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Development of an integrated scenario-based stochastic rolling-planning multistage logistics model considering various risks

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ABSTRACT

In this study, a new integrated scenario-based stochastic rolling-planning multistage logistics model is proposed to reduce overall logistics costs. To achieve this goal, two phases were considered in the model. In the first phase, a multi-criteria group decision-making model was developed to select a trustworthy supplier. In the second stage, the selected suppliers were integrated with other stakeholders to develop a rolling-planning-based logistics model using a variety of risky scenarios. Several risk factors including price variability, demand, and quality risks were considered in the model. By considering these risk factors, a new risk-embedded rolling-planning logistics method was established that regulates inventory, stock-out, and overstock problems by constantly controlling the production volume at the manufacturing site based on actual demands. In this model, the supplier's side material quality, price fluctuation risks, and customer-side demand risks were considered simultaneously. To evaluate the performance of the proposed model, a numerical example was set up, and the obtained results were compared with those of another model where fixed volume production and delivery approach was used instead of the rolling-planning approach. To verify the superiority and robustness of the proposed model, its performance was verified through a sensitivity analysis under different experimental conditions. The findings show that in a risk environment, the proposed model estimates lower logistics costs of 2697648.00 units compared to another model whose costs were 2721843.00 units.

1. Introduction

In the current production environment, a company's performance depends on a robust supply chain network. Its efficiency and profitability depend on the flow of products, funds, and information between stakeholders. This network comprises a diverse set of stakeholders, including suppliers, manufacturers, wholesalers, retailers, and consumers [1]. This network acquires raw materials, converts them into finished products, and distributes them to customers. However, this network has various risks, which can be classified into internal and external risks. Internal operational risks (production and distribution risk, demand risk, supply risk, etc.) have evolved within the supply chain because of improper coordination among different levels. External operational risks (e.g., natural disasters, terrorist attacks, and fluctuations in exchange rates) have evolved because of the interaction between a supply chain and its

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environment. These internal and external risks create disturbances in supply chains [2]. In this study, we mainly discuss internal risk factors. Production and distribution risks occur owing to the failure of the product of the required quality and quantity under time constraints. These risks may disturb the optimal flow of products at different levels. However, demand variability was the most significant risk factor in this network. Supply chains primarily depend on accurate demand forecasting. If the forecasted value is greater than the actual demand, inventory builds up. This increases the supply chain costs. In the opposite case, the supply chain loses profitability due to the loss of goodwill among customers. Supply chain efficiency decreases in both cases. A make-to-order approach can be used to address fluctuating demand. However, adopting this policy is risky, because it takes time to produce and deliver products to customers after they have generated orders. In addition, not all products are covered under this policy. These problems can be resolved by implementing make-to-stock strategies for common consumer goods. Manufacturers, wholesalers, and retailers must maintain inventory levels to satisfy consumer expectations. Demand fluctuates; therefore, stock-outs and overstock issues can occur. Therefore, inventory control is a key consideration for this policy because it is crucial for preserving customer satisfaction and optimizing profits. However, supply risk occurs because of incomplete supply. Failures in the flow of goods from the plant to the next stages may occur when the material is not supplied within the maximum allowable lead time and with the required quality. Under these circumstances, a supply chain logistics model must be developed that integrates customer-side demand and supplier-side supply risks.

Several authors have developed various models to solve logistics problems. Some of these models are discussed in detail in Section-2. This review shows that most researchers have developed logistics models to address customer-side demand risks by ignoring supplier-side material quality and price fluctuations. Moreover, lead time was not considered in these models. They also considered the simultaneous production and delivery systems. This is practically infeasible when the stakeholders are far from each other. In addition, previous models have been developed by considering deterministic, stochastic, and fuzzy demands. However, owing to the nature of unsteady demand, these methods are insufficient for dealing with real-world circumstances. However, most studies have ignored this issue. Additionally, most stakeholders independently plan their manufacturing, distribution, and inventories. However, these choices were interconnected. These decisions must be made in an integrated manner to acquire competitive advantages in the market. These are the primary research gaps in the field. Therefore, this study aimed to address these issues. To achieve this goal, an integrated scenario-based stochastic rolling-planning multistage risk-embedded logistics model is proposed. This model aims to minimize the total logistics cost by regulating the inventory level and eliminating overstock and stock-out situations in make-to-stock production systems.

The remainder of this paper is organized as follows: Section 2 presents a literature review. Section 3 presents the model characteristics and research methodology. Section 4 describes the methods, materials, and scenario-based stochastic rolling planning logistics model formulations. Section 5 presents the numerical experiment, a discussion of the results, and a sensitivity analysis of the model. Finally, the conclusions, limitations, and areas for future research are presented in Section 6.

2. Literature review

A company's performance depends on its strong supply chain management (SCM) network. Over the past few decades, numerous methods have been developed to solve supply chain logistics problems. An integrated strategy was proposed to create a closed-loop supply chain (CLSC) model [3]. Their model consisted of two stages. In the first stage, suppliers are selected from multiple alternatives by applying a fuzzy analytic network process (FANP) and fuzzy decision-making trial and evaluation laboratory (FDEMATEL) methods. In the second stage, the selected suppliers are linked to the DC to create a two-stage CLSC model. In their model, suppliers are considered manufacturers, which is feasible for solving small-scale logistics problems but is inadequate for large-scale problems. Moreover, they did not consider the supply risk in their models.

Globalization has brought not only opportunities but also risks to the business environment [4]. To deal with these risks, they emphasized that new strategies and methods must be developed to handle these risks. They proposed a CLSC model that considers demand uncertainty. Initially, they constructed a mixed-integer linear programming (MILP) model, and a few metaheuristics, including simulated annealing (SA), the Keshtel algorithm (KA), hybrid genetic-simulated annealing (H-GASA), and hybrid Keshtel-simulated annealing were used to assess the overall cost of the supply chain. However, they do not consider supplier-side uncertainty in their models.

A multi-objective mixed-integer programming (MOMILP) model was proposed to optimize the financial, environmental, and social impacts of a CLSC network [5]. In their model, a fuzzy robust optimization (FRO) approach was used to handle the uncertainties of demand and transportation costs. Finally, a goal programming (GP) approach was applied to solve this problem. However, the planning period, lead time, inventory, stockout, and overstock factors were ignored in this model. A supply chain network model for perishable goods with stochastic demand was developed [6]. In their model, the quality deterioration rate of a product with an increased transportation time was considered. Another study noted that determining the sales of a product at a given moment and for a specific consumer is highly important [7]. The significance of this efficiency increases when perishable goods are used. These goods not only have a variety of buyers but also need to be consumed before they expire. Using a vendor-managed inventory policy, they created a nonlinear programming model to ascertain the ideal perishable product sales levels in a two-echelon supply chain network. Three efficient meta-heuristics–the genetic algorithm (GA), particle swarm optimization (PSO), and co-evolutionary particle swarm optimization (CPSO) were applied to solve this problem.

A robust data-driven supply chain model was developed to procure food grains from India [8]. An MILP model was suggested as a means of achieving this objective to pinpoint the number and location of procurement centers as well as to reduce the overall costs of the supply chain. Deterministic data are used to evaluate the performance of the proposed model. An integrated multi-objective mixed-integer linear programming (MOMILP) model was proposed to solve the location inventory routing problem for perishable products in a typical supply chain network [9]. Two phases are considered in this model. In the first phase, the suppliers were selected by applying the preference-ranking organization method for enrichment evaluation (PROMETHEE). In the second phase, selected suppliers are linked to other stakeholders in the network. Because the problem is NP-hard, two-hybrid metaheuristics, such as parallel and series combinations of the GA and PSO, were used to solve it. They opined that their model could be extended by considering supplier-side uncertainty. For example, a fuzzy approach can be applied to select the best supplier by evaluating the uncertain information. To solve a typical supply chain multistage design network problem, an MILP model was proposed [10]. To solve this problem with their proposed model, they used a genetic algorithm (GA) because the problem was NP-hard. The performance of the model was evaluated in a deterministic environment.

Several risks, such as supply, demand, and transportation, have evolved owing to globalization [11]. These risks disrupt the flow of goods through various phases of the supply chain, eventually increasing the overall cost of the supply chain. To address these risks, they initially developed an MILP model in a deterministic environment and then converted their model into a risk-embedded MILP model to solve multi-echelon CLSC logistics problems. A new MILP model was developed to solve the CLSC network design problems in a deterministic environment [12]. Subsequently, a robust optimization (RO) approach was proposed to solve the problem in which various risks, such as supply, demand, and transportation, were addressed. This model works well in an uncertain environment, as opposed to a deterministic environment. However, this model can be further improved in future studies by considering the lead time, inventory, overstock, and stock-out facts.

The MILP model was proposed to solve the global supply chain network design problem by considering various operational risks [2]. However, their proposed model was limited to a single period. A multi-objective stochastic model (MOSM) was developed by incorporating several risk elements, such as demand, pricing, production, collection, disposal cost, and used-product return rate risk, to minimize logistics costs [13]. However, the lead time was disregarded, and the model was restricted to a single period. Another researcher developed a stochastic MILP model to solve forward-reverse logistics problems in a risk environment. Two types of customer zones are considered in the model. In the first zone, virgin products are sold, whereas used products are sold in the second zone. The demand in the first zone is stochastic, and that in the second zone is deterministic. However, the model was limited to a single product, and supplier quality, price, and transportation risks were avoided [14].

A new rolling planning-based two-stage logistics model was developed by considering customer-side demand risk [15]. Subsequently, the same authors extended their model by integrating an optimal product-delivery route [16]. However, they ignored supplier-side risks such as material quality and price fluctuation risks in the model. They also developed an integrated multi-criteria group decision-making (MCGDM) model to select the best supplier considering uncertain information [1]. They suggested that their proposed model could be further expanded by linking it with additional stakeholders such as manufacturing facilities and DCs.

The MOMILP model was developed to solve the mobile phone CLSC network design problem by considering the stochastic demands of customers [17]. They applied the chance-constraint programming (CCP) method to solve the design problems. Appropriate suppliers were selected using a fuzzy method and linked to other stakeholders. However, they did not consider supplier-side uncertainties, such as material quality and price fluctuation risk. They suggested that the material defect rate and delivery time could be integrated to further develop their model.

A bi-objective MILP model was developed to address a reverse logistics problem that considers environmental factors [18]. Initially, the model was deterministic; however, it was then changed to a scenario-based stochastic model considering two uncertain parameters: demand and return rate of the products. The problem was resolved using the epsilon constraint (EC) and augmented epsilon constraint (AEC) approaches. However, this model was restricted to a particular timeframe. A new stochastic model (SM) was constructed to solve the RL problem considering uncertain demand [19]. The constraints in the model involving stochastic demand were controlled using the CCP technique. Because some of the constraint functions were nonlinear, a linear approximation method (LAM) was applied to solve the problem. However, the study was limited to a single period and supplier-side uncertainties were avoided.

To handle dynamic reverse logistics issues, a mixed-integer nonlinear programming (MINLP) model was constructed that considered worldwide supply chain networks [20]. However, this model was converted to an MILP model to avoid computational complexity and reduce execution time. In this model, the customer demand is dynamic. However, the authors did not incorporate operational risks, such as supply, production, delivery, and transportation risks, in the model.

To solve the green reverse logistics problem, an MILP model that considers environmental factors was proposed [21]. Subsequently, this model was solved by applying a heuristic algorithm known as improved Bender decomposition (IBD) to obtain a faster solution than the other methods. However, customer demand and the quantity and quality of returned products are considered deterministic and practically uncertain in real-life applications. A new logistics model was proposed that simultaneously considers the uncertainty and risk parameters [22]. Subsequently, the model was solved by applying CCP, GA, and Monte Carlo simulation (MCS) together. However, the model does not consider the manufacturing site for producing virgin products or supplier-side uncertainty.

Reverse logistics with lot sizing issues have been addressed using a two-stage stochastic model (SM) [23]. In this approach, the demand and return are regarded as unpredictable. The scenario generation method (SGM) and scenario reduction method (SRM) were applied to generate a set of scenarios to approximate the underlying continuous distributions of return and demand. The model does not consider supplier or supplier-side risks. They mentioned that this model could be further improved by considering other uncertain factors such as quality, travel time, and facility capacity.

A multi-objective linear programming (MOLP) model was developed to solve sustainable reverse logistics problems by considering deterministic parameter values [24]. This study is limited to a single-period, single-product environment. A multistage, multi-period reverse logistics model with lot-sizing decisions under uncertainty was proposed [25]. In this model, return and demand quantities are regarded as unknown parameters. A discrete collection of scenarios was created using the moment-matching method to reflect the original continuous distribution of the stochastic parameters. However, the uncertainty of the supplier's end and the lead time for delivery were not considered in this model. From this review, it is clear that many well-established supply chain logistics models exist. The key points of the aforementioned review models are summarized in Table 1.

As shown in Table 1, most previous studies did not consider supplier-side risks, including material quality and price fluctuation risks. They considered the ideal supplier in their model by ignoring the supplier's risks. However, this assumption was unrealistic. This is because material quality and price can fluctuate in real life. Therefore, these risk factors should be considered when solving logistic problems. Conversely, customer-side demand may also be unsteady in nature; that is, customer demand can fluctuate in every period. This factor has also been ignored in previous studies (Table 1). Previous studies have considered simultaneous production and delivery systems to solve logistics problems. This policy is feasible when the stockholders are in close proximity. However, it is not feasible to solve large-scale logistics problems when stakeholders, such as suppliers, manufacturers, distributors, and customers, are far away from each other. To solve this problem, the product delivery lead time must be considered. This issue has been ignored in most previous studies. These are the main research gaps in current logistics problem areas, and we are highly motivated to bridge these gaps. To achieve this goal, a scenario-based stochastic rolling planning risk-embedded logistics model is proposed, where different risk factors such as material quality, price fluctuation risk, customer's unsteady demand risk, and lead time risk have been considered for developing the proposed model. The model consists of two phases. The best supplier is chosen in the initial phase using an integrated MCGDM model. In the second phase, the best supplier is merged with other stakeholders to create a multistage logistics model. However, this type of coordinated model has not yet been proposed. This is the novelty of this study.

3. Model characteristics and resarch methodology

In this study, an integrated logistics model is proposed to reduce the overall supply chain logistics costs. The model consisted of two phases. The model characteristics and research innovations of this study are as follows.

(a) Both strategic and planning decisions were considered. Strategic decisions consider reliable supplier selection processes, whereas planning decisions determine optimal order, production, and delivery quantities, as well as inventory levels for different stakeholders.

