Resilient supply chain network design without lagging sustainability responsibilities.

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Abstract

In the 21st century, global supply chains have experienced severe risks due to disruptions caused by crises and serious diseases, such as the great tsunami, SARS, and, more recently, COVID-19. Building a resilient supply chain is necessary for business survival and growth. Similarly, there is increasing regulatory and social pressure for managers to continuously design and implement sustainable supply chain networks, encompassing economic, social, and environmental components. Hence, a panacea approach is required to establish a compromise position between resiliency concerns and sustainability responsibilities. To address this, this work presents a hybrid integrated BWM-CoCoSo-multi-objective programming model (BC-MOPM) formulated to deliver a compromise between resilience and sustainability supply chain network design (RS-SCND). First, a thorough literature review analysis is conducted to explore the relationship and correlation between resilience and sustainability to develop a framework for the resiliency and sustainability criteria, in a supply chain context. Second, four objectives were formulated, including the minimisation of total cost and environmental impact and the maximisation of social and resilience paradigms. A real two-tier supply chain network is deployed to evaluate the applicability of the developed BC-MOPM. Furthermore, sensitivity analysis is conducted to establish the relative importance of the identified criteria to prove the model's robustness. Results demonstrate the capability of the BC-MOPM in revealing trade-offs between the resiliency and sustainability aspects.

Keywords: Resilient supply chain; Sustainable and resilient supply chain; Multi-objective optimisation; Social aspect; COVID-19 disruption.

1. Introduction

Technological developments and growing complexities in the global economy have made supply chain networks (SCNs) more vulnerable to disruptions caused by both natural disasters and human factors [1][2]. The growing need to evolve supply chain processes technologies might contribute to the uncertainty of operations [3]. Similarly, the embedding of new technologies into supply chain operations opens the door for possible technical risks that might lead to supply chain disruption [4][5] and [6].

Modern SCNs encounter different types of disruptions, largely due to uncertain and turbulent markets such as the 2008 global financial downturn [7] or pandemics, such as the COVID-19 pandemic disruption risks. The COVID-19 pandemic has focused attention on the paramount need for SC resilience to sustain economies and societies. Supply chain resilience is the ability to resist and recover quickly from disruptions and glitches. Resilience is the capability to alleviate most supply chain disruptions and minimise the effects when they occur [8] [9].

Over the last two decades, sustainable supply chain management has emerged as another crucial orientation for researchers and managers to comply with constitutional restrictions and societal needs. It refers to the simultaneous merging of three criteria, known as economic, environmental, and social [10] [11]. Supply chain disruptions can have a massive negative impact on economic sustainability. For instance, COVID-19 disruptions led to shortages and price increases of essential consumer goods, such as medical supplies, and the closure of several plants and transportation networks throughout global supply chains. In addition, supply chain disruptions might weaken social and environmental sustainability, causing managers to fight to achieve their positions during disruption events. Therefore, environmental sustainability practices are questionable due to the nature of various disruptions. Managers are motivated to build supply chain resilience to sustain their business. However, it is important to achieve supply chain resilience without disrupting economic, environmental, and social performance in supply chains. The relationships and correlations between resilience and sustainability are further discussed in section 2.3.

1.1 Problem statement

The need for resilient SCs, without disrupting sustainability responsibilities, has initiated the concept of resilient and sustainable supply chain network design (RS-SCND) proposed in this study; the concept is based on the ongoing debates in resilient SCNs [12] [13] [14] [15] and sustainable SCNs [16] [17] [14] [18]. The field of supply chain sustainability remains subject to common disruption events, whether expected or unexpected, that call for a formulation and analysis of sustainability aspects concerning these challenges. In the SCND context, although the positive impact of RS-SCND in addressing disruptions has been recognised in recent studies [19] [1] [20], there is a distinct lack of appropriate quantitative methodologies to develop a robust RS-SCND. [21] [22], and [23] mentioned that decision support systems and optimisation methodologies might boost resilient SCNs considering sustainability aspects. Where current literature shows a growing level of research on resilient SCNs and sustainable SCNs, there is still a gap in designing resilient SCNs that consider sustainability responsibilities. In industry, organisations are often in situations in which initiatives towards resiliency and sustainability influence each other. For instance, designing a sustainable SCN needs to only select facilities that are more sustainably developed. However, selecting a better sustainable-performance facility might lag in terms of flexible and agile facilities that are strongly needed to withstand a supply disruption. In this SCND mindset, managers would limit their options with those partners with strong relationships and collaborations towards sustainability. Therefore, this research aims to fill the gap by developing a quantitative model to improve resilience, economic, environmental, and social performance in periods of supply chain disruptions.

The agri-food supply chain is particularly crucial for most retailers nationwide because of the higher order frequency, especially for fresh fruit, vegetables, meats, etc. A significant impact of COVID-19 has been identified on the whole process, ranging from agricultural fields to consumers [24]. Uncertainty about the food supply during this period resulted in the lack of stock in different kinds of stores, although governments facilitate, with a higher priority, the movement of workers and agri-food products. A case study of agri-food is used to validate the proposed model on all of the four performance aspects mentioned above.

1.2 Research objectives

Considering the challenges identified and the importance of RS-SCND to business competitiveness, this study aims to address the following objectives (OBJ):

OBJ 1. To explore the relationship between resilience and sustainability paradigms in the context of supply chain management.

OBJ 2. To develop a theoretical framework of RS-SCND criteria.

OBJ 3. To evaluate supply facilities' performance vis-à-vis sustainability and resilience criteria.

OBJ 4. To build an empirical RS-SCND.

OBJ 5. To set the order size among multiple facilities based on minimum total cost and sustainability factors and resilient location value, to optimise the SCN structure.

The literature shows the absence of an applicable methodology that stimulates this work to promote a new integrated hybrid best-worst method (BWM) combined compromise solution (CoCoSo)-multi-objective programming model (BC-MOPM). Managers could use this model to obtain compromises among multiple, potentially conflicting, desires towards an effective SCN. RS-SCND is contingent depending upon the possible risks a given supply chain faces, and those risks differ from company to company and industry to industry [20]. However, the BC-MOPM deployed in this study provides a generic model for RS-SCND and it is validated on a real two-tier food supply chain network. To this end, the resilience, economic, environmental, and social performance are quantified via the application of a hybrid BWM-CoCoSo approach. This is followed by the development of a new optimisation model with four objectives to solve the SCND problem. The latter, and unlike other research, includes the multi-criteria decision-making (MCDM) methods, BWM-CoCoSo, with the outcomes integrated within its formulas. This integration supports the decision-making process by considering tangible factors such as costs and intangibles like flexibility, and social performance evaluation criteria into their SCND, including minimisation of total cost or maximisation of social performance.

The remainder of the paper is organised as follows: Section 2 presents literature related to resilient and sustainable SCNDs, research gaps, and research contributions. Section 3 introduces the research methodology consisting of the four stages undertaken to build the RS-SCND model. Section 4 analyses the application of the meat supply chain network, evaluates the BC-MOPM, and discusses the managerial and theoretical implications. Finally, Section 5 concludes the research and proposes directions for future studies.

2. Literature review

2.1 Resilient supply chain network design

Appropriate deployment of a SCND enables businesses to meet customer demand and sustain their market share. Conventionally, this body of knowledge presented an economic-oriented supply chain network design aimed at increasing profit margins [25]. SCND enables managers to consider a consistent and reliable supply of quality products [26] [27]. Recently, researchers and practitioners have given more attention to resilience SCND to efficiently sustain operations during and after disruptive events. A resilient SCN facilitates strategic planning to minimise the effect of disruptions [28] [15]. There are several strategies deployed by supply chains to manage the risk associated with major disruptions and to obtain a resilient SCN [14]. Implementing resilient strategies to mitigate the disruption risk might include keeping emergency stock at the retailers, reserving back-up capacity at the suppliers, and multiple sourcing. These strategies not only work to the advantage of the supply chain by sustaining and improving its market share but also customers benefit from more stable retail prices in the market. Resilient SCND and risk propagation analysis, including sourcing, reliable facility location and coordination, pricing, and risk sharing contracts are the major research concepts of risk mitigation in a supply chain network [29]. Note that building a resilient supply chain lies in developing both proactive and reactive plans. This requires several approaches to be considered: for instance, modelling disruption scenarios and their probability [30] [31], building strong collaboration with suppliers [32] [33], and developing proactive/or reactive strategies [34] [35]. The current work is scoped in building proactive supply chain resilience via the reconfiguration of SCN considering facilities' resilience performance vis-à-vis resilience criteria.

There is an increasing number of quantitative scholarly articles on supply chain resilience. Prior studies by [36] [37] [20] [38] [39] [40] [41] [42] explored and proposed supply chain resilience frameworks and models that will assist corporations in mitigating and managing supply chain disruptions. Similarly, [43] developed two two-stage stochastic models to configure a resilient SCN targeting a safety stock level. A review of extant studies revealed that despite the growing quantitative research for building resilient SCN, a vast majority of the literature has focused on quantifying supply chain resilient criteria rather than measuring supply chain resilient value as the objective for decision-makers [36].

In designing resilient SCNs, prior studies utilised mitigation strategies including flexibility, agility, preparedness, redundancy, and collaboration. SC resilience is built on the idea that firms need to create redundancy and flexibility that can be drawn upon if a disruption occurs [13]. Understanding customer's requirements and expectations in terms of relevant logistics performances can be achieved by introducing flexibility into a resilient SCND [9] [15]. However, an increasing number of studies have argued against the ability of resilient SCN to effectively tackle the multi-faceted problems associated with disruptions, suggesting that a sustainable SCND is more effective in this regard [17] [44].

2.2 Sustainable supply chain network design

The increasing impact of global warming has significantly changed the operational processes of the traditional SCN [45]. As resource depletion and environmental pollution problems are rapidly worsening, a sustainable SCN has received growing interest from both industry and research communities. Corporations are facing increasing challenges to balance economic performance with environmental and social issues [16] [18] [46]. The balance between cost curtailment and environmental protection has become an effective effort to boost sustainable competitiveness [45] [47] [48]. Businesses are responding to this issue by implementing sustainable management practices not only within their operations but also across their SCN [49]. Towards this target, managers have tried to merge sustainability development goals in their supply chain operations management; however, this practice requires applicable decision support models [49] [44]. It is suggested that corporations should invest more to protect environmental and social aspects in comparison with a situation in which only the economic aspect is considered [50].

Economic performance is paramount to supply chain sustainability [7]. The economic pillar of sustainable SCND includes cost, quality, historical performance, production capability, lead-time, reliability, and application of technology. Supply chain-related costs, such as procurement, production, distribution, inventory, and maintenance costs, are considered in sustainable SCND [51] [52] [53] [49] [53] [47] [54]. Other financial indicators, including credit period [55], performance history, market shares, production capacity, and operating expenses are also utilised in prior studies [56]. Appropriate government financial incentive subsidies based on products made with specific technologies significantly decrease the negative environmental impact of sustainable SCND [44]. Similarly, a risk-averse sustainable SCN was developed that considers various discount policies offered to customers in selecting the number of facilities and their related technology as well as the optimal flows across the network.

Carbon emissions across supply chain networks, most specifically by transportation, harm the environment pillar. Green inventory routing problems [57] [58], green logistics, and green economics have gained significant importance in SCND, especially in relation to carbon emissions [59]. Extant studies utilise resource consumption, pollution production, renewable and non-renewable energy consumption, and waste management as environmental indicators in a sustainable SCND [56]. Integrating appropriate carbon policies and regulatory frameworks in a sustainable SCND has environmental advantages. A SCN comprising suppliers, plants, distribution centres, direct shipment, and cross-docks was designed to minimise total costs and environmental effects by integrating SCND and order allocation problems simultaneously [60]. Similarly, shipment consolidation policies are utilised to reduce cost and environmental impact [16].

Burgeoning environment and societal concerns have stimulated quantitative sustainable supply chain-related studies that consider environmental, social, and economic criteria in SCND. Environmental criteria such as carbon emission were considered by [61] to build an optimisation model to minimise low-carbon production costs in a supply chain. Authors such as [17] [48] and [50] developed sustainable SCN models under uncertain conditions, which aim at maximising social benefits while minimising economic costs and environmental impacts. [62] integrated financial incentives into linear programming models to maximise supply chains' profit. Other recent studies by [56] [49], and [44] introduced sustainable SCN models to assist with location planning, routing, inventory management, and distribution.

Substantial numbers of SCND studies are conducted through the lenses of resilience and sustainability discretely. However, recent works, such as studies by [19] and [1] revealed that SCND should be dynamic and all-encompassing, consisting of both resilience and sustainable criteria, divulging the pressing need for RS-SCND frameworks and models. This study seeks to develop a hybrid integrated BC-MOPM model that incorporates all the elements of sustainability, along with the resilience to build a multi-tier RS-SCND to comprehensively assist in addressing the growing issue of supply chain glitches, including the disruptions that the world is currently witnessing due to COVID-19 restrictions.

2.3 Resilient and sustainable supply chain network design

To achieve research objective 1 (see section 1.1), this section explored the relationship between resilience and sustainability in SCND. Modern SCNs are threatened by both resiliency and sustainability-related issues, including flexibility, agility, redundancy, cost, as well as social and environmental concerns. In analysing the relationship between resilience and sustainability aspects, one may argue that facilities' capacity has a direct influence on supply chain resiliency [9] [23]. Similarly, societal and environmental attributes interface with resiliency and should be considered [63]. This approach informs the works of [64] and [18]. Corporations with resilient supply chains would gain superior operational performance which increases their market share and provides more sustainable development advantages. A sustainable supply chain that lags in resilience may not be able to sustain its operations in the long term, leading to limited demand fulfilment and competitiveness. The central relationship between resilience and sustainability proves the need for concurrent consideration of the two paradigms. Developing decision support systems and optimisation models might assist in building resilient supply chains without hampering sustainability performance [65] [21].

The positive correlation between resilience and sustainability has led to a pressing need for RS-SCND that simultaneously incorporates resilient and environmental considerations to manage network disruptions [19]. A recent RS-SCND-related study developed an integrated model for infrastructure networks as a strategy to mitigate power supply disruptions to improve economic and environmental performance, which revealed 21% and 25% reductions in terms of average total network cost and total carbon emissions respectively [1]. Another similar research established that while economic and environmental objectives can be conflicting, the integration of smart grids in electricity SCND can result in a concurrent increase in both environmental performance and network resilience under demand and supply uncertainties [20]. Exploration of the completeness and interrelationship between resilient and sustainability is still at an early phase [66] [63] [67] [20]

In the SCND context, research studies that simultaneously combine resilient and sustainable paradigms are scarce. Although several hybrid multi-attribute decision-making methods exist in the literature [68], the current work presents the first study that develops a hybrid integrated BC-MOPM model that incorporates all three elements of sustainability, consisting of economic, social, and environmental criteria along with resiliency to build a multi-tier RS-SCND to holistically tackle the pressing problem of supply chain disruption. The work hereby differs from those in the literature in integrating the multi-attribute decision-making methods' output into the multi-objective optimisation model. This would embed experts' opinions regarding existing facilities into the SCND and then into order allocation. In addition, this study addresses the call for suitable mathematical models to be developed for sustainable SCNs that are flexible and responsive to changing market requirements, incorporating the objective functions with appropriate constraints [2].

2.4 Criteria for resilient and sustainable supply chain network design

The literature review established resilience as a major criterion of SCND, including mitigation strategies comprised of flexibility, agility, preparedness, redundancy, and collaboration [9] [13] [69]. Studies also revealed the economic dimension as a key criterion of sustainable SCND, including cost, quality, historical performance, production capacity, and market share ([56] [49]. Lead time [14] and application of technology are also vital economic components of SCND. Extant literature presented the environment as a dominant criterion of sustainable SCND [44]. Environmental footprint, represented by carbon emissions, green policies, and water consumption are considered in a sustainable SCND [49] [70] [71]. Resource consumption, pollution production, energy consumption, and waste management are key features of a sustainable SCND [56]. Another major aspect of SCND is the social criteria, which comprises legislation and social responsibility issues [17].

Existing studies revealed employee rights and safety, anti-child labour, respect for legal policies and agreements, rights of collaborators, and information disclosure as strategies for developing the social pillar of sustainable SCND. The social aspect of sustainability is unavoidable in a sustainable SCND due to government legislation and social responsibility issues. Further, the volatility of markets and information asymmetry result in increased risks and uncertainties [17]. It is suggested that in developing a sustainable SCND under uncertainty, five stakeholder categories, including employees, local community, society, consumers, and value chain networks, should be considered.

From the above discussion, the resilience criteria are comprised of flexibility, agility, preparedness, redundancy, and collaboration [9] [13]. From a sustainability perspective, the economic criteria include cost, quality, historical performance, production capability, lead time, reliability, and application of technology [56] [49] [14]. Environmental sustainability criteria consist of interest in environmentalism, waste management, pollution control, environmental management certificate(s), and green design [44] [49] [72] [71] [56]. Lastly, employee rights and safety, anti-child labour, respect for legal policies and agreements, rights of collaborators, and information disclosure are established as social criteria to be considered in a SCND [17] [46] [56] [16]. An extensive review of prior literature enabled this work to achieve objective 2 by developing a theoretical framework of RS-SCND as presented in Figure 1.

