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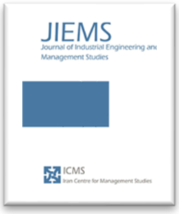

A Fuzzy – Chance Multi Objective Programming for Supply Network Multi Modal Transportation Routes

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Abstract

All Social orders depend on and advantage from the significant and important parcel of worldwide trade that it's backed by consolidation-based transportation over brief, medium, long and interconversion separations. By consolidating the cargo of different shippers into the same stacking units for their full or fractional journeys, consolidation looks for to extend operational and financial efficiency. This paper's focus is on consolidation-based transport and the tactical planning difficulties carriers confront when creating a set of scheduled services that viably and profitably match resource allocation with expected shipping requests over a medium- to long-term timeframe. The main contribution of this research is to provide a new integrated MOFCCP model for supply chain (SC) planning that simultaneously calculates the total tardiness, minimizes the total costs including fixed and variable travelling, purchasing and waiting cost and minimizes the total risk of travel routes. This study addresses the crucial supply chain challenges of multi modal transportation routes. Global SCs encounter major difficulties when it comes to SCM due to uncertainty. In this paper, a supply chain network (SCN) is designed using a novel multi-objective optimization model that accounts for multi modal transportation routes uncertainty. Fuzzy goal programming (FGP) is used to assist businesses in making decisions and the trade-off between the costs and benefit of alternative options because of multiple competing objectives. The primary goal of designing the suggested SCN is to minimize the overall risk of multi modal transportation costs. In order to manage the uncertainty, the novel multi-objective mathematical model is subjected to fuzzy chance constrained programming (FCCP), and a case study in steel company is carried out to investigate.

Keywords: Fuzzy Chance, Multi objective, Supply Chain Network, Transportation.

Paper Type: Original Research

1. Introduction

Every business that produces and sells a specific product needs a system that can coordinate all these processes well and give them order and integrity. In the past, when businesses were different, competition was not as serious and intense, and the need to use up-to-date and appropriate technologies was not felt to this extent (Rasi & Sohanian, 2021). In order to manage the flow of assets from suppliers of raw materials, manufacturers of products, and delivery of products to final consumers, SCs are essential. They also have a big influence on the business objectives of SCN partners. Considering the SC's imprecise and dynamic nature, sufficient data is required for the accurate estimation of the probability distribution for the parameters. Business should be well – informed about SC uncertainty so that they can apply SC resilience management in emergency situations and increase SC resilience (Mardan et al. 2019). The SCM process is rife with uncertainty, and global SCs have been dealing with significant difficulties. The accuracy of the input parameters is typically taken for granted in basic optimization models; in other words, tactical models presume that data uncertainty has no bearing on the model's quality or viability, but rather on the solution's viability ((Barzegar, et al. 2018). The use of digital technologies to improve SC efficiency and connectivity is known as SC digitization (Perano et al. 2023). Big data, block chain, IoT, artificial intelligence (AI), and cloud computing are among the technologies that are becoming more significant because they have altered how businesses operate, particularly when reacting to disruptions. It offers automation, real – time data sharing, and predictive and analytical capabilities. These characteristics aid businesses in improving operations and making wiser decisions (Ambasht, 2023). These technologies not only enhance day-to-day operations but also aid in waste reduction and energy management. This quick change in connections, computing control, and information has been fueled by industry 4.0. Technological developments have made this shift more noticeable (Chauhan et al. 2022), encompassing the Internet of Things (IoT), block chain, and AI. Recent research

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indicates that 44% increase in SC complexity and inefficiency indicates that companies may face significant growth barriers in the absence of a solid digital SC foundation (Li, et al. 2025). Uncertainty is widespread in the SCM process, and global SCs have been dealing with significant difficulties. Basic optimization models typically take the accuracy of the input parameters as a given; in other words, traditional models assume that data uncertainty has no bearing on the model's quality or feasibility. However, the feasibility of the solutions may be impacted by uncertainty conditions, which may alter the best solution under actual circumstances. In order to assist decision makers in making effective decisions in the face of uncertainty, optimization models under uncertainty have been steadily garnering increased attention in the academic community. Due to the numerous disruptions, the significance of the SC can be emphasized more and more in the current uncertain environment. For manufacturers and other stakeholders, creating an efficient SCN is therefore a crucial and difficult task (He & Abd Elazem, 2022). Risk management is a helpful tactic to regulate activities that could impact the system's performance under investigation; these activities typically involve handling uncertainty. Customer demand, product quality, and delivery time are all potential sources of internal risks in the SCN (Shekhovtsov et al. 2022). Natural disasters, terrorist attacks, and fluctuations in foreign exchange rates are examples of external risks that can affect the SCN. Since SC disruptions have long posed a serious threat to an organization's efficiency, controlling both internal and external risks can be crucial to achieving the objectives of a global SC expansion. Resilience to disruption and sustainability requirements are two pressures that modern SCs must increasingly manage them. This is especially true for sectors like chemicals, where complicated multimodal logistics, global sourcing and hazardous materials make them more susceptible to range of risk factors, such as political unrest, environmental disruptions, regulatory changes, and technological disruptions. These SCs also need to continue providing services at the same time. The main contributions of this study are listed below to give a clear picture of its importance and applicability:

1. A new integrated MOFCCP model for SC planning: We suggest MOFCCP model that simultaneously calculates the total tardiness, minimizes the total costs including fixed and variable travelling, purchasing and waiting cost and minimizes the total risk of travel routes.
2. In multimodal transportation network, the model integrates risk modeling framework that takes into consideration disruptions from different risk categories (e.g., production strategies, logistics layers, etc.) strong and proactive SC planning is made possible by this structure.
3. Depending on the mode of transportation (air, sea, rail, and road) and routes we select for the transfer, one of the most significant risks in tactical SCN is the transportation routes from suppliers to the distribution zones to supply the necessary raw materials. To the best of our knowledge, the majority of SCM studies do not take into account the risk of transportation routes in decision models, even though these routes can be crucial in reaching realistic goals. Therefore, taking these risks into account when making decisions about SC modeling is crucial, as it gives trade organizations a competitive edge and makes the SC flexible. In order to minimize the costs associated with tactical international SC, this paper suggests a multi objective comprehensive procurement and logistics scheme.

The structure of this paper is as follows: In section (2), we will present the literature and background related to the research. Section (3) outlines the suggested framework for SCM system in the presence of uncertainty and presents the research materials and methodologies. Section (4) examines the computational results. A summary of the conclusions & managerial insight drawn from the review is provided at the end of Section (5 &6).

2. Literature Review

In the ever-changing world of international trade, it is essential to establish robust and sustainable supply chains (SSCs). Operational efficiency and adaptability are largely dependent on the efficient management and digital integration of DPI information flows, which is a crucial enabler of this resilience (Ghasemi et al.2024). Different approaches to handling customer demands will directly impact the quality of service offered as well as the capacity to effectively manage production system. Make to stock (MTS), make to order (MTO), or hybrid MTS/MTO production strategies have been taken into consideration by the majority of production-inventory management systems that handle multiple products (Tabatabaei, 2025). Due to fierce competition among manufacturers, businesses should optimize their SC to boost their marketability. Li & Wormer (2008) investigated the design of SC with resource constraints. They used constraint planning approach to assess the issue and presented a project scheduling model under multiple resource constraints. Sawik (2009) created MIP model to schedule production and supply after researching a customer-oriented SC. Chan et al. (2010) introduced a multi-criteria supplier selection model. They took risk into account as a criterion for selection. Bhantagar etal. (2011) offered a thorough framework for assessing operational plans and techniques in order to establish a suitable balance production and transportation systems in SC. They examined the advantages of coordinating scheduling and planning choices.

