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ORIGINAL PAPER

Sourcing decisions with order allocation under supply disruption risk considering quantitative and qualitative criteria

Maheswar Singh Mahapatra[1,2] · Pravash Chandra Pradhan[1] · J. K. Jha[1]

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Abstract

This paper addresses sourcing decisions with order allocation in the presence of supplier disruption risks in a two-echelon supply chain considering both quantitative and qualitative aspects. A mixed-integer linear program is proposed for the optimal supplier selection and order allocation considering finite and expandable production capacity, failure probability, all-unit price discount, and spot-market cost. Due to the time complexity of the problem to get an optimal solution, we develop a heuristic which is found highly efficient in time complexity and highly competitive in solution quality. A multi-objective model is formulated to capture the qualitative aspect of suppliers by maximizing the total purchase value along with minimizing the expected total cost. We have applied NSGA-II and MOPSO, two widely used evolutionary algorithms, to solve the multi-objective model. A numerical illustration is presented along with sensitivity analysis considering a supplier base of twenty suppliers and a sourcing strategy up to six suppliers. It has been found that dual-sourcing and triple-sourcing are mainly part of the non-dominated Pareto front. Also, increasing demand would lead to a higher level of sourcing strategy, which also depends on the maximum capacity of suppliers and the minimum order to be allocated to the selected suppliers.

Keywords Supply disruption risks · Supplier selection · Order allocation · Failure probability · All-unit quantity discount · Multi-objective

✉ J. K. Jha
jkjhaiitk@gmail.com

[1] Department of Industrial and Systems Engineering, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal 721 302, India

[2] School of Business, FLAME University, Pune 412115, India

1 Introduction

The world economy has become more integrated and interdependent due to globalization, and many organizations around the world have preferred to focus on different value-added activities. The increasing importance of competitive factors such as cost, quality, flexibility and innovation has encouraged outsourcing to grow exponentially, which has paved a path for global organizations to adopt better sourcing strategies for competitive advantage in the international market (Rundh 2007). Over the last few years, globalization of commerce has made the supply chain more disseminated, and the supply of parts has become more vulnerable to disruption. Hence, organizations are trying to adopt different approaches as disruption mitigation strategies, out of which selection of a suitable number of suppliers is a prominent approach.

The selection of the right sourcing strategy in a supply chain is crucial for each manufacturing organization to gain a competitive advantage in terms of high-quality products at a lower cost with higher customer satisfaction. Due to the presence of different supply chain disruption risks (Salehi et al. 2016; Ghavamifar et al. 2018), the decision making for sourcing has become more complicated. In recent years, supplier failure is identified as one of the top supply chain risks (O'Marah 2009). Several researchers (Jüttner et al. 2003; Spekman and Davis 2004; Rao and Goldsby 2009) have explained various types of risks that may result in supplier failure. Supplier failure may lead to poor customer service, revenue loss, an unanticipated increase in acquisition cost, excessive downtime of production resources, and loss of market share. Different strategies such as local versus global sourcing, single- versus dual/multiple-sourcing, performance-based supply contracts, and optimizing order allocation among multiple suppliers have been proposed in the literature for minimizing the impact of supplier failure (Swink and Zsidisin 2006; O'Marah 2009). In the present research, we have considered single- versus multiple-sourcing to mitigation the supplier failure risk.

The occurrence of different catastrophic events and their impacts on supply chains is always a concern for any organization. From Fig. 1, it can be understood that the frequency of catastrophic events is increasing over the years due to various reasons. These types of events have a significant impact on supply chains. The December 26th Tsunami in the Indian Ocean in the year 2004 had a considerable impact on the fishing industry of the southern part of India due to the destruction of fishing infrastructure in the coastal area. The economic impact of this event on the local and global fish supply chain was enormous. As per The WorldFish Center Report, the fish supply to some markets dropped by 90% due to the Tsunami. Shortcomings of selecting a single-sourcing strategy can be understood by the case where Ericsson has to bear a loss of around 400 million Euros due to a fire at a supplier (Philips microchip) plant in the year 2003. In 1999, General Motors reported a quarterly loss of 900 million US dollars due to the labour strike at one of its supplier factories supplying brakes. Other pronounced events are the Toyota brake valve crisis, Boeing's loss of \$2.6 billion, and the

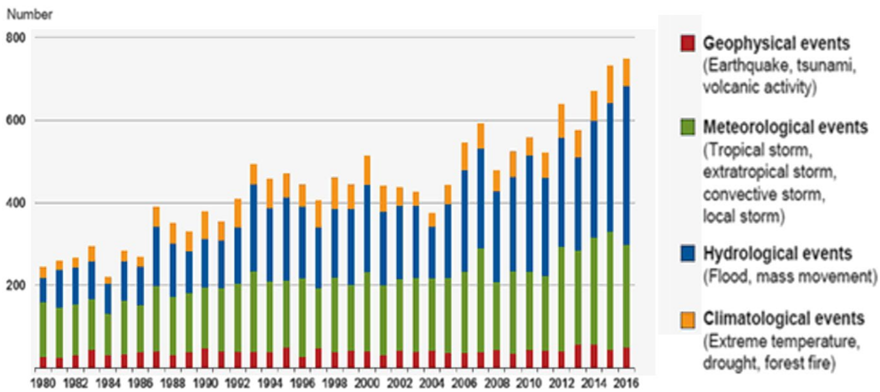

Fig. 1 Number of world natural catastrophes (1980–2016). *Source*: © 2017 Munich Re, Geo Risks Research, NatCatSERVICE

Taiwan earthquake, which have acted as an eye-opener for other organizations to think about mitigation strategies against such disruptive events.

The best way to overcome this type of supply disruption is to have multiple suppliers (Tomlin 2006; Taleizadeh 2017). At the same time, increasing the supply base may increase the total supply cost and require initial investments for new suppliers. A buyer with a multiple-sourcing strategy may miss the benefit of cost reduction due to a learning effect. The coordination and relationship between buyer and supplier will degrade with an increase in the number of suppliers. Upgradation of any product in a multiple-sourcing scenario is always a difficult task for a buyer. Even in the case of a multiple-sourcing strategy, suppliers are not much involved with product improvement.

Based on the above discussions, the next ambiguity is to decide the number of suppliers and the order allocation pattern when the failure probability of suppliers is different. The problem becomes more complex when other factors such as quantity discount, spot-market purchase cost for an additional order, expandable capacity are considered together. In this study, a mixed-integer linear program is proposed for the optimal supplier selection and order allocation, considering these factors. We develop a heuristic which is found to be highly efficient in time complexity and highly competitive in solution quality. Optimal or near-optimal solutions are found based on the lowest expected total cost which comprises of normal purchase cost, spot-market cost, lost cost, and fixed cost. The total purchase value is used to capture the qualitative aspect of suppliers, and a multi-objective problem is formulated to minimize the expected total cost (ETC) and maximize the total purchase value (TPV). We have used two widely used evolutionary algorithms, Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Multi-objective particle swarm optimization (MOPSO), to solve the multi-objective model.

The rest of the paper is organized as follows. Section 2 provides a brief literature review on supply disruption risk and disruption management, single- vs. multiple-sourcing strategies, sourcing decisions, and order allocation. Section 3 presents the mathematical models and formulations in detail. The solution methodology is described in Sect. 4. Section 5 presents numerical illustrations of the proposed models and the impacts of various parameters through sensitivity analysis. Managerial insights are presented in Sect. 6. Finally, Sect. 7 presents conclusions along with future research directions.

2 Literature review

A significant amount of literature is available on sourcing strategies addressing various issues such as criteria for supplier base selection, supplier qualification, supplier selection criteria, selection of the optimal number of suppliers, optimal order allocation, recovery strategies, and supplier relationship management. The present research is closely related to the following two aspects of sourcing strategy: selecting an optimal number of suppliers and optimal order allocation under supplier disruption risk. Therefore, we present literature on supply chain risk and disruption management followed by the literature related to single- vs. multiple-sourcing, supplier selection and order allocation with a single objective and multiple objectives.

2.1 Supply chain risks and disruption management

The supply chain risk leadership council (SCRL 2011) stated that business globalization provided opportunities to generate benefits in terms of enhancing the efficiency and effectiveness of an organization, but it has also exposed a supply chain to different types of risks, which make the supply chain more vulnerable to disruption. Rao and Goldsby (2009) reviewed and outlined various supply chain risks with their definitions. Hendricks and Singhal (2003) found that the performance of various outsourcing-dependent organizations is significantly reduced once they faced supply risk and resulted in up to 40% decrease in shareholder returns. Yin et al. (2018) studied managing global sourcing considering disruption risks with the combination of global sourcing and local sourcing.

Cavinato (2004) classified supply chain risk into five groups: (i) physical (ii) financial (iii) informational (iv) innovational and (v) relational. However, Chopra and Sodhi (2004) expressed that it would not be easy to segregate and identify risk due to interconnection among them. They explained that risk could be of any form, such as system risk, forecast risk, intellectual property risk, procurement risk, receivable risk, and other risks. It is also important that the cumulative impact of operational and disruption risks may result in an incorrect decision, more inventories, and higher supply chain cost. Later, Tang (2006) classified the supply chain risks into two broad categories: operational risk (inherent uncertainties such as supply uncertainty, demand uncertainty) and disruption risk (natural and manmade disasters such as earthquake, terrorist attack, currency fluctuations).

A conceptual framework known as 'SAM' (S: specifying the risk, A: assessment of risk and M: mitigation of risk) was proposed by Kleindorfer and Saad (2005) for supply chain risk management (SCRM) with ten working principles. Tang (2006) developed a framework to classify and review the studies related to SCRM and proposed an approach in which the author mentioned that controlling four aspects could manage supply chain risk: supply management, product management, demand management, and information management. Narasimhan and Talluri (2009) addressed the perspectives of risk management in a supply chain and presented the works carried out in the field of SCRM by addressing methodological and theoretical issues. SCRL (2011) defined SCRM as the coordination of activities to direct and control an enterprise's end-to-end supply chain under supply chain risks. SCRLC also explained that the efforts to implement SCRM must address four principles: leadership, governance, change management, and development of a business case. Simchi-Levi et al. (2015) explained that the deployment of limited resources optimally to mitigate risk in an organization is difficult due to hidden risks. They proposed a risk exposure model consisting of TTR (Time to Recover) model and TTS (Time to Survive) model, which provides an advantage over the legacy risk.

