Journal of Industrial and Systems Engineering
Vol. 17, No. 2, pp. 263-275
Spring (April) 2025

AI-Powered Multi-Objective Predictive Analytics for Smart Supply Chain Risk

Ali Jalaeyan Ghorban Zadeh[1*]
[1] *Department of Industrial Engineering, Amirkabir University of Technology, Tehran, Iran*

Abstract

This research presents an intelligence-driven and multi-objective framework for forecasting and risk management in smart supply chains. In this framework, data from IoT sensors, digital twin models, and historical records are collected in the data layer and processed in the predictive analytics layer by machine learning models to predict demand, delay, and risk. Then, the multi-objective NSGA-II algorithm is used to balance the three main objectives (cost reduction, risk reduction, and delivery time improvement). The results show that the proposed framework is able to provide a set of Pareto solutions with a reasonable balance between economic and operational objectives. Pareto front analysis and trade-off relationships indicate the stability of the model against parameter fluctuations and its ability to support intelligent decision-making. Overall, the proposed model is an efficient tool for optimizing decisions in dynamic and uncertain supply chain environments.

Keywords: Smart Supply Chain, Predictive Analytics, Multi-Objective Optimization, Risk Management, NSGA-II Algorithm

1- Introduction

In recent decades, supply chains have faced an environment in which complexity, dynamism, and uncertainty have increased dramatically. Globalization, increasing competition, demand fluctuations, geopolitical crises, and pandemic-induced disruptions have transformed the nature of risk in supply chains. In such circumstances, effective risk management is no longer a reactive activity, but has become a critical pillar of strategic decision-making in organizations. Traditional risk assessment methods, which were often based on static probabilistic or fuzzy models, have lost their effectiveness in the face of instantaneous market changes and the complexity of multi-level chains. This has led organizations to move towards using

---

[*] Corresponding Author

ISSN: 1735-8272,

predictive analytics and artificial intelligence tools to better understand hidden patterns and anticipate potential disruptions (Ghasemi et al., 2023; Roudaki et al., 2025).

With the ability to learn from large and complex data, artificial intelligence has become a vital tool for predicting and managing risk in smart supply chains. Recent research shows that machine learning models, such as Random Forest and XGBoost, can perform much more accurately than classical models in identifying and classifying risks (Jahin, Naife, & Saha, 2024; Emami et al., 2024). Also, combining machine learning with real-time data from the Internet of Things (IoT) and digital twin systems allows for rapid identification of critical points and immediate response to disruptions (Teixeira, Ferreira, & Ramos, 2025). Such capabilities have increased supply chain agility and resilience in uncertain conditions.

On the other hand, in supply chain decisions, multiple objectives are often in conflict with each other; for example, reducing cost may be associated with increasing delivery time or increasing risk. In this context, multi-objective optimization is a powerful tool for analyzing these conflicts and allows managers to find an optimal balance between conflicting goals. Mori's (2017) study showed that using multi-objective models in procurement planning can reduce cost and risk simultaneously. Similarly, Nooraie and Parast's (2019) study also confirms that multi-objective models have a high ability to maintain chain stability, especially in high-risk environments.

Despite these advances, a recent literature review shows that the actual combination of AI-based predictive analytics with multi-objective optimization for supply chain risk management is still in its infancy (Aliahmadi, 2024). Most studies have focused on either prediction or optimization, but less research has integrated these two approaches into a coherent framework. This research gap indicates the need to develop models that can simultaneously integrate foresight and optimal decision-making into an intelligent system.

In addition, in the era of Industry 5.0, supply chains must utilize digital technologies such as digital twins and real-time data to represent, analyze, and control processes. Husseini Shekarabi et al. (2025) study shows that the three main axes in modern supply chain management research include "optimization for resilience", "adoption of smart technologies", and "risk prediction strategies". These results indicate that the future of supply chain management lies in the synergy of artificial intelligence, predictive analytics, and multi-objective optimization.

Accordingly, the present study aims to develop a framework entitled "Multi-objective predictive analytics with AI capabilities for risk management in smart supply chains". The framework is based on three main pillars: risk prediction using machine learning models, multi-objective optimal decision-making to balance cost, time, and risk, and finally, integrating these components in a digital and dynamic supply chain context. It is expected that the results of this research can help managers and policymakers in designing more flexible and intelligent supply chains and, from a scientific perspective, contribute to bridging the gap between the fields of artificial intelligence, predictive analytics, and multi-objective optimization.