Yeung et al. (2011) investigated the scheduling of two-stage SCs with several shared delivery times. Understanding risks in multimodal transportation, including supply, economic, policy, security, environmental, and technological risks, is essential for SCs resilience in addition to operational considerations (Pizol, 2019). In order to manage these uncertainties, strong information architectures and AI-based risk assessment models are crucial. Real-time risk monitoring, backup plans, legal compliance, and environmentally friendly routing all contribute to resilience (Senthil etal.2018). Khorshidvand etal (2021) provided three models including Centralized Supply Chain (CSC), Decentralized Supply Chain (DCSC), and Modified Centralized Supply Chain (MCSC) are developed and then solved to cope with various real-world situations. Khorshidvand etal (2021) proposed a new hybrid method, in which SCC decisions and CLSCND objectives are simultaneously involved. First, this approach makes price, greenness, and advertisement decisions, and then it aims at maximizing profit and minimizing CO2 emission. A new nonlinear programming (NLP) model is developed based on the sensitivity of the return rate to green quality and the customers' maximum tolerance, while the demands are uncertain. In order to overcome the uncertain demands, a robust optimization (RO) model is used. A Lagrangian relaxation algorithm is also employed to solve large-scale instances in a logical running time. Aboutorab et al. (2022) illustrated how reinforcement learning could help SC managers identify risks proactively. Additionally, they described how RL operates and they described how RL operates and contrasted its effectiveness with other manual approaches used by risk management. Using an integrated Grey DEMATEL approach, Akter et al. (2022) assessed SC disruption risk factors in the emergency life-saving drug industry. Liu etal.(2022) in a multi-echelon SC viability problem with a constrained intervention budget examined a novel disruption propagation management problem. In order to reduce disruption risk based on the target participants' probability of being disrupted in the SC, they introduced two mixed-integer nonlinear programming models. Additionally, they introduced a novel method based on mathematical programming, the do-calculus, and casual Bayesian networks. Computational results on randomly generated instances and case study demonstrate the high efficiency of the suggested models. Tavana etal. (2022) presented an integrated multi-objective MIPM to take into account a sustainable closed-loop SCN that includes pickup and delivery, cross-docking, location-inventory-routing, and time windows. To solve the problem under uncertainty, they used fuzzy goal programming approach, and the sensitivity analysis and results obtained demonstrate the effectiveness of the suggested model. Transportation efficiency is increased by technological advancements, but there are risks that must be considered. Customer satisfaction and dependable transportation services are enhanced by SC collaboration, which creates a robust ecosystem (Jafari, 2024). Hejazi and Khorshidvand (2024) proposed mixed-integer linear programming (MILP). The multi-objective model is converted to a single-objective model through the ε-constraint method and is solved using the Gams software package. A new equation is presented to select the best practice among Pareto fronts to score the non-dominated solutions scientifically. Several numerical instances with random parametric settings corroborate the model's effectiveness. According to a trade-off analysis, the environmental and social considerations led to a significant cost increase and are complied with economic objectives. Transportation operations run smoothly and SC is protected when operational and security risks are addressed (Sarkar et al.2025). Tabatabei (2025) integrated production strategies, resilience, and risk management into a multi-modal transportation framework, offering a new development in SSCND. With an emphasis on the distribution, production, and inventory (DPI) triad, the SSCND literature highlights the necessity of strategic alignment in order to build a robust SC that can reduce risks in multimodal transportation. We do this by creating a unique multi-objective mixed-integer programming (MOMIP) model that is tailored to the SSCND and aims to minimize transportation time, maximize profit, and lessen environmental impacts. A specific goal programming technique is used to solve the model, guaranteeing that no objective is sacrificed for another. Key risks must be taken into account when managing a SC because they have the potential to significantly alter our original plans. This paper proposes a multi-objective comprehensive procurement and logistics system for a tactical international SC to reduce total latency, purchasing, waiting and traveling costs, and total risk of transportation routes with the uncertainty in mind. FCSP is used to solve the multi-objective model. In contrast, we often make decisions in a decision-making process based on the tradeoff between costs and benefits of alternative options, which is handled here using fuzzy goal programming. For the purposes of verifying the performance and applicability of the proposed model, a case study is conducted and some sensitivity analyses are performed to investigate the behavior of the objectives when the controllable parameters are changed.

3. Research Methodology

This section outlines the study's suggested methodology for creating effective SCM system in the face of uncertainty.

3.1. Problem statement

Given uncertainty about the risk of transportation routes, a multi-objective optimization model is developed to design SCN under uncertainty of transportation routes. In order to deal with the multi competing objectives, we used FGP techniques to help top managers in companies to balance the benefits and risks of the different design choices. The following assumptions are used to describe the problem:

1. There are J raw materials, which should be supplied by one of the qualified suppliers.
2. The ready time for each raw material in each qualified supply zone may be different and depends on the technical and supply constraints, as suppliers have different delivering speeds because they have different equipment, manpower and financial condition.

3. Raw materials may be sent immediately or kept in supply zone to be batched with other materials, in other words, one of the most important decisions that should be made in each supply zone is which material should be waited and batched with others.

4. There are different types of transportation system to transport raw materials from the supply zones to distribution hubs and then from the distribution hubs to manufacturer. Also, some raw materials may be physically, commercially, and legally restricted for some raw materials to be transported by sea, road, air, and rail.

5. Each mode of transportation (Sea, Road and Air) has its own capacity limitations.

6. Raw materials in the distribution hubs can be again sent or held to be batched:

7. Each transportation route also has its own risk level for the raw materials, and the risk of the route is defined as a triangular fuzzy number. The main objectives are to reduce the total lateness times, total travel, purchasing, and waiting costs, and to reduce the total transportation risk. The SCN proposed in Figure (1) shows the following:

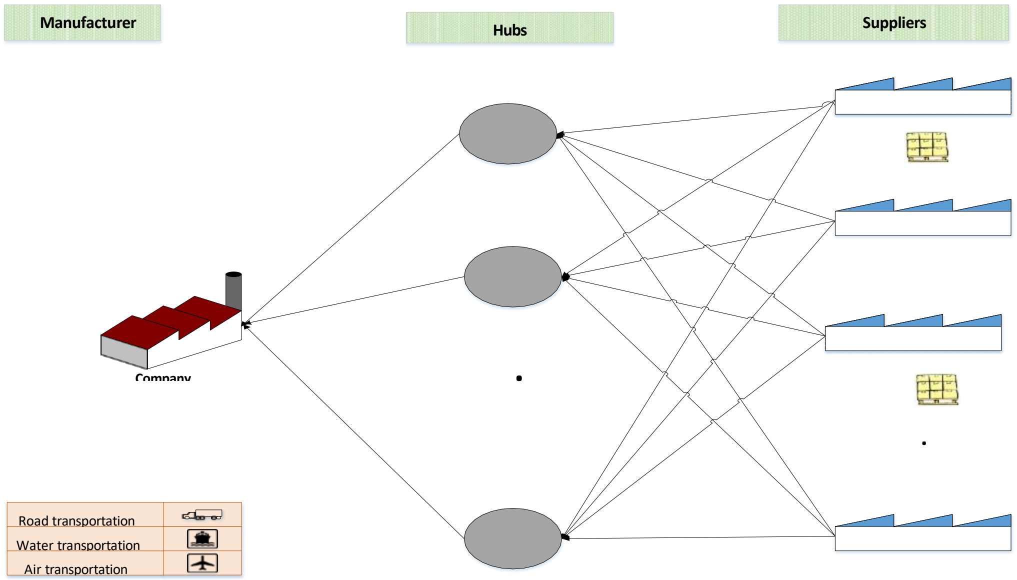


Figure 1. SCN of this research

Table 1. Sets and indices

J	Set of raw materials (j ∈ J)
S	Set of suppliers (s, s′ ∈ S)
T	Set of transportation modes (By Sea, Air, Road) (t, t′ ∈ T)
H	Set of distribution hubs (h, h′ ∈ H)
K	Set of batches (k, k′ ∈ K)

