1◦C rise in temperature, energy consumption would change within the range of 5%. Linnerud et al. (2011) explored the effect of climate change on electricity generation through thermal cooling.

2.4.2 Natural disasters

Natural Disasters (ND) are calamitous events with atmospheric, geologic, or hydrologic origins. They can have rapid or slow development and can disrupt the supply chain or the operation of power stations. They can have rapid or slow onset with worrying health, social, and economic consequences (Watson et al., 2007). They include storms, hurricanes, floods, earthquakes, droughts, tsunami, landslides, volcanic eruptions, and wildfires which can cause great damage or loss of life.

It is important to notice that natural disasters can be related to climate change (CC) but, not all of natural disasters are caused by climate change. Dealing with climate change means considering the root and cause of many natural disasters because climate change can increase the likelihood of weather-related natural disasters such as droughts which can be caused largely by global warming (Gallina et al., 2016; Van Aalst, 2006). However, in some cases natural disasters may be triggered by other causes, even by other natural disasters. For instance, in eastern Taiwan, slow earthquakes triggered by typhoons or for example the Fukushima disaster begun by an earthquake which triggered a tsunami, which resulted in a nuclear meltdown (Liu et al., 2009). It should be noted that many natural disasters rather than being global threats are specific to certain systems or regions. For instance, droughts are more common in France rather than in Canada.

Liu et al. (2000) identified natural calamities and animal triggered failures as one of the potential sources of system vulnerability. In the recent decade, there have been many natural disasters caused blackouts such as 2005 hurricane Katrina, 2011 Japan earthquake, 2012 hurricane Sandy and 2017 hurricane Irma. Hurricane Irma in Florida, USA, for example, caused one of the largest natural disaster-related power outages in the US history (Daileda, 2017). Roughly, 679 power cuts were reported in the US between 2003 and 2012 each impacting at least 50,000 customers as a result of weather events. In the previous decades, analysing methods of natural disaster-related issues in power systems considerably developed and owing to the complexity of the issue and its interdisciplinary characteristic, research is carried out across a broad range of fields (Wang et al., 2016). Two strong storms in December 1999 striked over the southern and northern parts of France, repectively and resulted in severe blackouts for more than 3.5 million households (Chevalier, 2006). Wang et al. (2016) reviewed the applicable and relevant models and methods to natural disaster scenarios particularly forecast models and restoration techniques. Extraction of shale gas by hydraulic fracturing or fracking was observed that could cause low-intensity earthquakes (measuring 2.3 and 1.5 on the Richter scale) in 2011 in North West England which resulted in shale gas extraction suspension nationally (Stamford and Azapagic, 2014).

2.4.3 Environmental and health safety

The energy system can potentially threaten the health of the public and can have negative impacts on the environment. Environmental and Health Safety (EHS) risk can then consequently pose a threat to the security of the energy supply chain by social pressure or legislation leading to stricter environmental laws. As a typical example, nuclear waste disposal is one of the constraints that challenges public health and the environment. Generally, these impacts can be categorised into radiological and non-radiological impacts and could be caused by accidents or even routine operations (Ramana, 2009). Tsoutsos et al. (2005) studied environmental impacts from the solar energy technologies (Photovoltaics (PV), solar thermal, solar power). It is indicated that considerable environmental benefits are provided from them compared to conventional energy sources. However, there would be potential negative environmental implications in their wide scale deployment. Aman et al. (2015) presented an overview of solar energy technologies and explored their Safety, Health and Environmental (SHE) effect to broader sustainability along with recommendations to control the potential negative impacts of widespread use of solar energy technologies. Fthenakis and Kim (2009) presented the normalised land requirements during the life cycles of conventional and RE alternatives. It was concluded that PV and biomass cycles need the least and largest amount of land among renewables, respectively. However, the estimates differ based on regional and technological conditions.

Carbon Dioxide (CO_2) is the most critical GHG and is produced, for instance, when fossil fuels are burnt. It is measured by the gCO_2eq/kWh that is grams of CO_2 equivalent per kilowatt-hour of electricity generated. Other GHGs like methane are quantified as equivalent amounts of CO_2. This is carried out by calculating their global warming potential in respect to CO_2 over a specified time frame, normally 100 years, with the aim of minimising long-term climate change (Parliamentary Office of Science and Technology, 2011).

2.4.4 Technical reliability

Technical Reliability (TR) risks usually concern system failure due to low capital investment or poor condition of the energy system. Asset maintenance also falls in this risk dimension. Poor maintenance or lack of asset replacement is a leading cause of incidents for instance cable failures which past their projected lifetime (Winzer, 2012). Therefore, this risk type is about shortcomings in the operation of power plants that hinder the proper operation and energy production. These risks are particularly significant for electricity generation from renewables, coal, and nuclear production (Checchi et al., 2009). In 2003, technical vulnerability caused 18 nuclear plants in Japan to be knocked out of service for several months (Chevalier, 2006). Faults in energy supply systems such as power outages resulted from accidents or human error led to malfunction of grid or generation plant (Ölz et al., 2007).

2.4.5 Operational safety

Operational Safety (OS) risk discusses the occurrence possibility of devastating damage concerned with a specific type of power generation not during normal operation but during accidents. This risk dimension differs from environmental and health safety in the sense that environmental and health safety concerns are caused by normal operations that would lead to environmental or health issues such as water or land contamination and air pollution. However, operational safety focuses on the risk of the energy system which causes damage during abnormal and accidental events. Beyond the affected power system boundaries, operational safety has knock-on effects via regulatory action. Nuclear power stations are regarded as the most dangerous one from operational safety perspective (Chalvatzis, 2012). For example, the Fukushima event started by the earthquake and subsequent tsunami which were natural disasters and disrupted the operation of the local power station. The immediate indirect impact was the Japanese policy decision to shut down all nuclear power reactors in the country which has caused significantly larger power supply disruption in Japan. One further indirect impact was regulatory decisions in Germany and more recently in Switzerland to accelerate shutting down of their nuclear energy sectors (Boston, 2013; Ranjan and Hughes, 2014; Reuters, 2017). Visschers and Siegrist (2013) conducted a longitudinal study to know how a serious accident impacts people's acceptance of nuclear power as well as determinants of acceptance.

2.4.6 Disease outbreak

Disease Outbreak (DO) refers to the disruption in energy generation due to an unexpected spread of a disease that can threaten personnel health in a specific region. Chevalier (2006) grouped an outbreak of a disease like Severe Acute Respiratory Syndrome (SARS) as an unexpected event among world energy uncertainties which can potentially lead to a disruption. This disruption can occur for instance by unwanted employees' sickness leave which results in a shortage of staff or by fluctuations in global energy carrier prices. As another example, in December 2019, a new coronavirus (COVID-19) was identified in Wuhan, China among patients with a form of viral pneumonia. The virus spread internationally very fast that numerous countries declared confirmed cases which put severe threat on lives and businesses (Peeri et al., 2020). It shows the severity of a disease outbreak and pandemic at regional and global level can suspend regular operations of businesses. It can potentially pose risk on energy supply which hence needs further urgent risk considerations.

2.4.7 Political instability

Political Instability (PI) refers to social unrest or geopolitical changes which would impact the security of the energy supply chain and would cause disruption. Political instability can impact on all aspects of energy supply chain including supply, network, and demand. It has been regarded as one of the causes of resource unavailability on the supply side of the energy supply chain. Varigonda (2013) studied the link between energy insecurity and state stability in India. Political challenges and conflicts can be a major burden on developing the transmission system. As an example Huda and McDonald (2016) explored energy cooperation in South Asia and explained the political impediments in implementing transnational pipelines and electricity grids by interviewing government officials, scholars, and other experts in Bangladesh, Nepal, Pakistan, and India. This point that energy industries are not functioning in a competitive market framework in the majority of supplier countries due to government interference will cause concern that energy would be utilised as a political weapon. Moreover, political instability such as civil wars, local conflicts, and terrorism in the supplier countries will threaten the security of supply (Checchi et al., 2009). Political decision is considered as one of the causes of sudden disruptions in oil markets (Correljé and van der Linde, 2006). It is indicated that further collusion between oil producer countries considering growing attention to oil reserves and generation could impact on export prices and delay new investments by adopting wait-and-see strategies (Costantini et al., 2007). A study by Asia Pacific Energy Research Centre (APERC) studied the geopolitical risks in the Middle East after the emergence of Islamic State and its impact on the energy supply in Asia (Japan Institute of Energy Economics, 2016). It is also indicated that there are a few studies that have tried to quantify the qualitative element of political stability for SOS measurement (Kruyt et al., 2009). The IEA (Blyth and Lefèvre, 2004; International Energy Agency, 2007) applied the average of two World Bank's worldwide governance indicators as political stability, absence of violence and regulatory quality for this aim. Jansen et al. (2004) quantified the measure of long-term socio-political stability on the United Nations Development Programme's (UNDP) Human Development Indicator (HDI).

2.4.8 Industrial action

Industrial Action (IA) is regarded as one of the major causes of disruptions in the energy supply and electricity generation. According to Varigonda (2013), industrial action is categorised as the social instability. The electricity sector as a state-controlled legacy has connections with powerful labour unions. These unions may be regarded as main barriers in the way of power sector's liberalisation and privatisation which is underway in many countries. Hence, the threat of coordinated industrial actions is often present. It should be noted that disruptions caused by industrial actions are considered as short-term or medium-term shocks (depending on the definition) (Chalvatzis, 2012). As an example, in the oil market, the Venezuelan industrial action in $2002-3$ also known as oil strike or oil lockout resulted in a gross peak supply loss of 2.6 mb/d (million barrels per day) and is regarded as one of the five most important disruptions of the past decades (Löschel et al., 2010).

2.4.9 Sabotage and terrorism

Sabotage and Terrorism (ST) makes the electricity supply chain confront a serious challenge of how to provide more security without compromising the inbuilt productivity benefits in highly complicated and interconnected power networks. A disruption of electricity supplies can have catastrophic impacts on national security. Power systems can never be safeguarded against a determined attack because the assets are widely dispersed.

Amin (2002) categorised terrorist attacks into three groups as follows:

1) *Attacks upon the power system*: the main target is the electricity infrastructure and as a result, outages rippling into the customer side. A single component such as a critical substation might be regarded as the point of attack or it might be a simultaneous, multi-pronged attack to disrupt the whole regional grid.

2) *Attacks by the power system*: the final aim is the population by utilising parts of the infrastructure as an armament. For example, terrorists may plan to crash an airplane on a nuclear power station causing significantly larger damage than just loss of power supply of that specific power station. As another example, terrorists may take advantage of power plant cooling towers to disperse chemical agents.

3) *Attacks through the power system*: the aim is the civil infrastructure such as utility networks. Setréus et al. (2012) identified components which are critical to system reliability and vulnerability and importance of each are quantified for two scenarios in a model of Britain's Power Transmission System (PTS). In the study of Gjerde et al. (2011), sabotage has identified as one of the threats to the security of the system. Tranchita et al. (2009) presented a methodology to evaluate the power system security with respect to the likelihood of terrorist acts, regarding the uncertainties related to load and generation.

One of the capabilities of smart grids is that it autonomously or by controlling from remote locations allows distribution systems to be largely automated as well as letting transmission systems be monitored at the regional scale. The goals of smart grid are always improving efficiency of delivery and enhancing availability of power. Achieving these goals is not simple and involves dealing with many likely risks and vulnerabilities such as increased vulnerability to cyber-attacks (Clements and Kirkham, 2010). Cyber-attackers can be grouped into five categories (Flick and Morehouse, 2011):

1) Non-malicious attackers who look at the system security as a puzzle to be solved.

2) Consumers driven by vengeance towards other consumers causing them to perceive ways to shut down their home's power.

3) Terrorists.

4) Disgruntled or ill-trained employees.

5) Competitors for the aim of financial gain.

Moreover, cyber-attacks can also be grouped into three major sets: (1) component-wise (2) protocol-wise, and (3) typology-wise (Aloul et al., 2012).

2.4.10 Resource availability

Resource Availability (RA) is relevant to both fossil fuels and renewable energy sources. The lack of resources to generate power can pose a significant risk to power networks. This risk dimension can be discussed in a broad range of contexts as there are various kinds of primary resources such as renewables or non-renewables. Here, it is discussed under two categories of fossil fuels and renewable energy as follows:

2.4.10.1 Fossil fuels

With regards to fossil fuels, Correljé and van der Linde (2006) distinguished three types of oil market disruptions:

1) *Sudden disruptions*: which may occur due to a political decision of not offering oil on the market, an international armed forces conflict or even technical/operational issues.

2) *Slowly emerging supply gaps*: they are caused by either lagging investments in production and/or transport capacity.

3) *Ideological choices of oil producing governments*.

Horsnell (2000) analysed the probability of oil market disruptions with an emphasis on the Middle East. He identified two types of discontinuities (policy and fundamental discontinuity) and three types of disruptions (force majeure, export restriction, and embargo) (Correljé and van der Linde, 2006). The international oil and gas markets have recently experienced a resource abundance period mainly as a result of shale oil and gas exploration which has increased US production to unprecedented level (Kilian, 2016). Exploitation of shale gas in the UK is at an early stage but its reserves and potential resources could be substantial. There is an ongoing debate on the way that shale gas can contribute to fossil fuel consumption reduction and hazardous climate change prevention (Stamford and Azapagic, 2014).

2.4.10.2 Renewable energy

For electricity generation, Renewable Energy (RE) (including hydropower) is growing very fast compared to natural gas and nuclear energy within the timescale of 2018 to 2050, by an average rate of 3.6% per year. While for non-hydropower RE, the average yearly increase during the same time frame is 5.7% (US Energy Information Administration, 2019). Renewables reached a record of nearly 3% of the global primary energy consumption. Moreover, renewable energy in power generation increased by 15.2% in 2015 slightly lower than 10-year average growth rate (British Petroleum, 2016). The renewable share of total electricity generation is expected to grow from 22% in 2012 to 29% (with US CPP[1] 30%) in 2040. Hydropower and wind make up the two main contributors to the rise in global electricity generation from renewable energy sources. They account for nearly 67% of the total increment from 2012 to 2040. The produced global electricity in 2004 was around 17450 TWh and estimated to be about 31657 TWh in 2030 (Dincer, 2011; Güler, 2009; Yu and Qu, 2010). Net electricity generation worldwide grows by 1.9% a year on average from 2012 to 2040. The corresponding number in OECD[2] nations is 1.2% per year where infrastructures are more mature and population growth is fairly sluggish or decreasing (US Energy Information Administration, 2019). As electricity is a secondary energy carrier and relies on primary energy sources, availability of primary resources (renewable or non-renewable) is absolutely essential for power generation (Chalvatzis, 2012).

RE technologies potentially have a lower risk profile in comparison with regular energy sources but they yet may be susceptible to technological, financial, and regulatory risk exposures. Johansson (2013) analysed energy security aspects of renewable energy systems in accordance with a wide typology on energy and security. Dependence on variable flowing resources and competition for hard to find land resources can be some causes of concern for energy security based on renewables. The intermittency of renewables that impacts on energy quality can be associated with resource availability. Sovacool (2009) explored the intermittency of renewables in the US and after conducting many interviews, concluded that intermittency of renewables can be foreseen and managed. Grave et al. (2012) explored the secured electricity

[1] US Clean Power Plan
[2] Organisation for Economic Cooperation and Development

generation capacity of intermittent renewable energy sources for Germany until 2030 in the short and long terms.

2.4.11 Market failure

Market Failure (MF) relates to the reliable market operation regarding smooth contracting and dispatching of energy. Market failures relating to the price, supply, and demand of energy sources in different markets can threaten energy security. As electricity cannot be stored, there is a necessity for immediate supply and demand to be in balance; otherwise the integrity of the system might be affected (Eydeland and Wolyniec, 2003). Price works as a balancing mechanism for demand and supply in a well-functioning market. Price can signal scarcity but is also influenced by other factors such as speculation, strategic communication and short-term shortages (Kruyt et al., 2009). High volatility of oil prices is the result of structural inflexibility on the oil market because of high fixed production costs, and low substitution elasticity, respectively (Costantini et al., 2007). The APERC (Koyama et al., 2016) explored the impact of the crude oil price drop on the world energy market. Market liquidity is also linked to price elasticity (Kruyt et al., 2009). Kilian (2016) studied how the increased availability of shale oil has affected US oil and gasoline prices. The process of electricity liberalisation and deregulation in Europe is causing new uncertainties for investors. Making a single electricity market should bring about more interconnections and less possibility for any disruption. However, in practice, capacity margins are inclined to lower new generating capacities. Furthermore, priority interconnected transmissions are not constructed at the right moment (due to many different reasons such as change or environmental resistance) (Chevalier, 2006). Fisher and Rothkopf (1989) explored various types of market failures which are significant in energy. Additionally, they studied the efficient allocation of resources and finally in case of market failure and distortion occurrence what remedies can be carried out. Liu et al. (2000) identified vulnerability in a competitive electricity market environment such as lack of incentives to construct transmission reinforcement and also to replace worn out control, protection, and generation equipment. Sensfuß (2008) analysed the effect of renewable electricity generation on the electricity market in Germany. Sáenz de Miera et al. (2008) tried to empirically explore the neglected benefit which is the reduction in the wholesale price of electricity due to more RE generation.

2.4.12 Affordability

Affordability (AF) refers to the price of energy and the capacity of domestic and business users to afford it. It demonstrates that availability of energy is not enough if energy is available at very high prices. It is related to vulnerable consumers who may not be able to meet their basic energy needs leading to what is known as energy poverty. At the same time, business and industrial consumers can be threatened by high prices since they impact on their profitability and may prevent investment and competitiveness. State owned electricity sectors have tried to address affordability by government controlled tariffs (Chalvatzis, 2012, 2009). The social dimension of SOS is important because SOS has a cost and in case of a price shock certain types of consumers who are exposed to volatile prices may not be able to afford supply of energy (Chevalier, 2006).

2.5 Energy Supply Chain Risk Classifications

Based on the literature review, it is revealed that there are five different perspectives for risk classifications as *context-based*, *position-based*, *temporal*, *origin-based*, and *hybrid* classifications. Context-based classification studies focus on the nature, context, discipline or occurrence realm of risks. For instance, physical, economic, social, and environmental risks defined by European Commission (2000) or geological, technical, economic, geopolitical, and environmental risks defined by Checchi et al. (2009) can be two typical examples. In position-based classification, risks are categorised in accordance with their position in the energy supply chain which can be upstream (generation), midstream (network), and downstream (demand). In temporal-based classification, researchers categorised risks on the basis of their timescales over which they operate that can be long, medium, or short time frames. Some risks have their origins inside the national border or energy system which can be regarded as *internal*, being related to production, transformation, and distribution of energy within national borders. Whereas on the other hand, many risks are related to imported energy that can be viewed as *external*. This kind of classification is discussed in the provenance-based attitude towards energy supply chain risk classification. Finally, there are hybrid classifications that consolidate two or more other classifications and provide a hybrid perspective of various dimensions. In the following sections, each classification is discussed and analysed within its respective literature.

2.5.1 Context-based classification

This type of risk classifications has been a recurring theme in the literature. Here, it is called context-based classification as the focus is on the context, nature, discipline or occurrence realms of risks. Bearing in mind that various risk categories are usually analysed in totally separate disciplines. For instance, studies regarding natural disasters (such as earthquakes, floods, storms) or studies about supply intermittency discuss the natural risk sources (Skea et al., 2008; van Kooten, 2010). Engineering studies of system reliability take into account the analysis of technical risk sources' impact (Billinton and Allan, 1996; Guo et al., 2009; Li, 2014, 2005; Makarov and Moharari, 1999). Table 2.1 summarises the context-based energy risk classifications.

Table 2.1 An overview of context-based classifications

Reference	Risk classifications
European Commission (2000)	physical, economic, social, environmental
Chevalier (2006)	climate change and environmental policies, geopolitical, regulatory, unexpected
Ölz et al. (2007)	energy market instabilities, technical failures, physical actions
Checchi et al. (2009)	geological, technical, economic, geopolitical, environmental
Cherp and Jewell (2011)	robustness, resilience, sovereignty
Winzer (2012)	technical, human, natural
Global Energy Institute (2019)	geopolitical, economic, reliability, environmental

European Commission (2000) categorised risks of energy supply into the following four groups:

I) *Physical risks*: include permanent or temporary disruptions. Permanent physical disruption happens when an energy source is exhausted, or production is halted. The temporary disruptions can be brought about due to an industrial action, a geopolitical crisis, or a natural calamity.

II) *Economic risks*: include erratic energy products price fluctuations on the European and global energy market.

III) *Social risks*: the instability of energy supplies caused either by unpredictable fluctuations in prices or physical disruptions which may lead to consequential social disruption. Industrial actions fall in this category.

IV) *Environmental risks*: the damage to the environment resulted from energy supply chain. It may be regarded as accidental events such as oil spills/slicks, nuclear accidents, and methane leaks. It might also be originated from polluting emissions such as urban pollution and GHG emissions. Global warming is another cause of concern that is why the Kyoto Protocol set targets of declining GHG emissions for EU.

Chevalier (2006) identified four categories of uncertainties which are surrounding the world energy scene:

I) *Climate change and environmental policies uncertainties*: predicting the short, medium, and long-term effects of climate change is quite difficult in a way that determining what actions should be performed based on specific policies.

II) *Geopolitical uncertainties*: raising amount of imported fuel in Europe from producer/transit countries with unstable or potentially unstable political and social situations would give rise to geopolitical uncertainty. Thus, it emphasises on the significance of diversified energy sources and would lead to higher prices, tight market and price volatility.

III) *Regulatory uncertainties*: energy market liberalisation aimed at having competition and liquidity to motivate fuel substitution and as a result improving SOS. Hence, new forms of interactions between market mechanisms and public regulatory interventions must be applied in order to overcome the complexity of reaching competition. Additionally, for energy investors, threat of regulatory changes should be regarded.

IV) *The unexpected*: there are a wide variety of unexpected events which are completely or almost unpredictable and pose risks on the energy security. Examples are terrorist attacks, civil unrest, wars, heat waves, hurricanes, earthquakes, tsunami, and pandemic diseases such as SARS and COVID-19.

Ölz et al. (2007) categorised energy security risks as the following three groups:

I) *Energy market instabilities*: came about by unpredicted changes in geopolitical or other external factors such as trade embargoes and supply disruption on international oil price fluctuations.

II) *Technical failures*: faults in energy supply systems such as power outages resulted from accidents or human error led to malfunction of grid or generation plant.

III) *Physical security threats (physical actions):* acts of terrorism, sabotage and also natural disasters can impact on any section of energy supply chain.

Checchi et al. (2009) identified the following five types of risks:

I) *Geological risks*: level of global energy consumption is growing, and the majority of global fossil-fuel reserves are governed by government firms in the Middle East and Eurasia, while fossil-fuel reserves in the EU are decreasing. All these reasons cause concern for the long-term availability of resources.

II) *Technical risks*: they concern system failures due to weather, low capital investment or weak status of the energy system. These risks are particularly significant for electricity generation.

III) *Economic risks*: include unpredictable fluctuations in the market price of energy products.

IV) *Geopolitical risks*: this point that energy industries are not functioning in a competitive market framework in the majority of supplier countries due to government interference will cause concern that energy would be utilised as a political weapon. Moreover, political instability such as civil wars, local conflicts, and terrorism in the supplier countries will threaten the security of supply.

V) *Environmental risks*: define the potential environmental effects for instance from oil spills, or nuclear accidents.

Cherp and Jewell (2011) proposed three perspectives on energy security as sovereignty, robustness, and resilience. They categorised threats by each perspective as follows:

I) *Robustness*: it has its roots in natural science and engineering and consists of threats such as failures of energy infrastructure, and extreme natural events, just to name a few.

II) *Resilience*: it stems from economics and complex systems analysis and includes threats such as technology changes, variations of climate, market volatility, and regulatory changes.

III) *Sovereignty*: it has its roots in political science and its related threats are sabotage and terrorist attacks, and political embargoes, just to name a few.

Winzer (2012) recommended three main sources of risks as technical, human, and natural risk sources as follows:

I) *Technical risk sources*: failure of infrastructure components such as transmission lines, or transformers due possibly to mechanical, thermal or communication network failures, or unintentional human error.

II) *Human risk sources*: sabotage and terrorism, political instability, and geopolitical risks (such as wars and economic sanctions), just to name a few examples.

III) *Natural risk sources*: this category consists of examples such as intermittency of RE supplies, decline in fossil fuels stocks, or even natural disasters.

The 2019 edition of index of the US energy security risk which employs 37 distinct measures of energy security risk and covers the time frame from 1970 to 2040 is made up of the following four sub-indexes that determine the main categories of risk to the US energy security (Global Energy Institute, 2019):

I) *Geopolitical*: oil and natural gas are considerably becoming globally-traded commodities while are fairly well concentrated in a handful of countries which have uncertain political stability or are reluctant business partners with the US. Thus, dependence on these energy sources incurs political and military risks.

II) *Economic*: price volatility may have severe negative effect which can put more pressure on family budgets and idle manufacturing facilities.

III) *Reliability*: disruptions to energy supplies are considered costly. Long-distance supply chains are susceptible to accidents and sabotage. Oil and natural gas fields geographically situated in weather-sensitive regions can get out of service. Lack of sufficient electricity generation or refinery capacity may result in outages and blackouts. Outdated and inadequate electrical grids may overload and fail.

IV) *Environmental*: Combusting these fuels would result in releasing GHG emissions such as carbon dioxide and correspondingly climate change poses risks on the economy and energy market.

It is evident that there are close interrelations between some categories of each individual classification perspective. For instance, based on the European Commission (2000), a temporary physical disruption caused by an industrial action grouped into the physical risks while industrial action itself has fallen into social risks. It demonstrates particularly when it comes to the roots or causes of each risk category, the interconnections between risk categories will play a crucial role for an effective explanation. Moreover, it is also clear that there are many common risk categories shared in accordance with distinct context-based classifications. For example, economic risk category is similar among other classifications with just different names such as resilience (Checchi et al., 2009; Cherp and Jewell, 2011; European Commission, 2000; Global Energy Institute, 2019). Thus, it goes clearly that some risk categories based on different perspectives may appear with various names but nearly similar definition.

The main drawback of the majority of context-based perspectives in the literature is that they lack thoroughness. It means they are not capable of covering all types of risks and there would be sometimes a few missing risk dimensions. The other negative aspect is lack of proper definition for each risk classifications. Mainly based on the work of Cherp and Jewell (2011) and considering other perspectives in the literature the following six classifications for the context-based classification are proposed: (1) Engineering science; (2) Economics; (3) Environmental science; (4) Sociology; (5) Politics; (6) Health sciences. This proposed classification is thought to be more comprehensive compared to other attitudes as it covers most relevant fields. It should be noted that some risk dimensions may belong to more than one group. For example, resource availability can be involved with many contexts such as economics, politics or sociology depending on which associated risk elements are being studied under the resource availability. Therefore, it is clear that certain risk dimensions will have to be considered under a definitional discussion in order to clarify their scope.

2.5.2 Position-based classification

Based on this classification, risks are classified in terms of position in the system which can be upstream (generation), midstream (network) and downstream (demand). In the upstream, the generation or supply of energy sources which can be either primary such as oil or secondary such as electricity is considered. Midstream or network manages transformation (transport/storage and refining/conversion) and distribution/transmission of the energy sources. Downstream or demand side of the energy supply chain is where energy/electricity is delivered to consumers. Climate change is a risk dimension which has effect on all levels of the system (generation, network and demand). It implies that risk dimensions are not limited to merely one position and may act simultaneously on various levels. Gracceva and Zeniewski (2014) considered the positions in the energy supply chain that risks may occur in any position (see Figure 1.2).

2.5.3 Temporal classification

Stirling (2014) indicated that vulnerabilities can be mitigated only via looking at their dynamics over time (expressed as temporality). Chevalier (2006) regarded the time dimension of SOS as very important. Egenhofer et al. (2004) also held the view that risks or threats to physical supply vary across short, medium, and long-term perspectives.

2.5.3.1 Short timescale

Those risks that threaten security in the short-term are shocks to the system. They are threats to security that generally operate over less than an hour. In the short term, risks are usually related to disruptive effects of a price shock or an unpredicted lack of supply.

2.5.3.2 Medium timescale

Medium-term risks are threats to security that generally occur and develop between a few days up to a few months. In the medium timescale, SOS may be threatened by enduring political or social turmoil, shortage of available resources or even delay/lack of investment in productive capacity, transmission, and storage.

2.5.3.3 Long timescale

Long-term risks are threats to security that generally operate over years and even decades. In the long timescale, the concern is more about the stability and sustainability of economic development which will be facilitated by the availability of sufficient energy supply. It may also include long-term changes in weather patterns which impact on renewable energy generation.

2.5.4 Origin-based classification

Chevalier (2006) elaborated dimensions such as space, time, and social for the SOS. The space dimension of SOS states that disruption in supply of energy can have local, national, and international causes and implications, and in this sense associates with geography. Here, origin reflects whether the risks have external or internal cause. Some elements of supply are external like world oil price or storms and some components are internal which are linked, for instance, to the organisation of energy industries, safety standards, and storage obligations. Liu et al. (2000) indicated that vulnerability sources are either internal or external to the infrastructure constituting the power system.

2.5.4.1 Internal events

Internal events can be controlled which means there is a freedom to select strategies which would have impact on reducing the likelihood of the threats (Checchi et al., 2009).

2.5.4.2 External events

Elements grouped into external risks are linked to energy imports dependency (Checchi et al., 2009). The major strategy available in the case of external events is responsive capacity development. It means maintaining the quality of energy services or improving the system's capacity to conform to events (e.g. by expanding the storage to enhance short-term flexibility) (Gracceva and Zeniewski, 2014).

2.5.5 Hybrid classification

This classification incorporates two or three previously indicated perspectives. It is divided into two major groups as

a) *Two-dimensional* which deals with two axes of *temporality* and *position*; *temporality* and *origin*; or *position* and *origin*.

b) *Three-dimensional* that involves *temporality*, *position*, and *origin* together.

Boston (2013) presented a hybrid classification by considering two dimensions of temporality and position in the system (Figure 2.1). For instance, loss of expertise is a long timescale risk that is positioned in both generation and network levels. Gracceva and Zeniewski (2014) categorised energy security risks based on three main dimensions including position, temporality, and origin.

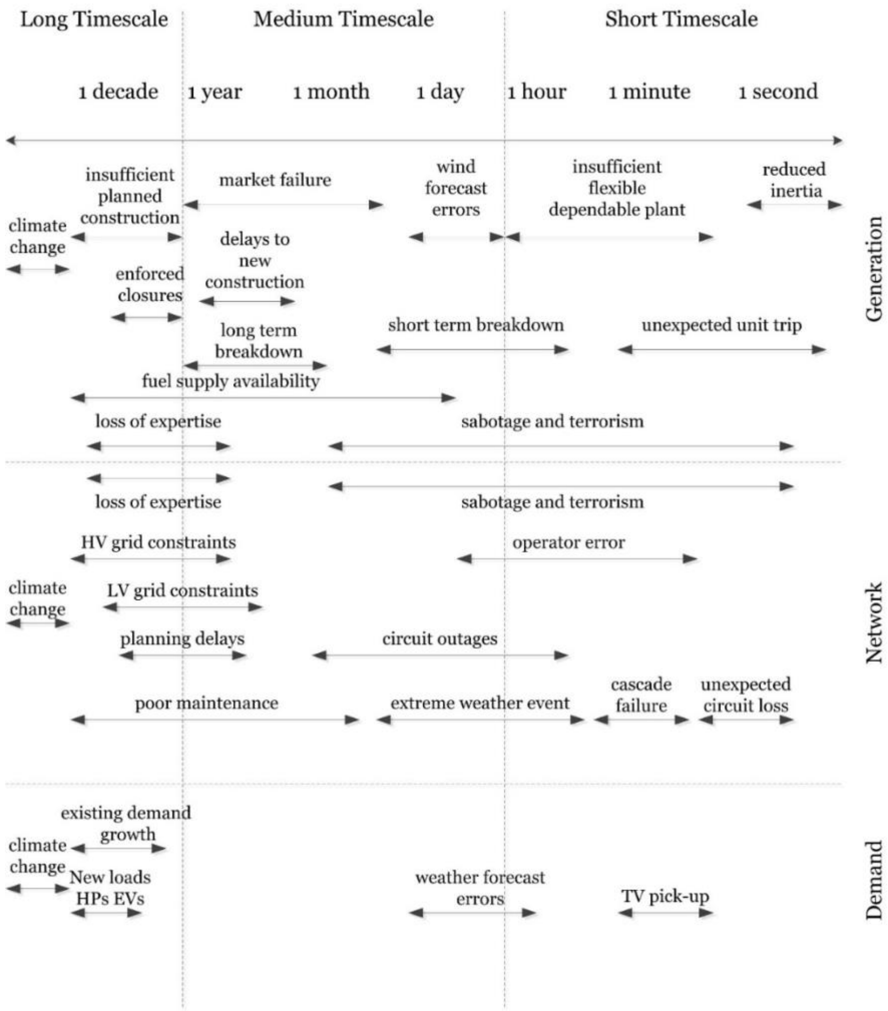


Figure 2.1 Risks in two dimensions (position and timescale) (adapted from Boston, 2013)

2.6 Knowledge Gap

After reviewing literature, firstly, there has been no comprehensive risk identification framework to help categorise energy supply chain risks in the UK (see RQ 1). Secondly, this thesis takes the view that there is some degree of interconnection between risks; that is, there should be causal relations among them, which indicates that the occurrence of one risk could lead to exposure to another. Based on the literature, there are just a limited number of studies in the supply chain risk management literature that have addressed interactions between risks (Babu et al., 2020; Chaudhuri et al., 2016; Qazi et al., 2017; Ritchie and Brindley, 2007; Wei et al., 2010). This is even less explored in the energy risk management literature, particularly when focusing on the UK power supply chain. Thus, it is critical to take advantage of a method that can analyse these types of interrelationships as well as effectively deal with subjective judgments of experts such as a combined NR-DEMATEL and then understand how these risks are ranked and prioritised (see RQs 2 and 3). Thirdly, there was a need for a specific study to aid policymakers in the UK power supply chain to effectively realize significant risk dimensions and risk mitigation strategies considering the identified risks based on causal interrelationships among them. It can be quite useful in the risk mitigation stage in the long-term by taking into account UK socio-economic situations (see RQs 4 and 5).

2.7 Conclusions

In this chapter, it was aimed at reviewing the literature on four main topics including (1) decision analysis methods in energy planning and risk management; (2) energy security; (3) energy supply chain risks; and (4) energy supply chain risk classifications.

The review of decision analysis methods and energy security revealed that there is a need for analysing interrelationships between energy risks as they inherently are linked together and there would be causal relations between them. After recognising this gap in the literature, it is important to come up with a framework to identify and classify energy risks. To this end, 12 energy supply chain risk dimensions were explained based on a systematic literature review search protocol (Table 5.1). Additionally, various energy supply chain risk classifications were also identified and elaborated drawing upon the literature in Section 2.5. The proposed risk identification framework is introduced later in Chapter 5 (Section 5.2).

It is surmised that the provided literature review can construct a basis for a comprehensive perspective towards energy risks by encompassing all energy risks throughout the entire UK energy supply chain. The framework and studies in response to research questions regarding outlined research aims and objectives are provided in Chapters 5, 6 and 7.

Chapter 3 Theories and Preliminaries

3.1 Introduction

In this chapter, some basic definitions, theories, and preliminaries are described. Understanding them is required to better grasp the idea behind the methods in Chapter 4 as well as analysis parts in Chapters 5, 6, and 7.

This chapter is comprised of seven sections including Multiple Criteria Decision Making (MCDM), weighting methods, uncertainty theory, graph theory, Concept of Stratification (CST), and game theory, respectively. As it was discussed in Chapter 1, the research aim is to develop decision-making tools based on various theories and methods. Thus, the main link that connects these tools to each other is the fact they are all related to decision analysis parts carried out in the next chapters of this thesis. Readers should refer to this chapter in order to understand the concept behind implementation steps of the utilised tools in the next chapters.

3.2 Multiple Criteria Decision Making

Multiple Attribute Decision-Making (MADM) methods are developed to select a suitable alternative from a pre-defined discrete set of alternative courses of action. As it is commonly seen in the literature, the terms MADM, MCDM, and Multi Criteria Decision Analysis (MCDA) are often used interchangeably (Govindan and Jepsen, 2016). MCDM methods aim to select a suitable course of action, choice, policy, or strategy in decision problems with multiple and often conflicting qualitative and/or quantitative criteria under certainty or uncertainty (Kuo, 2017; Srinivasa Raju and Nagesh Kumar, 2010). The main goal in MADM is to provide a number of attribute aggregation methods which make model development possible based on Decision Makers' (DMs') or subject experts' preferential system and judgement policy (Doumpos and Zopounidis, 2002; Tavana and Hatami-Marbini, 2011). The number of published applications of MADM has grown rapidly over the last two decades (Huang et al., 2011; Marttunen et al., 2017) considering a large number of available MADM methods (Mulliner et al., 2016, 2013).

3.3 Weighting Methods

In decision making, in order to obtain the relative importance of each criterion or factor under study, generally a rank-order weighting method can be used where weights of criteria are distributed as Equation (3.1), where $\sum_{i=1}^{n} w_i = 1$

$$w_1 \geq w_2 \geq \cdots \geq w_n \geq 0 \tag{3.1}$$

The rank-order weighting methods are also categorised into three groups (Wang et al., 2009):

1. *Subjective weighting methods* such as Analytic Hierarchy Process (AHP) and Best-Worst Method (BWM).

2. *Objective weighting method* such as Entropy method.

3. *Combination weighting method* such as additive synthesis.

Three elements are recognised in order to calculate weights (Wang et al., 2009) including (1) the variance degree; (2) the independence; and (3) the subjective preference of DMs.

3.4 Uncertainty Theory

Uncertainty in MADM has close relation with uncertainty theories. Booker and Ross (2011) stated that uncertainty could be defined as what is not known precisely, though, Zimmermann (2000) indicated that he had not been successful in finding any general definition for uncertainty. Since the introduction of Fuzzy Sets (FS) by Zadeh (1965), probability theory was challenged. The reason was that probability theory had been the sole representation for uncertainty. Subsequently, developments in mathematical uncertainty theories have been proposed such as the possibility theory in 1988 (Dubois and Prade, 2012), Dempster-Shafer evidence theory that has been developed by Dempster (1968), and then by Shafer (1976) to model belief or evidence (Kämpke, 1988), imprecise probability theory (Walley, 1991), and random intervals (Joslyn and Booker, 2004). Smarandache introduced a non-classical logic, which has roots in philosophy as an alternative to the existing logical systems, namely neutrosophic logic to offer mathematical insight about uncertainty (Smarandache, 2002, 1999). Smarandache (1999) proposed Neutrosophic Sets (NS) which show fuzzy information utilising the functions of truth, indeterminacy and falsity like Intuitionistic Fuzzy Sets (IFS). Atanassov (1986) introduced IFS as an enhancement of the Fuzzy Set Theory

(FST) of Zadeh (1965) to improve it via offering the concept of non-membership degree (Vafadarnikjoo et al., 2018). Independency of the indeterminacy function from the truth and falsity functions in NS, differentiates it from IFS (Ji et al., 2018). The IFS was generalised to the NS, so as to present valuable information on how a DM would effectively deal with uncertainty within subjective judgements (Vafadarnikjoo et al., 2018). Levary and Wan (1998) indicated that there are two types of uncertainties. First, uncertainty related to the prospective traits of the decision-making environment characterised by a set of scenarios. Second, uncertainty regarding the decision-making judgement associated with pairwise comparisons. This research deals with the second type of uncertainty. In the literature, apart from uncertainty theories, various decision support tools have been proposed to deal with uncertainty. An example is the work of Baudry et al. (2018) that proposed a new framework to support participatory decision-making under uncertainty. This trend reinforces the importance of decision-making under uncertainty where the focus is to produce reliable solutions for complex real-world problems. Temur (2016) also emphasised this growing trend in the integration of uncertainty theories with MADM methods in handling uncertainty. Please see Appendix A for detailed definitions on utilised uncertainty theories.

3.5 Graph theory

Graph theory is an area of mathematics. The definition of graph $G = (V, E)$ is a finite non-empty set V of objects (vertex set) and a set E (edge set-includes two-element subsets of V). Sometimes the vertex and edge sets of graph G is represented as $V(G)$ and $E(G)$, respectively (Benjamin et al., 2015). In Figure 3.1, graph G, is shown as an example where $V = \{a, b, c, d, e, f\}$, and $E = \{ab, bc, be, ac, ae, ce, cd\}$. Please see Appendix B for detailed definitions on graph theory.

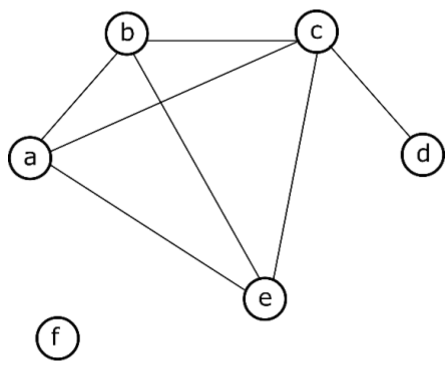


Figure 3.1 A graph G

3.6 Concept of Stratification

The Concept of Stratification (CST) as an innovative version of stratification has been introduced by Zadeh (2016). In CST, a number of states should be traversed by a system in order to reach the target set (i.e. a desired state). Inputs and outputs of any state are incrementally stratified on the basis of their distance from the target set (Asadabadi, 2018; Rajabi Asadabadi et al., 2018). The CST is a very similar concept to Dynamic Programming (DP), while being much more straightforward to comprehend and then apply. As an example, knowing the population of Washington is $658{,}000$ then the stratified count can provide more informative information. Given the area around Washington is partitioned into nested strata $S_1, S_2, \ldots, S_n$ centring on downtown Washington. Stratified count is the collection $(S_1, P_1), \ldots, (S_n, P_n)$ where P_i is the population of Stratum S_i. The population might be stratified on the basis of gender, career, race, and so on. It is also indicated that stratified polls can be a highly important tool for politicians who run for office (Zadeh, 2016). The following concepts are identified in CST (Rajabi Asadabadi et al., 2018):

System: It is defined as a set of objects which traverse states towards a state in the target set.

State: SE_t signifies t^{th} state and is characterised by the values of its related variables which are determined by experts. The system would transition from one state to the other by changing values of variables.

State-transition function: moves the system from i^{th} state to $(i+1)^{th}$ state as Equation (3.2).

$$SE_{(t+1)} = f(SE_t, u_t) \tag{3.2}$$

If the system is situated at state $t(SE_t)$, by receiving an input u_t, it transitions from SE_t to SE_{t+1}

Inputs and outputs: Many inputs (u_t) might exist for SE_t. Equation (3.3) shows the relation between each input and an output (v_t).

$$v_t = g(SE_t, u_t) \tag{3.3}$$

Target state: The goal of the system is to reach the target set.

Target set: It is defined when there are multiple target states.

Stratum: Stratum N is defined as a set of states from which a system can get the target state in N or less than N steps.

Reachability: It exists when there would be a path between two states.

Incremental enlargement process would equip CST with high dynamicity. The primary goal of enlargement is identifying possible paths towards the target where reaching the target is costly; consumes excessive resources or is presently vague and gets obvious at coming times (Asadabadi et al., 2018).

The foundation of CST is a model called Finite-State Machine (FSM) which is a discrete-time, discrete-state dynamical system. The importance of FSM lies in the fact that by using granulation and/or quantisation nearly any type of systems can be approximated to by a finite state system. Target set reachability plays a central role in FSM. Reachability includes moving or transitioning from a state SE_t to a state in the target set T_0 within a least number of steps (Zadeh, 2016). In Figure 3.2, the target set (T_0) is at the bottom and comprises two states. Then by absorbing two states via enlargement process, the first stratum (T_1) is recognised by four states. Similarly, all states are stratified with respect to their distances from target states (Rajabi Asadabadi et al., 2018).

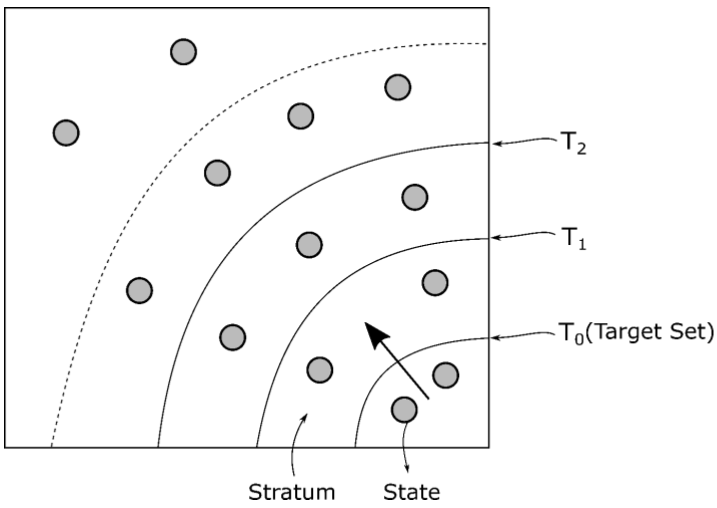


Figure 3.2 Target set, stratum, and state in CST

3.7 Game Theory

Since publication of *The Theory of Games and Economic Behaviour* by Von Neumann and Morgenstern (1947), game theory has been extensively utilised as a logical approach in various research realms such as economics and management. In this section, a basic model of game theory is explained.

3.7.1 A general model of game of chance

Generally, there are three types of games including *games of skill*; *games of chance*; and *games of strategy*. Apart from games of skill which are one-player games, the other two groups of games involve at least two players. Games of strategy involve two or more players, not including nature, each of whom has partial control over the outcomes (Kelly, 2003). Games of chance are grouped as either involving risk or involving uncertainty and are one-player games against nature (Table 3.1). Games of chance have been also called *individual decision making under risk or uncertainty*. In spite of being one-person games, they are modelled in terms of two players, thus they can be recognised within the field of game theory. In the game of chance involving risk, although the player does not know with certainty what moves will be made by nature, the player is aware of the meaningful probability of responses of nature, and thus realises the success probability of each of their strategies or actions. The expected monetary/utility value (EMV) can be utilised to reach a decision in this type of games (Colman, 1982).

Additionally, games of chance involving uncertainty, are one-player games against nature and probabilities of nature's responses are unknown. Three principles for making a decision in such circumstances have been suggested:

1) The maximax principle (super-optimistic approach) recommends that the player chooses the strategy that contains the greatest pay-off.

2) The maximin principle (super-pessimistic risk-averse strategy approach) recommends that a player avoids the worst possible pay-off. In other words, the player should choose the strategy that offers the best worst-case scenario.

3) The minimax principle (a good balance between the super-optimistic and the super-pessimistic; greatest regret avoidance) recommends that a player avoids the strategy of greatest regret. Utilising this approach, the payoff matrix must first be transformed into a regret matrix (Kelly, 2003).

Table 3.1 General game of chance model

PLAYER 1	**PLAYER 2 (NATURE)**			
	OUTCOME 1	OUTCOME 2	…	OUTCOME M
CHOICE 1	PF_{11}	PF_{12}	…	PF_{1M}
CHOICE 2	PF_{21}	PF_{22}	…	PF_{2M}
	$\vdots$	$\vdots$	…	$\vdots$
CHOICE $\boldsymbol{N}$	PF_{N1}	PF_{N2}	…	PF_{NM}

3.8 Conclusions

A number of theories which are connected to the applied methodologies in Chapters 4, 5, 6 and 7, and are necessary to understand the methods and analyses were described in the current chapter.

The aim was to provide a brief guideline for readers to become familiar with these theories which would help them understand the methods, models, theoretical contributions, analysis and consequently results which are presented later on in Chapters 5, 6 and 7. However, in the later chapters, readers are often referred to these theories, so as to acquire essential and basic information to understand the used technical terms and implementation steps. This understanding would make the later chapters less complicated to read and follow. In the next chapter, the proposed decision-making tools are explained in detail.

Chapter 4 Proposed Decision-Making Tools

4.1 Overview

In this chapter, proposed decision-making tools in the thesis are discussed. They are novel tools including methods and models which have theoretical contributions to the body of knowledge. The reasons why these tools are proposed and applied are explained in the related chapters in detail. In general, MCDM methods are considered as valid and reasonable methods to deal with causal relationships between risks and for risks prioritisation. This point was also confirmed in the literature as discussed in Loken (2007) who reviewed energy planning literature and indicated that energy planning is a suitable field for the MCDM applications. Also, in a study by Lin et al. (2018) who identified risk elements of the New Energy Power System (NEPS) in China and analysed their internal influence relations based on a MCDM method (i.e. D numbers and DEMATEL). However, there are other methods in the literature such as Bayesian Networks (BNs) which can deal with risks by analysing occurrence probability of risks. But in this study as it was explained, the identified risks based on the proposed framework are recognised as risk dimensions which are of macro-level nature such as climate change or natural disasters. It is believed that BNs can be more helpful in dealing with risk elements which are of micro-level nature and are positioned at the lowest level of the proposed framework. The reason is that obtaining occurrence probabilities for risk elements can be more straightforward and meaningful compared to macro-level risk dimensions such as climate change.

In this chapter, the application procedure for each one is described step by step. Furthermore, a brief background of their applications drawing upon the literature is also provided for some tools where it could benefit understanding of their importance in practical research contexts. The five new tools which are explained in this chapter are as follows:

1) Proposed Expert Selection Model (ESM) (Section 4.2).

2) Proposed Neutrosophic Revised Decision-Making Trial and Evaluation Laboratory (NR-DEMATEL) method (Section 4.3).

3) Proposed Hybrid Spanning Trees Enumeration and Best-Worst Method (STE-BWM) (Section 4.4).

4) Proposed Neutrosophic Enhance Best-Worst Method (NE-BWM) (Section 4.5).

5) Proposed stratified model of game of chance involving risk which is named as stratified decision-making model (Section 4.6).

4.2 Proposed Expert Selection Model

In many Multi Attribute Group Decision Making (MAGDM) problems there is a need to establish a number of subject experts or specialists to obtain their opinions or elicit information. The process deals with subjectivity, validity, and criteria fixing (Mediouni et al., 2019). In previous studies, the task of experts' weights determination was carried out in a relatively subjective, and unstructured way. Here, an Expert Selection Model (ESM) is proposed to facilitate this process while providing a profound logic to explain the overall process. It also helps get the importance weight of each expert which is useful to evaluate the chosen experts' assessments. The proposed versatile model can be applied in any similar decision-making situation. It is comprised of the following three steps:

Step 1: Initial Screening

An initial list of experts in the context of the study including both practitioners and scholars is drawn up. All the practitioners and academics in the field of study who can be regarded as potential experts and directly contactable are included in the list.

Step 2: Expert Eligibility Screening

In this phase, the Expert Eligibility Value (EEV) is calculated for each expert either practitioner or academic. The EEV for the chosen experts in this phase should be greater than or equal to a predefined inclusion value of α ($EEV \geq \alpha$). Four inclusion value ranges have been proposed which are measured in years as follows:

Undemanding inclusion ($\alpha < 3$)

Acceptable inclusion ($3 \leq \alpha < 10$)

Favourable inclusion ($10 \leq \alpha < 20$)

Solid inclusion ($\alpha \geq 20$)

Note that, the inclusion value can be changed based on stakeholders' opinion and the specific circumstances of the study. Nonetheless, defining such a value to filter out some potential experts can be cumbersome especially in specific fields that having access to experts is challenging. The EEV is calculated in close connection to years of experience influenced by other factors like education, level of experience, professional qualifications, and professional associations affiliation. The EEV for practitioners and academics can be calculated using Equation (4.1) and (4.2), respectively.

$$EEV = \left[\sum_{i=1}^{3}(Y_i \times L_i)\right] \times E_j \times \prod_{k=1}^{p} Q_m^k \times A_l \tag{4.1}$$

$$EEV = \left[\sum_{i=1}^{3}(Y_i \times L_i)\right] \times \prod_{k=1}^{p} Q_m^k \times A_l \tag{4.2}$$

Where,

Variable:

Y_i : Years of experience at each level of experience i

Parameters:

L_i : The importance weight of experience at each level of experience i

E_j : The importance weight of the highest level of achieved education ($j = 1,2,3,4$)

Q_m^k : The importance weight based on holding ($m = 1$) or not holding ($m = 2$) of k^{th} professional qualifications; equal importance weight for various qualifications is assumed for simplicity, Q_1^k is shown as Q_1 and also for Q_2^k as Q_2 (p is the number of professional qualifications that an expert holds)

A_l : The importance weight according to the highest-ranked professional association where an expert is a member of ($l = 1,2,3$)

In the EEV calculations for practitioners, L, E, Q^k and A can take on values based on Equation (4.3) to (4.6), respectively.

$$L = \begin{cases} Upper-level\ managers & L_1 \\ Mid-level\ managers & L_2 \\ First-level\ managers & L_3 \end{cases} \tag{4.3}$$

$$E = \begin{cases} PhD & E_1 \\ MSc/MA & E_2 \\ BSc/BA & E_3 \\ Below\ BSc/BA & E_4 \end{cases} \quad (4.4)$$

$$Q^k = \begin{cases} Holding\ k^{th}\ qualification & Q_1^k = Q_1 \\ No\ k^{th}\ qualification & Q_2^k = Q_2 = 1 \end{cases} \quad (4.5)$$

$$A = \begin{cases} Chartered & A_1 \\ Non - Chartered & A_2 \\ No\ Membership & A_3 \end{cases} \quad (4.6)$$

In EEV calculations for academics, E is not considered for academics as they all presumed to have been awarded doctorates (PhD) or equivalent degrees. Secondly, L for academics is the general academic hierarchy at universities which is shown in Equation (4.7) and can differ among various higher education settings. Q and A for academics are calculated in the same way as for practitioners.

$$L = \begin{cases} Professor & L_1 \\ Senior\ Lecturer & L_2 \\ Lecturer & L_3 \end{cases} \quad (4.7)$$

Step 3: Importance Weights Normalisation

The calculated EEV values are transformed into the scale between 0 and 1 to act as importance weights calculated by Equation (4.8), where e indicates the maximum number of experts who were involved in the study.

$$w_i = \frac{EEV_i}{\sum_{i=1}^{e} EEV_i} \quad (4.8)$$

4.3 Proposed Neutrosophic Revised DEMATEL Method

The DEMATEL method is built based on the graph theory (i.e. digraph) which enables analysts to analyse and solve problems by the visualisation method. These graphs are more helpful than undirected graphs because they can show the directed relationships of sub-systems (Gabus and Fontela, 1973, 1972; Vafadarnikjoo et al., 2015; Wu and Lee, 2007). This method puts all factors into two distinct categories called (1) cause; and (2) effect, by applying impact values between factors. In DEMATEL, factors are elements that a researcher is keen on determining their interrelationships by constructing a pair-wise relation matrix. Lee et al. (2013) proposed a revised DEMATEL that is applied in the current thesis. In the proposed NR-DEMATEL method, the revised DEMATEL is integrated with Neutrosophic Set Theory (NST). However, in other neutrosophic DEMATEL methods in the literature, the original DEMATEL was used. For instance, Kilic and Yalcin (2020) utilised neutrosophic DEMATEL and TOPSIS for the evaluation of environmental sustainability performance. Abdel-Baset et al. (2019b) showed application of neutrosophic DEMATEL and TOPSIS for project selection. F. Liu et al. (2018) proposed SVNN-DEMATEL and applied it in transport service provider selection problem. Tian et al. (2018) applied single-valued neutrosophic DEMATEL for market segment evaluation and selection. Abdel-Baset et al. (2018) used neutrosophic DEMATEL in order to develop supplier selection criteria.

Steps of the NR-DEMATEL are revised and elaborated as follows (Govindan et al., 2016; Vafadarnikjoo et al., 2016) (In this thesis, factors are considered as risk dimensions):

Step 1: Subject experts and factors identification

In this initial step, it is required to identify a set of factors that should be evaluated by an appropriate number of experts who have rich knowledge and experience in the subject matter. Note that experts may not necessarily be eligible for evaluation of all of the factors and they may choose to evaluate one or more factors that they can provide proper evaluation for. Moreover, assigning importance weights to each expert’s opinion is another crucial part that should be handled in a systematic way. The Hesitant Expert Selection Model (HESM) is explained in Section 5.4 to facilitate this expert selection and importance weight allocation process. The weight of k^{th} expert is represented as w_k in a way that $0 \leq w_k \leq 1$ and $\sum_{i=1}^{H} w_k = 1$ given H is the total number of experts providing their opinions.

Step 2: The initial direct-relation matrix B construction

The pairwise comparison matrix ($B_{n \times n}$) is generated by pairwise comparisons between the n factors being explored. It is carried out by experts who were asked to indicate the degree to which, factor i affects factor j. The influence of factor i on factor j indicates how changes in factor i can result in variations in factor j. The pairwise comparison between the i^{th}, and j^{th} factor given by the k^{th} expert is represented as $b_{ij}^{(k)}$ that takes on integers based on the seven-grade Likert scale ranging from 0 to 6 (Table 4.1). The provided scores will construct a $n \times n$ non-negative matrix $B^{(k)} = \left[b_{ij}^{(k)}\right]_{n \times n}$ with $1 \leq k \leq H$. Thus $B^{(1)}, B^{(2)}, \ldots, B^{(H)}$ are the matrices of H experts. The diagonal elements of each matrix $B^{(k)}$ are zero (Lee et al., 2013). Some rows of the matrix can have missing values in case that an expert is not well-qualified to evaluate the specific factor. In this case, missing values have been treated by the deletion method.

Step 3: The initial neutrosophic-based direct-relation matrix S construction

The Single-Valued Trapezoidal Neutrosophic Numbers (SVTNN) as revealed in Table 4.1 are utilised to substitute the influence scores in the direct relation matrix B. The $n \times n$ non-negative neutrosophic matrix $S^{(k)} = \left[s_{ij}^{(k)}\right]_{n \times n}$ where $1 \leq k \leq H$ is constructed by replacing the $b_{ij}^{(k)}$ values in $B^{(k)}$ with the corresponding SVTNN values as shown in Table 4.1.

Step 4: The initial weighted average matrix A construction

In order to deal with the less complex calculation in the later computational steps, the corresponding crisp values ($cs_{ij}^{(k)}$) of SVTNN values as shown in Table 4.1, are considered to generate the weighted crisp matrix $V^{(k)} = \left[v_{ij}^{(k)}\right]_{n \times n}$ where $v_{ij}^{(k)} = cs_{ij}^{(k)} \times w_k$. To compute the crisp amount of SVTNN, the described score function in

Equation (A.34) has been applied. The $n \times n$ weighted average matrix $A = [a_{ij}]_{n \times n}$ is then generated where $a_{ij} = \frac{\sum_{k=1}^{H} v_{ij}^{(k)}}{\sum_{k=1}^{H} w_k}$

Table 4.1 Linguistic scale of SVTNN

Linguistic Phrase	Influence score	SVTNN	Crisp Value
No Influence (NI)	0	$\langle(0.0,0.0,0.0,0.0);0.0,0.0,0.0\rangle$	0.00
Low Influence (LI)	1	$\langle(0.2,0.3,0.4,0.5);0.6,0.2,0.2\rangle$	0.26
Fairly Low Influence (FLI)	2	$\langle(0.3,0.4,0.5,0.6);0.7,0.1,0.1\rangle$	0.38
Medium Influence (MI)	3	$\langle(0.4,0.5,0.6,0.7);0.8,0.0,0.1\rangle$	0.50
Fairly High Influence (FHI)	4	$\langle(0.7,0.8,0.9,1.0);0.8,0.2,0.2\rangle$	0.68
High Influence (HI)	5	$\langle(1.0,1.0,1.0,1.0);0.9,0.1,0.1\rangle$	0.90
Absolutely High Influence (AHI)	6	$\langle(1.0,1.0,1.0,1.0);1.0,0.0,0.0\rangle$	1.00

Step 5: The normalised initial direct-relation matrix D construction

The normalised initial direct-relation matrix $D = [d_{ij}]_{n \times n}$ is generated by normalising the weighted average matrix A using Equations (4.9) and (4.10) where ε is a very small positive value like 10^{-5} (Lee et al., 2013). $\sum_{j=1}^{n} a_{ij}$ is the total direct effect that the factor i gives to other factors and $\sum_{i=1}^{n} a_{ij}$ is the total direct effect received by factor j.

$$p = max\left(\max_{1 \le i \le n} \sum_{j=1}^{n} a_{ij}, \varepsilon + \max_{1 \le j \le n} \sum_{i=1}^{n} a_{ij}\right) \tag{4.9}$$

$$D = \frac{A}{p} \tag{4.10}$$

Step 6: The total relation matrix T construction

The total relation matrix is produced by Equation (4.11) in which I is the identity matrix.

$$T = D(I - D)^{-1} \tag{4.11}$$

Step 7: The impact-relations map (IRM) construction

In the DEMATEL literature, the IRM (Lee et al., 2013) is also named as influence-relations map (Wang et al., 2012), causal diagram (Govindan et al., 2015), network relation map (Hsu et al., 2012), impact digraph map (Tzeng et al., 2007), and cause-effect diagram (Tzeng, 2014). An IRM is generated by applying Equation (4.12)-(4.14) as follows.

$$T = [t_{ij}]_{n\times n} i,j = 1,2,\ldots,n \tag{4.12}$$

$$c = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n} = [t_{.j}]_{1\times n} = [c_j]_{1\times n} \tag{4.13}$$

$$r = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = [t_{i.}]_{n\times 1} = [r_i]_{n\times 1} \tag{4.14}$$

Sum of rows (r) and sum of columns (c) are calculated according to matrix T. The r_i is the sum of the i^{th} row of the matrix T and represents the total effect, both direct and indirect, given by the factor i to other factors. And c_i is the sum of the i^{th} column of the matrix T and presents the total effect, both direct and indirect received by the factor i from other factors (Lee et al., 2013).

The $(r_i + c_i)$ is on the horizontal axis of IRM while $(r_i - c_i)$ makes the vertical axis of IRM. The $(r_i + c_i)$ represents the total sum of the effects given and received by the factor i. It is also named *Prominence* because it indicates the relative importance of each factor i. The $(r_i - c_i)$ is named *Relation* and represents the net effect that the factor i contributes to the system. In general, we have:

If $(r_i - c_i) > 0 \rightarrow$ the factor *i* is a member of cause group or a net causer

If $(r_i - c_i) < 0 \rightarrow$ the factor *i* is a member of effect group or is a net receiver

Cause factors impact on the entire system and their performance can influence the overall goal. Moreover, a factor belonging to a cause group should receive more attention. Effect factors tend to be easily impacted by other factors (Lin, 2013).

Step 8: Setting threshold value

Based on the total relation matrix (T), each element t_{ij} of matrix T, provides information about how factor i impacts on factor j. If all the information in matrix T converts to IRM then the map would be hardly conducive to appropriate decision making as it is too complicated to reveal any necessary information. This is particularly the case when there are numerous factors being explored. To obtain a proper IRM, researchers must set a threshold value for the impact level. Only factors with influence levels higher than the threshold value in matrix T can be chosen and converted into IRM (Tzeng et al., 2007). In the literature, the threshold value is determined in various ways. Si et al. (2018) indicated a number of them such as the brainstorming technique (Azadeh et al., 2015), the average of all elements in the matrix T (Sara et al., 2015), the maximum value of the diagonal elements of the matrix T (Tan and Kuo, 2014). In this study, the MMDE method (Lee and Lin, 2013; Li and Tzeng, 2009) is utilised which is explained in Appendix D. The reason is owing to its compelling rationale and logic as well as its capability in efficiently discovering strong relationships.

Step 9: The net influence matrix N construction

After depicting the intricate causal relationships among factors using the IRM and MMDE, Wang et al. (2014, 2012) further developed the net influence matrix $N = [Net_{ij}]_{n\times n}$ to assess the strength impact of a factor on another where $Net_{ij} = t_{ij} - t_{ji}$

4.4 Proposed Hybrid Spanning Trees Enumeration and BWM

In the original BWM, a DM (i.e. expert) must be able to provide one decision-making criterion as the best and another decision-making criterion as the worst with certainty with no room for hesitancy. In the real-world decision-making process applying the original BWM dealing with subjective judgements of human beings, it is not always that straightforward for DMs to choose only one criterion as either the best or the worst without any level of hesitancy. What if a DM has two or more criteria in mind as equal, yet as the most important (i.e. the best) or as equally the least important (i.e. the worst)? In other words, there might be a set of best and a set of worst criteria instead of just one single best/worst criterion. The original BWM does not suggest any solution in this case and expect a DM to offer only one criterion as the best and one criterion as the worst criterion. The BWM can only recognise one criterion as the best and one criterion as the worst and is unable to handle more than one criterion for each of the best and the worst group.

In order to deal with this type of uncertainty and capture the hesitancy of DMs, I propose the hybrid use of STE and the BWM. The STE can be accomplished by either EAST (Siraj et al., 2012) or GMAST (Lundy et al., 2017) which are explained in Appendix H. In the proposed approach, the following two additional steps (steps 2.1 and 2.2) shall be added to the original BWM which are explained in detail as follows (see Appendix E for the steps in the original BWM):

Step 1: Identifying set of decision-making criteria (in this thesis, risk dimensions or simply risks). The identified risks can be signified as shown in Equation (4.15).

$$N = \{C_1, C_2, \ldots, C_n\} \tag{4.15}$$

Step 2.1: Determining the best set of risks (i.e., the most critical or most important group of risks), and the worst set of risks (i.e., the least critical or least important group of risks). The best and worst set of risks are denoted by Θ and Γ which are identical subsets of N as represented in Equation (4.16) and (4.17), respectively.

$$\Theta = \{M_1, M_2, \ldots, M_m\} \quad \Theta \subset N, \Theta \neq \Gamma \tag{4.16}$$

$$\Gamma = \{L_1, L_2, \ldots, L_{n-m}\} \quad \Gamma \subset N, \Gamma \neq \Theta \tag{4.17}$$

Step 2.2: Applying STE to obtain the best risk

In this step, by applying STE (EAST or GMAST) the weights of each combination of the best and the worst risks is calculated and the maximum weight in Θ determines the best and the minimum weight in Γ determines the worst risk.

The maximum number of calculations equals to $m \times (n - m)$ because of $|\Theta| = m$ and $|\Gamma| = n - m$. For instance, if $|\Theta| = 2$, and $|\Gamma| = 3$, then $2 \times 3 = 6$ times, the STE calculations should be carried out.

Then the rest of the analysis should be followed from Step 3 in the original BWM which are explained in the Appendix E. The analysis applying the proposed STE-BWM is represented in Chapter 6 , Section 6.2.2.

4.5 Proposed Neutrosophic Enhanced BWM

The original BWM was described in Rezaei (2016, 2015) and follows a five-step approach. The Non-Linear model (NL-BWM) was proposed in Rezaei (2015) and the Linear model (L-BWM) was explained in Rezaei (2016). The proposed Neutrosophic Enhanced BWM (NE-BWM) is constructed based on the NL-BWM model and has two additional steps, which are explained as follows (In this thesis, criteria are risk dimensions):

Step 1: Decision criteria

A set of decision criteria (N) should be established in order to make a decision and do the analysis as shown in Equation (4.15).

Step 2: The best and worst criteria

A DM determines the best criterion (i.e. the most favourable one) and the worst criterion (i.e. the least favourable one).