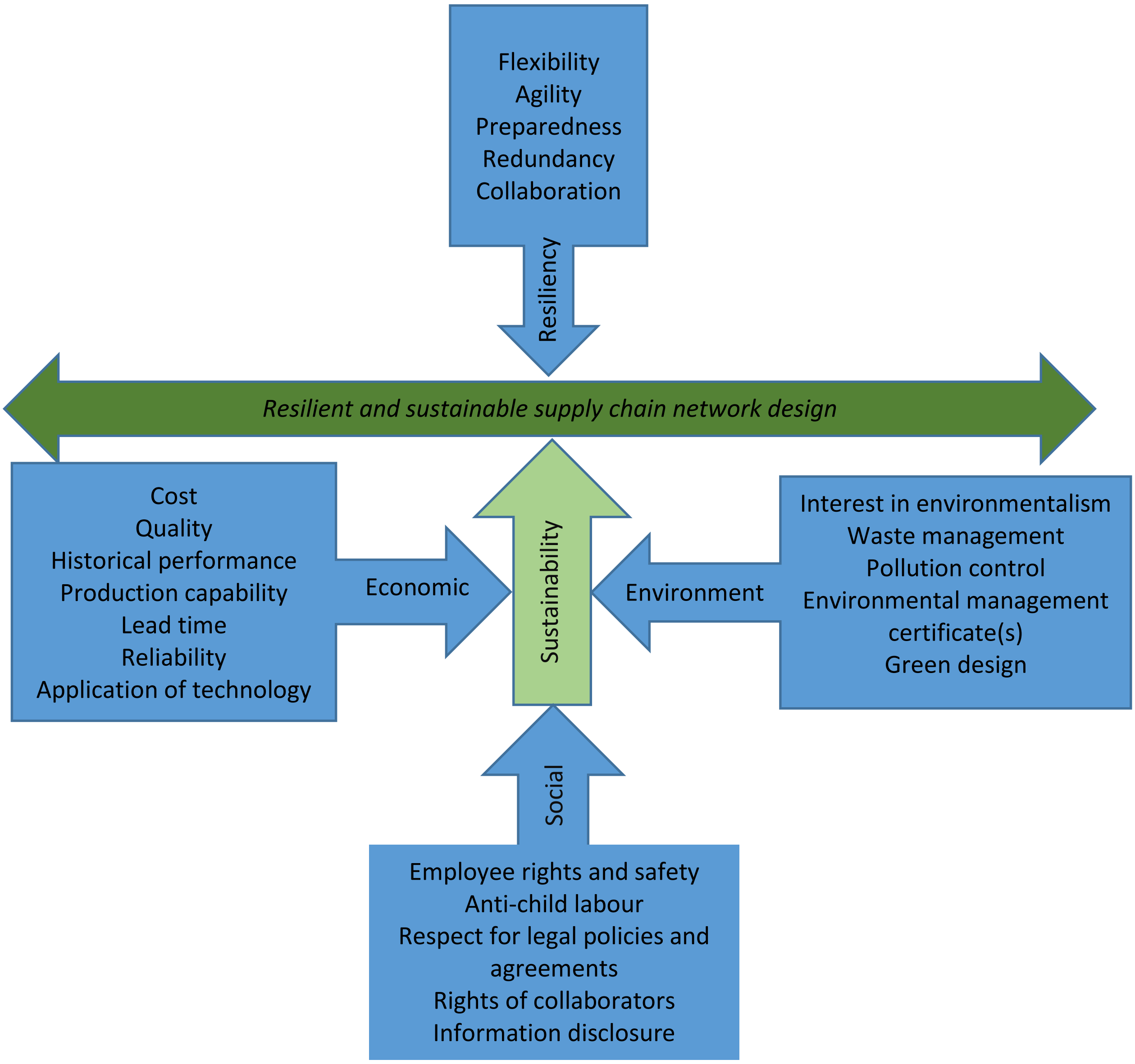

Fig. 1: Criteria for resilient and sustainable supply chain network design.

2.5 SC sustainability and resilience in the digital technology era

In the last few years, digital technologies have gained increasing attention from scholars and practitioners towards collaborative supply chain networks and visible logistics operations. This is due to their potential to improve collaboration, visibility, and management among supply chain partners and control of supply chain activities: e.g., inventory, procurement, production, etc. [73] [74]. Also, digital technologies are expected to boost sustainability initiatives in supply chains [75] [76]. In the same context, after the COVID-19 pandemic, there was a loud call to boost the embedment of digital technologies into supply chain activities to elevate their resilience state to handle economic, social, and environmental implications experienced via this massive disruption [77]. However, it should be noted that digital technology might also be a possible disruption risk to supply chains that comprise its sustainability [4] [5] [6].

Hence, the evolution of supply chains towards digitalization should be aligned with proper decision-making methodologies to ensure resilience and sustainability in supply chain operations that this work tries to address. The criticism of the current state of knowledge and the pressing need for resilient supply chains without disrupting sustainability has necessitated the concept of RS-SCND pursued in this study. Due to the potential positive impacts of resilience and sustainability on business competitiveness, continuity, profitability, and responsibility, many scholars have applied and/or developed many mathematical modelling techniques to build various SCND across many sectors and industries [63] [20] [67]. As presented in Table 1, these methods include but are not limited to mixed integer linear programming, multi-stage stochastic programming, and multi-objective possibilistic programming models. Quantitative research and mathematical modelling studies on sustainable resilient supply chains have increased in recent years. However, studies on resilience SCND without lagging sustainability remain underexplored [25]. In this work, a hybrid integrated BWM-CoCoSo-multi-objective programming model (BC-MOPM) was formulated to build a RS-SCND. We have chosen BWM due to its simplicity and accuracy in determining the criteria weights. The BWM facilitates the weight evaluation process and overcomes the difficulties that exist in methods like the analytical hierarchy process (AHP). In addition, to encounter the most optimal alternatives, the CoCoSo method has been developed because of its consistency and unique algorithm that ease the calculation process for researchers and participants. The integration of both tools into multi-objective programming allows us to optimise a fluent procedure for supply chain network design while measuring the value of complex variables like resiliency and sustainability are essential.

Table 1. RS-SCND literature identified and their contributions.

Sources	Resilience	Sustainability			Contributions	Sector(s)
		Environment	Economic	Social		
[13]	•		•		A resilient topology is developed that can recover from and react quickly to any disruptions.	Automobile
[56]		•	•	•	A model for integrating three problems of optimising logistics: location, routing, and inventory problem was introduced.	Perishables
[49]		•	•		A mixed integer linear programming model for a sustainable SCND problem, and an efficient distributed approximation approach to solving problems of costs and environmental footprint.	Transport
[14]	•		•		A multi-stage stochastic program to model disruptions' effect on facilities' capacity.	Manufacturing Online retail
[44]		•	•		A bi-level programming approach is considered to address the optimisation of a hierarchized sustainable SCND.	Manufacturing
[72]		•	•		A bi-objective multi-product constrained and integrated economic production quantity model is designed by considering the quality control and green production policies.	Not specified
[71]		•	•	•	A cost-efficient multi-stage stochastic program in which the greenhouse gas emissions are mitigated, and the social impact of the SC is considered.	Biofuel
[17]		•	•	•	A risk-averse sustainable multi-objective model for SCND under uncertainty by incorporating Conditional Value at Risk into the basic configuration of the two-stage stochastic programming was proposed.	Not specified
[46]		•	•	•	A multi-objective possibilistic programming model to design a sustainable medical SCN under uncertainty considering conflicting	Healthcare

					economic, environmental, and social objectives.	
[16]		•	•	•	A SCND model problem is introduced to cover three dimensions of sustainability by imposing proper carbon regulatory mechanisms.	Manufacturing
[9]	•		•		A stochastic model was proposed that could decrease the company's total costs.	Not specified

2.6 Research contributions

Empirical studies on SCND are increasing in recent years [27] [26] [43] [56] [62] [49]. However, studies on RS-SCND incorporating resilience with all three sustainability criteria to propose updated frameworks and models to advance existing knowledge remain underexplored. In addition, although there are many hybrid methods developed in existing literature [10] [26] [28] [17], there has been no single multi-tier SCN study that formulates a hybrid integrated BWM-CoCoSo-multi-objective programming model (BC-MOPM) to develop a RS-SCND. Incorporating BC-MOPM presents a superiority in terms of robustness and validity of results by combing BWM-CoCoSo output into the optimisation model (i.e., MOPM). This integrated methodology will assist in incorporating decision-makers opinions and related input parameters such as costs, safety, and carbon emission into the SCND.

An extensive review of relevant literature has assisted this paper in devising updated criteria for RS-SCND, as presented in Figure 1, and analysed and discussed in Sections 3 and 4. Given that extant studies have established the positive impacts of both resilient and sustainable SCNDs in addressing the negative effect of supply chain disruptions, there is a potential for SCNs to adopt a hybrid BC-MOPM to build RS-SCND and to minimise the adverse impacts of supply chain glitches across various business operations and activities to improve supply chain performance. Proposing an updated framework for the criteria of RS-SCND and the application of the BC-MOPM model on RS-SCND will make significant theoretical and practical contributions. Studies have revealed how mathematical models are utilised to optimise resilient and sustainable supply chain performance [72] [59] [58] [78].

The contributions of this research help in extending our understanding regarding the relationship between sustainable development and the need for resiliency in a supply chain context and how they might impact each other. For instance, supply chain disruption might weaken social and environmental sustainability, causing managers to fight to achieve their positions during disruption events. Similarly, economic disruptions could make small companies suffer or even cause them to fail, resulting in unemployment that negatively impacts social sustainability as supported by [74]. Very recently, [76] argued that the increasing rate of unemployment and weak financial growth due to the COVID-19 pandemic disruption yields negative social implications, higher poverty and crime rates, and undernourishment. Furthermore, managers and consumers might choose to increase their inventory levels to protect against disruption and, in the process, create additional waste and expired products that might compromise sustainability development criteria [40] and [79].

The presented framework that presents resilience and sustainability criteria has the potential to pave similar concurrent considerations of these criteria in other supply chains activities such as production planning and scheduling, procurement, logistics, warehousing, and manufacturing. Furthermore, managers in the industry could use the developed methodological tool to embed both resilience and sustainability aspects into their tactical and strategic planning. For instance, this can include the evaluation of current facilities vis-à-vis presented RSC. Also, it can be used strategically to redesign an existing supply chain network to achieve a new organisational strategy that pushes towards resilience development without lagging behind sustainability's responsibilities. Managers hereby may generalize the considered RSC on other activities and operations.

3. RS-SCND: Research methodology

Recent disruptions caused by the COVID-19 pandemic have massively increased the attention of both researchers and managers towards the need for a resilient supply chain network design in various industries. However, managers also have a continuous interest in building responsibilities of the triple bottom line of sustainability (i.e., economic, environmental, and social) to cope with growing governmental restrictions and to satisfy societal awareness.

This work aims to reconfigure a two-echelon supply chain network considering four objectives: cost, environmental impact, social, and resilience (CESR). In this regard, both tangible variables such as transportation costs and amount of CO_2 emissions, and intangible factors like collaboration and interest in environmentalism related elements are considered in modelling the four objective functions mathematically, for the agri-food case under study. Figure 2 depicts a schema for the SCN under study that includes three sets of facilities: *A*, *B*, and *C*. Unfinished products or raw materials (depending on the nature of the case supply chain) are shipped from facility *A* to facility *B* to be processed and shipped as finished products to facility *C*. The reconfiguration of this supply chain network design towards resiliency and sustainability is constructed of six stages:

Stage 1: A literature review analysis is conducted to explore resilience and sustainability criteria (RSC) as previously outlined in section 2. This stage ended up with Figure 1 (see section 2.4) presenting a framework for the considered criteria and sub-criteria for resiliency and sustainability. This stage helped in delivering research objectives 2 and 3 (see section 1.2).

Stage 2: The BWM method is used to quantify the weight of each RSC and sub-criteria based on importance (see Figure 1). For the current two-echelon SCN, this stage is conducted twice to incorporate the perspectives of decision-makers at facilities *C* and *B*. The application procedures of this stage are presented in section 3.1.

Stage 3: The CoCoSo method is used to obtain a numerical value for facilities' performance vis-à-vis resiliency and sustainability criteria. This stage is also conducted twice in which decision-makers at facilities *C* and *B* evaluate the resiliency and sustainability performance of facilities *B* and *A*, respectively. Section 3.2 shows the implementation steps of the CoCoSo method. Research objective 3 is delivered by completing Stages 2 and 3.

Stage 4: Four objective functions are formulated to reflect four desires (i.e., minimisation of total costs and environmental impact, and maximisation of the social aspect and resilient facilities value) in designing the RS-SCND. It is worth to mention that this model hereby integrates the outputs from stages 2, consisting of weight of RSC and 3, which are values of facilities' performance into the corresponding four objectives. The model formulation and related notations and constraints are presented in section 3.3.

Stage 5: The ε-constraint method is employed to optimise the four objectives (formulated in Stage 6) simultaneously. This stage leads to several Pareto solutions in which each solution consists of a supply chain structure in terms of facilities to be opened and the optimal order allocation among them considering the four objectives. The application procedures and details of the ε-constraint method are presented in section 3.4.

Stage 6: Decision-makers of the case study need to select one solution based on their preference to design the SCND and reveal order allocation among facilities that are targeted in research objectives 4 & 5.

Figure 3 presents a flow diagram for developing the proposed RS-SCND. In addition, a summary of the research methodology is presented in Appendix A2.

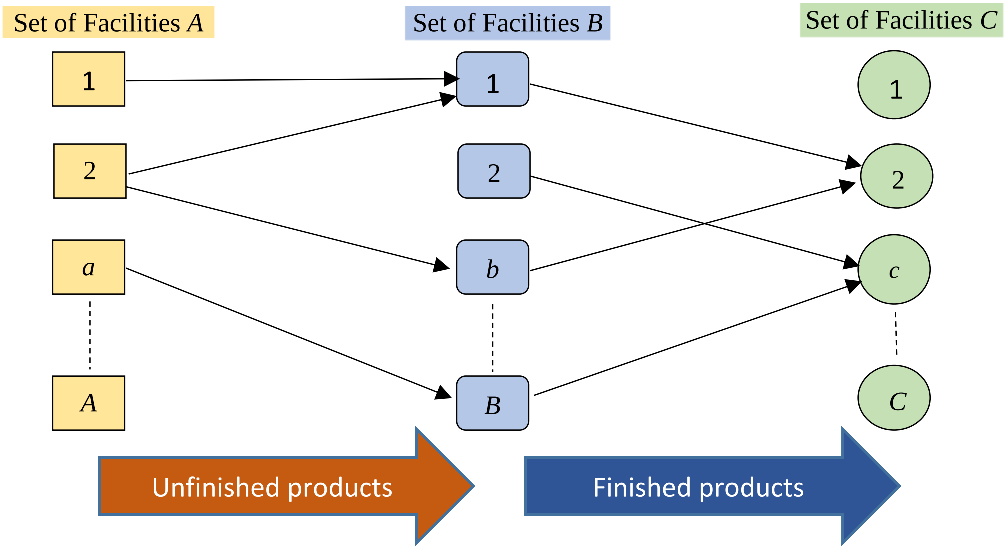

Fig. 2: Schema for the case SCND.

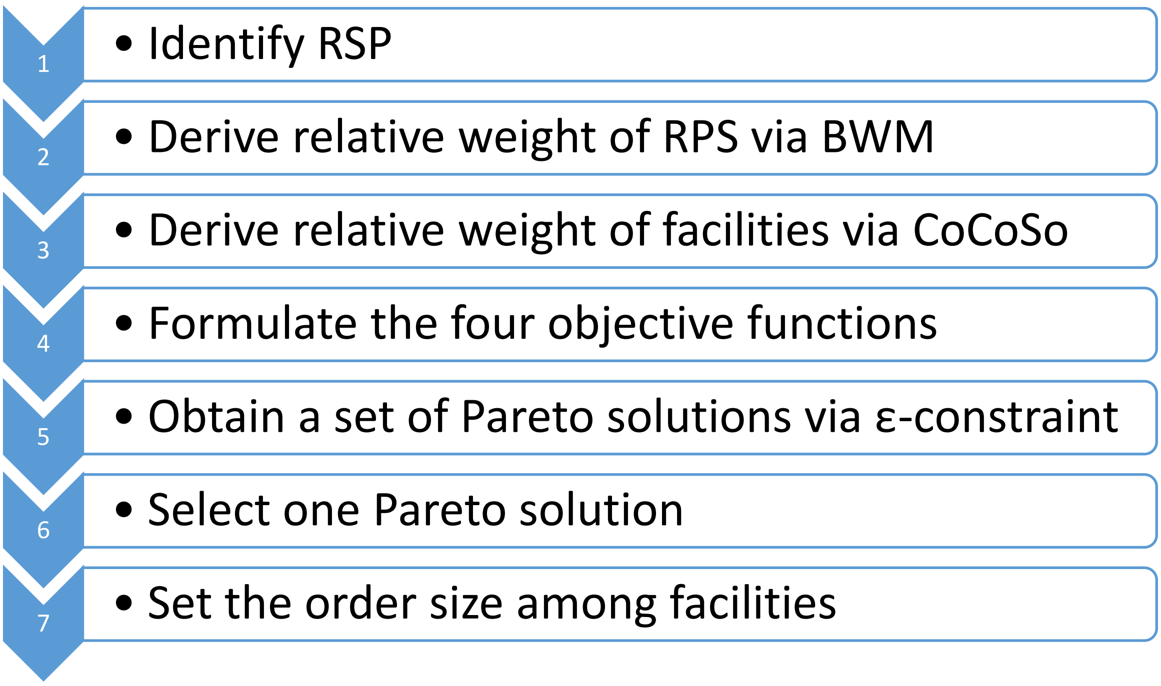

Fig. 3: A flow diagram towards RS-SCND.