Table 2. Parameters

b_{js}	If jth raw material can be supplied by the sth supplier is 1, otherwise 0
a_{jt}	If jth raw material can be transported by the tth types of transportation is 1, otherwise 0
d_{sh}	If sth supplier can transfer raw materials to hub hth is 1, otherwise 0
D_j	Demand of the raw material j
π_j	Conversion factor of the raw material j (kg)

Cp_t	Maximum capacity for the tth type of transportation (kg)
R_{js}	Ready time of the jth raw material by the sth supplier (supplier s cannot start the production process for the jth material earlier than its ready time due to technical and supply constraints)
P_{js}	Production time of the jth raw material by the sth supplier
c_{js}	Purchasing cost of the jth raw material by the sth supplier
t_{sht}	Transportation time from the sth supplier to the hth hub by the tth mode
t'_{ht}	Transportation time from the hth hub to the factory by the tth mode
$\overset{'}{\tau}_{jsth}$	Risk of transportation from the sth supplier to hth hub by the tth mode for the jth raw material
$\overset{''}{\tau}_{jht}$	Risk of transportation from the hth hub to the manufacturer by the tth mode for the jth raw material
ρ'	The maximum acceptable risk for the raw material j to be transported from supplier to manufacturer
γ_{st}	Fixed transportation cost from the sth supplier for the tth mode
γ'	Fixed transporation cost from the hth hub for the tth mode
γ''	Variable costs for transferring raw materials from the sth supplier to the hth hub by the tth mode
γ'''	Variable costs for transferring raw materials from the hth hub to the factory by the tth mode
β_j	Waiting cost for the jth raw material in supply zones
β'	Wating cost for the jth raw material in hubs
DD_j	Due date of the jth raw material in manufacturing site
α_j	Tardiness cost for the jth raw material
B	Available Budget in the supply chain network
M	An optional large number

Table3. Decision variables

x_{jskht}	If jth raw material supplied by the sth supplier is transferred to the hth hub in the kth batch by the tth mode is 1, otherwise0.
y_{jh}	If jth raw material in the kth batch transferred from the hth hub to the manufacturer by the tth mode is 1 , otherwise0.
z_{ksth}	If kth batch transferred from the sth supplier to the hth hub by the tth mode is 1, otherwise0.
z'_{kh}	If kth batch transferred from the hth hub to the manufacturer by the tth mode is 1, otherwise0.
σ_k	if kth batch in the supply zones formed is 1, otherwise 0.
σ'	if kth batch in the hubs formed is 1, otherwise 0.
CT_j	Completion time of the jth raw material in the supply zone
C	Completion time of the kth batch in the supply zone to be delivered to the destination hub
W_j	Waiting time of the jth raw material in the supply zone to be transferred to the hub
AT	Arrival time of the jth raw material from the supplier to the hub
LT_k	Leaving time of the kth batch from the hub to the manufacturer
W	Waiting time of the jth raw material in the hub to be transferred to the manufacturer
A	Arrival time of the jth raw material in the manufacturer
Tj	Tardiness time of the jth raw material

3.2. Mathematical Model

We will provide MILPM as following:

$$Minimize\ Obj1 = \sum_{j=1}^{J} \alpha_j T_j \tag{1}$$

$$\begin{aligned} Minimize\ Obj2 = {} & \sum_{k=1}^{K}\sum_{s=1}^{S}\sum_{h=1}^{H}\sum_{t=1}^{T} \gamma_{st}\, z_{ksht} + \sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{t=1}^{T} \gamma'_{ht}\, z'_{kht} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{h=1}^{H} \gamma''_{sht}\, x_{jskht} D_j \pi_j \\ & + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{h=1}^{H} \gamma'''_{ht}\, y_{jkht} D_j \pi_j + \sum_{j=1}^{J} W_j\, \beta_j + \sum_{j=1}^{J} W'_j\, \beta'_j \\ & + \sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{t=1}^{T} c_{js}\, x_{jskht} D_j \end{aligned} \tag{2}$$

$$Minimize\ Obj3 = \sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{k'=1}^{K}\sum_{t=1}^{T}\sum_{t'=1}^{T}\sum_{h=1}^{H}\left(1-\left(1-\tau'_{jsth}\right)\left(1-\tau''_{jht'}\right)\right) x_{jskht}\, y_{jk'ht'} \tag{3}$$

$$\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{t=1}^{T} x_{jskht} = 1 \qquad \forall j \tag{4}$$

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{h=1}^{H} x_{jskht} \le b_{js} \qquad \forall j\,, s \tag{5}$$

$$\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{h=1}^{H} x_{jskht} \le a_{jt} \qquad \forall j\,, t \tag{6}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} x_{jskht} \le M.d_{sh} \qquad \forall s, h \tag{7}$$

$$\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{h=1}^{H} x_{jskht}\, D_j \pi_j \le Cap_t \qquad \forall k, t \tag{8}$$

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{h=1}^{H} y_{jhkt} = 1 \qquad \forall j \tag{9}$$

$$\sum_{k=1}^{K}\sum_{h=1}^{H} y_{jhkt} \le a_{jt} \qquad \forall j\,, t \tag{10}$$

$$\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{t=1}^{T} x_{jskht} = \sum_{k=1}^{K}\sum_{t=1}^{T} y_{jhkt} \qquad \forall j\,, h \tag{11}$$

$$\sum_{j=1}^{J}\sum_{h=1}^{H} y_{jhkt}\, D_j \pi_j \le Cap_t \qquad \forall k, t \tag{12}$$

$$\sigma_k = \begin{cases} 1 & if \ \sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{h=1}^{H}\sum_{t=1}^{T} x_{jskht} > 0 \\ 0 & else \end{cases} \qquad \forall k \tag{13}$$

$$\sigma'_k = \begin{cases} 1 & if \ \sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{t=1}^{T} y_{jhkt} > 0 \\ 0 & else \end{cases} \qquad \forall k \tag{14}$$

$$CT_j = \sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{t=1}^{T} x_{jskht}\left(P_{js} + R_{js}\right) \qquad \forall j \tag{15}$$

$$CD_k = Max\left\{CT_j\right\}_{\forall j \in k} \qquad \forall k \tag{16}$$

$$W_j = Max\left\{CD_k - CT_j\right\} \qquad \forall j \in k \tag{17}$$

$$ATH_j = CT_j + W_j + \sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{t=1}^{T} x_{jskht}\, t_{sht} \qquad \forall j \tag{18}$$

$$LT_k = Max\left\{ATH_j\right\}_{\forall j \in k} \qquad \forall k \tag{19}$$

$$W'_j = Max\left\{LT_k - ATH_j\right\} \qquad \forall j \tag{20}$$

$$ATF_j = ATH_j + W'_j + \sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{t=1}^{T} y_{jhkt} t'_{ht} \qquad \forall j \tag{21}$$

$$T_j = Max\left\{0, ATF_j - DD_j\right\} \qquad \forall j \tag{22}$$

$$\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{k'=1}^{K}\sum_{t=1}^{T}\sum_{t'=1}^{T}\sum_{h=1}^{H}\left(1-\left[\left(1-\tau'_{jsth}\right)\left(1-\tau''_{jht'}\right)\right]\right) x_{jskht}\, y_{jk'ht'} \leq \rho'_j \qquad \forall j \qquad (23)$$

