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# A Socio-Economic and Environmental Vulnerability Assessment Model with Causal Relationships in Electric Power Supply Chains

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**Declaration of Interest**

The above authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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# A Socio-Economic and Environmental Vulnerability Assessment Model with Causal Relationships in Electric Power Supply Chains


## Abstract

The electric power industry is uniquely vulnerable to natural and human-made risks such as natural disasters, climate change, and cybersecurity. This study proposes a vulnerability assessment framework to identify and assess the risks associated with the electric power supply chain in the United Kingdom and study the causal relationship among them with the neutrosophic revised decision-making trial and evaluation laboratory (NR-DEMATEL) method. We further introduce a novel hesitant expert selection model (HESM) to assist decision-makers with expert selection and weight determination. We present a case study in the United Kingdom power supply chain to demonstrate the applicability and efficacy of the proposed method in this study. This is the first comprehensive risk interdependence analysis of the United Kingdom's power supply chain. The findings reveal natural disasters and climate change are the most crucial risks followed by industrial action, affordability, political instability, and sabotage/terrorism.



**Keywords:** vulnerability assessment; causal relationship; environmental economics; power supply chain; neutrosophic set theory, DEMATEL

## 1. Introduction

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 recognized as a national security issue by many governments such as the U.K. and more than 20 other countries, including both developed and developing states such as Australia, Canada, Finland, Germany, New Zealand, Switzerland, India, and Indonesia (Brunner and Suter, 2008; Silvast, 2017). Aware of the importance of disruptions, the U.K. Government has been publishing National Risk Registers (U.K. Cabinet Office, 2017) that outline significant risks ranging from natural hazards, diseases, major accidents, and societal risks. A widespread electricity supply failure in the U.K. has a high impact (level 4) severity, just one level less than an influenza pandemic (level 5). Furthermore, the U.K. has been one of the first industrialized countries to have plans for shutting down its coal-fired power stations (Thomas, Hook, and Tighe, 2019) and pursue one of the largest programs of offshore wind investment in the world (Diaz and Soares, 2020). All that while, the U.K. nuclear energy will be reduced as it has not managed to secure replacement contracts for many of its power stations that will be reaching the end of their lifespan in this decade.

The energy security concept has widened and developed over time and covers topics such as energy conversion and transport, which are particularly important in the electric power supply chain. Chester (2010) presented several aspects that constitute energy security, such as energy security as a risk management concept. On the other hand, disruptions can happen anywhere in the supply chain, including the electricity supply network. Thus, the link between energy security as a risk management concept and supply chain vulnerability assessment within the electric power supply chain is crucial. Supply chain vulnerability is a critical issue as a single disruption can potentially lead to further disruptions and even collapse of the entire supply chain (Kern et al., 2012). For instance, in the automotive industry, a production breakdown can cause economic losses of millions of dollars per day (Habermann et al., 2015; Kern et al., 2012). The recent COVID-19 outbreak has had a serious impact on all the supply chain members simultaneously and has caused a substantial disruption to the normal flow within supply chains due to border closures, lockdown in the retail markets, labor shortage, and interruptions in transportation, to name a few causes (Chowdhury et al., 2021). Take an example of the recent global semiconductors shortage, which has had a significant impact on the car and electronic devices manufacturing supply chain, which is predicted to continue until mid-2022 (Dempsey, 2021). The coronavirus pandemic initially caused this disruption due to delay and lack of supplies as plants had to close temporarily. Then the issue was exacerbated by the sudden surge in demand for electronic devices such as laptops and new equipment resulting from working at home (Hopkins, 2021). Furthermore, supply chain managers must know where supply chains are most vulnerable to allocate necessary resources (Chopra and Sodhi, 2004). Globalization 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 also led to growing interest in supply chain risk research (Hult et al., 2010; Kumar and Park, 2018; Yildiz et al., 2016). Shekarian et al. (2020) indicated that disruption management of supply chain risks had received growing attention in recent years (see Azadegan et al. 2019; Fartaj et al., 2020; Nezamoddini et al., 2020; Parast 2020; Yu et al., 2019). Basole and Bellamy (2014) indicated that supply chain risk identification and mitigation are complicated tasks due to the progressively global, complex, and intertwined nature of the supply chain. Klinke and Renn (1999) suggested dealing with risks rationally; one should characterize them and recognize the tools for designing proper responses. It has been recognized that there is a need for an integrated supply chain risk management, which takes into account multiple characteristics of supply chain risks regarding the multidisciplinary nature of supply chain management (Heckmann et al., 2015; Sanders et al., 2013).

This study considers the complexity within the energy supply chain and addresses the need for useful risk management tools and decision-making methods. In this study, a risk identification framework is proposed based on scrutinizing energy supply chain risks. Then, identified risks are analyzed by applying the neutrosophic revised decision-making trial and evaluation laboratory (NR-DEMATEL) method. Our study takes the view that there is some degree of interconnection between risks; that is, there could be causal relations among them, which indicates that the occurrence of one risk could lead to exposure to another (Colon et al., 2020; Hashemi et al., 2020; Zhou et al., 2021). To our knowledge, 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 energy supply chain. Thus, it is critical to take advantage of a method that can analyze these interrelationships and effectively deal with subjective judgments of experts such as a combined NR-DEMATEL. The DEMATEL method is widely used to analyze interdependent factors while considering causal relationships (Feng et al., 2018; Lin et al., 2021). In this study, the main advantage of DEMATEL is its ability to uncover causal relationships and interdependencies between various risks while utilizing minimal data. The neutrosophic set theory (NST) provides a considerable advantage over the fuzzy set (FS) (Bostancı, and Erdem, 2020; Rezaei-Malek et al., 2019) and the intuitionistic FS (IFS) theories (Ocampo and

Yamagishi, 2020) in processing experts' subjective judgments. The NST, unlike the FS theory, can quantify the rejection information derived from the falsity-membership function. In addition, the NST, unlike the IFS theory, is capable of defining the hesitancy function values independent of the falsity and truth-membership function values.

An expert selection model (ESM) is also proposed in our 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 decision aiders or analysts decide who can be realized as an expert based on their credentials and experience. It is also useful in assigning each expert a relative importance weight. This model is integrated with a hesitant fuzzy set (HFS) theory and named the hesitant expert selection model (HESM).

The contributions of this study are fourfold. We (1) present a simple but yet scientific framework for risk identification and classification; (2) apply an NR-DEMATEL method to analyze the interrelationships and interdependencies among identified risk dimensions; (3) introduce a HESM to assist researchers with the expert selection process systematically, and (4) aid policymakers in the U.K. energy production and distribution sector to effectively realize significant risk dimensions and the causal interrelationships among them which can be useful in the risk assessment phase.

The remainder of the paper is organized as follows. In Section 2, the literature, the U.K. energy supply chain, energy risk identification framework, and twelve identified risk dimensions are discussed. The proposed methodology and data analysis are represented in Section 3. Results and discussion are presented in Sections 4 and 5, respectively. Finally, Section 6 presents the concluding remarks, limitations, and suggestions for future research directions.

## 2. Literature review

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). The European Commission (EC, 2000) defined energy security as the uninterrupted physical availability of energy products on the market at a price that is affordable for all consumers (private and industrial). The concept of energy security focused on three pillars: efficiency, diversification of supplies, and price volatility (World Bank, 2005). Kruyt et al. (2009) defined four A's of energy security as 1) availability (geological elements), 2) accessibility (geopolitical elements), 3) affordability (economic elements), and 4) acceptability (environmental and societal elements). Cherp and Jewell (2014) 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.

Moreover, in the supply chain literature, risks or disruptions are unplanned and unforeseen events, which disrupt the normal flow of goods and materials within a supply chain. Subsequently, they impose operational and financial risks on stakeholders within the supply chain and can have 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 associated with natural or human-made catastrophes like floods, terrorism, and so on (Blackhurst et al., 2011; Craighead et al., 2007; Sodhi et al., 2012). In previous studies, Hammond and Waldron (2008) identified and ranked major risks concerning the U.K. electricity sector by considering various stakeholder groups and quantifying risks by multiplicating the likelihood of each risk and its consequences. Lin et al. (2018) identified risk elements of the new energy power system (NEPS) in China and analyzed their internal influence relations based on D numbers and DEMATEL. Silvast (2017) studied the electricity infrastructures and interruptions from the social science perspective and tried to answer how people and organizations react to these interruptions. Moreover, he explained how disruption to 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 analyze risks by identifying six different risk categories and developing unique risk management strategies for each class. Hunt, Bañares-Alcántara, and Hanbury (2013) proposed a decision support framework tool based on multi-criteria decision analysis for complex decision-making process prediction in the U.K. energy sources. A gap for a comprehensive perspective towards macro-level energy risks, including all energy sources through the entire U.K. energy supply chain, has been identified by reviewing the literature. An overarching approach focuses on risks related to specific energy supply risks and aims to include all risks from the supply, demand, and network positions. The rest of this section discusses the U.K. energy supply chain, the proposed energy risk identification framework, and the related literature.

### *2.1. The U.K. energy supply chain*

The energy supply chain is characterized by three interacting levels shown in Figure 1. Firstly, upstream is the generation of energy that can be primary, such as oil, gas, solid fuels, or secondary such as electricity. Secondly, midstream, or the network that manages the transmission of energy. Thirdly, downstream, or the demand side of the energy supply chain where energy is delivered to consumers in the transport, domestic, services, or industrial sectors.

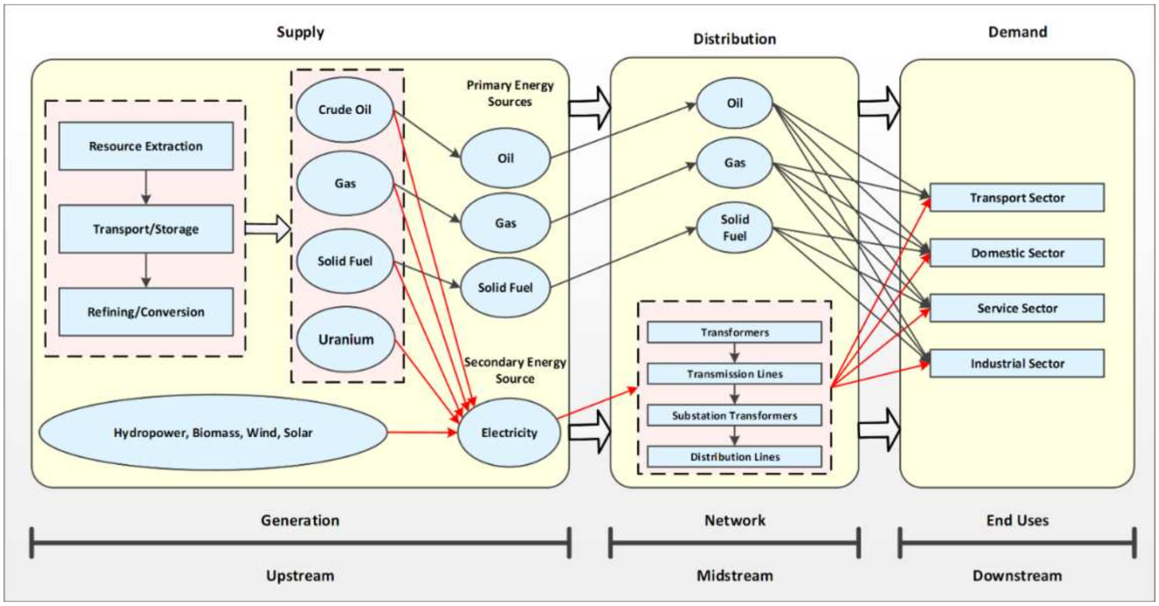


**Figure 1. Simplified U.K. energy supply chain (electric power supply chain in red) (adapted from Hammond and Waldron, 2008)**

Figure 2 presents the energy risk identification framework proposed in this study. The proposed risk identification framework is comprised of two main parts: (1) *risk classifications* and (2) *risk dimensions*.

