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Conceptualising a supply and demand resilience methodology using multi-criteria decision making

Abstract

Due to the growing globalisation and strategic sourcing, supply chains (SCs) are confronted with potential disruptions. Companies need to make further efforts and investments to improve their supply chain resilience (SCR) in becoming more prepared to minimise disruption risks. Sourcing is one of the main, strategic, key factors towards SC resilience. Also, organisations require resiliency in demand fulfilment to handle volatile marketplaces. This paper presents a methodology towards SCR to both supply and demand variations motivated by a real case study of a manufacturing company that works to improve its SC resilience. To this end, an integrated hybrid multi-attribute decision making-possibilistic bi-objective programming model (MADM-PBOPM) was developed. First, a new framework presenting pillars to assess suppliers' resilience was developed based on a thorough literature review and decision makers' input. Then, a hybrid DEMATEL-TOPSIS approach was proposed to quantify existing suppliers' resilience and assess its performance. It also helped in categorising resilience pillars (RPs) as causes and effects. Thereafter, the obtained weights of suppliers and pillars were integrated into the developed PBOPM. The latter helps the purchasing team to (1) order materials from suppliers based on their resilience and performance efficiency; and (2) elevate the company's resiliency to uncertain demands fulfilment. Therefore, the developed methodology can potentially be used by the purchasing teams to build up SCs that are resilient to supply disruption and demand uncertainty. This MADM-PBOPM model was validated as part of the case study investigation. Furthermore, the suppliers' assessment output was validated by using two sensitivity analysis approaches including criteria weight variation and other MADM approaches.

Keywords: COVID-19 disruption; Resilient sourcing; Supply chain resilience; Multi-objective programming; MCDM.

1. Introduction

Supply chains (SCs) are exposed to risks from different sources such as from the demand side, from the suppliers' side, from manufacturing processes, from control systems and from external factors (Christopher and Peck, 2004). The special characteristics of these risks are that they range from low to extremely high levels, fluctuate overtime and affect various geographic service areas differently; as shown during various virus pandemic such as SARS, Ebola, and recently, Coronavirus (COVID-19/SARS-CoV-2). Araz et al. (2020) underline that the COVID-19 risks represent one of the major disruptions encountered during the last decades which is "breaking many global supply chains". Particularly, from mid-February 2020, COVID-19 infected cases are drastically increasing across the globe leading to border closures and quarantined locations. It was reported that 94% of the "Fortune 1000" companies are seeing the coronavirus-outbreak as SC disruptions (Fortune, 2020). However, pandemic outbreaks are a special case of SC disruption (Ivanov, 2020). In this work, we consider the operational risks that may raise due to daily disruptions in the SC activities and process e.g., volatile marketplace, uncertain lead-time, and supply disruptions, but still have high-impact on SC operations (Kinra et al., 2019; and Xu et al., 2020).

At the same time, the COVID-19 pandemic has certainly accelerated the need to enhance resilience to protect SCs against future disruptions (Ivanov, 2020). For instance, several companies have raised the importance of analysing critical dependencies as a highly important paradigm in respond to the COVID-19 disruption to embrace the SC resilience elements (Deloitte, 2020). The supply chain resilience (SCR) literature is presented with a plethora of quantitative approaches to support SC managers in the design of resilient SCs (Ivanov et al., 2017). However, most previous studies have made efforts to develop resilience framework to single source of risk, especially from the supply-side risks (Spiegler et al., 2016).

A set of sources and outcomes of supply risks is well documented and categorised by Zsidisin (2003). Between the late 1980s and early 1990s, procurement decisions have shown emphasis on reducing the numbers of suppliers due to the costly and complex task of managing multiple suppliers. This has consequently led to ineffective risk management. Nowadays, companies are focusing on supplier relationship management and development, therefore the processes of evaluating and selecting suppliers is of great importance (Hosseini & Al Khaled, 2019).

Despite most works focusing more on risks arising from the supply side, disruptions also often occur due to variations in demand volume. Different from supply-side risks, demand-side risks have a reverse impact upstream SCs, impacting the whole SC system (Zhao et al., 2020). Demand-related resilience has been empirically evidenced by Blackhurst et al. (2011), Jüttner and Maklan (2011), Golgeci and Ponomarov (2013) and Purvis et al. (2016). Some of these works discussed the link between multi-sourcing strategies and demand uncertainty mitigation. The ability of selecting suppliers to adopt different roles: agile (fast and flexible) and lean (cost-efficient) is fundamental to cope with demand variations (Purvis et al., 2016). Towards efficient SC resilience-related strategies, it is important to consider both supply and demand uncertainties (Ramezanian and Behboodi, 2017). However, most of the SC resilience literature is still limited to explore a single source of risks. Also, related research studies solve, as outlined in section 2, the order allocation problem – assigning the lot size among selected suppliers - neglecting the output of the supplier evaluation process.

In this study, we address this gap in the literature by answering the following two research questions:

1) How to select suppliers and allocate orders in order to achieve resilience to both supply and demand uncertainties while maintaining good business performance?
2) How suppliers' normal business/resilience performance can be embedded into the lot-sizing decisions?

In this paper, we develop and validate a quantitative methodology towards SCR to both supply and demand variations. However, operational disruptions related to supply and demand include several tangible and intangible aspects (e.g., demand increase or decrease, flexibility, and agility) that would not be captured efficiently along with opinions of several experts without the employment of multi-criteria decision-making (MCDM) methods. These include multi-objective optimisation that helps in solving, for instance, the order allocation problem among suppliers towards specific managers' desires (e.g., minimum cost and maximum service level) (Keller, 2017). However, this optimisation method does not capture experts' opinions regarding alternatives' (i.e., suppliers) performance vis-à-vis several criteria (e.g., costs, agility, flexibility, and quality). In other words, this methodology would assign orders size to suppliers regardless their performance. MCDM also includes multi-attribute decision making (MADM) methods that help in evaluating alternatives based on their performance in a group of evaluation criteria (Tzeng and Huang, 2011). This calls for a methodology that integrates MADM output into the multi-objective optimisation to handle managers 'desires (e.g., minimum costs) and alternatives evaluation in the sourcing-related decision-making.

To the best of our knowledge, our work is the first to consolidate resilient supplier selection (RSS) methods with demand variation by developing an integrated hybrid multi-attribute decision making-possibilistic bi-objective programming model (MADM-PBOPM). This methodology helps in retrieving normal business/resilience performance of alternatives and assigning order size between or among alternatives, considering their performance, via the developed PBOPM. To this end, and unlike other order size solutions, this MADM output (alternatives' performance) is merged into the developed PBOPM. This supports the purchasing department (e.g., buyers) in incorporating their opinions regarding suppliers into the order allocation plan. Therefore, this research methodology aids the decision-making process for the purchasing team in precisely identifying the best resilient, in addition to the normal business concerns, suppliers. In addition, it supports decision makers towards an efficient resilient and economic order size allocation. Furthermore, the evaluation approach (via the proposed MADMA methods) could also be used by suppliers to test and improve their normal business and resilient capabilities. Thus, this work could guide, partially, SC managers in building SCR to guarantee business sustainability.

The remainder of this paper is organized as follows. In Section 2, we provide a literature review of the existing studies in SCR, supplier selection and its relevant methodologies. In Section 3, we present the problem statement and the technical description of our approach. Section 4 reveals the application of the proposed framework in the case company and discusses the main results obtained from the model with real dataset. We also indicate managerial implications for the focus company. Finally, in Section 5 we discuss major findings of this study and outline future directions.

2. Literature review

2.1. Supply chain resilience

Contemporary SCs are complex networks that aim to deliver the right quantity of products in the right place at the right time under uncertain global market conditions. The unstable conditions in global markets expose SCs to a multitude of disruptions (Pettit et al., 2010). Hence, the ability to react appropriately to disruptions is a strategic necessity for business continuity in SCs. Therefore, SCR has been receiving much attention within the business world throughout the past decade (Kochan & Nowicki, 2018). SCR has been defined by different authors in extant literature. In summary, SCR refers to the ability of SCs to cope with unexpected disruptions (Carvalho et al., 2012). We use the SCR definition by Ponis and

Koronis (2012) as it is comprehensive and covers different aspects of resilience in SCs. According to these authors, SCR is "*The ability to proactively plan and design the Supply Chain network for anticipating unexpected disruptive (negative) events, respond adaptively to disruptions while maintaining control over structure and function and transcending to a post event robust state of operations, if possible, more favourable than the one prior to the event, thus gaining competitive advantage*."

One dimension of SCR, which is mentioned in the above definition, is the capability of a SC to anticipate or sense disruptions. Sensing means minimising the lag between the event occurring and the SC's recognition of the event, therefore maximising the number of options available to the managers to deal with adverse events (Purvis et al, 2016). The other is the ability to respond adaptively to disruptions, which requires the SC to be both agile and flexible. Agility is "*the ability of a supply chain to rapidly respond to change by adapting its initial stable configuration*" (Wieland & Wallenburg, 2012) and to improvise when they can no longer operate in the same way they used to (Andersson et al. 2019). Whereas, flexibility is the ability of a SC to take different positions to better respond to disruptions and quickly adapt to significant changes (Lee, 2004). Therefore, Flexibility refers to having a variety of resources available, such as workforce, processes, and suppliers that lead to responsiveness in critical times (Ponomarov & Holcomb 2009). Very recently, (Deloitte, 2020) conducted a survey included 457 Board members of Swiss firms to identify avenues for building SCR, and they reported flexibility among the main aspects to elevate SCR. Transcending to a post-event robust state of operations requires SCs to be able to resist disruptions and remain effective (Vlajic et al., 2012), and thus, robustness can be identified as a dimension of SCR (Wieland & Wallenburg, 2013). Developing to a more favourable state of operations after dealing with disruptions is yet another dimension of SCR, which is explicitly stated in the definition. The development capability enables companies to keep up with environmental dynamics and to set a new trajectory by learning from disruptive events (Lengnick-Hall, Beck, & Lengnick- Hall 2011). The dimensions mentioned above are commonly cited across the extant SCR literature. We present sensing, agility, robustness development and flexibility as the RPs.

2.2. Resilient supplier selection

In this research, we aim to address resilient supplier selection as a SCR practice by proposing a comprehensive methodology. RSS is a crucial strategic decision in SCs, specifically in the context of disruption management (Hosseini & Al Khaled, 2019). This is because suppliers can be a source of external risk to organisations (Rajesh & Ravi, 2015). For a SC to be resilient, the selected suppliers should be the least vulnerable to disruptions. Moreover, suppliers need to be able to respond to demand uncertainty. Supplier selection is essentially a MCDM problem, and there are many proposed methodologies to deal with it, examples of which are mentioned in the following section.

The multitude of studies investigating supplier selection as a mean of achieving more resilient SCs indicate the importance of RSS. In this study, we mainly focused on the papers published in the last ten years that explicitly address RSS. We inputted the keyword “resilient supplier selection” in Scopus and Web of Science databases, as they are the most renowned scientific databases in the field of engineering. The search was focused on the title, abstract, and keywords of the papers, which resulted in finding 18 distinct papers. To take a step further, we searched the references mentioned in these papers and focused on the titles using the same keyword. We found seven relevant papers, which were not primarily detected in the search result. Altogether, 25 papers were analysed, we provide a concise and collective description of them next.

