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Designing a Closed-loop Green Supply Chain Network Considering Quality Costs of Raw Materials in a Fuzzy Environment

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Abstract – *When the reverse supply chain—which comprises the steps involved in bringing a product back into the supply chain, such as its collection, recycling, and destruction—is taken into account alongside the forward supply chain, it becomes evident how important this issue has become in recent years and how social and environmental factors have been taken into account to meet economic demands. This paper presents a five-level closed-loop green supply chain network, considering cost minimization, environmental effects, and time delays in sending products and raw materials. The model is presented under uncertainty of some parameters, considering the particular position of purchased raw materials. The tri-objective fuzzy model is converted into a crisp model using the Jiménez et al. (2007) method. The performance and efficiency of the model are analyzed using the Torabi-Hassini method and the augmented epsilon constraint method. GAMS software provides a numerical illustration of this process. Sensitivity analysis is used to the various degrees of confidence. The augmented epsilon-constrained method outperforms the Torabi-Hassini (TH) method for the first and second objective functions and vice versa for the third objective function. The computational time of the augmented epsilon-constrained method is also less than that of the TH method for all confidence levels.*

Keywords– *Closed Loop Green Supply Chain, Fuzzy Modelling, Uncertainty, Epsilon Constrained Method.*

I. INTRODUCTION

Companies now need to manage their supply chains to supply goods with competitive prices and superior quality in today's global marketplace. Establishing a green supply chain idea and setting yourself apart from rivals may also be accomplished by being ecologically conscious and making adjustments to meet environmental regulations. Meanwhile, businesses use "green supply chain management," which incorporates environmental considerations at every step of the process—from raw material extraction to product design, manufacturing procedures, final product distribution to clients, transportation, and end-of-life management.

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The forward supply chain encompasses operations that convert raw materials into completed goods, deliver these goods, and provide post-purchase services to satisfy client demands. Demand management, procurement, and order execution are critical challenges in these networks. In Abdallah et al. (2012) investigated activities like product recovery, recycling, and collecting from returns are all part of the reverse supply chain.

Maximizing energy and resource efficiency while reducing negative environmental effects are the objectives of supply chain management. In addition to design, the structures of these two types of networks should be taken into consideration concurrently. This ensures that the forward and reverse supply chains are optimized and prevents suboptimality-causing factors. A closed-loop supply chain is created by combining the forward and reverse supply chains (Amin and Zhang, 2013). Numerous academics have focused on this kind of supply chain, and it has been studied in a variety of domains, including facility location (Amin and Zhang, 2013), pricing (Chen and Chang, 2013), production planning (Winkler, 2011), and inventory management (Yang et al., 2013).

Customers' expectations for the end product's quality and the seamless fabrication of components at every link in the chain are crucial. Thus, the management's primary duty is to ensure that the production or provision of services that may draw in a high level of consumer satisfaction balances quality and cost. Therefore, to compete in the modern global market, it is imperative that businesses use the quality costing approach to develop goods that are both more affordable and of higher quality than those of their rivals. Costs related to the quality of a product or service that are borne by producers, customers, or society are referred to as quality costs. The costs of design and development, training, repairs, and preventative measures, as well as the costs of evaluating, inspecting, and auditing the organization's production and service operations, are among the expenses associated with finding non-conformities and risks that result in mistakes and defects.

These costs are incurred after the product is sold, and additional expenses resulting from both external and internal failures are included in the quality costs. The quality of the acquired raw materials is also very important when discussing the cost of quality, in addition to the quality of the finished product. Therefore, producers who choose to buy low-quality raw materials at a higher cost than those who choose to buy high-quality raw materials would incur additional expenditures to reach the appropriate quality, such as rework and environmental costs. It is also important to keep in mind that most optimization issues include input data that is deemed ambiguous because of factors like client demand, resource requirements, and cost.

This uncertainty results from inaccurate parameter estimates, computation mistakes, or inadequate and unavailable information. It is crucial to discuss the parameter uncertainty in these kinds of problems. Network designers should take this into account while designing networks, since failing to do so may force management to make difficult choices.

Referring to the contents of the article, a closed-loop green supply chain model is considered to minimize the environmental damage caused by exhaust gas emissions during the building of raw material transportation hubs, as well as the costs associated with the supply chain. When compared to the anticipated time of the consumers, the goods and manufacturing processes reduce the delays caused by the transit time between the centers.

This research is essential because it takes a novel method to include raw material quality costs in a closed-loop, green supply chain architecture. Prior research has concentrated chiefly on forward or reverse logistics; however, it is uncommon for both to be integrated with an emphasis on quality costs in unreliable situations. By putting forward a model that includes these components, our research fills this knowledge gap and offers a more thorough understanding of supply chain management.

Aspects of supply chain optimization, including facility location, price, production scheduling, and inventory management, have all been studied in the past. The integration of environmental factors with quality cost management has received little attention, nevertheless. By expanding on previous research and offering a more dependable method for managing costs and environmental effects, fuzzy logic is used in this study to overcome the inherent uncertainty in supply chain features.

This study's main contribution is the creation of a tri-objective model that concurrently lowers expenses, lessens environmental effects, and increases time efficiency. This study offers a unique approach to supply chain management using techniques like the enhanced epsilon constraint method for optimization and the Jiménez et al. (2007) method for transforming fuzzy models into crisp models. Reducing delays, decreasing greenhouse gas emissions, and guaranteeing high-quality products are among the goals.

To sum up, this study closes a significant vacuum in the literature by providing a thorough model that combines supply chain management with quality prices, environmental effect, and time efficiency. The model that has been suggested contributes to the advancement of theoretical knowledge and offers feasible solutions to companies that want to improve operational efficiency and sustainability. The study's conclusions have important ramifications for both academics and business as they emphasize how crucial it is to include quality and environmental concerns into supply chain plans.

Figure 1 depicts an overview of the methodology used in this study:

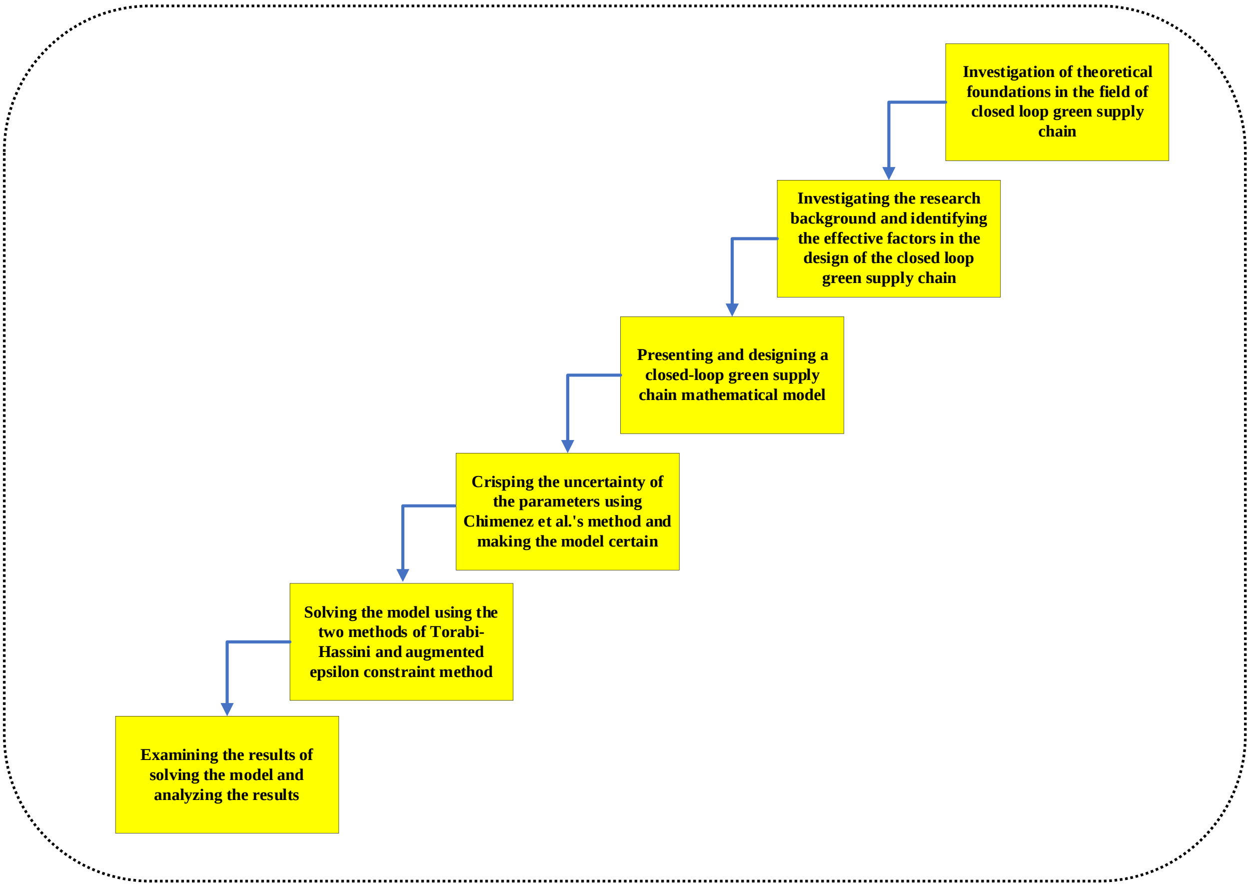

Fig. 1. Research procedure in this paper

The rest of the paper is organized in this manner. A summary of the study's background is given in Part II, network modeling is shown in Part III, and possible solutions are examined in Section VI. The approaches to solutions are then taken into account. Lastly, Section V presents the outcomes of the model solution, and Section VI presents the conclusion and recommendations for more study.

II. LITERATURE REVIEW

A handful of the many research that have been done on the modeling and design of supply chain networks are included below: A mixed integer linear programming model was created by Pishvaee and Razmi (2011) in order to create a closed-loop supply chain network. They also incorporated a number of ambiguous and fuzzy variables in their model and offered an interactive fuzzy solution. PrasannaVenkatesan and Kumanan (2012) used a multi-objective approach for a plastic furniture and home appliance manufacturing facility to establish a sourcing strategy and evaluate the choice of local suppliers with high reliability and low cost versus overseas suppliers with lower reliability and cost.

To maximize demand delivery dependability and minimize overall cost, this issue is modeled using a multi-period mixed integer programming model. In the face of uncertainty, Vahdani et al. (2013) outlined a systematic approach and established a trustworthy network of facilities in the closed-loop supply chain. Their proposal makes use of a robust and efficient technique to reliably implement the planned network architecture. They provide a multi-level network with various facilities, goods, suppliers, and levels. The basis for the model's solution method is the mixed integer linear programming model with two fuzzy objectives. A case study of the iron business is supposed to assist in bringing the conclusions more in line with reality. In order to optimize decision-making, Özceylan et al. (2014) provided a mixed integer nonlinear mathematical model. Hatefi and Jolai (2014) presented a supply chain network design model. They used dependability concepts in their model to examine facility failures. They propose a paradigm that divides the facilities into dependable and unreliable groups. When unreliable facilities malfunction, some of their capacity is lost. Thus, to meet customer demand, a portion of the capacity is needed, and this fraction is satisfied by transferring the commodities from dependable to unreliable facilities utilizing the subscription strategy. This paradigm views production, recycling, distribution, and collection facilities as a combination. It is multi-level and single-product. The target function includes lowering operational, transportation, fixed, and facility disturbance expenses. The following are thought to be unclear: transportation, fixed, operating expenditures, facility capacity, demand variables, and the rate of product returns. An effective optimization technique was used to deal with uncertainty.

The model aimed to minimize anticipated expenditures and nominal expenses under different scenarios. Pasandideh et al. (2015) presented a two-objective optimization of the supply chain network: customers, distribution centers with random failure rates, and manufacturing facilities. To lower total costs and increase customer happiness, the model sought to optimize the average number of commodities supplied to customers while accounting for distribution center reliability. Zeballos et al. (2014) suggested a multi-stage stochastic integer linear programming model for a multi-period, multi-product closed-loop supply chain. This model considers the unpredictability of raw material supply and consumer demand. It is a ten-layer network with five forward levels and five backward layers. In a fuzzy context, Ramezani et al. (2014) proposed a multi-product, multi-period model for creating a closed-loop supply chain network. Various means of transportation are available in the network to transfer products between two-level facilities. In their proposed model, the supply, manufacturing, distribution centers, and consumers are the four layers in a direct way, while the customers, collecting centers, and destruction centers are the three levels in the reverse route. Their model has three goals: the first is profit maximization, the second is service quality optimization. This is accomplished by shortening the time required for both forward and backward transit. The third goal minimizes the amount of inferior raw materials that the supplier provides, improving the quality of manufacturing components in production centers and optimizing Sigma's quality. Hatefi et al. (2015) presented a reliable model to protect the forward-integrated reverse logistics network from dangers associated with known variability in model parameters and risks of intermittent facility stoppage.

