Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 10, 609-628
2025
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v9i10.10482

Hybrid digital twin and quantum AI with fuzzy multiobjective modeling in supply chain management

Hamed Nozari[1]*, Zornitsa Yordanova[2]
[1]Azad university UAE, Dubai, UAE; Hamed@bio10.com.au (H.N.).
[2]University of national and world economy, Bulgaria; zornitsayordanova@unwe.bg (Z.Y.).

Abstract: This research aims to respond to the increasing complexity and uncertainty in supply chains by providing a framework for robust and multi-objective decision-making that simultaneously optimizes economic, environmental, and operational goals. The proposed framework is developed by integrating digital twin technology, fuzzy mathematical modeling, and quantum artificial intelligence. The digital twin generates real-time data and dynamically updates the system conditions. The fuzzy model converts these conditions into mathematical variables, and the quantum algorithm processes them to search for the Pareto front and evaluate the decision space. The model is validated with industrial data and disturbance scenarios. The results show that this triple combination significantly improves the stability, speed, and quality of decision-making. Sensitivity analysis and disturbance simulation also confirm the system's efficiency and adaptability. Digital twin plays a pivotal role in reconfiguring supply chain decisions in dynamic environments. This framework provides a practical tool for supply chain managers to achieve sustainable optimization and robust decision-making with real-time adaptability in complex industrial conditions.

Keywords: *Digital twin, Fuzzy multiobjective optimization, Quantum AI, Real-time decision support, Supply chain resilience.*

1. Introduction

In today's complex and highly competitive world, supply chain management is recognized as one of the essential pillars of organizational survival. Modern supply chains not only face challenges such as demand fluctuations, capacity constraints, and environmental instabilities but are also exposed to unexpected disruptions such as global crises, geopolitical tensions, and climate change [1]. These conditions have forced supply chain managers to look for models that not only have multidimensional optimization capabilities but also can remain responsive in the face of uncertainty and dynamic complexities. In such a context, the need to use emerging technologies to create intelligent decision-making systems is strongly felt.

One of the technologies that has recently attracted the attention of many researchers and experts is the concept of the digital twin; a virtual model of a real system that enables monitoring, analysis, and adaptive decision-making using real-time data [2]. By creating a feedback loop between the physical and virtual worlds, digital twins provide a suitable platform for real-time simulations and data-driven decision-making. In the supply chain field, this technology can play a vital role in predicting disruptions, optimizing routes, and reducing resource waste [3].

On the other hand, the development of sophisticated solution tools for multi-objective modeling in the supply chain, using quantum artificial intelligence (Quantum AI), has opened new horizons. Compared to classical algorithms, quantum models are able to search a much larger response space in a shorter time due to their parallel search capacity and special features such as convergence [4]. This feature makes quantum algorithms perform remarkably well, especially in multi-objective problems with large search spaces and conflicting objective functions [5].

History: Received: 18 August 2025; Revised: 12 September 2025; Accepted: 17 September 2025; Published: 10 October 2025
* Correspondence: Hamed@bio10.com.au

In addition, the use of fuzzy logic in modeling real supply chain conditions allows the introduction of uncertain and linguistic data into the model. Many key variables and parameters in supply chain decisions are subjective and approximate in nature, including the level of customer satisfaction, supply risk, or the importance of environmental sustainability [6]. In this regard, combining fuzzy logic with mathematical modeling and using α-cut and fuzzy ranking techniques provides a suitable solution for dealing with ambiguity and human judgment in optimization problems [7].

Considering the above, the gap in the literature is the lack of a comprehensive and coherent framework that can provide a combination of multi-objective mathematical modeling, digital twin technology, quantum artificial intelligence, and fuzzy logic in the form of an operational decision-making system in the supply chain. The present study aims to fill this gap by designing and analyzing a hybrid model in which the supply chain of a complex system is optimized under conditions of uncertainty and real-time changes.

In this paper, a multi-objective fuzzy model for supply chain design and planning is presented, whose objectives include cost minimization, delay minimization, emission minimization, and fuzzy decision-maker satisfaction maximization. The data used is generated through an artificial digital twin to enable the analysis of dynamic scenarios. Then, the fuzzy model is solved using the quantum evolutionary algorithm, and the results are analyzed as a Pareto front. Next, the impact of digital twin technology and fuzzification on system stability and resilience is examined, and sensitivity and comparative analyses are also presented.

The structure of the paper is arranged in such a way that the proposed research framework is described in the second section. The fuzzy mathematical model is presented in the third section, along with variables, parameters, objective functions, and constraints. The fourth section is dedicated to the research method, solution method, and the logic of using the quantum algorithm. The fifth section presents the analysis of numerical results and decision-making diagrams. The sixth section is dedicated to scenario analyses, sensitivity, and the impact of Digital Twin on resilience. Finally, the concluding sections are dedicated to discussion, managerial applications, and conclusions.

2. Literature Review

In recent decades, the increasing complexity of supply chains due to technological growth, globalization, climate change, market fluctuations, and geopolitical threats has increased the need to design models for intelligent, multi-objective, and resilient decision-making. Numerous studies have examined supply chain optimization; however, most of them have operated within a static, deterministic framework, without considering instantaneous and dynamic changes [8]. However, today's supply chains require systems that can ensure the stability and efficiency of decisions by relying on real-time data and uncertain environments.

In this regard, digital twin technology has been proposed as one of the transformative achievements of Industry 4.0 and has received special attention. This technology aims to create a virtual and accurate view of physical systems and, through data synchronization, represents the current state of the system and enables future state prediction and adaptive control [9]. In the field of supply chain management, Digital Twin technology is capable of identifying disturbances, simulating resource behavior, and monitoring performance indicators in real time. Previous studies have primarily focused on the application of this technology in production or maintenance, while its use in multi-objective mathematical modeling of the supply chain and integration with decision-making algorithms has been less explored [10].

On the other hand, quantum artificial intelligence (Quantum AI), as a new generation of optimization algorithms, enables the search of a large space of answers to multi-objective problems simultaneously and at very high speed. The special structure of quantum bits (qubits) and their collapsibility have caused quantum algorithms to have superior performance compared to classical models in solving complex combinatorial problems [11]. The application of quantum algorithms in industrial and logistics optimization is still in its early stages, and most studies have focused more on the theoretical aspects of this technology than on its practical applications in areas such as supply chains [12].