Haldar et al. (2012) designed a hybrid MCDM model as a quantitative method for RSS. They merged Analytical Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Quality Function Deployment (QFD) methods first to determine the importance of each criterion and then proceed with the selection of resilient suppliers. In their next research, Haldar et al. (2014), considered a disaster scenario where they developed a strategic RSS method in a fuzzy environment by considering a different set of supplier selection criteria. Later, by using fuzzy theory, Azadeh et al. (2014) introduced the idea of green RSS by proposing a model that uses Analytical Network Process (ANP) and Data Envelopment Analysis (DEA) to determine criteria weights for green RSS. Rajesh and Ravi (2015) used grey relational analysis (GRA) to acquire a set of possibility values based on the linguistic assessment of decision-makers for RSS. Torabi et al. (2015) developed a decision-making model for creating a resilient supplier base using a bi-objective mixed possibilistic, two-stage stochastic programming model that addresses the uncertainty caused by disruptions and operational risks. Moving forward, Chen et al. (2016) proposed a model that quantitatively analyses how resilient suppliers are by taking advantage of Weighted Goal Programming (WGP) and Preemptive Goal Programming (PGP) methods. Hosseini and Barker (2016) developed a Beysian Network model that uses green and SCR criteria to choose the most feasible suppliers. Sen et al. (2016) devised a decision support framework for RSS that considers both resilience and green criteria at the same time. Using fuzzy set theory, they introduced a performance index, i.e., “g-resilient”, to help with RSS. Taking advantage of normal business criteria (NBC), Pramanik et al. (2017) introduced a model for RSS using a hybrid AHP-TOPSIS-QFD method. Lee (2017) examined supply resiliency under supply failure risks by using a fuzzy multi-objective programming approach to minimise the cost, number of rejected items, and late deliveries. Parkouhi and Ghadikolaei (2017) proposed a model with which it is possible to determine the importance of RSS elements, using Fuzzy Analytic Network Process (FANP). Next, by using these elements, the supplier resiliency level can be specified through the grey VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method. Wang et al. (2017) suggested a combined methodology using AHP and GRA to evaluate supplier performance by determining weights for resilience criteria and ranking suppliers for RSS, respectively. Malek et al. (2017) introduced a comprehensive model using GRA for evaluating and selecting green and resilient suppliers. Foroozesh et al. (2018) used interval-valued fuzzy sets (IVFSs) and possibilistic statistical theories to select potential resilient suppliers. Their research presents a comprehensive possibilistic statistical group decision model based on IVFSs and asymmetric information to facilitate RSS in SCs. Jabbarzadeh et al. (2018) presented a hybrid methodology for the design of a sustainable and resilient supply network. They developed a stochastic bi-objective optimisation model that employs a fuzzy C-means clustering method. The proposed model is capable of helping decision-makers with selecting outsourcing options and resilience strategies. Alimohammadlou and Bonyani (2018) used DEMATEL, ANP, and fuzzy goal programming to propose an integrated fuzzy model for RSS. Later, Parkouhi et al. (2019) conducted a study considering two dimensions of resilience enhancers and resilience reducers for selecting and segmenting suppliers. They applied Grey Decision Making Trial and Evaluation Laboratory (Grey DEMATEL) technique to determine the importance degree of the criteria for each of the mentioned dimensions, and afterward, by using the Grey Simple Additive Weighting technique (GSAW) they determined the score of each supplier according to each dimension. Gan et al. (2019) proposed a hybrid method that combines triangular fuzzy number, the best-worst method (BWM), and the modular TOPSIS to first rank the decision-makers and then proceed with best possible RSS. Mohammed et al. (2019a), after identifying the RSS criteria by using a unified framework and the input from experts in the field, developed an approach in which they used DEMATEL method to determine the importance and the weights of each criterion. Next, they integrated the resulted weights into the ELimination Et Choix Traduisant la REalité (ELECTRE) algorithm accompanied by the TOPSIS method to rank the suppliers. In a final step, they used the Spearman’s rank correlation coefficient (SRCC) approach to attain the statistical difference between the ranking orders. Mohammed et al. (2019b) designed a hybrid MCDM fuzzy multi-objective programming approach to design SCs that are both resilient and green. They used Fuzzy AHP and TOPSIS methods to select the most feasible suppliers. Davoudabadi et al. (2019) devised a methodology in which they gathered decision-makers' input in the form of linguistic variables and converted them to interval-valued intuitionistic fuzzy (IVIF) numbers and then used the complex proportional assessment (COPRAS) method based on the attained IVIF numbers to rank the suppliers. Hosseini and Al Khaled (2019) merged classification and regression trees, binomial logistics regression, and neural networks to propose a model that quantifies suppliers' resilience. In their research, Hosseini et al. (2019) showed how to compute the probability of disruption scenarios for supplier selection by using a probabilistic graphical model. Next, they proposed a stochastic bi-objective mixed-integer programming model that supports the decision-making regarding when and how to use reactive and proactive strategies in supplier selection and also order allocation. Cavalcante et al. (2019) developed a hybrid method by combining simulation and machine learning in the context of data-driven decision-making support for RSS. Hasan et al. (2020) used Fuzzy Multi-Attribute Decision Making (F-MADM) and TOPSIS methods to develop a Decision Support System (DSS) that helps decision-makers include and process imprecise heterogeneous data in a unified framework to prioritise RSS.

Table 1 includes a summary of the mentioned studies, along with the respective RSS criteria used in the supplier selection.

Table1. Literature review on RSS

Reference	**Methodology**	**RSS criteria**
Haldar et al. (2012)	TOPSIS, AHP, QFD	• Buffer capacity • Supplier's resource flexibility • Lead time • SC density • SC complexity • Responsiveness • No. of critical nodes in a SC • Re-engineering
Haldar et al. (2014)	FTOPSIS, AFW	• Quality • Reliability of product • Functionality of product • Customer satisfaction • Cost of the product
Azadeh et al. (2014)	ANP, DEA	• Quality • Finance (Financial stability, Price, Past financial performance) • Service (On-time delivery, Credible delivery, Responsiveness, Design capability) • Corporate social responsibility • Environmental • Self-organisation • Reversibility • Flexibility
Rajesh and Ravi (2015)	GRA	• Quality • Cost • Risk awareness • SC

		• Flexibility • SC velocity • SC visibility • Vulnerability • Level of collaboration	• continuity management • Technological capability • Research and development • Safety • Concern for environment
Torabi et al. (2015)	Bi-objective mixed possibilistic two-stage stochastic programming model	• Cost • Delivery	• Capacity
Chen et al. (2016)	Weighted goal programming (WGP) and Preemptive Goal programming (PGP)	• Finance • Quality • Delivery • Relationship • Service	• Technology • Supply facility and infra-structure and market repu-tation • Management and organisa-tion • Efficacy of corrective ac-tion • Environment • Risk factors
Hosseini and Barker (2016)	Bayesian Network (BN)	• Total cost • Quality of products • Service • Delivery and response • Distance between supplier and customer • Total emitted CO_2 • CO_2 emission	• Probability of tornado oc-currence • Probability of flood occur-rence • Segregation • Surplus inventory • Backup supplier availabil-ity • Backup supplier
Sen et al. (2016)	Fuzzy set theory	• Investment in capacity buff-ers • Responsiveness • Capacity for holding strate-gic inventory for crises • Use of environment-friendly technology • Use of environment-friendly materials • Green market share • Partnership with green or-ganisations • Management commitment	• Adherence to environmen-tal policies • Green R&D projects • Staff training • Green process planning • Design for environment • Environmental certification • Pollution control initiatives
Pramanik et al. (2017)	AHP, TOPSIS, QFD	• Quality • Delivery time • Reliability • Processing time • Profit margin	• Buffer capacity • Number of critical nodes • Responsiveness • Re-engineering • Adaptive capability
Lee (2017)	A fuzzy multi-objective programming	• Price • Failure probability • Output capacity • Emergency capacity • Minimum order quantity	• Percentage of the rejected units delivered • Unit contracting cost of emergency capacity • Percentage of the units de-livered late • Supplier maintenance cost
Parkouhi and Ghadikolaei (2017)	FANP, grey VIKOR method	• Delivery • Flexibility • Quality	• Relationship building • Cost of product • Cost of relationship

		• Culture • Joint growth • Supplier's technology	• Supply constraint • Buyer-supplier constraint • Supplier's profile
Wang et al. (2017)	AHP, GRA	• Product quality • Commodity price and cost • Delivery and service • Time flexibility • Product flexibility • Quantity flexibility • Management level • Risk reduction and responsiveness • Reputation and prestige	• The political and legal environment • Service distance • The level of informatization • New product development • New technology development • Energy-saving and environmental protection • Eco-design • Pollution
Malek et al. (2017)	GRA	• Flexibility • Redundancy • Agility • Risk • Level of collaboration • Cost • Quality • Time • Delivery	• Green competencies • Environmental competencies • Safety competencies • Financial • Technical & equipment • Technological & innovation • Information technology • Human resource & training • Organisational management competencies
Foroozesh et al. (2018)	IVFSs	• Responsiveness	• Capacity for holding strategic inventory stocks
Jabbarzadeh et al. (2018)	Stochastic programming, fuzzy c-means clustering method	• Extra production capacity • Raw material • Manufactured products	• Shipped products • Lost sales
Alimohammadlou and Bonyani (2018)	DEMATEL, ANP, fuzzy goal programming	• Vulnerability • Agility • Information sharing • Redundancy • Sustainability • Financial strength • Safety • Visibility	• Demand management • Lead time • Human resource management • Collaboration • Adaptive capability • Risk management culture • Flexibility
Parkouhi et al. (2019)	Grey DEMATEL, GSAW	• Enhancers of supplier resiliency (e.g., Order lead time, Delivery reliability, Quality services, Cost-reduction capability, etc.)	• Reducers of supplier resiliency (e.g., Supplier's capacity limit, cost of inventory, Vulnerability, Financial risk, etc.)
Gan et al. (2019)	BWM, modular TOPSIS	• Surplus inventory • Location separation • Interdependency • Robustness	• Reliability • Rerouting • Reorganisation • Restoration
Mohammed et al. (2019a)	DEMATEL, ELECTRE, TOPSIS, SRCC	• Cost • Product quality • Technology capability • Implementation period • Successful previous related projects	• Performance history • Staff training and support • Robustness • Agility • Flexibility

Mohammed et al. (2019b)	Fuzzy AHP	• Redundancy • Agility	• Leanness • Flexibility
Davoudabadi et al. (2019)	IVIF-COPRAS	• Product quality • Reliability of the product • Functionality of the product • Customer satisfaction	• Cost of the product • Investment in capacity buffers • Responsiveness • Capacity for holding strategic inventory for crises
Hosseini and Al Khaled (2019)	Hybrid ensemble-AHP	• Cost • Quality • Lead time • Response rate • Surplus inventory	• Location separation • Interdependency • Robustness • Reliability
Hosseini et al. (2019)	Stochastic bi-objective mixed-integer programming	• Supplier capacity • Violation cost • Expected disruption rate of suppliers • Disruption cost	• Holding cost • Order cost • Penalty cost (of supplying low-quality products) • Distance between suppliers and the firm
Cavalcante et al. (2019)	Simulation, machine learning	• Delivery reliability (On-time delivery)	• Suppliers' risk profile
Hasan et al. (2020)	F-MADM, TOPSIS	• Pre-positioned inventory level • Lead time variability • Production capacity • Cost • Digitalization • Traceability • SC density • SC complexity • Re-engineering • Supplier's resource flexibility	• Automation disruption • Information management • Cyber security risk management • Supplier reliability • SC visibility • Level of collaboration • Restorative capacity • Rerouting • Agility

As shown in Table 1, there are several criteria that can be used to select resilient suppliers. To choose the NBC criteria, we asked the purchasing manager from the case study to review the complied list of the criteria in Table 1 and shortlist it by selecting the most important ones. Based on his answers, we identified Purchasing Costs, Scrap Quality, Delivery Reliability, Performance history, Turnover, Lead Time, and Operating capacity as the most important criteria. We also selected Sensing, Agility, Robustness, Development and Flexibility as the five RPs that were described earlier in section 2.1.