Step 3: Best-to-others vector

As shown in Table E.1, a DM expresses their preference of the best criterion over all other criteria using a scale from 1 to 9 (Ishizaka, 2012; Rezaei, 2015; Saaty, 2005, 1977). The resulting vector is represented by $A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$ where a_{Bj} signifies the preference of the best criterion B over criterion j. It is also obvious that $a_{BB} = 1$.

Step 4: Others-to-worst vector

A DM determines the preference of all criteria over the worst criterion using a scale from 1 to 9 (Table E.1). The resulting vector is represented by $A_W = (a_{1W}, a_{2W}, \dots, a_{nW})$ where a_{jW} indicates the preference of the criterion j over the worst criterion W. Clearly, $a_{WW} = 1$.

The following two steps are uniquely introduced for the proposed NE-BWM:

Step 5: DM's uncertain confidence on the best-to-others preferences

A DM is asked to provide their confidence on the best-to-others preferences, which would inherently include the uncertainty of their choice on the best criterion. Note that a DM is required to indicate their confidence using linguistic phrases presented in Table 4.2. Appendix F (Table F.1-Q1) presents a sample question used to acquire a DM's uncertainty on their best-to-others preferences. The neutrosophic value of the DM's confidence on the best-to-others preferences (ρ^+) is a SVTNN, which is then substituted for the provided verbal term (Table 4.2). It reveals the degree of DM's confidence on Separation I. The crisp values in Table 4.2 are calculated based on Equation (A.34).

Table 4.2 The confidence rating scale

Linguistic Phrase	Score	SVTNN	Crisp Value
No Confidence	0	⟨(0.0,0.0,0.0,0.0); 0.0,0.0,0.0⟩	0.00
Low Confidence	1	⟨(0.2,0.3,0.4,0.5); 0.6,0.2,0.2⟩	0.26
Fairly Low Confidence	2	⟨(0.3,0.4,0.5,0.6); 0.7,0.1,0.1⟩	0.38
Medium Confidence	3	⟨(0.4,0.5,0.6,0.7); 0.8,0.0,0.1⟩	0.50
Fairly High Confidence	4	⟨(0.7,0.8,0.9,1.0); 0.8,0.2,0.2⟩	0.68
High Confidence	5	⟨(1.0,1.0,1.0,1.0); 0.9,0.1,0.1⟩	0.90
Absolutely High Confidence	6	⟨(1.0,1.0,1.0,1.0); 1.0,0.0,0.0⟩	1.00

Step 6: DM's uncertain confidence on others-to-worst preferences

A DM is asked to provide their confidence on their others-to-worst preferences, which inherently include the uncertainty of their choice on the worst criterion. Note that a DM is required to indicate their confidence using linguistic phrases as represented in Table 4.2. Appendix F (Table F.1-Q2) presents a sample question used to acquire the DM's uncertainty on others-to-worst preferences. The neutrosophic value of the DM's confidence on the others-to-worst preferences (ρ^{-}) is a SVTNN which is then substituted for the verbal term (Table 4.2). It reveals the degree of DM's confidence on Separation II.

Step 7: Optimal weights

Model (4.18) (i.e. a non-linear model) was proposed in the original BWM and then transformed to Model (4.19) which provides the optimal weights (Rezaei, 2015). The proposed Model (4.20) can be established by applying ρ^{+} and ρ^{-} in the objective function of Model (4.18) where $0 < \rho^{+} \leq 1$ and $0 < \rho^{-} \leq 1$.

$$\min \max_{j} \left\{ \left| \frac{W_B}{W_j} - a_{Bj} \right|, \left| \frac{W_j}{W_W} - a_{jW} \right| \right\} \tag{4.18}$$

subject to

$$\sum_{j} w_j = 1$$

$$w_j \geq 0 \quad \forall j \in N$$

$$\min \varepsilon \tag{4.19}$$

subject to

$$\left| \frac{W_B}{W_j} - a_{Bj} \right| \leq \varepsilon \qquad \forall j \in N$$

$$\left| \frac{W_j}{W_W} - a_{jW} \right| \leq \varepsilon \qquad \forall j \in N$$

$$\sum_{j} w_j = 1$$

$$w_j \geq 0 \qquad \forall j \in N$$

$$\min \max_{j} \left\{ \rho^{+} \left| \frac{W_B}{W_j} - a_{Bj} \right|, \rho^{-} \left| \frac{W_j}{W_W} - a_{jW} \right| \right\} \tag{4.20}$$

subject to

$$\sum_{j} w_j = 1$$

$$w_j \geq 0 \qquad \forall j \in N$$

Model (4.20), is then transformed into Model (4.21) and (4.22).

$$\min \left\{ \frac{\varepsilon}{\rho^{+}} + \frac{\varepsilon}{\rho^{-}} \right\} \tag{4.21}$$

subject to

$$\left| \frac{W_B}{W_j} - a_{Bj} \right| \leq \frac{\varepsilon}{\rho^{+}} \quad \forall j \in N$$

$$\left| \frac{W_j}{W_W} - a_{jW} \right| \leq \frac{\varepsilon}{\rho^{-}} \quad \forall j \in N$$

$$\sum_{j} w_j = 1$$

$$w_j \geq 0 \quad \forall j \in N$$

Finally, by solving Model (4.22) the criteria weights are obtained.

$$\min \varepsilon \left(\frac{\rho^{-} + \rho^{+}}{\rho^{-} \rho^{+}} \right) \tag{4.22}$$

subject to

$$\frac{W_B}{W_j} - \frac{\varepsilon}{\rho^{+}} \leq a_{Bj} \qquad \forall j \in N$$

$$\frac{W_B}{W_j} + \frac{\varepsilon}{\rho^{+}} \geq a_{Bj} \qquad \forall j \in N$$

$$\frac{W_j}{W_W} - \frac{\varepsilon}{\rho^{-}} \leq a_{jW} \qquad \forall j \in N$$

$$\frac{W_j}{W_W} + \frac{\varepsilon}{\rho^{-}} \geq a_{jW} \qquad \forall j \in N$$

$$\sum_j w_j = 1$$

$$w_j \geq 0 \quad \forall j \in N$$

4.5.1 Consistency ratio

There are two types of consistency: cardinal and ordinal consistency (Siraj et al., 2015). The current Consistency Ratio (CR) values of BWM only measure cardinal and output-based consistency (Liang et al., 2019). Liang et al. (2019) proposed consistency thresholds for BWM on the basis of both input and output-based consistency measurement. The consistency thresholds are based on combination of (1) number of criteria, and (2) maximum grade values (i.e. scales) (Table 4.3).

Table 4.3 Consistency thresholds (adapted from Liang et al. (2019))

	Criteria						
Scales	3	4	5	6	7	8	9
3	0.2087	0.2087	0.2087	0.2087	0.2087	0.2087	0.2087
4	0.1581	0.2352	0.2738	0.2928	0.3102	0.3154	0.3273
5	0.2111	0.2848	0.3019	0.3309	0.3479	0.3611	0.3741
6	0.2164	0.2922	0.3565	0.3924	0.4061	0.4168	0.4225
7	0.2090	0.3313	0.3734	0.3931	0.4035	0.4108	0.4298
8	0.2267	0.3409	0.4029	0.4230	0.4379	0.4543	0.4599
9	0.2122	0.3653	0.4055	0.4225	0.4445	0.4587	0.4747

The CR for the proposed NE-BWM is described in this section. The lower the CR the higher the consistency of evaluations. Given a_{BW} is the preference of the best criterion over the worst criterion, then, a comparison is fully consistent when $a_{Bj} \times a_{jW} = a_{BW}$. The minimum consistency of a comparison is calculated as follows:

Consider $a_{ij} \in \{1, \dots, a_{BW}\}$ and that the highest possible value of a_{BW} is 9. Consistency decreases when $a_{Bj} \times a_{jW} \neq a_{BW}$ and the highest inequality occurs when $a_{Bj} = a_{jW} = a_{BW}$. Given the highest inequality as a result of assigning the maximum value by a_{Bj} and a_{jW} then, Model (4.22) can be used to calculate the consistency ratio based on Equation (4.23).

$$\left(a_{Bj} - \frac{\varepsilon}{\rho^{+}}\right) \times \left(a_{jW} - \frac{\varepsilon}{\rho^{-}}\right) = \left(a_{BW} + \varepsilon\left(\frac{\rho^{-} + \rho^{+}}{\rho^{-}\rho^{+}}\right)\right) \tag{4.23}$$

As for the minimum consistency, $a_{Bj} = a_{jW} = a_{BW}$, we can then obtain Equation (4.24).

$$\left(a_{BW} - \frac{\varepsilon}{\rho^{+}}\right) \times \left(a_{BW} - \frac{\varepsilon}{\rho^{-}}\right) = \left(a_{BW} + \varepsilon\left(\frac{\rho^{-} + \rho^{+}}{\rho^{-}\rho^{+}}\right)\right) \tag{4.24}$$

Based on Equation (4.24), Equation (4.25) can then be obtained.

$$\left(\frac{1}{\rho^{+}\rho^{-}}\right)\varepsilon^{2} - \left(\frac{a_{BW}\left(\rho^{+} + \rho^{-}\right) + \rho^{+} + \rho^{-}}{\rho^{+}\rho^{-}}\right)\varepsilon + \left(a_{BW}^{2} - a_{BW}\right) = 0 \tag{4.25}$$

a_{BW} can take on values $\{1, \ldots, 9\}$ (Table E.1) and based on Table 4.2, $\rho^{+} \in \{0.26, 0.38, 0.50, 0.68, 0.90, 1.00\}$ and $\rho^{-} = \{0.26, 0.38, 0.50, 0.68, 0.90, 1.00\}$. It is assumed that ρ^{+} and ρ^{-} could not be 0, as the evaluation of a DM with no confidence on their opinion could be easily dismissed. The maximum possible value of ε can be calculated solving Equation (4.25). The obtained values are recognised as the consistency index (CI) values and are represented in Appendix G. After solving Model (4.22), the ε^{*} would be obtained and then the CR can be calculated by Equation (4.26).

$$CR = \frac{\varepsilon^{*}}{CI} \tag{4.26}$$

4.5.2 Confidence difference

The Confidence Difference (CD) is proposed to measure the output of the NE-BWM. It is the difference between the confidence degree on separations I and II as shown in Equation (4.27).

$$CD = |\rho^{+} - \rho^{-}| \tag{4.27}$$

4.6 Proposed Stratified Decision-Making Model

The stratified game theory model comprised of N status (SS) and M outcome (OC) while under each SS_i there are n_i strategies that result in various payoff (PF) values under different nature's outcomes. As the model is game of chance involving risk, there would be a probability about each nature's move or outcomes (Section 3.7). In Table 4.4, the payoff matrix of the model, and in Table 4.5 the states are presented.

4.6.1 Notations

P: status transition probability matrix

Q: outcome transition probability matrix

S: state transition probability matrix

p_{ij}: the probability of transition from status i (SS_i) to status j (SS_j)

q_{ij}: the probability of transition from outcome i (OC_i) to outcome j (OC_j)

s_{ij}: the probability of transition from state i (SE_i) to state j (SE_j)

PF_{ijk}: the payoff value under SS_i, strategy j and OC_k

OP_k: the occurrence probability of OC_k $(k = 1, \dots, M)$

Table 4.4 The payoff values in the stratified game table

PLAYER 1		PLAYER 2 (NATURE)			
		OUTCOME 1	OUTCOME 2	…	OUTCOME M
STATUS 1	Strategy 1	PF_{111}	PF_{112}	$\cdots$	PF_{11M}
	Strategy 2	PF_{121}	PF_{122}	$\cdots$	PF_{12M}
				$\cdots$	
	Strategy n_1	$PF_{1n_1 1}$	$PF_{1n_1 2}$	$\cdots$	$PF_{1n_1 M}$
STATUS 2	Strategy 1	PF_{211}	PF_{212}	$\cdots$	PF_{21M}
	Strategy 2	PF_{221}	PF_{222}	$\cdots$	PF_{22M}
				$\cdots$	
	Strategy n_2	$PF_{2n_2 1}$	$PF_{2n_2 2}$	$\cdots$	$PF_{2n_2 M}$
				$\cdots$	
STATUS N	Strategy 1	PF_{N11}	PF_{N12}	$\cdots$	PF_{N1M}
	Strategy 2	PF_{N21}	PF_{N22}	$\cdots$	PF_{N2M}
				$\cdots$	
	Strategy n_N	$PF_{Nn_N 1}$	$PF_{Nn_N 2}$	$\cdots$	$PF_{Nn_N M}$

Table 4.5 The states in the stratified game table

PLAYER 1		**PLAYER 2 (NATURE)**			
		OUTCOME 1	OUTCOME 2	…	OUTCOME M
STATUS 1	Strategy 1 Strategy 2 Strategy n_1	STATE 1	STATE 2	…	STATE M
STATUS 2	Strategy 1 Strategy 2 Strategy n_2	STATE $M+1$	STATE $M+2$	…	STATE $2M$
⋮	⋮	⋮	⋮	…	⋮
STATUS *N*	Strategy 1 Strategy 2 Strategy n_N	STATE $NM-M+1$	STATE $NM-M+2$	…	STATE NM

4.6.2 Status transition probability matrix

There are N status in the model and given the probability of transitions between SS_i and SS_j as p_{ij}, the status transition probability matrix P can be shown as Equation (4.28)

$$P = \left[p_{ij} \right]_{N \times N} \tag{4.28}$$

For instance, p_{11}, is the probability of persistence at the current SS_1. In Figure 4.1, status transitions are depicted.

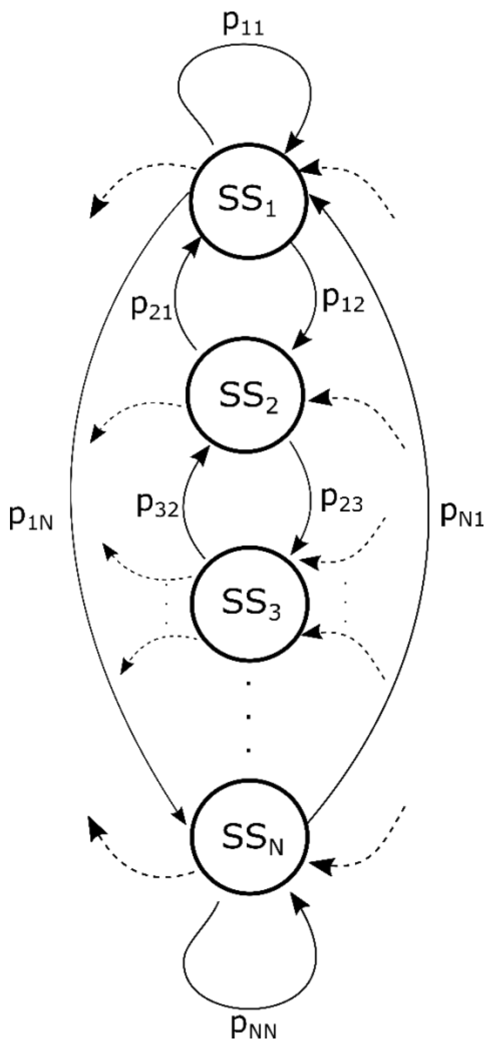


Figure 4.1 Graphical representation of status transitions and respective probabilities

4.6.3 Outcome transition probability matrix

There are M outcomes and given the probability of transition from OC_i to OC_j as q_{ij}, the outcome transition probability matrix Q can be shown as Equation (4.29)

$$Q = \left[q_{ij} \right]_{M \times M} \tag{4.29}$$

For instance, q_{11}, is the probability of persistence at the current OC_1. In Figure 4.2, outcome transitions are depicted.

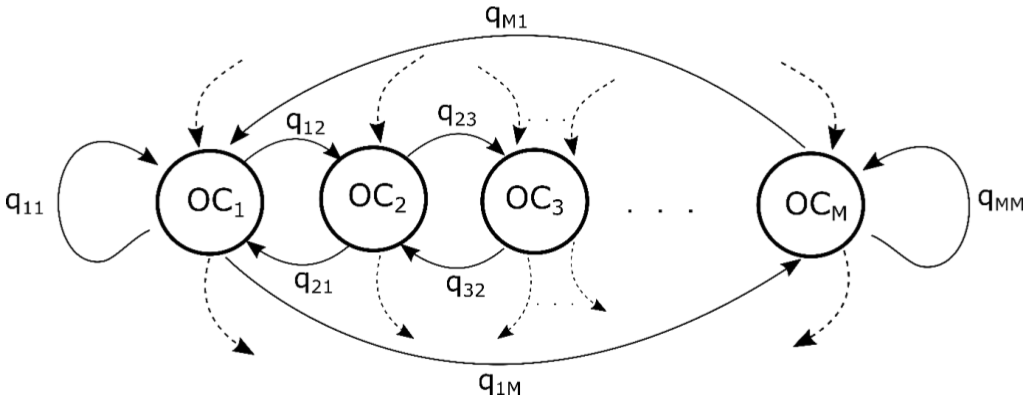


Figure 4.2 Graphical representation of outcome transitions and respective probabilities

4.6.4 State transition probability matrix

There are $N \times M$ states as represented in Table 4.5. Given s_{ij}, the probability of transition from state i (SE_i) to state j (SE_j), then state transition probability matrix S can be represented as Equation (4.30)

$$S = \left[s_{ij} \right]_{N \times M} \tag{4.30}$$

For instance, s_{11} is the probability that SE_1 persists which means SS_1 and OC_1 persist that can be calculated as $s_{11} = p_{11} \times q_{11}$. Given $N = 3$ and $M = 4$ the twelve states in the stratified game table are shown schematically in the Table 4.6. As such, in Appendix I (Table I.1), the S matrix is represented. It is clear that as the dimensions of the matrix (N and M) increase, the computational time would rise dramatically.

Table 4.6 Twelve states in the stratified game table for N=3 and M=4

PLAYER 1		**PLAYER 2 (NATURE)**			
		OC_1	OC_2	OC_3	OC_4
SS_1	Strategy 1 Strategy 2 Strategy n_1	SE_1	SE_2	SE_3	SE_4
SS_2	Strategy 1 Strategy 2 Strategy n_2	SE_5	SE_6	SE_7	SE_8
SS_3	Strategy 1 Strategy 2 Strategy n_3	SE_9	SE_{10}	SE_{11}	SE_{12}

The pseudo code for calculating the matrix S is represented in Table 4.7, and state transitions and respective probabilities are shown graphically in Figure 4.3.

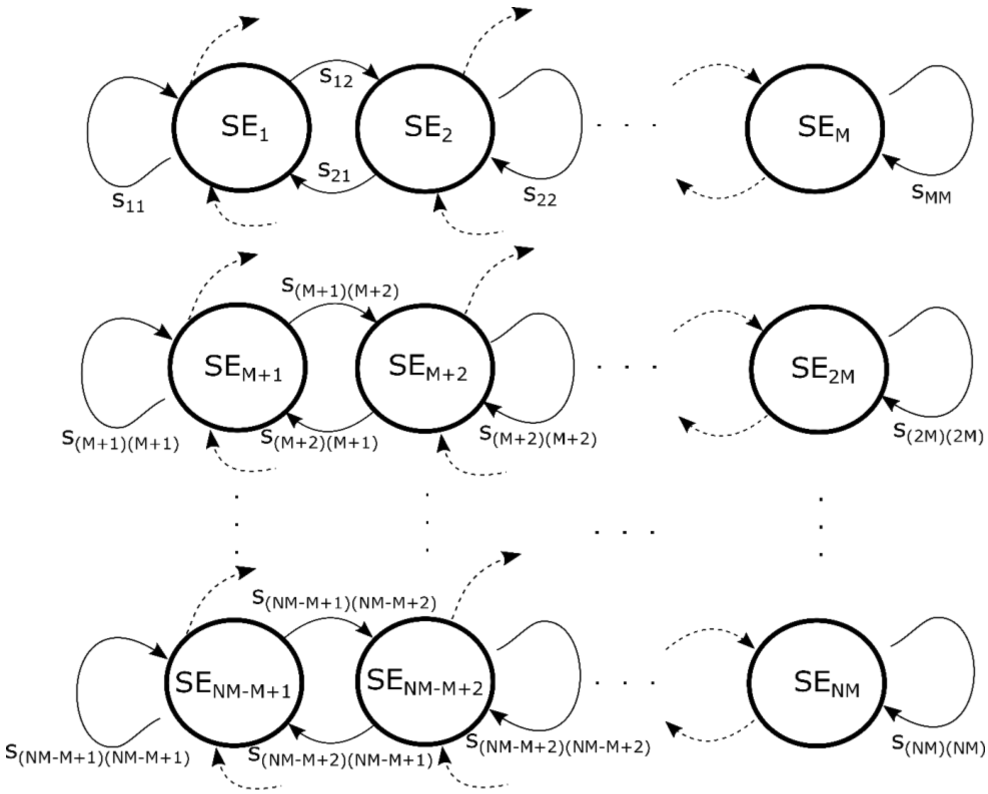


Figure 4.3 Graphical representation of state transitions and respective probabilities

4.6.5 Model assumptions

In the proposed model, it is assumed that the following assumptions are in place:

1) The same strategies exist under various status of the model meaning $n_1 = n_2 = ... = n_N = B$

2) The payoff values all acquire the benefit nature meaning their maximisation is the aim ($Z = maxPF_{ijk}$). Payoff values can also be represented as utility values in situations where obtaining monetary values is difficult or they are more based on the DMs' perceptions and evaluations rather than tangible monetary values ($Z = maxU_{ijk}$). Utility value is a dimensionless number between 0 and 1.

3) It is presumed that payoff/utility values stay constant throughout the state change.

4) The summation of all status transition probabilities is 1, and also the same is correct for outcome transition probabilities as shown in Equation (4.31) and (4.32).

$$\sum_{j=1}^{N} p_{ij} = 1 \qquad \forall i = 1, \dots, N \tag{4.31}$$

$$\sum_{j=1}^{M} q_{ij} = 1 \qquad \forall i = 1, \dots, M \tag{4.32}$$

Table 4.7 Pseudo code for the calculation of the state transition probability matrix

Input
N = number of status M = number of outcomes $P = \left[p_{ij}\right]_{N\times N}$ $Q = \left[q_{ij}\right]_{M\times M}$
Output
s_{ij} = the probability of transition from state i to state j

for $l=1$ to N
    for $k=1$ to N
        for $i=kM-M+1$ to kM
            for $j=lM-M+1$ to lM
                $s_{ij} = p_{kl} \times q_{(i-kM+M)(j-lM+M)}$
            end
        end
    end
end

4.6.6 Model solving

Given the assumptions, considering the current state of the system is x then by using Equation (4.33), the value of strategy b (V_b^x) given $b = 1,\dots,B$ can be obtained ($NM = N \times M$). Knowing that $k = 1$ if $j = \{1, M+1, 2M+1, \dots, NM-M+1\}$, $k = 2$ if $j = \{2, M+2, 2M+2, \dots, NM-M+2\}$,..., $k = M$ if $j = \{M, 2M, 3M, \dots, NM\}$. In case that utility values are used then Equation (4.34) is utilised.

$$V_b^x = \sum_{i=1}^{N} \sum_{j=iM-M+1}^{iM} s_{xj} PF_{ibk} \tag{4.33}$$

$$\forall b = 1, \dots, B, \forall x = 1, \dots, NM,\ k = \{1,2, \dots, M\}$$

$$V_b^x = \textstyle\sum_{i=1}^{N} \sum_{j=iM-M+1}^{iM} s_{xj} U_{ibk} \tag{4.34}$$

$$\forall b = 1, \dots, B, \forall x = 1, \dots, NM\ ,\ 0 \le U_{ibk} \le 1,\ k = \{1,2, \dots, M\}$$

Then, the after-transition payoff/utility decision matrix would be obtained as shown in Table 4.8. If the current state (before-transition state) of the system is known, then the corresponding column of that state in Table 4.8 is only considered, otherwise it is needed to give probability to those states for which there is uncertainty. Then, by calculating the EMV of each strategy the final strategy can be resulted (throughout this thesis, the same term EMV is used for both Expected Monetary Value and Expected Utility Value).

Table 4.8 The after-transition payoff/utility decision matrix

STRATEGY	**STATE**			
	STATE 1	STATE 2	…	STATE NM
STRATEGY 1	V_1^1	V_1^2	…	V_1^{NM}
STRATEGY 2	V_2^1	V_2^2	…	V_2^{NM}
			…	
STRATEGY *B*	V_B^1	V_B^2	…	V_B^{NM}

For example, the EMV of each strategy b (EMV^b) considering equal probabilities can be calculated as Equation (4.35).

$$EMV^b = \frac{\sum_{i=1}^{NM} V_b^i}{NM} \qquad \forall b = 1, \dots, B \tag{4.35}$$

4.7 Conclusions

All the methods applied in Chapters 5, 6, and 7 were explained in detail in the current chapter. The reason why each specific method is required and their importance in this thesis a long with their computational steps were described. A number of tools are novel and have theoretical contributions including ESM (Section 4.2), NR-DEMATEL (Section 4.3), hybrid STE-BWM (Section 4.4), NE-BWM (Section 4.5), and stratified decision-making model (Section 4.6).

In group decision-making where numerous experts with different levels of experience and knowledge are involved, it is important to assign a proper importance weight to each expert. In previous studies, the task of experts' weights determination was carried out in a relatively subjective, and unstructured way. In this thesis, a unique model named ESM was proposed to facilitate this process while providing a profound logic to explain the overall process. The proposed ESM is generalisable and can be used in other decision-making problems where experts' importance weights assignment is required. The application for the ESM is discussed in Hesitant ESM (HESM) in Section 5.4.

The NR-DEMATEL is tailored for the specific intention of this thesis which is exploring the causal interrelationships between identified macro-level energy risk dimensions. The proposed NR-DEMATEL has a theoretical contribution as it uses the revised DEMATEL rather than the original DEMATEL as it is discussed in Lee et al. (2013). The other advantage of the NR-DEMATEL is the integration with the Neutrosophic Set Theory (NST) which has considerable merits over most uncertainty theories such as Fuzzy Set Theory (FST) (see Appendix A). In this thesis, the subjective judgements of experts must be gathered and analysed and as there is always a degree of ambiguity in subjective opinions of humans (i.e. experts), this integration can help capture this ambiguity and vagueness in experts' opinions more efficiently. The application of the NR-DEMATEL is presented in Section 5.5.

For the ranking and prioritisation of the final most critical risk dimensions, hybrid STE-BWM and NE-BWM are developed as two extensions of the original BWM. In the original BWM (see Appendix E), an expert or Decision Maker (DM) has to provide a criterion as the best and a criterion as the worst with certainty, assuming there is no hesitancy. To improve the BWM, the hybrid STE-BWM is proposed by applying spanning trees enumeration which offers an opportunity for DMs (i.e. experts) to suggest more than one best or worst criteria. Additionally, in the original BWM (see Appendix E), two vectors of pairwise comparisons including best-to-others and others-to-worst vectors are treated with the same level of importance. In other words, the degree of a DM's confidence on the best-to-others preferences and others-to-worst preferences have been overlooked by giving equal importance to them in the original BWM. This observed feature was the motivation to propose NE-BWM. The application of NE-BWM and STE-BWM are presented in Chapter 6.

Ultimately, for risk mitigation analysis, a novel stratified decision-making model is proposed. It is based on Concept of Stratification (CST), game theory and Shared Socio-economic Pathway (SSP) to deal with long-term risk mitigation planning for the most critical identified risks (i.e. CC, and ND). The model is applied in the region of Highland and Argyll in Scotland to prioritise flooding risk mitigation strategies which were suggested by the Scottish Environment Protection Agency (SEPA). The model takes into account both UK socio-economic situations and flooding risk impacts for the long-term decision making (5 to 20-year time frame). Chapter 7 illustrates the application of the proposed stratified decision-making model.

Chapter 5 Risk Analysis by NR-DEMATEL

5.1 Introduction

In this chapter, the causal relationship between risks is studied, indicating that the occurrence of one risk could lead to exposure to the other one. Based on the literature review, there is just a limited number of studies in the supply chain risk management literature that have addressed cause-effect interrelations between risks (Chaudhuri et al., 2016; Ritchie and Brindley, 2007). This is even less explored in the energy risk management literature, particularly when focusing on the energy supply chain macro-level risk dimensions. Thus, it is critical to take advantage of a method that can analyse these types of interrelationships between energy risk dimensions. The selected input for this analysis is coming from experts' opinions (more details to follow) and therefore NR-DEMATEL is selected to provide a means to effectively deal with their subjective judgements. Few methods such as Interpretive Structural Modelling (ISM) and DEMATEL are suitable to analyse the interrelationships among multiple criteria. The DEMATEL is preferred over ISM because ISM cannot analyse the strength of interrelationships between multiple criteria. For this reason, ISM is often used in conjunction with other methods such as Matrice d'Impacts Croisés Multiplication Appliquée à un Classement (MICMAC) also known as "cross impact matrix multiplication applied to classification". The combination of ISM and MICMAC often adds another layer of complexity to the solution procedure. The DEMATEL method is widely used to rank related factors while considering the causal relationships among them (Feng et al., 2018). In summary, the main advantage of DEMATEL is its ability to uncover the causal relationships and interdependencies between various risks while utilising minimal data. As it was explained in Section 4.3, the proposed NR-DEMATEL has a theoretical contribution as it uses the revised DEMATEL rather than the original DEMATEL as it is discussed in Lee et al. (2013). Additionally, it is aimed at understanding causal relationships between macro-level energy risk dimensions within the UK which was less explored in the literature.

The Neutrosophic Set Theory (NST) provides a considerable advantage over the Fuzzy Set Theory (FST) and the Intuitionistic Fuzzy Set (IFS) theory in processing experts' subjective judgements. The NST, unlike the FST, can quantify the rejection information derived from the falsity-membership function. In addition, the NST, unlike the IFS theory, can define the hesitancy function values independently from the falsity and truth-membership function values (more details are provided in Section 3.4 and Appendix A).

An Expert Selection Model (ESM) is also proposed in this study, which provides a basis for the selection process in similar decision-making problems, where subject expert selection is required. In other words, it provides a reliable model that helps researchers decide who can be an expert or DM based on their credentials and experience. It is also useful in assigning on each expert a relative importance weight (for more information regarding ESM please see Section 4.2). This model is integrated with Hesitant Fuzzy Set (HFS) theory and named the Hesitant Expert Selection Model (HESM) in the study. In this chapter, the two first phases of the whole research are carried out as shown in Figure 5.1

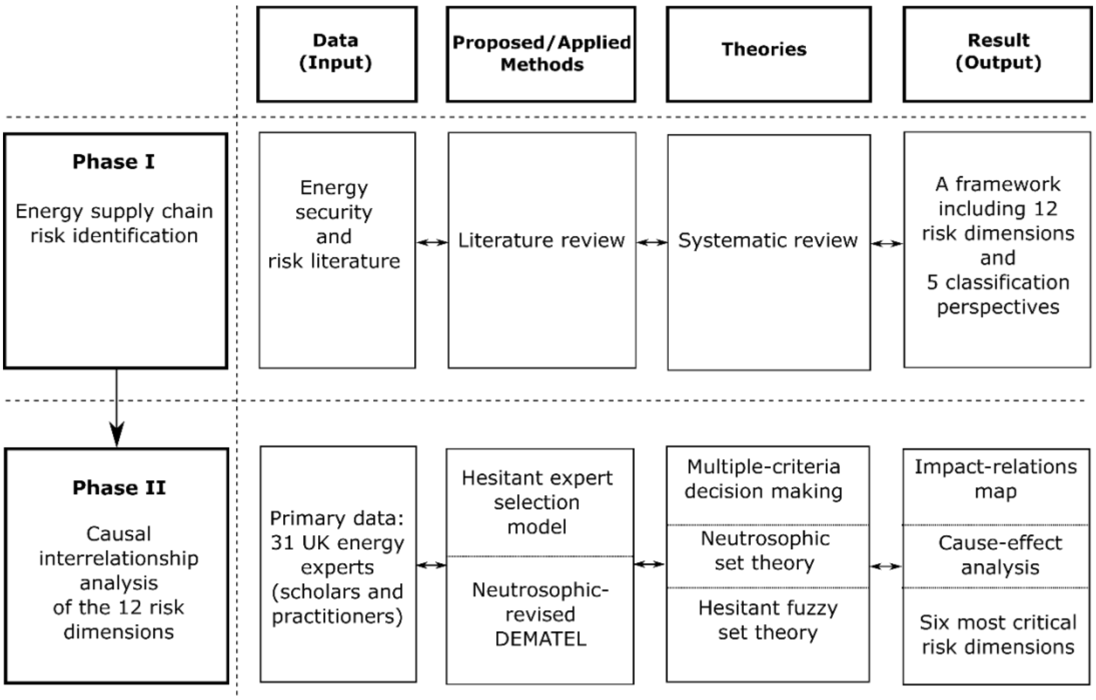


Figure 5.1 Phases I and II of the whole research carried out in this chapter

In Figure 5.2, the research steps for causal risk interrelations analysis in the applied method are illustrated.

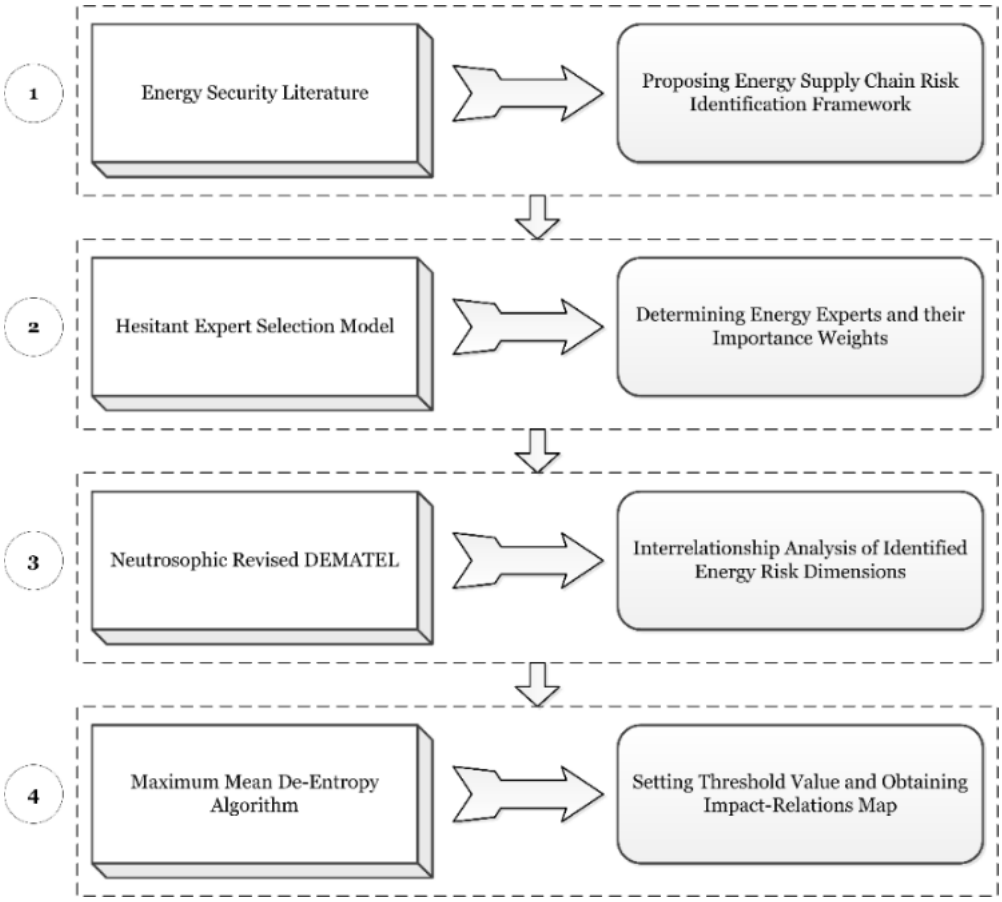


Figure 5.2 Research steps for causal risk interrelations analysis

The research in this chapter offers methodological and practical implications for both academics and practitioners. The research contributions in this chapter are fourfold as follows:

(I) Presenting a simple framework for risk identification and classification which can be used in strategic risk mitigation analysis resulted from systematic literature review and experts' feedback.

(II) Proposing a NR-DEMATEL method to analyse risk dimensions based on the causal interrelationships and interdependencies among them, which has been missing in the current energy risk management practices.

(III) Introducing a HESM to systematically assist researchers with the expert selection process.

(IV) Aiding policy makers in the UK energy supply chain to recognise most critical risks efficiently.

5.2 Energy Supply Chain Risk Identification Framework

An energy risk identification framework is proposed in this section (Figure 5.3). It facilitates the risk identification and classification process in the energy supply chain and further possible utilisation in the later process of risk management such as risk mitigation. The risk identification framework is comprised of three main sections as follows:

1) Risk classifications

2) Risk dimensions

3) Risk elements

Risk classifications essentially present the discipline and framing of risks aiming to position them within the wider risk literature. Risk classifications can help understand and analyse risk dimensions properly from various perspectives such as position and origin within the UK power supply chain. The framework identified *context-based*, *position-based*, *temporal*, *origin-based* and *hybrid* classifications. The context-based classification concentrates on the risk discipline and includes *economics*, *politics*, *sociology*, *health*, *engineering* and *environmental science* (Checchi et al., 2009; Cherp and Jewell, 2011; Chevalier, 2006; Winzer, 2012) (see Section 2.5.1). In position-based classification, risks are categorised in accordance with their position in the energy supply chain which can be upstream, midstream, or downstream (Gracceva and Zeniewski, 2014) (see Section 2.5.2). In temporal-based classification, researchers categorised risks on the basis of their timescales over which they operate that can be *long*, *medium* or *short* time frames (Chevalier, 2006) (see Section 2.5.3). Some risks have their origins inside the national border or energy system and named internal, while many risks are related to imported energy that are named external. This kind of classification is discussed in the *origin-based* attitude towards energy supply chain risk classification (Babich et al., 2007; Chevalier, 2006; Huang et al., 2016; Tang et al., 2014; Yang et al., 2009) (see Section 2.5.4). Finally, there are hybrid classifications that consolidate two or three other classifications and provide a hybrid perspective of various dimensions (Boston, 2013) (see Section 2.5.5).

Risk elements lie at the lowest level of the framework. They can also be divided into more detailed risk elements with more specific characteristics depending on the system under study and targeted plan for risk assessment. Ultimately, risk dimensions are those aspects of risks that are significant enough to include meaningful risk elements under their paradigm. They are recognised as macro-level risks in contrast to risk elements which are of micro-level nature. In other words, risk dimensions need to incorporate a number of risk elements in their context. For example, technical reliability is regarded as a risk dimension which can contain a wide variety of risk elements such as lack of cooperation, inability to synthesise information, or human error. To this end, the analysis can explore and go down the hierarchy depending on many factors such as the availability of information, the required managerial assessment, and the method of risk assessment.

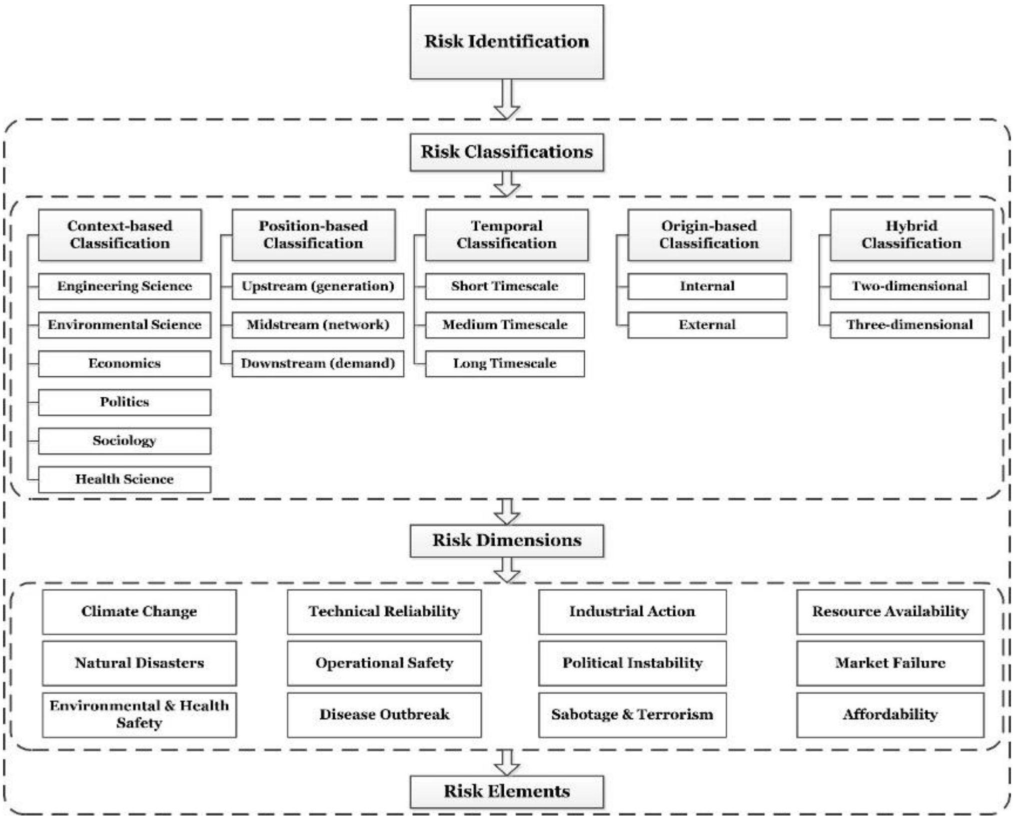


Figure 5.3 The framework of energy risk identification

Risk dimensions, as shown in the risk identification framework are the key components of the process because they assist analysis with obtaining appropriate risks that each one can facilitate the identification of risk elements. All the proposed risk dimensions are identified based on the literature and verified based on the experts' feedback. They are chosen in a way that all potential risk elements can be categorised under at least one dimension's definition. It is attempted to shed light on risk dimensions that are undertreated in the literature that may bring about severe consequences in case of occurrence. For instance, a disease outbreak or a pandemic is proposed in this framework as an almost untapped risk dimension in the literature.

The twelve risk dimensions were recognised based on a systematic and in-depth scrutinising of the literature. The systematic literature review was carried out to identify the critical risks and risk categories in the UK energy supply chain. The systematic literature review protocol is described in Table 5.1.

Table 5.1 The systematic literature review protocol

Element	Systematic review protocol
Research field	Energy security
Search keywords	energy AND risk, electricity AND generation AND risk, energy AND supply AND risk, energy AND supply AND chain AND risk, energy AND network AND risk
Database	Web of Science, Scopus, Google Scholar
Language	English
Document types	Journal articles, Reports, Books, Textbooks, and Conference Proceedings
Years of publication	1989-2018

As can be seen in Table 5.1, wide variety of documents from different disciplines were explored by using different keywords in several library databases. At initial stages, it soon became clear that finding risk dimensions cannot be carried out by merely looking at keywords, titles, or abstracts. Hence, cross-references found in the identified articles were utilised to reach more related papers. Ultimately, this approach returned approximately 100 documents, from 1989 to 2018, and offered enough substantial information to allow risk dimensions to emerge. Finally, to verify the identified risk dimensions, experts who participated in the survey were asked to indicate if the list of risks is comprehensive or any other risk is missing. Their feedback verified the identified risks as explained in more detail in data collection section (Section 5.3).

These risk dimensions were identified as: (1) Climate Change (CC); (2) Natural Disasters (ND); (3) Environmental and Health Safety (EHS); (4) Technical Reliability (TR); (5) Operational Safety (OS); (6) Disease Outbreak (DO); (7) Political Instability (PI); (8) Industrial Action (IA); (9) Sabotage and Terrorism (ST); (10) Resource

Availability (RA); (11) Market Failure (MF); and (12) Affordability (AF). The detailed description of all risks based on the literature are provided in Section 2.4. The approach towards identifying these risk dimensions was not only focusing on energy supply but also the whole energy supply chain from upstream to downstream. It might be argued that some of the risk dimensions are only threats to energy supply and some of them are not. As it is shown in the framework (Figure 5.3), the five risk classification approaches can provide more clear insights from different perspectives to make this issue clear. For example, the position-based classification deals with the impacted segment(s) of the energy supply chain. The other important point that already explained in origin-based classification is that some of the risk dimensions are caused by the energy system itself such as environmental and health safety that are classified as internal causes. These risks can then in case of occurrence pose a threat to the security of supply. Their incident is the result of poor organisation and performance of the energy system unlike the risks with external causes such as market failure (e.g. world oil price) which their causes have roots in the outside of the system. Thus, each risk classification perspective can provide insightful view on understanding the risk dimensions efficiently. All the proposed risk dimensions are categorised in a distinct way separating them from each other to avoid overlaps. Even risk dimensions, which are not extensively covered in the literature, have been included to enable a wide-ranging approach. The detailed definition of each risk classification regarding the literature is provided in Section 2.5.

Focusing on the UK power supply chain, twelve energy supply chain risk dimensions are evaluated based on the knowledge and experience of experts in the UK energy supply chain. The analysis is on the basis of the revised DEMATEL in the uncertain neutrosophic decision-making environment (namely NR-DEMATEL) so as to explore the causal interrelationships between risk dimensions. Moreover, the proposed ESM (Section 4.2) will be utilised by integrating HFS theory (Appendix A) (i.e. HESM) to obtain experts' importance weights.

5.3 Data Collection

Experts involved in this phase of research are comprised of both academics and practitioners with a proper level of knowledge and experience on the UK electricity supply chain. In total 161 experts were initially contacted through email to participate in the study by completing an online internet questionnaire. The data collection phase was carried out within four months (8th Nov 2017-5th Mar 2018) and collected the views of 31 experts including 25 academics and 6 practitioners, resulting in a response rate of 19% which is acceptable due to low response rate in web surveys from experts (Fan and Yan, 2010). This decision-making problem is categorised as Large-Scale Group Decision-Making (LSGDM) problems because higher than 20 experts participated in this study. The LSGDM problems can be characterised by involving at least 20 experts (H. Liu et al. 2018; Jiang et al. 2020). Experts' fields of knowledge in various energy sectors along with the number of experts in each category include renewable energy (21 experts); policy and economics (20 experts); energy storage and grid modernisation (10 experts); fossil and nuclear energy (6 experts); environmental impacts (5 experts); energy end use and efficiency (5 experts); and other (4 experts) (see Figure 5.4). As shown in Figure 5.4, four experts grouped as *other*, because they indicated their energy expertise areas as whole system analysis, energy social research, sustainability, societal engagement with sustainable energy, environmental psychology, behaviour change, geoengineering and technological systems which all grouped into the category named as *other*. Most experts (74%) had an overlapping expertise in more than one area.

Practitioner experts' professional associations include five organisations *Nuclear Institute*, *The Scottish Oil Club*, *Engineering Industries Association (EIA)*, *The Institution of Engineering and Technology (IET)*, and *Society of Petroleum Engineers (SPE)*. Professional associations of the academic experts' involved in our study comprise twenty-two organisations including *International Association for Energy Economics (IAEE)*, *Institute of Electrical and Electronics Engineers (IEEE)*, *IET*, *Higher Education Academy (HEA)*, *International Council on Large Electric Systems (CIGRE)*, *The Technical Chamber of Greece (TEE-TCG)*, *The Energy Institute*, *American Society of Heating, Refrigerating and Air-Conditioning Engineers (UK ASHRAE)*, *The Chartered Institute of Logistics and Transport*, *British Institute of Energy Economics (BIEE)*, *Institution of Mechanical Engineers (IMechE)*, *Institution of Chemical Engineers (IChemE)*, *European Association for the study of Science and Technology (EASST)*, *European Sociological Association (ESA)*, *Nuclear Institute*, *Royal Geographical Society*, *Athens Institute For Education and Research (ATINER)*, *Sustainable Consumption Research and Action Initiative (SCORAI)*, *Research Association on Monetary Innovation and Community and Complementary Currency Systems (RAMICS)*, *Marie Curie Fellows Association*, *Renewable and Appropriate Energy Laboratory (RAEL)*, and *Lindau Nobel Laureate Economics*.

Experts were asked to choose risk dimensions on which they considered themselves capable of providing reliable evaluations based on their knowledge and expertise. Then, for each risk dimension they were asked to come up with evaluations in comparison with other risk dimensions using the scale presented in Table 4.1.

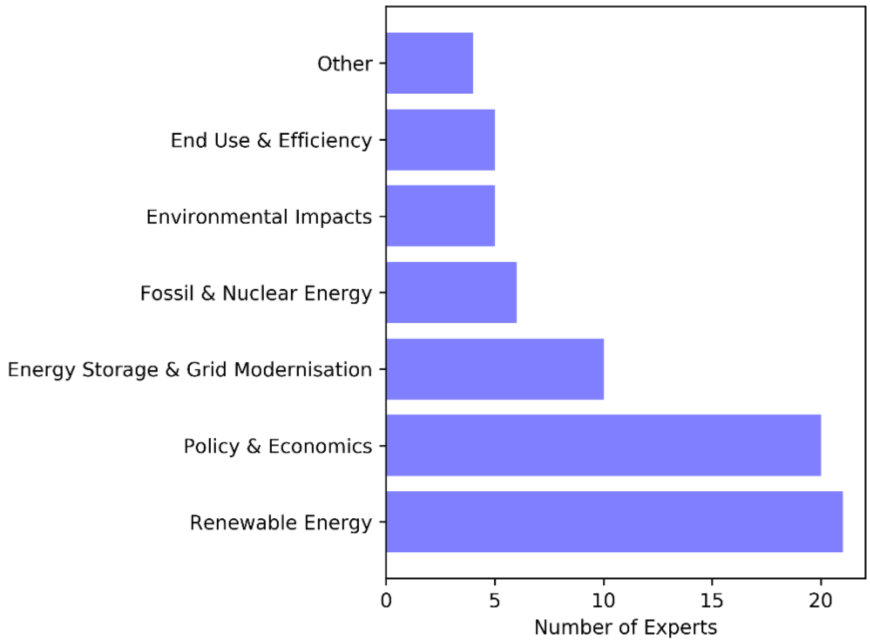


Figure 5.4 Experts' energy expertise areas

For instance, if the expert has chosen to assess *Climate Change (CC)* then the question appeared as "*To what extent do you think climate change can impact on the following risks in the UK power supply chain?*". The *"following risks"* refers to the other eleven risk dimensions (for more details see Appendix J). Thus, as there are twelve identified risk dimensions, each question needed to be answered by providing eleven evaluations. In order to capture the theory behind this type of questions construction see step 2 in Section 4.3. On average for each risk dimension, approximately 14 experts provided evaluations and each expert on average provided nearly 58 evaluations. This difference in number of experts would lead to more accurate evaluations and bias prevention because experts provide assessments about risk dimensions in which they have more experience and knowledge.

A trial pilot run had been carried out with five academics in our school (i.e., NBS) before the actual data collection in order to fine tune the questionnaire. Their feedback was used to resolve any potential issue in the survey such as the actual time for completing the survey, the way the questions are represented and so on. At the end of the survey, further questions were asked regarding professional qualifications and affiliations, years of experience, and comments to verify the previously twelve identified risk dimensions (in case there is any missing risk). Regarding the other potential risk dimensions, 6 experts indicated that *economic risks*, *public acceptability*, *lack of skilled workforce*, *reputational damages from poor management of Corporate Social Responsibility (CSR)*, *cyberterrorism/hacking*, *end users' wasteful practices* and *military risk* might be act as other potential risk dimensions as well. While other 25 experts believed that all major risks have been included in the study. In response, based on the proposed framework (Figure 5.3), defined *risk element* type of risks would make it possible for more detailed risks like the suggested ones to be categorised under each twelve risk dimensions' spectrums. For instance, the following categorisation can be expected for suggested risks by experts like *economic risks* under Market Failure (MF), *public acceptability* under Political Instability (PI) or Industrial Action (IA), *lack of skilled workforce* under Technical Reliability (TR), *reputational damages from poor management of CSR* under Environmental and Health Safety (EHS), *cyberterrorism/hacking* under Sabotage and Terrorism (ST), *end users' wasteful practices* under Affordability (AF), and *military risk* under Political Instability (PI).

5.4 Scenario Analysis by HESM for Experts' Weights Determination

The proposed ESM as explained in Section 4.2 combined with HFS theory (namely HESM) is applied by implementing the data provided by 31 experts. The average age of experts is 39 with the average experience of six years. Concerning education, 87% (27 out of 31) of all experts hold PhD degrees while the other 4 hold Masters' degrees. The gathered data show that regarding the professional association among practitioner experts, 4 out of 6 (67%) and among academic experts, 19 out of 25 (76%) hold professional association membership. As the experts were coming with miscellaneous backgrounds so their professional associations varied in a very broad range from social sciences to engineering and health sciences (Figure 5.3). Obviously, the experts are not at the same level of expertise and knowledge. As a result, the ESM has been applied so as to obtain the Expert Eligibility Values (EEV) (see Section 4.2) and correspondingly 31 experts' importance weights.

A scenario analysis applying HFS theory has been introduced and conducted in order to enhance the reliability of the expert selection scheme by obtaining a more cogent importance weight for each expert. In other words, instead of filtering out potential experts in the first place by the inclusion value of α determination, a more precise weight determination process through hesitant scenario analysis is introduced. With this aim in mind, three scenarios are proposed including *High-experience focused*, *Low-experience focused* and *Moderate*. Values are essentially defined based on circumstances of the study and in a way that they can produce distinctive weights representing *High*, *Moderate*, and *Low-experience focused* scenarios. These scenarios for academic and practitioner experts can be seen in Table 5.2 and Table 5.3, respectively.

For academic experts, experience is defined by working experience in academia such as university or college and not including experience in industry. In high-experience focused scenario, more attention is paid to years of experience in three levels of *Professorship*, *Senior lectureship* and *Lectureship* (Equation (4.7)) rather than *Professional Qualifications* (Equation (4.5)) or *Association Membership* (Equation (4.6)). As can be seen in Table 5.2, in high-experience focused, one year of experience as a professor (L_1) accounts for approximately 3 professional qualifications (Q_1), and 2 chartered professional association memberships (A_1). While in the moderate approach, one year of professorship (L_1) weighs as one chartered membership (A_1). On the other hand, in low-experience focused scenario, more concentration is on professional qualification and association membership attributes rather than academic experience. It means one year of experience as a professor (L_1) is as important as holding one professional qualification (Q_1) and less important as being a chartered member of a professional association in their subject (A_1).

Table 5.2 Academic experts' importance weight assignment scenarios

Scenario	Experience			Qualification		Association		
	L_1	L_2	L_3	Q_1	Q_2	A_1	A_2	A_3
High-experience focused	4	3	1	1.5	1	2	1.3	1
Moderate	2	1.5	1	1.5	1	2	1.3	1
Low-experience focused	1.5	1.3	1	1.5	1	2	1.3	1

As it can be seen in the Table 5.3, in calculation of the practitioner experts in the field, three scenarios are suggested like in academic case but with the difference that in practitioners' case, experience refers to practical experience while in academics' case, the academic experience like teaching and carrying out research in classic higher education levels is meant. It is shown in Table 5.3 that in moderate scenario, one year of experience in upper-level of management (L_1) (Equation (4.3)) counts equal to being a chartered member of the related field (A_1), and it also equals to having a related PhD degree (E_1) (Equation (4.4)). In high-experienced focused scenario, one year of work in an upper-level managerial position (L_1) accounts for twice as significant as holding a PhD degree (E_1) or a professional qualification (Q_1). Whereas on the other hand, in low-experience focused scenario working in upper-level managerial posts (L_1) are equally important as being a chartered member of a professional society (A_1) and slightly less significant than holding a PhD degree in the subject (E_1). For those scenarios the relative importance of industry experience is adjusted against education and professional qualifications.

Table 5.3 Practitioner experts' importance weight assignment scenarios

	Experience			Education				Qualification		Association		
Scenario	L_1	L_2	L_3	E_1	E_2	E_3	E_4	Q_1	Q_2	A_1	A_2	A_3
High-experience focused	4	3	1	2	1.5	1	0.8	2	1	3	2	1
Moderate	2	1.4	1	2	1.5	1	0.8	1.5	1	2	1.3	1
Low-experience focused	1.5	1.2	1	2	1.5	1	0.8	1.3	1	1.5	1.2	1

Based upon the proposed model, various scenarios of experience-oriented approaches for the two groups of academics and practitioners can be incorporated by applying HFS theory to assign importance weights to experts (here, each combination of scenarios is called a *case*). This approach is highly useful especially when judgement would not be straightforward and there is no preference in cases and there would be expected hesitancy in decisions between the degrees of experience. For example, three combinations (i.e. *high-high*, *moderate-moderate*, and *low-low*) out of nine possible scenario combinations are chosen for the analysis based on Table 5.2 and Table 5.3. The reason is that extreme and middle points are included, which make more sense to get the average in the absence of case preferences. The three cases and a fourth one, which is their weighted average by utilising HFS theory, are tested with reference to the weights presented in Table 5.4 (Govindan et al., 2015) and Table 5.5. By applying Best Non-fuzzy Performance (BNP), the crisp values in Table 5.4 can be obtained. Given (l, m, r) is a Triangular Fuzzy Number (TFN), the BNP can be calculated using $\frac{[(r-l)+(m-l)]}{3} + l$ (Bhosale and Kant, 2016).

Table 5.4 Linguistic variables and fuzzy weights for experts' weights scenarios

Linguistic Variables	TFN	Crisp Numbers
Very low	(0.0,0.1,0.3)	0.1
Low	(0.1,0.3,0.5)	0.3
Medium	(0.3,0.5,0.7)	0.5
High	(0.5,0.7,0.9)	0.7
Very high	(0.7,0.9,1.0)	0.9

In Table 5.5, the hesitant fuzzy information in each case in order to obtain the weighted average weights of all experts are revealed (see Equation (A.8) in order to calculate score function values). In cases 1, 2, and 3 for both academic and practitioner experts, high-experience, moderate, and low-experience scenarios (Table 5.2 and Table 5.3) have been applied in order to obtain the weighted average weights of experts.

Table 5.5 Hesitant fuzzy information for acquiring experts' weighted average weights

Case	Applied Scenarios	HFS	HFE	SFV	NSFV
1	High	{(0.5,0.7,0.9), (0.7,0.9,1.0)}	{0.7,0.9}	0.8333	0.5102
2	Moderate	{(0.1,0.3,0.5), (0.3,0.5,0.7)}	{0.3,0. 5}	0.4333	0.2653
3	Low	{(0.0,0.1,0.3), (0.1,0.3,0.5), (0.3,0.5,0.7)}	{0.1,0.3,0.5}	0.3667	0.2245

SFV=Score Function Value; NSFV=Normalised Score Function Value; HFS=Hesitant Fuzzy Set; HFE=Hesitant Fuzzy Element

Various experts' weights in case 1 (high), case 2 (moderate), case 3 (low) and weighted average weights of cases are represented in Table 5.6. The weighted average weights are calculated based on the normalised score function values shown in Table 5.5. Then, this weight is used in the analysis using NR-DEMATEL according to the sensitivity analysis of various cases of experts' weights which is provided in Section 5.6.

Table 5.6 Experts' weights in high, moderate, low, and weighted average cases

Experts	Case 1 (High)	Case 2 (Moderate)	Case 3 (Low)	Weighted average
1	0.0268	0.0395	0.0439	0.0340
2	0.0864	0.0636	0.0556	0.0734
3	0.0179	0.0263	0.0292	0.0227
4	0.0229	0.0338	0.0375	0.0291
5	0.0046	0.0068	0.0075	0.0058
6	0.2711	0.2041	0.1784	0.2325
7	0.0103	0.0152	0.0169	0.0131
8	0.0321	0.0473	0.0525	0.0407
9	0.0229	0.0338	0.0375	0.0291
10	0.0238	0.0351	0.0390	0.0302
11	0.0045	0.0066	0.0073	0.0057
12	0.0298	0.0241	0.0239	0.0270
13	0.0060	0.0088	0.0097	0.0076
14	0.0089	0.0132	0.0146	0.0113
15	0.0069	0.0101	0.0112	0.0087
16	0.0916	0.0692	0.0592	0.0784
17	0.0060	0.0088	0.0097	0.0076
18	0.0069	0.0101	0.0112	0.0087
19	0.0030	0.0044	0.0049	0.0038
20	0.0183	0.0176	0.0180	0.0180
21	0.0137	0.0203	0.0225	0.0174
22	0.0715	0.0527	0.0439	0.0603
23	0.0357	0.0527	0.0585	0.0453
24	0.0275	0.0197	0.0175	0.0232
25	0.0179	0.0263	0.0292	0.0227
26	0.0275	0.0263	0.0270	0.0271
27	0.0357	0.0527	0.0585	0.0453
28	0.0137	0.0203	0.0225	0.0174
29	0.0030	0.0044	0.0049	0.0038
30	0.0119	0.0176	0.0195	0.0151
31	0.0412	0.0290	0.0283	0.0351

5.5 NR-DEMATEL Analysis

The NR-DEMATEL method that has been elaborated in Section 4.3 is applied to evaluate the cause and effect interrelationships between identified energy risk dimensions. The analysed factors are the twelve risk dimensions Climate Change (CC); Natural Disasters (ND); Environmental Health and Safety (EHS); Technical Reliability (TR); Operational Safety (OS); Disease Outbreak (DO); Industrial Action (IA); Political Instability (PI); Sabotage and Terrorism (ST); Resource Availability (RA); Market Failure (MF); and Affordability (AF). The weighted average for experts' weights is considered in the calculation. The analysis of various experts' weights cases is presented in the Section 5.4. The total relation matrix obtained from the NR-DEMATEL analysis is shown in Table 5.7. Based on the total relation matrix, the Prominence, and Relation values along with total effect given by each risk dimension to others (r_i) and total effect received by each risk dimension from others (c_i) are calculated (regarding step 7 in Section 4.3), and are shown in Table 5.8.

Table 5.7 Total relation matrix

	CC	ND	EHS	TR	OS	DO	PI	IA	ST	RA	MF	AF
CC	0.1105	0.1856	0.2717	0.2722	0.2803	0.1859	0.2541	0.2243	0.1746	0.2744	0.2644	0.3129
ND	0.1362	0.0695	0.2517	0.2623	0.2849	0.1836	0.2245	0.2001	0.1446	0.2453	0.2311	0.2756
EHS	0.1183	0.0831	0.1514	0.2161	0.2438	0.1815	0.1952	0.2075	0.1488	0.2091	0.2065	0.2639
TR	0.1153	0.0793	0.2185	0.1584	0.2532	0.1320	0.2012	0.1998	0.1540	0.2201	0.2377	0.2862
OS	0.1005	0.0725	0.2468	0.2411	0.1724	0.1340	0.2018	0.2221	0.1617	0.2163	0.2241	0.2705
DO	0.1167	0.0986	0.2436	0.2071	0.2432	0.1027	0.2210	0.2258	0.1400	0.2032	0.2259	0.2611
PI	0.1537	0.1068	0.2234	0.2418	0.2622	0.1621	0.1814	0.2586	0.2192	0.2489	0.2693	0.3146
IA	0.1288	0.0825	0.2324	0.2768	0.2956	0.1721	0.2767	0.1764	0.1891	0.2726	0.2823	0.3224
ST	0.1165	0.0797	0.2527	0.2641	0.2847	0.1446	0.2661	0.2225	0.1257	0.2697	0.2816	0.3147
RA	0.1584	0.1074	0.2191	0.2262	0.2425	0.1316	0.2448	0.2070	0.1526	0.1711	0.2663	0.3038
MF	0.1623	0.0921	0.2112	0.2433	0.2562	0.1356	0.2333	0.2282	0.1499	0.2511	0.1787	0.3088
AF	0.1694	0.0982	0.2457	0.2583	0.2848	0.1507	0.2603	0.2404	0.1622	0.2707	0.2763	0.2258

Table 5.8 Prominence, relation, and total effect given/received by each risk to/from others

	Total effect given by each risk to other risks ($\boldsymbol{r_i}$)	Rank	Total effect received by each risk from other risks ($\boldsymbol{c_i}$)	Rank	Prominence ($\boldsymbol{r_i + c_i}$)	Rank	Relation ($\boldsymbol{r_i - c_i}$)	Rank	Causer/Receiver
CC	2.8109	1	1.5865	11	4.3973	10	1.2244	2	Net Causer
ND	2.5093	6	1.1553	12	3.6646	12	1.3540	1	Net Causer
EHS	2.2252	12	2.7682	6	4.9934	8	-0.5430	9	Net Receiver
TR	2.2557	11	2.8675	4	5.1232	7	-0.6119	10	Net Receiver
OS	2.2638	10	3.1037	2	5.3675	4	-0.8399	12	Net Receiver
DO	2.2890	9	1.8165	10	4.1054	11	0.4725	4	Net Causer
PI	2.6420	4	2.7604	7	5.4024	2	-0.1184	6	Net Receiver
IA	2.7076	2	2.6126	8	5.3201	5	0.0950	5	Net Causer
ST	2.6226	5	1.9226	9	4.5452	9	0.7001	3	Net Causer
RA	2.4307	8	2.8525	5	5.2833	6	-0.4218	7	Net Receiver
MF	2.4507	7	2.9441	3	5.3948	3	-0.4934	8	Net Receiver
AF	2.6426	3	3.4602	1	6.1029	1	-0.8176	11	Net Receiver

5.5.1 Impact-relations map

The Impact-Relations Map (IRM) (Figure 5.5), represents four quadrants. Quadrant *I* (core risks) is characterised by high Prominence, and positive Relation values. Risks in quadrant *II* (minor key risks) have positive Relation but low Prominence values. Both quadrant *I* and *II* include net causer risks (cause group) because of positive Relation values. Quadrant *III* (independent risks) has low Prominence, and negative Relation values while situated in the south-west part of the IRM and are disconnected from the system. Finally, risks in quadrant *IV* (impact or indirect risks) have high Prominence and negative Relation values and are mainly impacted by other risks. Risks in quadrants *III* and *IV* are net receivers (effect group) as their Relation values are negative. Thus, based on IRM and four quadrants, risk dimensions can be grouped into four categories of (1) core risks; (2) minor risks; (3) independent risks; and (4) impact/indirect risks.

The five risk dimensions of Natural Disasters (ND); Climate Change (CC); Sabotage and Terrorism (ST); Disease Outbreak (DO); and Industrial Action (IA) are positioned in quadrant *I* (core risks).

Based on the findings in Table 5.8 and depicted IRM in Figure 5.5, Natural Disasters (ND) has the highest relation value which means it has the highest influence on the system. It is followed by Climate Change (CC), Sabotage and Terrorism (ST), Disease Outbreak (DO), Industrial Action (IA), Political Instability (PI), Resource Availability (RA), Market Failure (MF), Environmental and Health Safety (EHS), Technical Reliability (TR), Affordability (AF), and the lowest factor in the relation category is Operational Safety (OS). In terms of Prominence, Affordability (AF) has the highest total effect which indicates its relative importance. Risk dimensions, Political Instability (PI), Market Failure (MF), Operational Safety (OS), Industrial Action (IA), Resource Availability (RA), Technical Reliability (TR), Environmental and Health Safety (EHS), Sabotage and Terrorism (ST), Climate Change (CC), Disease Outbreak (DO), and Natural Disasters (ND) stand in other ranks after Affordability (AF), respectively in the prominence list. Five risk dimensions of Natural Disasters (ND), Climate Change (CC), Sabotage and Terrorism (ST), Disease Outbreak (DO), and Industrial Action (IA) are positioned in quadrant I, which can be recognised as core factors. Additionally, they all belong to cause group which indicates these five risk dimensions are net causers because their $(r_i - c_i)$ values are positive.