(b) Reliable suppliers are selected by adopting an integrated multi-criteria group decision-making (MCGDM) model. This model is constructed using three different fuzzy methods: intuitionistic fuzzy set (IFS), fuzzy analytic hierarchy process (FAHP), and technique for order preference by similarity to ideal solution (TOPSIS). In this MCGDM model, multiple decision-makers are considered in the decision-making process. The decision-making capabilities of these decision-makers differ because of their varied levels of education and experience. To address this issue, decision makers use dissimilar weights. The IFS is used to estimate dissimilar weights for decision-makers. Then, the supplier selection criteria are selected by these decision-makers, and criteria weights are estimated using the FAHP method. To estimate the criteria weight, a pairwise comparison matrix is initially developed by each decision maker, and then its consistency is checked. After checking for consistency, pairwise comparison matrices were aggregated. While aggregating the comparison matrices, the weights of the decision makers are used in the

Table 1
Literature review summary.

Ref. no.	Applied methods	Supplier side uncertainties				Customer side demand uncertainties				Other assumptions		
		SS	SCC	QR	PR	FD	DD	SD	UD	LT	MS	MP
[3]	FANP, FDEMATEL, & MOMILP	✓				✓					✓	
[4]	MILP, GA, SA, KA, H-GASA, & H-KASA.							✓			✓	✓
[5]	MOMIP, FRO, & GP							✓			✓	
[6]	Stochastic model			✓				✓			✓	✓
[7]	NLP, GA, PSO, & CPSO						✓					✓
[8]	MILP						✓				✓	
[9]	PROMETHEE, MOMILP, GA, & PSO	✓				✓	✓				✓	✓
[10]	MILP, & GA						✓				✓	
[11]	MILP		✓	✓			✓	✓			✓	
[12]	MILP, RO						✓	✓			✓	
[15]	MILP								✓	✓	✓	✓
[16]	MILP								✓	✓	✓	✓
[17]	MOMILP, & CCP	✓						✓			✓	✓
[18]	MIP, EC, & AEC						✓	✓			✓	
[19]	SM, CCP, & LAM							✓			✓	
[20]	MINLP, & MILP								✓		✓	✓
[21]	MILP & IBD						✓				✓	✓
[22]	MILP, CCP, GA & MCS						✓	✓			✓	
[23]	SM, SGM, & SRM							✓				✓
[24]	MOLP						✓				✓	
[25]	SM							✓			✓	✓
This study	MILP, & rolling planning	✓	✓	✓	✓			✓	✓	✓	✓	✓

Notations: SS: supplier selection; SCC: supplier characteristics consideration; QR: quality risk; PR: price risk; FD: fuzzy demand; DD: deterministic demand; SD: stochastic demand; UD: unsteady demand; LT: lead time; MS: multistage; MP: multi period.

aggregating process. After the criteria weights were estimated, they were used in the TOPSIS method to select the best supplier. The methodology of the proposed integrated MCGDM model is illustrated in Fig. 1, and the mathematical formulations of these methods are described in Section 4.

(c) A multistage logistics model is created in the second phase once the best supplier has been chosen by collaborating with other stakeholders, as shown in Fig. 2.

(d) The second phase employs the rolling-planning approach. According to this strategy, the production quantities at the factory during the period "*t*" are equal to the total sales volume across all retail shops during the period "*t-1*." Fig. 3 depicts a flowchart of this approach. According to this strategy, all retail shops, distribution centers (DCs), and manufacturing plants initially maintain a particular finished product inventory. At the beginning of the period, customers purchased their products from retail shops, and their inventory gradually decreased. At the end of this period, retail shops update their inventory and place new orders with DCs to refill their stock. After receiving orders from retailers, distributors deliver them using their initial stocks, update their inventory levels, and place new orders with the manufacturing plant to refill their stocks. Similarly, manufacturing plants place new orders for suppliers to obtain new materials for producing the required products. When delivery orders are finalized between stockholders, delivery commences simultaneously. However, delivery does not occur until orders between stakeholders are confirmed. In addition, at the beginning of the period, when customers purchase products from retail shops, they are also produced in manufacturing plants. This production volume was equivalent to the initial inventory level of the plant. However, after the initial period, the production volume at the plant equals the total sales volume across all retail shops in the previous period. This concept is known as rolling-planning production scheduling. Thus, the entire planning period was executed successively.

(e) This model includes suppliers, manufacturers, distributors, and retail stores. The functions of all these locations start simultaneously, and the inventories are controlled independently. Multiple planning periods are considered in this model. However, one unit of the planning period is considered the lead time to produce products and deliver those products from one stage to the

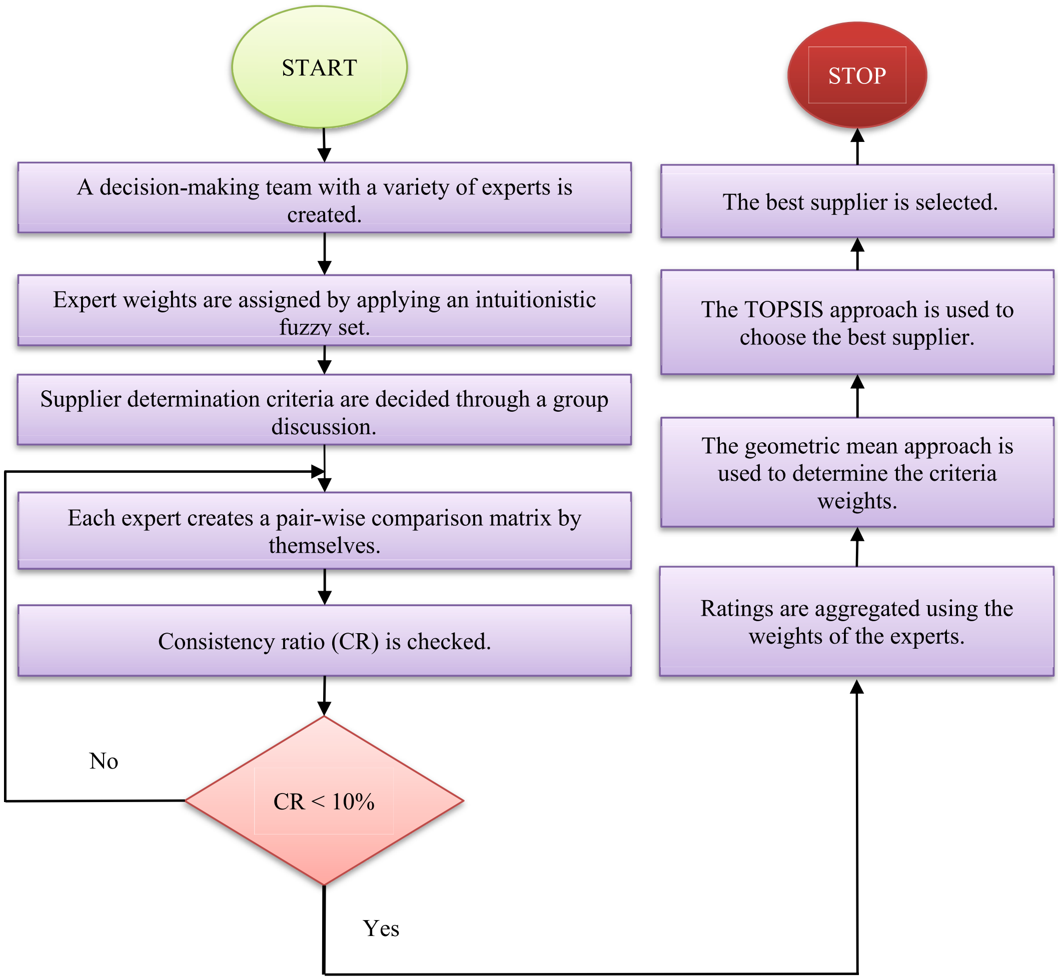

Fig. 1. Proposed supplier-selection methodology.

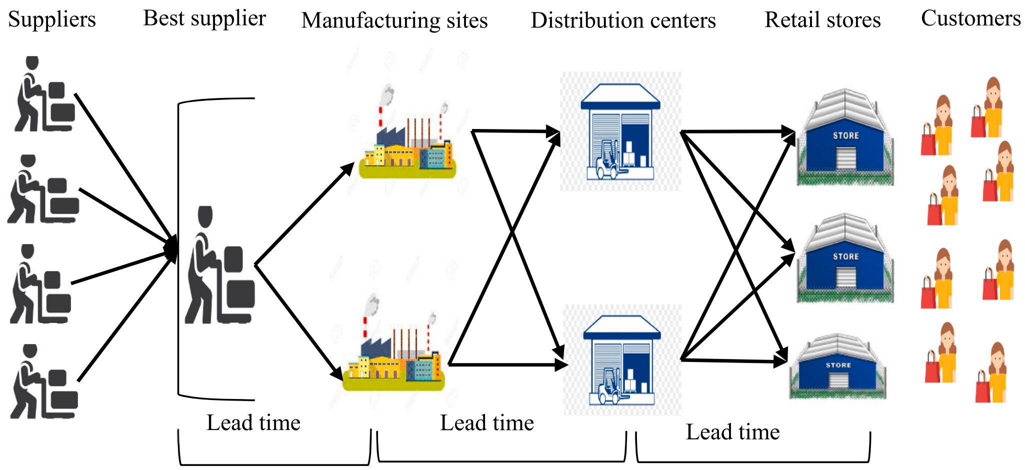

Fig. 2. Proposed multistage logistics model.

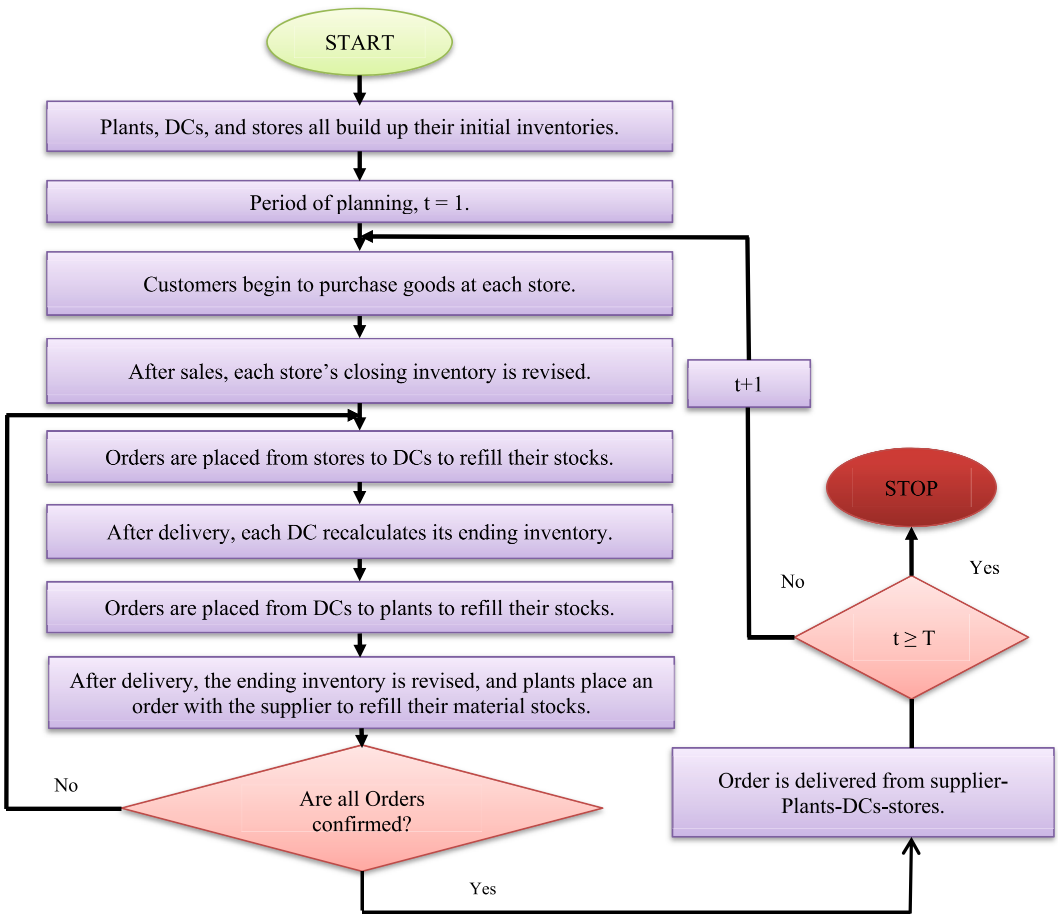

Fig. 3. Proposed rolling-planning flow diagram.

next. From Fig. 4, it can be observed that there are starting and ending times for each period. The duration between the start and end times was considered the lead time in this model. However, outside the period, there is a dotted line that indicates the order's arrival, and a solid arrowhead line indicates delivery of the order at period "t," which will arrive before the beginning of the "$t + 1$" period. However, the time required to create an order is not considered because of the mathematical complexity. This

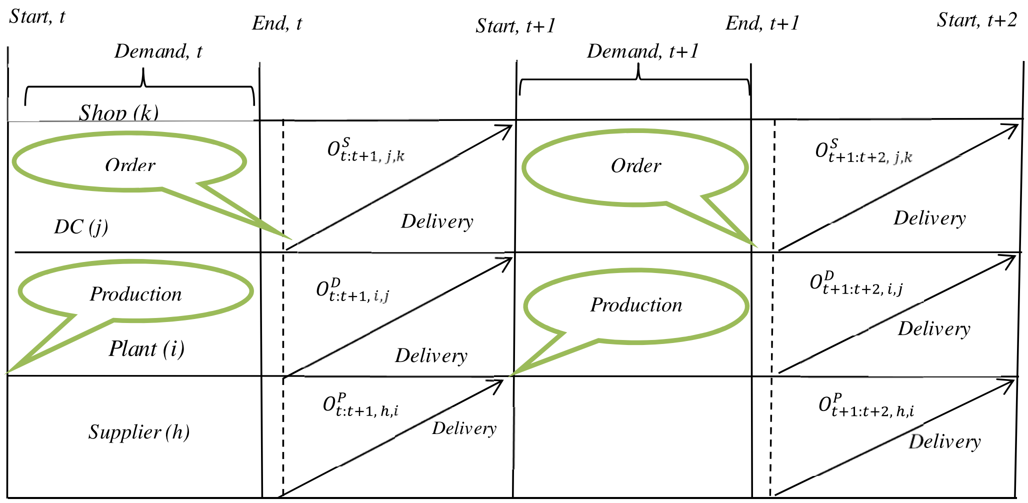

Fig. 4. Proposed product order and delivery chart.

is one limitation of the present study. Furthermore, if the lead time is not considered, the model will be converted into a simultaneous production and delivery system, which is not feasible for solving real-life large-scale logistics problems when stakeholders are located far away from each other. To solve this issue, we considered the lead time as one period. We assumed that the products arrived within the lead time. The lead-time delay was also not considered in this model.