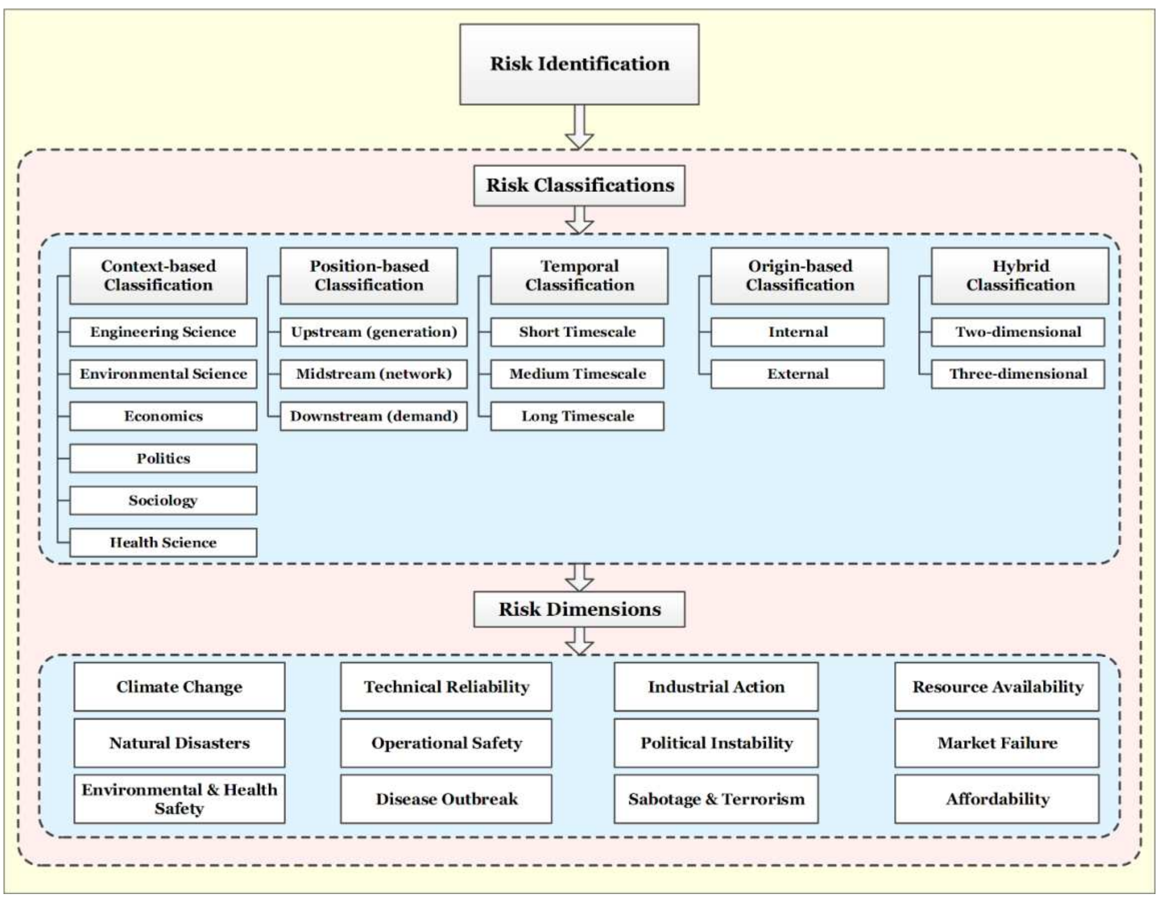


**Figure 2. The framework of energy risk identification**

### *2.2. Energy risk classifications*

Risk classifications essentially present the discipline and framing of risks to position them into the broader risk literature. Risk classifications can help understand and analyze risk dimensions properly from various perspectives, such as position and origin within the U.K. electric power supply chain. Risk dimensions can be described within the boundaries set by one, two, or three risk classifications (hybrid classification). For example, the risk dimension of Market Failure is contextually relevant to Economics; it mostly concerns downstream supply, and its temporality is short-term.

An extensive literature review enabled the identification of the five risk classifications: *context-based*, *position-based*, *temporal*, *origin-based,* and *hybrid*. Specifically, 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). The position-based classification groups risk according to their position in the energy supply chain, upstream, midstream, or downstream (Gracceva and Zeniewski, 2014). In temporal-based classification, risks are characterized according to the length of time they unfold (long, medium, or short) (Chevalier, 2006). Some risks have their origins within the boundaries of their operating system (internal) or outside of the studied system (external) (Babich et al., 2007; Chevalier, 2006; Huang et al., 2016; Tang et al., 2014; Yang et al., 2009). Finally, hybrid classifications consolidate two or three other classifications and provide an integrated perspective of various dimensions (two-dimensional or three-dimensional) (Boston, 2013).

### *2.3. Energy risk dimensions*

A variety of papers from different disciplines were explored by employing a structured literature review. Table 1 shows the utilized structured literature review protocol (Vafadarnikjoo, 2020).

**Table 1. The systematic literature review protocol**

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

At the initial stages, it became clear that finding risk dimensions cannot be carried out by merely looking at keywords, titles, or abstracts. For example, the topic search strings "energy AND supply AND electricity AND risk" on WoS returned 481 articles within 1989-2018. Hence, crossreferences found in the identified articles were utilized to reach more related papers. This approach returned approximately 100 documents 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. All the proposed risk dimensions are categorized distinctly, 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. For instance, a disease outbreak is proposed in this framework as an almost untapped risk dimension in energy security literature. The twelve energy supply chain risk dimensions presented in Table 2 are identified through the literature review.

**Table 2. Energy supply chain risk dimensions**

| Risk dimensions | Characteristics | References |
|---|---|---|
| Climate Change (C.C.) | A long-term alteration in the climate can change weather patterns and threaten renewable energy supply or capability for cooling thermal power stations. | Brusset and Bertrand (2018); Halldorsson and Kovacs (2010); Hammond and Waldron (2008); Jun et al. (2013); Mideksa and Kallbekken (2010); Trotta (2020) |
| Natural Disasters[1] (N.D.) | Natural disasters are calamitous events with atmospheric, geologic, or hydrologic origins. They can have rapid or slow development and disrupt the supply chain or the operation of power stations. | Apte et al. (2016); Daileda (2017); Liu et al. (2000); Tavana et al. (2018); Wang et al. (2016); Watson et al. (2007); Zobel (2014) |
| Environmental and Health Safety (E.H.S.) | The energy system can potentially threaten the public's health and can have negative impacts on the environment. This risk can then threaten the security of the energy supply chain by social pressure or legislation leading to stricter environmental laws. | Aman et al. (2015); Fthenakis and Kim (2009); Ramana (2009) |
| Technical Reliability (T.R.) | Technical risks usually concern system failure due to low capital investment or poor condition of the energy system. Asset maintenance also falls in this category. | Checchi, Behrens, and Egenhofer (2009); Chevalier (2006); Winzer (2012) |
| Operational Safety (O.S.) | It discusses the possibility of devastating damage concerned with a specific type of power generation not during regular operation but accidents. | Boston (2013); Chalvatzis (2012); Ranjan and Hughes (2014); Vainio, Paloniemi, and Varho (2017); Visschers and Siegrist (2013) |
| Disease Outbreak (D.O.) | It refers to the disruption in energy generation due to an unexpected spread of a disease that can threaten personnel health in a specific region. The COVID-19 virus pandemic is an example that could suspend regular operations of businesses. | Chevalier (2006); Verikios (2020) |
| Political Instability (P.I.) | It refers to social unrest or geopolitical changes that impact the security of the energy supply chain and causes disruption. | Checchi, Behrens, and Egenhofer (2009); Correlje and van der Linde (2006); Costantini et al. (2007); Kruyt et al. (2009); Varigonda (2013) |

[1]It is important to notice that N.D. can be related to C.C., but, not all-N.D. are caused by C.C. Dealing with C.C. means considering the root and cause of many N.D. because C.C. can increase the likelihood of weather-related N.D. such as droughts which can be caused largely by global warming (Gallina et al., 2016; Van Aalst, 2006). However, in some cases N.D. may be triggered by other causes, even by other N.D. For instance, Liu, Linde, and Sacks (2009) showed that, in eastern Taiwan, slow earthquakes can be triggered by typhoons or for example the Fukushima disaster begun by an earthquake which triggered a tsunami, which resulted in a nuclear meltdown. As another example, in 2005, hurricane Katrina caused landslides in Louisiana on the U.S. Gulf Coast (Labib and Read, 2015).

| | | |
|---|---|---|
| Industrial Action (I.A.) | It is regarded as one of the major causes of disruptions in the energy supply and, correspondingly, electricity generation. | Chalvatzis (2012); Löschel, Moslener, and Rübbelke (2010); Varigonda (2013) |
| Sabotage and Terrorism (S.T.) | It confronts the electricity industry with a serious challenge of providing more security without compromising the inbuilt productivity advantages in today's complicated and highly interconnected electric networks. | Amin (2002); Clements and Kirkham (2010); Flick and Morehouse (2010); Gjerde et al. (2011); Tranchita, Hadjsaid, and Torres (2009); Zobel and Khansa (2012) |
| Resource Availability (R.A.) | It is relevant to both fossil fuels and renewable energy sources. The lack of resources to generate power can pose a significant risk to the electric power network. | Chang (2014); Grave, Paulus, and Lindenberger (2012); Horsnell (2000); Ioannou, Angus, and Brennan (2017); Johansson (2013); Kilian (2016); Sovacool (2009); Stamford and Azapagic (2014); Wang et al. (2014a) |
| Market Failure (M.F.) | It relates to the reliable market operation regarding smooth contracting and dispatching of energy. | Alvarado (1999); Chevalier (2006); Costantini et al. (2007); Kruyt et al. (2009); Makkonen and Lahdelma (2001) |
| Affordability (AF) | It refers to the price of energy and the capacity of domestic and business users to afford it. | Chalvatzis (2012); Ioannidis and Chalvatzis (2017) |

Chen and Yano (2010) indicated that weather could affect the seasonal product demand as the U.S. National Research Council has estimated that the weather influences around 46% of U.S. gross domestic product. 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 (Wang et al., 2010). Climate change has resulted in the variability of weather conditions and subsequently affecting the sales of many products. Thus, Brusset and Bertrand (2018) introduced an approach to transfer weather risks to risk-takers utilizing weather index-based financial instruments to reduce sales volatility. Berger et al. (2016) utilized recent tools in decision theory to quantify the influence of deep uncertainty on the optimal level of emission abatement. Tranchita et al. (2009) presented a methodology to evaluate the power system security concerning the likelihood of terrorist acts regarding the uncertainties related to loading and generation. Chevalier (2006) explained the social dimension of security of supply (SOS) as SOS has a cost. In case of a price shock, certain types of consumers exposed to volatile prices may not be able to afford a supply of energy.

### 3. Methodology and data analysis

The research steps of the applied methodology are illustrated in Figure 3.

