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ORIGINAL RESEARCH PAPER

Green-Resilient Supplier Selection and Order Allocation Under Disruption by Utilizing Conditional Value at Risk: Mixed Response Strategies

Seyed Mojtaba Taghavi[1] · **Vahidreza Ghezavati**[1] · **Hadi Mohammadi Bidhandi**[1] · **Seyed Mohammad Javad Mirzapour Al-e-Hashem**[2]

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Abstract

Two important decisions in supply chains and logistics systems design are the supplier selection and order allocation (SS&OA) problem and the vehicle routing problem (VRP). Supply disruption may reduce the capacity of suppliers, and the transportation network disruption may decrease the number of vehicles in the fleet and disrupt some routes. Also, increasing environmental regulations and environmental awareness makes companies pay more attention to green supply chain management (GSCM). In this paper, we integrate green and resilient supplier selection and order allocation decisions with vehicle routing decisions under disruption. We present a multiproduct two-stage risk-averse mixed-integer stochastic linear programming for the green and resilient supplier selection and order allocation integrated with vehicle routing (G&RSS&OA-V) problem. We consider resilient strategies before disruption, including multiple sourcing, supplier fortification, prepositioned inventory at the protected supplier, and contract with third-party logistics providers (3PLs). The objective function is to minimize the total mean-risk cost and the cost of greenhouse emissions. We use conditional value at risk (CVaR) as a risk measure to control the risk of worst-case cost. The most significant decisions of this model are the strategic decisions of determining the optimal suppliers and the operational decisions of vehicles routing under disruption simultaneously. Other decisions include determining which suppliers should be fortified, the amount to be transported to the hybrid manufacturing-distribution (HMD) center through the supplier or prepositioned emergency inventory, and the amount of lost sales. In order to validate the proposed model and its features, several numerical examples along with sensitivity analysis are performed by GAMS software, which shows the efficiency and application of the developed model, and some managerial insights are reported. The results of the sensitivity analysis show that as α increases from 0.1 to 0.9, the mean-CVaR objective function cost increases to 13.2%. As λ increases from 0.1 to 0.9, the mean-CVaR objective function cost increases to 35.6%. The increase of these two risk factors makes the proposed model more risk-averse. As the expected shortage cost increases by 150%, the mean-CVaR objective function cost increases to 36% while the amount of expected shortage decreases by 56%.

Keywords Supplier selection/order allocation problem · Vehicle routing problem · Green paradigm and greenhouse emissions · Fuel consumption · Two-stage stochastic programming · Disruption risk and resilience

Introduction

Natural disasters such as floods, earthquakes, and hurricanes and intentional/unintentional human actions such as strikes, fires, terrorist attacks, and epidemic/pandemic outbreaks are some of the disruptions that may occur in the supply chain (Aldrighetti et al. 2021; Azimian et al. 2021). The effects of these major disruptions include the incomplete implementation of companies' production plans; delays in purchase orders; lost sales; inventory shortage; high supply, production, and transportation costs; disruption of the transport fleet; and disruption of routs. Following the outbreak of the coronavirus in 2020, many factories around the world shut down. The shutdowns had a major impact on the global supply chains. Some major automakers faced the threat of a shortage of parts. There were also concerns about supplies of Apple products as the disruptions continue.

✉ Vahidreza Ghezavati
V_ghezavati@azad.ac.ir; vrghezavati@gmail.com

[1] Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran

[2] Department of Industrial Engineering and Management Systems, Amirkabir University of Technology, Tehran, Iran

In today's competitive market, companies are looking to outsource the elements needed in their production planning. Therefore, the supplier selection and order allocation (SS&OA) play an essential role in supply chain management. The supplier selection problem is one of the strategic decisions that will be made in the long term. The SS&OA problem is vulnerable to supply disruption, which leads to a reduction or loss of supplier capacity, and among its effects are delays in customer orders and a lack of inventory. Various resilience strategies have been used to deal with these disruptions. Supply chain resilience is the ability of a network to withstand disruptions, adaptation, and recovery until customer demand is met and performance is guaranteed (Hosseini et al. 2019a, b). Multiple sourcing strategies, backup supplier, supplier recovery, supplier fortification, and prepositioned inventory have been reported as effective risk mitigation strategies in the resilient supply chain (Wang et al. 2022; Wofuru-Nyenkeet al. 2022; Esmaeili-Najafabadi et al. 2021).

The vehicle routing problem (VRP) is one of the operational decisions that will be made in the short term. The purpose of the VRP problem is to find the optimal set of routes for the vehicle fleet from one warehouse to a specific set of customers to meet customer demand with the objective function of minimizing the total cost of transportation, fixed cost of vehicles, and other related costs (Hamidi Moghaddam et al. 2021). In most vehicle routing problems, all transport routes and vehicles are always available and serving customers. However, once a disruption occurs, the transportation network may lose the capacity of the vehicle fleet or a number of routes may be inactive due to route disruptions, roadwork, quarantine for COVID-19, and heavy traffic. Transportation mitigation strategies can include contracting with 3PLs, backup vehicles, and various modes of transportation.

Environmental concerns have led to the enactment of laws and regulations by the government and international institutions. Therefore, companies are required to pay attention to environmental issues when configuring their supply chain network. For example, the use of up-to-date production technologies and transportation modes is one of the most effective ways to reduce environmental damage, which leads to lower greenhouse gas emissions, fuel consumption, and pollution, but at a higher cost (Tahmasebi Zadeh and Boyer 2021). The green paradigm protects the environment by minimizing the environmental wastes/pollution through the purchase of green materials from suppliers and green production using less-pollutant technologies (Panpatilet al. 2022). As a result of this increase in global awareness and government legislation on environmental impacts, it is necessary to integrate environmental issues into the SS&OA problem and VRP. In the green SS&OA problem and green VRP, we seek to reduce greenhouse gas (GHG) emissions in suppliers and reduce fuel consumption in the delivery of goods to customers by vehicles.

Traditionally, strategic decisions are made for the SS&OA problem and then operational decisions for the VRP. That is, first the major suppliers and order allocation are identified, and then routing decisions are made. While in the real world, both decisions are made simultaneously. Proactive optimization models under disruptions and developing resilient supply chain network designs can help supply chains and markets survive (Aldrighetti et al. 2021). Also, one of the topics of interest today is green supply chain management issues and environmental concerns. Thus, this paper presents the strategic and operational decision-making in a risk-averse, multiproduct green and resilient supplier selection and order allocation integrated with vehicle routing (G&RSS&OA-V) problem under supplier capacity, transport fleet, and route disruptions (David et al. 2022). Resilient strategies are adopted before disruption. We adopt multiple sourcing, fortification, and prepositioned inventory strategies under supply disruption. We also consider a 3PL contracting strategy to provide transportation services under the disruption of the transport fleet and route. Hence, we propose a new two-stage stochastic programming model for the risk-averse decision-maker with the mean-risk objective function. We use CVaR as a risk measure in optimizing the objective function, which seeks to minimize the worst-case scenario.

The structure of this paper is as follows. The "Literature Review" section prepares a review of the related literature. The green and resilient supplier selection and order allocation integrated with vehicle routing (G&RSS&OA-V) problem under disruption with formulation, assumptions, and limitations is elaborated in the "Model Description" section. The "Computational Analysis and Examples" section presents a computational experiment and sensitivity analysis. Finally, the "Conclusion" section states the conclusions and future research of this paper.

Literature Review

In this article, we aim to combine supply and transportation (vehicles and routs) disruption risk in the G&RSS&OA-V problem. Hence, in the following, the related literature is reviewed in the two research streams: supplier selection and order allocation under disruption and vehicle routing problem under disruption. In the scope of our review, we have ignored articles that only address the SS&OA and VRP without disruption.

Supplier Selection and Order Allocation Under Disruption

The SS&OA problem is a complex, multicriteria decision problem that deals with selecting the best suppliers and assigning orders to the suppliers. Sawik (2011) presented a risk-averse selection of supply portfolio in a make-to-order manufacturing strategy under disruption risks by using CVaR. Sawik (2013) proposed a risk-neutral, risk-averse, and mean-risk resilient supply portfolio under disruption with CVaR metric to control the risk of worst-case cost. Naqvi and Amin (2021) reviewed the supplier selection and order allocation problem in three categories: literature reviews, deterministic optimization models, and uncertain optimization models.

Torabi et al. (2015) designed the resilient supplier selection and order allocation problem in response to uncertainties caused by major disruptions and operational risks of supply. They used a biobjective two-stage mixed possibilistic, stochastic programming model to minimize total expected cost and maximize a resilience objective. They also considered proactive strategies such as suppliers' business continuity plans and fortifying suppliers. Esmaeili-Najafabadi et al. (2019) studied a joint supplier selection and order allocation problem under disruption risks. They developed a mixed-integer nonlinear programming model to minimize costs of centralized multiproduct supply chains and used two proactive strategies to reduce interruptions, including supplier protection and propositioned emergency inventory policy. Fattahi et al. (2020) developed a mixed-integer two-stage stochastic nonlinear programming in supply chain network design under a disrupted distribution center. They set a new measure of supply chain resilience as the expected amount of the supply chain's operational cost increase due to a disruption event during its recovery period. They reformulated a mixed-integer nonlinear programming model into a conic quadratic mixed-integer program that can be solved by commercial solvers such as CPLEX. They used the sample average approximation method to manage the large number of disruption scenarios and also examined the criterion of risk-based resilience using CVaR.

Kaur and Singh (2021) presented a multiperiod, multiproduct hybrid supplier selection and order allocation model under supply disruption risks and disruptive technologies. Suppliers are divided into efficient and inefficient suppliers using the DEA method, and efficient suppliers are evaluated and ranked using the FAHP-TOPSIS method, and then the risk of noncompliance of each supplier is calculated by TOPSIS. Finally, mixed-integer programming is applied to minimize the total cost of logistics and the associated disruption risk. Esmaeili-Najafabadi et al. (2021) proposed a mixed-integer nonlinear programming model for risk-averse supplier selection and order allocation in the centralized supply chains under local and regional disruption risks. They categorized the suppliers into domestic suppliers and foreign suppliers. Finally, they used value-at-risk (VaR) and conditional value-at-risk (CVaR) to analyze the risk aversion model. Chen et al. (2022) proposed a mixed-integer linear programming model multiperiod and multistage supply chain under supply disruption during COVID-19. They used product design change considering product life cycle and design change time as a proactive strategy.

