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# Exploring the synergy between sustainability and resilience in supply chains under stochastic demand conditions and network disruptions

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ABSTRACT

The impact of global events such as the outbreak of the COVID-19 pandemic, the 2021 Suez Canal obstruction, and the constraints imposed on Panama Canal operation due to severe drought conditions in 2023 underscore the urgent need for resilient and sustainable supply chains. However, integrated approaches that evaluate both sustainability and resilience simultaneously remain scarce. This article introduces a novel multi-phase, multi-period decision support framework for supplier selection and order allocation under demand uncertainty and network disruptions. Combining fuzzy multi-criteria decision-making with a fuzzy multi-objective mixed-integer nonlinear programming model, the framework optimizes triple bottom line sustainability alongside resilience. Applied to real-world pharmaceutical data, the results show that this integration enhances performance under disruptions but involves trade-offs, including up to 19.2 % higher costs and 42.3 % longer transport times. Despite increased environmental impact, the proposed framework offers a strategic tool for managing complex, high-risk international supply chains.

## 1. Introduction

International supply chains are vulnerable to disruptions. In recent years, the most important among these disruptions has been the outbreak and spread of the COVID-19 pandemic, which led to restrictions on goods movement, border closures, and reduced workforce availability at an unprecedented scale. The impact of the pandemic caused the world economy to contract by 3.5 % in 2020 with massive loss to global value chains [1]. Natural or manmade accidents can impact transportation infrastructure, warehouses, and distribution centers. Congestion or blockage of transportation routes where ships, trains, and trucks are queued up to unload or load cargo can delay shipments leading to logistic bottlenecks. The 2021 Suez Canal obstruction or the ongoing Panama Canal crisis due to extreme drought conditions is an example of this category of disruptions. The weeklong 2021 Suez Canal obstruction held up $9 billion in global trade each day of the blockage [2]. The nature and extent of global supply chain disruptions and the magnitude of their fiscal and logistic impact entails a detailed evaluation of supply chain network performance in terms of sustainability and resilience [3].

Supply chain sustainability involves management of supply chains based on a triple bottom line (TBL) concept of sustainability in which the three sustainability dimensions, i.e., economic, environment, and social are taken into account concurrently [4]. Supply chain sustainability aims for an effectual and proficient organization of capital, information, and material flows related to the acquisition, manufacture, and allocation of products [5]. Supply chain resilience can be defined as the inherent characteristic of a supply chain network to oppose disruptions and to regain functional capacity after the disrupting event has taken place. Certain major natural or manmade (intentional or unintentional) disruptions, i.e., earthquakes, floods, pandemics, territorial conflicts, and industrial accidents happen quite infrequently but various minor disruptions, i.e., power outages, road blocks, machine breakdowns etc. occurring along the supply chain network are fairly common. In extant literature, disruptions are treated as special cases of yield, capacity, and lead time uncertainty. In this research paper, disruptions and the evaluation of their impact is limited to random demand encountered in order time intervals that may lead to probabilistic disruptions, and instances such as supplier unavailability, inaccessible facilities, and lost storage capacity, all of which are potential sources of network disruptions. A direct consequence of the negative impact of disruptions is the degradation of supply chain network service level [6].

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Service level is a key supply chain network performance target specified by the decision makers (DMs). Service level is usually evaluated by measuring order cycle time, case fill rate, line fill rate, order fill rate, or a combination of any of these parameters. All organizations, manufacturing or otherwise, employ suitable demand forecasting techniques for estimating order quantities during inventory replenishment cycle for any given time period [7]. At this stage, demand uncertainty must be taken into consideration in order to protect against a stock-out situation in which demand exceeds forecast. This condition that the probability of inventory readily available should not fall below a definite threshold at the conclusion of a review period has been referred to as $\alpha$ service level by Chen and Krass [8]. This category of service level is consequential if the DMs are more concerned with the likelihood of a stock-out occurring rather than by its magnitude. A countermeasure employed in practice for avoiding the possibility of a stock-out is the addition of safety stock to the base inventory. In this method the aim is to calculate an inventory refill value that enables a desired supply chain network performance level, i.e., a low possibility of stock-out for any time period considered. In this situation, safety stock will act as a buffer and accommodate any demand that exceeds the forecast value for the review period or any variation during the lead time. It may be concluded that achieving a target service level can be considered a reliable indicator for a supply chain network to be regarded as resilient against probabilistic or network disruptions.

Supplier selection is a systematic activity through which firms assess and engage with one or more suppliers. The objective is to decrease buyer's risk, maximize purchasing value, and establish long-standing business connections between buyers and suppliers [9]. The process of selecting a supplier is a multi-criteria decision making (MCDM) phenomenon, which necessitates analyzing a number of competing criteria, for instance, price, quality of goods, delivery rate, volume flexibility, and so on, that must be considered for choosing reliable suppliers [10, 11]. In extant literature, for many years, only economic or the so-called conventional criteria were employed for supplier selection and order allocation (SS-OA). However, in recent years, the growing awareness towards incorporating TBL sustainability dimensions in manufacturing and supply chain management has motivated researchers to include environmental and social aspects in this process as well. This combination generally contributes more complexity to the SS-OA problem [12]. During sustainable supplier selection and order allocation (SSS-OA) while TBL sustainability criteria are used for evaluating potential suppliers, a multiple sourcing strategy is preferred for order allocation.

In supply chain management, adherence to sustainability practices usually offers superior logistics performance and resource utilization, which can give any firm engaged in overseas trade an edge while dealing with its competitors. A sustainable supply chain though proficient is still exposed to unanticipated disasters, natural or manmade alike. A simultaneous integration of TBL sustainability and resilience criteria for SS-OA not only ensures a robustly performing supply chain but will also help mitigate the impact of disruptions propagating through the network and ensuing service level degradation [13]. In published literature, supply chain network performance susceptible to disruptions has been evaluated by adopting different approaches. Many researchers have considered resilience as a performance evaluation criterion together with TBL sustainability in SS-OA problems while identifying its sub-criteria in the same pattern as economic, environmental, or social sub-criteria [14]. The combining of resilience with TBL sustainability criteria transforms an ordinary SS-OA problem into sustainable and resilient supplier selection and order allocation or SRSS-OA problem [15].

