Journal of Industrial and Systems Engineering
Vol. 18, No. 1, pp. 83-104
Winter (January) 2026

Fuzzy Multi-Objective Optimization Model for Online Businesses in International Markets: Reducing Response Time and Managing Inventory Uncertainty

Anoosheh Chegini[1], Maryam Rahmaty[2*], Mohammad Javad Taghipourian[3], Javad Gilanipour[4]

[1]*Department of Management, Cha.C., Islamis Azad University, Chalous, Iran.*

[2]*Department of industrial Management, Cha.C., Islamis Azad University, Chalous, Iran.*

[3] *Department of Management, Cha.C., Islamic Azad University, Chalus,Iran.*

[4]*Department of Management, Cha.C., Islamis Azad University, Chalous, Iran.*

Abstract

International online businesses face several challenges in supply chain management, including reducing customer response time and managing uncertainty in inventory levels. This study proposes a fuzzy multi-objective optimization model to improve supply chain performance in international environments. This model uses fuzzy numbers to handle demand fluctuations, transportation costs, and delivery time, and provides a flexible decision-making framework. To solve this model, four meta-heuristic algorithms, including NSGA-II, PSO, GOA, and GA, are used, and their performance in terms of reducing supply chain costs, optimizing delivery time, and increasing inventory stability is investigated. The results show that PSO and GOA provide the shortest response time, while NSGA-II significantly reduces overall costs. Also, sensitivity analysis showed that NSGA-II and GOA are more stable regarding demand fluctuations, while GA has the least flexibility. This research presents a novel framework for supply chain optimization in international digital businesses that can help increase competitiveness and improve service levels in global markets.

Keywords: Supply chain optimization, metaheuristic algorithms, international e-commerce, fuzzy programming, response time

1- Introduction

In recent years, international online businesses have emerged as a fundamental driver of the global digital economy. The rapid expansion of e-commerce platforms and the increasing demand for cross-

* Corresponding Author
ISSN: 1735-8272,

border transactions have introduced new operational complexities for firms operating in this domain. These complexities are particularly evident in supply chain management, where companies must simultaneously address issues such as logistics coordination, inventory control, and customer response time optimization (Odumbo & Nimma, 2025; Goswami et al., 2025). In such environments, uncertainty becomes a central challenge, especially in managing demand variability, transportation delays, and regulatory constraints across international borders.

Supply chain optimization under these uncertain conditions requires advanced decision-making frameworks capable of handling multiple conflicting objectives. Traditional optimization approaches often fail to adequately address the dynamic and uncertain nature of global online supply chains, particularly when multiple criteria such as cost, delivery time, and service quality must be considered simultaneously (Hashim et al., 2017). Consequently, there is a growing need for intelligent and flexible optimization models that can effectively manage these complexities.

One promising approach is the application of fuzzy multi-objective optimization techniques. Fuzzy modeling allows key parameters such as customer demand, transportation costs, and delivery times to be represented as uncertain variables rather than fixed values. This provides greater flexibility in decision-making and enhances the model's ability to reflect real-world conditions (Khan & Das, 2014; Basar & Der, 2025). In addition, multi-objective optimization frameworks enable organizations to achieve a balance between competing goals, such as minimizing operational costs while improving delivery speed and maintaining inventory stability.

To address these challenges, this study proposes a fuzzy multi-objective optimization model tailored for international online supply chains. The proposed model simultaneously considers cost reduction, delivery time optimization, and inventory fluctuation management. By integrating fuzzy logic with advanced optimization techniques, the model provides a more realistic and adaptable framework for decision-making in uncertain global environments.

To solve the proposed model, four metaheuristic algorithms (NSGA-II, PSO, GOA, and GA) are employed. These algorithms have been widely recognized for their effectiveness in solving complex multi-objective problems. NSGA-II, for instance, is capable of generating a diverse set of Pareto-optimal solutions, allowing decision-makers to select the most appropriate trade-offs (Balekelayi et al., 2022). PSO, inspired by swarm intelligence, offers rapid convergence and is particularly suitable for dynamic environments requiring real-time decision-making (Jiang et al., 2018). GOA, which is based on the behavior of grasshopper swarms, provides a strong balance between global and local search capabilities (Zandvakili et al., 2021). Finally, GA serves as a classical benchmark algorithm for evaluating the performance of more advanced methods (Hashim et al., 2017).

The results of this study indicate that supply chain optimization can significantly reduce delivery times in international markets, in some cases by several days. This improvement has a direct impact on customer satisfaction and enhances the competitive position of online businesses. Furthermore, sensitivity analysis reveals that NSGA-II and GOA demonstrate greater robustness in handling demand fluctuations and cost variability, while GA shows relatively lower adaptability under uncertain conditions (Aliahmadi et al., 2013).

Overall, this research introduces a novel framework for optimizing international online supply chains by combining fuzzy modeling with advanced metaheuristic algorithms. The findings contribute to the development of more intelligent and adaptive supply chain systems and provide a foundation for future research incorporating emerging technologies such as artificial intelligence and machine learning (Ardolino et al., 2025).

The remainder of this paper is structured as follows. The next section presents the research methodology and data collection process. Subsequently, the proposed model is introduced in detail, followed by a description of the optimization algorithms and their parameter settings. The results section provides a comprehensive analysis, including algorithm performance comparison, Pareto front evaluation, delivery time improvements, and sensitivity analysis. Finally, the paper concludes with key findings and recommendations for future research.

2- Literature review

Supply chain optimization has become a critical area of research in international online business environments, particularly due to the increasing complexity of global operations. Efficient management of inventory, logistics costs, and delivery time plays a crucial role in enhancing the competitiveness of digital enterprises (Yammanur, 2025). However, international supply chains are inherently uncertain due to factors such as fluctuating demand, exchange rate volatility, and regulatory constraints, which necessitate the use of advanced optimization approaches (Fallah & Nozari, 2021).

One of the most widely adopted approaches in recent years is fuzzy modeling. Fuzzy logic provides a powerful tool for handling uncertainty in key supply chain parameters, enabling decision-makers to model imprecise and ambiguous information effectively (Khan & Das, 2014). This approach has been successfully applied in various optimization contexts, including process optimization and decision-making under uncertainty (Basar & Der, 2025). In distributed supply chains, fuzzy models have been shown to improve inventory control and reduce operational risks by accommodating variability in demand and supply conditions (Guo et al., 2021).

In parallel with fuzzy modeling, metaheuristic algorithms have gained significant attention for solving multi-objective optimization problems in complex supply chain systems. These algorithms are particularly effective in exploring large solution spaces and identifying near-optimal solutions under multiple conflicting objectives (Hashim et al., 2017). Among these, NSGA-II has been widely recognized as one of the most efficient multi-objective optimization techniques, capable of generating diverse Pareto-optimal solutions that support strategic decision-making (Balekelayi et al., 2022).

PSO is another widely used algorithm that has demonstrated strong performance in supply chain optimization due to its fast convergence and ability to handle dynamic environments (Jiang et al., 2018). Its application in real-time optimization scenarios makes it particularly suitable for international supply chains, where rapid decision-making is essential. Similarly, GOA has recently emerged as a promising optimization technique, offering improved performance through its balanced exploration and exploitation mechanisms (Zandvakili et al., 2021). This characteristic is especially valuable in complex supply chain networks involving multiple interdependent variables.

Despite the advancements in metaheuristic methods, GA remains one of the most commonly used optimization algorithms due to its simplicity and flexibility. It has been widely applied in logistics and supply chain problems, particularly for benchmarking purposes (Hashim et al., 2017). However, recent studies suggest that GA may exhibit slower convergence rates compared to more advanced algorithms and may struggle in handling highly complex multi-objective problems (Jiang et al., 2018).