2.2 Single vs. multiple sourcing

Successful supply chain management is always dependent on the adoption of an effective sourcing strategy to overcome supply disruption risk (Yu et al. 2009). Further, Yu et al. (2009) classified sourcing strategy into three categories: (i) single, (ii) dual, and (iii) multiple. Berger et al. (2004) considered risks as catastrophic super event and unique event. The author proposed a decision tree-based model to determine the optimal number of suppliers required for a buying firm. Later, Berger and Zeng (2006) extended the model to find an optimal supplier size considering loss function, operating cost function and the probability of all suppliers failed. Burke et al. (2007) mentioned that when supplier capacities are larger than buyer's demand, and the buyer is not interested in diversification benefits, single-sourcing is the most dominating strategy, and multiple-sourcing is preferred in all other scenarios. Li and Debo (2009) proposed an analytical model for decision making between sole and second sourcing considering capacity investment cost. They found that both low and high capacity costs make second sourcing favourable. Glock (2012) and Sawik (2014) both studied single- vs. dual-sourcing under different setup, where Glock (2012) studied the influence of supplier learning effect on supplier selection and Sawik (2014) found supplier selection and customer order schedule jointly. Fang et al. (2013) compared different sourcing strategies such as single, dual, multiple, and contingent sourcing based on an approximate dynamic programming approach. They concluded that in any circumstances, more than two suppliers provide minimal additional benefit. Tsai (2016) determined the optimal number of standby suppliers required in the presence of supplier failure risk. Factors such as supply risk, operational cost, loss cost, and length of supply period were important for decision-making.

2.3 Supplier selection and order allocation

Minner (2003) and Thomas and Tyworth (2006) reviewed various aspects of supplier selection and order allocation. Berger et al. (2004) selected the optimal number of suppliers considering equal failure probability under disruptive events and compared supplier lost cost and supplier management cost. They concluded that the number of suppliers increases with an increase in failure risk. Ruiz-Torres and Mahmoodi (2007) extended the model to consider an individual unique failure probability for each supplier to consider the risk of a super-event and semi-super event into a decision tree model. Comparing all the experimental conditions, they found that sole-sourcing could overtake other sourcing strategies if the supplier is highly reliable. Yu et al. (2009) used a decision tree approach for supplier selection to compare the expected profit function considering the disruption of the primary supplier only.

Considering different supplier capacity and failure probability, Meena et al. (2011) developed an algorithm to find the optimal number of suppliers based on the expected total cost. They assumed equal order allocation among the selected suppliers. Lee (2015) formulated an NLP model with quantity discounts for supplier selection and order allocation. They applied a decision tree approach for arbitrary order allocation in the solution. Meena and Sarmah (2016) developed a problem-specific algorithm for order allocation, considering the same aspect of Lee (2015). Ray and Jenamani (2016a) used a newsvendor framework and developed a problem-specific algorithm for order allocation among the selected suppliers. They found that multiple sourcing is preferable over single-sourcing in a capacitated environment. Firouz et al. (2017) studied a multi-sourcing problem for a firm with multiple warehouses for a single product considering stochastic demand, varying prices, capacity, and quality. Azad and Hassini (2019) studied recovery strategies for single-sourcing and multi-sourcing cases when there is a supply network disruption. Hu and Dong (2019) emphasized the importance of supplier selection in a humanitarian relief operation considering various criteria such as price discounts, lead-time, and physical inventory.

Several authors (Ebrahim et al. 2009; Sawik 2010; Amin and Zhang 2012; Azadnia et al. 2015; PrasannaVenkatesan and Goh 2016; Ray and Jenamani 2016b) formulated sourcing decision as a multi-objective model. Pan and Wang (2014) formulated an integrated multi-objective supplier selection and order allocation model while maximizing the quality and minimizing the sum of purchase cost, ordering cost, and lost cost. Torabi et al. (2015) built a resilient supplier base through a bi-objective, two-stage stochastic programming model. They considered the minimization of the total expected cost and maximization of the resilience level of the supplier base. They did not include quantity discount, spot-market cost and the subjective aspects of suppliers in the model. Considering supply and demand risks, Nooraie and Parast (2015) formulated a multi-objective model for risk management to maximize supply chain visibility and minimize supply chain cost and risk. PrasannaVenkatesan and Goh (2016) developed a multi-objective mixed-integer programming model for supplier selection and order allocation with the expected cost minimization and total purchase value maximization. They considered purchase cost, supplier management cost, and lost cost Zhang et al. (2019). Recently maximized the expected total profit for a multi-period, multi-product model considering uncertain demand and quantity discount. Olanrewaju et al. (2020) proposed a cost minimization model specific to disaster management where they incorporated the buyer's penalty for not purchasing the minimum commitment quantity from a supplier. Sahebjamnia (2020) minimized the total expected cost and maximized the supplier resilience, whereas Wong (2020) proposed a multi-objective fuzzy goal programming model to consider the minimization of risk, cost and market penalty and the maximization of market bonus and green consensus.

Table 1 summarizes the related studies and presents a comparison with the present study. It can be observed that some of the researchers have addressed the suppliers' selection and order allocation problem considering quantity discount, lost cost, and disruption probability along with the issues of additional order allocation and qualitative aspect of suppliers. However, the problem is not modelled adequately considering spot-market purchase cost and expandable supplier capacity. Therefore, in this study, we address the following research questions considering the above factors.

(i) How many suppliers and which suppliers are to be selected?
(ii) How much of the order quantity to be allocated among the selected suppliers?
(iii) Whether consideration of the qualitative aspect of suppliers can influence the suppliers' selection and order allocation?

The contribution of this study is to simultaneously consider supplier's failure probability, quantity discount, spot-market purchase cost for an additional order, and the suppliers' expandable capacity to find the optimal supplier selection and order allocation. We consider a qualitative function, called supplier utility function, in terms of the total purchase value by which a buyer may benefit from all the criteria that the buyer wants to consider during the decision-making process. Therefore, we present a multi-objective model to maximize the total purchase value to address the qualitative aspect of suppliers and minimize the expected total cost. In terms of solution methodology, we developed a highly efficient heuristic for supplier selection and order allocation problem and presented two effective meta-heuristics to solve the multi-objective model.

3 Mathematical model

In this paper, a two-stage supply chain with one buyer and multiple suppliers is considered. It is assumed that there is a large base of prequalified suppliers. The buyer aims to select an optimal number of suppliers from the supplier base and allocate them orders optimally. All suppliers are exposed to failure due to disruptive events, which are characterized by a failure probability to represent the shutdown of a supplier. All suppliers offer an all-unit quantity discount to the buyer under a normal situation. We have considered minimum order quantity and maximum supplier capacity for each supplier. A decision tree approach is used to consider all possible disruption scenarios of the selected suppliers. A supplier can be either in an active state or a failed state. Therefore, the total number of possible scenarios for n selected suppliers is given by 2^n, as shown in Fig. 2. The buyer considers allocating

Table 1 Comparison of previous studies with the present study

Authors (year)	Objective type		Decision variables			Model parameters								Solution approach
	Single	Multiple	Number of suppliers	Normal order allocation	Additional order allocation	Fixed cost	Normal purchase cost	Spot-market purchase cost	Lost cost	Quantity discount	Supplier normal capacity	Supplier expandable capacity	Supplier qualitative aspect	
Berger et al. (2004)	Exp. total cost		✓			✓			✓					Decision tree
Ruiz-Torres and Mahmoodi (2007)	Exp. total cost		✓			✓			✓		✓			Decision tree
Yu et al. (2009)	Exp. total profit		✓				✓		✓					Profits comparison of single- and dual-sourcing
Meena et al. (2011)	Exp. total cost		✓			✓	✓		✓		✓			Heuristic
Lee (2015)	Exp. total cost		✓	✓		✓	✓		✓	✓	✓			Decision tree and arbitrary order allocation
Meena and Sarmah (2016)	Exp. total cost		✓	✓		✓	✓		✓	✓	✓			Heuristic

Table 1 (continued)

Authors (year)	Objective type		Decision variables			Model parameters								Solution approach
	Single	Multiple	Number of suppliers	Normal order allocation	Additional order allocation	Fixed cost	Normal purchase cost	Spot-market purchase cost	Lost cost	Quantity discount	Supplier normal capacity	Supplier expandable capacity	Supplier qualitative aspect	
Ray and Jenamani (2016a)	Exp. total profit		✓	✓			✓		✓		✓		✓	Newsvendor
PrasannaVenkatesan and Goh (2016)		Exp. total cost, total purchase value	✓	✓	✓	✓	✓		✓		✓		✓	MOPSO
Cheraghalipour and Farsad (2018)		Exp. total cost, supplier score	✓	✓		✓	✓		✓	✓	✓		✓	Revised multi-choice goal programming
Hu and Dong (2019)	Exp. total cost		✓	✓		✓	✓		✓	✓	✓			Gurobi
Zhang et al. (2019)	Exp. total profit		✓	✓			✓		✓	✓				Lagrangian relaxation

Table 1 (continued)

Authors (year)	Objective type		Decision variables			Model parameters								Solution approach
	Single	Multiple	Number of suppliers	Normal order allocation	Additional order allocation	Fixed cost	Normal purchase cost	Spot-market purchase cost	Lost cost	Quantity discount	Supplier normal capacity	Supplier expandable capacity	Supplier qualitative aspect	
Olanrewaju et al. (2020)	Exp. total cost		✓	✓		✓	✓		✓		✓			CPLEX 12.8
Sahebjamnia (2020)		Exp. total cost, supplier resilience	✓	✓		✓	✓		✓	-	✓		✓	Heuristic
Wong (2020)		Exp. total cost, total risk, green consensus, bonus	✓	✓			✓		✓		✓			Fuzzy goal programming

Table 1 (continued)

Authors (year)	Objective type		Decision variables			Model parameters								Solution approach
	Single	Multiple	Number of suppliers	Normal order allocation	Additional order allocation	Fixed cost	Normal purchase cost	Spot-market purchase cost	Lost cost	Quantity discount	Supplier normal capacity	Supplier expandable capacity	Supplier qualitative aspect	
This study	Exp. total cost		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		Heuristic
		Exp. total cost, total purchase value	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	NSGA II and MOPSO

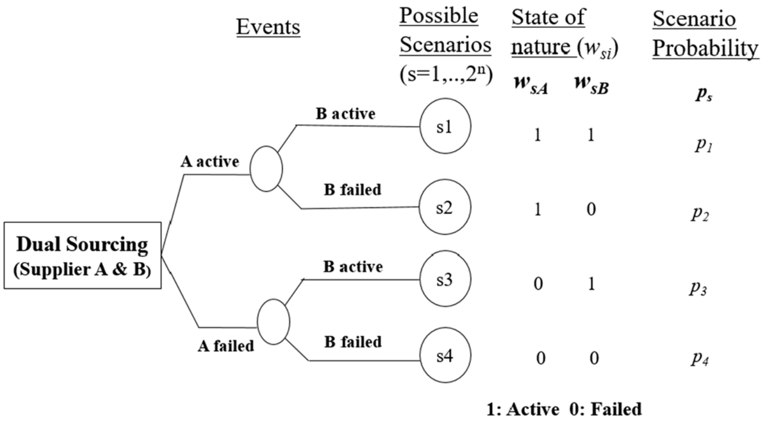

Fig. 2 An example of possible scenarios and state of nature for dual-sourcing

additional orders to the selected active suppliers as a contingency measure against the risk of supply disruption. Like other firms, the buyer is interested in sourcing the maximum possible orders from a preferred supplier to maximize the total purchase value. However, disruption of the preferred supplier may result in a huge monetary loss to the buyer, which leads to an increase in the total expected cost. Thus, due to the above two conflicting objectives, we have formulated two models. In the first model, we minimize the total expected cost to determine the best set of suppliers and order allocations to them. In the second model, we consider the maximization of the total purchase value and minimization of the total expected cost.