In their study, two types of trustworthy and untrustworthy hybrid distribution hubs were investigated. The total cost reduction model's objective function included the installation, process, and transportation costs of the stationary facility as well as the expected costs of moving items from reliable facilities to unreliable distribution hubs. To account for demand unpredictability, transportation mode selection choices, and the objective of minimizing the longest possible shipping time for goods along the payment chain, Cardona-Valdés et al. (2014) examined the mixed-integer stochastic two-objective model concerning the supply chain design problem. A multi-period, multi-product, closed-loop supply chain network was suggested by Karimi et al. (2015) for a dairy company with irregular return rates. A stochastic constraint linear programming model was created specifically for this inquiry. For the purpose of building the pharmaceutical supply chain network, Mousazadeh et al. (2015) provided a mixed integer linear programming model with two objectives: reducing overall cost and unmet demand. Because the input parameters are very uncertain, a probabilistic robust programming approach was used to address the uncertainty in the model. For closed-loop systems operating in uncertain contexts, Bing et al. (2015) studied supply chain optimization and network design. It was necessary to solve the fuzzy mixed integer linear programming model in order to make the best decisions possible regarding the number of reproduction products, the inventory level of products and parts, the location of each product within each center, and the number of parts purchased from foreign suppliers to maximize chain profit.

Kaya and Urek (2015) investigated the network design problem for a closed-loop supply chain in which distribution centers for new products were connected to centers for collecting used products. Their mixed integer nonlinear model of facility location, inventory, and pricing took into consideration the cost of new items, the amount of value derived from the collection of old products, and the optimal location for the facility. Maximizing the supply chain's overall profit was their aim. Huang et al. (2016) demonstrated a green supply chain that included many suppliers, a single manufacturer, and various retailers. With the use of game theory, they simultaneously optimize the production line design, the selection of suppliers, the mode of transportation, and the pricing tactics. Garg et al. (2015) proposed a closed-loop supply chain network that included environmental issues. An integer nonlinear programming with two objectives was used to model it. The model seeks to optimize chain profit overall and limit the number of cars in the forward chain in order to minimize the carbon effect. Zhen et al. (2019) introduced a multi-product, multi-level, sustainable, green closed-loop supply chain model with CO_2 emission control under fluctuating demand. The usage of a bi-objective optimization model with two objectives for total operating expenses and CO_2 emissions was recommended. The model also included decisions regarding environmental quality and factors affecting the capacity level of the facilities. Using the scenario-based method, the uncertain demand of the stochastic programming model was shown, and the Lagrangian release technique was used to solve the model.

Gitinavard et al. (2019) investigated a bi-objective multi-echelon supply chain model for perishable commodities that evaluates Pareto optimum points in the face of uncertainty. Kalantari Khalil Abad and Pasandideh (2020) examined a multi-objective method for developing environmentally friendly closed-loop supply chains with the goal of controlling uncertainty in effective parameters. Ghaderi et al. (2020) created group decision-making challenges using an intuitionistic fuzzy DEA cross-efficiency approach. According to Mohtashami et al. (2020), a queuing system integrated into a green closed-loop supply chain architecture may reduce energy consumption and its negative environmental effects. Using the advanced multi-objective particle swarm optimization approach, Nasr et al. (2020) carefully designed dispersed production of renewable energy in radial distribution networks. A closed-loop supply chain with station interruption that is multi-objective and multi-echelon was examined by Keshmiry Zadeh et al. (2021). A sustainable and environmentally conscious closed-loop tire supply chain was achieved by Tehrani and Gupta (2021) by optimizing the total profit given for the tire company by considering several recovery methods and the combined uncertainty associated with diverse network elements. They looked at employing a powerful fuzzy stochastic programming approach to validate the model in order to address mixed uncertainty. The results show how the model works, how useful it is in addressing real-world problems, and if it is feasible to establish an environmentally and economically sustainable closed-loop supply chain network for the tire industry. Gitinavard et al. (2021) investigated the use of possibilistic programming in constructing networks in the biomass supply chain with fuzzy estimates for uncertain membership functions.

Gholamian et al. (2021) noted that a multi-echelon green open-location-routing issue is considered using a robust-based stochastic optimization approach. In their 2021 study, Solgi et al. (2021) looked at high-tech, ecologically friendly brick production while considering energy-conscious consumption. A comprehensive possibilistic strategy built on the interdependencies of the criteria. In 2022, Boskabadi et al. (2022) introduced a revolutionary fuzzy mathematical model for building a distribution network in a multi-product, multi-cycle, multi-level, multi-factory, multi-retail, multi-mode green supply chain system. Their article aimed to reduce total network costs, maximize the net benefit per capita of each human resource, and decrease overall CO_2 emissions. The fuzzy trapezoidal membership function was used to account for client demand, and P-hub placement was used to locate distribution centers with multiple allocations. The best approach for transferring commodities around the network was also impacted by the volume of outsourced items, facility capacity, and the accessibility of different modes of transportation. The integrated meta-heuristic, MOPSO, and NSGA-II algorithms were used to solve the multi-objective mixed integer nonlinear mathematical model. For a green, two-channel, closed-loop supply chain network, Kazancoglu et al. (2022) suggested a multi-objective optimization model. In addition to achieving financial and environmental objectives, it maximizes network traffic. This model of mixed integer linear programming aims to investigate the best choices for levels and the best choices for transportation between these levels in a closed-loop supply chain network. Environmental goals are achieved by reducing the PM concentration and CO2 emissions of the network. The economic objectives are also fulfilled by reducing the total cost. The recommended model's validity was evaluated using a case study of the home appliance industry. Moayedi and Sadeghian (2023) used a forward green supply chain to study multi-objective stochastic planning under uncertainty with unreliable suppliers and unpredictable demand, scarcity, and transportation costs. In their piece, they also provide environmental solutions to reduce air pollution, such as reducing carbon dioxide emissions. Their multi-objective strategy aims to reduce the overall cost, the variance in the overall cost, the financial risk (i.e., the possibility of exceeding the budget), and the pollution created by the machinery used in transportation and manufacture. Two meta-heuristic algorithms—multi-objective particle swarm optimization (MOPSO) and non-dominated sorting genetic algorithm-II (NSGA-II)—were used to solve the model. The results show that multi-objective paper swarm optimization (MOPSO) is not as effective as the approach (NSGA-II). In order to construct closed-loop supply chain networks under hybrid uncertainty, Farrokh et al. (2023) looked at unique robust fuzzy stochastic programming method.

Table I. Related literature review

Author	Published year	Network Type	Research Objective	Solution Method	Results
Pishvaee and Razmi	2011	Closed-loop supply chain	Present a bi-objective fuzzy model with two goals: cost reduction and minimizing environmental impacts in a fuzzy environment.	Deterministic modelling and solving with Lingo software	Environmental impact reduction leads to cost increases. Cost reduction tends to form a centralized network.
PrasannaVenkatesan and Kumanan	2012	Supply chain	Present a bi-objective model to minimize costs and increase supplier reliability.	PSO algorithm method and simulation	The research concluded that using Particle Swarm Optimization (PSO) and simulation effectively designs multi-objective supply chain sourcing strategies under risk, improving decision-making in supply chain management.
Özceylan et al.	2014	Closed-loop supply chain	Present a single-objective model including minimization of transportation, purchasing, renovation, and separation operation costs at workstations.	Solving the model using random numbers in GAMS software and the impact of parameters on the objective function	An increase in demand leads to an increase in the objective function. An increase in demand leads to a rise in the number of workstations. An increase in purchasing costs leads to an overall cost increase.
Hatefi and Jolai	2014	Forward supply chain	Present a single-objective model to reduce chain costs in a fuzzy environment.	Using a probabilistic programming approach to deterministic modelling and solving it with GAMS software based on defined scenarios	Impact of capacity disruption on fixed costs of establishment and transportation costs. Effect of capacity disruption on disruption costs.
Cardona- Valdés et al.	2014	Forward supply chain	Present a bi-objective model to reduce warehouse opening and expected transportation costs and minimize the maximum travel time in the supply chain.	Solving with a heuristic method	Effectiveness of the proposed algorithm based on numerical examples.
Karimi et al.	2015	Closed-loop supply chain	Present a single-objective model to reduce chain costs.	Solving with Lingo software and comparison with actual company data	Reduction of closed-loop supply chain costs according to the proposed model and comparison with actual data.

Continue Table I. Related literature review

Author	Published year	Network Type	Research Objective	Solution Method	Results
Mousazadeh et al.	2015	Forward supply chain	Present a model with strategic and tactical decisions and goals of reducing costs and minimizing the maximum unmet demand of all products in all periods in a fuzzy environment.	Deterministic modelling with a probabilistic programming method and solving the model with the TH method and epsilon constraint and solving using GAMS software	Change in parameters of the TH method and demand and its impact on objective functions (decreasing the weight importance of functions decreases their satisfaction while increasing customer satisfaction).
Bing et al.	2015	Closed-loop supply chain	Present a single-objective model to reduce costs.	Solving the model using LamaSoft software	Impact of relocation on reducing chain costs. Impact of emission schemes on reducing pollutants.
Kaya and Urek	2015	Closed-loop supply chain	Present a single-objective model to maximize the network considering the sale of new products and the value of collected products.	Solving with GAMS software for small samples and then solving the model with a heuristic method for large samples	Efficiency of the model according to the results obtained.
Huang et al.	2016	Forward supply chain	Maximize chain profit by optimizing retail prices.	Fuzzy theory is used to obtain each retailer's best reaction function and the supplier's best reaction function, forming a bi-objective function and solving it with a genetic algorithm.	Use of environmentally friendly transportation methods for low-value materials. Increased pressure to reduce CO_2 emissions leads to a downgrade in product configuration. An increase in market comparison leads to a rise in products and emissions.
Garg et al.	2015	Closed-loop supply chain	Present a bi-objective model to maximize total chain profit and minimize the number of vehicles in the forward supply chain to minimize carbon impact.	Heuristic algorithm	Increased demand leads to increased profit in the first period and decreased return rates in the first period. Increased costs lead to an increase in vehicles.

Continue Table I. Related literature review

Author	Published year	Network Type	Research Objective	Solution Method	Results
Zhen et al.	2019	Sustainable green closed-loop supply chain	Present a bi-objective model to reduce chain costs and minimize CO_2 emissions.	Solving the model using the epsilon constraint method and the Lagrange relaxation method	The variable cost is more important than the fixed operational cost when the weight coefficient is less than 0.6. The importance of the CO_2 emission goal, with the control of fixed costs, and the importance of costs with the control of variable costs.
Tehrani and Gupta	2021	Sustainable green closed-loop supply chain	Present a tri-objective model to increase profits, minimize environmental impacts, and increase job opportunities in a fuzzy environment.	Data certainty with a robust fuzzy stochastic programming method and solving with GAMS software	Model effectiveness according to results obtained in the tyre industry.
Boskabadi et al.	2022	Green supply chain	Present a tri-objective model to minimize the total cost of the network, maximize net profit per capita for each human resource, and reduce CO_2 emissions across the network in a fuzzy environment.	Data certainty with a trapezoidal fuzzy method and solving the model using NSGA-II and MOPSO algorithms and a combined heuristic algorithm	The research concluded their model effectively designs a distribution network for a multi-product, multi-period green supply chain under demand uncertainty, optimizing sustainability and efficiency.
Kazancoglu et al.	2022	Green bi-channel closed-loop supply chain	Present a bi-objective model to minimize CO_2 emissions and minimize overall costs.	The solution approach used in the study by Kazancoglu et al. (2022) was an exact method, as it employed mixed-integer linear programming (MILP).	The research concluded that their mixed-integer linear programming (MILP) model effectively designs a green bi-channel closed-loop supply chain network, enhancing both environmental sustainability and operational efficiency.
Moayedi and Sadeghian	2023	Green forward supply chain	Present a tri-objective model, including minimizing the total overall cost, minimizing the variance of the total cost, minimizing the financial risk or the likelihood of not meeting a specified budget, and minimizing pollution from production machinery and transportation.	Solving the model with a meta-heuristic NSGA-II algorithm and MOPSO	The superiority of the NSGA-II algorithm compared to the Multi-Objective Ppaper Swarm Optimization (MOPSO).

Ghahremani-Nahr et al. (2023) looked at a good fuzzy mathematical programming model and a whale optimization solution method for the closed-loop supply chain network design. Quan and Guo (2023) used a fuzzy resilient programming paradigm to create a sustainable closed-loop supply chain network with efficiency-oriented multi-objective optimization. In order to overcome uncertainty in supply chain planning models, Gumte et al. (2024) looked at data-driven robust optimization. In response to unforeseen demand, Karthick and Uthayakumar (2024) created a sustainable supply chain model with two inspection flaws and carbon emissions. Khorshidvand et al. (2021) used a hybrid modeling technique that included factors like pricing, promotion, and unpredictable demand in order to construct a sustainable and ecologically friendly closed-loop supply chain. Using risk and resilience as a circular economy method, Lotfi et al. (2022) created a workable closed-loop supply chain network. Aslani Khiavi and Skandari (2022); Foroozesh and Karimi (2022); Hasan-Zadeh (2023); Hemmati et al. (2023) are among the research that have been done in this regard. A summary of the literature is included in Table I.

III. NECESSITY AND CONTRIBUTION OF RESEARCH

- Customers, rivals, governments, and international organizations all put pressure on businesses to comply with environmental rules these days. As a result, companies now include green supply chain management in their overall business plan. It is essential to tackle the green supply chain from the following perspectives: generating benefits for the environment and customer satisfaction along the entire supply chain; expanding into a new market by offering eco-friendly products; and cutting expenses by minimizing fuel expenses, resource consumption, employee hours, waste removal, and increased output. Gaining a competitive edge by adding value for consumers, satisfying them, and encouraging their devotion to goods boosts the profitability of the business.
- On the other hand, taking into account factors like lowering resource consumption, cutting pollution, and taking into account social and environmental pressures, along with improving customer satisfaction through timely product delivery and after-sales services, causes researchers and managers to pay more attention to the development and application of reverse logistics networks. Sub-optimality induced by designs is prevented by simultaneously designing forward and backward networks and by combining tactical choices (e.g., selecting vehicles for goods transportation) with strategic ones (e.g., selecting a supplier or placing facilities in the supply chain). It splits apart.
- Designing and improving a closed-loop multi-objective supply chain model that concurrently considers tactical and strategic decisions seems to be crucial in unexpected environments. This study's objective is to build a closed-loop green supply chain network that takes quality pricing, rework costs resulting from primary raw material procurement, and supply chain overhead into consideration.
- The implications of raw material quality levels on supply chain expenses and environmental repercussions throughout the course of a product's life cycle
- The impact of distance between centers on time delays, environmental consequences, and supply chain costs.