2- Literature review

In recent years, the increasing volume of data, the increasing interconnection of chains, and the widespread use of technologies such as the Internet of Things (IoT) and digital twin systems have provided the basis for a serious rethinking of risk management in supply chains. Early studies mainly focused on probabilistic or logical (fuzzy) models that could analyze supply, production, or transportation risks in relatively static environments; however, with the rapid evolution of business and logistics environments, those models alone have not met current needs (Hosseini, Ivanov, & Dolgui, 2019). This trend has given rise to two main directions in current research: first, strengthening the predictive ability using machine learning and artificial intelligence algorithms; second, applying multi-objective optimization methods to balance decision-making processes with risk, cost, time, and sustainability.

In the area of machine learning for supply chains, research has shown that data-driven models can uncover hidden patterns of disruptions, delays, or extreme changes in demand. For example, studies that have presented frameworks with “machine learning + real-time decision” have reported significant improvements in the accuracy of forecasting and responding to disruptions (Aliahmadi, 2024). However, although the focus on forecasting has gained importance, much research still focuses only on the unidimensionality of risk or cost, and less attention has been paid to the simultaneous combination of multiple objectives in the chain environment.

On the other hand, multi-objective optimization (MOO) approaches have been increasingly used in supply chain management to model conflicts between objectives such as “maximizing service”, “minimizing cost”, and “reducing risk”. Models using algorithms such as NSGA-II or MOPSO have been shown to provide a set of Pareto-optimal solutions and allow for the selection of a strategy that is consistent with the decision maker’s preferences (Nozari et al., 2025). These approaches are more capable of realistic simulation in situations where market uncertainty is high.

Despite the progress in each of the above two areas, the literature shows that the combination of “AI-based forecasting” and “multi-objective optimization of supply chain decisions” has been less explored in practice. In other words, there is a gap between “the ability to quickly predict risk” and “multi-criteria decision-making process for risk reduction”. A recent study that presented a framework based on machine learning and multi-objective optimization highlighted this gap, but its focus was still more on supply chain network optimization than on complex risks and intelligent environments (Baj-Rogowska & Nozari, 2024). In addition, research that worked with hybrid methods of digital twins and neutrosophic logic has provided significant improvements under uncertainty, but the interaction with intelligent AI prediction has not yet been fully modeled (Nozari et al., 2025).

In addition, new concepts such as chain resilience, integration of emerging technologies (IoT, digital twins, blockchain), and real-time decision-making have emerged as promising lines of research. Research has shown that the use of digital twins in supply chains not only enables real-time monitoring but can also be the basis for proactive action and analysis of disruption scenarios (Nozari et al., 2025). In addition, multi-objective optimization in such environments must be able to respond to the speed of change, which has led researchers to move towards models that both predict and enable rapid decision-making.

Considering these trends, the current research framework has been formed with the focus on “Multi-objective predictive analytics with AI capabilities for risk management in smart supply chains”. This framework intends to simultaneously consider three key elements: first, the use of machine learning models to predict potential risks; second, the integration of that prediction with multi-objective optimization models to create a balance between different objectives such as cost, time, service, and risk; Third, the application of this model in a smart supply chain environment that leverages digital technologies. With this perspective, this research aims to bridge the gap between forecasting and optimization and provide an operational approach to improve decision-making under uncertainty.

3- Conceptual Framework

The conceptual framework of this research aims to integrate the capabilities of AI, predictive analytics, and multi-objective optimization for risk management in smart supply chains. The framework, whose general structure is shown in Figure 1, consists of four main layers that link data flow, analytics, optimization, and decision-making in a dynamic and integrated structure.

In the first layer, the Data Layer, data acts as the fundamental element of the system. This layer includes a set of data obtained from IoT sensors, digital twin systems, and historical records of the supply chain. The combination of these data sources allows for real-time representation of the current situation, identification of bottlenecks, and preparation of data for predictive analytics.