3.1 Stage 2: Best Worst Method (BWM)

This BWM method, developed by [80], created new attention in various fields. In decision analysis, no method is built based on a linear programming (LP) formulation. However, the structure of BWM privileges a linear model that enhances the reliability of the weighting process. The idea of implementing a linear programming (LP) model allows BWM to serve as an operable model in complex decision environments. BWM is a promising technique that aids in solving complex decision-making problems [81] [82] [83].

In decision-making analysis studies, there are ways to obtain the weights of decision criteria (factors). Sometimes the problem directs a study to a database with available quantitative data that already exists. In this condition, methods like Shannon Entropy or CRITIC methods might be used. We call them objective methods. However, in many cases, there is no database or clear information about criteria, researchers, or decision-makers, and no suggestions exist to use subjective techniques like AHP, BWM, SWARA, etc. This class of tools needs qualitative judgment and comparisons among criteria to generate the relevant weights. The AHP method is used for making complex decisions and deals with an unbalanced scale of judgment; in fact, it is rather imprecise for the ranking of alternatives. The selection and preference of decision-makers have a high influence on AHP results. Generally, decision-makers evaluate alternatives based on ambiguity and multiplicity, and human assessment of qualitative attributes is always subjective and imprecise [84].

AHP and ANP are among the decision analysis tools that were seriously criticized for their inconsistency rate. The consistency level of the judgments comes from the rationality of the DM and his/her ability to discriminate between criteria/alternatives [85]. BWM, in several aspects, contributes to more reliable results than AHP in many applications [86]. In contrast to AHP or ANP, the BWM method facilitates the comparisons in a more structured manner, which makes it more understandable and produces more consistent comparisons; hence, more reliable weights can be achieved. Here we add some values of BWM over other similar tools:

1. By determining the best and the worst criteria before comparing the criteria, the decision-maker can configure a better understanding of the range of evaluation which could lead to more

reliable pairwise comparisons. This implies more consistent pairwise comparisons, which have been shown in the original BWM study.

2. The use of two pairwise comparison vectors established based on best and worst criteria can reduce the anchoring bias that the DM might experience during the process of conducting pairwise comparisons. In several pairwise comparison-based methods like Swing and SMART family or AHP, the main weakness is that the consistency of the pairwise comparisons cannot be tested. On the other hand, methods like AHP, SMART, and so forth that are based on full pairwise comparison matrices are not data and time efficient. In those methods, the DM confronts too many questions and might even contribute to confusion and inconsistency. BWM is the most efficient method that facilitates the possibility of checking the consistency of the provided pairwise comparisons in an efficient time and with fewer difficulties. BWM method is among the top MCDM tools that resolve the problem of consistency measurement [87].

The steps below identify the process needed to obtain weights of decision criteria [80].

Step 1 - The decision-maker(s) (DM) should determine a set of decision criteria: $\{c_1, c_2, \dots, c_n\}$

Step 2 - The DM(s) or experts identify the best and the worst criteria among the set of predefined criteria. The best criterion represents the most desirable while the worst criterion is the least important one among others.

Step 3 - The DM(s) performs several pairwise comparisons between the best criterion and the other criteria. In this step, DM(s) realizes the preference of the most important criterion over the other criteria using a scale from 1 to 9 (1: equally important, and 9: extremely more important). The comparison outcome is described as a Best-to-Other vector: $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$

where a_{Bj}represents the preference of the best criterion B over the criterion j and $a_{BB} = 1$

Step 4 - The same process of last step is established here, but this time the DM conducts pairwise comparisons between the other criteria and the worst criterion. The comparison results are expressed by Other-to-Worst vector: $A_W = (a_{1W}, a_{2W}, \dots, a_{nB})^T$

where a_{jw} represents the preference of the best criterion j over the criterion W and $a_{WW} = 1$.

Step 5 - Calculating the optimal weights: $(W_1^*, W_2^*, \dots, W_n^*)$

For each pair of $\frac{W_B}{W_j}$ and $\frac{W_j}{W_W}$, the optimal weight should meet the requirement that $\frac{W_B}{W_j} = a_{Bj}$ and $\frac{W_j}{W_W} = a_{jW}$. To satisfy the conditions, the maximum absolute differences $|\ \frac{W_B}{W_j} - \ a_{Bj}|$ and

$\left|\frac{w_j}{w_W} - a_{jW}\right|$ for all j is minimised. Also, taking into consideration the non-negativity characteristic and sum condition of the weights, the following problem can be formulated [88]:

$$\left|W_B - a_{Bj}W_j\right| \le \xi^* W_j, \quad for\ all\ j$$

$$\left|W_j - a_{jW}W_w\right| \le \xi^* W_w, \quad for\ all\ j \tag{1}$$

$$\sum_j W_j = 1\ ,\ W_j \ge 0\ for\ all\ j$$

For a fully consistent problem while $\xi^* = 0$, each constraint $\left|W_B - a_{Bj}W_j\right| \le \xi^* W_j$ is converted to one constraint $W_B - a_{Bj}W_j = 0$, while $\xi^* > 0$, each constraint $\left|W_B - a_{Bj}W_j\right| \le \xi^* W_j$ is converted to two other constraints. For more information, see [88].

BWM method offers its users the opportunity to calculate the consistency level of the comparisons. The consistency is defined as follows [80]. The consistency ratio of BWM can be expressed by using ξ^* and the corresponding consistency index (Table 1), as follows:

$$\text{Consistency Ratio} = \frac{\xi^*}{\text{Consistency index}} \tag{2}$$

The smaller the ξ^* value, the smaller the 'consistency ratio' is, and the more consistent the vectors are. The consistency index to measure formula 2 is found in Table 2. For example, if the number of criteria is 6, the relevant consistency index is 3.

Table 2. BWM consistency index

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency index	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

3.2 Stage 3: Combined Compromise Solution (CoCoSo) method

Each decision-making problem can be solved with dozens of techniques. The subject that limits them comes from the structure, usability, reliability, and easy understating. Although there are other tools like SAW or WPM that are simple to be employed, experts have criticized them. A complete and full ranking method should convey a normalisation approach, weight assignation, overall score aggregation, and, finally, a consistency rule. It is reported that applicability of CoCoSo has been proved since its creation [89] [90] [91]. In this study, we ranked the alternatives using CoCoSo when there are several factors that require a more concrete and robust anatomy (or instance, SAW, WPM, or AHP). We must say this new method, created in 2019, solves the multi-attribute decision problems with compromise results, less computation, lower DMs confusion, plus a higher degree of reliability. [61] stated the advantages of CoCoSo as its simple calculation, easy understanding, and available to ranking set. Moreover, the strategy of final score aggregation that is unique in CoCoSo has beneficial points on the optimisation problems. Combined compromise solution is a novel method developed by [89] to rate alternatives or options in a multiple-choice decision problem. The method was used in many disciplines like construction engineering [89], telecommunication industry [90], and logistics application [92]. The steps for finding the solution of CoCoSo are followed here:

Step 1 – Define the decision-making matrix, with the variable of order quantity (x_{ij}) from origin I to destination j, as shown below:

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}; \; i = 1, 2, ..., m; \; j = 1, 2, ..., n. \tag{3}$$

Step 2 – Normalize the initial matrix by equations (see Zeleny, 1973):

$$r_{ij} = \frac{x_{ij} - \min\limits_{i} x_{ij}}{\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij}}; \text{ for benefit criterion;} \tag{4}$$

$$r_{ij} = \frac{\max\limits_{i} x_{ij} - x_{ij}}{\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij}}; \text{ for cost criterion} \tag{5}$$

Step 3 - Obtain the total of the weighted normalized matrix and the power weighted matrix for each alternative as S_i and P_i, respectively:

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}). \tag{6}$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \tag{7}$$

Step 4 - Compute relative weights for each alternative using the three aggregation strategies by formulas (8), (9), and (10):

A) $$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{8}$$

B) $k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i}$ (9)

C) $k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{(\lambda \max_i S_i + (1-\lambda) \max_i P_i)}$; $0 \le \lambda \le 1.$ (10)

Equation 8 expresses the arithmetic mean of sums of WSM and WPM scores, while Equation 9 refers the sum of relative scores of WSM and WPM compared to the best. Equation 10 interprets the balanced compromise of WSM and WPM models' scores. In Equation 10, λ usually experts choose $\lambda = 0.5$. However, the flexibility and stability of the proposed CoCoSo can be translated to other values as well.

Step 5 – Obtaining the final ranking of the alternatives is determined based on k_i, values (the more significant, the better):

$$k_i = (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} + \tfrac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \tag{11}$$

3.3 Stage 4: The hybrid integrated BC-MOPM

In this section, the BWM-CoCoSo-multi-objective programming mode (BC-MOPM) is formulated. The proposed model helps in reconfiguring a supply chain network design considering resiliency and sustainability aspects; involved facilities in three echelons are defined in three separate sets (*A*, *B*, and *C*). This includes the identification of required facilities to be opened and then allocates the order size to be supplied from facilities *A* to *B* and from facilities *B* to *C*. In practice, facilities *C* could be the end consumers in the proposed supply chain network such as retailers. Notations used in the hybrid integrated BC-MOPM are as follows:

Sets

A set of first echelon facilities, noted as *a*

B set of second echelon facilities, noted as *b*

C set of third echelon facilities, noted as *c*

Parameters

$C_a^{purchase,\alpha}$ purchasing cost per item purchased from facility *a*

$C_b^{purchase,\beta}$ purchasing cost per item purchased from facility *b*

$C_{ab}^{transport,\alpha}$ transportation cost per mile per truck from facility *a* to facility *b*

$C_{bc}^{transport,\beta}$ transportation cost per mile per truck from facility *b* to facility *c*

$C_a^{handle,\alpha}$ handling cost per item at facility *a*

$C_b^{handle,\beta}$ handling cost per item at facility *b*

$C_a^{order,\alpha}$ ordering cost per item at facility *a*

$C_b^{order,\beta}$ ordering cost per item at facility *b*

$C_a^{inventory,\alpha}$ inventory holding cost per item at facility *a*

$C_b^{inventory,\beta}$ inventory holding cost per item at facility *b*

$d_{ab}^{travel,\alpha}$ travel distance from facility *a* to facility *b*

$d_{bc}^{travel,\beta}$ travel distance from facility *b* to facility *c*

N the maximum carry capacity of a truck

$q_a^{supply,\alpha}$ supply capacities of facility *a*

$q_b^{supply,\beta}$ supply capacities of facility *b*

$q_b^{demand,\beta}$ demand for items by facility *b*

$q_c^{demand,\gamma}$ demand for items by facility *c*

$u_a^{CO_2,\alpha}$ CO_2 footprint per item at facility *a*

$u_b^{CO_2,\beta}$ CO_2 footprint per item at facility *b*

$U_{ab}^{CO_2,\alpha}$ CO_2 footprint in gram/mile for a lorry from facility *a* to facility *b*

$U_{bc}^{CO_2,\beta}$ CO_2 footprint in gram/mile for a lorry from facility *b* to facility *c*

$v_a^{job,\alpha}$ number of job opportunities at facility *a*

$v_b^{job,\beta}$ number of job opportunities at facility *b*

$w_b^{economic,\beta}$ relative weight of economic pillar based on experts' evaluation at facility *b*

$w_c^{economic,\gamma}$ relative weight of economic criterion based on experts' evaluation at facility *c*

$w_b^{environment,\beta}$ relative weight of environmental criterion on experts' evaluation at facility *b*

$w_c^{environment,\gamma}$ relative weight of environmental criterion on experts' evaluation at facility *c*

$w_b^{social,\beta}$ relative weight of social criterion based on experts' evaluation at facility *b*

$w_c^{social,\gamma}$ relative weight of social criterion based on experts' evaluation at facility *c*

$w_b^{flexibility,\beta}$ relative weight of flexibility criterion based on experts' evaluation at facility *b*

$w_c^{flexibility,\gamma}$ relative weight of flexibility criterion based on experts' evaluation at facility *c*

$w_b^{agility,\beta}$ relative weight of agility criterion based on experts' evaluation at facility *b*

$w_c^{agility,\gamma}$ relative weight of agility criterion based on experts' evaluation at facility *c*

$w_b^{preparedness,\beta}$ relative weight of preparedness criterion on experts' evaluation at facility *b*

$w_c^{preparedness,\gamma}$ relative weight of preparedness criterion on experts' evaluation at facility *c*

$w_b^{redundancy,\beta}$ relative weight of redundancy criterion on experts' evaluation at facility *b*

$w_c^{redundancy,\gamma}$ relative weight of redundancy criterion on experts' evaluation at facility *c*

$w_b^{collaboration,\beta}$ relative weight of collaboration criterion on experts' evaluation at facility *b*

$w_c^{collaboration,\gamma}$ relative weight of collaboration criterion on experts' evaluation at facility *c*

$W_{ab}^{economic,\alpha}$ economic weight of facility *a* based on experts' evaluation at facility *b*

$W_{bc}^{economic,\beta}$ economic weight of facility *b* based on experts' evaluation at facility *c*

$W_{ab}^{environment,\alpha}$ environmental weight of facility *a* based on experts' evaluation at facility *b*

$W_{bc}^{environment,\beta}$ environmental weight of facility *b* based on experts' evaluation at facility *c*

$W_{ab}^{social,\alpha}$ social weight of facility *a* based on experts' evaluation at facility *b*

$W_{bc}^{social,\beta}$ social weight of facility *b* based on experts' evaluation at facility *c*

$W_{ab}^{flexibility,\alpha}$ weight of facility *a* in terms of flexibility on experts' evaluation at facility *b*

$W_{bc}^{flexibility,\beta}$ weight of facility *b* in terms of flexibility on experts' evaluation at facility *c*

$W_{ab}^{agility,\alpha}$ weight of facility *a* in terms of agility based on experts' evaluation at facility *b*

$W_{bc}^{agility,\beta}$ weight of facility *b* in terms of agility based on experts' evaluation at facility *c*

$W_{ab}^{preparedness,\alpha}$ weight of facility *a* in terms of preparedness based on experts' evaluation at facility *b*

$W_{bc}^{preparedness,\beta}$ weight of facility *b* in terms of preparedness based on experts' evaluation at facility *c*

$W_{ab}^{redundancy,\alpha}$ weight of facility *a* in terms of redundancy based on experts' evaluation at facility *b*

$W_{bc}^{redundancy,\beta}$ weight of facility *b* in terms of redundancy based on experts' evaluation at facility *c*

$W_{ab}^{collaboration,\alpha}$ weight of facility *a* in terms of collaboration based on experts' evaluation at facility *b*

$W_{bc}^{collaboration,\beta}$ weight of facility *b* in terms of collaboration based on experts' evaluation at facility *c*

Variables

x_{ab}^{α} order size to be shipped from first echelon facility *a* to second echelon facility *b*

x_{bc}^{β} order size to be shipped from second echelon facility *b* to third echelon facility *c*

$$y_a^{\alpha} = \begin{cases} 1, if\ first\ echelon\ facility\ a\ is\ seleced \\ 0,\ otherwise \end{cases}$$

$$y_b^{\beta} = \begin{cases} 1, if\ second\ echelon\ facility\ b\ is\ seleced \\ 0, otherwise \end{cases}$$

Objective functions:

The four objectives (CESR) functions were formulated as follows:

Objective function C: Minimisation of the total cost

The function in Eq. 12 demonstrates that the total cost is to be minimised. This formula, of economic performance, exists in terms 1 and 2. The weight of the economic aspect ($w_b^{economic,\beta}$ and $w_c^{economic,\gamma}$) is hereby multiplied by the minimum value ($\lambda_b^{economic,\beta}$ and $\lambda_c^{economic,\gamma}$) of selected facilities' weight vis-à-vis the economic dimension ($W_{ab}^{economic,\alpha}$ and $W_{bc}^{economic,\beta}$). In other words, unlike other modelling of the economic sustainability, this term aims to minimise the minimum economic performance of facilities *A* and *B*. Thus, this gives decision-makers the opportunity to embed economic performance of facilities within the modelling. This formula also includes traditional modelling costs related to purchasing ($C_a^{purchase,\alpha}$ and $C_b^{purchase,\beta}$), transportation ($C_{ab}^{transport,\alpha}$ and $C_{bc}^{transport,\beta}$), handling ($C_a^{handle,\alpha}$ and $C_b^{handle,\beta}$), ordering ($C_a^{order,\alpha}$ and $C_b^{order,\beta}$), and holding inventory ($C_a^{inventory,\alpha}$ and $C_b^{inventory,\beta}$) in from the facilities *A* and *B.* As the unit transportation cost is given per truck, a ceiling value of required quantity of trucks, for guaranteeing to meet the demand, is applied to determine the total transportation cost.