IV. PROBLEM DEFINITION AND MODELING

Figure (2) illustrates the five levels of the closed-loop green supply chain network that this research envisions: suppliers, production/reproduction centers, forward-directed distribution centers, collection/separation centers, and destruction centers.

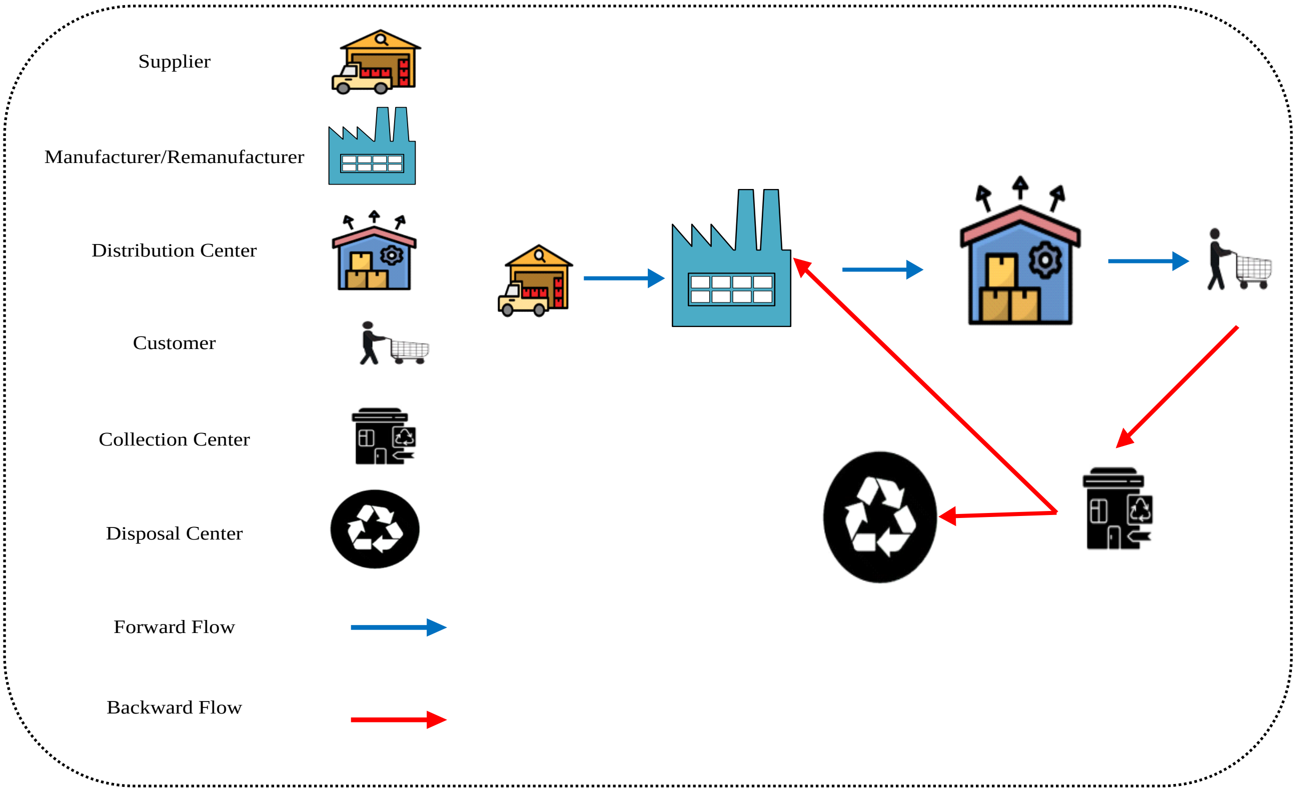

Fig. 2. Closed-loop green supply chain network considered in this research

In this network, manufacturing centers choose suppliers from the outset, purchase raw materials of varying grades, reprocess inferior raw materials to create products, and then distribute the finished goods to distribution centers. These centers then provide the clients with the things they have requested.

Through the collection/separation facilities in this network, the returned goods are retrieved. Following inspection, the goods are sorted into useable raw materials, which are then returned to the manufacturing facilities where they are replicated as upgraded or main products before being distributed to distribution locations. Additionally, waste raw materials are sent to destruction facilities for elimination.

A. Assumption

- The assumptions used for the proposed model are as follows:
- It has been taken out and modeled for this study based on the presumptions found in related concerns in the literature evaluation.
- Due to the ambiguity in the supplied data, most of the parameters are deemed fuzzy.
- Suppliers and buyers have a fixed and known location. The model is multi-period and multi-product.
- Consideration is given to a set temporal horizon that spans many eras.
- Reproduction and production hubs are integrated and seen as a single entity.
- Depending on the various quality standards, purchased raw materials are categorized into three categories: high, medium, and poor.
- It is known how much raw material is required to make each product unit.
- Customers may experience a product scarcity because of the unpredictable nature of client demand, which may exceed the amount of stock that is available.

- According to this concept, an incomplete order is regarded as a delayed order.
- By the conclusion of the intended term, every customer's demand must be met.
- At the start and finish of the period, there is no product inventory in the distribution facilities.
- Every product and every raw material has a limited capacity in the centers.
- Only between the facilities of the next two tiers of the supply chain network's layers is product flow formed.
- The reverse supply chain recycles returned goods and adds them back to the chain as raw materials. The remaining goods are disposed of and eliminated from the chain.

B. Indices

$s \in \{1,..,ST\}$	Index for suppliers
$f \in \{1,..,FT\}$	Index for production/reproduction centers
$d \in \{1,..,DT\}$	Index for distribution centers
$c \in \{1,..,CT\}$	Index for customers
$e \in \{1,..,ET\}$	Index for collection/separation centers
$m \in \{1,..,MT\}$	Index for disposal center
$i \in \{1,..,IT\}$	Index for the final completed product
$j \in \{1,..,JT\}$	Index for raw material
$t \in \{1,..,TT\}$	Index for the time period

C. Parameters

$\tilde{\gamma}_{ict}$	Customer center c's demand for product i in period t
$\tilde{\alpha}_{ict}$	Percentage of returned products i from demand point c in period t
$\tilde{\alpha}'_{jt}$	Percentage of destruction of unusable raw material j in period t
$\tilde{\alpha}''_{j}$	Percentage of recycling of each raw material type j
∂_{ij}	Percentage of raw material j needed to produce each unit of product i
β_{jst}	Minimum amount of raw material type j that must be provided by supplier s in period t
$\tilde{\delta}_{f}$	Fixed cost of setting up the production/reproduction center in the location f
$\tilde{\delta}'_{d}$	Fixed cost of setting up a distribution center in place d
$\tilde{\delta}''_{e}$	Fixed cost of setting up the collection/separation center at the location e

$\tilde{\delta}'''_m$	Fixed cost of setting up the destruction center at location m
$\tilde{\delta}''''_{if}$	Cost of production of product i in production center f
$\tilde{\varepsilon}_{idt}$	Cost of holding product i in distribution center d in period t
$\tilde{\varepsilon}'_{id}$	Cost of distributing and maintaining product i in the distribution center d
$\tilde{\varepsilon}''_{ie}$	Cost of collection/separation of returned product i at the collection center e
$\tilde{\varepsilon}'''_{je}$	Cost of recovering each unit of raw material j in the collection/separation center e
$\tilde{\varepsilon}''''_{jm}$	Cost of destroying each unit of raw material j in the destruction center m
$\tilde{\vartheta}_j$	Cost of transportation per unit of type j raw material per kilometer
$\tilde{\vartheta}'_i$	Cost Transportation per unit of type i product per kilometer
$\tilde{\mu}_{jst}$	Cost of purchasing each unit of raw material j from supplier s in period t
$\tilde{\mu}'_{jft}$	Cost of rework of each unit of raw material j in the production/reproduction center f in period t
$\tilde{\mu}''_{ict}$	Cost of shortage per unit of product i at demand point c in period t
$\tilde{\theta}_{jst}$	Capacity of supplier s to supply raw material j in period t
$\tilde{\theta}'_{ift}$	Capacity of production/reproduction centers f for product i in period t
$\tilde{\theta}''_{idt}$	Capacity of distribution center d for product i in period t
$\tilde{\theta}'''_{iet}$	Capacity of collection/separation center e for product i in period t
$\tilde{\theta}''''_{jmt}$	Capacity of recycling center m for raw material j in period t
π_{sf}	Distance of the supply center s from the production/reproduction center f
π^0_{fd}	Distance of the production/reproduction center f from the distribution center d
π'_{dc}	Distance of the distribution center d from the demand center c
π''_{ce}	Distance of the demand center c from the collection/separation center e
π'''_{ef}	Distance of the collection/separation center e from the production/reproduction center f
π''''_{em}	Distance of the collection/separation center e from the destruction center m
$\tilde{\tau}_f$	Effect of gas emitted during the establishment of the production center f
$\tilde{\tau}'_d$	Effect of gas emitted during the establishment of the distribution center d
$\tilde{\tau}''_e$	Effect of gas emitted during the establishment of the collection/inspection center e
$\tilde{\tau}'''_m$	Effect of gas emitted during the establishment of the destruction center m
$\tilde{\sigma}_{jsf}$	Effect of gas emitted per unit of raw material j from the supply center to the production center f

$\tilde{\sigma}'_{ifd}$	Effect of gas emitted for transporting each unit of product i from the production center f to the distribution center d
$\tilde{\sigma}''_{idc}$	Effect of gas emitted for transporting each unit of product i from the distribution center d to the customer center c
$\tilde{\sigma}'''_{ice}$	Effect of emitted gas per transportation of each unit of product i from the customer center c to the collection/separation center e
$\tilde{\sigma}''''_{jem}$	Effect of emitted gas per unit of raw material j from the collection/separation center e to the destruction center m
$\tilde{\rho}_{jef}$	Effect of emitted gas for transporting each unit of recycled raw material j from the collection/separation center e to the production center f
$\tilde{\rho}'_{jf}$	Effect of gas emitted for reworking raw material j in the production center f
$\tilde{\rho}''_{if}$	Effect of gas emitted per production of product i in the production center m
$\tilde{\rho}'''_{ie}$	Effect of gas emitted for separating raw material from product i in the collection/separation center e
$\tilde{\rho}'''_{jm}$	Effect of the emitted gas for the destruction of raw material j in the center of destruction m
$\tilde{\varphi}_{ict}$	Expected time of customer c for product i in period t
$\tilde{\varphi}'_{je}$	Separation time of raw material j in collection/separation center e
$\tilde{\omega}_{ifd}$	Transfer time of product i from production center f to distribution center d
$\tilde{\omega}'_{idc}$	Time to transfer product i from distribution d to customer c
$\tilde{\omega}''_{ice}$	Transfer time of product i from customer c to collection/separation e
$\tilde{\omega}'''_{jef}$	Transfer time of raw material j from collection/separation center e to production f
M	A big number

D. Positive variables

x_{jsft}	Number of raw material j shipped from supplier s to production/reproduction facility f in period t
x'_{jeft}	Number of raw material j transported from collection/separation center e to production/reproduction center f in period t
x''_{jemt}	Number of raw material j transported from collection/separation center e to recycling center m in period t
y_{ifdt}	Number of product i shipped from production/reproduction center f to distribution center d in period t
y'_{idct}	Number of product i shipped from distribution center d to demand point c in period t
y''_{icet}	Number of returned product i shipped from demand point c to collection/separation center e in period t

w_{jft}	Number of raw materials of type j reprocessed in production/reproduction center f in period t
w'_{ict}	Number of unsatisfied demand for product i for demand point c in period t
w''_{idt}	Inventory of product i at distribution center d in period t

E. Binary variables

v_f	1 if the production/reproduction center is built at location f; 0, otherwise
v'_d	1 if the distribution center is built in place d; 0, otherwise
v''_e	1 if the collection/separation center is built in place e; 0, otherwise
v'''_m	1 if the destruction center is established at location m; 0, otherwise
u_{jst}	1 if supplier s supplies raw material j in period t; and 0, otherwise
u'_{jsft}	1 if raw material j is transported from supplier s to production center f in period t; 0, otherwise

F. Mathematical model

The model's objective functions are to minimize chain costs, exhaust gas emission costs, and time delays. The first objective function includes the fixed establishment costs, the cost of obtaining raw materials from suppliers, the cost of recycling raw materials, operating expenses (production, distribution, collection/separation, destruction, reproduction), shortage costs, and transportation costs. It is the allocation of maintenance costs between facilities and inventories.

