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Enhancing Supply Chain Resilience in Disruption Caused by Catastrophes Such as Pandemics: An Integrated Grey Analysis-Stochastic Optimization Model

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ABSTRACT

This research presents a comprehensive decision-making model for optimizing global supply chain operations during disruptions caused by catastrophes, e.g., pandemics, making a significant contribution to the supply chain management literature. The model integrates Grey optimal ranking and employs a scenario-based stochastic Mixed-Integer Programming approach to enhance resilience. It addresses the 'ripple effect' of regional disruptions by modelling simultaneous impacts on supply, demand, and logistics. Computational examples, based on a real-world case during pandemic, validate the model's effectiveness in minimizing costs and ensuring availability, quality, and emission levels. The study reveals the numerical significance of traditional resilience measures, such as pre-positioning Recovery Materials Inventory and utilizing recovery supplies. Results demonstrate the model's capacity to mitigate the impacts of multi-regional disruptions. In essence, the research provides a quantifiable and practical contribution, offering insights for resilient supply chain management in the face of pandemic disruptions.

1. Introduction

Amid mounting global uncertainties and vulnerabilities, supply chain resilience has emerged as a top concern. This resilience not only entails the capacity to rapidly recover from disruptions but also the ability to maintain, execute, and restore planned operations amidst various risk factors. Manufacturers have recognized the urgent necessity for robust strategies to manage disruptions, whether stemming from events such as the COVID-19 pandemic, natural disasters, or political conflicts [12] . With a focus on resilience, these strategies encompass a wide array of risk-mitigation tactics, including sourcing from multiple vendors [2], establishing backup contracts, stockpiling recovery supplies, fortifying supplier resilience, positioning essential inventory strategically [26], and facilitating ad-hoc purchases [27].

The outbreak of the COVID-19 pandemic in 2019 brought about unique disruptions that

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simultaneously affected global supply, demand, and logistics. This pandemic introduced an unpredictable phenomenon known as the "ripple effect," extending disruptions even to those triggered by political conflicts. These disruptions within the supply chain spread across regions, complicating risk mitigation and recovery efforts. The ripple effect closely mirrored the spread of the pandemic itself, leading to a series of events: the outbreak in a source region, subsequent lockdowns, facility closures, production suspensions, shifts in demand for essential and non-essential products, propagation of disruptions across regions, and eventual recovery. To illustrate the weighty impact of the COVID-19 pandemic and political conflicts on supply chains, consider the automotive industry where the global chip shortage halted production at numerous manufacturers like Ford and Toyota. With critical electronic components sourced from Asia and facing pandemic-related disruptions, production lines came to a standstill. This ripple effect resulted in significant production gaps, extended wait times for new cars, and a sharp decline in vehicle sales, leading to billions in lost revenue for automotive giants and impacting millions of potential buyers [1; 19]. The profound impacts of the global pandemic and political tensions on worldwide supply chains were characterized by a surge in demand for essential goods and healthcare items, resulting in shortages. Conversely, non-essential product demand experienced a decline. Shortages in material supplies, reduced production capacity due to a scarcity of workers, and diminished logistical capacity became evident. The disruption of physical distribution channels led to widespread delays in transportation and distribution [12],

Furthermore, extending beyond resilience, the COVID-19 pandemic and political conflicts prompted a raised level of investigation in supply chain research—focusing on supply chain viability, which denotes the ability of a supply chain not only to withstand disruptions but also to dynamically adapt to changing environments. A viable supply chain integrates sustainability into its core, displaying agility in adaptation, resilience in recovery, and thriving in the face of global forces by meticulously managing capacity and resources to meet both present and future needs [11]. This study explores the effectiveness of conventional resilience measures, such as pre-positioning Recovery Materials Inventory (RMI), ensuring backup supplier loyalty, and recovery supplies, in ensuring the survival and recovery of supply chains amid a pandemic. Specifically, it addresses scenarios marked by simultaneous disruptions in supply, demand, and logistics originating from a strategic source region. These disruptions cascade across multi-regional supply chains, sequentially impacting suppliers and manufacturers in diverse regions. The study aims to evaluate the adaptability and effectiveness of traditional resilience strategies in the face of complex and interconnected disruptions during a pandemic.

This research makes a significant contribution by comprehensively addressing a crucial research question through the innovative development and application of a unique problem formulation. This formulation seamlessly integrates grey decision analysis and stochastic mixed-integer programming to evaluate a range of scenarios. The primary aim is to optimize the operational efficiency of multi-regional supply chains, particularly when facing pandemic-related disruptions originating from a central source region. This research distinctively addresses the challenge of backup supplier commitment, unlike [26], through a proactive approach. An initial phase of grey analysis strategically ranks backup suppliers, ensuring their reliable support during disruptions. This aligns with the overarching goal of developing a supplier selection framework that balances expert judgment with cost minimization via stochastic mixed-integer programming. Furthermore, the paper constructs scenarios that closely reflect the real-time unfolding and cascading consequences observed during the COVID-19 pandemic. These scenarios comprehensively analyse diverse pandemic characteristics, encompassing supply shortages, demand delays, and transportation disruptions, occurring in both concurrent and sequential patterns. To effectively manage and mitigate disruptions, the paper proposes a decision-making process that incorporates both proactive and reactive strategies, considering spatial and temporal factors. A multi-portfolio approach is employed to integrate decision-making for multi-regional supply chains facing significant disruption risks. This methodology concurrently identifies recovery supply portfolios for alternative suppliers, aligning them with supply schedules, production plans, and inventory management for tire manufacturing plants across the entire planning horizon. Ultimately, this approach enhances the overall performance and resilience of the supply chain.

The numerical examples presented in this paper, drawn from an actual case study of a pandemic in the real world, illustrate the effectiveness of integration of the grey decision method and the multi-portfolio strategy alongside its related stochastic optimization models. Innovative models using powerful optimization techniques improve supply chain resilience during pandemics. Existing regional mitigation strategies adapt adeptly to handle widespread disruptions, benefiting organizations regardless of risk tolerance. The "resilient portfolio strategy" minimizes costs, enhances service levels, and reduces risks through diversification and strategic location. This novel approach fills a gap in supply chain management literature, offering crucial tools for building robust, adaptable supply chains in the face of global pandemics. This research breaks new ground by showing that resilient supply chains pivot on strategic and backup supplier selection. It pioneers a framework that blends expert insights with quantitative analysis using "grey analysis," empowering organizations to navigate uncertainty during pandemics and other disruptions. This cutting-edge approach positions the paper as a game-changer in supplier selection, with potential to revolutionize industries facing disruption-related challenges.

The remainder of this paper is structured as follows: Section 2 provides a critical literature review, identifying research gaps. In Section 3, the problem statements and methodology are discussed. Section 4 presents the formulation of the stochastic scenario-based model, while Section 5 delves into its detailed discussion. Sections 6 and 7 focus on case study implementation and result analysis respectively. Finally, Section 8 draws conclusions and suggests future research directions.

2. Critical Review of Literature

This section presents a comprehensive review of relevant literature pertaining to managing disruption risks in supply chains. The analysis commences by scrutinizing portfolio approaches aimed at mitigating disruption impacts. Subsequently, it examines the concept of supply chain resilience and its relationship with the "ripple effect" phenomenon. Building upon this foundation, the review delves into research conducted on supply chain management during the COVID-19 pandemic. Finally, the discourse culminates in an exploration of strategies for maintaining supply chain viability in the face of pandemic-related disruption risks.

This research builds upon the foundational work of Sawik [20], who pioneered the introduction of a portfolio approach for integrated decision-making within global supply chains under disruption risks. This methodology caters to both risk-neutral and risk-averse scenarios, initially applied within a two-tier supply chain framework. Subsequent refinements and expansions, documented in studies like [21; 22; 28], broadened the approach's applicability to diverse supply chain settings. Notably, [21; 24; 25] explored resilient supply portfolios within both two-tier and multi-tier configurations, investigating diverse strategies such as supplier fortification, resource and material pre-positioning, Recovery Materials Inventory (RMI) utilization, and recovery supplies from backup vendors. The roles of RMI and reserve capacity in bolstering supply chain resilience and mitigating disruption risks were further scrutinized by [16].

Their analysis delves into the cost implications of RMI holding and reserve capacity fixed costs associated with reservation and emergency production. Notably, Locker et al. and Sawik's studies focused on optimizing RMI and reserve capacity allocation for mitigating disruption risks at a single location under stochastic demand conditions. Their findings reveal that the optimal RMI level can fluctuate based on holding costs and might remain constant under specific penalty cost scenarios. Conversely, the optimal reserve capacity tends to increase with demand variability. Further contributing to RMI optimization under disruption risks with deterministic demand in a pharmaceutical setting, [15] proposed and implemented optimal RMI levels. Collectively, these studies offer valuable insights into portfolio-based disruption management, supply chain resilience, and risk mitigation strategies, paving the way for a comprehensive understanding of disruption response and enhanced supply chain viability.

In contrast, the existing body of literature on supply chain resilience predominantly relies on two primary methodologies: mathematical programming (e.g., [21; 24; 25] and simulation [18]. A comprehensive review by Hosseini et al. [9] offers additional perspectives on quantitative methods for analysing supply chain resilience. One notable strategy for resilience enhancement under supply and demand uncertainties lies in sourcing, with in-house component production emerging as a highly effective approach [6]. Hosseini et al. [9] developed a stochastic bi-objective mixed-integer programming model encompassing both proactive and reactive resilience strategies like supplier segregation, backup contracts, supplier reliability, surplus inventory management, and supplier restoration capabilities. The model aims to maximize geographical separation between supplier locations while minimizing overall supplier selection costs. He et al. [8] introduced an optimization approach for inventory planning in a two-tier supply chain experiencing disruptions, coupled with correlated demand and price uncertainties. This approach leverages a dual sourcing strategy and real-option pricing methodology to mitigate disruption risks. A structured literature review conducted by Mishra et al. [17] further summarized valuable contributions in supply chain risk management, particularly focusing on the ripple effect phenomenon. Their work also introduces a novel robust dynamic Bayesian network approach for disruption risk assessment under the ripple effect.

The intricate cascading consequences of supply chain disruptions have propelled this topic to the forefront of research priorities. Studies like Liu et al. [14] dynamic Bayesian network approach offer valuable insights into these "ripple effects," particularly when data on disruption probabilities is limited. Their work delves into a manufacturer's performance under disruptive scenarios, focusing on worst-case outcomes. Others, such as Gholami-Zanjani et al. [7] and Lei et al. [13], explore the ripple effect's influence on designing resilient food supply chains and managing inventory for perishable items. Notably, Lei et al. [13] advanced SIS model, coupled with a complex network model, sheds light on the dynamic evolution and propagation of risk in intricate global supply chains. This approach unveils the interplay between supply chain structures and risk transmission, informing the selection of effective risk control strategies.

The COVID-19 pandemic has spurred a surge of research, particularly focused on supply chain resilience under pandemic disruption. A comprehensive review by Chowdhury et al. [5] tackled research on the pandemic's impact, resilience strategies, and the role of technology in implementing them. While the fast-tracked publication channels for COVID-19 research yielded a plethora of papers, few offer truly ground-breaking insights into pandemic-specific disruption management. Despite this, the literature provides a valuable trove of quantitative methods for predicting and mitigating pandemic impacts.

Pandemic-related disruption research can be categorized into four main avenues: analytical models, simulation models, deterministic optimization, and stochastic optimization [3]. Each category offers valuable insights for specific situations. Analytical models Chowdhury et al. [4] propose simple strategies for specific industries (e.g., [18] toilet paper case study), improving service levels with clear formulas and assumptions. Simulation models, pioneered by Ivanov Ivanov [10], analyse real-world scenarios. Ivanov's China-based study reveals that the timing of facility closures and re-openings significantly impacts supply chain performance, alongside factors like lead times and pandemic propagation speed. These research streams collectively shed light on various aspects of disruption management, providing diverse tools for navigating pandemic challenges.

