Sustainable supplier selection and order allocation under demand, supplier availability and supplier grading uncertainties

Citation for published version (APA):

Hosseini, Z. S., Flapper, S. D. P., & Pirayesh, M. (2022). Sustainable supplier selection and order allocation under demand, supplier availability and supplier grading uncertainties. *Computers & Industrial Engineering*, 165, [107811]. <https://doi.org/10.1016/j.cie.2021.107811>

Document license:
TAVERNE

DOI:
[10.1016/j.cie.2021.107811](https://doi.org/10.1016/j.cie.2021.107811)

Document status and date:
Published: 01/03/2022

Document Version:
Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

[Link to publication](#)

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license above, please follow below link for the End User Agreement:

www.tue.nl/taverne

Take down policy

If you believe that this document breaches copyright please contact us at:

openaccess@tue.nl

providing details and we will investigate your claim.

Sustainable supplier selection and order allocation under demand, supplier availability and supplier grading uncertainties

Zahra Sadat Hosseini^{a,*}, Simme Douwe Flapper^b, Mohammadali Pirayesh^c

^a Industrial Engineering Department, Yazd University, Yazd, Iran

^b Eindhoven University of Technology, Department of Industrial Engineering and Innovation Sciences, P.O. Box 513, 5600 MB Eindhoven, the Netherlands

^c Department of Industrial Engineering, Faculty of Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

ARTICLE INFO

Keywords:

Sustainable supplier selection
Order allocation
Uncertainty supplier availability
Hybrid BWM-ER method
Dynamic programming
Stochastic programming

ABSTRACT

Sustainable supplier selection is a pressing matter in supply chain management. This paper tackles the main pain points in decision making during supplier selection and order allocation (SSS & OA) under uncertainties for a multi-item, multi-period setting, where each supplier has its own pricing policy. In the first phase, a hybrid BWM-ER method is employed for evaluating and ranking suppliers. In this method, the best worst method (BWM) for determining weights of the sustainability criteria and evidential reasoning (ER) for evaluating suppliers under uncertainty are used. Based on constraints related to demand, capacity, inventory, and allowed shortages in the next phase, a bi-objective mathematical model is presented, to make a trade-off between sustainability and economic cost. The demand is assumed to be stochastic, and there are uncertainties in the availability of suppliers during different periods. The combination of these two uncertainties is studied via a set of scenarios. A new integrated solution approach based on stochastic programming and dynamic programming to solve the bi-objective model under uncertainties is presented. The proposed approach results are compared with the results obtained via revised multi-choice goal programming and the Epsilon constraint method for a real-life case. These comparisons show that by using the new method, better and faster results are obtained. Sensitivity analysis is used to reveal the effect of quantity discounts, uncertainties in suppliers' availability and demand. Results obtained for a real-life case study are presented and discussed.

1. Introduction

In recent years, the customer's desire for high quality and quick service provides challenges that did not exist before. To be a competitive player in this market, companies are seeking strategic alliances among their supply chain. In this context, evaluating and selecting suppliers to meet the company's strategic goals play a significant role (Ghadimi et al., 2017).

Before 1980, supplier selection was primarily based on costs. However, in recent years, besides economic factors, environmental and social factors have to be considered simultaneously for supplier selection. Due to global environmental pollution, which is of growing concern, environmental criteria are added. Decreasing available resources is another reason for including environmental-related constraints (Zailani, Jeyaraman, Vengadasan & Premkumar, 2012; Cheraghalipour and Farsad, 2018). Sustainable supplier selection (SSS) is crucial for creating a sustainable supply chain (Govindan et al., 2013).

Also in recent years, with the globalization of the market,

competition in various industries has increased sharply and has led to uncertain demand. Another issue is that access to suppliers during different periods is not the same and, under different circumstances, only a few potential suppliers may be able to meet producer demand. Manufacturers must have a comprehensive plan to survive and grow under such circumstances, (Moghaddam, 2015).

Given these issues, addressing SSS & OA, and providing a comprehensive plan to cope with uncertainty and reduction of purchase costs is significant. Although there is already some literature on the above available, there are some important issues left, taken care of in this paper.

This paper provides a decision framework to support SSS & OA for multiple periods in a multi-supplier, multi-item situation where,

- There are uncertainties in the availability of the suppliers in each period.
- Each supplier has its own pricing policy including discounts.
- Lost sales are allowed.

* Corresponding author.

- The demand in each period is stochastic.
- One supplier can produce/deliver more than 1 item.

In the first phase, sustainability criteria and sub-criteria to evaluate and select suppliers are chosen based on the opinions of company experts and a literature review. Next, BWM (Best Worst Method) as an effective multi-criteria-decision-making method is used to determine the weight of the criteria and sub-criteria. We use BWM because it requires fewer pairwise comparisons than the AHP method, the pairwise comparisons are more compatible, and the results are more reliable (Rezaei, 2015). Finally, the ER (Evidential Reasoning) method is employed for evaluating and ranking the suppliers. ER is selected because the sub-criteria are primarily qualitative, and the evaluators may not have much experience and complete understanding for evaluating the suppliers, resulting in a high uncertainty and the incompleteness of information about some of the sub-criteria. The proposed approach can overcome such problems. In the second phase, based on constraints such as demand, capacity, inventory level and allowed shortage, a mathematical model is designed to maximize the suppliers' values and minimize the total cost. The uncertainties in demand and the availability of suppliers in different periods are included via a set of scenarios. A new algorithm based on stochastic programming and dynamic programming is presented. This new algorithm is able to generate better solutions in less time. Finally, a real-life case study in Iran is presented.

This paper is organized as follows. Section 2 provides the relevant literature on SSS & OA. Section 3 provides the research methodology. In this section, the identification of the criteria, BWM approach, ER approach, mathematical model, and solution approach are presented. In Section 4, a real-life case study is presented to investigate the application of the method in practice. Section 5 provides insight in the influences of the different uncertainties and quantity discounts on the results, whereas in Section 6 our stochastic programming and dynamic programming method is compared with some existing methods. Section 7 provides an overview of the decision making process. Finally, in Section 8, the conclusion and directions for future research are given.

2. Literature Review

In this section, previous related studies are summarized. The topics that we consider in the literature review include SSS & OA. The research gap plus this paper's contribution are outlined at the end of this section.

2.1. SSS & OA

During the last decades, SSS & OA have been important issues. Extensive studies have been published on this subject, such as Alidaee and Kochenberger (2005), Li et al. (2009), Ho et al. (2010), Mafakheri et al. (2011), and Chai et al. (2013). Various criteria have been evaluated for selecting the best supplier. Degraeve and Roodhooft (1999) insisted on supplier selection only focusing on cost. Gradually, companies realized that the cost criteria alone might not provide the proper suppliers' evaluation, but also other factors need to be considered. Dickson (1966) provided 23 criteria for supplier evaluation. Weber Charles et al. (1991) investigated the criteria used in supplier selection in the research reported since 1966. They concluded that three essential criteria for selecting suppliers are quality, cost and delivery time. Li et al. (2009) considered the selection of suppliers with demand and price uncertainty. Razmi and Rafiei (2010) considered a two-stage approach for SS & OA. First, the suppliers are filtered according to their qualitative traits. In the second stage, mixed-integer nonlinear programming (MINLP) is used to assign order quantities during the planning period. Mendoza and Ventura

(2010) presented a mathematical model for determining the optimal inventory policy. This model uses a power-of-two (POT) approach for the effectiveness of the inventory system under control. Mafakheri et al. (2011) addressed the SS & OA with dynamic programming. Ghorbani et al. (2012) employed qualitative and quantitative criteria along with weighting based on strengths, weaknesses, opportunities, and threats (SWOT) analysis. Kannan et al. (2013) studied green SS and he used a fuzzy approach for ranking the suppliers. Nazari-Shirkouhi et al. (2013) presented a two-level fuzzy model where suppliers set multiple price levels for their products. They applied the decision maker's fuzzy goals (DMFG) approach for SS & OA. Ware et al. (2014) studied a supply chain problem, namely dynamic supplier selection (DSSP), in which the values of these parameters change from one period to another. Singh (2014) presented a heuristic algorithm for SS & OA. Scott et al. (2014) presented an integrated approach for SS & OA. They considered an integrated framework for a multi-stockholders, multi-suppliers environment with multiple stochastic criteria using a robust approach to solve it. Lee et al. (2014) used the DSS method to select the best suppliers with the highest quality and business operating level. Jadidi et al. (2014) employed three objective functions: price, rejects and lead-time. They suggested two approaches to solve the model, and then compared them. Guo and Li (2015) addressed a multi-level supply chain with a wholesaler, n retailers, and a group of suppliers. They considered different prices, ordering costs and lead-times. The purpose of the model was to select the supplier and the best policy with coordination between the levels of the chain. Kuo et al. (2015) used the association rules to rank the suppliers and the artificial neural network to allocate the orders. Moghaddam (2015) provided a mathematical model for identifying the best suppliers in a logistics network using Pareto solutions. They considered stochastic demands where a fuzzy method was applied to solve the model. Torabi et al. (2015) presented a stochastic programming model for SS & OA that applied the fortification of suppliers (FOS) and suppliers' business continuity plans (SBGP) strategies to create flexibility in the level of suppliers. Govindan et al. (2015) reviewed previous studies in green supplier evaluation and answered a number of questions in this area. Amorim et al. (2016) provided a mathematical model for SSS in the food industry. Sodenkamp et al. (2016) studied a model to minimize the risk via maximizing the cooperation among the stages of the supply chain using knowledge sharing. Prasanna Venkatesan et al. (2016) used a combined fuzzy-AHP approach for ranking the suppliers and used multi-objective particle swarm (MOPS) for SS & OA regarding the risk. Hamdan et al. (2016) presented a multi-period model for green SS & OA in which he applied a fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach for determining the weights of the selected criteria. Çebi et al. (2016) employed a two-stage fuzzy approach for SS & OA. Keshavarz et al. (2017) applied environmental (environmental pollution) and economic criteria for supplier evaluation under uncertainty. They employed two positive and negative functions for supplier evaluation where fuzzy programming was used to solve it. Noori-Daryan et al. (2017) addressed a multi-national decision model with limited capacity for the producer and one retailer in which the demand was assumed stochastic and dependend on cost, delivery time, and lost sales, where the QFD method and stochastic programming were used for order evaluation, allocation. In their model, the demand was considered stochastic. Ghadimi et al. (2017) used the sustainability criteria for supplier evaluation and multi-agent systems (MAS) for SS & OA. Hamdan et al. (2017a) examined the problem of green SS & OA under the varying availability of the suppliers. He used fuzzy TOPSIS and AHP for supplier evaluation. Hamdan et al. (2017b) addressed the green SS & OA problem considering quantity discounts. Vahidi et al. (2018) studied the problem of SSS. The authors used a stochastic programming and hybrid SWOT-

QFD for SS & OA. Cheraghalipour and Farsad (2018) investigated the problem of SSS & OA and used the BWM to determine the weights for the suppliers. They solved their model using revised multi-choice goal programming (RMCGP). Esmaili et al. (2018) examined the integration of SS & OA in the centralized supply chain with disruption risk. They employed protected supplier and pre-positioned emergency inventory strategy to mitigate disruption effects. Park et al. (2018) proposed a two-phase approach for SSS & OA in which first the sustainable supplier regions are identified, and next OA is performed. Lo et al. (2018) applied a hybrid BWM-TOPSIS for SS. They used a fuzzy approach to solve the OA model. Hosseini et al. (2019) proposed a stochastic bi-objective mixed integer programming model for SS & OA to support the decision about when to use both proactive and reactive strategies. Kellner et al. (2019) presented an approach that supports purchasing managers in defining mid-term supplier portfolios. Wong et al. (2019) constructed a fuzzy goal programming model focusing on the importance of a supplier portfolio and OA and pioneered the integration of a supplier's dynamic risk and green market segmentation in supplier selection problems. Jia et al. (2020) proposed an optimization model that balances multiple conflicting objectives, effectively solving our SSS & OA problem. Khoshfetrat et al. (2019) integrated sustainable supplier selection and order allocation with inflation, risk and fuzzy uncertainties. They considered six objective functions in the model that include total cost, economic score, environmental score, social score, inflation rate and risk level. Nasr et al. (2020) presented a novel two-stage fuzzy supplier selection and order allocation model in a closed-loop supply chain. They used fuzzy best-worst method for selecting the most suitable suppliers and fuzzy goal programming approach for solving the model. Li et al. (2020) proposed a novel two-stage comprehensive mathematical model for dynamically selecting suppliers and assigning an order quantity. They considered green factors and supplier risks to study the dynamic selection and order allocation problem. Kaur and Singh (2021) proposed a multi stage hybrid model for integrated supplier segmentation, selection and order allocation considering risks and disruptions. They evaluated suppliers based on Data Envelopment Analysis (DEA). Cui et al. (2021) presented a hybrid model that integrates fuzzy set theory, stepwise weight assessment ratio analysis and a Bayesian network for evaluating the critical SSS criteria in three multitier supply chain (MTSC). Sontake et al. (2021) developed an MILP for SS & OA, focusing on the selection of transportation alternatives while delivering items. Beikia et al. (2021) studied a novel integration of the language entropy weight method (LEWM) and multi-objective programming (MOP) method to address a sustainable supplier selection and order allocation problem.

2.2. Research gap

Table 1 summarizes the studies that have been mentioned before. The table shows that most studies have not considered various aspects of uncertainty in SS & OA. Stochastic demand and uncertainties in the availability of suppliers in different periods are two of the most critical

stochastic demand, disruption risks and dynamic programming applications are new features we introduced to the problem. Summarizing, the main contributions of this paper are as follows.