The second objective function includes minimizing the impacts of exhaust gases during setup and transportation, as well as gas emissions during product manufacture, raw material reprocessing, product separation from returned items, and raw material destruction. The third objective function also covers the reduction of time delays caused by the difference in product transit durations between existing centers and the time needed to separate recyclable raw materials from returned items from the time that customers expect.

$$\begin{aligned}
Min\ Z_1 = &\sum_{f} \tilde{\delta}_f \times v_f + \sum_{d} \tilde{\delta}'_d \times v'_d + \sum_{e} \tilde{\delta}''_e \times\times\ v''_e + \sum_{m} \tilde{\delta}'''_m \times v'''_m + \sum_{j.s.f.t} \tilde{\mu}_{jst} \times x_{jsft} + \sum_{j.f.t} \tilde{\mu}'_{jft} \times w_{jft} \\
&+ \sum_{i.c.t} \tilde{\mu}''_{ict} \times w'_{ict} + \sum_{i.f.d.t} \tilde{\varepsilon}_{if} \times y_{ifdt} + \sum_{i.d.c.t} \tilde{\varepsilon}'_{id} \times y'_{idct} + \sum_{i.c.e.t} \tilde{\varepsilon}''_{ie} \times y''_{icet} \\
&+ \sum_{j.e.f.t} \tilde{\varepsilon}'''_{je} \times x'_{jeft} + \sum_{j.e.m.t} \tilde{\varepsilon}''''_{jm} \times x''_{jemt} + \sum_{j.s.f.} \tilde{\vartheta}_j \times \pi_{sf} \times x_{jsft} + \sum_{i.f.d.t} \tilde{\vartheta}'_i \times \pi^0_{fd} \times y_{ifdt} \\
&+ \sum_{i.d.c.t} \tilde{\vartheta}'_i \times \pi'_{dc} \times y'_{idct} + \sum_{i.c.e.t} \tilde{\vartheta}'_i \times \pi''_{ce} \times y''_{icet} + \sum_{j.e.f.t} \tilde{\vartheta}_j \times \pi'''_{ef} \times x'_{jeft} \\
&+ \sum_{j.e.m.t} \tilde{\vartheta}_j \times \pi''''_{em} \times x''_{jemt} + \sum_{i.d.t} \tilde{\varepsilon}^0_{idt} \times w''_{idt}
\end{aligned} \quad (1)$$

$$\begin{aligned} min\, Z_2 = & \sum_{f} \tilde{\tau}_f \times v_f + \sum_{d} \tilde{\tau}'_d \times v'_d + \sum_{e} \tilde{\tau}''_e \times v''_e + \sum_{m} \tilde{\tau}'''_m \times v'''_m + \sum_{j.s.f.t} \tilde{\sigma}_{jsf} \times \pi_{sf} \times x_{jsft} \\ & + \sum_{i.f.d.t} \tilde{\sigma}'_{ifd} \times \pi^0_{fd} \times y_{ifdt} + \sum_{i.d.c.t} \tilde{\sigma}''_{idc} \times \pi'_{dc} \times y'_{idct} + \sum_{i.c.e.t} \tilde{\sigma}'''_{ice} \times \pi''_{ce} \times y''_{icet} \\ & + \sum_{j.e.f.t} \tilde{\rho}_{jef} \times \pi'''_{ef} \times x'_{jeft} + \sum_{j.e.m.t} \tilde{\sigma}''''_{jem} \times \pi''''_{em} \times x''_{jemt} + \sum_{j.f.t} \tilde{\rho}'_{jf} \times w_{jft} \\ & + \sum_{i.f.d.t} \tilde{\rho}''_{if} \times y_{ifdt} + \sum_{i.c.e.t} \tilde{\rho}'''_{ie} \times y''_{icet} + \sum_{j.m.e.t} \tilde{\rho}''''_{jm} \times x''_{jemt} \end{aligned} \tag{2}$$

$$\begin{aligned} min\; Z_3 = & \sum_{i.f.d.t} \widetilde{\omega}_{ifd} \times \pi^0_{fd} \times y_{ifdt} + \sum_{i.d.c.t} \widetilde{\omega}'_{idc} \times \pi'_{dc} \times y'_{idct} + \sum_{i.c.e.t} \widetilde{\omega}''_{ice} \times \pi''_{ce} \times y''_{icet} \\ & + \sum_{j.e.f.t} \widetilde{\omega}'''_{jef} \times \pi'''_{ef} \times x'_{jeft} + \sum_{j.e.f.t} \tilde{\varphi}'_{je} \times x'_{jeft} - \sum_{i.d.c.t} \tilde{\varphi}_{ict} \times y'_{idct} \end{aligned} \tag{3}$$

The constraints of the model are as follows:

$$w'_{ict} = \tilde{\gamma}_{ict} - \sum_{d} y'_{idct} + w'_{ic.t-1} \qquad \forall i.c. \quad t > 1 \tag{4}$$

$$\sum_{e} y''_{icet} = \tilde{\alpha}_{ict} \left(\tilde{\gamma}_{ic.t-1} - w'_{ic.t-1} \right) \qquad \forall\, i.c. \quad t > 1 \tag{5}$$

$$\sum_{s} x_{jsft} + \sum_{e} x'_{jeft} = \sum_{i,d} y_{ifdt} \times \partial_{ij} \qquad \forall\, j.f.t \tag{6}$$

$$w''_{idt} + \sum_{c} y'_{idct} = w''_{id.t-1} + \sum_{f} y_{ifdt} \qquad \forall\; i.d. \quad t > 1 \tag{7}$$

$$\sum_{m} x''_{jemt} = \tilde{\alpha}'_{jt} \times \sum_{i.c} y''_{icet} \times \partial_{ij} \qquad \forall\, j.e.t \tag{8}$$

$$\sum_{f} x'_{jeft} = \left(1 - \tilde{\alpha}'_{jt}\right) \times \sum_{i.c} y''_{icet} \times \partial_{ij} \qquad \forall\, j.e.t \tag{9}$$

$$\sum_{f} x_{jsft} \leq \tilde{\theta}_{jst} \qquad \forall\; j.s.t \tag{10}$$

$$\sum_{d} y_{ifdt} \leq \tilde{\theta}'_{ift} \times v_f \qquad \forall\; i.f.t \tag{11}$$

$$w''_{id.t-1} + \sum_{f} y_{ifdt} \leq \tilde{\theta}''_{idt} \times v'_d \qquad \forall\, i.d. \quad t > 1 \tag{12}$$

$$\sum_{c} y''_{icet} \leq \tilde{\theta}'''_{iet} \times v''_e \qquad \forall\, i.e.t \tag{13}$$

$$\sum_{e} x''_{jemt} \leq \tilde{\theta}''''_{jmt} \times v'''_m \qquad \forall\; j.m.t \tag{14}$$

$$\sum_{f} x'_{jeft} + \sum_{m} x''_{jemt} \leq v''_{e} \times \sum_{i} \tilde{\theta}'''_{iet} \times \partial_{ij} \qquad \forall\, j.e.t \qquad (15)$$

$$\tilde{\alpha}''_{j} \times \sum_{s} x_{jsft} = w_{jft} \qquad \forall\, j.f.t \qquad (16)$$

$$u''_{jsft} \leq u'_{jst} \qquad \forall\, j.s.f.t \qquad (17)$$

$$\sum_{f} x_{jsft} \geq \sum_{f} \beta_{jst} \times u''_{jsft} \qquad \forall\, j.s.t \qquad (18)$$

$$x_{jsft} \leq M \times u''_{jsft} \qquad \forall\, j.s.f.t \qquad (19)$$

$$w''_{id0} = 0 \qquad \forall\, i.d \qquad (20)$$

$$x_{jsft} \cdot y_{ifdt} \cdot y'_{idct} \cdot y''_{icet} \cdot x'_{jeft} \cdot x''_{jemt} \cdot w_{jft} \cdot w'_{ict} \cdot w''_{idt} \geq 0 \qquad \forall\, i.j.s.f.d.c.e.m.t \qquad (21)$$

$$v_{f} . v'_{d} . v''_{e} . v'''_{m} . u'_{jst} . u''_{jsft} \in \{0.1\} \qquad \forall\, j.s.d.f.e.m.t \qquad (22)$$

Constraint (4) indicates that the shortage for each customer is equal to the difference between total customer demand and total incoming flows from distributors to that customer in that period, plus the amount of shortage for that customer in the previous period. Constraint (5) also represents the flow rate of returned products and guarantees that all returned products are collected from customer centers. Constraints (6) and (7) show the flow rate of raw materials and product inventory in distribution centers. Constraints (8) and (9) show the amount of product flow in the destruction and reproduction centers. Constraints (10) to (15) show that the flow can flow between places where facilities have been built, and also, the amount of flow in each center must be smaller than or equal to the capacity of those centers. Constraint (16) shows the percentage of each type of raw material transported to production centers that need to be reworked. Constraint (17) shows that the contract will be completed if the supplier provides the raw materials. Constraint (18) shows that each supplier needs a minimum amount of customized raw materials to enter into a contract. Constraint (19) shows that the raw materials are transported if the contract is signed. Constraint (20) specifies the inventory of product *i* at the distribution center and *d* at the beginning of period *t*. Constraints (21) and (22) also show the type of decision variables of the problem.

V. SOLUTION APPROACH

Many input variables or characteristics, including cost, resources, and demand, are taken to be uncertain as the objective function in the actual world of optimization issues. This uncertainty may result from incomplete or unavailable data, inaccurate parameter estimations, or both. Until there is uncertainty, there are parts of the issue that are not known until it is solved, which leads to inaccurate predictions. There are two primary categories of environmental and systemic uncertainty in supply chains: Systemic uncertainty is related to the standard operations in the supply chain, such as manufacturing and distribution, whereas environmental uncertainty is associated with the performance of each link in the chain, such as manufacturers, suppliers, and so on.

To enhance the quality of decisions made at the technical, operational, and strategic levels of the supply chain, researchers try to include this two-sided uncertainty while creating reverse and closed-loop networks. Align them with the layout to more effectively illustrate the valuable aspects of actual issues. Uncertainty in optimization issues has been addressed via the use of many strategies. Four categories may be used to group these methods:

- Random-access programming
- Uncertain programming
- Random-state dynamic programming
- strong optimization.

Dantzig developed stochastic planning in the middle of the 1950s as a solution for uncertainty. In the random planning approach, chance and scenario-based planning are often employed to highlight uncertainty. Within the scenario-based approach, many scenarios with varying odds of data occurrence are used to infer uncertainty. On the other hand, when a particular probability distribution function for the desired parameter can be found, the chance programming approach is also used. There are three primary issues with this methodology:

- Determining the data's precise distribution and, thus, numericalizing the scenarios that use numbers from these distributions are difficult tasks.
- The dimensions of the derived optimization model rise exponentially with the number of scenarios, posing serious computing issues;
- The core problem loses much of its convex characteristic when the chance limit is taken into account.

This is the first time that multi-stage decision processes and their recursive solution have been expressed using stochastic dynamic programming. Uncertainty was brought up early on as a necessary component of this kind of planning. Researchers have lately been interested in an optimization-based technique, the most important aspect of which is that it does not need knowledge of the distribution function of non-deterministic parameters. The decision-maker's involvement in regulating the degree of conservatism is low in this method as neither the uncertainty budget nor the amount of uncertainty is specified. Although this result went a long way toward immunizing the issue against parameter uncertainty, it was deemed too cautious for widespread use.

The structure of constraints and objective functions are described in a fuzzy approach in fuzzy programming by taking into account model parameters in the form of fuzzy numbers, which, rather than referring to a single value, encompass a range of potential values. Set operations are then used to make the sauce. For fuzzy elements and their attributes, the fuzzy model turns into a deterministic model using the membership function will provide a fuzzy set. The membership function of a fuzzy set—that is, the function that illustrates how different members belong to a set—determines the set's level of fuzzyness. For different model components, we use different ways to try to find the degree of membership.

This method treats restrictions as fuzzy sets and random parameters as fuzzy numbers, with certain constraints being permissible to violate. The objective function is seen as a smaller, equal, bigger, or equal limit in fuzzy programming. To denote the fuzzy membership function, use the letter μ. The function, $\mu_{\tilde{A}}(x)$ denotes the extent of a member x's membership in the fuzzy set,. For two-membered sets, the range of classical membership functions is zero and one, whereas the range of fuzzy membership functions is a closed interval between zero and one. There are two different kinds of fuzzy numbers that are often used: trapezoidal and triangular. According to the image, as shown in Fig. (3), the triangular fuzzy number, A, is a fuzzy set in X with a membership function that is both trapezoidal and triangular.