2.3. MCDM in RSS

In modern supply chain management (SCM), the performance of prospective suppliers is assessed by multiple criteria rather than just a single criterion, i.e., cost. Selecting the right suppliers requires much more than just surveying price lists, and choices depend on a range of criteria that involve both qualitative and quantitative measures. Extensive MCDM methodologies have been suggested for supplier selection, e.g., DEMATEL, TOPSIS, ANP, AHP, DEA, Case-Based Reasoning (CBR), Genetic Algorithm (GA), Simple Multi-Attribute Rating Technique (SMART), mathematical programming, fuzzy set theory, etc., and their hybrids (Ho et al., 2010; and Pamucar et al., 2021). The MCDM methodologies used in the mentioned research for RSS are stated in Table 1.

2.4. Research gaps

After analysing the research in the extant literature, we could not find any work that proposed an integrated hybrid MADM-PBOPM capable of simultaneously addressing “supply resiliency” and “demand uncertainty” in RSS. We have addressed this gap in this paper. In addition, the reviewed research dedicated for solving the order allocation problem do not consider alternatives’ performance into the assigned order size. This traditional setting would not reflect decision makers’ perspective about alternatives’ capabilities in the assigned order size. Also, the literature pointed out the need for more integrated methodologies towards resilient SC that we address in this research. In this regard, we integrated alternatives’ normal business and resilience profile into a trade-off modelling between costs and resilience paradigms. In addition, the possibilistic modelling was employed to capture the uncertainty downstream the SC. In terms of the research methodology, this, as far as the authors know, the first study that employees integrated and hybrid DEMATEL, TOPSIS and possibilistic multi-objective optimisation approaches in supplier selection and order size allocation problem.

3. Research methodology

3.1 Problem statement

Several companies, mainly production, have become more subject to operational disruptions due the lean requirements and globalized structure. Furthermore, considering the recent tremendous impact of COVID-19 risks, managers of companies would be informed to build up their SCR. This target would enhance the network's capability to sense, resist, absorb, and retrieve its normal state after disruptions to sustain its business. A laboratory instrumentation OEM company (Company X, henceforth) works to develop its purchasing strategy with a goal of a resilient SC. This study is motivated by this need, via a research collaboration with Company X, in providing the purchasing team with a sourcing methodology that considers NBC and RPs. This work conceptualizes and introduces a methodology to achieve resilient sourcing towards SCR. The case network consists of potential suppliers and Company X. The latter purchases various items from different suppliers to assemble the finished products.

First, the NBC and RPs were presented based on literature and the purchasing manager's point of view. Figure 1 shows the developed framework for the identified NBC/RPs. Second, the relative importance of criteria and pillars, shown in Figure 1, was quantified by using DEMATEL. This step is followed by the assessment and ranking of suppliers based on their performance in terms of NBC/RPs by using TOPSIS. Then, a bi-objective programming model was formulated to allocate the optimal order size from each supplier. This order allocation considers supplier's performance by integrating suppliers' performance score and relative criteria weight into the BOPM. This model was further development in embracing the possibilistic set theory to improve Company X's resiliency to demand uncertainty rather than supply only. The PBOPM presents two objectives: minimisation of total related costs of sourcing and maximisation of resilience sourcing value. Then, a set of pareto solutions was derived from the PBOPM by using the ε-constraint method. Finally, the global criterion approach was applied to help buyers in selecting the final appropriate Pareto solution. Figure 2 depicts a general overview and steps for the developed hybrid integrated methodology towards SCR.

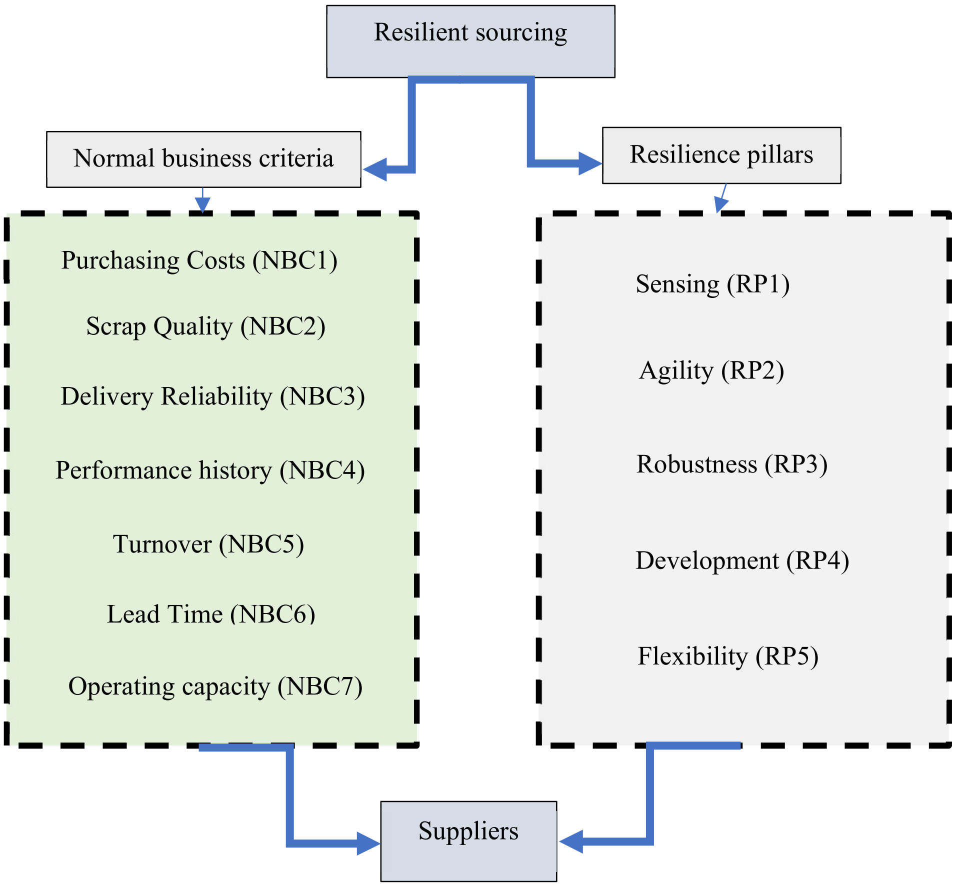


Figure 1. A holistic framework for the NBC/RP.

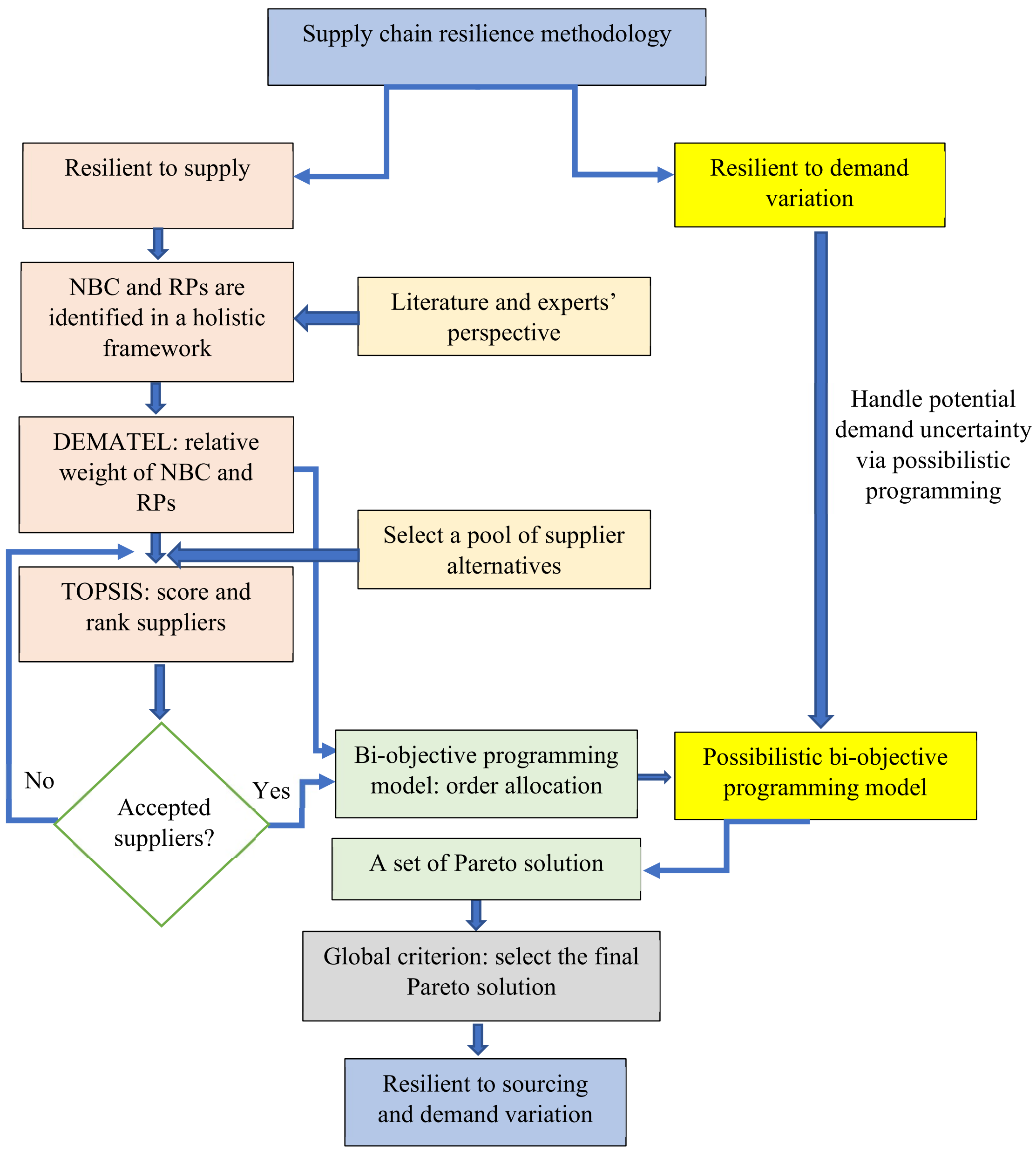


Figure 2. MADM-PBOPM supply chain resilience methodology.

3.2 DEMATEL

In 1971, the DEMATEL approach was first created by the United States Bastille laboratory. So far, it has been commonly employed to handle the correlation and weighting among and of criteria (Ortíz et al. 2016; Kaya and Yet, 2019; Kilic et al., 2020; Li et al., 2020; Li et al., 2020; and Mohammed, 2020 and 2019). This approach works on revealing the correlation and relationship among criteria in addition to their relative importance based on experts' judgment. In this research, DEMATEL was proposed to quantify relative weights of normal business criteria (NBC1-NBC7) and resilience pillars (RP1-RP5) - previously presented in Figure 1 - to be used as input parameters for the PBOPM. In this work, DEMATEL was applied as clarified in Appendix A.