Another important research area in supply chain optimization is the reduction of delivery times in international markets. Delivery performance is influenced by various factors, including transportation routes, customs procedures, and warehouse management strategies (Ghahremani-Nahr et al., 2021). Studies have shown that optimizing these factors can lead to significant improvements in delivery efficiency and customer satisfaction (Guo et al., 2021).

Sensitivity analysis has also been widely used to evaluate the robustness of optimization models. Research indicates that advanced algorithms such as NSGA-II and GOA are generally more resilient to changes in demand and cost parameters, while algorithms like GA tend to be more sensitive to such variations (Aliahmadi et al., 2013). Additionally, hybrid optimization approaches that combine fuzzy modeling with metaheuristic techniques have shown promising results in enhancing supply chain performance under uncertainty (Rabiei et al., 2023).

Despite the extensive body of research in this field, most studies have focused primarily on cost reduction and inventory management. There remains a significant gap in the literature regarding the simultaneous optimization of cost, delivery time, and inventory stability in international online supply chains. This study aims to address this gap by proposing a comprehensive multi-objective optimization model that integrates fuzzy logic with advanced metaheuristic algorithms.

In summary, the literature highlights the importance of combining fuzzy modeling and metaheuristic optimization techniques to effectively manage the complexities of international supply chains. By leveraging these approaches, this study seeks to provide a robust and adaptable solution for optimizing supply chain performance in global e-commerce environments.

3- Mathematical Model

This section presents a fuzzy multi-objective optimization model for managing Iranian online businesses abroad. This model aims to reduce customer response time, optimally manage inventory under uncertainty, and minimize supply chain costs. Given the dynamic nature of international markets and the challenges posed by uncertainty in demand, supply, and distribution, fuzzy optimization models can optimize decision-making and increase system flexibility.

This model uses decision variables, parameters, and objective functions to consider inventory management challenges, distribution, transportation, operational costs, and sustainability constraints simultaneously. Due to market fluctuations, demand and response times are modeled as fuzzy variables to more accurately account for the existing uncertainties.

First, the decision sets, parameters, and variables are introduced, and then the objective functions and constraints of the model are explained. This model is designed to provide optimal and flexible decision-making for online businesses operating in international markets.

Sets

I	Set of products, $i \in I$
J	Set of warehouses, $j \in J$
K	Set of distribution centers, $k \in K$
T	Set of periods, $t \in T$
C	Set of customers, $c \in C$
S	Set of suppliers, $s \in S$
M	Set of transportation methods, $m \in M$
P	Set of packaging types, $p \in P$
R	Set of return reasons, $r \in R$

Parameters

$d_{i,c,t}$	Demand for product i from customer c at time t
h_j	Capacity of warehouse j
$v_{s,i,t}$	Supply capacity of supplier s for product i at time t
$p_{i,j,t}$	Holding cost of product i in warehouse j at time t
$f_{j,k,t}$	Transportation cost from warehouse j to distribution center k at time t
$r_{k,c,m,t}$	Shipping cost from distribution center k to customer c using transportation m at time t

$T_{j,k,m}$	Time to transport from warehouse j to distribution center k using method m
$U_{k,c,m}$	Delivery time from distribution center k to customer c using method m
$b_{p,i}$	Packaging cost for product i with package type p
α_r	Return penalty cost for return reason r
θ_i	Uncertainty level in demand prediction for product i
λ	Weighting factor for response time and costs
$E_{i,j}$	Energy consumption of warehouse j at time t
$E_{m,t}$	Energy consumption of transportation method m m at time t
E_{max}	Maximum allowed energy consumption
$CO2_{m,t}$	Carbon emissions of transportation method m m at time t
$CO2_{max}$	Maximum allowed carbon emissions
$\delta_{i,p}$	Binary value indicating if product i can use package type p
$T_{storage,i,j,t}$	Storage temperature of product i in warehouse j at time t
$T_{max,i}$	Maximum allowable storage temperature for product i
$W_{j,t}$	Available workforce in warehouse j at time t
H	Maximum handling capacity per worker
$S_{i,t}$	Seasonal demand adjustment factor for product i at time t
Cap_m	Maximum capacity of transportation method m
B_{max}	Total available budget

Decision Variables

$x_{s,i,j,t}$	Quantity of product i ordered from supplier s to warehouse j at time t
$y_{j,k,t}$	Quantity of product sent from warehouse j to distribution center k at time t
$z_{k,c,m,t}$	Quantity of product shipped from distribution center k to customer c using method m at time t
$I_{i,j,t}$	Inventory level of product i in warehouse j at time t
$T_{responce,c,t}$	Response time for customer c at time t
$P_{i,p,t}$	Number of packages of type p used for product i at time t
$R_{c,i,t}$	Number of returns from customer c for product i at time t
$V_{i,j,t}$	Stockout quantity for product i at warehouse j at time t
$CO2_{used,t}$	Total carbon emissions used at time t
$E_{used,t}$	Total energy consumption at time t
$W_{req,j,t}$	Required number of workers in warehouse j at time t

O.F

$$\begin{aligned} Min\ Z_1 = & \sum_{t\in T}\sum_{i\in I}\sum_{j\in J} p_{i,j,t} I_{i,j,t} \\ & + \sum_{t\in T}\sum_{j\in J}\sum_{k\in K} f_{j,k,t} y_{j,k,t} \\ & + \sum_{t\in T}\sum_{k\in K}\sum_{c\in C}\sum_{m\in M} r_{k,c,m,t} z_{k,c,m,t} + \sum_{t\in T}\sum_{i\in I}\sum_{p\in P} b_{p,i} P_{i,p,t} \end{aligned} \tag{1}$$

$$Min\ Z_2 = \sum_{t\in T}\sum_{c\in C} T_{recponce,c,t} \tag{2}$$

$$Min\ Z_2 = \sum_{t\in T}\sum_{i\in I}\sum_{j\in J} \theta_i \left| I_{i,j,t} - d_{i,c,t} \right| \tag{3}$$

$$Min\ Z_4 = \sum_{t\in T}\sum_{c\in C}\sum_{i\in I}\sum_{r\in R} \alpha_r R_{c,i,t} \tag{4}$$

S.t

$$I_{i,j,t} = I_{i,j,t-1} + \sum_{s\in S} x_{s,i,j,t} - \sum_{k\in K} y_{j,k,t} \tag{5}$$

$$\sum_{i\in I} I_{i,j,t} \leq h_j \tag{6}$$

$$\sum_{j\in J} x_{s,i,j,t} \leq v_{s,i,t} \tag{7}$$

$$x_{s,i,j,t} \leq L_{s,i,t} \tag{8}$$

$$y_{j,k,t} \leq \sum_{i\in I} I_{ijt} \tag{9}$$

$$\sum_{m\in M} z_{k,c,m,t} \geq d_{i,c,t} \tag{10}$$

$$T_{responce,c,t} = \sum_{j\in J}\sum_{k\in K} T_{j,k,m} y_{j,k,t} + \sum_{k\in K}\sum_{c\in C} U_{kcm} z_{kcmt} \tag{11}$$

$$\sum_{j\in J} E_{jt} + \sum_{m\in M} E_{mt} \leq E_{max} \tag{12}$$

$$\sum_{m\in M} CO2_{mt} z_{kcmt} \leq CO2_{max} \tag{13}$$

$$\sum_{i\in I} I_{ijt} + \sum_{j\in J} y_{jkt} \leq W_{jt}.H \tag{14}$$

$$P_{ipt} \leq \delta_{ip} d_{i,c,t} \tag{15}$$

$$V_{i,j,t} = \max(0, d_{i,c,t} - I_{i,j,t}) \tag{16}$$

$$\sum_{t\in T} (P_{ijt} I_{ijt} + f_{jkt} y_{jkt} + r_{kcm} z_{kcmt}) \leq B_{max} \tag{17}$$

