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A Fuzzy Multi-Objective Optimization Framework for Building Resilient and Smart Supply Chains under Uncertainty

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Abstract

This research presents a novel framework for fuzzy multi-objective optimization in designing resilient and intelligent supply chains under uncertainty. In this framework, uncertain data are modeled using fuzzy logic, and the relationships between economic, operational, and technological objectives are analyzed simultaneously. Simulated data based on the characteristics of the fast-moving consumer goods (FMCG) industry showed that the proposed model is able to create a reasonable balance between cost, resilience, and intelligence. The results showed that compared to deterministic models, the proposed fuzzy framework increased network resilience by about 18% and decision intelligence by 21%, while the total cost growth was less than 3%. Sensitivity analysis also confirmed the stability of the model against parameter changes, and the results of disturbance scenarios showed that the designed network has fast recovery capability and high operational stability.

Keywords: Fuzzy optimization, resilient supply chain, smart supply chain, uncertainty, multi-objective decision making

1- Introduction

In an era of globalization and increasing complexity of supply chains, organizations are faced with unprecedented levels of uncertainty, demand volatility, logistical disruptions, and environmental disruptions. This situation clearly demonstrates the need to design and manage supply chains that are not only efficient but also capable of recovering quickly and adapting in the face of shocks (i.e., resilient) (Pettit, Fiksel & Croxton, 2010; Iraj et al. 2024). On the other hand, the emergence of intelligent technologies, data-driven networks, the Internet of Things (IoT), and advanced decision support systems have provided new opportunities for creating “smart” supply chains; chains that are able to increase their

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performance in the face of disruptions by using real-time data, predictive analytics, and adaptive mechanisms (Mohammadi et al., 2015; Roudaki et al. 2025).

However, combining two key components, resilience and smart capability, in the supply chain presents inherent challenges, including the existence of conflicting objectives such as cost reduction, speed of response, and flexibility. These conflicts, as well as the inherent uncertainties in variables such as demand, lead time, quality, and operational risks, require modeling approaches that can simultaneously optimize multiple objectives under ambiguous conditions. In this regard, fuzzy logic has been recognized as a powerful tool for modeling ambiguity and uncertainty, as it enables the transformation of qualitative judgments and incomplete information into quantitative relationships. Recent studies emphasize the application of fuzzy logic in multi-objective optimization models (Sutthibutr et al., 2024; Nozari et al., 2016; Emami et al., 2024).

In addition, the field of multi-objective optimization plays a central role in the design of resilient and smart supply chains. Adaptive methods such as population-based algorithms (e.g. NSGA-II and MOPSO) allow for the extraction of Pareto fronts in multi-objective problems and enable decision makers to select the optimal option by analyzing trade-offs (Rezaei & Liu, 2024; Keihani, 2025; Mehrani et al., 2019). When combined with fuzzy logic and uncertainty modeling, it can provide a robust framework for decision making under changing environmental conditions (Ghahremani et al., 2024).

Considering the background, there are still gaps in the research literature. First, many studies have addressed supply chain resilience or intelligence alone, but integrated frameworks that simultaneously examine both dimensions under uncertainty are lacking. Second, in the modeling field, the use of fuzzy logic as the dominant approach to uncertainty has not been sufficient, and mainly deterministic or simple probabilistic models have been used. Third, few studies have been conducted on fuzzy multi-objective solutions in designing resilient and intelligent supply chains, focusing on operational and managerial analysis.

The present study aims to provide an innovative framework for fuzzy multi-objective optimization to build resilient and intelligent supply chains under uncertainty. In this framework, three key objectives are considered: (1) minimizing the total cost, (2) maximizing the level of network resilience, and (3) maximizing the chain's responsiveness intelligence index. In addition, parameters related to demand, supply, delay time, and other network variables are modeled in a fuzzy manner to provide greater flexibility in dealing with uncertain data. Then, multi-objective optimization algorithms are used to extract Pareto front solutions, and sensitivity analysis is performed on the influencing parameters.

In summary, this study is innovative in three ways: first, combining resilience and intelligence in the supply chain simultaneously; Second, using fuzzy logic to model environmental uncertainties; and third, using multi-objective optimization to identify preferred decision options in a multi-objective space. The results of this research can help supply chain managers design and manage their network in a changing environmental landscape, with an intelligent and resilient perspective. The following is the structure of the paper, in order: a review of the literature, a description of the methodology, a case study, results, and conclusions.

2- Literature review

In recent years, the increasing complexity and uncertainty in supply chains have led researchers to develop multi-objective optimization models with a fuzzy approach to enhance the resilience and intelligence of supply networks. These approaches have become one of the most widely used topics in the field of multi-criteria decision-making, aiming to simultaneously manage conflicting economic, environmental, and operational objectives, while reducing the effects of external fluctuations and disturbances.