Theory: This study presents a bi-objective mathematical model with multiple suppliers, multiple items, and multiple periods for the SSS & OA problem. The first objective maximizes the total score of all suppliers concerning three sustainable aspects (TVP) and the second objective minimizes the total cost of the purchase (TCP). Both the suppliers' availability and demand for the different items during the periods are assumed to be stochastic.

Methodology: We utilize a hybrid BWM (Best Worst Method) and ER (Evidential Reasoning) method to rank the best supplier. One of the advantages of the hybrid BWM-ER method is that it considers the uncertainty caused by personal judgments and incomplete information. We introduced a novel integrated solution approach, based on stochastic programming and dynamic programming, to solve multi-objective problems under uncertainty.

Application: We applied the above to a real life case to get insight in its applicability in practice.

3. Methodology

In this study, we used the scenario-based solution approach. A scenario is a hypothesis about the future that expresses the interaction between different factors under certain conditions. It compared to sensitivity analysis, in the scenarios the values of several parameters are changed simultaneously. In this approach, random parameters have a finite number of values described by a discrete distribution. The scenarios considered in this paper differ from each other with respect to the demand for each item in each period, the availability of each supplier in each period, as well as the pricing policy used by each supplier in all periods.

We assume that the demanded quantities of the items are one of the primary sources of uncertainty. With respect to the demand for an item in a period, we consider three states: pessimistic, probabilistic, and optimistic, resulting in a finite set of scenarios during the time horizon considered for planning. There are also uncertainties with respect to the availability of suppliers in each period. Reasons for the latter can be natural disasters, equipment failure and bankruptcies. The probability of a supplier being available is determined based on experience and is denoted by pus_i . The actual availability and non-availability of a supplier during a period are indicated by 1 and 0, Let $uos_{it}^s = 1$ if supplier i in period t under scenario s is available and $uos_{it}^s = 0$ else. So the number of states indicating the availability of the n potentially available suppliers in each period is given by 2^n . For example, if there are five suppliers in every period, there will be 32 different states related to the availability of those five suppliers in every period. The probability of suppliers' access in period t is given by

$$\text{Probability of Suppliers' access in period } t = \prod_i \text{Max}\{uos_{it}^s \times pus_i, (1 - uos_{it}^s) \times (1 - pus_i)\}$$

issues in real life that have been neglected in almost all previous researches. In this study, we consider these uncertainties and present a plan to the company to make the best allocation with the least cost based on which of these scenarios occurs. Furthermore, the integration of

Now, due to the uncertainty in the demand and access of suppliers, the probability of each scenario s is given by $(\sum_{s=1}^S P_s = 1)$

$$P_s = \prod_t (\text{Probability of Suppliers access in period } t \times \text{Probability of demand in period } t)$$

Apart from the above demand and supplier availability uncertainties, each supplier may offer different prices with different discount plans for each item. In other words, each supplier may offer several different pricing policies. Also this aspect is included in our scenario analysis. The two-phased approach to SSS & OA used in this study is depicted in Fig. 1.

Fig. 1 shows that the SSS & OA problem consists of two phases. The first phase concerns the evaluation of suppliers. This phase consists of 5 steps. First, the supplier evaluation criteria are determined. Next, we utilize the BWM (Best Worst Method) to obtain the weights of the criteria and the sub-criteria. Then the suppliers' weights are calculated using the ER method. In the second phase; which is the link between multi-criteria assessment and the order allocation procedure, these weights are included in a mathematical model as an objective function to maximize the suppliers' total value of the purchase (TVP), causing a supplier with more significant weight to have a higher preference for order allocation. Hereafter, a bi-objective mixed-integer linear program (MILP) is presented to determine the optimal order quantity by each supplier in each period under each scenario using the two objective

functions, maximizing TVP and minimizing TCP (Total Cost of Purchase). Sustainability vs. economic costs is where most companies are interested in now, among others due to (expected) legislation, public pressure. Therefore, sustainability and economic cost are the objectives in this model. Both objectives are composed of a number of criteria, elements. Note that ordering a product at a supplier from a sustainability point of view is based on the supplier's overall sustainability, and not only on how sustainable the supplier generates and transports the products ordered. Finally, stochastic programming combined with dynamic programming is used to solve the mathematical model.

The ER method, BWM, the MILP model for the problem of SSS & OA, as well as the integrated dynamic programming and stochastic programming approach, are presented in the following sub-sections.

3.1. Phase 1: Supplier evaluation

Many decision problems include various qualitative and quantitative factors. Without considering all these factors, one cannot accurately

Table 1
A brief literature review of the sustainable supplier selection and order allocation problem.

Reference	Aspects			EOCUU	Example	Item	OA	UIS	SD	Solution approach
	Economic	Environmental	Social							
Lu et al. (2007)		*			NuEx	SI				AHP, Fuzzy logic
Ghorbani et al. (2012)	*				NuEx	SI	*			SWOT analysis, Shannon entropy
Kannan et al. (2013)	*	*		*	CaSt	SI	*			Fuzzy AHP, Fuzzy TOPSIS
Ware et al. (2014)	*				NuEx	MI	*			Mixed-integer non-linear program (MINLP), Dynamic supplier selection problem
Singh (2014)	*	*	*		NuEx	SI	*			TOPSIS, Mixed linear integer programming (MILP)
Guo et al. (2015)	*				NuEx	SI	*		*	Mixed integer nonlinear programming model
Torabi et al. (2015)	*				NuEx	MI	*	*		Possibility programming, Two-stage stochastic programming
Amorim et al. (2016)	*				CaSt	MI				Benders decomposition algorithm
Hamdan et al. (2016)	*	*		*	NuEx	SI	*			Fuzzy TOPSIS, AHP
Keshavarz et al. (2017)	*	*			NuEx	SI	*			EDAS (evaluation based on distance from average solution) method, Interval type-2 fuzzy sets
Ghadimi et al. (2017)	*	*	*		CaSt	MI	*			Multi-agent system approach
Momeni et al. (2017)	*			*	CaSt	SI				DEA, Evidential reasoning
Vahidi et al. (2018)	*	*			NuEx	MI	*			ϵ -constraint method and metaheuristics
Goren. (2018)	*	*	*		CaSt	SI	*			Fuzzy decision making trial and evaluation laboratory (DEMATEL), Taguchi loss functions
Lo et al. (2018)	*	*		*	NuEx	MI	*			BWM, Modified fuzzy TOPSIS, FMOLP
Cheraghalipour et al. (2018)	*	*	*		CaSt	MI	*	*		Hybrid BWM-RMCGP
Kellner et al. (2019)	*	*	*		CaSt	SI	*			Combining integer variables with Markowitz portfolio theory
Jia et al. (2020)	*	*	*		CaSt	SI	*		*	Distributionally robust goal programming model, Tractable approximation
Nasr et al. (2020)	*	*	*	*	CaSt	MI	*			Fuzzy best-worst method, Fuzzy goal programming approach
Kaur and Singh (2021)					NuEx	MI	*	*	*	Data envelopment analysis (DEA), Fuzzy analytical hierarchical process and technique
Cui et al. (2021)	*	*	*		CaSt	SI				Bayesian network
Beikia et al. (2021)	*	*	*		CaSt	MI	*			Novel integration of language entropy weight method (LEWM), Multi-objective programming (MOP) method
This research	*	*	*	*	CaSt	MI	*	*	*	BWM and Evidential Reasoning, Stochastic programming and dynamic programming

Notes: CaSt: Case Study EOCUU: Evaluation of criteria under uncertainty NuEx: Numerical Example S/M—I: Single/Multi-Item OA: Order allocation UIS: Uncertainty in suppliers SD: Stochastic demand.

Fig. 1. Two-phased approach for sustainable supplier selection and order allocation.

solve these problems. On the other hand, uncertain information and the presence of qualitative factors lead to more complexity. During the last two decades, extensive research on artificial intelligence and operation research has been conducted to deal with uncertain information. ER has been developed to support multi-criteria decision-making when uncertainties occur (Huynh et al., 2006). The ER approach is a method based on evidential theory (Yang and Singh, 1994) combined with multi-criteria decision-making. This method is applied in engineering design, risk and safety evaluation, engineering design choice, marine safety system analysis, etc. (Sen and Yang, 1995; Yang and Sen, 1994; Wang et al., 1996). The ER algorithm is based on a multi-criteria assessment matrix and the evidence combination rule of Dempster–Shafer (D-S). An incomplete assessment, resulting from a lack of information or the inability to perform precise judgments or the assessor's error in group decision-making, is considered with the degree of incompleteness of the combined pieces of evidence. Then, utility intervals are provided to determine the degree of incompleteness of the original information in decision analysis (Wang and Elhag, 2008; Huynh et al., 2006).

The ER method for supplier evaluation includes the following steps:

1. Determining the supplier evaluation criteria
2. Calculating the weights of the supplier evaluation criteria using BWM
3. Building the distribution model of ER for the supplier evaluation criteria
4. Developing the ER algorithm for combining the supplier evaluation criteria
5. Deriving the utility intervals based on the ER ranking method to rank the suppliers

Step 1: Determining the supplier evaluation criteria

Several sustainability criteria and sub-criteria were chosen based on previous studies (Zimmer et al., 2016; Cheraghalipour and Farsad, 2018) for supplier evaluation with regard to sustainable development aspects. Next, the criteria were studied and confirmed by the company's experts. The chosen criteria and a brief description of them are shown in Table 2.

Table 2

Selected criteria and sub-criteria (Zimmer et al., 2016; Luthra et al., 2017; Cheraghalipour et al., 2018).

S. NO.	Criteria	Sub-criteria	Brief description
1	Economic (EC)	Quality (ECQ)	Providing a significant quality level
2		Cost (ECC)	Capability of supplying the products at reasonable price
3		Delivery and service of product (ECDS)	It ensures the right delivery and service of the product
4		Technological & financial capacity (ECTF)	It deals with the technological and financial aspects associated with the supplier domain
5		Long-term relationship – continuity (ECLR)	Long-term relationship between manufacturer and supplier to purchase raw materials
6		Flexibility (ECF)	Supplier should be flexible enough to handle market variations
7	Environmental (EN)	Environmental management systems (ENEM)	The structure, planning and implementing of supplier's policies for environmental protection
8		Green design and purchasing (END)	Incorporating eco-friendly practices at the design and purchasing stages
9		Green packing and labeling (ENGL)	The capability of suppliers to take environmental considerations for packaging and labeling
10		Environmental pollution & waste management (ENPW)	The raw material is such that wastage and Pollution should be minimum while producing the product
11	Social (SO)	Energy consumption management (ENEC)	The capability of suppliers to management Energy consumption
12		Occupational health and safety (SOOHS)	It is concerned with the safety, health and welfare of the people engaged at supplier's workplace
13		Social management commitment (SOSMC)	The planning and implementing of supplier's commitment for Social management
14		The interests & rights of employees (SOIE)	Concerns with the employees' related factors and requirements to achieve sustainable effectiveness in the long term
15		Wages & working hours (SOWW)	It is concerned with the wages and working hours of the people engaged

Step 2: Calculating the weights of the supplier evaluation criteria using BWM

BWM, introduced by Rezaei in 2015 (Rezaei, 2015), is used for determining the weights of the supplier evaluation criteria. First, the best and worst criteria are determined based on the opinion of experts. In the next step, the best criterion will be compared with other criteria, and similarly, for the worst criterion. This results in a linear programming model via which the weights of the criteria are obtained such that the absolute differences of the weights are minimized. This method requires fewer pairwise comparisons than AHP. The pairwise comparisons are also more consistent compared to that of AHP, and the results are reliable.

The main steps for determining the criteria weights are as follows (Rezaei, 2015; Cheraghalipour and Farsad, 2018)

1. Identify sustainability related criteria
2. Choose the most (best) and least (worst) important criterion
3. Perform pairwise comparisons between the best criterion and all the other criteria
4. Perform pairwise comparisons between all the other criteria and the worst criterion.
5. Determine the importance weights of each criterion
6. Assess the validity and reliability of the comparisons

Step 3: Building the distribution model of ER

After choosing sustainable evaluation criteria for ranking suppliers and determining the proper weight for each of the criteria, the distribution model of ER should be built. First assessors should determine the scores of each sub-criterion relating to each supplier for each item. The scores that experts assign to each sub-criterion are the inputs of the ER model. According to the scores of the sub-criteria and based on the ER method, the scores of the main criteria are calculated. The ER algorithm is repeated at the level of the main criteria to determine the score of each supplier for each item. (Ayati et al., 2012)

Step 4: The ER algorithm for combining supplier evaluation criteria

The ER algorithm is developed to combine the elements of the distributed assessment matrix (D_i) and to assign the score to the i th main criterion. The algorithm's output, which is the score of the i th main criterion, is called the distributed score. After getting the distributed scores for all the main criteria, the ER algorithm is repeated at the level of the main criteria to obtain the suppliers' distributed scores. (Ayati et al., 2012)

Step 5: Deriving the utility intervals and ranking of the suppliers

All suppliers are assessed by the ER method and their distributed scores are obtained. The distribution score gives a broad view of the suppliers' status, but it is not directly applicable for comparison and ranking. We present the expected value for each supplier to compare and prioritize the suppliers based on sustainability criteria. (Ayati et al., 2012)

3.2. Phase 2: SSS & OA

3.2.1. Bi-objective mixed integer linear programming model

In this section, the bi-objective MILP model for SSS & OA is developed. The first objective is maximizing the TVP that is based on the weights derived from the ER method. The second objective is to minimize the TCP. The model is based on the following assumptions:

- The delivery time of the suppliers for each item is zero/neglectable.
- Order decisions have to be made just before the next period starts, where the availability of the suppliers and the demand for every item during each of the T planning periods aren't known.
- In principle each supplier can deliver every item.
- A supplier is available in a period at all or not.