Despite the breadth of existing research on disruptions caused by catastrophic events, natural disasters, and political conflicts, a robust solution to securing supply during such periods remains elusive. While the prevailing approach advocates for diversifying suppliers beyond strategic partners [23] it fails to provide sufficient incentives for alternative suppliers, who perceive themselves as temporary providers, to fully engage and invest in the long-term viability of the supply chain. This necessitates a more nuanced understanding of the complex factors motivating supplier behaviour and the development of strategies that foster a sense of mutual commitment and shared responsibility during times of crisis. This article proposes a ranking strategy for alternative suppliers, aiming to ensure a stable connection between manufacturing firms and these "semi-strategic" suppliers.

3. Problem Background and Methodologies

This article focuses on a business organization that operates in a pandemic-affected environment. The organization seeks to formulate a supplier selection mechanism that incorporates various factors impacting supplier performance during such a crisis. The primary objective is to optimize overall procurement costs for multiple components sourced from multiple suppliers. Within such a dynamic environment, supplier costs can undergo unpredictable fluctuations, rendering fixed supplier rankings impractical. This volatility arises from the potential for significant cost increases from specific suppliers during particular ordering periods. Recognizing the unique challenges posed by such situations, particularly pandemics and associated lockdown protocols, we advocate for an expert opinion-based Multi-Criteria Decision-Making (MCDM) approach as a valuable tool, supported by existing literature [23]. This paper addresses the issue of unpredictable supplier costs in a pandemic-affected environment through a two-step approach. First, we propose an MCDM-based methodology to determine individual supplier scores. These scores then serve as weights within a multi-portfolio framework and scenario-based stochastic Mixed-Integer Programming (MIP) model. This model optimizes supplier allocation to minimize total cost while addressing the stochastic nature of supply chain resilience. Subsequent sections of this paper detail the methodology used to design this comprehensive supplier selection strategy.

Moving to the second stage, a stochastic optimization model is introduced to optimize cost and resilience under uncertainty. The model setup involves defining indices, determining input parameters, formulating an objective function for cost and resilience optimization, and establishing constraints. Problem-solving includes determining variables, initializing constraints, employing the branch and bound algorithm for optimization, and iterating through calculations until the optimal solution is reached. The key points emphasize the interaction between grey analysis and stochastic optimization, highlighting their integration for robust supplier selection and allocation in the face of disruptive scenarios.

The model is represented by a flowchart in Figure 1.

4. Grey Ranking Optimal Ranking for Supplier Selection Methodology

Recognizing the unique challenges posed by disruption situations, particularly pandemics and associated lockdown protocols, we advocate for an expert opinion-based Multi-Criteria Decision-Making (MCDM) approach as a valuable tool, supported by existing literature [23].

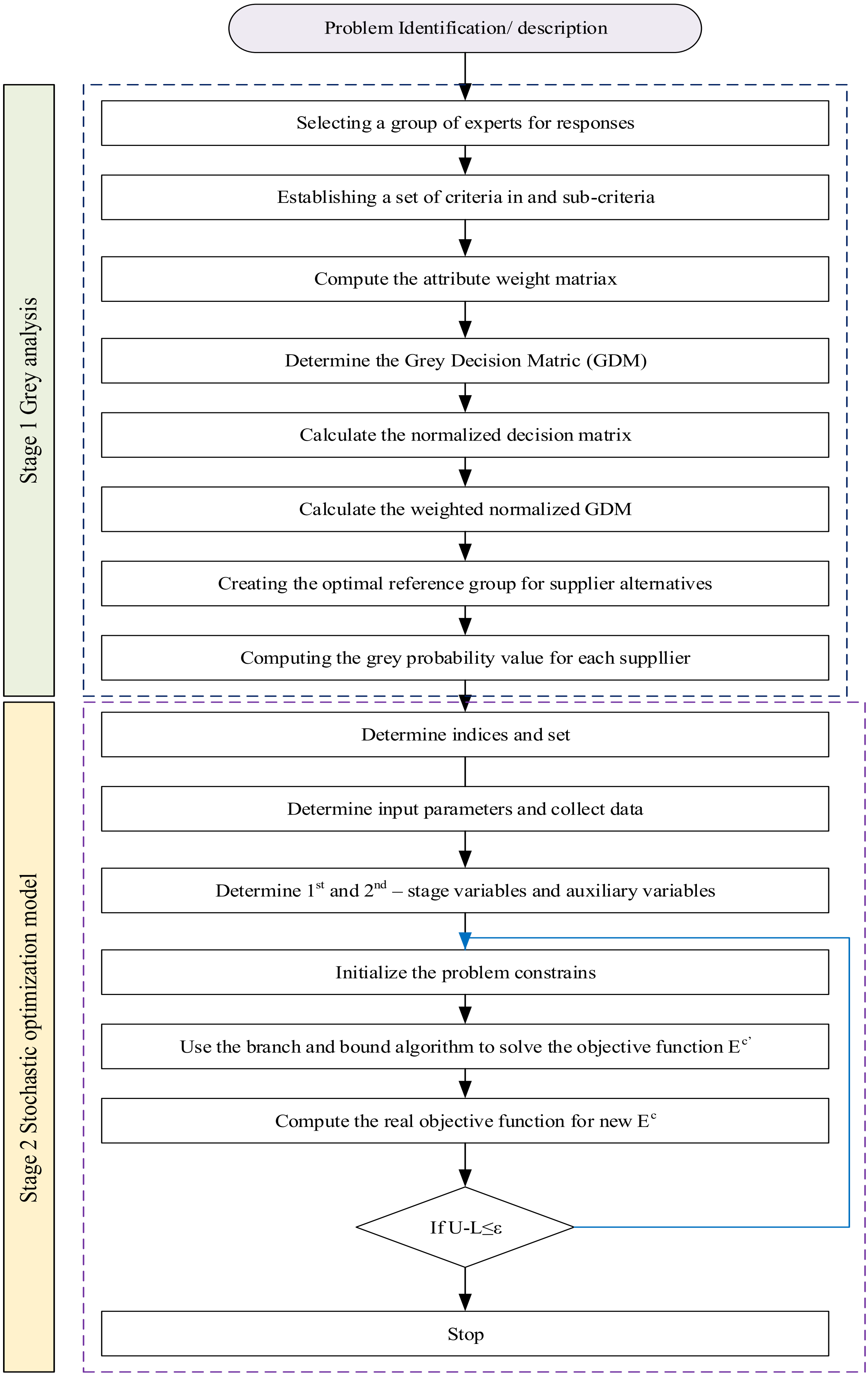


Fig: 1. Flowchart of research methodology

4.1 Determination of the supplier scoring

The decision to utilize the Grey Relational Analysis (GRA) methodology for establishing the initial scoring of backup supplier stems from its unique capability to integrate both quantitative and qualitative factors [23]. Additionally, GRA's suitability in handling scenarios with limited information availability [11] aligns perfectly with the complexities of our supplier ranking problem. The applied grey analysis methodology is depicted in Figure 1. Within our organization, a group of $\boldsymbol{S}$ alternative suppliers was identified through discussions involving five distinguished industrial experts, as illustrated in Figure 2.

Fig2: Details of experts involved in the study

4.2 *Defining the criteria and sub-criteria*

In alignment with insights from the existing literature and discussions with industrial experts, we formulated the criteria and sub-criteria (attribute) for supplier ranking, as outlined in Table 1. This table outlines a comprehensive framework for evaluating potential suppliers, considering critical aspects like cost, quality, service, environmental impact, capabilities, past relationship, pandemic resilience, and more. It delves deeper into each aspect through dedicated sub-criteria (attribute), empowering you to make informed supplier ranking decisions based on a detailed understanding of each candidate's strengths and weaknesses.

Table 1
Criteria and sub-criteria of the ranking of the suppliers.

Category	Sub-Criteria (Attribute)	Description	Code	Weight
Cost	Manufacturing Cost (X_1)	Expense of producing each item	MC	0.2
	Transportation Cost (X_2)	Expense of delivering items to the manufacturer	TC	0.1
Quality	Manufacturing Quality (X_3)	Level of quality maintained by the supplier during production	Qm	0.3
	Repair Response Time (X_4)	Responsiveness of the supplier in addressing defects	Tr	0.1
Internal Performance	Service Quality (X_8)	Overall service level provided by the supplier	S	0.1
	Item Price (X_9)	Price charged by the supplier to the manufacturer	P	0.2
Environmental Impact	Pollution & CO2 Emission (X_{10})	Environmental impact of the supplier's manufacturing processes	C	0.05
Supplier Capabilities	Manpower (X_{11})	Number of employees or workforce strength	M	0.05
	Flexibility (X_{12})	Ability to provide different or customized items	F	0.05
Relationships & Infrastructure	Past Relationship (X_{13})	History of collaboration between the supplier and the manufacturer	R	0.05
	Available Infrastructure/Resources (X_{14})	Financial resources and operational infrastructure of the supplier	AI	0.05
	Scale of Operations (X_{15})	Size and scope of the supplier's business operations	SO	0.05
	Production Capacity (X_{16})	The supplier's ability to meet production demands	SC	0.05
Pandemic Resilience	Geographical Location (X_{17})	Location of the supplier's operations and proximity to the manufacturer	GL	0.05
	Transportation Mode (X_{18})	Method used by the supplier for delivering items	TM	0.05
	Employee Distribution (X_{19})	Diversity of the supplier's workforce in terms of origin and demographics	DE	0.05
	Government Regulations (X_{20})	Impact of local laws and regulations on the supplier's operations	GR	0.05

4.3 Calculation of the weight matrix of the attributes

To identify the optimal backup supplier out of $\mathscr{s}$ options ($\mathcal{S} = \{1, 2, \ldots, \mathscr{s}\}$), a multi-departmental evaluation process was implemented. Key executives ($\mathcal{K} = \{1, 2, \ldots, \mathscr{k}\}$) assessed each supplier based on pre-defined factors ($X = \{1, 2, \ldots, x\}$). Their qualitative assessments of factor importance were converted to quantitative data for objective analysis. See Table 2.

Table 2
Ranking criteria of the grey analysis

Rating	Code	$\otimes \boldsymbol{W_j}$
Very poor	VP	[0.0, 0.1]
Poor	P	[0.1, 0.3]
medium poor	MP	[0.3, 0.4]
Fair	F	[0.4, 0.5]
Medium good	MG	[0.5, 0.6]
Good	G	[0.6, 0.9]
Very good	VG	[0.9, 1.0]

Here, $\otimes W_j$ refers to the grey value of weight of attributes j which is estimated through Eq. 1

$$\otimes W_j = \left[\underline{W}_j, \overline{W}_j\right] \forall j \in \mathrm{X} \quad (1)$$

The average weight for the attribute j is defined by in Eq. (2). Subsequently, the final weight matrix, calculated based on the responses of the experts, is presented in Table 2.

$$\otimes W_j = \frac{1}{\mathscr{k}}\left[\otimes W_j^1 + \otimes W_j^2 + \otimes W_j^3 + \cdots + \otimes W_j^{\mathscr{k}}\right] \forall j \in X \quad (2)$$

4.4 Grey decision matrix calculations

Each expert offers assessments of supplier s 's performance concerning attribute j using linguistic terms. The conversion of these linguistic values to grey values is accomplished using the scale outlined in Table 3.