3.1 Model assumptions

(i) Demand is known and constant.
(ii) The production capacity of each supplier is also known and constant.
(iii) A supplier will be either in an active state or in a completely failed state.
(iv) All suppliers offer a different all-unit quantity discount.
(v) Unit spot-market purchase cost for an additional order beyond the normal order is more than the unit normal cost, and unit lost cost is more than unit spot-market cost.
(vi) The failure probability of all suppliers is independent.

3.2 Notation and decision variables

Parameters	
S	Set of prequalified suppliers
N	Number of prequalified suppliers
n	Type of sourcing strategy, such as $n = 1$ means single-sourcing

Parameters	
$S(n)$	Set of n selected suppliers from the set S
$S'(n)$	Set of n suppliers selected from the reduced set $S'(n) \subseteq S$
F	Set of possible scenarios, index by s
k	Index of discount intervals for each supplier, $k = 1, 2, ..., K$
π_i	Probability of failure of the ith supplier
p_s	Probability of the sth scenario
d	Total demand of the buyer
v_i	Capacity of the ith supplier
e_i	Expandable capacity of the ith supplier
f_i	Fixed cost for buying from the ith supplier
c_{ik}	Unit normal cost charged by the ith supplier in the kth discount interval
a_i	Unit spot-market cost charged by the ith supplier for an additional order
l	Unit lost cost for an unmet demand, $l > a_i > c_{ik}, \forall i, k$
t_i	Preferential weight of the ith supplier
w_{si}	State of nature of the ith supplier under the sth scenario. $w_{si} = 0$ if the ith supplier is disrupted; $w_{si} = 1$, otherwise
$q_i^{\min}$	Minimum order quantity allocated to the ith selected supplier
u_{ik}	Upper bound of the kth discount interval of the ith supplier, $u_{i0} = \varepsilon, \forall i \in S$, where ε is a very small number
FC	Fixed cost incurred by the buyer for all selected suppliers
NPC_s	Normal purchase cost incurred by the buyer under the sth scenario
SPC_s	Spot-market purchase cost incurred by the buyer under the sth scenario
LC_s	Lost cost incurred by the buyer under the sth scenario
Decision variables	
x_{ik}	A binary variable for discount selection; if the quantity allocated to the ith supplier falls in the kth discount interval, then $x_{ik} = 1$, otherwise $x_{ik} = 0$
q_{ik}	Order quantity allocated to the ith supplier in the kth discount interval
m_{si}	Additional quantity supplied by the ith supplier under the sth scenario

3.3 Cost functions

The expected total cost of the buyer is the sum of the fixed cost (FC), normal purchase cost (NPC_s), spot-market purchase cost (SPC_s), and the lost cost (LC_s). Out of all these cost components, only fixed cost is scenario-independent and the remaining costs are scenario-dependent. Considering the states of nature of all selected suppliers in scenario s, the probability p_s of the sth scenario can be derived as (Ray and Jenamani 2016a)

$$p_s = \prod_{i \in S(n)} \left[\left(1 - \pi_i\right) w_{si} + \pi_i \left(1 - w_{si}\right) \right]. \tag{1}$$

$\left[\left(1 - \pi_i\right) w_{si} + \pi_i \left(1 - w_{si}\right) \right]$ in Eq. (1) represents the probability of the state of nature of the ith supplier under the sth scenario. This means in the sth scenario, if supplier i remains active, then $\left(1 - \pi_i\right) w_{si}$ becomes non-zero and $\pi_i \left(1 - w_{si}\right)$ becomes zero, and if supplier i fails, then $\left(1-\pi_i\right)w_{si}$ becomes zero and $\pi_i\left(1-w_{si}\right)$ becomes non-zero. Thus, the probability p_s is the multiplication of the probability of state of nature of all selected suppliers in the sth scenario.

3.3.1 Fixed cost (*FC*)

Irrespective of the proportion of total demand allocated to a selected supplier, the fixed cost is due to the supplier management cost of all selected suppliers in a sourcing strategy. The supplier management cost includes the cost of negotiation, cost of monitoring the quality of suppliers, and tooling cost provided to suppliers. The fixed cost is scenario independent and can be expressed as the sum of the fixed cost of all selected suppliers, which is given by

$$FC = \sum_{i \in S(n)} f_i. \tag{2}$$

3.3.2 Normal purchase cost (NPC_s)

Here, we have considered that suppliers offer all-unit quantity discount (Manerba and Mansini 2012; Manerba et al. 2018). The normal cost is to be paid by the buyer to the ith supplier for purchasing q_{ik} units at unit price c_{ik} in the kth discount interval in the sth scenario if the ith supplier is active, i.e. $w_{si} = 1$. Therefore, the normal purchase cost under the sth scenario can be obtained as

$$NPC_s = \sum_{i \in S(n)} \left(w_{si} \sum_{k=1}^{K} c_{ik} q_{ik} \right). \tag{3}$$

For the ith selected supplier, order allocation q_{ik} is positive for a given value of k and is zero for other values of k. This is ensured by using binary variables, which has been explained later while presenting the discount constraints.

3.3.3 Spot-market purchase cost (SPC_s)

The buyer incurs a spot-market purchase cost to compensate for the lost quantity due to the failure of at least one supplier. Under supplier failure conditions, remaining active suppliers can compensate for the lost quantity based on their available and expandable capacities at the spot-market purchase cost. Therefore, the spot-market purchase cost under scenario s can be written as

$$SPC_s = \sum_{i \in S(n)} a_i m_{si} w_{si}. \tag{4}$$

For the derivation of the spot-market purchase cost for the ith supplier under the scenario s, the unit spot-market purchase cost a_i is multiplied with the additional order quantity m_{si} and the state of nature w_{si}. This implies that the spot-market cost will be only paid to the suppliers which are active and provide some amount of additional order.

3.3.4 Lost cost (LC_s)

The lost cost is caused by the failure of the selected suppliers due to their disruption. The buyer has to accept a substantial loss when the total demand cannot be received from the selected suppliers. Though there is a provision for compensation of the lost quantity from the active suppliers through additional order at unit spot-market price, this quantity will be limited by the number of active suppliers and their capacity. The lost cost corresponding to the scenario s can be expressed as

$$LC_s = l\left(d - \left(\sum_{i \in S(n)} \left(w_{si} \sum_{k=1}^{K} q_{ik}\right) + \sum_{i \in S(n)} m_{si} w_{si}\right)\right). \tag{5}$$

The above expression is the multiplication of the unit lost cost l and the total lost quantity under scenario s. For each scenario $s \in F$, we calculate the lost quantity by subtracting the total available order from the total demand d. The total available order is the sum of q_{ik} (normal order) and m_{si} (additional order) obtained from selected suppliers $i \in S(n)$.

Now, considering all possible scenarios and the four cost components derived above, the expected total cost can be obtained as

$$ETC{=}FC + \sum_{s=1}^{|F|} p_s\left(NPC_s + SPC_s + LC_s\right). \tag{6}$$

On substitution for the respective terms in the above equation, we get

$$ETC = \sum_{i \in S(n)} f_i + \sum_{s=1}^{|F|} \left[\prod_{i \in S(n)} \left\{ \left(1 - \pi_i\right) w_{si} + \pi_i \left(1 - w_{si}\right) \right\} \left\{ \begin{array}{l} \sum_{i \in S(n)} \left(w_{si} \sum_{k=1}^{K} c_{ik} q_{ik} \right) + \sum_{i \in s(n)} a_i m_{si} w_{si} \\ + l\left(d - \left(\sum_{i \in S(n)} \left(w_{si} \sum_{k=1}^{K} q_{ik} \right) + \sum_{i \in S(n)} m_{si} w_{si} \right) \right) \end{array} \right\} \right]. \tag{7}$$

3.4 Qualitative function

The buyer always tends to allocate orders as much as possible to the most preferred supplier, which in turn maximizes the supplier utilization in terms of the total purchase value. However, due to disruption risk, the failure of the preferred supplier may lead to a huge loss to the buyer. To overcome this, the buyer allocates orders to alternative suppliers. The total purchase value for the ith supplier is calculated as the product of the supplier preferential weight t_i and the quantity received from the

ith supplier. There are various multi-criteria decision-making tools to evaluate the preferential weight of suppliers based on various qualitative attributes such as cost, product quality, delivery schedule, after-sale service, and capacity. Thus, the TPV can be obtained as

$$TPV = \sum_{s=1}^{|F|} p_s \sum_{i \in S(n)} t_i \left(\sum_{k=1}^{K} q_{ik} + m_{si} \right) w_{si}. \tag{8}$$

The above equation provides the supplier utility value for the buyer by allocating $q_{ik}+m_{si}$ quantity to the ith supplier in scenario s, where the preferential weight of the ith supplier is pre-evaluated as t_i using Analytic hierarchy process (AHP).

3.5 Model constraints

In this section, the related constraints of models are explained.

3.5.1 Normal order allocation

The total demand d of the buyer will be allocated to all selected suppliers. Considering the discount intervals, the total order constraint can be written as

$$\sum_{i \in S(n)} \sum_{k=1}^{K} q_{ik} = \min \left\{ d, \sum_{i \in S(n)} v_i \right\}. \tag{9}$$

All selected suppliers will be able to meet the total demand d, unless their capacities constrain them.

3.5.2 Minimum order allocation

The minimum order allocation constraint ensures that each selected supplier i must be allocated a pre-decided minimum order quantity $q_i^{\min}$ irrespective of cost and the value of preferential weight.

$$q_{ik} \geq q_i^{\min} x_{ik}, \quad \forall i \in S(n), \quad k = 1, 2, ..., K. \tag{10}$$

3.5.3 Capacity constraint

The following constraint ensures that the quantity q_{ik} allocated to each selected supplier i should not exceed the supplier's production capacity v_i.

$$q_{ik} \leq v_i x_{ik}, \quad \forall i \in S(n), \quad k = 1, 2, 3, ..., K. \tag{11}$$

3.5.4 Additional order allocation

In any scenario, active suppliers are only capable of supplying additional quantity above the normal order quantity. Therefore, Eq. (12) ensures that only active suppliers are allocated an additional order. As the unit lost cost l is higher than the unit spot-market purchase cost a_i, the model will always try to allocate the maximum possible additional order to meet the total demand, which is assured by Eq. (13).

$$m_{si}(1 - w_{si}) \leq \sum_{k=1}^{K} q_{ik} w_{si}, \quad \forall s \in F, \quad i \in S(n) \tag{12}$$

and

$$\sum_{i \in S(n)} \left(\sum_{k=1}^{K} q_{ik} + m_{si} \right) \leq d, \quad \forall s \in F. \tag{13}$$

3.5.5 Maximum order for individual supplier considering the expandable capacity

Suppliers are capable of expanding their capacity in case of emergency to supply additional order quantity through overtime payment or using the resources from other projects. As a result, suppliers will increase the unit price for additional order quantity. Therefore, the total order quantity, i.e. normal order q_{ik} and additional order m_{si}, cannot be more than the total capacity of a supplier, including expandable capacity (i.e., $v_i + e_i$), and the resulting constraint is given by

$$\sum_{k=1}^{K} q_{ik} + m_{si} \leq v_i + e_i, \quad \forall s \in F, \quad i \in S(n). \tag{14}$$

3.5.6 Discount constraint

In this study, we consider an equal number of discount intervals for all suppliers. However, we can convert an unequal number of discount slabs for suppliers into an equal number of discount slabs. This can be done by splitting the discount slabs of a supplier to match with the number of discount slabs of the supplier having the maximum number of discount slabs.