Various authors have evaluated supply chain network disruptions and their impact on the inventory management strategies employed for achieving a predefined or target service level. Guo et al. [16] have carried out a state of the art review of inventory management strategies adopted by suppliers and consumers worldwide in the wake of recent natural and manmade disruptions. Chen and Krass [8] have investigated inventory models in which the stock-out cost is replaced by a minimum service level constraint requiring that a certain service level be fulfilled during each review period. A single-period, two-stage service-constrained supply chain under the condition of variations in demand forecast has been evaluated by Sethi et al. [17]. Darmawan [18] has evaluated the supply chain network design problem first without disruptions using a heuristic and later tested the performance of the same supply chain network by introducing multiple disruption scenarios. The results of the tests show that a proactive strategy in addressing inventory management issues in supply chains susceptible to disruption risks always leads to robustly operating networks. Lee et al. [19] have presented a continuous review inventory model that takes into account lead time demand and controllable exponential backorder rate. Schmitt [20] has presented a model for a multi-tier supply chain network susceptible to disruptions. The numerical analysis carried out to demonstrate the proposed model has revealed that employing proactive inventory stocks to absorb the impact of short term disruptions or the beginning of extended disruptions, and using reactive backup arrangements to enable the supply chain to recover after protracted or lasting disruptive effects can lead to significant service level improvements. Radasanu [21] has evaluated the link between safety stock and service level and the design and execution of a successful inventory management policy. In this research work, a statistical model has also been proposed for calculating the quantity of safety stock that enables prevention of a stock-out situation with respect to a predefined customer service level. Shi et al. [22] has carried out an evaluation of proactive and reactive strategies adopted by DMs in mitigating the effects of disruptions on the performance of supply chain networks. The uncertainty of production cost has a significant impact on the type of strategy adopted by a firm while countering the effects of supply chain disruptions. Adenso-Diaz et al. [23] have developed a metric for analyzing the robustness of a supply chain network under the impact of successive collapse of its transportation links. The analysis of the results of the numerical experiments conducted to evaluate the performance of the metric shows that flow complexity and service level after disruptions are two of the most significant factors affecting supply chain network robustness.

The research work presented in this article addresses the knowledge gap that has emerged due to lack of a decision framework that incorporates TBL sustainability and resilience criteria simultaneously in every part of the SS-OA problem while considering the impact of demand uncertainty and network disruptions. In order to achieve this, a decision support framework developed and presented in the authors' earlier publication [15] has been modified and improved. The proposed multi-phase, multi-period sustainable and resilient SS-OA framework combines fuzzy MCDM techniques with fuzzy multi-objective mixed integer nonlinear programming (FMOMINLP) mathematical model (Section 2). The overall objective is to optimize TBL sustainability and resilience criteria concurrently for a multi-modal, multi-echelon supply chain network susceptible to disruption risks. The effectiveness of the proposed decision support framework has been demonstrated (Section 3) using data from the pharmaceutical industry, which is undoubtedly one of the most affected industry sectors after the advent and proliferation of the COVID-19 pandemic around the world in recent times. The multi-phase decision framework first considers the supply chain network to be functioning under normal operating conditions and performs SS-OA to generate a no disruption Pareto optimal solution in its initial phases (phases 1–3). Multiple probabilistic and network disruption scenarios are introduced and the supply chain network is once again optimized to achieve a target service level using a modified set of operating conditions in the later phases (phase 4 and 5) of the decision support framework. A comparison and analysis of the no disruption and disruption solutions is carried out to evaluate the performance of the proposed decision framework in achieving the DMs' specified performance target. The case study and data employed in the authors' earlier

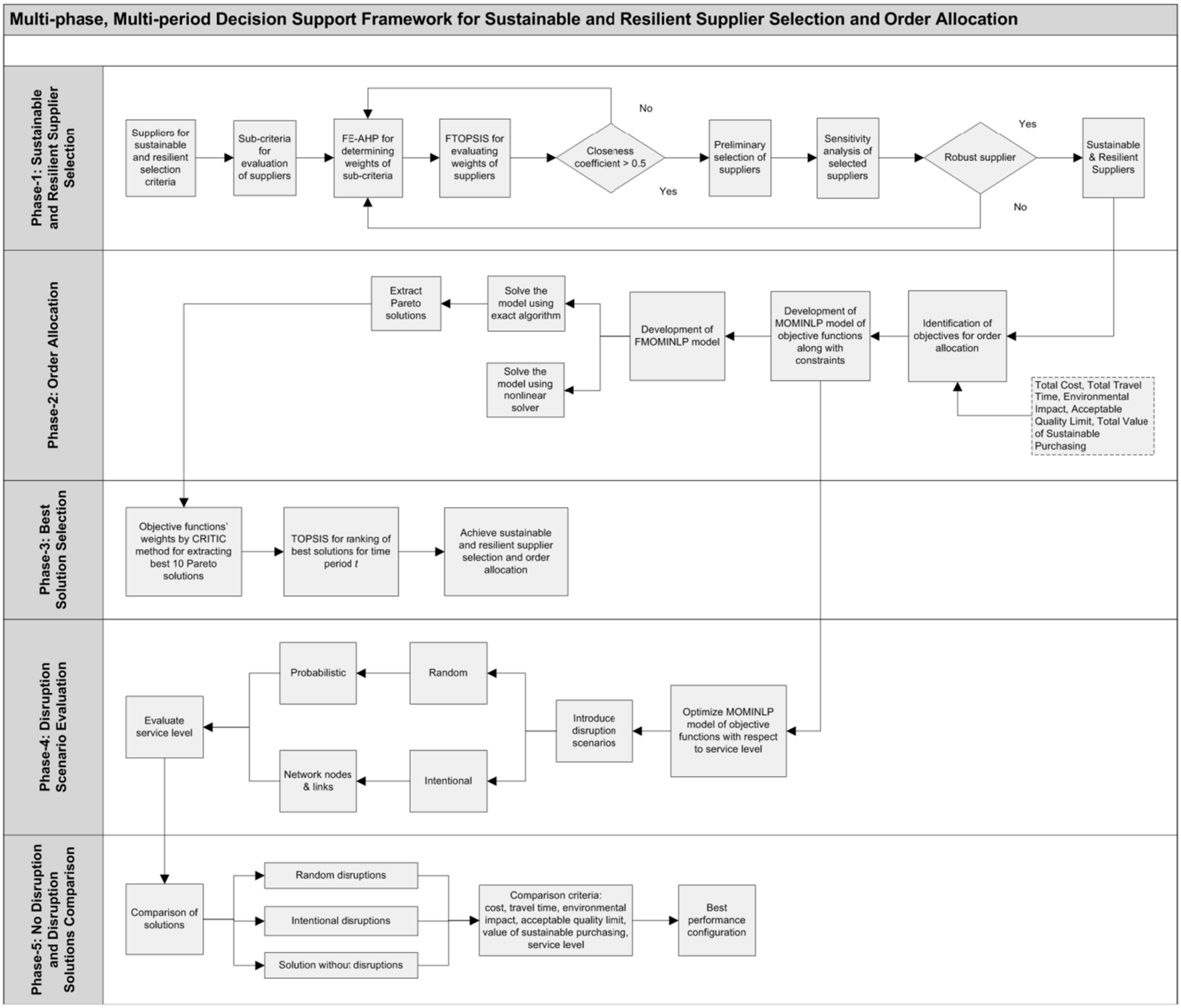



**Fig. 1.** The proposed multi-phase, multi-period decision support framework (Adapted from S. A. Kayani, S. S. Warsi, and R. A. Liaqait, "A smart decision support framework for sustainable and resilient supplier selection and order allocation in the pharmaceutical industry", *Sustainability*, vol. 15, no. 7, p. 5962, 2023, doi: 10.3390/su15075962, with permission).

publication [15] has been used once again for disruption scenarios' evaluation in the present research paper. This is necessary because without using the same case study and data, any comparison between no disruption and disruption solutions for the supply chain network considered would not have been possible. The article concludes with a general summary of the research findings and suggestions for future work (Section 4).