Fahimnia and Jabbarzadeh (2016) integrated supply chain sustainability and resilience and developed a sustainability performance scoring method. They designed a stochastic multiobjective fuzzy goal programming model under supply disruption. Hamdan and Cheaitou (2017) suggested a dynamic green supplier selection and order allocation with quantitative discounts and different supplier availability between planning periods. First, the decision-makers used fuzzy TOPSIS to assign two preferred suppliers' weights based on traditional and green. Second, top management used AHP to determine the weight of importance to each of the two criteria. Third, they used a biobjective integer linear programming model with all-unit quantity discounts to maximize order quantity to suppliers and minimize the total cost. Zahiri et al. (2017) proposed a multiobjective fuzzy possibilistic-stochastic programming model for a sustainable and resilient supply chain under uncertainty. Vahidi et al. (2018) proposed a sustainable and resilient SS&OA problem under operational and disruption risks. The first objective function has been developed to maximize the sustainability and resilience aspects of selected suppliers, and the second objective function aims to minimize the total expected cost of the biobjective two-stage possibilistic-stochastic programming model.

Ghomi-Avili et al. (2021) studied inventory-pricing decisions in a competitive green supply chain network design problem under supplier and distribution center disruptions. They introduced a robust bilevel model integrated by conditional value at risk (CVaR) to maximize the total profit and reduce the CO_2 emissions. They also used the Stackelberg game to model the competition and to show the customer response in a price-dependent demand environment with fuzzy coefficients for each supply chain. In their model, they used the strategy of contracting with reliable suppliers to mitigate supply disruption and the sharing strategy to reduce distribution center disruption risks. Yavari and Zaker (2020) presented biobjective linear programming in a resilient green closed-loop supply chain network for perishable products under supply and power network disruption. Their first goal is to minimize the total network costs, and their second goal is to minimize the total network carbon emissions. In order to deal with disruptions, they used intermediate facilities, lateral transshipment, emergency inventory, capacity expansion, and integrating interdependent networks as resilient strategies. Tirkolaee et al. (2020) designed a hybrid fuzzy decision-making and sustainable-reliable SS&OA model. They used the weighted goal programming method with three objective functions to minimize the total cost, maximize the weighted value of products, and to maximize the reliability of the supply chain.

Nayeri et al. (2021) proposed a multiobjective fuzzy robust stochastic model for a sustainable-resilient-responsive supply chain network under supply, manufacturer, and distribution center disruption. The purpose of their model is to minimize total costs and environmental damages while maximizing social impacts, responsiveness, and resilience levels. They used node criticality and node complexity as resilience measures. Hasani et al. (2021) proposed a robust green and resilient multiobjective supply chain optimization model under disruption for the global medical equipment manufacturing system. The first goal is to maximize the total profit. The second goal is to minimize the centralization facilities. The third goal is to minimize the CO_2 emissions from material transport between facilities. They used four mitigation strategies such as facility fortification, facility dispersion, semifinished products, and multiple sourcing. Yavari and Ajalli (2021) designed a biobjective mixed-integer linear programming model for a green resilient supply chain network under disruption risks to minimize total cost and carbon emissions. In order to deal with disruptions, they applied coalition between suppliers, multiple sourcing, emergency inventory, and capacity expansion.

Vehicle Routing Problem Under Disruption

The VRP inherently provides significant savings in transportation costs. The green VRP (GVRP) is also an attractive research field that is of interest to many researchers. Lin et al. (2014) reviewed GVRP models in energy consumption, greenhouse gas emissions, and reverse logistics and classified them to green VRP, pollution routing problem, and VRP in reverse logistics. Moghdani et al. (2021) systematically reviewed GVRP in its variants, objective functions, uncertainty, and solution approach.

Ahmadi-Javid and Seddighi (2013) designed a location-routing problem under disruption. The capacity of each producer–distributor and the vehicles are vulnerable. They applied the mixed-integer linear programming model to minimize the total cost under three risk-measurement policies: moderate, cautious, and pessimistic. Nasiri et al. (2018) proposed an integrated supplier selection and order allocation problem with vehicle routing and in multi-cross-dock supply chain in order to make a suitable trade-off between cost and responsiveness. They used mixed-integer linear programming to minimize the objective function including purchase, shipping, cross-docking, holding, and early/tardy delivery penalty costs.

Yavari et al. (2020) presented a location-inventory-routing problem for perishable products under route disruptions. They integrated the location-inventory-routing problem by price-sensitive demand, a product with a certain lifetime, and disruption in routes. They used a mixed-integer nonlinear programming model to maximize the profits of their entire network. Zhong et al. (2020) introduced a risk-averse, biobjective mixed-integer nonlinear programming model for disaster relief facility location and vehicle routing under stochastic demand. Their model included conditional value at risk with regret (CVaR-R) as a risk measure. They proposed two goals including CVaR-R of the waiting time and the CVaR-R of the network cost. Finally, they solved the proposed model by the hybrid genetic algorithm. Dehghan et al. (2021) proposed a scenario-based mixed-integer linear programming model for the capacitated location routing problem with simultaneous pickup and delivery under disrupted depots to minimize the expected cost of the fixed location, unfulfilled demand, and variable routing costs. They used three tailored metaheuristic algorithms to solve the proposed model.

Disruption risks cause customers not to receive their goods or services at scheduled times in a VRP problem. This causes dissatisfaction and loss of customers and over time causes significant financial losses to the transportation network. Therefore, it is absolutely necessary to consider a reliable VRP in the transportation network. Zhang et al. (2015) developed a reliable location-routing problem under depot disruption risks. They also designed a two-stage scenario-based mixed-integer programming model for the location-routing problem with the goal of minimizing costs. Then, they develop an efficient metaheuristic method to solve their proposed problem. Xie et al. (2016) formulated a reliable location-routing problem under depot disruption. Disruption in the depot makes it impossible to send the vehicle. Therefore, customers in that depot must be serviced by additional vehicles from other backup depots. Finally, they applied integer linear programming to minimize the fixed setup cost of depots, transportation cost, and the cost of penalties for missing services.

Rayat et al. (2017) presented a reliable multiperiod, multiproduct location-inventory-routing problem under disruption. They used a biobjective mixed-integer nonlinear programming model to minimize the first objective function, including the total locating, routing, and inventory costs. Their model also minimized the second objective function, which includes the total failure costs related to disrupted distribution centers. Cheng et al. (2018) studied a two-stage robust approach for designing a reliable logistic network under supply and transportation disruptions. In the first stage, location decisions are made before disruptions and recourse decisions are made after the disruptions. They solved the proposed model exactly by a column-and-constraint-generation algorithm, which works better than the Benders decomposition method. Elluru et al. (2019) proposed a resilient location routing model with time windows under the disrupted distribution center and route. They used proactive and reactive strategies to deal with the disruptions. In the proactive strategy, the risk factor of each distribution center is considered before the disruption. The reactive strategy identifies the disrupted routes and recalculates the distribution routes to minimize the penalty for time window delays. Then, the proposed model optimizes the facility expansion costs, unmet demand costs, and delay costs.

Table 1 classifies more characteristics of the literature in the field of the SS&OA problem and VRP under disruption. We also discuss the features of our work and demonstrate them in the last row of Table 1.

Gap Analysis

Table 1 and the reviewed articles show the gap in the literature, and we try to fill them. The limitation of most existing studies is that most of them consider the SS&OA problem and VRP separately. They assume that supply facilities and transportation networks are always reliable and available. They also do not care about green goals like minimizing greenhouse gas emissions and pollution, while in reality, integrating the SS&OA problem with VRP saves costs. Disruption risks can damage the facilities and transportation networks. Hence, disruption risks can affect the performance of logistics networks. As a result, it is very important to take into account integrated green and resilient SS&OA and VRP under disruption risks in the design phase of the logistics network in order to make decisions at the strategic planning level simultaneously with operational planning decision levels. Also, most of the articles addressed the supply disruption risk, and the number of articles that paid attention to the transportation network disruption risk (disruption in vehicles and network routes) is almost negligible. With regard to mitigation strategies, most articles considered proactive resilience strategies for supplier disruptions, and a few articles evaluated proactive resilience strategies for transportation network disruptions. A limited number of articles considered real-world assumptions, such as complete disruption of the transportation network and partial disruption of supply. In addition, another important limitation of the existing studies is that they assume the logistics network design problem for the risk-neutral decision-maker, while in real life, most decision-makers are risk-averse. Therefore, we conclude that the integrated risk-averse SS&OA and VRP have not been extensively studied and analyzed in the literature with the mean-risk objective function. Based on the mentioned features, the main contributions of our article are as follows:

1. This paper considers stochastic programming for the G&RSS&OA problem integrated with VRP (G&RSS&OA-V) that optimizes strategic supplier selection decisions and operational routing decisions.
2. The proposed model formulates new multiproduct risk-averse mathematical programming for the G&RSS&OA-V problem with the mean-risk objective function. We use CVaR as a risk measure, which is a linear, convex, well-behaved, and coherent risk measure to control the risk of worst-case cost (Sawik 2013). The proposed objective function minimizes the costs of supplier selection and order allocation, greenhouse emissions, fuel consumption (routing), resilience, lost sales, and CVaR simultaneously.
3. The G&RSS&OA-V problem, in addition to supply disruptions, also considers the transportation network disruptions (routes and vehicle transport fleet).
4. Aldrigetti et al. (2021) provided a review of the supply chain network design literature under disruption risks and suggested investing in different proactive resilience strategies in supplier selection and logistics network design. Our proposed model accounts for resilience strategies in the G&RSS&OA-V problem before the disruption.
5. Suppliers do not completely lose their capacity due to supply disruption but lose it partially. The resilient strategies adopted in this area are to fortify suppliers, multiple suppliers, and prepositioned inventory.
6. Some vehicles and some routes are completely deactivated due to transportation disruption. The resilient strategy in this area is to contract with a 3PL to serve the transportation network.