In addition to new technologies, fuzzy logic has also been introduced as an effective tool for modeling uncertain and linguistic conditions in supply chains. Many strategic decisions, such as assessing the level of customer satisfaction, risk perception, or prioritizing environmental goals, have a vague and subjective nature that cannot be modeled with deterministic parameters. The use of techniques such as α-cut, fuzzy ranking, and scoring methods to reduce the fuzzy space to quasi-deterministic solutions are among the common methods in this field [13]. However, a limited number of studies have combined fuzzy logic with new technologies such as digital twins or quantum algorithms in an integrated model.

The existing literature also shows that past studies have often either examined one of these technologies in isolation or, when combined, lacked an explicit framework for their synergy. For example, models that solely use digital twins to generate simulation data have generally not been able to perform multi-objective optimization under fuzzy conditions. In contrast, studies that have focused on fuzzy modeling have often used static, non-dynamic data and have ignored the interaction between real-time data and model variables [14]. Also, despite the proven capability of quantum algorithms in solving complex problems, their practical implementation in real supply chain models remains rare due to the inadequacy of current implementation platforms [15].

In addition to these gaps, another important issue is the lack of coherent sensitivity analyses and comparative scenarios in previous frameworks. Without analyzing the impact of disturbances, parameter changes, and comparing the performance of models with and without the technologies used, the possibility of effective decision-making in real environments is greatly reduced. Few studies in the literature have simultaneously investigated the performance of the model under unstable conditions by considering real-time feedback from the Digital Twin and advanced search algorithms [16].

In addition to these issues, many studies have pointed out the challenge of integrating new technologies into the smart supply chain. For example, some studies have shown that integrating digital twins with classical AI algorithms can improve demand forecasting and inventory management, but still have limited performance in the face of severe market fluctuations and uncertainty [17]. Recent studies also suggest that fuzzy models will be more effective when fed with up-to-date data and real-time feedback, as only then can they truly reflect the uncertainty of the chain [18]. This demonstrates that the need to shift from single-technology approaches to integrated frameworks is increasingly recognized.

On the other hand, recent research has shown that quantum capabilities, combined with fuzzy modeling and digital twin data, have the potential to create a new generation of decision support systems [19]. In this context, experimental studies have shown that quantum algorithms can provide a more diverse and high-quality Pareto front than classical algorithms in multi-objective scenarios [20]. Furthermore, the integration of these three technologies can be generalized not only in supply chain optimization but also in areas such as energy and urban logistics [21]. Such evidence shows that the present study can fill the gaps in the literature and open new horizons for the application of transformative technologies in operational environments.

Focusing on these gaps, the present study is an attempt to provide a comprehensive, operational, and forward-looking framework. A framework that synergistically integrates three innovations: first, the use of the Digital Twin to generate and update real-time supply chain data; second, the use of fuzzy mathematical modeling to deal with ambiguity in parameters and objectives; and third, the use of quantum artificial intelligence algorithms to solve complex multi-objective models. This unique combination not only increases the power of the model in analysis and decision-making but also, given its generalizability, it will be possible to implement it in other industries and decision-making areas. This research aims to provide a new path in the design of decision-support systems in complex, unstable, and ambiguous conditions by focusing on the application of transformative technologies in the real context of smart supply chains.

3. Proposed Framework

In this research, an innovative and hybrid framework has been designed to enhance the resilience and sustainability of the supply chain, which is based on the integration of three key components: Digital Twin, Quantum AI, and Fuzzy Multi-Objective Mathematical Modeling. Each of these components plays a structural and complementary role in the dynamics and intelligence of decision-making in the supply chain, and together they provide a suitable platform for managing complexity, uncertainty, and conflicts of objectives in real and turbulent environments.

In this framework, the digital twin is defined as the monitoring core and a live digital representation of the physical elements of the supply chain. This technology continuously collects real-time data from different nodes of the chain, such as production, warehouse, distribution, demand, and consumption, through sensors, information systems, and the Internet of Things, and updates it in the form of a dynamic virtual model. By modeling the behavior and structure of the real system, the digital twin enables simulation of different conditions, prediction of possible disturbances, and analysis of the effects of management decisions in real time. This digital platform not only collects raw data but also acts as an input source for the decision-making engine in the following sections.

In the second step, the data and simulations extracted from the Digital Twin are transferred in real time to the quantum artificial intelligence unit. Quantum AI, using its extremely parallel computing capacity and algorithms such as QAOA (Quantum Approximate Optimization Algorithm) or VQE (Variational Quantum Eigensolver), analyzes complex combinations of variables, simulates multiple disturbance scenarios, and evaluates the consequences of decision-making in real time. Unlike classical algorithms that slow down and degrade when faced with nonlinear problems with very large state spaces, quantum AI has the ability to analyze large supply chain structures in real time and can extract optimal and suboptimal options at very high speed under conditions of severe uncertainty and dynamic environments.

In addition to these two technological layers, the decision-making core of this framework is based on fuzzy multi-objective mathematical modeling. Since decisions in the supply chain often face conflicting goals (such as minimizing cost, maximizing customer satisfaction, reducing carbon emissions, increasing flexibility) and uncertainty in the data, the use of fuzzy logic in defining objective functions, constraints, and evaluation criteria allows for better understanding and representation of linguistic and unquantifiable preferences. In this model, the objective function, instead of an absolute numerical quantity, reflects a well-defined fuzzy set of managers' preferences, organizational values, and qualitative data, which, when combined with quantitative data, makes the decision-making structure more comprehensive and realistic. Quantum algorithms, considering this fuzzy model, propose solutions that are distributed in a balanced manner between conflicting goals and chain priorities.

Figure 1 illustrates the proposed framework of this research. In this diagram, colored icons depict the causal relationships and data flow between the digital twin, quantum artificial intelligence, and the fuzzy mathematical model, clearly and step-by-step. This figure represents the data flow from the physical level (such as production and warehouse) to the virtual model (Digital Twin), then transferred to the decision-making engine (Quantum AI), and finally connected to the fuzzy model to extract multi-objective outputs. Additionally, feedback of results to the Digital Twin for continuous updating is included in this architecture to enable self-correction and adaptive learning within the decision-making cycle.