$$z_{ksht} = \begin{cases} 1 & if \sum_{j=1}^{J} x_{jskht} > 0 \\ 0 & else \end{cases} \qquad \forall k, s, h, t \qquad (24)$$

$$\sum_{s=1}^{S}\sum_{h=1}^{H}\sum_{t=1}^{T} z_{ksht} = \sigma_k \qquad \forall k \qquad (25)$$

$$z'_{kht} = \begin{cases} 1 & if \sum_{j=1}^{J} y_{jhkt} > 0 \\ 0 & else \end{cases} \qquad \forall k, h, t \qquad (26)$$

$$\sum_{h=1}^{H}\sum_{t=1}^{T} z'_{kht} = \sigma'_k \qquad \forall k \qquad (27)$$

$$\sum_{k=1}^{K}\sum_{s=1}^{S}\sum_{h=1}^{H}\sum_{t=1}^{T} \gamma_{st}\, z_{ksht} + \sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{t=1}^{T} \gamma'_{ht}\, z'_{kht} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{h=1}^{H} \gamma''_{sht}\, x_{jskht} D_j \pi_j + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{h=1}^{H} \gamma'''_{ht}\, y_{jkht} D_j \pi_j + \sum_{j=1}^{J} W_j\, \beta_j$$
$$+ \sum_{j=1}^{J} W'_j\, \beta'_j + \sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{h=1}^{H}\sum_{t=1}^{T} c_{js}\, x_{jskht} D_j \leq B \qquad (28)$$

$$x_{jskht}, y_{jkht}, z'_{kht}, z_{ksht}, \sigma'_k, \sigma_k = \{0,1\} \qquad (29)$$

$$T_j, W_j, W'_j, ATF_j, ATH_j, LT_k, CD_k, CT_j \geq 0 \qquad (30)$$

Objective function (1&2&3) states simultaneously calculates the total tardiness, minimizes the total costs including fixed and variable travelling cost, purchasing and waiting cost and minimizes the total risk of travel routes. Constraint (4) stipulates that each raw material should be assigned to a single qualified supplier and transferred to a single distribution hub using only one mode of transportation (air, sea, road, or railway). Additionally, each raw material cannot be assigned to different batches. Constraint (5) indicates that only one of the eligible suppliers should provide each raw material. Since certain legal, physical, and commercial restrictions as well as safety standards should be taken into account when the raw material is prepared for forwarders to transport. Constraint (6) demonstrates that each raw material must be transported by the acceptable modes of transportation. The potential routes for the transfer of raw materials between suppliers and distribution centers are displayed in Constraint (7) and are contingent upon the geographic locations of the suppliers and distribution centers. The capacity for each mode of t is displayed in Constraint (8). Constraint (9) indicates that only one mode of transportation (air, sea, road, or railway) should be used to transport each raw material in the distribution hubs in a single batch. Constraint (10) demonstrates that only one permitted mode of transportation may be used to deliver each raw material from the distribution hubs to the manufacturer. The commodity balance formula for every distribution hub is shown in constraint (11). The capacity restriction for every means of transportation between the hubs and the manufacturer is shown in Constraint (12). Which batch should be formed in the distribution hubs and supply zones is indicated by constraints (13) and (14) respectively. Each raw material's completion time is determined by its own supplier using constraint (15). Constraint (16) indicates when each batch is prepared for transfer to the distribution hubs by computing the readiness time (dispatching time) for each batch. The waiting period for each raw material in the supply zone to finish its batch is determined by constraint (17). Constraint (18) determines when each raw material will arrive at the distribution center. Equation (19) is used to determine when each batch in the distribution hubs is ready to be shipped to the manufacturer. The waiting time for each raw material to be transported to the manufacturer in the distribution hubs is determined by equation (20). The raw material's arrival time at the manufacturer is determined by equation (21). The tardiness time for every raw material is determined by constraint (22). In other words, if the risk of a route is met, constraint (23) guarantees that the risk of the transportation routes for each raw material is met. In other words, a route can be selected as a means of transferring raw materials if its risk is less than the maximum risk. Each batch in the supply zones and distribution hubs can only be delivered to one manufacturer and one distribution hub, respectively, by a single mode of transportation constraints (24 - 27) in place. The budgetary restrictions on the SCN under investigation are outlined in constraint (28). The kinds of decision variables are indicated by constraints (29 and 30).

3.3. Linearization of the proposed MILP model

We linearize the objective function (3) by applying constraints (31-33), since it is a non-linear equation due to the multiplication of two binary variables.

$$Minimize\ Obj3 = Z_3$$

$$Z_3 = \sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{k'=1}^{K}\sum_{t=1}^{T}\sum_{t'=1}^{T}\sum_{h=1}^{H}\left(1-\left[\left(1-\tau'_{jsth}\right)\left(1-\tau''_{jht'}\right)\right]\right)\varphi_{jskhtk't'} \qquad \forall\, j \qquad (31)$$

$$x_{jskht} + y_{jhk't'} \leq 1 + \varphi_{jskhtk't'} \qquad \forall\, j,k,k',s,h,t,t' \qquad (32)$$

$$x_{jskht} + y_{jhk't'} \geq 2\,\varphi_{jskhtk't'} \qquad \forall\, j,k,k',s,h,t,t' \qquad (33)$$

Note that the constraints (13) and (16) are non-linear, so for linearizing them we proposed the equations (34) to (38).

$$CD_k \geq CT_j - M\left(1 - \sum_{s=1}^{S}\sum_{h=1}^{H}\sum_{t=1}^{T} x_{jshkt}\right) \qquad \forall j\,,k \qquad (34)$$

$$CD_k \leq CT_j + M\left(2 - \delta_{jk} - \sum_{s=1}^{S}\sum_{h=1}^{H}\sum_{t=1}^{T} x_{jshkt}\right) \qquad \forall j\,,k \qquad (35)$$

$$CD_k \leq M.\sigma_k \qquad \forall k \qquad (36)$$

$$\sum_{j=1}^{J} \delta_{jk} = \sigma_k \qquad \forall k \qquad (37)$$

$$\sum_{s=1}^{S}\sum_{h=1}^{H}\sum_{t=1}^{T} x_{jshkt} \geq \delta_{jk} \qquad \forall j\,,k \qquad (38)$$

To linearize constraints (14) and (19), we can apply constraints (39) to (43).

$$LT_k \geq ATH_j - M\left(1 - \sum_{h=1}^{H}\sum_{t=1}^{T} y_{jhkt}\right) \qquad \forall j\,,k \qquad (39)$$

$$LT_k \leq ATH_j + M\left(2 - \delta'_{jk} - \sum_{h=1}^{H}\sum_{t=1}^{T} y_{jhkt}\right) \qquad \forall j\,,k \qquad (40)$$

$$LT_k \leq M.\sigma'_k \qquad \forall k \qquad (41)$$

$$\sum_{j=1}^{J} \delta'_{jk} = \sigma'_k \qquad \forall k \qquad (42)$$

$$\sum_{h=1}^{H}\sum_{t=1}^{T} y_{jhkt} \geq \delta'_{jk} \qquad \forall j\,,k \qquad (43)$$

Equations (44) and (45) are replaced with Equation (17).

$$W_j \geq CD_k - CT_j - M\left(1 - \sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{h=1}^{H} x_{jskht}\right) \quad \forall j\,,k \qquad (44)$$

$$W_j \leq CD_k - CT_j + M\left(1 - \sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{h=1}^{H} x_{jskht}\right) \quad \forall j\,,k \qquad (45)$$

Equations (46) and (47) are replaced simultaneously with Equation (20).