3.3 TOPSIS

Yoon and Hwang (1995) created TOPSIS as an aid approach in selecting an alternative based on its distance from the negative ideal solution and the positive ideal solution. So far, it has been identified as one of the most employed MADM methods in the SCM context (Rashidi et al., 2020; Govindan et al., 2015). In this work, TOPSIS was applied to evaluate and obtain a ranking order of alternatives (i.e., suppliers) based normal business/resilience performance. Also, this output is embraced, as a score for each supplier, in the PBOPM. In this research, TOPSIS was implemented as clarified in Appendix A.

3.4 The integrated hybrid MADM-PBOPM

This section introduces the developed MADM-PBOPM that helps the purchasing team to (1) order materials from suppliers based on their resilience and normal business performance; and (2) enhance the company's resilience to demand uncertainty. This includes a BOPM that integrates the weight of NBC/RPs and suppliers achieved via DEMATEL and TOPSIS, respectively. This would help buyers to allocate order quantities among suppliers not merely based on normal business performance e.g., purchasing costs, but also their resilience performance. The two objective functions include: minimisation of total related costs (TRC) and maximisation of resilient sourcing value (RSV).

The sets, parameters and decision variables included in the model formulation are as follows:

Sets

I set of suppliers, $i = 1,\ldots,I$

Given Parameters

C_i^p unit purchasing cost offered by supplier i

C_i^t cost (unit/mile) of transporting units from supplier i

C_i^a unit ordering cost related to supplier i

d_i unit travelling distance in mile from supplier i

TC lorry shipping capacity (unit)

S_i unit supply capacity related to supplier i

D_n minimum demand of the manufacturer

D_x maximum demand of the manufacturer

W^n weight of NBC obtained via DEMATEL

W^r weight of RPs obtained via DEMATEL

o_i^n normal business performance value related to supplier *i* derived from TOPSIS

o_i^r resilience performance value related to supplier *i* derived from TOPSIS

Decision variables

q_i number of units ordered from supplier *i*

The two objective functions:

$$Min\ \ TRC = Min\,(W^n \sum_{i \in I} o_i^n q_i) + \sum_{i \in I} C_i^p q_i \ + \sum_{i \in I} C_i^a q_i + \sum_{i \in I} C_i^t \left\lceil \frac{q_i}{TC} \right\rceil \ d_i \tag{1}$$

$$Max\ \ RSV = W^r \sum_{i \in I} q_i o_i^r \tag{2}$$

The above-mentioned two objective functions are subject to the following constraints:

$$q_i \ \le S_i \ ; i = 1,2,\dots,I \tag{3}$$

$$\sum_{i \in I} q_i \ge D_{\mathrm{n}} \tag{4}$$

$$\sum_{i \in I} q_i \le D_x \tag{5}$$

$$q_i \ \ \ge 0 \ \ \forall i \tag{6}$$

Eq.1 shows the objective function that aims to minimise the related sourcing costs i.e. purchasing, administration (e.g., ordering) and transportation costs. As shown in the first term of Eq.1, the relative weight and score of NBC and suppliers revealed via DEMTAEL and TOPSIS, respectively, are integrated. This formulation supports buyers in allocating order quantities among suppliers considering relative importance of NBC and suppliers' NB performance. Eq.2 presents the objective function that aims to maximise the resilient sourcing value. In other words, it helps in pushing orders from the most resilient suppliers. To this end, resilience performance scores of suppliers revealed via TOPSIS were integrated as a coefficient of order quantities. The weight of resilience pillar was also multiplied by the formula to further express its importance from the buyers 'perspective. Eq.3 shows the supply constraint that limits the quantity of product ordered from supplier i by its capacity. Eqs.4 and 5 presents demand constraints that ensure fulfilment of the manufacturing company demands. Finally, Eq.6 shows a non-negativity constraint related to quantity of products.

3.4.1 Modelling supply chain resiliency to demand

Due to the high competition in the markets, uncertainties are existing in several input parameters. Among these, purchasing and transportation costs, supply capacity and demand are the most common. The latter is one of the crucial aspects that companies should consider in building up a resilient SC. This work not merely aims at building up sourcing approach that is resilient to supply, via resilient suppliers, but also to demand uncertainty. To this end, potential uncertainties in transportation and purchase costs, supply capacity and demands are formulated as triangular fuzzy numbers using the possibilistic approach developed by Jiménez et al. (2007). Based on this approach, the equivalent crisp model can be formulated as follows (Jiménez et al. 2007; and Mohammed, 2020):

$$Min\ TRC = \min(W^{n}\sum_{i\in I} o_i^n q_i) + \sum_{i\in I}\left(\frac{C_i^{p\,pes} + 2C_i^{p\,mos} + C_i^{p\,opt}}{4}\right) q_i + \sum_{i\in I} C_i^o q_i + \sum_{i\in I}\left(\frac{C_i^{t\,pes} + 2C_i^{t\,mos} + C_i^{t\,opt}}{4}\right)\left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{7}$$

$$Max\ RSV = W^{r}\left(\sum_{i\in I} o_i^r q_i\right) \tag{8}$$

Subject to:

$$\sum_{i\in I} q_i \le S_i \left[\frac{\alpha}{2}.\frac{S_{i1}+S_{i2}}{2} + \left(1-\frac{\alpha}{2}\right)\frac{S_{i3}+S_{i4}}{2}\right];\ i = 1,2,\dots,I \tag{9}$$

$$\sum_{i\in I} q_i \ge \left[\frac{\alpha}{2}.\frac{D_{n1}+D_{n2}}{2} + \left(1-\frac{\alpha}{2}\right)\frac{D_{n3}+D_{n4}}{2}\right] \tag{10}$$

$$\sum_{i\in I} q_i \leq \left[\frac{\alpha}{2}.\frac{D_{x1}+D_{x2}}{2} + \left(1-\frac{\alpha}{2}\right)\frac{D_{x3}+D_{x4}}{2}\right] \quad (11)$$

$$q_i \geq 0 \quad \forall i \quad (12)$$

where

α	confidence level for the uncertain data allocated by decision makers
mos	the most likely value
pes	the most pessimistic value
opt	the most optimistic value

In this model, the constraints that include uncertain parameters (i.e., demand and supply capacity) in the PBOPM should be satisfied with a confidence value of α that is usually set by buyers (Jiménez et al., 2007). Also, the three values (i.e., *mos, pes* and *opt*) identify the possible domain for an uncertain input parameter. For instance, uncertain demand that is varied between 100 and 130 could be presented as 100, 115 and 130 referring the *mos, pes, opt* values, respectively.

Figure 3 depicts a graphical illustration regarding the corresponding membership functions for two objective functions. They can be measured as follows:

$$\mu_1(TRC(x)) = \begin{cases} 1 & if \;\; TRC(x) \leq Max \\ \dfrac{Min - TRC(x)}{Min - Max} & if \;\; Min \leq TRC(x) \leq Max \\ 0 & if \;\; TRC(x) \geq Min \end{cases} \quad (13)$$

$$\mu_2(RSV(x)) = \begin{cases} 1 & if \;\; RSV(x) \leq Max \\ \dfrac{Min - RSV(x)}{Min - Max} & if \;\; Min \leq RSV(x) \leq Max \\ 0 & if \;\; RSV(x) \geq Min \end{cases} \quad (14)$$

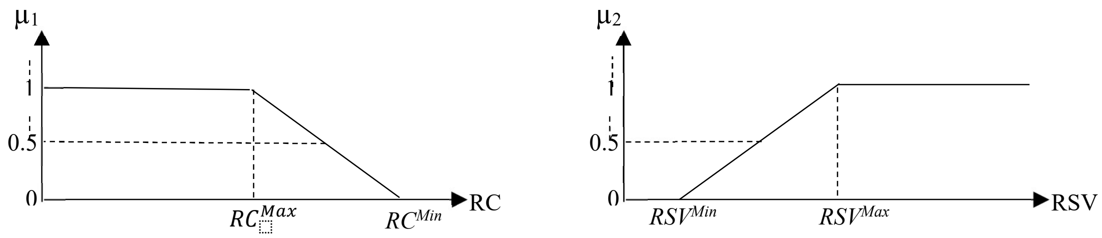
The minimum/maximum values for the two objectives can be measured as follows:

$$Min\ TRC = \min(W^{n} \sum_{i \in I} o_i^n q_i) + \sum_{i \in I} \left(\frac{C_i^{p\,pes} + 2C_i^{p\,mos} + C_i^{p\,opt}}{4} \right) q_i + \sum_{i \in I} C_i^o q_i + \sum_{i \in I} \left(\frac{C_i^{t\,pes} + 2C_i^{t\,mos} + C_i^{t\,opt}}{4} \right) \left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{15}$$

$$Min\ RSV = W^{r} \left(\sum_{i \in I} o_i^r q_i \right) \tag{16}$$

$$Max\ TRC = \min(W^{n} \sum_{i \in I} o_i^n q_i) + \sum_{i \in I} \left(\frac{C_i^{p\,pes} + 2C_i^{p\,mos} + C_i^{p\,opt}}{4} \right) q_i + \sum_{i \in I} C_i^o q_i + \sum_{i \in I} \left(\frac{C_i^{t\,pes} + 2C_i^{t\,mos} + C_i^{t\,opt}}{4} \right) \left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{17}$$

$$Max\ RSV = W^{r} \left(\sum_{i \in I} o_i^r q_i \right) \tag{18}$$



(a) RC (b) RSV

Figure 3. The corresponding membership functions for Min RC and Max RSV.

3.4.2 Generating Pareto solutions: ε-constraint

The ε-constraint is among the most efficient classical solution approaches used for solving multi-objective optimisation problem. It keeps one of the objectives as an objective function and shift the others to the constraint set limiting them by an ε-value (Ehrgott, 2005; and Wang et al., 2020). Decision makers hereby need to choose the objective function to be left based on their preferences. For instance, the cost minimisation would be left as an objective function if the company works towards a cost-oriented sourcing strategy. In this work, to minimise the related sourcing costs (based on the case company's preference) while limit the resilience sourcing value in the constraint, the equivalent ε-constraint formula (Z) is presented as follows (Nujoom et al., 2019 and 2018):

$$Min\ Z = \min(W^{n}\sum_{i\in I} o_i^n q_i) + \sum_{i\in I}\left(\frac{C_i^{p\,pes} + 2C_i^{p\,mos} + C_i^{p\,opt}}{4}\right) q_i + \sum_{i\in I} C_i^o q_i$$
$$+ \sum_{i\in I}\left(\frac{C_i^{t\,pes} + 2C_i^{t\,mos} + C_i^{t\,opt}}{4}\right)\left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{19}$$

Subject to Eqs. 9–12, and:

$$W^{r}\left(\sum_{i\in I} o_i^r q_i\right) \geq \varepsilon \tag{20}$$

As shown in Eq. 19, the minimisation to total related cost was left as an objective function and maximisation of resilience sourcing value is limited by an ε-value in the constraint set (see Eq.20). The boundaries of ε-value can be limited as follows:

$$\left[W^{r}\left(\sum_{i\in I} o_i^r q_i\right)\right]^{\min} \leq \varepsilon \leq \left[W^{r}\left(\sum_{i\in I} o_i^r q_i\right)\right]^{\max} \tag{21}$$

3.4.3 Selecting the final solution: global criterion

So far, several decision-making approaches were proposed to select the final solution out of a pool of solutions. In this work, the global criterion approach was proposed, as an aid tool, to facilitate the final solution selection. This approach derives the solution that reveals the shortest distance to the ideal solution. The decision-making formula *X* can be expressed as follows (Rangaiah, 2009):

$$Min\ F = \left(\sum_{n=1}^{i} \left|O_n - O_n^*\right|^{\rho}\right)^{1/\rho} ; n = 1,2,\ldots,i ; 1 < \rho < \infty \tag{22}$$

Where O_n refers to the value of the nth objective and O^{*n} refers to the ideal value of the nth objective. The latter can be derived via the individual optimisation of the two objectives. Generally, ρ is 1, as in this study.