$$\begin{aligned} Min\ C = {} & w_b^{economic,\beta} \cdot \lambda_b^{economic,\beta} + w_c^{economic,\gamma} \cdot \lambda_c^{economic,\gamma} \\ & + \sum_{a\in A}\sum_{b\in B} C_a^{purchase,\alpha} \cdot x_{ab}^{\alpha} + \sum_{b\in B}\sum_{c\in C} C_b^{purchase,\beta} \cdot x_{bc}^{\beta} \\ & + \sum_{a\in A}\sum_{b\in B} C_{ab}^{transport,\alpha} \cdot d_{ab}^{travel,\alpha} \left\lceil \frac{x_{ab}^{\alpha}}{N} \right\rceil + \sum_{b\in B}\sum_{c\in C} C_{bc}^{transport,\beta} \cdot d_{bc}^{travel,\beta} \cdot \left\lceil \frac{x_{bc}^{\beta}}{N} \right\rceil \\ & + \sum_{a\in A}\sum_{b\in B} C_a^{handle,\alpha} \cdot x_{ab}^{\alpha} + \sum_{b\in B}\sum_{c\in C} C_b^{handle,\beta} \cdot x_{bc}^{\beta} \\ & + \sum_{a\in A}\sum_{b\in B} C_a^{order,\alpha} \cdot x_{ab}^{\alpha} + \sum_{b\in B}\sum_{c\in C} C_b^{order,\beta} \cdot x_{bc}^{\beta} \end{aligned} \tag{12}$$

$$+\sum_{a\in A}\sum_{b\in B} C_a^{inventory,\alpha}\cdot x_{ab}^{\alpha} + \sum_{b\in B}\sum_{c\in C} C_b^{inventory,\beta}\cdot x_{bc}^{\beta}$$

Where

$$\lambda_b^{economic,\beta} \leq \sum_{a\in A} W_{ab}^{economic,\alpha}\cdot y_a^{\alpha} \qquad \forall\, b\in B \tag{12.1}$$

$$\lambda_c^{economic,\gamma} \leq \sum_{b\in B} W_{bc}^{economic,\beta}\cdot y_b^{\beta} \qquad \forall\, c\in C \tag{12.2}$$

Objective function E: Minimisation of the environmental impact

As shown in Eq. 13 the environmental impact is to be minimised. This includes environmental profiles of facilities *A* and *B* in terms 1 and 2, respectively. This is formulated by multiplying weight of environmental aspect ($w_b^{environment,\beta}$ and $w_c^{environment,\gamma}$) multiplied by the minimum selected environmental facilities' profiles ($\lambda_b^{environment,\beta}$ and $\lambda_c^{environment,\gamma}$). This term is not normally considered in other similar modelling of environmental sustainability. It facilitates the consideration of environmental performance, including all environmental criteria presented in Figure 1, of facilities in addition to the traditional modelling of environmental impact. The latter is presented in terms 3 and 4 that formulate the CO_2 footprint per item ($u_a^{CO_2,\alpha}$ and $u_b^{CO_2,\beta}$) for running facilities *A* and *B*. The CO_2 footprint due to transportation of items ordered from facilities *A* to *B* ($U_{ab}^{CO_2,\alpha}$) and *B* to *C* ($U_{bc}^{CO_2,\beta}$) with related travel distances are presented in the last two terms. For the same reason in the transportation cost as above, the number of trucks is necessarily rounded up for meeting the requirement.

$$Min\ E = w_b^{environment,\beta}\cdot \lambda_b^{environment,\beta} + w_c^{environment,\gamma}\cdot \lambda_c^{environment,\gamma} \tag{13}$$

$$+\sum_{a\in A}\sum_{b\in B} u_a^{CO_2,\alpha}\cdot x_{ab}^{\alpha} + \sum_{b\in B}\sum_{c\in C} u_b^{CO_2,\beta}\cdot x_{bc}^{\beta}$$

$$+\sum_{a\in A}\sum_{b\in B} U_{ab}^{CO_2,\alpha}\cdot d_{ab}^{travel,\alpha}\cdot \left\lceil \frac{x_{ab}^{\alpha}}{N}\right\rceil + \sum_{b\in B}\sum_{c\in C} U_{bc}^{CO_2,\beta}\cdot d_{bc}^{travel,\beta}\cdot \left\lceil \frac{x_{bc}^{\beta}}{N}\right\rceil$$

where

$$\lambda_b^{environment,\beta} \leq \sum_{a\in A} W_{ab}^{environment,\alpha}\cdot y_a^{\alpha} \qquad \forall\, b\in B \tag{13.1}$$

$$\lambda_c^{environment,\gamma} \leq \sum_{b\in B} W_{bc}^{environment,\beta} \cdot y_b^{\beta} \qquad \forall\, c \in C \qquad (13.2)$$

Objective function S: Maximisation of the social aspect

The objective function in Eq. 14 is to maximise the social impact, which consists of social performance of facilities and job opportunities. Terms 1 and 2 reflect the social aspect by multiplying weight of social aspect ($w_b^{social,\beta}$ and $w_c^{social,\gamma}$) multiplied by the minimum selected social facilities' profiles ($\lambda_b^{social,\beta}$ and $\lambda_c^{social,\gamma}$), respectively. These values are obtained by the application of the integrated BWM-CoCoSo method and based on experts' evaluation. The traditional consideration, normally presented in modelling social sustainability in the literature of job creation, ($v_a^{job,\alpha}$ and $v_b^{job,\beta}$), at the facilities in the two echelons is formulated in terms 3 and 4, respectively.

$$Max\ S = w_b^{social,\beta} \cdot \lambda_b^{social,\beta} + w_c^{social,\gamma} \cdot \lambda_c^{social,\gamma} + \sum_{a\in A} v_a^{job,\alpha} \cdot y_a^{\alpha} + \sum_{b\in B} v_b^{job,\beta} \cdot y_b^{\beta} \qquad (14)$$

where

$$\lambda_b^{social,\beta} \leq \sum_{a\in A} W_{ab}^{social,\alpha} \cdot y_a^{\alpha} \qquad \forall\, b \in B \qquad (14.1)$$

$$\lambda_c^{social,\gamma} \leq \sum_{b\in B} W_{bc}^{social,\beta} \cdot y_b^{\beta} \qquad \forall\, c \in C \qquad (14.2)$$

Objective function R: Maximisation of resilient location value

This objective function aims to maximise the resilient location value by maximising the resilient profiles (weights) of facilities *A* and *B*. This is formulated by multiplying the weight of resilience criteria, including flexibility ($w_b^{flexibility,\beta}$ and $w_c^{flexibility,\gamma}$), agility ($w_b^{agility,\beta}$ and $w_c^{agility,\gamma}$), preparedness ($w_b^{preparedness,\beta}$ and $w_c^{preparedness,\gamma}$), redundancy ($w_b^{redundancy,\beta}$ and $w_c^{redundancy,\gamma}$), and collaboration ($w_b^{collaboration,\beta}$ and $w_c^{collaboration,\gamma}$), by the weight of facilities. These two weights are derived by applying BWM and CoCoSo methods, respectively. This new objective function aims at delivering a resilient supply chain in terms of allocating facilities according to their resilience performance rather than sustainability only as most of the previous research shown in the literature (see section 2). Also, this formulation helps in considering experts' evaluation of facilities vis-à-vis resilience aspect.

$$Max\ R = w_b^{flexibility,\beta} \cdot \sum_{a\in A} W_{ab}^{flexibility,\alpha} \cdot y_a^\alpha + w_b^{agility,\beta} \cdot \sum_{a\in A} W_{ab}^{agility,\alpha} \cdot y_a^\alpha \tag{15}$$

$$+w_b^{preparedness,\beta} \cdot \sum_{a\in A} W_{ab}^{preparedness,\alpha} \cdot y_a^\alpha + w_b^{redundancy,\beta} \cdot \sum_{a\in A} W_{ab}^{redundancy,\alpha} \cdot y_a^\alpha$$

$$+w_b^{collaboration,\beta} \cdot \sum_{a\in A} W_{ab}^{collaboration,\alpha} \cdot y_a^\alpha$$

$$+ w_c^{flexibility,\gamma} \cdot \sum_{b\in B} W_{bc}^{flexibility,\beta} \cdot y_b^\beta + w_c^{agility,\gamma} \cdot \sum_{b\in B} W_{bc}^{agility,\beta} \cdot y_b^\beta$$

$$+w_c^{preparedness,\gamma} \cdot \sum_{b\in B} W_{bc}^{preparedness,\beta} \cdot y_b^\beta + w_c^{redundancy,\gamma} \cdot \sum_{b\in B} W_{bc}^{redundancy,\beta} \cdot y_b^\beta$$

$$+w_c^{collaboration,\gamma} \cdot \sum_{b\in B} W_{bc}^{collaboration,\beta} \cdot y_b^\beta$$

$$Max\ R = \left(w_b^{flexibility,\beta} \cdot \sum_{a\in A} W_{ab}^{flexibility,\alpha} + w_b^{agility,\beta} \cdot \sum_{a\in A} W_{ab}^{agility,\alpha} \right.$$

$$+ w_b^{preparedness,\beta} \cdot \sum_{a\in A} W_{ab}^{preparedness,\alpha} + w_b^{redundancy,\beta}$$

$$\left. \cdot \sum_{a\in A} W_{ab}^{redundancy,\alpha} + w_b^{collaboration,\beta} \cdot \sum_{a\in A} W_{ab}^{collaboration,\alpha} \right) \cdot y_a^\alpha$$

$$+ \left(w_c^{flexibility,\gamma} \cdot \sum_{b\in B} W_{bc}^{flexibility,\beta} + w_c^{agility,\gamma} \cdot \sum_{b\in B} W_{bc}^{agility,\beta} \right.$$

$$+ w_c^{preparedness,\gamma} \cdot \sum_{b\in B} W_{bc}^{preparedness,\beta} + w_c^{redundancy,\gamma}$$

$$\left. \cdot \sum_{b\in B} W_{bc}^{redundancy,\beta} + w_c^{collaboration,\gamma} \cdot \sum_{b\in B} W_{ab}^{collaboration,\beta} \right) \cdot y_b^\beta$$

The four objectives in this model are subject to the following constraints:

Constraint set 1: This is a demand constraint that ensures that all demands ($q_b^{demand,\beta}$ and $q_c^{demand,\gamma}$) set by facilities *B* (Eq.16) and facilities *C* (Eq.17) are fulfilled by facilities *A* and facilities *B*, respectively.

$$\sum_{a \in A} x_{ab}^{\alpha} \geq q_b^{demand,\beta} \qquad \forall b \in B \tag{16}$$

$$\sum_{b \in B} x_{bc}^{\beta} \geq q_c^{demand,\gamma} \qquad \forall c \in C \tag{17}$$

Constraint set 2: This is a capacity constraint that limits the total amount of orders to the capacity ($q_a^{supply,\alpha}$ and $q_b^{supply,\beta}$) of facility A (Eq.18) and facility B (Eq.19).

$$\sum_{b \in B} x_{ab}^{\alpha} \leq q_a^{supply,\alpha} \qquad \forall a \in A \tag{18}$$

$$\sum_{c \in C} x_{bc}^{\beta} \leq q_b^{supply,\beta} \qquad \forall b \in B \tag{19}$$

Constraint set 3: This the non-negativity constraint (Eq. 20) that ensures values of decision variables, of orders size among facilities, to be equal or greater than zero.

$$x_{ab}^{\alpha}, x_{bc}^{\beta} \geq 0 \quad \forall a \in A, b \in B, c \in C \tag{20}$$

Constraint set 4: This is the binary constraint (Eq. 21) that limits the value of supplier selection decision variables to be either 1 (if the supplier is selected) or zero (if the supplier is not selected).

$$y_a^{\alpha}, y_b^{\beta} \in \{1,0\} \qquad \forall a \in A, b \in B \tag{21}$$

3.4 Stage 5: Optimising the four objectives via ε-constraint

In this optimisation model, the ε-constraint method was employed for solving the four objectives optimisation problem. This is conducted by transforming the four-objective model into a single objective model by presenting one objective function and moving others to the constraints as follows [93]:

$$Min \quad objective \quad function = Min\, C \tag{22}$$

Subject to:

$$E \le \varepsilon_1 \tag{23}$$

$$[E]^{\min} \le \varepsilon_1 \le [E]^{\max} \tag{24}$$

$$S \ge \varepsilon_2 \tag{25}$$

$$[S]^{\min} \le \varepsilon_2 \le [S]^{\max} \tag{26}$$

$$R \ge \varepsilon_3 \tag{27}$$

$$[R]^{\min} \le \varepsilon_2 \le [R]^{\max} \tag{28}$$

In this model, the research team opted to keep the first objective function (*Min C*) as the objective function considering the paramount importance of the economic sustainability pillar. Therefore, the other three objective functions (i.e., *Min E, Min S,* and *Min R*) are shifted to the constraint set in addition to Eqs. 16-22.

In this method, the minimisation objective function is restricted to be less than or equal an epsilon value (see Eq. 23) and maximisation objective function is restricted to be more than or equal an epsilon value see Eqs. 25 and 27). These values are set between the minimum and maximum values for the objective function when optimised individually.

4. Application and evaluation of the BC-MOPM

In this section, the applicability and performance of the developed BC-MOPM are explored through its application on a real two-echelon food SCN in the UK. This network includes several supply chains where it consists of six farms (L1-L6) facilities (facility *A*), four slaughterhouses (H1-H4) facilities (facility *B*), and 11 retailers (facility *C*). As illustrated in section 3, the RS-SCND is structured over four stages. In stage one, RSPs were identified (see Figure 1) including five resilience criteria (R1-R5), economic criteria (E1-E7), five environmental criteria (V1-V5), and five social criteria (S1-S5).

4.1 Case study protocol

A case study approach [94] was regarded as appropriate for this study that aims to generate insights regarding how RS-SCND drive competitive performance. A case study is in-depth research into a topic or a phenomenon within its real-life contemporary setting or context [95]. An in-depth inquiry was designed to ascertain the vital components of resilient and sustainability that enhance SCN performance, to understand the effects of RS-SCND on business competitiveness and influences for action [7]. To attain such insights, case study research utilises quantitative or qualitative or mixed methods approach to fully understand the dynamics of the phenomenon [95]. This study uses quantitative method of data collection and analysis to fully apprehend experts' opinion regarding the resilient and sustainability criteria (see Figure 1) for the case supply chain network. Quantitative data was used for applying the proposed BWM-CoCoSo evaluation method (see sections 3.1 and 3.2). Combining these methods assists in quantifying the relative importance of criteria and evaluating the correspondence performance of facilities (i.e., *A* and *B*).

Considering the need for experts' opinions in conducting stages 2 and 3 to apply BWM and CoCoSo, respectively, the research team asked the focal point with those companies or retailers to nominate a group of decision-makers who are aware of these facilities. Accordingly, six decision-makers (DM_c) from retailers (i.e., facility *C*), that source meat products from these four slaughterhouses were nominated. Also, four decision-makers (DM_b) from slaughterhouses (i.e., facility *B*), that source livestock from those six farms were invited. Those decision-makers are responsible for purchasing livestock or meat products at their companies or shops and have an average of 5 years of experience. It is interesting to mention that decision-makers at retailers are not aware of suppliers of livestock and they have no business with them. The information was collected via individual meetings (around 1 hour); they are situated in different locations. First, the criteria were presented and clarified to participants. In this regard, participants were not fully comfortable with some criteria (e.g., resilience criteria) due to "lack of knowledge" and thus the research team aimed at defining each criterion to participants prior to the evaluation stage. Second, the required evaluation was performed with each decision-maker step-by-step as it was the first time for all of them to conduct such a comparison. In this setting, the six DM_c worked on evaluating RSC from retailing perspectives and evaluating resilience and sustainable performance of the four slaughterhouses. Similarly, the four DM_b shared their opinions about importance of RSC from their perspectives and resilience and sustainable performance of the six farms. The next three sub-sections present implementation steps and findings of stages 2-6 (see section 3) for the proposed RS-SCND methodology.

4.2 Stage 2: Resiliency and sustainability criteria' weight via BWM

The method used for weighting of criteria is BWM. This is a reliable method based on linear programming and will determine the weights of resilient, economic, environmental, and social factors for farms and slaughterhouses. We describe the process of weight generation for farms, collect the same for the slaughterhouses, and the results and parameters are presented. As the BWM process for each category of factors is equal to another one, relating to the farms we only focus on economic attributes, for instance. Accordingly, the best and worst factors are E_1 and E_5, in order. Table 3 shows the information and pairwise comparison.