The rest of the risk dimensions including the seven risk dimensions of Political Instability (PI); Resource Availability (RA); Environmental and Health Safety (EHS); Market Failure (MF); Technical Reliability (TR); Operational Safety (OS); and Affordability (AF) are positioned in quadrant IV (indirect risks). In addition, all the risk dimensions in the effect group, which are net receivers, are positioned in quadrant IV. There is no minor key and independent risk in this study because no risk dimension is positioned in quadrants II and III respectively.

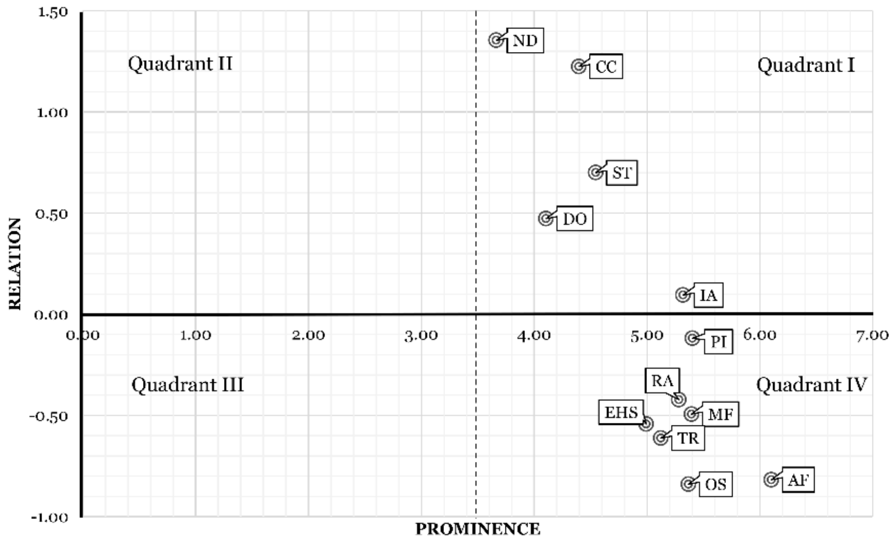


Figure 5.5 The IRM

5.5.2 Resulted rankings

As can be seen in Table 5.8, four rankings have been obtained: $(r_i, c_i, r_i + c_i, r_i - c_i)$ namely the Causers, Receivers, Prominence, and Relation lists, respectively. In DEMATEL, considering merely one ranking either Relation or Prominence would not be thoroughly compelling to reach a satisfactorily analysis. In fact, they both together with other analyses like causers, receivers and strong relationships should be considered for their complimentary features.

5.5.2.1 Net causers (cause group) and key factors

These risk dimensions are situated in quadrant *I* and include Natural Disasters (ND); Climate Change (CC); Sabotage and Terrorism (ST); Disease Outbreak (DO); and Industrial Action (IA). These risk dimensions are net causers that belong to the cause group (Figure 5.5 and Table 5.8). This means that in their occurrence, they can significantly influence or trigger other risks.

5.5.2.2 Net receivers (effect group)

These risk dimensions are situated in quadrant *IV* and include Operational Safety (OS); Affordability (AF); Technical Reliability (TR); Environmental and Health Safety (EHS); Market Failure (MF); Resource Availability (RA); and Political Instability (PI). Risk dimensions in this quadrant are more influenced rather than they influence other risks.

5.5.2.3 Prominence

In terms of Prominence, Affordability (AF) has the highest total effect (adding together given and received influences) which indicates its relative importance. It is followed by Political Instability (PI); Market Failure (MF); Operational Safety (OS); Industrial Action (IA); Resource Availability (RA); Technical Reliability (TR); Environmental and Health Safety (EHS); Sabotage and Terrorism (ST); Climate Change (CC); Disease Outbreak (DO); and Natural Disasters (ND).

5.5.2.4 Relation

Based on the findings in Table 5.8, and the IRM depicted in Figure 5.5, Natural Disasters (ND) has the highest Relation value, which means it has the highest influence on the system. It is followed by Climate Change (CC); Sabotage and Terrorism (ST); Disease Outbreak (DO); Industrial Action (IA); Political Instability (PI); Resource Availability (RA); Market Failure (MF); Environmental and Health Safety (EHS); Technical Reliability (TR); Affordability (AF); the lowest factor in the Relation category is Operational Safety (OS).

5.5.2.5 Causers

Among risks that can have higher influence on others without subtracting the received impacts: Climate Change (CC); Industrial Action (IA); Affordability (AF); Political Instability (PI); Sabotage and Terrorism (ST); Natural Disasters (ND); and Market Failure (MF) are the top seven risk dimensions, respectively (r_i list in Table 5.8). The results show that Climate Change (CC) is the most important risk dimension in terms of influencing other risks. However, when compared to Natural Disasters (ND), Climate Change (CC) receives more impact from other risks, which is the reason why Natural Disasters (ND) is the most significant net causer and not Climate Change (CC).

5.5.2.6 Receivers

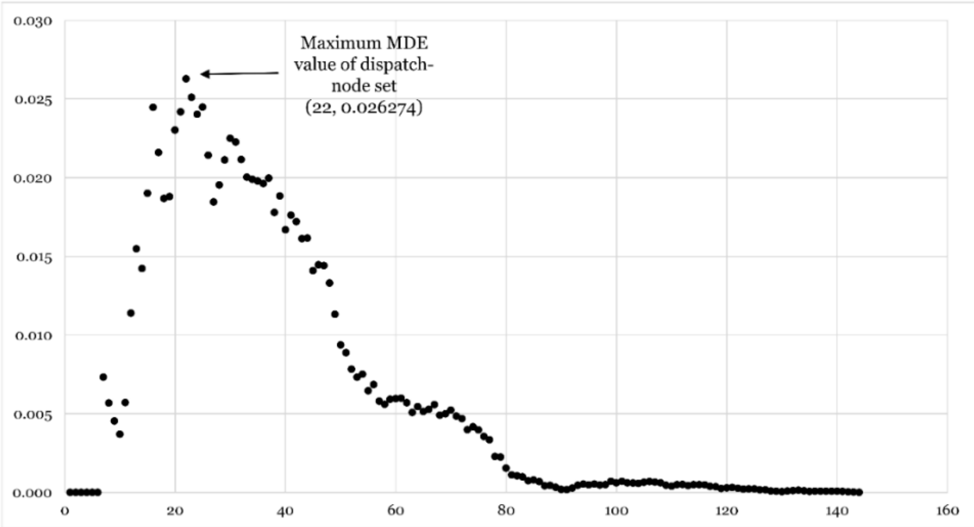
Among receivers or risks that can be highly influenced by others, Affordability (AF) and Operational Safety (OS) are found as the top ones followed by Market Failure (MF); Technical Reliability (TR); Resource Availability (RA); Environmental and Health Safety (EHS); and Political Instability (PI) (c_i list in Table 5.8).

5.5.3 Threshold value

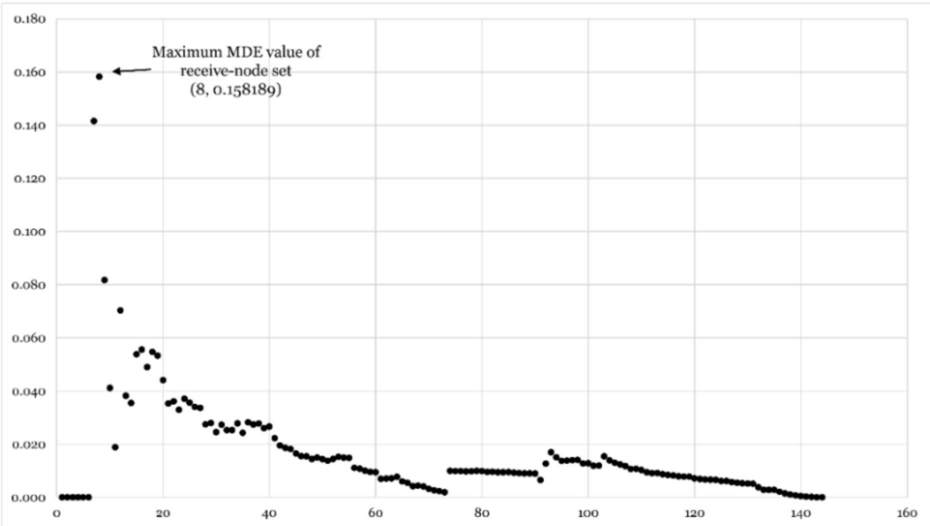
For setting the threshold value (Step 8 in Section 4.3), the MMDE algorithm has been applied. The results from steps 1 to 5 of the MMDE algorithm (Appendix D) are summarised in Table 5.9. All 144 MDE values of dispatch-node set ($MDE_t^{D_i}$) and receive-node set ($MDE_t^{R_e}$) are illustrated in Figure 5.6 and Figure 5.7, respectively.

Table 5.9 MMDE algorithm calculation results

Item	Data
$\boldsymbol{T^*}$	$\begin{Bmatrix}(0.3224,8,12),(0.3147,9,12),(0.3146,7,12),\\(0.3129,1,12),\dots,(0.0725,5,2),(0.0695,2,2)\end{Bmatrix}$
$\boldsymbol{T^{D_i}}$	$\{8,9,7,1,11,10,\dots,4,5,2\}$
$\boldsymbol{T_t^{D_i}}$ and $\boldsymbol{MDE_t^{D_i}}$	$T_1^{D_i}=\{8\}$, $MDE_1^{D_i}=0$; $T_2^{D_i}=\{8,9\}$, $MDE_2^{D_i}=0$; … ; $T_8^{D_i}=\{8,9,7,1,11,10,8,4\}$, $MDE_8^{D_i}=0.005679$; …; $T_{143}^{D_i}=\{8,9,\dots,4,5\}$, $MDE_{143}^{D_i}=0.000023$; $T_{144}^{D_i}=\{8,9,\dots,4,5,2\}$, $MDE_{144}^{D_i}=0$
$\boldsymbol{MDE_t^{D_i}}$	$\{0,0,0,0,0,0,0.007315,0.005679,0.004531,\dots,0.000023,0\}$
Max $\boldsymbol{MDE_t^{D_i}}$	0.026274
$\boldsymbol{T_{max}^{D_i}}$	$T_{22}^{D_i}=\{8,9,7,1,11,10,8,4,2,12,9,8,9,1,8,8,12,2,1,8,1,1\}=\{1,2,4,7,8,9,10,11,12\}$
$\boldsymbol{T^{R_e}}$	$\{12,12,12,12,12,12,5,12,5,5,5,11,11,5,\dots,2,2,2\}$
$\boldsymbol{T_t^{R_e}}$ and $\boldsymbol{MDE_t^{R_e}}$	$T_1^{R_e}=\{12\}$, $MDE_1^{R_e}=0$; … , $T_7^{R_e}=\{12,12,12,12,12,12,5\}$, $MDE_7^{R_e}=0.141515$; … , $T_{144}^{R_e}=\{12,12,12,12,12,12,5,\dots,2,2\}$, $MDE_{144}^{R_e}=0$
$\boldsymbol{MDE_t^{R_e}}$	$\{0,0,0,0,0,0,0.141515,0.158189,\dots,0.000023,0\}$
Max $\boldsymbol{MDE_t^{R_e}}$	0.158189
$\boldsymbol{T_{max}^{R_e}}$	$T_8^{R_e}=\{12,12,12,12,12,12,5,12\}=\{5,12\}$
$\boldsymbol{T^{Th}}$	$\begin{Bmatrix}(0.3224,8,12),(0.3147,9,12),(0.3146,7,12),\\(0.3129,1,12),(0.3088,11,12),\\(0.3038,10,12),(0.2956,8,5),(0.2862,4,12),\\(0.2849,2,5),(0.2848,12,5),(0.2847,9,5)\end{Bmatrix}$
Threshold value	0.2847



[Figure 5.6] The 144 MDE values of dispatch-node set ($MDE_t^{D_i}$)



[Figure 5.7] The 144 MDE values of receive-node set ($MDE_t^{R_e}$)

Regarding the obtained threshold value which is 0.2847 then risk dimensions with the influence level of equal or greater than 0.2847 in matrix T (Table 5.7) are chosen and the relationships between them are shown in Figure 5.8. As can be seen, eleven relationships among ten risk dimensions have the influence levels equal or greater than 0.2847. Environmental and Health Safety (EHS) and Disease Outbreak (DO) are the only risk dimensions that have no significant impact (either dispatching or receiving) on other risk dimensions because their influence levels are less than 0.2847. Compared to other threshold setting methods, by applying the average of all elements in the matrix T, the threshold will be 0.2073 leading us to identify 81 strong relationships, which is not helpful because it identifies numerous strong relationships. While using MMDE algorithm, the threshold value is 0.2847 providing us with 11 strong relationships.

5.5.4 Strong relationships and net relationships

Risk dimensions with influence level equal or greater than the threshold value (0.2847) from matrix T (Table 5.7), and the relationships between them are shown in Figure 5.8. Eleven relationships of ten risk dimensions have an influence level equal or greater than 0.2847. Environmental and Health Safety (EHS) and Disease Outbreak (DO) are the only risk dimensions that have no significant impact (either causing or receiving) on other risk dimensions because their influence level is below 0.2847.

The net influence matrix is represented (Table 5.10), and the corresponding values of eleven major relationships are illustrated (Figure 5.8). For instance, the influence level from Natural Disasters (ND) to Operational Safety (OS) is 0.2849 (Figure 5.8) while the net influence value from Natural Disasters (ND) to Operational Safety (OS) is -0.2124 (Table 5.10). The negative value of -0.2124 reveals that the level of influence from Operational Safety (OS) to Natural Disasters (ND) is lower than the level of influence from Natural Disasters (ND) to Operational Safety (OS) and the difference value is 0.2124. The total relation values and ranking of eleven major relationships among risk dimensions as depicted in Figure 5.8 along with their net influence values and corresponding ranking are presented (Table 5.11).

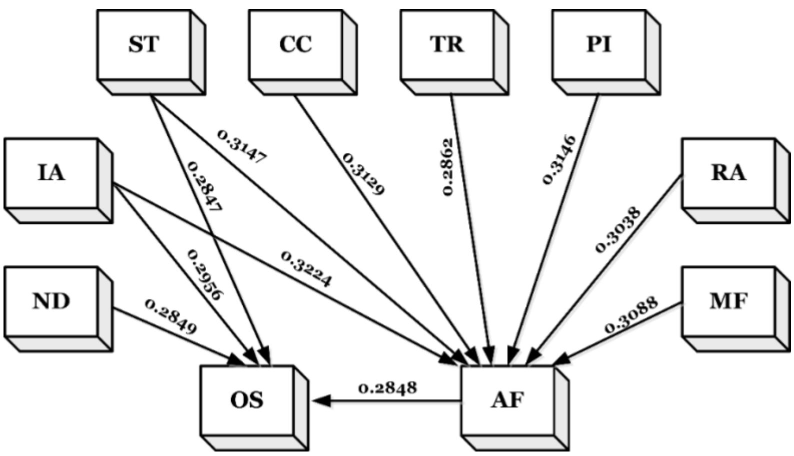


Figure 5.8 Total relations between risk dimensions based on the threshold value 0.2847

Table 5.10 Net influence matrix

	CC	**ND**	**EHS**	**TR**	**OS**	**DO**	**PI**	**IA**	**ST**	**RA**	**MF**	**AF**
CC												
ND	-0.0494											
EHS	-0.1534	-0.1686										
TR	-0.1569	-0.1830	0.0024									
OS	-0.1798	**-0.2124**	0.0030	-0.0121								
DO	-0.0692	-0.0850	0.0621	0.0751	0.1092							
PI	-0.1004	-0.1177	0.0282	0.0406	0.0604	-0.0589						
IA	-0.0955	-0.1176	0.0249	0.0770	**0.0735**	-0.0537	0.0181					
ST	-0.0581	-0.0649	0.1039	0.1101	**0.1230**	0.0046	0.0469	0.0334				
RA	-0.1160	-0.1379	0.0100	0.0061	0.0262	-0.0716	-0.0041	-0.0656	-0.1171			
MF	-0.1021	-0.1390	0.0047	0.0056	0.0321	-0.0903	-0.0360	-0.0541	-0.1317	-0.0152		
AF	**-0.1435**	-0.1774	-0.0182	**-0.0279**	**0.0143**	-0.1104	**-0.0543**	**-0.0820**	**-0.1525**	**-0.0331**	**-0.0325**	

In Table 5.11, total relation values and ranking of eleven major relationships among risk dimensions as depicted in Figure 5.8 along with their net influence values and corresponding ranking are presented.

Table 5.11 Total relation and net influence of eleven major relationships

From	To	Total Relation	Rank	Net Influence	Rank
IA	AF	0.3224	1	0.0820	5
ST	AF	0.3147	2	0.1525	2
PI	AF	0.3146	3	0.0543	7
CC	AF	0.3129	4	0.1435	3
MF	AF	0.3088	5	0.0325	9
RA	AF	0.3038	6	0.0331	8
IA	OS	0.2956	7	0.0735	6
TR	AF	0.2862	8	0.0279	10
ND	OS	0.2849	9	0.2124	1
AF	OS	0.2848	10	0.0143	11
ST	OS	0.2847	11	0.1230	4

The influence of Industrial Action (IA) on Affordability (AF) is the strongest relationship followed by ten other impacts (Table 5.11 and Figure 5.8). It shows that Industrial Action (IA); Natural Disasters (ND); Affordability (AF); and Sabotage and Terrorism (ST) can have strong influence on Operational Safety (OS). But only the influence of Natural Disasters (ND) on Operational Safety (OS) has the strongest net relationship (Table 5.11 and Figure 5.8) which could be expected due to the characteristic of the Operational Safety (OS) risk that is much more affected by Natural Disasters (ND) rather than having influence on it. Also, Industrial Action (IA); Sabotage and Terrorism (ST); Political Instability (PI); Climate Change (CC); Market Failure (MF); Resource Availability (RA); and Technical Reliability (TR) strongly affect Affordability (AF). Between Affordability (AF) and Operational Safety (OS), the strongest influence is received by Affordability (AF) (from Industrial Action (IA)) while Affordability (AF) itself subsequently has strong influence on Operational Safety (OS). The evaluation of strong relationships revealed that Environmental and Health Safety (EHS), and Disease Outbreak (DO) do not have any strong relationships with other risk dimensions. It also revealed that Affordability (AF) and Operational

Safety (OS) are the only two major strong individual influence receivers (Table 5.11 and Figure 5.8).

5.6 Sensitivity Analysis

The cases of high, moderate, low, and weighted average are explained in Section 5.4 (Table 5.6). Note that equal weights of experts are taken into consideration for the sensitivity analysis. The Prominence, and Relation values in NR-DEMATEL for all twelve risk dimensions under five sensitivity analysis cases have been calculated and presented in Table 5.12.

Table 5.12 Sensitivity analysis results under Equal, Moderate, High, Low, and Weighted Average weights

	Equal		Moderate		High		Low		Weighted Average	
	Prominence	Relation	Prominence	Relation	Prominence	Relation	Prominence	Relation	Prominence	Relation
AF	5.4749	-1.1400	5.8053	-0.8492	6.5720	-0.7587	5.5802	-0.8776	6.1029	-0.8176
MF	5.3871	-0.6225	5.1916	-0.5180	5.7102	-0.4491	5.0471	-0.5474	5.3948	-0.4934
PI	5.2044	-0.1824	5.1184	-0.1663	5.8297	-0.0654	4.8963	-0.2027	5.4024	-0.1184
OS	5.1112	-0.7924	5.0963	-0.8195	5.7903	-0.8749	4.8910	-0.8057	5.3675	-0.8399
IA	4.9834	-0.3369	5.0251	-0.0192	5.7628	0.2654	4.8176	-0.0993	5.3201	0.0950
TR	4.9635	-0.4959	4.8755	-0.5741	5.5099	-0.6635	4.6937	-0.5493	5.1232	-0.6119
RA	4.8252	-0.3113	4.9926	-0.3796	5.7384	-0.4780	4.7769	-0.3514	5.2833	-0.4218
EHS	4.4579	-0.4227	4.6650	-0.4906	5.5047	-0.6171	4.4186	-0.4518	4.9934	-0.5430
CC	4.2405	1.4377	4.2126	1.2668	4.6786	1.1619	4.0847	1.2996	4.3973	1.2244
ST	4.1989	0.9014	4.3085	0.7432	4.9105	0.6349	4.1314	0.7755	4.5452	0.7001
ND	3.7024	1.5008	3.5188	1.3501	3.8921	1.3604	3.4142	1.3552	3.6646	1.3540
DO	3.4615	0.4642	3.7915	0.4565	4.5799	0.4842	3.5637	0.4549	4.1054	0.4725

In Figure 5.9, Prominence values of all risk dimensions in five cases are illustrated. The demonstrated trend is almost the same for all risk dimensions over various experts' weights. As can be seen, the Weighted Average and Moderate lines are both positioned between the two extents of the High and Low charts with the difference that the Weighted Average chart is closer to the High chart, which is predictable based on the higher hesitant weights assigned to case 1 (Table 5.5). From a practical standpoint, it means that opinions of more experienced experts can be given higher value by choosing the Weighted Average generating close Prominence values to the High case. Moreover, the Equal line and either Low or Moderate lines overlapped in some risks producing exactly the same weights.

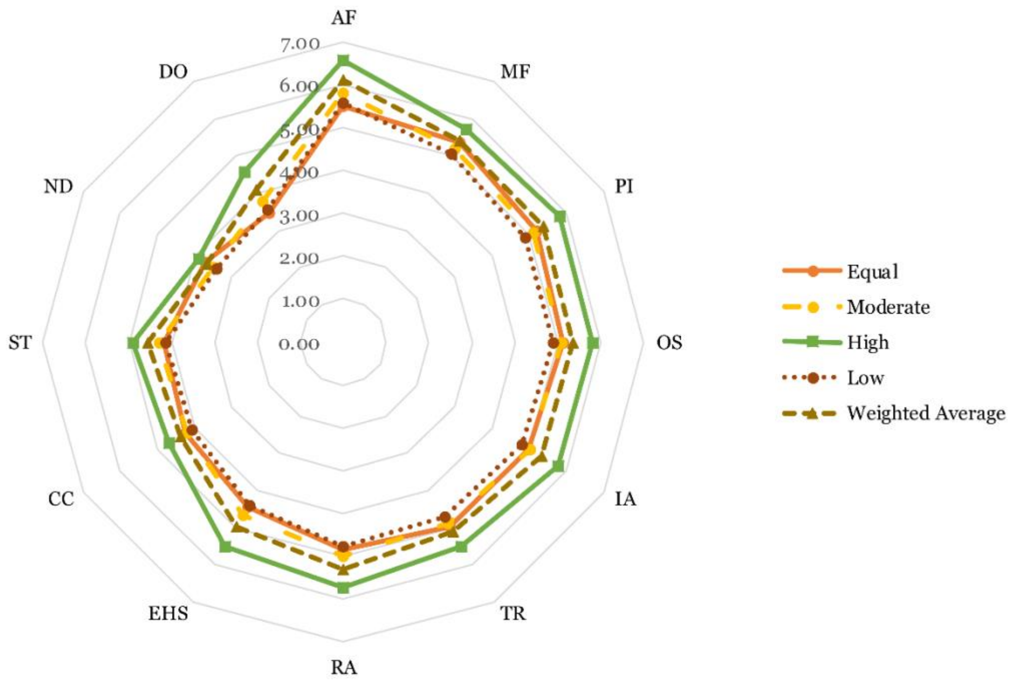


Figure 5.9 Prominence values of risks in various cases of experts' weights

In Figure 5.10, Relation values for different risk dimensions were depicted and as can be seen the lines overlapped almost perfectly except for the Equal chart that is significantly different in few risks such as Natural Disasters (ND), Sabotage and Terrorism (ST), Climate Change (CC), Affordability (AF), and Industrial Action (IA). It means that in the Equal case, the Relation values of risks can vary more compared to other cases.

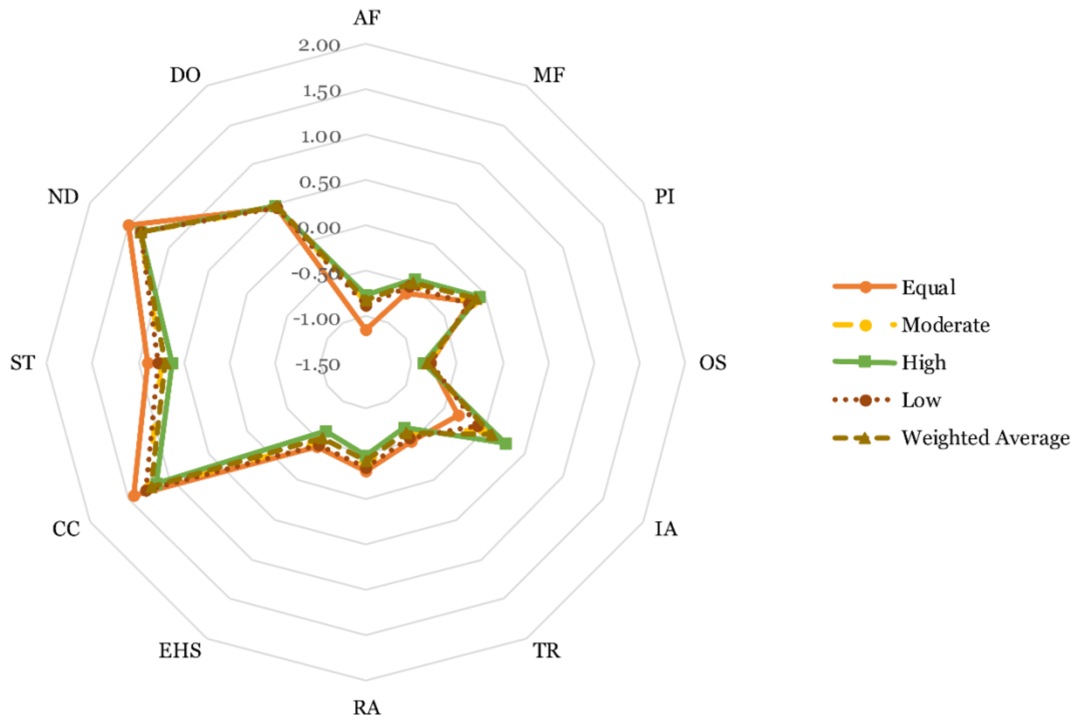


Figure 5.10 Relation values of risks in various cases of experts' weights

To better realise the changes of weights, the rankings of the Prominence and Relation values are provided in Table 5.13. And in Table 5.14, and Table 5.15 descriptive statistics for Relation and Prominence weights ranking are presented, respectively. Furthermore, the Kendall's coefficient of concordance is calculated to statistically test the level of agreement between rankings in five cases for the Prominence and Relation values (Table 5.16).

Table 5.13 Rankings obtained from sensitivity analysis under Equal, Moderate, High, Low, and Weighted Average weights

	Equal		Moderate		High		Low		Weighted Average	
	Prominence	Relation	Prominence	Relation	Prominence	Relation	Prominence	Relation	Prominence	Relation
AF	1	12	1	12	1	11	1	12	1	11
MF	2	10	2	9	6	7	2	9	3	8
PI	3	5	3	6	2	6	3	6	2	6
OS	4	11	4	11	3	12	4	11	4	12
IA	5	7	5	5	4	5	5	5	5	5
TR	6	9	7	10	7	10	7	10	7	10
RA	7	6	6	7	5	8	6	7	6	7
EHS	8	8	8	8	8	9	8	8	8	9
CC	9	2	10	2	10	2	10	2	10	2
ST	10	3	9	3	9	3	9	3	9	3
ND	11	1	12	1	12	1	12	1	12	1
DO	12	4	11	4	11	4	11	4	11	4

Table 5.14 Descriptive statistics of Relation rankings under five cases (Equal, Moderate, High, Low, and Weighted Average)

	N	Mean	Std. Deviation	Minimum	Maximum
AF	5	11.60	0.548	11	12
MF	5	8.60	1.140	7	10
PI	5	5.80	0.447	5	6
OS	5	11.40	0.548	11	12
IA	5	5.40	0.894	5	7
TR	5	9.80	0.447	9	10
RA	5	7.00	0.707	6	8
EHS	5	8.40	0.548	8	9
CC	5	2.00	0.000	2	2
ST	5	3.00	0.000	3	3
ND	5	1.00	0.000	1	1
DO	5	4.00	0.000	4	4

Table 5.15 Descriptive statistics of Prominence rankings under five cases (Equal, Moderate, High, Low, and Weighted Average)

	N	Mean	Std. Deviation	Minimum	Maximum
AF	5	1.00	0.000	1	1
MF	5	3.00	1.732	2	6
PI	5	2.60	0.548	2	3
OS	5	3.80	0.447	3	4
IA	5	4.80	0.447	4	5
TR	5	6.80	0.447	6	7
RA	5	6.00	0.707	5	7
EHS	5	8.00	0.000	8	8
CC	5	9.80	0.447	9	10
ST	5	9.20	0.447	9	10
ND	5	11.80	0.447	11	12
DO	5	11.20	0.447	11	12

Table 5.16 Kendall's W Test

	N	Kendall's W[a]	Chi-Square	df	P-value
Relation	5	0.978	53.800	11	0.000***
Prominence	5	0.971	53.400	11	0.000***

[a]Kendall's coefficient of concordance
***indicates statistical significance at 1% level

As high values of Kendall's $W = 0.978$, and $W = 0.971$ are obtained for Relation, and Prominence, respectively (Table 5.16), it can be realised that the obtained rankings for the Relation and Prominence values of twelve risk dimensions under five cases agree with each other at a statistically significant level ($P < 0.001$***) and there is no statistically significant difference between them. In other words, even if detailed differences occur, Relation, and Prominence rankings, which are central to this research, are not statistically sensitive to the changes in level of experience of experts under the predefined parameter settings described in the proposed HESM. However, the Weighted Average weights are used in this study, because the Weighted Average resembles a more rational weight assignment method since it aggregates all three other weights including Low, High, and Moderate.

The IRM diagrams for four cases including Equal, Moderate, Low, and High are depicted in Figure 5.11. The IRMs provided show that Natural Disasters (ND), Climate Change (CC), Sabotage and Terrorism (ST), and Disease Outbreak (DO) are consistently positioned in quadrant I under Equal (a), Moderate (b), Low (c), and High (d) cases while in case Moderate (b) the Natural Disasters (ND) is pushed to the border of two quadrants I and II. Furthermore, only in case High (d), Industrial Action (IA) is also moved to quadrant I.

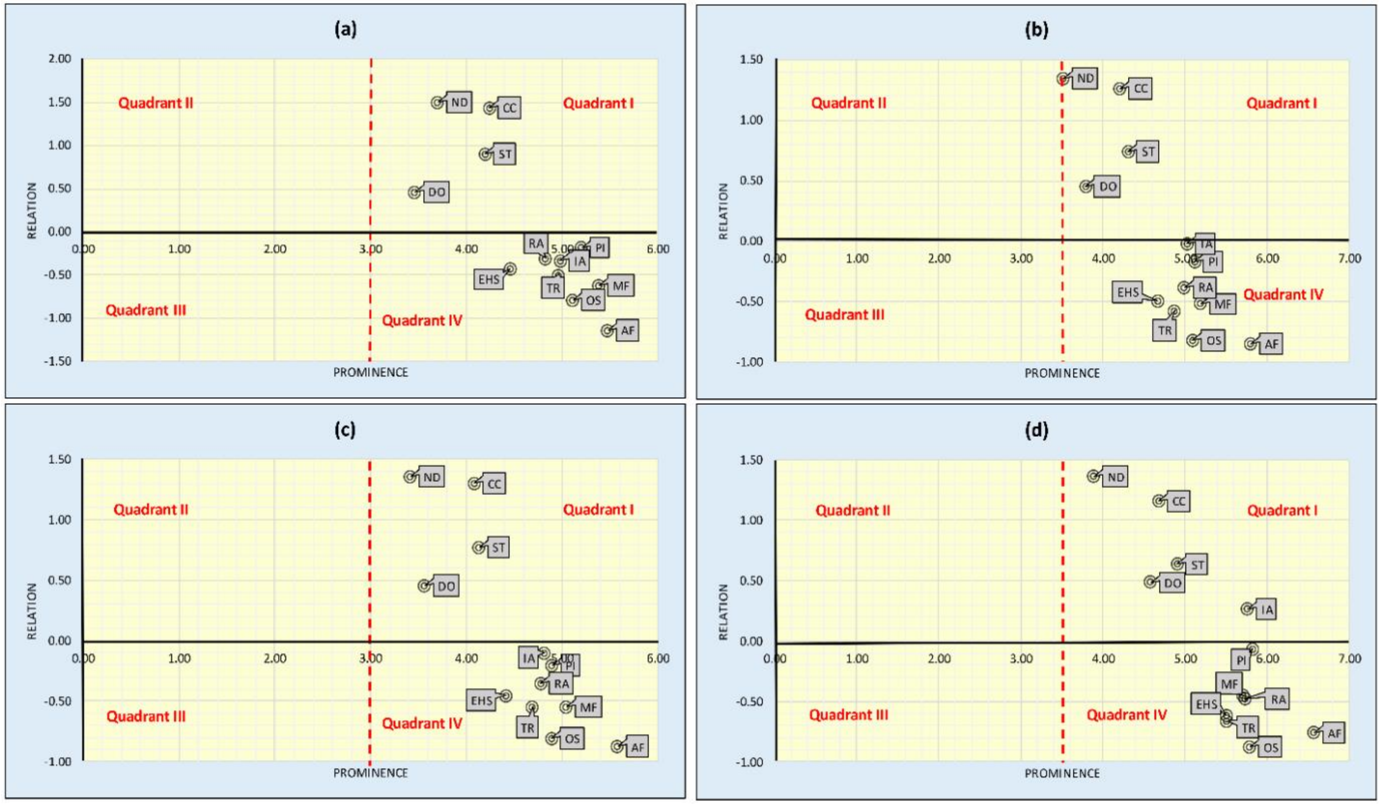


Figure 5.11 The IRMs in four cases of experts' weights Equal (a), Moderate (b), Low (c), and High (d)

5.7 Discussion

The identification of the key risks in an energy supply chain is fundamental to reducing the likelihood of disruption. Risks rarely occur independently, that is, the incidence of one risk can cause another to occur (domino effect or chain reaction). For the first time, this study highlighted these interdependencies, and provided significant insight into the relationship between the energy risks by identifying those risks that should be prioritised in order to minimise the occurrence of others. This approach has the potential to put forward risk mitigation strategies that focus on the highly interdependent risks. Therefore, policy makers must develop mitigation strategies that make best use of resources in a targeted approach since certain risks occur concurrently and are often amplified by other risks. For example, Industrial Action (IA) can strongly lead to Affordability (AF) risk. Equally, Natural Disasters (ND) can lead to risks relevant to Operational Safety (OS); therefore, vulnerability to natural disasters should be primarily tested against its potential to lead to operational safety damages (Figure 5.8). This approach can signify a departure from past practice that did not consider risks' interdependencies. However, as climate change reshapes both the natural environment and the regulatory framework that power supply chains operated in, it is imperative that risk assessment also changes to accommodate our best understanding of risk interdependencies.

Critical risk dimensions recognition and how the analysis results are being construed are on the basis of the chosen risk analysis perspective that can be either *proactive* or *reactive*. In case of proactive attitude towards risk analysis the focal point is on risks with higher damage potential to the system via the capability of propagating from one risk to another in the longer run. Therefore, a proactive approach considers a prospective situation of the system by taking into consideration net causers (i.e Relation). The reactive perspective focuses on the ongoing status of the system rather than the resulting risks. It seeks dealing with the current occurred critical risks rather than future ones (i.e. Prominence). In reactive perspective, it is tried to identify important risks to suggest strategies more in order to resolve the current systems' malfunctions rather than to prevent from future risks that might happen as a result of current risks. Based on the findings, Natural Disasters (ND) lies at the first rank of Relation list which means it has the highest total effect given to others (propagation capability), whereas on the other hand it stands at the bottom of Prominence list due to its low receiving effect (c_i value). It means, when Natural Disasters (ND) occur (the occurrence probability is not discussed in this study) can result in triggering many other risks in the system. It can influence other risks as it has the highest Relation value, while itself can hardly be influenced by them due to low c_i value. It indicates Natural Disasters (ND) has the capacity to bring about many other risks in future (it can be short-term, medium-term, or long-term), so if the risk analysis perspective is proactive, Natural Disasters (ND) must be absolutely more desirable and the mitigation strategy recommendations must be more preventive or proactive rather than reactive. Whereas on the other hand, in the reactive case, the opposite is true and the proposed mitigation strategies are more after temporary treatments. Overall, considering merely one factor either Relation or Prominence would not be thoroughly cogent and to reach a satisfactory risk analysis they both along with other analyses like causers, receivers, and strongest relationships should be considered. Note that net receivers are different from receivers, likewise for net causers and causers. Net causers and net receivers are those risk dimensions with positive and negative values in the relation list. Net causers belong to cause group and net receivers belong to effect group. On the other hand, causers and receivers are top risk dimensions in the (r_i) and (c_i) list (see Table 5.8).

The findings revealed that Natural Disasters (ND), Climate Change (CC), Sabotage and Terrorism (ST), Disease Outbreak (DO) and Industrial Action (IA) are core risk dimensions and among them Industrial Action (IA) has the highest Prominence value. Out of five high-ranked Prominence risk dimensions, Industrial Action (IA) is the only one that appears in the list of the top five Relation risk dimensions which are Affordability (AF), Political Instability (PI), Market Failure (MF), Operational Safety (OS), and Industrial Action (IA) (Table 5.8). The findings are summarised as follows:

1. Net causers (cause group) and key factors:

The Natural Disasters (ND), Climate Change (CC), Sabotage and Terrorism (ST), Disease Outbreak (DO), and Industrial Action (IA) are core risk dimensions (the first five factors in Relation list and positioned in quadrant I) and all are net causers that belong to cause group (see Figure 5.5, and Table 5.8). It means apart from their occurrence likelihoods, in case of occurring, they can significantly influence other risks.

2. Net receivers (effect group):

Operational Safety (OS), Affordability (AF), Technical Reliability (TR), Environmental and Health Safety (EHS), Market Failure (MF), Resource Availability (RA), and Political Instability (PI) are all risk dimensions in effect group or net receivers, respectively. It means these risk dimensions are more influenced by other risks rather that have impact on others.

3. Prominence:

Affordability (AF), Political Instability (PI), Market Failure (MF), Operational Safety (OS), Industrial Action (IA), Resource Availability (RA), Technical Reliability (TR), Environmental and Health Safety (EHS), Sabotage and Terrorism (ST), Climate Change (CC), Disease Outbreak (DO), and Natural Disasters (ND) are ranked in the prominence list, respectively. It represents the relative importance of each risk dimension by adding together their given and received influences.

4. Causers:

Among causers or risks that can have higher influence on others without subtracting the received impacts; Climate Change (CC), Industrial Action (IA), Affordability (AF), Political Instability (PI), Sabotage and Terrorism (ST), Natural Disasters (ND), and Market Failure (MF) are top seven risk dimensions, respectively (see r_i list in Table 5.8). It shows Climate Change (CC) is the most important factor influencing other risks but compared to Natural Disasters (ND) it receives more impact from other risks that is why Natural Disasters (ND) is the most significant net causer not Climate Change (CC).

5. Receivers:

Among receivers or risks that can be highly influenced by others, Affordability (AF) and Operational Safety (OS) were found as top ones followed by Market Failure (MF), Technical Reliability (TR), Resource Availability (RA), Environmental and Health Safety (EHS), and Political Instability (PI) (see c_i list in Table 5.8).

6. Strongest relationships:

The influence of Industrial Action (IA) on Affordability (AF) is the strongest relationship followed by ten other impacts Sabotage and Terrorism (ST) on Affordability (AF), Political Instability (PI) on Affordability (AF), Climate Change (CC) on Affordability (AF), Market Failure (MF) on Affordability (AF), Resource Availability (RA) on Affordability (AF), Industrial Action (IA) on Operational Safety (OS), Technical Reliability (TR) on Affordability (AF), Natural Disasters (ND) on Operational Safety (OS), Affordability (AF) on Operational Safety (OS) and Sabotage and Terrorism (ST) on Operational Safety (OS), respectively (see Table 5.11 and Figure 5.8). It shows that Industrial Action (IA), Natural Disasters (ND), Affordability (AF), and Sabotage and Terrorism (ST) can have strong influence on Operational Safety (OS). Also, Industrial Action (IA), Sabotage and Terrorism (ST), Political Instability (PI), Climate Change (CC), Market Failure (MF), Resource Availability (RA), and Technical Reliability (TR) strongly impact on Affordability (AF). Between Affordability (AF) and Operational Safety (OS), the strongest influence is received by Affordability (AF) as indicated from Industrial Action (IA) while Affordability (AF) itself subsequently has strong influence on Operational Safety (OS).

7. Strongest net relationships:

The influence of Natural Disasters (ND) on Operational Safety (OS) is the strongest net relationship followed by ten other strong net impacts of Sabotage and Terrorism (ST) on Affordability (AF), Climate Change (CC) on Affordability (AF), Sabotage and Terrorism (ST) on Operational Safety (OS), Industrial Action (IA) on Affordability (AF), Industrial Action (IA) on Operational Safety (OS), Political Instability (PI) on Affordability (AF), Resource Availability (RA) on Affordability (AF), Market Failure (MF) on Affordability (AF), Technical Reliability (TR) on Affordability (AF) and Affordability (AF) on Operational Safety (OS) respectively (see Table 5.11, and Figure 5.8).

8. The evaluation on strong relationships revealed that Environmental and Health Safety (EHS) and Disease Outbreak (DO) do not have any strong relationships with other risk dimensions. It also revealed that Affordability (AF) and Operational Safety (OS) are the only two major strong individual influence receivers (see Table 5.11, and Figure 5.8).

9. Considering all the analysis, the final suggestion would be to focus on the six risk dimensions of Natural Disasters (ND), Climate Change (CC), Industrial Action (IA), Affordability (AF), Political Instability (PI), and Sabotage and Terrorism (ST). It is surmised that offering mitigation strategies based on them can be quite beneficial for the UK power supply chain sustainability.

In the related literature, the importance of identified risks is confirmed. For instance, Mideksa and Kallbekken (2010) reviewed studies on the effect of climate change on electricity markets, although it was stated that there has been a surprisingly scant number of research on the effects of climate change on the energy sector mainly because of the wide-ranging consequences that are rarely brought together in any single study. The Venezuelan strike in 2002/3, also known as an oil strike or oil lockout resulted in a gross peak supply loss of 2.6 mb/d (million barrels per day) and is regarded as one of the five most important disruptions of the past decades indicating the immense significance of industrial action (Löschel et al., 2010). Tranchita et al. (2009) presented a methodology to evaluate the power system security with respect to the likelihood of terrorist acts, regarding the uncertainties related to load and generation. Chevalier (2006) explained the social dimension of SOS as the fact that SOS has a cost and in case of a price shock certain types of consumers who are exposed to volatile prices may not be able to afford a supply of energy.

Lin et al. (2018) identified security defence ability as one of the three main identified risk elements in NEPS in China out of 18 initially identified risks. The security defence ability can be associated with the risk dimension Sabotage and Terrorism (ST) which was among the final risk list in this Chapter. Hammond and Waldron (2008) recognised severe weather conditions as the fourth significant risk out of fifteen recognised ones. They assessed risks based on the multiplication of likelihood and consequence of the hazard occurring while in this chapter, the causal relationships between risks via proactive perspective were evaluated. In their study, reliance on primary fuels for electricity generation, lack of investment in new infrastructure and decommissioning of nuclear-reducing capacity identified as the first three important risks. *Terrorism* was identified as the 12th important risk in Hammond and Waldron (2008) out of 15 identified ones while in here Sabotage and Terrorism (ST) was identified as the 3rd factor in relation list and 9th in prominence ranking, out of the twelve identified risk dimensions. Sabotage and Terrorism (ST) was also among the final six identified significant risk dimensions in the UK. The same study highlighted the importance of severe weather conditions risk, which is also emphasised in findings in this chapter with the importance of Natural Disasters (ND), and Climate Change (CC). Chen and Yano (2010) indicated that weather could affect the seasonal product demand as the US National Research Council has estimated that around 46% of US gross domestic product is influenced by weather. Jira and Toffel (2013) indicated that suppliers' vulnerability to climate change is of high importance and that a growing number of supplier companies are being asked to share information about it from buyers leading many managers to better understand supply chain management in connection with climate change (Y. Wang et al., 2010). Climate change has resulted in the variability of weather conditions and subsequently affecting sales of many products. Thus, in order to reduce sales volatility Brusset and Bertrand (2018) introduced an approach to transfer weather risks to risk takers utilising weather index-based financial instruments. Berger et al. (2017) utilised recent tools in decision theory in order to quantify the influence of deep uncertainty on the optimal level of emission abatement.

Considering the causal interrelationships between risks with proactive perspective, Natural Disasters (ND), and Climate Change (CC) were also located at the top of the significant risks in relation list which are comparable to the *severe weather conditions* risk. Natural Disasters (ND) can be related to human-made Climate Change (CC), however, not all of Natural Disasters (ND) are caused by Climate Change (CC) while Climate Change (CC) can increase the likelihood of weather-related Natural Disasters (ND). However, in some cases Natural Disasters (ND) may be caused by other Natural Disasters (ND). Liu et al (2009) showed that, in eastern Taiwan, slow earthquakes can be triggered by typhoons. As another example,in 2005, hurricane Katrina caused landslides in Louisiana on the US Gulf Coast and caused a disruption for nearly one-quarter of total US oil production at the time. Moreover, extraction of shale gas by hydraulic fracturing or fracking was observed to cause low-intensity earthquakes (measuring 2.3 and 1.5 on the Richter scale) in April 2011 in North West England which resulted in shale gas extraction suspension nationally from May 2011 to December 2012 (Stamford and Azapagic, 2014). Dealing with Climate Change (CC) means regarding the root and cause of many Natural Disasters (ND) such as droughts which can be the result of Climate Change (CC) (Gallina et al., 2016; Van Aalst, 2006).

In support of the findings regarding no critical relation between Disease Outbreak (DO) and Natural Disasters (ND) or vice versa (Table 5.11), Watson et al. (2007) indicated that risk factors for outbreaks after Natural Disasters (ND) are linked primarily to population displacement rather than a fear likely from dead bodies and epidemics. The identified strong interaction between Natural Disasters (ND) and Operational Safety (OS) can be explained with the Fukushima event when a tsunami damaged one nuclear power plant and subsequent policies shut down almost all of them causing phasing out many nuclear plants in Japan and Germany (Boston, 2013). The association between Resource Availability (RA) and Political Instability (PI) seems to be critical in oil producing countries (Correljé and van der Linde, 2006), but the findings have not revealed such a strong relationship in the UK. The link between Market Failure (MF) and Affordability (AF) is documented in the study, which is predictable since Affordability (AF) deals with the price of the energy, which is determined, based on the economic functions in the UK liberalised energy market.

Finally, although this study focused on the UK power supply chain, but the results are relevant, and the findings can be applicable to the power sectors of other countries.

5.8 Conclusions

The power industry is uniquely vulnerable to natural and human-made risks such as natural disasters, climate change, and cybersecurity. In this chapter, a comprehensive framework for risk identification and classification focusing on the UK energy supply chain was proposed. It was based on scrutinising energy supply chain risks in the energy security literature via consolidating information from various fields such as engineering, social sciences, and natural sciences. The NR-DEMATEL was tailored in this study to analyse interrelationships between risks as well as dealing effectively with subjective judgements of experts. Furthermore, a novel proposed HESM along with scenario analysis provided a basis for the expert selection and weight assignment process. This is the first comprehensive risk causal relationships analysis of the UK energy supply chain. The findings revealed that Natural Disasters (ND) and Climate

Change (CC) are the most crucial risks followed by Industrial Action (IA), Affordability (AF), Political Instability (PI), and Sabotage/Terrorism (ST).

Three main disciplines are more related to the identified risks including: environmental science (Natural Disasters (ND), and Climate Change (CC)), sociology and politics (Industrial Action (IA); Political Instability (PI); Sabotage and Terrorism (ST)) and economics (Affordability (AF)).

The findings revealed that Natural Disasters (ND); Climate Change (CC); Sabotage and Terrorism (ST); Disease Outbreak (DO); and Industrial Action (IA) were core risk dimensions as all were situated in quadrant *I* and among them, Industrial Action (IA) had the highest Prominence value indicating its high relative importance. Out of five high-ranked Prominence risk dimensions (Affordability (AF); Political Instability (PI); Market Failure (MF); Operational Safety (OS); and Industrial Action (IA)), Industrial Action (IA) was the only one that appeared in the list of the top five Relation risk dimensions as well (Table 5.8). The final six critical risk dimensions in the study were Natural Disasters (ND); Climate Change (CC); Industrial Action (IA); Affordability (AF); Political Instability (PI); and Sabotage and Terrorism (ST) (Figure 5.12). Affordability (AF) has been added to the final list because Affordability (AF) ranked first in the Prominence list and was among 8 (out of 11) of the strongest relationships (Figure 5.8). Political Instability (PI) has also been recognised as one of the final risk dimensions as it ranked second in the Prominence ranking and sixth in the Relation list (Table 5.8) while also being the third strongest relationship (Table 5.11). Disease outbreak (DO) has not been included in the final list, as it has not been recognised among the strong relationships (Table 5.11).

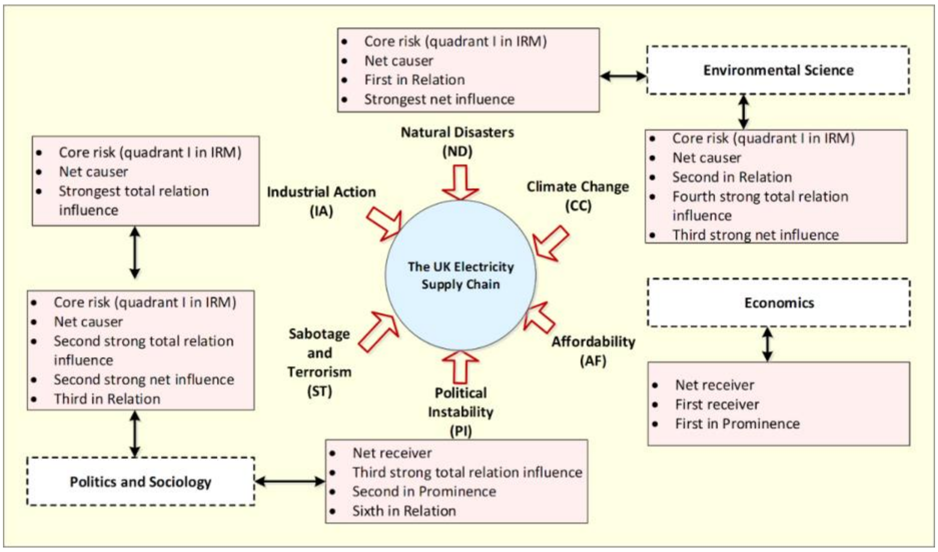


Figure 5.12 Final six critical risk dimensions to the UK electricity supply chain and their characteristics

The six most critical risks are particularly important for the UK's approach in reducing risk exposure. Specifically, Natural Disasters (ND) and Climate Change (CC), two very interlinked risks are core to the UK's power supply as legacy nuclear power stations are all located in coastal areas, threatened by storm-induced erosion and sea level rise. Furthermore, the UK's ambitious offshore wind program is at risk because of potential changes in sea winds that could affect power output. Moreover, like every country with an increasingly complex energy supply portfolio, the UK has to take into account the risk of Sabotage and Terrorism (ST), especially in the form of cyber-attacks. At the same time Political Instability (PI), and Affordability (AF) are largely related to the UK's power supply as they concern the issue of imported resources, largely natural gas in the UK, as the indigenous production is being reduced. Finally, despite the UK power supply chain being largely privatised, the risk of Industrial Action (IA) remains high mainly due to the still strong reliance on a small number of market players and strong unionisation of the sector.

5.8.1 Limitations and future research directions

This study suffers from few limitations which can be overcome in future research. These limitations and suggestions for future studies are explained as follows:

(1) First, the identified risk dimensions are generic macro-level risks in the UK energy supply chain and not dealing with micro-level risk elements. In other words, risks can be studied in more details in a specific part of the supply chain such as supply

or demand or even can be studied in a specific power generation sector such as offshore wind industry, just as an example. This would open up an avenue for future studies based on the result of the current study where the risk dimensions with generic nature were proposed. A more detailed analysis at the lower level called risk elements based on the proposed framework can be realised as beneficial. For instance, under ND (risk dimension), what natural calamities (risk elements) should be explored in a specific power supply chain region or sector such as offshore wind energy, and a similar exploration for other risk dimensions.

(2) Second, due to nature of MCDM methods the primary data has to be collected from experts in the field which can be strengthened in order to lead to a more reliable outcome by expanding the number of experts who are participating in the data collection process. The validation in primary data collection for quantitative methods can be considered as another source of concern which should be dealt with methods such as face validation or validation through expert elicitation.

(3) Third, the DEMATEL method has a quantitative approach to investigate the causal relationships between risks which might make it hard to elicit knowledge quantitatively from experts by using a Likert scale in some decision-making problems. That is why in this study, the revised DEMATEL was integrated with NST to facilitate this knowledge elicitation process from experts. However, results from the DEMATEL can be compared with qualitative approaches such as Know-Why method or even with other dynamic quantitative methods such as System Dynamics (SD) to verify the outcome.

(4) Fourth, the occurrence probability estimation of each micro-level risk elements with a reliable method and using the probability scores along with experts' opinions to prioritise risk elements can be regarded as another future research direction.

(5) Finally, proposing risk mitigation strategies that links to the outcome of vital risk elements identification to provide more detailed and efficient response to identified risk elements.

Chapter 6 Prioritisation of Risks

6.1 Introduction

In the previous chapter, the causal relationships between identified risk dimensions in the UK energy supply chain were studied. The results indicated that that Natural Disasters (ND) and Climate Change (CC) are the most crucial risks followed by Industrial Action (IA), Affordability (AF), Political Instability (PI), and Sabotage/Terrorism (ST). In this chapter, the objective is to develop and apply two extensions of the Best-Worst Method (BWM) to prioritise important energy risks obtained from the interrelationship analysis in previous chapter. Thus, objectives in this chapter are twofold: (1) to theoretically enhance the BWM method, and (2) to practically apply it in the UK energy supply chain risks prioritisation in order to show the applicability of methodological extensions of the BWM as well as confirming the most critical risk dimensions which were identified in the previous chapter.

The BWM is a Multi Attribute Decision Making (MADM) method for evaluating a set of alternatives against a set of decision criteria where two vectors of pairwise comparisons are used to calculate the importance weight of those decision criteria. The BWM is an efficient and mathematically sound method used to solve a wide range of MADM problems by reducing the number of pairwise comparisons and identifying the inconsistencies derived from the comparison process. In a number of MADM methods like the AHP and the BWM, it is required to acquire experts' opinions in pairwise comparisons of alternatives and criteria. And as there is linguistic imprecision and vagueness in human subjective judgements, it is essential to apply an uncertainty theory to deal with that imprecision. Each one of the uncertainty theories has unique characteristics (Yamaguchi et al., 2007). Reflecting on the drawbacks of each uncertainty theory has led to introducing new theories, such as the Neutrosophic Set Theory (NST) from mathematics, into the decision-making sphere and applying the new developed hybrid MADM methodologies under uncertainty. In spite of simplicity and efficiency of the BWM, it does not consider the Decision Makers' (DMs') (or experts') confidence about their pairwise comparisons. In this chapter, two extensions of the original BWM are applied in order to prioritise the obtained six risk dimensions from Phase *II* of the thesis. The proposed methods are hybrid Spanning Trees Enumeration and BWM (STE-BWM) and Neutrosophic Enhanced BWM (NE-

BWM) which were explained in Section 4.4, and 4.5, respectively. In Figure 6.1, more details are provided regarding the study in the current Chapter (Phase *III*).

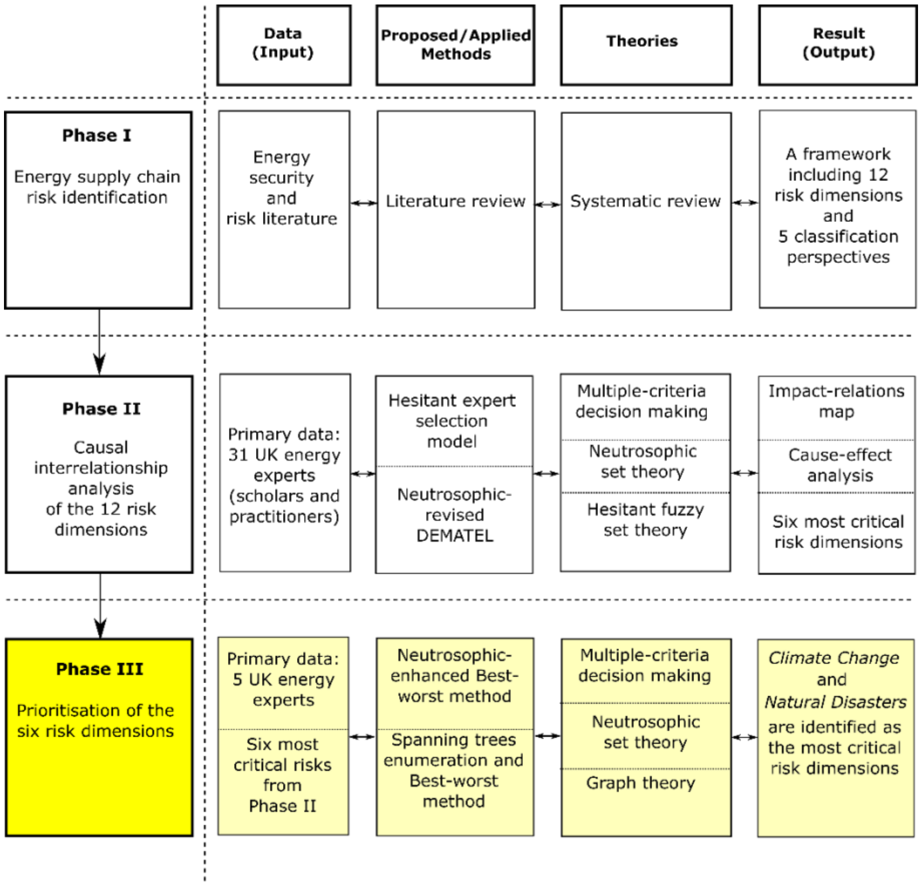


Figure 6.1 Phase III of the research carried out in this chapter

As was explained in Section 4.4, in the original BWM (Appendix E), a DM has to provide a criterion as the best and a criterion as the worst with certainty, assuming no hesitancy. In the real-world decision-making process applying the original BWM dealing with subjective judgements of human beings, it is not always that straightforward for DMs to choose a criterion as either the best or the worst because there is always a degree of hesitancy which must be regarded. Dong et al. (2019) investigated the incomplete preference relations and self-confident preference relations in MCDM and realised that using self-confident preference relations instead of incomplete preference relations improves the quality of decision-making. This finding confirms the importance of capturing the confidence level of DMs in a decision-making method like the BWM. Furthermore, a recent survey of the BWM literature by Mi et al. (2019) suggests that scholars should focus on the uncertainty extension of the original BWM as a predominant research direction. This is the general motivation to propose two extensions of the BWM to overcome this gap in the original BWM as follows:

1) The hybrid STE-BWM (Section 4.4)

This method by applying spanning trees enumeration offers an opportunity for DMs to suggest more than one best or worst criteria. The reason is that in many cases DMs are unable to choose only one criterion due to uncertainty, hesitancy or lack of information. Then, the proposed method can calculate which ones are actually the best, and the worst criteria based on already provided pair-wise comparison values by DMs.

2) The NE-BWM (Section 4.5)

In the original BWM, two vectors of pairwise comparisons including best-to-others and others-to-worst vectors are treated with the same level of importance. The first vector (i.e. best to others) is named as Separation I and the second vector (i.e. others-to-worst) is named as Separation II. The gap is that the importance of separations I, and II based on an uncertain confidence of a DM has not been taken into consideration. The original BWM unrealistically assumes a DM is 100% sure about the most and least favourable criteria. In addition, obtaining preference data from a DM is not easy due to the lack of underpinning theories for formulating uncertainty parameters in the original BWM because it does not consider uncertainty in the decision-making process. Thus, the NST is utilised in structuring the value assignment process in terms of ρ^+ and ρ^- values while dealing with a DM's uncertainty in the enhanced BWM. In fact, the NST provides a rating scale for DMs to express their level of confidence in terms of ρ^+ and ρ^- values. Not utilising such a theory, the proposed enhanced BWM would not be able to structure the confidence value acquisitions and thus, DMs would find it difficult or impossible to express their confidence levels. The reasons to choose the NST out of other uncertainty theories are summarised as follows:

(1) As indicated in Appendix E, fuzzy information and Fuzzy Set Theory (FST) has been commonly used in conjunction with the original BWM. Even though fuzzy set information proved handy, it is unable to express the information about rejection (Ashraf et al., 2019) which is effectively quantified in the NST by introducing the falsity-membership function.

(2) The NST has the capability to quantify the indeterminacy membership independently, which adds an extra level of suitability to it for structuring DMs' confidence level.

The research steps in this chapter is depicted in Figure 6.2 .

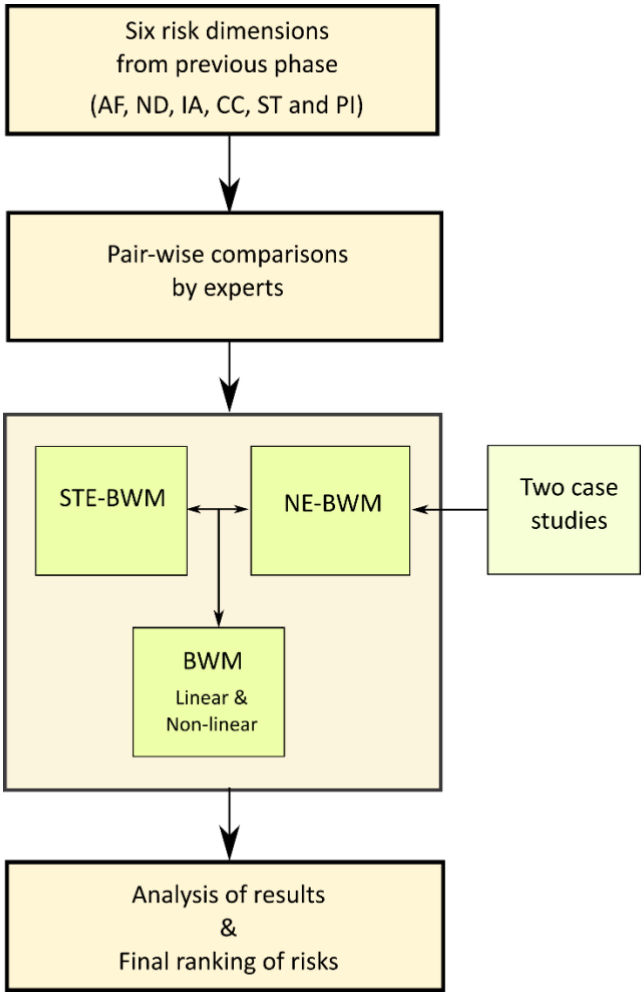


Figure 6.2 Research steps in Phase III in the current chapter

The research contributions in this chapter are summarised as follows:

(I) The proposed STE-BWM (Section 4.4) which is a hybrid method of spanning trees enumeration and BWM is applied in order to help identification of the best and the worst energy risk dimensions in case that DMs were not able to choose only one best and one worst risk dimension with full confidence.

(II) The proposed NE-BWM (Section 4.5) which considers the NST to structure a DM's uncertainty in terms of ρ^+ and ρ^- values is applied to prioritise the six energy risk dimensions (the concept and mathematical definitions of neutrosophic logic is provided in Appendix A).

(III) Two real-world cases are provided in Section 6.3 to demonstrate the applicability and efficacy of the proposed NE-BWM. The results are analysed in 21 test problems under various ρ^{+} and ρ^{-} values to verify the proposed NE-BWM.

(IV) A new output measurement index, namely confidence difference (CD) for the NE-BWM is proposed and discussed.

Finally, the obtained average weights in the original L-BWM, NL-BWM, and NE-BWM are computed and final ranking of energy risk dimensions is provided.

6.2 Methodology

The BWM, introduced by Rezaei (2015), is a relatively new method that has successfully attracted researchers' attention from various fields since its introduction. The simplicity of use, the smaller number of pairwise comparisons, and more consistent comparisons compared to similar methods like the AHP, have made the BWM a reliable and popular method. The BWM can help DMs in defining criteria weights in a decision-making problem. The best and the worst criteria must be determined by a DM. Secondly, pairwise comparisons are carried out between each of the two criteria (i.e. best and worst) and other criteria. Then, the weights of criteria are determined by solving a minimax problem. In the following Section 6.2.1, and Section 6.2.2 applications of two extensions of the original BWM under uncertainty NE-BWM, and STE-BWM are explained, respectively. For computation steps of proposed methods of NE-BWM, and STE-BWM see Section 4.5, and Section 4.4, respectively.

6.2.1 The NE-BWM

Although the ranking of BWM appears reasonable, the degree of a DM's confidence on the best-to-others preferences and others-to-worst preferences has been overlooked by giving equal importance to them in the original BWM. This is the motivation to propose the NE-BWM (Section 4.5).

Applying the original BWM requires a DM to provide their best and worst criteria as well as corresponding pairwise comparisons while failing to notice their subjective confidence or uncertainty on separations I and II. However, in real-world decision-making, there are situations where a DM has more confidence on their provided evaluations on one separation rather than the other. Additionally, human judgements are biased by linguistic imprecision and vagueness; thus, in order to improve the outcome validity of the original BWM in real-world decision-making problems, considering uncertainty over separations I and II into the original BWM can be beneficial. This notion encouraged this study to improve the efficiency of the original BWM by introducing ρ^+ and ρ^- namely the DM's confidence on the best-to-others preferences (the degree of certainty on Separation I) and the DM's confidence on others-to-worst preferences (the degree of certainty on Separation II), respectively. The $\rho^+$and ρ^- values represent the degree of DM's uncertainty about which criterion is the best and which one is the worst. This is because this uncertainty can be extended to pairwise comparisons and affect the confidence degree on separations I and II. In fact, in the original BWM, the two separations' values are considered as being equal to 1 (i.e. $\rho^+ = 1$, and $\rho^- = 1$).

6.2.2 The STE-BWM

As explained in Section 4.4, in the original BWM, a DM must be able to provide one decision-making criterion as the best and one decision-making criterion as the worst with certainty, assuming no hesitancy. In the real-world decision-making process applying the original BWM dealing with subjective judgements of human beings, it is not always straightforward for DMs to choose only one criterion as either the best or the worst, without any level of hesitancy. The BWM can only recognise one criterion as the best, and one criterion as the worst, and is unable to handle more than one criterion for each of the best, and the worst group. In this situation, where there would be more than one best, and more than one worst criteria, the STE can be applied to find out the one criterion as the best and one criterion as the worst.