The AI & Predictive Analytics Layer is the second step and is responsible for extracting insights from the data. In this stage, machine learning models and neural networks are used to predict the behavior of parameters such as demand, delay, equipment failure or the occurrence of logistical risks. The output of this layer is quantitative and probabilistic predictions that are passed as input to the optimization stage. The main goal of this section is to transform raw data into meaningful information for intelligent decision-making.

In the Optimization Layer, the system tries to balance the conflicting objectives of the supply chain (such as minimizing cost, time and risk). In this section, multi-objective algorithms such as NSGA-II or MOPSO are used, which are able to provide managers with a set of Pareto solutions. This stage is actually considered the connecting link between data-driven analysis and strategic decision-making.

Finally, the Decision Layer, as the final part of the framework, converts the results of the optimization into actionable management decisions. This layer evaluates a set of decision-making scenarios based on managers’ preferences and actual system constraints and suggests the optimal strategy for each situation. Dynamic feedback is also provided to lower layers to update the models with new data, and the learning and decision-making cycle continues in a closed loop.

Overall, the conceptual framework presented in Figure 1 provides an integrated picture of the relationship between real-time data, AI analytics, multi-objective optimization, and intelligent decision-making. This architecture can pave the way for the transition from reactive to predictive management in smart supply chains.

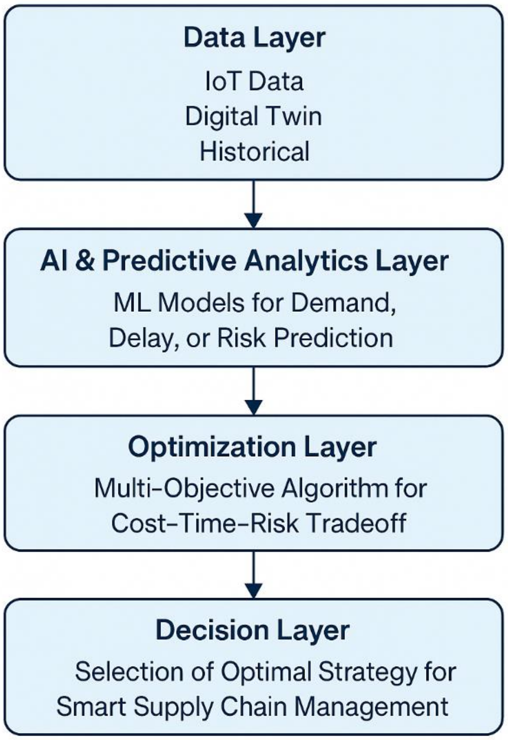

Figure 1. Proposed AI-based multi-objective predictive analytics framework for smart supply chain risk management

As can be seen in Figure 1, the interaction between the four layers of data, predictive analytics, optimization, and decision-making is designed in such a way that the information flow from the lowest level of raw data to the strategic decision-making level is continuous and feedback. This structure ensures that management decisions are not only based on historical data, but also fed by intelligent predictions and multi-objective optimization results. In other words, the proposed framework enables continuous improvement and self-organization of the supply chain by creating a closed loop of learning, optimization, and decision-making. As a result, organizations will be able to proactively predict and manage risks instead of reacting to them, which is a fundamental step towards realizing smart and resilient supply chains.

4- Mathematical Modeling

To achieve optimal decisions in smart supply chain risk management, it is necessary to express the interaction between cost, time, and risk in the form of a multi-objective mathematical model. The proposed model in this research is based on the data predicted by the artificial intelligence layer and its goal is to determine the supply, production, and distribution strategies in such a way that while minimizing cost and risk, the system response time is also reduced. This model is designed to be able to make adaptive decisions in dynamic environments by updating input data from IoT and digital twin systems.