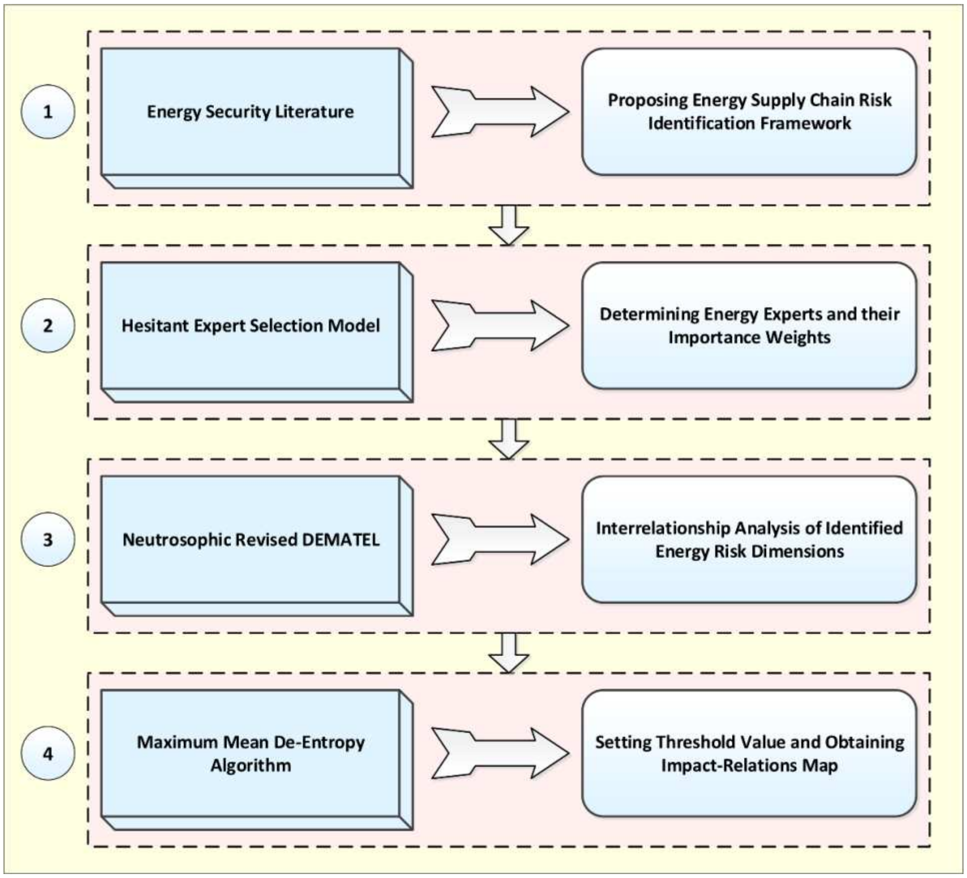


**Figure 3. Research steps**

### *3.1. The NR-DEMATEL method*

The DEMATEL method had a long-term presence in the scientific literature. The original DEMATEL is used to solve problems of a fragmented and antagonistic nature. DEMATEL method utilizes graph theory to allow decision-makers to visually analyze complex problems (Chang et al., 2011; Govindan et al., 2015; Kumar et al., 2019; Li et al., 2019; Lu et al., 2013; Yang and Tzeng, 2011). Decision analysts construct a pairwise matrix and determine the interrelations between factors in the study. The applicability of the combined NST and DEMATEL is verified in different decision-making problems (Abdel-Basset et al., 2019; Abdel-Basset et al., 2018; Kilic and Yalcin, 2020; Tian et al., 2018). In our study, we take advantage of the NR-DEMATEL, which integrates the revised DEMATEL (Lee et al., 2013) and the NST. The implementation procedure of the method is explained in the following steps (Govindan et al., 2016):

***Step 1:*** Subject experts and factors identification

In this initial step, it is required to identify a set of factors that are intended to be studied along with an appropriate number of experts who have rich knowledge and experience of the subject matter. Note that experts may not necessarily be eligible for the evaluation of all the factors, and they may choose to evaluate one or more factors that they can provide a robust evaluation for. Moreover, assigning importance weights to each expert's opinion is another crucial part that should be handled systematically. The proposed HESM is explained in Section 3.3 to facilitate this expert selection and importance weight allocation process. The weight of the $k^{th}$ expert is represented as $w_k$ where $0 \le w_k \le 1$ and $\sum_{i=1}^{H} w_k = 1$, given $H$ is the total number of experts offering 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 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 of factor $j$. The pairwise comparison between the $i^{th}$ factor and the $j^{th}$ factor given by the $k^{th}$ expert is denoted as $b_{ij}^{(k)}$ which takes on integers based on the seven-grade Likert scale ranging from 0 to 6 (Table 3). The scores stated by each expert will construct a $n\times n$ non-negative answer matrix $B^{(k)} = \left[ b_{ij}^{(k)} \right]_{n\times n}$ with $1 \le k \le H$. Thus $B^{(1)}, B^{(2)}, ..., B^{(H)}$ are the answer matrices of $H$ experts. The diagonal elements of each answer matrix $B^{(k)}$ are all set to zero, which means no influence is given by itself (Lee et al., 2013). Some rows of the matrix could have missing values meaning an expert was not well-qualified to evaluate a specific factor and thus did not provide an answer. In this case, missing values have been treated by the deletion method.

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

The SVTNNs (Table 3) are utilized 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 $1 \le k \le H$ is constructed by replacing the $b_{ij}^{(k)}$ values in $B^{(k)}$ with the corresponding SVTNN values (Table 3).

***Step 4*: The initial weighted average matrix $A$ construction**

Crisp values are values under certain decision-making environment which are obtained from the conversion of values from uncertain decision-making environment. The corresponding crisp values ($cs_{ij}^{(k)}$) of SVTNN values (Table 3) 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 deal with less complex calculations in the later computational steps. The described score function in Vafadarnikjoo et al. (2018) has been applied to get the crisp value of SVTNN in Table 3.

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

**Table 3. Linguistic values of SVTNNs for linguistic terms**

| Linguistic Phrase | Influence score | SVTNN | Crisp Value |
|---|---|---|---|
| No Influence | 0 | $\prec (0.0, 0.0, 0.0, 0.0); 0.0, 0.0, 0.0 \succ$ | 0.00 |
| Low Influence | 1 | $\prec (0.2, 0.3, 0.4, 0.5); 0.6, 0.2, 0.2 \succ$ | 0.26 |
| Fairly Low Influence | 2 | $\prec (0.3, 0.4, 0.5, 0.6); 0.7, 0.1, 0.1 \succ$ | 0.38 |
| Medium Influence | 3 | $\prec (0.4, 0.5, 0.6, 0.7); 0.8, 0.0, 0.1 \succ$ | 0.50 |
| Fairly High Influence | 4 | $\prec (0.7, 0.8, 0.9, 1.0); 0.8, 0.2, 0.2 \succ$ | 0.68 |
| High Influence | 5 | $\prec (1.0, 1.0, 1.0, 1.0); 0.9, 0.1, 0.1 \succ$ | 0.90 |
| Absolutely High Influence | 6 | $\prec (1.0, 1.0, 1.0, 1.0); 1.0, 0.0, 0.0 \succ$ | 1.00 |

***Step 5:*** The normalized initial direct-relation matrix $D$ construction

The normalized initial direct-relation matrix $D = \left[d_{ij}\right]_{n \times n}$ is generated by normalizing the weighted average matrix $A$ using Eqs. (1) and (2) where $\varepsilon$ is a very small positive number like $10^{-5}$ (Lee et al., 2013). $\sum_{j=1}^{n} a_{ij}$ is the total direct effect that factor $i$ gives to other factors, and $\sum_{i=1}^{n} a_{ij}$ is the total direct effect received by factor $j$.

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

$$D = \frac{A}{p} \tag{2}$$

***Step 6*****:** The total relation matrix $T$ construction

The total relation matrix is obtained by Eq. (3) in which $I$ is the identity matrix.

$$T = D(I - D)^{-1} \tag{3}$$

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

In the DEMATEL literature, the IRM (Lee et al., 2013) named an influence-relations map (Wang et al., 2012). An IRM is generated by applying Eqs. (4) to (6) as follows:

$$T = \left[t_{ij}\right]_{n\times n} \qquad i, j = 1, 2, \ldots, n \tag{4}$$

$$c = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n} = \left[t_{.j}\right]_{1\times n} = \left[c_j\right]_{1\times n} \tag{5}$$

$$r = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = \left[t_{i.}\right]_{n\times 1} = \left[r_i\right]_{n\times 1} \tag{6}$$

The sum of the rows ($r$) and the sum of the columns ($c$) are calculated using the 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 factor $i$ to other factors. The $c_i$ is the sum of the $j^{th}$ column of the matrix $T$ and shows the total effect, both direct and indirect, received by the factor $j$ 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 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 factor $i$ contributes to the system. In general, if $(r_i - c_i) \succ 0$ then factor *i* is a member of the cause group or a net causer, and if $(r_i - c_i) \prec 0$ then factor $i$ is a member of the effect group or is a net receiver. Cause factors impact 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 the threshold value**

Based on the total relation matrix $T$, each element $t_{ij}$ of matrix $T$ provides information about how factor $i$ impacts factor $j$. If all the information in matrix $T$ converts to IRM, then the map would hardly be conducive to appropriate decision-making as it is too complicated to reveal any useful information. This is particularly the case when numerous factors are being explored. The decision aider must set a threshold value for the impact level to obtain a proper IRM. Only factors with influence levels higher than the threshold value in the 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) mentioned 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), and 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 utilized because of its compelling rationale and logic (Appendix A) 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 IRM and MMDE, Wang et al. (2012; 2014b) further developed the net influence matrix $N = \left[ Net_{ij} \right]_{n \times n}$ to assess the impact of one factor on another where $Net_{ij} = t_{ij} - t_{ji}$ .

The twelve-energy supply chain risk dimensions (Table 2) are analyzed based on the knowledge and experience of experts in the U.K. electricity supply chain.

### *3.2. Data collection*

Experts involved in this research are comprised of both academics and practitioners with a proper level of knowledge and experience in the U.K. electric power supply chain. In total, 161 experts based on the ESM (Appendix B) were chosen and initially contacted through email to participate in the study by completing an online 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%. Experts' fields of knowledge in various energy sectors along with the number of experts in each category were: renewable energy (21 experts); policy and economics (20 experts); energy storage and grid modernization (10 experts); fossil and nuclear energy (6 experts); environmental impacts (5 experts); end-use energy efficiency (5 experts); and other (4 experts). Most experts (74%) had overlapping expertise in more than one area. 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 3. Please see Appendix C for more information about data, survey, and analysis.

### *3.3. Scenario analysis in HESM*

The proposed ESM, as explained in Appendix B combined with HFS theory (Appendix D), namely HESM, was applied using the data provided by 31 experts. Since not all the respondents acquired the same level of experience and knowledge, HESM has been applied to obtain the EEV values and correspondingly 31 experts' importance weights. A scenario analysis using HFS theory has been introduced and conducted to improve the reliability of the expert selection scheme by obtaining a more cogent importance weight for each expert. In other words, instead of omission of potential experts in the first place by the included value of $\alpha$ 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. Parameters' values are essentially defined based on the 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 academics and practitioners are presented in Tables 4 and 5, respectively.

In Table 4, in a high-experience-focused scenario, attention is paid to years of experience in three levels of the professorship, senior lectureship, and lectureship (Eq. (B.7)) rather than professional qualifications (Eq. (B.5)) or association membership (Eq. (B.6)). On the other hand, in the low-experience-focused scenario, more attention is paid to professional qualification and association membership rather than academic experience.

**Table 4. 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 |

Like the academics' adjustment scenarios, we have used three practitioners' scenarios (Table 5). For those scenarios, the relative importance of industry experience is adjusted against education and professional qualifications.

**Table 5. Practitioner experts' importance weight assignment scenarios**

| Scenario | Experience | | | Education | | | | Qualification | | Association | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $L_1$ | $L_2$ | $L_3$ | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $Q_1$ | $Q_2$ | $A_1$ | $A_2$ | $A_3$ |
| 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 |

According to 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 (where each scenario is called a *case*). This approach is very useful, especially when judgment would not be straightforward, and there is no preference in cases. There would be expected hesitancy in decisions between the degrees of experience. For example, three combinations (high-high, moderate-moderate, and low-low) out of nine possible scenario combinations are chosen for our consideration based on Tables 4 and 5. The reason is that they are extreme and middle points, which makes 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 utilizing HFS theory, are tested concerning the weights presented in Tables 6 and 7. By applying the best non-fuzzy performance (BNP), the crisp values in Table 6 can be obtained. Given $(l, m, r)$ is a triangular fuzzy number, BNP is calculated using $\frac{[(r-l)+(m-l)]}{3}+l$ (Bhosale and Kant, 2016).