Table 3
Final weight matrix

Rating	Code	$\otimes G_{sj}$
Very poor	VP	[0,1]
Poor	P	[1,3]
medium poor	MP	[3,4]
Fair	F	[4,5]
Medium good	MG	[5,6]
Good	G	[6,9]
Very good	VG	[9,10]

Let G_{sj}^{k} denote the linguistic value of supplier $s's$ performance for attribute$s$ as evaluated by expert k and $\otimes G_{sj}$ represent the corresponding grey value:

$$\otimes G_{sj} = \left[\underline{G_{sj}}, \overline{G_{sj}}\right] \; \forall j \in \mathcal{N}, \forall s \in \mathcal{S} \tag{3}$$

and the average evaluation is determined by Eq. (4):

$$\otimes G_{sj} = \frac{1}{k}\left[G_{sj}^{1} + G_{sj}^{2} + G_{sj}^{3} + \cdots G_{sj}^{k}\right] \forall j \in \mathrm{X}, \forall s \in \mathcal{S} \tag{4}$$

Now, let $\mathcal{D}$ stand for the grey decision matrix as defined in Eq. (5). Subsequent to the experts' responses, the grey decision matrix is computed according to the particulars of the case study:

$$\mathcal{D} = \begin{bmatrix} \otimes G_{11} & \cdots & \otimes G_{1j} \\ \vdots & \ddots & \vdots \\ \otimes G_{s1} & \cdots & \otimes G_{sj} \end{bmatrix} \tag{5}$$

4.5 The normalized grey decision matrix estimations

The grey decision matrix undergoes normalization to align the grey values within the [0, 1] range. The grey value of the normalized matrix is denoted as $\otimes \boldsymbol{G}_{sj}^{*}$. This normalization is achieved through the calculation outlined in Eq. (6). The resulting normalized matrix can be represented as $\mathcal{D}^{*}$ in Eq. (7). The normalized matrix derived from the decision matrix in the problem is provided in

$$\otimes \boldsymbol{G}_{sj}^{*} = \left[\frac{\underline{\boldsymbol{G}_{sj}}}{\boldsymbol{G}_{j}^{max}}, \frac{\overline{\boldsymbol{G}_{sj}}}{\boldsymbol{G}_{j}^{max}}\right] \forall j \in \mathbf{X}, \forall s \in \boldsymbol{S} \tag{6}$$

Where $\boldsymbol{G}_{j}^{max} = \boldsymbol{max}\left[\overline{\boldsymbol{G}_{sj}}\right] \; \forall j \in \boldsymbol{X}, \forall s \in \boldsymbol{S}$

$$\mathcal{D}^{*} = \begin{bmatrix} \otimes \boldsymbol{G}_{11}^{*} & \cdots & \otimes \boldsymbol{G}_{1j}^{*} \\ \vdots & \ddots & \vdots \\ \otimes \boldsymbol{G}_{s1}^{*} & \cdots & \otimes \boldsymbol{G}_{sj}^{*} \end{bmatrix} \tag{7}$$

4.6 The weighted normalized grey decision matrix calculations

The weighted normalized grey decision matrix is acquired by the multiplication of the normalized grey decision matrix with the weight matrix. The grey values within the resulting weighted normalized matrix are denoted as follows:

$$\otimes \boldsymbol{V}_{sj} = \left[\left(\otimes G_{sj}^{*}\right) * \left(\otimes W_{j}\right)\right] \tag{8}$$

Where $\otimes \boldsymbol{V}_{sj} = \left[\underline{\boldsymbol{V}_{sj}}, \overline{\boldsymbol{V}_{sj}}\right]$, $\underline{\boldsymbol{V}_{sj}} = \underline{\boldsymbol{G}_{sj}^{*}} * \underline{\boldsymbol{W}_{j}}$, and $\overline{\boldsymbol{V}_{sj}} = \overline{\boldsymbol{G}_{sj}^{*}} * \overline{\boldsymbol{W}_{j}} \; \forall j \in \boldsymbol{X}, \forall s \in \boldsymbol{S}$.

The weighted normalized Grey Decision matrix is further denoted as $\mathcal{D}^{**}$, as shown in Eq. (9).

$$\mathcal{D}^{**} = \begin{bmatrix} \otimes V_{11} & \cdots & \otimes V_{1j} \\ \vdots & \ddots & \vdots \\ \otimes V_{s1} & \cdots & \otimes V_{sj} \end{bmatrix} \tag{9}$$

4.7 Defining the optimal reference set of backup suppliers

The optimal reference value is determined for each attribute utilized in the evaluation of backup suppliers. It represents the highest value in the weighted normalized decision matrix for each attribute across various suppliers. The value is obtainable by Eq. (10), and it is denoted by $\mathcal{S}^{max}$.

$$\mathcal{S}^{\boldsymbol{max}} = \Big[\big[\max\big(\underline{V_{s1}}\big)\,\forall s \in \mathcal{S}, \max\big(\overline{V_{s1}}\big)\forall s \in \mathcal{S}\big], \big[\max\big(\underline{V_{s2}}\big)\,\forall s \in \mathcal{S}, \max\big(\overline{V_{s2}}\big)\forall s \in \mathcal{S}\big], \big[\max\big(\underline{V_{s3}}\big)\,\forall s \in \mathcal{S}, \max\big(\overline{V_{s3}}\big)\forall s \in \mathcal{S}\big], \dots, \big[\max\big(\underline{V_{sj}}\big)\,\forall s \in \mathcal{S}, \max\big(\overline{V_{sj}}\big)\forall s \in \mathcal{S}\big]\Big] \quad \text{or} \tag{10}$$

$$\mathcal{S}^{max} = \{\otimes G_1^{max}, \otimes G_2^{max}, \otimes G_3^{max}, \dots, \otimes G_j^{max}\}$$

4.8 Compute the grey likelihood for each backup supplier.

In this stage, the grey likelihood value is computed for each Supplier s in relation to the ideal reference set $\mathcal{S}^{max}$. This value is denoted by $P(\mathcal{S}_s \leq \mathcal{S}^{max})\forall s \in \mathcal{S}$. Eq. (11) illustrates the likelihood of the backup supplier's performance for each attribute.

$$P(\mathcal{S}_s \leq \mathcal{S}^{max}) = \frac{1}{X}\sum_{j \in \mathrm{X}} P\{\otimes V_{sj} \leq \otimes G_j^{max}\}\ \forall s \in \mathcal{S} \tag{11}$$

Thus, the grey likelihood of backup supplier illustrates the gap between the supplier's values and the ideal reference set. The idea case entails smaller likelihood value, the better is the performance, and hence, the ranking of the supplier. The likelihood that a grey number is less than or equal to another grey number can be estimated as by Eqs. (12, 13).

$$P(\mathcal{S}_s \leq \mathcal{S}^{max}) = \frac{1}{|\mathcal{N}|}\sum_{j \in \mathcal{N}} \frac{\max\left(0, \mathcal{L}_j^* - \max\left(0, \overline{V_{sj}} - \underline{G_j^{max}}\right)\right)}{\mathcal{L}_j^*} \tag{12}$$

Where $\boldsymbol{\mathcal{L}_j^* = \mathcal{L}(\otimes V_{sj}) + \mathcal{L}(\otimes G_j^{max})\forall j \in X}$, therefore, $\boldsymbol{\mathcal{L}(\otimes V_{sj}) = \overline{V_{sj}} - \underline{V_{sj}}}$, and $\boldsymbol{\mathcal{L}(\otimes G_j^{max}) = \overline{G_j^{max}} - \underline{G_j^{max}}\ \forall j \in X, \forall s \in \mathcal{S}}$.

By substituting the values of $\mathcal{L}$, then we obtain the total $\mathcal{L}_j^*$ through Eq. (13)

$$\mathcal{L}_j^* = \left(\overline{V_{sj}} - \underline{V_{sj}}\right) + \left(\overline{G_j^{max}} - \underline{G_j^{max}}\right) \tag{13}$$

The likelihood values provide the ranking of backup suppliers which is the input the subsequent step. The subsequent section provides an illustration of a mathematical model that integrates grey scoring into a stochastic Mixed-Integer Programming (MIP) based cost optimization model. This model aims to ascertain the ultimate allocation for suppliers, considering various factors such as quality, availability, emissions, and conducting production, supply, and inventory scheduling to optimize overall supply chain.

5. Stochastic Scenario-Based and Multi-Approach Resilient Optimization

This paper adopts the mathematical model developed by Sawik [26]. The model is adopted to match a supply chain scenario where a tire manufacturing plant produces a singular product type (tire). The essential raw material, natural rubber, is sourced from different suppliers to meet market demand. In this application, it is assumed that the supply chain is composed of $\boldsymbol{m} = m_1 + m_2 + m_3$ supply chain nodes, $i \in I = \{1, \ldots, m_1, m_1 + 1, \ldots, m_1 + m_2, m_1 + m_2 + 1, \ldots, m_1 + m_2 + m_3\}$, situated in various geographic regions, $K = \{1, \ldots, k\}$. The nodes encompass m_1 strategic suppliers, $i \in \{1, \ldots, m_1\}, m_2$ recovery backup suppliers, $i \in I = \{m_1 + 1, \ldots, m_1 + m_2\}$, and m_3 tire manufacturing plants, $i \in \{m_1 + m_2 + 1, \ldots, m_1 + m_2 + m_3\}$.

The collection of supply chain nodes within a specific region $k \in K$ is denoted by I^k . The strategic suppliers $i \leq m + 1$ are located in the originating disruption region $k = 1$, where I^1 = {1, . . ., m_1}. The tire manufacturing plants, and recovery backup suppliers are distributed across various regions. The originating region, $k = 1$ faces risks associated with disruptions (e.g., pandemic) at varying levels, $l \in L_1$ = {0, . . ., $\bar{L}_1$}, each associated with distinct probabilities, p_{1l}. The disruption level describes the severity of the disruption, which is represented by the duration of the disruption, available capacity of suppliers, and rate of fulfilling orders, etc. A greater level of disruption implies a disruption of higher severity. When the disruption level is denoted as $l = 0$, it signifies normal circumstances without disruptions, indicating maximum capacity availability and complete fulfilment of orders.

Disruptions having a level $l \in L_1 : l > 0$ in the originating region $k = 1$, have the potential to propagate and result in regional disruptions that are delayed and having different levels, $l \in L_k = \{0, 1, \ldots, \bar{L}_k\}$, across the other regions, $k \in K : k > 1$, each having unique probabilities, p_{kl}. The overall count of all conceivable scenarios is given by $\prod_{k \in K} (\bar{L}_k + 1)$.

Each scenario $s \in S = \{1, \ldots, \prod_{k \in K} (\bar{L}_k + 1)\}$ is denoted by an n vector with s dimensions $\lambda^s = \{\lambda_{1s}, \ldots, \lambda_{ns}\}$, where $\lambda_{ks} \in L_k$ is the level of disruption in region $k \in K$, under scenario $s \in S$. The probability, R_s, for every conceivable disruption scenario, $s \in S$, is shown below Eq. (14).

$$R_s = \prod_{k \in K} \prod_{l \in L_k : \lambda_{ks} = l} p_{kl}; s \in S \qquad (14)$$

With the exception of the strategic source region, $k = 1$, this model assumes that all regions are vulnerable only to disruptions (e.g., pandemic) that originate from the original disruption region. The presentation simplifies by assuming only a single region acting as the source of disruption and this disruption spreads to multiple other regions, which doesn't imply a loss of generality. In cases where the source region, $k = 1$, remains free from disruptions, and one of the remaining regions, $k \in K : k > 1$, at least has been disrupted, these scenarios are considered not feasible. This is due to the absence of regional pandemic source disruptions that could directly impact other areas. As a result, the likelihood of these implausible scenarios should be adjusted to zero, while the probability of scenarios where all regions remain undisrupted should be emphasized ($i.e., \lambda_{ks} = 0 \; \forall k \in K$) should be extended to $\sum_{s \in S : \lambda_{1s} = 0} R_S$ .The adjusted probability, P_s, for every possible scenario of disruption, $s \in S$ can be represented by Eq. (15).

$$P_S = \begin{cases} \sum_{\bar{s} \in S : \lambda_{1\bar{s}} = 0} R_{\bar{s}}, \text{ if } \sum_{k \in K} \lambda_{ks} = 0 \\ 0, \text{ if } \lambda_{1s} = 0 \text{ and } \sum_{k \in K : k > 1} \lambda_{ks} > 0 \\ R_s, \text{ otherwise} \end{cases} \qquad (15)$$

The optimization of the supply chain operations is performed across a finite set $T = \{1, \ldots, t\}$ of t planning time intervals when subjected to accumulated disruptions across the different regions. The outbreak of the disruption in the originating region is presumed to take place at the planning horizon start.