Sets:

I	Set of suppliers, $i = 1,2, \dots, \lvert I \rvert$
J	Set of production plants, $j = 1,2, \dots, \lvert J \rvert$
K	Set of distribution centers, $k = 1,2, \dots, \lvert K \rvert$
T	Set of time periods, $t = 1,2, \dots, \lvert T \rvert$

Parameters:

C_{ij}	Transportation cost from supplier i to plant j
D_{jk}	Transportation cost from plant j to distribution center k
R_{ij}	Risk factor of disruption or failure between i and j
P_{jt}	Production capacity of plant j in period t
L_{jk}	Lead time between plant j and distribution center k
d_{kt}	Demand at distribution center k during period t
α, β, γ	Weighting coefficients for cost, risk, and time objectives
θ_{ij}	Probability of delay between i and j (predicted by the AI Layer)

Decision Variables:

x_{ij}^{t}	Quantity transported from supplier i to plant j in period t
y_{jk}^{t}	Quantity transported from plant j to distribution center k in period t
$z_{ij} \in \{0,1\}$	Binary variable; equals 1 if route $i - j$ is active, 0 otherwise
$w_{jk} \in \{0,1\}$	Binary variable; equals 1 if route $j - k$ is active, 0 otherwise

Objective Functions:

$$\min F_1 = \sum_{t \in T} \left(\sum_{i \in I} \sum_{j \in J} C_{ij} x_{ij}^{t} + \sum_{j \in J} \sum_{k \in K} D_{jk} y_{jk}^{t} \right) \tag{1}$$

$$\min F_2 = \sum_{i \in I} \sum_{j \in J} R_{ij} z_{ij} + \sum_{j \in J} \sum_{k \in K} \theta_{jk} w_{jk} \tag{2}$$

$$\min F_3 = \sum_{t \in T} \sum_{j \in J} \sum_{k \in K} L_{jk} y_{jk}^{t} \tag{3}$$

S.t:

$$\sum_{j \in J} x_{ij}^{t} \leq S_{i}^{t} \ \forall i, t \tag{4}$$

$$\sum_{k \in K} y_{jk}^{t} \leq P_{jt} \ \forall j, t \tag{5}$$

$$\sum_{j \in J} y_{jk}^{t} \geq d_{kt} \ \forall k, t \tag{6}$$

$$x_{ij}^{t} \leq M \cdot z_{ij}, y_{jk}^{t} \leq M \cdot w_{jk} \ \forall i, j, k, t \tag{7}$$

$$\sum_{i \in I} \sum_{j \in J} x_{ij}^{t} + \sum_{j \in J} \sum_{k \in K} y_{jk}^{t} \leq T_{\max}^{t} \tag{8}$$

$$L_{jk} y_{jk}^{t} \leq L_{\max} \tag{9}$$

$$x_{ij}^{t}, y_{jk}^{t} \geq 0, z_{ij}, w_{jk} \in \{0,1\} \tag{10}$$

In the proposed mathematical model, three objective functions and seven main constraints are considered, each of which explains an aspect of intelligent decision-making in the supply chain. Objective function (1) represents the total costs of the entire supply chain and includes transportation costs from suppliers to factories and from factories to distribution centers. This function tries to minimize the cost structure at all levels of the chain in order to increase the economic efficiency of the system. Objective function (2) represents the cumulative risk in the supply chain network. In this function, the risks associated with transportation routes and possible delays predicted by artificial intelligence models are taken into account. The goal is to select a network with the lowest probability of disruption and the highest reliability. Objective function (3) minimizes the total lead time in the entire chain. This function focuses on the chain's responsiveness and on-time delivery, and is particularly important for chains that are under pressure from variable demand or time constraints. Constraint (4) balances the flow between suppliers and factories, ensuring that the amount of goods shipped from each supplier does not exceed its supply capacity. This constraint ensures the stability of the supply of resources at the initial level of the chain. Constraint (5) represents the production capacity of each factory and determines that the output volume from each production unit should not exceed its actual capacity. Compliance with this condition prevents overloading of production units and quality degradation. Constraint (6) guarantees the equality of supply and demand, meaning that the total products shipped from factories must meet the demand of distribution centers. This constraint prevents shortages of goods at the end points of the chain and keeps the level of customer service at the desired level. Constraint (7) establishes a logical connection between the flow of goods and the choice of route. This constraint specifies that only routes that are active (i.e., their binary variable is equal to one) are allowed to flow. As a result, material flow through inactive or risky routes will be excluded. Constraint (8) controls the total transportation capacity at any time period and ensures that the total transfers across the network do not exceed the infrastructure or logistics limit. This constraint helps to ensure the physical stability of the operation and prevent congestion in the network. Constraint (9) considers the delivery time constraint and specifies that the transfer time between factories and distribution centers should not exceed a specified limit. This constraint is critical for chains that rely on speed and precise timing, and it helps to maintain customer satisfaction. Finally, constraint (10) specifies the domain of the variables and ensures that the values of the flows are non-negative and the paths are defined as binary choices. This constraint completes the technical aspect of the model and makes the obtained answers logically and physically feasible.