(f) The inventory level was controlled to minimize overstock and stock-out events in all stores.
(g) The quality of the material incoming from the supplier to the plant was evaluated, and the expected and practical quality levels were justified. Defective raw materials were considered to be lost.
(h) The variation in material price was also evaluated in this model.
(i) Nine uncertain pair scenarios and their corresponding occurrence probabilities were considered to incorporate quality and price fluctuation risks into the model.
(j) Finally, a second model using a fixed production and delivery system (Model-2) instead of the rolling-planning method was used to compare the performance of the proposed model (Model-1). A mathematical formulation of the proposed model is presented in the following section.

4. Methods and Material

4.1. Fuzzy algebraic operations

If two triangular fuzzy numbers $\widetilde{A}$ and $\widetilde{B}$ are considered in any model, then their algebraic operations can be stated as follows:

$$\widetilde{A} = (l_1, m_1, u_1) \tag{1}$$

$$\widetilde{B} = (l_2, m_2, u_2) \tag{2}$$

$$\widetilde{A}^{-1} = (1/u_1, 1/m_1, 1/l_1) for l_1 > 0 \tag{3}$$

$$\widetilde{A} + \widetilde{B} = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \ \ for l_1, l_2 > 0 \tag{4}$$

$$\widetilde{A} \times \widetilde{B} = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \quad for l_1, l_2 > 0 \tag{5}$$

$$\widetilde{A} - \widetilde{B} = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{6}$$

$$\widetilde{A} / \widetilde{B} = (l_1 / u_2, m_1 / m_2, u_1 / l_2) for l_1, l_2 > 0 \tag{7}$$

$$R \times \widetilde{A} = (R \times l_1, R \times m_1, R \times u_1) \quad for\ R, l_1 > 0 \tag{8}$$

$$\widetilde{x}^k_{ij} = \left(x^{l_k}_{ij}, x^{m_k}_{ij}, x^{u_k}_{ij}\right) \tag{9}$$

In Eqs. (1) and (2), two triangular fuzzy numbers $\widetilde{A}$ and $\widetilde{B}$ are expressed. Eq. (3) represents the reciprocal value of the triangular fuzzy number $\widetilde{A}'$s reciprocal value. Eqs. (4)–(7), respectively, provide the addition, multiplication, subtraction, and division of the two triangular fuzzy numbers $\widetilde{A}$ and $\widetilde{B}$. A real number R is multiplied by a fuzzy number $\widetilde{A}$ as shown in Eq. (8). Eq. (9) denotes the comparative fuzzy rating, where multiple attributes are compared with each other, and the rating is given by a particular decision maker. In Eq. (9), $x_{ij}^{l_k}$ denotes the lower bound rating, $x_{ij}^{m_k}$ denotes the middle bound rating, and $x_{ij}^{u_k}$ denotes the upper bound rating of the i^{th} criterion compared to the j^{th} criterion given by the k^{th} decision maker.

4.2. Description of intuitionistic fuzzy set

The intuitionistic fuzzy set (IFS) is an extension of the classical fuzzy set that is used to deal with decision ambiguity and uncertainty [26]. Membership, non-membership, and degree of hesitancy comprise three components. When the intensity of one element increased, those of the other two elements decreased. When a person rates an object during a real-life decision-making process, three ambiguous circumstances may arise: A person may be uncertain or believe that the evaluated item is either good or bad. Similarly, a management team may encounter these three circumstances when grading decision experts. For instance, senior management may compare one expert to another. The IFS approach simplifies the mathematical handling of these issues. Therefore, in this study, the decision-makers' weights were determined using the IFS approach. The following describes the IFS method's mathematical formulation. It is possible to write the intuitionistic fuzzy set A in the finite set X as shown in Eq. (10).

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle | x \epsilon X\} \tag{10}$$

where, $\mu_A(x), \nu_A(x) : X \to [0, 1]$ are membership and non-membership functions, respectively, so that they follow the constraint as presented in Eq. (11).

$$0 \le \mu_A(x) + \nu_A(x) \le 1 \tag{11}$$

The intuitionistic degree of hesitation regarding whether or not x belongs to A is the third parameter of IFS, denoted by the symbol $\pi_A(x)$ and their relation is shown in Eq. (12).

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) \tag{12}$$

For every $x \epsilon X$, the intuitionistic degree of hesitation $\pi_A(x)$ follows the constraint as shown in Eq. (13).

$$0 \le \pi_A(x) \le 1 \tag{13}$$

The knowledge of x is more certain if $\pi_A(x)$ is small and the knowledge of x is unclear if $\pi_A(x)$ is large. Evidently, the common fuzzy set concept is recovered when $\mu_A(x) = 1 - \nu_A(x)$ for all elements in the universe [27]. Let $D_k = [\mu_k, \vee_k, \pi_k]$ be an IFS number for the rating of the k^{th} decision-maker. The weight of the k^{th} decision-maker (λ_k) can then be obtained using the following formula as presented in Eq. (14) [28]:

$$\lambda_k = (\mu_k + \pi_k(\mu_k / (\mu_k + \nu_k))) \Bigg/ \sum_{k=1}^{K} (\mu_k + \pi_k(\mu_k / (\mu_k + \nu_k))) \tag{14}$$

where the k^{th} decision-maker membership, non-membership, and hesitation degrees given by the top management are denoted by the symbol of μ_k, ν_k, andπ_k, respectively. The summation of weights of all decision-makers must be one as shown in Eq. (15).

$$\sum_{k=1}^{K} \lambda_k = 1 \tag{15}$$

where the k^{th} decision-maker (DM) weight is denoted by the symbol of λ_k. The total number of DMs is denoted by the capital letter K.

4.3. Fuzzy AHP technique

The first AHP approach was developed to solve a multi-criteria decision-making problem using linguistics variables [29]. Later, this method was expanded to compute the fuzzy criteria weights using unknown data [30]. In this study, the fuzzy AHP method was used to estimate the weights of the criteria. The steps involved in this process are as follows.

Step 1 Each DM constructs a pairwise comparison matrix based on the given criteria and fuzzy scale. For instance, if criterion *C-1* is favored over criterion *C-2*, a certain cell in the decision matrix (1, 2) will have the value *(l, m, u)*, whereas the adjacent cell (2, 1) will have the reverse value $(1/u, 1/m, 1/l)$. Thus, as expressed in Eq. (16), each DM constructs a complete pairwise decision matrix.

$$\widetilde{D}^k = \begin{bmatrix} \widetilde{x}_{11}^k & \widetilde{x}_{12}^k & \cdots & \widetilde{x}_{1n}^k \\ \widetilde{x}_{21}^k & \widetilde{x}_{22}^k & \cdots & \widetilde{x}_{2n}^k \\ \vdots & \vdots & \vdots & \vdots \\ \widetilde{x}_{m1}^k & \widetilde{x}_{m2}^k & \cdots & \widetilde{x}_{mn}^k \end{bmatrix}, \tag{16}$$

where $\widetilde{x}_{ij}^k$ denotes the rating of the i^{th} criterion over the j^{th} criterion given by the k^{th} DM. The notation $\widetilde{x}_{ij}^k$ denotes the triangular fuzzy number as $\widetilde{x}_{ij}^k = (x_{ij}^{l_k}, x_{ij}^{m_k}, x_{ij}^{u_k})$. Where $x_{ij}^{l_k}$ denotes the lower bound, $x_{ij}^{m_k}$ is the middle bound, and $x_{ij}^{u_k}$ is the upper bound of the fuzzy rating given by the k^{th} DM.

Step 2 The consistency ratio of the constructed matrix $\widetilde{D}^k$ was examined using Eqs. (17)–(19) as follows:

$$\widetilde{D}^k.w = \lambda_{max}.w \tag{17}$$

$$CI = (\lambda_{max} - n) / (n-1) \tag{18}$$

$$CR = CI/RI \tag{19}$$

Here w is the eigenvector and λ_{max} is the largest eigenvalue created by the k^{th} DM for matrix $\widetilde{D}^k$. Other notations, such as *n, CI, RI,* and *CR*, denote the criteria number, consistency index, random index, and consistency ratio, respectively. However, the value of *RI* depends on the matrix dimensions (n), as shown in Table 2. If *CR* is less than 0.10, the comparison matrix $\widetilde{D}^k$'s degree of inconsistency is deemed acceptable; otherwise, Step 1 involves adjusting comparison matrix $\widetilde{D}^k$.

Step 3 If more than one DM is included in the decision-making committee, preferences are compiled using Eq. (20).

$$\widetilde{d}_{ij} = \left(\sum_{k=1}^{K} x_{ij}^{l_k} \times \lambda_k, \sum_{k=1}^{K} x_{ij}^{m_k} \times \lambda_k, \sum_{k=1}^{K} x_{ij}^{u_k} \times \lambda_k \right), \tag{20}$$

where λ_k is the weight of the k^{th} DM, and $x_{ij}^{l_k}, x_{ij}^{m_k}$, and$x_{ij}^{u_k}$ denote the lower, middle, and upper bound ratings given by the k^{th} DM, respectively.

Step 4 The pair-wise aggregated matrix is constructed based on the aggregated ratings, as expressed in Eq. (21).

$$\widetilde{D} = \begin{bmatrix} \widetilde{d}_{11} & \widetilde{d}_{12} & \cdots & \widetilde{d}_{1n} \\ \widetilde{d}_{21} & \widetilde{d}_{22} & \cdots & \widetilde{d}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \widetilde{d}_{m1} & \widetilde{d}_{m2} & \cdots & \widetilde{d}_{mn} \end{bmatrix} \tag{21}$$

Step 5 Each criterion's fuzzy values are calculated using the geometric mean approach, as illustrated in Eq. (22).

$$\widetilde{r}_i = \sqrt[n]{\left(\prod_{j=1}^{n} \widetilde{d}_{ij} \right)} \tag{22}$$

Step 6 Each value of $\widetilde{r}_i$ is multiplied by a reverse vector to yield the fuzzy weight of criterion i as expressed in Eq. (23). Subsequently, the defuzzified and normalized weight values are determined using Eqs. (24) and (25), respectively.

$$\widetilde{w}_i = \widetilde{r}_i \times (\widetilde{r}_1 + \widetilde{r}_2 + \ldots + \widetilde{r}_n)^{-1} = (l_i, m_i, u_i) \tag{23}$$

$$w_i = (l_i + m_i + u_i) / 3 \tag{24}$$

$$N_i = w_i \Bigg/ \sum_{i=1}^{n} w_i \tag{25}$$

Table 2
Random index (*RI*).

Matrix size (*n*)	1	2	3	4	5	6	7	8	9	10
RI	0.0	0.0	0.52	0.89	1.12	1.26	1.36	1.81	1.46	1.49

4.4. TOPSIS method

The first TOPSIS method was introduced by Cheng & Hwang [31], with reference to Ching & Yoon [32], to select the best options from a set of alternatives based on a set of criteria. In this method, the distance between the alternatives is calculated using the Euclidean distance formula. The basic principle is that the selected alternative should be the shortest from the positive ideal solution (*PIS*) and the farthest from the negative ideal solution (*NIS*). This method consists of the following steps.

Step 1 Initially, a decision matrix was formed. The matrix (*D*) structure is expressed by Eq. (26) as follows:

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \ldots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \quad (26)$$

where x_{ij} is the numerical rating of the i^{th} alternative with respect to the j^{th} criterion, and $i = 1, 2 \ldots., m$ and $j = 1, 2 \ldots., n$.

Step 2 Using Eq. (27), matrix *D* is normalized.

$$r_{ij} = x_{ij} \bigg/ \sqrt{\sum_{i=1}^{m} x_{ij}^2} \quad (27)$$

Step 3 The weighted normalized decision matrix is constructed by multiplying the normalized decision matrix by its associated weights. The weighted normalized value v_{ij} was calculated using Eq. (28) as follows:

$$v_{ij} = r_{ij} \times w_{ij} \quad (28)$$

Step 4 The *PIS* and *NIS* are determined using Eqs. (29) and (30), respectively, as follows:

$$A^* = \left\{ \left(max\ v_{ij} \middle| j \in J^{BC} \right), \left(min\ v_{ij} \middle| j \in J^{NBC} \right) \right\} \quad (29)$$

$$A^- = \left\{ \left(min\ v_{ij} \middle| j \in J^{BC} \right), \left(max\ v_{ij} \middle| j \in J^{NBC} \right) \right\} \quad (30)$$

Here, J^{BC} is the benefit criterion and J^{NBC} is the non-benefit criterion.

Step 5 The separation of each option from the *PIS* is calculated using Eq. (31).

$$S_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^* \right)^2}, \quad (31)$$

where $i = 1, 2, \ldots., m$, and $j = 1, 2 \ldots, n$. Similarly, the separation of each alternative from the *NIS* is estimated using Eq. (32).

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2} \quad (32)$$

Step 6 The relative closeness coefficient for the ideal solution is calculated using Eq. (33), and the relative closeness coefficient of alternative A_i with respect to A^* is defined as

$$C_i^* = S_i^- \big/ \left(S_i^* + S_i^- \right) \quad (33)$$

where, $0C_i^* \leq 1$, and $i = 1, 2, \ldots., m$. The performances of the alternatives improved with increasing C_i^* value.

Step 7 Based on the closeness coefficient C_i^* value, alternatives are ordered in decreasing order.

4.5. Scenario-based stochastic rolling-planning logistics model formulation (Model-1)

The proposed model is constructed in the following way:

Indices:

H: Set of suppliers, $h = 1, 2, \ldots, H$.

I: Set of manufacturing factories: $i = 1, 2, \ldots., I$.

J: Set of distribution centers (DCs), $j = 1, 2, \ldots., J$.

K: Set of retail store clusters; $k = 1, 2, \ldots., K$.

T: Set of periods, $t = 1, 2, \ldots, T$.

S: Set of retail stores; $s = 1, 2, \ldots, S$.

E: Set of scenarios, $e = 1, 2, \ldots, E$.

P: Set of products, $p = 1, 2, \ldots, P$.