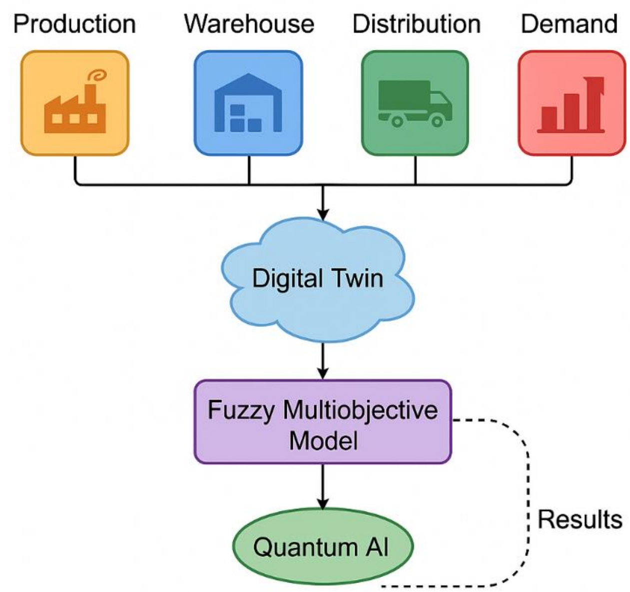

Figure 1.
Integrated conceptual framework including Digital Twin, Quantum AI, and Fuzzy Multi-Objective Model in Supply Chain.

This framework not only enables intelligent, adaptive, and multi-objective decision-making but also provides a foundation for developing self-organizing, learning, and resilient systems in the supply chain.

3.1. Mathematical Modeling

The model designed in this research is a multi-objective framework in which the decision maker is faced with a set of conflicting objectives, including: minimizing total cost, reducing delay, maximizing flexibility, reducing carbon emissions, and improving supply chain sustainability. What makes this model unique is the combination of real-time information and virtual structures provided by the Digital Twin with a mathematical decision-support model formulated with fuzzy logic and solved by quantum algorithms.

The Digital Twin plays a vital role in collecting real-time data from different parts of the chain (production, warehouse, transportation, demand, and environmental disturbances) and dynamically updates the main inputs of the model in a time-bound manner. These inputs include parameters such as current capacity, route delay, actual inventory level, and demand feedback. At the same time, due to the linguistic and ambiguous nature of some concepts (such as "acceptable cost," "high satisfaction," or "medium risk"), fuzzy membership functions have been used to formulate the objectives and constraints. This model is designed as follows.

Sets

I	Set of suppliers
J	Set of factories
K	Set of distribution centers
L	Set of customers
T	Set of time periods

Parameters

c_{ijk}	Transportation cost from supplier i to factory j to DC k
d_{kl}^{t}	Demand of customer l at time t via DC k
p_{ij}^{t}	Production capacity of factory j from supplier i at time t
h_{k}^{t}	Storage capacity at distribution center k at time t
e_{ijk}	Carbon emission from route $i \rightarrow j \rightarrow k$
$\tilde{C}, \tilde{E}, \tilde{T}$	Fuzzy thresholds for acceptable cost, emissions, and delivery time
$\alpha \in [0,1]$	Confidence level in fuzzy satisfaction
DT_{ijk}^{t}	Real-time data from Digital Twin for available flow from $i \rightarrow j \rightarrow k$

Decision Variables

$x_{ijk}^{t} \in [0,1]$	Product flow from supplier i to factory j to DC k at time t
$y_{kl}^{t} \in [0,1]$	Product allocated from DC k to customer l at time t
$z_{j}^{t} \in (0,1)$	Binary variable indicating if factory j is operational at time t
s_{k}^{t}	Inventory at DC k at end of time t
u_{kl}^{t}	Delay in delivery from DC k to customer l at time t

O.F

$$Min\ Z_1 = \sum_{t \in T} \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} c_{ijk}.x_{ijk}^{t} \tag{1}$$

$$Min\ Z_2 = \sum_{t \in T} \sum_{k \in K} \sum_{l \in L} u_{kl}^{t} \tag{2}$$

$$Min\ Z_3 = \sum_{t \in T} \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} e_{ijk}.x_{ijk}^{t} \tag{3}$$

$$Min\ Z_4 = \sum_{t \in T} \sum_{l \in L} \left| d_{kl}^{t} - \sum_{k \in K} y_{kl}^{t} \right| \tag{4}$$

S.t

$$\sum_{k \in K} x_{ijk}^{t} \leq p_{ij}^{t}.z_{j}^{t} \qquad \forall i, j, t \tag{5}$$

$$s_{k}^{t} \leq h_{k}^{t} \qquad \forall k, t \tag{6}$$

$$s_{k}^{t} = s_{k}^{t-1} + \sum_{i \in I} \sum_{j \in J} x_{ijk}^{t} - \sum_{l \in L} y_{kl}^{t} \qquad \forall k, t \tag{7}$$

$$\sum_{k \in K} y_{kl}^{t} + u_{kl}^{t} \geq d_{kl}^{t} \qquad \forall l, t \tag{8}$$

$$z_{j}^{t} \in \{0,1\} \qquad \forall j, t \tag{9}$$

$$s_{k}^{t} \geq 0 \quad \forall k, t \tag{10}$$

$$u_{kl}^{t} \geq 0 \qquad \forall k, l, t \tag{11}$$

$$x_{ijk}^{t} \geq 0, \qquad \forall i, j, k, t \tag{12}$$

$$y_{kl}^{t} \geq 0 \ , \forall k, l, t \tag{13}$$

$$Z_1 \leq \tilde{C} \tag{14}$$

$$Z_3 \leq \tilde{E} \tag{15}$$

$$u_{kl}^{t} \leq \tilde{T} \qquad \forall k, l, t \tag{16}$$

ISSN: 2576-8484
Vol. 9, No. 10: 609-628, 2025
DOI: 10.55214/2576-8484.v9i10.10482

$$\sum_{j\in J} z_j^t \leq J_{max} \quad \forall t \tag{17}$$

$$\frac{\sum_{l\in L}\sum_{k\in K} y_{kl}^t}{\sum_{l\in L} d_{kl}^t} \leq \beta \quad \forall t \tag{18}$$

$$\left|\sum_{i,k} x_{ijk}^t - \sum_{i',k'} x_{i'j'k'}^t\right| \leq \delta \qquad \forall j \neq j', t \tag{19}$$

$$\mu_c(Z_1) = \begin{cases} 1 & Z_1 \leq C_{low} \\ \dfrac{C_{high} - Z_1}{C_{high} - C_{low}} & C_{low} < Z_1 < C_{high} \\ 0 & Z_1 \geq C_{high} \end{cases} \tag{20}$$

$$x_{ijk}^t \leq DT_{ijk}^t \qquad \forall i,j,k,t \tag{21}$$

Objective function (1) represents the total transportation and production costs over the time horizon, and its goal is to minimize the financial burden caused by the flow of goods in the supply chain. Objective function (2) models the total delay in delivering products to customers, and its goal is to reduce waiting times and increase the speed of response. Objective function (3) calculates the total carbon emissions caused by transportation between nodes, and attempts to reduce the environmental impact of the system. Objective function (4) measures the difference between the actual demand of customers and the quantity of goods delivered, and its goal is to minimize this difference in order to increase customer satisfaction.