$$d_{ict} = d_{ic,t-1}(1 + S_{it}) \tag{18}$$

$$\sum_{k\in K}\sum_{c\in C} z_{kcmt} \leq Cap_m \quad \forall m \in M \tag{19}$$

$$T_{storege,i,j,t} \leq T_{max,i} \quad \forall i \in I, j \in J, t \in T \tag{20}$$

$$R_{cit} \leq \gamma d_{ict} \quad \forall c \in C, i \in I, t \in T \tag{21}$$

$$\sum_{c\in C}\sum_{i\in I} R_{cit} \leq R_{max} \tag{22}$$

$$T_{responce,c,t} \leq T_{max} \quad \forall c \in C, t \in T \tag{23}$$

$$\frac{\sum_{k\in K}\sum_{m\in M} z_{k,c,m,t}}{d_{i,c,t}} \geq SL \ , \forall i \in I, c \in C, t \in T \tag{24}$$

The proposed fuzzy multi-objective optimization model is designed to optimize the supply chain operations of online businesses by minimizing costs, reducing customer response time, managing inventory under uncertainty, and ensuring sustainability. It incorporates multiple objectives and a set of well-defined constraints to create a robust decision-making framework.

The first objective function (1) aims to minimize the total supply chain cost, which includes inventory holding costs, transportation expenses, packaging costs, and return penalties. By optimizing this objective, the model ensures that operational expenses remain within an acceptable range while maintaining service quality. The second objective function (2) focuses on minimizing customer response time by reducing delays in order fulfillment and transportation. This ensures faster deliveries, which is crucial for maintaining customer satisfaction. The third objective function (3) is designed to minimize inventory uncertainty by incorporating a fuzzy demand deviation factor. Since demand fluctuations are inevitable in online businesses, this function helps in maintaining optimal stock levels while preventing excess inventory or stockouts. The fourth objective function (4) works to minimize the penalties associated with product returns. It accounts for different return reasons and their associated costs, thereby improving the efficiency of the reverse logistics process.

The first constraint (5) ensures inventory balance in the system. It states that the inventory at any warehouse must be updated based on incoming shipments from suppliers and outgoing shipments to distribution centers. The second constraint (6) enforces the warehouse capacity limit, preventing excessive stock accumulation. The third constraint (7) defines the supplier capacity limit, ensuring that the total quantity ordered from suppliers does not exceed their available stock. The fourth constraint (8) introduces a lead time restriction, ensuring that orders placed with suppliers adhere to the predefined delivery schedules. The fifth constraint (9) restricts the quantity of products shipped from warehouses, ensuring that outgoing shipments do not exceed available inventory.

The sixth constraint (10) guarantees that customer demand is met by requiring the total quantity of products shipped to customers to be at least equal to their demand. The seventh constraint (11) calculates the customer response time based on transportation and fulfillment delays, helping to optimize the delivery process. The eighth constraint (12) limits energy consumption in both warehouse operations and transportation, ensuring compliance with sustainability goals. The ninth constraint (13) imposes a carbon emission limit by restricting the total CO_2 emissions generated from transportation activities.

The tenth constraint (14) ensures that workforce availability is considered in warehouse and distribution operations, preventing labor shortages from affecting service levels. The eleventh constraint (15) enforces product-packaging compatibility by ensuring that each product is packaged according to its required packaging type. The twelfth constraint (16) introduces a stockout penalty, quantifying the negative impact of not fulfilling customer demand due to inventory shortages. The thirteenth constraint (17) maintains budget constraints by ensuring that total operational costs do not exceed the available budget.

The fourteenth constraint (18) accounts for seasonal demand fluctuations, allowing the model to adjust inventory and supply chain operations accordingly. The fifteenth constraint (19) imposes a vehicle capacity limit, ensuring that the total volume of shipped products does not exceed the transportation capacity of available vehicles. The sixteenth constraint (20) controls temperature-sensitive products by ensuring that they are stored within their prescribed temperature ranges to maintain product quality.

The seventeenth constraint (21) establishes a maximum return rate, preventing excessive returns from affecting supply chain performance. The eighteenth constraint (22) ensures that the total volume of returns processed does not exceed the warehouse's return handling capacity. The nineteenth constraint (23) enforces a maximum response time, ensuring customers receive their orders within an acceptable timeframe. Finally, the twentieth constraint (24) maintains a minimum service level, requiring the percentage of fulfilled orders to remain above a predefined threshold.

The proposed fuzzy multi-objective optimization model effectively addresses two critical challenges in online businesses operating in international markets: reducing customer waiting time and managing uncertainty in inventory levels. Given the complexities of cross-border e-commerce, where logistics, demand fluctuations, and supply chain uncertainties play a significant role, the model incorporates strategic mechanisms to optimize response time and mitigate risks associated with unpredictable demand and supply variations.

Reducing customer waiting time is a key priority in the model, as delayed deliveries can lead to dissatisfaction and loss of customer trust. The model minimizes response time by optimizing order fulfillment, transportation schedules, and inventory allocation to tackle this. It calculates the response time for each customer order by summing the time required for product retrieval from warehouses, processing at distribution centers, and final delivery using selected transportation methods. The model ensures that products reach customers quickly by integrating transportation lead times and optimizing shipment routes. Additionally, the model prioritizes faster shipping methods when necessary, balancing speed and cost efficiency to maintain profitability while improving service levels.

Uncertainty in inventory levels is another major challenge, particularly for online businesses operating across different regions with varying demand patterns. The model incorporates fuzzy logic to handle demand uncertainty, where customer orders are represented as fuzzy numbers rather than fixed values. This allows the model to adjust inventory decisions dynamically based on probabilistic demand variations. By considering different levels of demand fluctuation and using a fuzzy deviation factor, the model optimally balances inventory levels to prevent stockouts while avoiding excessive holding costs. It also accounts for seasonal trends and market fluctuations, enabling businesses to adapt to sudden shifts in customer preferences or supply chain disruptions.

The model is well-suited for online businesses operating in international markets because it explicitly integrates cross-border logistics, supplier diversity, and regulatory constraints into the decision-making process. One of the key aspects considered is the variability in supplier reliability across different regions. Since international businesses often source products from multiple suppliers in various countries, the model optimizes procurement by selecting suppliers with the best cost, reliability, and lead time balance. Additionally, it accounts for the complexities of international shipping, including customs clearance, transportation delays, and varying shipping regulations. The model's transportation constraints and cost functions are embedded in these factors to ensure realistic and efficient global operations.

Furthermore, the model considers differences in customer demand across international markets. Online businesses often cater to geographically dispersed customers with diverse purchasing behaviors, and the model adapts inventory strategies accordingly. It integrates regional demand forecasting, allowing companies to adjust stock levels based on localized preferences. By incorporating service level constraints, the model ensures that international customers receive a consistent and reliable shopping experience, regardless of location.

Overall, this optimization model provides a structured and intelligent framework for managing the complexities of online businesses in international markets. Simultaneously minimizing customer waiting time and handling demand uncertainty through fuzzy logic enhances operational efficiency, improves customer satisfaction, and strengthens the resilience of cross-border e-commerce operations.