Parameters:

$\widetilde{D}_{t,p,k}$: Demand of cluster "k" for product "p" at period "t"

$\mu_{s,p}$: Average demand of retail store "s" for product "p"

$\sigma_{s,p}$: Standard deviation of demand at retail store "s" for product "p"

$ca_{i,j}$: Cost of shipping from facility "i" to DC "j"

$cb_{j,k}$: Cost of shipping from DC "j" to cluster "k"

CI_j^D: Stock capacity of DC "j"

CP_i: Manufacturing capacity of plant "i"

M: Big integer value

δ: Factor of safety.

LT: Product delivery lead time from one facility to another facility.

C_h: Capacity of supplier "h"

$MC_{h,t,e}$: Cost of material per unit from the supplier "h" at period "t", in scenario "e"

$TC_{h,i}$: Material-delivery cost per unit from supplier "h" to plant "i"

Q_h^m: Mean raw material quality of supplier "h"

$Q_{h,t,e}^r$: Real raw material quality of supplier "h" at period "t", in scenario "e"

PC_i: Cost of defective material at plant "i"

SC_k: Stock-out cost for unsatisfied demand at cluster "k"

IP_i: Inventory cost per unit at plant "i"

ID_j: Inventory cost per unit at DC "j"

IC_k: Inventory cost per unit at cluster "k"

$I_{p,i}^F$: Initial inventory for product "p" at plant "i"

$I_{p,j}^D$: Initial inventory for product "p" at DC "j"

$I_{p,k}^s$: Initial inventory for product "p" at cluster "k"

Pb_e: Probability of scenario "e"

Decision variables:

$O_{t:t+1,h,i,p,e}^P$: Material delivery quantities for product "p" from supplier "h" after period "t" and material that arrived at the manufacturing plant "i" before starting of period "$t + 1$" in scenario "e"

$P_{t,p,i,e}$: Manufacturing quantities of product "p" at manufacturing plant "i" at period "t" in scenario "e"

$O_{t:t+1,p,i,j,e}^D$: Delivered quantities of product "p" after period "t" from plant "i" and arrived at DC "j" before period "$t + 1$", in scenario "e"

$O_{t:t+1,p,j,k,e}^S$: Delivered quantities of product "p" after period "t" from DC "j" and arrived at cluster "k" before "$t + 1$" in scenario "e"

$I_{t,p,i,e}^F$: Ending inventory quantities of product "p" at plant "i" after period "t" in scenario "e"

$I_{t,p,j,e}^D$: Ending inventory quantities of product "p" at DC "j" after period "t" in scenario "e"

$I_{t,p,k,e}^S$: Ending inventory quantities of product "p" at cluster "k" after period "t" in scenario "e"

$A_{t,p,k,e}$: Number of stock-out parts of product "p" at cluster "k" at period "t" at scenario "e"

$DM_{p,h,i,t,e}$: Defective raw material that arrived from supplier "h" to plant "i" for product "p" at period "t" in scenario "e"

$B_{t,p,e}^D$: Binary variable that represents the transfer of product "p" from plant "i" to DC "j" at period "t" in scenario "e"

$B_{t,p,e}^s$: Binary variable that represents the transfer of product "p" from DC "j" to cluster "k" in scenario "e"

$E_{t,p,k,e}$: Binary variable that indicates the presence of the product's stock-out event of product "p" at cluster "k" at period "t" in scenario "e"

Objective function:

The objective function in Eq. (34) is defined to minimize the total logistics cost. This function comprises nine cost terms. The first cost term is the material purchasing cost from the selected supplier, the second term is the cost of transporting materials from the source to the manufacturing sites, the third term is the product delivery cost from manufacturing sites to distribution centers, the fourth term is the product delivery cost from distribution centers to stores, and the fifth to seventh terms are the inventory costs at manufacturing sites, distribution centers, and stores, respectively. The eighth term is the stock-out cost for unsatisfied store demand, and the ninth term is the defective material cost.

$$Z=\sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{e=1}^{E}O^{P}_{t:t+1,h,i,p,e}\times MC_{h,t,e}\times Pb_e+\sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{e=1}^{E}O^{P}_{t:t+1,h,i,p,e}\times TC_{h,i}\times Pb_e+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{e=1}^{E}O^{D}_{p,t:t+1,i,j,e}\times ca_{ij}\times Pb_e+\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{e=1}^{E}O^{S}_{p,t:t+1,j,k,e}\times cb_{j,k}\times Pb_e+\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{e=1}^{E}I^{F}_{t,p,i,e}\times IP_i\times Pb_e+\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{e=1}^{E}I^{D}_{t,p,j,e}\times ID_j\times Pb_e+\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{e=1}^{E}I^{S}_{p,k,t,e}\times IC_k\times Pb_e+\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{e=1}^{E}A_{p,k,t,e}\times SC_k\times Pb_e+\sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{e=1}^{E}DM_{p,h,i,t,e}\times PC_i\times Pb_e \tag{34}$$

Subject to

$$I^{S}_{p,k}=\left(\sum_{s=1}^{S}\left(\mu_{s,p}+\delta\sigma_{s,p}\sqrt{LT}\right)\right)\Big/K \tag{35}$$

$$I^{D}_{j,p}=\left(\sum_{s=1}^{S}\mu_{s,p}+\delta\times\sqrt{\sum_{s=1}^{S}\sigma^2_{s,p}}\right)\Big/J \tag{36}$$

$$I^{F}_{p,i}=\left(\sum_{s=1}^{S}\mu_{s,p}+\delta\times\sqrt{\sum_{s=1}^{S}\sigma^2_{s,p}}\right)\Big/I \tag{37}$$

$$P_{t=1,i,p,e}=\left(\sum_{s=1}^{S}\mu_{s,p}+\delta\times\sqrt{\sum_{s=1}^{S}\sigma^2_{s,p}}\right)\Big/I \tag{38}$$

$$\sum_{h=1}^{H}O^{p}_{t:t+1,h,i,p,e}=P_{p,i,t=1,e}\big/Q^{m}_{h} \tag{39}$$

$$DM_{p,h,i,t>1,e}=O^{p}_{t-1:t,h,i,p,e}\times\left(1-Q^{r}_{h,t,e}\right) \tag{40}$$

$$\sum_{i=1}^{I}P_{p,i,t>1,e}=\sum_{k=1}^{K}\widehat{D}^{S}_{t-1,p,k}-\sum_{i=1}^{I}DM_{p,h,i,t,e} \tag{41}$$

$$\sum_{h=1}^{H}O^{p}_{t:t+1,h,i,p,e}=P_{p,i,t>1,e}\big/Q^{m}_{h} \tag{42}$$

$$I^{S}_{1,p,k,e}=I^{S}_{c,p,k}-\widehat{D}^{S}_{1,p,k}+A_{1,p,k,e}(\forall p,k) \tag{43}$$

$$I^{D}_{1,p,j,e}=I^{D}_{c,p,j}-\sum_{k=1}^{K}O^{S}_{1:2,p,j,k,e}(2p,j) \tag{44}$$

$$I^{S}_{t,p,k,e}=I^{S}_{t-1,p,k,e}+\textstyle\sum_{j=1}^{J}O^{S}_{t-1:t,p,j,k,e}-\widehat{D}^{S}_{t,p,k}-A_{t-1,p,k,e}+A_{t,p,k,e}(\forall p,k,t\in T,t\geq 2) \tag{45}$$

$$I^{S}_{t-1,p,k,e}+\sum_{j=1}^{J}O^{S}_{t-1:t,p,j,k,e}\geq\widehat{D}^{S}_{t,p,k}+A_{t-1,p,k,e}-A_{t,p,k,e}(,p,k,t\in T,t\geq 2) \tag{46}$$

$$I^{D}_{t,p,j,e}=I^{D}_{t-1,p,j,e}-\sum_{k=1}^{K}O^{S}_{t:t+1,p,j,k,e}+\sum_{i=1}^{I}O^{D}_{t-1:t,p,i,j,e}\ (\forall p,j,t\in T,t\geq 2) \tag{47}$$

$$I^{D}_{c,p,j}\geq\sum_{k=1}^{K}O^{S}_{1:2,p,j,k,e}(2p,j,k) \tag{48}$$

$$I^D_{t-1,p,j,e} + \sum_{i=1}^{I} O^D_{t-1:t,p,i,j,e} \geq \sum_{k=1}^{K} O^S_{t:t+1,p,j,k,e}(: p, j, t \in T, t \geq 2) \tag{49}$$

$$\sum_{k=1}^{K}\left(I^S_{c,p,k} - I^S_{t,p,k,e} + A_{t,p,k,e}\right) - B^S_{t,p,e} * M \leq \sum_{j=1}^{J}\sum_{k=1}^{K} O^S_{t:t+1,p,j,k,e}\ (\forall p, t, k) \tag{50}$$

$$\sum_{j=1}^{J} I^D_{c,p,j} - \left(1 - B^S_{1,p,e}\right) * M \leq \sum_{j=1}^{J}\sum_{k=1}^{K} O^S_{1:2,p,j,k,e} \tag{51}$$

$$\sum_{j=1}^{J} I^D_{t-1,p,j,e} + \sum_{i=1}^{I}\sum_{j=1}^{J} O^D_{t-1:t,p,i,j,e} - \left(1 - B^S_{t,p,e}\right) * M \leq \sum_{j=1}^{J}\sum_{k=1}^{K} O^S_{t:t+1,p,j,k,e}(\forall p, t \in T, t \geq 2) \tag{52}$$

$$\sum_{k=1}^{K}\left(I^S_{c,p,k} - I^S_{t,p,k,e} + A_{t,p,k,e}\right) + \left(1 - B^S_{1,p,e}\right) * M \geq \sum_{j=1}^{J} I^D_{c,p,j}\ (\forall p, k, t) + \tag{53}$$

$$\sum_{k=1}^{K}\left(I^S_{c,p,k} - I^S_{t,p,k,e} + A_{t,p,k,e}\right) + \left(1 - B^S_{t,p,e}\right) * M \geq \sum_{j=1}^{J} I^D_{t-1,p,j,e} + \sum_{i=1}^{I}\sum_{j=1}^{J} O^D_{t-1:t,p,i,j,e}(\forall p, k, t \in T, t \geq 2) \tag{54}$$

$$\sum_{k=1}^{K}\left(I^S_{c,p,k} - I^S_{1,p,k,e} + A_{1,p,k,e}\right) \leq \sum_{j=1}^{J} I^D_{c,p,j} + B^S_{1,p,e} * M\ (\forall p) \tag{55}$$

$$\sum_{k=1}^{K}\left(I^S_{c,p,k} - I^S_{t,p,k,e} + A_{t,p,k,e}\right) \leq \sum_{j=1}^{J} I^D_{t-1,p,j,e} + \sum_{i=1}^{I}\sum_{j=1}^{J} O^D_{t-1:t,p,i,j,e} + B^S_{t,p,e} * M(\forall t \in T, t \geq 2) \tag{56}$$

$$\sum_{p=1}^{P} I^D_{c,p,j} \leq CI^D_j\ (\forall j) \tag{57}$$

$$\sum_{p=1}^{P} I^D_{c,p,j} + \sum\nolimits_{p=1}^{P}\sum\nolimits_{i=1}^{I} O^D_{0:1,p,i,j,e} \leq CI^D_j\ (\forall p, t = 1, j) \tag{58}$$

$$\sum_{p=1}^{P} I^D_{t-1,p,j,e} + \sum\nolimits_{p=1}^{P}\sum\nolimits_{i=1}^{I} O^D_{t-1:t,p,i,j,e} \leq CI^D_j\ (\forall j, t \in T, t \geq 2) \tag{59}$$

$$I^F_{1,p,i,e} = I^F_{c,p,i} + P_{1,p,i,e} - \sum_{j=1}^{J} O^D_{1:2,p,i,j,e}\ (\forall p, i) \tag{60}$$

$$I^F_{t,p,i,e} = I^F_{t-1,p,i,e} + P_{t,p,i,e} - \sum_{j=1}^{J} O^D_{t:t+1,p,i,j,e}(: p, i, t\epsilon T, t \geq 2) \tag{61}$$

$$P_{t=1,p,i,e} + I^F_{c,p,i} \geq \sum_{j=1}^{J} O^D_{1:2,p,i,j,e}(2p, i) \tag{62}$$

$$P_{t,p,i,e} + I^F_{t-1,p,i,e} \geq \sum_{j=1}^{J} O^D_{t:t+1,p,i,j,e}(: p, i, t \in T, t \geq 2) \tag{63}$$

$$\sum_{j=1}^{J}\left(I^D_{c,p,j} - I^D_{t,p,j,e}\right) - B^D_{t,p,e} M \leq \sum_{i=1}^{I}\sum_{j=1}^{J} O^D_{t:t+1,p,i,j,e}(\forall p, t) \tag{64}$$

$$\sum_{i=1}^{I}\left(P_{1,p,i,e} + I^F_{c,p,i}\right) - \left(1 - B^D_{1,p,e}\right) * M \leq \sum_{i=1}^{I} O^D_{1:2,p,i,j,e} \forall p, j\Bigg) \tag{65}$$

$$\sum_{i=1}^{I}\left(P_{t,p,i,e} + I^F_{t-1,p,i,e}\right) - \left(1 - B^D_{t,p,e}\right) * M \leq \sum_{i=1}^{I} O^D_{t:t+1,p,i,j,e}(: p, j, t \in T, t > 1) \tag{66}$$

$$\sum_{j=1}^{J}\left(I_{c,p,j}^{D}-I_{1,p,j,e}^{D}\right)+\left(1-B_{1,p,e}^{D}\right)*M\geq\sum_{i=1}^{I}\left(P_{1,p,i,e}+I_{c,p,i}^{F}\right)(,p) \tag{67}$$

$$\sum_{j=1}^{J}\left(I_{c,p,j}^{D}-I_{1,p,j,e}^{D}\right)\leq\sum_{i=1}^{I}\left(P_{1,p,i,e}+I_{c,p,i}^{F}\right)+B_{1,p,e}^{D}M(\forall p) \tag{68}$$

$$\sum_{j=1}^{J}\left(I_{c,p,j}^{D}-I_{t,p,j,e}^{D}\right)+\left(1-B_{t,p,e}^{D}\right)*M\geq\sum_{i=1}^{I}\left(P_{t,p,i,e}+I_{t-1,p,i,e}^{F}\right)(-p,t\in T,t\geq 2) \tag{69}$$

$$\sum_{j=1}^{J}\left(I_{c,p,j}^{D}-I_{t,p,j,e}^{D}\right)\leq\sum_{i=1}^{I}\left(P_{t,p,i,e}+I_{t-1,p,i,e}^{F}\right)+B_{t,p,e}^{D}M(,p,t\in T,t\geq 2) \tag{70}$$