$$W'_j \geq LT_k - ATH_j - M\left(1 - \sum_{h=1}^{H}\sum_{t=1}^{T} y_{jhkt}\right) \quad \forall j \qquad (46)$$

$$W'_j \leq LT_k - ATH_j + M\left(1 - \sum_{h=1}^{H}\sum_{t=1}^{T} y_{jhkt}\right) \quad \forall j \qquad (47)$$

Constraints (48)-(50) are linearization of constraint (22).

$$T_j \geq ATF_j - DD_j \quad \forall j \qquad (48)$$

$$T_j \leq ATF_j - DD_j + M(1 - \theta_j) \quad \forall j \qquad (49)$$

$$T_j \leq M.\theta_j \quad \forall j \qquad (50)$$

Constraints (51) and (52) are proposed to linearize constraint (25).

$$\sum_{j=1}^{J} x_{jskht} \leq M\, z_{ksht} \quad \forall k,s,h,t \qquad (51)$$

$$\sum_{j=1}^{J} x_{jskht} \geq 1 - M\,(1 - z_{ksht}) \quad \forall k,s,h,t \qquad (52)$$

Constraints (53) and (54) are replaced with constraint (26).

$$\sum_{j=1}^{J} y_{jhkt} \leq M z'_{kht} \quad \forall k,h,t \qquad (53)$$

$$\sum_{j=1}^{J} y_{jhkt} \geq 1 - M(1 - z'_{kht}) \quad \forall k,h,t \qquad (54)$$

The formulated Mixed Integer Programming (MIP) model encompasses KHT ((S+1)(J+1))+2(2K+3J) decision variables, which are comprised of KHT((S+1)(J+1))+2K binary variables and 6J+2K continuous variables. Furthermore, it incorporates 2K(T(1+H(1+S))+4J+3)+J(2T+S+11) constraints.

3.4. Fuzzy chance-constrained programming

Fuzzy mathematical programming serves as a valuable tool for the enhancement of models characterized by uncertain parameters (Tirkolaee et al. 2020). The anticipated value of fuzzy number, which can range from triangular to trapezoidal forms, is instrumental for decision-makers in attaining satisfactory level of confidence when faced with chance constraints. Assuming a confidence level (α) exceeding 0.5 and considering that α is represented as a triangular fuzzy number, one can analyze the relationship between the confidence level of the fuzzy number and the random variable r.

$$Cr\{\tilde{x} \leq r\} \geq \mu \leftrightarrow r \geq (2\mu - 1)x^p + 2(1 - \mu)x^m \qquad (55)$$

$$Cr\{\tilde{x} \geq r\} \geq \mu \leftrightarrow r \leq (2\mu - 1)x^o + 2(1 - \mu)x^m \qquad (56)$$

In the delineated model, the risk of transportation routes from supply zones to distribution hubs $\widetilde{\tau'_{jsht}} = (\tau'^{p}_{jsth}, \tau'^{m}_{jsth}, \tau'^{o}_{jsth})$ and from distribution hubs to manufacturer $\widetilde{\tau''_{jht}} = (\tau''^{p}_{jht}, \tau''^{m}_{jht}, \tau''^{o}_{jht})$ are the uncertain parameters characterized in the form of independent triangular fuzzy numbers. Consequently, the constraints can be adjusted appropriately through by reformulating constraints (31) to (57).

$$Cr\left\{\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{k'=1}^{K}\sum_{t=1}^{T}\sum_{t'=1}^{T}\sum_{h=1}^{H}\left(1-\left[\left(1-\tau'_{jsth}\right)\left(1-\tau''_{jht'}\right)\right]\right)\varphi_{jskhtk't'} \leq \rho'_j\right\} \geq \mu_j \;\; \forall j \tag{57}$$

Now, we can rewrite Equation (57) based on the operation of triangular fuzzy number as below:

$$Cr\left\{\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{k'=1}^{K}\sum_{t=1}^{T}\sum_{t'=1}^{T}\sum_{h=1}^{H}\left(\widetilde{\tau'''_{jshtt'}}\right)\varphi_{jskhtk't'} \leq \rho'_j\right\} \geq \mu_j \qquad \forall j \tag{58}$$

Also, constraint (58) should be defuzzy based on Equation (55) as below:

$$\sum_{s=1}^{s}\sum_{k=1}^{K}\sum_{k'=1}^{K}\sum_{t=1}^{T}\sum_{t'=1}^{T}\sum_{h=1}^{H}\left[(2\mu_j-1)\left(\widetilde{\tau'''_{jshtt'}}\right)^{p}\varphi_{jskhtk't'}+2\left(1-\mu_j\right)\left(\widetilde{\tau'''_{jshtt'}}\right)^{m}\varphi_{jskhtk't'}\right] \leq \rho'_j \;\; \forall j \tag{59}$$

3.5. Weighted goal programming

Goal programming (GP) was first articulated by Charnes & Cooper (1977) and stands as a prominent methodology within the domain of multi-objective programming. This analytical framework can be employed to derive solutions for optimization challenges characterized by conflicting objectives. Conversely, it is often the case that we engage with multi-objective problems encompassing multiple units and varying significance levels, thus necessitating the normalization of the objective function within goal programming to facilitate optimal decision-making in accordance with these significance levels. The assignment of weights to objectives serves to effectively address the varying levels of importance inherent in multi-objective problems. Consequently, the concept of weighted goal programming is delineated through the subsequent mathematical formulation:

$$Minimize \sum_{o=1}^{O} w_o\left(\frac{d_o^+ - d_o^-}{b_o}\right)$$

$Subject\ to$:

$$H_g(X) = or \leq or \geq 0 \quad g = 1,2,\dots,G$$

$$f_0 - d_o^+ - d_o^- = b_o \qquad o = 1,2,\dots,O$$

$$d_o^+, d_o^- \geq 0 \qquad\qquad o = 1,2,\dots,O$$

According to the principal of weighted goal programming, our goal should be to minimize the total of weighted negative deviations (d_o^-) and positive deviations (d_o^+). The index o is used and f_0 shows the oth objective function. While, the gth constraint set and the ideal value of the oth objective function are indicated by $H_g(X)$ and b_0 respectively. Also, equations (60) and (61) show how to calculate the negative and positive deviations.

$$d_o^- = \begin{cases} b_o - f_o & if\ f_o < b_o \\ 0 & otherwise \end{cases} \tag{60}$$

$$d_o^+ = \begin{cases} f_o - b_o & if\ f_o > b_o \\ 0 & otherwise \end{cases} \tag{61}$$

The significance of the oth objective function is denoted by w_o and the sum of w_o is equal to 1. It should also be mentioned that decision maker should determine these weights for each objective function based on their importance. We modify the proposed FMIP model to optimize the three objective functions. Our final fuzzy model is presented as follows:

$$Minimize\ \psi = w_1\left(\frac{d_1^+}{b_1}\right) + w_2\left(\frac{d_2^+}{b_2}\right) + w_3\left(\frac{d_3^+}{b_3}\right) \tag{62}$$

$Subject\ to$:

$$Obj_1 - d_1^+ + d_1^- = b_1 \tag{63}$$

$$Obj_2 - d_2^+ + d_2^- = b_2 \tag{64}$$

$$Obj_3 - d_3^+ + d_3^- = b_3 \tag{65}$$

The objective function of the weighted goal programming (WGP) is ψ that should be minimized. The type of each objective function is minimization, so the proposed WGP should be minimized the weighted sum of normalized positive deviations (Tirkolaee et al. 2021).