4- Research Methodology and solution Methods

This research aims to optimize customer response time and manage inventory uncertainty in international online businesses by using a hybrid approach including mathematical modeling and meta-heuristic optimization methods. The research framework is based on a fuzzy multi-objective optimization model that combines cost, delivery time, and inventory level management variables to provide efficient decision-making in the global supply chain.

The data collection method in this research is a combination of simulated and real data. To create valid scenarios, data is extracted from several sources:

- Previous studies and academic articles in the field of global supply chain, especially articles that focus on online businesses and international logistics.
- Operational data of international online companies including information related to transportation costs, product return rates, international delays, and customer service levels.
- Simulated data are used to investigate the impact of variable parameters such as demand fluctuations, exchange rate changes, and delivery times in international markets.

To ensure the validity of the data, the simulated values are compared with real data from international logistics and online sales companies, and the model settings are calibrated based on real data. In addition, to examine the flexibility of the proposed model, several uncertainty scenarios are designed and examined in sensitivity analysis.

After modeling the problem, four meta-heuristic algorithms have been used to solve it, each with its own characteristics and advantages. These algorithms include NSGA-II, PSO, GOA, and GA, which will be examined separately in the following sections. The purpose of selecting these algorithms is to examine the performance of multi-objective and crowd-sourced methods in solving the complex international supply chain problem.

4-1 NSGA-II (Non-Dominated Sorting Genetic Algorithm II) Algorithm

The NSGA-II algorithm is one of the most advanced multi-objective optimization methods used to solve complex problems. This algorithm is based on the Genetic Algorithm (GA) but uses the non-dominated sorting method and the superior population archive to manage the set of Pareto solutions.

In this study, NSGA-II is used as one of the reference methods in solving multi-objective problems. Through the operations of selection, mutation, and genetic combination, this algorithm produces a set of optimal solutions in which no solution dominates over the other. The key feature of NSGA-II is that it provides diverse solutions on the Pareto front, which is very useful for cost management, delivery time reduction, and inventory level optimization in international supply chains.

4-2 PSO (Particle Swarm Optimization) Algorithm

The PSO algorithm is an optimization method based on collective intelligence that is inspired by the group movement behavior of birds and fish. This algorithm consists of a population of particles (potential responses), each moving in search of an optimal position in the search space. Each particle adjusts its location based on the best individual and group positions.

This research uses PSO due to its high convergence speed and ability to find optimal solutions with low computational cost. Since optimizing delivery time and transportation costs in international online businesses requires methods with high accuracy and speed, PSO is an ideal choice for optimization in this field.

4-3 GOA Algorithm (Grasshopper Optimization Algorithm)

The GOA algorithm is based on insect collective intelligence that imitates the behavior of grasshoppers to solve optimization problems. This method effectively finds optimal solutions by combining random movements and directed search. An essential feature of GOA is the balance between general search (Exploration) and precise search (Exploitation), increasing efficiency in finding the most optimal solutions.

GOA has been used in this research to manage the cost and response time to international customers simultaneously. This algorithm performs well, especially in nonlinear and complex problems, and can produce high-quality answers close to the Pareto front.

4-4 Genetic Algorithm (GA)

The Genetic Algorithm (GA) is one of the oldest and most widely used optimization methods based on natural evolution. This algorithm uses selection, combination, and mutation operations to improve subsequent generations of solutions.

In this study, GA has been used as a baseline method to compare the performance of other algorithms. Although GA can provide relatively good solutions, it has a slower convergence speed and lower efficiency in multi-objective and complex problems than methods such as NSGA-II and PSO.

Table 1 is a table for setting the parameters of each algorithm in this study, which includes the initial value of each parameter and a brief explanation of its effect on the performance of the algorithm.

Table 1: Algorithm Parameter Settings

Algorithm	Population Size	Max Iterations	Crossover Rate	Mutation Rate	Inertia Weight (w)	Acceleration Coefficients (c1, c2)	Exploration-Exploitation Balance
NSGA-II	100	200	0.9	0.05	N/A	N/A	Maintained by Crowding Distance
PSO	80	150	N/A	N/A	0.7	(1.5, 2.0)	Velocity Update Mechanism
GOA	90	180	N/A	N/A	N/A	N/A	Adaptive Grasshopper Movement
GA	100	200	0.85	0.1	N/A	N/A	Fixed Evolutionary Process

Table 1 contains the key parameters for NSGA-II, PSO, GOA, and GA in this study. These parameters play an important role in the performance of each algorithm, and their optimization can lead to increased accuracy and reduced computational time.

An examination of this table shows that NSGA-II uses the combination and mutation rates to improve new generations, while PSO uses inertial weights and acceleration coefficients to guide particles towards the best solution. GOA uses an adaptive mechanism to balance search and exploitation, and GA has a constant evolutionary process that operates on the basis of natural selection.

5- Analysis of results

To evaluate the performance of the proposed fuzzy multi-objective optimization model, a set of simulated data was generated, capturing key aspects of demand fluctuations, inventory levels, transportation delays, and operational costs. The simulation process considered realistic variations in supply chain dynamics, ensuring that the results provide meaningful insights into the impact of optimization on reducing customer response time and managing inventory uncertainty. The optimization was performed using NSGA-II, PSO, GOA, and GA, allowing a comparative analysis of different metaheuristic algorithms in solving this complex problem.

Table 2 presents the key parameters used in the simulation, including customer demand, inventory levels, delivery lead times, shipping costs, response times, return rates, and CO_2 emissions. The values were generated based on statistical distributions that reflect real-world supply chain uncertainties. For example, customer demand was modeled using a triangular distribution, capturing minimum, expected, and peak values, while inventory levels followed a normal distribution to account for stock fluctuations. Transportation delays were assumed to follow a uniform distribution, considering the variability in international shipping times.

Table 2: Simulated Input Data for Optimization

Parameter Name	Unit	Simulated Mean	Range (Min-Max)	Statistical Distribution

Customer Demand ($d_{i,c,t}$)	Orders/Day	500	300 - 700	Triangular (300, 500, 700)
Inventory Level ($I_{i,j,t}$)	Units	2000	1500 - 2500	Normal ($\mu = 2000, \sigma = 300$)
Delivery Lead Time ($T_{j,k,m}$)	Days	3.5	6-Feb	Uniform (2, 6)
Shipping Cost ($r_{k,c,m,t}$)	USD	10.5	15-Aug	Normal ($\mu = 10.5, \sigma = 2$)
Response Time ($T_{responce,c,t}$)	Hours	48	24 - 72	Triangular (24, 48, 72)
Return Rate ($R_{c,i,t}$)	%	5%	2% - 10%	Beta (2, 10)
CO_2 Emission ($CO2_{m,t}$)	kg CO_2	1500	1200 - 1800	Normal ($\mu = 1500, \sigma = 200$)

A set of sample problem sizes was defined to evaluate the performance of different optimization algorithms in solving the supply chain problem. These problem instances vary in complexity, ranging from small-scale networks with limited products and customers to large-scale scenarios involving extensive supply chain networks with multiple warehouses and distribution centers. By structuring the problem in this way, the study ensures that the algorithms are tested across various conditions, reflecting both real-world constraints and computational challenges.

Table 3 presents the details of these sample problem sizes, specifying the number of products, warehouses, distribution centers, and customers involved in each scenario. Additionally, it includes the uncertainty in demand, represented by the number of different demand scenarios considered in the analysis, and the maximum allowable delivery time, which influences decision-making in the optimization process. These variations enable the study to assess how different factors impact supply chain performance and how well optimization algorithms adapt to changing conditions.