Let ϑ_{kl}; $k \in K: k > 1$, be the level, l regional disruption delay time, in the region, $k \in K: k > 1$, transmitted from the originating disruption region, $k = 1$, of disruption level, l in region, $k > 1$ begins, ϑ_{kl} , time intervals following the outbreak of the disruption in the originating region., $k = 1$. Denote by μ_{kl} , level, $l \in L_k : l > 0$ duration of disruption in region $k \in K$, i.e., the disruption in the region k, ends μ_{kl} time periods subsequent to its outbreak. Therefore, level of disruption $l > 0$ in region $k > 1$ ends, $\vartheta_{kl} + \mu_{kl}$, periods subsequent to the originating region outbreak, $k = 1$.

Increased lead times for delivery from both strategic and the backup suppliers to tire manufacturers result from originating disruptions in the primary/ originating region and the subsequent spread of these disruptions to the backup suppliers' regions. Denote by τ_{klj}, lead time of delivery from strategic or recovery backup supplier in the region $k \in K$ ($k = 1$, originating region for strategic suppliers, and region, $k > 1$, for a recovery supplier) to tire manufacturers, $j \in I : j > m_1 + m_2$, under a level l disruption in region k. Delivery lead times encompass both the time required for manufacturing by the supplier and the duration of transportation from the supplier $i \in I^k$ in region k to tire manufacturing plant j, σ_{kj}, and duration of regional disruption, μ_{kl} Eq. (16):

$$\tau_{klj} = \sigma_{kj} + \mu_{kl};\ j \in I, k \in K, l \in L_k : j > m_1 + m_2 \tag{16}$$

In addition, indicate by τ_{ij}^{s}, the lead time for delivery from either a strategic or backup supplier, $i \in I: i \leq m_1 + m_2$, to tire manufacturing plant, $j \in I: j > m_1 + m_2$, under regional scenario s of disruption, where $\tau_{ij}^{S} = \tau_{k,\lambda_{ks},j}$ and $i \in I^k$. Further, $\tilde{d}_{it}$ represents tires demand for period $t \in T$, needing fulfilment by tire manufacturer $j \in I: j > m_1 + m_2$. The aggregate initial demand for plant i and the collective initial demand for the manufacturers is, $\tilde{D}_i = \sum_{t \in T} \tilde{d}_{it}$ and $\tilde{D} = \sum_{i \in I: i > m_1 + m_2} \tilde{D}_i$, respectively.

Nevertheless, besides supply disruptions, the market demand is simultaneously disrupted due to the regional disruptions. The original demand isn't deterministic anymore and can vary randomly, depending on the disruption scenario. Let d_{it}^{s} represent the demand in period t and $D_{it}^{s} = \sum_{t' \in T: t' \leq t} d_{it'}^{s}$, denote the demand accumulated up to period t, which needs fulfilment by manufacturer (supplier) $i > m_1 + m_2$ under disruption scenarios.

Order fulfilment coefficient, g_{il}, Eq. (17) signifies the order proportion that a supplier $i \in I^k : i \leq m_1 + m_2$ can supply in the event of a level l disruption in region k. This co-efficient reflects the business repercussions due to regional disruptions on supplier's ability to fulfil orders.

$$g_{il} = \begin{cases} 1 & \text{if } l = 0, \\ \in [0,1) & \text{if } l > 0, \end{cases} \quad i \in I^k, l \in L_k, k \in K \tag{17}$$

Furthermore, the availability coefficient, $\delta_{ilt} \in$ is employed to depict regional disruptions impact on every supplier's capacity and every tire manufacturer, applicable in each time interval.

Eq. (18) The availability coefficient is specified for suppliers (if, $i \leq m_1 + m_2$) and manufacturers (if, $i > m_1 + m_2$), every time interval, $t \in T$, and all regional disruptions levels, $l \in L_k$, in region $k \in K$, where $i \in I^k$.

$$\delta_{\text{ilt}} = \begin{cases} 0 & \text{if } l > 0 \text{ and } t \in T_{kl}, \\ 1 & \text{otherwise} \end{cases} \quad i \in I^k, l \in L_k, k \in K, t \in T \tag{18}$$

Here, T_{kl} denotes the collection of all the periods of regional lockdown during level l of disruption in region k. Regional disruptions lengths and their delays in propagating from the originating region impact how regional lockdowns are scheduled. These details can be tailored to fit any disruption scenario.

The manufacturer's choices concerning the portfolio of recovery backup suppliers of raw materials are combined with the pre-positioning and utilization of Recovery Materials Inventory (RMI) of tires at the tire manufacturers. This combination encompasses scheduling for inventory, supply, and production. The goal is enhancing the overall performance of the supply chain in addressing risks from regional disruptions originating from a single source region.

It is crucial to emphasize that any mismatch between the stochastic supply of raw materials and the tire demand results in additional costs for the manufacturer. These costs encompass inventory holding expenses (ξ per unit and per period) and penalties for delayed demand fulfillment (η per unit and per period) or unmet demand entirely (γ per unit).

Assumptions:

The regional disruption is confined to a strategic source region, excluding other regions.

The planning horizon begins with the initiation of regional disruption in the originating region with primary suppliers.

Disruptions that originate in the strategic source region spread, leading to delayed disturbances in other regions. These propagated disruptions cause concurrent disruptions in supply, demand, and logistics throughout all the stages of the supply chain.

In every supply chain node, the risk of disruption is equal to the risk of regional disruption within the corresponding region where the node is located.

To bolster supply chain resilience, it is possible to strategically place the Recovery Materials Inventory (RMI) of parts at tire manufacturing plants. Additionally, recovery supplies of raw materials can be sourced from recovery suppliers located beyond the originating region of disruption containing primary suppliers.

Disruptions that spread across regions result in regional shutdowns, along with downtimes of suppliers and manufacturers that vary in duration and timeframe. The specific lengths and timeframes are contingent upon the durations of the disruptions and the delays in propagation, Eq. (19).

$$v_{ij}^{s} \in [0,1]; i \in I, j \in I: m_1 < i \le m_1 + m_2, j > m_1 + m_2, s \in S \text{ and}$$
$$\sum_{i\in I:\, i\le m_1} g_i^s W_{ij} + \sum_{i\in I: m_1 < i \le m_1+m_2} v_{ij}^{s} = 1; j \in I, s \in S : j > m_1 + m_2 \qquad (19)$$

In specific cases, suppliers have the capability to deliver the parts they manufacture to tire manufacturing plants within the same periods.

The supplier region's length of regional disruption is factored into the lead times of delivering raw materials from suppliers to the tire manufacturers.

To satisfy disruption-dependent product demand over the planning horizon, utilize accumulated product inventory. However, this results in penalty costs for surplus inventory, delayed demand fulfillment, or unmet demand.

Protective measures against pandemic disruptions in varying regions, such as vaccinating individuals, are not included to mitigate shutdown durations and safeguard the workers from infection risks.

6. Mathematical Model

This section introduces a Stochastic Mixed-Integer Programming (MIP) model aimed at minimizing the expected cost. The model is tailored for the risk-neutral mitigation and recovery of supply chains dealing with the risks associated with regional disruptions that spread across regions from a source region. It integrates grey scoring into the objective function to determine the final allocation for suppliers, with the primary objective of minimizing the expected cost, denoted as $\boldsymbol{E^c}$.

The novelty of this model stems from integration of the grey scoring model that assigns relative weights to suppliers with the cost minimization model. This integration ensures a suitable balance between the overall cost incurred and the minimization of risks. Moreover, it doesn't solely prioritize backup suppliers based on their costs and availability; rather, it considers other important factors such as quality and emission levels in the selection among suppliers during disruptions. Furthermore, the difference between our model and the existing literature is that our model considers distinct levels of backup suppliers. In other words, the grey analysis gives the highly ranked backup supplier a semi-strategic feature, maintaining the loyalty of these suppliers during disruptions. Thus, this problem can be characterized as a stochastic multi-portfolio selection problem, where the recovery backup supply portfolio is chosen to safeguard against all conceivable disruption scenarios. Simultaneously, for each disruption scenario, a recovery supply portfolio is selected. These portfolios are outlined as follows (refer to first and second-level variables definitions for detailed information), see Table 4.

Table 3
Variables definition

Variables in the First level
q_i ≥ 0, a pre-positioned Recovery Materials Inventory at plant, i∈I:i>m_1+m_2, (RMI pre-positioning)
W_ij∈ [0,1], portion of the overall parts demand allocated to a specific plant, j∈I:j>m_1+m_2, ordered from strategic supplier, i∈I:i≤m_1 (strategic supply portfolio)
Variables in the Second level
r_i^s ≥ 0, a pre-positioned Recovery Materials Inventory at plant, i∈I:i>m_1+m_2, which is utilized in the event of a disruption scenario s (RMI utilization)
u_i^s ∈ [1], in the sense that the value 1 is equivalent to that backup supplier, i∈I:m_1<i≤m_1+m_2, is considered as a recovery supplier under disruption scenario s; else u_i^s=0 (recovery supplier selection)
v_ij^s ∈ [0,1], proportion of overall demand for raw material at plant, j∈I:j>m_1+m_2, purchased from an alternative or backup supplier., i∈I:m_1<i≤m_1+m_2, under disruption scenario s (recovery supply portfolio)
x_ijt^s≥ 0 , parts production by supplier, i∈I:i≤m_1+m_2, in period t, for plant, j∈I:j>m_1+m_2, under disruption scenario s (production/supply scheduling)
y_it^s ≥0 , plant production, i∈I:i>m_1+m_2, in period t under disruption scenario s (scheduling of production)
z ̅_it^s ≥0 , plant products inventory, i∈I:i>m_1+m_2, when period t commences under disruption scenario s (scheduling of inventory)
_z_it^s ≥0 , product shortage in plant, i∈I:i>m_1+m_2, when disruption scenario s initiates at the onset of period t (inventory scheduling)
List of auxiliary variables
$\bar{\zeta}_{it}^{s} = \begin{cases} 1, \text{ when inventory of products exists in plant}, i \in I: i > m_1 + m_2, \text{at the beginning of period } t \text{ in the event of disruption scenario } s \\ 0, otherwise \end{cases}$
$\underline{\zeta}_{it}^{s} = \begin{cases} 1 \text{ when there is shortage in tires at the tire manufacturer } i \text{ at the beginning of time period } t \text{ under disruption scenario } s \\ 0, \quad otherwise \end{cases}$

Consider $\boldsymbol{E^c}$ ***in Eq***. (20) as the expected total cost of the supply chain which needs minimization.

$$E^c = \sum_{s\in S}\sum_{i\in I:m_1<i\leq m_1+m_2} P_s f_i u_i^s + \sum_{s\in S}\sum_{i\in I:j>m_1+m_2} P_s D_j \left(\sum_{i\in I:i\leq m_1} e_i g_i^s w_{ij}\right) + PQ * \sum_{s\in S}\sum_{i\in I:j>m_1+m_2} P_s D_j \left(\sum_{i\in I:m_1<i\leq m_1+m_2} e_i v_{ij}^s * (1-x_i) * w_i\right) + \sum_{i\in I:i>m_1+m_2}\left(a_i q_i + \sum_{s\in S} P_s b_i r_i^s\right) + \sum_{s\in S}\sum_{t\in T}\sum_{i\in I:i>m_1+m_2} P_s\left(\xi \bar{z}_{it}^s + \eta \underline{z}_{it}^s\right) + \gamma \sum_{s\in S}\sum_{i\in I:i>m_1+m_2} P_s \underline{z}_{i,h+1}^s \tag{20}$$

