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# Emergency order planning to produce multi product under disruptions with single and multiple sourcing

Ehsan Mardan *[1], Rezvaneh Kashani[1], Reza Kamranrad[1]

[1] Department of Industrial Engineering, Semnan University, Semnan, Iran.

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**Abstract**

Supply chains in the world are increasingly exposed to disruptions caused by disasters in every part of the world. The emergence of risk in today's business environment due to globalization, disruptions, poor infrastructure, forecast errors and various uncertainties affects every management decision. The present study was an attempt to propose an emergency order and production planning for a multi-product multi-item problem where products are made up of several ingredients. A side from the main supplier, the backup supplier can be used to supply each component where orders must be delivered within a certain time interval (specified time window). In the present study attempts are made to use sourcing strategies to realize supply chain flexibility under disruptions. A scenario-based mathematical model encompassing different uncertainties such as those arising from disruption and operational risks is formulated. A case study analysis is carried out to appraise the output of risk attitudes adopted by different decision-makers (both risk-neutral and risk-averse). The present study presents strategies to create flexible supply bases that diminish the cost of the worst scenario in the face of supply chain risks. By increasing the number of primary and supporting suppliers, VAR and C-VR values will increase, so the management offer is that the number of suppliers should be kept constant within acceptable limits to prevent a sharp increase in the number of suppliers. Suppliers should release orders in time by establishing time windows and setting deadlines in order to receive orders. Also, this paper shows that the values of VAR and C-VR decrease with the increase of primary supply capacity, and with the increase of primary supply capacity, costs are reduced by about 99%, which reduces the effect of disruption on the capacity of primary suppliers.

**Keywords**: disruption; emergency ordering; C-VR; supply chain.

**Paper Type**: Original Research

## 1. Introduction

Human life has been associated with disasters and disasters throughout history and has always been an attempt to identify dangers and escape from it. With the advancement of science and technology, the general knowledge about the nature of accidents and their consequences has increased but in the same proportion of its technology has caused numerous incidents that have affected the lives of all living creatures in a region. In disasters two aspects are of importance. First, preparedness in emergency situations and second dealing with consequences of disaster where these consequences include destructive effects of psychological and social impacts on human beings. Preparedness and reaction is very important and valuable is readiness in these conditions. Due to the increasing importance and complexity of supply chain management for organizations in today's noisy business environment, it is necessary to predict and implement the resilience abilities necessary to meet or prevent disruptions in organization activities. According to the literature, production outage can be defined as any disruption such as material shortages, machine failures, power outage, tool failures or any unexpected or manmade outages that may occur during the production process. The COVID19 epidemic is an example of this type of disruption, which has led to production outage by manufacturers such as Hyundai and Fiat Chrysler NV (Ivanov, 2020). Supply chain disruption as an unpredicted event halt or slows down the normal flow of substances (Bunch et al., 2007) and has possibly negative outcomes for supply chain members (Blackhurst et al., 2011). It is possible to spread even a very small initial disruption across the supply chain (Blackhurst et al., 2011). The proliferation of disruptions can significantly affect performance, including reduced profits, and in extreme cases, viability of supply chain. For example (Hendricks and Singhal, 2003), during a study concluded that disruptions can reduce market capitalization by 10%. When it comes to sourcing, selection of the best supply base can significantly affect the success rate of supply chains in different markets all around the world. survival and competitiveness of companies is dependent, to a large extent, on the procurement strategies used by them (Merzifonluoglu, 2015).

In such cases, optimal sourcing strategies are necessary to minimize supply shortages. Being larger, longer, and more sophisticated, Modern supply chains are more likely to increase disruption risk (Blackhurst* et al., 2005) (Scheibe and Blackhurst, 2018). When using a resilient backup sourcing strategy, the original suppliers are,

*Corresponding Author: ehsan_mardan@semnan.ac.ir

regardless of uncertain parameters, the first to receive notifications of orders, and backup suppliers will get notifications of emergency orders once new data on emergency orders is available. The noteworthy point is that in the flexible backup sourcing strategy proposed in the present study, the quantity of order released to the backup supplier is equal, in the best scenario, to the amount of order the original suppliers are notified about. Several researches have been done to understand how to increase the flexibility of organizations and supply chains against these irregularities (Bhamra et al., 2011). Although supply chain disruptions are inevitable, successful companies try to figure out how they can minimize disruptions and maintain effective supply chain operations. Sawik developed an approach to manage supply disruptions by selecting primary suppliers and retrieving orders from a company perspective (Sawik, 2016). Nevertheless, even when primary disruptions are limited to a single company, they may spread through the system, causing losses in other supply chains. Thus, a supply chain failure may trigger failures in other institutions and may even lead to the complete closure of the supply chain. Nevertheless, one can still cope with disruptions affecting a company by dispersing purchases among different suppliers (He et al., 2016).

In the present study, attempts are made to propose a novel decision model that can help design flexible supply strategies with the power to flexibly deal with uncertainties caused by disruptions. The proposed decision model encompasses a large number of standard industry strategies namely visibility, collaboration, backup suppliers, and spot purchases, and. Backup suppliers help companies effectively deal with unanticipated supply disruptions (Merzifonluoglu, 2015). Thanks to the spot purchasing strategy, buyers can instantly buy products on the day they need the goods, without having to conclude basic contracts. Cooperation and visibility between buyers and suppliers play an important role as powerful strategies for disruptive risk coverage which have a positive effect on suppliers' recovery rates and alertness of buyers. During the first stage of a two-stage model a primary decision is taken before the emergence of a stochastic destructive scenario. The primary decision contains selecting a supplier, determining storage capacity in supplier backup, and determining the investment in cooperation and visibility. In the second step, one can set scenario-dependent parameters to offset the adverse effects of decisions made in the first stage. Then, the company can use a backup supplier or local market to recover its capacity or wait to find an unreliable supplier. The main contributions of this paper are summarized as follows. First, a multi-period and multi-product planning model with uncertainty in production and demand is developed. Second, a flexible support protocol that operates on the basis of inventory reserve of an emergency support supplier is proposed. Third, the effectiveness of emergency planning decisions along with the sequential concepts that support the system with higher flexibility is evaluated. In this environment all the constituents that are supposed to be delivered by suppliers are needed to produce the end product and the absence of any item can make it impossible to manufacture the end product. These questions are answered in the following paper.

1-How can we proceed to identify single and multiple sourcing strategies in a multiple - product and multi-component environment?

2-How to integrate production planning and inventory model in the presence of uncertainty of raw materials as well as the final product demand?

3- How time constraints are applied in receiving orders?

The rest of this paper is organized as follows. The literature reviewed in section 2. In section 3, the proposed mathematical model is presented. In section 3, a mathematical model based on risk is proposed. Computational experiments and sensitivity analysis are presented in Section 4. Conclusions and managerial insights are presented in section 5.

## 2. Literature review

Supply chain disruptions have received a lot of attention from many researchers and professionals over the last decade. However, single suppliers are characterized by some benefits, such as minimizing costs incurred by the system by paying suppliers' management costs or reducing unit prices by offering discounts. Such a strategy, however, may increase system vulnerablity to potential supply disruptions. For example, (Ferrer, 2003) investigated a sole sourcing strategy for a newsvendor s problem (Xiao and Qi, 2008) examined one supplier and two competing retailers for a newsvendor problem. In another study, Sargut and Qi investigated a supplier with random supply efficiency in order to cope with a one-period inventory problem with definite demand. (Sargut and Qi, 2012) considered an unreliable supplier that only supplies a retailer. They relied on inventory reduction tactics without regard for any alternative source in the above articles, only for managing disruptions. Meanwhile, various studies consider sourcing reduction strategies as an effective tool to deal with uncertainty. The relevant literature has proposed two distinct types of sourcing reduction models. The first type, which forms typical multi-sourcing models, involves problems in which decisions are adopted about order quantities at a time and corrective actions are prohibited once new data on uncertainties are made available. Some of the main articles published in this field are listed in the following. Svoboda et al. reviewing the literature on multiple sourcing strategy, defining the characteristics of the strategy as a trade-off between the costs of multiple suppliers and the inventory shortage costs of a single supplier (Svoboda et al., 2021).