4. The integrated hybrid MADM-PBOPM: Application and evaluation

In this section, the MADM-PBOPM was applied on data collected from the purchasing manager in Company X. It is a medium-sized manufacturing company that assembles – assemble-to-order - and produces technical equipment for thermal desorption. Its equipment can be utilised for several applications e.g., monitoring of environmental measures and quality and safety of food products and detecting chemical warfare agents. The company has a production target to be met by 2020. A major element of its senior managers' plan is the development of the current purchasing strategy, withing a strategic target for the entire company, in enriching its resiliency. Based on a research collaborated project, this study was conducted to provide the purchasing team with a decision-making methodology that aims to improve their sourcing activity in building the resilience aspect. The purchasing manager shared some concerns regarding shortages of some critical items and a real sense that their business is subject to operational (i.e., assembly) disruption due to the poor performance of some current suppliers. However, the purchasing team had no clear methodology to coin resilient sourcing. Furthermore, the resilience to demand was suggested by the research team to handle demand uncertainty. This was suggested because the purchasing manager clarified that the company experience some unexpected demand that the company cannot normally handle due to relative low performance of current supplier. Thus, this study presented the following points to the purchasing team:

1. A framework that embraces NBC/RPs in which buyers should use in assessing suppliers' performance.
2. An easy, to re-adjust and re-apply, decision-making tool to help buyers in assessing and ranking suppliers.
3. A user-friendly tool that helps buyers to allocate quantities of order among suppliers, considering their performance. Then, they can use the Economic order quantity (EOQ) approach to determine the lot size.

It is important to mention that the previous evaluation process by buyers was based on limited NBC by using an old-school of filling forms. In other words, every buyer would use a form to write down his or her opinion regarding a supplier performance against some criteria (e.g., costs, lead time and quality). Also, there was no order allocation based on suppliers' performance as even low performance suppliers may be asked to provide a big order regardless its performance.

The application of the MADM-PBOPM was over two stages (1) assessing and ranking suppliers by using the DEMATEL-TOPSIS approach (see section 5.1) using Excel; and (2) allocating quantities of orders among suppliers by solving the PBOPM (see section 5.2) using LINGO[11].

4.1 Ranking suppliers via the DEMATEL-TOPSIS approach

Company X sources several materials and units from different suppliers. The purchasing manager was asked to nominate one key item, that has frequent shortage due to low supplier performance, to test the DEMATEL-TOPSIS approach. The purchasing manager suggested metal sheet that is currently sourced from six different suppliers. Also, the purchasing manager was asked to nominate a number of decision makers to involve in the evaluation process. Four buyers were asked by the purchasing manager to work with the research team on the evaluation process. Thus, the decision-making team includes five members: the purchasing manager, a buyer, a senior buyer and two junior buyers.

4.1.1 Quantifying criteria importance via DEMATEL

In this step, the five decision makers were first interviewed together to illustrate the evaluation process and to present the evaluation of NBC/RPs procedures. The identified criteria and pillars previously presented in Figure 1 were clarified during the interviews with decision makers participated in this evaluation process. NBC/RPs were unified based on literature review and the purchasing manager's perspective. It is worthy to mention that the purchasing team was not quite familiar with the RPs, mainly. However, the discussions and illustrations that were done during the group interview, have tackled this issue. Also, the purchasing manager has suggested to add two NBC including turnover and operating capacity. This addition was justified to know the expansion capabilities of a supplier in the near future. As clarified by him, this would help him to select suppliers that can cope with his company's growth.

Afterword, each decision maker was interviewed to build up the direct-relation matrix based on his or her opinion by performing a pairwise comparison among NBC/RPs, individually. This was based on the evaluation scale presented in Table A1. Tables 2 and 3 present the aggregated direct-relation matrix for NBC and RPs, respectively. It was generated by applying Eq.23, based on five influence matrices generated by the five decision makers.

Table 2. The aggregated decision matrix for NBC

Criteria	NBC1	NBC2	NBC3	NBC4	NBC5	NBC6	NBC7
NBC1	0	4	2	4	4	3	4
NBC2	4	0	0	4	3	1	2
NBC3	4	1	0	3	0	1	0
NBC4	2	3	2	0	1	1	0
NBC5	1	1	3	2	0	1	1
NBC6	3	1	4	4	0	0	0
NBC7	2	0	0	4	4	0	0

Table 3. The aggregated total-influence matrix for RPs

Pillars	RP1	RP2	RP3	RP4	RP5
RP1	0	1	4	0	1
RP2	1	0	0	2	0
RP3	4	3	0	0	1
RP4	4	2	4	0	4
RP5	0	4	1	4	0

Then, the normalised direct-relation matrices for NBC/RPs were generated by applying Eqs.24 and 25. Tables 4 and 5 show the two matrices. Tables 6 and 7 present the total-relation matrices T for the two criteria sets. These matrices were built by implementing Eq.26.

Table 4. The normalised direct-relation matrix for NBC

Criteria	NBC1	NBC2	NBC3	NBC4	NBC5	NBC6	NBC7
NBC1	0	0.1905	0.0952	0.1905	0.1905	0.1429	0.1905
NBC2	0.1905	0	0.0000	0.1905	0.1429	0.0476	0.0952
NBC3	0.1905	0.0476	0	0.1429	0.0000	0.0476	0.0000
NBC4	0.0952	0.1429	0.0952	0	0.0476	0.0476	0.0000
NBC5	0.0476	0.0476	0.1429	0.0952	0	0.0476	0.0476
NBC6	0.1429	0.0476	0.1905	0.1905	0.0000	0	0.0000
NBC7	0.0952	0.0000	0.0000	0.1905	0.1905	0.0000	0

Table 5. The normalised direct-relation matrix for RPs

Pillars	RP1	RP2	RP3	RP4	RP5
RP1	0	0.0714	0.2857	0.0000	0.0714
RP2	0.0714	0	0.0000	0.1429	0.0000
RP3	0.2857	0.2143	0	0.0000	0.0714
RP4	0.2857	0.1429	0.2857	0	0.2857
RP5	0.0000	0.2857	0.0714	0.2857	0

Table 6. The total-influence matrix (T) for NBC

Criteria	NBC1	NBC2	NBC3	NBC4	NBC5	NBC6	NBC7
NBC1	0.2409	0.3458	0.2622	0.4757	0.3630	0.2462	0.2866
NBC2	0.3323	0.1455	0.1356	0.3897	0.2809	0.1404	0.1858
NBC3	0.2968	0.1612	0.0946	0.2917	0.1081	0.1212	0.0770
NBC4	0.2154	0.2265	0.1722	0.1567	0.1417	0.1116	0.0694
NBC5	0.1607	0.1289	0.2099	0.2250	0.0777	0.1011	0.0942
NBC6	0.2906	0.1778	0.2852	0.3624	0.1128	0.0862	0.0777
NBC7	0.1898	0.1006	0.0978	0.3085	0.2668	0.0640	0.0584

Table 7. The total-influence matrix (T) for RPs

Pillars	RP1	RP2	RP3	RP4	RP5
RP1	0.1330	0.2008	0.3509	0.0642	0.1243
RP2	0.1544	0.0761	0.0984	0.1730	0.0675
RP3	0.3723	0.3204	0.1396	0.0834	0.1318
RP4	0.5143	0.4323	0.5131	0.1790	0.4102
RP5	0.2177	0.4539	0.2561	0.3922	0.1459

Next, the D_k and R_k values were determined by applying Eqs.27 and 28. These two values were utilised to generate prominence ($D_k + R_k$) and relation ($D_k - R_k$). These two values were used to categorised NBC/RPs into causes and effects. Tables 8 and 9 present the results of this step. As shown in Tables 8 and 9, the criterion or pillar is a cause when its "relation" value (i.e., $D_k - R_k$) is positive and an effect when its "relation" value is negative. The weight of NBC/RPs were quantified by dividing the prominence ($D_k + R_k$) of each criterion and/or pillar by the summation of all prominences ($\sum D_k + R_k$). Table 10 lists the revealed weight for NBC/RPs.

Table 8. DEMATEL output related to NBC

Criteria	Di	Ri	Di+Ri	Di-Ri	Cause-effect?
NBC1	2.2204	1.7265	3.9469	0.4939	Cause
NBC2	1.6101	1.2864	2.8965	0.3237	Cause
NBC3	1.1507	1.2575	2.4082	-0.1068	Effect
NBC4	1.0935	2.2098	3.3032	-1.1163	Effect
NBC5	0.9975	1.3510	2.3485	-0.3535	Effect
NBC6	1.3928	0.8707	2.2634	0.5221	Cause
NBC7	1.0859	0.8490	1.9350	0.2369	Cause

Table 9. DEMATEL output related to RPs

Pillars	D	R	D+R	D-R	Cause-effect?
RP1	0.8733	1.3917	2.2650	0.5184	Cause
RP2	0.5694	1.4835	2.0529	-0.9141	Effect
RP3	1.0476	1.3581	2.4058	-0.3105	Effect
RP4	2.0490	0.8919	2.9408	1.1571	Cause
RP5	1.4658	0.8798	2.3456	0.5860	Cause

Table 10. Numerical weights for NBC/RPs revealed via DEMATEL

Aspect	Criteria/Pillars	Weight	Ranking
NBC	**NBC1**	0.2648	1
	NBC2	0.1944	3
	NBC3	0.1616	4
	NBC4	0.2216	2
	NBC5	0.1576	5
	NBC6	0.1519	6
	NBC7	0.1298	7
RSP	**RP1**	0.1886	4
	RP2	0.1709	5
	RP3	0.2003	2
	RP4s	0.2449	1
	RP5	0.1953	3

4.1.2 Ranking suppliers via TOPSIS

In this section, the evaluation and ranking of suppliers are presented. In the individual meeting with the five decision makers, they were asked to evaluate the six suppliers of metal sheet vis-a-vis NBC/RPs using the scale presented in Table A2. Table 11 shows the aggregated decision evaluation matrix by taking the mean values of the five decision matrices.

Table 11. Aggregate decision matrix for TOPSIS

	NBC1	NBC2	NBC3	NBC4	NBC5	NBC6	NBC7	RP1	RP2	RP3	RP4	RP5
S1	4	5	5.5	4	7	6.5	7	3	2	5	3.5	5
S2	6.5	6	6.5	5	7.5	6.5	3	5	7	5	6.5	7
S3	7	5.5	6	6	4.5	4.5	4	4	4.5	7	4.5	5
S4	3.5	3	5	6.5	6.5	4	4	3	4	3.5	3.5	3
S5	6	5	4.5	6.5	4.5	5	6	5	5	7	7	7
S6	4	5	5.5	6	2.5	4	2.5	3.5	3.5	3	5	3.5

Based on the decision matrix, the normalised decision matrix was generated by applying Eq. 10, as shown in Table 12. The weighted normalised decision matrix was then generated by multiplying the normalised decision matrix by the relative weight of NBC/RPs (see Table 10) as shown in Table 13. This was followed by measuring the distance from best/worst performance for each supplier form NBC/RPs, individually. Tables 14 and 15 present the outcome of the latter step.