- Demand in different periods is described by the same distribution function.

The model is formulated as follows:

3.2.1.1. Subscripts

d_{ij}	Range of discount index of supplier i for item j ($d_{ij} = 1, 2, \dots, D_{ij}$)
i	Set of suppliers ($i = 1, 2, \dots, n$)
j	Set of items ($j = 1, 2, \dots, m$)
p	Transportation modes ($p = 1, 2, \dots, P$)
s	Set of disruption scenarios ($s = 1, 2, \dots, S$)
t	Set of periods ($t = 1, 2, \dots, T$)

3.2.1.2. Parameters

cat_{ijpt}	The capacity of transportation mode p for item j from supplier i in period t .
cap_{ij}	The capacity of supplier i to provide item j
dem_{jt}	Demand for item j in period t
foc_{ij}	Fixed cost of ordering for item j from supplier i
fsc_{ijpt}	Fixed cost of shipment for item j shipped from supplier i via transportation mode p in period t
hoc_{jt}	Holding cost of one unit of item j in period t
$LB_{ijd_{ij}}$	The lower bound of the quantity discount d_{ij} of supplier i for item j
M	A positive big number
msh_{jt}	Maximum allowed shortage level of item j in period t
mss_{jt}	Maximum allowed inventory level of item j in period t
pc_{ijt}	Cost for buying one unit of item j from supplier i in period t (no discount)
$pc_{ijtd_{ij}}^A$	The unit purchasing cost of item j for the total order range d_{ij} of supplier i (all-unit quantity discount)
$pc_{ijtd_{ij}}^I$	The unit purchasing cost of item j per unit between the separately bound of the range d_{ij} of supplier i (all-unit quantity discount)
pus_i	Probability of actual availability of supplier i in a period
shc_{jt}	Cost of Shortage per unit of item j in period t
sph_{ij}	Storage space required in the warehouse one unit of item j
$UB_{ijd_{ij}}$	Upper bound of the quantity discount d_{ij} of supplier i for item j
uos_{it}^s	1 if supplier i is available in period t under scenario s ; 0 otherwise
vsc_{ijpt}	Variable shipment cost for one unit item j shipped from supplier i by transportation mode p in period t
w_{ij}	Importance weight of supplier i for item j obtained from ER
θ_{ij}	1 if supplier i does not consider a discount for item j ; 0 otherwise
θ_{ij}^A	1 if supplier i considers an all-unit quantity discount for item j ; 0 otherwise
θ_{ij}^I	1 if supplier i considers an incremental quantity discount for item j ; 0 otherwise
P_s	probability of scenario s

3.2.1.3. Decision variables

H_{jt}^s	1 if item j in time period t for scenario s is stored; 0 otherwise
int_{jt}^s	Inventory level of item j at the end of time period t for scenario s
Q_{ijtp}^s	Amount of item j transported from supplier i by using the transportation mode p in time period t for scenario s
sh_{jt}^s	Shortage level of item j at the end of time period t for scenario s
U_{ijtp}^s	1 if item j from supplier i by transportation mode p in period t under scenario s is transported; 0 otherwise
x_{ijt}^s	Order quantity from the supplier i for item j in time period t for scenario s
y_{ijt}^s	1 if supplier i for item j in period t under scenario s is selected; 0 otherwise
$\xi_{ijd_{ij}}^A$	1 if supplier i chose discount interval d_{ij} for item j (all unit quantity discount); 0 otherwise
$\xi_{ijd_{ij}}^I$	1 if supplier i chose discount interval d_{ij} for item j (incremental quantity discount); 0 otherwise

3.2.1.4. Objective and constraints. A scenario-based supply chain model is formulated as follows to manage multiple demand scenarios in the supply chain

$$\max TVP = \sum_{s=1}^S P_s \sum_{t=1}^T \sum_{i=1}^n \sum_{j=1}^m w_{ij} \times x_{ijt}^s \times uos_{it}^s \quad (1)$$

$$\begin{aligned}
\min TCP = & \sum_{s=1}^S P_s \left(\left(\sum_{i=1}^n \sum_{j=1}^m \sum_{t=1}^T foc_{ij} \times y_{ijt}^s \times uos_{it}^s \right) + \left(\sum_{j=1}^m \sum_{t=1}^T hoc_{jt} \times inl_{jt}^s \right) + \left(\sum_{j=1}^m \sum_{t=1}^T shc_{jt} \times shl_{jt}^s \right) + \left(\sum_{i=1}^n \sum_{j=1}^m \sum_{p=1}^P \sum_{t=1}^T vsc_{ijpt} \times Q_{ijtp}^s \times uos_{it}^s \right) \right. \\
& + \left(\sum_{i=1}^n \sum_{j=1}^m \sum_{p=1}^P \sum_{t=1}^T fsc_{ijpt} \times (x_{ijt}^s / cat_{ijpt}) \times uos_{it}^s \right) + \sum_{i=1}^n \sum_{j=1}^m \sum_{t=1}^T \left[(pc_{ijt} \times \theta_{ij} \times x_{ijt}^s \times uos_{it}^s) + \left(\sum_{d_{ij}=1}^{D_{ij}} x_{ijt}^s \times pc_{ijd_{ij}}^A \times \theta_{ij}^A \times \xi_{ijd_{ij}}^A \times uos_{it}^s \right) + \theta_{ij}^l \times uos_{it}^s \right. \\
& \left. \left. \times \left(\sum_{d_{ij}=1}^{D_{ij}} pc_{ijd_{ij}}^l \times \xi_{ijd_{ij}}^l \times (x_{ijt}^s - UB_{ijd_{ij}-1}) + \sum_{d_{ij}=0}^{d_{ij}-1} pc_{ijd_{ij}}^l \times \xi_{ijd_{ij}}^l \times (UB_{ijd_{ij}} - LB_{ijd_{ij}}) \right) \right] \right) \quad (2)
\end{aligned}$$

s.t.

$$inl_{jt}^s - shl_{jt}^s = inl_{j,t-1}^s + \sum_{i=1}^n \sum_{p=1}^P Q_{ijtp}^s - dem_{jt}^s \quad \forall j, t, s \quad (3)$$

$$x_{ijt}^s \leq y_{ijt}^s \times cap_{ij} \quad \forall i, j, t, s \quad (4)$$

$$\sum_{j=1}^m y_{ijt}^s \leq m \times uos_{it}^s \quad \forall i, t, s \quad (5)$$

$$inl_{jt}^s.sph_j \leq H_{jt}^s \times mss_{jt} \quad \forall j, t, s \quad (6)$$

$$shl_{jt}^s \leq (1 - H_{jt}^s) \times msh_{jt} \quad \forall j, t, s \quad (7)$$

$$x_{ijt}^s = \sum_{p=1}^P Q_{ijtp}^s \quad \forall i, j, t, s \quad (8)$$

$$Q_{ijtp}^s \leq U_{ijtp}^s \times cat_{ijtp} \quad \forall i, j, p, t, s \quad (9)$$

$$\sum_{d_{ij}} \xi_{ijd_{ij}}^l = 1 \quad \forall i, j \quad (10)$$

$$\sum_{t=1}^T x_{ijt}^s \leq UB_{ijd_{ij}} + M \left(1 - (\xi_{ijd_{ij}}^l \times \theta_{ij}^l) \right) \quad \forall i, j, d_{ij}, s \quad (11)$$

$$\sum_{t=1}^T x_{ijt}^s > LB_{ijd_{ij}} - M \left(1 - (\xi_{ijd_{ij}}^l \times \theta_{ij}^l) \right) \quad \forall i, j, d_{ij}, s \quad (12)$$

$$\sum_{d_{ij}} \xi_{ijd_{ij}}^A = 1 \quad \forall i, j \quad (13)$$

$$\sum_{t=1}^T x_{ijt}^s \leq UB_{ijd_{ij}} + M \left(1 - (\xi_{ijd_{ij}}^A \times \theta_{ij}^A) \right) \quad \forall i, j, d_{ij}, s \quad (14)$$

$$\sum_{t=1}^T x_{ijt}^s > LB_{ijd_{ij}} - M \left(1 - (\xi_{ijd_{ij}}^A \times \theta_{ij}^A) \right) \quad \forall i, j, d_{ij}, s \quad (15)$$

$$\xi_{ijd_{ij}}^l, \xi_{ijd_{ij}}^A, H_{jt}^s, y_{ijt}^s, U_{ijtp}^s \in \{0, 1\} \quad \forall i, j, p, t, s, d_{ij} \quad (16)$$

$$x_{ijt}^s, Q_{ijtp}^s, inl_{jt}^s, shl_{jt}^s \geq 0 \& integer \quad \forall i, j, p, t, s, d_{ij} \quad (17)$$

Eq. (1) represents the first objective function TVP. The weight results from the ER method consisting of the suppliers score for three sustainability dimension (i.e. economic, environmental and social), are employed in this objective function. Based on the Scenario-Based method, we multiply the equation with the probability P_s that scenario s occurs. So, the mean value of the objective function is optimized.

Eq. (2) represents the second objective function TCP. This equation shows the total cost, including fixed ordering cost, holding cost, shortage cost, fixed and variable transportation costs and purchasing costs, which represent the cost of purchasing with no discount, the cost of purchasing with the all-unit quantity discount, and the cost of purchasing with incremental discounts, respectively. Similarly, based on the Scenario-Based method, the total cost is multiplied by P_s .

Constraint (3) shows inventory level changes based on the demand of each item in each period under each scenario, where $inl_{j0}^s = shl_{j0}^s = 0$. Constraint (4) shows the maximum capacity of suppliers. Constraint (5) guarantees that if a supplier is available during a period under the relevant scenario, it will be possible to order from this supplier any item. Constraint (6) guarantees that the amount of each item supplied by all suppliers in each period under each scenario should be less than or equal to a pre-specified value. Constraint (7) states that the shortage amount of each item should not be more than the predetermined quantity in each period under each scenario. Constraint (8) shows that the sum of the units of item j transferred from supplier i by all transmission modes p in period t under scenario s must be equal to the order quantity of item j purchased from supplier i in period t under scenario s . Constraint (9) states that the amount of item j transferred from supplier i by transportation mode p in period t under scenario s must be less than the capacity of that mode of transfer. Constraints (10)–(12) are applied to select the appropriate discount interval proposed by the suppliers who suggest all-unit quantity discounts. Similarly, Constraints (13)–(15) apply when suppliers offer incremental discounts. Constraint (16) indicates which decision variables are binary. Constraint (17) shows that the indicated decision variables can only take possible integer values.

3.2.1.5. Linearization of the second objective function. It is evident that the second and third part of the second objective function related to the discounts are non-linear because the decision variables x_{ijt}^s and $\xi_{ijd_{ij}}^A$ in the second part and x_{ijt}^s and $\xi_{ijd_{ij}}^l$ in the third part are multiplied. By adding auxiliary variables and some constraints to the model can be converted into a linear model. Using the method of Paydar and Saidi-Mehrabad

(2015) we introduce integer variable $FF_{ijt}^s = x_{ijt}^s \times \xi_{ijd_{ij}}^A$ in the second part of the equation and the integer variable $ZZ_{ijt}^s = x_{ijt}^s \times \xi_{ijd_{ij}}^L$ in the third part of the discount equation in the objective function (2). To include these new variables in the original model, the following constraints should be added to it.

$$FF_{ijt}^s \geq x_{ijt}^s - M(1 - \xi_{ijd_{ij}}^A) \quad \forall i, j, t, d_{ij}, s \quad (18)$$

$$FF_{ijt}^s \leq x_{ijt}^s + M(1 - \xi_{ijd_{ij}}^A) \quad \forall i, j, t, d_{ij}, s \quad (19)$$

$$FF_{ijt}^s \leq M\xi_{ijd_{ij}}^A \quad \forall i, j, t, d_{ij}, s \quad (20)$$

$$ZZ_{ijt}^s \geq x_{ijt}^s - M(1 - \xi_{ijd_{ij}}^L) \quad \forall i, j, t, d_{ij}, s \quad (21)$$

3.2.2. Integrated stochastic programming and dynamic programming approach

Dynamic programming transforms a large and complex optimization problem into a series of dependent smaller problems, each having a small number of variables. The dynamic programming algorithm will be used to find the optimum solution for the whole problem using smaller partial optimization techniques. Unlike linear programming, there is no standard framework for formulating dynamic programming.