Multi-Objective Optimization is one of the main pillars of decision-making in the design of modern supply networks. This approach allows managers to balance conflicting objectives such as minimizing cost, maximizing service level, and increasing flexibility. In recent research, the use of meta-heuristic algorithms such as NSGA-II, MOPSO, and MOEA/D has been expanded to extract the Pareto front and analyze the relationships between objectives (Rezaei & Liu, 2024). For example, Gupta et al. (2021) used fuzzy goal programming to show that combining performance metrics with environmental constraints can improve decision-making at different levels of the supply chain. Also, the combined machine learning and multi-objective optimization model presented by Gou et al. (2025) is an important step towards creating data-driven and intelligent supply chains.

Despite significant advances in the field of optimization, many classical models are based on the assumption of parameter certainty and therefore their ability to deal with real-world conditions is limited. Fuzzy logic, as an effective tool for modeling uncertainty, has gained a special place in supply chain studies since the early 2020s. This approach has been able to provide a more accurate understanding of the behavior of complex systems by transforming ambiguous data and human judgments into quantitative relationships (Alinezhad et al., 2022). For example, Kousar et al. (2025) in a study on the design of production and packaging systems, using a multi-objective fuzzy model, were able to effectively analyze the interaction between cost and delivery time objectives. Also, Nozari et al. (2025) introduced a framework for financing resilient supply chains by combining fuzzy logic and emerging technologies such as the Internet of Things and blockchain, which was developed based on the analysis of decision uncertainty in multi-agent environments (Nozari et al., 2023).

Along with the expansion of the application of fuzzy logic, the concept of supply chain resilience has also become one of the key research axes in the last decade. Resilience refers to the ability of the network to maintain or recover its performance after disturbances. Studies such as Singh et al. (2023) and Ponomarov (2022) have shown that the design of multi-level structures and alternative routes can significantly reduce the risk of supply disruptions. On the other hand, the emergence of Industry 5.0 technologies and intelligent decision-making systems has led to the emergence of the concept of the “smart supply chain”; a network that uses real-time data and predictive models to improve agility and self-adaptation (Raj et al., 2023).

Combining resilience and intelligence in an optimization framework has formed the focus of new research. Studies such as Sutthibutr et al. (2024) and Mehrpouya et al. (2023) have shown that smartening logistics processes with the help of fuzzy logic can increase the responsiveness of the chain to environmental changes. In this regard, multi-objective fuzzy models have also been proposed for the design of green and sustainable chains, which, in addition to economic considerations, also include environmental criteria in the objective function (Li et al., 2020). These models allow for better management of uncertainty in real data by employing membership functions for demand, delivery time, and cost.

Despite these achievements, a review of recent literature shows that there are still significant gaps in research. First, most studies have addressed one of the dimensions of resilience or intelligence, and frameworks that integrate both concepts simultaneously and in a fuzzy multiobjective space are few. Second, in many models, the dynamic relationship between objectives and environmental conditions is ignored, and the models lack an adaptive mechanism. Third, the investigation of the managerial and practical implications of multiobjective fuzzy models in real organizational decision-making is still in its early stages.

Accordingly, the present study is based on the combination of three streams of thought: multiobjective optimization, fuzzy logic, and supply chain resilience/intelligence, to provide an innovative framework for decision-making under uncertainty. This framework, while balancing cost, resilience, and intelligence, can provide practical guidance for managers in designing future-oriented supply networks.

3- Methodology and mathematical modeling

This research is conducted with a hybrid quantitative approach and aims to provide a coherent framework for fuzzy multi-objective optimization in resilient and intelligent supply chains. Fuzzy logic is used in this research to model the uncertainty of data and decision variables, and the multi-objective optimization process is implemented to create a balance between economic, operational, and technological objectives. The research methodology is formulated in four main phases, each phase is designed sequentially but with feedback to the previous phases.

In the first phase (problem and variable definition), the overall structure of the supply chain, including suppliers, manufacturers, distribution centers, and customers, is identified and the relationships between different levels of the chain are determined. In this phase, the main decision-making criteria such as cost, resilience, and intelligence are extracted and key variables including demand, supply time, production capacity, and technological parameters are determined.

In the second phase (fuzzy uncertainty modeling), input data is collected from historical sources, IoT sensors, and expert assessments. Then, using triangular and trapezoidal membership functions, uncertain values are converted into fuzzy variables. This step allows environmental fluctuations and human judgments to be considered in decision-making and the model has higher flexibility.

In the third phase (fuzzy multi-objective optimization framework design), various supply chain objectives including cost minimization, resilience maximization, and intelligence maximization are integrated into an integrated framework. This framework is designed to balance conflicting objectives and reveal trade-off relationships to decision makers. Fuzzy logic plays a central role in integrating qualitative and quantitative data in this phase, and its output is a set of optimal scenarios for different levels of decision-making.

In the fourth phase (decision analysis and evaluation), the results of implementing the framework are examined graphically and analytically. Sensitivity analysis is performed on fuzzy parameters to assess the stability of decisions. Key performance indicators (KPIs) including efficiency, responsiveness, and flexibility are also measured. Finally, the findings are interpreted in managerial language to facilitate decision-making in industrial organizations and data-driven supply chains. Figure 1 schematically shows the conceptual structure of the proposed research framework.