The normal order quantity allocated to a supplier will fall in one of the quantity intervals offered by the supplier. To ensure this, a binary decision variable x_{ik} is used and the following three constraints (15)–(17) have been formulated. The first two constraints (15) and (16) will ensure that the quantity allocated should be within the upper bound u_{ik} and the lower bound (upper bound of k-1, i.e., $u_{i,k-1} + \varepsilon$) of a discount interval k, and Constraint (17) ensures that the quantity allocated to a supplier must fall exactly in one discount interval.

$$q_{ik} \leq u_{ik}x_{ik} \quad \forall\, i \in S(n), \quad k = 1, 2, ..., K \tag{15}$$

$$q_{ik} \geq \left(u_{ik-1} + \varepsilon\right)x_{ik} \quad \forall\, i \in S(n), \quad k = 1, 2, ..., K \tag{16}$$

$$\sum_{k=1}^{K} x_{i,k-1} = 1 \quad \forall\, i \in S(n) \tag{17}$$

3.6 Model formulation

We have developed two models: cost-based sourcing (Model 1) and cost- and value-based sourcing (Model 2). Under cost-based sourcing, the objective of the buyer is to minimize the expected total cost. But many times for critical components, purchase managers have an interest in cost and purchase value both, and they look for a trade-off between cost and purchase value. Therefore, we developed the second model as a multi-objective optimization model to provide a trade-off between total cost and total purchase value for an effective sourcing-decision. Objective functions of both models are presented below along with constraints which are same for both models.

3.6.1 Model 1: cost-based sourcing

Minimize ETC [given by Eq. (7)]

Subject to

Constraints (9)–(17).

3.6.2 Model 2: cost and value-based sourcing

Minimize ETC [given by Eq. (7)]

and

Maximize *TPV* [given by Eq. (8)]

Subject to

Constraints (9)–(17).

4 Solution methodology

To solve the above models, we used two different methods. For the first model, we have developed an effective heuristic to avoid evaluating all possible combinations of suppliers under each sourcing strategy. Compared to earlier studies (Meena et al. 2011; Meena and Sarmah 2016), the proposed heuristic is different in the following aspects. First, we found the solution for supplier selection and order allocation simultaneously, which was not considered by Meena et al. (2011). Second, though Meena and Sarmah (2016) developed a heuristic for both supplier selection and order allocation, they did not consider spot-market cost and expandable suppliers' capacity, which have been considered in the proposed heuristic. Next, we reduced the supplier base to a much smaller supplier base based on the effective unit cost, which significantly decreased the time complexity of the heuristic. Details of the heuristic are presented in Sect. 4.1. For the second model, we applied two widely used evolutionary algorithms, NSGA-II (Deb et al. 2002) and MOPSO (PrasannaVenkatesan and Goh 2016), to solve the multi-objective model. A brief discussion and working principles are presented in Sect. 4.2.

4.1 Model 1: cost-based sourcing

The buyer has to select n best suppliers from the prequalified base of N suppliers ($n \leq N$). For this purpose, we need to compare the expected total cost for all possible combinations ${}^{N}C_{n}$ under each sourcing strategy $n = 1, 2, \ldots, N$. As a result, we need to evaluate the total $\sum_{n=1}^{N} {}^{N}C_{n}$ combinations to find the best sourcing strategy. Moreover, there are 2^{n} disruption scenarios for each combination. To avoid such an exhaustive search and reduce computational time, we have developed an efficient heuristic to find the solution for supplier selection and order allocations. In this regard, we have developed three algorithms. The first algorithm is proposed to reduce the supplier base N by deriving an effective unit cost, and the second algorithm is proposed for the order allocation and cost calculation for a given set of suppliers. Finally, Algorithm 3 is proposed for the optimal supplier selection and to determine the corresponding order allocation.

Algorithm 1: Reduction of the supplier base

Step 1: For each supplier i=1: N, perform Step 2.

Step 2: For the given demand d, calculate the effective unit cost for the ith supplier as below, considering the applicable discounted unit normal cost (c_{ik}) for all demand values from 1 to d.

Case 1: If $d \le v_i$, the effective unit cost for the i^{th} supplier $= \left(\sum_{j=1}^{d} j \times c_{ik}\right) / \sum_{j=1}^{d} j$.

Case 2: If $v_i < d \le v_i + e_i$, the effective unit cost for the i^{th} supplier

$$= \left(\sum_{j=1}^{v_i} j \times c_{ik} + \sum_{j=v_i+1}^{d} j \times a_i\right) / \sum_{j=1}^{d} j.$$

Case 3: If $d > v_i + e_i$, the effective unit cost for the i^{th} supplier

$$= \left(\sum_{j=1}^{v_i} j \times c_{ik} + \sum_{j=v_i+1}^{v_i+e_i} j \times a_i + \sum_{j=v_i+e_i+1}^{d} j \times l\right) / \sum_{j=1}^{d} j.$$

Step 3: Sort the suppliers in increasing order of their effective unit costs.

Step 4: Select the first $n+m$ number of suppliers from the sorted list in Step 3 as a reduced supplier base (S'), where $m \le N-n$, a non-negative integer.

In Algorithm 1, we compute the effective unit cost in the form of weighted unit cost, where every possible order quantity is considered as weight. Based on the demand, we combine the unit normal cost, unit spot-market cost, and the unit lost cost corresponding to all possible order quantity and compute the effective unit cost. Once we sort the suppliers in the increasing order of the effective unit cost, we select $n+m$ or at most N number of suppliers for the nth sourcing strategy. Here, we consider m additional suppliers to generate an effective solution. For a higher value of m, solution quality and execution time both increase. Therefore, a trade-off is possible for choosing a suitable value of m.

Algorithm 2: Order allocation under *n*th sourcing strategy $(n > 1)$

// Normal order allocation (Steps 1 to 8)

Step 1: Set discount interval $k = 2$ and $S'' = S'(n)$

Step 2: Allocate quantity $q_i^{\min}$ to supplier $i, \forall i \in S'(n)$ and set $q_i' = q_i^{\min}$, $\forall i \in S'(n)$. Evaluate leftover demand $\Delta d = \left(d - \sum_{i \in S'(n)} q_i' \right)$. If $\Delta d < 0$, then **Stop** and the *n*th sourcing strategy is infeasible; if $\Delta d > 0$, go to **Step 3**; else if $\Delta d = 0$ and $k < K$, set $k = k+1$ and go to **Step 2**, else go to **Step 8**.

Step 3: Find the unit normal cost for each supplier $i \in S''$ corresponding to the order quantity $q_i'' = max\left\{ q_i^{\min},\ min\left(u_{i,k-1},\ q_i^{\min} + \Delta d \right) \right\}$, and identify the supplier in the set S'' with the lowest unit normal cost (say supplier j) and revise the order allocation quantity for supplier j as $q_j' = q_j''$. Update set $S'' = S'' - \{j\}$.

Step 4: Calculate the leftover demand $\Delta d = \left(d - \sum_{i \in S'(n)} q_i' \right)$. If $\Delta d > 0$, perform **Step 5**, Otherwise, if $k < K$, set $k = k+1$, and go to **Step 2,** else go to **Step 8.**

Step 5: For each supplier $i \in S''$, find $q_i'' = max\left\{ q_i^{\min},\ min\left(u_{i,k-1},\ q_i^{\min} + \Delta d \right) \right\}$. Identify the supplier in the set S'' with the lowest unit normal cost (say, supplier j'). If the cost of allocating to supplier j' is less than that of supplier j for the same additional quantity $q_{j'}'' - q_{j'}^{\min}$, then revise the order allocation quantity for supplier j' as $q_{j'}' = q_{j'}''$. Set $S'' = S'' - \{j'\}$. If $S'' = \{\ \}$ go to **Step 6**, else go to **Step 4**.

Step 6: Calculate the leftover demand $\Delta d = \left(d - \sum_{i \in S'(n)} q_i' \right)$. If $\Delta d > 0$, perform **Step 7**. Otherwise, if $k < K$, set $k = k+1$ and go to **Step 2,** else go to **Step 8.**

Step 7: Set $S'' = S'(n)$. Find the unit normal cost for each supplier $i \in S''$ corresponding to the order quantity $q_i'' = min\{q_i' + \Delta d, v_i\}$, and identify the supplier in the set S'' with the lowest unit normal cost (say supplier j) and revise the order allocation quantity for supplier j as $q_j' = q_j''$. Update set $S'' = S'' - \{j\}$ and go to **Step 6**.

Step 8: Select the normal order allocations to the selected suppliers corresponding to the discount interval for which the total normal cost is the lowest, under the given sourcing strategy.

//Additional order allocation based on disruption (Steps 9 to 13)

Step 9: Set $s = 1$.

Step 10: If $s \le |F|$, set $S'' = S'(n)$ and $m_{si} = 0, \forall i \in S'(n)$, and perform **Step 11**. Otherwise, **Stop**.

Step 11: If $w_{si} = 1, \forall i \in S'(n)$, set $s = s+1$ and go to **Step 10.** Otherwise, calculate the unfulfilled demand $\Delta d = d - \sum_{i \in S'(n)} \left(w_{si} \sum_{k=1}^{K} q_{ik} + m_{si} \right)$.

Step 12: If $\Delta d > 0$, perform **Step 13**. Otherwise, set $s = s+1$ and go to **Step 10**.

Step 13: Identify the supplier with the lowest unit spot-market cost from set S'' (say supplier j) and set the additional order allocation quantity for supplier j as $m_{sj} = min\left(\Delta d,\ v_j + e_j - \sum_{k=1}^{K} q_{jk} \right)$ if $w_{sj} = 1$. Set $S'' = S'' - \{j\}$. If $S'' \ne \{\}$, calculate the unfulfilled demand

$\Delta d = d - \sum_{i \in S'(n)} \left(w_{si} \sum_{k=1}^{K} q_{ik} + m_{si} \right)$ and go to **Step 12**, otherwise go to **Step 10**.