Table 12. Normalised decision matrix for TOPSIS

	NBC1	NBC2	NBC3	NBC4	NBC5	NBC6	NBC7	RP1	RP2	RP3	RP4	RP5
S1	0.718	0.921	0.957	0.686	1.228	1.177	1.360	0.619	0.392	0.905	0.639	0.905
S2	1.167	1.105	1.132	0.857	1.316	1.177	0.583	1.031	1.373	0.905	1.187	1.268
S3	1.257	1.013	1.044	1.029	0.789	0.815	0.777	0.825	0.883	1.268	0.822	0.905
S4	0.629	0.552	0.870	1.115	1.140	0.724	0.777	0.619	0.784	0.634	0.639	0.543
S5	1.078	0.921	0.783	1.115	0.789	0.905	1.166	1.031	0.981	1.268	1.278	1.268
S6	0.718	0.921	0.957	1.029	0.439	0.724	0.486	0.722	0.686	0.543	0.913	0.634

Table 13. Weighted normalised decision matrix for TOPSIS

	NBC1	NBC2	NBC3	NBC4	NBC5	NBC6	NBC7	RP1	RP2	RP3	RP4	RP5
S1	0.190	0.179	0.155	0.152	0.194	0.179	0.177	0.117	0.067	0.181	0.156	0.177
S2	0.309	0.215	0.183	0.190	0.207	0.179	0.076	0.195	0.235	0.181	0.291	0.248
S3	0.333	0.197	0.169	0.228	0.124	0.124	0.101	0.156	0.151	0.254	0.201	0.177
S4	0.166	0.107	0.141	0.247	0.180	0.110	0.101	0.117	0.134	0.127	0.156	0.106
S5	0.285	0.179	0.127	0.247	0.124	0.138	0.151	0.195	0.168	0.254	0.313	0.248
S6	0.190	0.179	0.155	0.228	0.069	0.110	0.063	0.136	0.117	0.109	0.224	0.124

Table 14. Distance to best performance for TOPSIS

	NBC1	NBC2	NBC3	NBC4	NBC5	NBC6	NBC7	RP1	RP2	RP3	RP4	RP5
S1	0.143	0.036	0.028	0.095	0.014	0.000	0.000	0.078	0.168	0.073	0.156	0.071
S2	0.024	0.000	0.000	0.057	0.000	0.000	0.101	0.000	0.000	0.073	0.022	0.000
S3	0.000	0.018	0.014	0.019	0.083	0.055	0.076	0.039	0.084	0.000	0.112	0.071
S4	0.166	0.107	0.042	0.000	0.028	0.069	0.076	0.078	0.101	0.127	0.156	0.141
S5	0.048	0.036	0.056	0.000	0.083	0.041	0.025	0.000	0.067	0.000	0.000	0.000
S6	0.143	0.036	0.028	0.019	0.138	0.069	0.113	0.058	0.117	0.145	0.089	0.124

Table 15. Distance to worst performance for TOPSIS

	NBC1	NBC2	NBC3	NBC4	NBC5	NBC6	NBC7	RP1	RP2	RP3	RP4	RP5
S1	0.024	0.072	0.028	0.000	0.124	0.069	0.113	0.000	0.000	0.073	0.000	0.071
S2	0.143	0.107	0.056	0.038	0.138	0.069	0.013	0.078	0.168	0.073	0.134	0.141
S3	0.166	0.089	0.042	0.076	0.055	0.014	0.038	0.039	0.084	0.145	0.045	0.071
S4	0.000	0.000	0.014	0.095	0.111	0.000	0.038	0.000	0.067	0.018	0.000	0.000
S5	0.119	0.072	0.000	0.095	0.055	0.028	0.088	0.078	0.101	0.145	0.156	0.141
S6	0.024	0.072	0.028	0.076	0.000	0.000	0.000	0.019	0.050	0.000	0.067	0.018

Then, the distance of each supplier from the positive ideal solution (d_i^+) and from the negative ideal solution (d_i^-) from all NBC/RPs were determined. Finally, the closeness coefficient value (*CC*) was determined by applying Eq.37. The ranking of suppliers was taken based on the revealed *CC* value. Table 16 presents values of d_i^+ , d_i^- , *CC* and the final ranking of the six suppliers. Figure 4 shows a graphical illustration regarding suppliers' normal business performance, resilience performance, and total normal business and resilience performance.

Table 16. The rank of suppliers based on their *CC* value

	d_i^+	d_i^-	CC	Rank
S1	0.317	0.223	0.413	4
S2	0.141	0.371	0.725	1
S3	0.206	0.291	0.585	3
S4	0.359	0.166	0.317	5
S5	0.143	0.349	0.709	2
S6	0.348	0.141	0.289	6

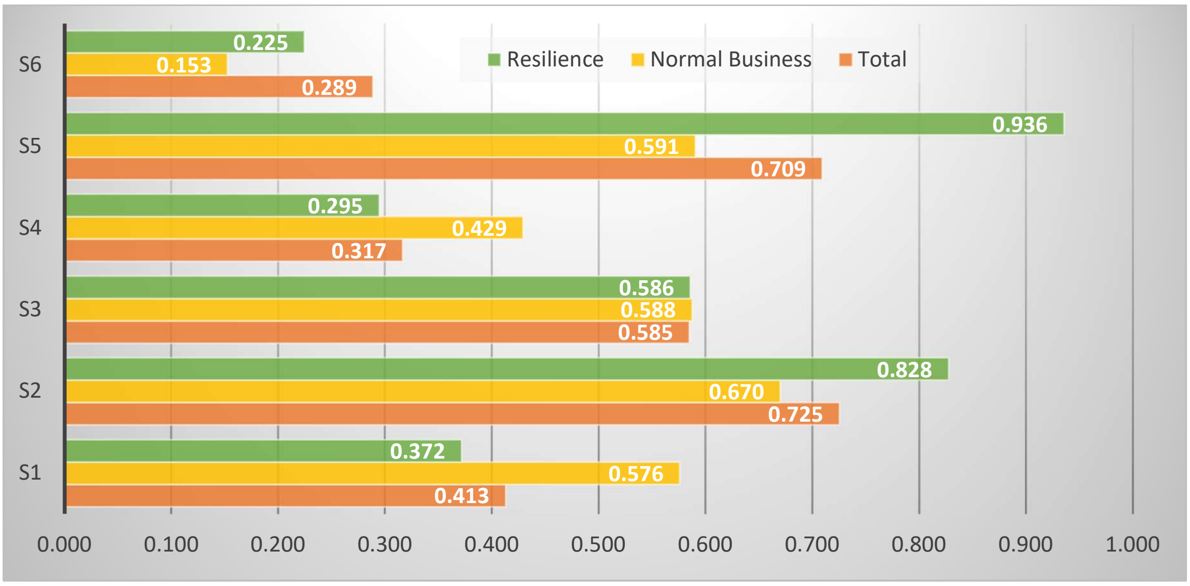


Figure 4. Suppliers' performance.

4.1.3 Sensitivity analysis

This section presents two sensitivity analyses that were accomplished to explore the robustness of the DEMATEL-TOPSIS evaluation process.

1. Sensitivity analysis via criteria weights

This analysis aims to change criteria weights and explore the correspondence suppliers' rank. To this end, 10 different sets (see Table 17) of weights were assigned randomly to NBC/RPs in the TOPSIS application (Eq.33 in the Appendix). Table 18 shows the obtained 10 ranks of suppliers based on the new 10 sets of NBC/RPs weight. The criteria weight sensitivity analysis proved that this model is partially subject to variation based on criteria weight as quite a few ranks (see Table 18) show reversal for some suppliers. This can be observed in sets 4 and 10 whereas supplier 2 is ranked second rather than its 1st rank in the other eight sets. Similarly, supplier 1 is ranked the 5th in sets 8 and 10 compared to its 4th rank in the others. This minor changes in the ranking could be due to a major variation in the weight of one, or more, of the important criteria. However, arguably, the model showed robustness in ranking suppliers 2 and 5 as the 1st and 2nd best suppliers for most sets of criteria weights, respectively.

Table 17. 10 different sets of weights assigned to the TOPSIS approach

Set	**NBC1**	**NBC2**	**NBC3**	**NBC4**	**NBC5**	**NBC6**	**NBC7**	**RP1**	**RP2**	**RP3**	**RP4**	**RP5**
1	0.692	0.692	0.494	0.791	0.198	0.791	0.494	0.593	0.395	0.198	0.296	0.494
2	0.791	0.593	0.889	0.889	0.791	0.099	0.099	0.593	0.395	0.692	0.198	0.494
3	0.099	0.494	0.494	0.296	0.494	0.889	0.494	0.198	0.395	0.198	0.494	0.296
4	0.593	0.593	0.889	0.494	0.692	0.198	0.296	0.296	0.889	0.296	0.791	0.692
5	0.494	0.395	0.889	0.889	0.791	0.395	0.198	0.099	0.692	0.296	0.791	0.198
6	0.889	0.395	0.198	0.889	0.296	0.593	0.791	0.494	0.395	0.296	0.494	0.494
7	0.395	0.296	0.296	0.791	0.099	0.494	0.494	0.889	0.099	0.395	0.692	0.395
8	0.494	0.099	0.099	0.099	0.889	0.198	0.494	0.593	0.494	0.593	0.791	0.099
9	0.296	0.198	0.296	0.791	0.593	0.791	0.889	0.791	0.395	0.395	0.198	0.494
10	0.198	0.395	0.296	0.692	0.889	0.395	0.296	0.099	0.494	0.395	0.791	0.099

Table 18. Ranking of the six suppliers in correspondence to the 10 sets of criteria weights

Set	Correspondence rank
1	S2>S5>S3>S1>S4>S6
2	S2>S5>S3>S1>S4>S6
3	S2>S5>S3>S1>S4>S6
4	S5>S2>S3>S4>S3>S6
5	S2>S5>S3>S1>S4>S6
6	S2>S5>S3>S1>S4>S6
7	S2>S5>S3>S1>S4>S6
8	S5>S2>S3>S4>S1>S6
9	S2>S5>S3>S1>S4>S6
10	S2>S5>S3>S4>S1>S6

2. Sensitivity analysis via other MADM approaches

In this analysis, the obtained rank via TOPSIS was validated via the application of other well-known MADM approaches known as MAPAC, VIKOR, MAIRCA and OCRA to compare the output. Table 19 shows the revealed rank for the six suppliers based on these approaches. It can be inferred that the obtained rank in having suppliers 2 and 5 ranked as the 1st and 2nd, respectively, is validated as all other approaches led to the same ranking apart from OCRA that ranked supplier 5 in the 3rd position. However, this is common considering the difference in the application steps among MADM approaches. It should be noted that these approaches were applied using the same criteria weight, previously shown in Table 10.