Since fixed ordering cost, shortage cost, holding cost, fixed and variable transportation costs and purchasing costs as well as the availability of suppliers vary in time in the developed model, the cost objective function (and its related constraints (3) to (14)) are determined by a dynamic value function using backward induction (Bellman and Kalaba, 1957).

$$\begin{aligned} V_{1t}(inl_j^s) = & \min \left\{ \left(\sum_{i=1}^n \sum_{j=1}^m foc_{ij} \times y_{ijt}^s \times uos_{it}^s \right) + \left(\sum_{j=1}^m hoc_{jt} \times inl_j^s \right) + \left(\sum_{j=1}^m shc_{jt} \times shl_j^s \right) \right. \\ & + \left(\sum_{i=1}^n \sum_{j=1}^m \sum_{p=1}^P fsc_{ijpt} \times \left(\frac{x_{ijt}^s}{cat_{ijpt}} \right) \times uos_{it}^s \right) + \left(\sum_{i=1}^n \sum_{j=1}^m \sum_{p=1}^P vsc_{ijpt} \times Q_{ijtp}^s \times uos_{it}^s \right) \\ & + \sum_{i=1}^n \sum_{j=1}^m \left(pc_{ijt} \times \theta_{ij} \times x_{ijt}^s \times uos_{it}^s \right) + \left(\sum_{d_{ij}=1}^{D_{ij}} FF_{ijt}^s \times pc_{ijd_{ij}}^A \times \theta_{ij}^A \times uos_{it}^s \right) \\ & + \left(\theta_{ij}^L \times uos_{it}^s \times \left(\sum_{d_{ij}=1}^{D_{ij}} pc_{ijd_{ij}}^L \times (ZZ_{ijt}^s - UB_{ijd_{ij}-1} \times \xi_{ijd_{ij}}^L) + \sum_{d_{ij}=0}^{d_{ij}-1} pc_{ijd_{ij}}^L \times (UB_{ijd_{ij}} - LB_{ijd_{ij}}) \right) \right) \\ & \left. + \sum_{s=1}^S P_s \left(V_{1,t+1} \left(\max \left(0, inl_j^s + \sum_{i=1}^n \sum_{p=1}^P Q_{ijtp}^s - dem_{jt}^s \right) \right) \right) \right\} \end{aligned} \quad (26)$$

$$ZZ_{ijt}^s \leq x_{ijt}^s + M(1 - \xi_{ijd_{ij}}^L) \quad \forall i, j, t, d_{ij}, s \quad (22)$$

$$ZZ_{ijt}^s \leq M\xi_{ijd_{ij}}^L \quad \forall i, j, t, d_{ij}, s \quad (23)$$

$$FF_{ijt}^s, ZZ_{ijt}^s \geq 0 \text{ \& integer} \quad (24)$$

After the above linearization of the discounts terms, the second objective function can be written as follows:

$$\begin{aligned} & \sum_{i=1}^n \sum_{j=1}^m \sum_{t=1}^T \left[\left(pc_{ijt} \times \theta_{ij} \times x_{ijt}^s \times uos_{it}^s \right) \right. \\ & + \left(\sum_{d_{ij}=1}^{D_{ij}} FF_{ijt}^s \times pc_{ijd_{ij}}^A \times \theta_{ij}^A \times uos_{it}^s \right) + \theta_{ij}^L \times uos_{it}^s \\ & \times \left(\sum_{d_{ij}=1}^{D_{ij}} pc_{ijd_{ij}}^L \times (ZZ_{ijt}^s - UB_{ijd_{ij}-1} \times \xi_{ijd_{ij}}^L) \right. \\ & \left. \left. + \sum_{d_{ij}=0}^{d_{ij}-1} pc_{ijd_{ij}}^L \times (UB_{ijd_{ij}} - LB_{ijd_{ij}}) \right) \right] \end{aligned} \quad (25)$$

$$t = 1, \dots, T \quad i = 1, \dots, n \quad j = 1, \dots, m \quad d_{ij} = 1, \dots, D_{ij} \quad p = 1, \dots, P \quad s = 1, \dots, S$$

Periods, $t = 1, 2, \dots, T$, denote the discrete-time decision moments. The state variable is the inventory level at the beginning of periods of decision for item j under scenario s (inl_j^s). The decision variable is the quantity ordered from supplier i for item j in period t under scenario s (x_{ijt}^s). $V_{1t}(inl_j^s)$ denotes the minimum total cost of purchase if the inventory level is inl for item j under scenario s .

The TVP and TCP objective functions need to be optimized simultaneously. We applied a distance-to-ideal method (Collette and Siarry, 2004) to integrate the TVP and TCP functions, using the optimal value of individual objective functions and their related constraints ((23 to (44)) (Mafakheri et al., 2011).

The above resulted in the following dynamic programming model:

$$\begin{aligned}
V_{2t}(inl_j^s) &= (TVP_{max}^t(inl_j^s) - \sum_{i=1}^n \sum_{j=1}^m w_{ij} \times x_{ijt}^s(inl_j^s) \times uos_{it}^s) / (TVP_{max} - TVP_{min}) \\
&+ ((\sum_{i=1}^n \sum_{j=1}^m foc_{ij} \times y_{ijt}^s \times uos_{it}^s) + (\sum_{j=1}^m hoc_{jt} \times inl_j^s) + (\sum_{j=1}^m shc_{jt} \times shl_j^s)) \\
&+ (\sum_{i=1}^n \sum_{j=1}^m \sum_{p=1}^P vsc_{ijpt} \times Q_{ijtp}^s \times uos_{it}^s) \\
&+ (\sum_{i=1}^n \sum_{j=1}^m \sum_{p=1}^P fsc_{ijpt} \times (\frac{x_{ijt}^s(inl_j^s)}{cat_{ijpt}}) \times uos_{it}^s) + \sum_{i=1}^n \\
&\sum_{j=1}^m ((pc_{ijt} \times \theta_{ij} \times x_{ijt}^s(inl_j^s) \times uos_{it}^s) \\
&+ (\sum_{d_{ij}=1}^{D_{ij}} FF_{ijtd_{ij}}^s(inl_j^s) \times pc_{ijtd_{ij}}^A \times \theta_{ij}^A \times uos_{it}^s) + (\theta_{ij}^I \times uos_{it}^s \\
&\times (\sum_{d_{ij}=1}^{D_{ij}} pc'_{ijtd_{ij}} \times (ZZ_{ijtd_{ij}}^s(inl_j^s) - UB_{ijtd_{ij}-1} \times \xi_{ijtd_{ij}}^I) + \sum_{d_{ij}=0}^{d_{ij}-1} pc'_{ijtd_{ij}} \times (UB_{ijtd_{ij}} - LB_{ijtd_{ij}})) \\
&- TCP_{min}^t(inl_j^s)) / (TCP_{max} - TCP_{min}) \\
&+ \sum_{s=1}^S p_s V_{2,t+1}(\max(0, inl_j^s + \sum_{i=1}^n \sum_{p=1}^P Q_{ijtp}^s - dem_{jt}))
\end{aligned}$$

$$0 \leq x_{ijt}^s \leq y_{ijt}^s \times cap_{ij} \quad \forall i, j, t, s$$

$$0 \leq inl_j^s \times sph_j \leq H_{jt}^s \times mss_{jt} \quad \forall j, t, s$$

$$0 \leq shl_j^s \leq (1 - H_{jt}^s) \times msh_{jt} \quad \forall j, t, s$$

$$0 \leq Q_{ijtp}^s \leq U_{ijtp}^s \times cat_{ijtp} \quad \forall i, j, p, t, s$$

$$\sum_{j=1}^m y_{ijt}^s \leq m \times uos_{it}^s \quad \forall i, t, s$$

$$x_{ijt}^s = \sum_{p=1}^P Q_{ijtp}^s \quad \forall i, j, t, s$$

$$\sum_{d_{ij}} \xi_{ijtd_{ij}}^I = 1 \quad \forall i, j$$

$$\sum_{t=1}^T x_{ijt}^s \leq UB_{ijtd_{ij}} + M(1 - (\xi_{ijtd_{ij}}^I \times \theta_{ij}^I)) \quad \forall i, j, d_{ij}, s$$

$$\sum_{t=1}^T x_{ijt}^s > LB_{ijtd_{ij}} - M(1 - (\xi_{ijtd_{ij}}^I \times \theta_{ij}^I)) \quad \forall i, j, d_{ij}, s$$

$$\sum_{d_{ij}} \xi_{ijtd_{ij}}^A = 1 \quad \forall i, j$$

$$\sum_{t=1}^T x_{ijt}^s \leq UB_{ijtd_{ij}} + M(1 - (\xi_{ijtd_{ij}}^A \times \theta_{ij}^A)) \quad \forall i, j, d_{ij}, s$$

$$\sum_{t=1}^T x_{ijt}^s > LB_{ijtd_{ij}} - M(1 - (\xi_{ijtd_{ij}}^A \times \theta_{ij}^A)) \quad \forall i, j, d_{ij}, s$$

$$FF_{ijtd_{ij}}^s \geq x_{ijt}^s - M(1 - \xi_{ijtd_{ij}}^A) \quad \forall i, j, t, d_{ij}, s$$

$$FF_{ijtd_{ij}}^s \leq x_{ijt}^s + M(1 - \xi_{ijtd_{ij}}^A) \quad \forall i, j, t, d_{ij}, s$$

$$0 \leq FF_{ijtd_{ij}}^s \leq M \xi_{ijtd_{ij}}^A \quad \forall i, j, t, d_{ij}, s$$

$$ZZ_{ijtd_{ij}}^s \geq x_{ijt}^s - M(1 - \xi_{ijtd_{ij}}^I) \quad \forall i, j, t, d_{ij}, s$$

$$ZZ_{ijtd_{ij}}^s \leq x_{ijt}^s + M(1 - \xi_{ijtd_{ij}}^I) \quad \forall i, j, t, d_{ij}, s$$

$$0 \leq ZZ_{ijtd_{ij}}^s \leq M \xi_{ijtd_{ij}}^I \quad \forall i, j, t, d_{ij}, s$$

$$\xi_{ijtd_{ij}}^I, \xi_{ijtd_{ij}}^A, H_{jt}^s, y_{ijt}^s, U_{ijtp}^s \in \{0, 1\} \quad \forall i, j, p, t, s, d_{ij}$$

$$x_{ijt}^s, Q_{ijtp}^s, inl_j^s, shl_{jt}^s \geq 0 \&integer \quad \forall i, j, p, t, s, d_{ij} \quad (27)$$

In the dynamic programming model, we try to minimize the total normalized deviation of each objective function from its optimal values when the inventory level for item j in period t under scenario s is (inl_j^s) . $TVP_{max}^t(inl_j^s)$ denotes the maximum value of the TVP function in period t for item j under scenario s when the inventory level is (inl_j^s) . $TCP_{min}^t(inl_j^s)$ denotes the minimum value of the TCP function in period t for item j under scenario s when the inventory level is (inl_j^s) . TVP_{max} is the maximum value of TVP function in all periods. It is sufficient to solve the problem once, maximizing the TVP as the only objective to obtain TVP_{max} . Next the optimal values of the orders in this situation have been put into the objective function TCP to obtain its worst value (TCP_{max}). TCP_{min} is the minimum value of the TCP function in all periods. A similar method as described above is applied where the problem is minimizing the TCP as the only objective function, and the best corresponding value is obtained. Then, as in the previous step, the optimal values in this state are substituted into the TVP objective function, and the worst value of

Fig. 2. Flow chart of dynamic programming algorithm to solve decision tree.

this function is specified (TVP_{min}). So the optimal solution is obtained by an integrated approach of dynamic programming and stochastic programming. We used the backward approach to solve the decision tree using the dynamic programming method. At each stage, the dynamic table associated with demand quantity under each scenario is solved so that the obtained objective function by adding the value of the objective function at that stage to the expected mean optimal value of the objective function corresponding to the inventory left at the next stage. Consequently, the probability of the occurrence of each scenario and stochastic changes during the periods is considered. The flow chart related to the dynamic programming algorithm to solve the decision tree is presented in Fig. 2.

4. Computational results

We use a case from practice to demonstrate the performance of our SSS&OA method. First, the case is introduced and then the dynamic programming model provided is utilized to generate the solutions.

4.1. Case study

We applied our SSS & OA method to the Composite Products Company. The composite products are among others used in the aerospace industry, for the repair of transition lines, and for thermal insulation. The company is engaged in consulting, designing and implementing production projects in this field. The criteria used for supplier selection in this company include price and quality. The manager of this company intends to make a better evaluation of suppliers and allocate order to

Table 3

Some details related to the case study.

List of firm's products	List of items	List of suppliers' names
Composite pipes and reservoir	Vinyl Resin	Supplier from Tehran (TES) Supplier from Ghazvin (GHS)
Epoxy adhesive	Unsaturated Polyester Resin	Supplier from Esfahan (ESS)
Different composite structures and coverings	Alkyd Resin	Taiwanese Supplier (TAS) European supplier (EUS)

Table 4

Best-to-others vectors for the main criteria.

Criteria	Economic (EC)	Environmental (EN)	Social (SO)
Economic (EC)	1	2	4

Table 5

Others -to-worst vectors for the main criteria.

Criteria	Social (SO)
Economic (EC)	4
Environmental (EN)	2
Social (SO)	1

them by considering aspects of sustainability. For this purpose, managers and experts of this company identified the suppliers of the items and chose proper criteria according to the list of global sustainability criteria.

Table 3 summarizes the list of products provided by the company, the raw materials required for them and the list of identified suppliers.

4.2. Phase 1: Supplier selection

Firstly, the proper importance weights for the sustainable criteria were obtained using BWM. In the next step, the suppliers were prioritized using the ER method. Since the criteria and sub-criteria were primarily qualitative and the evaluators did not have the whole experience and understanding for evaluating the suppliers, uncertainty was high. The new method allowed them to state this score as a probability distribution or even give no score to a criterion. Finally, an appropriate prioritization was assigned, and the weight of each supplier was determined.

4.2.1. Implementing best worst method

First, the best and worst main criteria were determined based on expert opinions. Then pairwise comparisons “best-to-others” and “others-to-worst” were performed. The results are shown in Tables 4 and 5.

The results of these comparisons are shown in Table 6. Note that step 5 of BWM was implemented using Lingo 17 software.

These steps were performed for all sub-criteria. In this way, their optimal weight and the consistency ratio for the economic criteria, the environmental criteria, and the social criteria were obtained.

4.2.2. Implementing ER

In this step, after having determined the optimal weights for each criterion and sub-criterion, suppliers were ranked using evidential reasoning. Table 7 shows the standard assessment scores of the

Table 6

Results of BWM for the main criteria.