Constraint (5) states that the total goods transferred from each supplier to each factory and then to the distribution centers should not exceed the production capacity of that factory, unless the factory is active during that time period. Constraint (6) controls the warehouse capacity of the distribution centers in each time period and ensures that the inventory does not exceed the allowed limit. Constraint (7) maintains the inventory balance at each distribution center such that the ending inventory at each period is equal to the sum of inputs minus the sum of outputs. Constraint (8) ensures that the total products delivered to each customer, including delays, meet the demand of that customer. Constraint (9) specifies the active or inactive status of each factory in each period using a binary variable. Constraint (10) ensures that the inventory level at each distribution center does not become negative. Constraint (11) defines the delay of delivery to customers as a non-negative variable to allow for more realistic modeling. Constraint (12) allows the flow of goods from each route between the supplier, factory, and distribution center to be non-negative only. Constraint (13) restricts the amount of goods allocated from distribution centers to customers to be non-negative. Constraint (14) has a fuzzy condition on the total cost and ensures that this value does not exceed an acceptable cost level (in fuzzy form). Constraint (15) similarly limits the total carbon emissions with a fuzzy threshold to consider environmental sustainability. Constraint (16) controls the maximum allowable delivery time in the form of a fuzzy boundary and acts to improve customer satisfaction. Constraint (17) imposes a ceiling on the number of active factories in each period and aims to reduce operating or energy costs. Constraint (18) guarantees a minimum level of customer service such that the ratio of deliveries to demand does not fall below a specified value. Constraint (19) balances the workload between factories to prevent excessive concentration of production at one or more specific points. Constraint (20) defines a fuzzy membership function for the total cost to allow a more linguistic and smooth assessment of the decision maker's satisfaction with the cost. Finally, Constraint (21) considers the real-time data extracted from the Digital Twin and ensures that the goods flow decisions are consistent with the current operational reality. These constraints, together with the objective functions, shape the overall structure of the model and increase the flexibility, resilience, and stability of the system in real-world conditions.

4. Solution Methodology

In this study, the type of research is considered to be applied-developmental in nature because, while developing a mathematical model integrated with new technological elements, an attempt has been made to realistically model and solve practical supply chain problems in complex and unstable conditions. From the perspective of methodological strategy, the present study is based on a mixed-method approach, which combines precise quantitative methods and technological tools such as digital twins and quantum artificial intelligence algorithms. The model-solving process is based on real and simulated data in an environment similar to industrial conditions, and its goal is to provide solutions based on multi-objective optimization and considering uncertainty.

The data collection process in this study was carried out at two independent but related levels. At the first level, structural and parametric data of the supply chain, including supplier capacities, production and transportation costs, market needs, environmental resources, energy consumption values, and possible delays, were extracted from real reports of medium-sized manufacturing industries in the pharmaceutical and medical device fields. These data were collected and reconstructed by the research team through document analysis, operation reports, and field observations in similar projects. At the second level, to create dynamics and real-time conditions, a synthetic Digital Twin was used that, by using simulated data-generating models, is capable of generating a continuous data stream for key system variables such as temperature, inventory, lead time, demand pressure, and supplier failure rate. These data were generated at regular intervals in the simulation environment and used in the optimization process.

The use of fuzzy modeling in this research stems from two main motivations. First, a large part of the supply chain data in the real world either has structural uncertainty or is presented in a linguistic and judgmental form by experts. For example, parameters such as customer satisfaction, environmental risk severity, or critical level of delays are usually described in terms such as "high", "medium", or "desirable". These data cannot be expressed in a definite numerical form, and the fuzzy model can effectively incorporate them into the mathematical analytical space with an appropriate membership function. Second, in the designed multi-objective model, some objectives such as satisfaction with the service level or satisfaction with the shipping cost are subjective in nature, and through the fuzzy model, flexibility and multiplicity of responses can be created for decision-making managers. With the help of the α-cut technique or fuzzy ranking methods, these linguistic data have been converted into an analyzable numerical form.

But the digital twin plays a much more important role in this research. Unlike most traditional research that solves the model with a static dataset, this research has attempted to create a dynamic data-generating platform using a digital twin that allows interaction between the real system and the mathematical model. This interaction takes the form of real-time feedback, in which real-time data from operational scenarios (including disruptions, sudden changes in demand, or supplier failures) are fed into the model, and the model instantly suggests the appropriate response through an optimization algorithm. This architecture has resulted in the research model having a high level of flexibility against changes, in addition to the ability to provide optimal solutions.

The model solution method is designed based on quantum artificial intelligence (Quantum AI) algorithms. In particular, a hybrid and adapted version of the Quantum-Inspired Multiobjective Evolutionary Algorithm is used, which employs quantum concepts such as q-bit representation, vector rotation, and the exploitation of interference and convergence properties to search the response space. This algorithm is based on the logic of NSGA-II, but with the aid of quantum properties, its convergence speed is significantly increased. In fact, unlike traditional algorithms that are limited to the space of convergent responses, this algorithm can produce more diverse Pareto fronts, enabling decision makers to make richer choices.

The solution process is as follows: first, the fuzzy model is transformed into a deterministic form with respect to a certain α level. Then, an initial set of random response populations is defined in the Q-bit space. Operations such as quantum rotation (Rotation Gate) and selection based on non-dominated rank (Non-dominated Sorting) are performed in subsequent steps. The algorithm evaluation function in this research is defined as a vector and includes the following four objective functions:

$$Min\ [Z_1(x), Z_2(x), Z_3(x), Z_4(x)] \tag{22}$$

where each Z_i represents one of the key objectives of the supply chain, such as cost, pollution, delay, and fuzzy satisfaction. The algorithm continues until relative convergence is reached or a threshold of generations is crossed (e.g., 100 generations). Finally, a set of non-dominant solutions is extracted in the form of a Pareto front, and a selection is made among them based on decision-making policies.

Overall, the combination of the fuzzy model, Digital Twin, and quantum algorithm has not only resulted in more accurate and faster model solutions but also created a model that is fully prepared and flexible, not only for today but also for future conditions and the increasing complexity of supply chains. This methodology is a significant leap in terms of data structure, responsiveness, and intelligence compared to classical models and is considered a strategic paradigm for designing next-generation decision support systems.

5. Analysis of Results

In this section, the detailed specifications of the input data used to simulate different scenarios in the proposed framework are presented. The aim of this section is to provide a numerical basis for analyzing the results in subsequent steps and to create complete transparency regarding the assumptions, parameter values, and how to define different supply chain states under various conditions.