Table 19. Validation of suppliers' ranking via other MADM approaches

Approach	Correspondence rank
TOPSIS	S2>S5>S3>S1>S4>S6
MAPAC	S2>S5>S1>S3>S4>S6
VIKOR	S2>S5>S3>S1>S4>S6
MAIRCA	S2>S5>S3>S1>S4>S6
OCRA	S2>S4>S5>S3>S6>S1

4.2 Allocating order quantity via MADM-PBOPM

In this section, the MADM-PBOPM (see section 4.2.1) was solved by using the ε-constraint method by keeping the minimisation of the total related cost as an objective function and limiting the maximisation of resilient sourcing value by an ε-value in the constraint set. Table

20 presents related data collected from Company X and retrieved from DEMATEL-TOPSIS. Data related to the uncertain inputs (i.e., transportation and purchase costs, supply capacity and demands) were set as fuzzy numbers in between the presented range. To achieve ε values, the maximum and minimum values for objective function two were determined via the individual optimisation (see Eqs.15 and 18). Then, the distance between the maximum and minimum values were segmented into ten segments. Each of the latter was assigned as an ε-value to derive a set of ten Pareto solutions. Regarding the integration between the output of DEMATEL-TOPSIS and PBOPM, the obtained relative importance and suppliers 'scores were derived from Tables 10 and 16, respectively. Finally, ten α-levels (from 0.1 to 10) were assigned incrementally, by a step of 0.1, to the constraint equations 9-11 in every iteration.

Table 21 presents the derived set of Pareto solutions, the membership functions values and the assigned ε-value for each solution. Pareto front between the two objectives is depicted in Figure 5. For instance, Solution#1 in Table 18 was achieved by an assignment of ε-value of 782.236 that led to a minimum total related cost equal to 88,8214.69 and a maximum resilient sourcing value equal to 789.88. Table 22 and Figure 6 present the revealed distribution of order quantities of metal sheet among the six suppliers.

Table 20. Real parameters collected for the application of MADM-PBOPM

	S1	S2	S3	S4	S5	S6
C_i^p £/unit	40	45	42	39	40	40
C_i^t £/mile	1.5	1.7	1.5	1.3	1.5	1.5
C_i^a *£/unit*	1.2	1.2	1.2	1.2	1.2	1.2
d_i *(mile)*	150	13	122	82	133	98
TC (units)	100	100	100	100	100	100
S_i (unit)	21850	16100	9200	6900	5750	9500
D_{min} (units)			20286			
D_{max} (units)			24380			
w^n	0.398	0.398	0.398	0.398	0.398	0.398
w^r	0.602	0.602	0.602	0.602	0.602	0.602
o_i^n	0.576	0.670	0.588	0.429	0.591	0.153
o_i^r	0.372	0.828	0.586	0.372	0.828	0.586

Table 21. Pareto solutions derived from the MADM-PBOPM via ε-constraint

#	α-level	μ_{RC}	μ_{RSP}	ε-value	Min RC	Max RSP
1	0.1	0.96	0.056	782.236	888214.69	789.88
2	0.2	0.81	0.15	795.123	894259.366	795.123
3	0.3	0.76	0.23	808.0345	910235.787	808.0345
4	0.4	0.70	0.31	820.9215	926212.185	820.9215
5	0.5	0.65	0.50	833.8085	942188.606	833.8085
6	0.6	0.59	0.58	846.6955	958165.027	846.6955
7	0.7	0.39	0.65	859.5825	974141.425	859.5825
8	0.8	0.25	0.77	872.4695	990117.846	872.4695
9	0.9	0.13	0.89	885.3565	1006107.676	885.3565
10	1	0.043	0.97	898.2435	1022118.275	898.2435

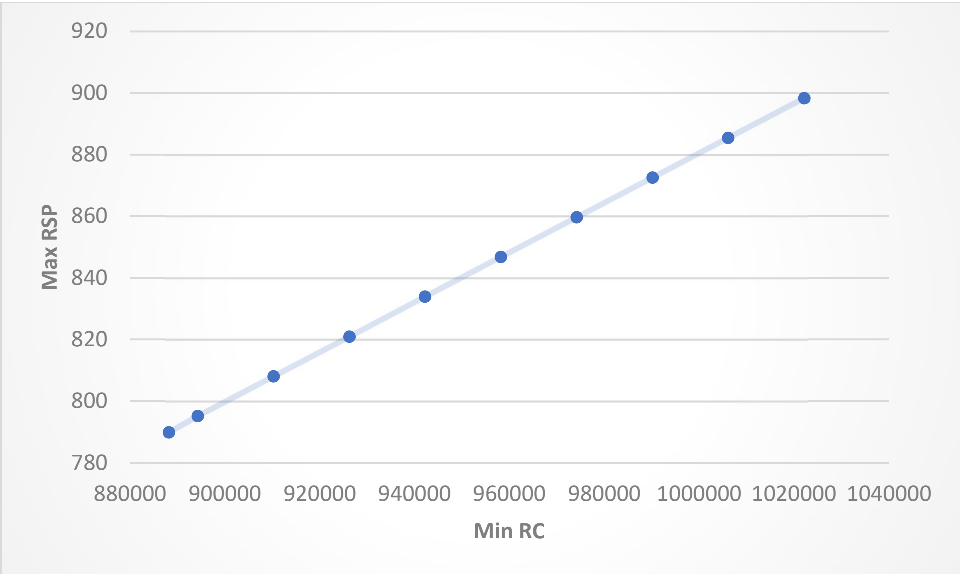


Figure 5. Pareto front between minimum related costs and maximum resilient sourcing value.

Table 22. Purchasing allocation among the six suppliers for Pareto solution#1

	Order allocation					
#	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
1	7342.359	6900	0	293.641	5750	0
2	6240.406	6900	1552.822	0	5750	0
3	5461.212	6900	2710.205	0	5750	0
4	4682.018	6900	3867.565	0	5750	0
5	3902.801	6900	5024.948	0	5750	0
6	3123.607	6900	6182.331	0	5750	0
7	2344.413	6900	7339.714	0	5750	0
8	1565.196	6900	8497.097	0	5750	0
9	749.2770	6900	9200,000	360.6630	5100	790.320
10	374.3020	6900	8439.770	1106.142	5750	932.901

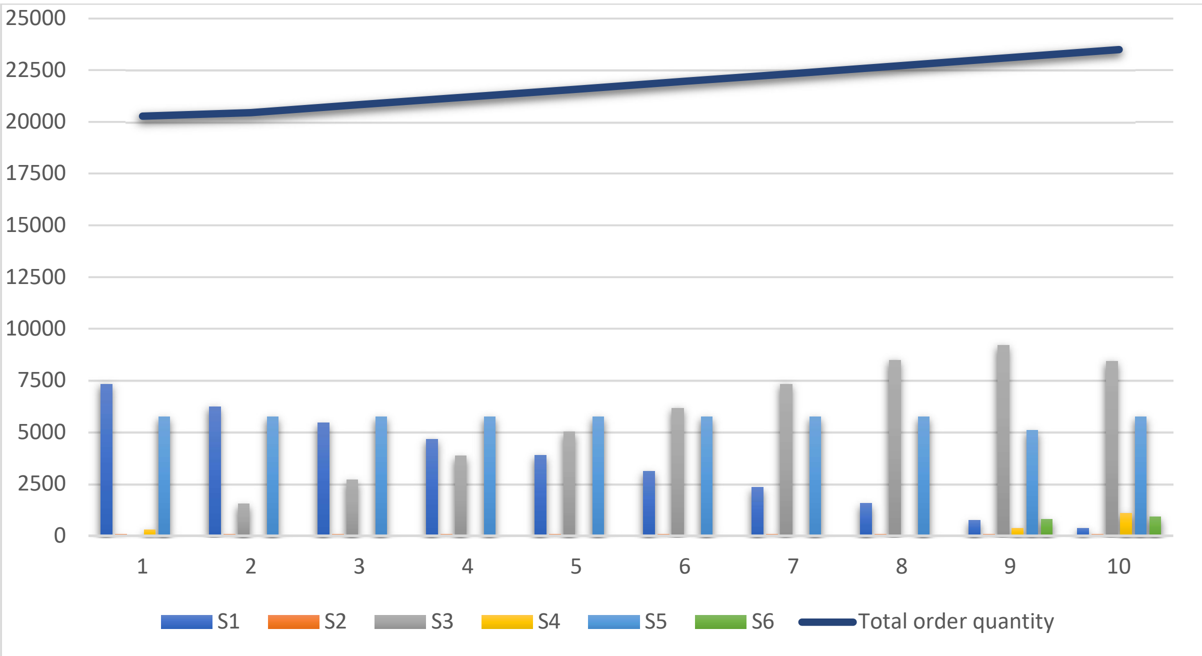


Figure 6. Quantity allocation among the six suppliers for Pareto solution#1.

Finally, the purchasing team should select one solution out of the ten (See Table 21) to achieve the final trade-off between minimisation of total related cost and resilient sourcing value and the order allocation among suppliers. Arguably, this was a challenging decision for the purchasing manager, particularly because the purchasing team is not familiar with such an output with precise details about related costs, resilient sourcing score and suppliers scores. Therefore, the research team suggested the application of global criterion approach to relax the purchasing team in identifying the appropriate output. The global criterion approach was used by applying Eq. 22 on the revealed Pareto solutions individually. Based on this step, solution#4 was identified as the possible appropriate solution because it turned out the shortest distance (Min X = 0.239) to the ideal solution. In this solution, only four suppliers are considered for purchasing the metal sheet. Figure 7 depicts the final allocation of required metal sheet quantities among the selected suppliers.

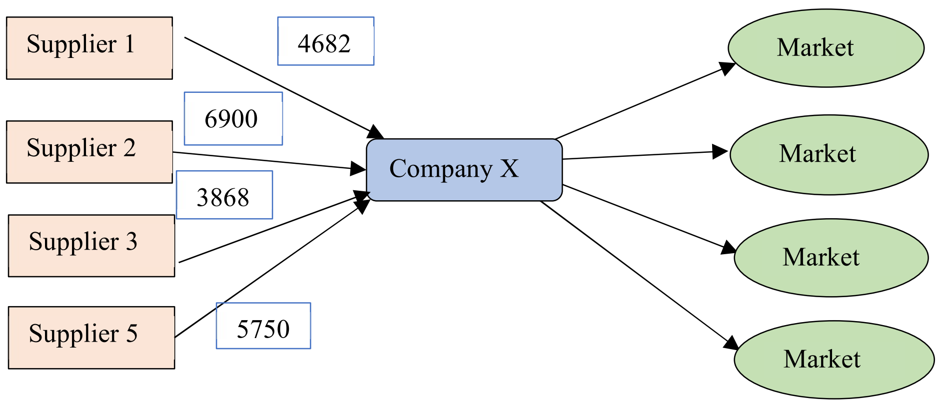


Figure 7. Metal sheet orders from the four suppliers based on solution#4.

4.3 Discussion

SC networks are prone to disruptions as a result of various potential unanticipated events e.g., natural catastrophes, terrorists and strikes. The concern of SC disruption is increasing due to growing need for globalisation and strategic suppliers. As a result, selection of resilient suppliers has become a paramount need for industry sector towards continuous competitive advantage. This is because the disruption in supply can halt companies' business and potentially impedes other activities along the SC network.

This study was conducted to support the purchasing team at a manufacturing company in developing its purchasing strategy towards SCR with a focus on selecting suppliers based on the resilience performance. To this end, an integrated hybrid MADM-PBOPM was developed to help decision makers to easily evaluate suppliers 'performance and allocate orders among them, accordingly.