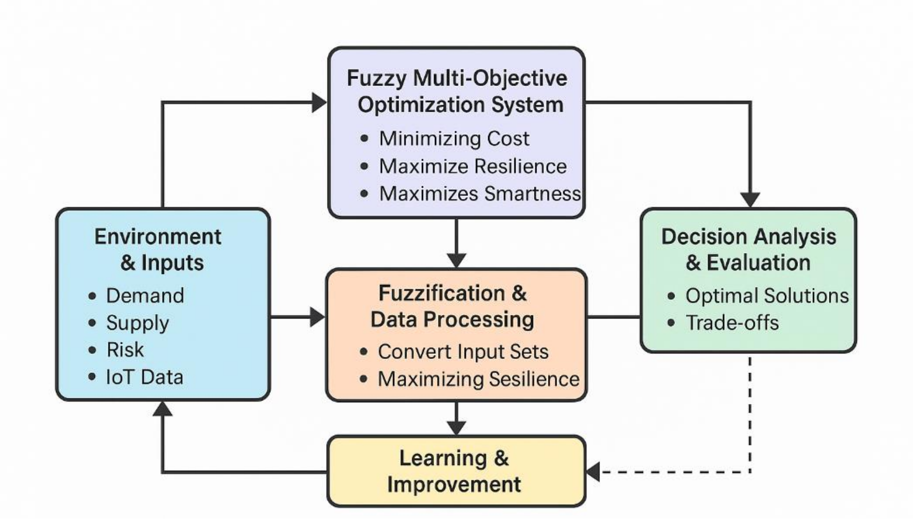

Figure 1. Proposed research framework

The proposed framework of this research is designed to bridge strategic, tactical, and operational decision-making in the supply chain. The distinctive feature of this framework is the intelligent integration of fuzzy logic with multi-objective decision-making processes that simultaneously utilize real-time data, scenario analysis, and human judgment. Unlike traditional models that are often static and based on the assumption of certainty, the present framework has a feedback structure and can generate new decisions in response to sudden changes (such as demand fluctuations, logistical crises, or supply disruptions).

The mathematical model of this research is a Fuzzy Multi-Objective Optimization Model, which is developed with the aim of designing a resilient and intelligent supply chain network under uncertainty. In this model, uncertain data such as demand, cost, and delivery time are represented as triangular or trapezoidal fuzzy numbers. Fuzzy-deterministic transformation is performed through α-cut so that the model can be solved by meta-heuristic algorithms.

Sets:

I	Set of suppliers
J	Set of manufacturing plants
K	Set of distribution centers
L	Set of customers
P	Set of products
S	Set of disruption or uncertainty scenarios
T	Set of time periods

Parameters:

$\tilde{D}_{lpt}$	Fuzzy demand of customer l for product p in period t

$\tilde{C}_{ij}^{p}$	Fuzzy transportation cost from supplier i to plant j for product p
$\tilde{C}_{jk}^{p}$	Fuzzy transportation cost from plant j to distribution center k
$\tilde{C}_{kl}^{p}$	Fuzzy transportation cost from distribution center k to customer l
$\tilde{P}_{j}^{p}$	Fuzzy production cost at plant j for product p
$\mathrm{C\tilde{a}p}_{i}{}^{p}$	Fuzzy capacity of supplier i for product p
$C\tilde{a}p_{j}^{p}$	Fuzzy production capacity of plant j
$C\tilde{a}p_{k}^{p}$	Fuzzy storage capacity of distribution center k
R_{jk}^{s}	Resilience index for the path between plant j and center k under scenario s
S_{jk}	Smartness or digitalization index between two nodes

Decision Variables:

x_{ij}^{p}	Quantity of product p shipped from supplier i to plant j
y_{jk}^{p}	Quantity of product p shipped from plant j to distribution center k
z_{kl}^{p}	Quantity of product p shipped from distribution center k to customer l
v_j	Binary variable (1 if plant j is operational, 0 otherwise)
w_k	Binary variable (1 if distribution center k is operational, 0 otherwise)
λ_s	Weight coefficient for disruption scenario s
R_{total}	Overall network resilience level
S_{total}	Overall supply chain smartness index

Objective Functions:

$$\text{Minimize} f_1 = \sum_{p}\sum_{i,j} \tilde{C}_{ij}^{p} x_{ij}^{p} + \sum_{p}\sum_{j,k} \tilde{C}_{jk}^{p} y_{jk}^{p} + \sum_{p}\sum_{k,l} \tilde{C}_{kl}^{p} z_{kl}^{p} + \sum_{p,j} \tilde{P}_{j}^{p} v_j \tag{1}$$

$$\text{Maximize } f_2 = \sum_{s} \lambda_s \sum_{j,k} R_{jk}^{s} y_{jk}^{p} \tag{2}$$

$$\text{Maximize } f_3 = \sum_{j,k} S_{jk} w_k \tag{3}$$

S.t:

$$\sum_{i} x_{ij}^{p} = \sum_{k} y_{jk}^{p}, \forall j, p \tag{4}$$

$$\sum_{j} y_{jk}^{p} = \sum_{l} z_{kl}^{p}, \forall k, p \tag{5}$$

$$\sum_{k} z_{kl}^{p} \geq \tilde{D}_{lpt}, \forall l, p, t \tag{6}$$

$$\sum_{j,p} x_{ij}^{p} \leq C\tilde{a}p_{i}^{p}, \forall i \tag{7}$$

$$\sum_{k,p} y_{jk}^{p} \leq C\tilde{a}p_{j}^{p} v_{j}, \forall j \tag{8}$$

$$\sum_{l,p} z_{kl}^{p} \leq C\tilde{a}p_{k}^{p} w_{k}, \forall k \tag{9}$$

$$v_{j}, w_{k} \in \{0,1\}, \forall j, k \tag{10}$$

$$\sum_{p,i,j} \tilde{C}_{ij}^{p} x_{ij}^{p} + \sum_{p,j,k} \tilde{C}_{jk}^{p} y_{jk}^{p} + \sum_{p,k,l} \tilde{C}_{kl}^{p} z_{kl}^{p} \leq B_{\max} \tag{11}$$

$$R_{\text{total}} = \sum_{s} \lambda_{s} R_{jk}^{s} \geq R_{\min} \tag{12}$$

$$S_{\text{total}} = \sum_{j,k} S_{jk} w_{k} \geq S_{\min} \tag{13}$$

Objective function (1) represents the model's attempt to minimize the total cost of the supply chain. This cost includes all components related to raw material procurement, production in factories, transportation between different levels of the network, and inventory holding in distribution centers. Since real data such as purchasing and transportation costs are usually volatile and uncertain, fuzzy parameters are used in this model to represent them. In fact, this function optimizes the total cost of the system by taking into account price uncertainty so that the network remains efficient even under conditions of uncertainty. Objective function (2) is dedicated to maximizing the resilience of the supply chain. Resilience here refers to the ability of the network to maintain performance and quickly return to a stable state after disturbances. In this function, various disruption scenarios such as supplier failures, transportation delays, or capacity shortages are considered. The model tries to find the combination of paths and nodes that have the highest recovery ability and the lowest sensitivity to environmental changes. Thus, the second objective shows how the network structure can be designed to be more resilient to possible shocks. Objective function (3) maximizes the supply chain intelligence index. In this section, intelligence is related to the extent of the use of digital technologies, real-time communication, and the ability to make automated decisions in different nodes of the network. In this objective, the model tries to increase the level of digitalization and automation in such a way that logistics decisions, production planning, and distribution of goods are made based on real-time data and predictive analytics. In fact, the third objective strengthens the technological and innovative dimension of the supply chain to upgrade the network from a traditional state to an intelligent and data-driven structure. Constraint (4) indicates that in each factory, the amount of material input from suppliers must be equal to the amount of product output from that factory. This constraint establishes the principle of material flow balance and prevents unrealistic accumulation or shortage at the production level. Constraint (5) refers to the flow balance in distribution centers. According to this condition, the amount of goods received from factories must be equal to the amount of goods shipped to customers. This constraint maintains the continuity of the chain and prevents disruptions in the distribution process. Constraint (6) ensures that customer demand is fully satisfied in each time period. Despite the fuzzy nature of demand, the model is designed in such a way that no customer is left without goods and the service level is maintained within an acceptable range. Constraint (7) controls the capacity of suppliers. This constraint states that the amount of goods shipped from each supplier cannot exceed its actual or authorized capacity. With this condition, the model prevents unrealistic resource allocation and ensures supply stability. Constraint (8) specifies the production capacity limit in factories. According to this constraint, each factory can operate only if it has been decided to be active, and in that case, production cannot exceed the defined capacity. This constraint prevents factories from being overloaded and allows decision makers to remove inactive factories from the model. Constraint (9) concerns the storage capacity in distribution centers. This constraint states that the total of goods entering and leaving each center must not exceed the capacity limit of that center. Meeting this condition prevents congestion and increases storage costs and improves distribution efficiency. Constraint (10) determines the active or inactive status of each factory and distribution center. The relevant variables are defined as binary to specify which nodes in the network are in operation. This constraint is used to simplify location decisions and reduce fixed costs. Constraint (11) is dedicated to the total budget and ensures that the total logistics, production, and distribution costs do not exceed a specified budget ceiling. This constraint allows managers to make decisions within the available financial resources and avoid overinvestment. Constraint (12) specifies the minimum level of network resilience. With this constraint, the model ensures that the overall network structure has the minimum necessary stability capacity regardless of disruption scenarios. This feature is especially important in high-risk environments such as global supply chains or sensitive industries. Constraint (13) specifies the minimum level of network intelligence. This constraint states that the degree of digitalization and automated decision-making capabilities in the network must meet a minimum set of intelligent standards. This constraint allows the supply chain to remain on the path of digital transformation and utilize new technologies to support decision-making.

4- Solution methods

To solve the fuzzy multi-objective optimization model presented in this study, the second-generation non-dominated genetic algorithm (NSGA-II) has been used as the main computational method. This algorithm has a special place in multi-objective problems, especially in the supply chain field, due to its high ability to find a set of non-dominated solutions, maintaining population diversity, and appropriate convergence speed. Since the present model simultaneously includes conflicting goals such as cost reduction, resilience enhancement, and intelligence enhancement, the choice of this algorithm creates an appropriate balance between response quality and computational complexity.