$$I_{t,p,k,e}^{S}\leq E_{t,p,k,e}M\ (\forall p,k,t) \tag{71}$$

$$A_{t,p,k,e}\leq\left(1-E_{t,p,k,e}\right)M\ (\forall p,k,t) \tag{72}$$

$$\sum_{j=1}^{J}O_{t:t+1,p,j,k,e}^{S}\leq I_{c,p,k}^{S}-I_{t,p,k,e}^{S}+A_{t,p,k,e}(,p,k,t) \tag{73}$$

$$\sum_{p=1}^{P}P_{t,p,i,e}\leq CP_{i}\ (\forall i) \tag{74}$$

$$\sum_{i=1}^{I}O_{t:t+1,p,i,j,e}^{D}\leq\sum_{k=1}^{K}O_{t:t+1,p,j,k,e}^{S}\ (\forall p,t\in T,t\geq 1) \tag{75}$$

$$\sum_{i=1}^{I}O_{t:t+1,h,i,p,e}^{P}\leq C_{h} \tag{76}$$

$$O_{t:t+1,h,i,p,e}^{P},P_{t,p,i,e},O_{t:t+1,p,i,j,e}^{D},O_{t:t+1,p,j,k,e}^{S},I_{t,p,i,e}^{F},I_{t,p,j,e}^{D},I_{t,p,k,e}^{S},A_{t,p,k,e},DM_{p,h,i,t,e}\geq 0 \tag{77}$$

$$B_{t,p,e}^{D},B_{t,p,e}^{s},E_{t,p,k,e}=0or1 \tag{78}$$

The constraint function in Eq. (35) was used to estimate the initial inventory of the clusters. In this function, $\mu_{s,p}$ denotes the mean demand of the product "p" at the store "s" and $\sigma_{s,p}$ denotes the standard deviation of the product "p" at the store "s". The safety factor is denoted by "δ" and its value is defined by the user. The lead time is denoted by LT and its duration is defined as the execution time. The number of clusters is denoted by "K". However, the same mean $\mu_{s,p}$ and standard deviation $\sigma_{s,p}$ of the demand of product "p" at the store "s" are also used to estimate the initial inventory at the DC as well as the manufacturing site as presented by constraint Eqs. (36) and (37), respectively. In this model, the first-period production volume at the manufacturing site was equal to the initial inventory of the plant. Hence, constraint function (38) was used to determine the production volume of the first period at the plant. The material delivered at the initial period from supplier "h" to plant "i", which arrives at the plant before the beginning of the 2nd period, is defined by Eq. (39). The quantity of defective materials estimated at the plant after the initial period is defined by Eq. (40). A rolling-planning approach is used to determine the plant's output amount after the first period, and these quantities are determined by adding the previous period's total sales volume from all the retailers. However, the production volume is influenced by the defective material quality in the plant, which is defined by Eq. (41). The amount of material transferred from supplier "h" to plant "i" after the ending of each period "t" is determined by Eq. (42). The final inventory of the cluster at the end of the first period is estimated using Eq. (43). The quantities delivered to each cluster in the second period are subtracted from the initial inventory, as indicated in Eq. (44) to determine the inventory for each DC at the end of the first period. The ending inventory for each cluster at the end of period "t" is calculated by adding the parts that arrived from the DC to clusters with their previous period inventory, deducting the real demand, and considering the ordering of the stock-out parts, as specified by Eq. (45). The restriction in Eq. (46) prevents stock-outs of parts while considering the inventory and quantities delivered from the previous term at each store. Eq. (47) establishes the DC inventory after the initial period. Eqs. (48) and (49) are used to limit the delivery quantity of product "p" from DC "j" to cluster "k" at the initial period and after the initial period, respectively. The total supply amount restriction from DC "j" to cluster "k" for product "p" at period "t" is shown in Eq. (50). The binary variable $B_{t,p,e}^{S}$ will be 1 and will not permit delivery if there is a stock-out event at any retail shop. Similar to the case of the constraint in Eq. (51) for the first period, or Eq. (52) for the second period: Eq. (53) is a constraint for controlling the binary variables $B_{1,p,e}^{S}$ of product "p". Eqs. (54) and (55) were applied from the second and first periods, respectively, to control for the binary variable $B_{t,p,e}^{S}$. The inventory of each cluster is constrained using Eq. (56), which controls the stock-out of parts. Eqs. (57)–(59), corresponding to the initial period, subsequent period, and any time $(t\geq 2)$, respectively, represent the inventory capacity limitations for each DC. The inventories at plant *"i"* at the end of the first period and at any period *(t* $\geq$ *2),* respectively, are described by Eqs. (60) and (61), respectively. Eqs. (62) and (63) are used to calculate the delivery constraint of product *"p"* from plant *"i"* to DC *"j"*. Delivery quantities from the plant to the DC cannot exceed the total of the plant's previous inventory plus the total of products produced during that time. Eq. (64) is used to get the delivery restriction from the manufacturing plant *"i"* to DC *"j"* for the total number of deliveries during period *"t"*. This constraint represents the limit of products to be delivered, which cannot exceed the actual inventory. The decision constraint for the deliveries of product *"p"* from plant *"i"* to DC *"j"* at period *"t"* is calculated using equations (65) and (66). If $B^D_{1,p,e}$ or $B^D_{t,p,e} = 1$, then parts are to be delivered. Otherwise, nothing is delivered to the DC. Eqs. (67)–(70) are employed to determine the restrictions of decision variables $B^D_{t,p,e}$. This constraint defines a binary variable as either "0" or "1." Eqs. (71) and (72) are used to estimate constraints to specify inventory after the period *"t"* or a stock-out event at each cluster *"k"*. Eq. (73) is used to determine the delivery quantity of product *"p"* from DC *"j"* to cluster *"k"*. Eq. (74) defines the production capacity of plant *"i"* at any period *"t"*. From the first period onwards, the delivery quantity from the manufacturing plants to the DCs and then from the DCs to the clusters is regulated by constraint function (75). The constraint function (76) represents the supplier's raw material delivery capacity. Finally, the constraints in Eq. (77) indicate that the values of all decision variables are greater than or equal to zero, and the constraint in Eq. (78) indicates that the values of all the binary variables may be either 0 or 1.

5. Experiments and results discussion

5.1. Experiment of the first phase

In this phase, reliable suppliers are selected using an integrated MCGDM model. The model was developed by integrating the IFS, fuzzy AHP, and TOPSIS approaches. The IFS method was used to estimate the weights of the decision-makers, and these weights were then used in the fuzzy AHP method to estimate the weights of the criteria. Finally, these criteria weights are used in the TOPSIS method to select the best supplier. After selecting the best supplier using the TOPSIS method, the supplier was used in the second phase to purchase raw materials for manufacturing plants and produce the required products. To achieve this goal, the following steps were applied.

Step 1 Estimation of decision-maker weights using the IFS approach: In this study, supplier selection criteria were selected through a group discussion among the decision-makers (DMs). Three DMs from three separate departments–*DM-1* from merchandising, *DM-2* from production, and *DM-3* from quality control were selected to make the supplier selection decision. However, these DMs are not equally important because of their varying levels of work experience, knowledge, and decision-making abilities. Therefore, dissimilar weights are required to consider the decision. It was infeasible to obtain numerical values to assign importance ratings to the DMs. Hence, the top management of the company initially used a linguistic scale, as presented in Table 3, to assign ratings to all DMs and numerically estimate their weights.

For instance, the top management of the company assumed that the decision of *DM-1* was more reliable than those of the other two DMs. This is why the top management assigned linguistics rating "*Very important*" to *DM-1*. On the other hand, the top management assumes that the decisions of *DM-2* and *DM-3* are equally important. This is why top management assigned linguistics rating "*Important*" for both *DM-2* and *DM-3*. According to these ratings, the membership, non-membership, and hesitation degrees for *DM-1* were $\boldsymbol{\mu}_{k=1} = 0.90$, $\boldsymbol{\nu}_{k=1} = 0.10$, and $\boldsymbol{\pi}_{k=1} = 0.00$, respectively. Similarly, for *DM-2*, $\boldsymbol{\mu}_{k=2} = 0.75$, $\boldsymbol{\nu}_{k=2} = 0.20$, and $\boldsymbol{\pi}_{k=2} = 0.05$, and for *DM-3*, $\boldsymbol{\mu}_{k=3} = 0.75$, $\boldsymbol{\nu}_{k=3} = 0.20$, and $\boldsymbol{\pi}_{k=3} = 0.05$ were assigned, respectively. Subsequently, by substituting these values into Eq. (14), the DMs weights were estimated as shown in Fig. 5. The highest weight was assigned to *DM-1*. Subsequently, these weights were used to estimate the criteria weights in Step-2.

Step 2 The fuzzy AHP algorithm is used to calculate the criteria weights, and five criteria are considered to evaluate the suppliers. These criteria are as follows: *C1*, mean material quality; *C2*, standard deviation of material quality; *C3*, mean material price; *C4*, standard deviation of material price; and *C5*, material shipping cost from the supplier to the manufacturing site. The criteria weights were first estimated to evaluate the suppliers in relation to the criteria. To do this, the three DMs created a pairwise comparison matrix using a linguistic scale and matching triangular fuzzy numbers, as shown in Table 4.

This scale was used by *DM-1*, *DM-2*, and *DM-3* to construct the pairwise comparison matrices, as illustrated in Tables (5)–(7). The

Table 3
Linguistic terms used to rate DMs.

Linguistic variables	Intuitionistic fuzzy number		
	μ_k	ν_k	π_k
Very important	0.90	0.10	0.00
Important	0.75	0.20	0.05
Medium	0.50	0.45	0.05
Unimportant	0.35	0.60	0.05
Very unimportant	0.10	0.90	0.00

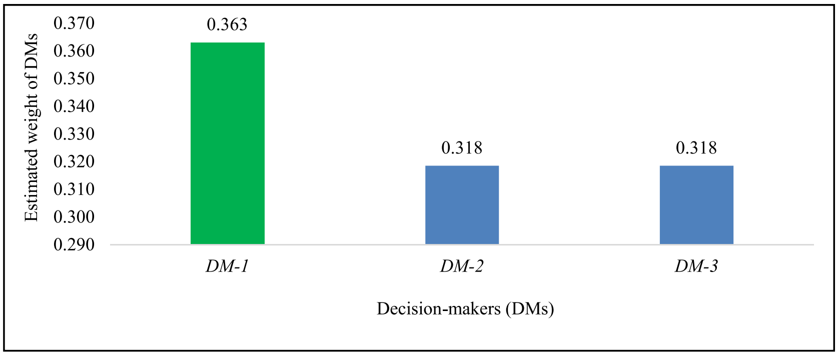

Fig. 5. Estimated weights of the DMs.

Table 4
Linguistic terms used for giving ratings for criteria.

Linguistic variables	Triangular fuzzy number
Equally important	1, 1, 1
Slightly important	1, 3, 5
Moderately important	3, 5, 7
Very important	5, 7, 9
Extremely important	7, 9, 9

Table 5
Pair-wise comparison matrix constructed by *DM-1*.

Criteria	*C1*			*C2*			C3			C4			*C5*		
C1	1.0	1.0	1.0	7.0	9.0	9.0	1.0	3.0	5.0	1.0	3.0	5.0	1.0	3.0	5.0
C2	0.11	0.11	0.14	1.00	1.00	1.00	0.20	0.33	1.00	1.00	1.00	1.00	0.14	0.20	0.33
C3	0.20	0.33	1.00	1.00	3.00	5.00	1.00	1.00	1.00	3.00	5.00	7.00	1.00	3.00	5.00
C4	0.20	0.33	1.00	1.00	1.00	1.00	0.14	0.20	0.33	1.00	1.00	1.00	0.20	0.33	1.00
C5	0.20	0.33	1.00	3.00	5.00	7.00	0.20	0.33	1.00	1.00	3.00	5.00	1.00	1.00	1.00

CR of the ratings was then assessed. For example, using the data from Table 6, $\lambda_{max} = 5.32$ was estimated using Eq. (17). Subsequently, the *CI* was calculated using Eq. (18), where $n = 5$, yielding a of $CI = 0.08$. Table 2 provides the value of *RI*, which was 1.12. Finally, Eq. (19) was used to estimate the value of *CR* as 0.07. This value (0.07) was lower than the permitted *CR* (0.10). This demonstrates the consistency of the pairwise comparison matrix created using *DM-2*. As shown in Table 8, the values of *CR* of other matrices constructed using *DM-1* and *DM-3* were also examined. After verifying the *CR*, the comparison matrices were aggregated using Eq. (20). For *DM-1*, *DM-2*, and *DM-3*, respectively, comparison ratings between *C1* and *C2* were (7, 9, 9), (5, 7, 9), and (7, 9, 9). The combined rating for this cell was calculated as follows: (7*0.363 + 5*0.318 + 7*0.318, 9*0.363 + 7*0.318 + 9*0.318, 9*0.363 + 9*0.318 + 9*0.318) = (6.36, 8.36, 9.00), where 0.363, 0.318, and 0.318 were the weight of *DM-1*, *DM-2*, and *DM-3*, respectively. As shown in Table 9, the aggregated scores for the additional cells were also combined. Eq. (22) was used to obtain the geometric average value of each criterion using the data in the second row of Table 9. For instance, the geometric mean for criterion *C1* is calculated as follows:

$\{(1 * 6.36 * 1.64 * 3.55 * 2.91)^{1/5}, (1 * 8.36 * 3.00 * 5.55 * 4.91)^{1/5}, (1 * 9.00 * 4.36 * 7.55 * 6.27)^{1/5}\} = (2.55, 3.69, 4.51)$. Similarly, the geometric average values of the other criteria were calculated and are presented in Table 10. The fuzzy weights of the criterion were then computed using Eq. (23). For example, the fuzzy weights for criterion *C1* were estimated as follows:

$$\widetilde{w_1} = (2.55 / 10.55, 3.69 / 7.81, 4.51 / 5.47) = (0.24, 0.47, 0.82)$$

Table 6
Pair-wise comparison matrix constructed by *DM-2*.