The expected cost per unit, denoted as $E^c, in\ Eq(20)$, encompasses various variable costs and fixed costs. Expenses associated with ordering raw materials from backup suppliers, $\sum_{s\in S}\sum_{i\in I:m_1<i\leq m_1+m_2} P_s f_i u_i^s$ are considered fixed costs. The variable costs include the expenditure for obtaining parts to fulfil partially delivered orders from strategic suppliers, represented as, $\sum_{s\in S}\sum_{j\in I:j>m_1+m_2} P_s \tilde{D}_j \left(\sum_{i\in I:i\leq m_1} e_i g_i^s w_{ij}\right)$, penalty cost associated with quality non-conformance by backup suppliers, and the cost of purchasing parts from recovery suppliers. The determination of relative weightage is based on the Grey Relational Analysis (GRA), where a grey possibility value is assigned to each recovery supplier w_i, where the model optimizes the selection process to yield the lowest possible cost by choosing suppliers while considering factors like the grey possibility value of the recovery suppliers, cost of purchasing parts from recovery suppliers and recovery suppliers quality levels x_i, which ensures to select recovery suppliers with the highest quality levels by penalizing non-conformance to quality, $PQ * \sum_{s\in S}\sum_{i\in I:j>m_1+m_2} P_s D_j \left(\sum_{i\in I:m_1<i\leq m_1+m_2} e_i v_{ij}^s * (1-x_i) * w_i\right)$. Other variable costs include pre-positioning RMI inventory and its usage costs $\sum_{i\in I:i>m_1+m_2}(a_i q_i + \sum_{s\in S} P_s b_i r_i^s)$, inventory holding cost of tires, $\sum_{s\in S}\sum_{t\in T}\sum_{i\in I:i>m_1+m_2} P_s \xi \bar{z}_{it}^s$, delayed demand penalty, $\sum_{s\in S}\sum_{t\in T}\sum_{i\in I:i>m_1+m_2} P_s \eta \underline{z}_{it}^s$, and unfulfilled demand penalty, $\gamma \sum_{s\in S}\sum_{i\in I:i>m_1+m_2} P_s \underline{z}_{i,h+1}^s$.

Expected cost: Optimizing the resilience of the supply chain to deal with the propagated regional disruption risks with the goal of minimizing the expected cost.

Minimize Eq. (20) subject to:

Selection constraints of strategic supply portfolio, Eq. (21)

$$\sum_{i\in I:i\leq m_1} w_{ij} = 1; j \in I: j > m_1 + m_2 \tag{21}$$

Selection constraints of backup supply portfolio in Eq. (22)

$$v_{ij}^s \leq u_i^s; i \in I, j \in I, s \in S: m_1 < i \leq m_1 + m_2, j > m_1 + m_2 \tag{22}$$

Eq. (23) ensures that parts' recovery supplies cannot be assigned to non-selected backup suppliers.

$$v_{ij}^s \leq u_i^s; i \in I, j \in I, s \in S: m_1 < i \leq m_1 + m_2, j > m_1 + m_2 \tag{23}$$

The constraint governing the selection of the recovery supply portfolio is formulated in Eq. (24). This constraint guarantees that the backup suppliers satisfy any unfulfilled demand for raw materials at each tire manufacturer. Here, $g_i^s w_{ij}, v_{ij}^s$ denote flow of raw materials to tire manufacturer j under scenario of disruption s from strategic and backup suppliers i respectively ($i \leq m_1$, and , $m_1 < i \leq m_1 + m_2$).

$$\sum_{i\in I:i\leq m_1} g_i^s w_{ij} + \sum_{i\in I:m_1<i\leq m_1+m_2} v_{ij}^s = 1; j \in I, s \in S: j > m_1 + m_2 \tag{24}$$

6.1 Recovery Materials Inventory (RMI) constraints

To prevent the surpassing of maximum capacity for pre-positioned inventory at each manufacturer, the constraint articulated in Eq. (25), denoted as the safety stock constraint, places limitations on the average lead time of delivery from recovery suppliers.

$$q_i \leq \bar{\tau}_i c_i; i \in I: i > m_1 + m_2 \tag{25}$$

Eq. (12) limits how much inventory can be used from the pre-positioned stock at each plant.

$$r_i^s \leq q_i; i \in I, s \in S: i > m_1 + m_2 \tag{26}$$

where $\boldsymbol{\bar{\tau}_j = \sum_{i\in I, s\in S:m_1<i\leq m_1+m_2} P_s \tau_{ij}^s / m_2}$, represents mean time for delivery from recovery suppliers to manufacturer $\boldsymbol{j}$.

Constraints for suppliers and manufacturers capacity

Eqs. (27) and (28) implement capacity constraints to guarantee the synchronization of part and product manufacturing in each time frame with the existing capacity of suppliers and manufacturing facilities. preventing potential production overruns under any disruption scenario.

$$\sum_{j\in I:j>m_1+m_2} x_{ijt}^s \le \delta_{it}^s c_i; i\in I, t\in T, s\in S: i\le m_1+m_2 \quad (27)$$

$$y_{it}^s \le \delta_{it}^s c_i; i\in I, t\in T, s\in S: i> m_1+m_2 \quad (28)$$

Supply constraints:

Eqs. (29) and (30) enforce constraints guaranteeing that the aggregated supply of parts adheres to the available quantities within the strategic and recovery supply portfolios, respectively.

$$\sum_{t\in T}\frac{x_{ijt}^s}{\tilde{D}_j} \le g_i^s w_{ij}; i\in I, j\in I, S\in S: i\le m_1, j>m_1+m_2 \quad (29)$$

$$\sum_{t\in T}\frac{x_{ijt}^s}{\tilde{D}_j} \le v_{ij}^s; i\in I, j\in I, s\in S: m_1<i\le m_1+m_2, j>m_1+m_2 \quad (30)$$

Suppliers-manufacturers coordinating constraints:

To prevent exceeding total supply capacity, Eq. (31) limits the total production of each tire manufacturing plant to the combined production of its main and backup suppliers (adjusted for delivery delays) and the available inventory within its RMI.

$$\sum_{t'\in T:t'\le t} y_{it'}^s \le \sum_{j\in I,t'\in T:j\le m_1+m_2,t'\le t-\tau_{ji}^s} x_{jit'}^s + r_i^s \quad (31)$$

Where $\boldsymbol{i\in I, t\in T, s\in S: i>m_1+m_2}$

6.2 Inventory constraints

Eqs. (32) to (34) in the inventory constraints are utilized to monitor product availability at each plant $\boldsymbol{i}$. These equations specify that the inventory or shortage during any given period $(\boldsymbol{t+1})$ is determined based on whether there is a surplus or shortfall between the cumulative total production and the demand up to that specific point.

$$\bar{z}_{i,t+1}^s - \underline{z}_{i,t+1}^s = \sum_{t'\in T:t'\le t} y_{it'}^s - D_{it}^s; i\in I, \quad (32)$$

Where $\boldsymbol{t\in T, s\in S: i>m_1+m_2}$

$$\bar{z}_{i,t+1}^s \ge \sum_{t'\in T:t'\le t} y_{it'}^s - D_{it}^s;\ i\in I, t\in T, s\in S: i>m_1+m_2 \quad (33)$$

$$\underline{z}_{i,t+1}^s \ge D_{it}^s - \sum_{t'\in T:t'\le t} y_{it'}^s;\ i\in I, t\in T, s\in S: i>m_1+m_2 \quad (34)$$

Equations (35) to (37) define a set of constraints that guarantee that at each period, the inventory level of a product is either positive (indicating surplus), negative (indicating shortage), or zero (indicating equilibrium between production and demand).

$$\bar{\zeta}_{it}^s + \underline{\zeta}_{it}^s \le 1; i\in I, t\in T^*, s\in S: i>m_1+m_2 \quad (35)$$

$$\frac{\bar{z}_{it}^s}{\tilde{D}_i} \le \bar{\zeta}_{it}^s; t\in T^*, s\in S: i>m_1+m_2 \quad (36)$$

$$\frac{\underline{z}_{it}^s}{\tilde{D}_i} \le \underline{\zeta}_{it}^s; t\in T^*, s\in S: i>m_1+m_2 \quad (37)$$

6.3 Quality and emission levels constraints

Eq. (38) serves the purpose of guaranteeing product quality upon receipt. It prohibits the allocation of any quantity to a supplier for a specific product in case its quality level fails to meet the organization's minimum standards.

$$M * (1 - R_i) \geq XA_j - X_i\ ,\quad i \in I, j \in I: m_1 < i \leq m_1 + m_2, j > m_1 + m_2 \qquad (38)$$

Equations (39) and (41) play a crucial role in fulfilling the fundamental requirements of the optimization problem. They guarantee that all variables are non-negative and binary.

$$Qmn - M * R_i \leq 0\ , i \in I: m_1 < i \leq m_1 + m_2 \qquad (39)$$

Where $Qmn = \sum_{s \in S} \sum_{j \in I: j > m_1 + m_2} \sum_{i \in I: m_1 < i \leq m_1 + m_2} P_s \widetilde{D}_j v_{ij}^s$

$$M * (1 - Z_i) \geq E_i - EA_j, i \in I, j \in I: m_1 < i \leq m_1 + m_2, j > m_1 + m_2 \qquad (40)$$

$$Q_{mn} - M *\ Z_i \leq 0\ , i \in I: m_1 < i \leq m_1 + m_2 \qquad (41)$$

Equation (40) implements a constraint based on pollution and CO2 emission levels, ensuring that no allocation for a particular product will be made to a supplier if its emissions surpass the permissible industrial standards. This helps promote environmental sustainability in the supply chain.

6.4 *Integer and non-negativity constraints*

$$r_i^s \geq 0; i \in I, s \in S: i > m_1 + m_2 \qquad (a)$$
$$u_i^s \in \{0,1\}; i \in I, s \in S: m_1 < i \leq m_1 + m_2 \qquad (b)$$
$$v_{ij}^s \in [0,1]; i \in I, j \in J, s \in S: m_1 < i \leq m_1 + m_2, j > m_1 + m_2 \qquad (c)$$
$$w_{ij} \in [0,1]; i \in I, j \in J: i \leq m_1, j > m_1 + m_2 \qquad (d)$$
$$x_{ijt}^s \geq 0; i \in I, j \in J, t \in T, s \in S: i \leq m_1 + m_2, j > m_1 + m_2 \qquad (e)$$
$$y_{it}^s \geq 0; i \in I, t \in T, s \in S: i > m_1 + m_2 \qquad (f)$$
$$\bar{z}_{it}^S \geq 0; i \in I, t \in T^*, s \in S: i > m_1 + m_2 \qquad (g)$$
$$\underline{z}_{it}^S \geq 0; i \in I, t \in T^*, s \in S: i > m_1 + m_2 \qquad (h)$$
$$\bar{\zeta}_{it}^s \in \{0,1\}; i \in I, t \in T^*, s \in S: i > m_1 + m_2 \qquad (i)$$
$$\underline{\zeta}_{it}^s \in \{0,1\}; i \in I, t \in T^*, s \in S: i > m_1 + m_2 \qquad (j) \qquad (34)$$

where $T^* = T \cup t + 1 = \{1, \dots, t, t + 1\}$ represents the planning horizon extension with a dummy period $t + 1$.

7. Case Study & Model Implementation

Natural rubber, which accounts for roughly 20% of the main raw materials, is the bedrock of tire production. Traditionally, it would be shipped directly from Malaysia, the strategic supplier, to the manufacturer in Egypt. However, due to the COVID-19 pandemic, new customs regulations and procedures have forced the cargo to transit through multiple ports, significantly extending delivery times. This delay has disrupted the supply chain, leading to unfulfilled demand for tires and higher overall costs.

This case study aims to compare two potential strategies for ensuring a reliable supply of natural rubber for tire production in Egypt:

Pre-positioning RMI (Recovery Materials Inventory): Stockpiling a buffer stock of natural rubber at the Egyptian plant to mitigate the impact of supply disruptions.