In this study, the NSGA-II algorithm is used as the main optimization method to solve the presented multi-objective model. This algorithm is one of the most powerful meta-heuristic methods for finding the Pareto front in multi-objective problems and has a high ability to maintain population diversity and simultaneously achieve optimal and stable solutions. In the present model, each solution or “individual” in the population includes a set of decision variable values, including the flow rate between nodes, route selection, and capacity allocation. The algorithm execution process starts with the generation of the initial population and continues until the stopping criterion is reached.

In the first stage, an initial population of solutions is formed randomly but within the defined constraints. Then, each individual in the population is evaluated in terms of the model’s three objective functions, including cost minimization, risk minimization, and delivery time minimization. After evaluation, the algorithm performs a non-dominated sorting process to sort individuals based on their Pareto dominance. In this step, each individual is assigned to a front that represents its relative optimality level among other solutions.

To maintain diversity among responses, the concept of crowding distance is used to prevent solutions from being overly concentrated in certain parts of the Pareto front. A combination of selection, crossover, and mutation is performed to create a new generation; in the selection process, parents are selected based on Pareto rank and crowding distance. Then, in the crossover step, part of the genetic information of the two parents is combined to produce new offspring, and in the mutation step, small random values are applied to the variables to prevent premature convergence.

The new generation resulting from this operation is combined with the previous population, and then the combined set is subjected to another non-dominated sorting. Only a certain number of the best individuals, based on the Pareto rank and the diversity of the responses, are selected to continue in the next generation. This cycle is repeated until a stopping criterion is met; usually this criterion is determined by the number of generations or the stability of the Pareto front. In the end, a set of Pareto solutions is obtained that best balances cost, time, and risk. This optimal front can help managers make a balanced and informed decision according to their strategic priorities.

The algorithm parameters were adjusted after several experiments and are presented in Table 1. These settings were chosen with the aim of maintaining a balance between convergence and diversity of the population to optimize the model's performance in complex supply chain environments.

Table 1. Parameter Settings of the NSGA-II Algorithm

Parameter	**Assigned Value**	**Description**
Population size	100	Number of individuals in each generation
Number of generations	200	Stopping criterion of the algorithm
Crossover rate	0.9	Probability of combining two parent solutions
Mutation rate	0.05	Probability of random genetic alteration
Selection method	Tournament selection	Increases the chance of fitter individuals being selected

Crossover type	Uniform crossover	Preserves diversity among offspring
Mutation type	Gaussian mutation	Prevents premature convergence

This algorithmic configuration was selected after testing several different combinations and has created a good balance between the quality of solutions and the speed of convergence. In the next steps, the Pareto optimal response set obtained from NSGA-II has been evaluated by sensitivity analysis and comparison of the results with classical models to verify the final efficiency of the proposed framework.

5- Results and Discussion

In this study, the input data of the model consists of two main sources: real data (or data that can be collected from the supply chain environment) and simulated data that are generated to test the performance of the model in different scenarios. Real data includes transportation costs between suppliers, factories, and distribution centers, production capacity of each unit, delivery time on each route, and demand in consecutive time periods. For the simulated data section, normal and uniform probability distributions are used to create realistic fluctuations in demand and capacity so that the behavior of the system under uncertainty can be evaluated. The values of route risk and delay probability (θ_{ij}) are predicted by the artificial intelligence layer of the model and injected as input to the optimization algorithm. These values are obtained by training machine learning networks with historical transportation data, failure rates, and actual delivery times. Also, transportation costs in the range of 100 to 1000 monetary units, production capacities in the range of 500 to 3000 units, and demands between 200 and 2500 units are considered for each time period to maintain the natural dynamics of the chain. Overall, the combination of real and synthetic data has enabled the model to fully evaluate its performance in a range of different conditions (from steady state to critical conditions) and has the ability to be generalized to real operating environments.