Algorithm 3: Supplier selection and order allocations

Step 1: Find the reduced supplier base S' using Algorithm 1.

Step 2: Set $n = 1$. Allocate the normal order as $min(d, v_i), \forall i \in S'(n)$ and the additional order allocation $m_{si} = 0 \ \forall i \in S'(n)$. Evaluate the corresponding expected total cost using Equation (7).

Step 3: Set $n = n + 1$, execute Algorithm 2 for all combinations of suppliers in set S', and evaluate the corresponding expected total cost using Equation (7). Select the suppliers corresponding to the combination for which *ETC*(*n*) is the lowest for the given *n*.

Step 4: Repeat Step 3 until *ETC* is decreased, and then the corresponding value of *n* and order allocations are selected as the optimal sourcing strategy and order allocations, respectively.

4.2 Model 2: cost and value-based sourcing

Cost and value-based sourcing are formulated as multi-objective problem to minimize the expected total cost and maximize the total purchase value. In the literature, solution methods for solving multi-objective optimization problems are broadly classified into two categories: (i) analytical methods (e.g. weighted sum method, goal programming, and ε-constraint method), (ii) evolutionary algorithms (e.g. NSGA-II, MOPSO, NCRO, and MOGOA). In the last couple of decades, various meta-heuristic approaches are developed to handle complex and customized problems. In this study, we applied two meta-heuristic approaches, NSGA-II (Deb et al. 2002) and MOPSO (PrasannaVenkatesan and Goh 2016), to solve the second model.

4.2.1 NSGA-II

NSGA-II is a widely used population-based evolutionary algorithm for solving a multi-objective problem, which generates a set of non-dominated solutions known as the Pareto front. Apart from the basic operators such as selection, crossover, and mutation in the Genetic Algorithm (Rofin et al. 2020), the generation of non-dominated solutions, maintaining the diversity using crowding distance and preserving the best solution are the key features of NSGA-II (Jha et al. 2019). The key steps involved in NSGA-II are briefly presented below.

(i) *Generation of an initial population*: a predefined number of populations representing a set of solutions is generated randomly. Each solution, called a chromosome, is represented by an array consisting of the value of all decision variables. A possible range is defined for each decision variable.

(ii) *Non-dominated sorting*: it is the process of finding solutions that are non-dominated in nature, i.e. no solution dominates the other solutions in the set. This non-dominated sorting is performed on the combined population of the parent and child solutions. It ensures the elitism principle.

(iii) *Crowding distance*: crowding distance is calculated between two nearby non-dominated solutions as the absolute difference of the objective function values. Through this measure, one can understand how non-dominated solutions are distributed along the front. During the selection process, the solution with a higher crowding distance will get preference, ensuring a better exploration of the search space. To endure the presence of two extreme/boundary solutions, a crowding distance of infinity is assigned for the extreme solutions.
(iv) *Genetic operators*: in order to search the solution space effectively, crossover and mutation are performed, where new child solutions are produced from the parent solutions. The solution space is exploited through crossover and is explored through mutation.
(v) *Selection*: selection is the process of finding solutions for the next generation. Here, solutions of the same population size are taken from the set of non-dominated solutions.

The pseudocode of NSGA-II is outlined below, and the flowchart of the algorithm is also presented in Fig. 3. For further details of NSGA-II, interested readers can refer to Deb et al. (2002).

Pseudocode of NSGA-II

Initialize problem parameters and algorithm parameters such as population size (N), number of iterations (itn), crossover probability ($\boldsymbol{p_c}$), and mutation probability ($\boldsymbol{p_m}$)

Generate initial population.

Update elite solutions found from Model 1.

for $i = i : itn$

Evaluate the fitness of parent solutions.

Perform crossover with probability $\boldsymbol{p_c}$ *based on tournament selection.*

Perform mutation with probability $\boldsymbol{p_m}$.

Evaluate the fitness of new child solutions after crossover and mutation.

Perform non-dominated sorting on the combined population.

Evaluate the crowding distance.

Select next-generation solutions from the combined population based on non-dominated front and crowding distance.

Update iteration number $i = i + 1$

end

Pareto plot of non-dominated solutions

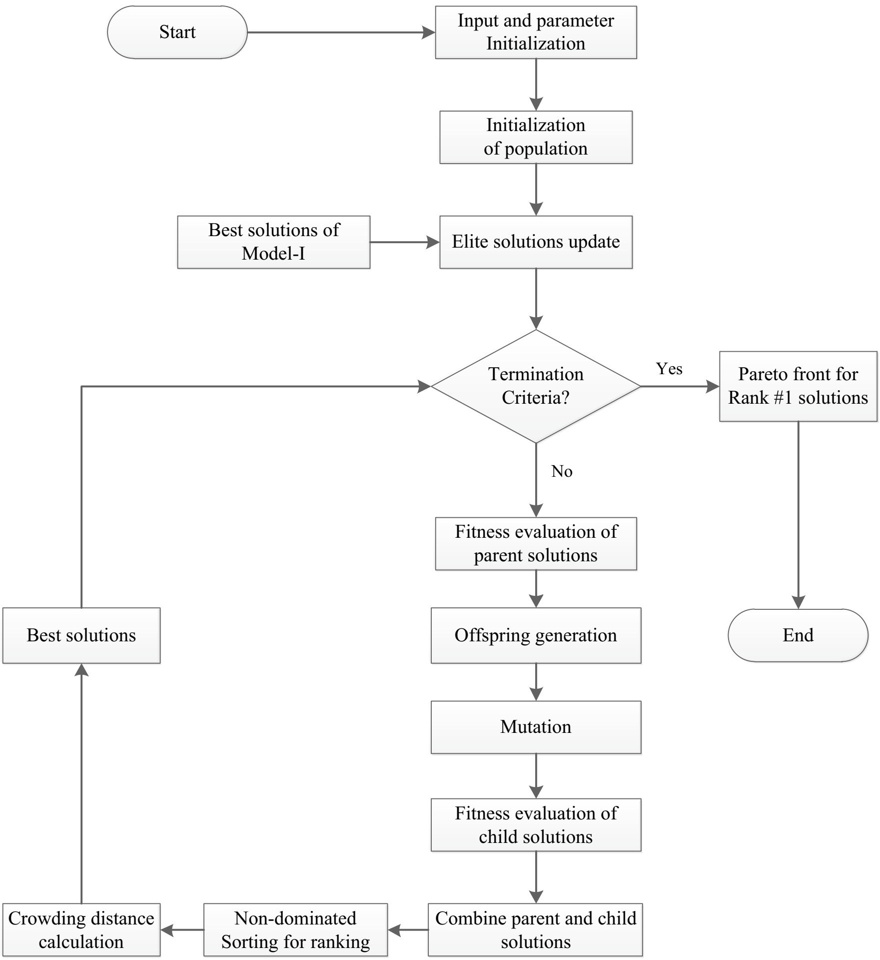

Fig. 3 Flowchart for NSGA-II

4.2.2 MOPSO

MOPSO is another important evolutionary algorithm that uses the search technique of particle swarm optimization (PSO) in the multi-objective domain. PSO is a stochastic optimization technique based on swarm movement that explores a complex solution space in cognitive and social dimensions (Eberhart and Kennedy 1995). PSO has worked significantly well for a variety of problems and even performed better than most of the traditional optimization techniques (Maiyar and Thakkar 2017).

In PSO, each solution is termed as a swarm, and its position and velocity are initialized at the beginning. Over the iterations, position and velocity are updated based on the local best solution (*pbest*) and global best solutions (*gbest*). For a given swarm of dimension d, the velocity v and the position x are updated as follows.

$$v_{k+1}^d = \omega v_k^d + c_1 r_{1k}^d \left(pbest_k^d - x_k^d \right) + c_2 r_{2k}^d \left(gbest_k^d - x_k^d \right),$$

and

$$x_{k+1}^d = x_k^d + v_{k+1}^d,$$

where ω, c_1, and c_2 are inertia, cognitive and social weights, respectively. The random numbers r_1, and r_2 are uniformly distributed in the interval [0, 1]. The fundamental difference among evolutionary algorithms lies in the search process, i.e. how a new solution is found in order to find the optimal or near-optimal solution. In PSO, we have one global best solution, whereas, in MOPSO, all the non-dominated solutions are part of global best solutions. Velocity and position are updated based on a randomly selected non-dominated solution from the set of global best solutions. Here, a similar approach is adopted in finding non-dominated solutions and crowding distance. PrasannaVenkatesan and Goh (2016) also used a similar approach. The pseudocode of MOPSO is presented below.

Pseudocode of MOPSO
Initialize problem parameters and algorithm parameters such as population size (N), number of iterations (itn), inertia weight ($\boldsymbol{\omega}$), social weight ($\boldsymbol{c_1}$), cognitive weight ($\boldsymbol{c_2}$), and mutation probability ($\boldsymbol{p_m}$).
Generate an initial population of swarms.
Update elite solutions found from Model 1 *in the initial population.*
for $i = i : itn$
Evaluate the fitness of member solutions.
Update position and velocity using local best and global best.
Perform mutation with probability $\boldsymbol{p_m}$.
Select the new mutated solution if it ensures better fitness, else discard it.
Update the set of global best solutions based on the non-dominated sorting and the crowding distance.
Update iteration number $i = i + 1$.
end
Pareto plot of non-dominated solutions.

5 Numerical illustration and discussions

This section demonstrats the proposed models through a numerical illustration followed by the impacts of various parameters on supplier selection and order allocation. We have considered a real case of an Indian aviation organization. The numerical data are closely based on the observations made in that organization.

The concerned organization spends more than 60% of its revenue on the sourcing of materials and services. The data illustrated are about sourcing a critical component whose current annual demand is 552 units and is expected to reach 864 units in the next four years. So, for the illustration, we have considered the annual demand as 864 units. All other important data are modified suitably to follow the confidentiality clause of the organization. To make the analysis insightful without making it complicated, we have considered 20 prequalified suppliers, and the details of all suppliers are presented in Table 2. The value of some parameters, such as the probability of failure and flexible capacity, are assumed rationally following the literature. The unit lost cost for each unit of unmet demand is considered as INR 2850. We implemented the proposed algorithmic approach to solve Model 1, while two evolutionary algorithms NSGA-II and MOPSO, are applied to solve the multi-objective problem in Model 2. All programs and analysis are performed in MATLAB 2018b on a personal computer with a Core i5 processor and 4 GB RAM.