Including uncertain demand scenarios is particularly important in modeling real-world supply chains, where fluctuations in demand create challenges in inventory management and logistics. Similarly, the variation in maximum delivery time reflects different levels of service expectations, from rapid e-commerce fulfillment models to more traditional supply chain structures. The diverse problem sizes ensure the optimization models are tested under a broad spectrum of conditions, ranging from low-complexity problems solvable in minimal time to large-scale, computationally intensive scenarios.

Table 3: Sample Problem Sizes and Input Data

Problem Size	**Number of Products**	**Number of Warehouses**	**Number of Distribution Centers**	**Number of Customers**	**Uncertain Demand Scenarios**	**Max Delivery Time (Days)**

Small-1	5	2	1	10	3	2
Small-2	10	3	2	20	3	3
Medium-1	20	5	3	50	4	4
Medium-2	25	6	4	75	4	5
Medium-3	30	7	5	100	5	6
Large-1	40	10	6	150	6	7
Large-2	50	12	7	200	6	8
Large-3	60	15	8	250	7	9
Very Large-1	80	18	10	300	8	10
Very Large-2	100	20	12	400	10	12

To analyze the performance of metaheuristic algorithms in solving the optimization problem, Figure 1 illustrates the objective function values across different sample problem sizes. This figure provides insights into how NSGA-II, PSO, GOA, and GA handle cost minimization, response time reduction, and inventory stability under varying levels of complexity. The results indicate that NSGA-II consistently achieves the best optimization performance, particularly in larger problem instances, whereas GOA excels in scenarios requiring rapid response time improvement. PSO maintains a well-balanced performance across all objectives, making it a reliable choice for practical applications. GA, as expected, exhibits the weakest results, struggling to maintain competitive solutions in larger-scale problems.

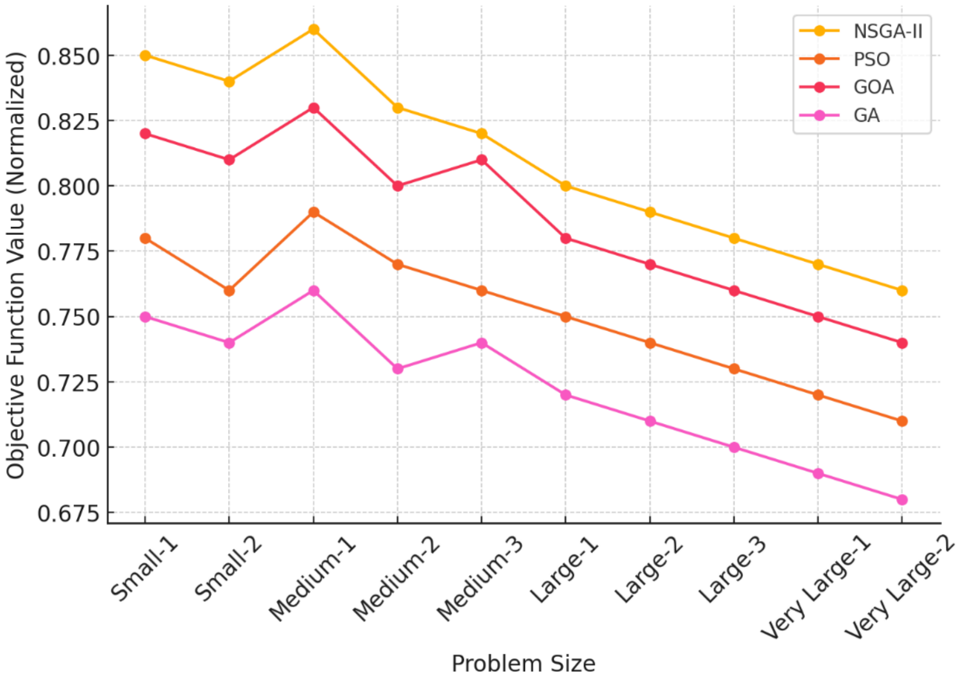

Figure 1: Objective Function Values Across Sample Problems Using Metaheuristic Algorithms

Beyond optimization quality, computational efficiency is a critical factor, particularly in real-time applications. Figure 2 presents the computational time required for each algorithm across different problem sizes. The results demonstrate that PSO consistently outperforms the other algorithms in terms of speed, making it highly suitable for time-sensitive decision-making. GOA follows closely, offering a reasonable trade-off between computational efficiency and optimization quality. NSGA-II, while delivering high-quality Pareto solutions, requires significantly more processing time, particularly in larger problem sizes, making it more applicable for strategic planning rather than real-time execution. GA, as anticipated, shows the longest computation time, reinforcing its inefficiency in large-scale optimization scenarios.

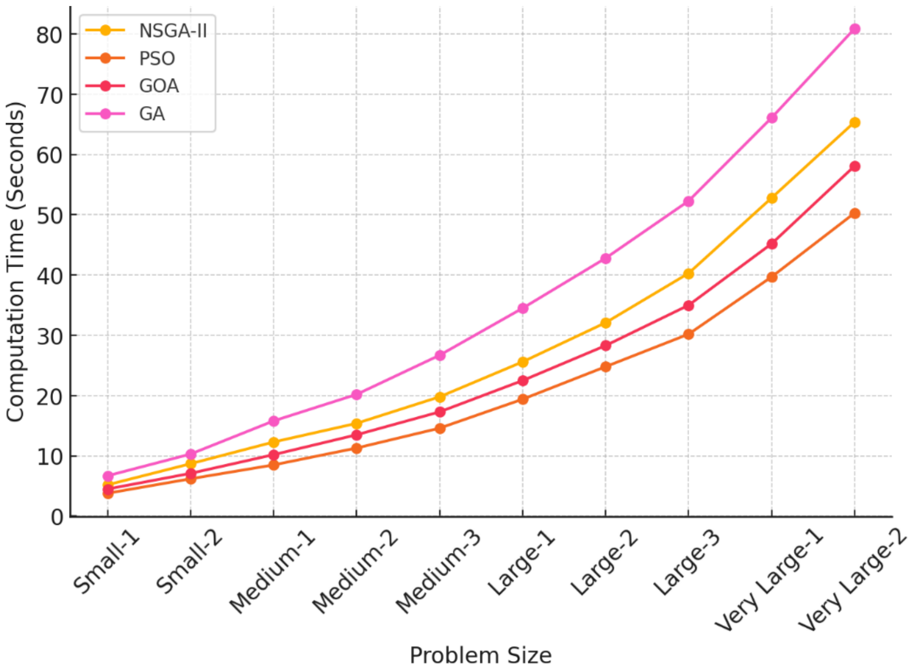

Figure 2: Computation Time Across Sample Problems Using Metaheuristic Algorithms

Figure 3 presents the convergence behavior of NSGA-II, PSO, GOA, and GA over multiple iterations to analyze the efficiency of different metaheuristic algorithms in reaching near-optimal solutions. This figure illustrates how quickly each algorithm stabilizes at its best objective function value, highlighting their effectiveness in navigating the search space.