Criteria	weight
Economic (EC)	0.5714286
Environmental (EN)	0.2857143
Social (SO)	0.1428571
ξ^*	0.0001285
Consistency ratio	0.0001285/1.63 = 0.00007883

Table 7

Suppliers criteria assessment standards.

Grade	Meaning
7	Excellent condition
6	Very good condition
5	Good condition
4	Fair condition
3	Poor condition
2	Very poor condition
1	Critical condition

evidential reasoning method for supplier assessment (Wang and Elhag, 2008).

The distributed assessments of five suppliers for three items are based on the opinions of the company's experts and decision-makers. For example, the score $\{(5, 1.0)\}$ is assigned to the sub-criterion “quality” for the second supplier, meaning that with 100% probability, the materials manufactured by this supplier are good. For the first supplier, the score $\{(4, 0.7), (5, 0.3)\}$ was set for the sub-criterion “environmental management”, meaning that with 30% probability this supplier is doing well and with 70% probability this supplier is doing average according to this sub-criterion. The other scores for the three items can be analyzed similarly.

To make the ER algorithm applicable, Microsoft Excel was used. The computations started from the sub-criteria level as a stepwise process. After combining the information at the sub-criteria level, the results were used as the input for the calculation at the main criteria level. Ultimately, a distribution score was obtained for each supplier for each item. For each supplier, a distributed score was determined for each main criterion. These steps were repeated at the main criteria level to determine the distribution score of each supplier. For example, the first supplier has the distributed score $\{(1, 0.01449), (2, 0.00621), (3, 0.27757), (4, 0.14313), (5, 0.50276), (6, 0.01528), (7, 0)\}$. When there was a lack of information on a sub-criterion for any reason and the information was incomplete, the column β_g got a value, showing the probability of information incompleteness. In this way, we could analyze the distributed scores of each supplier according to this table.

We need a number instead of a distribution to rank the suppliers. The maximum, minimum and average of the suppliers' values were

Table 8

Priority of suppliers based on sustainability criteria.

Item	Supplier	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Ranking order	Normalized weights
Item 1	Supplier 1	–	0	0	1	1	3	0.19013
	Supplier 2	1	–	0.709155	1	1	5	0.13914
	Supplier 3	1	0.290845	–	1	1	4	0.14166
	Supplier 4	0	0	0	–	0.737891	2	0.26159
	Supplier 5	0	0	0	0.262109	–	1	0.26748
Item 2	Supplier 1	–	0	0	0.088545	0	1	0.22316
	Supplier 2	1	–	0	0.86784	0.41944	3	0.19784
	Supplier 3	1	1	–	1	1	5	0.17471
	Supplier 4	0.911455	0.13216	0	–	0.017445	2	0.20854
	Supplier 5	1	0.58056	0	0.982555	–	4	0.19576
Item 3	Supplier 1	–	1	0	1	1	4	0.1785
	Supplier 2	0	–	0	0	0	1	0.24746
	Supplier 3	1	1	–	1	1	5	0.16152
	Supplier 4	0	1	0	–	0.86187	3	0.20097
	Supplier 5	0	1	0	0.13813	–	2	0.21155

calculated. The utility value of each degree was defined as follows (Wang and Elhag, 2008).

Du	Du	Du	Du	Du	Du	Du
(1) = 0	(2) = 0.1	(3) = 0.2	(4) = 0.4	(5) = 0.6	(6) = 0.8	(7) = 1

It is notable that in cases where there was complete information related to a supplier, the supplier's maximum and minimum values are equal. This is the case for the third supplier of item 1. Otherwise, the maximum and minimum values of that supplier are different. For instance, the first supplier's minimum and maximum values of item 2 are 0.55720 and 0.61147, respectively. Table 8 shows the preferences of the suppliers related to each other for each item. For example, for the second item the first supplier is superior to the second, third and fifth suppliers with 100% probability. The probability for the preference of the first supplier over the fourth one is 0.911455, which is greater than 0.5, meaning that the first supplier is also superior to the fourth one. Similarly, the fourth supplier is with 100% probability superior to the third one and with probability 0.86784 and 0.982555 superior to the second and fifth supplier respectively. The second supplier is with 100% probability superior to the third with probability 0.58056 superior to the fifth supplier. Finally, the fifth supplier is with 100% probability superior to the third supplier. The last column of this table shows the normalized weights of the suppliers obtained through the average suppliers' values.

4.3. Phase 2: SSS & OA

In this section, the bi-objective MILP is solved by an integrated approach combining dynamic programming and stochastic

Table 9

Demand in the two periods for each item.

State	Period 1		Period 2	
	Demand mode forecast	The amount of demand (item1, item 2, item3)	Demand mode forecast	The amount of demand (item1, item 2, item3)
1	Pessimistic demand	(800, 950, 350)	Pessimistic demand	(800, 950, 350)
2	Pessimistic demand	(800, 950, 350)	Probable demand	(960, 1100, 420)
3	Pessimistic demand	(800, 950, 350)	Optimistic demand	(1120, 1150, 500)
4	Probable demand	(960, 1100, 420)	Pessimistic demand	(800, 950, 350)
5	Probable demand	(960, 1100, 420)	Probable demand	(960, 1100, 420)
6	Probable demand	(960, 1100, 420)	Optimistic demand	(1120, 1150, 500)
7	Optimistic demand	(1120, 1150, 500)	Pessimistic demand	(800, 950, 350)
8	Optimistic demand	(1120, 1150, 500)	Probable demand	(960, 1100, 420)
9	Optimistic demand	(1120, 1150, 500)	Optimistic demand	(1120, 1150, 500)

programming. Using the data from Table 8 and other relevant case study data, the model for the problem of SSS & OA was solved. The input data values were obtained via the company's experts and are related to two periods for the five suppliers and the three items discussed in Phase 1. The data of the case study can be downloaded from <http://pirayesh.profocms.um.ac.ir/index.php/data-source>.

In this research, there were $2^5 = 32$ potential states with respect to the availability of the five suppliers. Therefore, the total number of scenarios in the two periods is $(3 \times 32)^2$, i.e. 9216 scenarios, where 3 represents the number of demand states, 32 represents the number of states related to the availability suppliers, and 2 represents the number of periods.

All demand modes for all three items in the two periods are shown in Table 9. In the third and fifth column of this table, the first amount is the demand for the first item, the second amount is the demand for the second item and the third amount is the demand for the third item.

For all suppliers, the access modes and their probability of occurrence in each period are given in Table 10. The last column of this table shows the total probability of suppliers' access in each period.

Combining the above two uncertainties results in Table 11, showing only some of the many scenarios. The probability of each scenario was derived from the probabilities of supplier availability and demand over the two time periods.

To solve the proposed MILP model, GAMS WIN 64 24.1.2 is applied and run on a personal computer with a 2.53 GHz CPU and 6 GB main memory. To show the efficiency of the proposed approach, we first assumed that the model has only one objective function. The model was solved once to maximize only the TVP, meaning that it's the best value was obtained for this objective function. The related results for the order

Table 10
Supplier access modes and their probability of occurrence.

State	Set of suppliers available	Set of suppliers unavailable	uos_{it}^s					pus_i					Total probability
			1	2	3	4	5	1	2	3	4	5	
1	{1,2,3,4,5}	{}	1	1	1	1	1	0.93	0.9	0.92	0.84	0.79	0.5109985
2	{1,2,3,4}	{5}	1	1	1	1	0	0.93	0.9	0.92	0.84	0.21	0.1358350
3	{1,2,3,5}	{4}	1	1	1	0	1	0.93	0.9	0.92	0.16	0.79	0.0973330
4	{1,2,4,5}	{3}	1	1	0	1	1	0.93	0.9	0.08	0.84	0.79	0.0444346
5	{1,3,4,5}	{2}	1	0	1	1	1	0.93	0.1	0.92	0.84	0.79	0.0567776
6	{2,3,4,5}	{1}	0	1	1	1	1	0.07	0.9	0.92	0.84	0.79	0.0384623
7	{1,2,3}	{4,5}	1	1	1	0	0	0.93	0.9	0.92	0.16	0.21	0.0258733
8	{1,2,4}	{3,5}	1	1	0	1	0	0.93	0.9	0.08	0.84	0.21	0.0118117
9	{1,3,4}	{2,5}	1	0	1	1	0	0.93	0.1	0.92	0.84	0.21	0.0150928
10	{2,3,4}	{1,5}	0	1	1	1	0	0.07	0.9	0.92	0.84	0.21	0.0102241
11	{1,2,5}	{3,4}	1	1	0	0	1	0.93	0.9	0.08	0.16	0.79	0.0084637
12	{1,3,5}	{2,4}	1	0	1	0	1	0.93	0.1	0.92	0.16	0.79	0.0108148
13	{2,3,5}	{1,4}	0	1	1	0	1	0.07	0.9	0.92	0.16	0.79	0.0073261
14	{1,4,5}	{2,3}	1	0	0	1	1	0.93	0.1	0.08	0.84	0.79	0.0049372
15	{2,4,5}	{1,3}	0	1	0	1	1	0.07	0.9	0.08	0.84	0.79	0.0033445
16	{3,4,5}	{1,2}	0	0	1	1	1	0.07	0.1	0.92	0.84	0.79	0.0042736
17	{1,2}	{3,4,5}	1	1	0	0	0	0.93	0.9	0.08	0.16	0.21	0.0022499
18	{1,3}	{2,4,5}	1	0	1	0	0	0.93	0.1	0.92	0.16	0.21	0.0028748
19	{1,4}	{2,3,5}	1	0	0	1	0	0.93	0.1	0.08	0.84	0.21	0.0013124
20	{1,5}	{2,3,4}	1	0	0	0	1	0.93	0.1	0.08	0.16	0.79	0.0009404
21	{2,3}	{1,4,5}	0	1	1	0	0	0.07	0.9	0.92	0.16	0.21	0.0019475
22	{2,4}	{1,3,5}	0	1	0	1	0	0.07	0.9	0.08	0.84	0.21	0.0008891
23	{2,5}	{1,3,4}	0	1	0	0	1	0.07	0.9	0.08	0.16	0.79	0.0006371
24	{3,4}	{1,2,5}	0	0	1	1	0	0.07	0.1	0.92	0.84	0.21	0.0011360
25	{3,5}	{1,2,4}	0	0	1	0	1	0.07	0.1	0.92	0.16	0.79	0.0008140
26	{4,5}	{1,2,3}	0	0	0	1	1	0.07	0.1	0.08	0.84	0.79	0.0003716
27	{1}	{2,3,4,5}	1	0	0	0	0	0.93	0.1	0.08	0.16	0.21	0.0002500
28	{2}	{1,3,4,5}	0	1	0	0	0	0.07	0.9	0.08	0.16	0.21	0.0001693
29	{3}	{1,2,4,5}	0	0	1	0	0	0.07	0.1	0.92	0.16	0.21	0.0002164
30	{4}	{1,2,3,5}	0	0	0	1	0	0.07	0.1	0.08	0.84	0.21	0.0000988
31	{5}	{1,2,3,4}	0	0	0	0	1	0.07	0.1	0.08	0.16	0.79	0.0000708
32	{}	{1,2,3,4,5}	0	0	0	0	0	0.07	0.1	0.08	0.16	0.21	0.0000188

quantities have been put into the objective function TCP to obtain its worst value. In the next step, the same process was performed for TCP. First, the objective function TCP was included in the model, then its best value was obtained, and the optimal value for each scenario was specified. Then, similar to the previous step, the optimal values in this stage were substituted in the TVP objective function, and the worst value of this function was obtained. In the third step, the optimal value of both objective functions was obtained simultaneously using Eq. (27), and the optimal order quantity for each scenario was determined. It was observed that the simultaneous results obtained for both objectives using this method are very close to those obtained by considering the objective functions separately. In other words, the new approach can provide the best optimal solution for multi-objective problems. The results are shown in Table 12.

Based on the trade-off solution (Mafakheri et al., 2011) and the percentage change of the objective function before and after using the multi-objective dynamic value function ((New value-previous value)/previous value), the value of the TVP function is reduced by 12% when compared with its maximum value. The value of the TCP function increased by 9% with respect to its minimum value. However, if we consider only the maximization of the TVP function, the value of the TCP function increased 46% with respect to its minimum value. Similarly, if we consider only the minimization of the TCP function, the value of the TVP function decreases by 32% with respect to its maximum value. Therefore, minimizing the deviation of the value of the objective functions from their optimal value by using a dynamic programming method leads to better solutions.

For several scenarios the order quantity and shortage level of each item are shown in Table 13. These results were obtained by solving the model using the integrated dynamic programming and stochastic

programming approach.

Examining the scenarios, we find that shortage (SHL) is very slightly sensitive to UB and LB values. This is because the cost of shortage is very high and the company prefers to meet demand under any circumstances. So, we only have shortages when suppliers are not available to meet demand. From the scenarios, we observe that inventory (INL) is less sensitive to UB and LB values compared to supplier access, holding costs and shortage costs. The main reason is that a higher priority supplier may not be available in some periods, so if a high priority supplier is available in those periods and costs are considered, the order will be based on that supplier's capacity.

5. Influence of different uncertainties and quantity discounts

Hereafter, the influence of the different uncertainties and quantity discounts on the results are studied.

Condition (1). Solve the bi-objective model where stochastic demand, uncertainties in suppliers available and quantity discounts are not considered.

Condition (2). Solve the bi-objective model where stochastic demand, uncertainties in suppliers available are not considered.

Condition (3). Solve the bi-objective model where uncertainties in suppliers available and quantity discounts are not considered.

Condition (4). Solve the bi-objective model where stochastic demand and quantity discounts are not considered.

Condition (5). Solve the bi-objective model where quantity discounts are not considered.

We have solved the model for each of these conditions. A summary of the results is presented in Table 14.