In order to cope with a sales newspaper problem, Wang et al. conducted a study on process improvement strategies meant to enhance the reliability of unreliable suppliers in the face of disruptions. In this study, they used as dual sourcing system with exactly the same sources and checked the system efficiency in different conditions (Wang et al., 2010). In the second type of multiple sourcing models which are referred to as emergency / contingency order models, orders will be delivered to an unreliable supplier before the uncertain parameters are met. Emergency orders can be sent to a reliable, expensive supplier once uncertainty is identified. Babich, considered a case with two suppliers, in which one supplier has a shorter waiting time as an emergency source (Babich, 2006). This assumption in its model that it can wait a while for the recovery of an unreliable supplier and safety stocks can be used during the waiting time (Qi, 2013). Dong and Tomlin tried to draw an analogy between the emergency order and interruption management insurances in their problem (Dong and Tomlin, 2012). Wang et al. investigated a supply chain in which the buyer purchases end items from a supplier to meet a random market demand in which supplier production is subject to random returns and demand may be met using emergency backup sourcing (Wang et al., 2014). Gupta et al. a system of two suppliers of two products was investigated in which two supply channels were unknown. In this case, the retailer offered the products to the end customers and customers chose each. pricing decisions including wholesale price and retail price were determined (Gupta and Ivanov, 2020). In an attempt to offer a flexible supply base in the face of operational disruption risks, Torabi et al developed a two-objective hybrid stochastic programming model to cope with problems posed by selection of supplier and the allocation of order (Torabi et al., 2015). Yoon et al suggested a two - objective random model. This model integrates the supplier selection and risk reduction strategies (Yoon et al., 2018). According to the literature, the uncertainties regarding the return of suppliers can be regarded as a main source of order reception uncertainty. Gupta et al. considered the stochastic ordering yield as a result of supply disruption, the disruption considered in their research work occurred within a selling period, and the yield was dependent on not only the point in time where the disruption took place within the selling period but also on the length of the selling period (Gupta and Ivanov, 2020). Only small segment of the literature focuses on the multi-product environment, whereas much studies have been carried out on the single-product environment. Tomlin and Wang investigated dual sourcing and hybrid flexibility problems in a company that is working to sell several products without permission to replace products (Tomlin and Wang, 2005). In contrast, Tomlin and Wang investigated two products that could replace a risk-neutral decision maker (Tomlin and Wang, 2008). As we know, only one deliverable product is considered by most of the existing articles on inventory management models with disruptions, except for the studies carried out by Tomlin and Wang, 2008. Furthermore, a potential order policy is used to enhance model efficiency in the face of uncertainties one may face during reception of raw materials.These models have concentrated preparedness or redundancy strategies, for example: rescheduling operations, optimal inventory policy, and risk assessment. Simchi et al. create visibility and cooperation, supply chain flexibility by improving the buyer-supplier relationship, reducing recovery time after disruptions, and the possibility of progressive disruption alerts (Simchi-Levi et al., 2018). The cost-benefit of applying the strategy, however, has not been taken into account in limited studies on visibility and collaboration. Dubey et al investigated the potential effect of behavioral dimensions such as trust and cooperation on resilience of supply chains (Dubey et al., 2017).Khalili et al argued that integrated production and sourcing planning can, thanks to its additional capacity of production equipment, pre-determination of position or inventory and back-up logistics, significantly contribute to enhancement of supply chain resilience (Khalili et al., 2017). Ivanov et al concluded that a flexible and efficient supply chain design is indispensable (Ivanov et al., 2019b). It is possible to develop low supply chain uncertainties by combining greater flexibility in the process and use of resources. Altay et al. investigated the potential impact of agility and resilience efforts of business organizations on supply chain performance before and after the event (Altay et al., 2018). In a systematic review of the relevant literature, Hosseini et al. tried to address mathematical quantitative models that have been specifically developed to enhance supply chain flexibility (Hosseini et al., 2019). Kumar (2019) investigated the strategic effect of product and market characteristics on producer decisions to complete the sales channel using a direct and online channel. the concept of interaction guides the members of the supply chain to a coherent work to identify the dependencies among themselves so that goals, redefined, and risks and outcomes of fair valuation are shared (Krishnan et al., 2022). The performance of the optimal supply chain requires implementation of a set of activities that are not always in the best position among supply chain members and this leads to poor performance of the whole chain. the optimal performance will be achievable if the companies are under contract to align with the goal of the whole supply chain and to deal with the economic issues of both parties and supply chain profitability (Choi et al., 2013). there are several other reasons for the adoption of contracts in a bilateral space due to the decrease in the conflicts in transactional relationships (Valentijn et al., 2015). (Kumar et al., 2020) They showed that there are only 24% of studies with proposed methods to deal with demand distribution planning in production-distribution environment. In this article, an inventory planning for a period is examined and a possible and random demand is assumed.Merzifonluoglu, has investigated the cash market, as a tool that can be used to effectively cope with disruption risks (Merzifonluoglu, 2015). In this strategy, daily market price is paid for receivables. Spot markets have been broadly used in the livestock, food, memory chip, and oil industries. in his attempt to formulate optimization models for a company's purchasing portfolio to maximize anticipated profit or minimize risk, Merzifonluoglu, used C-VR as a risk factor (Merzifonluoglu, 2015). In their attempt to detect optimal procurement strategies encompassing support contracts, forward contracts, and cash markets, they checked several scenarios. Snyder et al concluded flexibility and redundancy strategies make up the majority of recovery strategies for disruption risks (Snyder and Shen, 2006). Sawik, used emergency questionnaires to support suppliers and enhance the resilience of supply chains (Sawik, 2013). C-VR criteria were used to optimally select the supply portfolio for custom manufacturing companies with the risk of disruption and customer's constant demand. They used stochastic mixed integer programming models (MIP) to offer strategies that allow for flexible supplier selection and order allocation. In another study conducted by PrasannaVenkatesan and Goh, complex stochastic mixed integer programming was employed to deal with problems posed by integrated supplier selection and order allocation in the face of risks and under operating conditions (PrasannaVenkatesan and Goh, 2016). Khalili et al used probable mixed models for production and distribution planning for the risky two-tier supply chain (Khalili et al., 2017). Rezapour et al proposed mixed, nonlinear integer models, and concluded that flexible supply chains designed face different types of uncertainties (Rezapour et al., 2017).In their study, Hasani and Khosrojerdi, presented some resilience strategies and found that three strategies namely multiple sourcing, facility dispersion and facility reinforcement have the most dramatic effect on performance of supply chains (Hasani and Khosrojerdi, 2016). Sahebjamnia et al. offered a credibility-based fuzzy chance programming model to design a reliable distribution network under partial and full potential disruptions (Sahebjamnia et al., 2016). Behzadi et al. established a two-step model to select optimal sustainable and flexible strategies for an agricultural business supply chain (Behzadi et al., 2017). Sawik proposes a two-objective stochastic mixed integer programming approach for joint supplier selection and production and distribution planning in a multilevel supply chain (Sawik, 2016). Using the developed multi-objective model, PrasannaVenkatesan and Goh showed that the probability of supplier failure has a significant effect on the overall expected cost more than the supplier flexibility and loss cost (PrasannaVenkatesan and Goh, 2016). It has examined the challenge of supplier integration in the industry Also, supplier integration strategies are suggested by providing insights from expert interviews (Müller, 2019). Hlioui et al. presented an integrated production, re-supply, supplier selection and raw material quality control policy to minimize the total cost of a production-oriented supply chain system under unreliable changes and supplier stochastic parameters (Hlioui et al., 2017). Dutta and Shrivastava et al. Studies by modeling uncertainty during harvesting, product size, product quality, performance, selling price, cost, supply of unreliable sources, delay in transportation, etc. have focused on supply side issues (Dutta and Shrivastava, 2020). Merzifonluoglu, presented effective modeling techniques and solutions on maximizing the performance of a production system by optimally selecting customer demands, the amount of procurement, buying the spot market and using option contracts (Merzifonluoglu, 2017). Hosseini et al. By considering the possibility of supplier disruption using the Bayesian network approach, taking into account different levels of supplier capacity and stages of disruption, they have modeled the wave effect in the supply chain (Hosseini and Ivanov, 2019). Aazami et al. a seller-buyer model with demand as a linear function of price, advertising in an integrated production-distribution environment was developed. This study promotes promotion strategies such as discounts, returns and credits at the retail level to increase customer demand (Aazami and Saidi-Mehrabad, 2021).