6.3 Case Study Analysis by NE-BWM

Supply chain is a popular application area for the BWM in the literature (Mi et al., 2019). In this section, two supply chain cases are conducted to verify the proposed NE-BWM. In both cases, 21 test problems are chosen based on Table 4.2 and calculated Consistency Index (CI) values (Section 4.5.1) for them as shown in Appendix G (Table G.1).

6.3.1 Parameters setting

A partial factorial experiment has been conducted to obtain the 21 test problems including one original BWM test problem and 20 NE-BWM test problems based on various DM's confidence levels (Table 4.2). Based on Table 4.2, $\rho^{+} \in \{0.26, 0.38, 0.50, 0.68, 0.90, 1.00\}$ and $\rho^{-} = \{0.26, 0.38, 0.50, 0.68, 0.90, 1.00\}$ can make 36 possible combinations in total that out of which, 21 combinations are chosen. The obtained 20 test problems in NE-BWM are considered as they provide all unique possible CI values (Appendix G). In Figure 6.3, all 20 combinations in NE-BWM analysis are depicted as represented in Table 6.3, and Table 6.7 which are test problems 2 to 21. In one outcome out of 21, the NE-BWM problem would be equal to the original BWM problem where the DM is fully confident (i.e., $\rho^{+} = 1$ and $\rho^{-} = 1$) and obviously zero confidence shall not be taken into consideration.

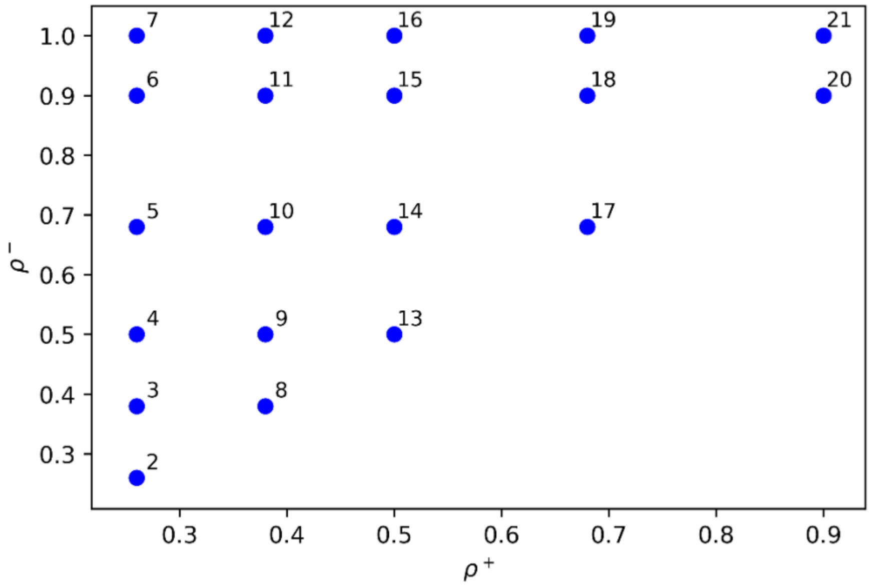


Figure 6.3 The obtained 20 test problems

6.3.2 Case 1: A supplier development problem

Rezaei et al. (2015) discussed the supplier development problem applying the BWM to evaluate eight identified supplier capability criteria and obtain their weights. The eight criteria included supplier capability (C_1^c), product quality capability (C_2^c), delivery capability (C_3^c), intangible capability (C_4^c), service capability (C_5^c), financial/cost capability (C_6^c), sustainable capability (C_7^c), and organisational capability (C_8^c). Here, the BWM evaluation data (Table 6.1 and Table 6.2) are utilised to compare the results of the original BWM, and the proposed NE-BWM in this case application. The best capability criterion is product quality capability (C_2^c), and the worst capability criterion is organisational capability (C_8^c) while $a_{BW} = 9$. Based on the CI table in Rezaei (2015), the CR for the original BWM would be $CR = \frac{0.8599}{5.23} = 0.1644$, the acceptable threshold proposed by Liang et al. (2019) is 0.4587 which indicates the pair-wise comparisons are cardinally consistent based on output-based consistency measurement.

Table 6.1 Best-to-others vector (Case 1)

Criteria	C_1^c	C_2^c	C_3^c	C_4^c	C_5^c	C_6^c	C_7^c	C_8^c
The best criterion (C_2^c)	6	1	2	8	5	3	4	9

Table 6.2 Others-to-worst vector (Case 1)

Criteria	The worst criterion (C_8^c)
C_1^c	2
C_2^c	9
C_3^c	8
C_4^c	2
C_5^c	3
C_6^c	5
C_7^c	4
C_8^c	1

In Table 6.3, the analysis of all test problems considering various ρ^+ and ρ^- for the original and NE-BWM are provided. Calculated weights of all criteria along with numbered new rankings, the objective function value (ε^*), and CR are shown in Table 6.3.

Table 6.3 Analysis of 21 test problems in Case 1

Original BWM											
N°		W_1^*	W_2^*	W_3^*	W_4^*	W_5^*	W_6^*	W_7^*	W_8^*	ε^*	CR
1		0.0532	0.3093	0.2713	0.0393	0.0671	0.1299	0.0985	0.0314	0.8599	0.1644
	ranking (0)	6	1	2	7	5	3	4	8	-	-
NE-BWM											
		W_1^*	W_2^*	W_3^*	W_4^*	W_5^*	W_6^*	W_7^*	W_8^*	ε^*	CR
2	$\rho^+ = 0.26$ $\rho^- = 0.26$	0.0624	0.3210	0.2324	0.0371	0.0775	0.1348	0.1022	0.0325	0.2236	0.1827
	ranking (0)	6	1	2	7	5	3	4	8	-	-
3	$\rho^+ = 0.26$ $\rho^- = 0.38$	0.0566	0.3125	0.2344	0.0417	0.0790	0.1379	0.1057	0.0322	0.2714	0.1895
	ranking (0)	6	1	2	7	5	3	4	8	-	-
4	$\rho^+ = 0.26$ $\rho^- = 0.50$	0.0438	0.3018	0.2323	0.0442	0.0752	0.1648	0.1066	0.0314	0.3037	0.1964
	ranking (1)	7	1	2	6	5	3	4	8	-	-
5	$\rho^+ = 0.26$	0.0648	0.2989	0.2333	0.0455	0.0786	0.1394	0.1081	0.0313	0.3719	0.2266

	$\rho^{-}=0.68$										
	ranking (0)	6	1	2	7	5	3	4	8	-	-
6	$\rho^{+}=0.26$ $\rho^{-}=0.90$	0.0659	0.2832	0.2534	0.0450	0.0748	0.1431	0.1047	0.0298	0.4431	0.2603
	ranking (0)	6	1	2	7	5	3	4	8	-	-
7	$\rho^{+}=0.26$ $\rho^{-}=1.00$	0.0521	0.2890	0.2585	0.0467	0.0772	0.1382	0.1078	0.0305	0.4703	0.2733
	ranking (0)	6	1	2	7	5	3	4	8	-	-
8	$\rho^{+}=0.38$ $\rho^{-}=0.38$	0.0591	0.3038	0.2665	0.0351	0.0659	0.1420	0.0968	0.0308	0.3268	0.1827
	ranking (0)	6	1	2	7	5	3	4	8	-	-
9	$\rho^{+}=0.38$ $\rho^{-}=0.50$	0.0630	0.3154	0.2342	0.0402	0.0726	0.1372	0.1049	0.0323	0.3776	0.1872
	ranking (0)	6	1	2	7	5	3	4	8	-	-
10	$\rho^{+}=0.38$ $\rho^{-}=0.68$	0.0589	0.2864	0.2566	0.0406	0.0741	0.1537	0.1000	0.0297	0.4319	0.1945
	ranking (0)	6	1	2	7	5	3	4	8	-	-

11	$\rho^{+}=0.38$ $\rho^{-}=0.90$	0.0614	0.3002	0.2333	0.0450	0.0768	0.1392	0.1127	0.0314	0.5081	0.2155
	ranking (0)	6	1	2	7	5	3	4	8	-	-
12	$\rho^{+}=0.38$ $\rho^{-}=1.00$	0.0547	0.2902	0.2598	0.0442	0.0746	0.1354	0.1107	0.0304	0.5457	0.2274
	ranking (0)	6	1	2	7	5	3	4	8	-	-
13	$\rho^{+}=0.50$ $\rho^{-}=0.50$	0.0624	0.3207	0.2323	0.0395	0.0756	0.1349	0.1021	0.0325	0.4300	0.1827
	ranking (0)	6	1	2	7	5	3	4	8	-	-
14	$\rho^{+}=0.50$ $\rho^{-}=0.68$	0.0592	0.2953	0.2541	0.0416	0.0724	0.1484	0.0988	0.0303	0.5047	0.1879
	ranking (0)	6	1	2	7	5	3	4	8	-	-
15	$\rho^{+}=0.50$ $\rho^{-}=0.90$	0.0581	0.2984	0.2282	0.0424	0.0773	0.1604	0.1043	0.0310	0.5696	0.1947
	ranking (0)	6	1	2	7	5	3	4	8	-	-
16	$\rho^{+}=0.50$ $\rho^{-}=1.00$	0.0540	0.3063	0.2365	0.0449	0.0769	0.1407	0.1088	0.0319	0.5925	0.1975

	ranking (0)	6	1	2	7	5	3	4	8	-	-
17	$\rho^{+}=0.68$ $\rho^{-}=0.68$	0.0609	0.3131	0.2365	0.0362	0.0756	0.1463	0.0997	0.0318	0.5848	0.1826
	ranking (0)	6	1	2	7	5	3	4	8	-	-
18	$\rho^{+}=0.68$ $\rho^{-}=0.90$	0.0555	0.2929	0.2629	0.0418	0.0732	0.1462	0.0975	0.0300	0.6776	0.1873
	ranking (0)	6	1	2	7	5	3	4	8	-	-
19	$\rho^{+}=0.68$ $\rho^{-}=1.00$	0.0537	0.3141	0.2357	0.0452	0.0740	0.1387	0.1063	0.0323	0.7117	0.1897
	ranking (0)	6	1	2	7	5	3	4	8	-	-
20	$\rho^{+}=0.90$ $\rho^{-}=0.90$	0.0566	0.3021	0.2650	0.0422	0.0662	0.1411	0.0962	0.0306	0.7740	0.1826
	ranking (0)	6	1	2	7	5	3	4	8	-	-
21	$\rho^{+}=0.90$ $\rho^{-}=1.00$	0.0564	0.3217	0.2352	0.0415	0.0714	0.1369	0.1042	0.0328	0.8203	0.1841
	ranking (0)	6	1	2	7	5	3	4	8	-	-

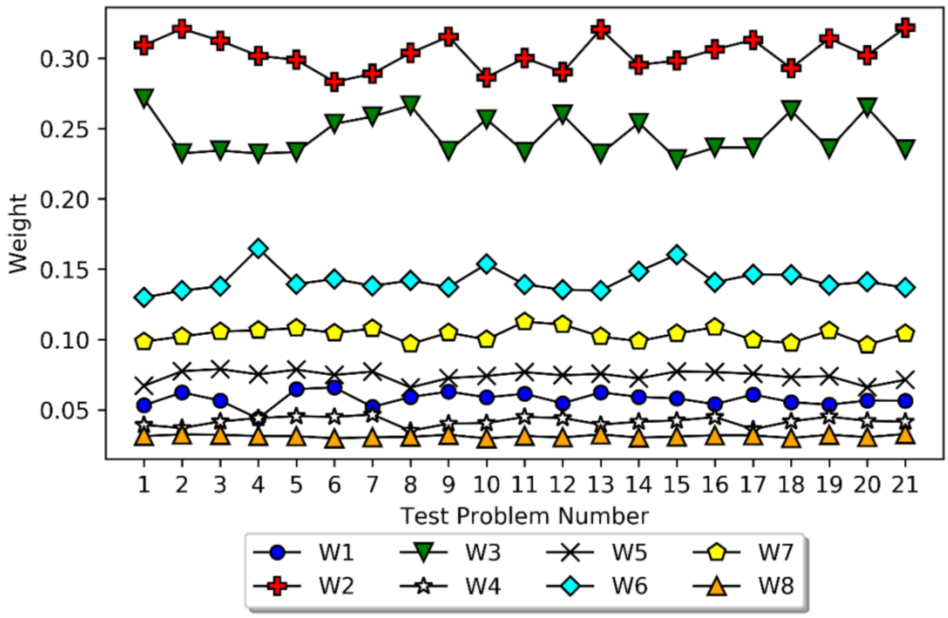


Figure 6.4 Trend and ranking of weights in 21 test problems in Case 1

In Case 1, no severe changes in criteria weights have been observed after alterations in ρ^+ and ρ^- (Figure 6.4). Only one new ranking (ranking 1) was observed in test problem 4 (Table 6.3 and Figure 6.4). The rest of the rankings remained the same as the original BWM's ranking (test problem 1 and ranking 0). In all the rankings, W_2 (i.e. weight of the best criterion, C_2^c) is at the top and W_8 (weight of the worst criterion C_8^c) lies at the lowest part of the diagram (Figure 6.4).

Table 6.4 The NE-BWM weights analysis in Case 1

Weights	N	Range	Mean	Ranks of Mean	Std. Deviation	Ranks of Std. Deviation
W_1	20	0.0221	0.0580	6	0.0051	4
W_2	20	0.0385	0.3033	1	0.0119	2
W_3	20	0.0383	0.2441	2	0.0135	1
W_4	20	0.0116	0.0420	7	0.0032	7
W_5	20	0.0131	0.0744	5	0.0035	6
W_6	20	0.0300	0.1430	3	0.0083	3
W_7	20	0.0165	0.1039	4	0.0047	5
W_8	20	0.0031	0.0313	8	0.0010	8

The descriptive statistics of 20 test problems (test problem 1 has not been considered because it regards the weights in the original BWM) in Case 1 and in the proposed NE-BWM are provided in Table 6.4. The standard deviations show that the weights of W_3 have been more spread out compared to others. Taking into consideration the ranking of mean values, no new ranking has been obtained.

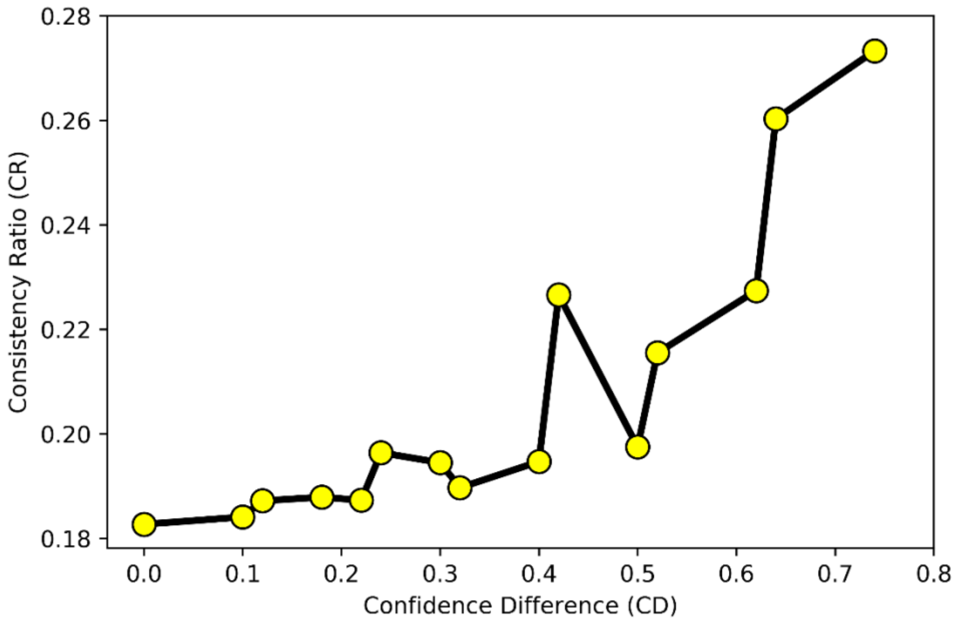


Figure 6.5 The CR-CD diagram in Case 1

The CR values are moving upward in Case 1, as CD values increase, showing that the consistency of the comparisons will decrease. Its surge is more vivid while the CD is at the peak (Figure 6.5). The highest CD value (i.e. 0.74) appeared in test problem 7 ($\rho^+ = 0.26$ and $\rho^- = 1.00$), but, in test problem 7, the ranking remained unchanged (Table 6.3) compared to the original BWM. This point shows that merely an increasing CD does not necessarily lead to a change in the ranking, although it reduces the consistency of the DM's comparisons.

6.3.3 Case 2: A supply chain social sustainability problem

Badri Ahmadi et al. (2017) applied the BWM to analyse eight identified social sustainability criteria in a developing economy context. Here, the criteria are assessed by the NE-BWM based on the provided evaluation data (Table 6.5 and Table 6.6). The social sustainability criteria are work safety and labour health (SSC_1), training education and community development (SSC_2), contractual stakeholders' influence (SSC_3), occupational health and safety management system (SSC_4), interests and rights of employees (SSC_5), rights of community (SSC_6), information disclosure (SSC_7), and employment practices (SSC_8). The best social sustainability criterion is work safety and labour health (SSC_1) and the worst social sustainability criterion is rights of community (SSC_6) and $a_{BW} = 9$. Based on the CI table in Rezaei (2015), the CR for the original BWM is obtained as $CR = \frac{1.7251}{5.23} = 0.3298$. The threshold in this evaluation based on cardinal and output-based consistency measurement is 0.4587 (Liang et al., 2019) indicating the pair-wise evaluations are consistent.

Table 6.5 Best-to-others vector (Case 2)

Criteria	SSC_1	SSC_2	SSC_3	SSC_4	SSC_5	SSC_6	SSC_7	SSC_8
The best criterion (SSC_1)	1	3	5	4	5	9	5	7

Table 6.6 Others-to-worst vector (Case 2)

Criteria	The Worst Criterion (SSC_6)
SSC_1	9
SSC_2	2
SSC_3	5
SSC_4	3
SSC_5	4
SSC_6	1
SSC_7	5
SSC_8	3

Table 6.7 Analysis of 21 test problems in Case 2

Original BWM											
N°		W_1^*	W_2^*	W_3^*	W_4^*	W_5^*	W_6^*	W_7^*	W_8^*	ε^*	CR
		0.3794	0.1206	0.1158	0.0981	0.0856	0.0354	0.1158	0.0492	1.7251	0.3298
1	ranking (0)	1	2	3	4	5	7	3	6	-	-
NE-BWM											
		W_1^*	W_2^*	W_3^*	W_4^*	W_5^*	W_6^*	W_7^*	W_8^*	ε^*	CR
2	$\rho^+ = 0.26$ $\rho^- = 0.26$	0.3431	0.1192	0.1048	0.1265	0.1048	0.0320	0.1048	0.0650	0.4485	0.3664
	ranking (1)	1	3	4	2	4	6	4	5	-	-
3	$\rho^+ = 0.26$ $\rho^- = 0.38$	0.3360	0.1075	0.1152	0.1426	0.0830	0.0322	0.1152	0.0683	0.5417	0.3783
	ranking (2)	1	4	3	2	5	7	3	6	-	-
4	$\rho^+ = 0.26$ $\rho^- = 0.50$	0.3410	0.0650	0.1269	0.1405	0.0935	0.0334	0.1269	0.0728	0.6014	0.3890
	ranking (3)	1	6	3	2	4	7	3	5	-	-
5	$\rho^+ = 0.26$	0.3433	0.0950	0.1389	0.0704	0.1091	0.0344	0.1389	0.0700	0.6575	0.4007

	$\rho^- = 0.68$										
	ranking (4)	1	4	2	5	3	7	2	6	-	-
6	$\rho^+ = 0.26$ $\rho^- = 0.90$	0.3411	0.0602	0.1474	0.0776	0.1125	0.0349	0.1474	0.0791	0.6983	0.4103
	ranking (5)	1	6	2	5	3	7	2	4	-	-
7	$\rho^+ = 0.26$ $\rho^- = 1.00$	0.3196	0.0601	0.1410	0.1222	0.1081	0.0329	0.1410	0.0752	0.7147	0.4153
	ranking (6)	1	6	2	3	4	7	2	5	-	-
8	$\rho^+ = 0.38$ $\rho^- = 0.38$	0.3509	0.0743	0.1071	0.1542	0.1071	0.0327	0.1071	0.0665	0.6555	0.3664
	ranking (7)	1	4	3	2	3	6	3	5	-	-
9	$\rho^+ = 0.38$ $\rho^- = 0.50$	0.3552	0.0712	0.1179	0.1491	0.0841	0.0338	0.1179	0.0708	0.7553	0.3745
	ranking (8)	1	5	3	2	4	7	3	6	-	-
10	$\rho^+ = 0.38$ $\rho^- = 0.68$	0.3662	0.0973	0.1335	0.0621	0.1097	0.0357	0.1335	0.0621	0.8573	0.3862
	ranking (9)	1	4	2	5	3	6	2	5	-	-

11	$\rho^+ = 0.38$ / $\rho^- = 0.90$	0.3552	0.0650	0.1401	0.0715	0.1145	0.0354	0.1401	0.0783	0.9364	0.3971
	ranking (5)	1	6	2	5	3	7	2	4	-	-
12	$\rho^+ = 0.38$ / $\rho^- = 1.00$	0.3556	0.0665	0.1441	0.0727	0.1084	0.0357	0.1441	0.0727	0.9624	0.4010
	ranking(10)	1	5	2	4	3	6	2	4	-	-
13	$\rho^+ = 0.50$ / $\rho^- = 0.50$	0.3552	0.1234	0.1085	0.0963	0.1085	0.0331	0.1085	0.0665	0.8625	0.3664
	ranking(11)	1	2	3	4	3	6	3	5	-	-
14	$\rho^+ = 0.50$ / $\rho^- = 0.68$	0.3371	0.1095	0.1131	0.1143	0.1131	0.0322	0.1131	0.0677	1.0091	0.3757
	ranking (7)	1	4	3	2	3	6	3	5	-	-
15	$\rho^+ = 0.50$ / $\rho^- = 0.90$	0.3629	0.1152	0.1325	0.0617	0.0971	0.0354	0.1325	0.0627	1.1304	0.3863
	ranking(12)	1	3	2	6	4	7	2	5	-	-
16	$\rho^+ = 0.50$ / $\rho^- = 1.00$	0.3571	0.1113	0.1344	0.0642	0.0993	0.0351	0.1344	0.0642	1.1716	0.3905

	ranking(13)	1	3	2	5	4	6	2	5	-	-
17	$\rho^{+}=0.68$ $\rho^{-}=0.68$	0.3762	0.1307	0.1149	0.0687	0.1149	0.0351	0.1149	0.0447	1.1731	0.3664
	ranking(11)	1	2	3	4	3	6	3	5	-	-
18	$\rho^{+}=0.68$ $\rho^{-}=0.90$	0.3358	0.1121	0.1117	0.1440	0.1050	0.0320	0.1117	0.0478	1.3554	0.3747
	ranking(14)	1	3	4	2	5	7	4	6	-	-
19	$\rho^{+}=0.68$ $\rho^{-}=1.00$	0.3738	0.1227	0.1284	0.0614	0.0925	0.0359	0.1284	0.0568	1.4204	0.3786
	ranking(15)	1	3	2	5	4	7	2	6	-	-
20	$\rho^{+}=0.90$ $\rho^{-}=0.90$	0.3428	0.1191	0.1047	0.1507	0.1016	0.0320	0.1047	0.0445	1.5526	0.3664
	ranking(14)	1	3	4	2	5	7	4	6	-	-
21	$\rho^{+}=0.90$ $\rho^{-}=1.00$	0.3731	0.1088	0.1176	0.0717	0.1176	0.0350	0.1176	0.0586	1.6447	0.3692
	ranking(16)	1	3	2	4	2	6	2	5	-	-

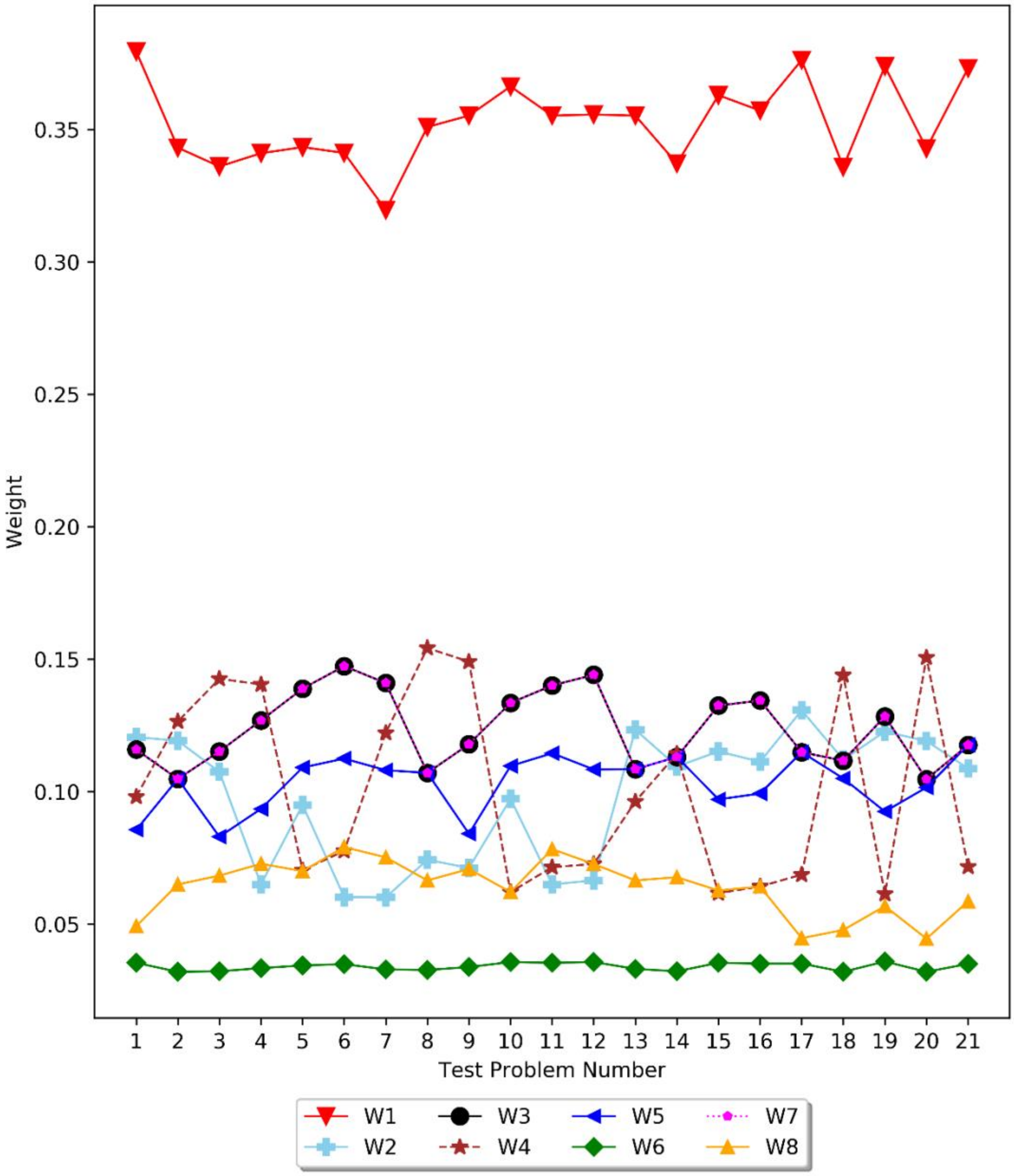


Figure 6.6 Trend and ranking of weights in 21 test problems in Case 2

Table 6.7 shows the analysis of 21 test problems in Case 2 and indicates that by taking into account various ρ^{+} and ρ^{-} values in 20 test problems of the NE-BWM, no ranking equal to the original BWM ranking has been obtained (Table 6.7). Figure 6.6 depicts the trend and rankings of weights in each test problem in Case 2. The best criterion's weight (W_1) is considerably higher than other weights, which has made other diagrams closer to each other and consequently has resulted in various rankings under different ρ^+ and ρ^- values (Figure 6.6). In total, 16 new rankings are obtained in addition to the ranking provided by the original BWM (Table 6.7).

Table 6.8 The NE-BWM weights analysis in Case 2

Weights	N	Range	Mean	Ranks of mean	Std. deviation	Ranks of std. deviation
W_1	20	0.0566	0.3511	1	0.0148	3
W_2	20	0.0706	0.0967	5	0.0246	2
W_3	20	0.0427	0.1241	2	0.0141	4
W_4	20	0.0928	0.1011	4	0.0363	1
W_5	20	0.0346	0.1042	3	0.0099	6
W_6	20	0.0039	0.0339	7	0.0015	7
W_7	20	0.0427	0.1241	2	0.0141	4
W_8	20	0.0346	0.0647	6	0.0101	5

The descriptive statistics of 20 test problems in Case 2 in the proposed NE-BWM are provided in Table 6.8. The standard deviation values show that weights of W_4 have changed more erratically. The mean values of weights in Case 2 have generated a new unique ranking. This result indicates that the mean weight may be able to represent an aggregated weight ranking by taking into account all of the uncertainties.

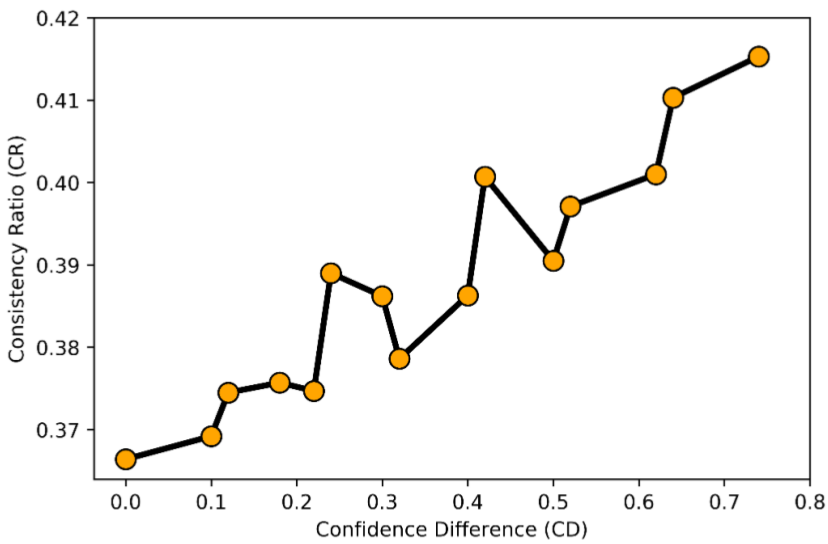


Figure 6.7 The CR-CD diagram in Case 2

Like Case 1, the $CR-CD$ diagram in Case 2 has an increasing trend, which means the greater the CD value, the higher CR , and the lower the consistency (Figure 6.7). The $CR-CD$ diagram in Case 2, has a more erratic trend compared to Case 1.

6.3.4 Discussion on case studies

The NE-BWM analyses show that in Cases 1 and 2, various weight rankings were obtained under different ρ^{+} and ρ^{-} values in 21 test problems. In both cases, there are 8 criteria with the same $a_{BW}=9$. Additionally, with reference to the original BWM (i.e. NL-BWM), it was resulted that $CR=0.1644$ (Case 1) and $CR=0.3298$ (Case 2). Under various DMs' confidence levels on separations I and II (i.e. ρ^{+} and ρ^{-} values), sixteen new rankings were obtained in Case 2 and only one new ranking in Case 1 (Table 6.3 and Table 6.7). Obtaining so many or few new different rankings distinctive to the original BWM ranking represents how the resulted ranking can be influenced and altered by DMs' uncertain opinions compared to the original BWM. It shows that under uncertainty the original BWM might not be generating the most suitable and reliable result, which validates the need for an uncertainty extension of the original BWM.

In this study, a new measurement index of the NE-BWM output (CD) has been proposed to better explain the consistency alteration in the provided comparisons. Results in both Cases show that an increase in the CD values, would raise the CR values, which indicates lower consistency in the comparisons and the DMs' judgements (Figure 6.5 and Figure 6.7). This means that the consistency of evaluations is susceptible to an unbalanced confidence of DMs on the two separations I and II (i.e. a higher CD value). This shows the integration of uncertainty with the BWM can lead to higher inconsistency as was already indicated in the literature.

The changes in CR values are more erratic in Case 2 (Figure 6.7). The CR value in the original BWM in Case 2 (i.e. $CR=0.3298$), is higher than its corresponding value in Case 1 (i.e. $CR=0.1644$). The reason for the more erratic change in CR in Case 2 can be due to the fact that its CR value in the original BWM shows higher inconsistency than in Case 1. Thus, the effect of a change in DMs' confidence on separations I and II (CD value alterations) would be more influential on CR values in Case 2 (noting that in the original BWM there is a full confidence on the separations I and II).

It is also concluded that there is no direct relation between CD and a change in ranking in the test problems of Cases 1 and 2. For instance, having the highest CD value (i.e. 0.74) in Case 1 did not alter the rankings. However, in Case 2, having the slightest CD value alterations produced new rankings. This finding shows CD alone cannot contribute to a change in ranking and CR values should be taken into consideration. Suppose, a DM is completely confident on their comparisons and has chosen best, and worst criteria (i.e. $\rho^{+}=1.00$, $\rho^{-}=1.00$, and $CD=0$) but the comparisons are suffering from a high CR value. In this instance, it would cause the outcome rankings to become more sensitive to a little scepticism of a DM on their choice about either Separation I or Separation II (an uncertain DM, or $CD>0$).

The overall outcomes from case studies can be summarised as follows:

(I) The new NE-BWM model can change the final ranking of the criteria weights. This change in ranking just represents how the resulted ranking can be influenced and altered by DMs' uncertain opinions compared to the full confident deterministic approach of DMs in the original BWM. This result shows that under uncertain real-world applications, the original BWM might not be able to generate the most suitable criteria weights and consequently the most reliable ranking because it presumes that DMs are fully confident, and there is no room for hesitancy.

(II) With growing inconsistency, the DMs' degree of confidence on the separations I and II can play a more critical role in obtaining new rankings. In other words, when the original BWM comparisons are consistent (smaller CR values) then the proposed NE-BWM cannot significantly affect the criteria weights and rankings under various ρ^{+} and ρ^{-} values in different test problems. It means that the final ranking and weights are more sensitive to the inconsistency of comparisons under various ρ^{+} and ρ^{-} values in different test problems.

(III) An increase in CD values, meaning an unbalanced confidence of DMs on the two separations I and II would raise the CR values indicating less consistency in comparisons.

(IV) The changes in CR values can be more erratic due to higher inconsistency, which makes the changes in CR more susceptible to CD value alterations.

(V) The mean values of weights can represent an aggregated weight and produce a unique ranking (i.e. in Case 2, Table 6.8). In some circumstances, applying this aggregated weight might be helpful. This would include situations where acquiring the DMs' confidence is impossible because the data is already gathered or for re-analysing the other original BWM studies by the NE-BWM.

6.4 Data Collection

The required primary data in the form of pair-wise comparisons for the implementation of the original BWM, NE-BWM, and STE-BWM are obtained from 5 UK energy experts out of 31 experts who already participated in Phase *II* of the research (Chapter 5) and have related strong expertise. Initially, 16 out of 31 experts who were capable to provide valuable insights on the six identified risk dimensions were contacted and 5 of them participated in this phase of the thesis by providing their evaluations. The data is collected through an online survey. In Table 6.9, the best (most critical), and worst (least critical) energy risk dimensions identified by experts are presented.

Table 6.9 Most and least critical risks determined by experts

	Identified as most critical by experts	Identified as least critical by experts
AF: Affordability	1	
ND: Natural Disasters	4	
IA: Industrial Action		1, 5
CC: Climate Change	2, 3, 5	
ST: Sabotage/Terrorism	4	3
PI: Political Instability		2, 4

In Table 6.10, the best-to-other vectors and in Table 6.11, the others-to-worst vectors based on the evaluations provided by experts are shown.

Table 6.10 Best-to-others vectors

Experts	The most critical risk	PI	ND	IA	CC	ST	AF
1	AF	1	3	5	2	4	1
2	CC	9	8	3	1	9	5
3	CC	5	3	3	1	4	7
4	ND	7	1	4	3	1	5
	ST	7	1	4	3	1	5
5	CC	6	2	8	1	2	3

Table 6.11 Others-to-worst vectors

Experts	1	2	3	4	5
The least critical risk	IA	PI	ST	PI	IA
ND	2	6	4	7	7
CC	3	9	9	5	9
ST	1	5	1	7	7
AF	5	7	5	4	5
PI	4	1	3	1	3
IA	1	5	5	3	1

In Table 6.12, the confidence levels of each expert are provided and can be used in the NE-BWM analysis. The applied scale is presented in Table 4.2 and the questions were utilised to acquire the confidence levels can be seen in Appendix F.

Table 6.12 Confidence levels

Experts	confidence on the best-to-others	ρ^+	confidence on the others-to-worst	ρ^-
1	Fairly high	0.68	Fairly high	0.68
2	Medium	0.50	Medium	0.50
3	Fairly high	0.68	Medium	0.50
4	Fairly high	0.68	Medium	0.50
5	High	0.90	High	0.90

The CR values are all in acceptable threshold lower than 0.1 based on Liang et al. (2019).

6.5 Analysis

In this section, the analysis of the STE-BWM, NE-BWM, and original BWM (L-BWM, and NL-BWM) based on the acquired data in Section 6.4 are provided. All the optimisations are carried out by using the LINGO 18.0.

6.5.1 The STE-BWM application

As can be seen in Table 6.9, and Table 6.10; expert 4, hesitated in choosing only one best criterion (i.e. the most critical) between Natural Disasters (ND) and Sabotage and Terrorism (ST); that is why both were selected. This was made possible through the provided survey. Thus, following the proposed steps of STE-BWM explained in Section 4.4, the best criterion for expert 4, can be realised.

Step 1: The identified set of risk dimensions are $N = \{AF, ND, IA, CC, ST, PI\}$

Step 2: The best and worst set of risk dimensions based on expert 4 are $\Theta = \{ND, ST\}$ and $\Gamma = \{PI\}$. Thus, $|\Theta| = 2$, and $|\Gamma| = 1$, then the STE calculations must be carried out two times (i.e. $|\Theta| \times |\Gamma| = 2$). One time for ND and PI, and the second time for ST and PI.

6.5.1.1 The EAST analysis for ND and PI

The EAST as explained in Appendix H is applied here.

Step 1: The identified set of risk dimensions are $C = \{AF, ND, IA, CC, ST, PI\}$

Step 2: Based on provided pair-wise comparison vectors by expert 4 for ND (i.e. the best risk dimension), and PI (i.e. the worst risk dimension) as shown in Table 6.10, and Table 6.11 the incomplete pair-wise comparison matrix A can be obtained (Table 6.13). The utilised scale is presented in Table E.1 in Appendix E.

Table 6.13 The incomplete pair-wise comparison matrix A by expert 4 (ND and PI)

		1 AF	2 ND	3 IA	4 CC	5 ST	6 **PI**
1	AF	1	0.20				**4**
2	**ND**	**5**	1	**4**	**3**	**1**	**7**
3	IA		0.25	1			**3**
4	CC		0.33		1		**5**
5	ST		1.00			1	**7**
6	PI	0.25	0.14	0.33	0.20	0.14	1

Step 3: The corresponding graph G of the pair-wise comparison matrix A (Table 6.13) is produced as shown in Figure 6.8.

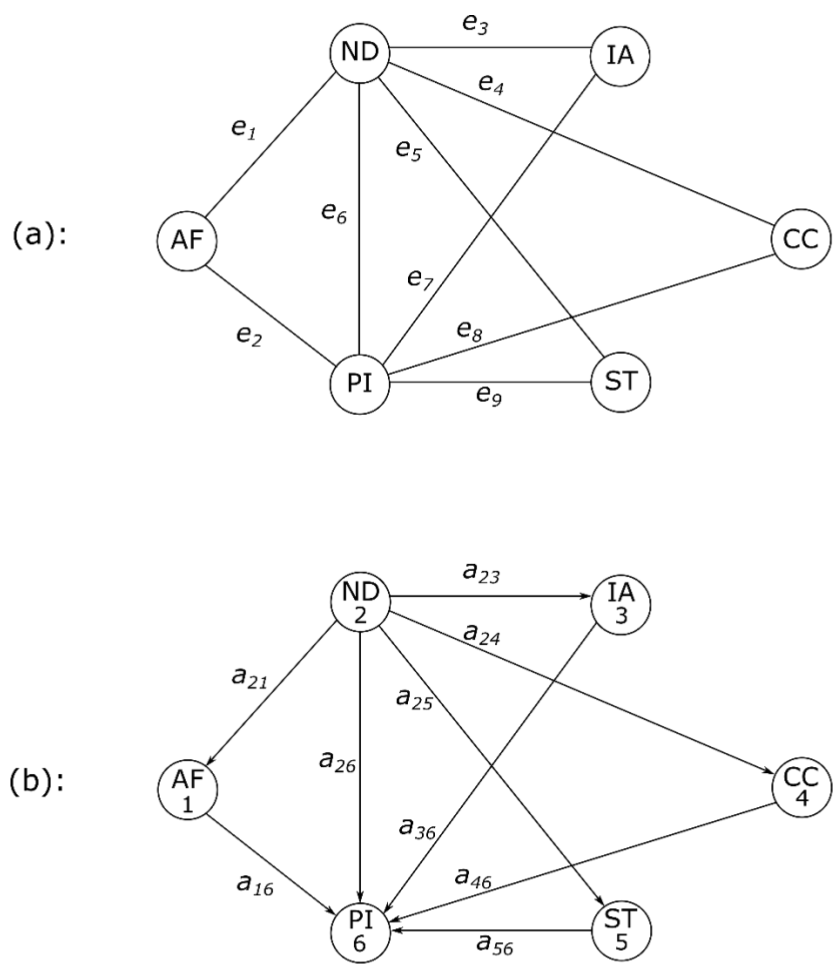


Figure 6.8 The undirected (a), and directed (b) graph G of the matrix A (ND and PI)

Step 4*:* The Kirchhoff's matrix-tree theorem (Theorem B.3 in Appendix B) is used to obtain the total number of spanning trees. It is known that for each tree, $n - 1 = 6 - 1 = 5$ edges are needed and as can be seen in Figure 6.8, the obtained graphs have 9 edges. It indicates that at most there will be $\binom{9}{5} = \frac{9!}{5! \times 4!} = 126$ potential trees and by using the Kirchhoff's matrix-tree theorem, the total number of spanning trees can be obtained as $\eta = 48$ (see Table C.1 in Appendix C).

According to the Kirchhoff's matrix-tree theorem (Theorem B.3 in Appendix B), the degree matrix and adjacency matrix of graph G are shown in Equation (6.1), and Equation (6.2), respectively.

$$D(G) = \begin{bmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 5 \end{bmatrix} \tag{6.1}$$

$$A(G) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{6.2}$$

Then the Laplacian matrix of graph G is obtained as represented in Equation (6.3)

$$L(G) = \begin{bmatrix} 2 & -1 & 0 & 0 & 0 & -1 \\ -1 & 5 & -1 & -1 & -1 & -1 \\ 0 & -1 & 2 & 0 & 0 & -1 \\ 0 & -1 & 0 & 2 & 0 & -1 \\ 0 & -1 & 0 & 0 & 2 & -1 \\ -1 & -1 & -1 & -1 & -1 & 5 \end{bmatrix} \tag{6.3}$$

$L^*(G)$ can be attained by omitting any row and the corresponding column of the Laplacian matrix (for instance, by removing row 1 and column 1 or row 2 and column 2 and so on). Then, $|L^*(G)| = 48$ which is the total number of spanning trees for the graph G (Figure 6.8) of the incomplete pairwise comparison matrix A (Table 6.13). Ultimately, the Gray code algorithm can be used to generate all 48 spanning trees as shown in Table C.1 in Appendix C.

Step 5: the weights of six risk dimensions in each of the 48 spanning trees are calculated. The weight of i^{th} risk dimension ($i = 1, \ldots, 6$) in k^{th} spanning tree ($k = 1, \ldots, 48$) is denoted as $w_i^{(k)}$ and computed based on Equations (H.49) and (H.50) in Appendix H. All weights are shown in Table 6.14

Table 6.14 Weights of risk dimensions in all spanning trees (ND and PI)

		weights					
No.	Arcs in spanning trees	1: AF	2: ND	3: IA	4: CC	5: ST	6: PI
1	$a_{21}, a_{26}, a_{36}, a_{25}, a_{24}$	0.0644	0.3221	0.1380	0.1074	0.3221	0.0460
2	$a_{21}, a_{26}, a_{25}, a_{24}, a_{23}$	0.0683	0.3417	0.0854	0.1139	0.3417	0.0488
3	$a_{21}, a_{36}, a_{25}, a_{24}, a_{23}$	0.0698	0.3488	0.0872	0.1163	0.3488	0.0291
4	$a_{21}, a_{26}, a_{36}, a_{24}, a_{56}$	0.0644	0.3221	0.1380	0.1074	0.3221	0.0460
5	$a_{21}, a_{36}, a_{25}, a_{24}, a_{56}$	0.0644	0.3221	0.1380	0.1074	0.3221	0.0460
6	$a_{21}, a_{26}, a_{36}, a_{25}, a_{46}$	0.0574	0.2869	0.1230	0.2049	0.2869	0.0410
7	$a_{21}, a_{36}, a_{25}, a_{24}, a_{46}$	0.0714	0.3571	0.0714	0.1190	0.3571	0.0238
8	$a_{21}, a_{36}, a_{25}, a_{24}, a_{16}$	0.0732	0.3659	0.0549	0.1220	0.3659	0.0183
9	$a_{26}, a_{36}, a_{25}, a_{24}, a_{16}$	0.1644	0.2877	0.1233	0.0959	0.2877	0.0411
10	$a_{21}, a_{36}, a_{24}, a_{56}, a_{23}$	0.0816	0.4082	0.1020	0.1361	0.2381	0.0340
11	$a_{21}, a_{25}, a_{24}, a_{56}, a_{23}$	0.0683	0.3417	0.0854	0.1139	0.3417	0.0488
12	$a_{21}, a_{26}, a_{24}, a_{56}, a_{23}$	0.0683	0.3417	0.0854	0.1139	0.3417	0.0488
13	$a_{21}, a_{24}, a_{46}, a_{56}, a_{23}$	0.0863	0.4317	0.1079	0.1439	0.2014	0.0288
14	$a_{21}, a_{25}, a_{46}, a_{56}, a_{23}$	0.0605	0.3024	0.0756	0.2160	0.3024	0.0432
15	$a_{21}, a_{36}, a_{46}, a_{56}, a_{23}$	0.0789	0.3947	0.0987	0.1645	0.2303	0.0329
16	$a_{21}, a_{26}, a_{46}, a_{56}, a_{23}$	0.0605	0.3024	0.0756	0.2160	0.3024	0.0432
17	$a_{24}, a_{16}, a_{46}, a_{56}, a_{23}$	0.1119	0.4196	0.1049	0.1399	0.1958	0.0280
18	$a_{25}, a_{16}, a_{46}, a_{56}, a_{23}$	0.1553	0.2718	0.0680	0.1942	0.2718	0.0388
19	$a_{36}, a_{16}, a_{46}, a_{56}, a_{23}$	0.1250	0.3750	0.0938	0.1563	0.2188	0.0313
20	$a_{26}, a_{16}, a_{46}, a_{56}, a_{23}$	0.1553	0.2718	0.0680	0.1942	0.2718	0.0388
21	$a_{21}, a_{16}, a_{46}, a_{56}, a_{23}$	0.0952	0.4762	0.1190	0.1190	0.1667	0.0238
22	$a_{21}, a_{36}, a_{25}, a_{46}, a_{23}$	0.0678	0.3390	0.0847	0.1412	0.3390	0.0282

23	a_{21}, a_{25}, a_{24}, a_{46}, a_{23}	0.0702	0.3509	0.0877	0.1170	0.3509	0.0234
24	a_{21}, a_{26}, a_{25}, a_{46}, a_{23}	0.0605	0.3024	0.0756	0.2160	0.3024	0.0432
25	a_{26}, a_{25}, a_{24}, a_{16}, a_{23}	0.1733	0.3032	0.0758	0.1011	0.3032	0.0433
26	a_{36}, a_{25}, a_{24}, a_{16}, a_{23}	0.1111	0.3333	0.0833	0.1111	0.3333	0.0278
27	a_{21}, a_{25}, a_{24}, a_{16}, a_{23}	0.0706	0.3529	0.0882	0.1176	0.3529	0.0176
28	a_{21}, a_{36}, a_{25}, a_{46}, a_{56}	0.0574	0.2869	0.1230	0.2049	0.2869	0.0410
29	a_{21}, a_{36}, a_{24}, a_{46}, a_{56}	0.0882	0.4412	0.0882	0.1471	0.2059	0.0294
30	a_{21}, a_{26}, a_{36}, a_{46}, a_{56}	0.0574	0.2869	0.1230	0.2049	0.2869	0.0410
31	a_{26}, a_{36}, a_{24}, a_{16}, a_{56}	0.1644	0.2877	0.1233	0.0959	0.2877	0.0411
32	a_{36}, a_{25}, a_{24}, a_{16}, a_{56}	0.1644	0.2877	0.1233	0.0959	0.2877	0.0411
33	a_{21}, a_{36}, a_{24}, a_{16}, a_{56}	0.0960	0.4800	0.0720	0.1600	0.1680	0.0240
34	a_{26}, a_{36}, a_{25}, a_{16}, a_{46}	0.1481	0.2593	0.1111	0.1852	0.2593	0.0370
35	a_{36}, a_{25}, a_{24}, a_{16}, a_{46}	0.0930	0.3488	0.0698	0.1163	0.3488	0.0233
36	a_{21}, a_{36}, a_{25}, a_{16}, a_{46}	0.0755	0.3774	0.0566	0.0943	0.3774	0.0189
37	a_{25}, a_{24}, a_{16}, a_{56}, a_{23}	0.1733	0.3032	0.0758	0.1011	0.3032	0.0433
38	a_{36}, a_{24}, a_{16}, a_{56}, a_{23}	0.1290	0.3871	0.0968	0.1290	0.2258	0.0323
39	a_{26}, a_{24}, a_{16}, a_{56}, a_{23}	0.1733	0.3032	0.0758	0.1011	0.3032	0.0433
40	a_{21}, a_{24}, a_{16}, a_{56}, a_{23}	0.0916	0.4580	0.1145	0.1527	0.1603	0.0229
41	a_{25}, a_{24}, a_{16}, a_{46}, a_{23}	0.0914	0.3429	0.0857	0.1143	0.3429	0.0229
42	a_{36}, a_{25}, a_{16}, a_{46}, a_{23}	0.1081	0.3243	0.0811	0.1351	0.3243	0.0270
43	a_{26}, a_{25}, a_{16}, a_{46}, a_{23}	0.1553	0.2718	0.0680	0.1942	0.2718	0.0388
44	a_{21}, a_{25}, a_{16}, a_{46}, a_{23}	0.0727	0.3636	0.0909	0.0909	0.3636	0.0182
45	a_{36}, a_{24}, a_{16}, a_{46}, a_{56}	0.1143	0.4286	0.0857	0.1429	0.2000	0.0286
46	a_{36}, a_{25}, a_{16}, a_{46}, a_{56}	0.1481	0.2593	0.1111	0.1852	0.2593	0.0370
47	a_{26}, a_{36}, a_{16}, a_{46}, a_{56}	0.1481	0.2593	0.1111	0.1852	0.2593	0.0370
48	a_{21}, a_{36}, a_{16}, a_{46}, a_{56}	0.1000	0.5000	0.0750	0.1250	0.1750	0.0250

Step 6*:* Finally, by getting the arithmetic average of all weights for each risk dimension (i.e. EAST) based on Equation (H.51) in Appendix H or geometric average (i.e. GMAST) based on Equation (H.52) in Appendix H, the final weight of each risk dimension can be obtained as shown in Table 6.15.

Table 6.15 Average weights of all spanning trees and rankings of risks (ND and PI)

	AF	ND	IA	CC	ST	PI
EAST	0.1010	0.3444	0.0938	0.1410	0.2858	0.0341
Ranking	4	1	5	3	2	6
GMAST	0.0943	0.3392	0.0913	0.1360	0.2788	0.0327
Ranking	4	1	5	3	2	6

6.5.1.2 The EAST analysis for ST and PI

The EAST as explained in Appendix H is applied here, similar to previous Section 6.5.1.1.

Step 1: The identified set of risk dimensions are $C = \{AF, ND, IA, CC, ST, PI\}$

Step 2: The incomplete pair-wise comparison matrix A can be obtained as shown in Table 6.16. It is constructed based on provided pair-wise comparison vectors by expert 4 for ST (i.e. the best risk dimension), and PI (i.e. the worst risk dimension) as shown in Table 6.10, and Table 6.11.

Table 6.16 The incomplete pair-wise comparison matrix A by expert 4 (ST and PI)

		1 AF	2 ND	3 IA	4 CC	5 ST	6 **PI**
1	AF	1				0.20	**4**
2	ND		1			1.00	**7**
3	IA			1		0.25	**3**
4	CC				1	0.33	**5**
5	**ST**	**5**	**1**	**4**	**3**	1	**7**
6	PI	0.25	0.14	0.33	0.20	0.14	1

Step 3: The corresponding graph G of the pair-wise comparison matrix A (Table 6.16) is produced as shown in Figure 6.9.

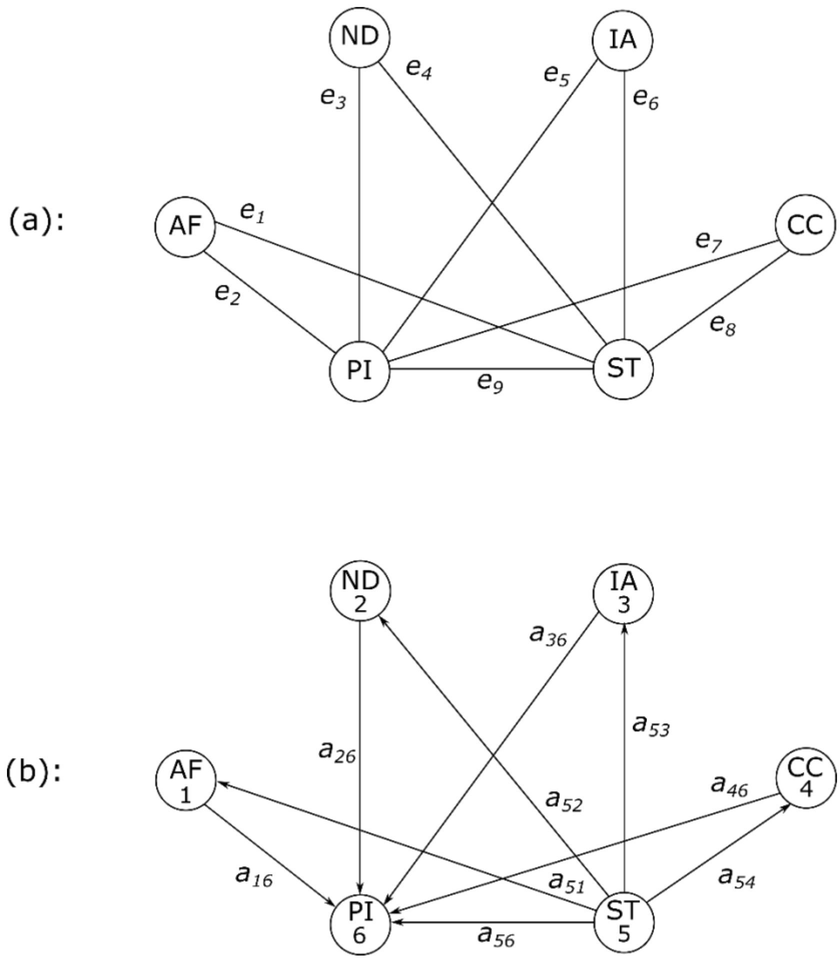


Figure 6.9 The undirected (a) and directed (b) graph G of the matrix A (ST and PI)

Step 4: The Kirchhoff's matrix-tree theorem (Theorem B.3 in Appendix B) is used to obtain the total number of spanning trees as $\eta = 48$ (see Table K.1 in Appendix K).

According to the Kirchhoff's matrix-tree theorem (Theorem B.3 in Appendix B), the degree matrix and adjacency matrix of graph G are shown in Equations (6.4) and Equation (6.5), respectively.

$$D(G) = \begin{bmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 5 & 0 \\ 0 & 0 & 0 & 0 & 0 & 5 \end{bmatrix} \tag{6.4}$$

$$A(G) = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{6.5}$$

Then, the Laplacian matrix of graph G is obtained as represented in Equation (6.6)

$$L(G) = \begin{bmatrix} 2 & 0 & 0 & 0 & -1 & -1 \\ 0 & 2 & 0 & 0 & -1 & -1 \\ 0 & 0 & 2 & 0 & -1 & -1 \\ 0 & 0 & 0 & 2 & -1 & -1 \\ -1 & -1 & -1 & -1 & 5 & -1 \\ -1 & -1 & -1 & -1 & -1 & 5 \end{bmatrix} \tag{6.6}$$

$L^*(G)$ can be obtained by omitting any row and the corresponding column of the Laplacian matrix. As a result, $|L^*(G)| = 48$ which is the total number of spanning trees for the graph G (Figure 6.9) of the incomplete pairwise comparison matrix A (Table 6.16). Finally, a Gray code algorithm can be used to generate all the 48 spanning trees as shown in Table K.1 in Appendix K.

Step 5*:* The weights of six risk dimensions in each of the 48 spanning trees are calculated. The weight of i^{th} risk dimension ($i = 1, \dots, 6$) in k^{th} spanning tree ($k = 1, \dots, 48$) is denoted as $w_i^{(k)}$ and computed based on Equation (H.49) in Appendix H, and Equation (H.50) in Appendix H. All weights are shown in Table 6.17.

Table 6.17 Weights of risk dimensions in all spanning trees (ST and PI)

		weights					
No.	Arcs in spanning trees	1: AF	2: ND	3: IA	4: CC	5: ST	6: PI
1	a_{16}, a_{26}, a_{36}, a_{46}, a_{56}	0.1481	0.2593	0.1111	0.1852	0.2593	0.0370
2	a_{16}, a_{26}, a_{36}, a_{46}, a_{54}	0.1143	0.2000	0.0857	0.1429	0.4286	0.0286
3	a_{16}, a_{26}, a_{36}, a_{56}, a_{54}	0.1644	0.2877	0.1233	0.0959	0.2877	0.0411
4	a_{16}, a_{26}, a_{36}, a_{46}, a_{53}	0.1250	0.2188	0.0938	0.1563	0.3750	0.0313
5	a_{16}, a_{26}, a_{46}, a_{56}, a_{53}	0.1553	0.2718	0.0680	0.1942	0.2718	0.0388
6	a_{16}, a_{26}, a_{36}, a_{46}, a_{52}	0.1481	0.2593	0.1111	0.1852	0.2593	0.0370
7	a_{16}, a_{36}, a_{46}, a_{56}, a_{52}	0.1481	0.2593	0.1111	0.1852	0.2593	0.0370
8	a_{16}, a_{26}, a_{36}, a_{46}, a_{51}	0.1000	0.1750	0.0750	0.1250	0.5000	0.0250
9	a_{26}, a_{36}, a_{46}, a_{56}, a_{51}	0.0574	0.2869	0.1230	0.2049	0.2869	0.0410
10	a_{16}, a_{26}, a_{56}, a_{53}, a_{54}	0.1733	0.3032	0.0758	0.1011	0.3032	0.0433
11	a_{16}, a_{26}, a_{46}, a_{53}, a_{54}	0.1119	0.1958	0.1049	0.1399	0.4196	0.0280
12	a_{16}, a_{26}, a_{36}, a_{53}, a_{54}	0.1290	0.2258	0.0968	0.1290	0.3871	0.0323
13	a_{16}, a_{56}, a_{52}, a_{53}, a_{54}	0.1733	0.3032	0.0758	0.1011	0.3032	0.0433
14	a_{16}, a_{46}, a_{52}, a_{53}, a_{54}	0.0914	0.3429	0.0857	0.1143	0.3429	0.0229
15	a_{16}, a_{36}, a_{52}, a_{53}, a_{54}	0.1111	0.3333	0.0833	0.1111	0.3333	0.0278
16	a_{16}, a_{26}, a_{52}, a_{53}, a_{54}	0.1733	0.3032	0.0758	0.1011	0.3032	0.0433
17	a_{56}, a_{51}, a_{52}, a_{53}, a_{54}	0.0683	0.3417	0.0854	0.1139	0.3417	0.0488
18	a_{46}, a_{51}, a_{52}, a_{53}, a_{54}	0.0702	0.3509	0.0877	0.1170	0.3509	0.0234
19	a_{36}, a_{51}, a_{52}, a_{53}, a_{54}	0.0698	0.3488	0.0872	0.1163	0.3488	0.0291
20	a_{26}, a_{51}, a_{52}, a_{53}, a_{54}	0.0683	0.3417	0.0854	0.1139	0.3417	0.0488
21	a_{16}, a_{51}, a_{52}, a_{53}, a_{54}	0.0706	0.3529	0.0882	0.1176	0.3529	0.0176
22	a_{16}, a_{36}, a_{46}, a_{52}, a_{54}	0.0930	0.3488	0.0698	0.1163	0.3488	0.0233
23	a_{16}, a_{36}, a_{56}, a_{52}, a_{54}	0.1644	0.2877	0.1233	0.0959	0.2877	0.0411
24	a_{16}, a_{26}, a_{36}, a_{52}, a_{54}	0.1644	0.2877	0.1233	0.0959	0.2877	0.0411
25	a_{26}, a_{36}, a_{46}, a_{51}, a_{54}	0.0882	0.2059	0.0882	0.1471	0.4411	0.0294
26	a_{26}, a_{36}, a_{56}, a_{51}, a_{54}	0.0644	0.3221	0.1380	0.1074	0.3221	0.0460
27	a_{16}, a_{26}, a_{36}, a_{51}, a_{54}	0.0960	0.1680	0.0720	0.1600	0.4800	0.0240
28	a_{16}, a_{36}, a_{46}, a_{52}, a_{53}	0.1081	0.3243	0.0811	0.1351	0.3243	0.0270
29	a_{16}, a_{46}, a_{56}, a_{52}, a_{53}	0.1553	0.2718	0.0680	0.1942	0.2718	0.0388
30	a_{16}, a_{26}, a_{46}, a_{52}, a_{53}	0.1553	0.2718	0.0680	0.1942	0.2718	0.0388

31	a_{26}, a_{36}, a_{46}, a_{51}, a_{53}	0.0789	0.2303	0.0987	0.1645	0.3947	0.0329
32	a_{26}, a_{46}, a_{56}, a_{51}, a_{53}	0.0605	0.3024	0.0756	0.2160	0.3024	0.0432
33	a_{16}, a_{26}, a_{46}, a_{51}, a_{53}	0.0952	0.1667	0.1190	0.1190	0.4762	0.0238
34	a_{26}, a_{36}, a_{46}, a_{51}, a_{52}	0.0574	0.2869	0.1230	0.2049	0.2869	0.0410
35	a_{36}, a_{46}, a_{56}, a_{51}, a_{52}	0.0574	0.2869	0.1230	0.2049	0.2869	0.0410
36	a_{16}, a_{36}, a_{46}, a_{51}, a_{52}	0.0755	0.3774	0.0566	0.0943	0.3774	0.0189
37	a_{26}, a_{56}, a_{51}, a_{53}, a_{54}	0.0683	0.3417	0.0854	0.1139	0.3417	0.0488
38	a_{26}, a_{46}, a_{51}, a_{53}, a_{54}	0.0863	0.2014	0.1079	0.1439	0.4317	0.0288
39	a_{26}, a_{36}, a_{51}, a_{53}, a_{54}	0.0816	0.2381	0.1020	0.1361	0.4082	0.0340
40	a_{16}, a_{26}, a_{51}, a_{53}, a_{54}	0.0916	0.1603	0.1145	0.1527	0.4580	0.0229
41	a_{36}, a_{56}, a_{51}, a_{52}, a_{54}	0.0644	0.3221	0.1380	0.1074	0.3221	0.0460
42	a_{36}, a_{46}, a_{51}, a_{52}, a_{54}	0.0714	0.3571	0.0714	0.1190	0.3571	0.0238
43	a_{26}, a_{36}, a_{51}, a_{52}, a_{54}	0.0644	0.3221	0.1380	0.1074	0.3221	0.0460
44	a_{16}, a_{36}, a_{51}, a_{52}, a_{54}	0.0732	0.3659	0.0549	0.1220	0.3659	0.0183
45	a_{46}, a_{56}, a_{51}, a_{52}, a_{53}	0.0605	0.3024	0.0756	0.2160	0.3024	0.0432
46	a_{36}, a_{46}, a_{51}, a_{52}, a_{53}	0.0678	0.3390	0.0847	0.1412	0.3390	0.0282
47	a_{26}, a_{46}, a_{51}, a_{52}, a_{53}	0.0605	0.3024	0.0756	0.2160	0.3024	0.0432
48	a_{16}, a_{46}, a_{51}, a_{52}, a_{53}	0.0727	0.3636	0.0909	0.0909	0.3636	0.0182

Step 6*:* Eventually, by getting the arithmetic average of all weights for each risk dimension (i.e. EAST) based on Equation (H.51) in Appendix H or geometric average (i.e. GMAST) based on Equation (H.52) in Appendix H, the final weight of each risk dimension can be obtained as shown in Table 6.18.

Table 6.18 Average weights of all spanning trees and rankings of risks (ST and PI)

	AF	ND	IA	CC	ST	PI
EAST	0.1010	0.2858	0.0938	0.1410	0.3444	0.0341
Ranking	4	2	5	3	1	6
GMAST	0.0943	0.2788	0.0913	0.1360	0.3392	0.0327
Ranking	4	2	5	3	1	6

6.5.1.3 Results

In this section, the obtained results and rankings from the EAST analysis for Natural Disasters (ND) and Political Instability (PI) (Table 6.15), and for Sabotage and Terrorism (ST) and Political Instability (PI) (Table 6.18), are incorporated to reach a conclusion that which one of Natural Disasters (ND) or Sabotage and Terrorism (ST) should be the best risk dimension based on the data obtained from expert 4. The aggregated weights and final rankings obtained from EAST and GMAST methods are represented in Table 6.19.

Table 6.19 Aggregated weights and final rankings from EAST and GMAST

		EAST			
		ND and PI	ST and PI	Average	Ranking
AF	w_1	0.1010065335	0.1010065335	0.1010065335	4
ND	w_2	0.3443855204	0.2857569085	0.3150712145	1
IA	w_3	0.0937656585	0.0937656585	0.0937656585	5
CC	w_4	0.1409772290	0.1409772290	0.1409772290	3
ST	w_5	0.2857569085	0.3443848954	0.3150709020	2
PI	w_6	0.0341081492	0.0341081492	0.0341081492	6
		GMAST			
		ND and PI	ST and PI	Average	Ranking
AF	w_1	0.0942570944	0.0942570944	0.0942570944	4
ND	w_2	0.3391580310	0.2788162447	0.3089871379	1
IA	w_3	0.0912640382	0.0912640382	0.0912640382	5
CC	w_4	0.1360483960	0.1360483960	0.1360483960	3
ST	w_5	0.2788162447	0.3391575505	0.3089868976	2
PI	w_6	0.0327443216	0.0327443216	0.0327443216	6

As it is shown in Table 6.19, Natural Disasters (ND) has a bit higher weight compared to the weight of Sabotage and Terrorism (ST) in both EAST and GMAST methods. Thus, in the BWM analysis the Natural Disasters (ND) has been chosen as the best risk dimension suggested by expert 4.