Criteria	*C1*			*C2*			*C3*			*C4*			*C5*		
C1	1.0	1.0	1.0	5.0	7.0	9.0	1.0	1.0	1.0	5.0	7.0	9.0	7.0	9.0	9.0
C2	0.11	0.14	0.20	1.00	1.00	1.00	0.14	0.20	0.33	1.00	1.00	1.00	0.20	0.33	1.00
C3	1.00	1.00	1.00	3.00	5.00	7.00	1.00	1.00	1.00	5.00	7.00	9.00	5.00	7.00	9.00
C4	0.11	0.14	0.20	1.00	1.00	1.00	0.11	0.14	0.20	1.00	1.00	1.00	0.20	0.33	1.00
C5	0.11	0.11	0.14	1.00	3.00	5.00	0.11	0.14	0.20	1.00	3.00	5.00	1.00	1.00	1.00

Table 7
Pair-wise comparison matrix constructed by *DM-3*.

Criteria	C1			C2			C3			C4			C5		
C1	1.0	1.0	1.0	7.0	9.0	9.0	3.0	5.0	7.0	5.0	7.0	9.0	1.0	3.0	5.0
C2	0.11	0.11	0.14	1.00	1.00	1.00	0.11	0.14	0.20	1.00	1.00	1.00	0.14	0.20	0.33
C3	0.14	0.20	0.33	5.00	7.00	9.00	1.00	1.00	1.00	7.00	9.00	9.00	1.00	3.00	5.00
C4	0.11	0.14	0.20	1.00	1.00	1.00	0.11	0.11	0.14	1.00	1.00	1.00	0.20	0.33	1.00
C5	0.20	0.33	1.00	3.00	5.00	7.00	0.20	0.33	1.00	1.00	3.00	5.00	1.00	1.00	1.00

Table 8
Consistency index ratio of the judgment.

DMs	λ_{max}	n	CI	RI	$CR = CI/RI$	Permitted CR	Remarks
DM-1	5.41	5	0.10	1.12	0.08	0.10	Consistent judgment
DM-2	5.32	5	0.08	1.12	0.07	0.10	Consistent judgment
DM-3	5.40	5	0.10	1.12	0.08	0.10	Consistent judgment

Table 9
Aggregated ratings.

Criteria	C1			C2			C3			C4			C5		
C1	1.00	1.00	1.00	6.36	8.36	9.00	1.64	3.00	4.36	3.55	5.55	7.55	2.91	4.91	6.27
C2	0.11	0.12	0.16	1.00	1.00	1.00	0.15	0.23	0.53	1.00	1.00	1.00	0.16	0.24	0.55
C3	0.44	0.50	0.79	2.91	4.91	6.91	1.00	1.00	1.00	4.91	6.91	8.27	2.27	4.27	6.27
C4	0.14	0.21	0.49	1.00	1.00	1.00	0.12	0.15	0.23	1.00	1.00	1.00	0.20	0.33	1.00
C5	0.17	0.26	0.73	2.36	4.36	6.36	0.17	0.27	0.75	1.00	3.00	5.00	1.00	1.00	1.00

Table 10
Estimated geometric average values of the criteria.

Criteria	Lower value	Middle value	Upper value
C1	2.55	3.69	4.51
C2	0.31	0.37	0.54
C3	1.70	2.36	3.09
C4	0.32	0.40	0.65
C5	0.59	0.99	1.77
Column-wise sum	5.47	7.81	10.55

The average weight of criterion *C1* was estimated using Eq. (24) as follows:

$$w_1 = (0.24 + 0.47 + 0.82) / 3 = 0.51$$

Similarly, using Eqs. (23) and (24), the fuzzy and average weights for the other criteria were determined. Finally, the average criteria weights were normalized using Eq. (25). Accordingly, the final criteria weights were obtained as shown in Fig. 6. This figure indicates that the highest weight was assigned to criterion *C1*. Finally, in Step-3, these criteria weights were used in the TOPSIS method to select the best supplier.

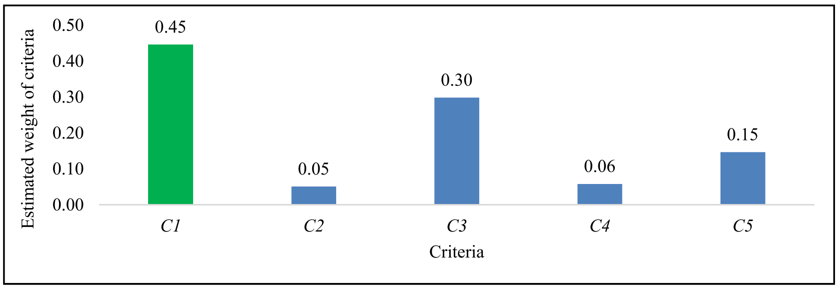

Fig. 6. Estimated criteria weight.

Step 3 Best supplier selection using the TOPSIS method: Initially, supplier evaluation data were collected for five criteria, as presented in Table 11. The data were normalized using Eq. (27). For example, the cell value of 0.95, that is, the data of supplier *S1* with respect to criterion *C1*, was normalized as follows:

$$r_{11} = 0.95 \Big/ \sqrt{2(0.95)^2 + (0.90)^2 + (0.80)^2 + (0.85)^2 + (0.90)^2} = 0.48$$

Similarly, the other data were normalized, as shown in Table 12. Then, using Eq. (28), the normalized data are multiplied by the criteria weights. For instance, the following was found for the weighted normalized data of *S1* for *C1:*

$$v_{11} = r_{11} * w_1 = 0.48 * 0.45 = 0.22.$$

Similarly, other weighted normalized data were determined, as presented in Table 13. A positive ideal solution *(PIS)* and a negative ideal solution *(NIS)* were identified. These criteria were initially classified into two categories: benefit (*BC*) and cost (*CC*). For *BC*, a larger value is preferable; therefore, the *PIS* has a higher value, and the *NIS* has a lower value. Additionally, a lower value is preferable for the *CC*; as a result, the *PIS* has a lower value, and the *NIS* has a greater value. Subsequently, *PIS* (A^*) and *NIS* (A^-) were identified using Eqs. (29) and (30), respectively. For example, criterion *C1* is *BC*; therefore, its *PIS* and *NIS* are identified as follows:

$$A^* = \{\max(0.22, 0.20, 0.18, 0.19, 0.20)\} = \{0.22\}$$

$$A^- = \{\min\ (0.22, 0.20, 0.18, 0.19, 0.20)\} = \{0.18\}$$

Similarly, the other *PIS* and *NIS* of the remaining criteria were determined as presented in the last two rows of Table 13. After identifying *PIS* and *NIS* using Eqs. (31) and (32), the distance of each alternative from *PIS* and *NIS* was estimated for all criteria. For example, distance *S1* was calculated as follows:

$$S1^* = \sqrt{(0.22-0.22)^2 + (0.02-0.00)^2 + (0.16-0.10)^2 + (0.02-0.02)^2 + (0.08-0.05)^2} = 0.069$$

$$S1^- = \sqrt{(0.22-0.18)^2 + (0.02-0.04)^2 + (0.16-0.16)^2 + (0.02-0.03)^2 + (0.08-0.08)^2} = 0.045$$

The distances between the other suppliers were calculated similarly, as shown in Table 14. Finally, the relative closeness coefficient of *S1* was calculated using Eq. (33), as follows:

$$\boldsymbol{C_1^* = 0.045 / (0.069 + 0.045) = 0.395}$$

The relative closeness coefficients of the remaining suppliers were also determined in the same manner. Subsequently, the suppliers were ordered in decreasing order according to the relative closeness coefficients, as shown in the final column of Table 14. The supplier ranking order is shown in Fig. 7. This figure shows that *S4* is the best supplier. *S4* was linked to the manufacturing site in the second phase of the experiment and the materials were purchased from this supplier.

5.2. Experiment of the second phase

In this experiment, the supplier-side material quality, price, and customer-side demand fluctuation risks were considered to evaluate the effectiveness of our proposed model. We assumed that the material quality and price were normally distributed. The mean and standard deviation of the material quality are denoted as *C1* and *C2*, respectively. The mean and standard deviation of the material price are denoted by *C3* and *C4*, respectively. The results are summarized in Table 11. When we placed an order with the supplier to purchase raw materials, we assumed that the material quality and prices would remain unchanged. However, this was not unchanged in real-life practice. This is because material quality and price can fluctuate over time. Therefore, we considered three uncertainty scenarios for these two parameters. We also considered the probability of the occurrence of these scenarios. For example, we assumed that when materials arrive from the supplier at the manufacturing site, the material quality may be lowered, denoted by $\boldsymbol{Q_l}$ with probability $\boldsymbol{Pb_{lq} = 0.25}$, medium $\boldsymbol{Q_m}$ with probability $\boldsymbol{Pb_{mq} = 0.50}$, and high $\boldsymbol{Q_h}$ with probability $\boldsymbol{Pb_{hq} = 0.25}$. Similarly, the material price can be lowered, denoted as $\boldsymbol{P_l}$ with probability $\boldsymbol{Pb_{lp} = 0.20}$, medium $\boldsymbol{P_m}$ with probability $\boldsymbol{Pb_{mp} = 0.50}$, and high $\boldsymbol{P_h}$ with probability $\boldsymbol{Pb_{hp} = 0.30}$. Subsequently, by applying the combination rule, nine uncertain pair scenarios were developed, and their corresponding data were generated randomly using the Box-Muller method [33]. In this method, the means and standard deviations of the quality and price of supplier *S4* were used. The generated period-wise data are listed in Table 15.

Table 11
Rating of the supplier based on five criteria.

Suppliers	*C1*	*C2*	*C3*	*C4*	*C5*
S1	0.95	0.04	80	10	25
S2	0.90	0.04	65	15	20
S3	0.80	0.04	50	20	20
S4	0.85	0.01	60	20	15
S5	0.90	0.10	70	10	25

Table 12
Normalized data.

	C1	C2	C3	C4	C5
Suppliers	0.45	0.05	0.30	0.06	0.15
S1	0.48	0.33	0.54	0.29	0.52
S2	0.46	0.33	0.44	0.43	0.42
S3	0.41	0.33	0.34	0.57	0.42
S4	0.43	0.08	0.41	0.57	0.31
S5	0.46	0.82	0.48	0.29	0.52

Note: The second row of Table 12 lists the criteria weights.

Table 13
Weighted normalized data.

Supplier	*C1(BC)*	*C2 (CC)*	*C3(CC)*	*C4(CC)*	*C5(CC)*
S1	0.22	0.02	0.16	0.02	0.08
S2	0.20	0.02	0.13	0.02	0.06
S3	0.18	0.02	0.10	0.03	0.06
S4	0.19	0.00	0.12	0.03	0.05
S5	0.20	0.04	0.14	0.02	0.08
PIS (A^*)	0.22	0.00	0.10	0.02	0.05
NIS (A^-)	0.18	0.04	0.16	0.03	0.08

Table 14
Determination of relative closeness coefficient.

Suppliers	S_i^*	S_i^-	$S_i^* + S_i^-$	$C_i^* = S_i^- / S_i^* + S_i^*$	Ranking
S1	0.069	0.045	0.115	0.395	4
S2	0.039	0.049	0.088	0.556	3
S3	0.043	0.068	0.110	0.613	2
S4	0.035	0.064	0.099	0.650	1
S5	0.064	0.035	0.099	0.350	5

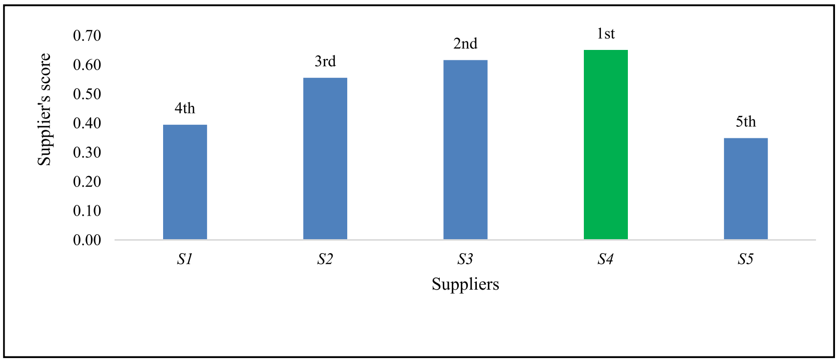

Fig. 7. Suppliers ranking position.

The other experimental conditions for the second-phase experiment were as follows: one supplier ($H = 1$), two manufacturing sites ($I = 2$), two DCs ($J = 2$), three clusters ($K = 3$), 20 retail stores ($S = 20$), five planning periods ($T = 5$), and one period lead time ($LT = 1$ period of time). The capacity of the supplier was 20000 units/period, production capacity was 15000 units/plant/period, DC stock capacity was 10000 units/DC, Big-M value 10000, and safety factor (SF) 1.88. The mean and standard deviation of the demand for the 20 stores are presented in Table 16.

By substituting the data values in Table 16 into Eq. (35), the initial inventory for each cluster was estimated as follows: Initial inventory for the first cluster:

$$I_{A,1}^{s} = \left(10 \times \left(200 + 1.88 \times 00\sqrt{1}\right) + 10 \times \left(150 + 1.88 \times 20 \times \sqrt{1}\right)\right) \Big/ 3 \approx 1543\text{units}.$$

A similar initial inventory was also used for the second and third clusters. Substituting the table values into Eq. (36), the initial inventory for each DC was estimated as follows: Initial inventory for the first DC:

Table 15
Nine uncertain pair-scenarios and their corresponding period-wise random data.

Scenarios	*e1*	*e2*	*e3*	*e4*	*e5*	*e6*	*e7*	*e8*	*e9*
Probability	0.050	0.125	0.075	0.10	0.25	0.15	0.050	0.125	0.075
Pair-scenarios	Q_lP_l	Q_lP_m	Q_lP_h	Q_mP_l	Q_mP_m	Q_mP_h	Q_hP_l	Q_hP_m	Q_hP_h
Period 1	0.8509, 64.70	0.8509, 67.89	0.8509, 78.78	0.8573, 64.70	0.8573, 67.89	0.8573, 78.78	0.8595, 64.70	0.8595, 67.89	0.8595, 78.78
Period 2	0.8503, 60.07	0.8503, 63.07	0.8503, 78.15	0.8512, 60.07	0.8512, 63.07	0.8512, 78.15	0.8575, 60.07	0.8575, 63.07	0.8575, 78.15
Period 3	0.8511, 63.26	0.8511, 71.57	0.8511, 75.99	0.8526, 63.26	0.8526, 71.57	0.8526, 75.99	0.8584, 63.26	0.8584, 71.57	0.8584, 75.99
Period 4	0.8525, 64.61	0.8525, 68.16	0.8525, 73.11	0.8570, 64.61	0.8570, 68.16	0.8570, 73.11	0.8593, 64.61	0.8593, 68.16	0.8593, 73.11
Period 5	0.8541, 62.97	0.8541, 63.98	0.8541, 66.30	0.8563, 62.97	0.8563, 63.98	0.8563, 66.30	0.8582, 62.97	0.8582, 63.98	0.8582, 66.30

Table 16
Mean demand and standard deviation of the product.