Model Description

Description of Green and Resilient Supplier Selection and Order Allocation Integrated with Vehicle Routing (G&RSS&OA-V) Problem Under Disruption Risk

Supplier selection and order allocation (SS&OA) decisions at the strategic planning level and routing (VRP) decisions at the operational planning level are what we seek to integrate. We use the green paradigm to minimize the total negative environmental impacts and resilience strategies to deal with disruptions. Environmental experts use the life cycle assessment (LCA) method to analyze the environmental impact of activities and processes (Pishvaee et al. 2012). For this purpose, we use the environmental LCA method to measure greenhouse emissions. In this paper, we consider strategic and operational decisions on the G&RSS&OA-V problem under supply and transport network disruption. The purpose of the proposed problem is to select main green suppliers, assign orders to suppliers, and find optimal green vehicle routing to meet customer demand so as to minimize the costs of selecting suppliers and order allocation, greenhouse emissions, fuel consumption (routing), lost sales, resilient strategies, and

Table 1 Review and classification of recent SS&OA and VRP model under disruption risk

References (authors)	Decision level			Mitigation strategy (proactive and reactive)								Green paradigm	Risk measure		Disruption		Vulnerable part			Transport		Objective function			
	Strategic	Tactical	Operational	Emergency inventory	Protection/fortification	Capacity expansion	Multiple sourcing	Recovery	Spot purchase	Backup supplier	3PL		CVaR	Other	Partial	Complete	Suppliers	Manufacturers	Distribution centers/depots	Route	Vehicle	(Mean) expected cost/profit	(Risk) CVaR cost/service level	Expected cost + CVaR	Other
Ahmadi-Javid and Seddighi (2013)	✓	-	✓	-	-	-	✓	-	-	-	-	-	✓	-	✓	-	-	✓	✓	-	✓	✓	-	-	-
Zhang et al. (2015)	✓	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	-	✓	-	-	✓	-	-	-
Torabi et al. (2015)	✓	-	-	✓	✓	-	✓	✓	-	✓	-	-	-	-	✓	-	✓	-	-	-	-	✓	-	-	✓
Xie et al. (2016)	✓	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	-	✓	-	-	✓	-	-	-
Fahimnia and Jabbarzadeh (2016)	✓	-	-	-	-	-	✓	-	-	-	-	✓	-	-	-	✓	✓	-	-	-	-	✓	-	-	✓
Rayat et al. (2017)	✓	-	✓	-	-	-	-	-	-	-	-	-	-	-	✓	-	-	-	✓	-	-	✓	-	-	✓
Hamdan and Cheaitou (2017)	✓	✓	-	-	-	-	-	-	-	-	-	✓	-	-	✓	-	✓	-	-	-	-	✓	-	-	✓
Zahiri et al. (2017)	✓	✓	-	-	-	-	✓	-	-	-	-	✓	-	-	✓	-	-	✓	-	-	-	✓	-	-	✓
Cheraghalipour and Farsad (2018)	✓	✓	-	-	-	-	✓	-	-	-	-	-	-	-	-	✓	✓	-	-	-	-	✓	-	-	✓
Sabouhi et al. (2018)	✓	-	-	✓	✓	-	✓	-	-	-	-	-	-	-	✓	-	✓	-	-	-	-	✓	-	-	-
Jabbarzadeh et al. (2018)	✓	-	-	-	-	✓	✓	-	-	-	-	-	-	-	✓	-	✓	✓	-	-	-	✓	-	-	✓
Ni et al. (2018)	✓	✓	-	✓	-	✓	-	✓	-	-	-	-	-	-	-	-	-	✓	-	-	-	✓	-	-	
Cheng et al. (2018)	✓	✓	-	-	-	-	-	-	-	-	-	-	-	✓	-	✓	✓	-	-	✓	-	-	-	-	-
Nasiri et al. (2018)	✓	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	-	✓
Namdar et al. (2018)	✓	-	-	-	-	-	✓	✓	✓	✓	-	-	✓	-	✓	-	✓	-	-	-	-	✓	✓	-	-
Vahidi et al. (2018)	✓	-	-	-	-	-	✓	-	-	✓	-	✓	-	-	✓	✓	✓	-	-	-	-	✓	-	-	✓
Azad and Hassini (2019)	✓	✓	-	-	-	-	✓	✓	-	-	-	-	-	-	✓	-	✓	-	-	-	-	✓	-	-	-
Sawik (2019)	✓	✓	-	-	-	-	-	✓	-	-	-	-	✓	-	✓	-	✓	✓	-	-	-	✓	✓	-	-
Hosseini et al. (2019a)	✓	✓	-	✓	-	-	-	✓	-	-	-	-	-	-	✓	-	✓	-	-	-	-	✓	-	-	-

Table 1 (continued)

References (authors)	Decision level			Mitigation strategy (proactive and reactive)								Green paradigm	Risk measure		Disruption		Vulnerable part					Objective function			
	Strategic	Tactical	Operational	Emergency inventory	Protection/fortification	Capacity expansion	Multiple sourcing	Recovery	Spot purchase	Backup supplier	3PL		CVaR	Other	Partial	Complete	Suppliers	Manufacturers	Distribution centers/depots	Transport: Route	Transport: Vehicle	(Mean) expected cost/profit	(Risk) CVaR cost/service level	Expected cost + CVaR	Other
Esmaeili-Najafabadi et al. (2019)	✓	-	-	✓	✓	-	✓	-	-	-	-	-	-	-	-	✓	✓	-	-	-	-	✓	-	-	✓
Elluru et al. (2019)	✓	-	✓	-	-	✓	-	-	-	-	-	-	-	-	-	✓	-	-	-	✓	-	✓	-	-	-
Yavari et al. (2020)	✓	✓	✓	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	-	-	✓	-	✓	-	-	-
Yavari and Zaker (2020)	✓	✓	-	✓	-	✓	-	-	-	-	-	✓	-	-	-	✓	-	✓	-	-	-	✓	-	-	✓
Zhong et al. (2020)	✓	-	✓	-	-	-	-	-	-	-	-	-	✓	-	-	-	-	-	-	-	-	-	✓	-	-
Fattahi et al. (2020)	✓	-	-	-	-	-	-	✓	-	-	-	-	✓	-	-	✓	-	-	✓	-	-	✓	✓	-	-
Ghomi-Avili et al. (2021)	✓	-	-	-	-	-	-	-	-	✓		✓	✓	-	✓	✓	✓	-	✓	-	-	✓	-	-	-
Sawik (2021)	✓	-	-	✓	-	-	✓	✓	-	-	-	-	✓	-	-	✓	✓	-	-	-	-	-	✓	-	✓
Hasani et al. (2021)	✓	✓	-	-	✓	-	✓	-	-	✓	-	✓	-	-	-	✓	✓	✓	-	-	-	✓	-	-	-
Kaur and Singh (2021)	✓	✓	-	✓	-	-	✓	-	-	-	-	-	-	-	✓	-	✓	-	-	-	-	✓	-	-	✓
Esmaeili-Najafabadi et al. (2021)	✓	-	-	-	-	-	✓	-	-	-	-	-	✓	✓	-	✓	✓	-	-	-	-	✓	✓	-	-
Dehghan et al. (2021)	✓	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	-	✓	-	-	✓	-	-	-
Yavari and Ajalli (2021)	✓	-	-	✓	-	✓	✓	-	-	-	-	✓	-	-	-	✓	✓	-	-	-	-	✓	-	-	✓
Nayeri et al. (2021)	✓	-	-	-	-	-	✓	-	-	-	-	✓	-	-	✓	✓	✓	✓	✓	-	-	✓	-	-	✓
Chen et al. (2022)	✓	✓	-	✓	-	-	✓	-	-	✓	-	-	-	-	-	✓	✓	-	-	-	-	✓	-	-	-
Proposed model	✓	-	✓	✓	✓	-	✓	-	-	-	✓	✓	✓	-	✓	✓	✓	-	-	✓	✓	-	-	✓	-

CVaR. In our study, the customer can be a central depot, a retailer, or an end customer.

The capacity of suppliers as well as the transportation network that serves customers is vulnerable to various types of disruption. If a disruption leads to a reduction in the capacity of suppliers, a reduction in the number of vehicles, a route ban, and a route breakdown, a series of costs such as lost sales costs and resilience strategies are imposed on the system to meet unfulfilled customer demand as much as possible. The root of disruptions is natural disasters (floods, earthquakes, hurricanes, etc.) and man-made disruptions (labor strikes, terrorist attacks, quarantine for COVID-19, etc.).

In this paper, we use a scenario-based approach that threatens supply and transport network disruption scenarios. Disruptions are usually formulated by a set of scenarios, so that a set of facilities is disrupted together under each disruption scenario (Snyder and Daskin 2006). In the G&RSS&OA-V problem under random disruption, the parameters are usually investigated through a set of discrete scenarios with a definite probability and applied to the model.

The characteristics of the disruptions in our problem are:

- In each scenario, a disruption event may attack each supplier, and the level of disruption in supplier capacity varies. Hence, the remaining capacity of each supplier can be different from other suppliers under any disruption scenario. Depending on the severity of the disruption, the degree of disruption varies in the range [0,1]. For example, $bb_{is} = 0.6$ means that 60% of the capacity of supplier i is available.
- In each scenario, each vehicle may be disrupted and completely removed from the transport network, and the parameter related to it is binary. For example, $vv_{ks} = 0$ means that vehicle k is broken in scenario s.
- In each scenario, each route may be disrupted and completely disabled in the transport network, and the parameter related to it is binary. For example, $rd_{jls} = 0$ means that the route j to l and vice versa is inactive under scenario s.
- Estimation of the probability of potential disruptions and their impact on the supply and transportation process under each scenario can be obtained through risk assessment analysis (Torabi et al. 2014).

In general, companies can increase resilience by creating redundancy in the entire supply chain (including prepositioned emergency inventory strategy and dual/multiple sourcing strategy), increasing supply chain flexibility, and changing corporate culture (Sheffi 2005). To cope with potential supply and transport network disruptions, we employ the following diverse (proactive) resilience strategies in the proposed model:

1. Employing a multiple sourcing strategy for outsourced materials/parts. One of the solutions to reduce disruption is dual or multiple sourcing instead of single sourcing. Dual or multiple sourcing is more expensive than single sourcing, but in the event of a disruption, it can respond to customer demand and prevent shortages and increase the credibility and reliability of companies (Torabi et al. 2015).
2. Fortifying suppliers.
3. Using prepositioned emergency inventory. Another common resiliency strategy is to maintain prepositioned inventory that is held in fortified suppliers and used after a disruption.
4. Concluding a contract with 3PL for servicing the transportation network.