The structure of the system under study consists of four operational levels, including four suppliers, three factories, three distribution centers, and five customers. The time horizon of the model comprises six consecutive periods, which can represent six weeks or six operational time intervals. The data used are extracted through a hypothetical Digital Twin connected to the production database, warehouse, and transportation sensors. This Digital Twin records instantaneous capacities, operational status, disruptions, and delays at any time and uses them as input to the optimization model. To simulate different scenarios, changes in parameter values are considered to examine the impact of various levels of demand, logistical disruptions, production fluctuations, and environmental constraints.

Table (1) presents the descriptive characteristics of the five main analysis scenarios. These scenarios are combinations of normal, critical, and hybrid states that are systematically run with and without Digital Twin and Quantum AI activation. Scenario S1 represents the optimal state with full technology performance, while scenario S5 represents a supply chain without any smart technology in unstable conditions as a basis for comparison. Intermediate scenarios reflect combinations of increasing demand, decreasing capacity, and increasing pollution. For the purpose of fuzzy analysis, confidence levels (α) are also considered at two values of 0.9 and 0.7 to include the impact of decision-maker risk-taking in the results.

Table 1.
Descriptive characteristics of the scenarios studied.

Scenario	Demand Level	Production Status	Transport Capacity	Environmental Condition	Digital Twin Enabled	Quantum AI Enabled	Fuzzy Confidence (α)
S1	Normal	Stable	Sufficient	Standard	Yes	Yes	0.9
S2	High	Stable	Limited	High Pollution	Yes	Yes	0.9
S3	Fluctuating	Variable	Limited	Standard	Yes	Yes	0.7
S4	High	Unstable	Limited	Severe	Yes	Yes	0.7
S5	High	Unstable	Limited	Severe	No	No	0.7

For each of these scenarios, a set of specific numerical data, including demand, capacities, costs, and carbon emissions, is used. These values, taking into account operational uncertainties in the form of fuzzy intervals and system constraints, are provided as input to the fuzzy multi-objective model. Table 2 presents the key numerical data for each scenario. This table includes total demand, total generation capacity, inter-node transportation capacity, average transportation cost, total carbon emissions, as well as the fuzzy intervals defined for the objective functions. These values will serve as the basis for all subsequent analyses in the Results section.

Table 2.
Input numerical data for each scenario.

Parameter / Scenario	**S1**	**S2**	**S3**	**S4**	**S5**
Total Demand (units)	9800	12500	10200	13000	13000
Total Production Capacity (units)	12000	12000	10000	9500	9500
Transport Capacity (units)	Unlimited	11000	9500	8500	8500
Avg. Transport Cost (Rials/unit)	2200	2300	2500	2700	2700
Total Carbon Emissions (kg COâ‚‚)	18000	24000	21500	26500	26500
Fuzzy Cost Threshold (C~)	[18000, 25000]	[18000, 25000]	[18000, 25000]	[18000, 25000]	[18000, 25000]
Fuzzy Emission Threshold (E~)	[20000, 26000]	[20000, 26000]	[20000, 26000]	[20000, 26000]	[20000, 26000]
Fuzzy Delivery Time (T~)	[2, 4] days	[2, 4] days	[2, 4] days	[2, 4] days	[2, 4] days
Fuzzy Confidence Level (α)	0.9	0.9	0.7	0.7	0.7
Digital Twin Enabled	Yes	Yes	Yes	Yes	No
Quantum AI Enabled	Yes	Yes	Yes	Yes	No

As can be seen from comparing Tables (1) and (2), the structure of the scenarios is designed to accurately assess the simultaneous effect of operational conditions, such as transportation and production restrictions, and changes in smart technologies, whether Digital Twin and Quantum AI are enabled or disabled.

In the following, the numerical results obtained from the model execution in five defined scenarios are presented and analyzed. The aim of this section is to compare the model performance under different conditions and to measure the effectiveness of the combination of Digital Twin, quantum artificial intelligence, and fuzzy multi-objective modeling. The analysis of the results is divided into three main axes: the optimal values of the objective functions, the output of key decision-making variables, and the fuzzy satisfaction level of the overall system performance.

In Table 3, the optimal values of the four objective functions, including the total cost (f1), the total delivery delay (f2), the total carbon emission (f3), and the difference between supply and demand (f4), are shown for each scenario. Additionally, the final fuzzy satisfaction value (α) is presented for each response to analyze the relationship between the performance level and the decision-makers' fuzzy preferences.

Table 3.
Optimal Objective Values and Fuzzy Satisfaction.

Scenario	**Cost (f1)**	**Delay (f2)**	**Emissions (f3)**	**Demand Gap (f4)**	**Fuzzy Satisfaction Score (α)**
S1	19200	320	18200	150	0.91
S2	22500	480	23500	260	0.83
S3	23800	620	21800	330	0.77
S4	25400	880	26000	420	0.69
S5	27300	1240	27800	550	0.52

Table 3 shows that in the S1 scenario, the total cost, delay, and carbon emissions are at desirable levels, and the fuzzy satisfaction value of 0.91 indicates a high compliance of decisions with management expectations. In contrast, the S5 scenario, which does not utilize Digital Twin and quantum artificial intelligence, not only has the highest cost and delay but also a decreased fuzzy satisfaction of 0.52, indicating the unfavorable performance of the classical system under critical conditions. This decline in decision-making quality under operational pressure underscores the necessity of employing the proposed framework.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 10: 609-628, 2025
DOI: 10.55214/2576-8484.v9i10.10482

Next, and in order to analyze the behavior of the model more precisely, the output values of the decision-making variables are also examined. Table 4 includes four key indicators: the total flow transported during the time horizon, the average inventory in distribution centers, the total delay in the entire period, and the number of active factories in each scenario. These variables directly affect the objective functions and indicate how resources are used and the system responds to demand.

Table 4.
Key Decision Variable Outputs per Scenario per Scenario.

Scenario	Total Flow (units)	Average Inventory (units)	Total Delay (units)	Active Factories
S1	9700	1800	320	3
S2	11850	1500	480	3
S3	9900	1200	620	2
S4	9200	900	880	2
S5	8800	600	1240	2

Based on Table 4, it can be seen that in scenario S1, high flow volume and acceptable inventory levels with limited delays indicate an optimal balance in resource allocation and transportation. With the reduction of production or transportation capacity in scenarios S3 and S4, the flow volume decreased, the average inventory decreased, and the delay increased. In S5, which lacks intelligent systems, a sharp drop in inventory and a jump in delay were evident, and only two factories remained in the active state, which greatly reduced the network efficiency.