6.5.2 The BWM and NE-BWM applications

In this section, using the data provided in Table 6.10 and Table 6.11 and the outcome of the STE-BWM using EAST and GMAST methods (Section 6.5.1), the original linear and non-linear BWM (L-BWM and NL-BWM) and the proposed NE-BWM are applied to prioritise the six energy risk dimensions. Note that, it is assumed in this analysis that all participated experts acquire relatively equal knowledge and expertise. Therefore, all experts are treated with equal level of importance weights in this study. The obtained weights from the applied methods as well as the final ranks of the risk dimensions are provided in Table 6.20 and Figure 6.10. The findings reveal that CC is the most critical energy risk dimension followed by ND, AF, ST, IA and PI.

Table 6.20 Weights and rankings of risks and aggregated final ranking

Risks	L-BWM	NL-BWM	NE-BWM	Average	Final ranks
AF	0.1447 (4)	0.1794 (2)	0.1824 (2)	0.1688	3
ND	0.1810 (2)	0.1752 (3)	0.1726 (3)	0.1763	2
IA	0.1189 (5)	0.1319 (5)	0.0843 (6)	0.1117	5
CC	0.3023 (1)	0.2455 (1)	0.2889 (1)	0.2789	1
ST	0.1467 (3)	0.1570 (4)	0.1586 (4)	0.1541	4
PI	0.1064 (6)	0.1110 (6)	0.1131 (5)	0.1102	6

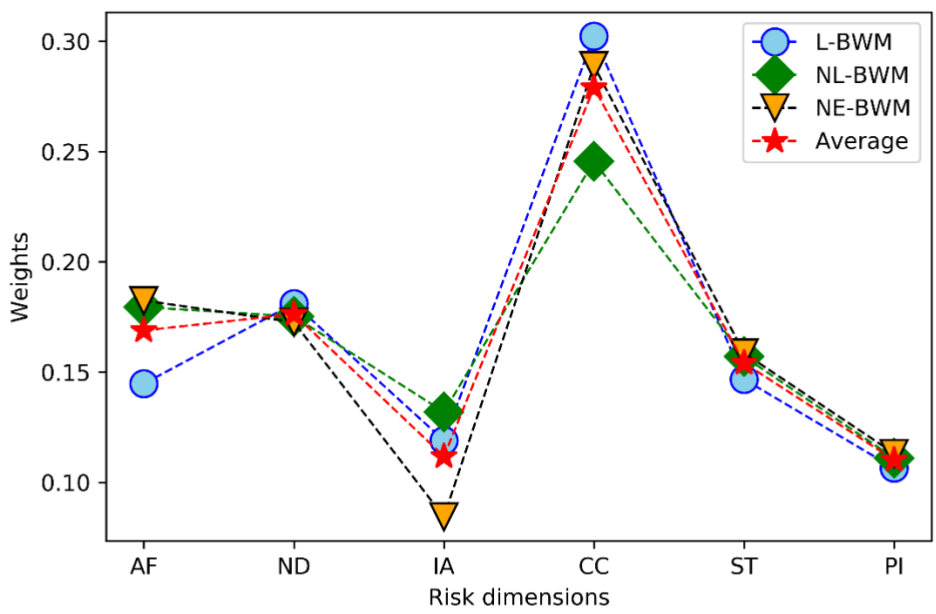


Figure 6.10 Weights and order of risk dimensions

6.6 Discussion

The applications of two proposed extended BWM under uncertain decision-making (i.e. NE-BWM and STE-BWM) were presented. The aim was the prioritisation of the six most important energy risk dimensions which have been obtained from the previous phase of thesis (Chapter 5). The results were compared to two original BWM including L-BWM and NL-BWM. As shown in Table 6.20, and Figure 6.10, the average weights have been used to introduce the final order of energy risk dimensions. The aggregated weights revealed that Climate Change (CC) is the most critical one followed by Natural Disasters (ND), Affordability (AF), Sabotage and Terrorism (ST), Industrial Action (IA), and Political Instability (PI), respectively. The Climate Change (CC) and Natural Disasters (ND) stood at the top of the list. Thus, it is of critical importance that policy makers focus on the Climate Change (CC), and Natural Disasters (ND) and identify the most critical Climate Change (CC), and Natural Disasters (ND) risk elements to the UK energy system.

The subjective uncertainty of the involved experts has been considered in two major ways as shown in STE-BWM for expert 4, and in NE-BWM for all experts. In the data collection survey, experts were provided with the opportunity to offer their opinions of the best (i.e. the most critical) and the worst (i.e. the least critical) risk dimension in terms of a set of criteria instead of only considering one single criterion. It was aimed at capturing uncertainty of experts in situations when there is a hesitancy or indeterminacy to choose one single risk dimension. Thus, as can be seen in Table 6.9 and Table 6.10, expert 4 had the hesitancy to choose only one best risk dimension (i.e. the most critical) over Natural Disasters (ND), and Sabotage and Terrorism (ST) and selected both of them as the best ones. The analysis results of the STE (i.e. EAST and GMAST) were shown in Section 6.5.1 and revealed that ND was marginally preferred over ST by expert 4, although they were not able to choose with absolute certainty only one risk dimension but with the aid of the STE method (i.e. EAST/GMAST) this issue has been overcome and the best risk dimension has been realised. Therefore, in the rest of the calculation steps in the BWM, and NE-BWM, Natural Disasters (ND) risk dimension was considered as the most important one recommended by expert 4.

Regarding the proposed NE-BWM, in order to capture the experts' uncertainty in selecting the best and worst risk dimension and subsequently the resulted comparisons in the original BWM, two parameters were proposed which are defined as $0 < \rho^+ \leq 1$ and $0 < \rho^- \leq 1$. In other words, in the original BWM, obtaining the weights of risks was irrespective of how certain an expert was about the two separations (I and II). The reason was that the two separations (I and II) were treated with equal importance while in real-world decision-making problems it would not be the case, mainly due to experts' indeterminacy in selecting the best and worst risks and consequently in the provided comparisons. As shown in Section 6.3, the performance of the proposed NE-BWM was also verified in two real-world case studies before its actual implementation in the energy risk dimensions analysis (See the Discussion in Section 6.3.4). In general, this lack of confidence could result from two interdependent causes: (1) hesitancy in opting the best and worst criteria, and/or (2) uncertainty or lack of confidence in the provided preferences (separations I and II). The ρ^+ and ρ^- are subjective values which can be dealt with by capturing the experts' opinions. Based on the NST (Table 4.2), ρ^+ and ρ^- represent the experts' degree of confidence on separations I and II. In the original BWM, either L-BWM or NL-BWM, experts are supposed to have the highest possible confidence on the two separations (i.e. $\rho^+ = 1$ and $\rho^- = 1$), in fact it is assuming experts have no uncertainty which is not realistic.

6.7 Conclusions

In this chapter, the application of the two proposed methods STE-BWM and NE-BWM in obtaining the final ranking of the six significant UK energy risk dimensions resulted from the previous phase of the thesis (Chapter 5) was shown. The objective was to develop and apply two extensions of the BWM (i.e. STE-BWM and NE-BWM) so as to prioritise important energy risks obtained from the interrelationship analysis in previous chapter. Thus, objectives in this chapter were twofold:

(1) to theoretically enhance the BWM method

(2) to practically apply it in the UK energy supply chain risks prioritisation in order to show the applicability of methodological extensions of the BWM as well as confirming the most critical risk dimensions which were identified in the previous chapter.

The findings revealed that Climate Change (CC) is the most critical energy risk dimension followed by Natural Disasters (ND), Affordability (AF), Sabotage and Terrorism (ST), Industrial Action (IA), and Political Instability (PI).

This study focused on representing the applicability of the methodological development of the original BWM in terms of capturing uncertainty. It revealed a need to improve the original BWM and proposed an extension of the method based on the NST called NE-BWM as well as STE-BWM which is based on spanning trees enumeration methods (EAST and GMAST).

The degree of the experts' confidence on the best-to-others preferences (Separation I), and others-to-worst preferences (Separation II) have been overlooked in the original BWM. The NE-BWM was proposed to overcome the explained shortcomings of the original BWM in the real-world under uncertainty applications. The validity of the proposed NE-BWM was analysed in two real-world cases in supply chain management. In each case, 20 test problems were analysed and compared with one test problem of the original NL-BWM. The CR calculation in the NE-BWM was also elaborated in detail. Furthermore, a new measurement index named CD was proposed which takes into consideration the extent of the discrepancy between the DMs' evaluations on the separations I and II. The NE-BWM can assist decision makers achieve more reliable rankings in real-world decision-making problems.

The STE-BWM would strengthen the capability of the original BWM (either L-BWM or NL-BWM) in capturing experts' uncertainty by offering them the opportunity to choose the best set and the worst set of criteria (i.e. risk dimensions) compared to choosing only one criterion as the best and one as the worst as is common in the original BWM.

6.7.1 Limitations and future research directions

Regarding the verification of the proposed NE-BWM, there is a limitation about the small number of application cases which might make it rather hard to generalise the findings from the proposed NE-BWM. The other limitation is about the complexity of implementation of the proposed STE-BWM which makes it costly and time consuming and not handy for all researchers in spite of its promising merits. An additional limitation is a common one among MCDM methods which is about limited number of involved experts. The reason might partly be due to the difficulty of recruiting higher number of experts from multidisciplinary fields such as risks in energy supply chain management.

In future studies, a Monte Carlo simulation can be a suitable choice to overcome the issue of a limited number of application cases which can improve the generalisability of results. For instance, by a larger sample or numerical simulations the generalisability of the obtained relationship between CD and CR in our case studies can be confirmed. Secondly, given that uncertainty leads to higher inconsistency (i.e., it has been confirmed that a higher CD value would result in a higher CR value), thus, there would be a necessity for processes that mitigate inconsistency to be further investigated. Thirdly, the proposed model can also be compared to the other uncertainty extensions of the original BWM integrated with uncertainty theories like FST. Using the idea of Interval Valued Neutrosophic Sets (IVNS) as another future research direction can be a suitable alternative to SVNS. It can be applied in conjunction with the enhanced BWM, in order to structure the confidence rating scale more properly by shifting from a single point to an interval.

Chapter 7 Risk Mitigation Analysis

7.1 Introduction and Background

In the previous chapter, it was found that Climate Change (CC), and Natural Disasters (ND) are the most critical energy risk dimensions in the UK energy supply chain. As a result, the next step of this thesis focuses on an innovative risk mitigation modelling based on the Concept of Stratification (CST) (see Section 3.6), game theory (see Section 3.7) and Shared Socio-economic Pathway (SSP) (see Section 7.2). The aim is to deal with the most significant natural disaster risk to the UK infrastructure (i.e. flooding) for the long-term policy making (between 5 to 20 years) with reference to the UK socio-economic status. In Figure 7.1, the details of the study in Chapter 7 are highlighted.

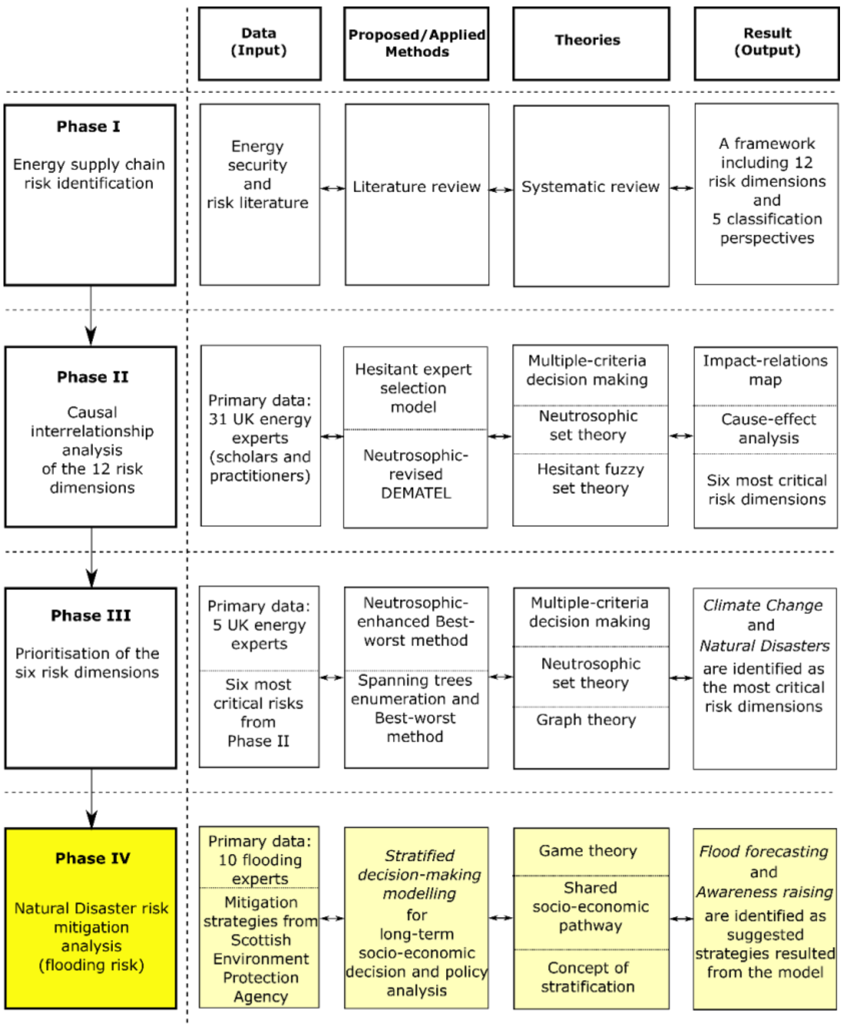


Figure 7.1 Final phase of the research carried out in this chapter

The UK has been a pioneer in developing a national evaluation of climate change risks (Warren et al., 2018), and has been ranked 8th least vulnerable, and 14th most ready for climate change in 2016, based on Notre Dame Global Adaptation Initiative (ND-GAIN) (Chen et al., 2015). In the UK, within the 2008 Climate Change Act there has been an obligation for the UK Government to evaluate the risks of current and estimated impacts of climate change through Climate Change Risk Assessment (CCRA) reports (Warren et al., 2018). The aim is to inform priorities for the UK Government's National Adaptation Programme (NAP). Two rounds of CCRA have been done so far, implementing different methodologies which are CCRA1 in 2012, and CCRA2 in 2017. The CCRA2 was carried out in partnership with the Adaptation Sub-Committee (ASC) (Warren et al., 2016). Warren et al. (2016) explains that in CCRA2, the goal was to determine where immediate actions are required over the five-year period of NAP (2018-2022) by recognising adaptation choices.

The CCRA2 recognised flooding and coastal change as one of the six risks with high priority in need of urgent action in the UK. Flooding is also recognised as a critical risk to infrastructure by CCRA2 (Committee on Climate Change, 2019; Sayers et al., 2015). Flooding in the UK is expected to increase while flood damage costs the UK around £1.3 billion yearly (Committee on Climate Change, 2012). By the 2080s, flooding can cost the UK approximately £27 billion yearly under a high global emission scenario (Foresight Future Flooding, 2004). In Figure 7.2, with reference to CCRA2, top six areas of inter-connected climate change risks for the UK is provided. The definition of urgency categories are presented as follows (Committee on Climate Change, 2016):

1. ***More action needed:*** It indicates that new, and stronger government policies or implementation activities are required so as to decrease long-term vulnerability to climate change.

2. ***Research priority:*** It emphasises the need for research in order to fill the gap and eliminate the uncertainty and evaluate further required actions.

3. ***Sustain current action***: It states that the current or planned activities are good enough and should be continued.

4. ***Watching brief:*** It indicates that evidence should be kept under review considering long-term risk levels monitoring so as to ensure proper action can be taken if needed.

The categories *more action needed*, and *research priority* are more urgent compared to *sustain current action*, and *watching brief*.

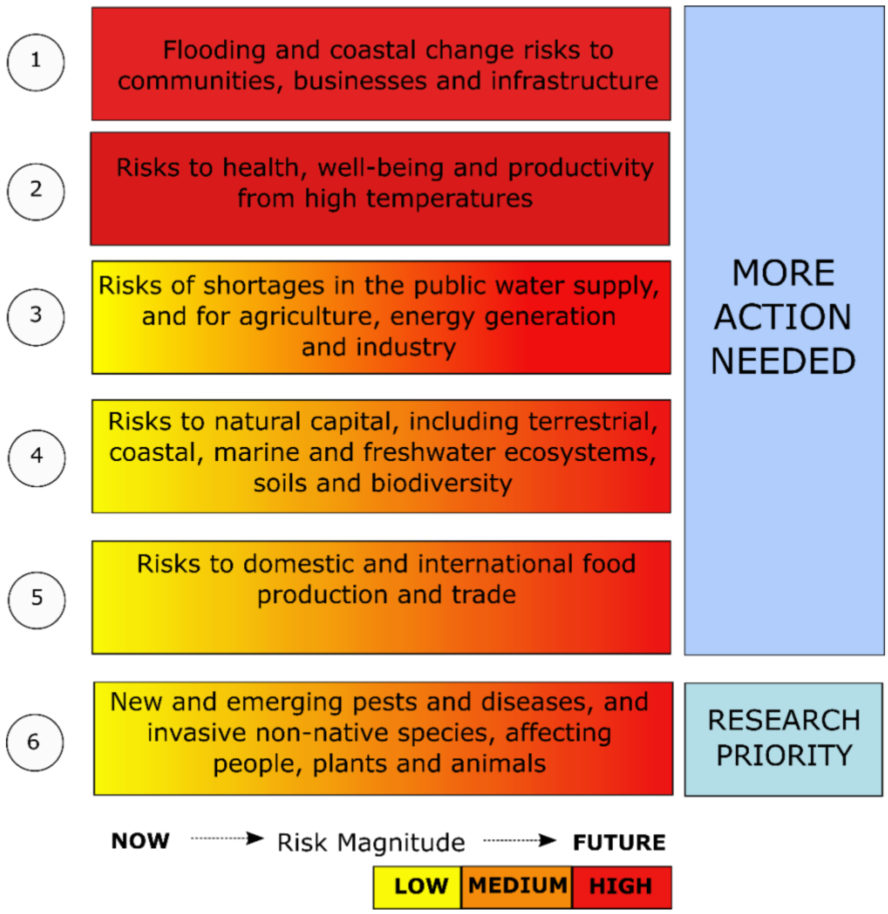


Figure 7.2 The top six UK climate change risks (Committee on Climate Change, 2016)

The CCRA2 estimates that there is a large increase in both the number of people at risk from flooding and related costs in the future, if no extra adaptation above current levels is put in place (Committee on Climate Change, 2019). Additionally, Dawson et al. (2018) indicated that flooding can result in severe disruptions and damage to power stations compared to other infrastructure assets (see Table 7.1 adapted from Dawson et al. (2018)).

Table 7.1 Various infrastructure assets at risk from flooding in the UK (%)

	Source of flooding		
	River or coastal	Surface water	Groundwater
Power stations	41	6	18
Railway track	17	9	17
Railway stations	14	3	16
Motorways and A-roads	9	6	9
Clean water and wastewater treatment plants	33	12	24

The way that climate change risks can affect the UK energy supply chain can be realised better by taking a systemic approach (Figure 7.3) with reference to Dawson et al. (2018). As it is shown in Figure 7.3, energy supply chain risks can be recognised as the systemic risks which are located at the bottom of the provided framework.

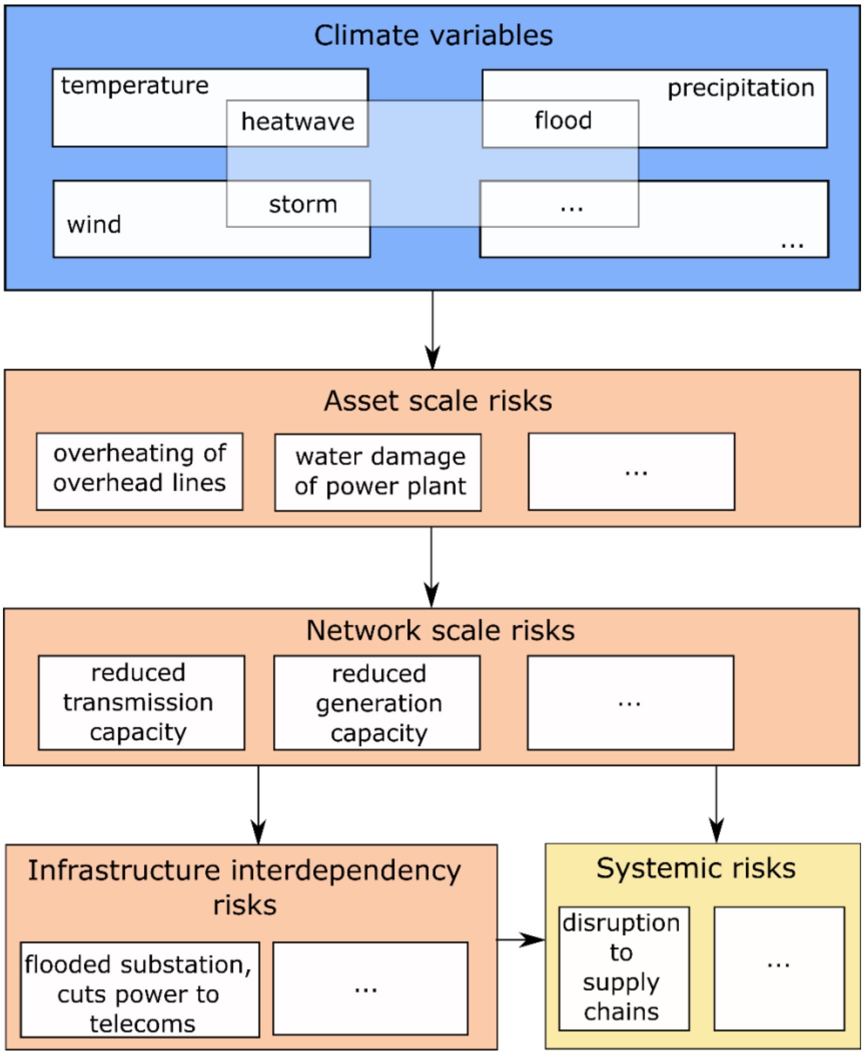


Figure 7.3 A systemic approach to climate change risk assessment framework for infrastructures (Dawson et al., 2018)

Knowing that, the literature strongly indicates that flooding is a crucial natural disaster threatening infrastructure and life in the UK. In this study, it is tried to introduce a useful decision analysis model from the realm of decision making in order to enhance long-term policy making in a flooding risk mitigation strategy selection. The focus of this research is on flooding in the Highland and Argyll district in Scotland. The reason is that the expected annual flood damage in Scotland is £252 million (56% river flooding, 23% surface water flooding, and 21% coastal flooding) within 2016-2021. This amount can be increased considering the climate change effects as well as challenges to mitigation and adaptation that the country might face in its long-term planning (Kenyon, 2007; SEPA, 2016). This considerable cost of flooding has sparked interest in flood risk assessment by policy makers necessitating sophisticated techniques to deal with long-term strategy selection via informed decisions. The

Scottish Environment Protection Agency (SEPA) is the Scotland's strategic flood risk management authority and has provided strategies for 14 local plan districts in Scotland. Among them, Highland and Argyll district has 4600 residential and 2700 non-residential properties which are at risk of flooding in the region with estimated annual damage across the region accrued to £26.5 million (SEPA, 2015) indicating the critical risk of flooding in the region.

The effects of flooding as a serious natural disaster in the UK can threaten the energy generation and distribution efficiency in the UK energy supply chain as the relationship between floods and energy infrastructure including generation and distribution is strong (Figure 7.4) (Dawson et al., 2018). It has been also indicated in the literature that taking into account uncertainty is critical for properly incorporating resilience into flood risk management programs. Additionally, a flood management program shall be assessed against a more comprehensive set of criteria such as those related to climate change adaptation (Associated Programme on Flood Management, 2015).

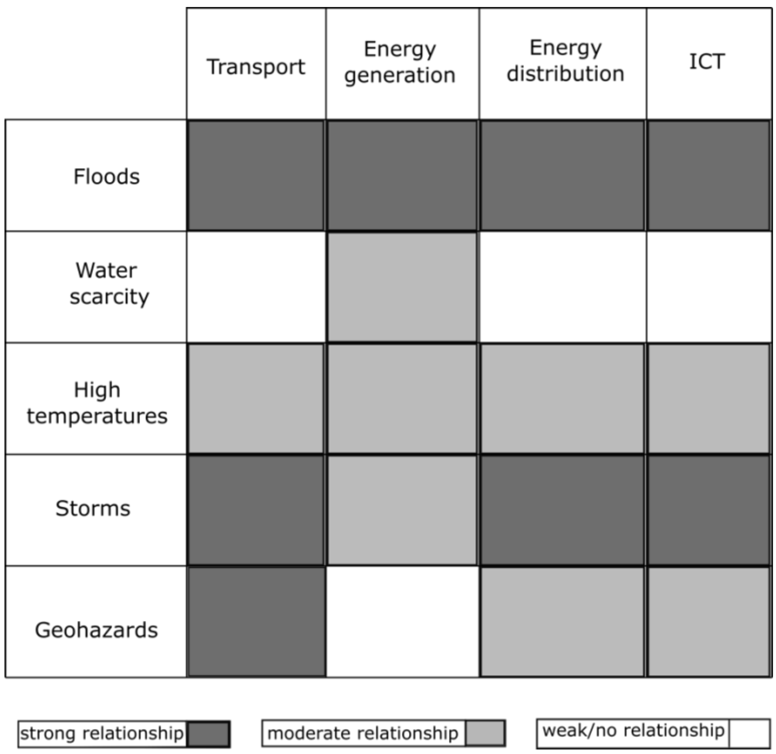


Figure 7.4 Relationships between climate hazards and infrastructure sectors [adapted from (Dawson et al., 2018)]

The contributions of this study are listed as follows:

(I) A novel stratified decision-making model is introduced on the basis of the Concept of Stratification (CST), game theory, and Shared Socio-economic Pathway (SSP).

(II) Managing impacts of flooding risk in the Highland and Argyll region in Scotland by identifying the most suitable strategies and proposing the priorities for action based on a novel stratified decision-making model. It is important to know that 4600 residential and 2700 non-residential properties are at risk of flooding in the region with estimated annual damage across the region accrued to £26.5 million (SEPA, 2015). This amount can increase in the next years due to climate change and UK socio-economic status. This would necessitate the need for such a decision model for long-term decision making due to importance of the issue in the region.

7.2 Methodology

The applied model is named stratified decision-making model which is based on the stratified model of game of chance involving risk that was explained in detail in Section 4.6. The main contribution of this model is proposing a stratified decision-making modelling for long-term decision making. It considers system's dynamics on the basis of the CST, game theory and SSP. The most suitable flooding risk mitigation strategies have been selected by taking into account the dynamic of the UK challenges to adaptation and mitigation based on SSP and flooding risk impacts based on MI, MO, and SV levels. The theories which are utilised in the applied model are CST and game theory which are explained in Section 3.6 and Section 3.7, respectively. Here, the SSP is explained. The SSP as discussed in Kriegler et al., (2012) defines two dimensions of Challenges to Adaptation and Challenges to Mitigation explained in the following parts:

Challenges to Adaptation:

Socio-economic conditions that, in the absence of climate-related policies, would result in higher vulnerability, and less adaptation capacity for a given level of climate change (Kriegler et al., 2012).

Challenges to Mitigation:

Socio-economic conditions that in the absence of climate-related policies, would result in higher emissions, and poorly suited technological, or institutional conditions to reduce emissions (Kriegler et al., 2012).

The nine possible SSPs based on the three-point scale on each dimension are presented in Figure 7.5. In this study, the three SSPs (i.e. SSP1, SSP5, and SSP9) are considered for simplicity. The SSP1, SSP5, and SSP9 correspond to low, moderate, and high challenges to adaptation and mitigation, respectively.

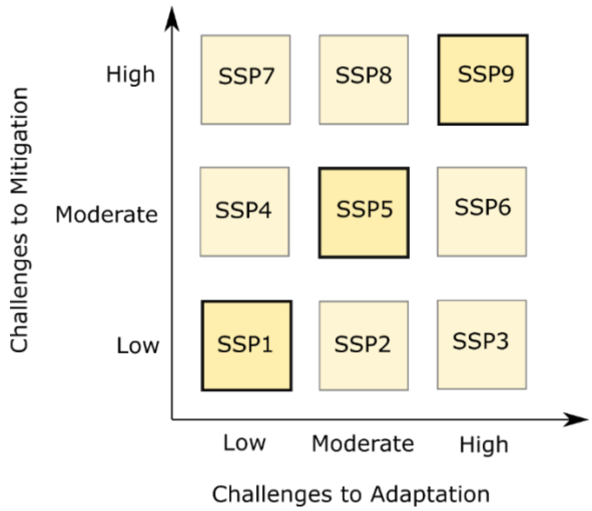


Figure 7.5 Nine SSPs on two dimensions of challenges to mitigation and adaptation

The obtained solutions in game theory are generally acquired via considering the interaction between the involved players. This process can be recognised in a form of "interactive decision theory" (Zhao et al., 2012). In decision making, not only the outcome from a particular strategy is seldom fully predictable but also the strategy-performance relationships would not remain unchanged. This indicates the importance of adaptive decision making depending on the observed performances of previous choices. This can be more crucial when other decision circumstances change simultaneously (Kahneman and Tversky, 1979; Lee, 2008). Game theory has been called the science of strategic decision making (Kelly, 2003). However, in some games like games of chance (i.e. one-player game against nature), the dynamic change of various states of the system in a long-term decision-making time frame has been overlooked. In games of chance, the current state of the system has been considered unchanged during the decision-making timescale. This fixed state of the game makes the obtained decision useful in a longer time frame if only the current state at the time of arriving to a decision persists, which in reality occurs rarely. The reason for this shortcoming might be due to lack of a proper theory to formulate dynamic change of states throughout a longer decision-making period.

This study benefited from integration of CST and game of chance involving risk to overcome the explained gap in the long-term decision analysis. The model introduces a novel decision-making framework for long-term decision-making planning. The proposed model is a stratified decision-making model under risk or a stratified decision-making model of game of chance involving risk. In this study, it is named as a stratified decision-making model. Colman (1982) explained that games of chance are called "individual decision making under risk or uncertainty". The stratified model is surmised to be cogently an effective methodology for interpreting the interplay between socio-economic situations and natural disasters in this study to make an optimum decision in the longer timescale. The outcomes of a game of chance depend partly on the player's choices and partly on nature, who is a second player. A number of DMs, experts or players can get involved to provide the parameters' values. Although the player does not know with certainty what moves will be made by nature, they know the meaningful probability of each of nature's responses and therefore the approximate probability of success for each of their strategies or actions. In this study, to show the applicability of the proposed decision model (Section 4.6), the model is utilised to evaluate flooding risk mitigation strategies in the Highland and Argyll district in Scotland, considering the dynamic nature of socio-economic situations and climate hazards severity impact levels in the long-term.

The CST, as explained in Section 3.6 is a computational system where the elements of computation are strata of data. An example of a system with a stratified structure can be a multi-layer perception (Zadeh, 2016). The stratified approach has gained attention in the academic literature. However, there are only a handful of studies exploring the capability of CST to date. For instance, Asadabadi (2018) developed a Stratified MCDM (S-MCDM). Asadabadi and Zwikael (2019) proposed an extended version of stratified MCDM in order to address an important challenge of time and cost estimations in project management. Asadabadi et al. (2017) showed the practicality of CST in the field of logistic informatics modelling and revealed how the user would benefit from hybrid utilisation of Fuzzy Inference System (FIS) and CST. Asadabadi et al. (2018) discussed and proposed Bi-Objective CST (BO-CST) and Fuzzy Bi-Objective CST (FBO-CST) models for the unequal importance objective weights in the original CST.

7.3 Data Collection

The data collection has been carried out in two stages: (1) screening; and (2) actual data collection.

1) Screening stage

In screening stage, 57 potential experts with sufficient knowledge and expertise in flood management have been chosen based on search of relevant websites and databases. Then, they were sent a short survey to self evaluate their level of knowledge and expertise in flood risk management in Scotland using a scale 1 to 100. Those who gave themselves a value greater than 70 have been considered for the actual data collection. Regarding the defined criteria, 13 experts have been chosen for the next actual stage of data collection.

2) Actual stage

In actual data collection, 13 surveys have been sent to experts and 10 responses have been received which have been considered for analysis. Thus, the data is collected from 10 flooding experts in the region of Scotland who participated in the online survey to answer the provided questions. In Appendix L, the questions used in the survey are explained in detail. The survey questions are constructed based on the rating scales provided in Table 7.2, and Table 7.3. In Table 7.2, the linguistic scale utilised by experts for estimating the utility values of each flooding risk mitigation strategy is provided.

Table 7.2 The verbal scale for obtaining utility values

Linguistic Phrase	Score	SVTNN	Expected Utility
No Effectiveness (NE)	0	<(0,0,0,0);0,0,0>	0
Low Effectiveness (LE)	1	<(0.2,0.3,0.4,0.5);0.6,0.2,0.2>	0.26
Fairly Low Effectiveness (FLE)	2	<(0.3,0.4,0.5,0.6);0.7,0.1,0.1>	0.38
Medium Effectiveness (ME)	3	<(0.4,0.5,0.6,0.7);0.8,0,0.1>	0.50
Fairly High Effectiveness (FHE)	4	<(0.7,0.8,0.9,1);0.8,0.2,0.2>	0.68
High Effectiveness (HE)	5	<(1,1,1,1);0.9,0.1,0.1>	0.90
Absolutely High Effectiveness (AHE)	6	<(1,1,1,1);1,0,0>	1

The following rating scale (Table 7.3) is introduced based on Haase et al. (2013) and Govindan et al. (2015) to obtain the estimated status transition and outcome transition probabilities. The Trapezoidal Intuitionistic Fuzzy Number (TrIFN) is a type of intuitionistic number which is explained in Appendix A that is applied here to capture subjective uncertainty of experts in the probability estimations.

Table 7.3 The rating scale used for acquiring probability estimations

Linguistic Phrase	Score	TrIFNs	Expected probability
Almost Zero (AZ)	0	$\langle (0,0,0,0),(0,0,0,0)\rangle$	0
Very Small (VS)	1	$\langle (0,0.1,0.2,0.3),(0,0.1,0.2,0.3)\rangle$	0.15
Small (S)	2	$\langle (0.1,0.2,03,0.4),(0,0.2,0.3,0.5)\rangle$	0.25
Moderate (M)	3	$\langle (0.3,0.4,05,0.6),(0.2,0.4,05,0.7)\rangle$	0.45
Large (L)	4	$\langle (0.5,0.6,07,0.8),(0.4,0.6,07,0.9)\rangle$	0.65
Very Large (VL)	5	$\langle (0.7,0.8,09,1),(0.7,0.8,09,1)\rangle$	0.85
Almost Certain (AC)	6	$\langle (1,1,1,1),(1,1,1,1)\rangle$	1

7.4 Analysis

As explained previously, the region Highland and Argyll in Scotland has been considered in this study. The recommended strategies can manage flood risk (i.e. a major climate hazard in the UK) to energy infrastructure as shown in Table 7.5 (SEPA, 2015).

The proposed model considers both the socio-economic status of the UK influencing the adaptation options utilising the concept of SSP (i.e. *low* challenges to mitigation and adaptation, *moderate* challenges to mitigation and adaptation, *high* challenges to mitigation and adaptation) (Kriegler et al., 2012), and impact level of the flooding risk (i.e. mild, moderate and severe) to the energy infrastructure. The model also considers the transitions between various possible states in a longer timeframe (5 to 20 years) by taking into account the transition probabilities between socio-economic status, and flooding risks. This helps provide a model that can be more reliable in identifying the most effective strategies for long-term planning.

The benefits obtained from strategies in each state (payoff or utility values) would not be always easy to assess precisely in quantitative values. Especially when the strategies include policy, regulatory, and community responses in addition to engineering responses. It is indicated that much of the evidence of adaption activity for UK infrastructures concentrates on engineering responses rather than policy, regulatory or community responses and the reason is that for engineering responses quantitatively assessing the benefits is typically easier (Dawson et al., 2018).

To categorise climate hazards based on impact severity, three levels of Mild (MI), Moderate (MO), and Severe (SV) are chosen regarding the flood risk matrix of Scottish Flood Forecasting Service (SFFS) (Figure 7.6). As shown in Figure 7.6, the potential impacts of flooding (river, tidal/coastal, and surface water) can be categorised in four levels of *minimal*, *minor*, *significant*, and *severe* based on the SFFS (2014). However, knowing *minimal* and *minor* levels are very close, thus for the sake of simplicity in later computational steps and considering other international definitions like Malaysian National Security Council (2003), just a level mild (MI) has been defined along with moderate (MO) and severe (SV). The provided three levels of MI, MO, and SV are well representative of the impact severity of floods. The three levels I, II and III or MI, MO, and SV have been defined respectively as follows (Rahman, 2012):

Level I, or MI

Climate hazards are controllable and with no possibility of spreading out. They are not complicated and may cause a small damage to life and property.

Level II, or MO

Climate hazards cover a wide range area and have potential to spread out while affecting public daily activities. They would possibly cause damage to a large number of properties and could cause loss of life. Their complexity level is higher than level I and in terms of search and rescue are very challenging but could be controlled by the government.

Level III, or SV

Any disaster caused at this level is more complex in nature compared to other levels and affects a wide area (more than two provinces) while causing the highest damage possible to life and property.

The risk assessment can be carried out on the basis of impact and likelihood of flooding to give a combined risk as shown in Figure 7.6. In this study, just the potential impact of flooding is considered in three levels of MI, MO, and SV in the introduced model, and likelihood of flooding risk is not considered as this would need to be based on climate modelling which is not the focus of this thesis.

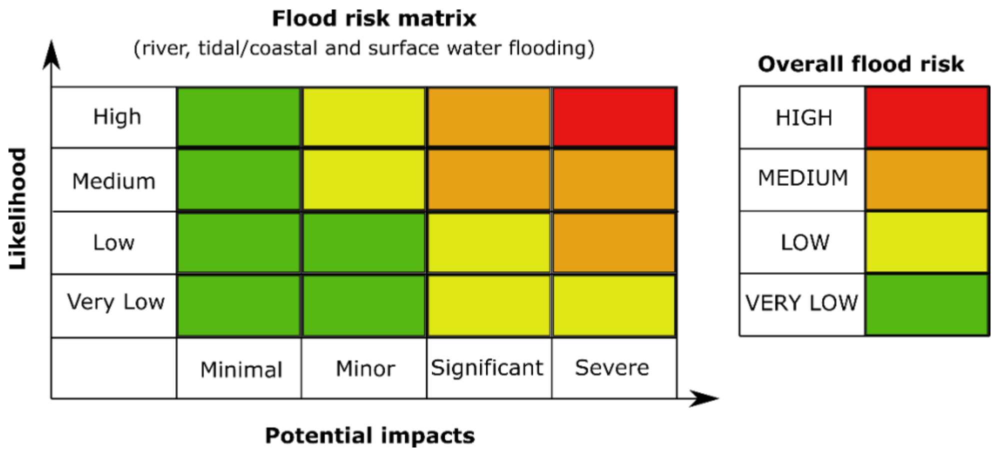


Figure 7.6 Flood risk matrix and overall flood risk (SFFS, 2014)

Floods can have direct or indirect damages. Direct flood damages are related to immediate effects of flood water with built, natural or human environments. Indirect damages cover disruptions of transportation and economy which influence people's income (Associated Programme on Flood Management, 2015).

It is assumed that the socio-economic situation can cause Low (L), Moderate (M), or High (H) challenges to mitigation and adaptation based on the SSP (Figure 7.5). Furthermore, the impact of flooding can be MI, MO, or SV. Thus, the stratified game table with three statuses ($N = 3$) and three outcomes ($M = 3$) can be constructed as shown in Table 7.4.

Table 7.4 The stratified game table of flood risk management for $N=3$ and $M=3$

Socio-Economic Situation	Strategies	Climate Hazards (Flooding)		
		Mild (MI)	Moderate (MO)	Severe (SV)
Low Challenges to Mitigation and Adaptation (L)	Awareness Raising Emergency Plans/Response Flood Forecasting Self Help Maintenance Planning Policies	SE_1	SE_2	SE_3
Moderate Challenges to Mitigation and Adaptation (M)	Awareness Raising Emergency Plans/Response Flood Forecasting Self Help Maintenance Planning Policies	SE_4	SE_5	SE_6
High Challenges to Mitigation and Adaptation (H)	Awareness Raising Emergency Plans/Response Flood Forecasting Self Help Maintenance Planning Policies	SE_7	SE_8	SE_9

Table 7.5 Flooding risk management strategies (SEPA, 2015)

No.	Strategy	Characteristics
1	Awareness raising	Raising public awareness of flood risk is a duty of responsible authorities. Enhanced awareness of individuals, homes, and businesses regarding flood risk and related measures can lessen the total impact.
2	Emergency plans/response	Many organisations have responsibility to provide an emergency response to flooding, including local authorities and emergency services. This response may be supported by the work of voluntary organisations.
3	Flood forecasting	Issuing flood warnings by the Scottish Flood Forecasting Service (SFFS) via offering daily flood guidance statements can provide the public with information to lower the impacts of flooding on their business.
4	Self help	Property and business owners can make sure they are protected against flood damage by taking simple, yet effective steps such as arranging a flood plan or property level protection via registering at Floodline and the Resilient Communities Initiative.
5	Maintenance	It is of local authorities' duty to evaluate watercourses and do clearance and repair works where such actions would significantly minimise flood risk.
6	Planning policies	The Scottish Planning Policy supports a catchment scale approach for sustainable flood risk management. It suggests that new development in areas with medium to high likelihood of flooding should be avoided.

7.4.1 Scenario settings for inputs in CST

The performance of the considered strategies is evaluated in 5 to 20-year planning horizon via the proposed model. The influence of inputs on the state change should be evaluated in the understanding that state 1 is the target state and cannot be improved. Incremental enlargement in CST as a tool to identify possible paths towards the target state is considered in various ways in each Scenario (Section 3.6).

7.4.1.1 Scenario 1: optimistic improvement

In this scenario, all possible improvements are considered even those which can make an enormous difference. That is transition by incremental enlargement from the worst state to the best state is possible.

7.4.1.2 Scenario 2: cautious improvement

In this scenario, the state transitions are occurring towards the improvement of the system or not becoming worse. The incremental enlargement takes place at one step towards the target state which means inputs of the system cannot make the transition possible from a very poor situation to the very best situation in one move, indicating cautious or more realistic improvement.

Table 7.6 Tabular CST for the flood risk management example

SE_t	Socio-economic situation	Flooding hazard	SE_{t+1}	
			Scenario 1	Scenario 2
1	L	MI	1	1
2	L	MO	1,2	1,2
3	L	SV	1,2,3	2,3
4	M	MI	1,4	1,4
5	M	MO	1,2,4,5	1,2,4,5
6	M	SV	1,2,3,4,5,6	2,3,5,6
7	H	MI	1,4,7	4,7
8	H	MO	1,2,4,5,7,8	4,5,7,8
9	H	SV	1,2,3,4,5,6,7,8,9	5,6,8,9

State 1 is the target state. Inputs can be categorised into variables *partly in control* or *out of control* like climate change and natural disasters; and *in control* of the system analysts and associated authorities such as economic policies. In this study, only the outcomes and resulted states under various scenarios are considered.

7.4.2 Parameters settings

In this section, parameters setting for the status and outcome transition probabilities and utility function values are explained.

7.4.2.1 Status and outcome transition probability values

In scenario 1, the values of $p_{11} = 1, p_{12} = p_{13} = p_{23} = 0$, and $q_{11} = 1, q_{12} = q_{13} = q_{23} = 0$ are fixed. In scenario 2, the values of $p_{11} = 1, p_{12} = p_{13} = p_{23} = p_{31} = 0$, and $q_{11} = 1, q_{12} = q_{13} = q_{23} = q_{31} = 0$ are fixed as shown in Table 7.7 and Appendix L. Status and outcome transitions are explained in Section 4.6.2 and Section 4.6.3. Other probabilities can change based on the experts' opinions and collected data (Table 7.7). The average of obtained values from experts are taken into consideration and all experts' opinions are treated with the same level of importance. Details about the utilised surveys and how probability values are acquired can be seen in Appendix L.

Table 7.7 Status and outcome transition probabilities setting for different scenarios based on average experts' opinions

Scenario **1**: optimistic							
	Status transition probability matrix				Outcome transition probability matrix		
	$p_{11}=1$	$p_{12}=0$	$p_{13}=0$		$q_{11}=1$	$q_{12}=0$	$q_{13}=0$
P	$p_{21}=0.37$	$p_{22}=0.63$	$p_{23}=0$	Q	$q_{21}=0.43$	$q_{22}=0.57$	$q_{23}=0$
	$p_{31}=0.35$	$p_{32}=0.40$	$p_{33}=0.25$		$q_{31}=0.32$	$q_{32}=0.34$	$q_{33}=0.34$
Scenario 2: cautious							
	Status transition probability matrix				Outcome transition probability matrix		
	$p_{11}=1$	$p_{12}=0$	$p_{13}=0$		$q_{11}=1$	$q_{12}=0$	$q_{13}=0$
P	$p_{21}=0.46$	$p_{22}=0.54$	$p_{23}=0$	Q	$q_{21}=0.44$	$q_{22}=0.56$	$q_{23}=0$
	$p_{31}=0$	$p_{32}=0.39$	$p_{33}=0.61$		$q_{31}=0$	$q_{32}=0.44$	$q_{33}=0.56$

In Figure 7.7, the graphical CST with transition probabilities based on optimistic scenario (scenario 1) is depicted. The values are calculated based on the provided probabilities in Table 7.7 and Equation (4.30). The pseudo code for the calculation of the state transition probability matrix presented in Table 4.7 can be helpful in the calculation process.

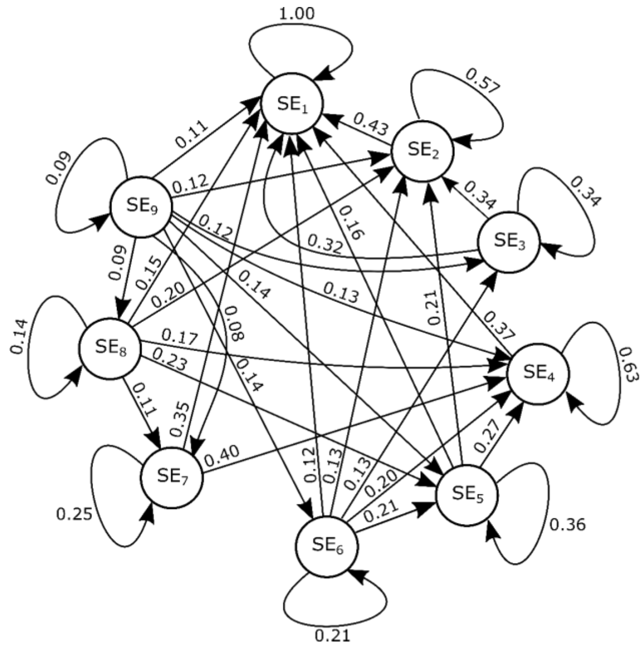


Figure 7.7 Graphical CST with transition probabilities for the flood risk planning (scenario 1)

In Figure 7.8, the graphical CST with transition probabilities based on cautious scenario (scenario 2) is provided.

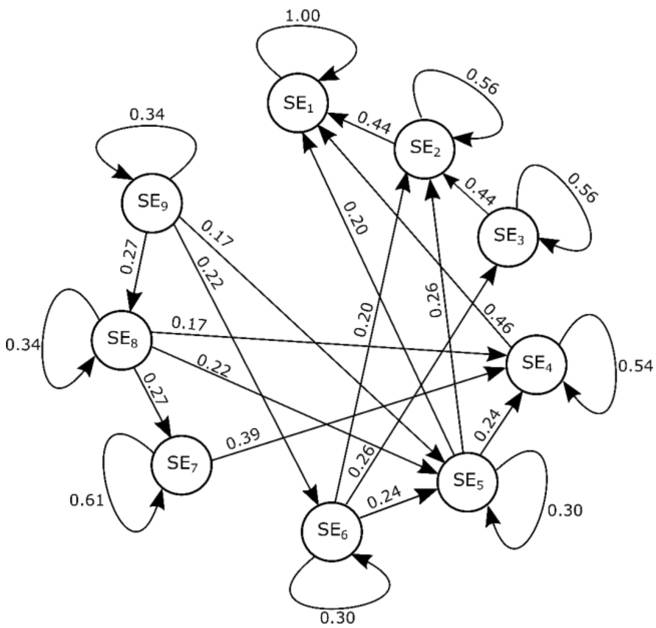


Figure 7.8 Graphical CST with transition probabilities for the flood risk planning (scenario 2)

7.4.2.2 Utility values

Based on the rating scale provided in Table 7.2, and the survey explained in Appendix L, the utility values of strategies are obtained on the basis of the average values offered by all experts (Table 7.8).

Table 7.8 Utility values

			outcome		
status		strategy	MI	MO	SV
L	1	Awareness raising	0.5960	0.5140	0.5400
	2	Emergency plans/response	0.5450	0.5110	0.5050
	3	Flood forecasting	0.5110	0.5100	0.5320
	4	Self help	0.4620	0.4720	0.4460
	5	Maintenance	0.4820	0.4880	0.4800
	6	Planning policies	0.4670	0.4770	0.4650
M	1	Awareness raising	0.4720	0.5250	0.5480
	2	Emergency plans/response	0.5520	0.5120	0.5143
	3	Flood forecasting	0.5730	0.5860	0.6080
	4	Self help	0.4940	0.5160	0.5180
	5	Maintenance	0.4960	0.4850	0.5700
	6	Planning policies	0.5350	0.5680	0.5970
H	1	Awareness raising	0.5613	0.6220	0.5310
	2	Emergency plans/response	0.5220	0.5680	0.5460
	3	Flood forecasting	0.6547	0.6310	0.6450
	4	Self help	0.5140	0.5620	0.5600
	5	Maintenance	0.6430	0.6200	0.6830
	6	Planning policies	0.6180	0.6240	0.6000

In Figure 7.9, the trend of utility values for each strategy under various flooding risk impact levels, and socio-economic status are depicted.

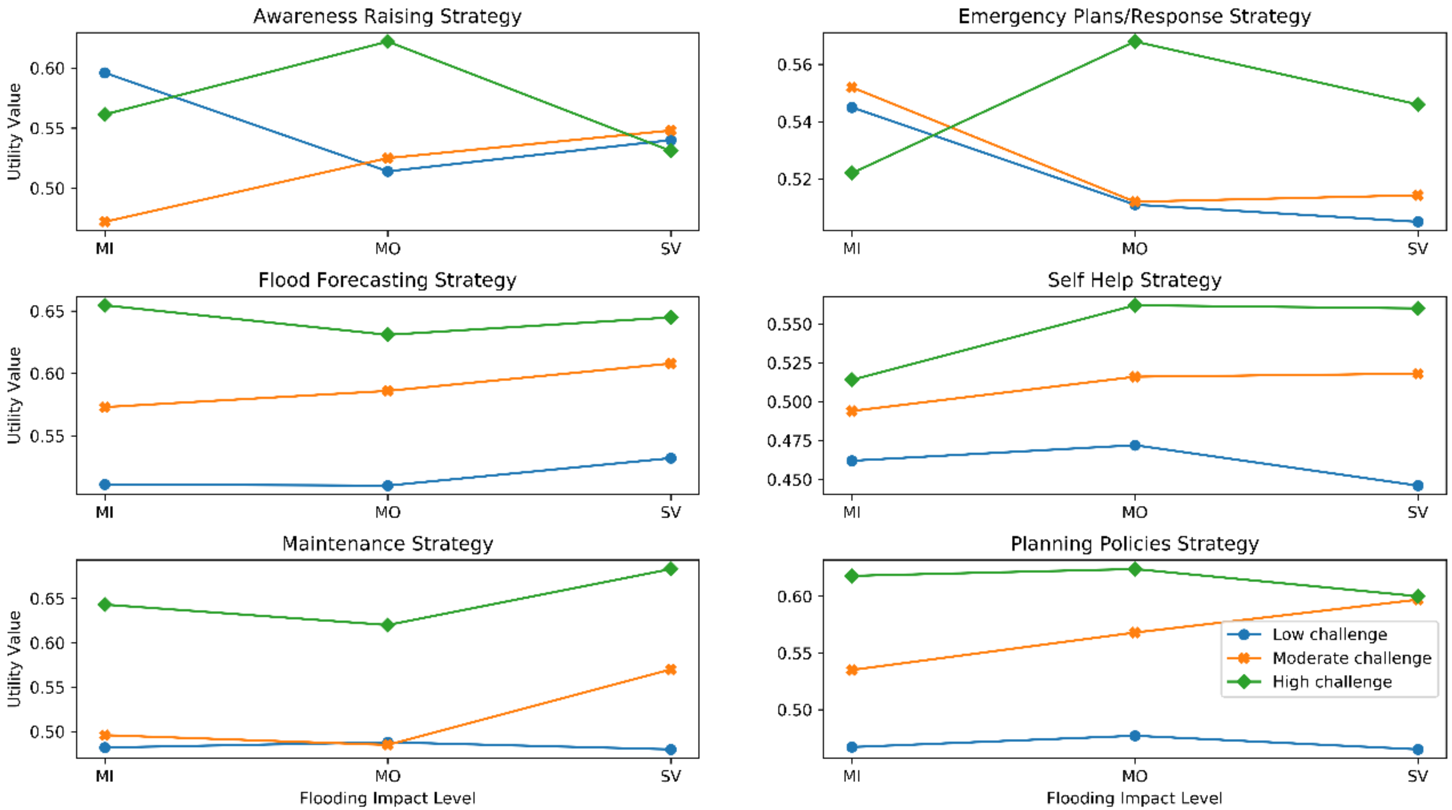


Figure 7.9 Utility values for each strategy under various flooding risk impact levels, and socio-economic status determined by experts

7.4.3 Results

The after-transition utility decision matrices for scenario 1 (Table 7.9), and scenario 2 (Table 7.11) are calculated based on Equation (4.34), and Table 4.8. The EMVs are also calculated based on Equation (4.35). The calculations are carried out under the assumption of equal current state probabilities (i.e. 0.11). The current state is the state at the present time of planning with current or very near future that the socio-economic status and flooding risk impact can be framed. If we are 100% sure about the current state, then this will get the probability 1 and other states will get probabilities of zero and automatically will be removed from the EMV calculation. In Section 7.5, the sensitivity analysis of the current state probabilities under various schemes are provided. Table 7.10, and Table 7.12 provide rankings of strategies under equal current state probabilities in scenarios 1 and 2, respectively.

The analysis findings suggest that in the area of Highland and Argyll in Scotland the best long-term flood mitigating strategy is flood forecasting (i.e. Strategy 3) followed by awareness raising (i.e. Strategy 1), emergency plans/response (i.e. Strategy 2), planning policies (i.e. Strategy 6), maintenance (i.e. Strategy 5), and self help (i.e. Strategy 4), respectively.

Table 7.9 The after-transition utility decision matrix (scenario 1)

Current state probability	**0.11**	**0.11**	**0.11**	**0.11**	**0.11**	**0.11**	**0.11**	**0.11**	**0.11**	
Strategies	SE_1	SE_2	SE_3	SE_4	SE_5	SE_6	SE_7	SE_8	SE_9	**EMV**
Strategy **1**	0.5960	0.5493	0.5491	0.5179	0.5196	0.5282	0.5377	0.5421	0.5414	**0.5369**
Strategy **2**	0.5450	0.5256	0.5198	0.5494	0.5279	0.5235	0.5421	0.5327	0.5286	**0.5274**
Strategy **3**	0.5110	0.5104	0.5178	0.5501	0.5545	0.5629	0.5717	0.5711	0.5778	**0.5420**
Strategy **4**	0.4620	0.4677	0.4600	0.4822	0.4922	0.4913	0.4878	0.5017	0.5013	**0.4781**
Strategy **5**	0.4820	0.4854	0.4834	0.4908	0.4881	0.5048	0.5279	0.5233	0.5383	**0.4976**
Strategy **6**	0.4670	0.4727	0.4697	0.5098	0.5238	0.5312	0.5320	0.5423	0.5448	**0.5053**

Table 7.10 Rankings of strategies under equal current state probabilities (scenario 1)

	SE_1	SE_2	SE_3	SE_4	SE_5	SE_6	SE_7	SE_8	SE_9	**EMV**
Strategy **1**	1	1	1	3	4	3	3	3	3	**2**
Strategy **2**	2	2	2	2	2	4	2	4	5	**3**
Strategy **3**	3	3	3	1	1	1	1	1	1	**1**
Strategy **4**	6	6	6	6	5	6	6	6	6	**6**
Strategy **5**	4	4	4	5	6	5	5	5	4	**5**
Strategy **6**	5	5	5	4	3	2	4	2	2	**4**

Table 7.11 The after-transition utility decision matrix (scenario 2)

Current state probability	$\mathbf{0.11}$	$\mathbf{0.11}$	$\mathbf{0.11}$	$\mathbf{0.11}$	$\mathbf{0.11}$	$\mathbf{0.11}$	$\mathbf{0.11}$	$\mathbf{0.11}$	$\mathbf{0.11}$	
Strategies	SE_1	SE_2	SE_3	SE_4	SE_5	SE_6	SE_7	SE_8	SE_9	**EMV**
Strategy **1**	0.5960	0.5501	0.5286	0.5290	0.5239	0.5336	0.5265	0.5588	0.5581	$\mathbf{0.5395}$
Strategy **2**	0.5450	0.5260	0.5076	0.5488	0.5279	0.5107	0.5337	0.5407	0.5391	$\mathbf{0.5257}$
Strategy **3**	0.5110	0.5104	0.5223	0.5445	0.5482	0.5634	0.6228	0.6176	0.6230	$\mathbf{0.5570}$
Strategy **4**	0.4620	0.4676	0.4574	0.4793	0.4885	0.4897	0.5062	0.5274	0.5438	$\mathbf{0.4864}$
Strategy **5**	0.4820	0.4854	0.4835	0.4896	0.4878	0.5100	0.5857	0.5754	0.6074	$\mathbf{0.5177}$
Strategy **6**	0.4670	0.4726	0.4703	0.5037	0.5163	0.5318	0.5856	0.5949	0.6003	$\mathbf{0.5217}$

Table 7.12 Rankings of strategies under equal current state probabilities (scenario 2)

	SE_1	SE_2	SE_3	SE_4	SE_5	SE_6	SE_7	SE_8	SE_9	**EMV**
Strategy **1**	1	1	1	3	3	2	5	4	4	**2**
Strategy **2**	2	2	3	1	2	4	4	5	6	**3**
Strategy **3**	3	3	2	2	1	1	1	1	1	**1**
Strategy **4**	6	6	6	6	5	6	6	6	5	**6**
Strategy **5**	4	4	4	5	6	5	2	3	2	**5**
Strategy **6**	5	5	5	4	4	3	3	2	3	**4**

7.5 Sensitivity Analysis

In this section, the sensitivity of the rankings based on the probability of current state is analysed under two scenarios 1 and 2 to see how sensitive the final ranking is to changes of current state's probability. As can be seen in Table 7.13, five schemes of various probabilities are suggested while the sum of probabilities shall be equal to 1 in all of them. In the default scheme, equal probabilities for all states are considered which was also used as the main analysis in the previous section. Scheme 1, emphasises the occurrence of High socio-economic situations (high challenges to mitigation and adaptation) by assigning the highest probability to them. Scheme 2, contrary to the scheme 1, considers the probability of Low socio-economic situations (low challenges to mitigation and adaptation) higher than others. In scheme 3, the SV flooding risk has the highest probability, and finally in scheme 4, the MI flooding risk has the highest probability.

Table 7.13 Test schemes for sensitivity analysis of current state probability

SE_t	Socio-economic situation	Flooding risk	Default scheme	Scheme **1**	Scheme **2**	Scheme **3**	Scheme **4**
1	L	MI	0.11	0.03	**0.20**	0.03	**0.20**
2	L	MO	0.11	0.03	**0.20**	0.10	0.10
3	L	SV	0.11	0.03	**0.20**	**0.20**	0.03
4	M	MI	0.11	0.10	0.10	0.03	**0.20**
5	M	MO	0.11	0.10	0.10	0.10	0.10
6	M	SV	0.11	0.10	0.10	**0.20**	0.03
7	H	MI	0.11	**0.20**	0.03	0.03	**0.20**
8	H	MO	0.11	**0.20**	0.03	0.10	0.10
9	H	SV	0.11	**0.20**	0.03	**0.20**	0.03

The obtained EMVs from the sensitivity analysis under scenario 1 are shown in Table 7.14. Trends and rankings of EMVs for strategies under various schemes in scenario 1 is depicted in Figure 7.10. It is resulted that the three lowest ranking strategies (Strategies 4 to 6) in the default scheme are not sensitive to the changes in current state probability while the first three strategies (Strategies 1 to 3) are more sensitive in Schemes 2 and 4. It shows when the current socio-economic situation is facing low challenges to adaptation and mitigation (Scheme 2), the most prioritised strategy would be awareness raising (Strategy 1) followed by emergency plans/response (Strategy 2) and flood forecasting (Strategy 3). It is also resulted that in scheme 4 (under mild flooding risk), the awareness raising (Strategy 1) is the most useful strategy followed by flood forecasting (Strategy 3) and emergency plans/response (Strategy 2).

Table 7.14 EMVs and rankings of strategies under various schemes (scenario 1)

	Default Scheme	Scheme 1	Scheme 2	Scheme 3	Scheme 4
Strategy 1	0.5369 (2)	0.5316 (2)	0.5441 (1)	0.5344 (2)	0.5400 (1)
Strategy 2	0.5274 (3)	0.5285 (3)	0.5263 (2)	0.5221 (3)	0.5331 (3)
Strategy 3	0.5420 (1)	0.5570 (1)	0.5262 (3)	0.5443 (1)	0.5399 (2)
Strategy 4	0.4781 (6)	0.4864 (6)	0.4692 (6)	0.4796 (6)	0.4761 (6)
Strategy 5	0.4976 (5)	0.5098 (5)	0.4862 (5)	0.5000 (5)	0.4956 (5)
Strategy 6	0.5053 (4)	0.5226 (4)	0.4869 (4)	0.5083 (4)	0.5020 (4)

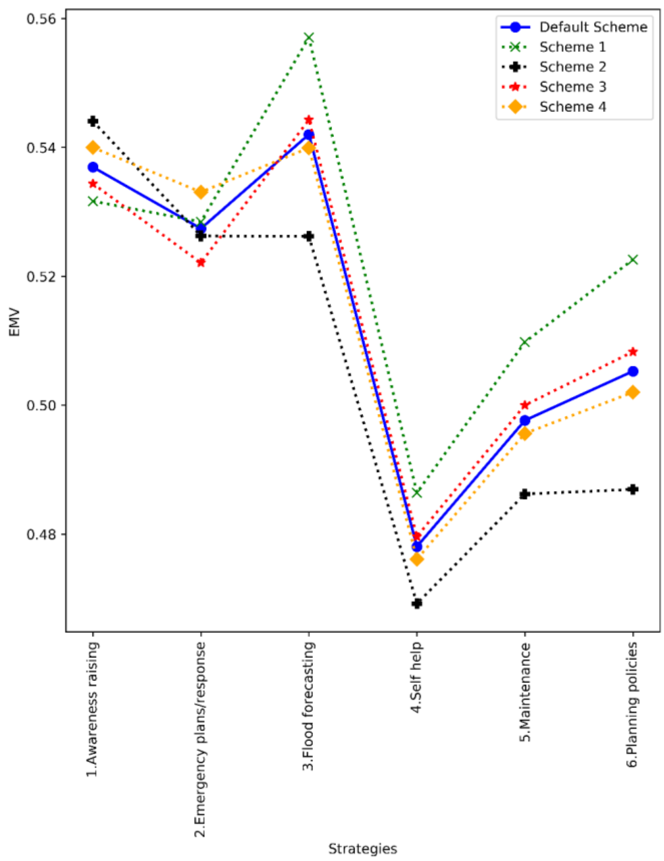


Figure 7.10 Trends and rankings of EMVs for strategies under various schemes (scenario 1)

The sensitivity analysis findings in scenario 2 (Table 7.15), indicate that the last prioritised strategy which is self help (Strategy 4) is not sensitive to changes in current state probability. Furthermore, the most significant strategy in scenario 2 (flood forecasing), which is ranked first in almost all Schemes, (except Scheme 2) is not sensitive to the changes either. In Figure 7.11, trends and rankings of EMVs for strategies under various schemes (scenario 2) are shown.

Table 7.15 EMVs and rankings of strategies under various schemes (scenario 2)

	Default Scheme	Scheme 1	Scheme 2	Scheme 3	Scheme 4
Strategy 1	0.5395 (2)	0.5376 (4)	0.5429 (1)	0.5369 (2)	0.5422 (2)
Strategy 2	0.5257 (3)	0.5288 (5)	0.5229 (3)	0.5198 (5)	0.5317 (3)
Strategy 3	0.5570 (1)	0.5846 (1)	0.5303 (2)	0.5597 (1)	0.5545 (1)
Strategy 4	0.4864 (6)	0.5028 (6)	0.4705 (6)	0.4900 (6)	0.4826 (6)
Strategy 5	0.5177 (5)	0.5460 (3)	0.4920 (4)	0.5218 (4)	0.5143 (5)
Strategy 6	0.5217 (4)	0.5536 (2)	0.4906 (5)	0.5255 (3)	0.5177 (4)

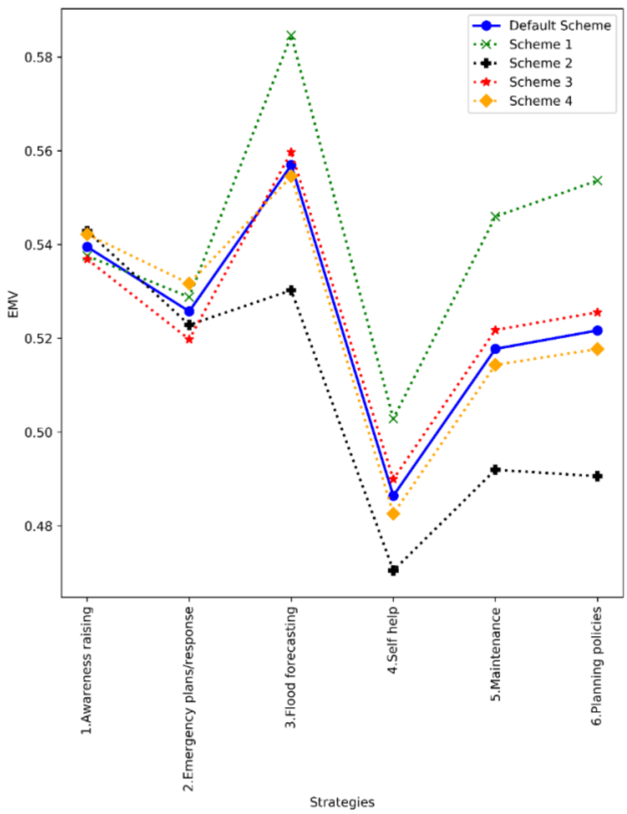


Figure 7.11 Trends and rankings of EMVs for strategies under various schemes (scenario 2)

7.6 Discussion

Without any doubt, flooding is a major threat for the UK and can affect lives, infrastructures, and businesses. This impact is not diminishing and is predicted to grow in the future due to climate change and severe weather conditions (Few, 2003; Ntontis et al., 2019). As mentioned before, it was predicted that flooding could cost the UK approximately £27 billion under a high global emission scenario yearly by the 2080s which is approximately 21 times higher than the £1.3 billion based on CCRA1 report in 2012 (Committee on Climate Change, 2012; Foresight Future Flooding, 2004).