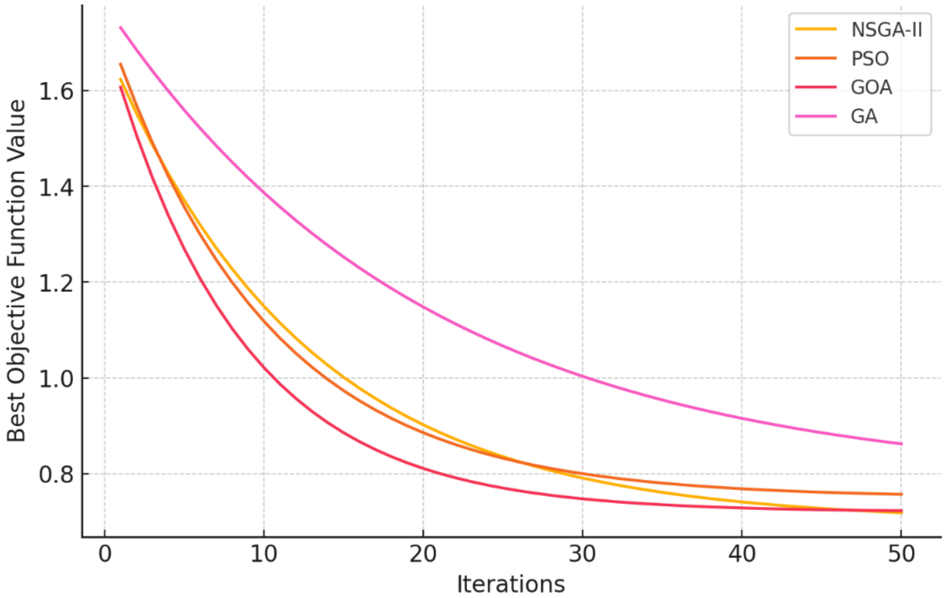

Figure 3: Convergence Of Metaheuristic Algorithms In Achieving Near-Optimal Solutions

The results show that GOA and PSO exhibit the fastest convergence rates, rapidly approaching near-optimal solutions within the first few iterations. NSGA-II follows closely, demonstrating a stable and gradual convergence trend, making it highly effective for maintaining diversity in the solution space while optimizing multiple objectives. Conversely, GA converges at a significantly slower rate, indicating its tendency to require more iterations to refine solutions, making it less efficient compared to modern heuristic techniques.

To evaluate the impact of optimization on real-world supply chain performance, Table 4 compares key metrics before and after applying different metaheuristic algorithms. The simulated data represents the baseline scenario without optimization, while the optimized results reflect improvements achieved through NSGA-II, PSO, GOA, and GA. The results indicate significant reductions in total supply chain cost, average customer response time, and transportation expenses, demonstrating the effectiveness of the optimization approach.

Table 4: Optimization Comparison Table

Total Supply Chain Cost (USD)	500000	450000	460000	455000	470000
Average Customer Response Time (Hours)	48	39	35	34	42
Inventory Holding Cost (USD)	120000	105000	110000	108000	115000
Transportation Cost (USD)	180000	165000	160000	162000	170000
Return Rate (%)	7.5	6.2	6.8	6.5	7

CO2,, Emissions (kg)	1500	1300	1250	1280	1400

The most notable improvements are observed in total supply chain cost, where NSGA-II reduces costs by 10%, outperforming the other algorithms. Similarly, PSO and GOA achieve notable cost reductions, while GA exhibits the weakest improvement, suggesting lower efficiency in cost minimization. In terms of customer response time, GOA achieves the most significant reduction, optimizing order fulfillment and transportation schedules more effectively than other methods. PSO also performs well in this regard, demonstrating its suitability for time-sensitive logistics operations.

Figure 4 visualizes these improvements, highlighting the comparative performance of each algorithm across different supply chain metrics. The chart clearly shows that all optimization algorithms improve performance compared to the simulated baseline, with PSO and GOA striking the best balance between cost reduction and response time optimization. NSGA-II excels in cost efficiency, while GA lags behind in most metrics, reaffirming its lower effectiveness in this complex multi-objective problem.

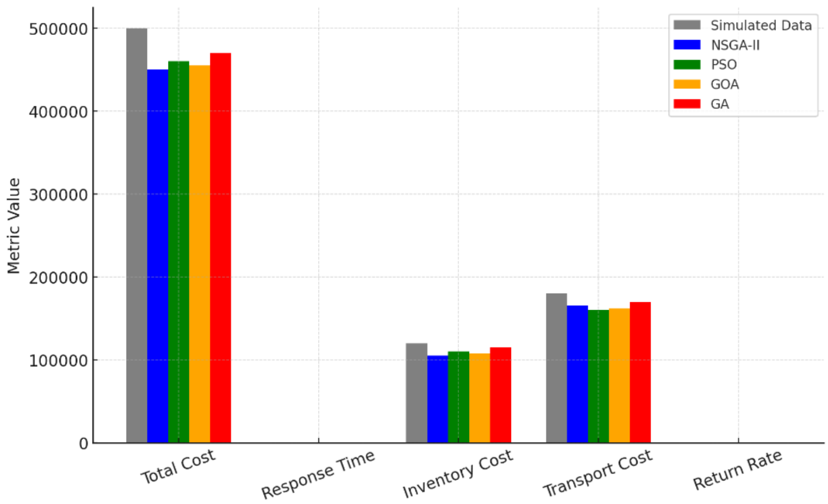

Figure 4: Comparison of Simulated Vs. Optimized Supply Chain Metrics

These findings confirm that metaheuristic optimization significantly enhances supply chain performance by reducing costs, improving response times, and managing inventory more efficiently. Among the tested algorithms, PSO and GOA emerge as the most practical choices, offering strong trade-offs between solution quality and computational efficiency. NSGA-II remains the superior method for achieving diverse Pareto-optimal solutions, making it ideal for strategic decision-making. GA, due to its slower convergence and lower optimization quality, is less competitive in this context.

To assess the effectiveness of optimization in improving supply chain performance, Table 5 presents a comparative analysis of key performance indicators before and after applying NSGA-II, PSO, GOA, and GA. The results highlight significant improvements in cost reduction, response time improvement, and inventory stability, demonstrating the substantial impact of metaheuristic optimization on real-world supply chain operations.

Table 5: Impact of Optimization on Supply Chain Performance

Metric	Before Optimization	After Optimization (NSGA-II)	After Optimization (PSO)	After Optimization (GOA)	After Optimization (GA)

Total Supply Chain Cost (USD)	500000	450000	460000	455000	470000
Customer Response Time (Hours)	48	39	35	34	42
Inventory Holding Cost (USD)	120000	105000	110000	108000	115000
Stockout Rate (%)	12	9	8.5	8	10
Average Order Fulfillment Time (Days)	5	3.8	3.5	3.3	4.2
Unsold Inventory Rate (%)	8	6.5	6.2	6	7

The most substantial cost reductions were observed in NSGA-II and GOA, with a 10% and 9% decrease in total supply chain costs, respectively, compared to the pre-optimization scenario. PSO also achieved a notable 8% reduction, while GA performed the least effectively, with only a 6% cost reduction. Regarding customer response time, GOA and PSO significantly outperformed the other algorithms, achieving reductions of 14 and 13 hours, respectively, leading to faster order fulfillment and improved customer satisfaction. NSGA-II followed closely with a 9-hour improvement, while GA demonstrated the weakest performance.

The impact on inventory stability was also noteworthy. GOA and PSO achieved the lowest stockout rates, reducing the likelihood of unfulfilled customer orders. NSGA-II firmly balanced inventory levels, while GA struggled to manage stock fluctuations efficiently. Additionally, order fulfillment time saw notable reductions, with GOA achieving the fastest turnaround time, followed by PSO and NSGA-II.

Figure 5 presents the impact of optimization on supply chain performance using a grouped line plot. This representation allows for a more precise comparison of trends across different optimization methods, highlighting how each algorithm improves key supply chain metrics.