## 2. Development of integrated decision framework for SRSS-OA problem

The decision support framework developed to address the SRSS-OA problem exposed to the impact of disruptions comprises of five phases. Brief functional details of each phase have been included below:

1. In phase 1, prospective suppliers have been evaluated based on TBL sustainability and resilience criteria. Fuzzy extended AHP (FE-AHP) has been used for criteria weighting while fuzzy TOPSIS (FTOPSIS) has been applied to rank the potential suppliers.
2. In phase 2, a multi-objective mathematical model has been developed for optimal order allocation to the selected suppliers. The mathematical model employs mixed-integer nonlinear programming and it has been fuzzified to incorporate real world uncertainty.
3. In phase 3, a combination of TOPSIS and Criteria Importance through Intercriteria Correlation (CRITIC) method has been employed to select and rank the best solutions.
4. In phase 4, the multi-objective, mixed-integer, nonlinear programming (MOMINLP) mathematical model has been reconsidered and optimized with respect to supply chain network service level while taking into account multiple random and intentional disruption scenarios.
5. In phase 5, in order to arrive at the best performance configuration for the network, the impact of the disruption scenarios on the service level of the supply chain has been evaluated and the different solutions generated have been compared against fixed criteria.

A cross-functional flow diagram of the decision support framework has been included in Fig. 1. It is pertinent to mention here that phases 1–3 of the decision framework have already been discussed in detail in a previous publication [15] of the authors. Therefore, only a brief overview of these phases has been presented in the current research paper owing to space limitation.

### 2.1. Mathematical model for order allocation

A brief description of the MOMINLP mathematical model has been presented in this section adapted from [15]. Fuzzy Set Theory (FST) has been applied to integrate real-life unpredictability in mathematical modeling. The details of the five objectives, i.e., total cost (TC), total travel time (TTT), environmental impact (EI), acceptable quality limit (AQL), and total value of sustainable purchasing (TVSP) along with necessary assumptions, variable sets, and parameters used in the mathematical model can be accessed in [15].

The objective function for total cost minimizes the sum of purchasing, ordering, inventory holding, transportation, transfer, and the custom clearance costs incurred at different stages along the length of the network model. The objective function for total travel time is to be minimized and it is given as a sum of transportation, transfer, and custom clearance time intervals. The objective function for environmental impact minimizes the cumulative carbon dioxide emissions during the transportation process for all three modes of transport considered. The objective function for acceptable quality limit aims to minimize order lot size defects and their ranges. In the last objective function, the economic, environmental, and social criteria weights calculated using FE-AHP are multiplied by the chosen suppliers' weights determined using FTOPSIS and the magnitude of the order quantity allocated to each supplier for maximizing the total sustainable value of procured goods. The demand, resource, and capacity constraints included in the last part of the mathematical model are to be satisfied by using a confidence value $\varphi$ based on the feedback received from the DMs.

Supplier vulnerability is an ever-present concern for the DMs. In order to quantify the anticipated risk while evaluating a potential supplier, a risk criteria weight is calculated based on the procedure adapted from Li et al. [24]. In this procedure, for all suppliers being evaluated, DMs' scores for the resilience sub-criteria are combined with the resilience sub-criteria weights determined through a suitable MCDM technique (E-AHP for the purpose of this research study). For each supplier, a risk expectation value is calculated using the equation given below:

$$R_s = \sum_{j=1}^{n} F(C_j) \cdot w_j \tag{1}$$

In the above equation, $F(C_j)$ denotes the risk value and $w_j$ is the optimal weight of the resilience sub-criterion $C_j$, respectively. In the next step, a risk threshold $\alpha_R$ is considered based on the expected risk-bearing capacity of the supplier and the risk preference of the DM. Risk expectation values of all suppliers being evaluated are determined using Eq. (1) and compared with $\alpha_R$. Only those $R_s$ values are retained that fall below DM specified risk threshold and are re-labeled as $R'_s$. The normalized risk weight $w_i^{Risk}$ for each alternative supplier can then be calculated using the following equation:

$$w_i^{Risk} = \frac{R'_s}{\sum_{i=1}^{I} R'_s} \tag{2}$$

The risk weights calculated using the procedure outlined above are applied in those sections of the MOMINLP mathematical model that deal with total cost and total travel time in order to incorporate resilience in the order allocation part of the SRSS-OA problem presented in this research work.

#### 2.1.1. Solving algorithm and selection of best Pareto optimal solution

In this research paper, Augmented $\varepsilon$-Constraint 2 (AUGMECON2) has been employed for solving the FMOMINLP mathematical model [25]. The large number of optimal solutions generated using AUGMECON2 necessitates that an analytical approach must be adopted for identifying and selecting the best solution. For this purpose, TOPSIS incorporating objective functions weights calculated by means of CRITIC method has been applied for ranking and selecting the best Pareto optimal solution for each time period $t$. A graphical representation of this procedure has been presented in Fig. 2.