Table 11
Information about supplier access and demand in two periods.

Scenario	Set of suppliers available in period 1	Set of suppliers unavailable in period 1	Demand in period 1	Set of suppliers available in period 2	Set of suppliers unavailable in period 2	Demand in period 2	Probability of Supplier access in period 1	Probability of demand in period 1	Probability of Supplier access in period 2	Probability of demand in period 2	Total probability scenario
1	{1,2,3,4,5}	{}	Pessimistic	{1,2,3,4,5}	{}	Pessimistic	0.5109985	0.3333	0.5109985	0.3333	0.29007471
101	{1,2,3,4}	{5}	Pessimistic	{1,3,4,5}	{2}	Pessimistic	0.1358350	0.3333	0.0567776	0.3333	0.00085676
200	{1,2,3,5}	{4}	Pessimistic	{1,2,4}	{3,5}	Pessimistic	0.0973330	0.3333	0.0118117	0.3333	0.00012771
302	{1,2,4,5}	{3}	Pessimistic	{1,4,5}	{2,3}	Pessimistic	0.0444346	0.3333	0.0049372	0.3333	0.00002437
433	{1,3,4,5}	{2}	Pessimistic	{1,2}	{3,4,5}	Probable	0.0567776	0.3333	0.0022499	0.3333	0.00001419
522	{2,3,4,5}	{1}	Pessimistic	{1,5}	{2,3,4}	Probable	0.0384623	0.3333	0.0009404	0.3333	0.00000401
636	{1,2,3}	{4,5}	Pessimistic	{2}	{1,3,4,5}	Probable	0.0258733	0.3333	0.0258733	0.3333	0.00007436
741	{1,2,4}	{3,5}	Pessimistic	{1,2,3,4}	{5}	Optimistic	0.0118117	0.3333	0.1358350	0.3333	0.00017823
848	{1,3,4}	{2,5}	Pessimistic	{2,3,5}	{1,4}	Optimistic	0.0150928	0.3333	0.0073261	0.3333	0.00001228
941	{2,3,4}	{1,5}	Pessimistic	{2,3,5}	{1,4}	Optimistic	0.0102241	0.3333	0.0073261	0.3333	0.00000832
4056	{1,2,5}	{3,4}	Probable	{2,3}	{1,4,5}	Pessimistic	0.0084637	0.3333	0.0019475	0.3333	0.00000183
4153	{1,3,5}	{2,4}	Probable	{2,4}	{1,3,5}	Pessimistic	0.0108148	0.3333	0.0008891	0.3333	0.00000106
4250	{2,3,5}	{1,4}	Probable	{2,5}	{1,3,4}	Pessimistic	0.0073261	0.3333	0.0006371	0.3333	0.00000051
4352	{1,4,5}	{2,3}	Probable	{3}	{1,2,4,5}	Pessimistic	0.0049372	0.3333	0.0002164	0.3333	0.00000011
4478	{2,4,5}	{1,3}	Probable	{4}	{1,2,3,5}	Probable	0.0033445	0.3333	0.0000988	0.3333	0.00000003
4578	{3,4,5}	{1,2}	Probable	{5}	{1,2,3,4}	Probable	0.0042736	0.3333	0.0000708	0.3333	0.00000003
4672	{1,2}	{3,4,5}	Probable	{}	{1,2,3,4,5}	Probable	0.0022499	0.3333	0.0000188	0.3333	0.000000004
4773	{1,3}	{2,4,5}	Probable	{1,3,4,5}	{2}	Optimistic	0.0028748	0.3333	0.0567776	0.3333	0.00001813
4870	{1,4}	{2,3,5}	Probable	{2,3,4,5}	{1}	Optimistic	0.0013124	0.3333	0.0384623	0.3333	0.00000560
4967	{1,5}	{2,3,4}	Probable	{1,2,3}	{4,5}	Optimistic	0.0009404	0.3333	0.0258733	0.3333	0.00000270
8076	{2,3}	{1,4,5}	Optimistic	{1,3,5}	{2,4}	Pessimistic	0.0019475	0.3333	0.0108148	0.3333	0.00000233
8173	{2,4}	{1,3,5}	Optimistic	{2,3,5}	{1,4}	Pessimistic	0.0008891	0.3333	0.0073261	0.3333	0.00000072
8270	{2,5}	{1,3,4}	Optimistic	{1,4,5}	{2,3}	Pessimistic	0.0006371	0.3333	0.0049372	0.3333	0.00000034
8369	{3,4}	{1,2,5}	Optimistic	{1,2}	{3,4,5}	Pessimistic	0.0011360	0.3333	0.0022499	0.3333	0.00000028
8498	{3,5}	{1,2,4}	Optimistic	{1,3}	{2,4,5}	Probable	0.0008140	0.3333	0.0028748	0.3333	0.00000026
8595	{4,5}	{1,2,3}	Optimistic	{1,4}	{2,3,5}	Probable	0.0003716	0.3333	0.0013124	0.3333	0.00000005
8692	{1}	{2,3,4,5}	Optimistic	{1,5}	{2,3,4}	Probable	0.0002500	0.3333	0.0009404	0.3333	0.00000002
8789	{2}	{1,3,4,5}	Optimistic	{2,3}	{1,4,5}	Probable	0.0001693	0.3333	0.0019475	0.3333	0.00000003
8926	{3}	{1,2,4,5}	Optimistic	{4}	{1,2,3,5}	Optimistic	0.0002164	0.3333	0.0000988	0.3333	0.00000002
9023	{4}	{1,2,3,5}	Optimistic	{5}	{1,2,3,4}	Optimistic	0.0000988	0.3333	0.0000708	0.3333	0.0000000008
9120	{5}	{1,2,3,4}	Optimistic	{}	{1,2,3,4,5}	Optimistic	0.0000708	0.3333	0.0000188	0.3333	0.0000000001
9214	{}	{1,2,3,4,5}	Optimistic	{4}	{1,2,3,5}	Optimistic	0.0000188	0.3333	0.0000988	0.3333	0.0000000002

Table 12

Summary of the model solution results obtained with the three modes.

modes	TVP	TCP
Solve the model with the TVP objective function	1107.904	674,531,512
Solve the model with the TCP objective function	748.592	459,945,854
Solve the model with Integrated stochastic programming and dynamic programming approach	969.292	504,263,132

Table 13

The order quantity from each supplier and the shortage level under each scenario.

Scenario 1		Scenario 101		Scenario 200		Scenario 302	
Variable	Value	Variable	Value	Variable	Value	Variable	Value
x_{121}^1	950	x_{121}^{101}	950	x_{121}^{200}	950	x_{121}^{302}	950
x_{131}^1	150	x_{131}^{101}	150	x_{131}^{200}	150	x_{131}^{302}	150
x_{221}^1	300	x_{221}^{101}	300	x_{211}^{200}	250	x_{211}^{302}	200
x_{231}^1	350	x_{231}^{101}	350	x_{221}^{200}	300	x_{221}^{302}	300
x_{311}^1	800	x_{311}^{101}	800	x_{231}^{200}	350	x_{231}^{302}	350
x_{411}^1	250	x_{411}^{101}	250	x_{311}^{200}	800	x_{411}^{302}	850
x_{122}^1	650	x_{122}^{101}	650	x_{122}^{200}	650	x_{122}^{302}	650
x_{232}^1	200	x_{132}^{101}	200	x_{232}^{200}	200	x_{132}^{302}	200
x_{312}^1	550	x_{312}^{101}	550	x_{412}^{200}	550	x_{412}^{302}	550
Scenario 4250		Scenario 4352		Scenario 4478		Scenario 4578	
Variable	Value	Variable	Value	Variable	Value	Variable	Value
x_{211}^{4250}	410	x_{111}^{4350}	360	x_{211}^{4478}	360	x_{311}^{4578}	800
x_{321}^{4250}	800	x_{121}^{4350}	950	x_{221}^{4478}	800	x_{321}^{4578}	450
x_{331}^{4250}	350	x_{131}^{4350}	270	x_{331}^{4478}	350	x_{331}^{4578}	250
x_{311}^{4250}	800	x_{411}^{4350}	850	x_{411}^{4478}	850	x_{411}^{4578}	410
x_{321}^{4250}	600	x_{421}^{4350}	450	x_{421}^{4478}	600	x_{421}^{4578}	950
x_{331}^{4250}	220	x_{431}^{4350}	300	x_{431}^{4478}	220	x_{431}^{4578}	300
x_{212}^{4250}	550	x_{312}^{4350}	550	x_{412}^{4478}	710	x_{531}^{4578}	20
x_{222}^{4250}	650	x_{322}^{4350}	650	x_{422}^{4478}	800	x_{512}^{4578}	710
x_{232}^{4250}	200	x_{332}^{4350}	200	x_{432}^{4478}	270	x_{522}^{4578}	800
–	–	–	–	–	–	x_{532}^{4578}	270
Scenario 8926		Scenario 9023		Scenario 9120		Scenario 9214	
Variable	Value	Variable	Value	Variable	Value	Variable	Value
x_{311}^{8926}	800	x_{411}^{9023}	850	x_{511}^{9120}	1000	shl_{11}^{9214}	1120
x_{321}^{8926}	850	x_{421}^{9023}	950	x_{521}^{9120}	1080	shl_{21}^{9214}	1150
x_{331}^{8926}	250	x_{431}^{9023}	300	x_{531}^{9120}	400	shl_{31}^{9214}	500
shl_{11}^{8926}	320	shl_{11}^{9023}	270	shl_{11}^{9120}	120	x_{412}^{9214}	850
shl_{21}^{8926}	300	shl_{21}^{9023}	200	shl_{21}^{9120}	70	x_{422}^{9214}	950
shl_{31}^{8926}	250	shl_{31}^{9023}	200	shl_{31}^{9120}	100	x_{432}^{9214}	300
x_{412}^{8926}	850	x_{512}^{9023}	1000	shl_{12}^{9120}	1120	shl_{12}^{9214}	270
x_{422}^{8926}	950	x_{522}^{9023}	1080	shl_{22}^{9120}	1150	shl_{22}^{9214}	200
x_{432}^{8926}	300	x_{532}^{9023}	400	shl_{32}^{9120}	500	shl_{32}^{9214}	200
shl_{12}^{8926}	270	shl_{12}^{9023}	120	–	–	–	–
shl_{22}^{8926}	200	shl_{22}^{9023}	70	–	–	–	–
shl_{32}^{8926}	200	shl_{32}^{9023}	100	–	–	–	–

Table 14

Summary of the results under different conditions.

Condition	Solve the model with the TVP objective function		Solve the model with the TCP objective function		Solve the model with Integrated stochastic programming and dynamic programming approach		Number of scenarios
1	1202.967	592,289,000	862.943	476,087,000	1138.0114	515,714,600	1
2	1202.967	530,868,400	839.496	385,285,300	1143.994	429,864,600	1
3	1190.108	585,863,100	852.334	471,472,000	1123.3047	522,907,389	9
4	1188.360	697,035,800	864.954	508,247,500	993.6404	530,012,283	1024
5	1107.904	735,526,920	784.498	564,573,513	953.7499	590,840,433	9216
Original model	1107.904	674,531,512	748.592	459,945,854	969.2926	504,263,132	9216

Fig. 3. Results using the three multi-objective problem solution methods.

Under the first condition there is no stochastic demand, no uncertainties in the availability of suppliers and no quantity discounts. The model was solved under this condition and the values of the objective functions were obtained. Under the second condition, only a quantity discount was added to the model. It is clear that by adding this discount, the values of the objective functions improved compared to the first condition, especially for the TCP function. Under the third condition, the only uncertainty concerns demand, and nine scenarios were created. It is shown that the values of both objective functions are slightly worse. Under the fourth condition, only the uncertainty with respect to the availability of the suppliers was considered. It is observed that the value of both objective functions deteriorate, especially for the TVP objective function. The main reason is the unavailability of higher value suppliers in some of the scenarios. Under the fifth condition, both stochastic demand and uncertainties in the availability of the suppliers are assumed. It is observed that combining these two uncertainties decreases the value of each objective function most. Using the original model, considering stochastic demand, uncertainties in suppliers available and quantity discounts simultaneously, it is clear that the values of the objective functions improve compared to the fifth condition due to the quantity discounts.

6. Comparison integrated dynamic programming and stochastic programming method with some existing methods

In order to validate the proposed approach of dynamic programming and stochastic programming, it is compared with the Epsilon constraint method (ECM) (Copado-Méndez et al., 2016) and revised multi-choice goal programming (RMCGP) (Chang, 2007; Cheraghalipour and Far-sad, 2018).

First, we use the Epsilon constraint method to solve the mathematical model proposed in this research. We solve the problem with the objective function TCP and add the objective function TVP to the problem's constraints. In order to find optimal Pareto solutions to the

problem, we increase ε .

Then our proposed model is written based on the revised multi-choice goal programming method. According to this method, the objective function is defined as $\min \delta_1(d_1^+ + d_1^-) + \alpha_1(e_1^+ + e_1^-) + \delta_2(d_2^+ + d_2^-) + \alpha_2(e_2^+ + e_2^-)$. Decision variable d_i^+ is the positive deviation of the objective function i , d_i^- is the negative deviation of the objective function i , e_i^+ is the positive deviation of the related (upper/lower) bound for the value of the objective function i and e_i^- is the negative deviation of the related (upper/lower) bound for the value of the objective function i . $obj_1 = TVP$ and $obj_2 = TCP$ are considered as a constraint. Then, to solve the revised model, the weight of each objective function δ_i and the weight of the total deviation of related upper/lower bound α_i are required. To find the best solution, we performed weights sensitivity analysis. The results of using these methods are shown in Fig. 3.