Contracting with backup suppliers: Securing agreements with additional suppliers to provide natural rubber in case of disruptions from the strategic supplier.

7.1 Strategy 1: Pre-positioning RMI (Recovery Materials Inventory)

In this strategy, we focus solely on the strategic supply chain, disregarding backup suppliers. This is reflected in the omission or zeroing out of all variables related to backup suppliers, including those for recovery supply portfolio selection constraints.

Therefore, the index used for the supply chain node, denoted as $i \in I$, can be interchanged with the index used for the geographic region, represented by $k \in K$. The basic input parameters for the strategic supply chain are provided below and in Table 5.

Table 4
Input parameters for the RMI model

$\boldsymbol{m = 5}$ supply chain nodes, including $\boldsymbol{m_1 = 4}$ strategic suppliers, $\boldsymbol{m_2 = 0}$ backup suppliers, and $\boldsymbol{m_3 = 1}$ plant	
$\boldsymbol{K = \{1, 2, 3, 4, 5\}}$	Five geographic regions
Strategic source regions: 1- Malaysia, 2-Indonesia, 3-Thailand, 4-Africa, Plant region: 5 – Egypt (Alexandria).	
$\boldsymbol{I = K, I^k = \{k\}, k \in K}$	5 nodes of the supply chain, one node per each region
$\boldsymbol{\bar{L}_1 = 4, \bar{L}_{2,3,4} = 2, \bar{L}_5 = 4}$	Regional disruption levels
$\boldsymbol{\prod_{k\in K}(\bar{L}_k + 1) = 128}$	sum of the entire potential disruption scenarios
$\boldsymbol{T = \{1, \ldots, 12\}, t = 12}$	**12** planning intervals (months)
Demand for parts/products:	
$\boldsymbol{\tilde{d}_{5t}}$ =55740, 55740, 61740 ,49675, 59740 ,53675, 55740, 61740, 57675, 59740, 59675 61740.	Original demand per period
$\boldsymbol{\tilde{D}}$=692620	Total original demand for tires
$\boldsymbol{g_{kl} = (h - \mu_{kl})/h; k \in k, l \in L_k: k \le m_1 + m_2}$	the rates of supplier's order fulfilment by suppliers within region k under the impact of disruption level l.
$\boldsymbol{c_1 = c_2 = c_3 = c_4 = \tilde{D}/12, c_5 = 0.1\tilde{D}_5}$	standard per-period capacity for both manufacturers and suppliers.
Costs:	
$\boldsymbol{a_i = max_{i\in I: i\le m_1+m_2} e_i, i > m_1 + m_2}$	per-part cost for pre-positioning RMI at tire manufacturer $\boldsymbol{i}$
$\boldsymbol{b_i = max_{i\in I: i\le m_1+m_2} \frac{e_i}{4}, i > m_1 + m_2}$	per-part cost of using RMI at tire manufacturer $\boldsymbol{i}$
$\boldsymbol{\xi = 0.1 max_{i\in I: i\le m_1+m_2} e_i}$	inventory holding cost per tire and per period
$\boldsymbol{\gamma = \{30, 300\}}$	cost incurred per product due to the unfulfilled demand
$\boldsymbol{\eta = 0.01\gamma}$	the cost accrued per unit tire and per period as penalty for delayed demand for product
$\boldsymbol{e_i = 50, 52, 55, 53, 65, and\ 60}$	cost per unit (tire) for the rubber acquired from the supplier $\boldsymbol{i \le m_1 + m_2}$

Leveraging historical disruption data, and considering the diverse frequencies of these disruptions, probabilities of regional disruptions are outlined for each region $k \in K$ and disruption level, $l \in L_k$.

Lower probability for higher intensity disruption.

$l = 0$; no disruption

$l = 1$; minor disruption

$l = 2$; medium disruption

$l = 3$; major disruption

$$p_{1l} = \begin{cases} 0.475, if\ l = 1 \\ 0.285\ \ if\ \ l = 2 \\ 0.19\ if\ \ \ l = 3 \\ 0.05\ if\ l = 0 \end{cases}$$

$$p_{2l} = \begin{cases} 0.95, & \text{if } l = 1 \\ 0.05, & \text{if } l = 0 \end{cases}$$

$$p_{3l} = \begin{cases} 0.95, & \text{if } l = 1 \\ 0.05, & \text{if } l = 0 \end{cases}$$

$$p_{4l} = \begin{cases} 0.95, & \text{if } l = 1 \\ 0.05, & \text{if } l = 0 \end{cases}$$

$$p_{5l} = \begin{cases} 0.3, if\ l = 1 \\ 0.285\ if\ l = 2 \\ 0.15\ if\ l = 3 \\ 0.3\ if\ l = 0 \end{cases}$$

Duration of a level, $l \in L_k: l > 0$ regional disruption in region, $k \in K$:

$$m_1 + m_{2_{kl}} = \begin{cases} 1, & \text{if } l = 1, \text{(minor length disruption)} \\ 2, & \text{if } l = 2 \text{ (medium length disruption)} \; k \in K, l \in L_k \\ 3, & \text{if } l = 3 \text{ (major length disruption)} \end{cases}$$

Duration of delay of level, l disruption in region, $k \in K: k > 1$, emanating from the original regions of disruption:

$$\vartheta_{kl} = \begin{cases} 1, & \text{if } 4 < k \leq m_1 + m_2, l = 1 \\ 2, & \text{if } 4 < k \leq m_1 + m_2, l = 2 \\ 1, & \text{if } k > m_1 + m_2, l \in \{1,2,3\} \\ 2, & \text{if } k > m_1 + m_2, l \in \{4,5,6\} \end{cases} k \in K, l \in L_k: k > 1, l > 0$$

Coefficients of availability, calculated based on downtime and regional lockdown schedules, applicable to both suppliers and tire manufacturing plants.:

$$\delta_{\text{ilt}} = \begin{cases} 0, \text{if } i = 1, l = 1, t = 1 \\ 0, \text{if } i = 1, l = 2, t \in \{1,2,3\} \\ 0, \text{if } i = 1, l = 3, t \in \{1,2,3,4,5,6\} \\ 0, \text{if } i = 2,3, l = 1, t = 2 \\ 0, \text{if } i = 4,5, l = 1, t \in \{3,4,5\} \\ 0, \text{if } i = 6, l = 1, t = 2 \\ 0, \text{if } i = 7, l = 1, t = 2 \\ 0, \text{if } i = 7, l = 2, t \in \{2,3,4\} \\ 0, \text{if } i = 7, l = 3, t \in \{2,3,4,5,6,7\} \\ 1, \text{otherwise} \end{cases}$$

Demand profile A:

$$\mathrm{d}_{\mathrm{kt}}^{\mathrm{s}} = \begin{cases} 0.5\tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} \leq 2; \mathrm{t} \in \{2,3\} \\ 1.5\tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} \leq 2; \mathrm{t} \in \{4,5\} \\ \tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} \leq 2; \mathrm{t} \notin \{2,3,4,5\} \\ 0.75\tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} = 3; \mathrm{t} \in \{3,4,5,6\} \\ 1.25\tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} = 3; \mathrm{t} \in \{7,8,9,10\} \\ \tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} = 3; \mathrm{t} \notin \{3,\ldots,10\} \end{cases} \mathrm{k} \in \mathrm{L_k}: \mathrm{k} > 6, \mathrm{l} > 0, \mathrm{k} = \mathrm{i}$$

The fulfilment of the demand of the market during period t within region k under scenario of disruption s, is allocated to tire manufacturing plant i, where $\mathrm{i} > \mathrm{m_1} + \mathrm{m_2}$ and $\mathrm{i} = \mathrm{k}$. In customer regions, denoted by $\mathrm{k} = 7$, the quick propagation of disruptions propagating from the originating region of disruption, $\mathrm{k} = 1$, albeit delayed by merely one period, aligns with the initial decrease in demand of 50% over a span of two periods. This is followed by an ensuing surge in the original demand, escalating by 50% across the subsequent two time periods. In contrast, the gradual propagation of disruptions, delayed by two periods, corresponds to the initial reduction of 25% over a duration of four periods. This is succeeded by a subsequent elevation in the original demand, growing by 25% over the ensuing four periods.

Demand profile B:

$$\mathrm{d}_{\mathrm{kt}}^{\mathrm{s}} = \begin{cases} 0.75\tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} \leq 2; \mathrm{t} \in \{2,3,4,5\} \\ \tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} \leq 2; \mathrm{t} \notin \{2,3,4,5\} \\ 0.5\tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} = 3; \mathrm{t} \in \{3,4\} \\ \tilde{\mathrm{d}}_{\mathrm{kt}}, & \text{if } \lambda_{\mathrm{ks}} = 3; \mathrm{t} \notin \{3,4\} \end{cases} \mathrm{k} \in \mathrm{L_k}: \mathrm{k} > 6, \mathrm{l} > 0, \mathrm{k} = \mathrm{i}$$

In the customer region, denoted as $k = 7$, swift propagation of pandemic disruptions spreading from the originating region of disruption, $k = 1$, and delayed by a single period, aligns with an initial demand decrease of 25% over a span of four periods. Conversely, gradual spreading of the disruption, delayed by two periods, corresponds to an original reduction in the demand of 50%, occurring across two time periods.

Notice the demand for profile A experiences an initial decrease followed by an increase after the markets open again, aiming to offset the decreased demand amid the shutdown. In contrast, the demand for profile B is consistently declining due to market shutdown.

Manufacturing and transportation time required from supplier, $i \in I: i \leq 6$ to tire manufacturing plant, $j \in I: j > 6$

$$\sigma_{ij} = \begin{cases} 1, & \text{if } i \in \{2,3\} \\ 2, & \text{if } i \in \{1,4\} \end{cases} \quad j \in I: j > 6$$

$$R_i = \begin{cases} 0 \text{ if } X_i < XA_j \\ 1 \text{ otherwise} \end{cases} \quad i \in I, j \in I: m_1 < i \leq m_1 + m_2, j > m_1 + m_2$$

$$Z_i = \begin{cases} 0 & \text{if } E_i > EA_j \\ 1 & \text{otherwise} \end{cases} \quad i \in I, j \in I: m_1 < i \leq m_1 + m_2, j > m_1 + m_2$$

M= 1000000 (A noticeably vast number to enforce the binary constraints)

$$\sum_{t' \in T: t' \leq t} y^s_{it'} \leq \sum_{j \in I, t' \in T: j \leq m_1 + m_2, t' \leq t - \tau^s_{ji}} x^s_{jit'} * Factor + r^s_i;$$

Where, $Factor = 31$ (It's a conversion factor as supplies come in tons of natural rubber, while manufactured products are tires, so 31 tons of rubber are required to produce 1 tire)

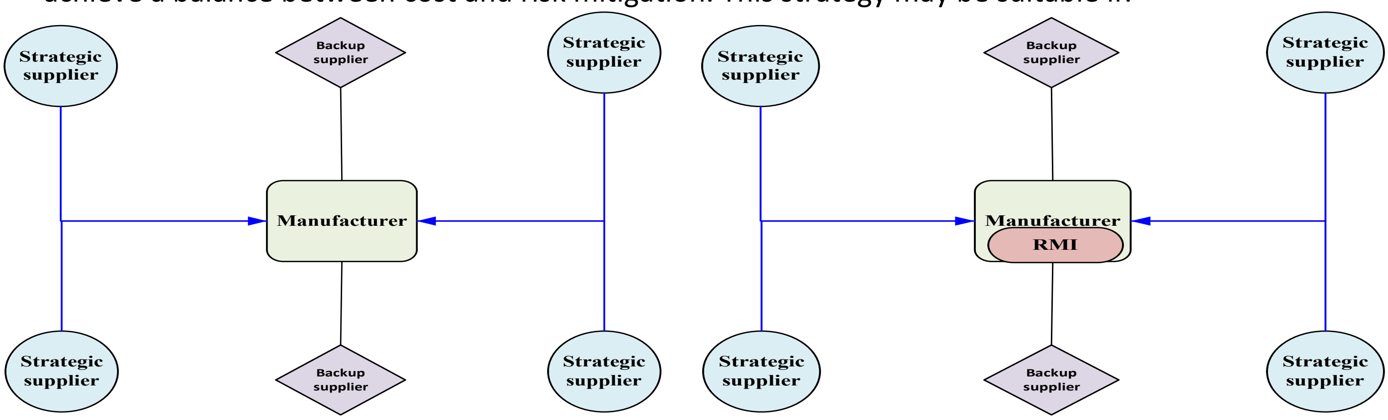
7.2 Strategy 2: Contracting with backup suppliers.