**This research desires to fill the following research gaps:**

Although many studies have considered the integration of production and inventory, to our best of our knowledge, the potential sourcing in a multi-item environment has been addressed only in few studies. This study was an attempt to detect single and multiple sourcing strategies under multiple disruption scenarios in a multi-product, multi-component environment. It also suggests the integrated framework of production and inventory planning in the presence of raw materials and the end product demand uncertainty, which is an emergency response strategy to address it. Also, no study has carried out on the effect of time window and creating time limit on receiving orders, which is addressed in this study. Table 1 provides the characters of previous studies also in this paper, some solutions for creating flexible source databases that reduce the cost of the worst-scenario in the face of supply chain risks in this paper, VAR and C-VR methods are used to guide the risk management of local supply chain that has not been previously performed in other papers.

**Table 1.** Classification of disruption problems-related articles

| Authors / Year | Type of demand | | Type of sourcing | | | | Alternative and emergency source | | product type | | time window | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | certain | uncertain | Single source | Two sources | Multiple sources | Single and multiple sources | ✓ | X | Single product | Multiple products | ✓ | X |
| (Parlar and Perry, 1996) | * | | | * | | | | * | * | | | * |
| (Dada et al., 2003) | * | | | | * | | | * | * | | | * |
| (Ferrer, 2003) | * | | * | | | | | * | * | | | * |
| (Tomlin and Wang, 2005) | | * | | * | | | | * | | * | | * |
| (Babich, 2006) | | * | * | | | | * | | * | | | * |
| (Tomlin, 2006) | | * | * | | | | * | | * | | | * |
| (Chopra et al., 2007) | | * | * | | | | * | | * | | | * |
| (Babich et al., 2007) | | * | | | * | | | * | * | | | * |
| (Xiao and Qi, 2008) | * | | * | | | | | * | * | | | * |
| (Keren, 2009) | * | | * | | | | | * | * | | | * |
| (Wang et al., 2010) | | * | * | * | | | | * | * | | | * |
| (Sargut and Qi, 2012) | * | | * | | | | | * | * | | | * |
| (Altay et al., 2018) | | * | | | * | | | * | * | | | * |
| (Yoon et al., 2018) | * | | | | * | | | * | | * | | * |
| (Namdar et al., 2018) | | * | | | | * | * | | * | | | * |
| (Scheibe and Blackhurst, 2018) | | * | | | * | | | * | | * | | * |
| (Ivanov et al., 2019a) | | * | | | * | | | * | | * | | * |
| (Hosseini et al., 2019) | * | | | | * | | | * | | * | | * |
| (Svoboda et al., 2021) | * | | | | * | | | * | | * | | * |
| (Aazami and Saidi-Mehrabad, 2021) | | * | | | | * | | * | | * | | * |
| (Krishnan et al., 2022) | | * | | | * | | | * | | * | | * |
| This study | | * | | | | * | * | | | * | * | |

## 3. Problem definitions

This study has been carried out in a multi-product and multi-item environment where each end product is composed of different components. If a component is not provided, the company will be unable to produce the relevant end product. Two types of suppliers (reliable and unreliable) have been taken into account in this model. Orders are dealt with within a double-stage decision-making process, where raw materials are first released to the main suppliers. Once the unknown parameters are identified, orders are released to the emergency supplier. In this process, the buyer and emergency supplier conclude a flexible order contract. In this contract, decisions are made with respect to the capacity of the emergency supplier in the first stage and it is stored for the second stage. It is possible to order the reserved amount to the emergency supplier. Furthermore, a part of the reserved amount must be ordered, and any order will be imposed higher than the stored amount. In this system only one supplier (single sourcing) or several suppliers (multiple sourcing) may be involved. In addition, in this study a novel decision model is put forward in order to develop supply strategies with the ability to flexibly deal with uncertainties caused by disruptions such as standard industry strategies (backup suppliers, spot purchasing, visibility) and collaboration. Backup suppliers provide companies with the power to deal with unexpected primary supply disruptions. Spot purchasing strategy is defined as buyers make an instant purchase at market price when the product is required, without having to go through substantive contracts. One powerful strategy to cover disruption risk is cooperation and visibility between buyers and suppliers which has a positive impact on suppliers' recovery rates and buyers' warning capability. Two-stage stochastic programming model was used to develop weak supplier strategy that is widely used in decision making problems. The two-stage model is characterized by an initial decision which is taken in the first step before the emergence of a stochastic destructive scenario. This decision mostly encompasses selection of suppliers, determining the storage capacity of suppliers, and determining the investment in cooperation and visibility. Scenario-dependent parameters are determined in the second stage to offset the adverse effects of decisions made during the first stage. Then, in order to recover its capacity, the company can either wait for an unreliable supplier or simply rely on local market or backup suppliers.

## Model development and formulation

Two-stage stochastic programming model which is recognized as one of the most extensively used methods for dealing with two-stage decision problems, was used to develop the risk minimization mathematical model. In the two - stage problems, the initial decision is taken during the first step prior to release of notifications related to realization of random scenario and determination of the scenario-dependent parameters in the second stage. In decision - making models, when the condition of the parameters is not specified in the first step, the second step cannot be started and decision making, but in the traditional models, this is not the case and there is no decision - making steps. The advantage of VAR and C-VR to evaluate the risk criterion is this option is better for continuous distribution with a certain confidence level over a given time period.

### 3.1. Assumptions

• It can be assumed that the backup supplier is always accessible. In other words, the possibility of a simultaneous disruption between the main supplier and the backup is insignificant.
• The major suppliers' capacity equals the total demand where each initial supplier can fulfill the entire demand of the manufacturer or buyer in the absence of potential disruptions.
• Primary suppliers have several levels of recovery rate and buyers have several levels of warning capability.
•Each cooperation strategy is characterized by its potential effect on recovery rate or supplier rate
• Cooperation levels are characterized by their diverse recovery rates and executive costs they incur.

### 3.2. In mathematical formulation

| **Sets and indexes:** | |
|---|---|
| **r** | Set of raw materials required to produce products $r = 1.... R$ |
| **p** | Set of manufactured products $p = 1... P$ |
| **i** | Set of unreliable or primary suppliers $i = 1... I$ |
| **j** | Set of reliable or backup suppliers $j = 1... J$ |
| **t** | Set of periods of time $t = 1... T$ |
| **s** | Set of uncertainty scenarios $s = 1... S$ |
| **l** | Different levels of warning capability for different suppliers $l = 1... L$ |
| **u** | Different levels of recovery capabilities for different suppliers $u = 1... U$ |