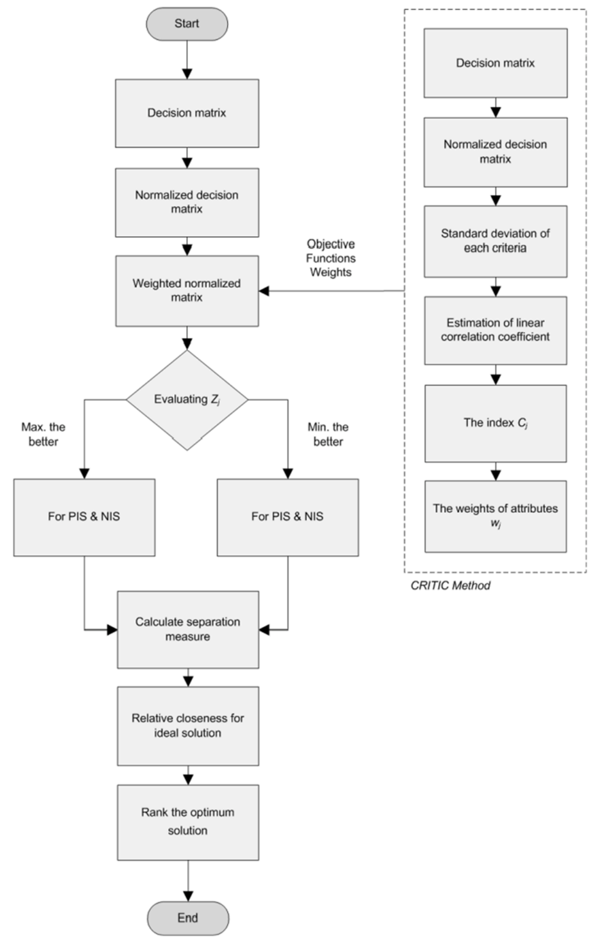



**Fig. 2.** Ranking and selection of best Pareto optimal solution.

#### 2.1.2. Evaluation of disruption scenarios

The disruption scenario analysis presented in the following section takes into account two types of disruptions, i.e., random and intentional. We have adopted a procedure that evaluates the impact of demand uncertainty on the target service level of a supply chain network as specified by the DMs. Probabilistic demand can give rise to lead time disruptions and in the absence of careful planning such disruptions usually lead to stock-out situations. We have also implemented a quantitative metric termed Supply Chain Index (SCI) for identifying key nodes and links with in a supply chain network and then systematically disabled certain nodes in order to evaluate the impact of these so called intentional knockout actions on the performance of the overall network determined in terms of predefined comparison criteria [26].

## 3. Implementation of the proposed decision support framework

### 3.1. Application case study

The decision support framework presented in Fig. 1 has been implemented with the help of operational data collected from the pharmaceutical industry. On a global scale, pharmaceutical firms have evolved complex, intercontinental supply chain networks vulnerable to disruption risks. The pharmaceutical supply chain considered in the present research study comprises of five suppliers (three effective and two backup), one seaport, one dry port, three warehouses, and two

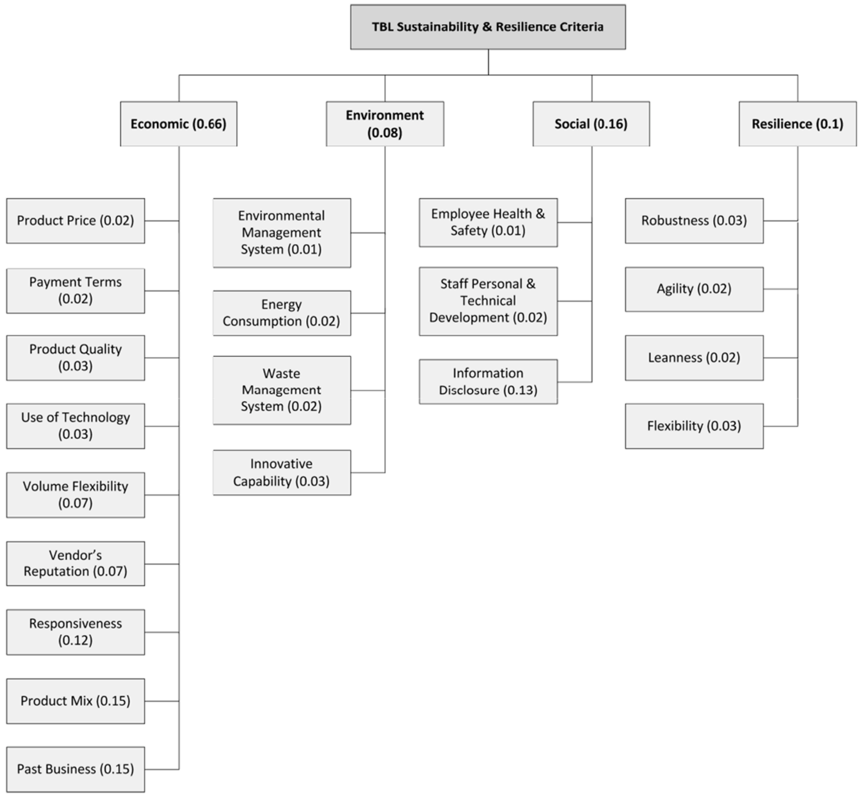



**Fig. 3.** TBL sustainability and resilience criteria and sub-criteria along with respective weights.

customers.

The results and discussion presented in the following sections has been adapted from [15] for the sake of continuity. The data pertaining to the capacity of suppliers, warehouses, and transportation modes, and customers' demand etc. was acquired from multiple firms manufacturing pharmaceutical items for many years and located in different geographical regions. The complete data has been presented in the supplementary material available alongside [15]. In the subsequent description, the time periods $t_1$-$t_4$ are based on the four quarters (Q1-Q4) of the calendar year 2022, respectively.

### 3.1.1. Sustainable and resilient supplier ranking

The TBL sustainability and resilience criteria and sub-criteria along with their respective global and local weights (inserted in parentheses) determined using FE-AHP have been included in Fig. 3. FTOPSIS has been applied for selecting the prospective suppliers with the closeness coefficient threshold for supplier ranking set at 0.5. Supplier-1, supplier-2, and supplier-3 have been chosen for optimal order allocation while supplier-4 and supplier-5 have been retained as backup suppliers to address any potential contingency when one or more of the selected suppliers become unavailable.

Using a modification of the procedure identified by Forghani et al. [27], a sensitivity analysis has been carried out to analyze the robustness of the chosen suppliers. On the basis of the feedback received from the DMs, eight sub-criteria have been short-listed for inclusion in the sensitivity analysis. For the economic criterion, four sub-criteria, i.e., product price, payment terms, responsiveness, and vendor's reputation have been chosen while for the environment criterion, two sub-criteria, i.e., environmental management system and innovative capability have been selected. The DMs have rated one sub-criteria each, i.e., information disclosure and flexibility as the most important sub-criteria for sensitivity analysis from the social and resilience categories, respectively. A set of six different cases of varying degrees of sub-criteria weights has been considered and evaluated with reference to the current values of sub-criteria weights. In spite of the variations introduced in the sub-criteria weights, the ranking of the suppliers has remained unchanged. The outcome of the sensitivity analysis indicates that the MCDM methods applied have produced robust results for the SRSS-OA problem. The final line up of the prospective suppliers has been included in Table 5 in [15].