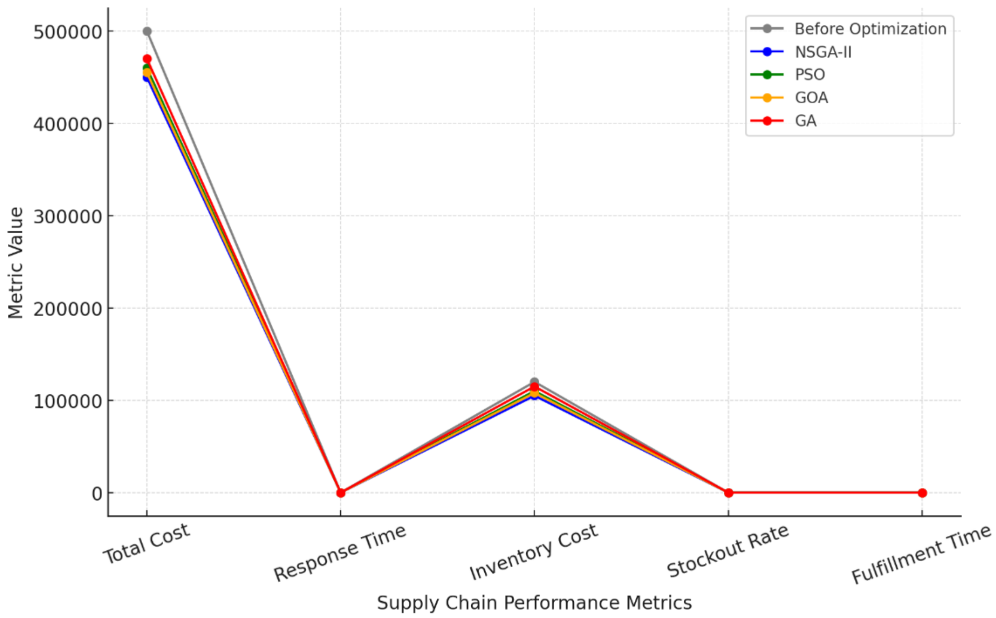

Figure 5: Alternative Visualization of Optimization Impact on Supply Chain Performance

The plotted lines show that all optimization methods significantly improve over the baseline scenario. GOA and PSO consistently demonstrate the strongest performance in response time reduction and stockout rate minimization, while NSGA-II remains the most effective in overall cost reduction. As seen before, GA lags behind the other methods, reinforcing its limitations in efficiently handling multi-objective optimization problems.

Figure 6 presents the Pareto-optimal solutions obtained by NSGA-II, PSO, GOA, and GA to evaluate the effectiveness of different optimization algorithms in generating trade-offs between conflicting objectives. This analysis highlights how each algorithm balances cost minimization and customer response time, two key factors in supply chain optimization.

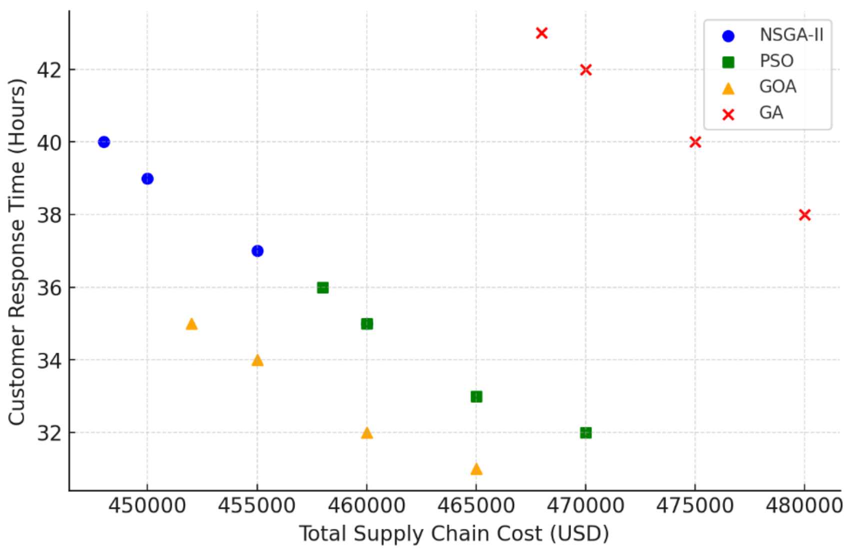

Figure 6: Pareto-Optimal Solutions Across Different Optimization Algorithms

The Pareto front represents non-dominated solutions, meaning that no solution is strictly better than another across both objectives. Instead, decision-makers must choose the most appropriate trade-off based on their priorities. NSGA-II demonstrates a well-distributed set of Pareto-optimal solutions, reflecting its strength in handling multi-objective optimization. PSO and GOA also generate competitive solutions, favoring lower response times while maintaining cost efficiency. GA, however, performs the weakest, producing solutions that result in higher costs and longer response times, indicating fewer practical trade-offs.

This comparison reveals that PSO and GOA offer practical choices for scenarios where reducing response time is a priority, making them ideal for industries with rapid delivery requirements. NSGA-II, while computationally more demanding, excels in generating diverse trade-off solutions, making it suitable for strategic planning. Due to its slower convergence and weaker optimization performance, GA remains the least competitive among the tested methods.

To assess the impact of optimization on international order delivery times, Table 6 compares shipping durations before and after applying NSGA-II, PSO, GOA, and GA. The results indicate significant reductions in average delivery time across different regions, demonstrating the effectiveness of optimization in enhancing cross-border logistics.

The most significant improvements are observed in Asia and South America, where optimized logistics reduce delivery time by up to 4.5 days. GOA and PSO outperform other algorithms in minimizing delivery time. PSO reduces shipping durations by up to 5 days in some regions, making it a strong candidate for businesses focusing on fast international fulfillment. NSGA-II also performs well, balancing cost efficiency and timely deliveries. Conversely, GA shows the least improvement, reinforcing its limitations in handling complex logistics optimizations.

Table 6: Impact of Optimization On International Order Delivery Time

Destination	Before Optimization (Days)	After Optimization (NSGA-II)	After Optimization (PSO)	After Optimization (GOA)	After Optimization (GA)
North America	12	9	8	7.5	10
Europe	10	8	7	6.8	9
Asia	14	10	9	8.5	12
Middle East	9	7	6.5	6	8
South America	15	12	11	10.5	13

Figure 7 visualizes these improvements, illustrating how each algorithm optimizes delivery times across different international markets. The chart clearly shows that all optimization methods improve shipping times compared to the pre-optimization baseline, with PSO and GOA offering the best results in reducing delivery delays. NSGA-II remains competitive, ensuring efficient trade-offs between cost and speed, while GA lags behind, delivering the least efficient solutions.