| Parameters: | |
|---|---|
| $G_i$: | Fixed fee to contract with primary suppliers i for raw material r |
| $A_j$: | Fixed fee to contract with backup suppliers i for raw material r |
| $\pi_s$: | The probability of the scenario of the s |
| $PIU_{r,i,t}$: | Cost of purchasing each unit of raw material r from backup supplier i as reserved material during the period t |
| $PIRR_{r,j,t}$: | The purchase cost of each raw material unit r from backup j in period t |
| $BP_{p,s}$: | Backorder penalty cost of product p under scenario s |
| $M$: | Large number |
| $\theta_{i,s}$: | Equal to one if the primary supplier i is disrupted under scenario s and otherwise zero |
| $\Phi_{p,s}$: | Number of lost product P under the s scenario in the last period |
| $\rho_u$: | Probability of primary supplier failure u |
| $\psi_u^s$: | Percentage of residual capacity of the primary supplier u disrupted in scenario s |
| $HCI_{p,t}$: | The unit maintenance cost of the raw material i in period t |
| $HCP_{p,t}$: | The cost of maintenance of the product p in period t |
| $\zeta_i^{ut}$: | recovery rate for primary i supplier at level u in period t |
| $\xi_i^{lt}$: | alarm capability for primary supplier i at level l at period t |
| $re_{i,u}$: | The cost of improving the recovery level for primary supplier i at the u at period t |
| $\omega_{i,l}$: | The level of promotion of the alarm level for primary supplier i at the u at period t |
| $D_{p,t,s}$: | The value of product demand in period t under the s |
| $BOM_{r,p}$: | The amount of raw material r required for the P |
| $o_i$: | primary supplier capacity i |
| $RPC_{p,t}$: | The cost per unit production p in period t |
| $Ti_{r,i,t}$: | The time rate of delivery of the initial material order r by the primary supplier i |
| $Tj_{r,j,t}$: | Rate of delivery time of reserved raw material order r by the backup supplier j |

| | |
|---|---|
| $\boldsymbol{T_r}$: | Minimum order of delivery time of order delivery in reserve and non-reservation, by the producers |

**Continuous positive variables:**

| | |
|---|---|
| $\boldsymbol{FD_{p,t,s}}$: | The amount of demand met for product p during the period t under the scenario s |
| $\boldsymbol{PR_{p,t,s}}$: | Production rate for product p during the period t and scenario s |
| $\boldsymbol{b_{j,t}}$: | Amount of capacity booked in the contract with the backup supplier during the period t |
| $\boldsymbol{x_{r,i,t}}$: | The amount of raw material r purchased from primary supplier i during the period t |
| $\boldsymbol{h_{r,j,t,s}}$: | The amount of reserved order of raw material i from backup support j during the period t under the scenario s |
| $\boldsymbol{lb_{i,s,t}}$: | The capacity to repair to the supplier involved with the disruption during the period t |
| $\boldsymbol{B_{p,t,s}}$: | The amount of backorder for product p during the period t under the scenario s |
| $\boldsymbol{C_{i,t,s}}$: | Amount of raw material consumed i during the period t under the scenario s |
| $\boldsymbol{II_{r,t,s}}$: | The inventory of raw material r during the period t under the scenario s |
| $\boldsymbol{IP_{p,t,s}}$: | The inventory of product p during the t under the scenario s |

**Zero-one variables:**

| | |
|---|---|
| $\boldsymbol{y_{i,t}}$: | It is equal to one, if the primary supplier I is selected during the period t and zero otherwise |
| $\boldsymbol{y'_{j,t}}$: | It is equal to one, if a reservation agreement is concluded with the backup supplier j during the period t and zero otherwise |
| $\boldsymbol{\gamma^u_{i,t}}$: | It is equal to one, If the primary supplier i during the period t is placed at the recovery level, zero otherwise |
| $\boldsymbol{\lambda^l_{i,t}}$: | It is equal to one, If the primary supplier i during the period t is placed at the alarm level, zero otherwise |

## 3.3. Problem solving method

### 3.3.1. Objective function and constraints

Minimization of costs arising from contracts with suppliers, production costs, ordering costs, maintenance costs, and finally back orders is the objective of this section.

$$\begin{aligned} MINZ = \sum_i \sum_t G_i . y_{i,t} &+ \sum_r \sum_i \sum_t PIU_{r,i,t} . x_{r,i,t} \\ &+ \sum_j \sum_t A_j . b_{j,t} \\ &+ \sum_i \sum_u \sum_t re_{i,u} . \gamma^u_{i,t} + \sum_i \sum_l \sum_t \omega_{i,l} . \lambda^l_{i,t} + \sum_s \pi_s . ( \sum_r \sum_j \sum_t PIRR_{r,j,t} . h_{r,j,t,s} \\ &+ \sum_r \sum_t HCI_{p,t} . II_{r,t,s} + \sum_p \sum_t HCP_{p,t} . IP_{p,t,s} + \sum_p \sum_t BP_{p,s} . B_{p,t,s} + \sum_p \Phi_{p,s} . B_{p,T,s} \\ &+ \sum_p \sum_t RPC_{p,t} . PR_{p,t,s} \end{aligned} \tag{1}$$

$$\sum_r x_{r,i,t} \leq \left((1-\theta^s_i). y_{i,t}. o_i\right) + \theta^s_u . \left( \left(\psi^s_u . y_{i,t}. o_i\right) + \sum_u lb_{i,s,t} * \zeta^u_{i,t} \right), \qquad \forall i,s,t \tag{2}$$

$$\sum_i x_{r,i,t} + \sum_j h_{i,j,t,s} = II_{i,t,s} + C_{i,t,s}, \qquad \forall r,s,t=1 \tag{3}$$

$$\sum_i x_{r,i,t} + \sum_j h_{i,j,t,s} + II_{i,t-1,s} = II_{i,t,s} + C_{i,t,s}, \qquad \forall r,s,t \geq 2 \tag{4}$$

$$PR_{p,t,s} - B_{p,t-1,s} = IP_{p,t,s} + D_{p,t,s} - B_{p,t,s}, \qquad \forall p,s,t=1 \tag{5}$$

$$PR_{p,t,s} + IP_{p,t-1,s} - B_{p,t-1,s} = P_{p,t,s} + D_{p,t,s} - B_{p,t,s}, \qquad \forall p,s,t \geq 2 \tag{6}$$

$$FD_{p,t,s} + B_{p,t,s} = D_{p,t,s}, \qquad \forall p,t,s \tag{7}$$

$$\sum_p (BOM_{r,p}.PR_{p,t,s}) = C_{r,t,s}, \qquad \forall r,t,s \tag{8}$$

$$\textstyle\sum_r h_{i,j,t,s} \leq b_{j,t}, \ \forall j,s,t \tag{9}$$

$$b_{j,t} \leq M.y'_{j,t}, \qquad \forall j$$

$$lb_{i,s,t}.\zeta^u_{i,t} \leq M.\gamma^u_{i,t}, \qquad \forall i,u,t,s \tag{11}$$

$$\sum_u \gamma^u_{i,t} = y_{i,t}, \qquad \forall i,t \tag{12}$$

$$lb_{i,s,t}.\xi^{lt}_i \leq M.\lambda^l_{i,t}, \qquad \forall i,l,s \tag{13}$$

$$\sum_l \lambda^l_{i,t} = y_{i,t}, \qquad \forall i,t \tag{14}$$

$$\sum_i y_{i,t} = 1, \qquad \forall t \tag{15}$$

$$\sum_j y'_{j,t} = 1, \qquad \forall t \tag{16}$$

$$y_{i,t} + y'_{j,t} \leq 2, \qquad \forall i,j,t \tag{17}$$

$$\sum_i x_{r,i,t}.\left(1 - Ti_{r,i,t}\right) + \sum_j h_{i,j,t,s}.\left(1 - Tj_{r,j,t}\right) \leq (1 - t_r).\left(II_{i,t,s} + C_{i,t,s}\right), \qquad \forall r,t,s \tag{18}$$

$$y_{i,t}, y'_{j,t}, \lambda^l_{i,t}, \gamma^u_{i,t} \in \{0,1\} \tag{19}$$

$$FD_{p,t,s}, PR_{p,t,s}, b_{j,t}, x_{r,i,t}, h_{r,j,t,s}, lb_{i,s,t}, B_{p,t,s}, C_{i,t,s}, II_{r,t,s}, IP_{p,t,s} \geq 0 \tag{20}$$

Equation 1, the objective function is minimizing total costs. Equation 2 shows the amount of raw material purchased by the order from the original suppliers due to the absence of scenario or scenario occurrence and recovery of its capacity. Equation 3 and 4 are balance Equations related to the amount of inventory of each type of raw material in different periods under the existing scenarios. Equations 5 and 6 are balance constraints related to the inventory of each product during different periods under the existing scenarios. Equation 7 balances demand to meet demand and unfulfilled orders. Equation 8 calculates the amount of raw material consumed of each type and in each period in the total production of products. Equation 9 indicates the bookable capacity of back up suppliers. Equation 10 indicates selected backup suppliers according to its capacity. Equation 11 indicates the level of capacity recovered in each period. According to Equation 12 the number of capacity levels that could be recovered in each period cannot exceed 1. Equation 13 indicates the level of warning capacity in each period. Equation 14 indicates that it activates only one alarm level in each period. Equation 15 indicates that only one primary supplier is selected in each period. Equation 16 indicates that only one backup supplier is selected in each period. Equation 17 indicates the possibility of using more than one source. Equation 18 indicates the time limit for sending and delivering raw materials at a specified time rate. Equations 19 and 20 show the binary and positive variables.