**Table 6. Linguistic variables and fuzzy weights for experts' weights scenarios (Govindan et al., 2015)**

| Linguistic Variables | Fuzzy Numbers | 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 7, the hesitant fuzzy information is revealed in each case to obtain the weighted average weights of experts (see Farhadinia (2013) for the calculation of score function values).

**Table 7. Hesitant fuzzy information for acquiring experts' mean weights**

| Case | Applied Scenarios | Hesitant Fuzzy Set | Hesitant Fuzzy Element | Score Function Value | Normalized Score Function Value |
|---|---|---|---|---|---|
| 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 |

Various experts' weights in case 1 (High), case 2 (Moderate), case 3 (Low), and Weighted Average weights of cases are represented in Table 8. The Weighted Average weights are calculated based on the normalized score function values shown in Table 7. 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 4.6.

**Table 8. Experts' weights in high, moderate, low, and weighted average cases**

| Experts | Case 1 (High) | Case 2 (Moderate) | Case 3 (Low) | Weighted Average | Experts | Case 1 (High) | Case 2 (Moderate) | Case 3 (Low) | Weighted Average |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.0268 | 0.0395 | 0.0439 | 0.0340 | 17 | 0.0060 | 0.0088 | 0.0097 | 0.0076 |
| 2 | 0.0864 | 0.0636 | 0.0556 | 0.0734 | 18 | 0.0069 | 0.0101 | 0.0112 | 0.0087 |
| 3 | 0.0179 | 0.0263 | 0.0292 | 0.0227 | 19 | 0.0030 | 0.0044 | 0.0049 | 0.0038 |
| 4 | 0.0229 | 0.0338 | 0.0375 | 0.0291 | 20 | 0.0183 | 0.0176 | 0.0180 | 0.0180 |
| 5 | 0.0046 | 0.0068 | 0.0075 | 0.0058 | 21 | 0.0137 | 0.0203 | 0.0225 | 0.0174 |
| 6 | 0.2711 | 0.2041 | 0.1784 | 0.2325 | 22 | 0.0715 | 0.0527 | 0.0439 | 0.0603 |
| 7 | 0.0103 | 0.0152 | 0.0169 | 0.0131 | 23 | 0.0357 | 0.0527 | 0.0585 | 0.0453 |
| 8 | 0.0321 | 0.0473 | 0.0525 | 0.0407 | 24 | 0.0275 | 0.0197 | 0.0175 | 0.0232 |
| 9 | 0.0229 | 0.0338 | 0.0375 | 0.0291 | 25 | 0.0179 | 0.0263 | 0.0292 | 0.0227 |
| 10 | 0.0238 | 0.0351 | 0.0390 | 0.0302 | 26 | 0.0275 | 0.0263 | 0.0270 | 0.0271 |
| 11 | 0.0045 | 0.0066 | 0.0073 | 0.0057 | 27 | 0.0357 | 0.0527 | 0.0585 | 0.0453 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 12 | 0.0298 | 0.0241 | 0.0239 | 0.0270 | 28 | 0.0137 | 0.0203 | 0.0225 | 0.0174 |
| 13 | 0.0060 | 0.0088 | 0.0097 | 0.0076 | 29 | 0.0030 | 0.0044 | 0.0049 | 0.0038 |
| 14 | 0.0089 | 0.0132 | 0.0146 | 0.0113 | 30 | 0.0119 | 0.0176 | 0.0195 | 0.0151 |
| 15 | 0.0069 | 0.0101 | 0.0112 | 0.0087 | 31 | 0.0412 | 0.0290 | 0.0283 | 0.0351 |
| 16 | 0.0916 | 0.0692 | 0.0592 | 0.0784 | | | | | |

## 4. Results

Next, we present the results in the following six sections:

### *4.1. The NR-DEMATEL analysis*

The analyzed factors are the twelve risk dimensions climate change (C.C.); natural disasters (N.D.); environmental health and safety (E.H.S.); technical reliability (T.R.); operational safety (O.S.); disease outbreak (D.O.); industrial action (I.A.); political instability (P.I.); sabotage and terrorism (S.T.); resource availability (R.A.); market failure (M.F.); and affordability (AF). The Weighted Average (Table 8) for the experts' weights is considered in the calculation (Section 3.2). The total relation matrix obtained from the NR-DEMATEL analysis is represented in Table 9. Based on the total relation matrix, the Prominence and Relation values along with the total effect given by each risk dimension to others ($r_i$) and the total effect received by each risk dimension from others ($c_i$) are calculated (Step 7 in Section 3.1) and presented in Table 10.

**Table 9. Total relation matrix**

| | C.C. | N.D. | E.H.S. | T.R. | O.S. | D.O. | P.I. | I.A. | S.T. | R.A. | M.F. | AF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C.C.** | 0.1105 | 0.1856 | 0.2717 | 0.2722 | 0.2803 | 0.1859 | 0.2541 | 0.2243 | 0.1746 | 0.2744 | 0.2644 | 0.3129 |
| **N.D.** | 0.1362 | 0.0695 | 0.2517 | 0.2623 | 0.2849 | 0.1836 | 0.2245 | 0.2001 | 0.1446 | 0.2453 | 0.2311 | 0.2756 |
| **E.H.S.** | 0.1183 | 0.0831 | 0.1514 | 0.2161 | 0.2438 | 0.1815 | 0.1952 | 0.2075 | 0.1488 | 0.2091 | 0.2065 | 0.2639 |
| **T.R.** | 0.1153 | 0.0793 | 0.2185 | 0.1584 | 0.2532 | 0.1320 | 0.2012 | 0.1998 | 0.1540 | 0.2201 | 0.2377 | 0.2862 |
| **O.S.** | 0.1005 | 0.0725 | 0.2468 | 0.2411 | 0.1724 | 0.1340 | 0.2018 | 0.2221 | 0.1617 | 0.2163 | 0.2241 | 0.2705 |
| **D.O.** | 0.1167 | 0.0986 | 0.2436 | 0.2071 | 0.2432 | 0.1027 | 0.2210 | 0.2258 | 0.1400 | 0.2032 | 0.2259 | 0.2611 |
| **P.I.** | 0.1537 | 0.1068 | 0.2234 | 0.2418 | 0.2622 | 0.1621 | 0.1814 | 0.2586 | 0.2192 | 0.2489 | 0.2693 | 0.3146 |
| **I.A.** | 0.1288 | 0.0825 | 0.2324 | 0.2768 | 0.2956 | 0.1721 | 0.2767 | 0.1764 | 0.1891 | 0.2726 | 0.2823 | 0.3224 |
| **S.T.** | 0.1165 | 0.0797 | 0.2527 | 0.2641 | 0.2847 | 0.1446 | 0.2661 | 0.2225 | 0.1257 | 0.2697 | 0.2816 | 0.3147 |
| **R.A.** | 0.1584 | 0.1074 | 0.2191 | 0.2262 | 0.2425 | 0.1316 | 0.2448 | 0.2070 | 0.1526 | 0.1711 | 0.2663 | 0.3038 |
| **M.F.** | 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 10. Prominence ($r_i$+$c_i$), Relation ($r_i$-$c_i$), and total effect given/received by each risk to/from others ($r_i$ and $c_i$)**

| | $r_i$ | Rank | $c_i$ | Rank | Prominence | Rank | Relation | Rank | Causer/Receiver |
|---|---|---|---|---|---|---|---|---|---|
| **C.C.** | 2.8109 | 1 | 1.5865 | 11 | 4.3973 | 10 | 1.2244 | 2 | Net Causer |
| **N.D.** | 2.5093 | 6 | 1.1553 | 12 | 3.6646 | 12 | 1.3540 | 1 | Net Causer |
| **E.H.S.** | 2.2252 | 12 | 2.7682 | 6 | 4.9934 | 8 | -0.5430 | 9 | Net Receiver |
| **T.R.** | 2.2557 | 11 | 2.8675 | 4 | 5.1232 | 7 | -0.6119 | 10 | Net Receiver |
| **O.S.** | 2.2638 | 10 | 3.1037 | 2 | 5.3675 | 4 | -0.8399 | 12 | Net Receiver |
| **D.O.** | 2.2890 | 9 | 1.8165 | 10 | 4.1054 | 11 | 0.4725 | 4 | Net Causer |
| **P.I.** | 2.6420 | 4 | 2.7604 | 7 | 5.4024 | 2 | -0.1184 | 6 | Net Receiver |
| **I.A.** | 2.7076 | 2 | 2.6126 | 8 | 5.3201 | 5 | 0.0950 | 5 | Net Causer |
| **S.T.** | 2.6226 | 5 | 1.9226 | 9 | 4.5452 | 9 | 0.7001 | 3 | Net Causer |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **R.A.** | 2.4307 | 8 | 2.8525 | 5 | 5.2833 | 6 | -0.4218 | 7 | Net Receiver |
| **M.F.** | 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 |

### *4.2. Impact-relations map (IRM)*

The IRM (Figure 4) represents four quadrants. Quadrant I (core risks) is characterized by high Prominence and positive Relation values. Risks in quadrant II (minor key risks) have positive Relation but low Prominence values. Both quadrants I and II include net causer risks (cause group) due to positive Relation values. Quadrant III (independent risks) has low Prominence and negative Relation values while situated in the southwest part of the IRM and is 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.

The five risk dimensions of N.D., C.C., S.T., D.O., and I.A. are positioned in Quadrant I (core risks). Additionally, they all belong to a cause group that indicates they are net causers because of their positive $(r_i - c_i)$ values. This means that when they occur, they can significantly influence or trigger other risks. The rest of the risk dimensions, including the seven risk dimensions of P.I.; R.A.; E.H.S.; M.F.; T.R.; O.S.; and AF, are positioned in quadrant IV (indirect risks). Risk dimensions in this quadrant are influenced more than they influence other risks. There is no minor key and independent risk in this study because no risk dimension is positioned in quadrants II and III, respectively.

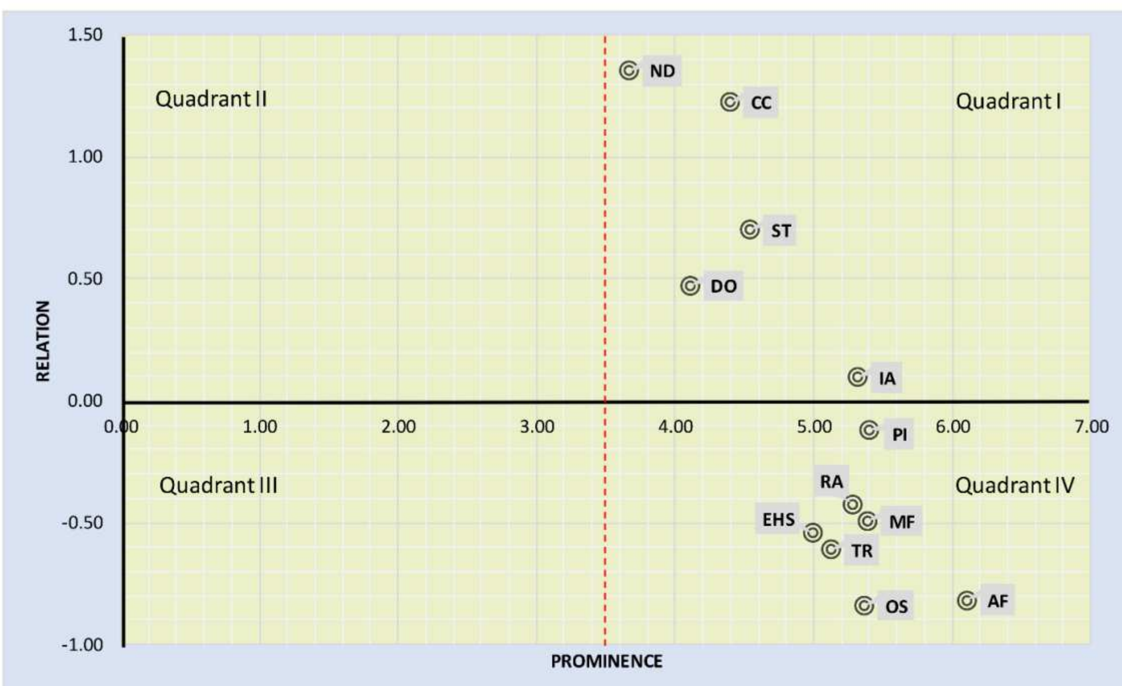


**Figure 4. The IRM**

### *4.3. Ranking results*

As can be seen in Table 10, 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 satisfactory analysis. In fact, they both, together with other analyses like causers, receivers, and strong relationships (Section 4.5), should be considered for their complementary views.