As Fig. 1 shows, our problem network consists of three layers of suppliers, a hybrid manufacturing-distribution (HMD) center, and customers. The HMD center produces different products and dispatches them to customers through vehicle routing. The HMD center outsources materials/parts to a set of selected suppliers. Suppliers are divided into two categories. The first category is that suppliers do not use resilience strategies. The second category is suppliers which use resilience strategies. The transportation network can also use a resilience strategy. In this paper, we use a HMD center, the advantages of which include reducing pollution and saving on transportation network costs. Based on customer demand, we determine the HMD center production–distribution plan and supply plan. We may not meet demand under supply and transportation network disruption, so shortage is allowed as lost sales. The location of suppliers, HMD center, and customers are fixed and predefined.

Two-Stage Risk Aversion Stochastic Programming Framework with CVaR Criteria

Two-stage stochastic programming is a common approach in SS&OA problems because of the two-stage nature of decisions. Birge and Louveaux (1997) defined the general formulation of a two-stage stochastic programming framework. In these models, strategic decisions such as selecting the main suppliers are made in the first stage before knowing the realization of stochastic parameters. However, when stochastic parameters are revealed, the operational and tactical decisions such as production, transportation, and routing should be considered the second-stage decisions (Govindan et al. 2017).

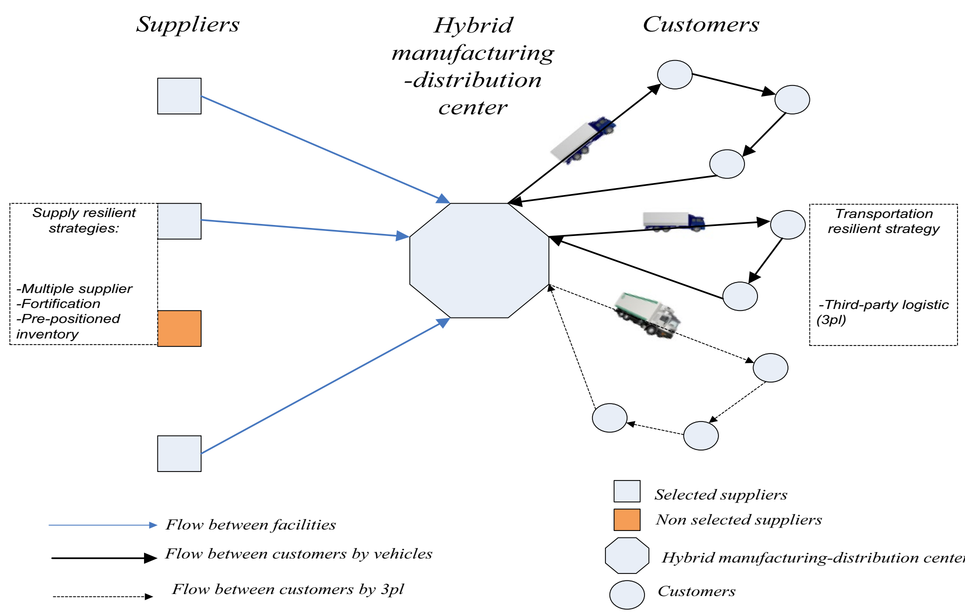

Fig. 1 The proposed network for RSS&OA-V problem

Rockafellar and Uryasev (2000) described conditional value risk (CVaR), and in this study, we use a mean-risk model in order to integrate risk parameters in two-stage stochastic programming models. Thus, we can apply a linear programming problem based on phrase (1) (Soleimani and Govindan, 2014, Noyan 2012).

$$
\begin{aligned}
&\min(1+\lambda)C^T X + \sum_s p_s(q_s)^T y_s + \lambda\left(\xi + \tfrac{1}{1-\alpha}\sum_s p_s z_s\right)\\
&st:\\
&W_s y_s = h_s - T_s X, \forall s\\
&y_s \geq 0, \forall s\\
&z_s \geq (q_s)^T y_s - \xi, \forall s\\
&z_s \geq 0, \forall s\\
&\xi \in R\\
&0 \leq \lambda \leq 1
\end{aligned}
\tag{1}
$$

ξ is a decision variable that illustrates the optimal value of VaR in the risk-averse model. z_s is the tail cost in scenario s defined as the nonnegative value that the cost of scenario s exceeds VaR. Phrase (1) is a two-stage stochastic programming model integrated with CVaR in the G&RSS&OA-V problem under disruption. We present the entire model in the next segment.

The G&RSS&OA-V Model

Decisions of the G&RSS&OA-V problem include identifying major green suppliers, order allocation to suppliers, green production rate per customer, green vehicle routing, resilience strategies, and lost sales. In the proposed problem, we consider scenario-based modeling under supply and transportation network disruption caused by natural and man-made disasters, in which the probability of occurrence of each scenario is definite. The explanations of each scenario are in accordance with "Description of Green and Resilient Supplier Selection and Order Allocation Integrated with Vehicle Routing (G&RSS&OA-V) Problem Under Disruption Risk." In each scenario, the capacity of the suppliers decreases due to disruption, so that the remaining capacity of each supplier under each scenario is known. Also, some vehicles and some routes under disruption may be inactive. In each scenario, it is clear which vehicles and routes are inactive after the disruption. In addition, proactive resilience strategies can help to satisfy the customer's unmet demand as much as possible. Therefore, we propose a single-objective mixed-integer two-stage stochastic linear programming model for the G&RSS&OA-V problem under disruption with the mean-risk objective function. We use CVaR as a risk measure; we seek to minimize the sum of the total expected cost and CVaR cost.

The G&RSS&OA-V problem decision-making process has a two-stage nature with a scenario-based approach. Here, the variables of selecting supplier, fortifying supplier, determining prepositioned inventory, and contracting with 3PL are scenario-independent. These are the first-stage variables and are fixed under each scenario. While the variables of flow between facilities, the production rate, routing, and sales lost are scenario-dependent. These are second-stage or recourse variables and can change in relation to all disruptions. The G&RSS&OA-V problem is an NP-hard problem in terms of complexity because it is the integration of two NP-hard problems. One is the SS&OA problem, which belongs to the category of integer linear programming problems (Karp 1972), and the other is the VRP (Golden et al. 2008). Despite the complexity of the G&RSS&OA-V

problem, its most important superiority is the cost savings resulting from merging the two problems.

One of the disadvantages of the stochastic programming approach is the lack of sufficient historical data in most real situations, which makes it difficult to estimate random distributions for uncertain parameters (Pishvaee and Torabi 2010). This issue is also true regarding the scenario-dependent parameters under the supply and transportation network disruption risks. Therefore, it is almost impossible to find probability distributions for such uncertain parameters. Due to the unavailability of the required data, they rely on judgmental data extracted from specialists and field experts (Torabi et al. 2015).

In the following, we first describe the assumptions, sets, subsets, parameters, and decision variables and then illustrate our risk-averse two-stage stochastic linear programming model.

Model Assumptions and Limitations

The assumptions considered in the proposed model are as follows:

1. Each material/part is supplied only by a certain number of suppliers, not all suppliers.
2. Each product contains only a given number of parts, not all parts.
3. We assume multiple potential locations to select and contract with suppliers.
4. The HMD center produces and distributes products and meets customer demand through a routing system.
5. The transport fleet is heterogeneous and the capacity of vehicles is different. Customer demand meet through vehicles in the network. Each vehicle also meets its dedicated customers with the goal of minimizing routing costs.
6. Shortage in customer demand is allowed in the form of lost sales under disruption
7. Suppliers and the transport network may face frequent disruptions that lead to reduced supply capacity and the transport network. Hence some costs such as lost sales and costs of implementing resilience strategies are imposed on the present problem.
8. In this study, supply resilience strategies include multiple sourcing, supplier fortification, and pre-positioned inventory. Transport network resilience strategy is to conclude a contract with a3PL.
9. The cost of transport by 3PL is much higher than the cost of transport by the network itself.
10. 3PLcapacity does not decrease due to disruption and there is also a limited capacity for transporting products.
11. Each random scenario occurs independently of other scenarios with a certain probability.
12. The remaining capacity rate in each supplier, complete disruption of vehicles, and complete disruption of routes are stochastic and scenario-based.
13. Emitted greenhouse gases and fuel consumption depend on distance, cargo weight, type, and speed of a vehicle.

The main assumption of our model is the use of a hybrid manufacturing-distribution (HMD) center, the advantages of which are saving space, reducing time, reducing costs, reducing emissions (the main goal of the green paradigm), saving transportation, using common equipment in two manufacturing and distribution centers, and coordinating policy of two manufacturing and distribution centers. To distribute products to customers, routing is used by a heterogeneous transport fleet, which leads to a reduction in costs, including the cost of transportation, and reducing the cost of transportation also reduces pollution (Ostermeier and Hübner 2018). In real life, disruption in suppliers is partial and disruption in vehicles and routes is complete. The resilient strategies employed have different levels of resilience to be more realistic assumptions. In general, the assumptions of the proposed model are based on real life.

Model Formulation

Sets and subsets:

$\boldsymbol{I}$	set of all suppliers
i	index of suppliers, $i \in I$
L	set of all customers
j,l	index of all customers, $j, l \in L$
A	set of all nodes (includes customer nodes plus origin node (HMD center))
a	Total number of nodes
S	set of disruption scenarios
s	index of disruption scenarios, $s \in S$
M	set of products
m	index of products, $m \in M$
P	set of materials/parts

p index of materials/parts, $p \in P$

E set of fortification level

e index of fortification level, $e \in E$

K' set of primary vehicles

k' index of primary vehicles, $k \in K$

K'' set of vehicles in the 3PL

k'' index of vehicles in the 3PL, $k^{'} \in K^{'}$

K set of all vehicles, $K = K^{'} \cup K^{\varepsilon}$

M_p set of products in which part p is used, $M_p \subseteq M$

p_i set of materials/parts that supplied through supplier i, $p_i \subseteq P$

p_m set of materials/parts used in product m, $p_m \subseteq P$

Parameters:
Demand:

d_{ml} demand of customer l from product m

Fixed cost:

c_i fixed selection and ordering cost in supplier i

cg_{ie} fixed fortification cost of supplier i at level e

cp_{ip} fixed supply cost per part/material p in supplier i

cv fixed cost of concluding a contract with 3PL for service by the transportation fleet

Variable cost:

pn_{ip} greenhouse emission cost for supply and transportation per part/material p in supplier i by HMD center

pf_{jp} greenhouse emission cost for pre-positioned emergency inventory per part/material p in supplier i by HMD center

cm_{jlk} fuel consumption cost for transport from node j to l by vehicle k

$cvm_{jlk'}$ fuel consumption cost for transport from node j to l by 3PL (vehicle k')