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & if\ x < a \\ \frac{x-a}{b-a} & if\ \ a \le x \le b \\ \frac{c-x}{c-b} & if\ b < x < c \\ 0 & if\ x \ge c \end{cases} \tag{23}$$

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & if\ x < a \\ \dfrac{x-a}{b-a} & if\ \ a \le x \le b \\ 1 & if\ \ b \le x \le c \\ \dfrac{d-x}{d-c} & if\ \ c < x < d \\ 0 & if\ x \ge d \end{cases} \tag{24}$$

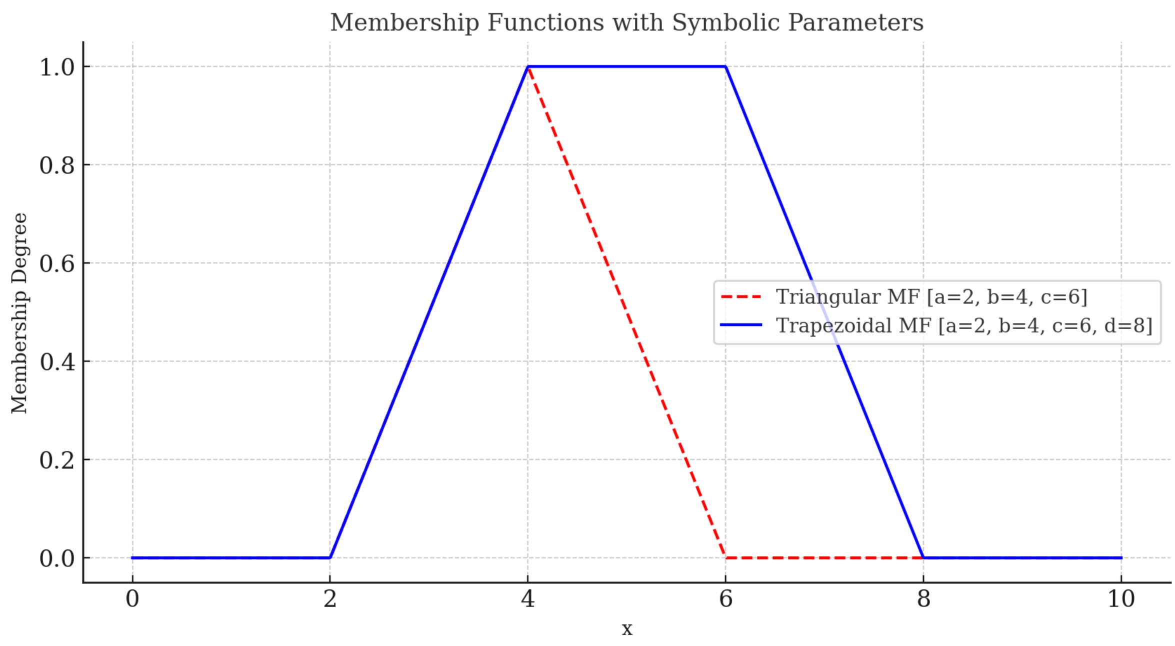

Fig. 3. Triangular and trapezoidal membership function

A mathematical model of the mixed integer programming type is presented in this work. Since uncertainty is an inherent part of the real world, most of the parameters that were used were considered triangular fuzzy numbers due to their uncertain nature. The model was solved in the following two steps: first, fuzzy parameters were employed to solve the model using Jiménez et al. (2007)'s technique. Things become similar. The multi-objective deterministic model that was constructed in the first phase is solved in the second step using the suggested approaches.

A. Equivalent auxiliary crisp model

Examine the fuzzy mathematical programming model that follows, in which all of the parameters are given in fuzzy form: In order to convert the proposed mixed integer fuzzy model into a corresponding deterministic model, this work used the methodology described by Jiménez et al. (2007).

$$
\begin{aligned}
&Min \quad Z = \tilde{c}\,X \\
&\text{s.t.} \\
&\tilde{a}_i\,X \geq \tilde{b}_i && i = 1,2,\ldots,I \\
&\tilde{a}_i\,X = \tilde{b}_i && i = I+1, I+2,\ldots,m \\
&X \geq 0
\end{aligned}
\tag{25}
$$

Suppose $\tilde{c} = (c^p . c^m . c^o)$ has the following definition for its membership function if it is a symmetric triangular fuzzy number:

$$
\mu_{\tilde{c}}(x) = \begin{cases} 0 & if \quad x < c^p \\ f_c(x) = \dfrac{x - c^p}{c^m - c^p} & if \quad c^p \leq x \leq c^m \\ 1 & if \quad x = c^m \\ g_c(x) = \dfrac{c^o - x}{c^o - c^m} & if \quad c^m \leq x \leq c^o \\ 0 & if \quad x > c^o \end{cases}
\tag{26}
$$

Finding the fuzzy parameters for the objective functions in Jiménez et al. (2007)'s method based on the concepts of the triangular fuzzy number, d, with relations (27) and (28) as respective, has the following specified expected distance (EI) and mathematical expectation (EV):

$$
\begin{aligned}
EI(\tilde{c}) = [E_1^c, E_2^c] &= \left[\int_0^1 f_c^{-1}(x)dx \;, \int_0^1 g_c^{-1}(x)dx\right] = \left[\int_0^1 (x(c^m - c^p) + c^p)dx\right] \\
&+ \left[\int_0^1 (x(c^o - c^m) + c^o)\,dx\right] = \left[\tfrac{1}{2}(c^p + c^m), \tfrac{1}{2}(c^m + c^o)\right]
\end{aligned}
\tag{27}
$$

$$
EV(\tilde{c}) = \frac{E_1^c + E_2^c}{2} = \frac{c^p + 2c^m + c^o}{4}
\tag{28}
$$

According to the minimum level of acceptable possibility ($\emptyset$), for the fuzzy Constraints of the model, which has an uncertain parameter, it is converted into a deterministic limit by equation (29) as follows:

$$
\left[(\emptyset)\;\frac{a_i^o + a_i^m}{2} + (1-\emptyset)\;\frac{a_i^p + a_i^m}{2}\right] X \geq \left[(\emptyset)\;\frac{b_i^o + b_i^m}{2} + (1-\emptyset)\;\frac{b_i^p + b_i^m}{2}\right]
\tag{29}
$$

And for the equal constraints of the model, which have non-deterministic parameters, the equivalent crisp constraint of transformation is displayed as relations (30) and (31):

$$
\left[\left(\frac{\emptyset}{2}\right) \times \frac{a_i^o + a_i^m}{2} + \left(1 - \frac{\emptyset}{2}\right) \times \frac{a_i^p + a_i^m}{2}\right] X \leq \left[\left(\frac{\emptyset}{2}\right) \times \frac{b_i^o + b_i^m}{2} + \left(1 - \frac{\emptyset}{2}\right)\;\frac{b_i^p + b_i^m}{2}\right]
\tag{30}
$$

$$
\left[\left(1 - \frac{\emptyset}{2}\right) \times \frac{a_i^o + a_i^m}{2} + \left(\frac{\emptyset}{2}\right) \times \frac{a_i^p + a_i^m}{2}\right] X \geq \left[\left(1 - \frac{\emptyset}{2}\right) \times \frac{b_i^o + b_i^m}{2} + \left(\frac{\emptyset}{2}\right) \times \frac{b_i^p + b_i^m}{2}\right]
\tag{31}
$$

The supplementary crisp model, which is the same as the primary problem model, is stated as follows in accordance with the items mentioned:

$$\begin{aligned}
min\ \ Z_1 = & \sum_{f}(\frac{\delta_f^p + 2\delta_f^m + \delta_f^o}{4}) \times v_f + \sum_{d}(\frac{\delta_d'^p + 2\delta_d'^m + \delta_d'^o}{4}) \times v_d' + \sum_{e}(\frac{\delta_e''^p + 2\delta_e''^m + \delta_e''^o}{4}) \times v_e'' \\
& + \sum_{m}(\frac{\delta_m'''^p + 2\delta_m'''^m + \delta_m'''^o}{4}) \times v_m''' + \sum_{j.s.f.t}(\frac{\mu_{jst}^p + 2\mu_{jst}^m + \mu_{jst}^o}{4}) \times x_{jsft} \\
& + \sum_{j.f.t}(\frac{\mu_{jft}'^p + 2\mu_{jft}'^m + \mu_{jft}'^o}{4}) \times w_{jft} + \sum_{i.f.d.t}(\frac{\varepsilon_{if}^p + 2\varepsilon_{if}^m + \varepsilon_{if}^o}{4}) \times y_{ifdt} \\
& + \sum_{i.d.c.t}(\frac{\varepsilon_{id}'^p + 2\varepsilon_{id}'^m + \varepsilon_{id}'^o}{4}) \times y_{idct}' + \sum_{i.c.e.t}(\frac{\varepsilon_{ie}''^p + 2\varepsilon_{ie}''^m + \varepsilon_{ie}''^o}{4}) \times y_{icet}'' \\
& + \sum_{j.e.f.t}(\frac{\varepsilon_{je}'''^p + 2\varepsilon_{je}'''^m + \varepsilon_{je}'''^o}{4}) \times x_{jeft}' + \sum_{j.e.m.t}(\frac{\varepsilon_{jm}''''^p + 2\varepsilon_{jm}''''^m + \varepsilon_{jm}''''^o}{4}) \times x_{jemt}'' \\
& + \sum_{i.c.t}(\frac{\mu_{ict}'''^p + 2\mu_{ict}'''^m + \mu_{ict}'''^o}{4}) \times w_{ict}' + \sum_{j.s.f.t}(\frac{\vartheta_j^p + 2\vartheta_j^m + \vartheta_j^o}{4}) \times \pi_{sf} \times x_{jsft} \\
& + \sum_{i,f,d,t}(\frac{\vartheta_i'^p + 2\vartheta_i'^m + \vartheta_i'^o}{4}) \times \pi_{fd}^0 \times y_{ifdt} + \sum_{i.d.c.t}(\frac{\vartheta_i'^p + 2\vartheta_i'^m + \vartheta_i'^o}{4}) \times \pi_{dc}' \times y_{idct}' \\
& + \sum_{i.c.e.t}(\frac{\vartheta_i'^p + 2\vartheta_i'^m + \vartheta_i'^o}{4}) \times \pi_{ce}'' \times y_{icet}'' + \sum_{j.e.f.t}(\frac{\vartheta_j^p + 2\vartheta_j^m + \vartheta_j^o}{4}) \times \pi_{ef}''' \times x_{jeft}' \\
& + \sum_{j.e.m.t}(\frac{\vartheta_j{}^p + 2\vartheta_j{}^m + \vartheta_j{}^o}{4}) \times \pi_{em}'''' \times x_{jemt}'' + \sum_{i.d.t}(\frac{\varepsilon_{idt}^{0\,p} + 2\varepsilon_{idt}^{0\,m} + \varepsilon_{idt}^{0\,o}}{4}) \times w_{idt}'
\end{aligned} \tag{32}$$

$$\begin{aligned}
min\ \ Z_2 = & \sum_{f}(\frac{\tau_f^p + 2\tau_f^m + \tau_f^o}{4}) \times v_f + \sum_{d}(\frac{\tau_d'^p + 2\tau_d'^m + \tau_d'^o}{4}) \times v_d' + \sum_{e}(\frac{\tau_e''^p + 2\tau_e''^m + \tau_e''^o}{4}) \times v_e'' \\
& + \sum_{m}(\frac{\tau_m'''^p + 2\tau_m'''^m + \tau_m'''^o}{4}) \times v_m''' + \sum_{j.s.f.t}(\frac{\sigma_{jsf}^p + 2\sigma_{jsf}^m + \sigma_{jsf}^o}{4}) \times \pi_{sf\times}x_{jsft} \\
& + \sum_{i.f.d,t}(\frac{\sigma_{ifd}'^p + 2\sigma_{ifd}'^m + \sigma_{ifd}'^o}{4}) \times \pi_{fd}^o \times y_{ifdt} + \sum_{i.d.c.t}(\frac{\sigma_{idc}''^p + 2\sigma_{idc}''^m + \sigma_{idc}''^o}{4}) \times \pi_{dc}' \times y_{idct}' \\
& + \sum_{i.c.e.t}(\frac{\sigma_{ice}'''^p + 2\sigma_{ice}'''^m + \sigma_{ice}'''^o}{4}) \times \pi_{ce}'' \times y_{icet}'' + \sum_{j.e.m.t}(\frac{\sigma_{jem}''''^p + 2\sigma_{jem}''''^m + \sigma_{jem}''''^o}{4}) \\
& \times \pi_{em}'''' \times x_{jemt}'' + \sum_{j.e.f.t}(\frac{\rho_{jef}^p + 2\rho_{jef}^m + \rho_{jef}^o}{4}) \times \pi_{ef}''' \times x_{jeft}' + \sum_{j.f.t}(\frac{\rho_{jf}'^p + 2\rho_{jf}'^m + \rho_{jf}'^o}{4}) \\
& \times w_{jft} + \sum_{i.f.d.t}(\frac{\rho_{if}''^p + 2\rho_{if}''^m + \rho_{if}''^o}{4}) \times y_{ifdt} + \sum_{i.c.e.t}(\frac{\rho_{ie}'''^p + 2\rho_{ie}'''^m + \rho_{ie}'''^o}{4}) \times y_{icet}'' \\
& + \sum_{j.m.e.t}(\frac{\rho_{jm}''''^p + 2\rho_{jm}''''^m + \rho_{jm}''''^o}{4}) \times x_{jemt}''
\end{aligned} \tag{33}$$

$$
\begin{aligned}
min\ \ Z_3 = &\sum_{i,f,d,t}\left(\frac{\omega_{ifd}^{p} + 2\omega_{ifd}^{m} + \omega_{ifd}^{o}}{4}\right) \times \pi_{fd}^{o} \times y_{ifdt} \\
&+ \sum_{i,d,c,t}\left(\frac{\omega_{idc}'^{p} + 2\omega_{idc}'^{m} + \omega_{idc}'^{o}}{4}\right) \times \pi_{dc}' \times y_{idct}' \\
&+ \sum_{i,c,e,t}\left(\frac{\omega_{ice}''^{p} + 2\omega_{ice}''^{m} + \omega_{ice}''^{o}}{4}\right) \times \pi_{ce}'' \times y_{icet}'' \\
&+ \sum_{j,e,f,t}\left(\frac{\omega_{jef}'''^{p} + 2\omega_{jef}'''^{m} + \omega_{jef}'''^{o}}{4}\right) \times \pi_{ef}''' \times x_{jeft}' \\
&+ \sum_{j,e,f,t}\left(\frac{\varphi_{je}'^{p} + 2\varphi_{je}'^{m} + \varphi_{je}'^{o}}{4}\right) \times x_{jeft}' \\
&- \sum_{i,d,c,t}\left(\frac{\varphi_{ict}^{p} + 2\varphi_{ict}^{m} + \varphi_{ict}^{o}}{4}\right) \\
&\times y_{idct}'
\end{aligned} \tag{34}
$$