#### *4.3.1. Prominence*

In terms of Prominence, AF has the highest total effect (adding together given and received influences), which indicates its relative importance. It is followed by P.I., M.F., O.S., I.A., R.A., T.R., E.H.S., S.T., C.C., D.O., and N.D.

#### *4.3.2. Relation*

Based on the findings in Table 10 and the IRM depicted in Figure 4, N.D. has the highest Relation value, which means it has the greatest influence on the system. It is followed by C.C., S.T., D.O., I.A., P.I., R.A., M.F., E.H.S., T.R., and AF, the lowest factor in the Relation category is O.S.

#### *4.3.3. Causers*

Among risks that can substantially influence others without subtracting the received impacts: C.C., I.A., AF, P.I., S.T., N.D., and M.F. are the top seven risk dimensions, respectively ($r_i$ list in Table 10). The results show that C.C. is the most important risk dimension in terms of influencing other risks. However, when compared to N.D., C.C. receives more impact from other risks, which is the reason why N.D. is the most significant net causer and not C.C.

#### *4.3.4. Receivers*

Among receivers or risks that can be highly influenced by others, AF and O.S. are found as the top ones, followed by M.F., T.R., R.A., E.H.S., and P.I. ($c_i$ list in Table 10).

### *4.4. Threshold value*

The results from steps 1 to 5 of the MMDE algorithm (Appendix A) revealed that the obtained threshold value is 0.2847. All 144 MDE values of the dispatch-node set ($MDE$) and the receive-node set ($MDE_t^{R_e}$) are illustrated in Figures 5 and 6, respectively. 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 so many strong relationships. While using the MMDE algorithm, the threshold value is 0.2847, providing us with 11 strong relationships.


**Figure 5.** **The 144 MDE values of the dispatch-node set ($MDE_t^{D_i}$)**


**Figure 6.** **The 144 MDE values of the receive-node set ($MDE_t^{R_e}$)**

### *4.5. Strong relationships and net relationships*

Risk dimensions with an influence level equal to or greater than the threshold value (0.2847) from the matrix $T$ (Table 9) and the relationships between them are shown in Figure 7. Eleven relationships of ten risk dimensions have an influence level equal to or greater than 0.2847. E.H.S. and D.O. 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.

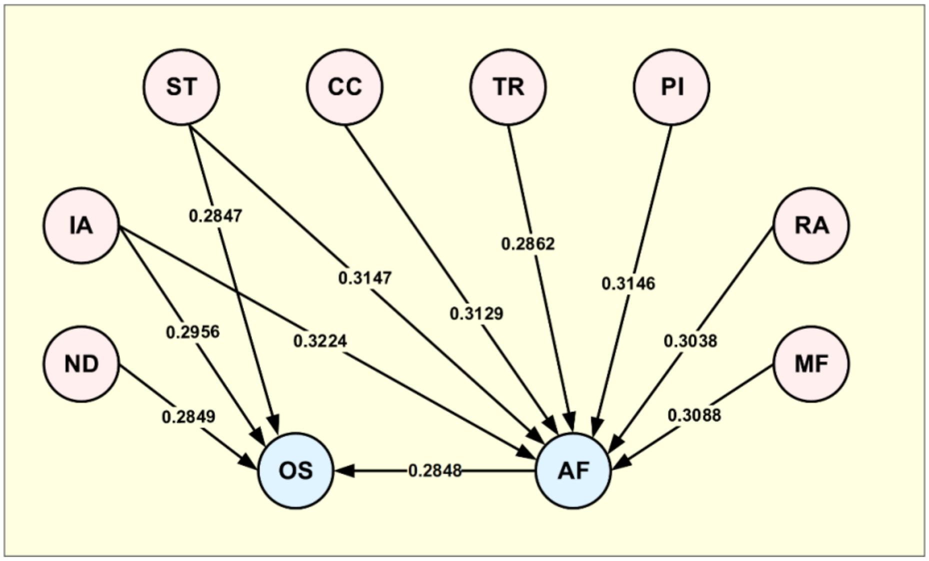


**Figure 7. Total relations between risk dimensions based on the threshold value 0.2847**

The net influence matrix is represented (Table 11), and the corresponding values of eleven major relationships are illustrated (Figure 7). For instance, the influence level from N.D. to O.S. is 0.2849 (Figure 7), while the net influence value from N.D. to O.S. is -0.2124 (Table 11). The negative value of -0.2124 reveals that the level of influence from O.S. to N.D. is lower than the level of influence from N.D. to O.S., and the difference value is 0.2124. The total relation values and ranking of eleven major relationships among risk dimensions, as depicted in Figure 7, along with their net influence values and corresponding ranking, are presented (Table 12).

**Table 11. Net influence matrix**

| | C.C. | N.D. | E.H.S. | T.R. | O.S. | D.O. | P.I. | I.A. | S.T. | R.A. | M.F. | AF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C.C.** | - | - | - | - | - | - | - | - | - | - | - | - |
| **N.D.** | -0.0494 | - | - | - | - | - | - | - | - | - | - | - |
| **E.H.S.** | -0.1534 | -0.1686 | - | - | - | - | - | - | - | - | - | - |
| **T.R.** | -0.1569 | -0.1830 | 0.0024 | - | - | - | - | - | - | - | - | - |
| **O.S.** | -0.1798 | **-0.2124** | 0.0030 | -0.0121 | - | - | - | - | - | - | - | - |
| **D.O.** | -0.0692 | -0.0850 | 0.0621 | 0.0751 | 0.1092 | - | - | - | - | - | - | - |
| **P.I.** | -0.1004 | -0.1177 | 0.0282 | 0.0406 | 0.0604 | -0.0589 | - | - | - | - | - | - |
| **I.A.** | -0.0955 | -0.1176 | 0.0249 | 0.0770 | **0.0735** | -0.0537 | 0.0181 | - | - | - | - | - |
| **S.T.** | -0.0581 | -0.0649 | 0.1039 | 0.1101 | **0.1230** | 0.0046 | 0.0469 | 0.0334 | - | - | - | - |
| **R.A.** | -0.1160 | -0.1379 | 0.0100 | 0.0061 | 0.0262 | -0.0716 | -0.0041 | -0.0656 | -0.1171 | - | - | - |
| **M.F.** | -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** | - |

**Table 12. Total relation and net influence of eleven major relationships**

| From | To | Total Relation | Rank | Net Influence | Rank |
|---|---|---|---|---|---|
| **I.A.** | **AF** | 0.3224 | 1 | 0.0820 | 5 |
| **S.T.** | **AF** | 0.3147 | 2 | 0.1525 | 2 |
| **P.I.** | **AF** | 0.3146 | 3 | 0.0543 | 7 |
| **C.C.** | **AF** | 0.3129 | 4 | 0.1435 | 3 |
| **M.F.** | **AF** | 0.3088 | 5 | 0.0325 | 9 |
| **R.A.** | **AF** | 0.3038 | 6 | 0.0331 | 8 |
| **I.A.** | **O.S.** | 0.2956 | 7 | 0.0735 | 6 |
| **T.R.** | **AF** | 0.2862 | 8 | 0.0279 | 10 |
| **N.D.** | **O.S.** | 0.2849 | 9 | 0.2124 | 1 |
| **AF** | **O.S.** | 0.2848 | 10 | 0.0143 | 11 |
| **S.T.** | **O.S.** | 0.2847 | 11 | 0.1230 | 4 |

The influence of I.A. on AF is the strongest relationship, followed by ten other impacts (Table 12 and Figure 7). I.A., N.D., AF and S.T. can have a strong influence on O.S. But only the influence of N.D. on O.S. has the strongest net relationship (Table 12 and Figure 7), which could be expected due to the characteristic of the O.S. risk that is much more affected by N.D. rather than influencing it. Also, I.A., S.T., P.I., C.C., M.F., R.A., and T.R. strongly affect AF. Between AF and O.S., the strongest influence is received by AF (from I.A.), while AF itself subsequently has a strong influence on O.S. The evaluation of strong relationships revealed that E.H.S. and D.O. do not have any strong relationships with other risk dimensions. It also revealed that AF and O.S. are the only two major strong individual influence receivers (Table 12 and Figure 7).

### *4.6. Sensitivity analysis*

In the obtained results, the Weighted Average was considered. In this section, we run a sensitivity analysis considering five cases to see to what extent results are sensitive to the weights of experts. The four cases of high, moderate, low, and weighted average are explained in Section 4.3. (Table 8). Note that equal weights of experts are also taken into consideration for this 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 13.

**Table 13. Sensitivity analysis results under Equal, Moderate, High, Low, and Weighted Average weights (Pro.=Prominence and Rel.=Relation)**

| | Equal | | Moderate | | High | | Low | | Weighted Average | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Pro.** | **Rel.** | **Pro.** | **Rel.** | **Pro.** | **Rel.** | **Pro.** | **Rel.** | **Pro.** | **Rel.** |
| **AF.** | 5.4749 | -1.1400 | 5.8053 | -0.8492 | 6.5720 | -0.7587 | 5.5802 | -0.8776 | 6.1029 | -0.8176 |
| **M.F.** | 5.3871 | -0.6225 | 5.1916 | -0.5180 | 5.7102 | -0.4491 | 5.0471 | -0.5474 | 5.3948 | -0.4934 |
| **P.I.** | 5.2044 | -0.1824 | 5.1184 | -0.1663 | 5.8297 | -0.0654 | 4.8963 | -0.2027 | 5.4024 | -0.1184 |
| **O.S.** | 5.1112 | -0.7924 | 5.0963 | -0.8195 | 5.7903 | -0.8749 | 4.8910 | -0.8057 | 5.3675 | -0.8399 |
| **I.A.** | 4.9834 | -0.3369 | 5.0251 | -0.0192 | 5.7628 | 0.2654 | 4.8176 | -0.0993 | 5.3201 | 0.0950 |
| **T.R.** | 4.9635 | -0.4959 | 4.8755 | -0.5741 | 5.5099 | -0.6635 | 4.6937 | -0.5493 | 5.1232 | -0.6119 |
| **R.A.** | 4.8252 | -0.3113 | 4.9926 | -0.3796 | 5.7384 | -0.4780 | 4.7769 | -0.3514 | 5.2833 | -0.4218 |
| **E.H.S.** | 4.4579 | -0.4227 | 4.6650 | -0.4906 | 5.5047 | -0.6171 | 4.4186 | -0.4518 | 4.9934 | -0.5430 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **C.C.** | 4.2405 | 1.4377 | 4.2126 | 1.2668 | 4.6786 | 1.1619 | 4.0847 | 1.2996 | 4.3973 | 1.2244 |
| **S.T.** | 4.1989 | 0.9014 | 4.3085 | 0.7432 | 4.9105 | 0.6349 | 4.1314 | 0.7755 | 4.5452 | 0.7001 |
| **N.D.** | 3.7024 | 1.5008 | 3.5188 | 1.3501 | 3.8921 | 1.3604 | 3.4142 | 1.3552 | 3.6646 | 1.3540 |
| **D.O.** | 3.4615 | 0.4642 | 3.7915 | 0.4565 | 4.5799 | 0.4842 | 3.5637 | 0.4549 | 4.1054 | 0.4725 |

In Figure 8, the 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 diagrams with the difference that the Weighted Average diagram is closer to the High diagram, which is predictable based on the higher hesitant weights assigned to case 1 (Table 7). From a practical standpoint, it means that opinions of more experienced experts can be given a higher value by choosing the Weighted Average, generating closer Prominence values to the High case. Moreover, the Equal line and either Low or Moderate lines overlap in some risks producing the same weights.