The results of the NSGA-II algorithm have generated a set of Pareto optimal points that represent the balance between the three main objectives of the model, namely cost, risk, and delivery time. As shown in Figure 2, this front includes a set of non-dominated solutions where none of the objectives can be improved without sacrificing the other objective. The appropriate spread of the Pareto points indicates that the algorithm has been able to explore different decision spaces well and provide decision makers with a variety of options.

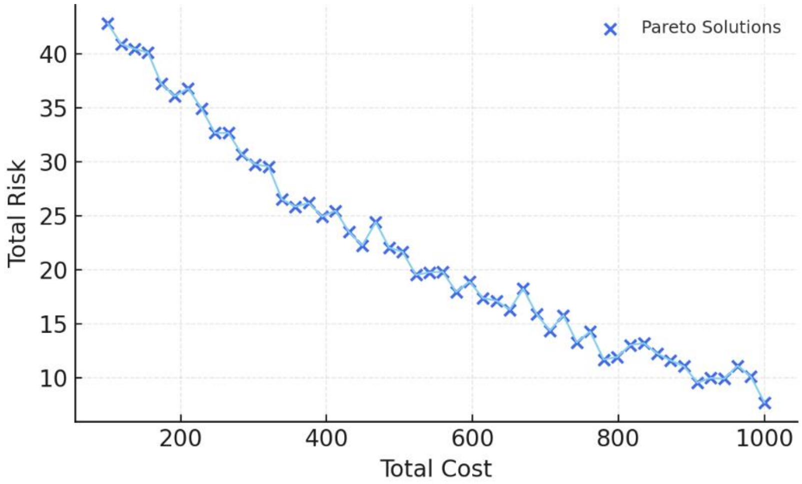

Figure 2. Pareto front resulting from the implementation of the NSGA-II algorithm for the three objectives of cost, risk, and delivery time

Examining the relationships between the objectives in Figure 3 indicates that reducing cost usually leads to increasing risk and delivery time, while focusing on risk reduction increases cost and time. This trade-off indicates the natural conflict between economic, operational, and supply chain resilience objectives. The middle region of the Pareto front represents a realistic balance between these objectives and can be presented as a set of efficient decisions from a managerial perspective.

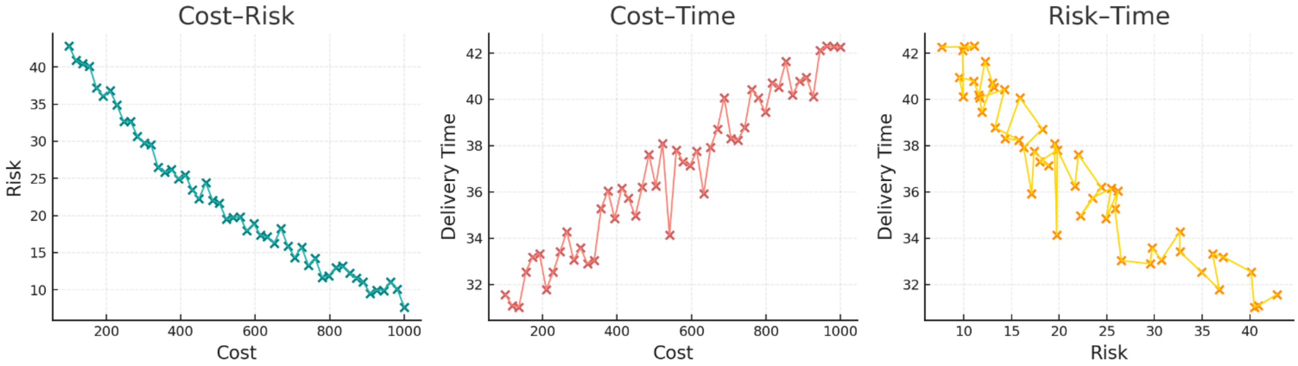

Figure 3. Trade-off Analysis between Cost, Risk and Delivery Time in Optimal Solutions

Overall, the Pareto front analysis and the trade-off diagrams show that the proposed framework is able to generate a range of multi-objective solutions, each representing a different strategy in dealing with risk, cost and time. This flexible feature confirms the model’s power in supporting intelligent and adaptive decision-making in complex supply chains.