Shortage cost:

ls_m lost sale cost per unit of product m

Capacity constraints:

ca_i maximum capacity of fortified supplier i for holding pre-positioned emergency inventory

cap_i maximum initial capacity of supplier i for supplying parts/materials

$cape$ maximum capacity of HMD center for producing and distributing the product

$capp_k$ maximum capacity of vehicle k

Factors:

w_p weight of part/material p

bb_{is} remaining capacity rate of supplier i for supplying parts/materials under scenario s

p_s probability of occurrence of scenario s

zm_{pm} consumption coefficient of part/material p in product m

ww_m weight of product m, $ww_m = \sum_{p \in P_m} zm_{pm} w_p, \forall m$

vv_{ks} binary parameter equals "1" if the vehicle k is not disrupted under scenario s, otherwise equals "0"

rd_{jls} binary parameter equals "1" if the route of node i to node j is not disrupted under scenario s, otherwise equals "0"

α confidence level

λ risk weight (factor)

Decision variables:

XN_{ipms} the amount of part/material p supplied and shipped for product m from non-fortified supplier i under scenario s

XF_{ipms} the amount of part/material p supplied and shipped for product m from fortified supplier i under scenario s

N_{ms} the amount of lost sales of product m in the HMD center under scenario s

O_{ipms} the amount of part/material p use for product m from pre-positioned emergency inventory of supplier i under scenario s

Q_{mkls} the amount of product m assemble by the manufacturer for the customer l shipped by vehicle k under scenario s

Mo_{ip} the amount of pre-positioned emergency inventory of part/material p in fortified supplier i

v_{lk} non-negative variable to remove subtours

VaR value at risk

Co_s auxiliary variable for calculating the conditional value at risk under scenario s

x_i binary variable equals "1" if supplier i is selected, otherwise equals "0"

y_{ie} binary variable equals "1" if selected supplier i fortified at level e, otherwise equals "0"

vl binary variable equals "1" in case of concluding a contract with 3PL for servicing the transportation fleet, otherwise equals "0"

z_{jlks} binary variable equals "1" if primary vehicle k travels from node j to node l under scenario s, otherwise equals "0"

Objective Function

The objective function aims to minimize the total mean-CVaR cost.

$$MinTc = (1+\lambda)\sum_{i\in I} c_i x_i \tag{2}$$

$$+(1+\lambda)\sum_{i\in I}\sum_{e\in E} cg_{ie} y_{ie} \tag{3}$$

$$+(1+\lambda)\sum_{i\in I}\sum_{p\in P} cp_{ip} Mo_{ip} \tag{4}$$

$$+(1+\lambda)cv.vl \tag{5}$$

$$+\sum_{i\in I}\sum_{p\in P_m}\sum_{m\in M}\sum_{s\in S} p_s pn_{ip} XN_{\text{ipms}} \tag{6}$$

$$+\sum_{i\in I}\sum_{p\in P_m}\sum_{m\in M}\sum_{s\in S} p_s pn_{ip} XF_{\text{ipms}} \tag{7}$$

$$+\sum_{i\in I}\sum_{p\in P_m}\sum_{m\in M}\sum_{s\in S} p_s pf_{ip} O_{\text{ipms}} \tag{8}$$

$$+\sum_{m\in M}\sum_{s\in S} p_s ls_m N_{ms} \tag{9}$$

$$+\sum_{\substack{j\in J\\ j\neq l}}\sum_{l\in L}\sum_{k\varepsilon\in K\varepsilon}\sum_{s\in S} p_s cm_{jlk''z_{jlk\varepsilon}s} \tag{10}$$

$$+\sum_{\substack{j\in J\\ j\neq l}}\sum_{l\in L}\sum_{k\varepsilon\in K\varepsilon}\sum_{s\in S} p_s cvm_{jlk\varepsilon} z_{jlk\varepsilon s} \tag{11}$$

$$+\lambda\left(VaR + \frac{1}{1-\alpha}\sum_{s\in S} p_s Co_s\right) \tag{12}$$

The detailed objective function is the following: we consider the total cost of the two-stage mean-risk stochastic mathematical programming model as follows (Rahimi and Ghezavati 2018).

Total cost = (1 + λ) × Fixed costs + Expected costs + λ × CVaR costs

Expressions (1) to (11) represent the objective function of the model, which is described in the following sentences: term (1) includes the fixed cost of selecting and ordering with vulnerable suppliers multiplied by the risk weight plus one. Term (2) shows the fixed fortification cost of suppliers at different levels multiplied by the risk weight plus one. Term (3) indicates the fixed supply cost of prepositioned emergency inventory of fortified suppliers multiplied by the risk weight plus one. Phrase (4) includes the fixed cost of concluding a contract with 3PL for servicing the transportation fleet multiplied by the risk weight plus one. Term (5) is the greenhouse emission cost for supply and transportation of parts/materials from nonfortified suppliers to the HMD center. Phrase (6) calculates the greenhouse emission cost for supply and transportation of parts/materials from fortified suppliers to the HMD center. Term (7) covers the purchase and transportation cost of parts/materials as prepositioned emergency inventory from fortified suppliers for the HMD center. Term (8) calculates the lost sales cost of the HMD center. Term (9) includes the fuel consumption cost for transport by network vehicles from the HMD center to customers. Term (10) includes the fuel consumption cost for transport by 3PL from the HMD center to customers. In term (11), to achieve a better risk estimate of the worst-case scenario in the G&RSS&OA-V problem, we minimize the cost of CVaR under the disruption risk by considering resilience strategies. We use CVaR with the auxiliary function provided by Rockafellar and Uryasev (2000, 2002). λ is the risk factor that indicates the decision-makers' willingness to risk VaR (value at risk). α is the confidence level that controls the risk of losses due to supply and transportation network disruption, and Co_s is the cost of scenario s that exceeds VaR.

Constraints

$$\begin{aligned} s.t.&\\ \mathrm{Co}_s \geq& \sum_{i\epsilon I}\sum_{p\epsilon P_m}\sum_{m\epsilon \mathrm{M}} p_s pn_{ip} XN_{ipms} + \sum_{i\epsilon I}\sum_{p\epsilon P_m}\sum_{m\epsilon \mathrm{M}} p_s pn_{ip} XF_{ipms}\\ &+\sum_{i\epsilon I}\sum_{p\epsilon P_m}\sum_{m\epsilon \mathrm{M}} p_s pf_{ip} O_{ipms} + \sum_{m\epsilon \mathrm{M}} p_s ls_m N_{ms} \qquad \forall s\\ &+ \sum_{\substack{j\in J\\ j\neq l}}\sum_{l\epsilon L}\sum_{k\epsilon K} p_s cm_{jlk'} O_{jlk'\,s} + \sum_{\substack{j\in J\\ j\neq l}}\sum_{l\epsilon L}\sum_{k^{\varepsilon}\epsilon k^{\varepsilon}} p_s cm_{jlk^{\varepsilon}} O_{jlk''\,s} - VaR \end{aligned} \tag{13}$$

$$Co_s \geq 0 \;\; \forall s \tag{14}$$

$$\sum_{e\epsilon \mathrm{E}} y_{ie} \leq x_i \;\; \forall i \in I \tag{15}$$

$$\sum_{p\epsilon P} w_p Mo_{ip} \leq ca_i \sum_{e\epsilon E} y_{ie} \;\; \forall i \in I \tag{16}$$

$$\sum_{p\epsilon P_i}\sum_{m\epsilon \mathrm{M}_p} w_p XN_{ipms} \leq \left(x_i - \sum_{e\epsilon E} y_{ie}\right) bb_{is} cap_i \;\; \forall i, s \tag{17}$$

$$\sum_{p\epsilon P_i}\sum_{m\epsilon \mathrm{M}_p} w_p XF_{ipms} \leq cap_i \sum_{e\epsilon E} y_{ie} b_{ies} \;\; \forall i, s \tag{18}$$

$$\sum_{m\epsilon \mathrm{M}_p} O_{ipms} \leq MO_{ip} \;\; \forall i, p, s \tag{19}$$

$$\sum_{k\epsilon K}\sum_{l\epsilon \mathrm{L}} Q_{mkls} \leq \frac{1}{zm_{pm}} \sum_{i\epsilon \mathrm{I}} \left(XN_{ipms} + XF_{ipms} + O_{ipms}\right) \;\; \forall m, p, s \tag{20}$$

$$\sum_{k\epsilon K} Q_{mkls} + O_{ms} \geq d_{ml} \;\; \forall m, l, s \tag{21}$$

$$\sum_{m\in M}\sum_{l\in L} ww_m Q_{mk'ls} \leq \mathrm{capp}_k{}'.vv_k{}'s \;\; \forall k's \tag{22}$$

$$\sum_{m\in M}\sum_{l\in L} ww_m Q_{mk\varepsilon ls} \leq \mathrm{capp}_k{}''.vl \;\; \forall k\varepsilon, s \tag{23}$$

$$\sum_{\substack{j\in A\\ j\neq l}} z_{\mathrm{jlks}} = \sum_{\substack{j\in A\\ j\neq l}} z_{\mathrm{ljks}} \;\; \forall l, k, s \tag{24}$$

$$\sum_{l\in L} z_{\mathrm{jlks}} \leq 1 \;\; \forall j = 0, k, s \tag{25}$$

$$\sum_{m\in M} Q_{\mathrm{mkls}} \leq M \sum_{\substack{j\in A\\ j\neq l}} z_{\mathrm{jlks}} \;\; \forall l, k, s \tag{26}$$

$$v_{jk} - v_{lk} + az_{\mathrm{jlks}} \leq a - 1 \quad \begin{array}{c}\forall j, l \in A : j \neq l\\ j \neq 0, k, s\end{array} \tag{27}$$

$$\sum_{m\in M}\sum_{l\in L}\sum_{k\in K} ww_m Q_{\mathrm{mkls}} \leq \mathrm{cape} \;\; \forall s \tag{28}$$

$$MO_{ip}, N_{ms}, XN_{ipms}, XF_{ipms}, O_{ipms}, Q_{mkls}, v_{lk}, VaR, Co_s \geq 0 \;\; \forall i, j, m, p, k, s \tag{29}$$

$$x_i, y_{ie}, z_{jlks}, vl\epsilon\{0, 1\} \;\; \forall i, j, k, e, s \tag{30}$$