$$
w_{ict}' \geq \left[\left(\frac{\emptyset}{2}\right) \times \frac{\gamma_{ict}^{o} + \gamma_{ict}^{m}}{2} + \left(1 - \frac{\emptyset}{2}\right) \times \frac{\gamma_{ict}^{p} + \gamma_{ict}^{m}}{2}\right] - \sum_{d} y_{idct}' + w_{ic,t-1}' \qquad \forall i, c, t < T \tag{35}
$$

$$
w_{ict}' \leq \left[\left(1 - \frac{\emptyset}{2}\right) \times \frac{\gamma_{ict}^{o} + \gamma_{ict}^{m}}{2} + \left(\frac{\emptyset}{2}\right) \times \frac{\gamma_{ict}^{p} + \gamma_{ict}^{m}}{2}\right] - \sum_{d} y_{idct}' + w_{ic,t-1}' \qquad \forall i, c, t < T \tag{36}
$$

$$
\begin{aligned}
\sum_{e} y_{icet}'' \geq &\left[\left(\frac{\emptyset}{2}\right) \times \frac{\alpha_{ict}^{o} + \alpha_{ict}^{m}}{2} + \left(1 - \frac{\emptyset}{2}\right) \times \frac{\alpha_{ict}^{p} + \alpha_{ict}^{m}}{2}\right] \\
&\times \left(\left[\left(\frac{\emptyset}{2}\right) \times \frac{\gamma_{ict-1}^{o} + \gamma_{ict-1}^{m}}{2} + \left(1 - \frac{\emptyset}{2}\right) \times \frac{\gamma_{ict-1}^{p} + \gamma_{ict-1}^{m}}{2}\right] \right. \\
&\left. - \ w_{ict-1}' \right)
\end{aligned} \qquad \forall i, c, t \tag{37}
$$

$$
\begin{aligned}
\sum_{e} y_{icet}'' \leq &\left[\left(1 - \frac{\emptyset}{2}\right) \times \frac{\alpha_{ict}^{o} + \alpha_{ict}^{m}}{2} + \left(\frac{\emptyset}{2}\right) \times \frac{\alpha_{ict}^{p} + \alpha_{ict}^{m}}{2}\right] \\
&\times \left(\left[\left(1 - \frac{\emptyset}{2}\right) \times \frac{\gamma_{ic,t-1}^{o} + \gamma_{ic,t-1}^{m}}{2} + \left(\frac{\emptyset}{2}\right) \times \frac{\gamma_{ict-1}^{p} + \gamma_{ict-1}^{m}}{2}\right] \right. \\
&\left. - \ w_{ic,t-1}' \right)
\end{aligned} \qquad \forall i, c, t \tag{38}
$$

$$
\begin{aligned}
\sum_{m} x_{jemt}'' \geq &\left[\left(\frac{\emptyset}{2}\right) \times \frac{\alpha_{jt}'^{o} + \alpha_{jt}'^{m}}{2} + \left(1 - \frac{\emptyset}{2}\right) \times \frac{\alpha_{jt}'^{p} + \alpha_{jt}'^{m}}{2}\right] \\
&\times \sum_{i,c} y_{icet}'' \times \partial_{ij}
\end{aligned} \qquad \forall\, j, e, t \tag{39}
$$

$$\sum_{m} x''_{jemt} \leq \left[\left(1-\frac{\emptyset}{2}\right)\times\frac{\alpha'^{o}_{jt}+\alpha'^{m}_{jt}}{2}+\left(\frac{\emptyset}{2}\right)\times\frac{\alpha'^{p}_{jt}+\alpha'^{m}_{jt}}{2}\right]\times\sum_{i,c} y''_{icet} \times\partial_{ij} \qquad \forall\, j,e,t \tag{40}$$

$$\sum_{f} x'_{jeft} \geq \left(1-\left[\left(\frac{\emptyset}{2}\right)\times\frac{\alpha'^{p}_{jt}+\alpha'^{m}_{jt}}{2}+\left(1-\frac{\emptyset}{2}\right)\times\frac{\alpha'^{o}_{jt}+\alpha'^{m}_{jt}}{2}\right]\right)\times\sum_{i,c} y''_{icet} \times \partial_{ij} \qquad \forall\, i,e,t \tag{41}$$

$$\sum_{f} x'_{jeft} \leq \left(1-\left[\left(1-\frac{\emptyset}{2}\right)\times\frac{\alpha'^{p}_{jt}+\alpha'^{m}_{jt}}{2}+\left(\frac{\emptyset}{2}\right)\times\frac{\alpha'^{o}_{jt}+\alpha'^{m}_{jt}}{2}\right]\right)\times\sum_{i,c} y''_{icet} \times \partial_{ij} \qquad \forall\, i,e,t \tag{42}$$

$$\sum_{f} x_{jsft} \leq \left[(\emptyset)\times\frac{\theta^{p}_{jst}+\theta^{m}_{jst}}{2}+(1-\emptyset)\times\frac{\theta^{o}_{jst}+\theta^{m}_{jst}}{2}\right] \qquad \forall\ j,s,t \tag{43}$$

$$\sum_{d} y_{ifdt} \leq \left[(\emptyset)\times\frac{\theta'^{p}_{ift}+\theta'^{m}_{ift}}{2}+(1-\emptyset)\times\frac{\theta'^{o}_{ift}+\theta'^{m}_{ift}}{2}\right]\times\ v_{f} \qquad \forall\ i,f,t \tag{44}$$

$$w''_{id,t-1}+\sum_{f} y_{ifdt} \leq \left[(\emptyset)\times\frac{\theta''^{p}_{idt}+\theta''^{m}_{idt}}{2}+(1-\emptyset)\times\frac{\theta''^{o}_{idt}+\theta''^{m}_{idt}}{2}\right]\times v'_{d} \qquad \forall\, i,d,t>1 \tag{45}$$

$$\sum_{c} y''_{icet} \leq \left[(\emptyset)\times\frac{\theta'''^{p}_{iet}+\theta'''^{m}_{iet}}{2}+(1-\emptyset)\times\frac{\theta'''^{o}_{iet}+\theta'''^{m}_{iet}}{2}\right]\times v''_{e} \qquad \forall\, i,e,t \tag{46}$$

$$\sum_{e} x''_{jemt} \leq \left[(\emptyset)\times\frac{\theta''''^{p}_{jmt}+\theta''''^{m}_{jmt}}{2}+(1-\emptyset)\times\frac{\theta''''^{o}_{jmt}+\theta''''^{m}_{jmt}}{2}\right]\times v'''_{m} \qquad \forall\ j,m,t \tag{47}$$

$$\sum_{f} x'_{jeft}+\sum_{m} x''_{jemt} \leq v''_{e} \times\sum_{i}\left[(\emptyset)\times\frac{\theta'''^{p}_{iet}+\theta'''^{m}_{iet}}{2}+(1-\emptyset)\times\frac{\theta'''^{o}_{iet}+\theta'''^{m}_{iet}}{2}\right]\times\partial_{ij} \qquad \forall\, j,e,t \tag{48}$$

$$w_{jft} \geq \left[\left(\frac{\emptyset}{2}\right)\times\frac{\alpha''^{o}_{j}+\alpha''^{m}_{j}}{2}+\left(1-\frac{\emptyset}{2}\right)\times\frac{\alpha''^{p}_{j}+\alpha''^{m}_{j}}{2}\right]\times\sum_{s} x_{jsft} \qquad \forall\ j,f,t \tag{49}$$

$$w_{jft} \leq \left[\left(1-\frac{\emptyset}{2}\right)\times\frac{\alpha''^{o}_{j}+\alpha''^{m}_{j}}{2}+\left(\frac{\emptyset}{2}\right)\times\frac{\alpha''^{p}_{j}+\alpha''^{m}_{j}}{2}\right]\times\sum_{s} x_{jsft} \qquad \forall\ j,f,t \tag{50}$$

Subject to Constraints (6) to (7) and (17) to (22).

B. Proposed fuzzy solution approach

In general, there are numerous ways for solving multi-objective linear programming (MOLP) models, which may be termed the method of the weighted sum of objectives, goal programming method, Torabi-Hassini method, epsilon-constrained method, etc. This study employs the Torabi-Hassini and the augmented epsilon-constrained techniques to solve the model, which is discussed below.

B.A. Torabi-Hassini method (TH)

The positive ideal solution depends on the degree of confidence. $\left(\emptyset - \mathrm{PIS}\right)$ and the negative ideal solution $\left(\emptyset - \mathrm{NIS}\right)$ are determined for each objective function. To obtain positive ideal solutions $\left(Z_i^{\emptyset-\mathrm{PIS}}, x_i^{\emptyset-\mathrm{PIS}}\right)$and negative $\left(Z_i^{\emptyset-\mathrm{NIS}}. x_i^{\emptyset-\mathrm{NIS}}\right)$ Every objective function, where *i* is the objective function of minimization, has to have the model solved independently. For each objective function, the following conditions may then be met to satisfy the positive and negative ideal solutions:

$$Z_i^{\emptyset-PIS} = min\, Z_i \quad , \quad Z_i^{\emptyset-NIS} = max\, Z_i \tag{51}$$

Next, the following is the determination of the linear membership functions for each objective function:

$$\mu^{\emptyset}{}_i(x) = \begin{cases} 1 & \text{if} \quad \mathrm{Z_i} \leq Z_{\mathrm{i}}^{\emptyset-PIS} \\ \dfrac{Z_{\mathrm{i}}^{\emptyset-NIS} - \mathrm{Z_i}}{Z_{\mathrm{i}}^{\emptyset-NIS} - Z_{\mathrm{i}}^{\emptyset-PIS}} & \text{if} \quad Z_{\mathrm{i}}^{\emptyset-PIS} \leq \mathrm{Z}_i \leq Z_{\mathrm{i}}^{\emptyset-NIS} \\ 0 & \text{if} \quad \mathrm{Z_i} \geq Z_{\mathrm{i}}^{\emptyset-NIS} \end{cases} \tag{52}$$

$\mu^{\emptyset}{}_i(x)$ specifies the satisfaction level of the *i*-th objective function for the confidence level $\emptyset$

The effective solution is thus guaranteed when the multi-objective model is subsequently reduced to a single-objective model using the TH approach. Its cumulative function is as follows:

$$\begin{aligned} &Max\ \lambda(x) = \gamma_{\emptyset} \times \lambda_0 + \left(1 - \gamma_{\emptyset}\right) \times \textstyle\sum_h \theta_h^{\emptyset} \times \mu_h^{\emptyset}(x) \text{s.t.} \\ &\lambda_0 \leq \mu_h^{\emptyset}(x) \quad . \qquad h = 1, .., I \\ &x \in F(x) \qquad . \qquad \lambda_0\ and\ \lambda \in [0,1] \end{aligned} \tag{53}$$

$F(x)$ specifies the reasonable area involved in model limitations. Also, $\theta_h^{\emptyset}$and $\gamma_{\emptyset}$ specify the relative importance of the *i*-th objective function and the degree of balanced importance of the degree of satisfaction of the objective functions (correction coefficient). Remarkably, the optimal value of the variable $\lambda_0 = min\{\mu_h^{\emptyset}(x)\}$ shows the minimum level of satisfaction of the objective functions, and the cumulative function *TH* is the comparison value between the operator min and the weighted collective operator searches based on the value of $\gamma_{\emptyset}$, and in other words, decision-makers can obtain two unbalanced and balanced solutions by changing the values of parameters $\theta_h^{\emptyset}$and $\gamma_{\emptyset}$ based on their preference.

Increasing the correction factor causes the value of the minimum satisfaction level of the functions to gain more weight. On the other hand, $1-\gamma_{\emptyset}$ will be smaller, and as a result, the level of satisfaction of the functions will be closer to each other, and more constraints will be fulfilled (Pishvaee and Torabi, 2010).