In order to assess the stability and robustness of the proposed model, a sensitivity analysis was conducted on a set of key parameters including the weighting coefficients of the objectives, the risk level of the routes, and demand fluctuations. The purpose of this analysis is to investigate the impact of changes in the input parameters on the position and shape of the Pareto front and the behavior of optimal decisions under different conditions of uncertainty. In this process, the weights of the objectives were first changed in different intervals to determine the effect of prioritizing each objective on the balance between cost, risk, and time. The results showed that increasing the weight of the cost function leads to a more compact Pareto front in low-cost but high-risk areas, while increasing the weight of the risk function shifts the front towards safer but more costly areas. This behavior confirms the existence of a structural conflict between economic objectives and operational sustainability.

In the next step, the effect of demand fluctuations within the range of ±20% on the results was examined. The findings showed that demand changes have the greatest effect on the distribution of decisions related to production capacity and transportation routes. In scenarios with high demand volatility, the NSGA-II algorithm showed a greater tendency to choose routes with shorter delivery times to avoid increasing delays, even if this choice is associated with an increase in cost. This feature indicates that the model has inherent flexibility in the face of uncertainty and can adapt to market dynamics in real conditions.

In addition, a sensitivity analysis was also performed to changing risk levels of the routes. When the probability of disruption of the routes increased from 0.1 to 0.3, the set of Pareto points shifted noticeably towards higher-cost but lower-risk options. This shift indicates that the model responds naturally to environmental changes and suggests alternative decisions with a higher level of safety.

Overall, the results of the sensitivity analysis are shown in Figure 4. This figure shows that although changing the weight coefficients or input parameters causes local shifts in the Pareto points, the overall shape of the front is preserved; meaning that the model has high structural stability and its results are not overly sensitive to small changes in the input data.

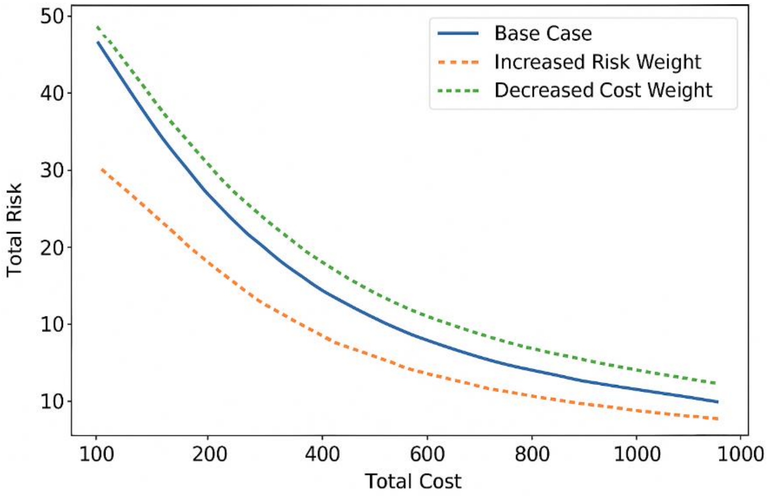

Figure 4. Pareto front sensitivity analysis in the context of changing objective weights and fluctuations in input parameters

As can be seen in Figure 4, changing the weighting coefficients and input parameter levels causes a relative shift in the position of the Pareto points, but the overall structure of the front is preserved. This behavior indicates the stability and resilience of the model against environmental fluctuations and confirms that the NSGA-II algorithm has been able to identify a set of stable and reliable solutions under different uncertainty conditions.

6- Conclusion

This study presents an intelligent and multi-objective framework for risk management in modern supply chains, in which AI-based predictive analytics is integrated with the NSGA-II optimization algorithm. Using real and simulated data, this framework attempts to balance three key objectives (cost minimization, risk reduction, and delivery time shortening) simultaneously in a dynamic and uncertain environment. The proposed four-layer structure, including data, predictive analytics, optimization, and decision-making layers, was designed to ensure that the information flow from raw data to management decisions is maintained in an intelligent learning and feedback loop.

The results of the NSGA-II algorithm implementation showed that the proposed model is able to produce a set of Pareto solutions that represent a reasonable balance between economic and operational objectives. Pareto front analysis and trade-off diagrams showed that cost reduction is usually accompanied by increased risk or delivery time, but the middle region of the front, as an equilibrium point, offers options that are managerially optimal and feasible. This behavior shows that the model is effective not only in finding optimal responses but also in maintaining the diversity and stability of decisions.