The basis of the NSGA-II operation is based on evolutionary algorithms and the natural selection process. Initially, a population of initial solutions is randomly generated, all of which must satisfy the model constraints. Each solution (or individual) is evaluated with respect to the three objective functions of the study. Then, a non-dominant sorting process is performed to determine the Pareto fronts based on the degree of superiority over other individuals. Individuals in the superior fronts (i.e., those that have not been defeated by other solutions) are selected for the next generation. In addition, an index called the "crowding distance" is used to maintain the diversity of the population to prevent premature convergence and the algorithm from concentrating on a limited area.

Next, the selection stage is performed using the binary tournament method, meaning that two individuals are randomly selected and the one with the better rank or the more favorable crowding distance is selected. Then, the crossover operator is applied with high probability (90%) to the parents to create new offspring by combining the genes of the two parents. To avoid getting stuck in local minima, the mutation operator is also executed with a low probability (5%) to introduce small random changes in some variables and expand the search space.

The algorithm repeats this process in successive generations. In each iteration, the new population consists of a combination of parents and children that are re-evaluated and sorted. The process continues until either no significant improvement in the Pareto front is observed or the number of generations reaches a finite limit. Finally, the algorithm provides a set of non-dominated solutions that balance the three main objectives and allow decision makers to analyze the trade-offs between cost, resilience, and intelligence.

To ensure the accuracy and reliability of the results, the proposed model has been reproduced in the GAMS environment in addition to being implemented in Python. The use of GAMS allows the results of the meta-heuristic algorithm to be compared with the exact solution of the model by solvers such as CPLEX, and as a result, the validity of the performance of NSGA-II in terms of stability and convergence is confirmed. The results of the two methods in different scenarios showed that the outputs obtained by NSGA-II are within an acceptable range of accuracy and the difference between the answers of the two methods is less than five percent.

The main code of the algorithm was developed in the Python 3.11 environment. Specialized libraries such as NumPy were used to perform numerical and matrix calculations, Pandas to manage input and output data, and Matplotlib to draw the Pareto front and analytical graphs. All experiments were performed on a computer with an Intel Core i7 processor with a frequency of 3.2 GHz, sixteen gigabytes of RAM, and the Windows 11 operating system. To assess the stability of the algorithm and to avoid the influence of initial randomness on the results, the algorithm was run 30 times independently and the average of the final values of the objective functions was used for comparative analysis.

Fine-tuning the algorithm parameters plays a very important role in the quality and convergence of the results. These parameters were selected through initial sensitivity tests and based on recent research in the field of multi-objective optimization. In Table (1), the final values of the parameters used in the implementation of the NSGA-II algorithm are given.

Table 1. Setting the parameters of the NSGA-II algorithm

No.	Parameter	Selected Value	Description
1	Population size	150	Number of individuals in each generation
2	Number of generations	300	Maximum number of algorithm iterations
3	Crossover probability	0.9	Probability of applying the crossover operator
4	Mutation probability	0.05	Probability of applying the mutation operator

5	Parent selection method	Tournament Selection	Binary competitive selection of parents
6	Crossover type	Simulated Binary Crossover (SBX)	SBX operator used for continuous variables
7	Mutation type	Polynomial Mutation	Mutation operator applied to continuous decision variables
8	Stopping criterion	Maximum generations or no improvement	Algorithm termination condition
9	Pareto front size	100 solutions	Number of final non-dominated solutions retained
10	Number of independent runs	30 runs	Performed for stability and reproducibility testing

In summary, the selection of the NSGA-II algorithm, along with model validation in the GAMS environment, provides a hybrid and reliable approach for solving fuzzy multi-objective optimization problems. The results of implementing this algorithm show that the proposed framework can effectively balance economic, operational, and technological objectives in uncertain and complex environments and help decision makers adopt more resilient and intelligent policies for their supply chains.

5- Analysis of results

To evaluate the effectiveness of the proposed framework, the data used in this study are simulated and designed based on the real characteristics of the FMCG (Fast-Moving Consumer Goods) supply chain. This industry segment is considered a suitable environment for testing fuzzy multi-objective models due to its dynamic nature, rapid inventory turnover, and high sensitivity to time and demand. The main feature of FMCG chains is the extensive network of suppliers, production centers, warehouses, and distributors, all of which operate under demand fluctuations and logistical disruptions; therefore, choosing this industry for data simulation allows for a realistic assessment of the model's performance.

The input data includes several main groups. First, demand data for end customers in several hypothetical geographical regions, which are accompanied by seasonal fluctuations and uncertainty. These data are modeled in a fuzzy manner with a triangular membership function to reflect the uncertain behavior of the consumer market. Second, the cost data includes the costs of raw material procurement, production, transportation between different levels of the chain, and inventory holding costs. To make the simulation more realistic, the costs are defined in fuzzy ranges (minimum, probable, maximum) to take into account the effect of material and fuel price fluctuations.