### 3.4. value at risk

Value at risk (VAR) is a measure of the risk of loss for investments. It estimates how much a set of investments might lose (with a given probability), given normal market conditions, in a set time period such as a day. VAR is typically used by firms and regulators in the financial industry to gauge the amount of assets needed to cover possible losses. For a given portfolio, time horizon, and probability p, the p VAR can be defined informally as the maximum possible loss during that time after excluding all worse outcomes whose combined probability is at most p. The VAR is not a coherent risk measure since it violates the sub-additivity property, $x, y \in L$, then $\rho(x + y) \leq \rho(x) + \rho(y)$.

However, it can be bounded by coherent risk measures like Conditional Value-at-Risk (C-VR) or entropic value at risk (E-VR). C-VR is defined by average of VAR values for confidence levels between 0 and α. However, VAR, unlike C-VAR, has the property of being a robust statistic. A related class of risk measures is the 'Range Value at Risk' (R-VR), which is a robust version of C-VR. For $X \in L_{M+}$ (with $L_{M+}$the set of all Borel measurable functions whose moment-generating function exists for all positive real values) we have

$VaR_{1-\alpha}(X) \leq RVaR_{\alpha,\beta}(X) \leq CVaR_{1-\alpha}(X) \leq EVaR_{1-\alpha}(X)$,

Where;

$VaR_{1-\alpha}(X) := inf_{t \in R}\{ t: P_r(x \leq t) \geq 1- \alpha\}$,

$CVaR_{1-\alpha}(X) := \frac{1}{\alpha}\int_0^{\alpha} VaR_{1-\gamma}(X)\ d_{\gamma}$,

$RVaR_{\alpha,\beta}(X) := \frac{1}{\beta-\alpha}\int_{\alpha}^{\beta} VaR_{1-\gamma}(X)\ d_{\gamma}$,

$EVaR_{1-\alpha}(X) := inf_{Z>0}\{ Z^{-1}\ \ln( M_X(Z)/\alpha)\}$,

To manage uncertainty, a C-VR analysis was applied for analysis of the model. It is assumed that a risk-neutral decision maker optimizes expected values of almost all objectives.

Although disruptions are infrequent, the expectable value is not the best optimization option. Thus, Minimization of maximum damage to a system in the face of disruptions seems to be the most effective option. In the face of the worst-case scenario, this approach could be a serious obstacle for the supply chain network. In such a case, the decision maker is likely to take risks and may give priority to other optimization procedures such as robust optimization, value at risk (VAR), conditional value at risk (C-VR) and the worst value of the objective function.

In the present study, the model which is used to control supply risk in portfolio management is analyzed using value at risk (VAR) and conditional value at risk (C-VR) in the process of financial engineering. Usually, two-stage random models are large models that require a solution method, but in this model, considering a limited number of scenarios, the model was run in a couple of minutes.

In this mathematical model, attempts are made to minimize the anticipated costs in a risk-neutral environment, but the decision maker neutralizes an unbridled risk at the worst expected cost.

For example, in %100(1-α), the output scenario may be the value (VAR) expected where α∈ (0,1) is predetermined at a reliable and probabilistic level. (C-VR) refers to a conservative measure taken in the face of the risk imposed by an investment on less profitable products. Conditional value at risk a (a- C-VR) refers to the minimum expected amount of costs in the worstcase cases 100% (1-α).

Using the confidence level α, one can easily control the risk of losses incurred by chain disruptions. Suppose that a decision maker intends to approve only portfolios where the likelihood of scenarios with costs greater than (VAR) doesn't exceed (1-a). The level of confidence besides determines the risk mode. Its greater value indicates the greater risk against the decision maker. The equivalent of the opposite risk model is presented after introducing two non-negative variables ($z_s$, Γ) and an additional constraint. The cost of follow $z_s$ is defined as a value whose costs are greater than that in the s. The performance of the objective function is to minimize the cost of the worst mode scenario and order allocation problem. Equation (21) is a risk Equation that measures the extent to which the cost of following $z_s$ in the scenario s is greater than that of Γ. Thus, the inclusion of the conditional value at risk makes it possible to consider the risk of the decision maker in the model.

$$Min - C - var = \Gamma + (1-\alpha)^{-1}\sum_s \pi_s . Z_s \qquad 21$$

$$\sum_i \sum_t G_i . y_{i,t} + \sum_r \sum_i \sum_t PIU_{r,i,t} . x_{r,i,t} + \sum_j \sum_t A_j . b_{j,t} + \sum_i \sum_u \sum_t re_{i,u} . \gamma_{i,t}^u + \sum_i \sum_l \sum_t \omega_{i,l} . \lambda_{i,t}^l + \sum_s \pi_s . ( \sum_r \sum_j \sum_t PIRR_{r,j,t} . h_{r,j,t,s} + \sum_r \sum_t HCI_{p,t} . II_{r,t,s} + \sum_p \sum_t HCP_{p,t} . IP_{p,t,s} + \sum_p \sum_t BP_{p,s} . B_{p,t,s} + \sum_p \Phi_{p,s} . B_{p,T,s} + \sum_p \sum_t RPC_{p,t} . PR_{p,t,s} - \Gamma \le Z_s \tag{22}$$

## 4. Analysis of results

### 4.1. Analysis based on different experiments

The proposed plan is introduced for a nut and bolt factory located in Iran (Semnan). The company is considered one of the leading companies in Iran in the field of manufacturing industrial bolts and nuts, including the automotive industry, construction and bridges and buildings. Raw materials are supplied from several reliable and unreliable suppliers. For the purpose of data collection, several meetings were penciled in with employees of the company with different ranks, which creates commitment contracts of the board of directors during the data collection process needed to test problems in which there are 5 primary suppliers and one backup supplier. Suppose that there is a negative correlation between the purchase price and the likelihood of disruption in a supplier system.
The purchase price plus the cost of contract concluded for the most reliable supplier, incur the highest costs.
The most trustworthy supplier that is least significantly affected by disruptions is recognized as supplier 1.
While, the supplier with the most disruption is considered as the supplier 5.
The following 4 parameters are considered by increasing the supplier index number increasingly or decreasingly.

$$\psi_1^s \ge \psi_2^s \ge \cdots \ge \psi_5^s, \quad \forall s \tag{23}$$

$$G_1 \ge G_2 \ge \cdots \ge G_5, \quad \forall i \tag{24}$$

$$PIU_{r,1,t} \ge PIU_{r,2,t} \ge \cdots \ge PIU_{r,5,t}, \quad \forall r, i, t \tag{25}$$

$$\rho_1 \le \rho_2 \le \cdots \le \rho_5, \quad \forall i \tag{26}$$

Price changes and percentage changes in the remaining capacity of the disruption for the 5 suppliers are listed in Table 2 as follows:

**Table 2**. Price changes and changes in the percentage of remaining capacity of the disruption

| Percentage of remaining capacity of the disruption | Price | Index number |
|---|---|---|
| 0.80-0.75 | 200-180 | 1 |
| 0.74-0.70 | 150-175 | 2 |
| 0.69-0.60 | 145-130 | 3 |
| 0.59-0.55 | 130-115 | 4 |
| 0.54-0.50 | 115-100 | 5 |

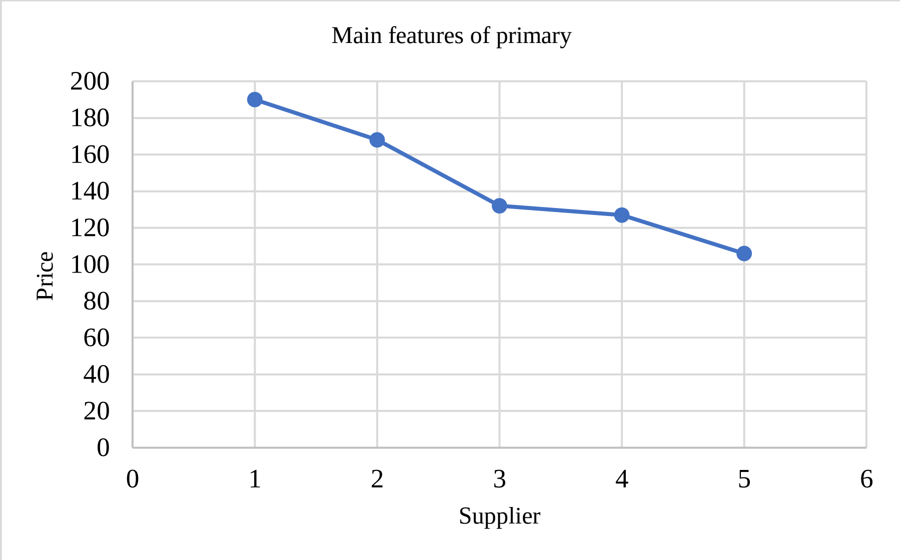


**Figure 1**. Increase in price based on the number of suppliers

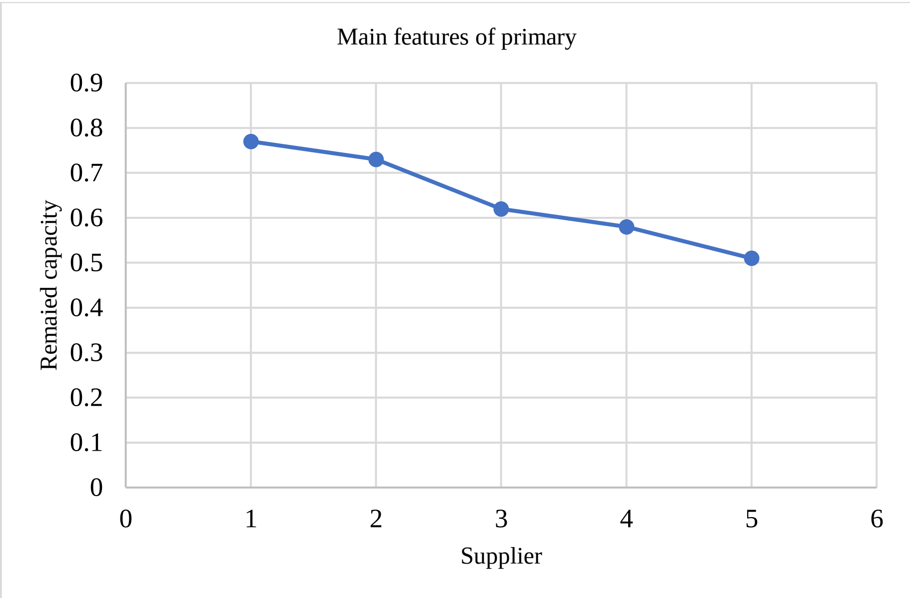


**Figure 2.** Increase in the percentage of capacity remaining from the disruption based on the number of suppliers

### 4.2. Analysis of optimal solutions of model for multi-source strategy by considering disruptions

The value of C-VR increases with any rise in confidence level α. α is a measure of risk confrontation and incompatibility, and any rise in this measure triggers risks with greater incompatibility. As the risk against the decision maker increases, the total cost indicated by (C-VR) increases. Because, the decision maker concentrates selecting suppliers by decreasing the likelihood of financial loss or the worst-case scenario. Also, according to this strategy, decision-maker will focus more on supply diversity through the selection of more suppliers in terms of risk-taking. In this model, the decision maker is assumed to be able to select not more than two primary suppliers and a secondary supplier in each period. Due to the reduction in 1- order of ordering the supplier 2- residual capacity of the disruption 3-contract costs with suppliers, at most α levels, suppliers will be selected at lower prices and lower management costs. With respect to the existing disruption and the assumption of the maximum of two suppliers in each of α , the two suppliers are selected in each period .As the level of risk-neutral reduces, the decision maker will sometimes assign his/her order to the cheapest supplier in case of highest rate of disruption. In this situation, buyers increase their level of reliability in the face of disruptions by investing in a recovery and warning strategy. Due to the recovery and alert levels in the facilities of the primary suppliers, a percentage of their lost capacity will be recovered and a percentage of the orders is allocated to the supporting suppliers to prevent the imbalance between supply and demand due to the costs of the contract and the purchase and recovery. Given that it is possible to conclude a contract between suppliers with backup suppliers with unlimited capacity and on the other hand there is the ability to recover by receiving an alarm the order will be fulfilled according to all available capacity for raw materials at different levels of disruption. Suppliers with cheaper prices and lower capability will be selected even at higher α. In larger disruptions, suppliers with slightly higher prices and higher reliability are more likely to be selected.

The results of low-level disruptions in primary suppliers are listed in Table 3:

**Table 3.** Lower disruptions in the primary suppliers

| Service level | C-VR | VAR | Confidence level (a) |
|---|---|---|---|
| 0.949 | 287121945 | 0 | 0 |
| 1 | 287154820 | 287167800 | 0.25 |
| 1 | 287167800 | 287167800 | 0.5 |
| 1 | 287167800 | 287167800 | 0.75 |
| 1 | 287167800 | 287167800 | 0.95 |
| 1 | 287167800 | 287167800 | 0.99 |

**Table 4**. Comparison of primary and secondary suppliers by considering lower disruptions

| supplier selected in C-VR Secondary with fewer disruptions | | | supplier selected in C-VR Primary with fewer disruptions | | | Level Confidence (α) |
|---|---|---|---|---|---|---|
| Period 3 | Period 2 | Period 1 | Period 3 | Period 2 | Period 1 | |
| 2 | 1 | 3 | 5<br>U4/L3 | 5<br>U4/L3 | 5<br>U4/L3 | 0 |
| 1 | 1 | 1 | 5<br>U4/L3 | 5<br>U4/L3 | 5<br>U4/L3 | 0.25 |
| 1 | 1 | 1 | 5<br>U4/L3 | 5<br>U4/L3 | 5<br>U4/L3 | 0.5 |
| 1 | 1 | 1 | 5<br>U4/L3 | 5<br>U4/L3 | 5<br>U4/L3 | 0.75 |
| 1 | 1 | 1 | 5<br>U4/L3 | 5<br>U4/L3 | 5<br>U4/L3 | 0.95 |
| 1 | 1 | 1 | 5 | 5 | 5 | 0.99 |

As shown in Table 4, at high-level disruptions, the most expensive and with the least disruptions are selected up to α less than 80%. At α greater than 90%, supplier 3 is selected from the primary suppliers. The results of high-level disruptions in primary suppliers are listed in Table 5:

**Table 5**. High-level disruptions in primary suppliers

| Service level | C-VR | VAR | Confidence Level ( α ) |
|---|---|---|---|
| 0.938 | 287725289 | 287654761 | 0 |
| 0.938 | 287816250 | 287654761 | 0.25 |
| 0.964 | 287898325 | 287655761 | 0.5 |
| 0.964 | 287912354 | 287655761 | 0.75 |
| 0.995 | 287968971 | 287968971 | 0.95 |
| 0.999 | 28768971 | 287968971 | 0.99 |