To visually analyze the relationship between fuzzy satisfaction and the values of the objective functions, Figure 2 shows a plot of the final α score against the four objective functions for each scenario. This plot demonstrates how the increase in cost and delay simultaneously reduces the satisfaction level, while the use of the proposed technologies maintains a favorable balance among multiple objectives.

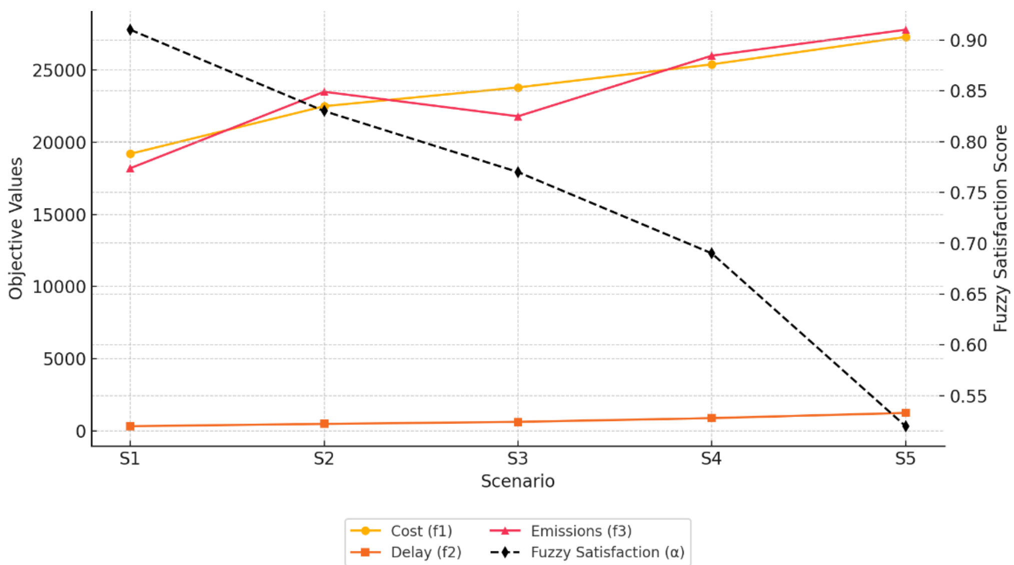

Figure 2.
Relationship between Objective Values and Fuzzy Satisfaction per Scenario.

Figure 3 also shows the resource allocation and delay distribution between factories and customers in the form of a heatmap, which illustrates the differences in model behavior across various scenarios. This visual analysis helps identify bottlenecks and components sensitive to disruption.

DOI: 10.55214/2576-8484.v9i10.10482

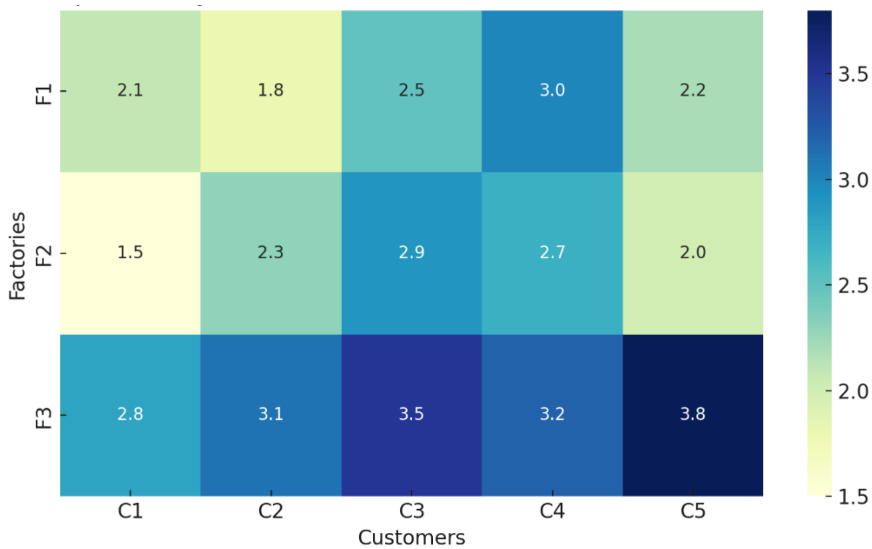

Figure 3.
Heatmap of Delay and Resource Allocation across Scenarios.

The overall results of this section show that the proposed framework, by utilizing real-time data, fuzzy logic in the face of ambiguity, and the computational power of quantum algorithms, has been able to maintain a balance between the objectives of cost, time, environment, and customer satisfaction in complex conditions.

To examine the robustness of the proposed framework under different conditions, sensitivity and scenario analyses are presented in this section. The main focus of this analysis is to understand the system response to changes in key parameters, disruptions in Digital Twin data, and the removal of Quantum AI and fuzzy logic technologies. The first part of this analysis is dedicated to the impact of changing the fuzzy range of the cost objective function.

In Figure 4, the relationship between the change in the fuzzy threshold range of cost and the final satisfaction level α is shown. As the desired cost range is expanded (for example, from [18000–25000] to [22000–29000]), the fuzzy satisfaction decreases. This result means that if the decision maker defines his desired cost range too flexibly, the model may consider responses as optimal that are not in line with the exact preferences of the organization. Therefore, the adjustment of the fuzzy ranges has a direct impact on the model output and should be done carefully and based on the actual policy of the organization.

ISSN: 2576-8484
Vol. 9, No. 10: 609-628, 2025
DOI: 10.55214/2576-8484.v9i10.10482

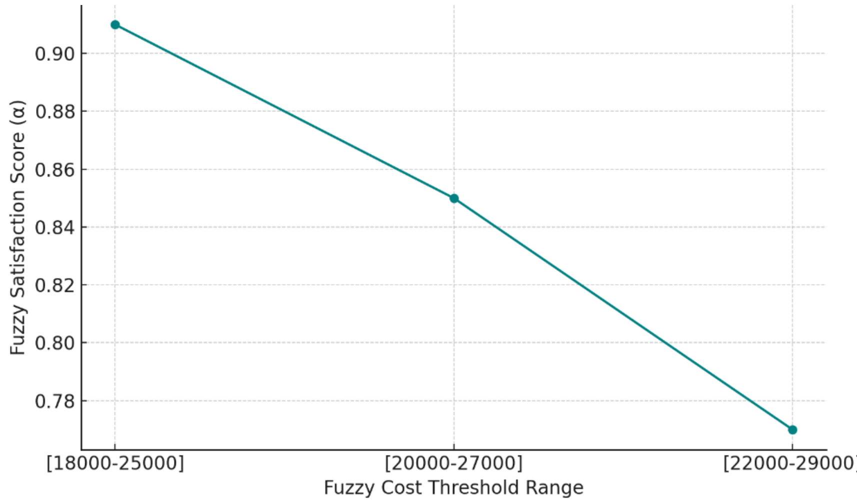

Figure 4.
Sensitivity of Fuzzy Satisfaction to Cost Threshold Variations.