Type of product	Store no.	Mean demand (units/store)	Standard deviation (units/store)
A	1–10	200	40
	11–20	150	20

$$I^D_{A,1} = (10 \times 101 he\ firs + 1.88 e\sqrt{10(40)^2 + 10)(20)^2})) \Big/ 2 \approx 1883 \text{units}.$$

A similar amount of the initial inventory was used for the second DC. Finally, the values in Eq. (37), the initial inventory for each of the manufacturing sites were estimated as follows: Initial inventory for the first manufacturing plant:

$$I^F_{A,1} = (10 \times tfacturi\sqrt{10(40)^2 + 10)(20)^2})) \Big/ 2 \approx 1883 \text{units}.$$

A similar initial inventory was used for the second manufacturing plant. The material-carrying cost from the supplier to the manufacturing site was 15 units/unit. The shipping costs for the delivery of one product unit from the manufacturing site to the DCs and from the DCs to the clusters are listed in Tables 17 and 18, respectively. A large difference in the delivery cost from DC1 to Cluster 3 and from DC2 to Cluster 1 was established to confirm that the proposed model does not find an expensive delivery route. The unsteady demand data for these five periods are listed in Table 19. The inventory costs for plants, DC, and stores were 10, 15, and 5 units per product, respectively. The stock-out and defective material costs were 100 and 150 units/product, respectively. After setting the experimental conditions, the proposed logistics model, developed in sub-section 4.5 was solved using the MILP optimizer from the GNU Linear Programming Kit (GLPK) software, and the results are discussed in subsection 5.3.

5.3. Discussion of the results

In the first phase of this study, the best supplier, *S4*, was selected from five suppliers using an integrated MCGDM model. These materials were purchased from supplier *S4*. In the second phase, the proposed logistics model (Model-1), developed in sub-section 4.5, was executed to evaluate its performance in minimizing total logistics, stock-out, and inventory costs. Five cases were considered to achieve this goal. In Case-1, Model-1 was evaluated by setting the safety factor (*SF*) to 0.0. Using this *SF* of 0.0, nine uncertainty pair scenarios were evaluated simultaneously for each period, and the expected logistics costs were estimated, as presented in Table 20. To compare the performance of the proposed model, another model known as Model-2 was developed. The objective function of Model-2 is the same as Model-1. The main distinguishing characteristics of Model-2 from that of Model-1 were that in Model-2, the production volume at the manufacturing site was always fixed for every period, and this fixed production volume was transferred from the manufacturing site to the following stage. On the other hand, in Model-1, a rolling-planning production scheduling approach was applied where the production volume at the manufacturing site is controlled by the actual customers' demand. To compare the results obtained from Model-1 for Case-1, subsequently, the same data were used in Model-2, and accordingly, the expected logistics costs were estimated, as presented in Table 21. Lowered logistics costs were obtained by Model-1, as opposed to Model-2, as presented in

Table 17
Shipping cost for delivering one unit of product from manufacturing site to DC.

$ca_{i,j}$		DC(*j*)	
		1	2
Manufacturing site (*i*)	1	14	15
	2	14	15

Table 18
Shipping cost for delivering one unit of product from the DC to cluster.

$cb_{j,k}$		Cluster (k)		
		1	2	3
DC(j)	1	15	15	150
	2	150	15	15

Table 19
Unsteady demand for each cluster.

Periods	Cluster 1	Cluster 2	Cluster 3
1	1274	1216	1278
2	1241	1389	1396
3	1271	1230	1284
4	1245	1155	1270
5	1326	1342	1200

Table 20
Expected total logistics cost by the proposed model (Model-1).

Cost elements	Case-1	Case-2	Case-3	Case-4	Case-5
	SF-0.00	SF-1.00	SF-1.50	SF-1.80	SF-1.88
E−1	1327948.00	1338094.00	1343240.00	1346240.00	1346953.00
E−2	290629.00	292765.00	293848.00	294479.00	294630.00
E−3	253750.00	264045.00	269265.00	272310.00	273035.00
E−4	262500.00	273150.00	278550.00	281714.00	282452.00
E−5	500200.00	91500.00	0.00	0.00	0.00
E−6	0.00	1665.00	8190.00	14790.00	16490.00
E−7	0.00	0.00	0.00	0.00	0.00
E−8	151124.00	143152.00	139111.00	136753.00	136192.00
E−9	342000.00	345148.00	346744.00	347675.00	347897.00
Total cost (units)	3128151.00	2749519.00	2678948.00	2693961.00	2697648.00

Notation: E−1: Expected material cost; E−2: Expected material delivery cost from supplier to manufacturing plants; E−3: Expected product delivery cost from manufacturing plants to DCs; E−4: Expected product delivery cost from DCs to stores; E−5: Expected stock-out cost at stores; E−6: Expected inventory cost at stores; E−7: Expected inventory cost at DCs; E−8: Expected inventory cost at manufacturing plants; E−9: Expected defective material cost.

Table 21
Expected total logistics cost by the second model (Model-2).

Cost elements	Case-1	Case-2	Case-3	Case-4	Case-5
	SF-0.00	SF-1.00	SF-1.50	SF-1.80	SF-1.88
E−1	1239791.00	1290091.00	1315596.00	1330472.00	1334015.00
E−2	271441.00	282454.00	288038.00	291295.00	292071.00
E−3	216714.00	227536.00	232731.00	235500.00	236060.00
E−4	238299.00	247967.00	252875.00	255729.00	256398.00
E−5	682548.00	281246.00	138510.00	75167.00	61528.00
E−6	0.00	1665.00	5443.00	8764.00	9756.00
E−7	1688.00	1756.00	1791.00	1811.00	1816.00
E−8	175000.00	182100.00	185700.00	187800.00	188300.00
E−9	317749.00	330641.00	337177.00	340990.00	341898.00
Total costs (units)	3143230.00	2845455.00	2757862.00	2727529.00	2721843.00

Tables 20 and 21 and Fig. 8. However, in Case-1, both models achieved higher stock-out costs, as shown in Fig. 9. To reduce the stock-out cost, Case-2 was considered. In Case-2, *SF 1.0* was considered. Then, Model-1 and Model-2 were executed, and their expected logistics costs were estimated accordingly. The total logistics and stock-out costs decreased significantly compared with Case-1, as shown in Tables 20 and 21 and Figs. 8 and 9. Again, Case-3 was considered where *SF 1.50* was used. Using *SF 1.50*, both models were evaluated, and their expected logistics costs were estimated again. It was again found that the total logistics and stock-out costs were decreased by both models compared with Case-2. In this case, the lowest logistics cost and zero stock-out cost were obtained in Model-1, as opposed to Model-2. In addition, the total inventory cost obtained by Model-1 was also lower than that obtained by Model-2, as shown in Fig. 10. Subsequently, Case-4, where *SF 1.80*, and Case-5, where *SF 1.88* were considered consecutively. Accordingly, the

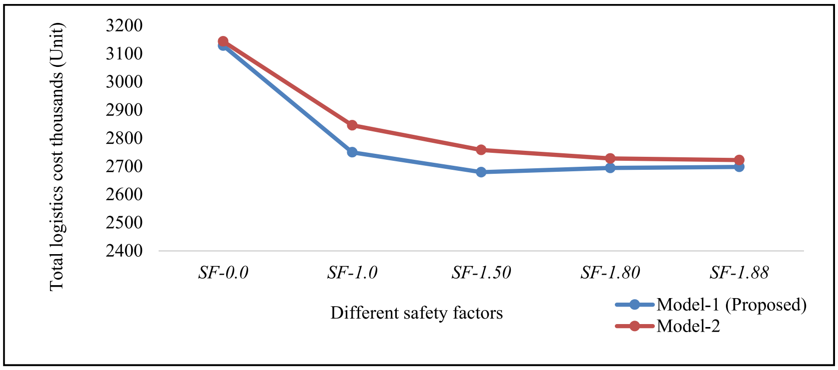

Fig. 8. Total logistics cost.

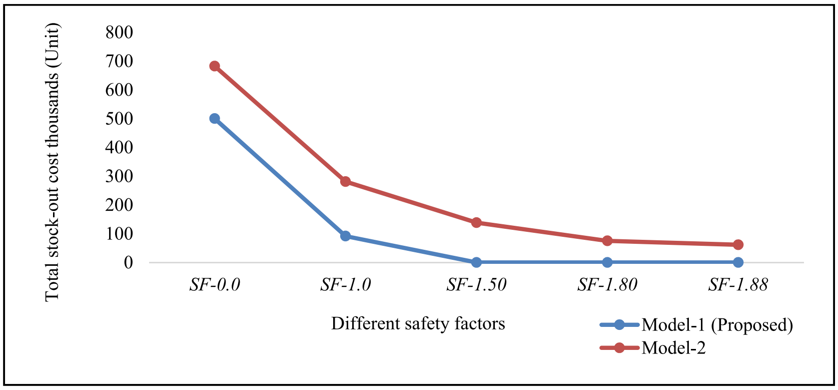

Fig. 9. Total stock-out cost.

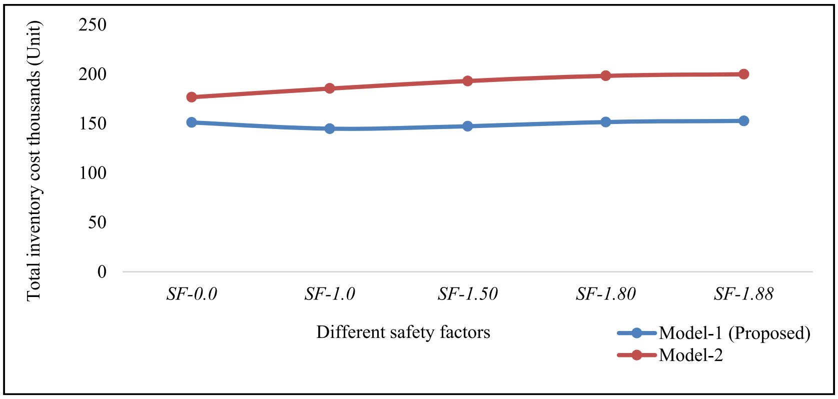

Fig. 10. Total inventory cost.

total logistics, stock-out, and inventory costs were estimated, and lower logistics, stock-out, and inventory costs were obtained by Model-1 as opposed to Model-2, as presented in Tables 20 and 21 and Figs. 8–10, respectively. From this analysis, it was found that, in all cases, the minimum logistics, stock-out, and inventory costs were obtained by Model-1, as opposed to Model-2. According to this analysis, total logistics costs of 2678948.00, 2693961.00, and 2697648.00, units were obtained by Model-1, using *SF* values of *1.50, 1.80*, and *1.88*, respectively. There were minor differences between the logistics costs using *SF* values of *1.50, 1.80*, and *1.88* within Model-1. However, 93.32 %, 96.41 %, and 96.99 % service levels were obtained using *SF 1.50, 1.80*, and *1.88*, respectively. Thus, by incurring almost the same cost, a higher service level was obtained using *SF 1.88*. Therefore, considering the total logistics, stock-out, and inventory costs, as well as the higher service level, the total logistics cost of 2697648.00 units obtained by Model-1 was considered optimal logistics costs in this study when materials were purchased from the best supplier *S4*. This cost was also lower than that of

Model-2, where the total logistics cost was estimated at 2721843.00 units using *SF 1.88*. However, to justify the impact of supplier selection decisions on logistics costs, the proposed model was evaluated again, where the second-ranked supplier *S3* was considered. In this case, materials were purchased from supplier *S3*, and the total logistics cost was estimated accordingly. The total logistics cost increased compared with the earlier case, where the best supplier *S4* was considered for purchasing the materials, as shown in Fig. 11. For example, using *SF 1.88* and purchasing material from the second-ranked supplier *S3*, the total logistics cost was obtained 2722742.00 units, which was greater than 2697648.00 units. Next, materials were purchased from the third-ranked supplier, *S2*, and the total logistics costs were estimated. As shown in Fig. 12, the total logistics cost increased noticeably compared to earlier conditions, where the best supplier *S4* was used for purchasing the materials. For example, using *SF 1.88* and purchasing material from the third-ranked supplier *S2*, the total logistics cost was 2778500.00 units, which was also greater than 2697648.00 units. From these results, as shown in Figs. 11 and 12, it is clear that the total logistics cost was influenced by the supplier's selection decision, and the minimum logistics cost was obtained when the materials were purchased from the best supplier, *S4*. After evaluating five cases and observing the effect of supplier selection decisions on the total logistics cost, we found that the minimum total logistics, stock-out, and inventory costs were obtained using our proposed model as opposed to the second model. Therefore, our proposed model performs better at minimizing the total logistics costs than the second model in a risky environment.

5.4. *Sensitivity analysis and model validation*

To check the robustness and strength of the proposed model and generate consistent results, a sensitivity analysis was performed by setting two conditions. In Condition 1, five sets (Set-2 to 6) of real-life logistics problems were simulated. In these sets, different problem sizes, i.e., the number of suppliers, plants, and DCs were considered dissimilar, as presented in Table 22. After setting the experimental conditions, Model-1 was solved using the MILP optimizer from (GNU Linear Programming Kit) software, and the results were compared with the original results (Set-1). Pictorial images of these comparisons are presented in Figs. 13–17. These results clearly show that similar logistics cost patterns are generated by changing the problem size in the model. These results demonstrate that the proposed model can solve real-life large-scale logistics problems and generate consistent results. However, the solution execution time depends on the type of software and computer packages used to solve the model. In this study, we used an Intel(R) Core (TM) i5-10210U CPU@1.60GHz 2.11 GHz computer processor with an execution time of only 10 s.

On the other hand, to check the consistency of the results generated by the proposed model Condition 2 was applied. Under these conditions, the original problem (Set-1, *SF-1.88*) was executed ten times by generating random values using the Box–Muller method [33]. For these ten trials, random values were generated using the values of criteria *C1*, *C2*, *C3*, and *C4* of supplier S4. Using these random values, Model-1 was executed ten times. The mean and standard deviation for each cost element were determined as presented in Table 23, and their pictorial images are shown in Fig. 18. This figure shows the mean of each cost element, and the error bars indicate the standard deviation of the costs. The standard deviations, i.e., errors were very small for the cost elements. These results prove that the proposed model generates consistent results in repeated simulation environments. Therefore, through a sensitivity analysis based on Condition-1 and 2, it was observed that real-life large-scale logistics problems can be solved by the proposed model. This generates similar results in a repetitive simulation environment. Therefore, the proposed model was validated. From these discussions, we conclude that companies should select the best supplier from multiple alternatives to minimize total supply chain logistics costs. Additionally, a company should adopt a risk-embedded logistics model to handle the various risks of running a business in a dynamic business environment. To achieve this goal, a new approach, such as our proposed model, can be applied in real-life applications to minimize total supply chain logistics costs.