Constraints (13) and (14) are risk constraints and used to calculate CVaR costs (Rockafellar and Uryasev 2000, 2002). Constraint (13) is the tail cost for scenario s which is defined as the cost of each scenario minus VaR. Constraint (14) Co_s is a nonnegative variable under scenario s. Constraint (15) states that fortification of a supplier depends on the selection of that supplier, and supplier fortification is done maximum in one level. Constraint (16) sets the maximum capacity of prepositioned emergency inventory at each fortified supplier. Constraint (17) indicates the maximum capacity of unfortified suppliers after disruption. Constraint (18) illustrates the maximum capacity of fortified suppliers after disruption. Constraint (19) indicates the maximum prepositioned emergency inventory of each part/material under each scenario in each fortified supplier. Constraint (20) demonstrates the amount of products produced at the HMD center under each scenario. Constraint (21) states that the amount of product produced by the HMD center plus its lost sales is greater than the demand for that product. Constraint (22) indicates the capacity of each vehicle. Under complete disruption, it reaches zero. If not, it is equal to $capp_{k'}$. Constraint (23) specifies the 3PL capacity for vehicles. In case of concluding a contract with 3PL, the capacity is equal to $capp_{k''}$; otherwise, it is equal to zero. Equation (24) guarantees that each vehicle (related to the network itself or 3PL) that enters a node must also leave it. Constraint (25) ensures that each vehicle on each route exits the origin node (HMD center) only once. Constraint (26) represents that the amount of products produced in the HMD center per customer depends on the existence of the transportation route to that customer. Equation (27) is the subtour elimination constraint that causes each tour to start from one HMD center and multiple customers (Miller et al. 1960). Constraint (28) expresses the capacity of production and distribution in the HMD center. Constraints (29) and (30) also specify the type of decision variables.

Computational Analysis and Examples

Considering that the G&RSS&OA-V problem is NP-hard, in order to solve the model in a reasonable time, we present a small- or medium-sized computational example to validate the proposed problem. In fact, due to the limitations of the GAMS software, it can be an acceptable size for the computational example. The objective is to minimize the expected costs plus CVaR costs (mean-CVaR) of the supply network under disruption. The input data are hypothetical for computational examples. The examples are implemented in GAMS software to discover the optimal solution to the proposed G&RSS&OA-V problem. All calculations were performed on a laptop with an Intel Core i7 processor with 8 GB RAM. We consider a problem consisting of four suppliers, two fortification levels, two product types, three parts/material types, one HMD center (origin node), seven customers, five vehicles related to the transportation network, and five vehicles related to 3PL. In the real world, we cannot consider all the parameters definitively, especially the remaining capacity rate in each vulnerable supplier, complete disruption of vehicles, and complete disruption of routes and related costs. Then, we consider them as stochastic parameters. Khalili et al. (2017) described each risk by two parameters: risk probability and risk severity. In this study, we assume four cases for risk severity in stochastic parameters (high, mid, low, and no disruption). Thus, to deal with the uncertainty, we create ten scenarios with a definite probability together with the severity of the disruption of unfortified suppliers and vehicles in Table 2 in the test example. Table 3 illustrates the severity of the disruption in fortified suppliers in the test example. Table 4 shows the severity of route disruption in scenarios. Table 5 demonstrates the generated parameters. In all computational analyses, the parameters are generated by uniform distribution.

Computational Results

The G&RSS&OA-V problem was solved based on the data in Tables 2, 3, 4, and 5. Table 6 shows different components of objective function, risk measure, and expected lost sale for the described example ($\alpha=0.1$, $\lambda=0.1$).

In the first-stage decisions, among the four suppliers, the model selects suppliers 1, 2, 3, and 4. All four suppliers are fortified at level two. Prepositioned emergency inventory is stored in all four suppliers. Also, a contract is concluded with 3PL to serve the transportation network. Regarding the second-stage decisions, we investigate the outputs related to the four scenarios 2, 5, 8, and 10 in which the severity of supply disruption is high, med, low, and no disruption, respectively.

Scenario 2 uses the strategy of multiple suppliers to purchase part/material 1, including fortified suppliers 1, 2, and 4. Also, scenario 2 uses the strategy of multiple suppliers to purchase part/material 3, including fortified suppliers 2 and 3. In scenario 2, the prepositioned emergency inventory is stored in suppliers 3 and 4. Table 7

Table 2 Likelihood and severity of disruption in unfortified suppliers and vehicles in test example

Disruption scenario	Severity of disruption in unfortified suppliers	p_s	bb_{is}				Severity of vehicle disruption	vv_{ks}				
			i					k				
s			1	2	3	4		1	2	3	4	5
1	High	0.08	0.18	0.23	0.18	0.19	High	0	0	1	0	1
2	High	0.11	0.19	0.21	0.12	0.18	Mid	1	1	0	1	0
3	High	0.08	0.15	0.19	0.25	0.16	Low	1	1	1	1	0
4	Mid	0.09	0.35	0.32	0.33	0.28	High	1	0	1	0	0
5	Mid	0.11	0.32	0.33	0.28	0.28	Mid	0	1	1	0	1
6	Mid	0.1	0.3	0.35	0.34	0.34	Low	1	0	1	1	1
7	Low	0.08	0.5	0.47	0.5	0.36	High	0	0	0	1	1
8	Low	0.12	0.38	0.37	0.38	0.47	Mid	0	1	0	1	1
9	Low	0.11	0.5	0.5	0.37	0.43	Low	1	0	1	1	1
10	No disruption	0.12	1*	1*	1*	1*	No disruption	1*	1*	1*	1*	1*

*When we have no disruption

Table 3 Severity of disruption in fortified suppliers in test example

Disruption scenario	Severity of disruption in fortified suppliers	b_{ies} $(e=1)$				b_{ies} $(e=2)$			
		i				i			
s		1	2	3	4	1	2	3	4
1	High	0.31	0.35	0.3	0.31	0.35	0.44	0.45	0.38
2	High	0.33	0.34	0.26	0.26	0.43	0.45	0.4	0.36
3	High	0.35	0.35	0.27	0.31	0.38	0.44	0.43	0.35
4	Mid	0.38	0.44	0.36	0.44	0.55	0.53	0.53	0.47
5	Mid	0.36	0.44	0.38	0.42	0.54	0.52	0.47	0.53
6	Mid	0.36	0.4	0.45	0.37	0.54	0.51	0.53	0.53
7	Low	0.55	0.57	0.59	0.5	0.66	0.62	0.69	0.67
8	Low	0.5	0.56	0.57	0.59	0.63	0.68	0.7	0.66
9	Low	0.57	0.56	0.58	0.5	0.65	0.62	0.65	0.69
10	No disruption	1*	1*	1*	1*	1*	1*	1*	1*

*When we have no disruption

shows the amount of production and lost sales under scenario 2 for products 1 and 2. The network uses vehicles 1 and 2 in routing. Also, 3PL uses vehicle 7 in routing.

Scenario 5 uses the strategy of multiple suppliers to purchase part/material 1, including fortified suppliers 1, 2, 3, and 4. There is the prepositioned inventory in the fortified suppliers 1, 2, 3, and 4 under scenario 5. Table 7 shows the amount of production and lost sales under scenario 5 for products 1 and 2. The network uses vehicles 2, 3, and 5 in routing. 3PL also uses vehicles 6, 7, 8, and 9.

Scenario 8 uses the strategy of multiple suppliers to purchase part/material 1, including fortified suppliers 1, 2, 3, and 4. There is the prepositioned inventory in the fortified suppliers 1, 2, 3, and 4 under scenario 8. Table 7 shows the amount of production and lost sales under scenario 8 for products 1 and 2. The network uses vehicles 2, 4, and 5 in routing. 3PL also uses vehicles 6, 7, 8, 9, and 10.

Scenario 10 uses the strategy of multiple suppliers, including fortified suppliers 1, 2, 3, and 4, to purchase part/material 1. There is the prepositioned inventory in the fortified suppliers 1, 2, 3, and 4 under scenario 10. Table 7 shows the amount of production and lost sales under scenario 10 for products 1 and 2. Vehicles 1, 2, 3, 4, and 5 are also used in routing. 3PL also uses vehicles 6, 7, 9, and 10.

Table 7 shows that the production rate among the scenarios increases from high to low, and vice versa, the amount of lost sales between the scenarios decreases from high to low.

Sensitivity Analysis on the Risk Parameters

In this section, we present a complete sensitivity analysis of the risk-averse parameters α and λ. We then apply different values of α and λ in the mean-risk model to understand how they affect the proposed G&RSS&OA-V model. There are usually two well-known financial metrics for controlling the risk of supply disruptions based on α confidence level, which are:

- Value at risk (VaR) is a decision variable based on $\alpha\%$ costs so that for $\alpha\%$ scenarios, the result will not exceed VaR.
- Conditional value at risk (CVaR) is the expected cost of the portfolio in the worst $(1-\alpha)$ % total costs, i.e., $(1-\alpha)$ % of results more than VaR, and the average value of these results (greater than VaR) is represented by CVaR. The mathematical properties of CVaR are superior to VaR. CVaR is a coherent risk measure. For example, the CVaR portfolio is a continuous and convex function, while VaR may even have a discontinuous function (Sarykalin et al.2008; Sawik 2013).

A risk-averse decision-maker wants to use CVaR to minimize the worst-case scenario that goes beyond VaR. In the mean-CVaR model, the supply portfolio integrated with routing decisions is selected along with green paradigm and proactive resilience strategies to minimize both expected costs and CVaR costs.

α is one of the fundamental parameters of risk-averse decision-making, the effects of which should be analyzed on the proposed model. We put seven cases for alpha ($\alpha=0.1$, 0.3, 0.5, 0.6, 0.7, 0.8, 0.9) with a fixed value of lambda ($\lambda=0.1$) to investigate how alpha (α) affects the objective function.