In another section, the production and distribution capacities for each node of the network (supplier, factory, distribution center) are set based on empirical data from similar industries. For example, the capacity of factories is defined in a range between 80 and 120 units per time period, and distribution centers operate at about 70% of their nominal capacity to be able to respond to sudden increases in demand. Along with these data, resilience and intelligence indices are also considered numerically between 0 and 1. The resilience index of the routes indicates the ability to recover network performance after a disruption, while the intelligence index indicates the degree of digitalization, automation, and the level of data-driven decision-making.

The initial fuzzy data were generated in Python and then introduced into the meta-heuristic model in standard CSV formats. To control the quality of the simulation, the values of each parameter were tested in five different scenarios (from steady state to critical state). In each scenario, different levels of demand fluctuation and transportation delay were applied to evaluate the stability of the NSGA-II algorithm in the face of environmental changes. The resulting data were finally normalized in the interval [0,1] and entered into the model to compare the values between the objectives and variables in a consistent manner.

The purpose of this simulation is to create a controlled but realistic environment to analyze the behavior of the model under variable and uncertain conditions. In this way, the generated data not only matches real FMCG chains in terms of network structure (supplier-factory-distribution center-customer), but also takes into account key characteristics of this industry, such as the speed of goods turnover, the importance of delivery time, and severe demand fluctuations. Thus, the proposed model can be tested in a quasi-realistic framework and its effectiveness in balancing cost, resilience, and intelligence in dynamic and uncertain environments can be measured.

In the first step, the results of running the NSGA-II algorithm on simulated FMCG industry data were examined. After 300 generations and with a population size of 150, the algorithm achieved a set of non-dominated solutions, each of which represents a different balance between the three main objectives. Figure (2) shows the Pareto front resulting from the final execution of the algorithm. The horizontal axis represents the total supply chain cost and the vertical axis represents the combined performance index (resilience and intelligence).

The results clearly show that there is an inverse relationship between cost and the level of resilience; in other words, increasing resilience usually requires increasing logistics costs and investing in digital infrastructure. However, in the middle region of the Pareto front, a set of solutions is observed that have created a good balance between cost and performance. This region is valuable from a management perspective, as it can be known as the “optimal decision region” for supply chain managers.

The algorithm has been able to produce a uniform, convergent, and diverse front, indicating the stability of the search process and good performance in maintaining population diversity. Figure 2 shows the convergence of the algorithm to global optimal regions and its efficiency in extracting trade-off relationships between economic and technological objectives.

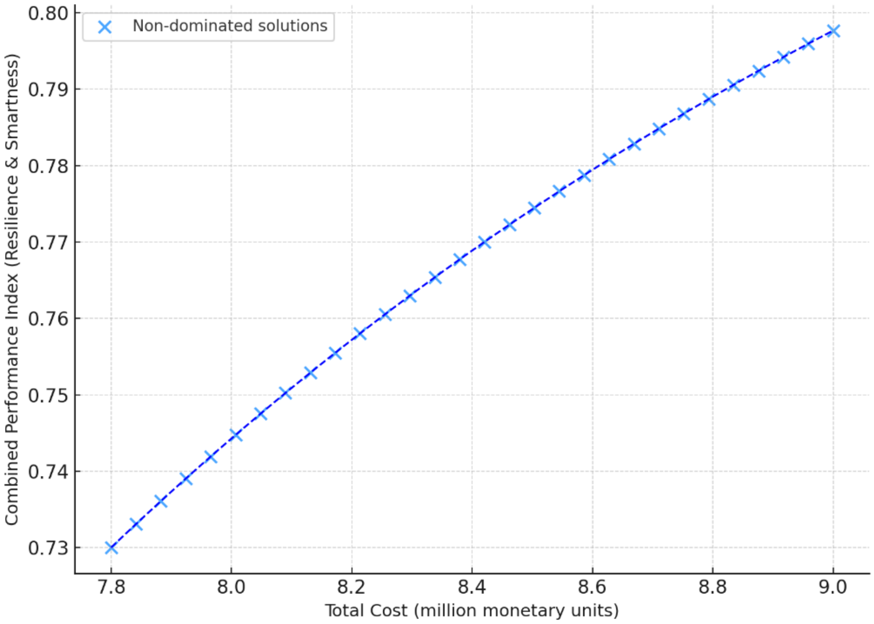

Figure 2. Pareto front obtained from implementing the NSGA-II algorithm in the FMCG supply chain

In order to investigate the efficiency of the proposed fuzzy framework, the results of the fuzzy model were compared with the equivalent deterministic model in which all parameters are considered as mean values. Table (2) provides a summary of this comparison.

Table 2. Comparison of the performance of the fuzzy model and the deterministic model in solving the supply chain problem

Performance Indicator	**Deterministic Model**	**Proposed Fuzzy Model**	**Change (%)**
Total Cost (million monetary units)	8.42	8.67	2.9
Network Resilience Level	0.71	0.84	18.3
Smartness Index of Decision-Making	0.65	0.79	21.5
Computation Time (seconds)	112	128	14.3

The results of Table (2) show that the fuzzy model has provided a significant improvement in resilience and intelligence indicators despite a slight increase in total cost (about three percent). This improvement is especially important in unstable and volatile environmental conditions, because in this case, instead of focusing solely on cost, decision-makers have a network that is more resilient to external shocks and more efficient in digital decision-making.