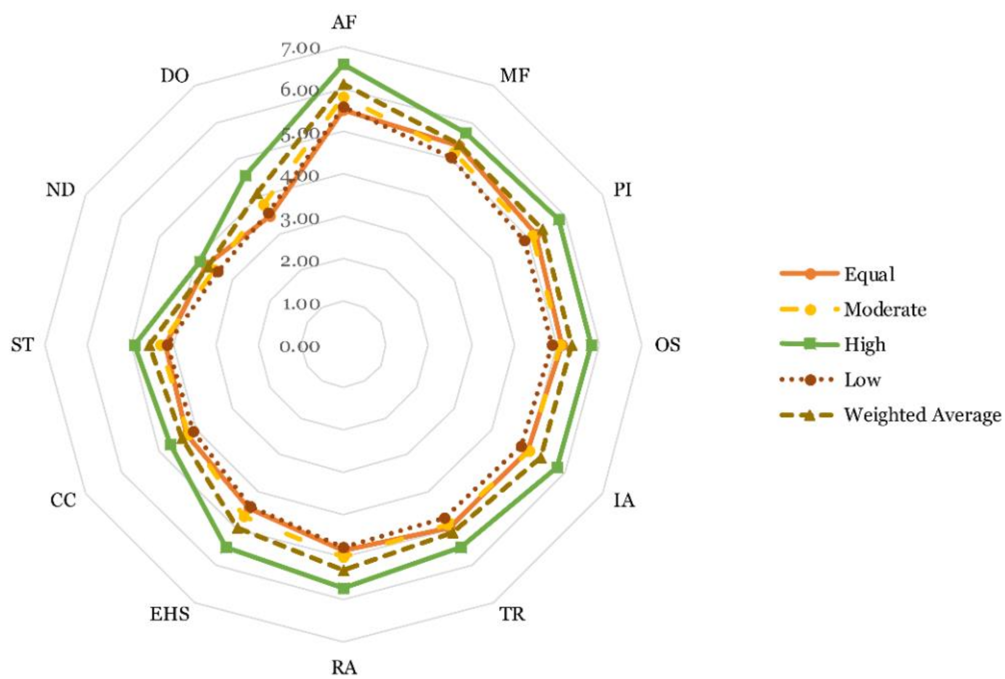


**Figure 8. Prominence values of risks in various cases of experts' weights**

In Figure 9, Relation values for different risk dimensions are depicted, and as can be seen, the lines overlap almost perfectly except for the Equal diagram that is significantly different in few risks such as N.D., S.T., C.C., AF, and I.A. It means that in the Equal case, the Relation values of risks can vary much more compared to other cases.

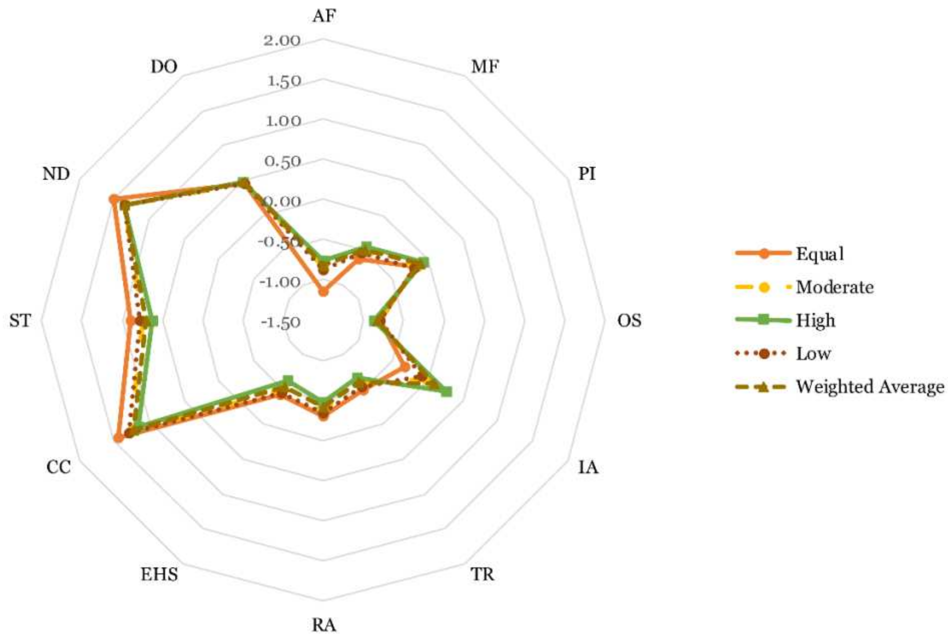


**Figure 9. Relation values of risks in various cases of experts' weights**

To better realize the changes of weights, the rankings of the Prominence and Relation values are provided in Table 14. And in Tables 15 and 16, descriptive statistics for Relation and Prominence weights ranking are presented, respectively. Furthermore, 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 17).

**Table 14. Rankings obtained from sensitivity analysis under Equal, Moderate, High, Low and Weighted Average weights (Pro=Prominence and Rel=Relation)**

| | Equal | | Moderate | | High | | Low | | Weighted Average | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Pro | Rel | Pro | Rel | Pro | Rel | Pro | Rel | Pro | Rel |
| AF | 1 | 12 | 1 | 12 | 1 | 11 | 1 | 12 | 1 | 11 |
| M.F. | 2 | 10 | 2 | 9 | 6 | 7 | 2 | 9 | 3 | 8 |
| P.I. | 3 | 5 | 3 | 6 | 2 | 6 | 3 | 6 | 2 | 6 |
| O.S. | 4 | 11 | 4 | 11 | 3 | 12 | 4 | 11 | 4 | 12 |
| I.A. | 5 | 7 | 5 | 5 | 4 | 5 | 5 | 5 | 5 | 5 |
| T.R. | 6 | 9 | 7 | 10 | 7 | 10 | 7 | 10 | 7 | 10 |
| R.A. | 7 | 6 | 6 | 7 | 5 | 8 | 6 | 7 | 6 | 7 |
| E.H.S. | 8 | 8 | 8 | 8 | 8 | 9 | 8 | 8 | 8 | 9 |
| C.C. | 9 | 2 | 10 | 2 | 10 | 2 | 10 | 2 | 10 | 2 |
| S.T. | 10 | 3 | 9 | 3 | 9 | 3 | 9 | 3 | 9 | 3 |
| N.D. | 11 | 1 | 12 | 1 | 12 | 1 | 12 | 1 | 12 | 1 |
| D.O. | 12 | 4 | 11 | 4 | 11 | 4 | 11 | 4 | 11 | 4 |

**Table 15. Descriptive statistics of Relation rankings under five cases (Equal, Moderate, High, Low, Weighted Average)**

| | N | Mean | Std. Deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| AF | 5 | 11.60 | 0.548 | 11 | 12 |

| | | | | | |
|---|---|---|---|---|---|
| **M.F.** | 5 | 8.60 | 1.140 | 7 | 10 |
| **P.I.** | 5 | 5.80 | 0.447 | 5 | 6 |
| **O.S.** | 5 | 11.40 | 0.548 | 11 | 12 |
| **I.A.** | 5 | 5.40 | 0.894 | 5 | 7 |
| **T.R.** | 5 | 9.80 | 0.447 | 9 | 10 |
| **R.A.** | 5 | 7.00 | 0.707 | 6 | 8 |
| **E.H.S.** | 5 | 8.40 | 0.548 | 8 | 9 |
| **C.C.** | 5 | 2.00 | 0.000 | 2 | 2 |
| **S.T.** | 5 | 3.00 | 0.000 | 3 | 3 |
| **N.D.** | 5 | 1.00 | 0.000 | 1 | 1 |
| **D.O.** | 5 | 4.00 | 0.000 | 4 | 4 |

**Table 16. Descriptive statistics of Prominence rankings under five cases (Equal, Moderate, High, Low, Weighted Average)**

| | **N** | **Mean** | **Std. Deviation** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|
| **AF** | 5 | 1.00 | 0.000 | 1 | 1 |
| **M.F.** | 5 | 3.00 | 1.732 | 2 | 6 |
| **P.I.** | 5 | 2.60 | 0.548 | 2 | 3 |
| **O.S.** | 5 | 3.80 | 0.447 | 3 | 4 |
| **I.A.** | 5 | 4.80 | 0.447 | 4 | 5 |
| **T.R.** | 5 | 6.80 | 0.447 | 6 | 7 |
| **R.A.** | 5 | 6.00 | 0.707 | 5 | 7 |
| **E.H.S.** | 5 | 8.00 | 0.000 | 8 | 8 |
| **C.C.** | 5 | 9.80 | 0.447 | 9 | 10 |
| **S.T.** | 5 | 9.20 | 0.447 | 9 | 10 |
| **N.D.** | 5 | 11.80 | 0.447 | 11 | 12 |
| **D.O.** | 5 | 11.20 | 0.447 | 11 | 12 |

**Table 17. 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 17), it can be realized 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 the 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 10. The IRMs show that N.D., C.C., S.T., and D.O. are consistently positioned in Quadrant I under Equal (a), Moderate (b), Low (c), and High (d) cases, while in case Moderate (b) N.D. is pushed to the border of two quadrants I and II. Furthermore, only in case High (d), I.A. is also moved to quadrant I.