The first stage of the research output (see section 5.1.1) showed the superiority of RPs over NBC since they revealed higher importance weights based on decision makers' evaluation. This conforms with the company's general goal towards achieving a resilient business as justified by the purchasing manager. The research team expects that once the decision makers build up the company's resiliency, the evaluation would reveal the traditional superiority of NBC. In the same context, RPs of development revealed the highest weight (0.2449) followed by robustness (0.2003) as presented in Table 15. This was justified by the purchasing manager that current suppliers have elements of other pillars e.g., flexibility and agility but there is a lack of robustness and resilience development based on experienced disruptions. However, the research team argued, with the purchasing team, that the sensing pillar should also be taken into account since it has a significant contribution in elevating resilience performance. Finally, it was agreed to run the evaluation of NBC/RPs after addressing the resilience concern.

In the supplier evaluation context (see section 5.1.2), arguably, all supplier revealed low performance. It is hereby worthy to mention that the suppliers' evaluation results were validated via two sensitivity analysis approaches. First, 10 different sets of criteria weights were assigned to the TOPSIS approach to explore its impact on the obtained suppliers' rank. Second, the evaluation was conducted by using other four MADM approaches (i.e., VIKOR, OCRA, MABAC, and MAICRA) and the results were compared. Suppliers can be segmented into three segments based on the CC values presented in Table 16:

1. good performance ($7 < CC < 8$): suppliers 2 and 5;
2. intermediate performance ($CC >= 5$): supplier 3; and
3. low performance ($CC < 5$): suppliers 1, 4 and 6.

It was agreed to prioritise the improvement of supply performance with suppliers 1, 4 and 6. This improvement includes either working with these suppliers to improve their performance based on the identified pillars or switch to other suppliers. Once those suppliers are either improved or replaced by others, the purchasing team will work on improving intermediate performance suppliers followed by good performance suppliers. Finally, it is worthy to mention that the supply of metal sheet will be limited by four suppliers as per the potential purchasing strategy to be achieved by 2020.

The last stage of the research output presented the optimal allocation of quantities of orders among suppliers. Based on the selected solution (Solution#4 in Table 19), the purchasing team was advised to satisfy its company need from the metal sheet by ordering 4,682 units from supplier 1, 6,900 units from supplier 2, 3,868 units from supplier 2 and 5,750 from supplier 5, as previously shown in Figure 7. A shown in Table 19, most solutions present no orders allocated to suppliers 4 and 6. These suppliers were categorised in the low performance group that needs urgent performance improvement or replacement. This was achieved by the integration of weight of NBC/RPs and supplier’s performance into the order allocation planning determined via PBOPM.

Finally, the purchasing manager suggested to apply the quantification of NBC/RPs twice a year. Also, the supplier evaluation to be conducted after every supplier visit or receival of a new supply proposal from suppliers. The research team hereby frozen all equations and coding of DEMATEL/TOPSIS apart from the decision matrices that will be used frequently by the purchasing team.

4.4 Managerial and theoretical implications

This methodology helped the purchasing team in identifying a clear resilience sourcing approach. It includes a decision-making tool used for diagnosing current suppliers ’resiliency. Based on this evaluation, the purchasing team was advised to work heavily with most suppliers to enhance their performance vis-à-vis RPs. Otherwise, those low performance suppliers will have to leave the field to new more resilient suppliers. In terms of being resilient to demand, the formulated bi-objective model has proved its applicability to handle uncertain demand considering the two defined objectives. The purchasing manager clarified that the proposed evaluation approach shall be followed in the upcoming evaluation processes that are scheduled every six months for current suppliers. This will be conducted by asking buyers to evaluate suppliers and then return their evaluation to the purchasing manager who will insert them into the Excel sheet for the aggregation and final evaluation. Furthermore, it was suggested to review their evaluation regarding criteria every six months as well as to consider any possible changes into their business orientation.

In terms of theory, this research presents a new framework represented by Sensing, Agility, Robustness, Development and Flexibility towards resilient supplier profile. This framework was built not only based on literature, but also expert’s opinions to accommodate real resilient sourcing needs. Furthermore, the proposed methodology presents the integration between MADM methods’ output and multi-objective optimisation modelling. This helps in incorporating both quantitative and qualitative evaluation – based on decision makers’ opinions – into the mathematical optimisation. It was approved that decision makers’ evaluation, given for the MADM application procedures, is given attention in the assigned order sizes where low performance suppliers were excluded.

5. Conclusions

In modern SCs, decision makers need to manage globalized chains including dealing with various national and international firms. This modernisation led companies getting more and more possible threats of SC disruptions due to unexpected events e.g., supplier closure, human-made catastrophes, and natural disaster. For instant, current COVID-19 pandemic has affected several SCs. Dun and Bradstreet (2020) mentioned that Wuhan city houses one or more direct suppliers for 51,000 firms and one or more tier-two suppliers for at least 5 million firms around the world. Among factors that may influence SCR, suppliers and demand uncertainty play a paramount role in being proactive and reactive against SC disruptions. Thus, it is significant to diagnose the surviving ability of (1) suppliers vis-à-vis resilience pillars; and (2) companies to cope with uncertain demand.

In view of the significant role of being operationally resilient to supply and demand towards a robust business against SC disruptions, this work proposes supplier selection and order allocation methodology to deliver a resilient business to supply and demand disruptions. The work begun by exploring SCR pillars, in the sourcing context, towards a unified framework to assess suppliers' performance. This includes NBC (e.g., purchasing cost and delivery reliability) and RPs (e.g., flexibility and agility). Then, the relative importance of these criteria/pillars were quantified via DEMATEL and then its outcome used in TOPSIS to assess suppliers 'resiliency. Next, to have a business that is resilient to demand uncertainty, the PBOPM was developed, incorporating the outcome from DEMATEL (relative criteria weight) and TOPSIS (supplier's performance score). Two objectives were formulated towards the minimisation of total related costs of sourcing and maximisation of resilient sourcing value. Then, this model was optimised in revealing a set of solutions by applying the ε-constraint approach. Finally, the final possible appropriate solution was recommended based on the global criterion outcome.

This research has some limitations that could be explored in future research agendas. This work might be extended by simulating several scenarios for short- and long-term supply disruptions by some suppliers. Also, the impact of other supply resilience factors such as environmental uncertainty on business resiliency could be examined. In this case study, there are six suppliers evaluated by five decision makers, it would be useful to investigate the efficacy of the current methodology in a case of larger numbers of suppliers and decision makers. Mainly, this will examine how the order allocation would be set by having many suppliers. Furthermore, the experts' opinions were taken as certain inputs which may not reflect the most real-world states, and therefore further development might employ the fuzzy set theory to capture closer evaluations. In this context, the relative importance weights of NBC, RPs, and normal busines and resilience performance scores were rated subjectively by buyers/managers, and thus it is recommended to conduct a sensitivity analysis on the changes in these weights. Finally, the application and evaluation of the presented methodology was limited by a manufacturing company in one country. Future research could apply this methodology to other sectors and countries.

Appendix A

DEMATEL

In this research, DEMATEL was implemented as follows (Tzeng et al., 2007; Wu et al., 2021; and Mohammed, 2020):

Step 1: Apply Eq.23 to build the direct-relation matrix C to compare among criteria based on the scale listed in Table A1.

Table A1. Initial evaluation scale

Linguistic Variable	Scale
No influence (NI)	0
Low influence (LI)	1
Medium influence (MI)	2
High influence (HI)	3
Very high influence (VHI)	4

$$C = \frac{C_1 + C_2 + \cdots + C_m}{m} = \begin{bmatrix} 0 & c_{12} & \dots & c_{1i} & \dots & c_{1n} \\ c_{21} & 0 & \dots & c_{2i} & \dots & c_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ c_{i1} & \dots & \dots & \dots & \dots & c_{in} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ c_{n1} & c_{n2} & \dots & c_{ni} & \dots & 0 \end{bmatrix} \quad (23)$$

c_{ij}^{k} represents the judgement of the $\underline{k^{th}}$ decision makers, *m* is the number of participants and *n* is a number of evaluation criteria.

Step 2: Apply Eqs.24 and 25 to build the normalised direct-relation matrix *N*.

$$N = x \cdot C \quad (24)$$

where

$$x = min\left[\frac{1}{max\sum_{i=1}^{n} c_{ij}}, \frac{1}{max\sum_{j=1}^{n} c_{ij}}\right] (i, j = 1,2, \dots, n) \tag{25}$$

Step 3: Apply Eq.26 to build the total-relation matrix T that illustrates the relationship among criteria.

$$\mathrm{T} = \mathrm{N}(\mathrm{I} - \mathrm{N})^{-1} \tag{26}$$

Step 4: Measure the $D_k + R_k$ value and $D_k - R_k$ value to categorise each criterion either as a cause or an effect as follows:

$$\mathrm{D}_i = \sum_{j=1}^{n} t_{ij} \ (i = 1,2, \dots, n) \tag{27}$$

$$\mathrm{R}_j = \sum_{i=1}^{n} t_{ij} \ (j = 1,2, \dots, n) \tag{28}$$

Step 5: Apply Eq.29 to quantify the relative weight of criteria.

$$w_n = \frac{D_k + R_k}{(\sum_{k=1}^{n}(D_k + R_k))} \tag{29}$$

TOPSIS

TOPSIS was applied as follows (Mohammed et al., 2019; and 2021):

Step 1: Build the normalised decision matrix (*N*) via Eqs.30 and 21. Table A2 lists the linguistic and numerical scale applied for assessing alternatives.

$$N = \left[d_{ij}\right] \tag{30}$$

where

$$n_{ij} = \left(\frac{d_{ij}}{\sqrt{\sum_i d_{ij}^2}}\right) \tag{31}$$

Where d_{ij} are element from the decision matrix build by decision makers to evaluate supplier *i* vis-à-vis criterion *j*.

Step 2: Multiply matrix N_{ij} by the weight for NBC/RPs as in Eq.32 to build the weighted normalised decision matrix W.

$$W = \left[e_{ij} \right]_{nxm} \tag{32}$$

where e_{ij} is obtained by using the following equation:

$$e_{ij} = n_{ij} \; w_j \tag{33}$$

Step 3: Measure the distance from the positive (A^{+}) and negative (A^{-}) ideal solutions from each NBC/RPs for each supplier as follows:

$$A^{+} = \left\{ v_1^{+}, v_2^{+}, \ldots, v_i^{+} \right\} \tag{34}$$

$$A^{-} = \left\{ v_1^{-}, v_2^{-}, \ldots, v_i^{-} \right\} \tag{35}$$

Step 4: Measure the distance of each supplier from the positive ideal solution (d_i^{+}) and from the negative ideal solution (d_i^{-}) for all NBC/RPs as follows:

$$d_i^{+} = \sum_{j \in n} d \left(v_{ij}, v_j^{+} \right); \; d_i^{-} = \sum_{j \in n} d \left(v_{ij}, v_j^{-} \right); \tag{36}$$

where v_j^{+} and v_j^{-} are the positive and negative ideal points for criterion 'j', respectively.

Step 5: Measure the closeness coefficient (CC) as shown in Eq.37.

$$CC = \frac{d_i^{-}}{d_i^{+} + d_i^{-}} \tag{37}$$

Table A2. linguistic and numerical scale applied for assessing alternatives

Linguistic Variable	Scale
Very Low (VL)	1
Low (L)	3
Medium (M)	5
High (H)	7
Very High (VH)	9

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