4. Case Study

This section examines the validation of the proposed model through a real case study in steel industry. This case study considers four suppliers and three distribution hubs located in various countries, along with ten raw materials and three modes of transportation: Sea, Road, and Air. The distribution hubs are primarily situated in China, Germany, and Russia, while our suppliers are based in Europe and Asia. In selecting raw materials, we utilized 123 analysis to categorize our imported raw materials into three classes: 1, 2, and 3. the raw materials chosen are strategic materials classified as 1. 123 analysis, which is based on the Pareto principle, indicates that the top 20% of items typically represent 80% of the sales volume. This approach enables our company to reduce costs by concentrating on 1 item, thereby avoiding unnecessary inventory and effectively managing our budget by allocating funds to the most critical raw materials that can enhance the company's turnover. The confidence level of Equation (59) is 0.8 and available budget is set to 1 million USD. All the required input data related to demands, purchasing costs, production times, shipping costs and other parameters belonged to the summer of 2024. Furthermore, the weights assigned to the objectives are$w_1 = 0.35, w_2 = 0.5$ and $w_3 = 0.15$, which are set by experts from the SC, production planning, sales and marketing, advisors and foreign purchasing departments. Transportation and supplying limitations are listed in Tables 4,5 and 6.

Table 4. The capability provided by each supplier

	M1	M2	M3	M4		M6	M7	M8	M9	M10
1	1	1	1	0	0	0	0	0	0	0
2	1	1	1	1	1	1	1	1	1	0
3	1	1	1	1	1	1	1	1	1	0
4	0	0	0	0	0	1	1	1	1	1

Table 5. The multimodal transportation for delivering raw material from supplier to every hub

	China	Germany	Russia
Supplier 1	-	(Air, Sea)	-
Supplier 2	(Air, Sea)	(Air, Sea)	(Air, Road)
Supplier 3	-	(Air, Sea)	(Air, Road)
Supplier 4	(Air, Sea)	(Air, Sea)	-

Table 6. The multimodal transportation for delivering each raw material from hubs to the factory

	China	**Germany**	**Russia**
Possible transportation modes	(Air, Sea)	(Air, Sea)	(Air, Road)

The mathematical model is executed using LINGO software. The computational outcomes are presented in Table (7). The optimal value for total tardiness is zero, while the cumulative costs for traveling, purchasing, and waiting amount to 856,315. Additionally, the total risk associated with the transportation routes under the best conditions is roughly 0.5.

Table7. Ideal values of the goals

Goals	Values
b_1	0
b_2	856315
b_3	0.508454

The proposed mathematical MILP model has been implemented to derive an efficient policy for the case study, as well as to assess its complexity and performance. Following the application of fuzzy goal programming (FGP) within the proposed MILP, the primary decision variables and the objective value are presented in Table (8). It is important to note that the run time can extend up to 1120 seconds. As illustrated in Table (8), we have achieved the first goal. However, the positive deviations for the second and third goals are 64905 and 0.2, respectively.

Table8. Values of the goal variables

Variables	ψ	Obj1	Obj2	Obj3	d_1^+	d_1^-	d_2^+	d_2^-	d_3^+	d_3^-
Values	0.0957244	0	718220	0.8208252	0	0	64905	0	0.2720612	0

The efficient solutions are listed in Tables (9 & 10). As it can be seen from Tables (9 &10), suppliers 2 and 4 are selected among four qualified suppliers to supply raw materials. All drivers (M1 to M5) are assigned to supplier 2 to be processed, and all modules are supplied by suppliers 2 and 4. Supplier 2 should supply modules M7 and M9 and other modules should be provided by supplier 4. All drivers transfer from supplier 2 to the distribution hub located in Russia except drivers 200 w and 45 w that should be shipped to Russia. Also, drivers 120 w, 180 w and 57w should be transported to Russia by road. All modules should be shipped by sea, but just only street module 38 in 1 should be transferred to Russia by air. Modules M7, M9 and M10 should be shipped to China, and M7 should be transferred to Russia. When modules and drivers arrive in China and Russia, all of them shipped to manufacturer in the separate batches by sea except street module 64 in 1 and driver on board Module which are in the same batch and should be shipped together from China to manufacturer by sea. The solution of the test problem is shown graphically in Figure (2). All drivers and Modules are transferred from the selected suppliers and distribution hubs asap except driver on board module (M10) that should be waited 15 days in distribution hub located in China to be batched with street module 64 in 1(M6) then be delivered to manufacturer together.

Table9. Efficient solution from suppliers to Hubs

Suppliers	Raw Materials	Mode of Shipment	Hubs
Supplier 1	-	-	-
Supplier 2	Driver 47 w (M4)	Road	Germany
	Driver 45 w (M5)	Sea	Russia
	Driver 100 w (M1)	Road	Germany
	Driver 150 w (M2)	Road	Germany
	Driver 200 w (M3)	Sea	Russia
	Indoor Linear Module (M7)	Sea	Russia
	Street Module 36 in 1(M9)	Air	Germany
Supplier 3	-	-	-
Supplier 4	Street Module 64 in1(M6)	Sea	China
	Indoor Back light Module (M8)	Sea	China
	Driver on board Module (M10)	Sea	China

Table10. Efficient solution (From Hubs to Manufacturer)

Hubs	Raw Materials	Mode of Shipment
	Driver 45 w (M5)	Sea
Russia	Indoor Linear Module (M7)	Sea
	Driver 200 w (M3)	Sea
Germany	Driver 100 w (M1)	Road
	Driver 150 w (M2)	Road
	Driver 47 w (M4)	Road
	Street Module 24 in 1(M9)	Air
China	Indoor Back Module (M8)	Sea
	Street Module 64 in1(M6) and Driver on board Module (M10)	Sea

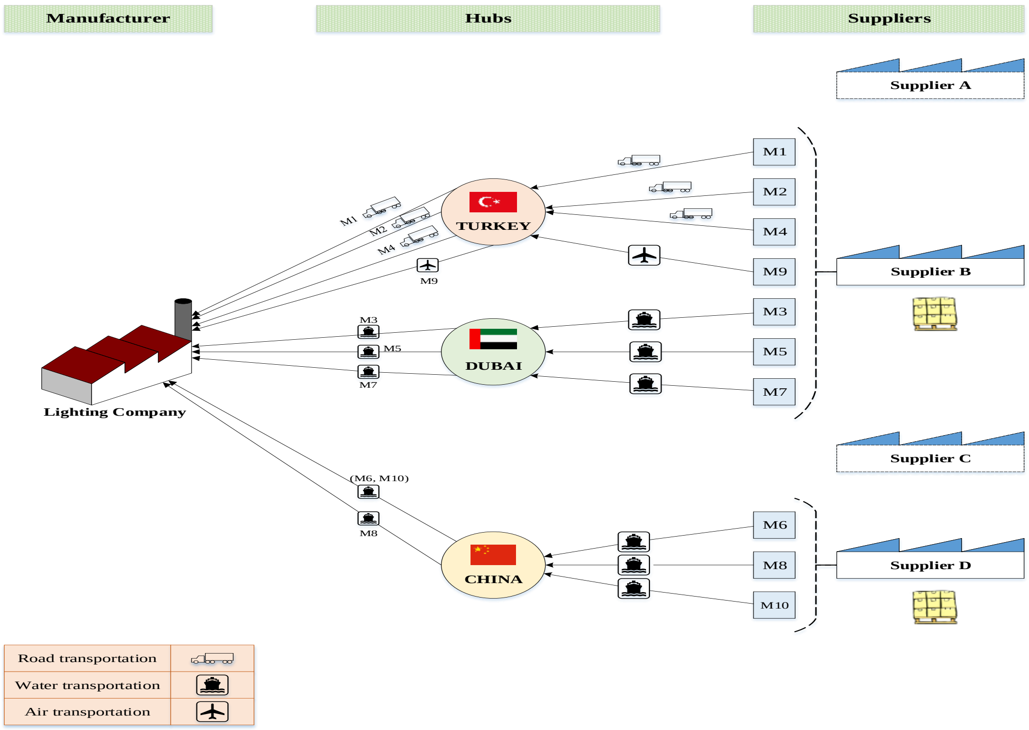
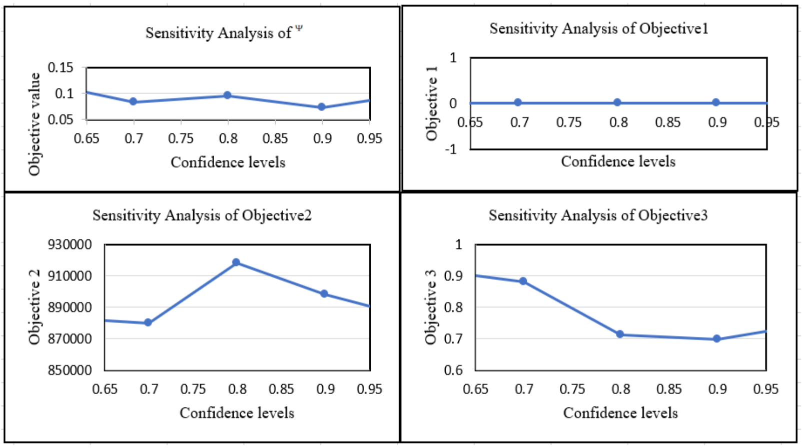