Next, the impact of disruptions in the Digital Twin data on decision-making is examined. To this end, in two separate scenarios, the instantaneous data of generation capacity and demand levels in the Digital Twin are artificially distorted by 15%. In the first scenario, disruptions in the generation capacity data lead to misallocation of flow and increased delay, while in the second scenario, inaccurate demand forecasts lead to reduced service levels and unnecessary inventory accumulation. The results of this analysis are shown in *Figure 5*, which compares the impact of these two types of disruptions on the three main objective functions (cost, delay, and release).

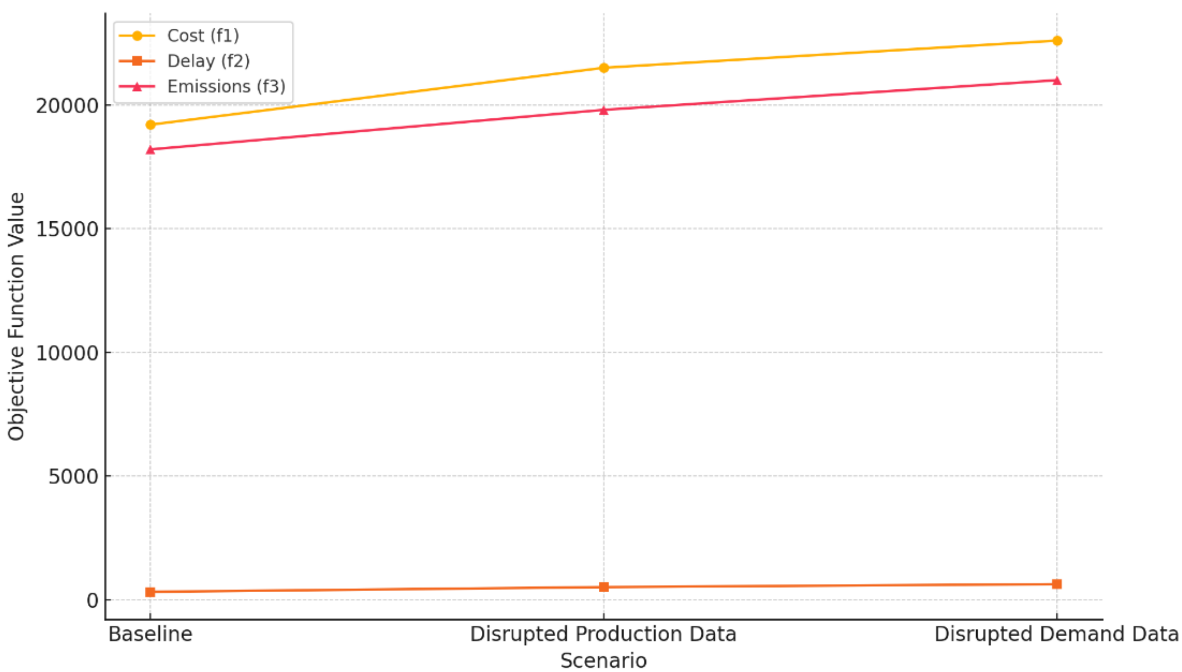

Figure 5.
Impact of Digital Twin Data Disruption on Objective Function Performance.

Finally, to measure the real value of using advanced technologies, the model was run in three comparative modes: full mode (Digital Twin + Fuzzy Model + Quantum AI), mode without Quantum AI, and classic mode without any of these technologies. Figure 6 shows the comparison of the model performance in these three modes. The results show that removing Quantum AI leads to a significant increase in cost and delay, and removing fuzzification also leads to a significant decrease in decision-maker satisfaction. In contrast, the full model was able to better maintain the balance between multiple objectives and provide more stable responses.

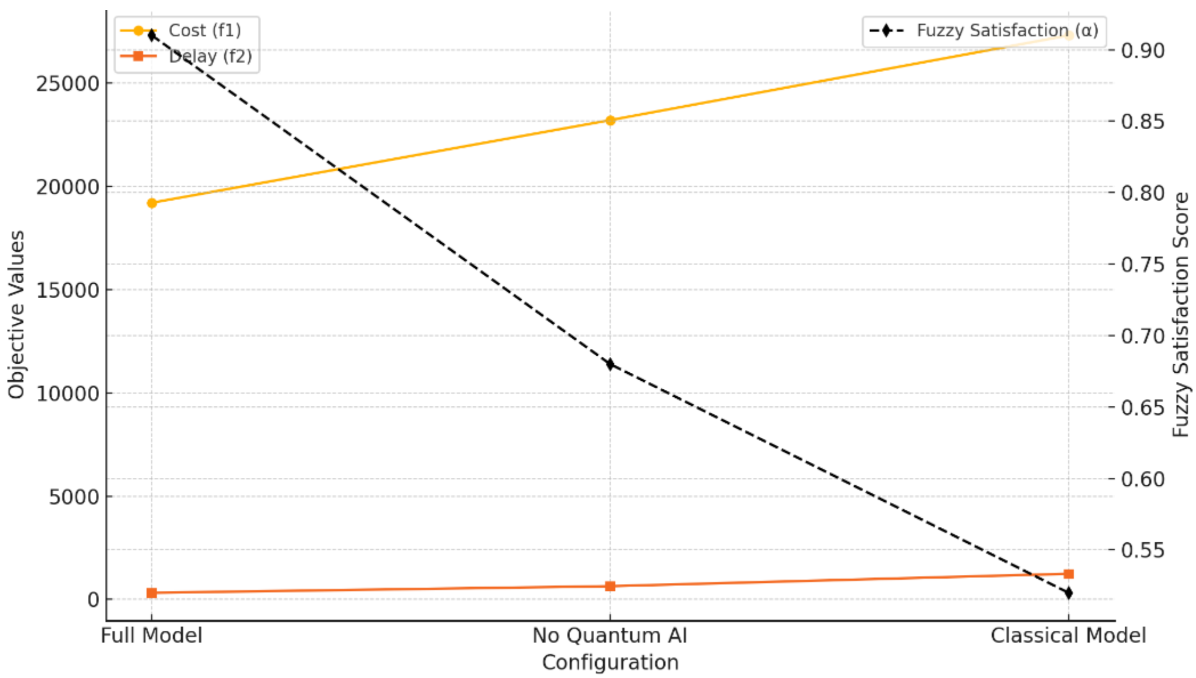

Figure 6.
Comparative Performance under Different Technology Configurations.