### 3.1.2. Sustainable and resilient order allocation

The FMOMINLP mathematical model has been implemented in two stages: (a) each objective function has been optimized independently by using a nonlinear solver and to determine ideal solutions, (b) AUGMECON2 has been used for solving all objective functions concurrently for generating Pareto solutions and to calculate optimum order quantities for each selected supplier. The last stage in the order allocation process, i.e., selection of the best Pareto optimal solution generated by AUGMECON2 has been carried out based on the procedure outlined in Fig. 2. The best solution for each time period along with the corresponding value of the relative closeness coefficient (CC) has been included in Table 12 in [15].

A detailed graphical representation has been developed in order to illustrate the breakdown of the order quantities that have been allocated to the selected suppliers for the time periods $t_1$-$t_4$ while being transported along the supply chain network and included as Fig. 5 (a–d) in [15].

## 3.2. Evaluation of demand uncertainty and network disruptions

The effectiveness of the decision support framework has been evaluated by considering the attainment of a predetermined service level by the supply chain as a performance target under the influence of random (probabilistic) and intentional (network) disruptions. The order allocation solutions generated using the FMOMINLP mathematical model have been compared for both no disruption and disruption situations in order to identify the best performance configuration for the multi-

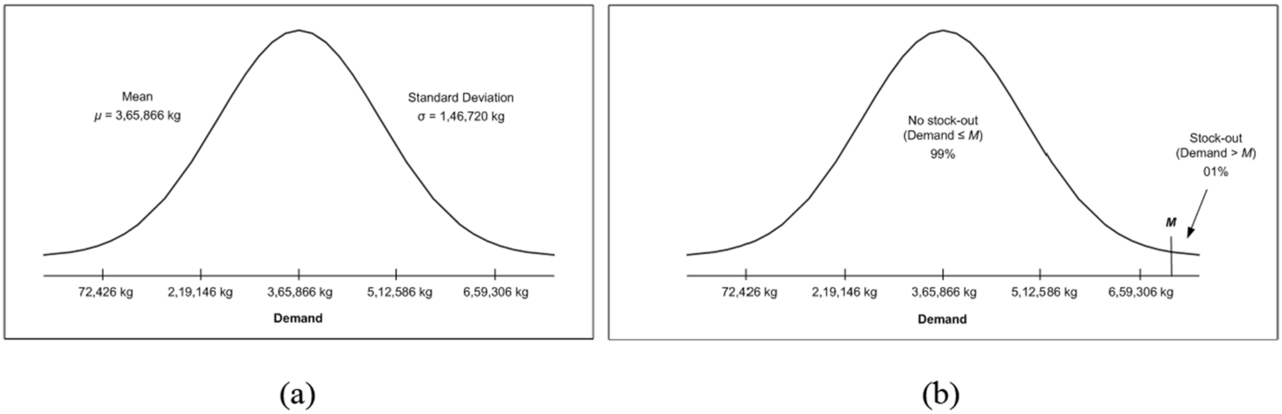



**Fig. 4.** Probability distribution of demand and replenishment level *M*.

modal, multi-echelon supply chain network considered in the application case study problem.

### 3.2.1. Random (Probabilistic) disruptions

If demand is unvarying or deterministic for a review period, all inventory replenishment decisions can be made using the economic order quantity (EOQ) model. On the other hand, if the demand rate is variable or probabilistic, then it can only be described by a probability distribution and the EOQ model is no longer applicable. With probabilistic demand, inventory decisions become more complicated as the specific instance the reordering point will be reached, the interval involving reorders, or the point in time the ordered quantity will arrive in the inventory may not be estimated beforehand. This lead time uncertainty may cause occasional shortages or stock-outs and the supply chain network service level may be affected. When lead time disruptions are taken into account for evaluating the affect of demand uncertainty on supply chain network service level, a continuous probability distribution, i.e., normal or a discrete probability distribution, i.e., Poisson or binomial may be used [8,19,28].

The demand forecast data of last 05 years (included in the supplementary material A1) for the pharmaceutical supply chain network presented in this research work shows considerable variation. The demand uncertainty has an impact on the service level of the supply chain network and the DMs are always concerned that in the face of demand fluctuations, a stock-out might occur. In order to investigate this situation, a deliberate 01 % chance of stock-out is introduced, which reduces the service level of the supply chain network to 99 %. This possibility of a stock-out happening is a random and a lead time disruption and to ensure that the service level is maintained by the supply chain for the review period considered, i.e., 03 months or one quarter, a safety stock is required over and above the forecast demand quantity.

The two customers serviced by the supply chain network are autonomous and produce medicament items like veterinary medicine and health supplements. The raw materials consumed by both manufacturing units are similar therefore their separate demand order quantities have been consolidated for evaluation purposes in the following analysis.

The particular type of product (or the raw material for the two customers) that has been considered while implementing the application case study problem is acquired from overseas suppliers and involves extended durations of transportation time. The two customers have adopted a periodic review system for inventory control partly due to the multi-product nature of their manufacturing operation and in response

**Table 1**
Optimal results for lead time disruption (Q1 data).

| TC ($) | TTT (h) | EI (gm) | AQL (kg) | TVSP |
|---|---|---|---|---|
| 109,565,460.290 | 1041.448 | 2480,202.685 | 22,198.113 | 134,590.410 |

to the logistics of the import and procurement operation as well. The lead time although considerable is assumed shorter than the duration of the review period and any order placed at the beginning of the review period will be received prior to the commencement of the next review period. For the periodic review inventory management system, the value of order quantity $Q$ for any review period is given by:

$$Q = M - H \tag{3}$$

In the above equation, $M$ is the replenishment level and $H$ is the inventory on hand at the review period. The order quantity should be calculated in a manner that it brings the replenishment level $M$ to such a position that will suffice until the order made at the following review period arrives in the inventory. In this case the total duration considered will be equal to the review period and the added lead time. The normal probability distribution of demand during the review period and the lead time for the application case study problem has been included in Fig. 4(a). The mean value $\mu$ of the demand is 3,65,866 kg with a standard deviation $\sigma$ of 1,46,720 kg. Using the normal probability distribution, the relation for $M$ is given as,

$$M = \mu + z\sigma \tag{4}$$

where, $z$ is the requisite number of standard deviations needed to achieve the acceptable value of stock-out probability. Using the above equation and substituting the values of $\mu$ and $\sigma$ from Fig. 4(a), and the value of $z$ from the normal probability distribution table for 01 % probability of stock-out, the value of replenishment level $M$ is calculated as 7,07,725 kg (Fig. 4(b)). The value of the safety stock required to ensure a 99 % service level for the supply chain network can be calculated using Eq. (3) by substituting the values of the forecast inventory at the start of the review period and of the replenishment level determined above. For the application case study presented here and the review period considered, this value turns out to be 1,17,742 kg.