In Fig. 3, the results for TCP and TVP obtained by using the new integrated dynamic programming and stochastic programming approach are compared with the results obtained with the ECM and the RMCGP methods. As shown in this figure, the best solution using the proposed approach is better than the best Pareto solutions obtained via ECM and the sensitivity analysis results for RMCGP. That is, that with the same cost, the value of the TVP objective function will be higher with the proposed solution approach and suppliers with higher priority will be selected. Another advantage of our proposed solution approach to the commonly used solution methods is that the model is solved based on dynamic programming. The main problem will become smaller, and we need less time to solve it. The results of using these methods are shown in Table 15. One of the problems with the other methods available for our problem is that since the number of scenarios is vast, they require a computer system with large memory to solve the problem using GAMS software. However, in our proposed approach, dynamic programming is used. Dynamic programming is utilized when the sub-problems are dependent. In this category of problems, traditional approaches where sub-problems are solved repeatedly, are not efficient. In the dynamic

Table 15
Summary of model results based on the three solution methods.

Solution method	TVP	TCP	CPU time
Solve the model with Epsilon constraint method	929.7983	504,801,917	86.17
Solve the model with revised multi-choice goal programming	927.4005	503,521,243	91.97
Solve the model with Integrated stochastic programming and dynamic programming approach	969.2926	504,263,132	48.64

Fig. 4. Decision-making process for sustainable supplier selection and order allocation.

programming approach, the sub-problems are solved once, and their solutions are stored in a table to be used in further analysis. Following this algorithm reduces the computational burden. So, it can be solved with any computer system and does not require large memory.

7. Decision making process for SSS & OA

The decision making process for SSS & OA is shown in Fig. 4. First, supply chain decision makers use the company's internal data and external sources (competitors, etc.) and identify the suppliers of each item. Then, suppliers are evaluated and ranked using the hybrid BWM-ER Method. Next, using the proposed model, the appropriate suppliers are selected and the order quantity to them is determined under each scenario. At this stage, a report of possible scenarios in case of uncertainty is presented and decision makers can select the relevant scenario and allocate the order according to the amount of demand and availability of the suppliers in that period. Finally, a purchase order is issued to the selected suppliers for each item. The relevant supplier supplies the desired item in the specified amount. After delivering the items to the company, the decision-makers review them, and if done in accordance with the order, approve them and store the information obtained from each supplier in each period in the knowledge database.

With the introduction of this new framework, the company needs less time to make decisions in situations with uncertainty (almost 70% less time). The main reason for this is that all scenarios are considered. Now a company has a formal method, implemented in easy to use software tool, whereas before the decisions were made manually. Moreover, by using the hybrid BWM-ER method, decision makers do not have to worry about incorrect evaluation of suppliers. That's because in our method, uncertainty in the evaluation of quality criteria or even lack of information about a particular criterion is considered, increasing the correct evaluation of suppliers.

8. Conclusion & further research

In this research, we study the SSS & OA problem in a multi-supplier, multi-period, and multi-item context. The different suppliers compete via the discounts, prices, and the maximum quantities they offer per item, as well as via their availability in each period. Appropriate weights are assigned to each selection criterion by applying the hybrid BWM and ER method to obtain suppliers ranking. A mathematical model has been developed for the SSS & OA problem under stochastic demand, uncertainties in suppliers' availabilities and quantity discounts. A new integrated approach based on dynamic and stochastic programming is

introduced to solve the model. To validate the proposed approach, it is compared with ECM and RMCGP. It is observed that the results obtained with the new proposed approach are better and obtained faster. To evaluate the performance of the new framework further, the influence of the different uncertainties and quantity discounts on the results are studied. It is clear that by adding quantity discounts, the values of the objective functions are improved, also when both stochastic demand and uncertainties in the availability of the suppliers are assumed. It is observed when both uncertainties occur, the value of each objective function decreases. By considering the three quantity discounts, stochastic demand and uncertainties in the availability of the suppliers the results obtained are more realistic. The proposed approach has been adopted by the managers in the company of the case study as a comprehensive framework for decision making processes under uncertainty.

The following topics for further research are suggested:

- The model can be extended by including other stochastic parameters, such as uncertain supplier delivery times, or demand depending on various parameters such as price or time.
- We applied our selection and allocation method to only one case in practice. More case studies should be done to get a better insight into the applicability of the method in practice.
- Data mining can be used to support the process from data collection, analytics and action advice generation. For example, text mining can be used to choose sustainable sub-criteria, or classification methods can be used to evaluate and select suppliers. For example, logistic

regression and artificial neural network can be used to determine the weight of each supplier through data.

- In this paper, the company and suppliers make their own decisions and may not directly interact or cooperate with other entities or competitors within the supply network. As a future research, a bi-level and Nash game approaches can be used to coordinate its non-cooperative and competitive members at different stages.

CRediT authorship contribution statement

Zahra Sadat Hosseini: Conceptualization, Methodology, Software, Validation, Writing – original draft, Writing – review & editing, Investigation, Supervision. **Simme Douwe Flapper:** Writing – review & editing, Investigation. **Mohammadali Pirayesh:** Conceptualization, Methodology, Investigation.

Declaration of Competing Interest

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

Appendix A

Results intermediate steps BWM, ER case study
See [Tables A1–A6](#).

Table A1
Results BWM for the economic criteria.

Criteria	Weight
ECQ	0.3129128
ECC	0.3520269
ECDS	0.1173423
ECTF	0.0756199
ECLR	0.1029839
ECF	0.0391141
ξ^*	1.000000
Consistency ratio	1.000000/4.47 = 0.2237136

Table A2
Results BWM for the environmental criteria.

Criteria	Weight
ENEM	0.3786797
END	0.1338835
ENGL	0.07322331
ENPW	0.2071068
ENEC	0.2071068
ξ^*	0.1715736
Consistency ratio	0.1715736/2.3 = 0.07459217

Table A3
Results BWM for the social criteria.

Criteria	Weight
SOOHS	0.2742919
SOSMC	0.4514162
SOIE	0.2742919
SOWW	0.1036726
ξ^*	0.3542487
Consistency ratio	0.3542487/ 1.63 = 0.2173304

Table A4

Distributed assessment information for the five suppliers (Item 1).

Suppliers criteria	Supplier 1 (TES)	Supplier 2 (GHS)	Supplier 3 (ESS)	Supplier 4 (TAS)	Supplier 5 (EUS)
Economic (0.5714286)					
ECQ (0.3129128)	{{(5,1.0)}}	{{(4,1.0)}}	{{(3,1.0)}}	{{(6,1.0)}}	{{(7,1.0)}}
ECC (0.3520269)	{{(3, 1.0)}}	{{(5,1.0)}}	{{(6,1.0)}}	{{(3,1.0)}}	{{(1,1.0)}}
ECDS (0.1173423)	{{(5, 0.95),(6,0.05)}}	{{(3,1.0)}}	{{(2, 0.8),(1, 0.2)}}	{{(4, 0.9),(3,0.1)}}	{{(2, 0.95),(1,0.05)}}
ECTF (0.0756199)	{{(5, 0.7),(6,0.3)}}	{{(2, 0.85),(1,0.15)}}	{{(2,1.0)}}	{{(6, 0.95),(5,0.05)}}	{{(7,1.0)}}
ECLR (0.1029839)	{{(5, 1.0)}}	{{(2, 0.8),(3, 0.2)}}	{{(3, 0.95),(4,0.05)}}	{{(6,1.0)}}	{{(1, 0.6),(2,0.4)}}
ECF (0.0391141)	{{(4, 0.6),(3,0.4)}}	{{(3, 0.95),(2,0.05)}}	{{(2, 0.8),(1,0.2)}}	{{(6,1.0)}}	{{(7,1.0)}}
Environmental (0.2857143)					
ENEM (0.3786797)	{{(4, 0.6),(5,0.4)}}	{{(2, 0.5),(3,0.5)}}	{{(3, 0.8),(2, 0.2)}}	{{(6, 0.9),(5, 0.1)}}	{{(7, 1.0)}}
END (0.1338835)	{{(1, 0.7),(2,0.3)}}	{{(1, 1.0)}}	{{(1, 0.7),(2, 0.3)}}	{{(1, 0.5),(2, 0.5)}}	{{(7, 0.7),(6,0.3)}}
ENGL (0.0732233)	{{(4, 1.0)}}	{{(4, 0.6),(3,0.4)}}	{{(4, 0.9),(5, 0.1)}}	{{(4, 0.5),(5, 0.5)}}	{{(4, 1.0)}}
ENPW (0.2071068)	{{(4, 0.5),(3,0.5)}}	–	{{(3, 0.6),(2, 0.4)}}	{{(6, 0.7),(5, 0.3)}}	{{(7, 0.9),(6,0.1)}}
ENEC (0.2071068)	–	{{(1, 0.5),(2,0.5)}}	{{(1, 0.95),(2,0.05)}}	–	–
Social (0.1428571)					
SOOHS (0.274291)	{{(5, 0.9),(6,0.1)}}	{{(3, 0.7),(2,0.3)}}	{{(4, 0.8),(5,0.2)}}	{{(6, 0.95),(5,0.05)}}	{{(7,1.0)}}
SOSMC (0.451416)	{{(4, 0.85),(3,0.15)}}	{{(2, 0.6),(1,0.4)}}	{{(3, 0.7),(4,0.3)}}	{{(6, 0.9),(7,0.1)}}	{{(7,1.0)}}
SOIE (0.2742919)	–	{{(3, 0.8),(2,0.2)}}	{{(3, 0.9),(4,0.1)}}	–	{{(7, 0.6),(6,0.4)}}
SOWW (0.103672)	{{(5, 1.0)}}	{{(3, 1.0)}}	{{(5, 1.0)}}	{{(6, 0.8),(5,0.2)}}	{{(7, 0.5),(6,0.5)}}

Table A5

The aggregated distributed assessments for the five suppliers (Item 1).

Supplier	Suppliers criteria	Degrees of belief assessed to each grade							β_g
		1	2	3	4	5	6	7	
Supplier 1(TES)	Economic (EC)	0	0	0.36524	0.01569	0.59892	0.02015	0	0
	Environmental (EN)	0.07717	0.03307	0.09315	0.47502	0.17387	0	0	0.14771
	Social (SO)	0	0	0.07572	0.42907	0.30376	0.02319	0	0.168263
	The whole Supplier	0.01449	0.00621	0.27757	0.14313	0.50276	0.01528	0	0.040551
Supplier 2(GHS)	Economic (EC)	0.01248	0.17299	0.20718	0.05499	0.55236	0	0	0
	Environmental (EN)	0.22112	0.34406	0.25052	0.03433	0	0	0	0.14997
	Social (SO)	0.16833	0.40340	0.42827	0	0	0	0	0
	The whole Supplier	0.06641	0.24279	0.24915	0.04376	0.36950	0	0	0.028393
Supplier 3(ESS)	Economic (EC)	0.0594	0.10733	0.10814	0.33067	0.39446	0	0	0
	Environmental (EN)	0.25608	0.2095	0.48162	0.04752	0.00528	0	0	0
	Social (SO)	0	0	0.55679	0.34308	0.10013	0	0	0
	The whole Supplier	0.09362	0.11787	0.24237	0.27247	0.27367	0	0	0
Supplier 4(TAS)	Economic (EC)	0	0	0.37404	0.07938	0.00271	0.54387	0	0
	Environmental (EN)	0.05466	0.05466	0	0.02794	0.07274	0.58813	0.05542	0.14646
	Social (SO)	0	0	0	0	0.02141	0.79882	0.04149	0.138286
	The whole Supplier	0.00948	0.00948	0.22880	0.05391	0.01596	0.63445	0.01277	0.03515
Supplier 5(EUS)	Economic (EC)	0.46688	0.11227	0	0	0	0.02785	0.393	0
	Environmental (EN)	0	0	0	0.05056	0	0.04716	0.76975	0.13253
	Social (SO)	0	0	0	0	0	0.08790	0.91210	0
	The whole Supplier	0.28530	0.06861	0	0.00880	0	0.03262	0.58160	0.023072

Table A6

The expected utilities of the five suppliers.