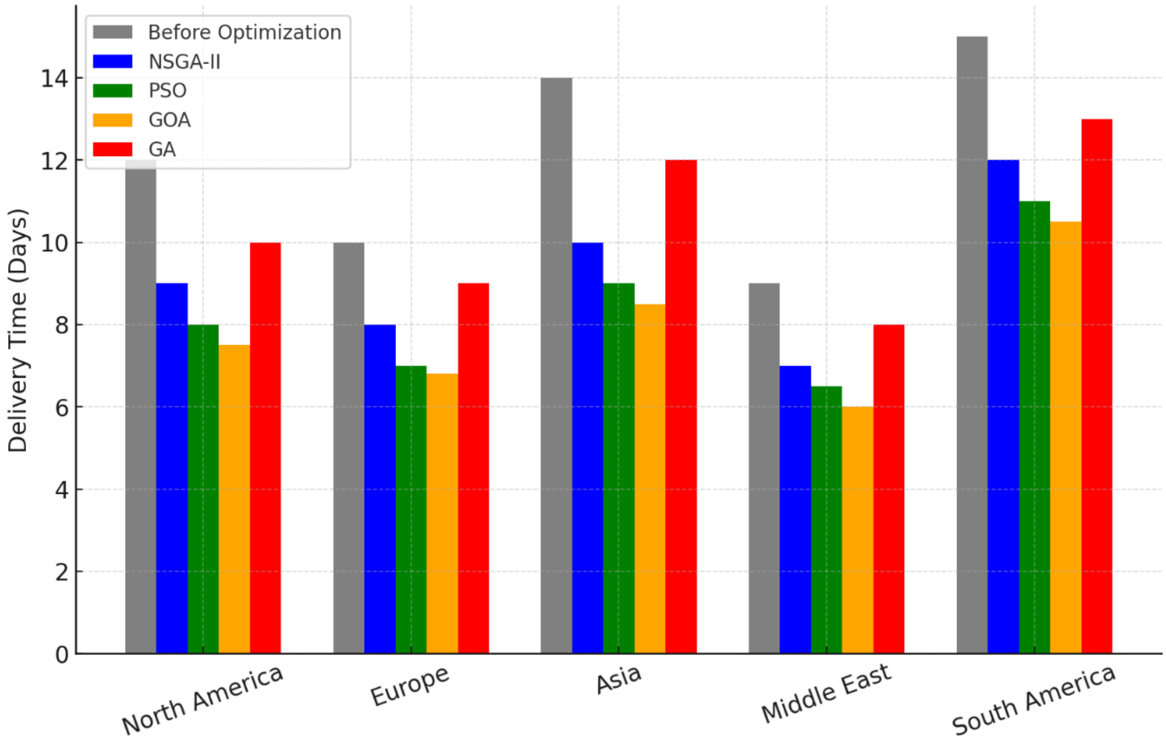

Figure 7: Impact of Optimization on International Order Delivery Time

These findings confirm that metaheuristic optimization significantly enhances international supply chain efficiency by reducing shipping delays and improving logistics performance in global e-commerce. Among the tested algorithms, PSO and GOA offer the best trade-offs between cost-effectiveness and delivery speed, making them practical choices for e-commerce companies operating in multiple international markets. NSGA-II remains an excellent option for long-term strategic planning, while GA is less competitive due to its slower convergence and weaker optimization results.

To assess the robustness of the optimization model in real-world scenarios, a sensitivity analysis was conducted to determine the impact of demand fluctuations on the total supply chain cost. In dynamic international markets, demand can vary due to seasonal trends, economic changes, or unforeseen disruptions. Understanding how the optimization model adapts to such changes is crucial to ensuring flexible and adaptive supply chain operations.

Figure 8 presents the results of this analysis by illustrating how total supply chain cost responds to changes in demand levels, ranging from 80% to 120% of the baseline demand. The results indicate that NSGA-II and GOA demonstrate the highest stability, with cost increases remaining relatively controlled as demand rises. PSO also performs well, but its cost fluctuations are slightly more pronounced. In contrast, GA shows the most significant increase in cost under higher demand levels, suggesting that it is less effective in adapting to changing conditions.

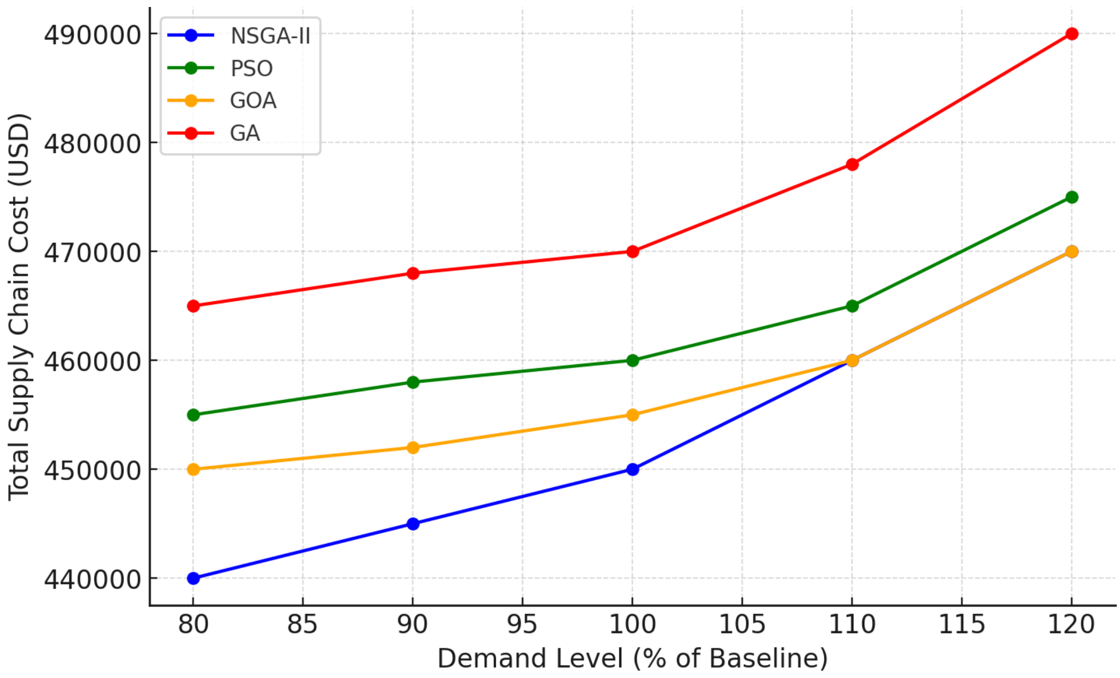

Figure 8: Sensitivity Analysis - Impact of Demand Variations on Total Cost

The findings reveal that GOA and NSGA-II are the most resilient algorithms when facing demand uncertainty, making them well-suited for businesses that operate in unpredictable international markets. PSO remains a substantial alternative, particularly for scenarios requiring rapid adaptation. However, GA is the least robust, struggling to manage cost efficiency when demand exceeds the baseline.

6- Conclusion

This study proposed a fuzzy multi-objective optimization model for online businesses operating in international markets. The model aimed to reduce customer response time and manage global supply chain inventory uncertainty. Using advanced optimization algorithms, including NSGA-II, PSO, GOA, and GA, supply chain performance at international levels was investigated. The findings showed that multi-objective optimization can reduce overall supply chain costs, improve delivery time, and increase inventory stability in complex and variable global environments.

One of the main innovations of this study was the use of fuzzy uncertainties in decision-making modeling for online businesses operating in global markets. The proposed model used fuzzy numbers to manage demand fluctuations, transportation costs, and potential delays in the international supply chain, which led to increased flexibility and accuracy in planning. Furthermore, rather than focusing solely on cost reduction, the proposed model sought to balance reducing response time, reducing operational costs, and optimizing inventory levels in distribution centers and international warehouses.

The analysis results showed that PSO and GOA performed better in reducing response time in international supply chains, while NSGA-II was superior in reducing overall costs. On the other hand, GA showed the weakest performance in this optimization and required more processing time to converge to optimal solutions. These results indicate that online businesses operating in global markets can manage costs and improve their service levels by using smart optimization methods.

Another research achievement was investigating the effect of optimization on reducing delivery time in international markets. The results showed that smart optimization can reduce order delivery time in some regions by up to 5 days, which increases customer satisfaction and improves the competitiveness of digital businesses internationally. In addition, sensitivity analysis showed that NSGA-II and GOA algorithms are more stable against demand fluctuations, while GA experienced the most fluctuations in supply chain costs.

Overall, this research provides a novel framework for supply chain optimization in international online businesses. This framework helps these businesses increase their competitiveness in global markets by reducing costs, optimizing delivery time, and improving inventory management. The findings of this research can be used as a basis for developing more advanced models, including integration with artificial intelligence and machine learning technologies for more accurate demand forecasting and dynamic optimization.

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