The value of replenishment level $M$ has been used to determine revised demand values for both customers and the FMOMINLP mathematical model has been re-implemented using quarter-1 (Q1) data so as to generate Pareto optimal values of all objective functions with 01 %

**Table 2**
SCI scores for pharmaceutical supply chain network (Q1 data).

| Node | Port-1 | Port-2 | Warehouse-1 | Warehouse-2 | Warehouse-3 |
|---|---|---|---|---|---|
| **SCI** | 0.11857 | 0.00129 | 0.16127 | 0.10864 | 0.02962 |

stock-out probability or 99 % service level. The results have been presented in Table 1.

*3.2.2. Intentional (Network) disruptions*

The performance of a supply chain is intimately linked with the interconnectivity of its constituting elements, i.e., nodes and edges. An evaluation of this interconnectivity may help to identify those nodes and edges that are critical for the proper functioning of the network. All nodes within a supply chain system, in theory, should contribute towards adding value to the network and all nodes are considered important and significant to the smooth operation of the supply chain. But in practice, some nodes within the supply chain network may be deemed more important than the others due to their location or due to the contribution they make to the value addition process, i.e., a critical supplier, a vital point of entry to a geographical location, or an indispensible distribution center etc. The degree of connectivity and throughput rate of a node may be used as two design characteristics that signify the relative value of a node within a supply chain network [29]. A simple quantitative metric that combines these two attributes in order to identify critical nodes has been proposed by Plaganyi et al. [26]. For a supply chain node $j$ being evaluated, this quantitative metric termed Supply Chain Index (SCI) is given by the relation:

$$SCI_j = \sum_{i=1}^{n} s_{ji} p_j^2 \tag{5}$$

For a supply chain model comprising of $n$ nodes, $s_{ji}$ denotes the fraction of the entire product that a receiver node $j$ receives from a supplier node $i$ relative to the overall product flowing into the receiver node $j$, in such a manner that for node $j$, the following condition is satisfied:

$$\sum_i s_i = 1 \tag{6}$$

In Eq. (5), the variable $p_j$ identifies the segment of the entire product in the supply chain network that flows into the receiver node $j$, so that the product of the two variables $s$ and $j$ represents both connectance and magnitude of flow. The node(s) with the maximum SCI score(s) will be identified as the critical node(s). The SCI can be applied by using either the volume of the product handled by the supply chain or the value added at various stages as the product travels along the network depending upon the type of the system being considered or suitable data being available.

The pharmaceutical supply chain network presented in this research work has been evaluated using SCI in order to identify critical nodes based on the order quantity data of the two customers. The results for the Q1 data have been included in Table 2 where port-1 refers to the seaport and port-2 refers to the dry port. The terminal elements of the supply chain network, i.e., suppliers and customers have been excluded from this analysis.

From the data presented in Table 2 and graphically compared in Fig. 5, the seaport and warehouse-1 have been identified as the critical nodes as they carry the maximum values of SCI score in their respective categories. The seaport appears to be indispensible for the successful execution of the supply chain network operations while the largest volume of the order quantity is handled by warehouse-1 with warehouse-2 being a close second. The SCI score of the dry port is only a fraction of the value determined for the seaport yet the dry port may have an important role to play as it facilitates overland shipments by a

**Table 3**
Optimal results for supplier-2 not available (Q1 data).

| TC ($) | TTT (h) | EI (gm) | AQL (kg) | TVSP |
|---|---|---|---|---|
| 111,133,593.220 | 1047.350 | 2510,740.612 | 27,488.138 | 125,006.218 |

**Table 4**
Optimal results for port-2 not functional (Q1 data).

| TC ($) | TTT (h) | EI (gm) | AQL (kg) | TVSP |
|---|---|---|---|---|
| 109,606,018.440 | 872.508 | 1713,678.691 | 25,137.492 | 132,992.103 |

**Table 5**
Optimal results for warehouse-2 out of service (Q1 data).

| TC ($) | TTT (h) | EI (gm) | AQL (kg) | TVSP |
|---|---|---|---|---|
| 109,494,201.010 | 809.444 | 1070,580.615 | 22,524.350 | 135,190.722 |