In this study, suggested uncertainty and climate change adaptation criteria have been used together with flood risk impacts in one single decision-making model. The main contribution of this study is proposing a stratified decision-making model for long-term decision making. It considers system's dynamics on the basis of the CST, game theory and SSP. The most suitable flooding risk mitigation strategies have been selected by taking into account the dynamic of UK challenges to adaptation and mitigation based on SSP and flooding risk impacts based on MI, MO, and SV levels. The model applicability has been verified in the case of flooding risk mitigation strategy in an area selected to be at Highland and Argyll in Scotland. After primary data collected from the involved experts in the region of Scotland, the proposed model as described in Section 4.6, and Section 7.2 was applied and analysed (Section 7.4). The sensitivity analysis of the probabilities of current state was provided in Section 7.5 in order to verify the obtained results. The final order of strategies is provided in Figure 7.12.

The literature also supports the importance of *Flood Forecasting* as many studies explored it by developing various techniques such as neural network model (Campolo et al., 1999), and MCDM (Levy, 2005). Neal et al. (2018) supported the finding in this study that *Flood Forcasting* should be prioritised to effectively deal with flood impacts proactively. They indicated that a medium to long-term forecast of coastal flooding can be useful for the UK government and response agencies. Nye et al. (2011) emphasised on the criticality of *Awareness Raising* strategy in the literature which confirms the identification of this strategy as the second most suitable flooding risk mitigation strategy in this chapter. They indicated that social aspects of flooding, particularly flood warning and awareness raising can lead to a more balanced sociotechnical risk management portfolio (Johnson et al. 2005). Carter et al. (2009) also emphasised on the awareness raising of the flood risk threat among stakeholders and indicated that it can be enhanced by sustainability appraisal. Coles et al. (2017) highlighted the significance of the third important strategy in this study which is *Emergency Plans/Response*. They proposed an integrated model of numerical modelling and geographical analysis of service areas for ambulance, fire and rescue services by demonstrating two floods in York, UK in order to assess vulnerability of sheltered and care homes. Finally, one way to handle the impacts of flooding that the UK policy guidelines suggest is the community resilience concept by designing interventions which is close to the concept of *Self Help* strategy in the obtained result which ranks at the sixth place (Ntontis et al., 2019).

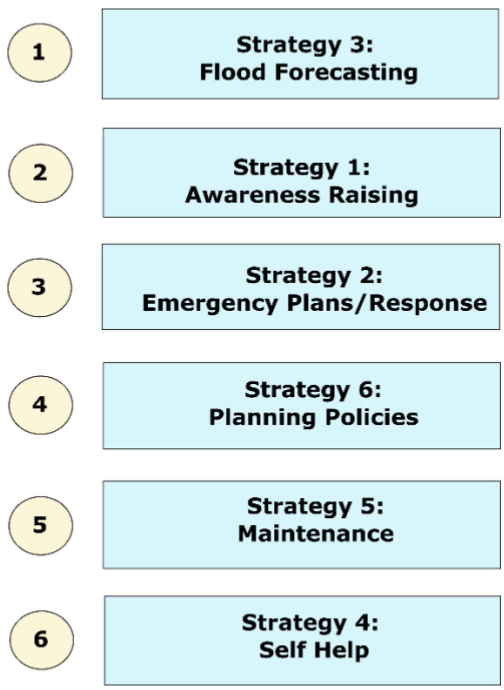


Figure 7.12 Final order of strategies

7.7 Conclusions

In this Chapter 7, a hybrid risk mitigation modelling based on CST (Section 3.6), game theory (Section 3.7), and SSP (Section 7.2) was proposed in order to obtain a reliable and applicable model for flooding risk mitigation strategy selection in the long-term. The model was applied in the region of Highland and Argyll in Scotland based on primary data obtained from experts to prioritise flooding risk mitigation strategies which were recommended by SEPA.

In the literature, various decision analysis methods such as MCDM have been used for flood risk management, however it is believed the proposed stratified decision-making model is unique and innovative as it can offer predictive insights by incorporating advantages of CST, game theory, and SSP in one model. Game theory represents an abstract model of decision making, not the social reality of decision making itself. Thus, while game theory ensures that a result follows a model logically, it cannot ensure that the result itself represents reality, unless the model is an accurate one (Kelly, 2003). The integration of CST and game theory provide with a stratified model to overcome this static issue of game theory which enables the proposed model more dynamic. Then, for applying the proposed model in the context of disaster management (i.e. flooding) the SSP was taken into account to understand UK socio-economic conditions in three levels of low (L), moderate (M), and high (H). As the proposed model has two dimensions, impact of flooding was considered, based on SFFS (2014), by providing three impact levels of mild (MI), moderate (MO) and severe (SV).

Thus, the resulted model aims to take into account both UK socio-economic situations and flooding risk impacts for the long-term decision making (5 to 20-year time frame). The socio-economic situation is categorised into 3 status namely L, M, and H challenges to adaptation and mitigation based on SSP and flooding risk impacts with regard to MI, MO, and SV levels. These two dimensions generated nine states as shown in Table 7.4. The findings indicated that the most important strategies which can provide long-term benefit in mitigating flooding risk impact in the area of Highland and Argyll in Scotland are flood forecasting (i.e. Strategy 3), awareness raising (i.e. Strategy 1), emergency plans/response (i.e. Strategy 2), planning policies (i.e. Strategy 6), maintenance (i.e. Strategy 5), and self help (i.e. Strategy 4), respectively (Figure 7.12).

7.7.1 Limitations and future research directions

In spite of the proposed model's merits it suffers from a few downsides. Firstly, for the sake of simplicity, two dimensions of challenges to adaptation and mitigation based on SSP have been used to conceptualise the socio-economic conditions in only three levels (low, moderate, and high). However, in future studies in order to take into account the full picture, researchers may apply a model with all 9 possible levels. This may pose another obstacle of acquiring data from experts which would make it extremely hard for experts to offer their assessments due to high number of evaluations. As a result, it leads to the second limitation of this study that is utilising primary data acquired from subject experts. To overcome this issue, in future research, researchers can take advantage of mixed primary and secondary data and decrease the dependence of the results on subjective judgements. It can help strengthen the model's reliability and robustness. The other concern may arise regarding the quantitative validation which might be difficult for this type of models. However, face validation or validation through expert elicitation should be relied upon for this aim. Thirdly, adding a third dimension of sustainable development goals or agenda to the model can be another interesting future research topic. It is also important to understand the potential synergic or dysergic behaviour of strategies apart from the adaptation and mitigation challenges and impact level dimensions, particularly in the longer time frame. However, it might add an extra level of complexity to the model which requires researchers to add more innovative features into the proposed stratified model. In other words, it would be beneficial to realise if strategies can potentially offer more helpful merits in terms of social justice or community well-being at the time following a flood. Fourthly, the proposed model can be utilised in similar strategic decision-making settings such as natural disasters or energy systems in other countries or regions. In this way, the applicability and versatility of the model can be confirmed. The proposed model can deal with types of problems which are comprised of two dimensions such as socio-economic situations and climate hazards (as in the current study) for strategic, long-term, or even medium-term decision making. One application can be the evaluation of strategies for dealing with the impact of pandemics under various readiness of governments or local authorities for choosing the best strategies to respond in medium-term decision-making timeframes such as within 1.5-3 years. Finally, it is also interesting to propose theories to more efficiently capture the utility values and transition probabilities in the stratified model.

Chapter 8 Conclusions

In this chapter, conclusions, contributions, implications, limitations, and future research directions are presented in subsequent sections.

8.1 Conclusions

Large infrastructures like electricity supply networks are widely presumed to be crucial for the functioning of societies as they create conditions for essential economic activities. Electric power outages have been recognised as a national security issue by many governments like the US and more than 20 other countries including the UK (Brunner and Suter, 2008; Silvast, 2017). This thesis aimed at answering the following questions:

1. What are the critical risks in the UK power supply chain?

2. What are the causal relationships among the critical risks?

3. How are these risks ranked and prioritised?

4. How can policy makers deal with mitigating the most critical risks in the longer timeframe by taking into account socio-economic situations?

5. What are the most appropriate risk mitigation strategies in response to the most critical risks?

An overview on the energy security literature led this study to a comprehensive framework for identifying risks in energy supply chain and then to their interrelationship analysis. The reason is that, risks usually act in close interconnection to each other and barely act independently that means there would be causal relations among them in that occurrence of one risk would cause the other one. The following two research questions were answered in Chapter 5:

1. What are the critical risks in the UK power supply chain?

2. What are the causal relationships among the critical risks?

In Chapter 5, an energy supply chain risk assessment model was proposed to address the identified UK energy supply chain risks. The study provided an insight on the energy supply chain risk management both practically and theoretically. It is aimed to be helpful and practical for practitioners as well as scholars in the energy supply chain to use an explicable risk identification framework while analysing an energy system such as UK power supply chain. First, a risk identification and classification framework was proposed based on scrutinising energy supply chain risks. Then, causal relationships between identified risks were analysed by applying the NR-DEMATEL method. The proposed model considered experts' subjective judgement applying the NR-DEMATEL. A novel HESM to systematically assist DMs with the expert selection and importance weight determination was also introduced. The proposed method was utilised in the energy supply chain in the UK to demonstrate its applicability and efficacy. It identified twelve risk dimensions each one can potentially include a myriad of consolidated micro-level risks (i.e. risk elements).

This provided an opportunity to make a more comprehensive framework by presenting detailed risks namely risk elements as a sub-group of risk dimensions. The results suggest that the UK energy supply chain should focus on the following six risks out of the 12 identified risks when formulating the risk mitigation strategies: Natural Disasters (ND), Climate Change (CC), Industrial Action (IA), Affordability (AF), Political Instability (PI), and Sabotage and Terrorism (ST). They were chosen in a way that the majority of potential risk elements would be covered under their definitions and can easily be categorised under one of the dimensions. Considering all the analysis, the final suggestion would be to focus on the six risk dimensions of Natural Disasters (ND), Climate Change (CC), Industrial Action (IA), Affordability (AF), Political Instability (PI), and Sabotage and Terrorism (ST) and offering mitigation strategies based on them can be quite beneficial for the UK energy supply chain being sustainable. This finding would allow managers to allocate their resources efficiently by focusing on the dominant risks and the interdependencies among them. Additionally, it would open up avenues for further suggestions on risk mitigation strategies, which can improve the performance of the entire UK energy supply chain.

Although this study focused on the UK energy supply chain, it is believed the results are relevant and the findings can be applicable to the power sectors of other countries. This is because the UK power sector fuel mix is similar to the fuel mix in other countries (Chalvatzis et al., 2019). For example, characteristics such as elimination of coal, ambitious offshore wind capacity, other renewables expansion plans are gaining momentum across Europe and the US (Hills et al., 2018; Ioannidis et al., 2019; Ioannidis and Chalvatzis, 2017; Li et al., 2018). Therefore, several aspects of the UK's power supply system are similar to the current or forthcoming systems in other countries as they all face strict decarbonisation agendas all while the nuclear power stocks are not replaced at the end of their lifespan (Chalvatzis and Ioannidis, 2017b). As a result, risks such as Affordability (AF) gained popularity in the past when countries rushed to subsidise the emergence of renewable energy sources. Similarly, countries with thermal power stations face Operational Safety (OS) challenges to cool those power stations while Climate Change (CC) increases the frequency and intensity of heatwaves, and ultimately reducing access to cooling water. This is a core issue for nuclear power stations but one that expands to all thermal power stations as one of the prevailing risks. At the same time, risks deriving from exposure to Political Instability (PI), Sabotage and Terrorism (ST), and Industrial Action (IA) are highly dependent on country-specific circumstances relevant to the power industry structure, the economic and geopolitical balances, and industrialisation trends (Pappas et al., 2018; Pappas and Chalvatzis, 2017).

Therefore, it is argued that this study is generalisable to other countries firstly by methodological virtue, as it can be applied to other countries to reveal their own power sector's detailed risk analysis; and secondly, by highlighting the prioritisation of risks specific to certain power supply technologies (which are similar among countries). Currently, a sweeping transformation is taking place across the power sector of most countries, which requires decisions over electricity planning with risk vulnerability being one of the most important issues to be considered. Technologies subject to significant risks are being left behind as uninvestable. To this end, results are useful for context setting for countries other than the UK, but it is maintained that more research would be required for any specific country's electricity planning.

The answer to the third research question "How are these risks ranked and prioritised?" was discussed in Chapter 6. That was focused on representing the applicability of the methodological development of the original BWM in terms of capturing uncertainty. A need to improve the original BWM and propose an uncertain extension of the method based on the NST called NE-BWM as well as STE-BWM was revealed and discussed in detail. The STE-BWM method by applying spanning trees enumeration offers an opportunity for experts to suggest more than one best or worst criteria. The reason is that in some cases experts are unable to choose only one risk dimension as either the best or worst one due to uncertainty, hesitancy, or lack of information. Thus, the proposed STE-BWM can obtain which ones are actually the best and worst criteria based on already provided pair-wise comparison values by experts. Furthermore, original BWM considers two vectors of pairwise comparisons as equally important which is unrealistic. Thus, the proposed NE-BWM dealt with this issue. The first vector (i.e. best-to-others) was named as Separation I and the second vector (i.e. others-to-worst) was named as Separation II. Then, the NST was utilised in structuring the value assignment process in terms of ρ^+ and ρ^- values while dealing with an expert's uncertainty in the NE-BWM. In fact, the NST provides a rating scale for DMs to express their level of confidence in terms of ρ^+ and ρ^- values.

The applications of two proposed extended BWM under uncertain decision-making (i.e. NE-BWM and STE-BWM) in prioritising the six most critical risk dimensions in energy supply chain were presented. For obtaining final ranking of risks, weights obtained from both the original BWM (L-BWM and NL-BWM), and NE-BWM were integrated. The aggregated weights revealed that Climate Change (CC) is the most critical one followed by Natural Disasters (ND), Affordability (AF), Sabotage and Terrorism (ST), Industrial Action (IA), and Political Instability (PI), respectively.

Ultimately, Chapter 7, discussed the answers to the 4th and 5th research questions:

4. How can policy makers deal with mitigating the most critical risks in the longer timeframe by taking into account socio-economic situations?

5. What are the most appropriate risk mitigation strategies in response to the most critical risks?

In a standard decision-making model of game of chance, the best strategy is chosen on the basis of the current state of the system under various outcomes of the nature. However, there is a shortcoming about this standard model that may be applicable only to short-term decision-making period. This drawback is mainly due to not evaluating the dynamic characteristics and changes in the states of system and outcomes of the nature which might occur in the longer timescale. In Chapter 6, it was obtained that Climate Change (CC), and Natural Disasters (ND) are the most critical energy risk dimensions in the UK power supply chain. In Chapter 7, an innovative risk mitigation model based on the CST (see Section 3.6), game theory (see Section

3.7), and SSP (see Section 7.2) was introduced to deal with these two most critical risk dimensions. The aim was to deal with the most significant climate change risk to UK infrastructure (i.e. flooding) for the long-term policy making (between 5 to 20 years) with reference to the UK socio-economic status. In the study, the game of chance involving risk and CST were integrated to incorporate the dynamic nature of the decision environment for the long-term disaster risk planning taking into account various states of the system. It was demonstrated how this methodology can suitably be applied to obtain ad-hoc models, solutions, and analysis in the strategic decision-making process of flooding risk strategy evaluation. The model applicability was shown in an uncertain decision-making context while taking into account the dynamic nature of socio-economic situations, and flooding hazards. The proposed model has been applied to a flooding risk mitigation strategy planning in the Highland and Argyll district in Scotland. The findings indicated that the most important strategies which can provide long-term benefit in mitigating flooding risk impact in the area of Highland and Argyll in Scotland are flood forecasting (i.e. Strategy 3), awareness raising (i.e. Strategy 1), emergency plans/response (i.e. Strategy 2), planning policies (i.e. Strategy 6), maintenance (i.e. Strategy 5) and self help (i.e. Strategy 4), respectively.

8.2 Contributions

This thesis benefited from both theoretical and applied contributions that can yield insightful recommendations to both academics and practitioners. The research contributions are highlighted in Table 8.1. Novelty, scientific soundness, and value of each research objective are presented in Table 8.2.

Table 8.1 Contributions

No.	Description	Chapter	RQ	Type
1	A framework for risk analysis which can be used in strategic risk mitigation analysis resulted from systematic literature review and experts' feedback	5	1	Theoretical
2	A NR-DEMATEL method to analyse risk dimensions based on the causal relationships between them	5	2	Applied
3	Introducing an expert selection model based on HFS theory (i.e HESM) to systematically assist researchers with the expert selection process. It has provided a reliable model that help decide who can be an expert based on their credentials and experience as well as assigning each expert a relative importance weight	5	2	Theoretical
4	Aiding policy makers in the UK energy supply chain to recognise most critical risks	5	2	Applied
5	The proposed STE-BWM which is a hybrid method of spanning trees enumeration and BWM. It can help identification of the best and the worst energy risk dimensions if the involved experts are not able to choose only one best and one worst risk dimension with full confidence	6	3	Theoretical
6	The proposed NE-BWM by introducing two new parameters as the DMs' confidence on the best-to-others preferences and the DMs' confidence on the others-to-worst	6	3	Theoretical

	preferences. The NE-BWM considers the NST to structure uncertainty of experts in terms of ρ^+ and ρ^- values which can prioritise the six energy risk dimensions			
7	Two real-world cases to illustrate the applicability of the proposed NE-BWM by considering partial factorial experiment for confidence rating levels selection of the experts are explored. The results are analysed in 21 test problems under various ρ^+ and ρ^- values	6	3	Applied
8	A new output measurement index, namely confidence difference (CD) for the NE-BWM is proposed and discussed.	6	3	Applied
9	A novel stratified decision-making model is introduced on the basis of the Concept of Stratification (CST), game theory, and Shared Socio-economic Pathway (SSP)	7	4	Theoretical
10	Managing impacts of flooding risk in the Highland and Argyll region in Scotland by identifying the most suitable strategies and proposing the priorities for action based on a novel stratified decision-making model.	7	5	Applied

Table 8.2 Novelty, scientific soundness, and value for each research objective

Research Objectives	Novelty	Scientific Soundness	Value
RO #1: Proposing a risk classification and identification framework in the UK energy supply chain	Novel comprehensive risk identification framework to help categorise energy supply chain risks in the UK	Verified by systematic literature review and experts' feedback	It offers a structure for researchers in the energy risk management field to classify and organise the risk identification process in future studies
RO #2: Analysing causal interrelationships between identified risks	The proposed NR-DEMATEL has a theoretical contribution as it uses the revised DEMATEL and NST	The DEMATEL is a well-established MCDM method for evaluating the causal interrelationships between factors. Additionally, the result is supported by the primary data from 31 experts, making the result reliable as it is a LSGDM problem (more than 20 participants)	It offers value for policy makers in the UK energy supply chain to understand the causal interrelationships between risks at macro-level
RO #3: Prioritising identified UK energy supply chain risks	Two novel extensions of the original BWM are proposed (i.e. STE-BWM and NE-BWM)	The original BWM is a recently developed MCDM method which has various merits. In addition to application in energy risk management in this thesis, two real case studies from supply chain management verified the applicability of NE-BWM.	It provides (1) two extensions of BWM which can be used by researchers in any other MCDM problems, (2) a ranking for energy risks which can assist policy makers to recognise most critical risks
RO #4: Long-term risk mitigation planning	A novel stratified decision-making model is proposed for long-term decision making considering two dimensions of socio-economic situations and climate hazards	The model has been verified by showing its application in the region Highland and Argyll in Scotland for managing flood risks (i.e. a major climate hazard in the UK) to energy infrastructure by providing an order for risk mitigation strategies. The data for the analysis were gathered from 10 experts with suitable level of practical knowledge	It provides researchers with (1) a decision-making model that can be used for strategic or medium-term decision making by taking into account at least two dimensions in the model (2) an insight for flood risk managers and policy makers in the region by knowing priorities for action in the longer timescale

8.3 Implications

The implications of the results for academics and policy makers are listed in Table 8.3

Table 8.3 Implications

No.	Description	For
1	The proposed energy risk identification framework would provide a guideline to further explore the detailed analysis of risk elements in a specific sector in energy supply chain	Academics
2	The identified most important risk dimensions including Natural Disasters (ND), Climate Change (CC), Industrial Action (IA), Affordability (AF), Political Instability (PI), and Sabotage/Terrorism (ST) can inform decision-making in the energy supply chain	Policy makers
3	The proposed Expert Selection Model (ESM) would be a valuable tool for researchers in MCDM field to identify experts and their importance weights in a more systematic way	Academics
4	The proposed STE-BWM and NE-BWM both can be used by researchers in future studies in the MCDM field in various decision-making problems	Academics
5	The stratified decision-making model would be a helpful model for long-term decision-making process by considering system's dynamics. It can be utilised in project management, or other fields where two dimensions with various levels would construct a number of states	Academics
6	The identified prioritised list of flooding risk mitigation strategies including flood forecasting, awareness raising, emergency plans/response, planning policies, maintenance, and self help can be useful for policy makers in Highland and Argyll region in Scotland	Policy makers

8.4 Limitations

In this section, limitations are provided separately regarding each study presented in Chapter 5, Chapter 6, and Chapter 7.

In Chapter 5, the first limitation is the static, snapshot approach to risk interrelations, meaning the dynamics of the risk dimensions over time has not been considered. Secondly, the identified risk dimensions are macro-level risks in the UK energy supply chain and not dealing with risk elements (i.e. micro-level risks). In other words, risks can be studied in more detail in a specific part of the supply chain such as supply or demand or even can be studied in a specific power generation sector such as offshore wind industry, just as an example. Thirdly, due to the nature of MCDM methods the primary data has to be collected from experts in the field which can be regarded as a limitation. Fourthly, the DEMATEL method has a quantitative approach to explore the cause-effect and interrelationships between risks which might make it hard to elicit knowledge quantitatively from experts by using a Likert scale in some decision-making problems. That is why in this study, the revised DEMATEL was integrated with NST to facilitate this knowledge elicitation process from experts. The fourth limitation is related to the generic nature of the risk dimensions which was due to the broad extent of energy supply chain. This limitation has made recruiting subject experts for covering all interdisciplinary subject areas extremely lengthy and costly.

In Chapter 6, the first limitation is the small number of application cases which makes it difficult to generalise the findings from the proposed NE-BWM. The second limitation is about the complexity of implementation of the proposed STE-BWM which makes it costly and time consuming and not handy for all researchers in spite of its promising merits. The third limitation is a common one within MCDM field which is about limited number of experts involved that is partly due to the difficulty of recruiting higher number of experts from a transdisciplinary field like risks in energy supply chain management.

In Chapter 7, for the sake of simplicity, two dimensions of challenges to adaptation and mitigation based on SSP have been used to conceptualise the socio-economic conditions in only three levels (low, moderate, and high). It was a limitation of the model because considering all 9 SSPs would make it too complicated for both experts and researcher. The second limitation of this study was utilising primary data for acquiring parameters' values which are based on subject experts. Primary data are prone to be biased due to the nature of subjective judgements when humans are involved in the decision-making process.

8.5 Future Research Directions

In Chapter 5, as directions for future study, firstly, a more detailed analysis of six identified critical risks in order to lead to a more reliable outcome by expanding the number of experts who are participating in the data collection process can be beneficial because it would provide more insight for policy makers. Secondly, proposing a predictive dynamic model that can estimate the influence and interrelationships among risks over the longer period can provide insights into how risks act under various socio-political and economic conditions over time. System Dynamics (SD) can be an attractive approach in pursuing this research direction. Thirdly, a more detailed analysis at the lower level called risk elements (i.e., micro-level risks) based on the proposed framework would be interesting. Fourthly, the occurrence probability estimation of each risk elements with a reliable method and using the probability scores along with experts' opinions to prioritise risk elements can be regarded as another future research direction. Fifthly, results from the DEMATEL can be compared with qualitative approaches such as Know-Why method or even with other dynamic quantitative methods such as SD to verify the outcome. Finally, proposing risk mitigation strategies that links to the outcome of vital risk elements identification to provide more detailed and efficient response to identified risk elements.

In Chapter 6 in future research directions, firstly, a simulation approach can be a reasonable solution to overcome the issue of a limited number of application cases in order to provide findings that are more generalisable. Secondly, given that uncertainty leads to higher inconsistency (i.e., it has been confirmed that a higher CD value would result in a higher CR value), thus, there would be a necessity for processes that mitigate inconsistency to be further investigated. Thirdly, the proposed model might also be compared to the other uncertainty extensions of the original BWM integrated with uncertainty theories like FST.

In Chapter 7, in order to take into account the full potential of the proposed stratified decision-making model, researchers may revise the model in order to make it capable of encompassing all 9 possible levels within SSPs. In this way the result can be more comprehensive by recognising all possible socio-economic conditions in the UK. Secondly, to overcome the limitation of primary data, in future research, researchers can take advantage of a mixed primary and secondary data and decrease the dependence of the results on subjective judgements. It can help strengthen the model's reliability and robustness. Thirdly, adding a third dimension of sustainable development goals or agenda to the model can be another interesting future research topic. However, it might add an extra level of complexity to the model which requires researchers to add more innovative features into the proposed stratified model. In other words, it would be beneficial to realise if strategies can potentially offer more helpful merits in terms of social justice or community well-being at the time following a flood. Fourthly, the proposed model can be utilised in similar strategic decision-making settings such as natural disasters or energy systems in other countries or regions. In this way, the applicability and versatility of the model can be confirmed. Finally, it is also interesting to propose theories to more efficiently capture the utility values and transition probabilities in the stratified model.

Glossary of Terms

Terms	Acronyms
Analytic Hierarchy Process	AHP
Asia Pacific Energy Research Centre	APERC
Adaptation Sub-Committee	ASC
Bayesian Network	BN
Best Non-fuzzy Performance	BNP
Best-to-Others vector	BO
Bi-Objective CST	BO-CST
Best-Worst Method	BWM
Climate Change Risk Assessment	CCRA
Circular Economy	CE
Carbon Dioxide	CO_2
COmplex PRoportional ASsessment	COPRAS
Clean Power Plan	CPP
Consistency Ratio	CR
Corporate Social Responsibility	CSR
Concept of Stratification	CST
Decision-Making Trial and Evaluation Laboratory	DEMATEL
Decision Maker	DM
Dynamic Programming	DP
Enumerating All Spanning Trees	EAST
Evaluation based on Distance from Average Solution	EDAS
Expert Eligibility Value	EEV
ELimination Et Choix Traduisant la REalit (in French) or elimination and choice expressing reality	ELECTRE
Expected Monetary Value	EMV
Expert Selection Model	ESM
Fuzzy Bayesian Network	FBN
Fuzzy Bi-Objective CST	FBO-CST
Fuzzy-Delphi Method	FDM
Fuzzy Filtering Method	FFM

Terms	**Acronyms**
Fuzzy Inference System	FIS
Fuzzy Sets	FS
Finite-State Machine	FSM
Fuzzy Set Theory	FST
Grams of CO_2 equivalent per kilowatt-hour of electricity generated	gCO_2eq/kWh
Green-House Gas	GHG
Geometric Mean of All Spanning Trees	GMAST
Grey Relational Analysis	GRA
Human Development Indicator	HDI
Hesitant Expert Selection Model	HESM
Hesitant Fuzzy Element	HFE
Hesitant Fuzzy Sets	HFS
International Energy Agency	IEA
Intuitionistic Fuzzy Best-Worst Method	IF-BWM
Intuitionistic Fuzzy Sets	IFS
Intuitionistic Fuzzy Multiplicative Best-Worst Method	IFM-BWM
Intergovernmental Panel on Climate Change	IPCC
Impact-Relations Map	IRM
Interval Rough Number	IRN
Interpretive Structural Modelling	ISM
Interval Valued Neutrosophic Sets	IVNS
Linear Best-Worst Method	L-BWM
Linguistic Neutrosophic Geometric Heronian Mean	LNGHM
Linguistic Neutrosophic Prioritised Geometric Heronian Mean	LNPGHM
Large-Scale Group Decision-Making	LSGDM
Multiple Attribute Decision Making	MADM
Multi Attribute Group Decision Making	MAGDM
Multi Criteria Decision Analysis	MCDA
Multiple Criteria Decision Making	MCDM
Multiple Criteria Group Decision-Making	MCGDM

Terms	Acronyms
Matrice d'Impacts Croisés Multiplication Appliquée à un Classement meaning "Cross Impact Matrix Multiplication Applied to Classification"	MICMAC
Mixed Integer Linear Model	MILM
Maximum Mean De-Entropy algorithm	MMDE
Model of Short-term Energy Security	MOSES
Maclaurin Symmetric Mean	MSM
Multi-Objective Optimisation by Ratio Analysis plus the full MULTIplicative form	MULTIMOORA
National Adaptation Programme	NAP
Normal Accident Theory	NAT
Notre Dame Global Adaptation Initiative	ND-GAIN
Neutrosophic Enhanced Best-Worst Method	NE-BWM
New Energy Power System	NEPS
Neutrosophic Hesitant Fuzzy Set	NHFS
Non-Linear Model	NLM
Non-Linear Best-Worst Method	NL-BWM
Normal Neutrosophic Sets	NNS
Neutrosophic Revised-DEMATEL	NR-DEMATEL
Neutrosophic Sets	NS
Normalised Score Function Value	NSFV
Neutrosophic Set Theory	NST
Organisation for Economic Cooperation and Development	OECD
Others-to-Worst vector	OW
Probabilistic Hesitant Fuzzy Elements	PHFE
Preference Ranking Organisation Method for Enrichment Evaluations	PROMETHEE
Power Transmission System	PTS
Photovoltaics	PV
Renewable Energy	RE
Renewable Energy Sources	RES-E

Terms	**Acronyms**
Severe Acute Respiratory Syndrome	SARS
System Dynamics	SD
The Scottish Environment Protection Agency	SEPA
The Scottish Flood Forecasting Service	SFFS
Score Function Value	SFV
Safety, Health and Environment	SHE
Stratified Multiple Criteria Decision Making	S-MCDM
Security of Supply	SOS
Shared Socio-economic Pathway	SSP
Spanning Trees Enumeration	STE
Spanning Trees Enumeration and BWM	STE-BWM
Single Valued Neutrosophic	SVN
Single-Valued Neutrosophic Dombi Weighted Arithmetic Average	SVNDWAA
Single-Valued Neutrosophic Dombi Weighted Geometric Average	SVNDWGA
Single-Valued Neutrosophic Numbers	SVNN
Single-Valued Neutrosophic Sets	SVNS
Single-Valued Trapezoidal Neutrosophic Numbers	SVTNN
Single-Valued Trapezoidal Neutrosophic Normalised Weighted Bonferroni Mean	SVTNNWBM
Triangular Fuzzy Number	TFN
Trapezoidal Neutrosophic Number	TNN
Trapezoidal Neutrosophic Weighted Arithmetic Averaging	TNWAA
Trapezoidal Neutrosophic Weighted Geometric Averaging	TNWGA
TOmada de Deciso Interativa e Multicritrio (in Portuguese) meaning interactive and multicriteria decision-making	TODIM
Technique for Order Preference by Similarity to Ideal Solution	TOPSIS
Trapezoidal Intuitionistic Fuzzy Number	TrIFN
United Nations Development Programme	UNDP
Vlsekriterijumska Optimizacija I Kompromisno Resenje (in Serbian)	VIKOR

Appendix A: Uncertainty Theories-Definitions

A.1 Fuzzy logic

A.1.1 Fuzzy set

In this section the definitions of the FST are provided:

Definition A.1. A special Fuzzy Set (FS) $F = \{(x, \mu_F(x)), x \in R\}$ would define a fuzzy number (Kwong and Bai, 2002). A Triangular Fuzzy Number (TFN) is represented as a triplet (l, m, r) where $l \leq m \leq r$. Equation (A.1) presents the membership function of a TFN (Vafadarnikjoo et al., 2018, 2015):

$$f_A(x) = \begin{cases} 0 & x < l \\ \dfrac{x-l}{m-l} & l \leq x \leq m \\ \dfrac{r-x}{r-m} & m \leq x \leq r \\ 0 & x > r \end{cases} \tag{A.1}$$

Definition A.2. Given $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$ are two TFNs. Then Equations (A.2)-(A.5) are true (Vafadarnikjoo et al., 2018, 2015):

$$\tilde{A} - \tilde{B} = (a_1, a_2, a_3) - (b_1, b_2, b_3) = (a_1 - b_3, a_2 - b_2, a_3 - b_1) \tag{A.2}$$

$$\tilde{A} + \tilde{B} = (a_1, a_2, a_3) + (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{A.3}$$

$$\tilde{A} \times \tilde{B} = (a_1, a_2, a_3) \times (b_1, b_2, b_3) \approx (a_1 b_1, a_2 b_2, a_3 b_3) \tag{A.4}$$

$$\tilde{A} \div \tilde{B} = (a_1, a_2, a_3) \div (b_1, b_2, b_3) \approx (a_1/b_3, a_2/b_2, a_3/b_1) \tag{A.5}$$

A.1.2 Hesitant fuzzy set

The Hesitant Fuzzy Set (HFS) was first introduced by Torra (2010) and is a generalisation of IFS. By HFS theory, it is possible to acquire DMs' or experts' subjective judgements more properly by giving them the opportunity to choose among a couple of possible values. The reason is that experts usually encounter a degree of hesitance or indeterminacy before expressing their subjective judgements and by using HFS theory this issue is addressed (Vafadarnikjoo et al., 2020). In this study, HFS theory is applied in the proposed Hesitant Expert Selection Model (HESM) to obtain experts' importance weights as explained in Section 5.4.

Definition A.3. (Farhadinia, 2013; Torra, 2010; Torra and Narukawa, 2009) HFS on X (i.e. a fixed set) is defined in terms of a function when applied to X generates a subset of $[0,1]$. Xia and Xu (2011) presented HFS as Equation (A.6):

$$E = \{\langle x, h_E(x)\rangle : x \in X\} \tag{A.6}$$

The $h_E(x)$ can take values within $[0,1]$, signifying the possible membership degree of the element $x \in X$ to the set E. Additionally, Hesitant Fuzzy Element (HFE) was defined by Xia and Xu (2011) as $h = h_E(x)$.

Definition A.4. (Farhadinia, 2013) Let $h = U_{\gamma \epsilon h}\{\gamma\} = \{\gamma_j\}_{j=1}^{l(h)}$ be a HFE, in which $l(h)$ represents the number of values in h. Equation (A.7) shows a score function S of a HFE h. Where $\{\delta(j)\}_{j=1}^{l(h)}$ is a positive-valued monotonic ascending order of index j.

$$S(h) = \frac{\sum_{j=1}^{l(h)} \delta(j)\gamma_j}{\sum_{j=1}^{l(h)} \delta(j)} \tag{A.7}$$

Considering $l(h) = N$ and $\delta(j) = j$ are given and Equation (A.8) is resulted.

$$S(h) = \frac{\sum_{j=1}^{N} j\gamma_j}{\sum_{j=1}^{N} j} = \frac{2}{N(N+1)} \sum_{j=1}^{N} j\gamma_j \tag{A.8}$$

A.1.3 Intuitionistic fuzzy set

Atanassov (1986) introduced the Intuitionistic Fuzzy Set (IFS) theory as the extension of the original FST. The IFS theory is characterised by both membership and non-membership functions unlike FST which only benefits from membership function (Govindan et al., 2015; Nikjoo and Saeedpoor, 2014).

Definition A.5. (Atanassov, 1986): Let X be a fixed set. Then an IFS, A can be defined as Equation (A.9)

$$A = \{\langle x, \mu_A(x), v_A(x)\rangle | x \in X\} \tag{A.9}$$

Where, $\mu_A(x): X \to [0,1]$ (i.e. membership degree of $x \in X$ to set A), $v_A(x): X \to [0,1]$ (i.e. non-membership degree of $x \in X$ to set A) and $0 \le \mu_A(x) + v_A(x) \le 1$, $x \in X$. Furthermore, the $\pi_A(x)$ is defined as the hesitancy level of $x \in X$ to set A based on Equation (A.10).

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x)\,,\ x \in X \tag{A.10}$$

Definition A.6. (Govindan et al., 2015). A Trapezoidal Intuitionistic Fuzzy Number (TrIFN) A, given $b_1 \le a_1 \le b_2 \le a_2 \le a_3 \le b_3 \le a_4 \le b_4$in $\mathbb{R}$ is signified as $A = \langle (a_1, a_2, a_3, a_4), (b_1, b_2, b_3, b_4)\rangle$ which the membership and non-membership functions of A are provided in Equation (A.11) and (A.12)

$$\mu_A(x) = \begin{cases} 0 & x \prec a_1 \\ \dfrac{x - a_1}{a_2 - a_1} & a_1 \le x \le a_2 \\ 1 & a_2 \le x \le a_3 \\ \dfrac{x - a_4}{a_3 - a_4} & a_3 \le x \le a_4 \\ 0 & a_4 \prec x \end{cases} \tag{A.11}$$

$$v_A(x) = \begin{cases} 1 & x \prec b_1 \\ \dfrac{x - b_2}{b_1 - b_2} & b_1 \le x \le b_2 \\ 0 & b_2 \le x \le b_3 \\ \dfrac{x - b_3}{b_4 - b_3} & b_3 \le x \le b_4 \\ 1 & b_4 \prec x \end{cases} \tag{A.12}$$

Definition A.7. (Govindan et al., 2015). The expected value (EV) of a TrIFN $A = \langle (a_1, a_2, a_3, a_4), (b_1, b_2, b_3, b_4)\rangle$ is presented as Equation (A.13)

$$EV(A) = \frac{1}{8}(a_1 + a_2 + a_3 + a_4 + b_1 + b_2 + b_3 + b_4) \tag{A.13}$$

A.2 Grey systems

Grey systems theory was first introduced by Deng (1989). Grey theory can be applied in various research fields such as grey systems analysis, decision making, modelling and forecasting. Successful applications of grey system span a broad range of research in agriculture (Tang et al., 2008), energy (Malekpoor et al., 2018), transport (Hsu and Wen, 2000), innovation (Chalvatzis et al., 2019), just to name a few. In manufacturing sectors, the applications have produced considerable profits. The main merit of grey systems theory is its capability to produce satisfactory outcomes by using a relatively small amount of data (Govindan et al., 2016; Xia et al., 2015).

Grey systems theory compared to many mainstream uncertainty theories, such as FST has appreciable features, particularly when it is necessary to deal with uncertain data and lack of information (Govindan et al., 2016; Yamaguchi et al., 2007):

• Grey systems generate satisfactory results utilising a relatively small amount of data.

• Grey systems are robust regarding the noise and lack of modelling information.

• Grey systems theory yields fairly flexible, non-parametric assumptions.

The basic definitions of grey systems are provided as follows:

Definition A.8. A grey number $\otimes X$ is defined as an interval with known upper and lower bounds which are shown by $\overline{X}$ and $\underline{X}$, respectively, but there is no known distribution information for X (Deng, 1989; Vafadarnikjoo et al., 2018). It is represented in Equation (A.14).

$$\otimes X = [\underline{X}, \overline{X}] = [X' \in \otimes X | \underline{X} \leq X' \leq \overline{X}] \tag{A.14}$$

Definition A.9. Given $\otimes X_1 = [\underline{X}_1, \overline{X}_1]$ and $\otimes X_2 = [\underline{X}_2, \overline{X}_2]$ are two grey numbers then the basic operations of grey numbers can be defined as Equation (A.15) to (A.18) (Govindan et al., 2016; Liu and Lin, 2006).

$$\otimes X_1 + \otimes X_2 = [\underline{X}_1 + \underline{X}_2, \overline{X}_1 + \overline{X}_2] \tag{A.15}$$

$$\otimes X_1 - \otimes X_2 = [\underline{X}_1 - \overline{X}_2, \overline{X}_1 - \underline{X}_2] \tag{A.16}$$

$$\otimes X_1 \times \otimes X_2 = [min(\underline{X}_1\underline{X}_2, \underline{X}_1\overline{X}_2, \overline{X}_1\underline{X}_2, \overline{X}_1\overline{X}_2), max(\underline{X}_1\underline{X}_2, \underline{X}_1\overline{X}_2, \overline{X}_1\underline{X}_2, \overline{X}_1\overline{X}_2)] \tag{A.17}$$

$$\otimes \mathrm{X}_1 \div \otimes \mathrm{X}_2 = [\underline{\mathrm{X}}_1, \overline{\mathrm{X}}_1] \times \left[\frac{1}{\overline{\mathrm{X}}_2}, \frac{1}{\underline{\mathrm{X}}_2}\right] \tag{A.18}$$

Definition A.10. The length of a grey number $\otimes X$ is defined as Equation (A.19).

$$L(\otimes X) = [\overline{X} - \underline{X}] \tag{A.19}$$

Definition A.11. Comparison of grey numbers (Li et al., 2007):

Given $\otimes X_1 = [\underline{X}_1, \overline{X}_1]$ and $\otimes X_2 = [\underline{X}_2, \overline{X}_2]$ are two grey numbers, the possibility degree of $\otimes X_1 \leq \otimes X_2$ can be defined as Equation (A.20).

$$P\{\otimes X_1 \leq \otimes X_2\} = \frac{max\left(0, L^* - max(0, \overline{X}_1 - \underline{X}_2)\right)}{L^*} \tag{A.20}$$

Where $L^* = L(\otimes X_1) + L(\otimes X_2)$

There are four possible cases on the real number axis to determine the relationship between $\otimes X_1$ and $\otimes X_2$:

(1) If $\underline{X}_1 = \underline{X}_2$, and $\overline{X}_1 = \overline{X}_2$, then $\otimes X_1 = \otimes X_2$. Hence, $P\{\otimes X_1 \leq \otimes X_2\} = 0.5$

(2) If $\underline{X}_2 > \overline{X}_1$, then $\otimes X_2 > \otimes X_1$. Hence, $P\{\otimes X_1 \leq \otimes X_2\} = 1$

(3) If $\overline{X}_2 < \underline{X}_1$, then $\otimes X_2 < \otimes X_1$. Hence, $P\{\otimes X_1 \leq \otimes X_2\} = 0$

4-a) If $\{\otimes X_1 \leq \otimes X_2\} > 0.5$, then $\otimes X_2 > \otimes X_1$

4-b) If $\{\otimes X_1 \leq \otimes X_2\} < 0.5$, then $\otimes X_2 < \otimes X_1$

Definition A.12. (Stanujkic et al., 2012). Whitenised (whitened or crisp value) of a grey number is a deterministic number with its value between the upper and lower bounds of a grey number $\otimes X$. The whitenised value $x_{(\lambda)}$ can be defined as Equation (A.21) in which λ is whitening coefficient and $\lambda \in [0,1]$.

$$x_{(\lambda)} = (1 - \lambda)\underline{x} + \lambda\overline{x} \tag{A.21}$$

For $\lambda = 0.5$, the Equation (A.22) will be resulted:

$$x_{(\lambda=0.5)} = \frac{1}{2}(\underline{x} + \overline{x}) \tag{A.22}$$

Definition A.13. Signed Distance: (Eberly, 2006; Stanujkic et al., 2012). Given $\otimes X_1 = [\underline{X}_1, \overline{X}_1]$ and $\otimes X_2 = [\underline{X}_2, \overline{X}_2]$ are two grey numbers. Then, the distance between $\otimes X_1$ and $\otimes X_2$ can be calculated as signed difference between their centres as shown in Equation (A.23).

$$d(\otimes X_1, \otimes X_2) = \frac{\underline{x}_1 + \overline{x}_1}{2} - \frac{\underline{x}_2 + \overline{x}_2}{2} = \frac{1}{2}[(\underline{x}_1 - \underline{x}_2) + (\overline{x}_1 - \overline{x}_2)] \tag{A.23}$$

Definition A.14. (Liu and Lin, 2006). Given $\otimes X = [\underline{X}, \overline{X}]$ is a grey number and $k > 0$ then Equation (A.24) is obtained.

$$\boldsymbol{k} \times [\underline{X}, \overline{X}] = [k\underline{X}, k\overline{X}] \tag{A.24}$$

A.3 Neutrosophic logic

A.3.1 Neutrosophic set theory

Atanassov (1986) proposed IFS as a development of the FST. The IFS was generalised to the Neutrosophic Set (NS), so as to present valuable information on how a DM would effectively deal with uncertainty within subjective judgements (Smarandache, 1999, 1998). However, values of truth, indeterminacy, and falsity functions must be within $[0,1]$ in order to be able to apply NS in real-world problems. The issue was that, they were within $]0^-, 1^+[$, where $1^+ = 1 + \varepsilon$, and $0^- = 0 - \varepsilon$, are non-standard finite numbers (Ji et al., 2018; Rivieccio, 2008). Wang et al. (2010) solved the issue by introducing Single-Valued Neutrosophic Sets (SVNS) where truth, indeterminacy, and falsity functions are real values within $[0,1]$ (Ji et al., 2018; Scherz and Vafadarnikjoo, 2019). Another generalisation of intuitionistic numbers is a Single-Valued Trapezoidal Neutrosophic Number (SVTNN). In Table A.1 a comparison between four uncertainty approaches is presented (Govindan et al., 2016; Liu and Lin, 2006; Smarandache, 2002).

Table A.1 A comparison between four uncertainty theories

	Grey Systems Theory	Probability Theory	FS Theory	NS Theory
Study objects	poor information uncertainty	stochastic uncertainty	cognitive uncertainty	transcendental uncertainty
Basic Sets	grey hazy sets	cantor sets	fuzzy sets	neutrosophic sets
Methods	information coverage	probability distribution	function of affiliation	truth, falsity, indeterminacy membership functions
Requirement	any distribution	typical distribution	experience	3D neutrosophic space
Objective	laws of reality	laws of statistics	cognitive expression	neutrosophic mathematics
Characteristics	small samples	large samples	experience	philosophical viewpoint

Recently, a growing number of scholars are working on SVNS from the Multi Attribute Group Decision Making (MAGDM) realm (Table A.2). While NST has been developed rapidly over the past few years, there are relatively limited studies looking into its practical applications, as most of the literature has focused on its theoretical advances (Vafadarnikjoo et al., 2018).

Table A.2 Decision-making under the NST environment

Article	Characteristics
Abdel-Basset et al. (2019a)	Proposed a type-2 neutrosophic number integration with the TOPSIS method.
Wang et al. (2018)	Developed a series of Maclaurin Symmetric Mean (MSM) aggregation techniques under single-valued neutrosophic linguistic environments and proposed procedures for solving MCDM problems.
Liang et al. (2018)	Developed a method based on the Single-Valued Trapezoidal Neutrosophic Normalised Weighted Bonferroni Mean (SVTNNWBM) operator to deal with Multiple Criteria Group Decision-Making (MCGDM) problems.
Peng and Dai (2018)	Introduced the Single Valued Neutrosophic (SVN) distance and similarity measures expressed by SVNN and a novel score function.
Li et al. (2017)	Proposed two aggregation operators based on neutrosophic information namely the Linguistic Neutrosophic Geometric Heronian Mean (LNGHM) and the Linguistic Neutrosophic Prioritised Geometric Heronian Mean (LNPGHM). Also, developed two MCDM methods under linguistic neutrosophic environments.
Deli and Subas (2017)	Presented a methodology for solving MADM problems with SVNN.
Chen and Ye (2017)	Proposed the Single-Valued Neutrosophic Dombi Weighted Arithmetic Average (SVNDWAA) and the Single-Valued Neutrosophic Dombi Weighted Geometric Average (SVNDWGA) operators to aggregate SVNN.
Peng and Liu (2017)	Proposed three algorithms to solve the single-valued neutrosophic soft decision-making problem by EDAS, similarity measure, and level soft set.
Stanujkic et al. (2017)	Extended MULTIMOORA (Multi-Objective Optimisation by Ratio Analysis plus Full Multiplicative Form) by integration with SVNS.
Liu and Zhang (2017)	Integrated the Neutrosophic Hesitant Fuzzy Set (NHFS) with the VIKOR method.
Ye (2017a)	Developed Trapezoidal Neutrosophic Weighted Geometric Averaging (TNWGA) and Trapezoidal Neutrosophic Weighted Arithmetic Averaging (TNWAA) operators. On the basis of TNWGA, TNWAA, and the score function of the Trapezoidal Neutrosophic Number (TNN), a MADM method is established.
Ye (2017b)	Introduced a simplified neutrosophic harmonic averaging projection measure between each alternative and the ideal choice in the MADM problems.
Ye (2017c)	Proposed two correlation coefficients between Normal Neutrosophic Sets (NNS) and then developed a MADM method with NNS.
Ye (2017d)	Proposed a MAGDM method under an interval neutrosophic uncertain linguistic environment.
Ye (2017e)	Proposed a bidirectional projection measure of interval numbers and neutrosophic numbers and then developed a bidirectional projection-based MAGDM method.

In this section, some basic definitions of the NST are explained.

Definition A.15. (Smarandache, 1999; Vafadarnikjoo et al., 2018) Given U be a finite set of objects, and x denotes a generic element in U. The NS, A in U is presented by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$, and a falsity-membership function $F_A(x)$. The $T_A(x)$, $I_A(x)$, and $F_A(x)$ are the elements of $]0^-, 1^+[$. The NS can be shown as Equation (A.25).

$$A = \{< x, (T_A(x), I_A(x), F_A(x)) >: x \in U, T_A(x), I_A(x), F_A(x) \in]0^-, 1^+[\ \} \tag{A.25}$$

Note that $0^- \leq T_A(x) + I_A(x) + F_A(x) \leq 3^+$

Definition A.16. (Vafadarnikjoo et al., 2018; H. Wang et al., 2010) Given U be a finite set of elements, and x denotes a generic element in U. A SVNS, A in U is signified by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$, and a falsity-membership function $F_A(x)$. The $T_A(x)$, $I_A(x)$, and $F_A(x)$ are the elements of $[0,1]$. The SVNS can be shown as Equation (A.26)

$$A = \{< x, (T_A(x), I_A(x), F_A(x)) >: x \in U, T_A(x), I_A(x), F_A(x) \in\ [0,1]\ \} \tag{A.26}$$

Note that $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$

For convenience, a SVNS $A = \{< x, (T_A(x), I_A(x), F_A(x)) >: x \in U\}$ is sometimes shown as a $A = \{< T_A(x), I_A(x), F_A(x) >: x \in U\}$ called a simplified form.

Definition A.17. (Deli and Subas, 2014; Vafadarnikjoo et al., 2018) A SVTNN $\tilde{a} =< (a_1, b_1, c_1, d_1); w_{\tilde{a}}, u_{\tilde{a}}, y_{\tilde{a}} >$, $a_1, b_1, c_1, d_1 \in \mathbb{R}$, $a_1 \leq b_1 \leq c_1 \leq d_1$, and $w_{\tilde{a}}, u_{\tilde{a}}, y_{\tilde{a}} \in [0,1]$ is a particular SVNN that $T_{\tilde{a}}(x)$, $I_{\tilde{a}}(x)$, and $F_{\tilde{a}}(x)$ are presented as Equations (A.27)-(A.29) respectively.

$$T_{\tilde{a}}(x) = \begin{cases} (x - a_1)w_{\tilde{a}}/(b_1 - a_1) & a_1 \leq x < b_1 \\ w_{\tilde{a}} & b_1 \leq x \leq c_1 \\ (d_1 - x)w_{\tilde{a}}/(d_1 - c_1) & c_1 < x \leq d_1 \\ 0 & otherwise \end{cases} \tag{A.27}$$

$$I_{\tilde{a}}(x)=\begin{cases}(b_1-x+u_{\tilde{a}}(x-a_1))/(b_1-a_1) & a_1\le x<b_1\\ u_{\tilde{a}} & b_1\le x\le c_1\\ (x-c_1+u_{\tilde{a}}(d_1-x))/(d_1-c_1) & c_1<x\le d_1\\ 1 & otherwise\end{cases} \tag{A.28}$$

$$F_{\tilde{a}}(x)=\begin{cases}(b_1-x+y_{\tilde{a}}(x-a_1))/(b_1-a_1) & a_1\le x<b_1\\ y_{\tilde{a}} & b_1\le x\le c_1\\ (x-c_1+y_{\tilde{a}}(d_1-x))/(d_1-c_1) & c_1<x\le d_1\\ 1 & otherwise\end{cases} \tag{A.29}$$

Definition A.18. (Ye, 2017a) Given $\tilde{a} =< (a_1,b_1,c_1,d_1); w_{\tilde{a}}, u_{\tilde{a}}, y_{\tilde{a}} >$ and $\tilde{b} =< (a_2,b_2,c_2,d_2); w_{\tilde{b}}, u_{\tilde{b}}, y_{\tilde{b}} >$ be two SVTNN and $\lambda > 0$ and $w_{\tilde{a}}, u_{\tilde{a}}, y_{\tilde{a}}, w_{\tilde{b}}, u_{\tilde{b}}, y_{\tilde{b}} \in [0,1]$, $a_1,b_1,c_1,d_1,a_2,b_2,c_2,d_2 \in \mathbb{R}$, $a_1 \le b_1 \le c_1 \le d_1$, and $a_2 \le b_2 \le c_2 \le d_2$ then Equations (A.30)-(A.31) are defined.

$$\tilde{a}+\tilde{b} =< (a_1+a_2, b_1+b_2, c_1+c_2, d_1+d_2); w_{\tilde{a}}+w_{\tilde{b}}-w_{\tilde{a}}w_{\tilde{b}}, u_{\tilde{a}}u_{\tilde{b}}, y_{\tilde{a}}y_{\tilde{b}} > \tag{A.30}$$

$$\lambda\tilde{a} =< (\lambda a_1, \lambda b_1, \lambda c_1, \lambda d_1); 1-(1-w_{\tilde{a}})^{\lambda}, u_{\tilde{a}}^{\lambda}, y_{\tilde{a}}^{\lambda} > \tag{A.31}$$

When $a_1,b_1,c_1,d_1,a_2,b_2,c_2,d_2 > 0$ then Equations (A.32)-(A.33) are correct.

$$\tilde{a}\tilde{b} =< (a_1a_2, b_1b_2, c_1c_2, d_1d_2); w_{\tilde{a}}w_{\tilde{b}}, u_{\tilde{a}}+u_{\tilde{b}}-u_{\tilde{a}}u_{\tilde{b}}, y_{\tilde{a}}+y_{\tilde{b}}-y_{\tilde{a}}y_{\tilde{b}} > \tag{A.32}$$

$$\tilde{a}^{\lambda} =< (a_1^{\lambda}, b_1^{\lambda}, c_1^{\lambda}, d_1^{\lambda}); w_{\tilde{a}}^{\lambda}, 1-(1-u_{\tilde{a}})^{\lambda}, 1-(1-y_{\tilde{a}})^{\lambda} > \tag{A.33}$$

Definition A.19. (Wang and Zhong, 2009; Ye, 2017a) Let $\tilde{a} =< (a,b,c,d); w_{\tilde{a}}, u_{\tilde{a}}, y_{\tilde{a}} >$ be a SVTNN. The score function of $\tilde{a}$ is computed based on Equation (A.34):

$$S(\tilde{a}) = \frac{1}{12}(a+b+c+d)(2+w_{\tilde{a}}-u_{\tilde{a}}-y_{\tilde{a}}) \qquad S(\tilde{a}) \in [0,1] \tag{A.34}$$

Definition A.20. (Ye, 2017a) For comparison of two SVTNNs $\tilde{a} =< (a_1,b_1,c_1,d_1); w_{\tilde{a}}, u_{\tilde{a}}, y_{\tilde{a}} >$ and $\tilde{b} =< (a_2,b_2,c_2,d_2); w_{\tilde{b}}, u_{\tilde{b}}, y_{\tilde{b}} >$ on the basis of Equation (A.34), if $S(\tilde{a}) > S(\tilde{b})$ then $\tilde{a} > \tilde{b}$; if $S(\tilde{a}) = S(\tilde{b})$ then $\tilde{a} = \tilde{b}$.

Appendix B: Graph Theory-Definitions

Definition B.1: order and size of a graph (Benjamin et al., 2015). The order of a graph G is the number of vertices (i.e. n) and the size of a graph G is the number of edges (i.e. m) (In Figure 3.1, $n = 6$ and $m = 7$).

Definition B.2: the degree of a vertex v (Benjamin et al., 2015). The degree of a vertex v in a graph G is shown as $deg_G v$ and is defined as the number of edges incident with the vertex v. Thus, in a graph G with n vertices, we have $0 \leq deg_G v \leq n - 1$.

For instance, in graph G, in Figure 3.1, $deg_G f = 0$ (isolated vertex), $deg_G a = 3$, $deg_G b = 3$, $deg_G c = 4$, $deg_G d = 1$, $deg_G e = 3$

Definition B.3: undirected graphs (Metcalf and Casey, 2016). In undirected graphs relationships between any two vertices are mutual.

It means for instance if e and c in Figure 3.1 are connected vertices by an edge in an undirected graph, then e is related to c, and c is related e. The graph G in Figure 3.1, is an example of undirected graphs which are also named *simple graphs*. Social networks such as a high school class is an example where students in such a network can be modelled by undirected graphs. The reason is that the relationships between students in a high school class or people in any other social networks are mutual.

Definition B.4: complete graph (Zhang, 2012). A graph K with order n (i.e. K_n) is a complete graph if between any pair of distinct vertices there exists an edge (Figure B.1).

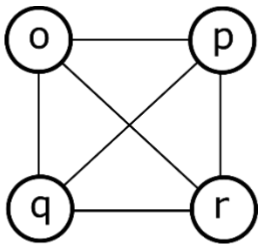


Figure B.1 A complete graph K_4

Definition B.5. path (Hein, 2001). A path is defined as a sequence of edges that is denoted by a sequence of vertices.

For instance, in Figure B.1, there is a path p, q, r, o with the length of 3

Definition B.6. cycle (Hein, 2001). A cycle is a path with equal beginning and ending vertices where no edge occurs more than once.

For instance, in Figure B.1, a path p, q, r, p is a cycle

Definition B.7: connected graph (Hein, 2001). If there is a path between every pair of vertices, then the graph is named a connected graph.

Definition B.8: subgraphs (Benjamin et al., 2015). A graph H is named a subgraph of a graph G if every vertex and edge of H is a vertex and edge of G.

Definition B.9: spanning subgraphs (Benjamin et al., 2015). If the subgraph H of a graph G, has the same vertices as G, then H is a spanning subgraph of G.

Definition B.10: trees (Benjamin et al., 2015). A tree is a connected graph that contains no cycles. It is common to signify a tree by T.

Theorem B.1. A graph G is a tree if and only if every two vertices of G are connected by only one path (The proof is provided in Benjamin et al. (2015)).

Definition B.11: spanning trees (Wu and Chao, 2004). A spanning tree of a graph G is a subgraph of G which is a tree and includes all the vertices in G.

Definition B.12: a branch and a chord (Chakraborty et al., 2019). Let G be a connected graph then an edge in a spanning tree T of G is named a branch and an edge of G which is absent in the given spanning tree T is named chord.

Definition B.13: directed graphs or digraphs (Bang-Jensen and Gutin, 2006). A digraph D that is often written as $D = (V, A)$ includes a non-empty finite set $V(D)$ of elements (vertices) and a finite set $A(D)$ of ordered pairs of distinct vertices (arcs). $V(D)$ and $A(D)$ named vertex set and arc set respectively.

In Figure B.2, a digraph D is depicted as an example. The $V(D)$ and $A(D)$ in this example are as follows:

$V(D) = \{x, y, z, t, u, v, w\}$

$A(D) = \{(x, y), (y, z), (y, t), (z, t), (t, u), (u, v), (u, w), (w, u)\}$

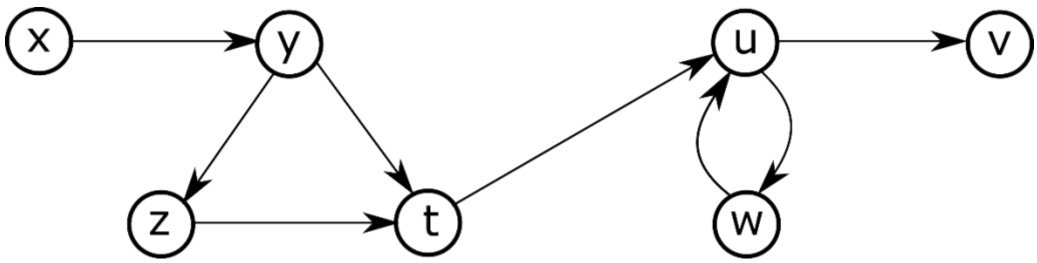


Figure B.2 A digraph D

In digraphs, for an arc like (y, z) the first vertex y is called *tail* and the second vertex is named *head* (i.e. z). It is also said that y dominates z or z is dominated by y. An arc (y, z) is often signified as yz (Bang-Jensen and Gutin, 2018). In this thesis, the arc (y, z) is shown as a_{yz}.

Theorem B.2: Cayley's tree formula. Cayley (1889) introduced the formula n^{n-2} for counting the number of spanning trees in a complete graph with order n (K_n). The proof is provided in Wu and Chao (2004).

For instance, for a K_4 graph (Figure B.1), $4^{4-2} = 16$ spanning trees can be obtained as shown in Figure B.3.

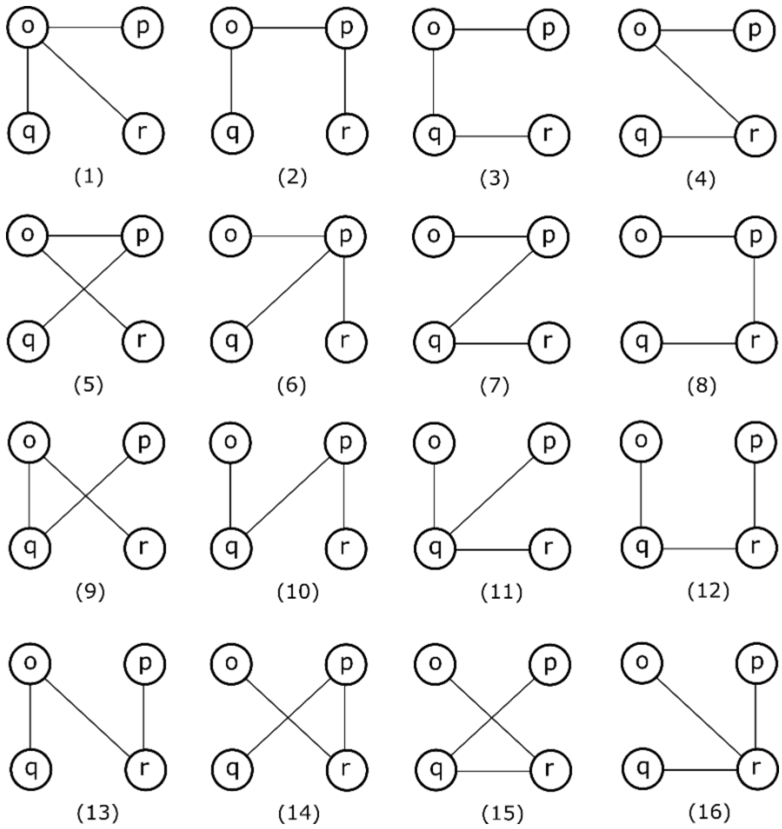


Figure B.3 All spanning trees of a complete graph K_4

Definition B.14: degree matrix (Chartrand et al., 2011). Let G be a graph with $V(G) = \{v_1, v_2, \dots, v_n\}$, then the degree matrix $D(G) = [d_{ij}]$ is a diagonal $n \times n$ matrix with diagonal values as are shown in Equation (B.35)

$$d_{ij} = \begin{cases} deg v_i, & if\ i = j \\ 0, & if\ i \neq j \end{cases} \tag{B.35}$$

Definition B.15: adjacency matrix (Siraj et al., 2012). Let G be a graph with $V(G) = \{v_1, v_2, \dots, v_n\}$, then the adjacency matrix $A(G) = [c_{ij}]$ where each element c_{ij} represents the number of edges from vertex v_i to vertex v_j.

Theorem B.3. Kirchhoff's matrix-tree theorem (Chartrand et al., 2011). Let G be a labelled graph with adjacency matrix $A(G)$ and degree matrix $D(G)$, then the absolute value of any cofactor of the Laplacian matrix $D(G) - A(G)$ results in the number of distinct spanning trees of G.

The Kirchhoff's matrix-tree theorem helps determine the number of distinct spanning trees of labelled graphs in general and not only in complete graphs.

Appendix C: All spanning trees by Gray code algorithm for ND and PI

There are many algorithms in the literature for generating all possible spanning trees in undirected graphs as reviewed by Chakraborty et al. (2019). In this research, I have used Gray code algorithm developed by Naskar et al. (2009) using Gray codes. First, an initial tree T_0 must be generated by any method such as Breadth-First Traversal (Hein, 2001). The T_0 is comprised of $n-1$ branches and $m-(n-1)$ chords. Then, $2^{m-(n-1)}$ binary representations are produced each of length $m-(n-1)$ namely Gray codes. Subsequently, combination of $n-1$ branches and $m-(n-1)$ chords are calculated for each Gray code in a way that output will contain $(n-1)$ edges. Finally, each combination should be checked if there is no cycle and it is a spanning tree. In this section, generating all spanning trees by the Gray code algorithm is shown.

The undirected graph G of the pairwise comparison matrix A provided by expert 4 in the UK energy risk dimensions analysis in Chapter 6 (Section 6.5.1.1). It indicates ND (Natural Disasters) as the most critical risk dimension (i.e. the best) and PI (Political Instability) as the least critical risk dimension (i.e. the worst) in the STE-BWM and is represented in the Figure C.1.

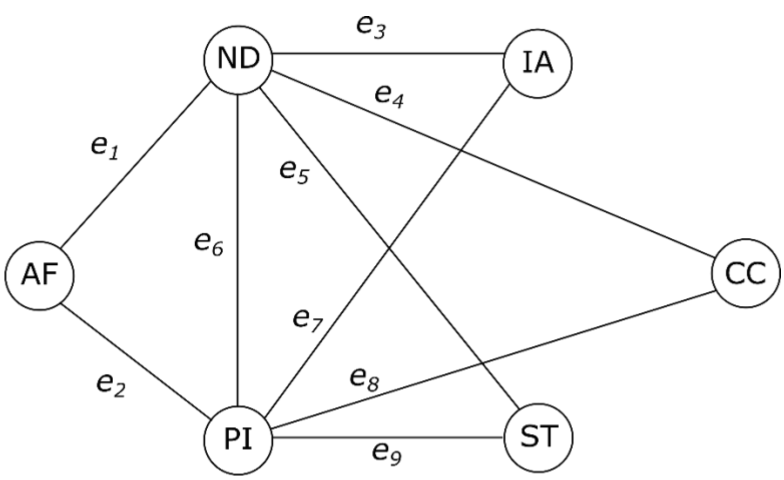


Figure C.1 The graph of pairwise-comparisons (ND and PI)

The initial tree (tree no 1 in Table C.1) is shown in the Figure C.2 which is used as the starting tree, in the Gray code algorithm.