Table 3. Best and worst items in Farms facility under economic attributes

Best to Others	E1	E2	E3	E4	E5	E6	E7
E1	1	4	3	5	7	2	5
Others to Worst	E1	E2	E3	E4	E5	E6	E7
E5	7	3	4	4	1	5	3

Then according to BWM algorithm, the weights for economic factors are seen in Table 4. The consistency rate is 0.07212 (< 0.1) which is a very acceptable range. This shows that cost and reliability are classified as the most important with scores of 0,344 and 0,208.

Table 4. Weights of economic factors

Weights	E1	E2	E3	E4	E5	E6	E7
	0,3440	0,1040	0,1387	0,0832	0,0388	0,2080	0,0832

Accordingly, the weights of other dimensions are also computed as shown in Table 5. It must be noted that the consistency index in all these categories remains as 0,053, 0,077, and 0,085 for resilient, environmental, and social. This guarantees reliability and confidence in the computation process. Evidently, and according to the experts, in farms facilities R_2 (agility) is chosen as the highest in importance, among others. For environmental and social aspects, pollution control and employee rights and safety, respectively, are most important. On the other side, we can conclude that decision-makers' green design (0.077) and right of collaborators (0.067) are the least important elements in this study.

Table 5. Collection of weights for Farms

Weights					
Resilient	R_1	R_2	R_3	R_4	R_5
	0,214	0,375	0,214	0,053	0,147
Environmental	V_1	V_2	V_3	V_4	V_5
	0,153	0,23	0,384	0,153	0,077
Social	S_1	S_2	S_3	S_4	S_5
	0,485	0,114	0,142	0,067	0,19

We have completed the same process for slaughterhouses facilities, as shown in Table 6. Similar to the farms results, R_2 (agility), waste management (V_2), anti-child labour (S_2), and E3 (historical performance) were found as the most important criteria in the resilience, environmental, social, and economic dimensions, respectively. Eq. 2 (the consistency ratio) was applied, and its results indicate that the consistency rate for facility *B* is estimated as 0.11, 0.10, 0.083, and 0.055 for economic, resilient, environmental, and social categories. We conclude that in total the weighting process for both facilities were performed with an acceptable range of consistency. In other words, it can be inferred that a consistent judgment was reached, the consistency ratio is less than 10%, generally, by the experts or decision-makers who participated in this process for weighting criteria related to the current supply chain facilities' performance. This proved the superiority of the BWM method compared to other MCDM tools in overcoming the problem of consistency measurement [87].

Table 6. BWM weights for Facility of Slaughterhouses

Weights							
Resilient	R1	R2	R3	R4	R5		
	0,156	0,365	0,156	0,234	0,086		
Environmental	V_1	V_2	V_3	V_4	V_5		
	0,167	0,416	0,167	0,167	0,083		
Social	S1	S2	S3	S4	S5		
	0,151	0,4	0,151	0,069	0,227		
Economic	E1	E2	E3	E4	E5	E6	E7
	0,19	0,127	0,268	0,095	0,076	0,051	0,19

4.3 Stage 3: Resiliency and sustainability facilities' weight via CoCoSo

In this section of the study, we employ the CoCoSo method to score the resilience and sustainability performance of farms and slaughterhouses under consideration. One of the inputs is the weights from the last step; other inputs are the rating of each farm and slaughterhouse with respect to the four dimensions of economic, environmental, resilience, and social aspects. It is worthy clarifying that we run the CoCoSo method several times. It was run once for the economic attributes, and three other times for the environmental, social, and resilience attributes; these steps are repeated for farm and slaughterhouses separately. To avoid the presentation of several tables and then a very lengthy paper, we present the ranking of farms under the economic criteria.

Similar to the previous section, we interpret the process of computation just for one dimension of one facility; the rest will act equally. Finally, the table for main criteria of each facility appears. For instance, we consider the initial matrix of farms regarding to the economic factors (see Eq. 3). Here in Table 7, it is observable. Among the seven criteria (factors), E1 and E5 have cost optimisation directions. Based on formulas 4 and 5, the normalized matrix is obtained shown by Table 8. The next step is to compute the weighted normalized matrix and power weighted matrix using Eqs. 6 and 7, given orderly *Sj* and *Pj* values for each alternative. Table 9 shows the values of *Sj* and *Pj* (i.e., weighted normalized matrix and the power weighted matrix for each alternative, respectively). It also presents Min, Max and sum values required to apply Eqs. 8, 9, and 10 used for obtaining the final alternative ranking as per Eq. 11.

Table 7. Initial matrix for sustainability evaluation of farms under economic dimension

Initial matrix	E1	E2	E3	E4	E5	E6	E7
L1	7	9	7	7	6	7	6
L2	5	9	7	7	5	7	5
L3	5	8	7	5	5	7	5
L4	7	7	7	6	5	4	3
L5	7	7	5	5	7	5	3
L6	3	6	4	5	5	3	3

Table 8. Normalized decision matrix

	E1	E2	E3	E4	E5	E6	E7
L1	0	1	1	1	0,5	1	1
L2	0,5	1	1	1	1	1	0,667
L3	0,5	0,667	1	0	1	1	0,667
L4	0	0,333	1	0,5	1	0,25	0
L5	0	0,333	0,333	0	0	0,5	0
L6	1	0	0	0	1	0	0

Table 9. The values of *Sj* and *Pj*

	E1	E2	E3	E4	E5	E6	E7	*Sj*
L1	0	0,104	0,138	0,083	0,019	0,208	0,083	0,636
L2	0,172	0,104	0,138	0,083	0,038	0,208	0,055	0,8
L3	0,172	0,069	0,138	0	0,038	0,208	0,055	0,682
L4	0	0,034	0,138	0,041	0,038	0,052	0	0,305
L5	0	0,034	0,046	0	0	0,104	0	0,184
L6	0,344	0	0	0	0,038	0	0	0,382
							Min	0,184
							Max	0,8
	E1	E2	E3	E4	E5	E6	E7	*Pj*
L1	0	1	1	1	0,973	1	1	5,973
L2	0,787	1	1	1	1	1	0,966	6,754
L3	0,787	0,958	1	0	1	1	0,966	5,713
L4	0	0,892	1	0,94	1	0,749	0	4,585
L5	0	0,892	0,858	0	0	0,865	0	2,616
L6	1	0	0	0	1	0	0	2
							Min	2
							Sum (*Sj*+*Pj*)	30,63
							Max	6,754

The last stage is formed by using Eqs. 8, 9, and 10 to compute the K_a, K_b, and K_c values for reaching final ranking of alternatives (Li). Table 10 presents the ranking of Lj alternatives under economic circumstance. The same manner will be considered for environmental, social, and resilience (R1-R5) indicators. As Table 10 indicates, the L_2 (farm 2) has the highest score and is selected as best option. In this table, farm number 6 is determined as the worst alternative. The three K_a, K_b, and K_c values indicate that farm 2 is the favorite option and this shows the reliability of the results. The column K is the overall score obtained by Eq. 11 and is utilised for next stage of our multi-objective formulation (section 4.4). At the end, we have Tables 11 and 12 that release the required and elaborated vectors for further utilisation of multi-objective model. Based on the evidence, in Table 10, considering environmental factors, farm 2 is selected as the best item but farm 1 can be the best option according to social factors. In slaughterhouses, all three economic, environmental, and social dimensions confirm that H4 reveals the best performance. It should be noted that Tables 7-10 are computed and repeated for all environment, social, and resilience criteria for both farms and slaughterhouses based on the CoCoSo algorithm. Due to the huge number of Tables and dimensions for this problem, we simply present Table 10 as a sample of our calculations. Therefore, the same Table for farms considering environment, social, and resilience dimensions are supposed. This helped to avoid a very lengthy paper. Then, the score of each dimension, economic, environment, social, and resilience, is needed for the next process in modeling the supply chain network. This clarifies the existence of the *K* score in Table 10. To test the accuracy of the CoCoSo method and to compare its results, a comparative analysis was conducted with other well-known MCDM tools, including complex proportional assessment of alternatives (COPRAS) [96][97], technique for order performance by similarity to ideal solution (TOPSIS) [98], multi-attributive border approximation area comparison (MABAC) [99], and measurement of alternatives and ranking according to Compromise solution (MARCOS)[100]. All these methods have been implemented in research projects and have advantages in their application. COPRAS is based on proportional index of criteria and alternatives and simultaneously considers maximum and minimum criteria evaluation, while MABAC acts based on the values of the criterion functions which are calculated for the alternatives and the distance of the criterion function from the border approximation area, where ranking of the alternatives is elaborated. TOPSIS relies on minimum and maximum distance from ideal and anti-ideal existing solutions. MARCOS enables decision-makers to consider anti-ideal and ideal solutions at the very beginning of the initial matrix. This leads to effective determination of utility degree and offers the possibility to consider a large set of criteria and alternatives. In this study, comparison were made between CoCoSo and other four methods discussed (see Table 11). The comparative findings show that L2 is the best item according to all 5 methods. In addition, this indicates that the 2^{nd} ranking alternatives remain the same with the CoCoSo results as shown in Figure 4. It can be inferred that the L2 and L3 are the best options among others. In addition, 20 various weight replacement tests (see Table 12) were operated to check the CoCoSo results vis-à-vis criteria weight sensitivity. Table 13 exhibits the ranking of CoCoSo over those various tests. The results show 94% similarity among those tests that, arguably, delivered the same ranking. The scores are presented in Tables 14 and 15, for farms and slaughterhouses, respectively.

Table 10. The ranking of L*j* alternatives and the overall ranking for the economic dimension related to farms

	Ka	Ranking	Kb	ranking	Kc	ranking	K	Ranking
L1	0,215	2	6,429	3	0,874	2	**3,575**	3
L2	0,246	1	7,704	1	1	1	**4,22**	1
L3	0,208	3	6,546	2	0,846	3	**3,583**	2
L4	0,159	4	3,946	4	0,647	4	**2,32**	4
L5	0,091	5	2,308	5	0,37	5	**1,351**	5
L6	0,012	6	2,07	6	0,05	6	**0,82**	6

Table 11 – The comparison of CoCoSo ranking with other MCDM tools

	CoCoSo	TOPSIS	COPRAS	MABAC	MARCOS
L1	3	4	3	4	5
L2	1	1	1	1	1
L3	2	2	2	2	2
L4	4	6	5	3	3
L5	5	5	6	6	4
L6	6	3	4	5	6

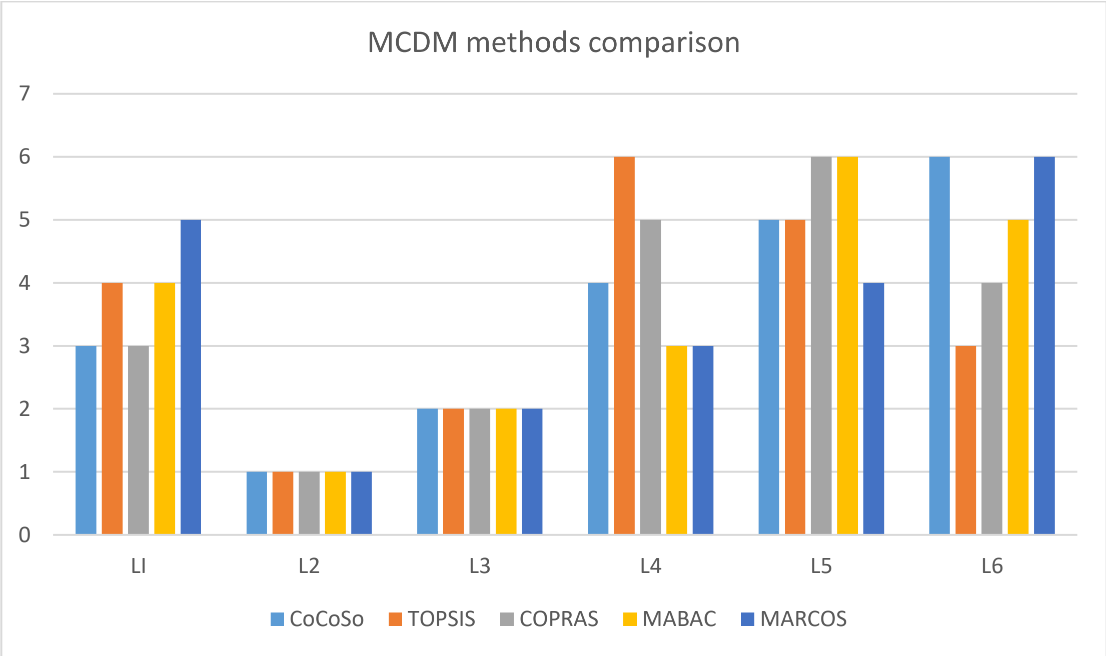

Figure 4. The comparison of CoCoSo with other MCDM tools

Table 12 – CoCoSo sensitivity analysis via various criteria weight

	W1	W2	W3	W4	W5	W6	W7
T1	0,104	0,344	0,139	0,083	0,039	0,208	0,083
T2	0,104	0,139	0,344	0,083	0,039	0,208	0,083
T3	0,104	0,139	0,083	0,344	0,039	0,208	0,083
T4	0,104	0,139	0,083	0,039	0,344	0,208	0,083
T5	0,104	0,139	0,083	0,039	0,208	0,344	0,083
T6	0,104	0,139	0,083	0,039	0,208	0,083	0,344
T7	0,344	0,139	0,104	0,083	0,039	0,208	0,083
T8	0,344	0,139	0,083	0,104	0,039	0,208	0,083
T9	0,344	0,139	0,083	0,039	0,104	0,208	0,083
T10	0,344	0,139	0,083	0,039	0,208	0,104	0,083
T11	0,344	0,139	0,083	0,039	0,208	0,083	0,104
T12	0,344	0,104	0,083	0,139	0,039	0,208	0,083
T13	0,344	0,083	0,104	0,139	0,039	0,208	0,083
T14	0,344	0,083	0,139	0,104	0,039	0,208	0,083
T15	0,344	0,083	0,139	0,039	0,104	0,208	0,083
T16	0,344	0,083	0,139	0,039	0,208	0,104	0,083
T17	0,344	0,083	0,139	0,039	0,208	0,083	0,104
T18	0,039	0,208	0,083	0,344	0,104	0,139	0,083
T19	0,139	0,083	0,083	0,344	0,104	0,039	0,208
T20	0,039	0,208	0,344	0,083	0,104	0,139	0,083

Table 13 – CoCoSo results for the sensitivity analysis

	CoCoSo org	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20
LI	3	2	2	2	3	3	2	2	2	3	3	3	2	2	2	3	3	3	2	2	2
L2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L3	2	3	3	3	2	2	3	3	3	2	2	2	3	3	3	2	2	2	3	3	3
L4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
L5	5	5	5	5	5	5	5	5	5	5	6	6	5	5	5	5	6	6	5	5	5
L6	6	6	6	6	6	6	6	6	6	6	5	5	6	6	6	6	5	5	6	6	6

Table 14 – Score of farms based on the vector of each dimension

	Economic	Environmental	Social	R1	R2	R3	R4	R5
L1	**3,573**	3,193	6,426	1,055	2,826	1,005	0,452	1,085
L2	**4,222**	3,217	5,713	1,055	2,355	1,005	0,452	0,723
L3	**3,583**	3,079	4,019	0,754	3,297	1,005	0,395	1,085
L4	**2,326**	1,652	1,7	0,603	2,826	1,005	0,452	0,603
L5	**1,351**	1,626	5,32	0,904	2,355	0,402	0,226	0,603
L6	**0,82**	1,411	1	0,452	0,471	0,201	0,282	0,603

Table 15. Score of slaughterhouses based on the vector of each dimension

	Economic	Environmental	Social	R1	R2	R3	R4	R5
H1	1,468	1,549	3,879	0,626	1,46	0,156	0,704	0,608
H2	2,182	4,217	2,379	0,626	2,556	0,156	0,704	0,521
H3	2,379	2,6	1,083	0,47	1,826	0,156	0,939	0,521
H4	3,362	6,035	6,092	0,939	2,556	0,156	1,408	0,608

To summarize, we can report that according to the farms score, L2 revealed the best economic and environmental performance leaving the best social performance to L1. Regarding the resilience performance, for instance, L3 showed the best agile performance. Among the second-tier supply (i.e., slaughterhouses), H4 is the best facility for the four evaluation dimensions. Arguably, this stage's evaluation stability is compared to the first tier (i.e., farms) evaluation, and supported attainment of research objective 3 by evaluating facilities performance vis-à-vis resilience and sustainability criteria (see Figure 1).