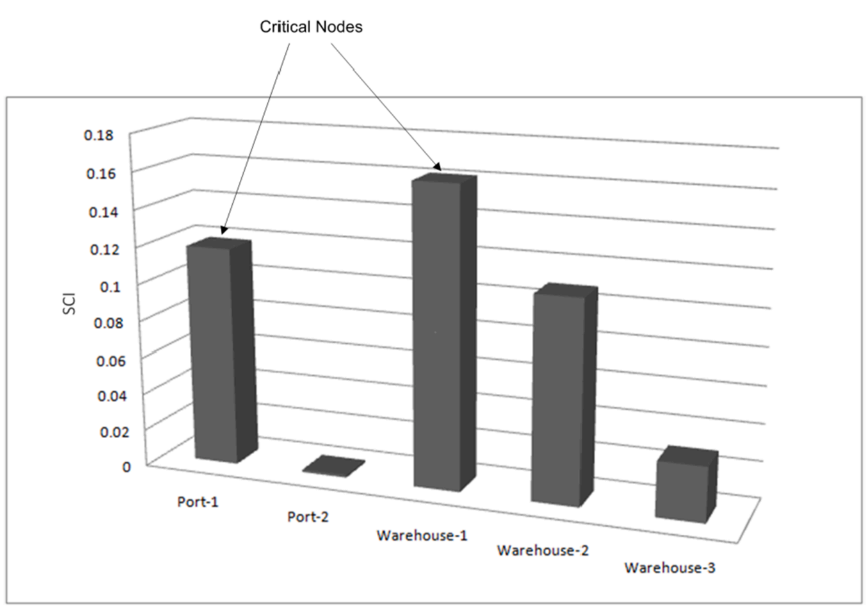



**Fig. 5.** A comparison of SCI scores of pharmaceutical supply chain network nodes.

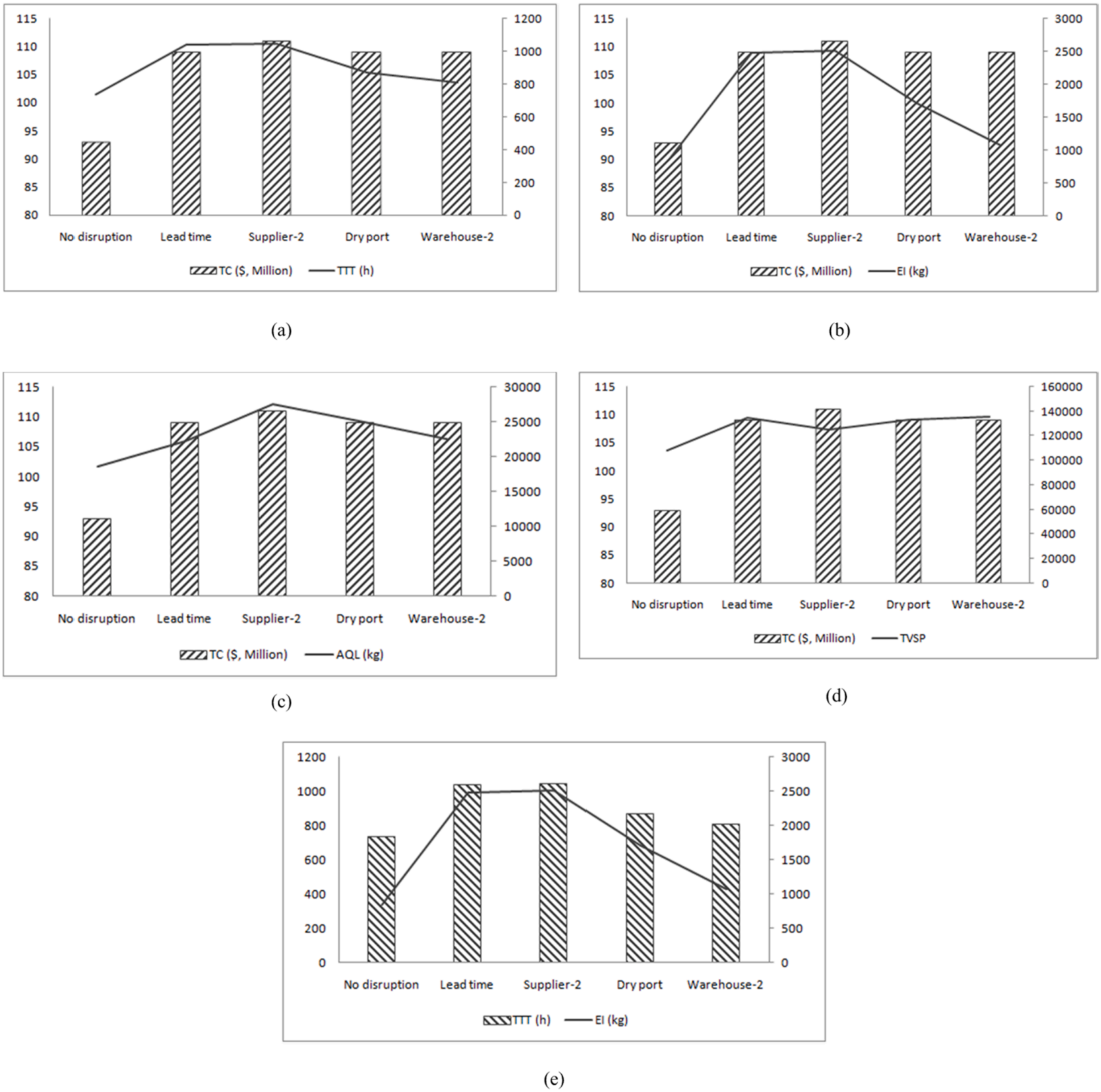



**Fig. 6.** Graphical comparison of no disruption and disruption solutions.

supplier located in a geographically contiguous country.

In order to analyze the performance of the pharmaceutical supply chain network in maintaining a predetermined value of the service level, i.e., 99 % (same as that considered for the lead time disruption for comparison purposes) in the face of disrupting events that knockout one or more of the supply chain components, we have intentionally removed certain nodes from the network, and re-implemented the FMOMINLP mathematical model using Q1 data with revised demand values. Three disruption scenarios have been considered and evaluated one by one while keeping the rest of the problem settings constant: (a) supplier-2 not available, (b) port-2 not functional, and (c) warehouse-2 out of service. For mitigating the adverse effects caused by the unavailability of supplier-2, supplier-4 has been incorporated as a substitute supplier. The results for the three network disruption scenarios considered have been included in Tables 3–5, respectively.

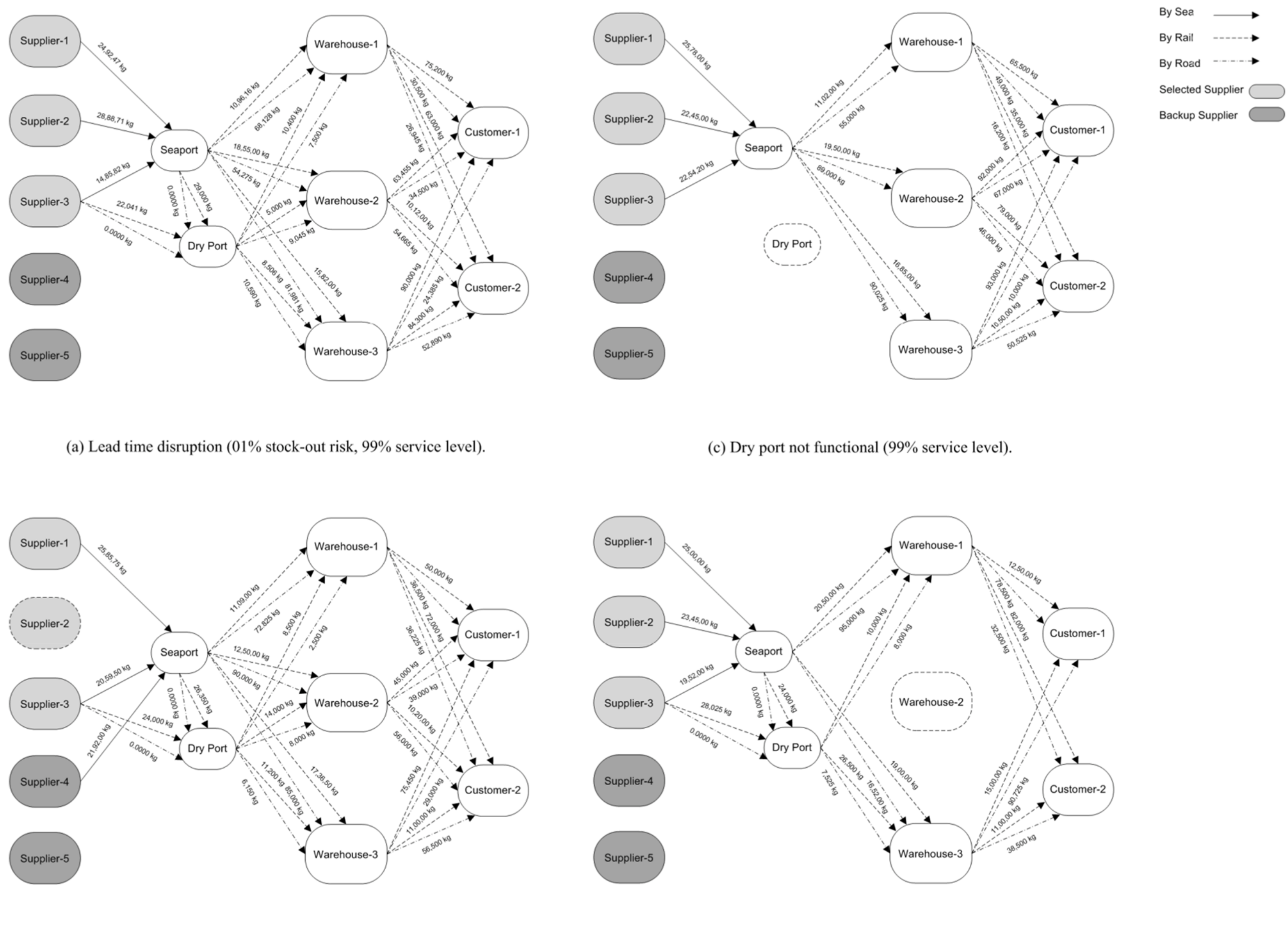
### 3.2.3. *Comparison of no disruption and disruption scenarios*