5.1 Results of Model 1

The results obtained using the proposed algorithms outlined in Sect. 4.1 are compared with the results obtained using the inbuilt optimization function in MATLAB. Based on Table 2, the supplier base has been increased stepwise from 4 to 20 with a step size of 4. Therefore, we choose a supplier base of 4, 8, 12, 16, and 20 and consider sourcing strategy from a single supplier to six suppliers. Using Algorithm 1, we reduce the supplier base from 20 to the number of suppliers equal to the sourcing strategy plus three suppliers ($m=3$) in increasing order based on the computed effective unit cost. We select three additional suppliers for further processing after comparing the outcomes of additional suppliers from 1 to 6. Table 3 presents a detailed comparison between the optimal solutions obtained using the inbuilt optimization function *intlinprog* of MATLAB and the proposed heuristic approach. The heuristic solution method is highly efficient in terms of execution time. As we increase the sourcing strategy (i.e., the number of selected suppliers), the execution time of the optimal solution increases exponentially. For example, with the supplier base of $N=20$, dual-sourcing took 3.13 s, triple-sourcing took 42.05 s, 293.95 s for four suppliers, 1238.44 s for five suppliers, and 4874.38 s for six suppliers, but the proposed heuristic took less than 2 s for all cases. The heuristic method is highly competitive in terms of solution quality as the average solution gap is only 0.66%, and the maximum solution gap is 1.62%. The optimal solution for the numerical problem matches for both solution methods.

From Table 3, it is found that triple-sourcing is the best sourcing strategy for the considered problem based on the lowest ETC. Suppliers 1, 10, and 17 are selected, and the corresponding normal order allocations are 50, 454, and 360, respectively. Normal order allocation is an important aspect to get the lowest ETC because additional order allocation under various disruption scenarios (F) depends on the normal order allocation. Table 4 presents the additional order allocation details of the

Table 2 Input data of 20 prequalified suppliers

Supplier i	π_i	f_i	a_i	v_i	e_i	t_i	$q_i^{\min}$	Discounted quantities and unit normal prices							
								u_{i1}	c_{i1}	u_{i2}	c_{i2}	u_{i3}	c_{i2}	u_{i4}	c_{i4}
Supplier 1	0.20	7500	2160	900	100	0.0555	50	200	1590	400	1510.50	550	1399.20	900	1319.70
Supplier 2	0.07	25,000	1920	450	180	0.0347	80	120	1640	280	1525.20	350	1459.60	450	1394.00
Supplier 3	0.10	21,000	1960	750	130	0.0619	60	130	1625	350	1543.75	550	1430.00	750	1365.00
Supplier 4	0.07	29,000	2300	600	150	0.0648	75	100	1640	270	1558.00	420	1459.60	600	1394.00
Supplier 5	0.15	16,000	2050	520	170	0.0562	60	150	1550	250	1472.50	400	1379.50	520	1333.00
Supplier 6	0.12	20,000	2100	560	90	0.0589	75	120	1625	220	1527.50	420	1413.75	560	1348.75
Supplier 7	0.08	24,000	1980	600	100	0.0584	100	130	1675	250	1541.00	450	1507.50	600	1457.25
Supplier 8	0.18	10,000	2140	480	130	0.0466	90	110	1575	200	1464.75	360	1401.75	480	1338.75
Supplier 9	0.15	19,000	2060	640	50	0.0555	80	100	1600	300	1536.00	450	1424.00	640	1344.00
Supplier 10	0.10	22,500	1950	500	150	0.0392	100	100	1495	250	1450.15	400	1345.50	500	1285.70
Supplier 11	0.12	21,000	1890	720	150	0.0572	50	180	1650	320	1518.00	500	1468.50	720	1419.00
Supplier 12	0.20	12,000	2080	680	80	0.0346	75	120	1510	300	1434.50	460	1389.20	680	1313.70
Supplier 13	0.08	30,000	2100	610	160	0.0428	70	100	1660	280	1560.40	410	1460.80	610	1411.00
Supplier 14	0.09	28,000	1960	570	120	0.0350	85	140	1580	250	1485.20	360	1422.00	570	1374.60
Supplier 15	0.10	21,000	2010	600	140	0.0368	100	160	1620	300	1506.60	400	1409.40	600	1377.00
Supplier 16	0.20	25,000	2070	850	200	0.0611	100	130	1640	300	1558.00	550	1492.40	850	1361.20
Supplier 17	0.13	18,000	1875	550	120	0.0568	90	80	1525	230	1464.00	360	1387.75	550	1326.75
Supplier 18	0.10	28,500	2060	580	220	0.0411	80	170	1575	320	1480.50	450	1401.75	580	1323.00
Supplier 19	0.12	25,000	2100	600	150	0.0653	100	160	1600	350	1504.00	480	1392.00	600	1360.00
Supplier 20	0.15	23,000	2050	800	100	0.0347	90	100	1640	300	1574.40	550	1492.40	800	1410.40

Table 3 Comparison between optimal and heuristic solutions

N	n	Supplier selection		Normal order allocation		ETC			Execution time (s)	
		Optimal	Heuristic	Optimal	Heuristic	Optimal	Heuristic	% gap	Optimal	Heuristic
4	1	[3]	[3]	[750]	[750]	1,389,711	1,389,711	0	0.04	0.0031
	2	[1, 3]	[1, 3]	[804, 60]	[804, 60]	1,308,348	1,308,348	0	0.14	0.0043
	3	[1, 2, 3]	[1, 2, 3]	[50, 120, 694]	[684, 120, 60]	1,318,347	1,331,133	0.97	0.10	0.0049
	4	[1, 2, 3, 4]	[1, 2, 3, 4]	[50, 120, 594, 100]	[584, 120, 60, 100]	1,358,393	1,370,375	0.88	0.09	0.0034
8	1	[3]	[3]	[750]	[750]	1,389,711	1,389,711	0	0.14	0.0046
	2	[3, 5]	[1, 3]	[614, 250]	[804, 60]	1,306,350	1,308,348	0.15	0.51	0.0138
	3	[1, 3, 5]	[3, 5, 8]	[50, 564, 250]	[60, 444, 360]	1,309,707	1,310,822	0.09	1.91	0.0425
	4	[1, 2, 3, 5]	[1, 3, 5, 8]	[50, 350, 60, 404]	[634, 60, 60, 110]	1,330,182	1,343,100	0.97	4.29	0.1085
	5	[1, 3, 5, 6, 8]	[1, 3, 5, 7, 8]	[50, 60, 60, 494, 200]	[50, 60, 424, 130, 200]	1,358,919	1,372,240	0.98	3.70	0.2987
	6	[1, 2, 3, 5, 6, 8]	[1, 2, 3, 5, 6, 8]	[50, 120, 60, 60, 464, 110]	[50, 80, 60, 254, 220, 200]	1,393,014	1,409,517	1.18	1.70	0.3855
12	1	[3]	[3]	[750]	[750]	1,389,711	1,389,711	0	0.17	0.0041
	2	[2, 10]	[3, 10]	[364, 500]	[364, 500]	1,281,569	1,284,573	0.23	1.14	0.0140
	3	[5, 10, 11]	[1, 5, 10]	[400, 414, 50]	[50, 314, 500]	1,274,861	1,286,131	0.88	7.17	0.0393
	4	[1, 8, 10, 11]	[1, 5, 10, 12]	[50, 360, 404, 50]	[50, 250, 489, 75]	1,293,307	1,299,011	0.44	30.32	0.1225
	5	[1, 8, 10, 11, 12]	[1, 6, 10, 11, 12]	[50, 200, 489, 50, 75]	[50, 220, 469, 50, 75]	1,317,393	1,325,771	0.64	70.27	0.3309
	6	[1, 5, 8, 10, 11, 12]	[1, 3, 5, 10, 11, 12]	[50, 60, 110, 474, 50, 120]	[50, 60, 60, 500, 50, 144]	1,344,279	1,355,675	0.85	90.31	1.0874
16	1	[3]	[1]	[750]	[864]	1,389,711	1,412,157	1.62	0.23	0.0042
	2	[2, 10]	[3, 10]	[364, 500]	[364, 500]	1,281,569	1,284,573	0.23	1.79	0.0138
	3	[5, 10, 11]	[1, 10, 14]	[400, 414, 50]	[50, 500, 314]	1,274,861	1,291,665	1.32	19.22	0.0392
	4	[1, 8, 10, 11]	[1, 5, 10, 12]	[50, 360, 404, 50]	[50, 250, 489, 75]	1,293,307	1,299,011	0.44	113.67	0.1114
	5	[1, 8, 10, 11, 12]	[1, 3, 5, 10, 12]	[50, 200, 489, 50, 75]	[50, 60, 60, 500, 194]	1,317,393	1,334,265	1.28	393.69	0.3486
	6	[1, 5, 8, 10, 11, 12]	[1, 3, 5, 9, 10, 12]	[50, 60, 110, 474, 50, 120]	[50, 60, 60, 100, 500, 94]	1,344,279	1,364,545	1.51	965.40	1.1404

Table 3 (continued)

N	n	Supplier selection		Normal order allocation		ETC			Execution time (s)	
		Optimal	Heuristic	Optimal	Heuristic	Optimal	Heuristic	% gap	Optimal	Heuristic
20	1	[3]	[1]	[750]	[864]	1,389,711	1,412,157	1.62	1.07	0.0065
	2	[10, 18]	[10, 18]	[414, 450]	[414, 450]	1,268,106	1,268,106	0	3.13	0.0143
	3	**[1, 10, 17]**	**[1, 10, 17]**	**[50, 454, 360]**	**[50, 454, 360]**	**1,265,828**	**1,265,828**	**0**	**42.05**	**0.0384**
	4	[1, 10, 11, 17]	[1, 10, 12, 17]	[50, 404, 50, 360]	[50, 500, 75, 239]	1,285,202	1,290,345	0.40	293.95	0.1075
	5	[1, 8, 10, 12, 17]	[1, 3, 10, 12, 17]	[50, 110, 494, 120, 90]	[50, 60, 500, 164, 90]	1,309,488	1,323,488	1.07	1238.44	0.3689
	6	[1, 5, 8, 10, 12, 17]	[1, 3, 5, 10, 12, 17]	[50, 60, 110, 479, 75, 90]	[50, 60, 60, 500, 75, 119]	1,336,087	1,348,389	0.92	4874.38	1.0892

Over all optimal solution is shown in bold font

Table 4 Additional order allocation under disruption (an example of triple sourcing)

Disruption	Status (1: active, 0: failed)			Deliverable normal order	Additional order allocation			Probability
	Supplier 1	Supplier 10	Supplier 17		Supplier 1	Supplier 10	Supplier 17	
Scenario 1	0	0	0	0 + 0 + 0	0	0	0	0.0026
Scenario 2	1	0	0	50 + 0 + 0	814	0	0	0.0104
Scenario 3	0	0	1	0 + 0 + 360	0	0	310	0.0174
Scenario 4	0	1	0	0 + 454 + 0	0	196	0	0.0234
Scenario 5	1	0	1	50 + 0 + 360	144	0	310	0.0696
Scenario 6	1	1	0	50 + 454 + 0	164	196	0	0.0936
Scenario 7	0	1	1	0 + 454 + 360	0	0	50	0.1566
Scenario 8	1	1	1	50 + 454 + 360	0	0	0	0.6264