4.4 Stages 4-6: Reconfiguring the meat supply chain network design via BC-MOPM

In this section, the supply chain network design problem is solved by optimising the four objective functions (see section 3.3). As mentioned previously, the case study is to reconfigure a two-stage meat supply chain network towards resiliency and sustainability. Table 16 presents input parameters for the four objectives and their constraints. These data were collected from the considered facilities (i.e., six farms, four slaughterhouses, and 11 retailers) in collaboration with the focal point, which was the point of contact between the research team and related facilities. The research team hereby prepared a sheet with verbal descriptions of required data and gave it to the focal point who helped in the data gathering stage. It is worthy to mention that that the focal point works at a private agency that is responsible for quality assurance of livestock and meat production in the case country. As shown in Table 16, data is presented as a range. For instance, the purchasing cost p_a^c varies between 130 to 150 (GBP/unit) depending on the farm. Similarly, number of jobs at each facility (j_a^u) varies between 13 and 18 (jobs/facility) according to the facility's labour size. This network presents a meat supply chain network in the UK. Secondary datasets were collected from a Google map to identify shipping distances among facilities, and the Environmental and Energy Study Institute (EESI, 2015) study measures carbon footprint per mile per truck. Carbon footprint per livestock was collected from decision-makers and they mentioned that their record is based on national records. The integration, evaluation, and data retrieved from the BWM-CoCoSo methods are previously presented in Tables 3-5, 14, and 15. The four objective functions were coded via the LINGO[18] software.

Table 16. Input parameters used for the case study

Cost-related parameters		
$C_a^{purchase,\alpha}$= 130 – 150 (GBP/unit)	$C_{ab}^{transport,\alpha}$= 1-1.5 (GBP/Mile)	$C_a^{order,\alpha}$= 3 – 3.6 (GBP/unit)
$C_b^{purchase,\beta}$= 160 – 175 (GBP/unit)	$C_{bc}^{transport,\beta}$= 1-1.5 (GBP/Mile)	$C_b^{order,\beta}$= 4 - 5 (GBP/unit)
$C_a^{inventory,\alpha}$= 5 – 5.5 (GBP/unit)	$C_a^{handle,\alpha}$= 3.5 -4 (GBP/unit)	$d_{ab}^{travel,\alpha}$43 – 250 (Mile)
$C_b^{inventory,\beta}$= 7 - 8.5 (GBP/unit)	$C_b^{handle,\beta}$= 4 -5 (GBP/unit)	$d_{bc}^{travel,\beta}$= 110 – 205 (Mile)
N= 50 (Unit/truck)		
Supply and demand parameters		
$q_a^{supply,\alpha}$= 900 – 2000 (Unit)	$q_b^{supply,\beta}$= 650 - 1800 (Unit)	$q_b^{demand,\beta}$= 410 – 650 (Unit)
$q_c^{demand,\gamma}$= 330 – 540 (Unit)		
Carbon footprint-related parameters		
$u_a^{CO_2,\alpha}$= 75 (Kg/Unit)	$u_b^{CO_2,\beta}$ = 100 (Kg/Unit)	$U_{ab}^{CO_2,\alpha}$= 145 (gram/Mile)
$U_{ab}^{CO_2,\alpha}$= 161.8 (gram/Mile)		
Social-related parameters		
$v_a^{job,\alpha}$= 13 – 18 (Job/facility)	$v_b^{job,\beta}$= 20 – 26 (Job/facility)	

As mentioned previously, the four objective functions are optimised via the ε-constraint method. In this work, the minimisation of economic factors was left as an objective function and others were moved to the constraint set. This requires identification of ε1, ε2, and ε3 to solve the optimisation problem (see Eqs 23-28). These values could be any value varied between the minimum and maximum value for the considered objective function. To this end, each objective function was optimised twice as a minimum and maximum objective function, individually. This revealed the maximum and minimum values for each objective function, as reported in Table 17. This range between the two extremes was segmented into 15 segments; each segment represents a different ε value. By this step, ten values for ε1, ε2, and ε3 are derived. These Max and Min values show the expected range for each objective value. It should be noted that these ranges could be divided to any other numbers (e.g., 10 or 20) to obtain the required number of solutions. In other words, scholars who wish to replicate this modelling solution might segment the epsilon values into, for instance, 30 segments to reveal 30 Pareto solutions. This might be needed if decision-makers are not happy with any of the revealed 15 solutions where another epsilon value could be set until the solution is convenient to decision-makers.

Table 17. Maximum and minimum values related to CESR

Objective functions	Max	Min
C	3177089	1011674
E	1.44E+07	2030902
S	4472	1777
R	242	96.8

Then, these 15 values for ε1, ε2, and ε3 were substituted in Eqs. 23, 25, and 27, respectively. It should be noted that the model was run 15 times to accommodate the 15 values. Accordingly, every iteration, with a different combination of ε values, may give a different Pareto solution. Table 18 presents a set of 15 Pareto solutions. Also, Figure 5 presents a graphical illustration of the trade-offs among the four objectives. It is worth mentioning that due to the high number (more than two) of objective functions, some iterations revealed unstable results which were eliminated. In other words, if scholars repeat this optimisation, they need to try a different ε value in case they obtain an unstable solution. The latter could be a sudden or unexpected increase or decrease in one or more of the objective function values that do not correspond with the smooth flow of previous and latter solutions. Scholars could also identify these solutions using the graphical illustration of Pareto frontiers among the four objective functions.

Table 18. A set of 15 Pareto solutions based on 15 ε values' iterations

#	Min C	Min E	Max S	Max R
1.00	1011674.00	2030902.00	1777.00	96.80
2.00	1166346.50	2854692.53	1962.86	106.95
3.00	1321019.00	3678483.07	2148.72	117.11
4.00	1475691.50	4502273.60	2334.59	127.26
5.00	1630364.00	5326064.13	2520.45	137.42
6.00	1785036.50	6149854.67	2706.31	147.57
7.00	1939709.00	6973645.20	2892.17	157.72
8.00	2094381.50	7797435.73	3078.03	167.88
9.00	2249054.00	8621226.27	3263.90	178.03
10.00	2403726.50	9445016.80	3449.76	188.18
11.00	2558399.00	10268807.33	3635.62	198.34
12.00	2713071.50	11092597.87	3821.48	208.49
13.00	2867744.00	11916388.40	4007.34	218.65
14.00	3022416.50	12740178.93	4193.21	228.80
15.00	3177089.00	13563969.47	4379.07	238.95

Model class: mixed integer linear programming	Variables: 117
Solution type: Global optimum	Constraints: 65

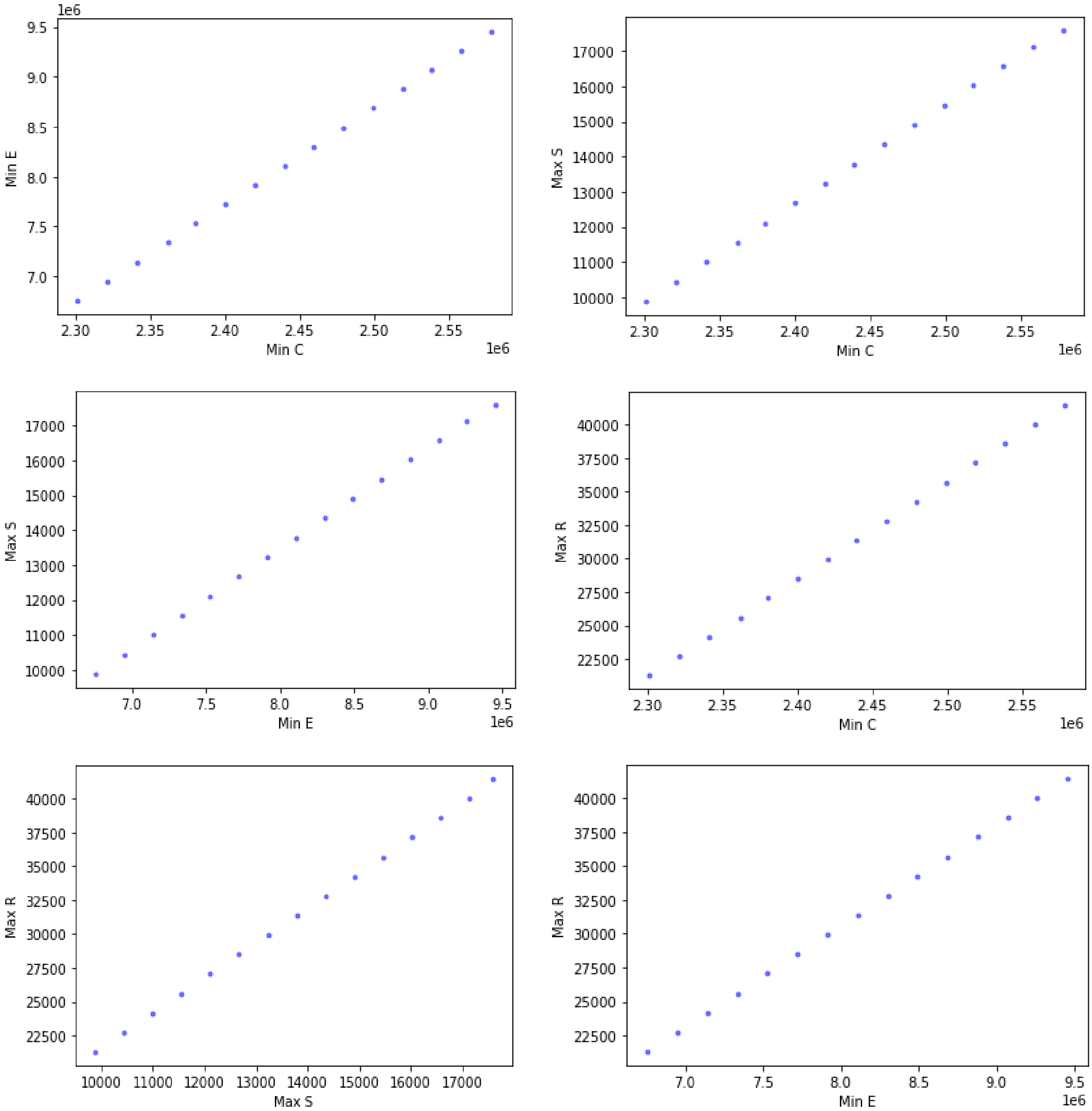

Figure 5. Pareto frontiers.

As shown in Table 18, trade-offs among the four objectives are obtainable. For example, solution number 1 requires 1011674 GPB to design the supply chain network that emits a total carbon footprint of 2030902. However, this would create a social impact represented by 1777 job opportunities value. In terms of resiliency, this solution gives a resiliency value of 96.8. It can be noticed that this solution revealed the minimum cost and environmental impact in addition to minimum social impact and resilience value. As shown in Figure 5, the expected paradox between total cost and resilience value can be noticed; for instance, a desirable increase in the latter would require an undesirable extra cost. This cost could be related to higher purchasing cost from resilient facilities. Thus, the contradiction between minimisation of total costs and maximisation of resilient facility value exists in which the improvement of one objective worsens the other. On the other hand, some objectives optimisation showed correlation; for instance, the Pareto front between maximisation of social aspect and resilient facility value in which improvement in one objective enhances the other. For the multi-objective optimisation application on real case studies, it is possible to miss the conflict between correlated objectives. At the same time, this does not remove the independency between them since they are related to some common parameters that are all considered when optimising them together. For instance, they are both limited by the same constraint sets. In such cases, some researchers intend to solve the objectives individually (Kostin *et al.,* 2012). However, this option does not work in this model as they are optimised with other two objectives. For instance, this may lead to a larger carbon footprint as it may request more facilities to be opened. On one hand, this might reflect an undesired increase in the environmental impact but, on the other hand, it may push towards more facilities to be opened which feed into multiple supply sources to partially build resiliency in the supply chain context.

This model also aims to allocate annual order sizes from opened facilities. The revealed 15 solutions (see Table 18) hereby are associated with fifteen facility structures and order sizes. In other words, each reveals a Pareto solution that would give values for the objective function, facilities to be opened, and order size. The decision-makers hereby would need to choose one convenient Pareto solution. This might be a challenging role, especially for hesitant decision-makers regarding their desires. It means some decision-makers prioritise economic-oriented objectives and thus would seek the solution that gives the cheapest design cost. Others may be interested in building a resilient supply chain regardless of required investment cost and thus would go with the solution that might lead to the highest resilience state. However, such a solution might reveal a higher environmental impact as the optimisation model would push towards multiple facilities that lead to more CO_2 emissions.

In this work, this final selection of possible Pareto solution was given to solution number 8 as a compromise among the four objectives. Table 19 presents the correspondence order size associated with this solution that recommends to open farms (facilities *A*) L1, L3, L4, and L6 and abattoirs (facilities *B*) H1, H2, H3, and H4. This means, for instance, the order size (quantity of units to be purchased from farm 1 is 1300 units). Similarly, the order size from slaughterhouse 3 is 440 units. It is worthy to clarify that decision-makers (e.g., a supply chain manager) may discuss the overall orientation (sustainable development or building supply chain resilience or a mixture of both) for their company with managers. This would help the managers to select a solution that satisfies the company's orientation. For instance, if a company's senior manager plans to strategically elevate the company's environmental and/or social profile, the supply chain manager would need to select a solution that gives higher values for these aspects regardless of other objectives values. These findings enabled this work to achieve research objectives 4 and 5 by structuring a SCN and allocating orders among facilities based on resilience and sustainability objectives (see section 3.3).

Table 19. The selected order size based on solution 8

Facilities *A*	Quantity	Facilities *B*	Quantity
L1	1300	H1	1500
L3	280	H2	560
L4	400	H3	440
L6	1120	H4	340

4.5 Theoretical implications

Although several research studies have investigated the resilience supply chain, the resilient supply chain network design to comply with sustainability requirements has not been explored much. As far as we can tell, this is the first quantitative work of two-tier SCND that merges resilience requirements without lagging sustainability responsibilities.

The need for securing resilient green food has become a paramount initiative, especially because of the world's growing population. Thus, decision-makers must encounter resilience and sustainability aspects in designing a food supply chain network to avoid and withstand disruption risks and to fulfil growing demands for sustainable food. Further, this is a paramount need due to the consideration of policy makers and decision-makers to merge digital technologies into supply chain activities and operations due to their potentials (e.g., higher visibility, enhanced collaboration, efficient inventory management, etc.). On the other hand, this evolution in managing supply chains makes it prone to possible technological risks or disruptions [5] and [6]. Therefore, this study highlights the requirements for restricting a food supply chain network and it considers these two aspects from tactical and strategic perspectives. Mainly, this work considers multi-tier suppliers that are a must for a green and resilient food supply chain [101]. The research methodology shows how important the consideration of multi-tier facilities' performance is in building resilience and sustainability within the entire supply chain, mainly, and secondly, it demonstrates the increasing societal demand to reveal the entire identify of meat products in marketplaces. In this case, the quality of food products does not depend on manufacturers only, but also on original suppliers of livestock [102]. In the resilience context, for instance, several retailers and slaughterhouses struggle with fulfilling food demands because of the present COVID-19 pandemic. It can be argued that a lot of these disruptions were at the 1^{st}-tier or 2^{nd}-tier facilities due to quarantines or border closures. This also shows the importance of the current research methodology in considering resilience in a two-tier food supply chain to potentially withstand such a disruption in the future. Hence, food supply chain networks must be reconfigured based on sustainability and resilience criteria. To embed this tactically, orders allocation should also consider resilience and sustainable performance of those facilities to proactively build resilience planning, in addition to the continuity of sustainable development. In the context of building relationships among food SC partners, managers at food companies should support suppliers in embedding resilience and sustainability criteria into their operations. Generally, this research reflects theoretical and managerial implications.

Theoretically, this research further explores the correlation and relationship between resilience and sustainability in a supply chain context. It hereby presents a holistic framework that includes criteria for resilience, economic, environmental, and social performance. Although this methodology is applied to a two-tier food supply chain, it has the potential to be reapplied to a different supply chain structure subject to minor changes in the modelling. This should consider the transportation level (whether 1, 2, 3, etc.) and the input data for the case under consideration. Also, the proposed framework has the potential to be extended to other supply chain activities such as production planning and scheduling, procurement, logistics, warehousing, and manufacturing. Furthermore, this research presents an attempt towards the integration between multi-criteria decision-making methods and multi-objective optimisation.

This would help managers to include tangible and intangible evaluation criteria (costs and safety) into their decision desires (e.g., minimisation of total cost or maximisation of social aspect). Last but not least, the general weak resilience profile and sustainability performance of the case facilities supports the call for embedding digital technologies with the potential to elevate resilience profiles and sustainability performance of those facilities as discussed previously (see sections 1 and 2.5) [74] [75] [76] [77]. For instance, weak environmental and social sustainability performance are noticed for some facilities. Block-chain technology as a digital technology has the potential to support the environmental criteria, including interest in environmentalism and environment-related certifications considered in this work via its traceability, reliability, and transparency capabilities in supply chain management [98].