According to Fig. 2, with increasing alpha (α), the model's risk aversion behavior increases; in other words, the model acts more conservatively. As you can see in Fig. 2,

Table 4 Severity of route disruption scenarios (rd_{jls}) in test example

Disruption scenario (s)	1	2	3	4	5	6	7	8	9	10
Severity of route disruption route ($j.l$)	High	Mid	Low	High	Mid	Low	High	Mid	Low	No dis
1.2	1	1	1	0	1	1	0	0	0	1*
1.3	0	1	1	0	1	1	1	1	1	1*
1.4	1	0	1	0	1	1	1	1	0	1*
1.5	1	1	0	1	1	0	0	1	1	1*
1.6	0	0	1	1	0	1	0	1	1	1*
1.7	1	1	1	1	1	1	1	0	1	1*
1.8	0	1	1	1	0	1	1	1	1	1*
2.1	1	1	1	0	1	1	0	0	0	1*
2.3	0	0	1	1	1	1	1	1	1	1*
2.4	1	0	1	1	0	1	1	1	1	1*
2.5	0	1	1	0	1	1	0	1	1	1*
2.6	1	1	0	1	0	1	0	1	1	1*
2.7	0	1	1	0	1	0	1	0	1	1*
2.8	1	1	1	1	1	1	1	1	0	1*
3.1	0	1	1	0	1	1	1	1	1	1*
3.2	0	0	1	1	1	1	1	1	1	1*
3.4	1	1	1	0	1	0	0	1	1	1*
3.5	1	0	1	1	1	1	1	0	1	1*
3.6	0	1	1	0	0	1	0	0	0	1*
3.7	1	1	0	1	1	1	0	1	1	1*
3.8	1	1	1	1	0	1	1	1	1	1*
4.1	1	0	1	0	1	1	1	1	0	1*
4.2	1	0	1	1	0	1	1	1	1	1*
4.3	1	1	1	0	1	0	0	1	1	1*
4.5	0	1	1	1	0	1	0	0	1	1*
4.6	1	1	0	1	1	1	0	0	1	1*
4.7	0	1	1	0	1	1	0	1	0	1*
4.8	0	1	1	1	1	1	1	1	1	1*
5.1	1	1	0	1	1	0	0	1	1	1*
5.2	0	1	1	0	1	1	0	1	1	1*
5.3	1	0	1	1	1	1	1	0	1	1*
5.4	0	1	1	1	0	1	0	0	1	1*
5.6	1	1	1	1	1	1	1	1	0	1*
5.7	0	0	1	0	0	1	0	1	1	1*
5.8	1	1	1	0	1	1	1	1	1	1*
6.1	0	0	1	1	0	1	0	1	1	1*
6.2	1	1	0	1	0	1	0	1	1	1*
6.3	0	1	1	0	0	1	0	0	0	1*
6.4	1	1	0	1	1	1	0	0	1	1*
6.5	1	1	1	1	1	1	1	1	0	1*
6.7	0	1	1	0	1	1	1	1	1	1*
6.8	1	0	1	0	1	0	0	1	1	1*
7.1	1	1	1	1	1	1	1	0	1	1*
7.2	0	1	1	0	1	0	1	0	1	1*
7.3	1	1	0	1	1	1	0	1	1	1*
7.4	0	1	1	0	1	1	0	1	0	1*
7.5	0	0	1	0	0	1	0	1	1	1*
7.6	0	1	1	0	1	1	1	1	1	1*
7.8	1	0	0	1	0	1	1	1	1	1*

Table 4 (continued)

Disruption scenario (s)	1	2	3	4	5	6	7	8	9	10
8.1	0	1	1	1	0	1	1	1	1	1*
8.2	1	1	1	1	1	1	1	1	0	1*
8.3	1	1	1	1	0	1	1	1	1	1*
8.4	0	1	1	1	1	1	1	1	1	1*
8.5	1	1	1	0	1	1	1	1	1	1*
8.6	1	0	1	0	1	0	0	1	1	1*
8.7	1	0	0	1	0	1	1	1	1	1*

*When we have no disruption

Table 5 Parameters and scalars of the test example

Parameters	Severity	Distribution
c_i	-	Uniform(20,000,40,000)
ca_i	-	Uniform(10,000,20,000)
cap_j	-	Uniform(5000,7000)
$capp_k$	-	Uniform(6000,12,000)
ls_m	-	Uniform(20,000,40,000)
d_{ml}	-	Uniform(200,500)
cp_{ip}	-	Uniform(100,200)
cm_{jlk}	-	Uniform(10,30)
$cm_{jlk'}$	-	Uniform(30,60)
cg_{ie}	-	Uniform(1000,2000)
pn_{ip}	-	Uniform(40,60)
pf_{ip}	-	Uniform(70,90)
zm_{pm}	-	Uniform(1,3)
w_p	-	Uniform(2,4)
bb_{is}	High	Uniform(0.1,0.25)
	Mid	Uniform(0.25,0.35)
	Low	Uniform(0.35,0.5)
b_{ies} $(e=1)$	High	Uniform(0.25,0.35)
	Mid	Uniform(0.35,0.45)
	Low	Uniform(0.5,0.6)
b_{ies} $(e=2)$	High	Uniform(0.35,0.45)
	Mid	Uniform(0.45,0.55)
	Low	Uniform(0.6,0.7)
cv	-	20,000
$cape$	-	100,000

Table 6 Different components of the main example

First-stage costs	Second-stage costs	Mean-CVaR	CVaR	VaR	Expected lost sale
2,596,086	5,689,224	8,605,587	606,688	356,079	155

VaR and CVaR values increase with increasing alpha. Also, with the increase of alpha, the first-stage costs do not change significantly. It is worth noting that the second-stage costs and the mean-CVaR costs increase with increasing alpha with a slight slope.

Table 8 demonstrates the effect of different alpha on the VaR, CVaR, first-stage cost, second-stage cost, and mean-CVaR. According to Table 8, there is the lowest mean-CVaR in $\alpha=0.1$. Also, by increasing α from 0.1 to 0.9, the mean-CVaR objective function value grows from 8,115,034 to 9,187,824, that is, the objective function increases by 13.2%.

As shown in Fig. 5, at different α (0.1, 0.5, 0.7), CVaR increases with increasing λ. According to Fig. 6, at different α (0.1, 0.5, 0.7), the cost of mean-CVaR objective function increases while λ increases. For example, at $\alpha=0.1$, as λ increases from 0.1 to 0.9, the mean-CVaR objective function value grows from 8,115,034 to 11,004,211; that is, the objective function increases by 35.6%.

Lambda (λ) is the risk weight, and as λ increases, the degree of risk-averse decision-making increases and the model becomes more conservative. Therefore, by increasing the parameter λ and/or α, we achieve a high degree of risk aversion decision-making.

Sensitivity Analysis on the Lost Sale (Shortage) Cost

In the supply chain, a demand management strategy can be used to mitigate network risk (Tang 2006). The shortage cost (ls_m) in the form of lost sales is a parameter that is effective in regulating demand management. By adjusting the shortage cost (ls_m), we examine its effects on this model. To analyze the effect of ls_m on the objective function, we set four cases of ls_m according to Table 9 with a constant value for $\alpha=0.1$, $\lambda=0.1$. Table 9 shows the results of this experiment. The higher the shortage cost (ls_m), the higher the mean-CVaR and CVaR cost and the lower the expected shortage quantity. Therefore, increasing ls_m leads to a decrease in shortage and an increase in resilience. Also, as the cost of shortages (ls_m) increases, the number of selected suppliers does not change. According to Table 9, as the expected shortage cost increases from 12,500 to 30,000 (a 150% increase), the mean-CVaR objective function cost increases from 5,949,329 to 8,115,034 (a 36% increase),

Table 7 Comparison between production and lost sales

Scenario	Severity of disruption in supply	Severity of transportation network disruption	The amount of product (Q_{mkls})	Quantity	The amount of lost sale (N_{ms})	Quantity
2	High	Mid	$\sum_{k,l} Q_{(m=1).k.l.2}$	305	$N_{1.2}$	289
			$\sum_{k,l} Q_{(m=2).k.l.2}$	813	$N_{2.2}$	219
5	Mid	Mid	$\sum_{k,l} Q_{(m=1).k.l.5}$	1354	$N_{1.5}$	136
			$\sum_{k,l} Q_{(m=2).k.l.5}$	2329	$N_{2.5}$	0
8	Low	Mid	$\sum_{k,l} Q_{(m=1).k.l.8}$	1611	$N_{1.8}$	99
			$\sum_{k,l} Q_{(m=2).k.l.8}$	2329	$N_{2.8}$	0
10	No disruption	No disruption	$\sum_{k,l} Q_{(m=1).k.l.10}$	2016	$N_{1.10}$	41
			$\sum_{k,l} Q_{(m=2).k.l.10}$	2329	$N_{2.10}$	0

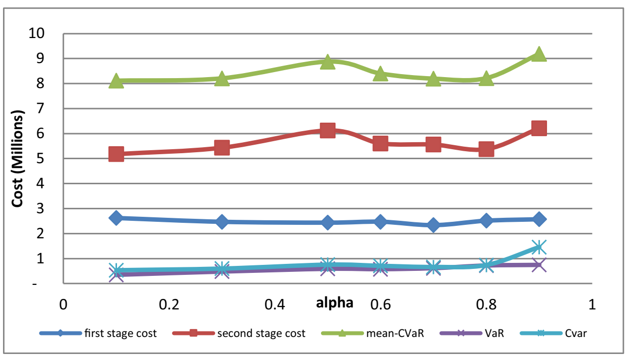

Fig. 2 Alpha vs. cost, mean-CVaR, VaR, and CVaR

while the amount of expected shortage amount decreases from 315 to 138 (a 56% decrease).

Also, in Table 9, we intend to examine the strategies that help suppliers to become more resilient during disruptions. The strategy of fortifying suppliers at four levels of shortage cost shows that four suppliers are fortified at level 2. The prepositioned inventory strategy at four shortage cost levels states that inventory is increasing. This increase indicates that the assumed model has to increase the inventory of this strategy to reduce the shortage and more resilience, while the objective function cost increases with the increase of this strategy. In the multiple-sourcing strategy, p1 means procurement of material/part 1 with supplier *i*. p1,2 means procurement of material/part 1 and material/part 2 with supplier *i*. p1,2,3 means procurement of material/part 1, material/part 2, and material/part 3 with supplier *i*. As can be seen in Table 9, in some cases, we have single-sourcing, double-sourcing, and triple-sourcing strategies. The multiple-sourcing strategy helps to reduce the scarcity and increase the resilience of the model. In general, double or multiple sourcing is more expensive than single sourcing, but it prevents shortages in the event of a disruption and increases the reliability of the system.