B.B. Augmented epsilon constraint method

To explain the mechanism of this approach, consider the following problem:

$$min\ Z_i(x) \quad max\ Z_j(x) \qquad s.t. \quad x \in S \tag{54}$$

x is the vector of choice variables, *S* is the feasible space, and the numbers *i* and *j* are the objective functions of the minimization and maximization types, respectively. The objective functions are chosen such that one is the primary function and the other functions become constraints in the epsilon constraint technique. The epsilon constraint approach may be expressed in the following generic form:

$$\begin{gathered} min \quad Z_1(x)\text{s.t.} \\ Z_i(x) \leq \varepsilon_i^{\emptyset}\ , Z_{\mathrm{j}}(x) \geq \varepsilon_j^{\emptyset}\ , x \in S \end{gathered} \tag{55}$$

where ${\varepsilon^{\emptyset}}_i$ and ${\varepsilon^{\emptyset}}_j$ determine the degree of optimality of each objective function in the constraints. In this paper, the augmented constraint epsilon method is used, and its general form is as follows:

$$\begin{gathered} min \quad (\ Z_1(x) - eps\ \times (S_{\mathrm{i}}/r_{\mathrm{i}}\ +\ S_{\mathrm{j}}/r_{\mathrm{j}}))\text{s.t.} \\ Z_i(x) + S_{\mathrm{i}} =\ \varepsilon_i^{\emptyset}\ Z_j(x) -\ S_j =\ \varepsilon_j^{\emptyset}\ \ x \in S\ \ , S_i, S_j \in R^+ \end{gathered} \tag{56}$$

where r_i, r_j are the ranges of the objective functions. S_i, S_j are auxiliary variables of the constraints, and eps can be between 10^{-6} and 10^{-3} (Mavrotas, 2009). Enhanced epsilon constraint technique phases are as follows: The issue is always solved in accordance with one of the objective functions, yielding the ideal values for each objective function. $\left(Z_j^{\emptyset-PIS}\ and\ Z_i^{\emptyset-PIS}\right)$. The values of the other objective functions are determined in this stage by combining the best solution for each objective function with other functions. $\left(Z_i^{\emptyset-NIS},\ Z_j^{\emptyset-NIS}\right)$ according to the relation, Get the value of r_i and r_{j} from the following relations:

$$r_i = Z_i^{\emptyset-NIS} - Z_i^{\emptyset-PIS},\ \ r_j = Z_j^{\emptyset-PIS} - Z_j^{\emptyset-NIS} \tag{57}$$

Make a predefined number q_i and q_j division out of the distance between the two sub-objective functions' ideal values and obtain a table of values according to the following relationship for ε_i and ε_j

$$\begin{gathered} \varepsilon_i^{\emptyset}\ = Z_i^{\emptyset-NIS} - \frac{r_i}{q_i} \times n_i \quad,\ \ n_i = 0,1, \ldots q_i \varepsilon_j^{\emptyset}\ = Z_j^{\emptyset-NIS} + \\ \frac{r_j}{q_j} \times n_j \quad,\ \ n_j = 0,1, \ldots q_j \end{gathered} \tag{58}$$

Utilize the initial objective function to solve the issue for every value of $\varepsilon_i^{\emptyset}$ and $\varepsilon_j^{\emptyset}$. Each solution obtained in this step represents a Pareto value for the problem. Choosing the optimal Pareto solution from among the Pareto solutions reported by the decision maker.

With development in the augmented epsilon constraint method, the objective function changes as follows:

$$min \quad (Z_1(x) - eps \times (S_2/r_2 + 10^{-1} \times S_3/r_3 + \cdots 10^{-(p-2)} \times S_p/r_p)) \tag{59}$$

These changes are applied to perform lexicography optimization on the rest of the objective functions, which may have other optimizations. For example, with this formulation, the solver finds the optimal solution for Z_1 and then tries to optimize Z_2, then Z_3, etc., but with the previous formulation method, the optimization order is $Z_3 - Z_2$ is different. This method forces the constrained objective functions to an orderly optimum. Suitable for solving multi-objective mixed integer programming problems, the goal of this approach is to demonstrate and assess an improvement over the original epsilon constraint technique.

By modifying its settings, this approach may reliably generate the Pareto set. By merging the missing or extra variables, the created epsilon constraint approach converts the constraints into equality and eliminates wasteful solutions. Meanwhile, according to the lexicographic technique, these variables constitute the second term in the function, but with a lesser priority. The model is forced to generate only workable solutions when the target is utilized. To choose the best solution from the group of effective ones, fuzzy logic was used in the following procedure.

For each of the objective function, the linear membership function is defined as (60), which indicates the degree of optimality of the i-th objective function in the m-th efficient solution, is the linear membership function for each of the objective functions.

$$\delta^{\emptyset}{}_i(x) = \begin{cases} 1 & \text{if} \quad \mathrm{Z_i} \le Z_{\mathrm{i}}^{\emptyset-PIS} \\ \dfrac{Z_{\mathrm{i}}^{\emptyset-NIS} - Z_i}{Z_{\mathrm{i}}^{\emptyset-NIS} - Z_{\mathrm{i}}^{\emptyset-PIS}} & \text{if} \quad Z_{\mathrm{i}}^{\emptyset-PIS} \le \mathrm{Z}_i \le Z_{\mathrm{i}}^{\emptyset-NIS} \\ 0 & \text{if} \quad \mathrm{Z_i} \ge Z_{\mathrm{i}}^{\emptyset-NIS} \end{cases} \tag{60}$$

where Z_i are the *i*-th value of the objective function in the *m*-th efficient solution, Z_i^{max} and Z_i^{min} are the minimum value of the *i*-th objective function and the maximum of the *i*-th objective function in the efficiency table, respectively. For each effective solution, the degree of membership $\rho^{\emptyset}$ according to the membership functions and also a weight-like $\theta_i^{\emptyset}$ for each objective function is defined as follows:

$$\rho^{\emptyset} = \frac{\sum_i \theta_i^{\emptyset} \times \delta^{\emptyset}{}_i(x)}{\sum_i \theta_i^{\emptyset}} \tag{61}$$

VI. COMPUTATIONAL RESULTS

This section includes a numerical example to show the applicability of the suggested model. The data utilized were extracted and simulated from the papers reviewed in the literature review (Ramezani et al., 2014; Karimi et al., 2015; Pishvaee and Torabi, 2010). Table II lists the sample's dimensions; Table III lists the amount of raw material required to produce each product unit; and Table V lists additional problem parameters. GAMS 23.6.5 software and the CPLEX solver were used to code and solve the model. All computations were performed in a Windows 7 (64-bit) environment and on a personal computer equipped with a Core i3 processor, 1.8 GHz.

In this test problem, the weights of the objective functions$\left(\theta_i^{\emptyset}\right)$ for the first to third objective functions, respectively 0.5, 0.3, and 0.2 were considered, and since the first objective function has a higher priority, The value of the correction factor $(\gamma_{\emptyset})$ is considered to be 0.1.

Table I. Test Problem

Index	*Description*	*Value*
ST	Number of suppliers	3
FT	Number of production/reproduction centers	3
DT	Number of distribution centers	3
CT	Number of customers	4
ET	Number of collection/separation centers	2
MT	Number of disposal centers	2
IT	Number of completed products	3
JT	Number of raw materials	5
TT	Number of time periods	5

Table II. The amount of raw material needed to produce each unit of product

	Raw materials				
Completed Products	**1**	**2**	**3**	**4**	**5**
1	0	2	1	0	1
2	1	0	2	0	0
3	0	1	0	1	0

Table III. Parameters included in the test problem

Parameters	**Values**	**Parameters**	**Values**
$\tilde{\mu}'_{ict}$	$uniform \sim (200 , 300)$	$\tilde{\varepsilon}_{idt}$	$\boldsymbol{uniform \sim (7, 10)}$
$\tilde{\gamma}_{ict}$	$uniform \sim (400 ,900)$	$\tilde{\alpha}_{ict}$	$\boldsymbol{uniform \sim (0.5, 0.7)}$
β_{jst}	$uniform \sim (1000 , 1500)$	$\tilde{\alpha}'_{jt}$	$\boldsymbol{uniform \sim (0.15 , 0.20)}$
$\tilde{\sigma}_{jsf}$	$uniform \sim (0.1 , 0.6)$	$\tilde{\vartheta}_{j}$	$\boldsymbol{uniform \sim (0.5, 2)}$
$\tilde{\sigma}'_{ift}$	$uniform \sim (0.3 , 0.8)$	$\tilde{\vartheta}'_{i}$	$\boldsymbol{uniform \sim (0.5, 2.3)}$
$\tilde{\sigma}''_{idc}$	$uniform \sim (0.3, 1)$	$\tilde{\delta}''''_{if}$	$\boldsymbol{uniform \sim (6, 9)}$
$\tilde{\sigma}'''_{ice}$	$uniform \sim (0.5 , 1.3)$	$\tilde{\varepsilon}'_{id}$	$\boldsymbol{uniform \sim (4, 7)}$
$\tilde{\rho}_{jef}$	$uniform \sim (0.3 , 0.8)$	$\tilde{\varepsilon}''_{ie}$	$\boldsymbol{uniform \sim (3 , 6)}$
$\tilde{\sigma}''''_{jem}$	$uniform \sim (0.1, 0.6)$	$\tilde{\varepsilon}'''_{je}$	$\boldsymbol{uniform \sim (2, 4)}$
$\tilde{\rho}'_{jf}$	$uniform \sim (0.95 , 1.55)$	$\tilde{\varepsilon}''''_{jm}$	$\boldsymbol{uniform \sim (2 , 4)}$
$\tilde{\rho}''_{if}$	$uniform \sim (0.75 , 1.8)$	$\tilde{\theta}_{jst}$	$\boldsymbol{uniform \sim (3500 , 7500)}$
$\tilde{\rho}'''_{ie}$	uniform $\sim (0.6 , 1.6)$	$\tilde{\theta}'_{ift}$	$\boldsymbol{uniform \sim (1500 , 2500)}$
$\tilde{\rho}''''_{jm}$	uniform $\sim (1.35 , 1.75)$	$\tilde{\theta}''_{idt}$	$\boldsymbol{uniform \sim (1000, 2500)}$
$\tilde{\delta}_{f}$	450000,65000,750000	$\tilde{\theta}'''_{iet}$	$\boldsymbol{uniform \sim (300 , 7000)}$
$\tilde{\delta}'_{d}$	300000,40000, 500000	$\tilde{\theta}''''_{jmt}$	$\boldsymbol{uniform \sim (1000 , 2000)}$
$\tilde{\delta}''_{e}$	190000,250000	$\tilde{\mu}_{jst}$	$\boldsymbol{uniform \sim (20 , 30)}$
$\tilde{\delta}'''_{m}$	150000,210000	$\tilde{\mu}'_{jft}$	$\boldsymbol{uniform \sim (10 , 15)}$

The solution results for the uncertain model regarding the two approaches are given in Table V.

Table V. The solution of the model in uncertain mode using the TH method and AUGMENCON2

Solution approach	Objective function z_1	z_2	z_3	Membership function $\mu(z_1)$	$\mu(z_2)$	$\mu(z_3)$	CPU-time
TH	14019500.00	1005321.105	1322.669	0.66	0.79	0.58	1.84
AUGMENCON2	13810880.49	970517.97	1389.710	0.57	0.6	0.5	77.48

Tables VI and VII show the solution results of two methods for different $\emptyset$ levels. Figures (4) to (7) also illustrate the results schematically. As can be seen, with the increase in the confidence level $(\emptyset)$, the costs of the entire supply chain increase. Therefore, it increases the costs of the model, in other words, at higher confidence levels $(\emptyset)$ there is a greater need for raw materials, products, and other sources to collect returned products and meet customers' needs.

Table VI . Computational results for $\gamma_{\emptyset} = 0.1$, $\theta_1^{\emptyset}$=0.5, $\theta_2^{\emptyset} = 0,3.$ $\theta_3^{\emptyset} = 0,2$ (TH method)

TH method							
$\emptyset - level$	Objective function z_1	z_2	z_3	Membership function $\mu(z_1)$	$\mu(z_2)$	$\mu(z_3)$	CPU-time
0.6	11809400	1095585.63	1548.38	0.838	0.682	0.54	2.13
0.7	12632720	1044384.003	1286.712	0.78	0.763	0.775	1.82
0.8	12320660	1120777.663	1515.176	0.833	0.715	0.599	1.33
0.9	13267900	1098335.45	1353.196	0.707	0.732	0.677	1.95
1	13554280	1087738.79	1403.855	0.725	0.83	0.564	1.7

Table VII. Computational results for $\theta_1^{\emptyset}$=0.5, $\theta_2^{\emptyset} = 0,3.$ $\theta_3^{\emptyset} = 0,2$ (AUGMECON2 method)

AUGMECON2 method							
$\emptyset - level$	*Objective function* z_1	z_2	z_3	*Membership function* $\mu(z_1)$	$\mu(z_2)$	$\mu(z_3)$	*CPU-time*
0.6	13035905.65	985556.59	1207.48	0.61	0.6	0.2	0.56
0.7	13108183.36	994577.36	1285.56	0.57	0.6	0.61	0.59
0.8	12899882.96	1025060.97	1661.19	0.71	0.6	0.07	0.55
0.9	12258691.16	1123154.04	1778.04	0.88	0.4	0.03	0.56
1	13064999.95	1087539.94	1669.12	0.74	0.6	0.00	0.55