This strategy involves securing agreements with additional suppliers to provide natural rubber in case of disruptions from the strategic supplier Figure 3 (a). This approach eliminates the need for RMI and its associated costs, but it introduces additional procurement and coordination challenges. This strategy may be suitable if:

- The cost of contracting with backup suppliers is lower than the cost of holding RMI.
- The risk of disruptions from the strategic supplier is high or severe.
- Having multiple suppliers provides additional flexibility and security.

7.3 Strategy 3: Combining RMI and Backup Suppliers

This hybrid strategy leverages the benefits of both RMI and backup suppliers Figure 3. (b). By holding a smaller RMI buffer and having agreements with backup suppliers, this approach aims to achieve a balance between cost and risk mitigation. This strategy may be suitable if:



Strategy 2: Contracting with backup suppliers (3) Strategy 3: Combining RMI and Backup recovery Suppliers

Fig.3: Schematics for Strategy 2 and Strategy 3.

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For the sake of the implementation of the model in a real-world application for strategy 2 and strategy 3, data has been collected for corresponding case study in the rubber manufacturing company. These data are described in Table 6:

Table 6
Input parameters for the resilient model (both RMI and backup suppliers)

$m = 7$ supply chain nodes, including $m_1 = 4$ strategic suppliers, $m_2 = 2$ backup suppliers, and $m_3 = 1$ plant	
$K = \{1,2,3,4,5,6,7\}$	Number of geographic regions equals 7
Strategic source regions: 1- Malaysia, 2-Indonesia, 3-Thailand, 4-Africa, Backup source regions: 5-Turkey, 6-Europe, Plant region: 7 – Egypt (Alexandria).	
$I = K, I^k = \{k\}, k \in K$	There are five nodes in the supply chain, each representing a distinct region.
$\bar{L}_1 = 4, \bar{L}_{2,3,4,5,6} = 2, \bar{L}_7 = 4$	levels of regional disruption
$\prod_{k \in K} (\bar{L}_k + 1) = 512$	The cumulative count of all potential disruption scenarios.
$T = \{1, \ldots, 12\}, h = 12$	planning durations = 12 months
Demand for parts/products:	
$\tilde{d}_{7t}$ =55740, 55740, 61740, 49675, 59740, 53675, 55740, 61740, 57675, 59740, 59675 61740.	Original demand in each unit of time
$\tilde{D}$ =692620	the sum of original demand for tires
$g_{kl} = (h - \mu_{kl})/h; k \in k, l \in L_k: k \leq m_1 + m_2$	The rates at which suppliers fulfil orders in region k under level l disruption
$c_1 = c_2 = c_3 = c_4 = \frac{\tilde{D}}{12}$, $c_5 = c_6 = \frac{\tilde{D}}{24}, c_7 = 0.1\tilde{D}_5$	per-period standard capacity of manufacturers and suppliers
Costs:	
$a_i = \max_{i \in I: i \leq m_1 + m_2} e_i, i > m_1 + m_2$	Cost incurred per part for RMI pre-positioning at the tire manufacturing plant. i
$b_i = \max_{i \in I: i \leq m_1 + m_2} \frac{e_i}{4}, i > m_1 + m_2$	Cost per part associated with the utilization of RMI at the tire manufacturing plant i
$f_i = 1600, 1600$	Predetermined cost incurred for placing an order with a backup supplier, $1 < \mathrm{i} \leq \mathrm{m}_1 + \mathrm{m}_2$
$\xi = 0.1\max_{i \in I: i \leq m_1 + m_2} e_i$	Cost incurred per-unit and per-period for holding tires inventory
$\gamma = \{30,300\}$	Per-unit cost imposed as a penalty for unmet tires demand
$\eta = 0.01\gamma$	Penalty cost incurred per unit and per period due to delayed demand for products
e_i = 50 52 55 53 65 60	Price per unit (tire) for rubber procured from the supplier, where i is less than or equal to the sum of m_1 and m_2
Grey relative analysis parameters	
$\mathrm{X_i}$ = 0.98,0.94	Quality level of backup supplier i , $i \in I: m_1 < i \leq m_1 + m_2$
$\mathrm{XA_j}$ = 0.90	Quality level set by the manufacturer $i \in I: i > m_1 + m_2$
PQ = 150	Cost incurred per unit as a penalty for non-conformance to quality standards
W_i =0.716572, 0.620256	Grey possibility values of backup supplier i, $i \in I: m_1 < i \leq m_1 + m_2$
E_i = 0.08,0.13	Emission level of backup supplier i , $i \in I: m_1 < i \leq m_1 + m_2$
$\mathrm{EA_j}$ = 0.15	Emission level set by the manufacturer $i \in I: i > m_1 + m_2$

The probabilities of disruption for each region denoted by k belonging to the set K, and each corresponding level denoted by l belonging to the set L_k.
Lower probability for higher intensity disruption.
$l = 0$; no disruption
$l = 1$; minor disruption
$l = 2$; medium disruption
$l = 3$; major disruption

$$p_{1l} = \begin{cases} 0.475, if\ l = 1 \\ 0.285\ \ if\ \ l = 2 \\ 0.19\ if\ \ \ l = 3 \\ 0.05\ if\ l = 0 \end{cases}$$

$$p_{2l} = \begin{cases} 0.95, & \text{if } l = 1 \\ 0.05, & \text{if } l = 0 \end{cases}$$

$$p_{3l} = \begin{cases} 0.95, & \text{if } l = 1 \\ 0.05, & \text{if } l = 0 \end{cases}$$

$$p_{4l} = \begin{cases} 0.95, & \text{if } l = 1 \\ 0.05, & \text{if } l = 0 \end{cases}$$

$$p_{5l} = \begin{cases} 0.6, & \text{if } l = 1 \\ 0.4, & \text{if } l = 0 \end{cases}$$

$$p_{6l} = \begin{cases} 0.8, & \text{if } l = 1 \\ 0.2, & \text{if } l = 0 \end{cases}$$

$$p_{7l} = \begin{cases} 0.475, if\ l = 1 \\ 0.285\ \ if\ \ l = 2 \\ 0.19\ if\ \ \ l = 3 \\ 0.05\ if\ l = 0 \end{cases}$$

The rest of the data is the same as strategy 1.

8. Results And Discussion

The resolution of the models and the determination of the minimum cost and optimal quantity for the decision variables are achieved through the implementation of the Lingo programming language. The developed model is carried out in LINGO 20 by using an Intel Core-i7 processor loaded by 16 GB RAM and operating systems "Windows 11Pro". The resolution of the Mixed integer programming MIP problems in LINGO are solved using parallel branch-and-bound algorithm based on the relaxed linear-programming model. In the numerical analysis, the focus is on a tire manufacturing organization, where a significant portion of raw materials, particularly natural rubber, is sourced from a group of suppliers. The supplier information, pre-evaluated using GRA analysis as outlined in Section 3.1, is readily available. Additional data pertaining to the remaining components of the supply chain is also provided, see Table 6.

8.1 Demand profiles and penalty costs.

As previously mentioned, the tire manufacturer can go through two main demand profiles, A and B. To some extent, the manufacturer is forced to enter a certain demand profile as per the demand and the supply chain disruption severity. As a result, each profile has a different efficiency. The comparison between these demand profiles are performed based on the following equations.

Expected Unmet Demand

$$\sum_{s \in S} \sum_{i \in I: i > m_1 + m_2} P_S \underline{z}^s_{i,h+1}$$

Expected Recovery Supplies

$$\sum_{s \in S} \sum_{i \in I: m_1 < i \le m_1 + m_2} \sum_{j \in I: j > m_1 + m_2} \sum_{t \in T: t > \tau^s_{ij}} P_S x^s_{ij, t - \tau^s_{ij}}$$

Pre-positioned RMI

$$\sum_{i \in I: i > m_1 + m_2} q_i$$

Expected Used RMI

$$\sum_{s \in S} \sum_{i \in I: i > m_1 + m_2} P_S r^s_i$$

Expected service level

$$E^{sl} = 1 - \left(\sum_{s \in S} \sum_{i \in I: i > m_1 + m_2} P_S z^s_{i,h+1}\right) / \left(\sum_{s \in S} \sum_{i \in I: i > m_1 + m_2} P_S D^s_{ih}\right)$$

Table 7 reveals the difference between demand profile A and demand profile B in different perspectives. For example, profile B has less cost and higher service level, this is because the demand profile B has less quantity which means less costs and it gives enough time to the manufacturer to improve the quality.

Table 7
Results of demand profiles A and B for RMI + Recovery supplier case at a penalty of EGP300.

Case	Expected cost	Expected Unfulfilled demand	Expected Recovery Supplies	Pre-Positioned RMI	Expected used RMI	Expected Service level
A (Reduction then increase)	64,384,065.04	55,329.91	95,653.66	69,262.00	41,441.80	0.88
B (Reduction only)	57,669,859.56	34,518.86	95,889.72	69,262.00	31,313.19	0.92

However, both profiles experience the possibility of unfulfilled demand which costs the manufacturer penalty of each unfulfilled unit. The penalty value has a significant effect on the supply chain. Table 8 illustrates the effect of the penalty cost on the supply chain cost and service level, assuming a fixed demand profile (A).

Table 5
Comparison between the 2 penalty costs for RMI + Recovery supplier case at demand profile a

Case	Expected cost (EGP)	Expected Unfulfilled demand (Tons)	Expected Recovery Supplies	Pre-Positioned RMI	Expected used RMI	Expected Service level
EGP300	64,384,065	55,329	95,653	69,262	41,441	0.88
EGP30	43,632,780.04	81,649	95,009	-	-	0.82

The table shows that a lower penalty cost leads to a lower expected cost, but also to a higher expected unfulfilled demand and a lower service level. This is because a lower penalty cost means that the manufacturer is less penalized for not meeting demand, so they are less likely to invest in pre-positioning RMI or recovery capabilities. As a result, they are more likely to experience unfulfilled demand, which can lead to a lower service level. The decision of which penalty cost to use depends on a trade-off between cost and service level. If the manufacturer is very concerned about cost, they may choose a lower penalty cost, even if it means a lower service level. However, if the manufacturer is very concerned about service level, they may choose a higher penalty cost, even if it means a higher cost.

8.2 Demand fulfillment levels.

The main goal of this project is to satisfy the manufacturer's demand consistently. We aim to achieve this by building a robust supply chain that identifies and incorporates alternative suppliers. Ultimately, this will lead to a reduction in the gap between production and demand, minimizing unfulfilled orders. Table 9 compares strategy 3 with non-resilient supply chain for the tire manufacturer to fulfill demand. This table reveals that relying solely on RMI suppliers leaves a persistent gap between production and demand, causing unfulfilled orders. However, integrating backup suppliers alongside RMI, significantly reduces unfulfilled orders by bolstering production and demonstrating the crucial role of proactive supply chain strategies in achieving the manufacturer's goal of a resilient and demand-fulfilling chain. Comparatively, the non-resilient case showcases the negative consequences of not implementing proactive measures. Demand consistently exceeds production, resulting in a significant backlog of unfulfilled orders.