Managerial Insights

Based on the analyzed results, the following managerial insights are provided:

- Applying the G&RSS&OA-V problem improves the performance of SS&OA and VRP problems under economic

Table 8 Effect of different alpha on VaR, CVaR, first-stage cost, second-stage cost, and mean-CVaR ($\lambda = 0.1$)

α	0.1	0.3	0.5	0.6	0.7	0.8	0.9
VaR	349,642	480,390	590,427	576,408	616,189	723,134	746,948
CVaR	533,704	599,208	756,815	709,747	663,818	741,922	1,459,407
First-stage cost	2,622,188	2,470,178	2,436,527	2,473,741	2,337,033	2,514,960	2,572,953
Second-stage cost	5,177,257	5,433,567	6,123,415	5,608,118	5,559,949	5,377,333	6,211,635
Mean-CVaR	8,115,034	8,210,684	8,879,277	8,400,207	8,197,068	8,217,981	9,187,824

λ is also another essential parameter of risk-averse decision-making, the effects of which should be analyzed on the proposed model. To analyze how λ affects the objective function, we set five cases of λ (0.1, 0.5, 0.9, 5, 10) ith a constant value for $\alpha = 0.1$. Figure 3 and Fig. 4 show the results of this experiment. As shown in Fig. 3, at a constant alpha (α) value by increasing the λ values, the first-stage costs decrease and the second-stage costs increase. According to Fig. 4, at a constant alpha (α) value, as the λ values increases, the Var and CVaR costs increase

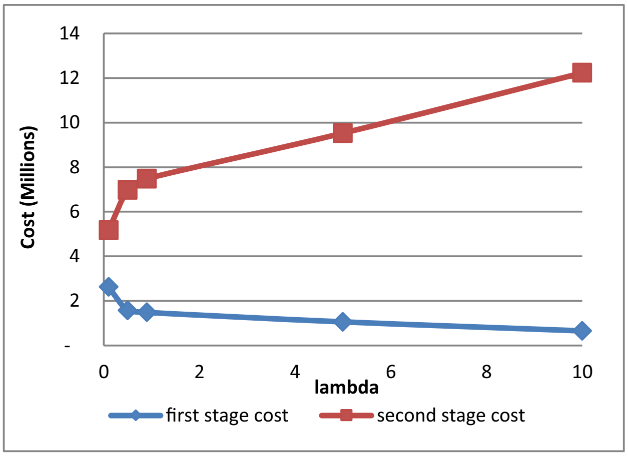

Fig. 3 Lambda vs. first-stage cost and second-stage cost

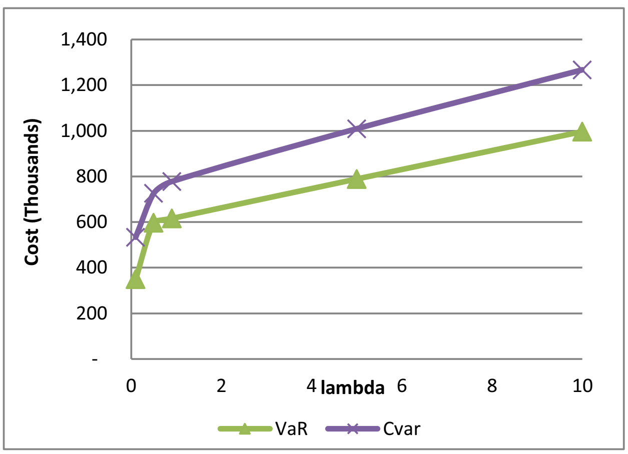

Fig. 4 Lambda vs. VaR and CVaR cost

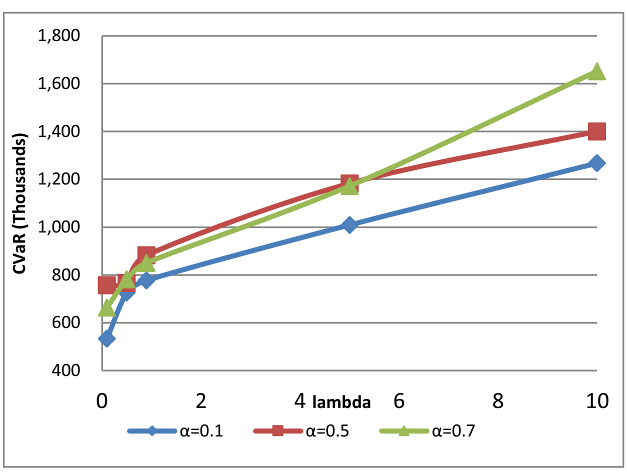

Fig. 5 CVaR values for different lambda

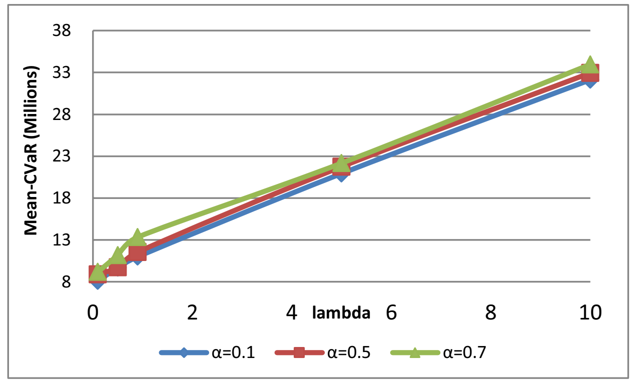

Fig. 6 Mean-CVaR values for different lambda

and environmental aspects, and resilience strategies significantly contribute to the problem performance under disruption. Hence, managers can make optimal decisions about proactive resilience strategies and green paradigm.

- The supplier selection and order allocation integrated with vehicle routing (SS&OA-V) problem is mainly investigated for the risk-neutral decision-maker, and our results show that the supply and transportation network disruption and green requirements significantly affect the structure of the SS&OA-V problem, so the proposed problem should be considered a risk-averse G&RSS&OA-V problem.
- The type of disruption events and the probability of disruption events have a great impact on the configuration of supplier selection and the transportation network.
- By increasing the weight factor parameter (λ) and the confidence level (α), the model becomes more risk-averse or, in other words, acts more conservatively. Managers can tune their risk level in CVaR through the confidence level (α) and its weight factor (λ).
- Also, increasing the shortage cost (ls_m) leads to less shortage and more resilience of the model. Managers can tune demand management through parameter ls_m.

Conclusion

In this paper, we proposed the multiproduct green and resilient supplier selection and order allocation integrated with vehicle routing (G&RSS&OA-V) problem under disruption risks to optimize total cost. We tried to consider the most practical environmental objectives and resilience strategies in the problem. To the best of our knowledge, this is the first time that the SS&OA-V problem with an efficient and practical combination of GSCM and proactive resilience strategies with risk aversion decisions is proposed to minimize greenhouse emissions and fuel consumption simultaneously. The objective function of our model includes minimizing the

Table 9 Effect of different $ls_{(m)}$ on selected suppliers, mean-CVaR, CVaR, expected lost sale, fortified suppliers, prepositioned inventory, and multiple sourcing ($\alpha = 0.1$, $\lambda = 0.1$)

Distribution associated with shortage costs	Shortage cost	Selected suppliers	Mean-CVaR	CVaR	Expected lost sale	Fortified suppliers ($e = 2$)	Sum of prepositioned inventory	Multiple sourcing (i)			
								1	2	3	4
Uniform(5000,20,000)	ls ($m = 1$) = 11,208 ls ($m = 2$) = 19,704	1, 2, 3, 4	5,949,329	469,786	315	1, 2, 3, 4	8729	p1,2	p1,2,3	p1,2,3	p1
Uniform(20,000,40,000)	ls ($m = 1$) = 25,943 ls ($m = 2$) = 30,326	1, 2, 3, 4	8,115,034	533,704	138	1, 2, 3, 4	18,310	p1	p1,2	p1,3	p1
Uniform(40,000,60,000)	ls ($m = 1$) = 43,549 ls ($m = 2$) = 54,279	1, 2, 3, 4	10,186,617	707,913	115	1, 2, 3, 4	21,045	p1	p1,2	p1,2,3	p1
Uniform(60,000,80,000)	ls ($m = 1$) = 67,374 ls ($m = 2$) = 79,597	1, 2, 3, 4	11,905,326	884,838	98	1, 2, 3, 4	21,045	p1	p1,2	p1,2,3	p1

p1 include material/part 1. p1,2 include material/part 1and material/part 2. p1,2,3 include material/part 1, material/part 2, and material/part 3

mean-risk (mean-CVaR) costs to optimize the performance of the worst-case scenario of the G&RSS&OA-V problem in a two-stage stochastic programming model. Our proposed model includes three stochastic parameters: the remaining capacity rate in each supplier, complete disruption of vehicles, and complete disruption of routes. We considered multiple sourcing, supplier fortification, prepositioned inventory, and concluding a contract with a 3PL as resilience strategies.

In order to validate the proposed model, numerical examples are solved by using GAMS software. We used three important model parameters for sensitivity analysis. Various computational experiments are performed to examine these parameters on the objective function of the proposed model. In future research, we can consider other disruption risks (political and economic crises) and operational risks (cost fluctuations, climate changes) and their impact on suppliers and HMD center. Considering new proactive and reactive resilience strategies and green objectives will be another research avenue, accounting for the occurrence of multiple successive disruptions instead of one. In addition, applying other transportation modes, such as air transportation under the transportation network disruption, will lead to greater resilience. Further, the approach of this model can be used with the concept of sustainability which, in addition to economic factors and environmental concerns, also plans and manages social responsibility. Providing a metaheuristic algorithm to solve large-scale problems and identify an example of a problem that can sufficiently represent a set of all disruption scenarios can be another future area of research. In order to manage the uncertainty of the input data, we propose optimization approaches such as robust and fuzzy.

Author Contribution Seyed Mojtaba Taghavi: conceptualization, methodology, investigation, resources, software, formal analysis, writing—original draft, and writing—review and editing. Vahidreza Ghezavati: conceptualization, methodology, investigation, formal analysis, writing—review and editing, validation, and supervision. Hadi Mohammadi Bidhandi: investigation, writing—review and editing, validation, and supervision. Seyed Mohammad Javad Mirzapour Al-e-Hashem: investigation, writing—review and editing, validation, and supervision.

Data Availability The random datasets generated during and/or analyzed during the current study are available in the (Google Drive) repository (https://drive.google.com/file/d/1UVd6EX5PI5HfN5Two1nPsYykIeuVAvSO/view?usp=sharing).

Declarations

Competing Interests The authors declare no competing interests.

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