**Table 6.** Comparison of primary and secondary by considering larger disruptions

| supplier selected in C-VR Secondary with fewer disruptions | | | supplier selected in C-VR Primary with fewer disruptions | | | Level Confidence (α) |
|---|---|---|---|---|---|---|
| Period 3 | Period 2 | Period 1 | Period 3 | Period 2 | Period 1 | |
| 1 | 2 | 2 | 1<br>U3 | 1<br>U3 | 1<br>U3 | 0 |
| 1 | 2 | 2 | 1<br>U3 | 1<br>U3 | 1<br>U3 | 0.25 |
| 1 | 2 | 2 | 1<br>U2/L2 | 1<br>U2/L2 | 1<br>U2/L2 | 0.5 |
| 2 | 1 | 2 | 1<br>U2/L2 | 1<br>U2/L2 | 1<br>U2/L2 | 0.75 |
| 2 | 2 | 1 | 3<br>U4/L3 | 3<br>U4/L3 | 3<br>U4/L3 | 0.95 |
| 3 | 3 | 3 | 3 | 3 | 3 | 0.99 |

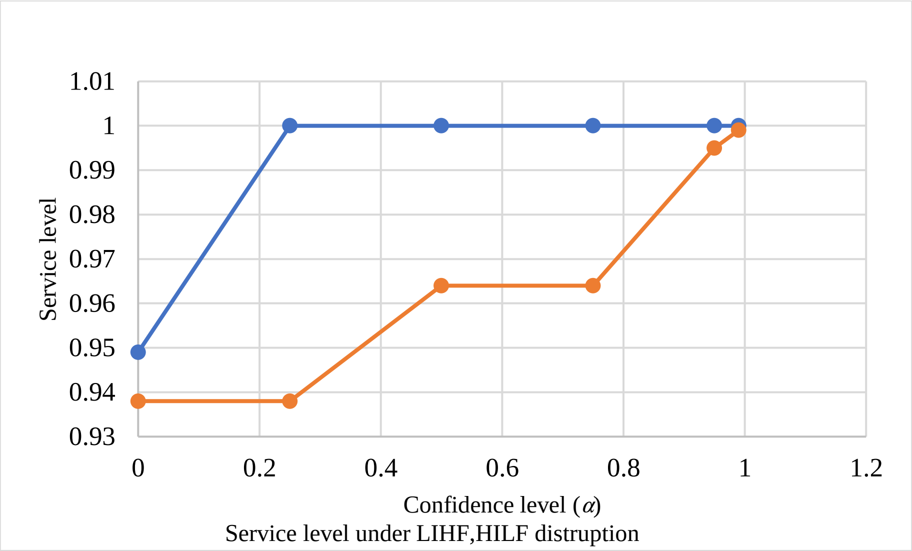


**Figure 3**. Service level versus confidence level

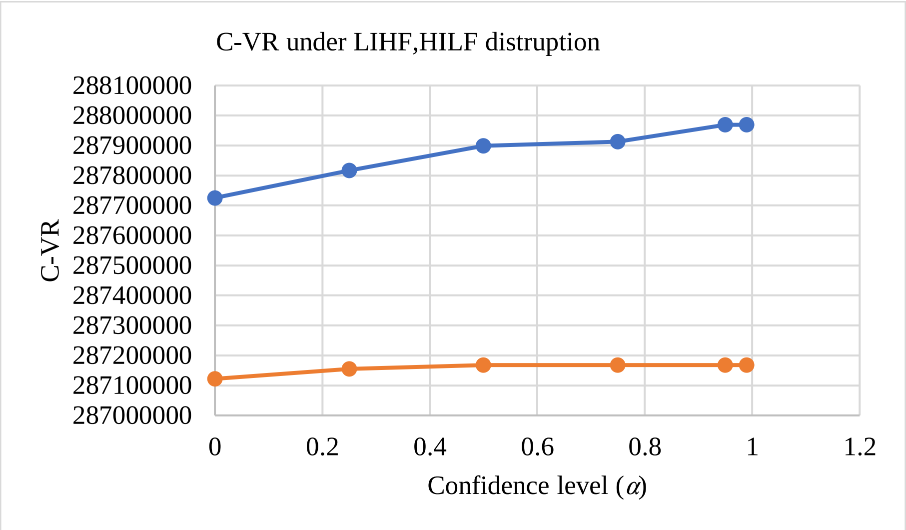


**Figure 4**. C-VR versus confidence level

**Table 7**. The effect of demand variations on the amount of objective function and unfulfilled orders

| The amount of back order | the amount of C-VR | the amount of VAR | Demand changes |
|---|---|---|---|
| 37685 | 324441000 | 324441000 | 1500-2000 |
| 49086 | 415064500 | 415064500 | 2000-2500 |
| 58712 | 505688000 | 505688000 | 2500-3000 |
| 72667 | 596311600 | 596311600 | 3000-3500 |
| 49685 | 686935100 | 686935100 | 3500-4000 |

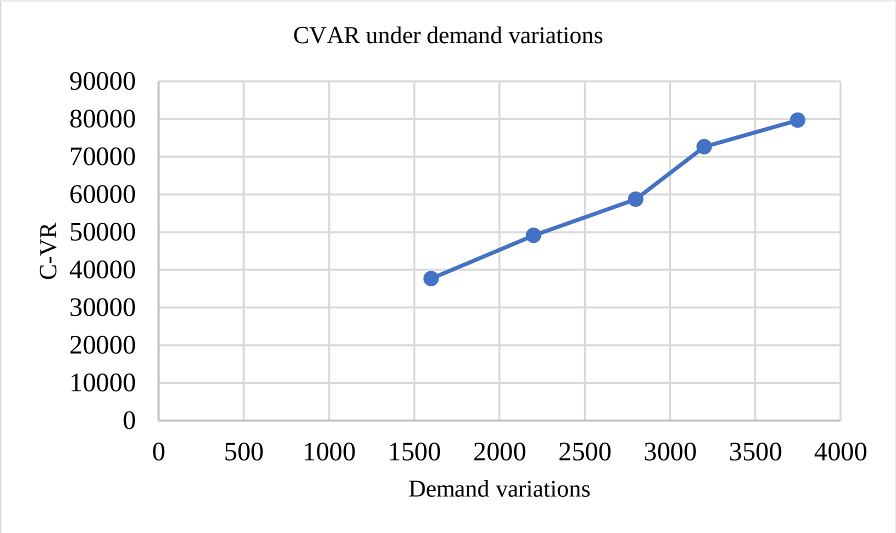


**Figure 5**. C-VR versus demand variations

As shown in Figure 5, as demand increases, the values of VAR and C-VR increase at a decreasing rate. Costs, including lost sales penalties, will increase significantly, as demand increases and suppliers' capacity remains constant. Disruption in capacity and different scenarios have a significant effect on all incremental intervals of VAR and C-VR values.