Table 6
Fulfilment strategies for demand profile A: comparison of production and demand across different approaches

Period	RMI + Backup suppliers (Strategy 3) * cumulative production	cumulative demand	Non-resilient case cumulative production	cumulative demand
1	41,142	37,067	-	37,067
2	41,142	59,572	-	59,573
3	59,167	82,300	19,740	82,301
4	78,892	126,542	39,479	126,543
5	115,082	179,748	75,669	179,750
6	151,271	213,530	111,858	213,532
7	186,144	252,582	148,048	252,585
8	230,169	295,839	194,107	295,842
9	272,926	336,248	240,166	336,251
10	316,272	378,103	286,225	378,106
11	359,599	417,787	332,284	417,791
12	403,514	458,844	377,194	458,848

8.3 Strategies compared with non-resilient case in demand profile A assuming EGP300 penalty for the unfulfilled demand/unit.

The results from the stochastic mixed-integer programming model provide valuable insights into the effectiveness of different resilience strategies in minimizing total costs and ensuring a robust supply chain, as shown in Table 10. The "RMI + Recovery Supplier" strategy emerges as the most cost-efficient, with an expected cost of EGP64,384,065.04, outperforming other strategies. This strategy not only minimizes costs but also demonstrates superior performance in meeting customer demands, as evidenced by the highest service level of 0.88. The use of both Recovery Materials Inventory (RMI) and a Recovery Supplier proves advantageous, with the lowest unfulfilled demand and the utilization of recovery supplies to mitigate disruptions. In comparison, relying solely on RMI or a recovery supplier results in higher unfulfilled demand.

Table 7
Comparison between different strategies 1, 2, 3 and the non-resilient case.

Case	RMI + Recovery supplier	RMI	Recovery supplier	Non-resilient
Expected cost	64,384,065.04	63,632,162.21	68,343,974.52	70,477,455.29
Expected unfulfilled demand	55,329.91	81,649.47	81,649.47	81,649.47
Expected recovery supplies	95,653.66	0	111,815.11	0
Pre-positioned RMI	69,262.00	0	0	0
Expected used RMI	41,441.80	0	0	0
Expected service level	0.88	0.82	0.82	0.82

The percentage differences highlight the notable advantages of the "RMI + Recovery Supplier" strategy. It incurs a 6.02% lower cost than the recovery supplier strategy. Moreover, it achieves a 6.10% reduction in unfulfilled demand compared to the remaining strategies. These percentages underscore the significance of the combined approach in minimizing costs and enhancing the overall performance of the supply chain. In contrast, the "Non-resilient" strategy, without specific resilience measures, incurs the highest costs and unfulfilled demand, emphasizing the importance of adopting resilient strategies in mitigating disruptions and optimizing supply chain performance.

8.4 Compared demand profiles

In this section, we delve into the contrast between demand profiles A and B to determine the optimal strategy. As illustrated in Figure 4, after the initial propagation delay period 1, we can see that in the first 2 periods after it, profile A has a smaller gap between cumulative production and demand due to the larger decrease in demand. However, beyond the third production period, after reopening of the markets in profile A, the increased need to compensate for lost demand in shutdown leads to a widening gap between the production quantity and the escalating demand in profile A. Notably, this disparity sees a substantial increase in profile A compared to profile B as time progresses, due to the fact that demand profile B only decreases over time compared to its original demand. This emphasizes the growing challenge of meeting demand in profile A over time, particularly due to the impact of disruptions on the production-to-demand ratio.

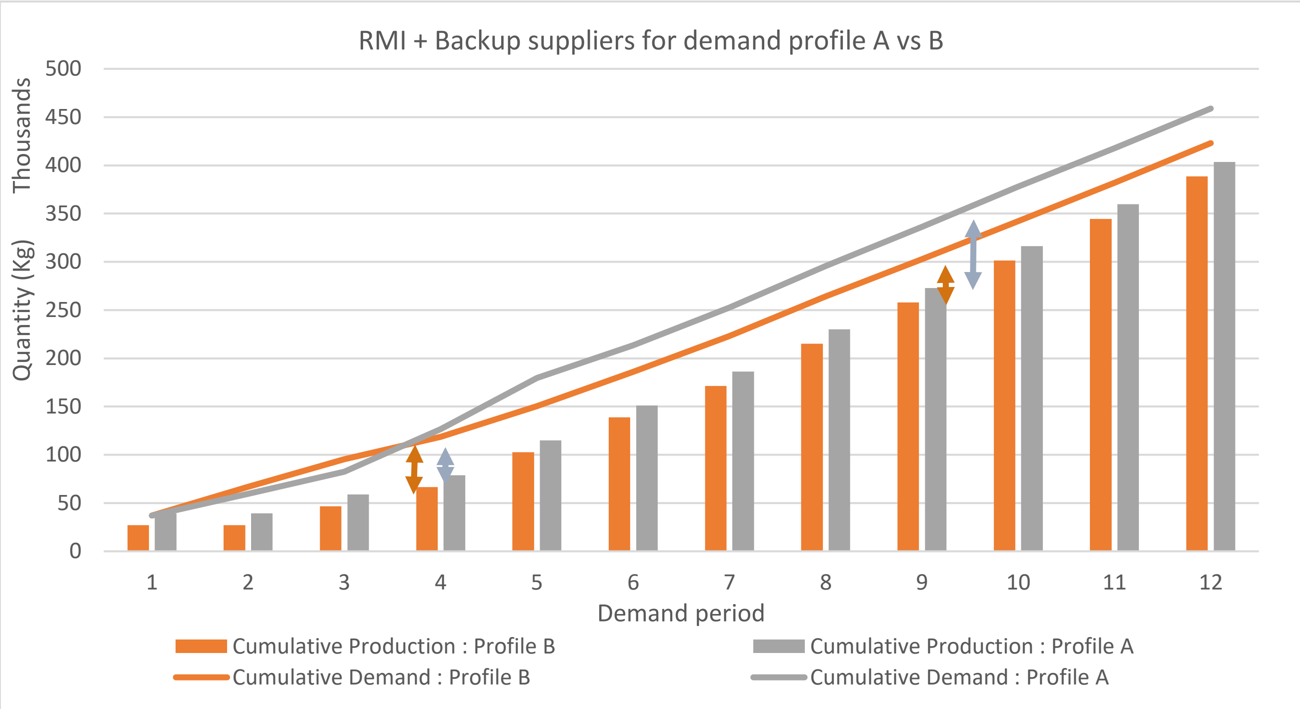

Fig.4: RMI + Backup suppliers for demand profile A vs demand profile B

8.5 Managerial Implications

For supply chain practitioners navigating disruption risks, this analysis yields three actionable imperatives: First, implement a hybrid mitigation strategy combining pre-positioned Recovery Materials Inventory (RMI) and diversified backup suppliers—this approach reduces expected costs by 8.6% (to EGP64.4M vs. EGP70.5M for non-resilient models) while cutting unfulfilled demand by 32% (55K vs. 82K tons) and elevating service levels to 88% (vs. 82%) by dynamically leveraging inventory buffers and alternative sourcing during regional disruptions. Second, proactively shape demand and penalty structures: prioritize stable demand profiles (e.g., Profile B's gradual reduction, which lowers costs by 10.4% vs. Profile A's volatile surges) and calibrate penalties strategically low penalties (EGP30/unit) reduce costs by 32% but increase stockouts by 47%, while high penalties (EGP300) protect service levels at higher operational costs. Critically, treat resilience as non-negotiable insurance—inaction exposes firms to peak costs and severe service erosion, whereas upfront investments in RMI capacity (EGP69.3K pre-positioned) and backup contracts transform disruptions from crises into manageable events, ensuring supply continuity even under propagating regional shocks.

9. Conclusions

This research presents a comprehensive decision-making model for optimizing global supply chain operations under pandemic disruption risks and their cascading consequences. It offers significant advancements in supply chain disruption management through four key contributions.

Firstly, the model integrates Grey optimal ranking within a stochastic Mixed-Integer Programming (MIP) framework. This novel approach enables the robust evaluation and selection of recovery suppliers in the face of uncertainty, considering pandemic-related factors, quality metrics, and emission levels. By simultaneously minimizing costs and ensuring resource availability at optimal levels of cost, quality, and emissions, this integration significantly enhances supply chain resilience during disruptions. Secondly, the research adopts a multi-portfolio approach via a scenario-based stochastic MIP model. This innovative method achieves risk-neutral optimization of supply chain resilience under pandemic disruption scenarios, encompassing supply, production, and inventory scheduling. Notably, the integration of Grey Relational Analysis (GRA) provides a comprehensive understanding of the complex dynamics within the disrupted supply chain, enabling informed decision-making for enhanced resilience. Thirdly, the study goes beyond conventional analyses by explicitly modeling pandemic disruption scenarios that account for the cascading regional risks known as the "ripple effect." This novel approach captures the intricate interplay between concurrent supply, demand, and logistics disruptions, offering a holistic perspective on the interconnected impacts of disruptions and paving the way for more robust response strategies. Finally, the research strengthens its findings through numerical examples drawn from a pandemic case study. Through a comparison of optimal solutions for both resilient and non-resilient supply portfolios, the study validates the effectiveness of traditional resilience measures like pre-positioning Recovery Materials Inventory (RMI) and utilizing recovery supplies from backup suppliers in mitigating the effects of pandemic disruptions across multiple regions and their corresponding ripple effects.

In conclusion, this research stands as a pivotal contribution to the field of supply chain disruption management. By integrating Grey optimal ranking, adopting a multi-portfolio approach, explicitly considering ripple effects, and validating its findings through practical examples, the proposed model offers a powerful tool for optimizing global supply chain operations in the face of complex pandemic disruptions.

The subsequent analysis delves into the practical implications of the decision-making model. Comparisons between demand profiles A and B reveal efficiency disparities, influenced by factors such as cost, service level, and penalty costs for unfulfilled demand. The study emphasizes the trade-off between cost and service level, highlighting the significance of penalty costs in shaping supply chain decisions. Further examination focuses on the fulfillment of demand levels under different strategies. The integration of backup suppliers alongside Recovery Materials Inventory (RMI) is found to be crucial in minimizing unfulfilled orders, showcasing the importance of proactive supply chain strategies in achieving demand-fulfilling chains. The stochastic mixed-integer programming model results provide valuable insights into the effectiveness of various resilience strategies. The "RMI + Recovery Supplier" strategy emerges as the most cost-efficient, offering superior performance in meeting customer demands. Percentage differences underscore the advantages of this combined approach, emphasizing its significance in minimizing costs and enhancing overall supply chain performance compared to alternative strategies.

10. Limitations and Future Directions

Enhancing supply chain resilience not only involves diversifying suppliers and implementing flexible sourcing strategies but also fortifying critical nodes against natural disasters. This could involve pre-positioning Recovery Materials Inventory (RMI) at strategically located suppliers who have invested in infrastructure resilience measures. However, it is crucial to acknowledge the significant investment costs associated with such fortification strategies, requiring careful cost-benefit analysis and resource allocation to optimize the balance between resilience and economic viability. In addition, considering scenarios that involve more than one region as sources of disruption and examining how disruptions indirectly spread between neighbouring regions would lead to a deeper comprehension of how disturbances unfold. Incorporating indirect propagation into models would offer a more precise depiction of how disturbances ripple out and would improve the efficacy of resilience planning.

Furthermore, the model exhibits exponential time complexity $O((L_{max}+1)^K)O$ due to its reliance on exhaustive scenario enumeration, where K is the number of regions and L_{max} is the maximum disruption level per region. While per-scenario variables (supplier allocations, production, inventory) scale polynomially with suppliers (m), plants (n), and periods (T) as $O(m \cdot n \cdot T)$. The exponential scenario growth dominates computational cost. Without decomposition or sampling, solving times become prohibitive for large-scale instances, limiting practical scalability

Disclosure Statement

The authors report there are no competing interests to declare.

A data availability statement

All data presented in this manuscript is included herein. Other forms of data are unavailable due to confidentiality constraints.

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