Figure2. The presentation of the efficient solution

In models that incorporate numerous input variables, sensitivity analysis serves as a crucial component of model development and quality assurance, and it can be beneficial in assessing the influence of an uncertain variable for various objectives. The sensitivity analysis is conducted based on the confidence levels (μ) and the budget levels (B) within the SCM framework. We examine five distinct levels of the confidence parameter to evaluate the behavior of 3 proposed objective values by modifying them. As illustrated in Table (11), the confidence levels are set at 0.6, 0.7, 0.8, 0.9, and 1. The results obtained from varying the confidence levels are documented in Table (11) and Figure (3). As depicted in Figure (3), the objective values exhibit a pendulous behavior in response to the increase in confidence levels. In other words, the objective functions demonstrate fluctuations across different change intervals.

Table 11. Sensitivity analysis results

Variables	Values of μ				
	0.6	0.7	0.8	0.9	1
Ψ	0.1319036	0.0731298	0.0867244	0.0821416	0.1112497
Objective1	0	0	0	0	0
Objective2	873180	889680	937220	877895	873090
Objective3	0.9614734	0.8709796	0.7308352	0.6876792	0.7674280


Sensitivity Analysis of Ψ

Sensitivity Analysis of Objective1

Sensitivity Analysis of Objective2

Sensitivity Analysis of Objective3

Figure3. Sensitivity analysis on confidence levels

The results of the sensitivity analysis concerning the budget levels are presented in Table (12). There are 5 levels for conducting the sensitivity analysis, which are (-0.2, -0.1, 0, 0.1, and 0.2). In other terms, the highest budget that can be allocated to the SCN is 1.3 million dollars, while the lowest budget is 900,000 dollars. The computational findings are displayed in Table (12).

Table 12. Sensitivity analysis results of budget levels

Variables	Change interval of B				
	-20%	-10%	0%	+10%	+20%
Ψ	NFS*	0.0983569	0.0967244	0.0948908	0.0884214
Objective1	NFS	0	0	0	0
Objective2	NFS	885090	928230	938605	898170
Objective3	NFS	0.7689730	0.7208352	0.7208352	0.728254

*No Feasible Solution

Furthermore, as illustrated in Figure (8), there exists an indirect effect associated with an increase in budget levels. Additionally, it is noteworthy that the proposed model becomes unfeasible when the budget is reduced by 20%, resulting in the SCN's inability to deliver a viable solution. Consequently, it is crucial for the top manager to regard the available budget as a fundamental parameter and to establish the necessary levels under various real-world conditions, particularly in uncertain scenarios. As can be seen in the results of Table 13, the status of announcing the need for work service during different periods is shown. Based on the value obtained for t=2, has the lowest repair cost. Therefore, the results are described ac- cording to it. The objective functions in the period t=2 to perform repair operations are as follows:

- If the vehicles in the 1st city need to be repaired, the serviceman should go from the 3rd, 4th, and 5th cities.
- If the vehicles in the 2nd city need servicing, the serviceman should go from the 3rd and 4th cities.
- If the vehicle needs service in the 3rd city, the serviceman should go from the 1st, 4th and 5th cities.
- If the vehicle needs service in city 4, the serviceman should go from the first and second cities.
- In case the vehicles in city 5 need service, the serviceman should go from the second and third cities.
- In Table 13, the cities of vehicle dispatch and the visited cities are shown. The results are shown based on the second objective function.

Table 13. Details of service worker dispatch and visit

Visited City	City of dispatch
The third and fourth city	First city
The fourth and fifth city	Second City
First, the second and fifth city	Third City
First, the second and third city	Fourth city
First and third city	Fifth city

The optimal time to enter each city and the waiting time for vehicle repair are also shown in Table 14. Based on the calculated time advance, it is determined that the maximum possible time to enter each city and repair vehicles is 19 minutes. In Table 14, the time related to the arrival of the vehicles and the duration of the repair of each of them, if needed and advanced, are shown.

Table 14. Optimum time of arrival and repairs of vehicles

Advancing time	Repair time	Arrival time	City
0	0	0	First city
19	16	3	Second City
19	13	6	Third City
14	7	7	Fourth city
14	7	7	Fifth city

Based on the calculated time advance, vehicles going to cities 3 and 2 will leave the desired after receiving the repair service city at time 19, in addition to being visited. The same occurs for vehicles going to cities 4 and 5 within 14 minutes after the start of the process. In addition, by sorting the arrival time in each of the visited cities in ascending order, we can determine the priority order of repairs. According to the specified priority, first, the pro- cess starts in the first city, then the third and second cities, and finally, the repairs are completed by referring to the fourth and fifth cities.

4.3 sensitivity analysis

In this section, the sensitivity of the values of ε will be measured on the value of the objective functions, and the results, including reliable values by determining the distance of ε for the objective functions will be reported. To do that, different values for ε are defined in Table 15 and the objective functions are solved using them. As can be seen in Table 15, the values of the objective function do not show a significant change with the increase of ε up to a certain value, but from some point on (for example, the second objective function), the increase in the value of ε reports a remarkable increase in the objective function values (epsilon change from 600 to 900). Based on the obtained results, for testing different values of epsilon, the feasible region and the improving vector of the objective functions have been created. According to the results, the level of significant changes of epsilon between 50 and 900 has been determined as the improvement operator. Determining this interval specifies that if the epsilon value is considered to be less than 50 and greater than 900, the answer to the problem is outside the feasible area. There- fore, the range of epsilon variations to search for the local optimal solution for the first objective function is 650 as the optimal solution for the first objective function occurs on this point. The optimal situation for the second objec- tive function is obtained at epsilon 600. Hence, if epsilon is selected between 600 and 650, non-dominant answers are attained for the problem, otherwise, non-dominant answers are considered. Table 15 shows the results of solving the model with a step length equal to 50. Using the values obtained from calculating the value of the objective function through different epsilons, the Pareto frontier created for the problem is shown in Figure 6.