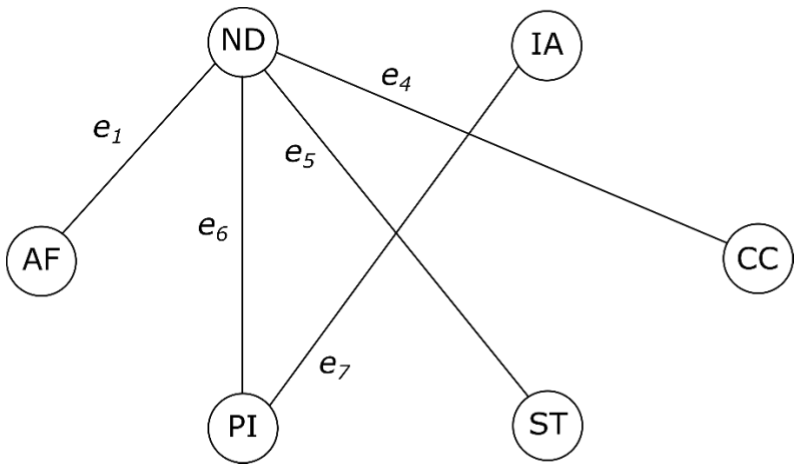


Figure C.2 The initial tree used in the Gray code algorithm (ND and PI)

In Table C.1, the # means the graph is not a tree

Table C.1 All-tree matrix (ATM) of the Gray code algorithm (ND and PI)

Graph no.	Tree no.	e_1	e_6	e_7	e_5	e_4	e_2	e_8	e_9	e_3	Gray code
1	1	1	1	1	1	1	0	0	0	0	0000
2	#	1	1	1	1	0	0	0	0	1	0001
3	#	1	1	1	0	1	0	0	0	1	0001
4	2	1	1	0	1	1	0	0	0	1	0001
5	3	1	0	1	1	1	0	0	0	1	0001
6	#	0	1	1	1	1	0	0	0	1	0001
7	#	1	1	1	1	0	0	0	1	0	0010
8	4	1	1	1	0	1	0	0	1	0	0010
9	#	1	1	0	1	1	0	0	1	0	0010
10	5	1	0	1	1	1	0	0	1	0	0010
11	#	0	1	1	1	1	0	0	1	0	0010
12	6	1	1	1	1	0	0	1	0	0	0100
13	#	1	1	1	0	1	0	1	0	0	0100
14	#	1	1	0	1	1	0	1	0	0	0100
15	7	1	0	1	1	1	0	1	0	0	0100
16	#	0	1	1	1	1	0	1	0	0	0100
17	#	1	1	1	1	0	1	0	0	0	1000
18	#	1	1	1	0	1	1	0	0	0	1000
19	#	1	1	0	1	1	1	0	0	0	1000

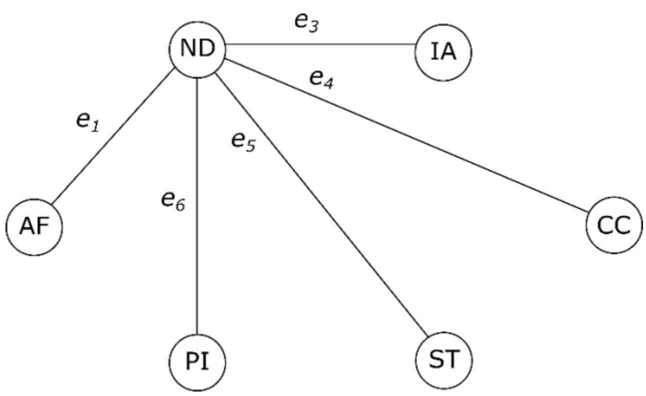
20	8	1	0	1	1	1	1	0	0	0	1000
21	9	0	1	1	1	1	1	0	0	0	1000
22	#	0	1	1	1	0	0	0	1	1	0011
23	#	0	1	1	0	1	0	0	1	1	0011
24	#	0	1	0	1	1	0	0	1	1	0011
25	#	0	0	1	1	1	0	0	1	1	0011
26	#	1	0	1	1	0	0	0	1	1	0011
27	10	1	0	1	0	1	0	0	1	1	0011
28	11	1	0	0	1	1	0	0	1	1	0011
29	12	1	1	0	0	1	0	0	1	1	0011
30	#	1	1	0	1	0	0	0	1	1	0011
31	#	1	1	1	0	0	0	0	1	1	0011
32	#	0	0	0	1	1	0	1	1	1	0111
33	#	0	0	1	0	1	0	1	1	1	0111
34	#	0	1	0	0	1	0	1	1	1	0111
35	13	1	0	0	0	1	0	1	1	1	0111
36	#	0	0	1	1	0	0	1	1	1	0111
37	#	0	1	0	1	0	0	1	1	1	0111
38	14	1	0	0	1	0	0	1	1	1	0111
39	#	0	1	1	0	0	0	1	1	1	0111
40	15	1	0	1	0	0	0	1	1	1	0111
41	16	1	1	0	0	0	0	1	1	1	0111
42	17	0	0	0	0	1	1	1	1	1	1111
43	18	0	0	0	1	0	1	1	1	1	1111
44	19	0	0	1	0	0	1	1	1	1	1111
45	20	0	1	0	0	0	1	1	1	1	1111
46	21	1	0	0	0	0	1	1	1	1	1111
47	#	0	1	1	1	0	0	1	0	1	0101
48	#	0	1	1	0	1	0	1	0	1	0101
49	#	0	1	0	1	1	0	1	0	1	0101
50	#	0	0	1	1	1	0	1	0	1	0101
51	22	1	0	1	1	0	0	1	0	1	0101
52	#	1	0	1	0	1	0	1	0	1	0101
53	23	1	0	0	1	1	0	1	0	1	0101
54	#	1	1	0	0	1	0	1	0	1	0101
55	24	1	1	0	1	0	0	1	0	1	0101

56	#	1	1	1	0	0	0	1	0	1	0101
57	#	0	1	1	1	0	1	0	0	1	1001
58	#	0	1	1	0	1	1	0	0	1	1001
59	25	0	1	0	1	1	1	0	0	1	1001
60	26	0	0	1	1	1	1	0	0	1	1001
61	#	1	0	1	1	0	1	0	0	1	1001
62	#	1	0	1	0	1	1	0	0	1	1001
63	27	1	0	0	1	1	1	0	0	1	1001
64	#	1	1	0	0	1	1	0	0	1	1001
65	#	1	1	0	1	0	1	0	0	1	1001
66	#	1	1	1	0	0	1	0	0	1	1001
67	#	0	1	1	1	0	0	1	1	0	0110
68	#	0	1	1	0	1	0	1	1	0	0110
69	#	0	1	0	1	1	0	1	1	0	0110
70	#	0	0	1	1	1	0	1	1	0	0110
71	28	1	0	1	1	0	0	1	1	0	0110
72	29	1	0	1	0	1	0	1	1	0	0110
73	#	1	0	0	1	1	0	1	1	0	0110
74	#	1	1	0	0	1	0	1	1	0	0110
75	#	1	1	0	1	0	0	1	1	0	0110
76	30	1	1	1	0	0	0	1	1	0	0110
77	#	0	1	1	1	0	1	0	1	0	1010
78	31	0	1	1	0	1	1	0	1	0	1010
79	#	0	1	0	1	1	1	0	1	0	1010
80	32	0	0	1	1	1	1	0	1	0	1010
81	#	1	0	1	1	0	1	0	1	0	1010
82	33	1	0	1	0	1	1	0	1	0	1010
83	#	1	0	0	1	1	1	0	1	0	1010
84	#	1	1	0	0	1	1	0	1	0	1010
85	#	1	1	0	1	0	1	0	1	0	1010
86	#	1	1	1	0	0	1	0	1	0	1010
87	34	0	1	1	1	0	1	1	0	0	1100
88	#	0	1	1	0	1	1	1	0	0	1100
89	#	0	1	0	1	1	1	1	0	0	1100
90	35	0	0	1	1	1	1	1	0	0	1100
91	36	1	0	1	1	0	1	1	0	0	1100

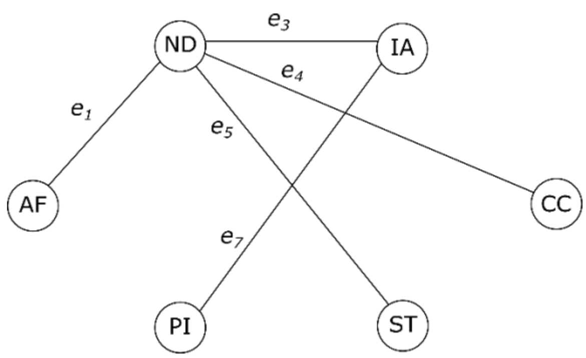
92	#	1	0	1	0	1	1	1	0	0	1100
93	#	1	0	0	1	1	1	1	0	0	1100
94	#	1	1	0	0	1	1	1	0	0	1100
95	#	1	1	0	1	0	1	1	0	0	1100
96	#	1	1	1	0	0	1	1	0	0	1100
97	37	0	0	0	1	1	1	0	1	1	1011
98	38	0	0	1	0	1	1	0	1	1	1011
99	39	0	1	0	0	1	1	0	1	1	1011
100	40	1	0	0	0	1	1	0	1	1	1011
101	#	0	0	1	1	0	1	0	1	1	1011
102	#	0	1	0	1	0	1	0	1	1	1011
103	#	1	0	0	1	0	1	0	1	1	1011
104	#	0	1	1	0	0	1	0	1	1	1011
105	#	1	0	1	0	0	1	0	1	1	1011
106	#	1	1	0	0	0	1	0	1	1	1011
107	41	0	0	0	1	1	1	1	0	1	1101
108	#	0	0	1	0	1	1	1	0	1	1101
109	#	0	1	0	0	1	1	1	0	1	1101
110	#	1	0	0	0	1	1	1	0	1	1101
111	42	0	0	1	1	0	1	1	0	1	1101
112	43	0	1	0	1	0	1	1	0	1	1101
113	44	1	0	0	1	0	1	1	0	1	1101
114	#	0	1	1	0	0	1	1	0	1	1101
115	#	1	0	1	0	0	1	1	0	1	1101
116	#	1	1	0	0	0	1	1	0	1	1101
117	#	0	0	0	1	1	1	1	1	0	1110
118	45	0	0	1	0	1	1	1	1	0	1110
119	#	0	1	0	0	1	1	1	1	0	1110
120	#	1	0	0	0	1	1	1	1	0	1110
121	46	0	0	1	1	0	1	1	1	0	1110
122	#	0	1	0	1	0	1	1	1	0	1110
123	#	1	0	0	1	0	1	1	1	0	1110
124	47	0	1	1	0	0	1	1	1	0	1110
125	48	1	0	1	0	0	1	1	1	0	1110
126	#	1	1	0	0	0	1	1	1	0	1110

As an example, the spanning trees (no 2-6 in Table C.1) are depicted as follows:

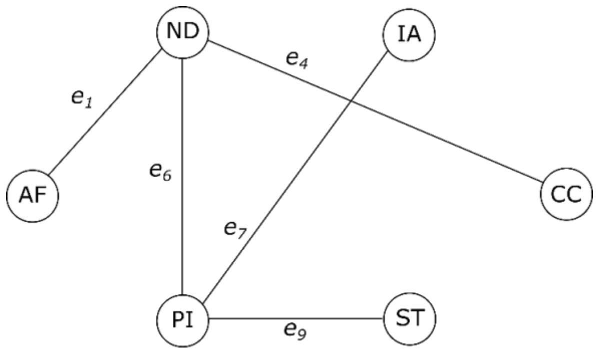
(2):



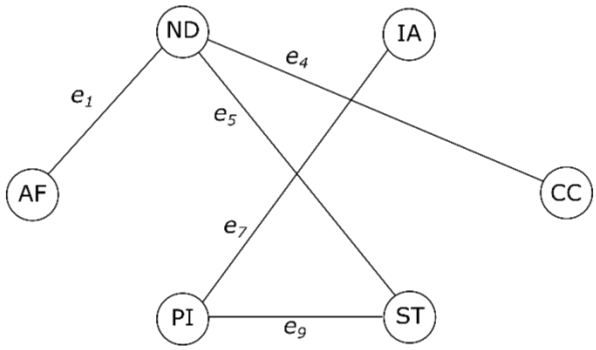
(3):



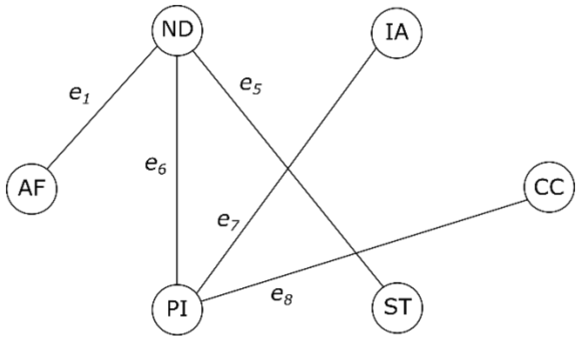
(4):



(5):



(6):



Appendix D: Maximum Mean De-Entropy Algorithm

The concept of entropy is utilised in information theory and is a measure for capturing uncertainty. The higher the entropy, the higher the expected uncertainty of single events indicating the higher instability level of the system. The Maximum Mean De-Entropy (MMDE) algorithm utilises the concept of entropy to determine the helpful information in the total relation matrix of the DEMATEL method. It is carried out by obtaining a threshold to filter the redundant information in total relation matrix (Lee and Lin, 2013; Li and Tzeng, 2009).

Definition D.1. (Lee and Lin, 2013). Given $X = (x_1, x_2, \dots, x_n)$ with a corresponding probability $P = (p_1, p_2, \dots, p_n)$ then the entropy $H(x)$ is defined as Equation (D.36) Where $\sum p_i = 1$ and $p_i \ln p_i = 0$ if $p_i = 0$

$$H(p_1, p_2, \dots, p_n) = -\sum p_i \ln p_i \tag{D.36}$$

By *Definition D.1*, $H(p_1, p_2, \dots, p_n)$ is the largest if $p_1 = p_2 = \cdots = p_n$, and the largest entropy is represented as $H\left(\frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n}\right)$.

Definition D.2. (Lee and Lin, 2013). Given X is a finite discrete scheme, the de-entropy of X is defined as H^D in Equation (D.37). Unlike entropy, which is used as a measure of uncertainty, the de-entropy can expound the amount of helpful information obtained from a specific dataset which reduces information uncertainty (Li and Tzeng, 2009).

$$H^D = H\left(\frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n}\right) - H(p_1, p_2, \dots, p_n) \tag{D.37}$$

Definition D.3. (Lee and Lin, 2013) For each t_{ij} element of matrix T, that refers to a directed influence relation from factor x_i (dispatch-node) to factor x_j (receive-node), it can be shown as a triplet of (t_{ij}, x_i, x_j). Hence, the matrix T can be regarded as a set T with n^2 pair ordered elements (in the set T, ordered dispatch-node set $T^{D_i}$and ordered receive-node set T^{R_e} exist). Given m is the number of variables in T^{D_i} or T^{R_e} and the frequency of variables x_i or x_j is k, then the probability of the variable would be $p_i = \frac{k}{m}$ noting that $\sum p_i = 1$. $C(T^{D_i})$ or $C(T^{R_e})$ denotes the cardinal number of an ordered set T^{D_i} or T^{R_e} while $N(T^{D_i})$ or $N(T^{R_e})$ represents the cardinal number of different elements in set T^{D_i} or T^{R_e} . For example, if $T^{D_i} = \{1,2,2,3,1\}$ then $C(T^{D_i}) =$

5 and $N(T^{D_i}) = 3$. The steps of the MMDE algorithm for obtaining a threshold value based on a matrix T are elaborated as follows (Lee and Lin, 2013):

Step 1: Ordered triplets T^* construction

Converting T into an ordered set $T = \{t_{11}, t_{12}, \dots, t_{21}, t_{22}, \dots, t_{nn}\}$ then rearranging elements in descending order and converting to respective ordered triplets (t_{ij}, x_i, x_j) set called T^*

Step 2: Dispatch-node set (T^{D_i}) and receive-node set (T^{R_e}) construction

Taking the second and third elements from T^* and then obtaining a new ordered dispatch-node set (T^{D_i}) and receive-node set (T^{R_e}) as shown in Equation (D.38) and (D.39) respectively.

$$T^{D_i} = \{x_i\} \tag{D.38}$$

$$T^{R_e} = \{x_j\} \tag{D.39}$$

Step 3: $MDE_t^{D_i}$ and $MDE_t^{R_e}$ calculation

Taking the first t elements of T^{D_i} and T^{R_e} as new sets $T_t^{D_i}$ and $T_t^{R_e}$ respectively. By Equation (D.40)-(D.43), $MDE_t^{D_i}$ and $MDE_t^{R_e}$ can be obtained.

$$H_t^{D_i} = H\left[\frac{1}{N(T^{D_i})}, \frac{1}{N(T^{D_i})}, \dots, \frac{1}{N(T^{D_i})}\right] - H\left[\frac{k_1}{C(T^{D_i})}, \frac{k_2}{C(T^{D_i})}, \dots, \frac{k_t}{C(T^{D_i})}\right] \tag{D.40}$$

$$H_t^{R_e} = H\left[\frac{1}{N(T^{R_e})}, \frac{1}{N(T^{R_e})}, \dots, \frac{1}{N(T^{R_e})}\right] - H\left[\frac{k_1}{C(T^{R_e})}, \frac{k_2}{C(T^{R_e})}, \dots, \frac{k_t}{C(T^{R_e})}\right] \tag{D.41}$$

$$MDE_t^{D_i} = \frac{H_t^{D_i}}{N(T_t^{D_i})} \tag{D.42}$$

$$MDE_t^{R_e} = \frac{H_t^{R_e}}{N(T_t^{R_e})} \tag{D.43}$$

Step 4: MMDE, $T_{max}^{D_i}$ and $T_{max}^{R_e}$ identification

Finding the maximum value of $MDE_t^{D_i}$ and $MDE_t^{R_e}$ and their respective set $T_t^{D_i}$ and $T_t^{R_e}$ represented as $T_{max}^{D_i}$ and $T_{max}^{R_e}$

Step 5: Maximum information set construction and threshold value determination

Taking the first u elements in T^* as the subset, T^{Th} , which comprises all elements of $T_{max}^{D_i}$ and $T_{max}^{R_e}$, then the minimum impact value in T^{Th} is the threshold value.

Appendix E: Best-Worst Method

The Best-Worst Method (BWM) functions in a similar way to that of the Analytic Hierarchy Process (AHP) as both methods use pairwise comparisons. However, the BWM benefits from some advantages over the AHP, which has made it more popular in recent years. One merit is the BWM's requirement of fewer comparisons than those required in the AHP. Secondly, the BWM consists of a lower complexity of comparisons as in the BWM only whole numbers (i.e., $1-9$ scale) are utilised, while in the AHP, fractional numbers are also used (i.e. ${}^{1}/_{9}-9$ scale). Using whole numbers makes the evaluation process and interpretations much easier since they can more easily be measured by human perception and cognition. Thirdly, the BWM properly maintains the consistency of pairwise comparisons because the redundant comparisons are eliminated. This means that the derived BWM results are more reliable than the ones obtained by the AHP (Mi et al., 2019).

The BWM has been successfully applied in a wide range of studies. Some of the recent applications of the BWM include: Circular Economy (CE) in the leather industry in Bangladesh (Moktadir et al., 2020); third-party logistics (Pamucar et al., 2019); renewable energy integration (Vishnupriyan and Manoharan, 2018); power plants alternatives selection (Omrani et al., 2018); battery energy storage systems (Zhao et al., 2018); financial performance analysis (Alimohammadlou and Bonyani, 2018); sustainable architecture (Amoozad Mahdiraji et al., 2018); acute leukaemia classification (Alsalem et al., 2018) and sustainable supplier selection in the plastics industry (Cheraghalipour and Farsad, 2018).

Huge efforts have been made to develop the BWM theoretically and integrate it with other techniques. Mi et al. (2019) recently reviewed the BWM literature providing insightful detailed information on the BWM theoretical extensions and practical applications. They have indicated that 67% of the BWM publications are related to the integration of the BWM. Almost half of this amount focused on the singleton integrations of the BWM while the rest integrated more than one method with the BWM. The most popular singleton integrations of the BWM include uncertainty (i.e. fuzzy information), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIKOR, and Fuzzy-Delphi Method (FDM).

A recent list of the BWM integrations include the Euclidean BWM (Kocak et al., 2018); the Probabilistic Hesitant Fuzzy Elements (PHFE) and the BWM (Li et al., 2019); the Z-number extension of the BWM (Aboutorab et al., 2018); the mixed grey-based BWM and TODIM (Bai et al., 2019); the hybrid fuzzy BWM, and Complex Proportional Assessment (COPRAS) method (Amoozad Mahdiraji et al., 2018); the integrated BWM and VIKOR method (Cheraghalipour et al., 2018; Garg and Sharma, 2018; Gupta, 2018a); the hybrid fuzzy TOPSIS and the BWM (Gupta, 2018b; Gupta and Barua, 2018; Lo et al., 2018); the hybrid BWM and ELECTRE method (Yadav et al., 2018); the fuzzy BWM and fuzzy MULTIMOORA (A. Liu et al., 2018); rough numbers and the BWM (i.e. RBWM) and VIKOR (S. Liu et al., 2018); the integrated Interval Rough Number (IRN) and the BWM (IRN-BWM) (Pamucar et al., 2019); the Mixed Integer Linear Model (MILM) to provide better approximate solutions to the original Non-Linear Model (NLM) in the BWM (Beemsterboer et al., 2018); the fuzzy BWM (Guo and Zhao, 2017; Hafezalkotob and Hafezalkotob, 2017; Ijadi Maghsoodi et al., 2019); the IF-BWM (Mou et al., 2017), and the hybrid Intuitionistic Fuzzy Multiplicative BWM (IFM-BWM) (Mou et al., 2016).

The original Linear-BWM (L-BWM) procedure is explained below (Badri Ahmadi et al., 2017; Rezaei, 2016):

Step 1: Identifying decision-making criteria (in this thesis, risk dimensions)

A set of risk dimensions is identified. The identified risks can be signified by the notations $\{r_1, r_2, \dots, r_n\}$.

Step 2: Determining the best (i.e., the most critical) and the worst (i.e., the least critical) risks

In this step, decision-makers identify the best (i.e., the most critical) and the worst (i.e., the least critical) risk dimensions. To do this, there is no need to construct a vector comparison matrix.

Step 3: Establishing the Best-to-Others (BO) preference vector using a 9-point scale

In this stage, experts use the linguistic $1-9$ rating scale (Table E.1) to construct a preference vector of the most critical risk (i.e., best) over other risks. A rating scale of 1 means equal preference, and 9 means extreme preference. The resulting BO vector can be represented as $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$. The notation a_{B1} denotes the preference of the most critical (i.e., the best) risk dimension B compared to risk dimension 1 , and obviously, the value of a_{BB} will be 1.

Step 4: Establishing the Others-to-Worst (OW) preference vector using a 9-point scale

In this stage, experts use the linguistic $1-9$ rating scale (Table E.1) to construct a preference vector of others to the worst (i.e., the least critical) risk dimension. The OW vector can be represented as $A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T$. In the OW vector, the notation a_{1W} denotes the value of a verbal scale for a risk dimension 1 over the worst (i.e., the least critical) risk dimension W, and, naturally, the value of a_{WW} would be equal to 1.

Table E.1 The importance rating scale

Numerical scale	Verbal scale
1	Equally important
2	Weakly more important
3	Moderately more important
4	Moderately Plus more important
5	Strongly more important
6	Strongly Plus more important
7	Very Strongly Plus more important
8	Very Very Strongly more important
9	Extremely more important

Step 5: Finding the optimal weights of identified risks $(w_1^*, w_2^*, \dots, w_n^*)$

In this step, the optimised weight of each risk dimension is calculated by minimising the maximum absolute differences, as shown in the objective function of Model (E.44).

$$\min max_j \{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\} \tag{E.44}$$

subject to

$$\sum_j w_j = 1$$

$$w_j \geq 0 \text{ for all } j$$

Model (E.44) is converted to a linear programming problem, which can be represented as Model (E.45):

$$\text{Min } \xi^L \tag{E.45}$$

subject to

$$|w_B - a_{Bj}w_j| \leq \xi^L \text{ for all j}$$

$$|w_j - a_{jW}w_W| \leq \xi^L \text{ for all j}$$

$$\sum_j w_j = 1$$

$$w_j \geq 0 \text{ for all } j$$

Appendix F: Acquiring DMs' confidence levels

Table F.1 Acquiring DMs' confidence on the best-to-others and the others-to-worst preferences

Q1. Reflecting on your chosen best criterion and your provided preferences, to what degree do you have confidence on your provided best-to-others preferences? Please choose one of the following choices:						
☐ No Confidence	☐ Low Confidence	☐ Fairly Low Confidence	☐Moderate Confidence	☐Fairly High Confidence	☐High Confidence	☐Absolute Confidence
Q2. Reflecting on your chosen worst criterion and your provided preferences, to what degree do you have confidence on your provided others-to-worst preferences? Please choose one of the following choices:						
☐ No Confidence	☐ Low Confidence	☐ Fairly Low Confidence	☐Moderate Confidence	☐Fairly High Confidence	☐High Confidence	☐Absolute Confidence

Appendix G: The CI values in NE-BWM

In this appendix, CI values corresponding to various a_{BW}, ρ^{+} and ρ^{-} values have been shown (Table G.1). Note that by swapping values for ρ^{+} and ρ^{-} the CI values will not change (The reason for that is clear in Equation (4.25) as interchanging ρ^{+} and ρ^{-} would not produce a new solution. For instance, for $a_{BW} = 2$ and $\rho^{-} = 0.68$ and $\rho^{+} = 0.90$ the CI would be $CI = 0.274$ which is the same CI value for $a_{BW} = 2$ and $\rho^{-} = 0.90$ and $\rho^{+} = 0.68$). Thus, for convenience those ρ^{-} and ρ^{+} values are shown which produce unique CI values. The CI values for $a_{BW} = 1$ are not shown because it is not possible that the best and worst criteria are equally important.

Table G.1 The CI values in NE-BWM

ρ^{+}	ρ^{-}	$a_{BW}=2$	$a_{BW}=3$	$a_{BW}=4$	$a_{BW}=5$	$a_{BW}=6$	$a_{BW}=7$	$a_{BW}=8$	$a_{BW}=9$
0.26	**0.26**	0.092	0.218	0.363	0.520	0.687	0.860	1.040	1.224
0.26	**0.38**	0.109	0.257	0.428	0.612	0.807	1.010	1.218	1.432
0.26	**0.50**	0.120	0.283	0.468	0.668	0.878	1.095	1.318	1.546
0.26	**0.68**	0.132	0.307	0.506	0.718	0.941	1.169	1.403	1.641
0.26	**0.90**	0.140	0.325	0.533	0.754	0.984	1.219	1.459	1.702
0.26	**1.00**	0.143	0.331	0.542	0.765	0.997	1.235	1.476	1.721
0.38	**0.38**	0.135	0.318	0.530	0.760	1.004	1.258	1.520	1.789
0.38	**0.50**	0.153	0.361	0.600	0.860	1.134	1.420	1.715	2.017
0.38	**0.68**	0.172	0.404	0.670	0.956	1.258	1.571	1.892	2.220
0.38	**0.90**	0.187	0.438	0.723	1.028	1.348	1.678	2.015	2.358
0.38	**1.00**	0.193	0.450	0.740	1.051	1.376	1.711	2.053	2.400
0.50	**0.50**	0.177	0.419	0.697	1.000	1.321	1.655	2.000	2.354
0.50	**0.68**	0.204	0.481	0.800	1.146	1.511	1.892	2.284	2.686
0.50	**0.90**	0.227	0.533	0.883	1.261	1.658	2.070	2.493	2.926
0.50	**1.00**	0.234	0.551	0.911	1.298	1.706	2.127	2.559	3.000
0.68	**0.68**	0.241	0.570	0.948	1.360	1.796	2.251	2.720	3.202
0.68	**0.90**	0.274	0.647	1.076	1.542	2.034	2.547	3.075	3.617
0.68	**1.00**	0.286	0.675	1.121	1.605	2.115	2.646	3.193	3.752
0.90	**0.90**	0.319	0.754	1.255	1.800	2.377	2.979	3.600	4.238
0.90	**1.00**	0.336	0.793	1.320	1.893	2.500	3.132	3.785	4.455
1.00	**1.00**	0.354	0.838	1.394	2.000	2.641	3.310	4.000	4.708

Appendix H: Spanning Trees Enumeration

H.1 Enumerating All Spanning Trees

Siraj et al. (2012) introduced the Enumerating All Spanning Trees (EAST) method to obtain prioritisation weights of criteria in pair-wise comparisons. The procedure of EAST is explained in the following steps (In this thesis, criteria are risk dimensions):

Step 1: Obtain the criteria set

$$C = \{F_1, F_2, \dots, F_n\} \tag{H.46}$$

Step 2: Acquire the pair-wise comparison matrix of criteria

The obtained pair-wise comparisons can be either complete (without missing values) or incomplete (with missing values).

$$A = \left[a_{ij}\right] \quad i, j = 1, \dots, n \tag{H.47}$$

Step 3: Produce the corresponding graph of the pair-wise comparison matrix

The graph can be produced by taking each criterion as a vertex then each non-empty, non-diagonal element of the pair-wise comparison matrix reveals that there is an edge between the two related vertices as in Equation (H.48), (i, j) represents an edge between vertex i and j.

$$(i, j) = \begin{cases} \hfill exists, & a_{ij} \notin \emptyset \\ does\ not\ exist, & a_{ij} \in \emptyset \end{cases} \quad i \neq j \tag{H.48}$$

Step 4: Generate all spanning trees

The total number of possible spanning trees (η) can be calculated using Kirchhoff's matrix-tree theorem (Theorem B.3 in Appendix B). Then, a Gray code algorithm (Appendix C) can be used to generate all spanning trees.

Step 5: Compute the weights of criteria from each spanning tree

Knowing that each obtained spanning tree has $(n-1)$ edges. The weight of i^{th} criterion in k^{th} spanning tree ($w_i^{(k)}$) can be computed by solving a system of n linear equations. For any spanning tree, the $(n-1)$ equations out of n are constructed based on Equation (H.49), and the last one indicates the sum of weights must be equal to 1 as shown in Equation (H.50).

$$w_i^{(k)} = a_{ij} w_j^{(k)} \quad \forall k = 1, \dots, \eta \quad i, j = 1, \dots, n \quad i \neq j \tag{H.49}$$

$$\sum_{i=1}^{n} w_i^{(k)} = 1 \qquad \forall k = 1, \dots, \eta \tag{H.50}$$

Step 6: Calculate the average of all weights and prioritise criteria

Assuming η is the total number of generated spanning trees then the final weights of criteria (w_i) can be obtained based on the Equation (H.51)

$$w_i = \frac{\sum_{k=1}^{\eta} w_i^{(k)}}{\eta} \quad \forall i = 1, \dots, n \tag{H.51}$$

H.2 Geometric Mean of All Spanning Trees

Lundy et al. (2017) explored the quality of the Geometric Mean of All Spanning Trees (GMAST) method and indicated that as EAST fails to adhere to geometric properties, GMAST can outperform EAST in obtaining final weights. The steps 1 to 5 in the GMAST is the same as EAST as explained in Section H.1 and the step 6 is as follows:

Step 6: Calculate the geometric mean of all weights and prioritise criteria as shown in Equation (H.52).

$$w_i = \sqrt[\eta]{\prod_{k=1}^{\eta} w_i^{(k)}} \quad \forall i = 1, \dots, n \tag{H.52}$$

Appendix I: Twelve states in a stratified game table

Table I.1 Twelve states in a stratified game table for N=3 and M=4

	SE_1	SE_2	SE_3	SE_4	SE_5	SE_6	SE_7	SE_8	SE_9	SE_{10}	SE_{11}	SE_{12}
SE_1	$p_{11} \times q_{11}$	$p_{11} \times q_{12}$	$p_{11} \times q_{13}$	$p_{11} \times q_{14}$	$p_{12} \times q_{11}$	$p_{12} \times q_{12}$	$p_{12} \times q_{13}$	$p_{12} \times q_{14}$	$p_{13} \times q_{11}$	$p_{13} \times q_{12}$	$p_{13} \times q_{13}$	$p_{13} \times q_{14}$
SE_2	$p_{11} \times q_{21}$	$p_{11} \times q_{22}$	$p_{11} \times q_{23}$	$p_{11} \times q_{24}$	$p_{12} \times q_{21}$	$p_{12} \times q_{22}$	$p_{12} \times q_{23}$	$p_{12} \times q_{24}$	$p_{13} \times q_{21}$	$p_{13} \times q_{22}$	$p_{13} \times q_{23}$	$p_{13} \times q_{24}$
SE_3	$p_{11} \times q_{31}$	$p_{11} \times q_{32}$	$p_{11} \times q_{33}$	$p_{11} \times q_{34}$	$p_{12} \times q_{31}$	$p_{12} \times q_{32}$	$p_{12} \times q_{33}$	$p_{12} \times q_{34}$	$p_{13} \times q_{31}$	$p_{13} \times q_{32}$	$p_{13} \times q_{33}$	$p_{13} \times q_{34}$
SE_4	$p_{11} \times q_{41}$	$p_{11} \times q_{42}$	$p_{11} \times q_{43}$	$p_{11} \times q_{44}$	$p_{12} \times q_{41}$	$p_{12} \times q_{42}$	$p_{12} \times q_{43}$	$p_{12} \times q_{44}$	$p_{13} \times q_{41}$	$p_{13} \times q_{42}$	$p_{13} \times q_{43}$	$p_{13} \times q_{44}$
SE_5	$p_{21} \times q_{11}$	$p_{21} \times q_{12}$	$p_{21} \times q_{13}$	$p_{21} \times q_{14}$	$p_{22} \times q_{11}$	$p_{22} \times q_{12}$	$p_{22} \times q_{13}$	$p_{22} \times q_{14}$	$p_{23} \times q_{11}$	$p_{23} \times q_{12}$	$p_{23} \times q_{13}$	$p_{23} \times q_{14}$
SE_6	$p_{21} \times q_{21}$	$p_{21} \times q_{22}$	$p_{21} \times q_{23}$	$p_{21} \times q_{24}$	$p_{22} \times q_{21}$	$p_{22} \times q_{22}$	$p_{22} \times q_{23}$	$p_{22} \times q_{24}$	$p_{23} \times q_{21}$	$p_{23} \times q_{22}$	$p_{23} \times q_{23}$	$p_{23} \times q_{24}$
SE_7	$p_{21} \times q_{31}$	$p_{21} \times q_{32}$	$p_{21} \times q_{33}$	$p_{21} \times q_{34}$	$p_{22} \times q_{31}$	$p_{22} \times q_{32}$	$p_{22} \times q_{33}$	$p_{22} \times q_{34}$	$p_{23} \times q_{31}$	$p_{23} \times q_{32}$	$p_{23} \times q_{33}$	$p_{23} \times q_{34}$
SE_8	$p_{21} \times q_{41}$	$p_{21} \times q_{42}$	$p_{21} \times q_{43}$	$p_{21} \times q_{44}$	$p_{22} \times q_{41}$	$p_{22} \times q_{42}$	$p_{22} \times q_{43}$	$p_{22} \times q_{44}$	$p_{23} \times q_{41}$	$p_{23} \times q_{42}$	$p_{23} \times q_{43}$	$p_{23} \times q_{44}$
SE_9	$p_{31} \times q_{11}$	$p_{31} \times q_{12}$	$p_{31} \times q_{13}$	$p_{31} \times q_{14}$	$p_{32} \times q_{11}$	$p_{32} \times q_{12}$	$p_{32} \times q_{13}$	$p_{32} \times q_{14}$	$p_{33} \times q_{11}$	$p_{33} \times q_{12}$	$p_{33} \times q_{13}$	$p_{33} \times q_{14}$
SE_{10}	$p_{31} \times q_{21}$	$p_{31} \times q_{22}$	$p_{31} \times q_{23}$	$p_{31} \times q_{24}$	$p_{32} \times q_{21}$	$p_{32} \times q_{22}$	$p_{32} \times q_{23}$	$p_{32} \times q_{24}$	$p_{33} \times q_{21}$	$p_{33} \times q_{22}$	$p_{33} \times q_{23}$	$p_{33} \times q_{24}$
SE_{11}	$p_{31} \times q_{31}$	$p_{31} \times q_{32}$	$p_{31} \times q_{33}$	$p_{31} \times q_{34}$	$p_{32} \times q_{31}$	$p_{32} \times q_{32}$	$p_{32} \times q_{33}$	$p_{32} \times q_{34}$	$p_{33} \times q_{31}$	$p_{33} \times q_{32}$	$p_{33} \times q_{33}$	$p_{33} \times q_{34}$
SE_{12}	$p_{31} \times q_{41}$	$p_{31} \times q_{42}$	$p_{31} \times q_{43}$	$p_{31} \times q_{44}$	$p_{32} \times q_{41}$	$p_{32} \times q_{42}$	$p_{32} \times q_{43}$	$p_{32} \times q_{44}$	$p_{33} \times q_{41}$	$p_{33} \times q_{42}$	$p_{33} \times q_{43}$	$p_{33} \times q_{44}$

Appendix J: Survey for NR-DEMATEL

Q1. On which of the following risk dimension(s) in the UK power supply chain can you provide assessments? (Please choose as many as you can. Based on your selection you will rate the influence of each selected items to others.)

- ☐ Climate Change (CC)
- ☐ Natural Disasters (ND)
- ☐ Environmental and Health Safety (EHS)
- ☐ Technical Reliability (TR)
- ☐ Operational Safety (OS)
- ☐ Disease Outbreak (DO)
- ☐ Political Instability (PI)
- ☐ Industrial Action (IA)
- ☐ Sabotage and Terrorism (ST)
- ☐ Resource Availability (RA)
- ☐ Market Failure (MF)
- ☐ Affordability (AF)

Based on the chosen risk dimension(s) in the **Q1**, the expert will answer to a number of questions, in the **Q2** it is assumed that the expert selected *Climate Change (CC)* so he/she is only asked to answer one question with 11 evaluations (The influence scale is explained in Table 4.1).

Q2. To what extent do you think *Climate Change (CC)* can impact the following risks in the UK power supply chain? (*NI=No Influence, LI=Low Influence, FLI=Fairly Low Influence, MI= Medium Influence, FHI=Fairly High Influence, HI=High Influence, AHI=Absolutely High Influence*).

	Influence Scale						
Climate Change influence on:	NI	LI	FLI	MI	FHI	HI	AHI
Natural Disasters (ND)	☐	☐	☐	☐	☐	☐	☐
Environmental and Health Safety (EHS)	☐	☐	☐	☐	☐	☐	☐
Technical Reliability (TR)	☐	☐	☐	☐	☐	☐	☐
Operational Safety (OS)	☐	☐	☐	☐	☐	☐	☐
Disease Outbreak (DO)	☐	☐	☐	☐	☐	☐	☐
Political Instability (PI)	☐	☐	☐	☐	☐	☐	☐
Industrial Action (IA)	☐	☐	☐	☐	☐	☐	☐
Sabotage and Terrorism (ST)	☐	☐	☐	☐	☐	☐	☐
Resource Availability (RA)	☐	☐	☐	☐	☐	☐	☐
Market Failure (MF)	☐	☐	☐	☐	☐	☐	☐
Affordability (AF)	☐	☐	☐	☐	☐	☐	☐

Appendix K: All spanning trees by Gray code algorithm for ST and PI

The undirected graph G of the pairwise comparison matrix A provided by expert 4 in the UK energy risk dimensions analysis in Chapter 6 (Section 6.5.1.2). It indicates ST (Sabotage and Terrorism) as the most critical risk dimension (i.e. the best), and PI (Political Instability) as the least critical risk dimension (i.e. the worst) in the STE-BWM and is represented in the Figure K.1.

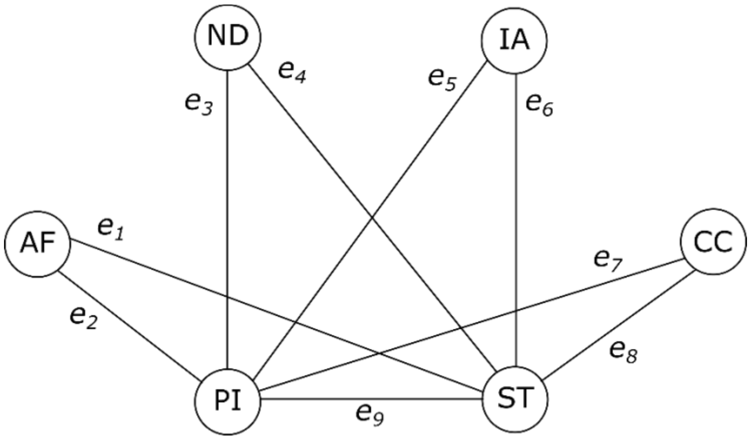


Figure K.1 The graph of pairwise-comparisons (ST and PI)

The initial tree (tree no 1 in Table K.1) is shown in the Figure K.2 which is used as the starting tree, in the Gray code algorithm.

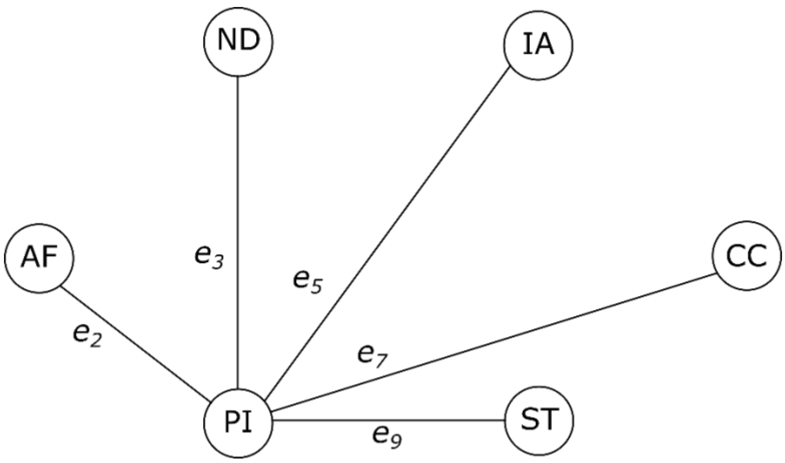


Figure K.2 The initial tree used in the Gray code algorithm (ST and PI)

In Table K.1, the # means the graph is not a tree

Table K.1 All-tree matrix (ATM) of the Gray code algorithm (ST and PI)

Graph no.	Tree no.	e_2	e_3	e_5	e_7	e_9	e_1	e_4	e_6	e_8	Gray code
1	1	1	1	1	1	1	0	0	0	0	0000
2	2	1	1	1	1	0	0	0	0	1	0001
3	3	1	1	1	0	1	0	0	0	1	0001
4	#	1	1	0	1	1	0	0	0	1	0001
5	#	1	0	1	1	1	0	0	0	1	0001
6	#	0	1	1	1	1	0	0	0	1	0001
7	4	1	1	1	1	0	0	0	1	0	0010
8	#	1	1	1	0	1	0	0	1	0	0010
9	5	1	1	0	1	1	0	0	1	0	0010
10	#	1	0	1	1	1	0	0	1	0	0010
11	#	0	1	1	1	1	0	0	1	0	0010
12	6	1	1	1	1	0	0	1	0	0	0100
13	#	1	1	1	0	1	0	1	0	0	0100
14	#	1	1	0	1	1	0	1	0	0	0100
15	7	1	0	1	1	1	0	1	0	0	0100
16	#	0	1	1	1	1	0	1	0	0	0100
17	8	1	1	1	1	0	1	0	0	0	1000
18	#	1	1	1	0	1	1	0	0	0	1000
19	#	1	1	0	1	1	1	0	0	0	1000
20	#	1	0	1	1	1	1	0	0	0	1000
21	9	0	1	1	1	1	1	0	0	0	1000
22	#	0	1	1	1	0	0	0	1	1	0011
23	#	0	1	1	0	1	0	0	1	1	0011
24	#	0	1	0	1	1	0	0	1	1	0011
25	#	0	0	1	1	1	0	0	1	1	0011
26	#	1	0	1	1	0	0	0	1	1	0011
27	#	1	0	1	0	1	0	0	1	1	0011
28	#	1	0	0	1	1	0	0	1	1	0011
29	10	1	1	0	0	1	0	0	1	1	0011
30	11	1	1	0	1	0	0	0	1	1	0011
31	12	1	1	1	0	0	0	0	1	1	0011

32	#	0	0	0	1	1	0	1	1	1	0111
33	#	0	0	1	0	1	0	1	1	1	0111
34	#	0	1	0	0	1	0	1	1	1	0111
35	13	1	0	0	0	1	0	1	1	1	0111
36	#	0	0	1	1	0	0	1	1	1	0111
37	#	0	1	0	1	0	0	1	1	1	0111
38	14	1	0	0	1	0	0	1	1	1	0111
39	#	0	1	1	0	0	0	1	1	1	0111
40	15	1	0	1	0	0	0	1	1	1	0111
41	16	1	1	0	0	0	0	1	1	1	0111
42	17	0	0	0	0	1	1	1	1	1	1111
43	18	0	0	0	1	0	1	1	1	1	1111
44	19	0	0	1	0	0	1	1	1	1	1111
45	20	0	1	0	0	0	1	1	1	1	1111
46	21	1	0	0	0	0	1	1	1	1	1111
47	#	0	1	1	1	0	0	1	0	1	0101
48	#	0	1	1	0	1	0	1	0	1	0101
49	#	0	1	0	1	1	0	1	0	1	0101
50	#	0	0	1	1	1	0	1	0	1	0101
51	22	1	0	1	1	0	0	1	0	1	0101
52	23	1	0	1	0	1	0	1	0	1	0101
53	#	1	0	0	1	1	0	1	0	1	0101
54	#	1	1	0	0	1	0	1	0	1	0101
55	#	1	1	0	1	0	0	1	0	1	0101
56	24	1	1	1	0	0	0	1	0	1	0101
57	25	0	1	1	1	0	1	0	0	1	1001
58	26	0	1	1	0	1	1	0	0	1	1001
59	#	0	1	0	1	1	1	0	0	1	1001
60	#	0	0	1	1	1	1	0	0	1	1001
61	#	1	0	1	1	0	1	0	0	1	1001
62	#	1	0	1	0	1	1	0	0	1	1001
63	#	1	0	0	1	1	1	0	0	1	1001
64	#	1	1	0	0	1	1	0	0	1	1001
65	#	1	1	0	1	0	1	0	0	1	1001
66	27	1	1	1	0	0	1	0	0	1	1001
67	#	0	1	1	1	0	0	1	1	0	0110

68	#	0	1	1	0	1	0	1	1	0	0110
69	#	0	1	0	1	1	0	1	1	0	0110
70	#	0	0	1	1	1	0	1	1	0	0110
71	28	1	0	1	1	0	0	1	1	0	0110
72	#	1	0	1	0	1	0	1	1	0	0110
73	29	1	0	0	1	1	0	1	1	0	0110
74	#	1	1	0	0	1	0	1	1	0	0110
75	30	1	1	0	1	0	0	1	1	0	0110
76	#	1	1	1	0	0	0	1	1	0	0110
77	31	0	1	1	1	0	1	0	1	0	1010
78	#	0	1	1	0	1	1	0	1	0	1010
79	32	0	1	0	1	1	1	0	1	0	1010
80	#	0	0	1	1	1	1	0	1	0	1010
81	#	1	0	1	1	0	1	0	1	0	1010
82	#	1	0	1	0	1	1	0	1	0	1010
83	#	1	0	0	1	1	1	0	1	0	1010
84	#	1	1	0	0	1	1	0	1	0	1010
85	33	1	1	0	1	0	1	0	1	0	1010
86	#	1	1	1	0	0	1	0	1	0	1010
87	34	0	1	1	1	0	1	1	0	0	1100
88	#	0	1	1	0	1	1	1	0	0	1100
89	#	0	1	0	1	1	1	1	0	0	1100
90	35	0	0	1	1	1	1	1	0	0	1100
91	36	1	0	1	1	0	1	1	0	0	1100
92	#	1	0	1	0	1	1	1	0	0	1100
93	#	1	0	0	1	1	1	1	0	0	1100
94	#	1	1	0	0	1	1	1	0	0	1100
95	#	1	1	0	1	0	1	1	0	0	1100
96	#	1	1	1	0	0	1	1	0	0	1100
97	#	0	0	0	1	1	1	0	1	1	1011
98	#	0	0	1	0	1	1	0	1	1	1011
99	37	0	1	0	0	1	1	0	1	1	1011
100	#	1	0	0	0	1	1	0	1	1	1011
101	#	0	0	1	1	0	1	0	1	1	1011
102	38	0	1	0	1	0	1	0	1	1	1011
103	#	1	0	0	1	0	1	0	1	1	1011

104	39	0	1	1	0	0	1	0	1	1	1011
105	#	1	0	1	0	0	1	0	1	1	1011
106	40	1	1	0	0	0	1	0	1	1	1011
107	#	0	0	0	1	1	1	1	0	1	1101
108	41	0	0	1	0	1	1	1	0	1	1101
109	#	0	1	0	0	1	1	1	0	1	1101
110	#	1	0	0	0	1	1	1	0	1	1101
111	42	0	0	1	1	0	1	1	0	1	1101
112	#	0	1	0	1	0	1	1	0	1	1101
113	#	1	0	0	1	0	1	1	0	1	1101
114	43	0	1	1	0	0	1	1	0	1	1101
115	44	1	0	1	0	0	1	1	0	1	1101
116	#	1	1	0	0	0	1	1	0	1	1101
117	45	0	0	0	1	1	1	1	1	0	1110
118	#	0	0	1	0	1	1	1	1	0	1110
119	#	0	1	0	0	1	1	1	1	0	1110
120	#	1	0	0	0	1	1	1	1	0	1110
121	46	0	0	1	1	0	1	1	1	0	1110
122	47	0	1	0	1	0	1	1	1	0	1110
123	48	1	0	0	1	0	1	1	1	0	1110
124	#	0	1	1	0	0	1	1	1	0	1110
125	#	1	0	1	0	0	1	1	1	0	1110
126	#	1	1	0	0	0	1	1	1	0	1110

Appendix L: Survey for stratified decision-making modelling

In order to acquire the utility values and status transition probabilities, the following three sections are designed within the survey.

Section 1: Utility values estimations for each strategy using the scale provided in the Table 7.2.

Each expert was first asked to read the following definitions for the specific flooding risk mitigation strategy and answer Q1. Six questions like Q1 for each strategy are required to be answered by each expert. Here, just one of the questions for *Awareness Raising* is provided for the sake of simplicity. The definitions provided for each strategy are based on SEPA (2015) and provided in Table 7.5.

Awareness Raising: Raising public awareness of flood risk is a duty of responsible authorities. Enhanced awareness of individuals, homes, and businesses regarding flood risk and related measures can lessen the total impact.
Socio-economic scenarios for climate change analysis in the UK:
L=Low Challenges to Mitigation and Adaptation **M**=Moderate Challenges to Mitigation and Adaptation **H**=High Challenges to Mitigation and Adaptation
Challenges to Adaptation: Socio-economic conditions that, in the absence of climate-related policies, would result in higher vulnerability, and less adaptation capacity for a given level of climate change. ***Challenges to Mitigation:*** Socio-economic conditions that in the absence of climate-related policies, would result in higher emissions, and poorly suited technological, or institutional conditions in order to reduce emissions.
Impact levels of flooding hazard to the energy infrastructure:
MI=Mild Impact Climate hazards are controllable and with no possibility of spreading out. They are not complicated and may cause a small damage to life and property.
MO=Moderate Impact Climate hazards cover a wide range area and have a potential to spread out while affecting public daily activities. They would possibly cause damage to a large number of properties and cause death. Their complexity level is higher than level MI and in terms of search and rescue are very challenging but could be controlled by the government.
SV=Severe Impact Any disaster caused at this level is more complex in nature compared to other levels and would affect a wide area (more than two states) and also would cause the highest damage possible to life and property

Q1: How is the effectiveness of "Awareness Raising" strategy in relation to flood prevention/preparedness/recovery in the Highland and Argyll, Scotland region under following circumstances? (You can choose more than one phrase in case you are uncertain between few choices). *NE=No Effectiveness; LE=Low Effectiveness; FLE=Fairly Low Effectiveness; ME= Medium Effectiveness; FHE=Fairly High Effectiveness; HE=High Effectiveness; AHE=Absolutely High Effectiveness*							
	NE	**LE**	**FLE**	**ME**	**FHE**	**HE**	**AHE**
1.(L) challenges, and (MI) risk impact	☐	☐	☐	☐	☐	☐	☐
2.(L) challenges, and (MO) risk impact	☐	☐	☐	☐	☐	☐	☐
3.(L) challenges, and (SV) risk impact	☐	☐	☐	☐	☐	☐	☐
4.(M) challenges, and (MI) risk impact	☐	☐	☐	☐	☐	☐	☐
5.(M) challenges, and (MO) risk impact	☐	☐	☐	☐	☐	☐	☐
6.(M) challenges, and (SV) risk impact	☐	☐	☐	☐	☐	☐	☐
7.(H) challenges, and (MI) risk impact	☐	☐	☐	☐	☐	☐	☐
8.(H) challenges, and (MO) risk impact	☐	☐	☐	☐	☐	☐	☐
9.(H) challenges, and (SV) risk impact	☐	☐	☐	☐	☐	☐	☐

Section 2: Obtaining status transition probabilities using scale provided in Table 7.3 by getting answers of questions Q2-Q4.

To be more clear, under optimistic scenario (scenario 1) (Table L.1), the aim is to identify the values shown as p_{21}, p_{31} , and p_{32} by getting the answers of questions Q2, Q3 and Q4 respectively. Under cautious scenario (scenario 2) (Table L.2), the aim is to identify the values shown as p_{21}, and p_{32} by getting the answers of questions Q2, and Q4 respectively. Knowing that sum of probabilities in each row must be equal to 1.

Table L.1 Status transition probability matrix under optimistic scenario

		L	M	H
	L	$p_{11} = 1.00$	$p_{12} = 0.00$	$p_{13} = 0.00$
P	M	p_{21}	$1 - p_{21}$	$p_{23} = 0.00$
	H	p_{31}	p_{32}	$1 - (p_{31} + p_{32})$

Table L.2 Status transition probability matrix under cautious scenario

		L	M	H
	L	$p_{11} = 1.00$	$p_{12} = 0.00$	$p_{13} = 0.00$
P	M	p_{21}	$1 - p_{21}$	$p_{23} = 0.00$
	H	$p_{31} = 0.00$	p_{32}	$1 - p_{32}$

Q2: What is the probability of status transition from Moderate Challenges to Mitigation and Adaptation (M) to Low Challenges to Mitigation and Adaptation (L) in the next 5 to 20-year timescale in Scotland under following scenarios? *AZ=Almost Zero; VS=Very Small; S=Small; M= Moderate; L=Large; VL=Very Large; AC=Almost Certain*							
	AZ	**VS**	**S**	**M**	**L**	**VL**	**AC**
1. Optimistic Scenario	☐	☐	☐	☐	☐	☐	☐
2. Cautious Scenario	☐	☐	☐	☐	☐	☐	☐

Q3: What is the probability of status transition from High Challenges to Mitigation and Adaptation (H) to Low Challenges to Mitigation and Adaptation (L) in the next 5 to 20-year timescale in Scotland under following scenario? *AZ=Almost Zero; VS=Very Small; S=Small; M= Moderate; L=Large; VL=Very Large; AC=Almost Certain*							
	AZ	**VS**	**S**	**M**	**L**	**VL**	**AC**
Optimistic Scenario	☐	☐	☐	☐	☐	☐	☐

Q4: What is the probability of status transition from High Challenges to Mitigation and Adaptation (H) to Moderate Challenges to Mitigation and Adaptation (M) in the next 5 to 20-year timescale in Scotland under following scenarios? *AZ=Almost Zero; VS=Very Small; S=Small; M= Moderate; L=Large; VL=Very Large; AC=Almost Certain*							
	AZ	**VS**	**S**	**M**	**L**	**VL**	**AC**
1. Optimistic Scenario	☐	☐	☐	☐	☐	☐	☐
2. Cautious Scenario	☐	☐	☐	☐	☐	☐	☐

Section 3: Obtaining outcome transition probabilities using scale provided in Table 7.3 by getting answers of questions Q5-Q7

To be more clear, under optimistic scenario (scenario 1) (Table L.3), the aim is to identify the values shown as q_{21}, q_{31} , and q_{32} by getting the answers of questions Q5, Q6 and Q7 respectively. Under cautious scenario (scenario 2) (Table L.4), the aim is to identify the values shown as q_{21}, and q_{32} by getting the answers of questions Q5, and Q7 respectively. Knowing that sum of probabilities in each row must be equal to 1.

Table L.3 Outcome transition probability matrix under optimistic scenario

		MI	MO	SV
	MI	$q_{11} = 1.00$	$q_{12} = 0.00$	$q_{13} = 0.00$
Q	MO	q_{21}	$1 - q_{21}$	$q_{23} = 0.00$
	SV	q_{31}	q_{32}	$1 - (q_{31} + q_{32})$

Table L.4 Outcome transition probability matrix under cautious scenario

		MI	MO	SV
	MI	$q_{11} = 1.00$	$q_{12} = 0.00$	$q_{13} = 0.00$
Q	MO	q_{21}	$1 - q_{21}$	$q_{23} = 0.00$
	SV	$q_{31} = 0.00$	q_{32}	$1 - q_{32}$

Q5: What is the transition probability of flooding risk impact from Moderate risk impact (MO) to Mild risk impact (MI) in the next 5 to 20-year timescale in the Highland and Argyll area in Scotland under following scenarios? *AZ=Almost Zero; VS=Very Small; S=Small; M= Moderate; L=Large; VL=Very Large; AC=Almost Certain*							
	AZ	**VS**	**S**	**M**	**L**	**VL**	**AC**
1. Optimistic Scenario	☐	☐	☐	☐	☐	☐	☐
2. Cautious Scenario	☐	☐	☐	☐	☐	☐	☐

Q6: What is the transition probability of flooding risk impact from Severe risk impact (SV) to Mild risk impact (MI) in the next 5 to 20-year timescale in the Highland and Argyll area in Scotland under following scenario? *AZ=Almost Zero; VS=Very Small; S=Small; M= Moderate; L=Large; VL=Very Large; AC=Almost Certain*							
	AZ	**VS**	**S**	**M**	**L**	**VL**	**AC**
Optimistic Scenario	☐	☐	☐	☐	☐	☐	☐

Q7: What is the transition probability of flooding risk impact from Severe risk impact (SV) to Moderate risk impact (MO) in the next 5 to 20-year timescale in the Highland and Argyll area in Scotland under following scenarios? *AZ=Almost Zero; VS=Very Small; S=Small; M= Moderate; L=Large; VL=Very Large; AC=Almost Certain*							
	AZ	**VS**	**S**	**M**	**L**	**VL**	**AC**
1. Optimistic Scenario	☐	☐	☐	☐	☐	☐	☐
2. Cautious Scenario	☐	☐	☐	☐	☐	☐	☐

References

Abdel-Basset, M., Saleh, M., Gamal, A., Smarandache, F., 2019a. An approach of TOPSIS technique for developing supplier selection with group decision making under type-2 neutrosophic number. Appl. Soft Comput. 77, 438–452. https://doi.org/10.1016/j.asoc.2019.01.035

Abdel-Basset, M., Atef, A., Smarandache, F., 2019b. A hybrid neutrosophic multiple criteria group decision making approach for project selection. Cognitive Systems Research 57, 216–227. https://doi.org/10.1016/j.cogsys.2018.10.023

Abdel-Basset, M., Manogaran, G., Gamal, A., Smarandache, F., 2018. A hybrid approach of neutrosophic sets and DEMATEL method for developing supplier selection criteria. Des Autom Embed Syst 22, 257–278. https://doi.org/10.1007/s10617-018-9203-6

Aboutorab, H., Saberi, M., Asadabadi, M.R., Hussain, O., Chang, E., 2018. ZBWM: The Z-number extension of Best Worst Method and its application for supplier development. Expert Syst. Appl. 107, 115–125. https://doi.org/10.1016/j.eswa.2018.04.015

Afgan, N.H., Carvalho, M.G., 2002. Multi-criteria assessment of new and renewable energy power plants. Energy 27, 739–755. https://doi.org/10.1016/S0360-5442(02)00019-1

Ali, T., Ma, H., Nahian, A.J., 2019. An Analysis of the Renewable Energy Technology Selection in the Southern Region of Bangladesh Using a Hybrid Multi-Criteria Decision Making (MCDM) Method. Int. J. Renew. Energy Res. 9, 1838–1848.

Alimohammadlou, M., Bonyani, A., 2018. A comparative analysis of dynamic and cross-sectional approaches for financial performance analysis. Am. J Finance Account. 5, 253–275. https://doi.org/10.1504/AJFA.2018.093037

Aloul, F., Al-Ali, A.R., Al-Dalky, R., Al-Mardini, M., El-Hajj, W., 2012. Smart Grid Security: Threats, Vulnerabilities and Solutions. Int. J. Smart Grid Clean Energy 1, 1–6.

Alsalem, M.A., Zaidan, A.A., Zaidan, B.B., Hashim, M., Albahri, O.S., Albahri, A.S., Hadi, A., Mohammed, K.I., 2018. Systematic Review of an Automated Multiclass Detection and Classification System for Acute Leukaemia in Terms of Evaluation and Benchmarking, Open Challenges, Issues and Methodological Aspects. J. Med. Syst. 42, 204. https://doi.org/10.1007/s10916-018-1064-9

Aman, M.M., Solangi, K.H., Hossain, M.S., Badarudin, A., Jasmon, G.B., Mokhlis, H., Bakar, A.H.A., Kazi, S.N., 2015. A review of Safety, Health and Environmental (SHE) issues of solar energy system. Renew. Sustain. Energy Rev. 41, 1190–1204. https://doi.org/10.1016/j.rser.2014.08.086

Amin, M., 2002. Security challenges for the electricity infrastructure. Computer 35, supl8–supl10. https://doi.org/10.1109/MC.2002.1012423

Amoozad Mahdiraji, H., Arzaghi, S., Stauskis, G., Zavadskas, E.K., 2018. A Hybrid Fuzzy BWM-COPRAS Method for Analyzing Key Factors of Sustainable Architecture. Sustainability 10, 1626. https://doi.org/10.3390/su10051626

Ang, B.W., Choong, W.L., Ng, T.S., 2015. Energy security: Definitions, dimensions and indexes. Renew. Sustain. Energy Rev. 42, 1077–1093. https://doi.org/10.1016/j.rser.2014.10.064

Aplak, H.S., Sogut, M.Z., 2013. Game theory approach in decisional process of energy management for industrial sector. Energy Convers. Manag. 74, 70–80. https://doi.org/10.1016/j.enconman.2013.03.027

Asadabadi, M.R., 2018. The stratified multi-criteria decision-making method. Knowl.-Based Syst. 162, 115–123. https://doi.org/10.1016/j.knosys.2018.07.002

Asadabadi, M.R., Saberi, M., Chang, E., 2018. Targets of Unequal Importance Using the Concept of Stratification in a Big Data Environment. Int. J. Fuzzy Syst. 20, 1373–1384. https://doi.org/10.1007/s40815-017-0430-y

Asadabadi, M.R., Saberi, M., Chang, E., 2017. Logistic informatics modelling using concept of stratification (CST), in: 2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE). Presented at the 2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), IEEE, Naples, Italy, pp. 1–7. https://doi.org/10.1109/FUZZ-IEEE.2017.8015510

Asadabadi, M.R., Zwikael, O., 2019. Integrating risk into estimations of project activities' time and cost: A stratified approach. Eur. J. Oper. Res. S0377221719309294. https://doi.org/10.1016/j.ejor.2019.11.018

Ashraf, S., Abdullah, S., Smarandache, F., Amin, N. ul, 2019. Logarithmic Hybrid Aggregation Operators Based on Single Valued Neutrosophic Sets and Their Applications in Decision Support Systems. Symmetry 11, 364. https://doi.org/10.3390/sym11030364

Asia Pacific Energy Research Centre (Ed.), 2007. A quest for energy security in the 21st century: resources and constraints. Inst. of Energy Economics, Japan, Tokyo.

Associated Programme on Flood Management, 2015. Effectiveness of flood management measures, Integrated Flood Management Tools Series.

Atanassov, K.T., 1986. Intuitionistic Fuzzy Sets. Fuzzy Sets Syst. 20, 87–96.

Azadeh, A., Zarrin, M., Abdollahi, M., Noury, S., Farahmand, S., 2015. Leanness assessment and optimization by fuzzy cognitive map and multivariate analysis. Expert Syst. Appl. 42, 6050–6064. https://doi.org/10.1016/j.eswa.2015.04.007

Babich, V., Burnetas, A.N., Ritchken, P.H., 2007. Competition and Diversification Effects in Supply Chains with Supplier Default Risk. Manuf. Serv. Oper. Manag. 9, 123–146. https://doi.org/10.1287/msom.1060.0122

Babu, H., Bhardwaj, P., Agrawal, A.K., 2020. Modelling the supply chain risk variables using ISM: a case study on Indian manufacturing SMEs. J. Model. Manage. ahead-of-print. https://doi.org/10.1108/JM2-06-2019-0126

Badri Ahmadi, H., Kusi-Sarpong, S., Rezaei, J., 2017. Assessing the social sustainability of supply chains using Best Worst Method. Resour. Conserv. Recycl. 126, 99–106. https://doi.org/10.1016/j.resconrec.2017.07.020

Bai, C., Kusi-Sarpong, S., Badri Ahmadi, H., Sarkis, J., 2019. Social sustainable supplier evaluation and selection: a group decision-support approach. Int. J. Prod. Res. 57, 7046–7067. https://doi.org/10.1080/00207543.2019.1574042

Bang-Jensen, J., Gutin, G., 2018. Classes of directed graphs. Springer Berlin Heidelberg, New York, NY.

Bang-Jensen, J., Gutin, G., 2006. Digraphs: theory, algorithms and applications, 2. print. ed. Springer, London.