A brief evaluation and comparison of the no disruption solution to the results of the supply chain network being assessed subject to 01 probabilistic and 03 network disruptions as described in the previous sections has been presented below.

In Fig. 6, except for part (e), objectives TTT, EI, AQL, and TVSP have been separately plotted against TC values for relative analysis of order allocation results as TC has been considered the principal objective function during multi-objective optimization using AUGMECON2.

A substantial increase in the value of the total cost has been observed between the no disruption solution and the results for all 04 disruption scenarios analyzed, as included in Fig. 6(a–d), respectively. For the target service level, i.e., 99 % maintained by the supply chain network, only a minor variation exists between the optimal values of the total cost determined for all disruption scenarios when evaluated using the FMOMINLP mathematical model.

An increasing trend has been noted in the values of the total travel




(a) Lead time disruption (01% stock-out risk, 99% service level).

(c) Dry port not functional (99% service level).

(b) Supplier-2 not available (99% service level).

(d) Warehouse-2 out of service (99% service level).

**Fig. 7.** Breakdown of order allocation quantities for $t_1$ under disruption scenarios.

time between the no disruption solution and disruptions caused by the lead time variation and unavailability of supplier-2 (Fig. 6(a)). In case of the disruption scenarios created due to the dry port and warehouse-2 being knocked out, the total travel time is reduced as the goods are transported through alternate routes.

A noticeable difference in the values of the acceptable quality limit has been observed for the no disruption and disruption solutions presented in Fig. 6(c). The maximum increase in the value of the acceptable quality limit is associated with the substitution of the backup supplier for replacing supplier-2.

An increase has been observed in the total values of sustainable purchasing for all disruption scenarios considered (Fig. 6(d)). This increase is attributable to the service level requirement imposed on the supply chain network. The reduced risk performance of the backup supplier (ranked 4 out of the total 5 suppliers considered) is reflected by its total value of sustainable purchasing, which is the lowest among all disruption scenarios presented in Fig. 6(d).

The variation in the value of the total travel time is closely linked with the environmental performance of the supply chain network (Fig. 6(e)). A significant increase has been noted in the values of the environmental impact for the lead time disruption and the substitution of the backup supplier. As total travel time is reduced due to removal of the dry port and the warehouse-2 from the supply chain network, the environmental impact is correspondingly reduced. An increase or decrease in the value of the environmental impact is only linked with the total cost through a relative variation in the value of the total travel time.

A graphical representation of the breakdown of the optimal order quantities for all four disruption scenarios considered above determined using Q1 data has been included in Fig. 7.

## 4. Conclusion

In this research paper, a novel comprehensive multi-phase, multi-period decision support framework has been proposed that combines TBL sustainability and resilience criteria concurrently for SS-OA under demand uncertainty and network disruptions. The decision framework has been illustrated using real-life data acquired from the pharmaceutical industry. This industry sector has gained critical importance in the aftermath of COVID-19 pandemic but it has been left out in many of the earlier research works as highlighted in the introduction section. The decision support framework has been implemented in two parts, i.e., in the first part comprising of phases 1–3, sustainable and resilient SS-OA has been carried out, which is followed by disruption scenario evaluation and comparison of no disruption and disruption solutions in the second part consisting of phase 4 and phase 5, respectively.

The analysis of the results indicates that the proposed decision framework can serve as a useful tool for performing multi-criteria optimization of complex supply chain networks extending beyond international borders, operating in diverse economic, environmental, and social settings, and subject to influence from multiple types of disruption scenarios. Following inferences can be made from the analysis presented in Section 3.2:

1. It has been observed that all disruption scenarios being evaluated lead to a significant increase in the total cost when compared with the no disruption solution due to the enhanced order quantities

required for achieving and maintaining the target supply chain network service level. A maximum increase of 19.2 % has been observed for the disruption scenario when supplier-2 becomes unavailable.
2. Lead time variation and the unavailability of a supplier causes an increase in the total travel time while the disabling of nodes and links with in the supply chain network leads to a reduction in the total travel time as the order quantity is transported through alternate routes with shorter distances. This may also cause the volume of the order quantity being transported along a particular route to increase and lead to constraining the capacity of the transportation mode or the warehouse handling the shipment. A maximum increase of 42.3 % has been noticed in the value of TTT when the backup supplier is substituted to replace supplier-2 with lead time disruption a close second at 41.5 %.
3. Any change in the logistics performance of the supply chain network is directly linked with a relative variation in the value of the environmental impact. Lead time disruption and the replacement of supplier-2 with the backup supplier bring about almost a threefold increase in the value of EI when compared with the no disruption solution, respectively.
4. The substitution of a backup supplier is always a contingency measure. It has been noted that this substitution causes maximum variation in the value of the AQL (a 48.1 % increase) that can lead to a negative impact on the quality control practices of the customers. The results also indicate that the relatively low risk performance of the backup supplier may cause a detrimental effect on the TVSP value of the supply chain network operation as well.

In future applications, an interesting avenue for further research is the implementation of the proposed decision support framework to optimize a closed-loop supply chain network facing disruption risks. The case study presented in this research work employs a periodic review model to calculate a replenishment level for depleting inventory. As a potential mathematical extension of the decision framework, different scenarios should be considered and evaluated where other categories or variations of inventory models with probabilistic demand have been used. The impact of using multiple probability distributions for describing demand can be incorporated in this analysis as well.

## CRediT authorship contribution statement

**Saheeb Ahmed Kayani:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Salman Sagheer Warsi:** Writing – review & editing, Resources, Methodology, Conceptualization.

## 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.

## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rineng.2025.104954.

## Data availability

The data used has been included in the file Supplementary Material A1.

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