Sensitivity analysis also showed that changing the weighting coefficients and fluctuations in input parameters cause relative shifts in the positions of the Pareto points, but the overall shape of the front remains constant. This finding indicates the structural stability and resilience of the model against environmental uncertainties. As a result, the proposed framework has high flexibility and generalizability and can be used in various operational scenarios, from manufacturing supply chains to global logistics networks.

Overall, the main achievement of this research is the simultaneous combination of AI prediction capabilities and multi-objective optimization in an integrated decision support system that can help managers select optimal strategies, reduce the impact of disruptions, and improve the resilience of the chain. It is suggested that in future research, real-time data from digital twin systems and IoT sensors be used so that the model can automatically respond to environmental changes as an adaptive system. Also, the development of hybrid versions based on reinforcement learning and advanced meta-heuristic algorithms such as MOEA/D or NSGA-III can provide a future research path to improve the efficiency and scalability of the model.

References

Aliahmadi, B. (2024). Design and development of a machine learning-based supply chain optimization model: A framework for multiobjective smart decision making. *Journal of Business and Future Economy, 1*(3), 1–13.

Baj-Rogowska, A., & Nozari, H. (2024). Multi objective Machine Learning for Real-Time Decision Making in Smart Supply Chains. *Journal of Business and Future Economy, 1*(3), 47–62. https://journals.iau.ae/index.php/JBFE/article/view/17

Emami, A., Hazrati, R., Delshad, M. M., Pouri, K., Khasraghi, A. S., & Chobar, A. P. (2024). A novel mathematical model for emergency transfer point and facility location. *Journal of Engineering Research, 12*(1), 182-191.

Ghasemi, F., Khadem, M., & Chobar, A. P. (2023). Supplier Selection for Supply Chain by Risk-Averse Decision Maker with Multi-Criteria Decision Making. *International journal of industrial engineering and operational research, 5*(3), 50-62.

Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review, 125*, 285-307. https://doi.org/10.1016/j.tre.2019.03.001

Husseini Shekarabi, A., Ahmad, A., & Choudhury, S. (2025). Supply chain resilience optimization and digital technologies: A bibliometric analysis. *Journal of Computational Logistics and Industrial Systems*, *12*(2), 45–63. https://link.springer.com/article/10.1007/s40171-025-00458-8

Jahin, M. A., Naife, S. A., & Saha, A. K. (2024). AI in supply chain risk assessment: A systematic literature review and bibliometric analysis. *arXiv*. https://arxiv.org/abs/2401.10895

Mori, M. (2017). Risk-cost optimization for procurement planning in multi-tier supply chains. *European Journal of Operational Research*, *261*(1), 88–96. https://doi.org/10.1016/j.ejor.2017.01.022

Nooraie, V., & Parast, M. M. (2019). A multi-objective model for risk mitigating in supply chain. *International Journal of Production Research*, *57*(12), 3852–3873. https://doi.org/10.1080/00207543.2019.1633024

Nozari, H., & colleagues. (2025). A digital twin-based neutrosophic multi-objective framework for smart supply chains. *Journal of [Title]*. https://link.springer.com/article/10.1007/s10845-025-02689-z

Pourghader Chobar, A., Sabk Ara, M., Moradi Pirbalouti, S., Khadem, M., & Bahrami, S. (2022). A multi-objective location-routing problem model for multi-device relief logistics under uncertainty using meta-heuristic algorithm. *Journal of Applied Research on Industrial Engineering*, *9*(3), 354-373.

Roudaki, M., Pourghader Chobar, A., Nagahi, A., Keihani, H., & Alamiparvin, R. (2025). Evaluation of supply chain performance using combination of DEA and fuzzy TOPSIS: A case from Iranian electric industry. *Journal of industrial engineering and management studies*, *12*(1), 114-124.

Teixeira, A. R., Ferreira, J. V., & Ramos, A. L. (2025). Intelligent supply chain management: A systematic literature review on artificial intelligence contributions. *Information*, *16*(5), 399. https://doi.org/10.3390/info16050399