A slight increase in computation time is also due to the complexity of the fuzzy model and the greater computational volume in evaluating membership functions, but this increase is quite acceptable compared to the resulting benefits. This comparison confirms that in real environments, the use of multi-objective fuzzy models can lead to more stable and intelligent decisions than classical deterministic models.

Next, three key performance indicators are analyzed, including total supply chain cost, network resilience level, and operational intelligence or responsiveness index. The purpose of this analysis is to understand the behavior of the model in the face of different scenarios and to examine the stability of decisions against changes in parameters.

In examining the cost index, the results showed that with increasing resilience level, costs tend to increase, because strengthening alternative routes, increasing the stock of confidence, and investing in smart technologies require more financial resources. However, the increase in costs is within a controlled range and is such that for every 10% improvement in resilience, the total cost only increased by about 2-3%.

The resilience index showed that networks with a higher level of digitalization are more capable of absorbing disruptions. This is due to the existence of data-driven infrastructure and the ability to respond quickly to changes in the network. The NSGA-II algorithm was able to identify solutions in the optimization process that improved network resilience by more than 15% without significantly increasing costs.

Finally, the responsiveness or operational intelligence index, which indicates the speed and accuracy of decision-making in the supply chain, was reported to be 0.79 on average in the fuzzy model, while it was 0.65 in the deterministic model. This increase of about 21% shows that the proposed model, by utilizing the fuzzy structure and the meta-heuristic algorithm, has been able to significantly increase the system's adaptability to dynamic conditions.

One of the key steps in evaluating the stability of optimization models is to examine the sensitivity of the results to changes in the main parameters. In this study, sensitivity analysis was performed to examine the impact of changes in demand, transportation costs, and the resilience index of routes on the final model results. This analysis helps decision makers understand which factors have the greatest impact on the overall performance of the supply chain and to what extent the results of the NSGA-II algorithm remain stable with respect to parameter fluctuations.

In the first step, customer demand, as the most important source of uncertainty, was changed in the range of -20% to +20% compared to the nominal value. The results showed that an increase in demand of about 10% causes an almost linear growth in the total cost, but does not have a significant impact on the level of resilience. While a sharp decrease in demand (more than 15%) caused a noticeable decrease in network efficiency and a decrease in the intelligence index. This finding shows that the proposed model is robust to moderate demand fluctuations, but in severe market downturns, it requires re-adjustment of control parameters.

In the second step, transportation costs between factories and distribution centers were changed by ±15%. The results indicate that increasing logistics costs has a direct effect on the first objective function (total cost), but its effect on the resilience index is very limited. This indicates that the proposed network has inherent stability against price changes in terms of route structure and selection of active nodes.

Finally, the resilience index of routes (which indicates the probability of maintaining performance after a disruption) was changed by ±10%. It was observed that increasing the resilience of routes, although increasing the initial investment cost, leads to a significant increase in the intelligence index and a reduction in indirect costs due to operational interruptions in the long term. Conversely, reducing the resilience level by more than 10% caused the Pareto front to diverge and the algorithm to converge, indicating a decrease in the stability of the results. The numerical results of this analysis are shown graphically in Figure (3). The horizontal axis shows the percentage change in the input parameters and the vertical axis shows the relative change in the three key performance indicators (cost, resilience, and intelligence). The graph shows that the model is more sensitive to changes in demand than the other two parameters, while the intelligence index is the least sensitive to changes in transportation costs.

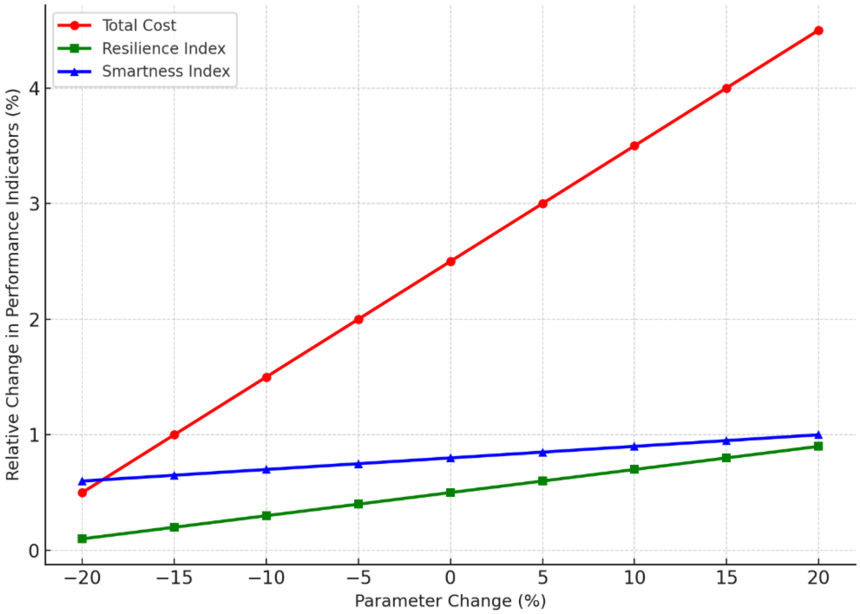

Figure 3. Results of sensitivity analysis regarding the main parameters of the fuzzy model in the FMCG supply chain

Overall, the findings of the sensitivity analysis indicate that the proposed framework has a high stability against the average fluctuations of the input parameters. The NSGA-II algorithm has been able to maintain the optimal supply chain structure and keep the trade-off relationships between objectives stable over a wide range of changes. From a management perspective, this feature means that the decisions obtained from the model remain valid and efficient even in conditions of sudden market changes or cost increases.