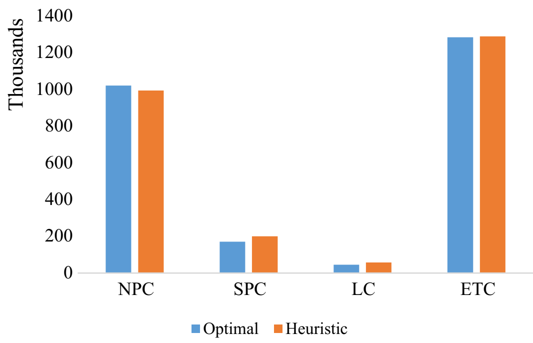

Fig. 4 Comparison of different cost components

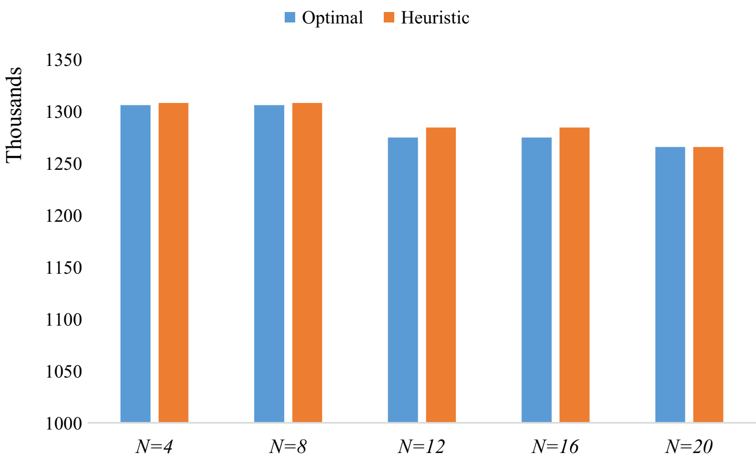

Fig. 5 Comparison of ETC for different supplier bases

optimal order allocation solution under the different disruption scenarios for illustration and easier understanding.

To get further insights, Fig. 4 is presented to compare the share of different cost components, on an average basis, obtained using the optimal solution approach and the heuristic approach. The average value of each cost component is calculated considering their values obtained for all supplier bases: 4, 8, 12, 16, and 20. The normal purchase cost (NPC) is a major component in the ETC, followed by the spot-market purchase cost (SPC) and the lost cost (LC), whereas the fixed cost (FC) primarily depends on sourcing strategy, i.e. the number of selected suppliers. Next, it can be observed from Fig. 5 that as we increase the supplier base, the ETC decreases because there are alternative suppliers with a lower unit cost. Figures 6 and 7 show that with an increase in the supplier base, the reduction in NPC is relatively more than the reduction in ETC, which is partially compensated due to an increase in the SPC. This can probably be attributed

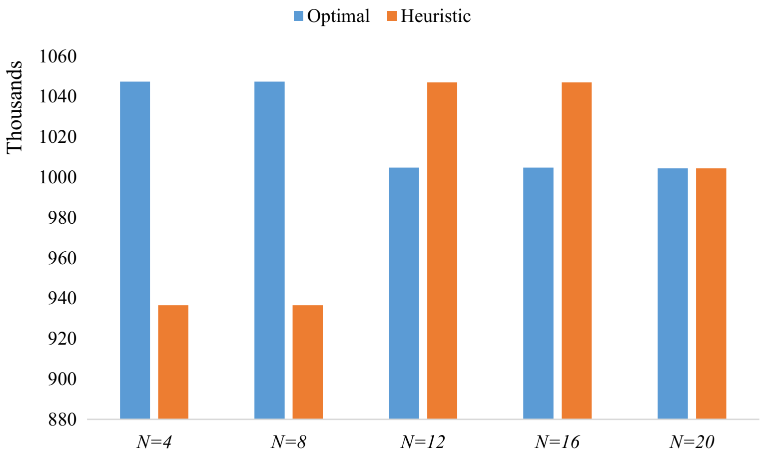

Fig. 6 Comparison of *NPC* for different supplier bases

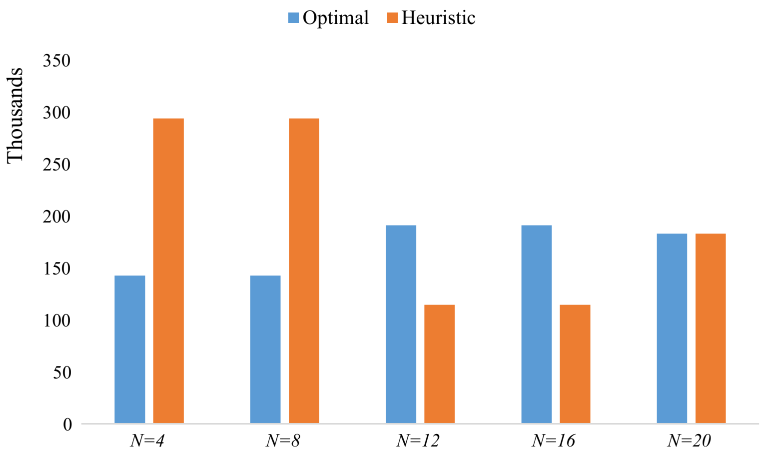

Fig. 7 Comparison of *SPC* for different supplier bases

to the situation in which NPC is reducing due to the allocation of normal orders to low-cost suppliers, and SPC is increasing due to the allocation of additional orders.

It can also be observed that with an increase in the supplier base, NPC is decreasing, and SPC is increasing monotonically for the optimal solution, but they are compensatory in nature for the heuristic solution. It signifies that the heuristic approach gives a lower NPC value for a few instances compared to the optimal solution, even though the ETC is a little higher. For example, when we select only one supplier from the supplier base of 20, the optimal solution method selects supplier 3 with NPC as 921,375 and ETC as 1,389,711, whereas the heuristic solution method selects supplier 1 with NPC as 912,177 and ETC as 1,412,157.

5.2 Sensitivity analysis

To get some meaningful insights, sensitivity analysis is carried out to study the impact of different parameters such as normal unit cost (c_{ik}), unit spot-market cost (a_i), failure probability (π_i), and total demand (d) on supplier selection and order allocation.

5.2.1 Sensitivity on the unit normal cost (c_{ik})

To understand the influence of the unit normal cost of suppliers on order allocation, we have considered the best sourcing strategy and changed the unit normal cost of supplier 17, keeping other parameters unchanged. Table 5 shows that there is a change in supplier selection and normal order allocation. Supplier selection does not change due to a reduction in unit normal cost, as the unit normal cost is the lowest for the selected suppliers in comparison to other suppliers in the supplier base, but it changes when unit normal cost increases. However, the normal allocation changes when the unit normal cost reduces by 7.5%. On the other hand, due to an increase in the unit normal cost of supplier 17, this supplier is not selected, and there is no impact on order allocations. It depends on the comparative value of the unit normal cost of suppliers. As a result, dual-sourcing becomes the base strategy when the unit normal cost increases. Further, the reduction in unit normal cost leads to a reduction in expected normal purchase cost and expected total cost. With the change in the unit normal cost, the expected lost cost does not change if the selected suppliers remain the same.

5.2.2 Sensitivity on the unit spot-market cost (a_i)

We have analyzed the sensitivity of the unit spot-market purchase cost by changing the unit spot-market price of supplier 1, keeping the value of other parameters unchanged. We have changed the unit spot-market cost by 5% and 10% on both sides, and Table 6 provides detailed results. The unit spot-market cost is also an important factor in supplier selection and order allocation. For 5% and 10% increase in unit spot-market cost, supplier 1 is not selected, instead supplier 11 is selected, which is in line with the unit normal cost that signifies that an increase in unit cost (normal or spot-market) leads to the selection of a different set of suppliers when the unit cost of suppliers is highly competitive. Similarly, for 10% decrease in unit spot-market cost, normal order allocation also changes between supplier 10 and supplier 17.

5.2.3 Sensitivity on the failure probability (π_i)

We study the impact of failure probability on a triple-sourcing strategy by swapping the failure probability of two suppliers at a time. Therefore, there will be three possible cases (${}^3C_2 = 3$). Table 7 presents the detailed results. Failure probability

Table 5 Sensitivity of unit normal cost for supplier 17

Change in unit normal cost of supplier 17	Supplier selection	Normal order allocation	Various expected cost			
			Normal cost	Spot-market cost	Lost cost	Total cost
7.5% decrease	[1, 10, 17]	[50, 400, 414]	968,481	186,570	30,294	1,233,345
5.0% decrease	[1, 10, 17]	[50, 454, 360]	983,698	183,058	30,294	1,245,051
2.5% decrease	[1, 10, 17]	[50, 454, 360]	994,087	183,058	30,294	1,255,439
2.5% increase	[10, 18]	[414, 450]	1,014,867	106,308	95,931	1,268,106
5.0% increase	[10, 18]	[414, 450]	1,014,867	106,308	95,931	1,268,106
7.5% increase	[10, 18]	[414, 450]	1,014,867	106,308	95,931	1,268,106

Table 6 Sensitivity of unit spot-market cost for supplier 1

Change in unit spot-market cost for supplier 1	Supplier selection	Normal order allocation	Various expected cost			
			Normal cost	Spot-market cost	Lost cost	Total cost
10% decrease	[1, 10, 17]	[50, 400, 414]	968,481	186,570	30,294	1,233,345
5.0% decrease	[1, 10, 17]	[50, 454, 360]	1,004,475	179,404	30,294	1,262,173
5.0% increase	[10, 11, 17]	[454, 50, 360]	1,013,475	173,234	18,177	1,266,386
10% increase	[10, 11, 17]	[454, 50, 360]	1,013,475	173,234	18,177	1,266,386

Table 7 Sensitivity of failure probability for suppliers 1, 10 and 17

Case	Failure probability of suppliers [1, 10, 17]	Supplier selection	Normal order allocation	Various expected cost			
				Normal cost	Spot-market cost	Lost cost	Total cost
Base case	[0.20, 0.10, 0.13]	[1, 10, 17]	[50, 454, 360]	1,004,475	183,058	30,294	1,265,828
Case 1	[0.13, 0.10, 0.20]	[1, 11]	[814, 50]	1,007,185	187,275	38,413	1,261,374
Case 2	[0.20, 0.13, 0.10]	[1, 10, 17]	[50, 454, 360]	1,001,293	187,993	29,952	1,267,238
Case 3	[0.10, 0.20, 0.13]	[1, 11]	[814, 50]	1,039,412	147,048	29,549	1,244,510

influences all cost components except fixed cost, which signifies its importance in supplier selection and order allocation. As a result, the best sourcing strategy may change. This precisely happens when the failure probability of supplier 1 changes from 0.20 to 0.10 or 0.13. The best sourcing strategy changes from triple-sourcing to dual-sourcing, and supplier 1 and supplier 11 are selected instead of supplier 1, supplier 10, and supplier 17. It also impacts the expected total cost and total purchase value.