4.6 Managerial implications

The system developed in this paper equips supply chain designers and managers with a decision support methodology to design SCN considering resilience and sustainability paradigms, methods that concern the industry in general. Also, this work presents an analytical BWM-CoCoSo-evaluation approach to evaluate resilience, economic, environmental, and social performance of facilities. This could be used by managers to evaluate resilience and sustainability performance of their current facilities towards short-term improvement and strategic targets for growth. Apart from the multi-objective model, this evaluation approach could be used by managers to diagnose the resilience and sustainability profile of their existing supply chains. To this end, for instance, supply chain managers can use the approach presented in sections 3.1 and 3.2 of the methodology. In the others, they should follow the methodology described in stages 1-3. This should give an evaluation of facilities' performance just as those presented in sections 4.1 and 4.2. In this context, the revealed facilities' weights have an impact on the optimisation of the SCND and values of the four objectives due to their integration into the model formulation. However, these weights are subjective in which they are established based on experts' opinions regarding those facilities' performance. Thus, decision-makers should be carefully selected in the replication of this methodology to avoid any bias in allocating facilities and corresponding orders size. They may determine that a certain aspect of their firm needs improvement, such as social or resilience aspect. Finally, the developed BC-MOPM reveals a set of compromises among resilience, economic, environmental, and social aspects that can help managers to weigh their options in reconfiguring existing SCNs or in designing new ones.

5. Conclusion and directions for further enhancement

Supply chain networks are prone to risks due to their dynamic nature. These risks enforce managers to rebuild their supply chain networks and to embed resilience elements to ensure business continuity. Supply chain resilience has a strong correlation with sustainable development goals. This also requires managers to build up resilience in their supply chains without overlooking their sustainability responsibilities (economic, environmental, and social). However, the multiple criteria decision-making process is challenging and requires a unified, resilient, and sustainable handling approach.

This work aims at developing a supply chain network design that considers resilience enforcement and considers the triple bottom line of sustainability. Thus, a four-objective optimisation model was developed to design a two-tier supply chain. The objectives are minimisation of economic and environmental aspects and maximisation of resilience and social aspects. The economic aspect included costs of purchasing, transportation, inventory, handling, and ordering. The carbon footprint per truck per mile and unit produced at the facilities were used for the environmental aspect. The social aspect was formulated based on possible job opportunities due to a facility opening. The resilience aspect was presented in terms of flexibility, agility, preparedness, redundancy, and collaboration. These resiliency criteria in addition to the sustainability criteria and sub-criteria were presented into a holistic framework developed based on literature analysis.

The developed optimisation model integrates the relative importance of these resilience and sustainability criteria derived by the BWM method. It also integrates the resilience and sustainability value of presented facilities obtained by the CoCoSo method. Unlike similar supply chain network design methodology, this is the first study to present this integration for a two-tier supply chain configuration. This integration helps in embedding decision-makers' perspectives regarding relative importance of resiliency and sustainability and performance profiles of facilities in terms of these two paradigms. The evaluation stages (1 and 2) revealed a low interest into the environmental and social criteria compared to economic and resilience criteria. Arguably, it also showed a relatively low environmental and social performance profiles for most farms and slaughterhouses at the two-tier upstream chain. It can be also inferred that the developed integrated optimisation model can reconfigure the two-tier supply chain network considering resilience and sustainability by presenting trade-offs among them.

These are also associated with order sizes that help purchasing teams to set optimal order size from suggested opened facilities.

7.1 Limitations and future research directions

This model was applied onto a national supply chain network and thus would be very interesting to validate on a global supply chain network. This might give further insights to decision-makers in considering multiple facilities to enforce resiliency but sacrificing sustainability aspects largely by considering different transportation means. In other words, this might lead to the cost of achieving a profile of resiliency. Also, all input data were used in a deterministic nature that might not reflect all real-world settings. Thus, this work could be extended in handling the uncertainty and vagueness in some input parameters such as purchasing cost, transportation costs, supply capacity, retailers' demand, and carbon footprint per truck per mile. To this end, the employment of the fuzzy set theory within the BWM-CoCoSo-multi-objective programming model (BC-MOPM) modelling is proposed. This includes, first, applying fuzzy BWM-fuzzy CoCoSo to capture possible uncertainty in the excerpts' opinions; and second, extending the MOPM formulation to a fuzzy MOPM to capture uncertainties in related-input data such as transportation costs and demand. The latter could adapt the fuzzy approach proposed by [103] or [104].

In this context of case study limitations, decision-makers at retailers were not aware of 2nd-tier facilities' performance. Thus, this methodology could be reapplied on a multi-tier supply chain that has more integration and collaboration among its partners. This is expected to reflect more managerial implications regarding the role of integration and collaboration towards resilience and sustainability in supply chain management. In this regard, this work discussed the need for resilient and sustainable SCNs in the digital technology era. However, the developed methodology does not incorporate digitalization elements into the evaluation process for facilities. This could be an interesting research avenue to widen the criteria for resilient and sustainable supply chain network design (see Figure 1) to include digitalisation as a third pillar. Scholars are encouraged to identify related factors such as monitoring and tracking, virtual reality services, availability of digital twin logistics, to evaluate facilities accordingly.

Furthermore, the case study presents a limited data scale, and it would be fruitful to explore the BC-MOPM performance on a large-sized supply chain network. Decision-makers may enforce consideration of a particular resilience and sustainability performance into their modelling. This would require formulating additional constraints that limit the qualified facilities based on a predetermined resilience and sustainability margin by decision-makers. The latter hereby may consider different levels of performance targets that will be strategically applied gradually. Also, this study is limited by consideration of proactive SC resilience in terms of facilities' resilience performance. Thus, it would be useful for scholars to extend this methodology considering proactive and reactive SC resilience planning. This could include modelling of several disruption risks and investigation of the performance of reactive plans.

Appendix

A1: A list of abbreviation

BWM	Best worst method
CoCoSo	Combined compromise solution
MOPM	Multi-objective programming model
BC-MOPM	Best worst method-combined compromise solution-multi-objective programming model
RS-SCND	Resilient and sustainable supply chain network design
SCN	Supply chain network
ISM	Institute of Supply Management
SC	Supply chain
RSC	Resilience and sustainability criteria
MCDM	Multiple-criteria decision-making
CESR	Cost and environmental impact, and social and resilience
Eq	Equation
COPRAS	Complex proportional assessment of alternatives
TOPSIS	Technique for order performance by similarity to ideal solution
MABAC	Multi-attributive border approximation area comparison
MARCOS	Measurement of alternatives and ranking according to Compromise solution
CRITIC	The CRiteria Importance Through Intercriteria Correlation
ANP	Analytic network process
SWARA	Stepwise weight assessment ratio analysis
AHP	Analytic hierarchy process
LP	Linear programming
DM	Decision-maker
CO_2	Carbon dioxide
EESI	Environmental and Energy Study Institute

A2: Summary of the research methodology

This paper presents an integrated BC-MOPM to redesign a two-tier supply chain network considering sustainability and resilience responsibilities. This was conducted as follows:

Step 1: Analyse the literature to identify the relationship between sustainability and resilience in the supply chain context. This step helped in (1) highlighting the need for considering both paradigms in designing a supply chain network, and (2) identifying resilience and sustainability criteria.

Step 2: Apply BWM to quantify the relative importance of criteria (i.e., identified in Step 1).

Step 3: Apply CoCoSo to quantify facilities' performance vis-à-vis resilience and sustainability criteria.

Step 4: Develop the four objective functions and related constraints. The four objectives are: minimisation of cost and environmental impact, and maximisation social aspect and resilient location value. This development includes the integration of values revealed from Steps 2 and 3, in addition to other input parameters (e.g., purchasing, costs, CO_2 emission, etc.).

Step 5: Derive a set of Pareto solution – out of the four objectives model – by using the ε-constraint method. However, this step needs to solve the four objectives individually to obtain their minimum and maximum values that are needed to assign ε values.

Step 6: Ask decision-makers (e.g., supply chain manager) to select one solution based on the company's preferences. For instance, if they push towards minimal costs**,** the decision-maker would select a solution that is associated with minimum costs.

Step 7: Present the order allocation plan that is associated with the selected solution.

References:

[1] M. Yavari, H. Zaker, An integrated two-layer network model for designing a resilient green-closed loop supply chain of perishable products under disruption, J Clean Prod. 230 (2019). https://doi.org/10.1016/j.jclepro.2019.04.130.

[2] A. Gunasekaran, R. Dubey, S.P. Singh, Flexible Sustainable Supply Chain Network Design: Current Trends, Opportunities and Future, Global Journal of Flexible Systems Management. 17 (2016) 109–112. https://doi.org/10.1007/s40171-016-0131-7.

[3] Y. Wang, J.H. Han, P. Beynon-Davies, Understanding blockchain technology for future supply chains: a systematic literature review and research agenda, Supply Chain Management. 24 (2019) 62–84. https://doi.org/10.1108/SCM-03-2018-0148.

[4] A. Sheel, V. Nath, Effect of blockchain technology adoption on supply chain adaptability, agility, alignment and performance, Management Research Review. 42 (2019) 1353–1374. https://doi.org/10.1108/MRR-12-2018-0490.

[5] A. Bayramova, D.J. Edwards, C. Roberts, The role of blockchain technology in augmenting supply chain resilience to cybercrime, Buildings. 11 (2021). https://doi.org/10.3390/buildings11070283.

[6] M. Klumpp, D. Loske, Sustainability and resilience revisited: Impact of information technology disruptions on empirical retail logistics efficiency, Sustainability (Switzerland). 13 (2021). https://doi.org/10.3390/su13105650.

[7] N. Zubairu, J. Dinwoodie, K. Govindan, L. Hunter, S. Roh, Supply chain strategies as drivers of financial performance in liquefied natural gas networks, Supply Chain Management. 26 (2021) 579–591. https://doi.org/10.1108/SCM-08-2020-0389.

[8] A. Mohammed, A.B.L. de S. Jabbour, A. Diabat, COVID-19 pandemic disruption: a matter of building companies' internal and external resilience, Int J Prod Res. (2021). https://doi.org/10.1080/00207543.2021.1970848.

[9] M. Kamalahmadi, M. Shekarian, M. Mellat Parast, The impact of flexibility and redundancy on improving supply chain resilience to disruptions, Int J Prod Res. 60 (2022) 1992–2020. https://doi.org/10.1080/00207543.2021.1883759.

[10] I. Erol, I.M. Ar, I. Peker, Scrutinizing blockchain applicability in sustainable supply chains through an integrated fuzzy multi-criteria decision making framework, Appl Soft Comput. 116 (2022). https://doi.org/10.1016/j.asoc.2021.108331.

[11] M. Tang, H. Liao, Z. Wan, E. Herrera-Viedma, M.A. Rosen, Ten years of Sustainability (2009 to 2018): A bibliometric overview, Sustainability (Switzerland). 10 (2018). https://doi.org/10.3390/su10051655.

[12] M. Ghomi-Avili, A. Khosrojerdi, R. Tavakkoli-Moghaddam, A multi-objective model for the closed-loop supply chain network design with a price-dependent demand, shortage and disruption, Journal of Intelligent and Fuzzy Systems. 36 (2019) 5261–5272. https://doi.org/10.3233/JIFS-181051.

[13] S. Rezapour, R.Z. Farahani, M. Pourakbar, Resilient supply chain network design under competition: A case study, Eur J Oper Res. 259 (2017) 1017–1035. https://doi.org/10.1016/j.ejor.2016.11.041.

[14] M. Fattahi, K. Govindan, E. Keyvanshokooh, Responsive and resilient supply chain network design under operational and disruption risks with delivery lead-time sensitive customers, Transp Res E Logist Transp Rev. 101 (2017). https://doi.org/10.1016/j.tre.2017.02.004.

[15] A. Bhattacharya, J. Geraghty, P. Young, P.J. Byrne, Design of a resilient shock absorber for disrupted supply chain networks: A shock-dampening fortification framework for mitigating excursion events, Production Planning and Control. 24 (2013). https://doi.org/10.1080/09537287.2012.666861.

[16] M. Sherafati, M. Bashiri, R. Tavakkoli-Moghaddam, M.S. Pishvaee, Achieving sustainable development of supply chain by incorporating various carbon regulatory mechanisms, Transp Res D Transp Environ. 81 (2020). https://doi.org/10.1016/j.trd.2020.102253.

[17] M. Rahimi, V. Ghezavati, F. Asadi, A stochastic risk-averse sustainable supply chain network design problem with quantity discount considering multiple sources of uncertainty, Comput Ind Eng. 130 (2019) 430–449. https://doi.org/10.1016/j.cie.2019.02.037.

[18] X. Zhang, A. Adamatzky, F.T.S. Chan, S. Mahadevan, Y. Deng, Physarum solver: a bio-inspired method for sustainable supply chain network design problem, Ann Oper Res. 254 (2017). https://doi.org/10.1007/s10479-017-2410-x.

[19] A. Mohammed, I. Harris, A. Soroka, R. Nujoom, A hybrid MCDM-fuzzy multi-objective programming approach for a G-resilient supply chain network design, Comput Ind Eng. 127 (2019) 297–312. https://doi.org/10.1016/j.cie.2018.09.052.

[20] A. Jabbarzadeh, B. Fahimnia, S. Rastegar, Green and Resilient Design of Electricity Supply Chain Networks: A Multiobjective Robust Optimization Approach, IEEE Trans Eng Manag. 66 (2019). https://doi.org/10.1109/TEM.2017.2749638.

[21] D. Ivanov, Simulation-based ripple effect modelling in the supply chain, Int J Prod Res. 55 (2017) 2083–2101. https://doi.org/10.1080/00207543.2016.1275873.

[22] M. Brandenburg, T. Rebs, Sustainable supply chain management: A modelling perspective, Ann Oper Res. 229 (2015). https://doi.org/10.1007/s10479-015-1853-1.

[23] A. Pavlov, D. Ivanov, D. Pavlov, A. Slinko, Optimization of network redundancy and contingency planning in sustainable and resilient supply chain resource management under conditions of structural dynamics, Ann Oper Res. (2019). https://doi.org/10.1007/s10479-019-03182-6.

[24] S. Aday, M.S. Aday, Impact of COVID-19 on the food supply chain, Food Quality and Safety. 4 (2020) 167–180. https://doi.org/10.1093/fqsafe/fyaa024.

[25] M. Izadikhah, M. Azadi, M. Toloo, F.K. Hussain, Sustainably resilient supply chains evaluation in public transport: A fuzzy chance-constrained two-stage DEA approach, Appl Soft Comput. 113 (2021). https://doi.org/10.1016/j.asoc.2021.107879.

[26] S. Rezaei, J. Behnamian, Benders decomposition-based particle swarm optimization for competitive supply networks with a sustainable multi-agent platform and virtual alliances, Appl Soft Comput. 114 (2022). https://doi.org/10.1016/j.asoc.2021.107985.

[27] J. Wang, Q. Wan, A multi-period multi-product green supply network design problem with price and greenness dependent demands under uncertainty, Appl Soft Comput. 114 (2022). https://doi.org/10.1016/j.asoc.2021.108078.

[28] S. Piya, A. Shamsuzzoha, M. Khadem, Analysis of supply chain resilience drivers in oil and gas industries during the COVID-19 pandemic using an integrated approach, Appl Soft Comput. 121 (2022). https://doi.org/10.1016/j.asoc.2022.108756.

[29] V. Rajagopal, S. Prasanna Venkatesan, M. Goh, Decision-making models for supply chain risk mitigation: A review, Comput Ind Eng. 113 (2017) 646–682. https://doi.org/10.1016/j.cie.2017.09.043.

[30] S. Hosseini, D. Ivanov, J. Blackhurst, Conceptualization and Measurement of Supply Chain Resilience in an Open-System Context, IEEE Trans Eng Manag. 69 (2022) 3111–3126. https://doi.org/10.1109/TEM.2020.3026465.

[31] N. Goldbeck, P. Angeloudis, W. Ochieng, Optimal supply chain resilience with consideration of failure propagation and repair logistics, Transp Res E Logist Transp Rev. 133 (2020). https://doi.org/10.1016/j.tre.2019.101830.

[32] S. Valipour Parkouhi, A. Safaei Ghadikolaei, H. Fallah Lajimi, Resilient supplier selection and segmentation in grey environment, J Clean Prod. 207 (2019) 1123–1137. https://doi.org/10.1016/j.jclepro.2018.10.007.

[33] C.F. Durach, F. Wiengarten, T.Y. Choi, Supplier–supplier coopetition and supply chain disruption: first-tier supplier resilience in the tetradic context, International Journal of Operations and Production Management. 40 (2020) 1041–1065. https://doi.org/10.1108/IJOPM-03-2019-0224.

[34] S. Elluru, H. Gupta, H. Kaur, S.P. Singh, Proactive and reactive models for disaster resilient supply chain, Ann Oper Res. 283 (2019) 199–224. https://doi.org/10.1007/s10479-017-2681-2.

[35] W.J. Tan, A.N. Zhang, W. Cai, A graph-based model to measure structural redundancy for supply chain resilience, Int J Prod Res. 57 (2019) 6385–6404. https://doi.org/10.1080/00207543.2019.1566666.

[36] S. Hosseini, N. Morshedlou, D. Ivanov, M.D. Sarder, K. Barker, A. al Khaled, Resilient supplier selection and optimal order allocation under disruption risks, Int J Prod Econ. 213 (2019). https://doi.org/10.1016/j.ijpe.2019.03.018.

[37] S. Hosseini, D. Ivanov, A. Dolgui, Review of quantitative methods for supply chain resilience analysis, Transp Res E Logist Transp Rev. 125 (2019). https://doi.org/10.1016/j.tre.2019.03.001.