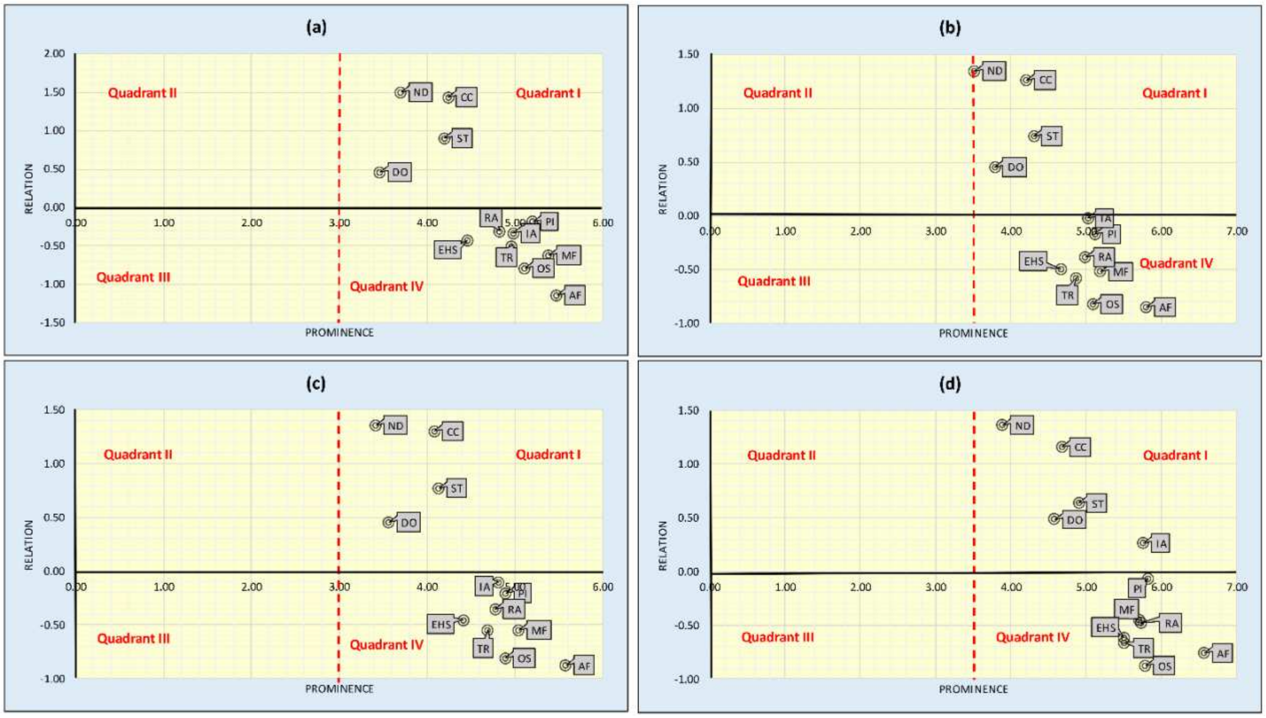


**Figure 10. The IRMs in four cases of experts' weights Equal (a), Moderate (b), Low (c), and High (d)**

## 5. Discussion

Our findings revealed that Natural Disasters, Climate Change, Sabotage and Terrorism, Disease Outbreak, and Industrial Action are core risk dimensions as all are situated in Quadrant I. And among them, Industrial Action has the highest Prominence value, which indicates its high relative importance. Out of five high-ranked Prominence risk dimensions (Affordability, Political Instability, Market Failure, Operational Safety, and Industrial Action), Industrial Action is the only one that appears in the list of the top five Relation risk dimensions as well (Table 10). The final six critical risk dimensions in our study are Natural Disasters, Climate Change, Industrial Action, Affordability, Political Instability, and Sabotage and Terrorism (Figure 11). We have added Affordability to the final list because Affordability ranks first in the Prominence list and is among 8 of the strongest relationships (out of 11) (Figure 7). Political Instability has also been recognized as one of our final risk dimensions as it ranks second in the Prominence ranking and sixth in the Relation list (Table 10) while also being the third strongest relationship (Table 12). Disease Outbreak has not been included in the final list, as it has not been recognized among the strong relationships (Table 12).

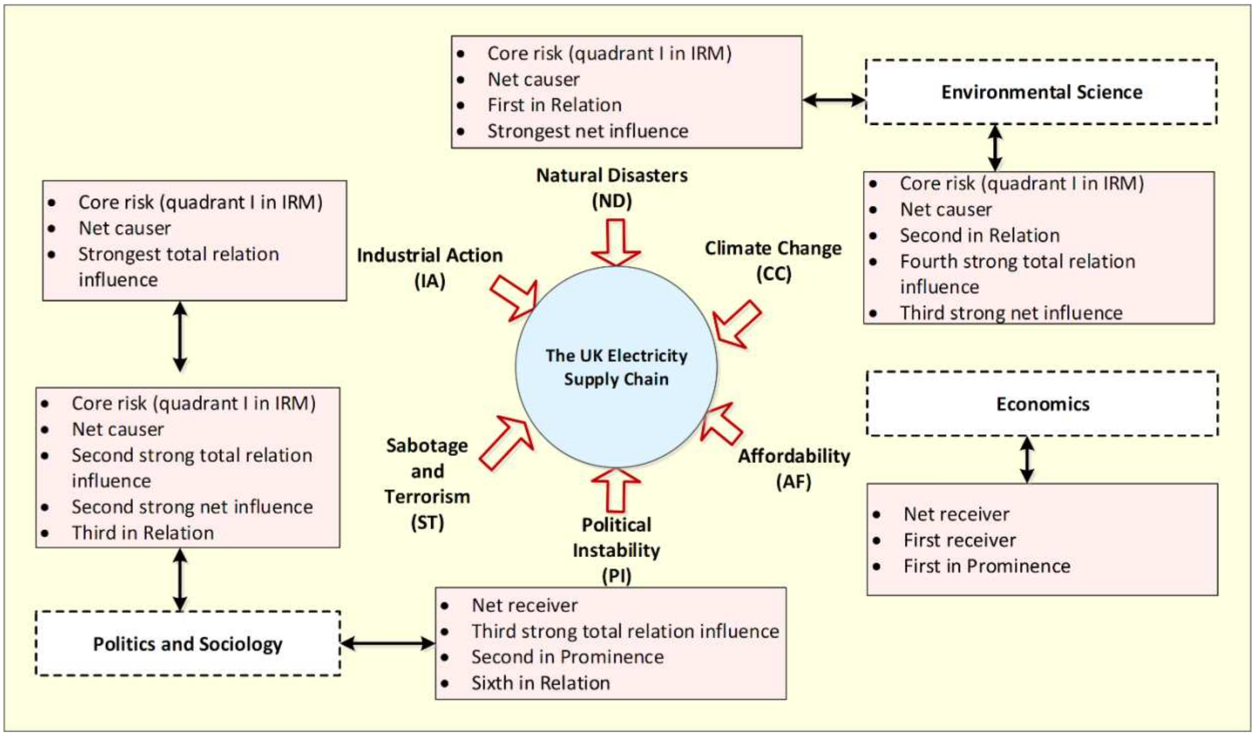


**Figure 11. Final six critical risk dimensions to the U.K. electricity supply chain and their characteristics**

The six most critical risks are particularly important for the U.K.'s approach to reducing risk exposure. Specifically, Natural Disasters and Climate Change, two very interlinked risks, are core to the U.K.'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 U.K.'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 U.K. has to consider the risk of Sabotage and Terrorism, especially in the form of cyber-attacks. At the same time, Political Instability and Affordability are primarily related to the U.K.'s power supply as they concern imported resources, largely natural gas in the U.K., as the indigenous production is reduced. Finally, despite the U.K. power supply chain being largely privatized, the risk of Industrial Action remains high, mainly due to the strong reliance on a small number of market players and strong unionization. Reflecting on previous studies, 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, which is among our final list. Hammond and Waldron (2008) recognized severe weather conditions as the fourth significant risk of fifteen recognized ones. The same study highlighted the importance of extreme weather conditions risk, which is also emphasized in our findings regarding Natural Disasters and Climate Change.

Three main disciplines are more related to the identified risks, including environmental science (Natural Disasters and Climate Change), sociology, and politics (Industrial Action, Political Instability, and Sabotage and Terrorism), and economics (Affordability). In the related literature, the importance of identified risks is confirmed. However, there is a shortage 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. For instance, Mideksa and Kallbekken (2010) reviewed studies on the effect of climate change on electricity markets. Regarding Industrial Action, the Venezuelan strike in 2002/3, also known as an oil strike or oil lockout, was an example that resulted in a gross peak supply loss of 2.6 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, Moslener, and Rübbelke 2010). In support of the finding regarding no critical relation between Disease Outbreak and Natural Disasters or vice versa (Table 12), Watson et al. (2007) indicated that risk factors for outbreaks after Natural Disasters are linked primarily to population displacement rather than a fear likely from dead bodies and epidemics. They identified strong interaction between Natural Disasters and Operational Safety could 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 and Political Instability seems to be critical in oil-producing countries (Correljé and van der Linde, 2006), but our findings have not revealed such a strong relationship in the U.K. The link between Market Failure and Affordability is documented in our study, which is predictable since Affordability deals with the price of the energy, which is determined based on the economic functions in the U.K.'s liberalized energy market.

Although our research focused on the U.K. electric power supply chain, we believe the results are relevant, and the findings apply to the power sectors in other countries. This is because the U.K. power sector fuel mix is similar to the fuel mix in other countries (Chalvatzis et al., 2018). For example, the characteristics such as eliminating coal, ambitious offshore wind capacity and expansion plans, the widespread use of natural gas, and low hydropower capacity are gaining momentum across Europe and the U.S. (Hills et al., 2018; Ioannidis et al., 2019). However, some aspects of the U.K.'s power supply system are similar to the current or forthcoming systems in other countries as they all face strict decarburization agendas (Chalvatzis and Ioannidis, 2017b). Similarly, countries with thermal power stations face Operational Safety challenges to cool those power stations. At the same time, Climate Change increases the frequency and intensity of heatwaves and ultimately reducing access to cooling water. This is a core issue for nuclear power stations that concerns all thermal power stations as one of the prevailing risks. At the same time, risks deriving from exposure to Political Instability, Sabotage and Terrorism, and Industrial Action are highly dependent on country-specific circumstances relevant to the power industry structure, the economic and geopolitical balances, and industrialization trends (Pappas et al., 2018). Therefore, it is argued that our study is generalizable 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 prioritization of risks specific to certain power supply technologies (which are similar among countries). To this end, our results are useful for context settings for countries other than the U.K. Still, we maintain that more research would be required for any specific country's electricity planning.

## 6. Conclusions

The identification of the key risks in an electric power 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 highlights these interdependencies and provides significant insight into the relationship between the energy risks by identifying those risks that should be prioritized to minimize the occurrence of others. This approach will put forward a risk mitigation strategy that focuses on highly interdependent risks. Therefore, policymakers must develop mitigation strategies that make the best use of resources in a targeted approach since certain risks occur concurrently and are often amplified by other threats. For example, Industrial Action can strongly lead to Affordability risk. Equally, Natural Disasters can lead to risks relevant to Operational Safety; therefore, vulnerability to natural disasters should be primarily tested against its potential to lead to operational safety damages (Figure 7). 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. As a result, we proposed a comprehensive framework for risk identification focusing on the U.K. electricity supply chain. It is based on scrutinizing energy supply chain risks in energy security literature by consolidating information from various engineering and social sciences fields. We tailored and used the NR-DEMATEL in our study that can analyze interrelationships between risks and deal effectively with subjective judgments of experts. Furthermore, in our research, a novel proposed HESM, along with scenario analysis, provides a basis for the expert selection and weight assignment process.

This study provided methodological and practical implications for energy supply chain risk management. It identified twelve risk dimensions, each of which could potentially include a myriad of consolidated sub-risk dimensions. This would offer an opportunity to make a more comprehensive framework by providing detailed risks, namely risk elements, as a sub-group of risk dimensions. The results suggested that the U.K. electric power supply chain should focus on the following six risks out of the 12 risks identified in the electric power supply chain: Natural Disasters, Climate Change, Industrial Action, Affordability, Political Instability, and Sabotage and Terrorism when formulating the risk mitigation strategies. This finding would allow the managers in the electricity production and distribution sector to efficiently manage their resources by focusing on the dominant risks and interdependencies. In addition, it would open up avenues for further risk mitigation strategies that can improve the performance of the entire U.K. electricity supply chain.

This study suffers from few limitations which can be overcome in future research. First, the identified risk dimensions are generic risks in the U.K. electric power supply chain. In other words, risks can be studied in more detail in a specific part of the supply chain, such as supply or demand, or can be studied in a specific power generation sector such as the offshore wind industry. Second, in this study, the primary data had to be collected from experts, which can be strengthened in future studies by expanding the number of involved experts to reach a more reliable outcome. Third, the DEMATEL method has a quantitative approach to investigate the cause-effect and interrelationships between risks, making 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, triangulation can be carried out, and results from the DEMATEL can be compared with qualitative approaches such as the know-why method (Neumann, 2015) or other dynamic quantitative methods such as System Dynamics (SD) to verify the outcome. Finally, the probability estimation of each risk element with a reliable method such as Bayesian networks can be regarded as another future research direction by using probability scores and experts' opinions to prioritize risk elements.