5.2.4 Sensitivity on the total demand (*d*)

We analyzed the impact of total demand on supplier selection and order allocation by varying the total demand (d). We consider total demand as 400, 600, 1000, 1500, and 2000. Table 8 presents the details of supplier selection, order allocation, and costs. As the total demand increases, the number of selected suppliers also increases, and a new supplier is included in the new list of selected suppliers. However, the order among the selected suppliers is reallocated in the revised solution, based on their relative unit cost. For example, supplier 10 is the only supplier when the total demand is 400, and it remains as part of the solution when demand is 2000. Supplier 17 is added when demand is 600 and remains as part of the solution when demand is 2000.

5.3 Results of Model 2

We have used NSGA-II and MOPSO as mentioned in Sect. 4.2 to solve the multi-objective problem for minimizing the ETC and maximizing the TPV. We have set the various parameters of NSGA-II and MOPSO by carrying out several trials based on various combinations of the respective key parameters. Thus, population size as 100, number of iterations as 150, crossover probability as 0.9, and mutation probability as 0.1 are set for NSGA-II. For MOPSO, we set inertia weight (ω) as 0.8, accelerating coefficients, i.e., social weight c_1 as 0.5 and cognitive weight c_2 as 1.5, and the population size and the number of iterations are kept at the same value as in NSGA-II. Based on these parameter settings, we found the non-dominated Pareto

Table 8 Sensitivity on total demand (d)

Demand (d)	Supplier selection	Normal order allocation	Various expected cost			
			Normal cost	Spot-market cost	Lost cost	Total cost
400	[10]	[400]	462,852	0	114,000	599,352
600	[10, 17]	[500, 100]	705,933	104,377	22,230	873,040
1000	[10, 17, 18]	[460, 90, 450]	1,182,726	174,311	30,227	1,456,264
1500	[10, 11, 17, 18]	[500, 50, 370, 580]	1,768,852	294,338	18,817	2,172,007
2000	[5, 10, 11, 17, 18]	[400, 500, 50, 470, 580]	2,337,499	431,154	23,025	2,897,678

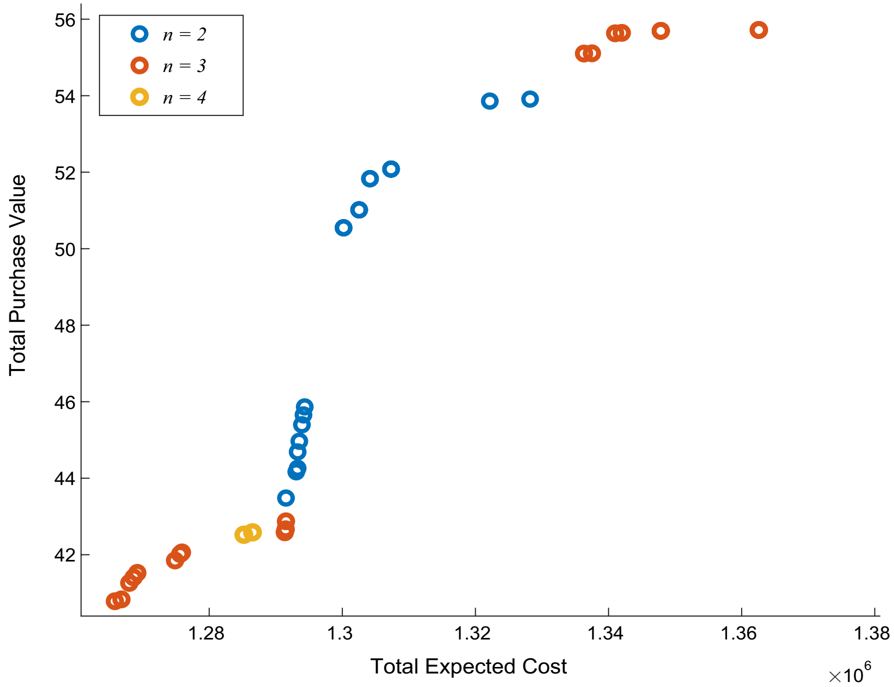

Fig. 8 Pareto plot of non-dominated solutions using NSGA-II

front as in Fig. 8 for NSGA-II and in Fig. 9 for MOPSO. The overall pattern of Pareto solutions is similar for both the evolutionary algorithms. However, the solutions obtained using NSGA-II are more diverse though extreme solutions are similar.

Based on the Pareto solutions (Figs. 8, 9), we have found that mostly dual-sourcing and triple-sourcing solutions are part of non-dominated solutions. There are only two solutions where the number of selected suppliers are four. Triple-sourcing provides both the extreme solutions, i.e. the minimum ETC and the maximum TPV value, whereas solutions corresponding to the dual-sourcing lie between these two. The minimum ETC is observed as INR 1,265,828 (the corresponding TPV is 42.67) against the optimal solution found in Model 1. The maximum TPV is observed as 55.72 (corresponding ETC is 1362584) against the normal order allocation of 60 units to supplier 3 204 units to supplier 4, and 600 units to supplier 19.

As preferential weights have a substantial influence on TPV, it is natural that suppliers with higher preferential weight will be preferred. At the same time, failure probability is another important factor in determining the TPV, as this will decrease the probability of not meeting the total demand. For further analysis, we make the preferential weights for all suppliers equal and found that the maximum TPV becomes 43.20, a little higher than the TPV value corresponding to the minimum ETC of INR 1,265,828. This is achieved through a sourcing strategy with more suppliers with the following order allocation details: 425 units for supplier 2, 147 units for supplier 3, 80 units for supplier 4, 109 units for supplier 7, and 103 units for

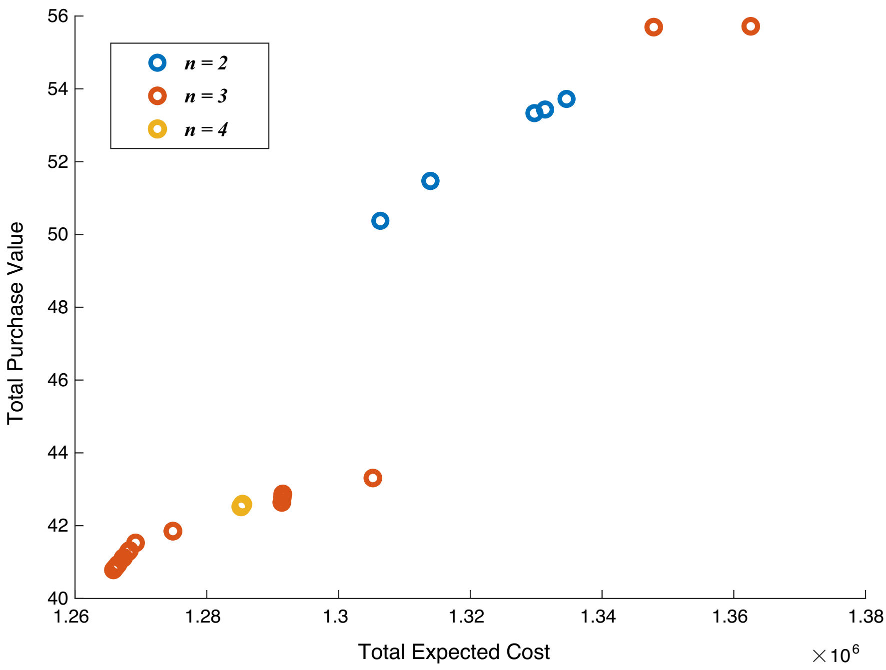

Fig. 9 Pareto plot of non-dominated solutions using MOPSO

supplier 13, so that probability of not meeting the total demand under different disruption scenarios is reduced. This little gain in TPV will not be worth as the ETC becomes INR 1,452,338. However, the insights are important for better decision making.

6 Managerial insights

In this section, we have presented key managerial insights that are observed in the previous sections. Unit normal cost considering the discount was found to be the most important deciding factor in the selection as well as order allocation to a set of suppliers. Failure probability coupled with unit spot-market cost is also an important combination in deciding supplier selection and order allocation. It may be noted that single-sourcing is highly risky in case of a completely failed scenario, thus it is always better to avoid because, in case of failure, the amount of lost cost is very high. Further, the actual number of suppliers to be selected for the lowest expected total cost would depend on the constraints imposed, i.e. total demand, minimum order allocation constraint, and capacity of the suppliers. At the same time, the selection of too many suppliers would also create a practical problem of managing and ensuring uniformity in quality. Therefore, if the total demand can be met with two or three suppliers, it may be a good idea to go with double- or triple-sourcing. It may be noted that this is more indicative rather than a general decision. However, the optimal solution can only be obtained once all factors are taken into account. Based on the sensitivity analysis, it has been observed that the reduction in the unit cost of the selected suppliers does not change the supplier combination but changes the order allocation. Similarly, an increase in unit cost can potentially alter supplier selection and order allocation. The probability of disruption is another important factor, which alters supplier selection as well as order allocation. Optimal supplier selection and order allocation can be evaluated based on the prevailing parameter values. Increasing demand would lead to a higher level of sourcing strategy, and it also depends on the capability of each supplier in terms of maximum capacity and minimum order allocation required once a supplier is selected.

7 Conclusions

This paper addresses sourcing decisions with optimal order allocation in the presence of supplier disruption risks. We have developed two models, considering the various decision-making scenarios. To the best of our knowledge, this paper has considered minimum ordering policy, consideration of compensation with unique spot-market cost, an all-unit quantity discount, flexibility in supplier capacity, and lost cost, which are not addressed together in the literature. A mixed-integer linear programming model with the objective of minimization of ETC has been formulated in Model 1. In Model 2, a multi-objective MILP model to minimize ETC and maximize TPV is formulated, and NSGA-II and MOPSO have been applied to obtain non-dominated Pareto optimal solutions.

A highly efficient heuristic is developed to solve Model 1 instead of finding an optimal solution through an exhaustive search. A detailed comparison is made between optimal solutions and heuristic solutions. The heuristic is not only very time efficient but also highly competitive in terms of solution quality. A sensitivity analysis of the key parameters is carried out and analyzed. It has been observed that unit normal cost, unit spot-market cost, failure probability, and total demand are important. It is important to note that all the parameters have their impact on optimal decision-making and need to be considered in combination.

The multi-objective model has been developed to provide decision alternatives before a purchase manager to choose the best sourcing strategy considering the various aspects. It has been found that dual-sourcing and triple-sourcing solutions are mainly part of the non-dominated Pareto front. For this study, the buyer should select triple-sourcing for the best ETC and TPV. Preferential weights and failure probability are two important factors that affect TPV.

The current model has been considered for a single product and single period scenario, whereas it can be extended for a multi-period multi-product sourcing problem. The demand considered here is of deterministic type. It would be interesting to study the results of a dynamic demand scenario. The model has been formulated to minimize the total cost from the buyer's perspective, whereas the supplier's perspective could be another possible future work.

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