Table 15. Model solution results with ε-constraint method

ε	Cost (currency)	Repair time (minute)
50	1512	57
100	1563	55
150	1582	62
200	1550	57
250	1530	68
300	1513	75
350	1598	58
400	1565	54
450	1548	56
500	1507	58
550	1580	52
600	1512	50
650	1505	72
700	1550	98
750	1560	78
800	1513	81
850	1515	82
900	1598	70

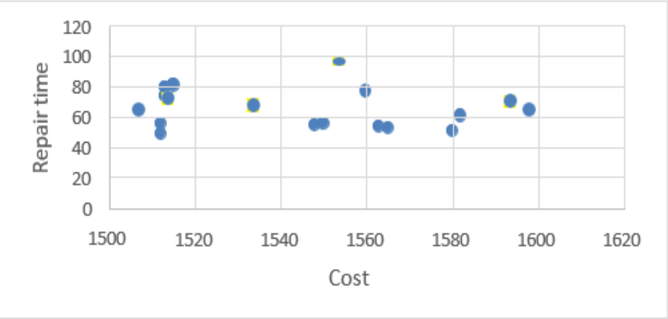


Figure 6. Pareto frontier

Also, in Figure 7 and 8 the non-dominating points obtained from the epsilon constraint method for the considered multi-objective problem are shown for 10% increase and decrease in the amount of demand. According to the created frontier, the convergence of responses is evident. In Figure 8, the solutions are shown for 10% increase. In this case, 15 non-dominant solutions have been generated for the problem. Figures 9 show non-dominated solu- tions for 10% reduction. According to the considered reduction, the number of non-dominated solutions is equal to 24. In this case, the obtained solutions have an acceptable convergence.

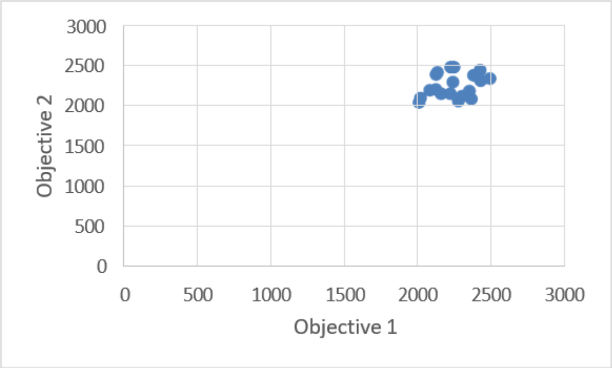


Figure 7. Non-dominated solution for 10% increasing in demand

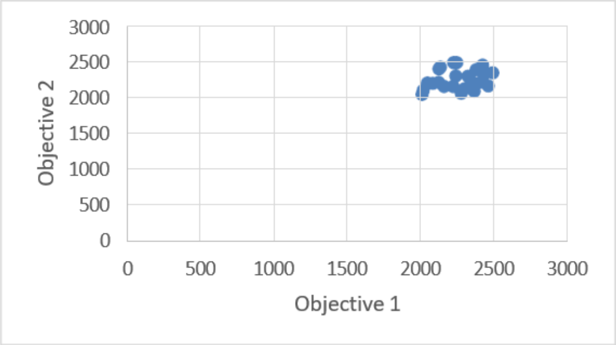


Figure 8. Non-dominated solution for 10% decreasing in demand

4.4 Managerial Insight

Current research can provide valuable managerial insight in several ways:

1. Optimal resource allocation: The research can help managers understand and optimize the allocation of heterogeneous vehicles and other resources across different time periods. It provides insights into how to assign vehicles efficiently to meet multiple objectives, such as minimizing transportation costs, maximizing customer satisfaction, or minimizing carbon emissions.
2. Facility breakdown management: By incorporating facility breakdowns into the model, the research of-fers insights into how managers can effectively handle unexpected disruptions in operations. It provides guidance on how to reconfigure the routing and locating of vehicles to minimize the impact of break- downs on overall system performance.
3. Trade-off analysis: The model's multi-objective nature enables managers to analyze trade-offs between different objectives, such as cost and repair time. By quantifying these trade-offs, managers can make more informed decisions and identify optimal solutions that balance conflicting goals.
4. Sensitivity analysis: The research can provide insights into the sensitivity of the model's results to vari-ous parameters and assumptions. Managers can use this information to identify critical factors and assess the robustness of their decisions.

Overall, the research offers managers a comprehensive decision support tool that can guide them in making informed decisions regarding multi-period, multi-objective routing and locating of heterogeneous vehicles, taking into account facility breakdowns. It provides valuable insights into optimizing resources, managing disruptions, and finding the best trade-offs to achieve operational efficiency and customer satisfaction.

4. Conclusion

This study proposes a multi-objective optimization model for optimal route allocation of vehicles to visit cities in a two-level supply chain with heterogeneous vehicles. Two objective functions are considered: minimizing the total cost and duration of vehicle repair. To solve the proposed mathematical model, the epsilon constraint method has been used. This method can determine the dominant and non-dominant answers without the subjective judg- ments of experts. The application of proposed model has been applied through the numerical solution of the loca- tion of the optimal route allocation for the visit of different vehicles, which confirms the applicability of the math- ematical model. The numerical test results, in terms of optimal route allocation by solving the proposed model, clearly determine the current route allocation plan for the best routes for each vehicle to visit each city. Current study may have several limitations, including: proposed model is based on certain assumptions that might not reflect the real-world conditions accurately. These assumptions can limit the applicability and generalizability of the model. Also, Mathematical models often simplify complex real-world scenarios to make them mathematically solvable. These simplifications may lead to oversimplification and neglect certain important factors, leading to limitations in the model's accuracy and practicality. The model's accuracy and effectiveness strongly depend on the availability and quality of data used for parameter estimation and validation. Limited or inaccurate data can significantly impact the reliability and usefulness of the model's results. The proposed model may be specific to certain contexts, such as certain types of transportation networks or vehicle fleets. The model's applicability and generalizability to different scenarios or industries might be limited. Therefore, it is important to consider these limitations while interpreting and utilizing the findings of the research. Researchers should strive to address these limitations and explore further avenues for improvement and validation. Decisions about facility routes in re- sponse to site visits are usually made based on the experience of decision-makers or temporary decision-making. Hence, the proposed model improves both efficiency and effectiveness in this field, and the findings of this study provide guidance for improvement of decision-making for route allocation in the context of locating-routing and will be beneficial for designing a suitable strategy in the future. The proposed model may rely on several assump- tions regarding vehicle capacities, travel times, and demand patterns that might not accurately reflect real-world conditions. These assumptions could limit the applicability of the findings to practical scenarios. The multi-period and multi-objective nature of the routing-locating model introduces significant complexity, which may lead to challenges in computational efficiency and solution feasibility. This complexity could restrict the model's scalabil- ity for larger supply chains or more extensive vehicle fleets. The effectiveness of the model is contingent upon the availability and accuracy of data related to vehicle performance, facility breakdown rates, and demand forecasts. Inaccurate or incomplete data may adversely affect the model's outcomes and decision-making capabilities. The model may not fully account for the dynamic nature of supply chain environments, including sudden changes in demand, unexpected facility breakdowns, or variations in traffic conditions. This limitation could impact the ro- bustness of the proposed solutions in real-time applications. While the model aims to optimize multiple objectives, it may not encompass all relevant objectives or performance metrics that stakeholders consider important in a circular economy context. This focus could limit the comprehensiveness of the solutions provided. The practical implementation of the proposed model in real-world scenarios may face challenges, such as resistance to change from stakeholders, integration with existing systems, and the need for training personnel to adapt to new pro- cesses. The model may be developed based on specific geographical or regulatory contexts, which could limit its generalizability to other regions or industries with different operational characteristics and constraints. By ac- knowledging these limitations, the research can provide a more nuanced understanding of the model's applicabil- ity and areas for future exploration. For further research, it is suggested to add the property of the time window for vehicle departure in the proposed model. Also, due to the fact that the demand is not known in the real world, a robust planning model should be provided by considering the random feature for this parameter.

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