## Appendix A: Maximum mean de-entropy algorithm (MMDE)

The concept of entropy is utilized in information theory to measure the expected information content of certain messages. It is a criterion for capturing the amount of uncertainty represented by a discrete probability distribution. The higher the entropy, the higher the expected uncertainty of single events meaning the system is more unstable. The MMDE algorithm applies the concept of entropy to determine the effective information in the total relation matrix of the DEMATEL method. It is carried out by drawing a threshold to filter the unnecessary information (Lee and Lin, 2013; Li and Tzeng, 2009).

***Definition 1.*** (Lee and Lin, 2013) Given $X=(x_1,x_2,...,x_n)$ with a corresponding probability, $P=(p_1,p_2,...,p_n)$ then the entropy $H(x)$ is defined as Eq. (A.1) where $\sum p_i = 1$ and $p_i \ln p_i = 0$ if $p_i = 0$.

$$H(p_1,p_2,...,p_n) = -\sum p_i \ln p_i \tag{A.1}$$

According to *Definition 1*, $H(p_1,p_2,...,p_n)$ is the largest when $p_1 = p_2 = ... = p_n$, and we denote the largest entropy as $H\left(\frac{1}{n},\frac{1}{n},...,\frac{1}{n}\right)$.

***Definition 2.*** (Lee and Lin, 2013) Another measure for the decreased level of entropy is called de-entropy. Given $X$ is a finite discrete scheme, the de-entropy of $X$ is defined as $H^D$ in Eq. (A.2). 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).

$$H^D = H\left(\frac{1}{n},\frac{1}{n},...,\frac{1}{n}\right) - H(p_1,p_2,...,p_n) \tag{A.2}$$

***Definition 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 $(t_{ij},x_i,x_j)$. Hence, the matrix $T$ can be considered as a set $T$ with $n^2$ pair ordered elements. There is an ordered dispatch-node set $T^{D_i}$ and an ordered receive-node set $T^{R_e}$ in the set $T$. 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 $\sum p_i = 1$. $C\left(T^{D_i}\right)$ or $C\left(T^{R_e}\right)$ denotes the cardinal number of an ordered set $T^{D_i}$ or $T^{R_e}$, while $N\left(T^{D_i}\right)$ or $N\left(T^{R_e}\right)$ represents the cardinal number of different elements in the set $T^{D_i}$ or $T^{R_e}$. For example, if $T^{D_i} = \{1,2,2,3,1\}$ then

$C\left(T^{D_i}\right)=5$ and $N\left(T^{D_i}\right)=3$. 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**

Transforming the total relation matrix $T$ into an ordered set $T=\{t_{11},t_{12},...,t_{21},t_{22},...,t_{nn}\}$, then rearranging elements in descending order and transforming to a corresponding ordered triplets $(t_{ij},x_i,x_j)$ set called $T^*$.

***Step 2*: Dispatch-node set $\left(T^{D_i}\right)$ and receive-node set $\left(T^{R_e}\right)$ construction**

Taking the second and third elements from $T^*$ and then obtaining a new ordered dispatch-node set $\left(T^{D_i}\right)$ and receive-node set $\left(T^{R_e}\right)$ (Eqs. (A.3)-(A.4)).

$$T^{D_i}=\{x_i\} \tag{A.3}$$

$$T^{R_e}=\{x_j\} \tag{A.4}$$

***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 Eqs. (A.5) to (A.8), $MDE_t^{D_i}$ and $MDE_t^{R_e}$ can be obtained.

$$H_t^{D_i}=H\left[\frac{1}{N\left(T^{D_i}\right)},\frac{1}{N\left(T^{D_i}\right)},...,\frac{1}{N\left(T^{D_i}\right)}\right]-H\left[\frac{k_1}{C\left(T^{D_i}\right)},\frac{k_2}{C\left(T^{D_i}\right)},...,\frac{k_t}{C\left(T^{D_i}\right)}\right] \tag{A.5}$$

$$H_t^{R_e}=H\left[\frac{1}{N\left(T^{R_e}\right)},\frac{1}{N\left(T^{R_e}\right)},...,\frac{1}{N\left(T^{R_e}\right)}\right]-H\left[\frac{k_1}{C\left(T^{R_e}\right)},\frac{k_2}{C\left(T^{R_e}\right)},...,\frac{k_t}{C\left(T^{R_e}\right)}\right] \tag{A.6}$$

$$MDE_t^{D_i}=\frac{H_t^{D_i}}{N\left(T_t^{D_i}\right)} \tag{A.7}$$

$$MDE_t^{R_e}=\frac{H_t^{R_e}}{N\left(T_t^{R_e}\right)} \tag{A.8}$$

***Step 4*: MMDE, $T_{\max}^{D_i}$ and $T_{\max}^{R_e}$ identification**

Finding the maximum value of $MDE_t^{D_i}$, $MDE_t^{R_e}$, and their corresponding set, $T_t^{D_i}$ and $T_t^{R_e}$, denoted 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 B: Expert Selection Model (ESM)

In many multi-attribute group decision-making (MAGDM) problems, it is required to identify multiple experts to obtain their opinions or elicit information. Here, we propose a novel expert selection scheme to facilitate the selection process while providing insightful logic to explain the overall procedure. It also helps obtain the importance weight of each expert, which is useful to evaluate the chosen experts' assessments. The proposed versatile scheme can be applied in any similar decision-making situation. It is comprised of the following three phases:

***Phase 1*: Initial screening**

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

***Phase 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 $\alpha$ ( $EEV \geq \alpha$ ). Four inclusion value ranges have been proposed, which are measured in years as *Undemanding inclusion* ($\alpha < 3$), *Acceptable inclusion* ($3 \leq \alpha < 10$), *Favorable inclusion* ($10 \leq \alpha < 20$), and *Solid inclusion* ($20 \leq \alpha$). Note that the inclusion value is chosen based on stakeholders' opinions 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 where having access to experts is challenging. The EEV for practitioners and academics can be calculated using Eqs. (B.1) and (B.2), respectively.

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

$$EEV = \left[ \sum_{i=1}^{3} \left( Y_i \times L_i \right) \right] \times \prod_{k=1}^{p} Q_m^k \times A_l \tag{B.2}$$

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 $(m = 2)$ $k^{th}$ professional qualifications; as we assumed equal importance weight for various qualifications 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 Eqs. (B.3) to (B.6), respectively.

$$L = \begin{cases} Upper-level\ managers & L_1 \\ Mid-level\ managers & L_2 \\ First-level\ managers & L_3 \end{cases} \tag{B.3}$$

$$E = \begin{cases} PhD & E_1 \\ MSc / MA & E_2 \\ BSc / BA & E_3 \\ Below\ BSc / BA & E_4 \end{cases} \tag{B.4}$$

$$Q^k = \begin{cases} Holding\ k^{th}\ qualification & Q_1^k = Q_1 \\ No\ k^{th}\ qualification & Q_2^k = Q_2 = 1 \end{cases} \tag{B.5}$$

$$A = \begin{cases} Chartered & A_1 \\ Non-chartered & A_2 \\ No\ membership & A_3 \end{cases} \tag{B.6}$$

In the EEV calculations, $E$ is not considered for academics as they are all presumed to have been awarded doctorates or equivalent degrees. Secondly, $L$ for academics is the general academic hierarchy at universities that is shown in Eq. (B.7) which can differ among various higher education settings. The $Q$ and $A$ for academics are calculated in the same way as for practitioners.

$$L = \begin{cases} \Pr ofessor & L_1 \\ Senior\ Lecturer & L_2 \\ Lecturer & L_3 \end{cases} \tag{B.7}$$

***Phase 3*: Normalization of the importance weights**

The calculated EEV values are transformed into the scale between 0 and 1 to act as normalized importance weights calculated by Eq. (B.8), where $e$ indicates the maximum number of experts who are involved in the study.

$$w_i = \frac{EEV_i}{\sum_{i=1}^{e} EEV_i} \tag{B.8}$$

## Appendix C: Data, Survey, and Analysis Programs for NR-DEMATEL

The primary data collected from experts via a secure online link saved anonymously on the Qualtrics platform. All the analyses were carried out by the use of programming software *R Studio, SPSS,* and *Microsoft Excel*. The following two types of questions (Q1 and Q2) were utilized in the online survey:

**Q1**. On which of the following risk dimension(s) in the U.K. 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 item on others).

| | |
|---|---|
| ☐ | Climate Change (C.C.) |
| ☐ | Natural Disasters (N.D.) |
| ☐ | Environmental and Health Safety (E.H.S.) |
| ☐ | Technical Reliability (T.R.) |
| ☐ | Operational Safety (O.S.) |
| ☐ | Disease Outbreak (D.O.) |
| ☐ | Political Instability (P.I.) |
| ☐ | Industrial Action (I.A.) |
| ☐ | Sabotage and Terrorism (S.T.) |
| ☐ | Resource Availability (R.A.) |
| ☐ | Market Failure (M.F.) |
| ☐ | Affordability (AF) |

Based on the chosen risk dimension(s) in **Q1**, the expert will answer a number of questions; in **Q2**. For example, it is assumed that the expert selected Climate Change (C.C.), so he/she is only asked to answer one question with 11 evaluations (the influence scale is explained in Table 3).

**Q2**. To what extent do you think *Climate Change (C.C.)* can impact the following risks in the U.K. 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).

| Risk Dimension | Influence Scale | | | | | | |
|---|---|---|---|---|---|---|---|
| | NI | LI | FLI | MI | FHI | HI | AHI |
| Natural Disasters (N.D.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Environmental and Health Safety (E.H.S.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Technical Reliability (T.R.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Operational Safety (O.S.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Disease Outbreak (D.O.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Political Instability (P.I.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Industrial Action (I.A.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Sabotage and Terrorism (S.T.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Resource Availability (R.A.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Market Failure (M.F.) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Affordability (AF) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

## Appendix D: Neutrosophic and hesitant fuzzy set theories

### *Neutrosophic Set Theory (NST)*

The IFS theory was initially introduced by Atanassov (1986), which was a development of the FS theory (Zadeh, 1965). Then, the IFS has been generalized to a new theory by Smarandache (1999). The distinction between Neutrosophic Sets (NSs) and IFSs is that the function of indeterminacy in NSs is independent of truth and falsity functions (Ji, Wang, and Zhang 2016; Vafadarnikjoo et al., 2020; Vafadarnikjoo et al., 2021). This advantage strengthens the need to obtain cogent indeterminacy, truth, and falsity function values. For detailed mathematical definitions on Single-Valued Neutrosophic Sets (SVNS), Single-Valued Neutrosophic Numbers (SVNN), and Single-Valued Trapezoidal Neutrosophic Numbers (SVTNN), see Vafadarnikjoo et al. (2018). In short, A SVTNN is a particular type of SVNNs that is represented in the form of $\tilde{a} = \langle (a_1, b_1, c_1, d_1); w_{\tilde{a}}, u_{\tilde{a}}, y_{\tilde{a}} \rangle$ where $w_{\tilde{a}}, u_{\tilde{a}}, y_{\tilde{a}} \in [0,1]$ and $a_1, b_1, c_1, d_1 \in \mathbb{R}$ , $a_1 \leq b_1 \leq c_1 \leq d_1$ (Vafadarnikjoo et al., 2020).

***Hesitant fuzzy sets (HFS)***

Torra (2010) introduced Hesitant HFS as a generalization of the IFS theory. It permits the membership degree of an element to be a set of several possible values in the interval $[0,1]$. In this way, it is possible to elicit improved experts' judgments by allowing them to choose a range of possible values. The reason is that experts usually encounter a degree of hesitance or indeterminacy before expressing their subjective judgments, and by using HFS theory, this issue is resolved. In this study, HFS theory is applied in the proposed HESM to obtain experts' importance weights, as explained in Section 3.3.

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