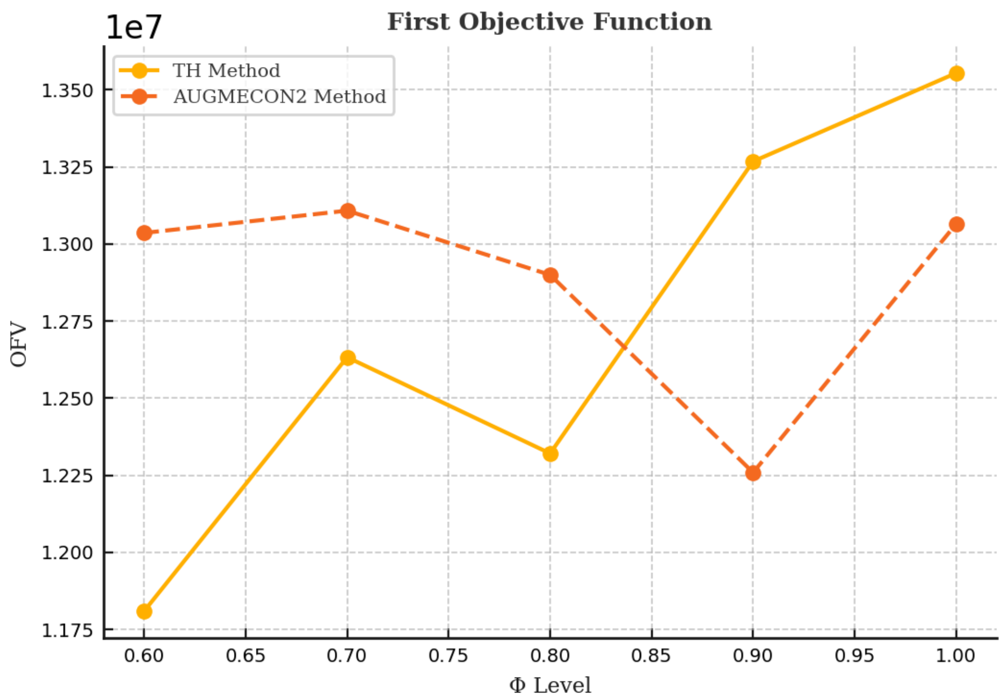

Fig. 4. Comparison of the two methods based on the first objective function

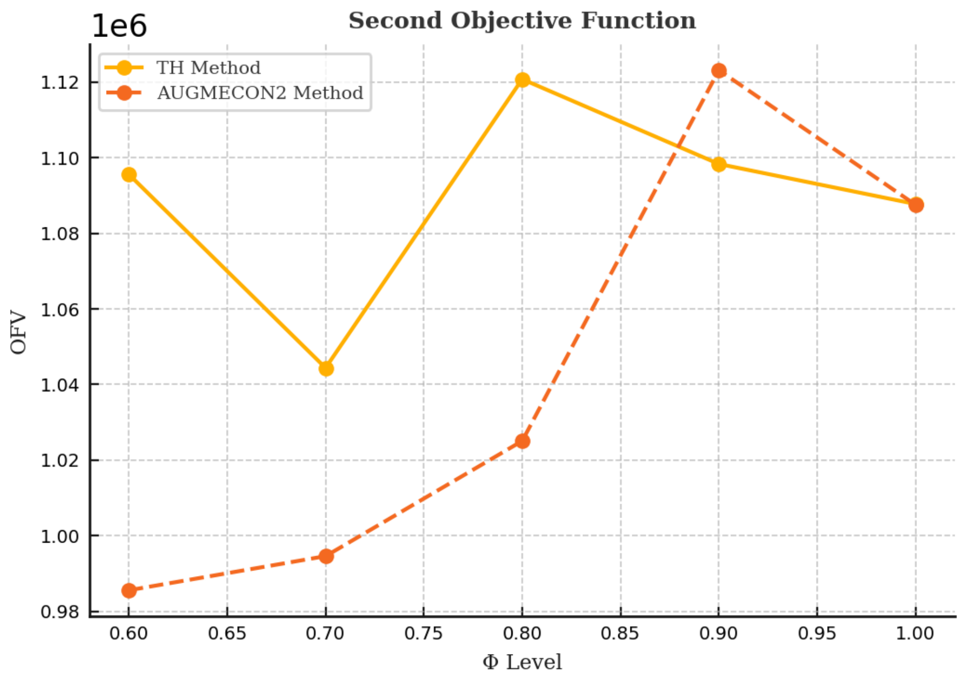

Fig. 5. Comparison of the two methods based on the second objective function

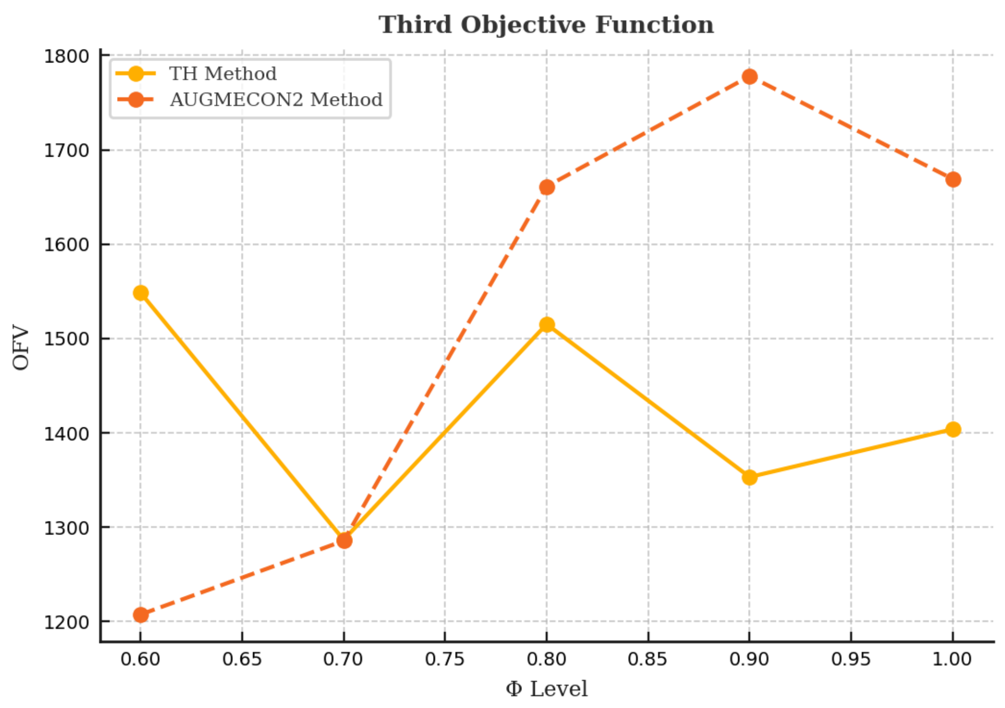

Fig. 6. Comparison of the two methods based on the third objective function

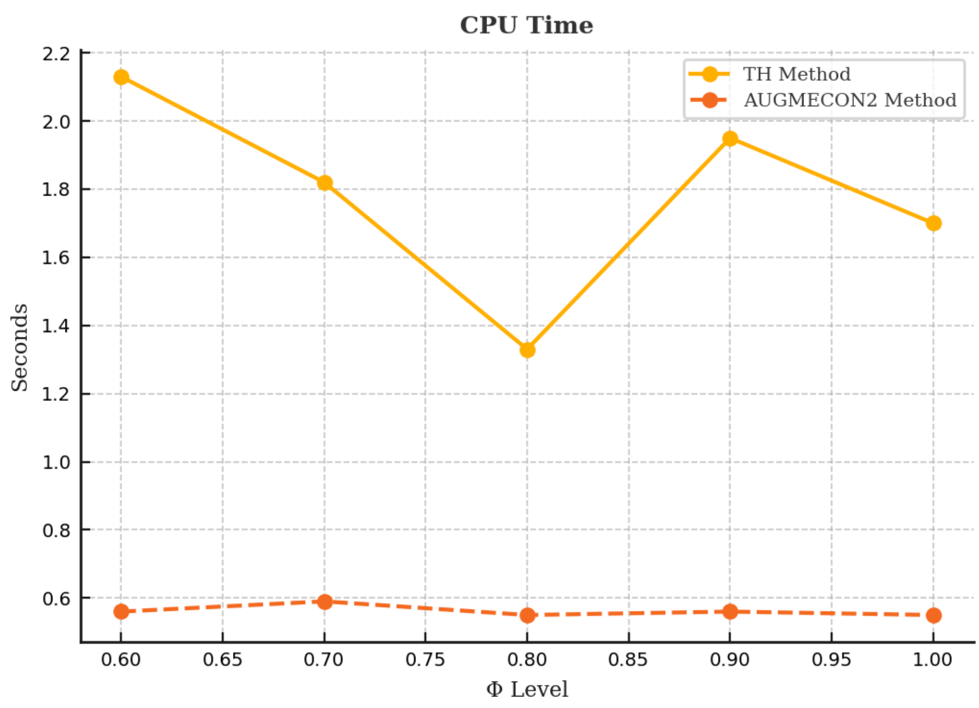

Fig.7. Comparison of the two methods based on CPU-time

Regarding the above, we interpreted results based on two categories as membership function and CPU-time for both used approaches as follows:

A. Membership function

A.A. Membership function trends across confidence levels

- TH method: This method displays a range of membership function values that generally tend to be higher than those seen in the AUGMECON2 method across similar scenarios. For example, at a confidence level of 0.6, the membership values for objectives z_1, z_2, and z_3 are respectively 0.838, 0.682, and 0.54, indicating moderate to high satisfaction with these objectives.
- AUGMECON2 method: At the same confidence level (0.6), AUGMECON2 shows membership values of 0.61, 0.6, and 0.2 for z_1, z_2, and z_3, respectively. Notably, the satisfaction of the third objective (z_3) is considerably lower compared to the TH method, suggesting a stricter constraint application or a trade-off being made against this objective.

A.B. Analysis of objective satisfaction under high confidence levels

- TH method: As the confidence level increases (approaching 1.0), the TH method seems to maintain relatively stable membership values, with a slight decrease observed in the satisfaction of the third objective (z_3). For instance, at a confidence level of 1.0, the values are 0.725, 0.83, and 0.564.
- AUGMECON2 method: In contrast, the AUGMECON2 method shows a significant drop in the satisfaction of the third objective as confidence levels increase. At a confidence level of 1.0, the membership values are 0.74, 0.6, and 0.00, indicating almost no satisfaction with the third objective.

A.C. Implications for method selection

- Flexibility vs. precision: The TH method appears more flexible, maintaining a balance across objectives even as uncertainty (confidence levels) increases. This makes it suitable for environments where compromise among objectives is acceptable for broader goal attainment.
- Rigorous constraint handling: The AUGMECON2 method, while providing less satisfaction across all objectives, particularly at higher confidence levels, seems to prioritize meeting specific objectives or constraints more rigorously. This approach may be necessary in environments where failing to meet particular standards could have significant repercussions.

B. CPU_time

B.A. CPU time trends across confidence levels

- TH method: The TH method consistently shows lower CPU times across all confidence levels compared to AUGMECON2. For example, at a confidence level of 0.6, the TH method has a CPU time of 2.13 seconds, whereas, at the same level, AUGMECON2 records a significantly higher time of 0.56 seconds.
- AUGMECON2 method: The AUGMECON2 method generally requires more CPU time at all levels of confidence. This increase in CPU time suggests a more computationally intensive process, likely due to the method's thorough exploration of the solution space and rigorous constraint satisfaction.

B.B. Comparison of high and low confidence levels

- TH method: At the lowest observed confidence level (0.6), the TH method is extremely efficient, taking just over two seconds. Even at the highest confidence level (1.0), the CPU time increases only marginally to 1.7 seconds, indicating stable computational performance despite increased complexity and uncertainty.

- AUGMECON2 method: Conversely, AUGMECON2 starts with a CPU time of 0.56 seconds at a confidence level of 0.6 and increases slightly to 0.55 seconds at a confidence level of 1.0. Despite higher times overall, the increase in CPU time is insignificant as confidence levels rise, suggesting that the method scales relatively well with increasing complexity.

B.C. Implications for method selection

- Speed vs. thoroughness: the TH method's lower CPU times suggest it is better suited for situations requiring quick solutions. It is ideal for operational environments where decisions must be made rapidly, such as in logistics or emergency supply chain management.
- Comprehensive solution search: the AUGMECON2 method, with its higher CPU times, might be more appropriate for scenarios where the depth of analysis and the quality of the solution are more critical than speed. This might be the case in strategic planning or scenarios involving high-stakes decision-making where precision is paramount.

VII. CONCLUSION

This paper addressed the use of mixed integer linear tri-objective programming to optimize a closed-loop green supply chain network.. The model sought to reduce expenses, time delays, and the effects exhaust gas emissions had on the environment. Handling several products with different raw material quality and modeling fuzzy numbers to include data uncertainty on demand, capacity, time, gas impacts, and rework percentages are important characteristics. First, we used Jiménez et al. (2007)'s approach to convert the model into a deterministic format. The model was then solved using the TH and increased epsilon constraint techniques. By giving weights to each objective function and solving at various confidence levels, the tri-objective model was reduced to a single goal using the TH technique. The most efficient solution was selected after being generated via the enhanced epsilon approach.

An example problem was created, put into the GAMS software, and solved using the CPLEX solver in order to demonstrate the efficacy of the model. This example was limited to modest dimensions, however, since NP-Hardness occurs when the problem's complexity is increased, as it does for other issues in the literature. As a result, GAMS proved insufficient for higher dimensions, and the model's applicability in real life was not confirmed.

The following is a summary of the suggestions for more research:

- ❖ Mathematical model
  - ✓ Considering recycling, repair, secondary customer centers
  - ✓ Adding the objective function of maximizing reliability for suppliers or means of transportation
  - ✓ Adding the objective function of maximizing social effects, including maximizing job opportunities created to create a sustainable supply chain problem development through changes in solution methods
  - ✓ Considering the disruption for production centers or suppliers
  - ✓ Considering capacity levels for facilities or modes of transportation
- ❖ Solution approaches
  - ✓ Considering trapezoidal fuzzy numbers to determine the parameters
  - ✓ Solving the related model provided by other single-aggregated objective methods such as LP-metric, bounded-objective (BOM), goal programming method (GP), etc.
  - ✓ Solving the presented models using multi-objective handling optimization algorithms such as non-dominated sorting genetic algorithm (NSGA-II), non-dominated ranked genetic algorithm (NRGA), multi-objective simulated annealing algorithm (MOSA), etc.
  - ✓ The second or third objective function is considered the main function in the developed epsilon constraint method, and the results obtained are checked and compared with those obtained using the existing method.

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