Basole, R.C., Bellamy, M.A., 2014. Supply Network Structure, Visibility, and Risk Diffusion: A Computational Approach. Decis. Sci. 45, 753–789. https://doi.org/10.1111/deci.12099

Baudry, G., Macharis, C., Vallée, T., 2018. Range-based Multi-Actor Multi-Criteria Analysis: A combined method of Multi-Actor Multi-Criteria Analysis and Monte Carlo simulation to support participatory decision making under

uncertainty. Eur. J. Oper. Res. 264, 257–269. https://doi.org/10.1016/j.ejor.2017.06.036
Beemsterboer, D.J.C., Hendrix, E.M.T., Claassen, G.D.H., 2018. On solving the Best-Worst Method in multi-criteria decision-making. IFAC-Pap. 51, 1660–1665. https://doi.org/10.1016/j.ifacol.2018.08.218
Benjamin, A., Chartrand, G., Zhang, P., 2015. The fascinating world of graph theory. Princeton University Press, Princeton.
Berger, L., Emmerling, J., Tavoni, M., 2017. Managing Catastrophic Climate Risks Under Model Uncertainty Aversion. Manag. Sci. 63, 749–765. https://doi.org/10.1287/mnsc.2015.2365
Bhattacharya, A., Geraghty, J., Young, P., Byrne, P.J., 2013. Design of a resilient shock absorber for disrupted supply chain networks: a shock-dampening fortification framework for mitigating excursion events. Production Planning & Control 24, 721–742. https://doi.org/10.1080/09537287.2012.666861
Bhosale, V.A., Kant, R., 2016. An integrated ISM fuzzy MICMAC approach for modelling the supply chain knowledge flow enablers. Int. J. Prod. Res. 54, 7374–7399. https://doi.org/10.1080/00207543.2016.1189102
Billinton, R., Allan, R.A., 1996. Reliability Evaluation of Power Systems. Springer Science & Business Media.
Blackhurst, J., Dunn, K.S., Craighead, C.W., 2011. An Empirically Derived Framework of Global Supply Resiliency: Framework of Global Supply Resiliency. J. Bus. Logist. 32, 374–391. https://doi.org/10.1111/j.0000-0000.2011.01032.x
Blyth, W., Lefèvre, N., 2004. Energy security and climate change policy interactions: an assessment framework. International Energy Agency.
Bode, C., Macdonald, J.R., 2017. Stages of Supply Chain Disruption Response: Direct, Constraining, and Mediating Factors for Impact Mitigation. Decis. Sci. 48, 836–874. https://doi.org/10.1111/deci.12245
Bode, C., Wagner, S.M., 2015. Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions. J. Oper. Manag. 36, 215–228. https://doi.org/10.1016/j.jom.2014.12.004
Bolsover, A., 2015. Real-time risk assessment and decision support. Proc. Safety Prog. 34, 183–190. https://doi.org/10.1002/prs.11702
Booker, J.M., Ross, T.J., 2011. An evolution of uncertainty assessment and quantification. Sci. Iran. 18, 669–676. https://doi.org/10.1016/j.scient.2011.04.017
Boston, A., 2013. Delivering a secure electricity supply on a low carbon pathway. Energy Policy 52, 55–59. https://doi.org/10.1016/j.enpol.2012.02.004
British Petroleum, 2016. BP statistical review of world energy.
Brunner, E.M., Suter, M., 2008. An Inventory of 25 National and 7 International Critical Information Infrastructure Protection Policies, in: International CIIP Handbook 2008/2009. Center for Security Studies, ETH Zurich.
Brusset, X., Bertrand, J.-L., 2018. Hedging weather risk and coordinating supply chains. J. Oper. Manag. 64, 41–52. https://doi.org/10.1016/j.jom.2018.10.002
Campolo, M., Andreussi, P., Soldati, A., 1999. River flood forecasting with a neural network model. Water Resour. Res. 35, 1191–1197. https://doi.org/10.1029/1998WR900086
Carter, J.G., White, I., Richards, J., 2009. Sustainability appraisal and flood risk management. Environmental Impact Assessment Review 29, 7–14. https://doi.org/10.1016/j.eiar.2008.06.003

Cayley, A., 1889. A theorem on trees. Q. J. Math. 23, 376–378.
Chakraborty, M., Chowdhury, S., Chakraborty, J., Mehera, R., Pal, R.K., 2019. Algorithms for generating all possible spanning trees of a simple undirected connected graph: an extensive review. Complex Intell. Syst. 5, 265–281. https://doi.org/10.1007/s40747-018-0079-7
Chalvatzis, K.J., 2012. Analysis of the evaluation of electricity supply security : case studies for electricity sector incumbents and policy makers in Greece and Poland (PhD Thesis). University of East Anglia.
Chalvatzis, K.J., 2009. Electricity generation development of Eastern Europe: A carbon technology management case study for Poland. Renew. Sustain. Energy Rev. 13, 1606–1612. https://doi.org/10.1016/j.rser.2008.09.019
Chalvatzis, K.J., Ioannidis, A., 2017a. Energy supply security in the EU: Benchmarking diversity and dependence of primary energy. Appl. Energy 207, 465–476. https://doi.org/10.1016/j.apenergy.2017.07.010
Chalvatzis, K.J., Ioannidis, A., 2017b. Energy Supply Security in Southern Europe and Ireland. Energy Procedia 105, 2916–2922. https://doi.org/10.1016/j.egypro.2017.03.660
Chalvatzis, K.J., Malekpoor, H., Mishra, N., Lettice, F., Choudhary, S., 2019. Sustainable resource allocation for power generation: The role of big data in enabling interindustry architectural innovation. Technol. Forecast. Soc. Change 144, 381–393. https://doi.org/10.1016/j.techfore.2018.04.031
Chalvatzis, K.J., Rubel, K., 2015. Electricity portfolio innovation for energy security: The case of carbon constrained China. Technol. Forecast. Soc. Change 100, 267–276. https://doi.org/10.1016/j.techfore.2015.07.012
Chartrand, G., Lesniak, L., Zhang, P., 2011. Graphs & digraphs, 5th ed. ed. Chapman and Hall/CRC, Boca Raton, FL.
Chaudhuri, A., Srivastava, S.K., Srivastava, R.K., Parveen, Z., 2016. Risk propagation and its impact on performance in food processing supply chain: A fuzzy interpretive structural modeling based approach. J. Model. Manag. 11, 660–693. https://doi.org/10.1108/JM2-08-2014-0065
Checchi, A., Behrens, A., Egenhofer, C., 2009. Long-term energy security risks for Europe: a sector-specific approach, CEPS working document. CEPS, Brussels.
Chen, C., Noble, I., Hellmann, J., Coffee, J., Murillo, M., Chawla, N., 2015. University of Notre Dame Global Adaptation Index (Country Index Technical Report).
Chen, F.Y., Yano, C.A., 2010. Improving Supply Chain Performance and Managing Risk Under Weather-Related Demand Uncertainty. Manag. Sci. 56, 1380–1397. https://doi.org/10.1287/mnsc.1100.1194
Chen, J., Ye, J., 2017. Some Single-Valued Neutrosophic Dombi Weighted Aggregation Operators for Multiple Attribute Decision-Making. Symmetry 9, 82. https://doi.org/10.3390/sym9060082
Cheraghalipour, A., Farsad, S., 2018. A bi-objective sustainable supplier selection and order allocation considering quantity discounts under disruption risks: A case study in plastic industry. Comput. Ind. Eng. 118, 237–250. https://doi.org/10.1016/j.cie.2018.02.041
Cheraghalipour, A., Paydar, M.M., Keshteli, M.H., 2018. Applying a hybrid BWM-VIKOR approach to supplier selection: a case study in the Iranian agricultural implements industry. Int. J. Appl. Decis. Sci. 11, 274–301. https://doi.org/10.1504/IJADS.2018.092796

Cherp, A., Jewell, J., 2014. The concept of energy security: Beyond the four As. Energy Policy 75, 415–421. https://doi.org/10.1016/j.enpol.2014.09.005
Cherp, A., Jewell, J., 2011. The three perspectives on energy security: intellectual history, disciplinary roots and the potential for integration. Curr. Opin. Environ. Sustain. 3, 202–212. https://doi.org/10.1016/j.cosust.2011.07.001
Chester, L., 2010. Conceptualising energy security and making explicit its polysemic nature. Energy Policy 38, 887–895. https://doi.org/10.1016/j.enpol.2009.10.039
Chevalier, J.-M., 2006. Security of energy supply for the European Union. Eur. Rev. Energy Mark. 1, 1–20.
Chopra, S., Sodhi, M.S., 2004. Managing risk to avoid supply-chain breakdown. MIT Sloan Manag. Rev. 46, 53–61.
Chou, J.-S., Ongkowijoyo, C.S., 2014. Risk-based group decision making regarding renewable energy schemes using a stochastic graphical matrix model. Autom. Constr. 37, 98–109. https://doi.org/10.1016/j.autcon.2013.10.010
Clements, S., Kirkham, H., 2010. Cyber-security considerations for the smart grid, in: IEEE PES General Meeting. Presented at the Energy Society General Meeting, IEEE, Minneapolis, MN, pp. 1–5. https://doi.org/10.1109/PES.2010.5589829
Coles, D., Yu, D., Wilby, R.L., Green, D., Herring, Z., 2017. Beyond 'flood hotspots': Modelling emergency service accessibility during flooding in York, UK. Journal of Hydrology 546, 419–436. https://doi.org/10.1016/j.jhydrol.2016.12.013
Colman, A.M., 1982. Game theory and experimental games: the study of strategic interaction, 1st ed. ed, International series in experimental social psychology. Pergamon Press, Oxford [Oxfordshire] ; New York.
Committee on Climate Change, 2019. Progress in preparing for climate change: 2019 Report to Parliament. Committee on Climate Change.
Committee on Climate Change, 2016. UK Climate Change Risk Assessment 2017: Synthesis report, priorities for the next five years.
Committee on Climate Change, 2012. UK Climate Change Risk Assessment 2012: Floods and Coastal Erosion. Link: http://randd.defra.gov.uk/Document.aspx?Document=CCRASummaryFloodsandCoastalErosion.pdf
Considine, T.J., 2000. Markup pricing in a short-run model with inventories. Presented at the International Society for Inventory Research, Boston, MA, USA.
Correljé, A., van der Linde, C., 2006. Energy supply security and geopolitics: A European perspective. Energy Policy 34, 532–543. https://doi.org/10.1016/j.enpol.2005.11.008
Costantini, V., Gracceva, F., Markandya, A., Vicini, G., 2007. Security of energy supply: Comparing scenarios from a European perspective. Energy Policy 35, 210–226. https://doi.org/10.1016/j.enpol.2005.11.002
Craighead, C.W., Blackhurst, J., Rungtusanatham, M.J., Handfield, R.B., 2007. The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities. Decis. Sci. 38, 131–156. https://doi.org/10.1111/j.1540-5915.2007.00151.x
Daileda, C., 2017. Hurricane Irma caused one of the largest natural disaster power outages in U.S. history. MashableUK.
Dawson, R.J., Thompson, D., Johns, D., Wood, R., Darch, G., Chapman, L., Hughes, P.N., Watson, G.V.R., Paulson, K., Bell, S., Gosling, S.N., Powrie, W., Hall,

J.W., 2018. A systems framework for national assessment of climate risks to infrastructure. Philos. Trans. R. Soc. Math. Phys. Eng. Sci. 376, 20170298. https://doi.org/10.1098/rsta.2017.0298

Deli, I., Şubaş, Y., 2017. A ranking method of single valued neutrosophic numbers and its applications to multi-attribute decision making problems. Int. J. Mach. Learn. Cybern. 8, 1309–1322. https://doi.org/10.1007/s13042-016-0505-3

Deli, I., Subas, Y., 2014. Single valued neutrosophic numbers and their applications to multicriteria decision making problem. Neutrosophic Sets Syst. 2, 1–13.

Dempster, A.P., 1968. A Generalization of Bayesian Inference. J. R. Stat. Soc. Ser. B Methodol. 30, 205–232. https://doi.org/10.1111/j.2517-6161.1968.tb00722.x

Deng, J., 1989. Introduction to grey system theory. J. Grey Syst. 1, 1–24.

Dincer, F., 2011. The analysis on wind energy electricity generation status, potential and policies in the world. Renew. Sustain. Energy Rev. 15, 5135–5142. https://doi.org/10.1016/j.rser.2011.07.042

Dong, Y., Liu, W., Chiclana, F., Kou, G., Herrera-Viedma, E., 2019. Are incomplete and self-confident preference relations better in multicriteria decision making? A simulation-based investigation. Inf. Sci. 492, 40–57. https://doi.org/10.1016/j.ins.2019.04.015

Doumpos, M., Zopounidis, C., 2002. Multicriteria decision aid classification methods, Applied optimization. Kluwer Academic Publishers, Dordrecht ; Boston.

Dubois, D., Prade, H., 2012. Possibility Theory, in: Meyers, R.A. (Ed.), Computational Complexity. Springer New York, New York, NY, pp. 2240–2252. https://doi.org/10.1007/978-1-4614-1800-9_139

Eberly, D.H., 2006. 3D game engine design: a practical approach to real-time computer graphics. Morgan Kaufmann Publishers.

Egenhofer, C., Gialoglou, K., Luciani, G., Boots, M., Scheepers, M., Costantini, V., Gracceva, F., Markandya, A., Vicini, G., 2004. Market-based Options for Security of Energy Supply. SSRN Electron. J. https://doi.org/10.2139/ssrn.593824

Elena Arce, M., Saavedra, Á., Míguez, J.L., Granada, E., 2015. The use of grey-based methods in multi-criteria decision analysis for the evaluation of sustainable energy systems: A review. Renew. Sustain. Energy Rev. 47, 924–932. https://doi.org/10.1016/j.rser.2015.03.010

European Commission, 2000. Green Paper - Towards a European strategy for the security of energy supply.

Eydeland, A., Wolyniec, K., 2003. Energy and power risk management: new developments in modeling, pricing, and hedging. Wiley, Hoboken, N.J.

Fan, W., Yan, Z., 2010. Factors affecting response rates of the web survey: A systematic review. Computers in Human Behavior 26, 132–139. https://doi.org/10.1016/j.chb.2009.10.015

Farhadinia, B., 2013. A Novel Method of Ranking Hesitant Fuzzy Values for Multiple Attribute Decision-Making Problems. Int. J. Intell. Syst. 28, 752–767. https://doi.org/10.1002/int.21600

Feng, Y., Hong, Z., Tian, G., Li, Z., Tan, J., Hu, H., 2018. Environmentally friendly MCDM of reliability-based product optimisation combining DEMATEL-based ANP, interval uncertainty and Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR). Inf. Sci. 442–443, 128–144. https://doi.org/10.1016/j.ins.2018.02.038

Few, R., 2003. Flooding, vulnerability and coping strategies: local responses to a global threat. Progress in Development Studies 3, 43–58. https://doi.org/10.1191/1464993403ps049ra
Fisher, A.C., Rothkopf, M.H., 1989. Market failure and energy policy A rationale for selective conservation. Energy Policy 17, 397–406. https://doi.org/10.1016/0301-4215(89)90010-4
Flick, T., Morehouse, J., 2011. Securing the Smart Grid. Elsevier. https://doi.org/10.1016/C2009-0-63095-6
Foresight Future Flooding, 2004. Executive Summary. Foresight Flood and Coastal Defence Project. Link: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/300332/04-947-flooding-summary.pdf
Fthenakis, V., Kim, H.C., 2009. Land use and electricity generation: A life-cycle analysis. Renew. Sustain. Energy Rev. 13, 1465–1474. https://doi.org/10.1016/j.rser.2008.09.017
Gabus, A., Fontela, E., 1973. Perceptions of the world problematique: Communication procedure, communicating with those bearing collective responsibility (DEMATEL report no. 1). Battelle Geneva Research Center, Geneva, Switzerland.
Gabus, A., Fontela, E., 1972. World problems, an invitation to further thought within the framework of DEMATEL. Battelle Geneva Research Center, Geneva, Switzerland.
Gallina, V., Torresan, S., Critto, A., Sperotto, A., Glade, T., Marcomini, A., 2016. A review of multi-risk methodologies for natural hazards: Consequences and challenges for a climate change impact assessment. J. Environ. Manage. 168, 123–132. https://doi.org/10.1016/j.jenvman.2015.11.011
Garg, C.P., Sharma, A., 2018. Sustainable outsourcing partner selection and evaluation using an integrated BWM–VIKOR framework. Environ. Dev. Sustain. https://doi.org/10.1007/s10668-018-0261-5
Gjerde, O., Kjolle, G.H., Detlefsen, N.K., Bronmo, G., 2011. Risk and vulnerability analysis of power systems including extraordinary events, in: 2011 IEEE Trondheim PowerTech. Presented at the 2011 IEEE PES PowerTech - Trondheim, IEEE, Trondheim, pp. 1–5. https://doi.org/10.1109/PTC.2011.6019251
Global Energy Institute, 2019. Index of U.S. energy security risk.
Govindan, K., Jepsen, M.B., 2016. ELECTRE: A comprehensive literature review on methodologies and applications. Eur. J. Oper. Res. 250, 1–29. https://doi.org/10.1016/j.ejor.2015.07.019
Govindan, K., Khodaverdi, R., Vafadarnikjoo, A., 2016. A grey DEMATEL approach to develop third-party logistics provider selection criteria. Ind. Manag. Data Syst. 116, 690–722. https://doi.org/10.1108/IMDS-05-2015-0180
Govindan, K., Khodaverdi, R., Vafadarnikjoo, A., 2015. Intuitionistic fuzzy based DEMATEL method for developing green practices and performances in a green supply chain. Expert Syst. Appl. 42, 7207–7220. https://doi.org/10.1016/j.eswa.2015.04.030
Gracceva, F., Zeniewski, P., 2014. A systemic approach to assessing energy security in a low-carbon EU energy system. Appl. Energy 123, 335–348. https://doi.org/10.1016/j.apenergy.2013.12.018
Grave, K., Paulus, M., Lindenberger, D., 2012. A method for estimating security of electricity supply from intermittent sources: Scenarios for Germany until

2030. Energy Policy 46, 193–202. https://doi.org/10.1016/j.enpol.2012.03.050
Güler, Ö., 2009. Wind energy status in electrical energy production of Turkey. Renew. Sustain. Energy Rev. 13, 473–478. https://doi.org/10.1016/j.rser.2007.03.015
Guo, H., Watson, S., Tavner, P., Xiang, J., 2009. Reliability analysis for wind turbines with incomplete failure data collected from after the date of initial installation. Reliab. Eng. Syst. Saf. 94, 1057–1063. https://doi.org/10.1016/j.ress.2008.12.004
Guo, S., Zhao, H., 2017. Fuzzy best-worst multi-criteria decision-making method and its applications. Knowl.-Based Syst. 121, 23–31. https://doi.org/10.1016/j.knosys.2017.01.010
Gupta, H., 2018a. Evaluating service quality of airline industry using hybrid best worst method and VIKOR. J. Air Transp. Manag. 68, 35–47. https://doi.org/10.1016/j.jairtraman.2017.06.001
Gupta, H., 2018b. Assessing organizations performance on the basis of GHRM practices using BWM and Fuzzy TOPSIS. J. Environ. Manage. 226, 201–216. https://doi.org/10.1016/j.jenvman.2018.08.005
Gupta, H., Barua, M.K., 2018. A novel hybrid multi-criteria method for supplier selection among SMEs on the basis of innovation ability. Int. J. Logist. Res. Appl. 21, 201–223. https://doi.org/10.1080/13675567.2017.1382457
Haase, N., Renkewitz, F., Betsch, C., 2013. The Measurement of Subjective Probability: Evaluating the Sensitivity and Accuracy of Various Scales. Risk Anal. 33, 1812–1828. https://doi.org/10.1111/risa.12025
Habermann, M., Blackhurst, J., Metcalf, A.Y., 2015. Keep Your Friends Close? Supply Chain Design and Disruption Risk. Decis. Sci. 46, 491–526. https://doi.org/10.1111/deci.12138
Hafezalkotob, Ashkan, Hafezalkotob, Arian, 2017. A novel approach for combination of individual and group decisions based on fuzzy best-worst method. Appl. Soft Comput. 59, 316–325. https://doi.org/10.1016/j.asoc.2017.05.036
Hammond, G.P., Waldron, R., 2008. Risk assessment of UK electricity supply in a rapidly evolving energy sector. Proc. Inst. Mech. Eng. Part J. Power Energy 222, 623–642. https://doi.org/10.1243/09576509JPE543
Heckmann, I., Comes, T., Nickel, S., 2015. A critical review on supply chain risk – Definition, measure and modeling. Omega 52, 119–132. https://doi.org/10.1016/j.omega.2014.10.004
Hein, J.L., 2001. Discrete structures, logic, and computability, 2nd ed. ed. Jones and Bartlett Publishers, Boston.
Hendricks, K.B., Singhal, V.R., 2003. The effect of supply chain glitches on shareholder wealth. J. Oper. Manag. 21, 501–522. https://doi.org/10.1016/j.jom.2003.02.003
Hills, J.M., Michalena, E., Chalvatzis, K.J., 2018. Innovative technology in the Pacific: Building resilience for vulnerable communities. Technol. Forecast. Soc. Change 129, 16–26. https://doi.org/10.1016/j.techfore.2018.01.008
Horsnell, P., 2000. The Probability of Oil Market Disruption: with an Emphasis on the Middle East. James A. Baker III Institute for Public Policy of Rice University.
Hsu, C.-H., Wang, F.-K., Tzeng, G.-H., 2012. The best vendor selection for conducting the recycled material based on a hybrid MCDM model combining DANP with VIKOR. Resour. Conserv. Recycl. 66, 95–111. https://doi.org/10.1016/j.resconrec.2012.02.009

Hsu, C.-I., Wen, Y.-H., 2000. Application of Grey theory and multiobjective programming towards airline network design. Eur. J. Oper. Res. 127, 44–68. https://doi.org/10.1016/S0377-2217(99)00320-3

Huang, H., Shen, X., Xu, H., 2016. Procurement Contracts in the Presence of Endogenous Disruption Risk. Decis. Sci. 47, 437–472. https://doi.org/10.1111/deci.12167

Huang, I.B., Keisler, J., Linkov, I., 2011. Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends. Sci. Total Environ. 409, 3578–3594. https://doi.org/10.1016/j.scitotenv.2011.06.022

Huang, J.P., Poh, K.L., Ang, B.W., 1995. Decision analysis in energy and environmental modeling. Energy 20, 843–855. https://doi.org/10.1016/0360-5442(95)00036-G

Huda, M.S., McDonald, M., 2016. Regional cooperation on energy in South Asia: Unraveling the political challenges in implementing transnational pipelines and electricity grids. Energy Policy 98, 73–83. https://doi.org/10.1016/j.enpol.2016.07.046

Hult, G.T.M., Craighead, C.W., Ketchen Jr., D.J., 2010. Risk Uncertainty and Supply Chain Decisions: A Real Options Perspective. Decis. Sci. 41, 435–458. https://doi.org/10.1111/j.1540-5915.2010.00276.x

Hunt, J.D., Bañares-Alcántara, R., Hanbury, D., 2013. A new integrated tool for complex decision making: Application to the UK energy sector. Decis. Support Syst. 54, 1427–1441. https://doi.org/10.1016/j.dss.2012.12.010

Ijadi Maghsoodi, A., Mosavat, M., Hafezalkotob, Ashkan, Hafezalkotob, Arian, 2019. Hybrid hierarchical fuzzy group decision-making based on information axioms and BWM: Prototype design selection. Comput. Ind. Eng. 127, 788–804. https://doi.org/10.1016/j.cie.2018.11.018

Intergovernmental Panel on Climate Change (Ed.), 2007. Climate change 2007: impacts, adaptation and vulnerability: contribution of Working Group II to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, U.K. ; New York.

International Energy Agency, 2007. Energy security and climate policy: assessing interactions. International Energy Agency, Paris.

Ioannidis, A., Chalvatzis, K.J., 2017. Energy Supply Sustainability For Island Nations: A Study on 8 Global Islands. Energy Procedia 142, 3028–3034. https://doi.org/10.1016/j.egypro.2017.12.440

Ioannidis, A., Chalvatzis, K.J., Li, X., Notton, G., Stephanides, P., 2019. The case for islands' energy vulnerability: Electricity supply diversity in 44 global islands. Renew. Energy 143, 440–452. https://doi.org/10.1016/j.renene.2019.04.155

Ioannou, A., Angus, A., Brennan, F., 2017. Risk-based methods for sustainable energy system planning: A review. Renewable and Sustainable Energy Reviews 74, 602–615. https://doi.org/10.1016/j.rser.2017.02.082

Ishizaka, A., 2012. Clusters and pivots for evaluating a large number of alternatives in AHP. Pesqui. Oper. 32, 87–102. https://doi.org/10.1590/S0101-74382012005000002

Jansen, J.C., Van Arkel, W.G., Boots, M.G., 2004. Designing indicators of long-term energy supply security. The Netherlands Environmental Assessment agency.

Japan Institute of Energy Economics, 2016. Geopolitical risks in the Middle East after the emergence of Islamic State and the impact on the energy supply in Asia. Asia Pacific Energy Research Centre, Institute of Energy Economics, Japan, Tokyo.

Jewell, J., 2011. The IEA Model of Short-Term Energy Security (MOSES): Primary Energy Sources and Secondary Fuels (IEA Energy Papers No. 2011/17). https://doi.org/10.1787/5k9h0wd2ghlv-en

Jiang, S., Shi, H., Lin, W., Liu, H.-C., 2020. A large group linguistic Z-DEMATEL approach for identifying key performance indicators in hospital performance management. Applied Soft Computing 86, 105900. https://doi.org/10.1016/j.asoc.2019.105900

Ji, P., Wang, J., Zhang, H., 2018. Frank prioritized Bonferroni mean operator with single-valued neutrosophic sets and its application in selecting third-party logistics providers. Neural Comput. Appl. 30, 799–823. https://doi.org/10.1007/s00521-016-2660-6

Jira, C. (Fern), Toffel, M.W., 2013. Engaging Supply Chains in Climate Change. Manuf. Serv. Oper. Manag. 15, 559–577. https://doi.org/10.1287/msom.1120.0420

Johansson, B., 2013. Security aspects of future renewable energy systems–A short overview. Energy 61, 598–605. https://doi.org/10.1016/j.energy.2013.09.023

Johnson, C.L., Tunstall, S.M., Penning-Rowsell, E.C., 2005. Floods as Catalysts for Policy Change: Historical Lessons from England and Wales. International Journal of Water Resources Development 21, 561–575. https://doi.org/10.1080/07900620500258133

Joslyn, C., Booker, J.M., 2004. Generalized Information Theory for Engineering Modeling and Simulation, in: Engineering Design Reliability Handbook. CRC Press, pp. 157–196.

Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47, 263–292.

Kämpke, T., 1988. About assessing and evaluating uncertain inferences within the theory of evidence. Decis. Support Syst. 4, 433–439. https://doi.org/10.1016/0167-9236(88)90006-1

Kaya, İ., Çolak, M., Terzi, F., 2018. Use of MCDM techniques for energy policy and decision-making problems: A review. Int. J. Energy Res. 42, 2344–2372. https://doi.org/10.1002/er.4016

Kelly, A., 2003. Decision making using game theory: an introduction for managers. Cambridge University Press, Cambridge, UK ; New York.

Kenyon, W., 2007. Evaluating flood risk management options in Scotland: A participant-led multi-criteria approach. Ecol. Econ. 64, 70–81. https://doi.org/10.1016/j.ecolecon.2007.06.011

Kern, D., Moser, R., Hartmann, E., Moder, M., 2012. Supply risk management: model development and empirical analysis. Int. J. Phys. Distrib. Logist. Manag. 42, 60–82. https://doi.org/10.1108/09600031211202472

Kilian, L., 2016. The Impact of the Shale Oil Revolution on U.S. Oil and Gasoline Prices. Rev. Environ. Econ. Policy 10, 185–205. https://doi.org/10.1093/reep/rew001

Kilic, H.S., Yalcin, A.S., 2020. Comparison of municipalities considering environmental sustainability via neutrosophic DEMATEL based TOPSIS. Socio-Economic Planning Sciences 100827. https://doi.org/10.1016/j.seps.2020.100827

Kleindorfer, P.R., Saad, G.H., 2009. Managing Disruption Risks in Supply Chains. Prod. Oper. Manag. 14, 53–68. https://doi.org/10.1111/j.1937-5956.2005.tb00009.x

Klinke, A., Renn, O., 1999. Prometheus unbound : challenges of risk evaluation, risk classification, and risk management. https://doi.org/10.18419/OPUS-8558
Kocak, H., Caglar, A., Oztas, G.Z., 2018. Euclidean Best–Worst Method and Its Application. Int. J. Inf. Technol. Decis. Mak. 17, 1587–1605. https://doi.org/10.1142/S0219622018500323
Kolios, A., Read, G., Ioannou, A., 2016. Application of multi-criteria decision-making to risk prioritisation in tidal energy developments. International Journal of Sustainable Energy 35, 59–74. https://doi.org/10.1080/14786451.2014.880438
Kouvelis, P., Chambers, C., Wang, H., 2009. Supply Chain Management Research and Production and Operations Management: Review, Trends, and Opportunities. Prod. Oper. Manag. 15, 449–469. https://doi.org/10.1111/j.1937-5956.2006.tb00257.x
Koyama, K., Matsumoto, T., Kutani, I., Kobayashi, Y., 2016. The effect of the crude oil price drop on the global energy market. Asia Pacific Energy Research Centre.
Kriegler, E., O’Neill, B.C., Hallegatte, S., Kram, T., Lempert, R.J., Moss, R.H., Wilbanks, T., 2012. The need for and use of socio-economic scenarios for climate change analysis: A new approach based on shared socio-economic pathways. Glob. Environ. Change 22, 807–822. https://doi.org/10.1016/j.gloenvcha.2012.05.005
Kruyt, B., van Vuuren, D.P., de Vries, H.J.M., Groenenberg, H., 2009. Indicators for energy security. Energy Policy 37, 2166–2181. https://doi.org/10.1016/j.enpol.2009.02.006
Kumar, A., Sah, B., Singh, A.R., Deng, Y., He, X., Kumar, P., Bansal, R.C., 2017. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. Renew. Sustain. Energy Rev. 69, 596–609. https://doi.org/10.1016/j.rser.2016.11.191
Kumar, R.L., Park, S., 2019. A Portfolio Approach to Supply Chain Risk Management. Decis. Sci. 50, 210–244. https://doi.org/10.1111/deci.12332
Kuo, T., 2017. A modified TOPSIS with a different ranking index. Eur. J. Oper. Res. 260, 152–160. https://doi.org/10.1016/j.ejor.2016.11.052
Kwong, C.K., Bai, H., 2002. A fuzzy AHP approach to the determination of importance weights of customer requirements in quality function deployment. J. Intell. Manuf. 13, 367–377.
Lee, D., 2008. Game theory and neural basis of social decision making. Nat. Neurosci. 11, 404–409.
Lee, H.-S., Tzeng, G.-H., Yeih, W., Wang, Y.-J., Yang, S.-C., 2013. Revised DEMATEL: Resolving the Infeasibility of DEMATEL. Appl. Math. Model. 37, 6746–6757. https://doi.org/10.1016/j.apm.2013.01.016
Lee, P.T.-W., Lin, C.-W., 2013. The cognition map of financial ratios of shipping companies using DEMATEL and MMDE. Marit. Policy Manag. 40, 133–145. https://doi.org/10.1080/03088839.2012.757374
Leimeister, M., Kolios, A., 2018. A review of reliability-based methods for risk analysis and their application in the offshore wind industry. Renewable and Sustainable Energy Reviews 91, 1065–1076. https://doi.org/10.1016/j.rser.2018.04.004
Levary, R.R., Wan, K., 1998. A simulation approach for handling uncertainty in the analytic hierarchy process. Eur. J. Oper. Res. 106, 116–122. https://doi.org/10.1016/S0377-2217(97)00134-3

Levy, J.K., 2005. Multiple criteria decision making and decision support systems for flood risk management. Stoch. Environ. Res. Risk Assess. 19, 438–447. https://doi.org/10.1007/s00477-005-0009-2
Li, C.-W., Tzeng, G.-H., 2009. Identification of a threshold value for the DEMATEL method using the maximum mean de-entropy algorithm to find critical services provided by a semiconductor intellectual property mall. Expert Syst. Appl. 36, 9891–9898. https://doi.org/10.1016/j.eswa.2009.01.073
Li, G.-D., Yamaguchi, D., Nagai, M., 2007. A grey-based decision-making approach to the supplier selection problem. Math. Comput. Model. 46, 573–581. https://doi.org/10.1016/j.mcm.2006.11.021
Li, J., Wang, J., Hu, J., 2019. Multi-criteria decision-making method based on dominance degree and BWM with probabilistic hesitant fuzzy information. Int. J. Mach. Learn. Cybern. 10, 1671–1685. https://doi.org/10.1007/s13042-018-0845-2
Li, W., 2014. Risk Assessment of Power Systems: Models, Methods, and Applications. IEEE.
Li, X., 2005. Diversification and localization of energy systems for sustainable development and energy security. Energy Policy 33, 2237–2243. https://doi.org/10.1016/j.enpol.2004.05.002
Li, X., Chalvatzis, K., Stephanides, P., 2018. Innovative Energy Islands: Life-Cycle Cost-Benefit Analysis for Battery Energy Storage. Sustainability 10, 3371. https://doi.org/10.3390/su10103371
Li, Y.-Y., Zhang, H.-Y., Wang, J.-Q., 2017. Linguistic neutrosophic sets and their application in multicriteria decision-making problems. Int. J. Uncertain. Quantif. 7, 135–154. https://doi.org/10.1615/Int.J.UncertaintyQuantification.2017019627
Liang, F., Brunelli, M., Rezaei, J., 2019. Consistency Issues in the Best Worst Method: Measurements and Thresholds. Omega 102175. https://doi.org/10.1016/j.omega.2019.102175
Liang, R., Wang, J., Li, L., 2018. Multi-criteria group decision-making method based on interdependent inputs of single-valued trapezoidal neutrosophic information. Neural Comput. Appl. 30, 241–260. https://doi.org/10.1007/s00521-016-2672-2
Lin, R.-J., 2013. Using fuzzy DEMATEL to evaluate the green supply chain management practices. J. Clean. Prod. 40, 32–39. https://doi.org/10.1016/j.jclepro.2011.06.010
Lin, S., Li, C., Xu, F., Liu, D., Liu, J., 2018. Risk identification and analysis for new energy power system in China based on D numbers and decision-making trial and evaluation laboratory (DEMATEL). J. Clean. Prod. 180, 81–96. https://doi.org/10.1016/j.jclepro.2018.01.153
Linnerud, K., Mideksa, T.K., Eskeland, G., 2011. The Impact of Climate Change on Nuclear Power Supply. ATW Int. Z. Für Kernenerg. 56, 687–695.
Liu, A., Xiao, Y., Ji, X., Wang, K., Tsai, S.-B., Lu, H., Cheng, J., Lai, X., Wang, J., 2018. A Novel Two-Stage Integrated Model for Supplier Selection of Green Fresh Product. Sustainability 10, 2371. https://doi.org/10.3390/su10072371
Liu, C., Linde, A.T., Sacks, I.S., 2009. Slow earthquakes triggered by typhoons. Nature 459, 833–836. https://doi.org/10.1038/nature08042
Liu, C.-C., Jung, J., Heydt, G.T., Vittal, V., Phadke, A.G., 2000. The strategic power infrastructure defense (SPID) system. A conceptual design. IEEE Control Syst. Mag. 20, 40–52. https://doi.org/10.1109/37.856178

Liu, F., Aiwu, G., Lukovac, V., Vukić, M., 2018. A multicriteria model for the selection of the transport service provider: A single valued neutrosophic DEMATEL multicriteria model. Decis. Mak. Appl. Manag. Eng. 1, 121–130. https://doi.org/10.31181/dmame1802128l

Liu, H.-C., You, X.-Y., Tsung, F., Ji, P., 2018. An improved approach for failure mode and effect analysis involving large group of experts: An application to the healthcare field. Quality Engineering 30, 762–775. https://doi.org/10.1080/08982112.2018.1448089

Liu, P., Zhang, L., 2017. An extended multiple criteria decision making method based on neutrosophic hesitant fuzzy information. J. Intell. Fuzzy Syst. 32, 4403–4413. https://doi.org/10.3233/JIFS-16136

Liu, S., Hu, Y., Zhang, Y., 2018. Supply Chain Partner Selection under Cloud Computing Environment: An Improved Approach Based on BWM and VIKOR. Math. Probl. Eng. 2018, 1–11. https://doi.org/10.1155/2018/7012827

Liu, S., Lin, Y., 2006. Grey information: theory and practical applications, Advanced information and knowledge processing. Springer, London.

Lo, H.-W., Liou, J.J.H., Wang, H.-S., Tsai, Y.-S., 2018. An integrated model for solving problems in green supplier selection and order allocation. J. Clean. Prod. 190, 339–352. https://doi.org/10.1016/j.jclepro.2018.04.105

Loken, E., 2007. Use of multicriteria decision analysis methods for energy planning problems. Renew. Sustain. Energy Rev. 11, 1584–1595. https://doi.org/10.1016/j.rser.2005.11.005

Löschel, A., Moslener, U., Rübbelke, D.T.G., 2010. Indicators of energy security in industrialised countries. Energy Policy 38, 1665–1671. https://doi.org/10.1016/j.enpol.2009.03.061

Lundy, M., Siraj, S., Greco, S., 2017. The mathematical equivalence of the "spanning tree" and row geometric mean preference vectors and its implications for preference analysis. Eur. J. Oper. Res. 257, 197–208. https://doi.org/10.1016/j.ejor.2016.07.042

Makarov, Y.V., Moharari, N.S., 1999. A generalized power system reliability and security index, in: IEEE PowerTech Conference. https://doi.org/10.1109/PTC.1999.826567

Malaysian National Security Council, 2003. Policy and mechanism of national disaster management and relief-Directive no. 20.

Malekpoor, H., Chalvatzis, K., Mishra, N., Mehlawat, M.K., Zafirakis, D., Song, M., 2018. Integrated grey relational analysis and multi objective grey linear programming for sustainable electricity generation planning. Ann. Oper. Res. 269, 475–503. https://doi.org/10.1007/s10479-017-2566-4

Marttunen, M., Lienert, J., Belton, V., 2017. Structuring problems for Multi-Criteria Decision Analysis in practice: A literature review of method combinations. Eur. J. Oper. Res. 263, 1–17. https://doi.org/10.1016/j.ejor.2017.04.041

Matos, M.A., 1999. A fuzzy filtering method applied to power distribution planning. Fuzzy Sets Syst. 102, 53–58. https://doi.org/10.1016/S0165-0114(98)00202-4

Maxim, A., 2014. Sustainability assessment of electricity generation technologies using weighted multi-criteria decision analysis. Energy Policy 65, 284–297. https://doi.org/10.1016/j.enpol.2013.09.059

Mediouni, A., Zufferey, N., Subramanian, N., Cheikhrouhou, N., 2019. Fit between humanitarian professionals and project requirements: hybrid group decision procedure to reduce uncertainty in decision-making. Ann. Oper. Res. 283, 471–496. https://doi.org/10.1007/s10479-018-2782-6

Metcalf, L., Casey, W., 2016. Cybersecurity and applied mathematics. Syngress, Amsterdam ; Boston.
Mi, X., Tang, M., Liao, H., Shen, W., Lev, B., 2019. The state-of-the-art survey on integrations and applications of the best worst method in decision making: Why, what, what for and what's next? Omega 87, 205–225. https://doi.org/10.1016/j.omega.2019.01.009
Mideksa, T.K., Kallbekken, S., 2010. The impact of climate change on the electricity market: A review. Energy Policy 38, 3579–3585. https://doi.org/10.1016/j.enpol.2010.02.035
Moktadir, Md.A., Ahmadi, H.B., Sultana, R., Zohra, F.-T.-, Liou, J.J.H., Rezaei, J., 2020. Circular economy practices in the leather industry: A practical step towards sustainable development. J. Clean. Prod. 251, 119737. https://doi.org/10.1016/j.jclepro.2019.119737
Mou, Q., Xu, Z., Liao, H., 2017. A graph based group decision making approach with intuitionistic fuzzy preference relations. Comput. Ind. Eng. 110, 138–150. https://doi.org/10.1016/j.cie.2017.05.033
Mou, Q., Xu, Z., Liao, H., 2016. An intuitionistic fuzzy multiplicative best-worst method for multi-criteria group decision making. Inf. Sci. 374, 224–239. https://doi.org/10.1016/j.ins.2016.08.074
Mulliner, E., Malys, N., Maliene, V., 2016. Comparative analysis of MCDM methods for the assessment of sustainable housing affordability. Omega 59, 146–156. https://doi.org/10.1016/j.omega.2015.05.013
Mulliner, E., Smallbone, K., Maliene, V., 2013. An assessment of sustainable housing affordability using a multiple criteria decision making method. Omega 41, 270–279. https://doi.org/10.1016/j.omega.2012.05.002
Naskar, S., Basuli, K., Sarma, S.S., 2009. Generation of All Spanning Trees. SSRN Electron. J. https://doi.org/10.2139/ssrn.1433035
Neal, R., Dankers, R., Saulter, A., Lane, A., Millard, J., Robbins, G., Price, D., 2018. Use of probabilistic medium- to long-range weather-pattern forecasts for identifying periods with an increased likelihood of coastal flooding around the UK. Met. Apps 25, 534–547. https://doi.org/10.1002/met.1719
Nikjoo, A.V., Saeedpoor, M., 2014. An intuitionistic fuzzy DEMATEL methodology for prioritising the components of SWOT matrix in the Iranian insurance industry. Int. J. Oper. Res. 20, 439–452. https://doi.org/10.1504/IJOR.2014.063152
Ntontis, E., Drury, J., Amlôt, R., Rubin, G.J., Williams, R., 2019. Community resilience and flooding in UK guidance: A critical review of concepts, definitions, and their implications. J Contingencies and Crisis Management 27, 2–13. https://doi.org/10.1111/1468-5973.12223
Nye, M., Tapsell, S., Twigger-Ross, C., 2011. New social directions in UK flood risk management: moving towards flood risk citizenship?: Flood risk citizenship. J. Flood Risk Manage 4, 288–297. https://doi.org/10.1111/j.1753-318X.2011.01114.x
Okoro, U., Kolios, A., 2018. Multicriteria risk assessment framework for components' risk ranking: Case study of a complex oil and gas support structure. J. Multi-Crit. Decis. Anal. 25, 113-129. https://doi.org/10.1002/mcda.1651
Okoro, U., Kolios, A., Cui, L., 2017. Multi-criteria risk assessment approach for components risk ranking – The case study of an offshore wave energy converter. International Journal of Marine Energy 17, 21–39. https://doi.org/10.1016/j.ijome.2016.12.001

Ölz, S., Sims, R., Kirchner, N., 2007. Contribution of renewables to energy security. OECD/IEA.
Omrani, H., Alizadeh, A., Emrouznejad, A., 2018. Finding the optimal combination of power plants alternatives: A multi response Taguchi-neural network using TOPSIS and fuzzy best-worst method. J. Clean. Prod. 203, 210–223. https://doi.org/10.1016/j.jclepro.2018.08.238
Pamucar, D., Chatterjee, K., Zavadskas, E.K., 2019. Assessment of third-party logistics provider using multi-criteria decision-making approach based on interval rough numbers. Comput. Ind. Eng. 127, 383–407. https://doi.org/10.1016/j.cie.2018.10.023
Pappas, D., Chalvatzis, K.J., 2017. Energy and Industrial Growth in India: The Next Emissions Superpower? Energy Procedia 105, 3656–3662. https://doi.org/10.1016/j.egypro.2017.03.842
Pappas, D., Chalvatzis, K.J., Guan, D., Ioannidis, A., 2018. Energy and carbon intensity: A study on the cross-country industrial shift from China to India and SE Asia. Appl. Energy 225, 183–194. https://doi.org/10.1016/j.apenergy.2018.04.132
Parliamentary Office of Science and Technology, 2011. Carbon Footprint of Electricity Generation.
Peeri, N.C., Shrestha, N., Rahman, M.S., Zaki, R., Tan, Z., Bibi, S., Baghbanzadeh, M., Aghamohammadi, N., Zhang, W., Haque, U., 2020. The SARS, MERS and novel coronavirus (COVID-19) epidemics, the newest and biggest global health threats: what lessons have we learned? Int. J. Epidemiol. 1–10. https://doi.org/10.1093/ije/dyaa033
Peng, X., Dai, J., 2018. Approaches to single-valued neutrosophic MADM based on MABAC, TOPSIS and new similarity measure with score function. Neural Comput. Appl. 29, 939–954. https://doi.org/10.1007/s00521-016-2607-y
Peng, X., Liu, C., 2017. Algorithms for neutrosophic soft decision making based on EDAS, new similarity measure and level soft set. J. Intell. Fuzzy Syst. 32, 955–968. https://doi.org/10.3233/JIFS-161548
Perrow, C., 1999. Normal accidents: living with high-risk technologies, Princeton paperbacks. Princeton University Press, Princeton, N.J.
Pohekar, S.D., Ramachandran, M., 2004. Application of multi-criteria decision making to sustainable energy planning—A review. Renew. Sustain. Energy Rev. 8, 365–381. https://doi.org/10.1016/j.rser.2003.12.007
Qazi, A., Quigley, J., Dickson, A., Ekici, Ş.Ö., 2017. Exploring dependency based probabilistic supply chain risk measures for prioritising interdependent risks and strategies. European Journal of Operational Research 259, 189–204. https://doi.org/10.1016/j.ejor.2016.10.023
Rahman, B.A., 2012. Issues of disaster management preparedness: A case study of directive 20 of National Security Council Malaysia. Int. J. Bus. Soc. Sci. 3.
Rajabi Asadabadi, M., Saberi, M., Chang, E., 2018. Letter: The concept of stratification and future applications. Appl. Soft Comput. 66, 292–296. https://doi.org/10.1016/j.asoc.2018.02.035
Ramana, M.V., 2009. Nuclear Power: Economic, Safety, Health, and Environmental Issues of Near-Term Technologies. Annu. Rev. Environ. Resour. 34, 127–152. https://doi.org/10.1146/annurev.environ.033108.092057
Ranjan, A., Hughes, L., 2014. Energy security and the diversity of energy flows in an energy system. Energy 73, 137–144. https://doi.org/10.1016/j.energy.2014.05.108

Ren, J., Jenkinson, I., Wang, J., Xu, D.L., Yang, J.B., 2009. An Offshore Risk Analysis Method Using Fuzzy Bayesian Network. Journal of Offshore Mechanics and Arctic Engineering 131, 041101. https://doi.org/10.1115/1.3124123

Reuters, 2017. Swiss Voters Back Plan to Phase Out Nuclear Power. N. Y. Times.

Rezaei, J., 2016. Best-worst multi-criteria decision-making method: Some properties and a linear model. Omega 64, 126–130. https://doi.org/10.1016/j.omega.2015.12.001

Rezaei, J., 2015. Best-worst multi-criteria decision-making method. Omega 53, 49–57. https://doi.org/10.1016/j.omega.2014.11.009

Rezaei, J., Wang, J., Tavasszy, L., 2015. Linking supplier development to supplier segmentation using Best Worst Method. Expert Syst. Appl. 42, 9152–9164. https://doi.org/10.1016/j.eswa.2015.07.073

Ritchie, B., Brindley, C., 2007. Supply chain risk management and performance: A guiding framework for future development. Int. J. Oper. Prod. Manag. 27, 303–322. https://doi.org/10.1108/01443570710725563

Rivieccio, U., 2008. Neutrosophic logics: Prospects and problems. Fuzzy Sets Syst. 159, 1860–1868. https://doi.org/10.1016/j.fss.2007.11.011

Rutherford, J.P., Scharpf, E.W., Carrington, C.G., 2007. Linking consumer energy efficiency with security of supply. Energy Policy 35, 3025–3035. https://doi.org/10.1016/j.enpol.2006.10.031

Saaty, T.L., 2005. Analytic Hierarchy Process, in: Armitage, P., Colton, T. (Eds.), Encyclopedia of Biostatistics. John Wiley & Sons, Ltd, Chichester, UK, p. b2a4a002. https://doi.org/10.1002/0470011815.b2a4a002

Saaty, T.L., 1977. A scaling method for priorities in hierarchical structures. J. Math. Psychol. 15, 234–281. https://doi.org/10.1016/0022-2496(77)90033-5

Sáenz de Miera, G., del Río González, P., Vizcaíno, I., 2008. Analysing the impact of renewable electricity support schemes on power prices: The case of wind electricity in Spain. Energy Policy 36, 3345–3359. https://doi.org/10.1016/j.enpol.2008.04.022

Sanders, N.R., Zacharia, Z.G., Fugate, B.S., 2013. The Interdisciplinary Future of Supply Chain Management Research. Decis. Sci. 44, 413–429. https://doi.org/10.1111/deci.12022

Sara, J., Stikkelman, R.M., Herder, P.M., 2015. Assessing relative importance and mutual influence of barriers for CCS deployment of the ROAD project using AHP and DEMATEL methods. Int. J. Greenh. Gas Control 41, 336–357. https://doi.org/10.1016/j.ijggc.2015.07.008

Sayers, P.B., Horritt, M., Penning-Rowsell, E., McKenzie, A., 2015. Climate Change Risk Assessment 2017: Projections of future flood risk in the UK. Sayers and Partners on behalf of the Committee on Climate Change, London.

Scherz, M., Vafadarnikjoo, A., 2019. Multiple Criteria Decision Analysis under uncertainty in sustainable construction: a neutrosophic modified best-worst method. IOP Conf. Ser. Earth Environ. Sci. 323, 012098. https://doi.org/10.1088/1755-1315/323/1/012098

Sensfuß, F., Ragwitz, M., Genoese, M., 2008. The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36, 3086–3094. https://doi.org/10.1016/j.enpol.2008.03.035

SEPA, 2016. Scotland’s flooding future 2016-2021 (infographic).

SEPA, 2015. Flood risk management strategy: Highland and Argyll. Scottish Environment Protection Agency (SEPA).
Setréus, J., Månsson, D., Hilber, P., Arnborg, S., 2012. Component ranking in Great Britain transmission system based on either equipment failures or sabotage. Proc. Inst. Mech. Eng. Part O J. Risk Reliab. 226, 96–108. https://doi.org/10.1177/1748006X11427372
SFFS, 2014. Your guide to using the Flood Guidance Statement. Scottish Flood Forecasting Service.
Shafer, G., 1976. A mathematical theory of evidence. Princeton Univ. Press, Princeton, NJ.
Si, S.-L., You, X.-Y., Liu, H.-C., Zhang, P., 2018. DEMATEL Technique: A Systematic Review of the State-of-the-Art Literature on Methodologies and Applications. Math. Probl. Eng. 2018, 1–33. https://doi.org/10.1155/2018/3696457
Silvast, A., 2017. Making electricity resilient: risk and security in a liberalized infrastructure. Routledge, Taylor & Francis Group, London ; New York.
Siraj, S., Mikhailov, L., Keane, J.A., 2015. Contribution of individual judgments toward inconsistency in pairwise comparisons. Eur. J. Oper. Res. 242, 557–567. https://doi.org/10.1016/j.ejor.2014.10.024
Siraj, S., Mikhailov, L., Keane, J.A., 2012. Enumerating all spanning trees for pairwise comparisons. Comput. Oper. Res. 39, 191–199. https://doi.org/10.1016/j.cor.2011.03.010
Skea, J., Anderson, D., Green, T., Gross, R., Heptonstall, P., Leach, M., 2008. Intermittent renewable generation and the cost of maintaining power system reliability. IET Gener. Transm. Distrib. 2, 82–89. https://doi.org/10.1049/iet-gtd:20070023
Smarandache, F., 2002. Neutrosophy, A New Branch of Philosophy. Infinite Study.
Smarandache, F., 1999. A unifying field in logics: neutrosophic logic. neutrosophy, neutrosophic set, probability. American Research Press, Rehoboth.
Smarandache, F., 1998. Neutrosophy: neutrosophic probability, set, and logic. American Research Press, Rehoboth.
Sodhi, M.S., Son, B.-G., Tang, C.S., 2012. Researchers' Perspectives on Supply Chain Risk Management. Prod. Oper. Manag. 21, 1–13. https://doi.org/10.1111/j.1937-5956.2011.01251.x
Sovacool, B.K., 2009. The intermittency of wind, solar, and renewable electricity generators: Technical barrier or rhetorical excuse? Util. Policy 17, 288–296. https://doi.org/10.1016/j.jup.2008.07.001
Srinivasa Raju, K., Nagesh Kumar, D., 2010. Multicriterion analysis in engineering and management. PHI Learning, New Delhi.
Staid, A., Guikema, S.D., 2015. Risk Analysis for U.S. Offshore Wind Farms: The Need for an Integrated Approach. Risk Anal. 35, 587–593. https://doi.org/10.1111/risa.12324
Stamford, L., Azapagic, A., 2014. Life cycle environmental impacts of UK shale gas. Appl. Energy 134, 506–518. https://doi.org/10.1016/j.apenergy.2014.08.063
Stanujkic, D., Magdalinovic, N., Jovanovic, R., Stojanovic, S., 2012. An objective multi-criteria approach to optimization using MOORA method and interval grey numbers. Technol. Econ. Dev. Econ. 18, 331–363. https://doi.org/10.3846/20294913.2012.676996

Stanujkic, D., Zavadskas, E.K., Smarandache, F., Brauers, W.K.M., Karabasevic, D., 2017. A Neutrosophic Extension of the MULTIMOORA Method. Informatica 28, 181–192.
Stauffer, D., 2003. Risk: The weak link in your supply chain. Harv. Manag. Update 8, 3–5.
Stirling, A., 2014. From sustainability, through diversity to transformation: towards more reflexive governance of technological vulnerability, in: Vulnerability in Technological Cultures: New Directions in Research and Governance. MIT Press.
Strantzali, E., Aravossis, K., 2016. Decision making in renewable energy investments: A review. Renew. Sustain. Energy Rev. 55, 885–898. https://doi.org/10.1016/j.rser.2015.11.021
Suganthi, L., Iniyan, S., Samuel, A.A., 2015. Applications of fuzzy logic in renewable energy systems – A review. Renew. Sustain. Energy Rev. 48, 585–607. https://doi.org/10.1016/j.rser.2015.04.037
Tan, W.-K., Kuo, C.-Y., 2014. Prioritization of Facilitation Strategies of Park and Recreation Agencies Through DEMATEL Analysis. Asia Pac. J. Tour. Res. 19, 859–875. https://doi.org/10.1080/10941665.2013.812570
Tang, S.Y., Gurnani, H., Gupta, D., 2014. Managing Disruptions in Decentralized Supply Chains with Endogenous Supply Process Reliability. Prod. Oper. Manag. 23, 1198–1211. https://doi.org/10.1111/poms.12160
Tang, Y.-Q., Cui, Z.-D., Wang, J.-X., Yan, L.-P., Yan, X.-X., 2008. Application of grey theory-based model to prediction of land subsidence due to engineering environment in Shanghai. Environ. Geol. 55, 583–593. https://doi.org/10.1007/s00254-007-1009-y
Tavana, M., Hatami-Marbini, A., 2011. A group AHP-TOPSIS framework for human spaceflight mission planning at NASA. Expert Syst. Appl. S095741741100635X. https://doi.org/10.1016/j.eswa.2011.04.108
Temur, G.T., 2016. A novel multi attribute decision making approach for location decision under high uncertainty. Appl. Soft Comput. 40, 674–682. https://doi.org/10.1016/j.asoc.2015.12.027
The World Bank Group, 2005. Energy security issues.
Tian, Z.-P., Wang, J.-Q., Zhang, H.-Y., 2018. Hybrid single-valued neutrosophic MCGDM with QFD for market segment evaluation and selection. IFS 34, 177–187. https://doi.org/10.3233/JIFS-171055
Torra, V., 2010. Hesitant fuzzy sets. Int. J. Intell. Syst. 529–539. https://doi.org/10.1002/int.20418
Torra, V., Narukawa, Y., 2009. On hesitant fuzzy sets and decision, in: 2009 IEEE International Conference on Fuzzy Systems. Presented at the 2009 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), IEEE, Jeju Island, South Korea, pp. 1378–1382. https://doi.org/10.1109/FUZZY.2009.5276884
Tranchita, C., Hadjsaid, N., Torres, A., 2009. Security assessment of the electricity infrastructure under terrorism. Int. J. Crit. Infrastruct. 5, 245. https://doi.org/10.1504/IJCIS.2009.024873
Tsoutsos, T., Frantzeskaki, N., Gekas, V., 2005. Environmental impacts from the solar energy technologies. Energy Policy 33, 289–296. https://doi.org/10.1016/S0301-4215(03)00241-6
Tzeng, G., Chiang, C., Li, C., 2007. Evaluating intertwined effects in e-learning programs: A novel hybrid MCDM model based on factor analysis and

DEMATEL. Expert Syst. Appl. 32, 1028–1044. https://doi.org/10.1016/j.eswa.2006.02.004
Tzeng, S., 2014. Applying DEMATEL to Investigate the Relationship Between Factors Affecting Parole Boards' Decision-Making in Taiwan. Prison J. 94, 118–136. https://doi.org/10.1177/0032885513512096
UK Cabinet Office, 2017. National Risk Register of Civil Emergencies.
US Energy Information Administration, 2019. International Energy Outlook 2019 with projections to 2050.
Vafadarnikjoo, A., Ahmadi, H.B., Hazen, B.T., Liou, J.J.H., 2020. Understanding Interdependencies among Social Sustainability Evaluation Criteria in an Emerging Economy. Sustainability 12, 1934. https://doi.org/10.3390/su12051934
Vafadarnikjoo, A., Mishra, N., Govindan, K., Chalvatzis, K., 2018. Assessment of consumers' motivations to purchase a remanufactured product by applying Fuzzy Delphi method and single valued neutrosophic sets. J. Clean. Prod. 196, 230–244. https://doi.org/10.1016/j.jclepro.2018.06.037
Vafadarnikjoo, A., Mobin, M., Khatami Firouzabadi, S.M.A., 2016. An Intuitionistic Fuzzy-Based DEMATEL to rank risks of construction projects. Presented at the Industrial Engineering and Operations Management (IEOM), Detroit, MI, USA.
Vafadarnikjoo, A., Mobin, M., Salmon, C., Javadian, N., 2015. An integrated gray-fuzzy cause and effect approach to determine the most significant categories of project risks. Presented at the Industrial and Systems Engineering Research Conference (ISERC) Conference, Nashville, TN, USA.
Van Aalst, M.K., 2006. The impacts of climate change on the risk of natural disasters. Disasters 30, 5–18. https://doi.org/10.1111/j.1467-9523.2006.00303.x
van Kooten, G.C., 2010. Wind power: the economic impact of intermittency. Lett. Spat. Resour. Sci. 3, 1–17. https://doi.org/10.1007/s12076-009-0031-y
Varigonda, K.C., 2013. An assessment of the impact of energy insecurity on state stability in India. Energy Policy 62, 1110–1119. https://doi.org/10.1016/j.enpol.2013.06.091
Vishnupriyan, J., Manoharan, P.S., 2018. Multi-criteria decision analysis for renewable energy integration: A southern India focus. Renew. Energy 121, 474–488. https://doi.org/10.1016/j.renene.2018.01.008
Visschers, V.H.M., Siegrist, M., 2013. How a Nuclear Power Plant Accident Influences Acceptance of Nuclear Power: Results of a Longitudinal Study Before and After the Fukushima Disaster. Risk Anal. 33, 333–347. https://doi.org/10.1111/j.1539-6924.2012.01861.x
Von Neumann, J., Morgenstern, O., 1947. Theory of games and economic behavior. Princeton University Press.
Walley, P., 1991. Statistical reasoning with imprecise probabilities, 1st ed. ed, Monographs on statistics and applied probability. Chapman and Hall, London ; New York.
Wang, H., Smarandache, F., Zhang, Y., Sunderraman, R., 2010. Single valued neutrosophic sets. Rev. Air Force Acad. 17, 10–14.
Wang, J., Yang, Y., Li, L., 2018. Multi-criteria decision-making method based on single-valued neutrosophic linguistic Maclaurin symmetric mean operators. Neural Comput. Appl. 30, 1529–1547. https://doi.org/10.1007/s00521-016-2747-0

Wang, J., Zhong, Z., 2009. Aggregation operators on intuitionistic trapezoidal fuzzy number and its application to multi-criteria decision making problems. J. Syst. Eng. Electron. 20, 321–326.
Wang, J.-J., Jing, Y.-Y., Zhang, C.-F., Zhao, J.-H., 2009. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew. Sustain. Energy Rev. 13, 2263–2278. https://doi.org/10.1016/j.rser.2009.06.021
Wang, W.-C., Lin, C.-L., Wang, S.-H., Liu, J.-J., Lee, M.-T., 2014. Application of importance-satisfaction analysis and influence-relations map to evaluate design delay factors. J. Civ. Eng. Manag. 20, 497–510. https://doi.org/10.3846/13923730.2013.801922
Wang, W.-C., Lin, Y.-H., Lin, C.-L., Chung, C.-H., Lee, M.-T., 2012. DEMATEL-based model to improve the performance in a matrix organization. Expert Syst. Appl. 39, 4978–4986. https://doi.org/10.1016/j.eswa.2011.10.016
Wang, Y., Chen, C., Wang, J., Baldick, R., 2016. Research on Resilience of Power Systems Under Natural Disasters—A Review. IEEE Trans. Power Syst. 31, 1604–1613. https://doi.org/10.1109/TPWRS.2015.2429656
Wang, Y., Gilland, W., Tomlin, B., 2010. Mitigating Supply Risk: Dual Sourcing or Process Improvement? Manuf. Serv. Oper. Manag. 12, 489–510. https://doi.org/10.1287/msom.1090.0279
Warren, R., Watkiss, P., Wilby, R.L., Humphrey, K., Ranger, N., Betts, R., Lowe, J., Watts, G., 2016. UK Climate Change Risk Assessment Evidence Report: Chapter 2, Approach and Context. Report prepared for the Adaptation Sub-Committee of the Committee on Climate Change, London.
Warren, R.F., Wilby, R.L., Brown, K., Watkiss, P., Betts, R.A., Murphy, J.M., Lowe, J.A., 2018. Advancing national climate change risk assessment to deliver national adaptation plans. Philos. Trans. R. Soc. Math. Phys. Eng. Sci. 376, 20170295. https://doi.org/10.1098/rsta.2017.0295
Watson, J.T., Gayer, M., Connolly, M.A., 2007. Epidemics after Natural Disasters. Emerg. Infect. Dis. 13, 1–5. https://doi.org/10.3201/eid1301.060779
Wei, H., Dong, M., Sun, S., 2009. Inoperability input-output modeling (IIM) of disruptions to supply chain networks. Syst. Engin. 13, 324–339. https://doi.org/10.1002/sys.20153
Wilbanks, T.J., Bhatt, V., Bilello, D.E., Bull, S.R., Ekmann, J., Horak, W.C., Huang, Y.J., Levine, M.D., Sale, M.J., Schmalzer, D.K., Scott, M.J., 2008. Effects of Climate Change on Energy Production and Use in the United States. U.S. Climate Change Science Program and the subcommittee on Global Change Research, Department of Energy, Office of Biological & Environmental Research, Washington, DC., USA.
Winzer, C., 2012. Conceptualizing energy security. Energy Policy 46, 36–48. https://doi.org/10.1016/j.enpol.2012.02.067
Wright, P., 2005. Liberalisation and the security of gas supply in the UK. Energy Policy 33, 2272–2290. https://doi.org/10.1016/j.enpol.2004.04.022
Wu, B.Y., Chao, K.-M., 2004. Spanning trees and optimization problems. Chapman & Hall/CRC, Boca Raton.
Wu, W.-W., Lee, Y.-T., 2007. Developing global managers' competencies using the fuzzy DEMATEL method. Expert Syst. Appl. 32, 499–507. https://doi.org/10.1016/j.eswa.2005.12.005
Wu, Y., Xu, C., Zhang, T., 2018. Evaluation of renewable power sources using a fuzzy MCDM based on cumulative prospect theory: A case in China. Energy 147, 1227–1239. https://doi.org/10.1016/j.energy.2018.01.115

Xia, M., Xu, Z., 2011. Hesitant fuzzy information aggregation in decision making. Int. J. Approx. Reason. 52, 395–407. https://doi.org/10.1016/j.ijar.2010.09.002
Xia, X., Govindan, K., Zhu, Q., 2015. Analyzing internal barriers for automotive parts remanufacturers in China using grey-DEMATEL approach. J. Clean. Prod. 87, 811–825. https://doi.org/10.1016/j.jclepro.2014.09.044
Yadav, G., Mangla, S.K., Luthra, S., Jakhar, S., 2018. Hybrid BWM-ELECTRE-based decision framework for effective offshore outsourcing adoption: a case study. Int. J. Prod. Res. 56, 6259–6278. https://doi.org/10.1080/00207543.2018.1472406
Yamaguchi, D., Li, G.-D., Chen, L.-C., Nagai, M., 2007. Reviewing crisp, fuzzy, grey and rough mathematical models, in: 2007 IEEE International Conference on Grey Systems and Intelligent Services. Presented at the 2007 IEEE International Conference on Grey Systems and Intelligent Services, IEEE, Nanjing, China, pp. 547–552. https://doi.org/10.1109/GSIS.2007.4443334
Yang, Z. (Ben), Aydın, G., Babich, V., Beil, D.R., 2009. Supply Disruptions, Asymmetric Information, and a Backup Production Option. Manag. Sci. 55, 192–209. https://doi.org/10.1287/mnsc.1080.0943
Ye, J., 2017a. Some Weighted Aggregation Operators of Trapezoidal Neutrosophic Numbers and Their Multiple Attribute Decision Making Method. Informatica 28, 387–402.
Ye, J., 2017b. Simplified neutrosophic harmonic averaging projection-based method for multiple attribute decision-making problems. Int. J. Mach. Learn. Cybern. 8, 981–987. https://doi.org/10.1007/s13042-015-0456-0
Ye, J., 2017c. Multiple Attribute Decision-Making Method Using Correlation Coefficients of Normal Neutrosophic Sets. Symmetry 9, 80. https://doi.org/10.3390/sym9060080
Ye, J., 2017d. Multiple attribute group decision making based on interval neutrosophic uncertain linguistic variables. Int. J. Mach. Learn. Cybern. 8, 837–848. https://doi.org/10.1007/s13042-015-0382-1
Ye, J., 2017e. Bidirectional projection method for multiple attribute group decision making with neutrosophic numbers. Neural Comput. Appl. 28, 1021–1029. https://doi.org/10.1007/s00521-015-2123-5
Yildiz, H., Yoon, J., Talluri, S., Ho, W., 2016. Reliable Supply Chain Network Design. Decis. Sci. 47, 661–698. https://doi.org/10.1111/deci.12160
Yu, X., Qu, H., 2010. Wind power in China—Opportunity goes with challenge. Renew. Sustain. Energy Rev. 14, 2232–2237. https://doi.org/10.1016/j.rser.2010.03.038
Zadeh, L.A., 2016. Stratification, target set reachability and incremental enlargement principle. Inf. Sci. 354, 131–139. https://doi.org/10.1016/j.ins.2016.02.047
Zadeh, L.A., 1965. Fuzzy sets. Inf. Control 8, 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X
Zhang, W., 2012. Computational ecology: graphs, networks and agent-based modeling. World Scientific, New Jersey.
Zhao, Haoran, Guo, S., Zhao, Huiru, 2018. Comprehensive Performance Assessment on Various Battery Energy Storage Systems. Energies 11, 2841. https://doi.org/10.3390/en11102841
Zhao, M., Freeman, N.K., 2019. Robust Sourcing from Suppliers under Ambiguously Correlated Major Disruption Risks. Prod. Oper. Manag. 28, 441–456. https://doi.org/10.1111/poms.12933

Zhao, R., Neighbour, G., Han, J., McGuire, M., Deutz, P., 2012. Using game theory to describe strategy selection for environmental risk and carbon emissions reduction in the green supply chain. J. Loss Prev. Process Ind. 25, 927–936. https://doi.org/10.1016/j.jlp.2012.05.004

Zimmermann, H.-J., 2000. An application-oriented view of modeling uncertainty. Eur. J. Oper. Res. 122, 190–198. https://doi.org/10.1016/S0377-2217(99)00228-3