Item	Supplier	$E_{max}(R_h)$	$E_{min}(R_h)$	$E_{avg}(R_h)$
Item 1	Supplier 1	0.46782	0.42727	0.44754
	Supplier 2	0.34171	0.31331	0.32751
	Supplier 3	0.33345	0.33345	0.33345
	Supplier 4	0.63334	0.59819	0.61576
	Supplier 5	0.64115	0.61808	0.62962
Item 2	Supplier 1	0.61147	0.55720	0.58433
	Supplier 2	0.53671	0.49938	0.51804
	Supplier 3	0.45746	0.45746	0.45746
	Supplier 4	0.56544	0.52665	0.54605
	Supplier 5	0.52786	0.49729	0.51258
Item 3	Supplier 1	0.43611	0.40832	0.42222
	Supplier 2	0.60579	0.56489	0.58534
	Supplier 3	0.40613	0.35797	0.38205
	Supplier 4	0.49438	0.45634	0.47536
	Supplier 5	0.51599	0.48482	0.5004

References

- Alidaee, B., & Kochenberger, G. A. (2005). A note on a simple dynamic programming approach to the singlesink, fixed-charge transportation problem. *Transportation Science*, 39(1), 140–143.
- Amorim, P., Curcio, E., Almada-Lobo, B., Barbosa-Póvoa, A. P. F. D., & Grossmann, I. E. (2016). Supplier selection in the processed food industry under uncertainty. *European Journal of Operational Research*, 252, 801–814.
- Ayati, E., Pirayesh Neghab, M., Ali, Sadeghi, A., Asghar, & Mohammadzadeh Moghaddam, A. (2012). Introducing roadside hazard severity indicator based on evidential reasoning approach. *Safety Science*, 50(7), 1618–1626.
- Beiki, H., Mohammad Seyedhosseini, S., Ponkratov, V., Olegovna Zekiy, A., & Ivanov, S. A. (2021). Addressing a sustainable supplier selection and order allocation problem by an integrated approach: A case of automobile manufacturing. *Journal of Industrial and Production Engineering*, 38(4), 239–253.
- Bellman, R., & Kalaba, R. (1957). Dynamic programming and statistical communication theory. *Proceedings of the National Academy of Sciences*, 43(8), 749–751.
- Çebi, F., & Otay, I. (2016). A two-stage fuzzy approach for supplier evaluation and order allocation problem with quantity discounts and lead time. *Information Sciences*, 339, 143–157.
- Chai, J., Liu, J. N., & Ngai, E. W. (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. *Expert Systems with Applications*, 40(10), 3872–3885.
- Chang, C.-T. (2007). Multi-choice goal programming. *Omega*, 35(4), 389–396.
- Cheraghali, P., & Farsad, S. (2018). A bi-objective sustainable supplier selection and order allocation considering quantity discounts under disruption risks: A case study in plastic industry. *Computers & Industrial Engineering*, 118, 237–250.
- Collette, Y., & Siarry, P. (2004). *Multiobjective Optimization: Principles and Case Studies*. Berlin, Germany: Springer-Verlag.
- Copado-Méndez, P. J., Pozo, C., Guillén-Gosálbez, G., & Jiménez, L. (2016). Enhancing the ϵ -constraint method through the use of objective reduction and random sequences: Application to environmental problems. *Computers & Chemical Engineering*, 87, 36–48.
- Cui, L., Wu, H., & Dai, J. (2021). Modelling flexible decisions about sustainable supplier selection in multitier sustainable supply chain management. *International Journal of Production Research*, 1–22.
- Degraeve, Z., & Roodhooft, F. (1999). Effectively selecting suppliers using total cost of ownership. *Journal of Supply Chain Management*, 35(1), 5–10.
- Dickson, G. (1966). An analysis of vendor selection systems and decisions. *Journal of Purchasing*, 2(1), 5–17.
- Esmaeili-Najafabadi, E., Fallah Nezhad, M. S., Pourmohammadi, H., Honarvar, M., & Vahdatzad, M. A. (2018). A joint supplier selection and order allocation model with disruption risks in centralized supply chain. *Computers & Industrial Engineering*.
- Ghadimi, P., Ghassemi Toosi, F., & Heavey, C. (2017). A multi-agent systems approach for sustainable supplier selection and order allocation in a partnership supply chain. *European Journal of Operational Research*, 269(1), 286–301.
- Ghorbani, M., Bahrami, M., & Arabzad, M. (2012). An integrated model for supplier selection and order allocation; using Shannon entropy, SWOT and linear programming. *Procedia - Social and Behavioral Sciences*, 41, 521–527.
- Goren, H. (2018). Hacer Guner Goren, A decision framework for sustainable supplier selection and order allocation with lost sales. *Journal of Cleaner Production*, 183, 1156–1169.
- Govindan, K., Khodaverdi, R., & Jafarian, A. (2013). A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. *Journal of Cleaner Production*, 47, 345–354.
- Wong, J. T. (2019). Dynamic procurement risk management with supplier portfolio selection and order allocation under green market segmentation. *Journal of Cleaner Production*, 119835.
- Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2015). Multi criteria decision making approaches for green supplier evaluation and selection: A literature review. *Journal of Cleaner Production*, 98, 66–83.
- Guo, C., & Li, X. (2015). A multi-echelon inventory system with supplier selection and order allocation under stochastic demand. *International Journal of Production Economics*, 151, 37–47.
- Hamdan, S., & Cheaitou, A. (2016). Supplier selection and order allocation with green criteria: An MCDM and multi-objective optimization approach. *Computers and Operation Research*, 81, 282–304.
- Hamdan, S., & Cheaitou, A. (2017a). Dynamic green supplier selection and order allocation with quantity discounts and varying supplier availability. *Computers & Industrial Engineering*, 110, 573–589.
- Hamdan, S., & Cheaitou, A. (2017b). Datasets for supplier selection and order allocation with green criteria, all-unit quantity discounts and varying number of suppliers. *Data in Brief*, 13, 444–452.
- Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research*, 202(1), 16–24.
- Hosseini, S., Morshedlou, N., Ivanov, D., Sarder, M. D., Barker, K., & Khaled, A. A. (2019). Resilient supplier selection and optimal order allocation under disruption risks. *International Journal of Production Economics*.
- Huynh, V. N., Nakamori, Y., & Murai, T. (2006). Multiple-attribute decision making under uncertainty: the evidential reasoning approach revisited. *IEEE Transactions on Systems, Man, and Cybernetics*, 36(4), 804–822.
- Jadidi, O., Cavaliere, S., & Zolfaghari, S. (2014). An improved multi-choice goal programming approach for supplier selection problems. *Applied Mathematical Modelling*, 39(14), 4213–4222.
- Jia, R., Liu, Y., & Bai, X. (2020). Sustainable supplier selection and order allocation: Distributionally robust goal programming model and tractable approximation. *Computers & Industrial Engineering*, 106267.
- Kannan, D., Khodaverdi, R., Olfat, L., Jafarian, A., & Diabat, A. (2013). Integrated fuzzy multi criteria decision making method and multiobjective programming approach for supplier selection and order allocation in a green supply chain. *Journal of Cleaner Production*, 47, 355–367.
- Kaur, H., & Singh, S. P. (2021). Multi-stage hybrid model for supplier selection and order allocation considering disruption risks and disruptive technologies. *International Journal of Production Economics*, 231, Article 107830.
- Kellner, F., & Utz, S. (2019). Sustainability in supplier selection and order allocation: Combining integer variables with Markowitz portfolio theory. *Journal of Cleaner Production*.
- Keshavar, M., Amiri, M., Zavadskas, E., Turskis, Z., & Antucheviciene, J. (2017). A new multi-criteria model based on interval type-2 fuzzy sets and EDAS method for supplier evaluation and order allocation with environmental considerations. *Computers & Industrial Engineering*, 112, 156–174.
- Ware, N. R., Singh, S. P., & Banwet, D. K. (2014). A mixed-integer non-linear program to model dynamic supplier selection problem. *Expert Systems Application*, 41, 671–678.
- Keshavarz Ghorabae, M., Amiri, M., Zavadskas, E. K., Turskis, Z., & Antucheviciene, J. (2017). A new multi-criteria model based on interval type-2 fuzzy sets and EDAS method for supplier evaluation and order allocation with environmental considerations. *Computers & Industrial Engineering*, 112, 156–174.
- Weber Charles, A., John, R., & Current & Benton, W. C. (1991). Vendor selection criteria and methods. *European Journal of Operational Research*, 50, 2–18.
- Khoshfetrat, S., Rahiminezhad Galankashi, M., & Almasi, M. (2019). Sustainable supplier selection and order allocation: a fuzzy approach. *Engineering Optimization*, 1–14.
- Kuo, T., Hsu, C.-W., & Li, J.-Y. (2015). Developing a green supplier selection model by using the DANP with VIKOR. *Sustainability*, 7(2), 1661–1689.
- Lee, J., Cho, H., & Kim, Y. S. (2014). Assessing business impacts of agility criterion and order allocation strategy in multi-criteria supplier selection. *Expert Systems with Applications*, 42(3), 1136–1148.
- Li, S., Alper, M., & Huang, W. (2009). Selection of contract suppliers under price and demand uncertainty in a dynamic market. *European Journal of Operational Research*, 198(3), 830–847.
- Li, F., Wu, C.-H., Zhou, L., Xu, G., Liu, Y., & Tsai, S.-B. (2020). A model integrating environmental concerns and supply risks for dynamic sustainable supplier selection and order allocation. *Soft Computing*.
- Lo, H., James, J. H., Liou, Her-Shing Wang, & Tsai, Yi-Song (2018). An integrated model for solving problems in green supplier selection and order allocation. *Journal of Cleaner Production*, 190, 339–352.
- Lu, L. Y. Y., Wu, C. H., & Kuo, T. C. (2007). Environmental principles applicable to green supplier evaluation by using multi-objective decision analysis. *International Journal of Production Research*, 45(18–19), 4317–4331.
- Luthra, S., Govindan, K., Kannan, D., Mangla, S. K., & Garg, C. P. (2017). An integrated framework for sustainable supplier selection and evaluation in supply chains. *Journal of Cleaner Production*, 140, 1686–1698.
- Mafakheri, F., Breton, M., & Ghoniem, B. (2011). Supplier selection-order allocation: A two-stage multiple criteria dynamic programming approach. *International Journal of Production Economics*, 132, 52–57.
- Mendoza, A., & Ventura, J. A. (2010). An effective method to supplier selection and order quantity allocation. *International Journal of Business and Systems Research*, 2(1), 1–15.
- Moghaddam, K. S. (2015). Fuzzy multi-objective model for supplier selection and order allocation in reverse logistics systems under supply and demand uncertainty. *Expert Systems Application*, 42, 6237–6254.
- Momeni, M., & Vandchali, H. R. (2017). Providing a structured methodology for supplier selection and evaluation for strategic outsourcing. *International Journal of Business Performance and Supply Chain Modelling*, 9(1), 66.
- Nasr, A. K., Tavana, M., Alavi, B., & Mina, H. (2020). A novel fuzzy multi-objective circular supplier selection and order allocation model for sustainable closed-loop supply chains. *Journal of Cleaner Production*, 287, Article 124994.
- Nazari-Shirkouhi, S., Shakouri, H., Javadi, B., & Keramati, A. (2013). Supplier selection and order allocation problem using a two-phase fuzzy multi-objective linear programming. *Applied Mathematical Modelling*, 37(22), 9308–9322.
- Noori-Daryan, M., Taleizadeh, A. A., & Jolai, F. (2017). Analyzing pricing, promised delivery lead time, supplier-selection, and ordering decisions of a multi-national supply chain under uncertain environment. *International Journal of Production Economics*.
- Park, K., GüE, Okudan Kremer, & Ma, J. (2018). A regional information-based multi attribute and multi-objective decision-making approach for sustainable supplier selection and order allocation. *Journal of Cleaner Production*, 187, 590–604.
- Paydar, M. M., & Saidi-Mehrabad, M. (2015). Revised multi-choice goal programming for integrated supply chain design and dynamic virtual cell formation with fuzzy parameters. *International Journal of Computer Integrated Manufacturing*, 28(3), 251–265.
- Prasanna Venkatesan, S., & Goh, M. (2016). Multi-objective supplier selection and order allocation under disruption risk. *Transportation Research Part E*, 95, 124–142.
- Razmi, J., & Rafiei, H. (2010). An integrated analytic network process with mixed-integer non-linear programming to supplier selection and order allocation. *The International Journal of Advanced Manufacturing Technology*, 49(9–12), 1195–1208.
- Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, 53, 49–57.
- Scott, J., Ho, W., Dey, P. K., & Talluri, S. (2014). A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments. *International Journal of Production Economics*, 166, 226–237.
- Sen, P., & Yang, J. B. (1995). Multiple criteria decision making in design selection and synthesis. *Journal of Engineering Design*, 6(3), 207–230.

- Singh, A. (2014). Supplier evaluation and demand allocation among suppliers in a supply chain. *Journal of Purchasing and Supply Management*, 20(3), 167–176.
- Sodenkamp, M., Tavana, M., & Di Caprio, D. (2016). Modeling synergies in multi-criteria supplier selection and order allocation: An application to commodity trading. *European Journal of Operational Research*, 254(3), 859–874.
- Sontake, A., Jain, N., & Singh, A. R. (2021). Sustainable Supplier Selection and Order Allocation Considering Discount Schemes and Disruptions in Supply Chain. In *Operations Management and Systems Engineering* (pp. 61–94). Singapore: Springer.
- Torabi, S. A., Baghersad, M., & Mansouri, S. A. (2015). Resilient supplier selection and order allocation under operational and disruption risks. *Transportation Research Part E*, 79, 22–28.
- Vahidi, F., Torabi, S. A., & Ramezankhani, M. J. (2018). Sustainable supplier selection and order allocation under operational and disruption risks. *Journal of Cleaner Production*, 174, 1351–1365.
- Wang, Y. M., & Elhag, T. M. S. (2008). Evidential reasoning approach for bridge condition assessment. *Expert Systems with Applications*, 34, 689–699.
- Wang, J., Yang, J. B., & Sen, P. (1996). Multi-person and multi-attribute design evaluations using evidential reasoning based on subjective safety and cost analysis. *Reliability Engineering & System Safety*, 52(2), 113–127.
- Yang, J. B., & Sen, P. (1994). A general multi-level evaluation process for hybrid multiple attribute decision making with uncertainty. *IEEE Transactions on Systems, Man, and Cybernetics*, 24(10), 1458–1473.
- Yang, J. B., & Singh, M. G. (1994). An evidential reasoning approach for multiple attribute decision making with uncertainty. *IEEE Transactions on Systems, Man, and Cybernetics*, 24(1), 1–18.
- Zailani, S., Jeyaraman, K., Vengadasan, G., & Premkumar, R. (2012). Sustainable supply chain management (SSCM) in Malaysia: A survey. *International Journal of Production Economics*, 140(1), 330–340.
- Zimmer, K., Fröhling, M., & Schultmann, F. (2016). Sustainable supplier management – a review of models supporting sustainable supplier selection, monitoring and development. *International Journal of Production Research*, 54(5), 1412–1442.