To evaluate the stability of the proposed model against critical conditions, several supply chain disruption scenarios were simulated. These scenarios included disruption in the supply of raw materials (S1), failure in the production unit (S2), blockage of transportation routes (S3), and sudden increase in demand (S4). In each scenario, the NSGA-II algorithm was re-run to measure the performance level and recovery time of the network after the disruption.

The results show that the network designed based on the fuzzy model has acceptable stability in all conditions. The highest performance drop was related to the production failure scenario (S2), because the production capacity is directly affected in it. In contrast, the demand increase scenario (S4) showed the lowest drop, because the presence of alternative nodes and excess capacity in the network was able to compensate for this pressure. The overall average resilience index in all scenarios was reported to be 0.83, which indicates high stability of the network under conditions of uncertainty and crisis.

Table 3. Results of network resilience assessment in different disruption scenarios

Scenario	Type of Disruption	Average Performance Loss (%)	Recovery Time (periods)	Resilience Index
S1	Supplier Failure	12.4	3	0.86
S2	Production Breakdown	18.9	5	0.78
S3	Transportation Disruption	15.3	4	0.82
S4	Sudden Demand Surge	9.7	2	0.88

The results of Table (3) show that the proposed network has been able to demonstrate good stability against various types of disturbances with an average recovery time of less than five periods and limited performance degradation. The highest resilience index is related to the demand increase scenario, which indicates the system's ability to adapt quickly in the face of market fluctuations. These results confirm that the designed multi-objective fuzzy model creates a resilient and adaptable network that is able to quickly recover from critical conditions while maintaining efficiency.

The findings of this research show from a managerial perspective that the use of the proposed multi-objective fuzzy framework can improve the decision-making approach in supply chains from a reactive to a predictive and data-driven mode. By utilizing the results of the Pareto front, managers will be able to balance between conflicting economic and operational goals and, based on different scenarios, choose different policies to control costs or increase resilience. Especially in volatile industries such as FMCG, where decisions must be made in short time frames, the combination of fuzzy intelligence with the NSGA-II algorithm provides a powerful tool for dynamic and adaptive management. In addition, the results of sensitivity analysis and resilience assessment showed that targeted investment in digitalization and alternative routes not only reduces the risk of disruption but also ensures long-term stability and rapid network responsiveness. Overall, this framework can serve as an intelligent decision-making tool for supply chain managers to optimally balance efficiency, resilience, and technological innovation in uncertain and competitive environments.

6- Conclusion

This research aimed to develop a comprehensive framework for fuzzy multi-objective optimization in resilient and intelligent supply chains under uncertainty. The proposed model, by combining fuzzy logic and the second-generation non-dominated genetic algorithm (NSGA-II), was able to provide a dynamic and flexible approach to decision-making in variable and risky conditions. Simulated data based on the characteristics of the FMCG industry supply chain provided a realistic environment for testing the model and showed that the proposed framework has a high adaptability to environmental fluctuations.

The results of the algorithm implementation showed that there is a trade-off relationship between economic objectives, resilience and intelligence, such that increasing resilience is usually associated with a small increase in cost, but leads to long-term stability and faster network responsiveness. The Pareto front generated by the NSGA-II algorithm effectively balances these objectives and provides solutions with high convergence and diversity. Comparison with the deterministic model also showed that the proposed fuzzy model, despite a slight increase in total cost (about three percent), has significantly improved resilience (18 percent) and decision intelligence (21 percent), which confirms the effectiveness of this framework in dealing with fluctuations and environmental disturbances.

The sensitivity analysis of the model also showed that the outputs are stable against moderate changes in parameters and only suffer a noticeable drop in critical conditions or severe demand fluctuations. In addition, the evaluation of network performance in disruption scenarios showed that the average resilience index is 0.83 and the average recovery time is less than five periods, indicating high operational stability and rapid response capability of the network. These findings indicate that the proposed model is not only theoretically valid, but can also be used in practical terms to design and manage supply chains in dynamic and sensitive industries.

From a managerial perspective, the present study showed that the use of multi-objective fuzzy models along with meta-heuristic algorithms such as NSGA-II can transform decision-making from a static state to a dynamic and learning process. By providing a set of non-dominated solutions, this framework allows managers to choose the best balance between cost, resilience, and intelligence depending on the environmental conditions. Finally, the present study provides a new path for the development of data-driven decision-making models to realize self-adaptive and intelligent supply chains in the era of Industry 5.0.

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