6. Conclusion

In this study, a scenario-based stochastic rolling planning three-stage logistics model was developed. In this model, various risk factors such as customer demand, material quality, material price fluctuation risks, and lead time were considered. The aim of this

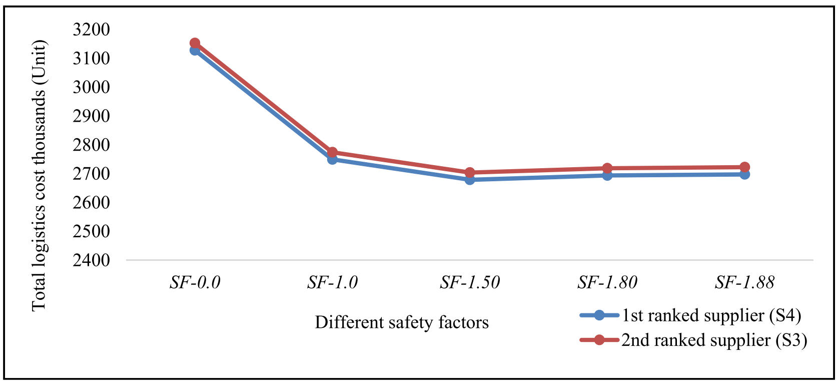

Fig. 11. Logistics cost comparison when materials were purchased from *S4* and *S3* by Model-1.

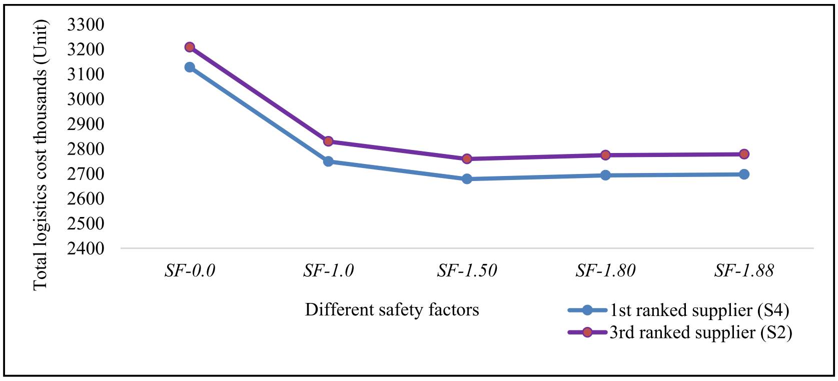

Fig. 12. Logistics-cost comparison when materials were purchased from *S4* and *S2* by Model-1.

Table 22
Expected logistics cost by varying problem size (Model-1).

Sets	Problem size (h-i-j-s)	*SF-0.00*	*SF-1.00*	*SF-1.50*	*SF-1.80*	*SF-1.88*
Set-1	1-2-2-20	3128151.00	2749519.00	2678948.00	2693961.00	2697648.00
Set-2	2-2-2-20	3300035.00	2923294.00	2853679.00	2869239.00	2873073.00
Set-3	2-2-3-20	3307785.00	2933049.00	2863434.00	2878824.00	2882908.00
Set-4	2-3-3-20	3300772.00	2926765.00	2857633.00	2873304.00	2877900.00
Set-5	2-3-4-20	3327402.00	2956356.00	2890553.00	2907079.00	2911760.00
Set-6	3-4-4-20	3341269.00	2969870.00	2904002.00	2920068.00	2924737.00

Note: Set-1 is the original set.

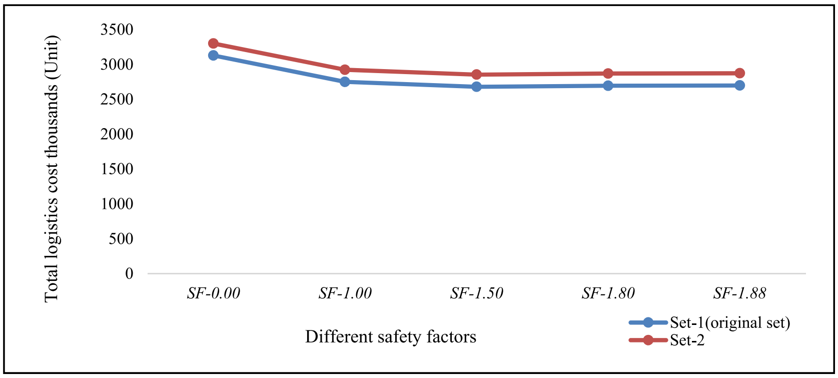

Fig. 13. Logistics costs comparison between Set-1 and Set-2.

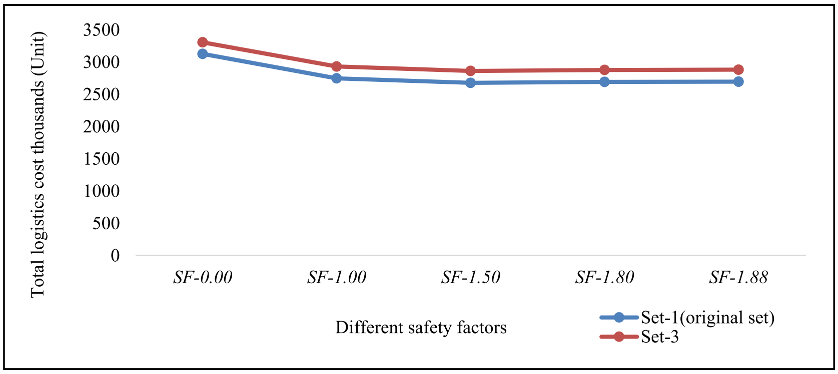

Fig. 14. Logistics costs comparison between Set-1 and Set-3.

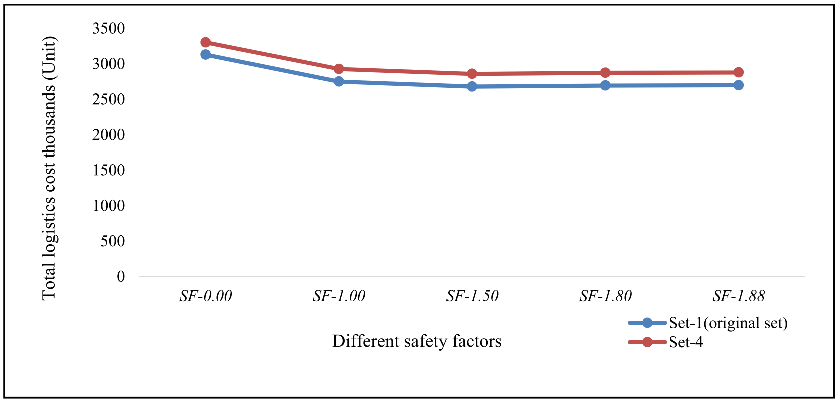

Fig. 15. Logistics costs comparison between Set-1 and Set-4.

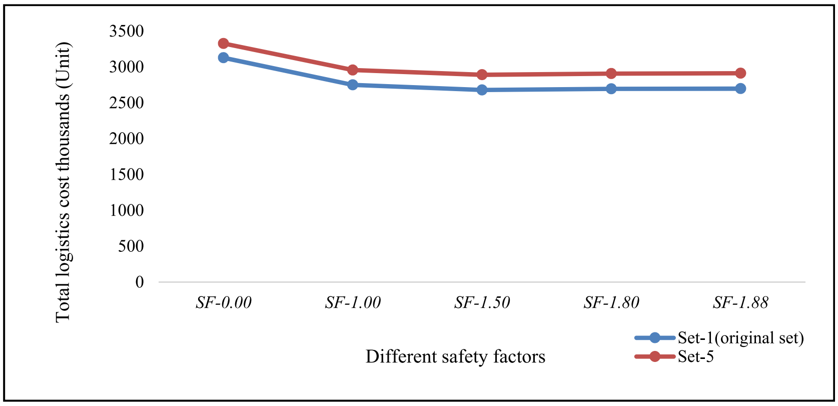

Fig. 16. Logistics costs comparison between Set-1 and Set-5.

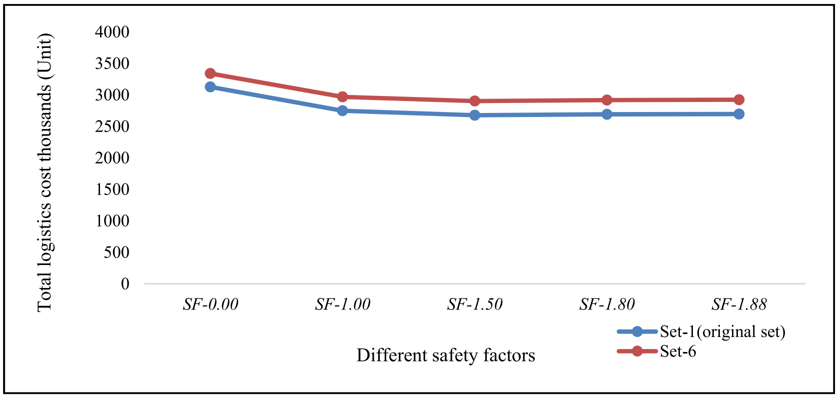

Fig. 17. Logistics costs comparison between Set-1 and Set-6.

model was to minimize the total logistics cost by controlling the inventory, stock-out, and overstock levels. Two phases were considered for achieving this goal. In the first phase, reliable suppliers are selected using an integrated MCGDM model. Using this integrated MCGDM model, the decision-maker weights were estimated by the IFS method, then these weights were used in the fuzzy AHP method to estimate the weights of the criteria, and finally, these weights were used in the TOPSIS method to estimate the weights of suppliers, accordingly, the best supplier was selected. In the second phase, the selected suppliers are integrated with other stakeholders, and a three-stage logistics model is developed. In this model, various risk factors such as customer demand, material quality, and material price fluctuation risks are considered to develop a risk-embedded logistics model. However, the major contributions of this study are as follows: (a) supplier-side risks such as quality and price fluctuation risks have been considered, which were ignored in

Table 23
Mean and standard deviation of different cost elements from ten trials by Model-1.

Cost elements	Mean	Standard deviation
E−1	1393385.00	31423.00
E−2	294629.00	208.00
E−3	273035.00	0.00
E−4	282451.00	2.00
E−5	0.00	0.00
E−6	16490.00	2.00
E−7	0.00	0.00
E−8	136437.00	355.00
E−9	347900.00	1773.00

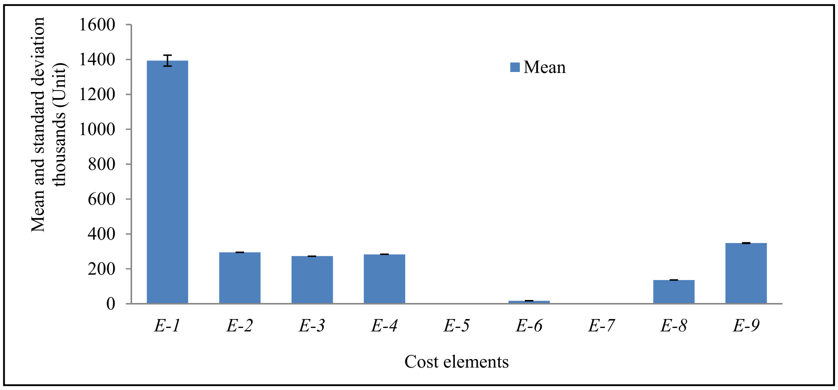

Fig. 18. Mean and standard deviation of different cost elements from ten trials by Model-1.

most previous studies; (b) considering quality and price fluctuation risks, nine uncertain pair scenarios, and their corresponding occurrence probabilities have been considered; (c) customer side unsteady demand risk was considered which has been ignored in most previous studies; (d) lead time was considered for a delivery product from one stage to another stage instead of simultaneous production and delivery system that has been ignored in most previous studies; (e) the rolling-planning production system has been implemented in this model; (f) the impact of supplier-selection decisions on logistics costs was also addressed in the model. Finally, by setting up a numerical example, the performance of the proposed model is verified by comparing it with another model. From this numerical example, it is observed that the proposed model shows better performance in minimizing the total logistics, stock-out, and inventory costs than the another model. To test the robustness and strength of the proposed model, a sensitivity analysis was performed by setting two numerical conditions. In Condition-1, five different problem sizes (Set-2 to 6) were considered by changing the number of suppliers, manufacturing plants, and distribution centers. The model was then executed successively, and the obtained results were compared with the original results (Set-1). From this analysis, it was observed that by changing the problem sizes, similar types of logistics costs were generated by the model. This ensured that the proposed model could solve large-scale logistics problems. Again, according to Condition-2, the original problem (Set-1) was executed ten times by generating random data based on the four criteria (*C1, C2, C3, and C4*), and the mean and standard deviation for each of the cost elements were determined. These results show that a similar type of logistics cost was generated in every trial, and the minimum standard deviation was generated for each cost element. Therefore, it was confirmed that the proposed model can generate consistent results in a repetitive simulation environment. Further, based on the results and sensitivity analysis of the numerical example used in this study, we claim that our proposed model is valid and can be applied to solve practical real-life problems. This model can be applied to discrete product manufacturing industries such as food items, clothing, cell phones, and furniture to control stock-out and overstock situations in their retail outlets. However, the proposed model has some limitations that should be addressed in future studies. For example, (a) hypothetical data were used to evaluate the performance of the model in the laboratory, therefore, real-life industrial data can be used to evaluate the model, (b) this model was developed to reduce overall logistics costs under considering a make-to-stock discrete product manufacturing environment, so, it can be modified for a make-to-order policy in future, (c) this model can be improved by considering the variation in lead time, and transportation cost instead of the fixed lead time and transportation costs, (d) time to create order can be considered in future studies (e) additionally, this model can be extended to develop a closed-loop supply chain logistics model by considering various environmental factors in the future studies.

Data availability statement

The Data included in article/supp. Material/referenced in article can allow other scholars to reuse these data on the following Links:Harvard data verse network: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/NFWWOW.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Md. Mohibul Islam: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Masahiro Arakawa:** Writing – review & editing, Validation, Supervision, Software, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e22289.

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