[38] J.T. Margolis, K.M. Sullivan, S.J. Mason, M. Magagnotti, A multi-objective optimization model for designing resilient supply chain networks, Int J Prod Econ. 204 (2018) 174–185. https://doi.org/10.1016/j.ijpe.2018.06.008.

[39] J. Pires Ribeiro, A. Barbosa-Povoa, Supply Chain Resilience: Definitions and quantitative modelling approaches – A literature review, Comput Ind Eng. 115 (2018) 109–122. https://doi.org/10.1016/j.cie.2017.11.006.

[40] L. V. Snyder, Z. Atan, P. Peng, Y. Rong, A.J. Schmitt, B. Sinsoysal, OR/MS models for supply chain disruptions: A review, IIE Transactions (Institute of Industrial Engineers). 48 (2016). https://doi.org/10.1080/0740817X.2015.1067735.

[41] X. Wang, Y. Wu, L. Liang, Z. Huang, Service outsourcing and disaster response methods in a relief supply chain, Ann Oper Res. 240 (2016) 471–487. https://doi.org/10.1007/s10479-014-1646-y.

[42] B. Fahimnia, C.S. Tang, H. Davarzani, J. Sarkis, Quantitative models for managing supply chain risks: A review, Eur J Oper Res. 247 (2015). https://doi.org/10.1016/j.ejor.2015.04.034.

[43] E.L. Tucker, M.S. Daskin, B. v. Sweet, W.J. Hopp, Incentivizing resilient supply chain design to prevent drug shortages: policy analysis using two- and multi-stage stochastic programs, IISE Trans. 52 (2020). https://doi.org/10.1080/24725854.2019.1646441.

[44] M. Kaboli Chalmardi, J.F. Camacho-Vallejo, A bi-level programming model for sustainable supply chain network design that considers incentives for using cleaner technologies, J Clean Prod. 213 (2019). https://doi.org/10.1016/j.jclepro.2018.12.197.

[45] L. Zhen, L. Huang, W. Wang, Green and sustainable closed-loop supply chain network design under uncertainty, J Clean Prod. 227 (2019). https://doi.org/10.1016/j.jclepro.2019.04.098.

[46] M.S. Pishvaee, J. Razmi, S.A. Torabi, An accelerated Benders decomposition algorithm for sustainable supply chain network design under uncertainty: A case study of medical needle and syringe supply chain, Transp Res E Logist Transp Rev. 67 (2014). https://doi.org/10.1016/j.tre.2014.04.001.

[47] N. Kazemi, S.H. Abdul-Rashid, R.A.R. Ghazilla, E. Shekarian, S. Zanoni, Economic order quantity models for items with imperfect quality and emission considerations, International Journal of Systems Science: Operations and Logistics. 5 (2018) 99–115. https://doi.org/10.1080/23302674.2016.1240254.

[48] Y.C. Tsao, V. van Thanh, J.C. Lu, V. Yu, Designing sustainable supply chain networks under uncertain environments: Fuzzy multi-objective programming, J Clean Prod. 174 (2018). https://doi.org/10.1016/j.jclepro.2017.10.272.

[49] Y. Guo, F. Hu, H. Allaoui, Y. Boulaksil, A distributed approximation approach for solving the sustainable supply chain network design problem, Int J Prod Res. 57 (2019). https://doi.org/10.1080/00207543.2018.1556412.

[50] H. Ghaderi, A. Moini, M.S. Pishvaee, A multi-objective robust possibilistic programming approach to sustainable switchgrass-based bioethanol supply chain network design, J Clean Prod. 179 (2018). https://doi.org/10.1016/j.jclepro.2017.12.218.

[51] S. Sarkar, B.C. Giri, Stochastic supply chain model with imperfect production and controllable defective rate, International Journal of Systems Science: Operations and Logistics. 7 (2020) 133–146. https://doi.org/10.1080/23302674.2018.1536231.

[52] A. Gharaei, M. Karimi, S.A. Hoseini Shekarabi, Joint Economic Lot-sizing in Multi-product Multi-level Integrated Supply Chains: Generalized Benders Decomposition, International Journal of Systems Science: Operations and Logistics. 7 (2020) 309–325. https://doi.org/10.1080/23302674.2019.1585595.

[53] A. Gharaei, S.A. Hoseini Shekarabi, M. Karimi, Modelling And optimal lot-sizing of the replenishments in constrained, multi-product and bi-objective EPQ models with defective products: Generalised Cross Decomposition, International Journal of Systems Science: Operations and Logistics. 7 (2020) 262–274. https://doi.org/10.1080/23302674.2019.1574364.

[54] C. Duan, C. Deng, A. Gharaei, J. Wu, B. Wang, Selective maintenance scheduling under stochastic maintenance quality with multiple maintenance actions, (2018). https://doi.org/10.1080/00207543.2018.1468856.

[55] N.H. Shah, U. Chaudhari, L.E. Cárdenas-Barrón, Integrating credit and replenishment policies for deteriorating items under quadratic demand in a three echelon supply chain, International Journal of Systems Science: Operations and Logistics. 7 (2020) 34–45. https://doi.org/10.1080/23302674.2018.1487606.

[56] M. Biuki, A. Kazemi, A. Alinezhad, An integrated location-routing-inventory model for sustainable design of a perishable products supply chain network, J Clean Prod. 260 (2020). https://doi.org/10.1016/j.jclepro.2020.120842.

[57] G.J.L. Micheli, F. Mantella, Modelling an environmentally-extended inventory routing problem with demand uncertainty and a heterogeneous fleet under carbon control policies, Int J Prod Econ. 204 (2018). https://doi.org/10.1016/j.ijpe.2018.08.018.

[58] C. Franco, E.R. López-Santana, J.C. Figueroa-García, Solving the interval green inventory routing problem using optimization and genetic algorithms, in: Communications in Computer and Information Science, 2017. https://doi.org/10.1007/978-3-319-66963-2_49.

[59] C. Franco, E.R. López-Santana, G. Méndez-Giraldo, A column generation approach for solving a green bi-objective inventory routing problem, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2016. https://doi.org/10.1007/978-3-319-47955-2_9.

[60] K. Govindan, A. Jafarian, V. Nourbakhsh, Bi-objective integrating sustainable order allocation and sustainable supply chain network strategic design with stochastic demand using a novel robust hybrid multi-objective metaheuristic, Comput Oper Res. 62 (2015). https://doi.org/10.1016/j.cor.2014.12.014.

[61] H. Lai, H. Liao, Z. Wen, E.K. Zavadskas, A. Al-Barakati, An improved cocoso method with a maximum variance optimization model for cloud service provider selection, Engineering Economics. 31 (2020). https://doi.org/10.5755/j01.ee.31.4.24990.

[62] S.A. Haji Esmaeili, J. Szmerekovsky, A. Sobhani, A. Dybing, T.O. Peterson, Sustainable biomass supply chain network design with biomass switching incentives for first-generation bioethanol producers, Energy Policy. 138 (2020). https://doi.org/10.1016/j.enpol.2019.111222.

[63] A. Mohammed, I. Harris, A. Soroka, M. Naim, T. Ramjaun, M. Yazdani, Gresilient supplier assessment and order allocation planning, Ann Oper Res. 296 (2021) 335–362. https://doi.org/10.1007/s10479-020-03611-x.

[64] S. Seuring, A review of modeling approaches for sustainable supply chain management, in: Decis Support Syst, 2013: pp. 1513–1520. https://doi.org/10.1016/j.dss.2012.05.053.

[65] M. Giannakis, T. Papadopoulos, Supply chain sustainability: A risk management approach, in: Int J Prod Econ, Elsevier, 2016: pp. 455–470. https://doi.org/10.1016/j.ijpe.2015.06.032.

[66] D. Ivanov, Revealing interfaces of supply chain resilience and sustainability: a simulation study, Int J Prod Res. 56 (2018) 3507–3523. https://doi.org/10.1080/00207543.2017.1343507.

[67] D. Swanson, L. Goel, K. Francisco, J. Stock, An analysis of supply chain management research by topic, Supply Chain Management. 23 (2018) 100–116. https://doi.org/10.1108/SCM-05-2017-0166.

[68] M. Rabbani, S.A.A. Hosseini-Mokhallesun, A.H. Ordibazar, H. Farrokhi-Asl, A hybrid robust possibilistic approach for a sustainable supply chain location-allocation network design, International Journal of Systems Science: Operations and Logistics. 7 (2020) 60–75. https://doi.org/10.1080/23302674.2018.1506061.

[69] W. Joradon, C. Colicchia, D.B. Grant, SUSTAINABLE AND RESILIENT SUPPLY CHAIN MANAGEMENT: SCALE DEVELOPMENT, n.d.

[70] A. Gharaei, S.A. Hoseini Shekarabi, M. Karimi, E. Pourjavad, A. Amjadian, An integrated stochastic EPQ model under quality and green policies: generalised cross decomposition under the separability approach, International Journal of Systems Science: Operations and Logistics. 8 (2021) 119–131. https://doi.org/10.1080/23302674.2019.1656296.

[71] M. Fattahi, K. Govindan, A multi-stage stochastic program for the sustainable design of biofuel supply chain networks under biomass supply uncertainty and disruption risk: A real-life case study, Transp Res E Logist Transp Rev. 118 (2018) 534–567. https://doi.org/10.1016/j.tre.2018.08.008.

[72] A. Gharaei, S.A. Hoseini Shekarabi, M. Karimi, E. Pourjavad, A. Amjadian, An integrated stochastic EPQ model under quality and green policies: generalised cross decomposition under the separability approach, International Journal of Systems Science: Operations and Logistics. 8 (2021) 119–131. https://doi.org/10.1080/23302674.2019.1656296.

[73] M. Yang, M. Fu, Z. Zhang, The adoption of digital technologies in supply chains: Drivers, process and impact, Technol Forecast Soc Change. 169 (2021). https://doi.org/10.1016/j.techfore.2021.120795.

[74] F.F. Rad, P. Oghazi, M. Palmié, K. Chirumalla, N. Pashkevich, P.C. Patel, S. Sattari, Industry 4.0 and supply chain performance: A systematic literature review of the benefits, challenges, and critical success factors of 11 core technologies, Industrial Marketing Management. 105 (2022) 268–293. https://doi.org/10.1016/j.indmarman.2022.06.009.

[75] M. Goto, T. Sueyoshi, Sustainable development and corporate social responsibility in Japanese manufacturing companies, Sustainable Development. 28 (2020). https://doi.org/10.1002/sd.2035.

[76] S.A. Khan, M.S. Mubarik, S. Kusi-Sarpong, H. Gupta, S.I. Zaman, M. Mubarik, Blockchain technologies as enablers of supply chain mapping for sustainable supply chains, Bus Strategy Environ. (2022). https://doi.org/10.1002/bse.3029.

[77] G. Qader, M. Junaid, Q. Abbas, M.S. Mubarik, Industry 4.0 enables supply chain resilience and supply chain performance, Technol Forecast Soc Change. 185 (2022). https://doi.org/10.1016/j.techfore.2022.122026.

[78] R. Dubey, A. Gunasekaran, Sushil, T. Singh, building theory of sustainable manufacturing using total interpretive structural modelling, International Journal of Systems Science: Operations and Logistics. 2 (2015) 231–247. https://doi.org/10.1080/23302674.2015.1025890.

[79] S.I. Mari, Y.H. Lee, M.S. Memon, Sustainable and resilient supply chain network design under disruption risks, Sustainability (Switzerland). 6 (2014). https://doi.org/10.3390/su6106666.

[80] J. Rezaei, Best-worst multi-criteria decision-making method, Omega (United Kingdom). 53 (2015). https://doi.org/10.1016/j.omega.2014.11.009.

[81] G. van de Kaa, T. Fens, J. Rezaei, Technology Analysis & Strategic Management Residential grid storage technology battles: a multi-criteria analysis using BWM Residential grid storage technology battles: a multi-criteria analysis using BWM, Technol Anal Strateg Manag. 31 (2018).

[82] A. Ijadi Maghsoodi, M. Mosavat, A. Hafezalkotob, A. Hafezalkotob, Hybrid hierarchical fuzzy group decision-making based on information axioms and BWM: Prototype design selection, Comput Ind Eng. 127 (2019). https://doi.org/10.1016/j.cie.2018.11.018.

[83] M. Mohammadi, J. Rezaei, Bayesian best-worst method: A probabilistic group decision making model, Omega (United Kingdom). 96 (2020). https://doi.org/10.1016/j.omega.2019.06.001.

[84] A. Gnanavelbabu, P. Arunagiri, Ranking of MUDA using AHP and Fuzzy AHP algorithm, 2018. www.sciencedirect.comwww.materialstoday.com/proceedings.

[85] J. Rezaei, A Concentration Ratio for Nonlinear Best Worst Method, Int J Inf Technol Decis Mak. 19 (2020) 891–907. https://doi.org/10.1142/S0219622020500170.

[86] A. Sabilla Ajrina, R. Sarno, R. Hari Ginardi, Comparison Of AHP and BWM Methods Based on Geographic Information System For Determining Potential Zone of Pasir Batu Mining, n.d.

[87] F. Liang, M. Brunelli, J. Rezaei, Consistency issues in the best worst method: Measurements and thresholds, Omega (United Kingdom). 96 (2020). https://doi.org/10.1016/j.omega.2019.102175.

[88] J. Rezaei, Best-worst multi-criteria decision-making method: Some properties and a linear model, Omega (United Kingdom). 64 (2016). https://doi.org/10.1016/j.omega.2015.12.001.

[89] Gokasar, I., Pamucar, D., Deveci, M., & Ding, W. (2023). A novel rough numbers based extended MACBETH method for the prioritization of the connected autonomous vehicles in real-time traffic management. Expert Systems with Applications, 211, 118445.

[90] Andrić Gušavac, B., Karagoz, S., Popović, M., Pamućar, D., & Deveci, M. (2022). Reconcilement of conflicting goals: a novel operations research-based methodology for environmental management. Environment, Development and Sustainability, 1-38.

[91] Pamucar, D., Deveci, M., Stević, Ž., Gokasar, I., Isik, M., & Coffman, D. M. (2022). Green Strategies in Mobility Planning Towards Climate Change Adaption of Urban Areas Using Fuzzy 2D Algorithm. Sustainable Cities and Society, 87, 104159.

[92] Deveci, M., Pamucar, D., Gokasar, I., Pedrycz, W., & Wen, X. (2022). Autonomous Bus Operation Alternatives in Urban Areas Using Fuzzy Dombi-Bonferroni Operator Based Decision Making Model. IEEE Transactions on Intelligent Transportation Systems.

[93] Gokasar, I., Timurogullari, A., Özkan, S. S., Deveci, M., & Lv, Z. (2022). MSND: Modified Standard Normal Deviate Incident Detection Algorithm for Connected Autonomous and Human-Driven Vehicles in Mixed Traffic. IEEE Transactions on Intelligent Transportation Systems.

[94] Gokasar, I., Timurogullari, A., Deveci, M., & Garg, H. (2022). SWSCAV: Real-time traffic management using connected autonomous vehicles. ISA transactions.

[95] Aydin, N., Şeker, Ş., & Deveci, M. (2022). Multi-Objective Optimization of Car Sharing Points Under Uncertainty for Sustainable Transportation. IEEE Transactions on Engineering Management.

[96] E.K. Zavadskas, A. Kaklauskas, V. Sarka, The new method of multicriteria complex proportional assessment of projects, Technological and Economic Development of Economy 1 (3) (1994) 131–139.

[97] Zavadskas, E. K., Kaklauskas, A., Peldschus, F., & Turskis, Z. (2007). Multi-attribute assessment of road design solutions by using the COPRAS method. The Baltic journal of Road and Bridge engineering, 2(4), 195-203.

[98] Behzadian, M., Otaghsara, S. K., Yazdani, M., & Ignatius, J. (2012). A state-of the-art survey of TOPSIS applications. *Expert Systems with applications*, *39*(17), 13051-13069.

[99] Pamučar, D., & Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). *Expert systems with applications*, *42*(6), 3016-3028.

[100] Stević, Ž., Pamučar, D., Puška, A., & Chatterjee, P. (2020). Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to Compromise solution (MARCOS). *Computers & Industrial Engineering*, *140*, 106231.

[101] J.F. Galvez, J.C. Mejuto, J. Simal-Gandara, Future challenges on the use of blockchain for food traceability analysis, TrAC - Trends in Analytical Chemistry. 107 (2018) 222–232. https://doi.org/10.1016/j.trac.2018.08.011.

[102] A. Park, H. Li, The effect of blockchain technology on supply chain sustainability performances, Sustainability (Switzerland). 13 (2021).

[103] Pishvaee, M.S. and Torabi, S.A., 2010. A possibilistic programming approach for closed-loop supply chain network design under uncertainty. *Fuzzy sets and systems*, *161*(20), pp.2668-2683.

[104] Torabi, S.A., Namdar, J., Hatefi, S.M. and Jolai, F., 2016. An enhanced possibilistic programming approach for reliable closed-loop supply chain network design. *International journal of production research*, *54*(5), pp.1358-1387.