Table 8 shows the effect of primary supplier capacity variations for raw material production on the target values to reduce costs based on VAR and C-VR with α = 99%:

**Table 8.** The effect of primary supplier capacity variations to produce raw material on the target values to reduce costs based on VAR and C-VR with α = 99%

| the amount of C-VR | the amount of VAR | Changes in primary supplier capacity |
|---|---|---|
| 287167800 | 287167800 | 1000-2000 |
| 286738300 | 286738300 | 2500-3000 |
| 286130500 | 286130500 | 3500-4000 |
| 285882700 | 285882700 | 4500-5000 |
| 285668800 | 285668800 | 5000-5500 |

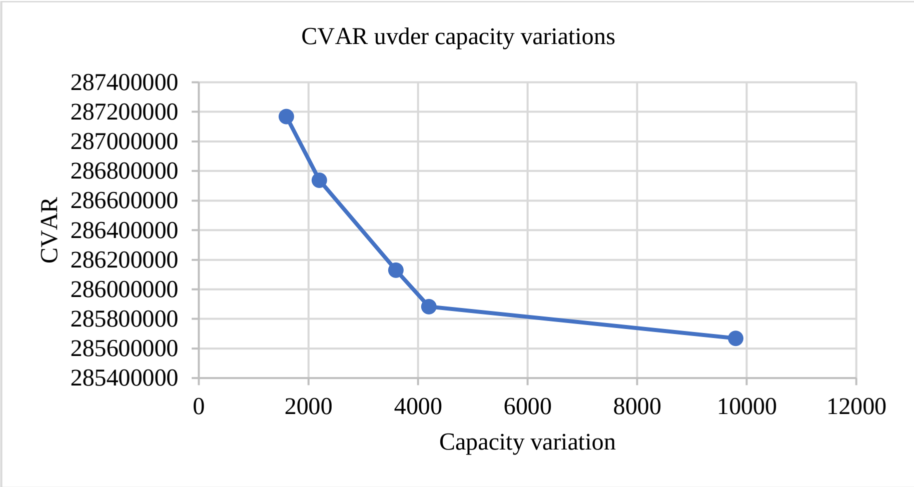


**Figure 6**. C-VR versus capacity variations

As shown in Figure 6, the values of VAR and C-VR decrease with increasing primary supply capacity. As the primary supplier capacity increases, the costs, including lost sales penalties reduces. The effect of the disruption on the capacity of primary suppliers will be reduced. Table 9 indicate of VAR and C-VR values based on increasing number of suppliers:

**Table 9.** The values of VAR and CVAR by increasing the number of suppliers

| Backup supplier selected | | | Primary supplier selected | | | CVAR | VAR | Level Confidence (α) I = 7 J = 4 |
|---|---|---|---|---|---|---|---|---|
| Period 3 | Period 2 | Period 1 | Period 3 | Period 2 | Period 1 | | | |
| 2 | 2 | 2 | 5<br>U2/L1 | 5<br>U2/L1 | 5<br>U2/L1 | 252841754 | 0 | 0 |
| 2 | 2 | 2 | 5<br>U2/L1 | 5<br>U2/L1 | 5<br>U2/L1 | 252843800 | 252843800 | 0.25 |
| 2 | 2 | 2 | 5<br>U2/L1 | 5<br>U2/L1 | 5<br>U2/L1 | 252843800 | 252843800 | 0.5 |
| 2 | 2 | 2 | 5<br>U2/L1 | 5<br>U2/L1 | 5<br>U2/L1 | 252843800 | 252843800 | 0.75 |
| 2 | 2 | 2 | 5<br>U2/L1 | 5<br>U2/L1 | 5<br>U2/L1 | 252843800 | 252843800 | 0.95 |
| 2 | 2 | 2 | 5 | 5 | 5 | 252843800 | 252843800 | 0.99 |

**Table 10**. The values of VAR and CVAR by considering primary supplier and backup supplier

| Backup supplier selected | | | Primary supplier selected | | | C-VR | VAR | Level Confidence (α) I = 7 J = 4 |
|---|---|---|---|---|---|---|---|---|
| Period 3 | Period 2 | Period 1 | Period 3 | Period 2 | Period 1 | | | |
| 5 | 5 | 7 | 9<br>U1/L1 | 9<br>U1/L1 | 9<br>U1/L1 | 277966980 | 0 | 0 |
| 5 | 5 | 7 | 9<br>U1/L1 | 9<br>U1/L1 | 9<br>U1/L1 | 277968500 | 277968500 | 0.25 |
| 5 | 5 | 7 | 9<br>U1/L1 | 9<br>U1/L1 | 9<br>U1/L1 | 277968500 | 277968500 | 0.5 |
| 5 | 5 | 7 | 9<br>U1/L1 | 9<br>U1/L1 | 9<br>U1/L1 | 277968500 | 277968500 | 0.75 |
| 5 | 5 | 7 | 9<br>U1/L1 | 9<br>U1/L1 | 9<br>U1/L1 | 277968500 | 277968500 | 0.95 |
| 5 | 5 | 7 | 9<br>U1/L1 | 9<br>U1/L1 | 9<br>U1/L1 | 277968500 | 277968500 | 0.99 |

As shown in Table 10, it is assumed that there are ten primary suppliers and seven backup suppliers. The primary supplier has constant values at different confidence levels over different periods, when the values for the backup supplier are different under the same conditions.

**Table 11.** Table provision of selected primary and provisioning of backup selection

| Primary supplier selected | | | C-VR | | | VAR | Level Confidence (α) I = 7 J = 4 | Level Confidence (A ) I = 14 J = 10 |
|---|---|---|---|---|---|---|---|---|
| Period 3 | Period 2 | Period 1 | Period 3 | Period 2 | Period 1 | | | |
| 10 | 9 | 1 | 10 U4/ L2 | 10 U4/ L2 | 10 U4/ L2 | 298166821 | 0 | 0 |
| 10 | 9 | 1 | 10 U4/ L2 | 10 U4/ L2 | 10 U4/ L2 | 298167600 | 264805900 | 0.25 |
| 10 | 9 | 1 | 10 U4/ L2 | 10 U4/ L2 | 10 U4/ L2 | 298167600 | 264805900 | 0. 5 |
| 10 | 9 | 1 | 10 U4/ L2 | 10 U4/ L2 | 10 U4/ L2 | 298167600 | 264805900 | 0.75 |
| 10 | 9 | 1 | 10 U4/ L2 | 10 U4/ L2 | 10 U4/ L2 | 298167600 | 264805900 | 0.95 |
| 10 | 9 | 1 | 10 U4/ L2 | 10 U4/ L2 | 10 U4/ L2 | 298167600 | 264805900 | 0.99 |

We consider fourteen primary suppliers and ten backup suppliers. The selected primary supplier with different reliability levels during different periods takes constant values of VAR contingent upon the supporting supplier has variable values of VAR with the same values of confidence levels during different periods.

## 5. Managerial insights and conclusion

In the present study attempts are made to investigate a multi-product multi-item environment in which the final product is manufactured by several items. Decision-making is carried out within the framework of a two-stage stochastic programming model in which items are released to unreliable suppliers during the first stage and within a specific time interval and the original plan to manufacturer end product is determined, while emergency decisions are made, including emergency order and emergency production plan in the second stage.
Also, the present study presents strategies to create flexible supply bases that minimize the cost of the worst scenario in the face of supply chain risks. VAR and C-VR techniques are used. These techniques are centralized to guide supply chain risk management. The hybrid stochastic optimization problem is developed as a mixed-integer programming with C-VR as a risk criterion. A scenario-based method calculates potential disruption scenarios. VAR and C-VR values increase, as the number of primary and backup suppliers increase. In the present study attempts were made to further delve into disruption planning and minimize disruptions to gain a profounder comprehension of the relationship between flexibility and supply chain characteristics. The results of this research can help supply chain managers to redesign the order allocation process and select their traditional supplier and match the dynamic industry dynamics. The proposed framework can be used as a decision - making tool by the business organization that can help supply chain managers to evaluate the suppliers' options to technological capabilities as well as their ability to ensure business continuity from disasters. Research findings indicate that the supplier segmentation and prioritization process in this paper will help business organizations to proactively design a set of reliable suppliers who minimize the risk of supplier and thereby reduce the impact of disruptions in disaster occurrence. In addition, the number of suppliers must be kept constant within acceptable limits to prevent a sharp increase in the number of suppliers. Suppliers should release orders in time by setting up time windows and setting deadlines to receive orders. Also, this study shows that by increasing the initial supply capacity, VAR and C - VR values decrease and by increasing the initial supply capacity, the costs decrease to about 99 % which reduces the initial degradation effect on capacity. In the end, for future papers, it is suggested that emergency orders with disruption be checked by applying other restrictions, such as limiting the number of goods and receiving orders from the supplier and the number of items. It is suggested to use methods other than C-VR for risk assessment. And the impact of the disorder in this context should be investigated.

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