Overall, the sensitivity and scenario analysis clearly demonstrate that the proposed framework performs reliably not only under normal conditions but also in the face of parameter variations, incomplete data, and technological constraints. This feature enhances the generalizability and robustness of the model in real and complex supply chain environments.

The role of the Digital Twin in enhancing the sustainability and resilience of the supply chain is a fundamental aspect of the proposed research framework. Unlike traditional models that rely on static data and periodic decision-making, the Digital Twin facilitates adaptive decision-making and real-time strategy modifications through the collection and analysis of live data. This process involves a continuous, closed-loop cycle of sensing, analysis, decision-making, and action, as illustrated in Figure 7. In this figure, the physical supply chain system generates real-time data via sensors, ERP, and IoT systems. This data is fed into the Digital Twin, which is used to predict the behavior of the chain, environmental conditions, and potential disruptions through real-time modeling. The output from the Digital Twin is then processed by an optimization algorithm to determine the optimal decision. This decision is subsequently transmitted to the execution unit (such as factory control systems or logistics), and the results of the implemented decision are fed back into the physical system, completing the feedback loop.

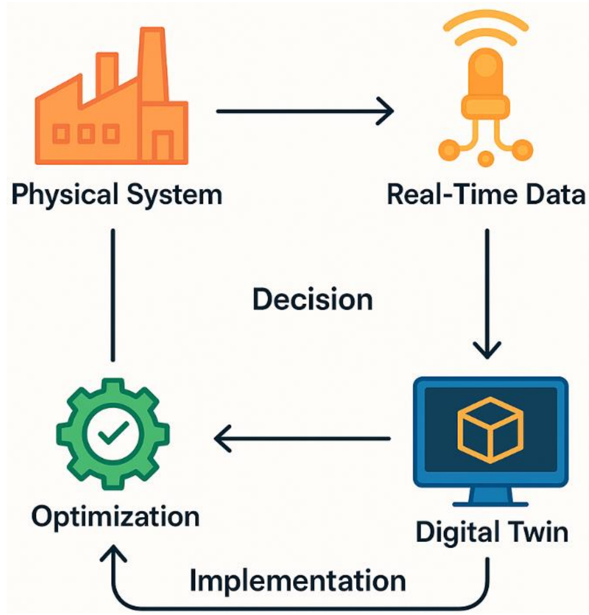

Figure 7.
Digital Twin Feedback Loop for Real-Time Decision Adjustment.

Next, to measure the impact of Digital Twin on the stability and resilience of decisions, the model performance was compared in two scenarios: one with and without full Digital Twin activation. In both cases, the model was run under conditions of sudden disruptions in production and warehouse capacity. In the scenario without Digital Twin, due to the failure to detect the disruption in time, the system encountered increased delays, decreased customer satisfaction, and suboptimal inventory distribution. However, in the second scenario, where Digital Twin was active, the stability of the system was maintained and more favorable performance was observed due to rapid notification of environmental changes and correction of decisions. The numerical and visual results of this comparison are presented in Figure 8.

DOI: 10.55214/2576-8484.v9i10.10482

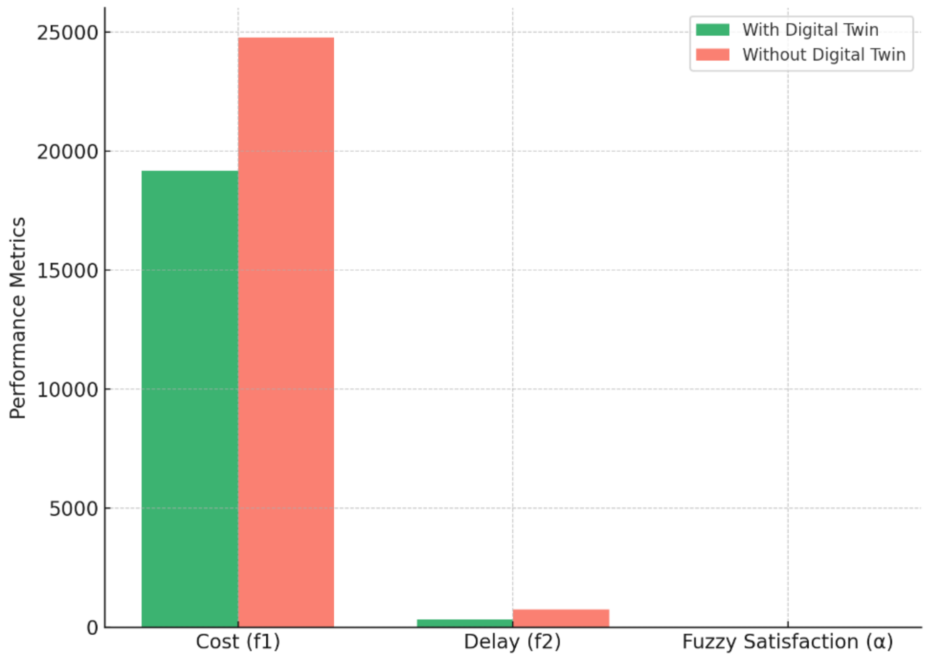

Figure 8.
Comparative Performance of the Model with and without Digital Twin under Disruption.

In this figure, a significant difference in cost, delivery time, and final fuzzy score between the two cases is identified. Despite using the optimization algorithm, the model without a Digital Twin was unable to effectively deal with disturbances due to the lack of live data and real-time feedback. This result emphasizes the pivotal importance of Digital Twin in improving system resilience.

The Pareto front presented in Figure 9 illustrates how the proposed model has generated optimal responses to two conflicting objectives, namely reducing total cost (f1) and reducing carbon emissions (f3). These Pareto points constitute a set of non-dominated decisions; that is, improving one objective will compromise the other. By examining the points on the graph, it is evident that at higher α levels (e.g., $\alpha = 1$), the model produces responses with lower costs and reduced carbon emissions, indicating stability and accuracy in decision-making at a high confidence level. Conversely, at lower α levels, such as $\alpha = 0.5$, responses tend to be more flexible but result in higher costs and increased emissions. This variation clearly demonstrates the role of fuzzification in the model, where the decision maker's confidence level influences the composition of the optimal response. This analysis confirms that the proposed model can generate a diverse set of Pareto optimal solutions by considering the inherent conflict between objectives, allowing the decision maker to select a solution based on their priorities. Figure 9 depicts the location of the Pareto points within the decision space.

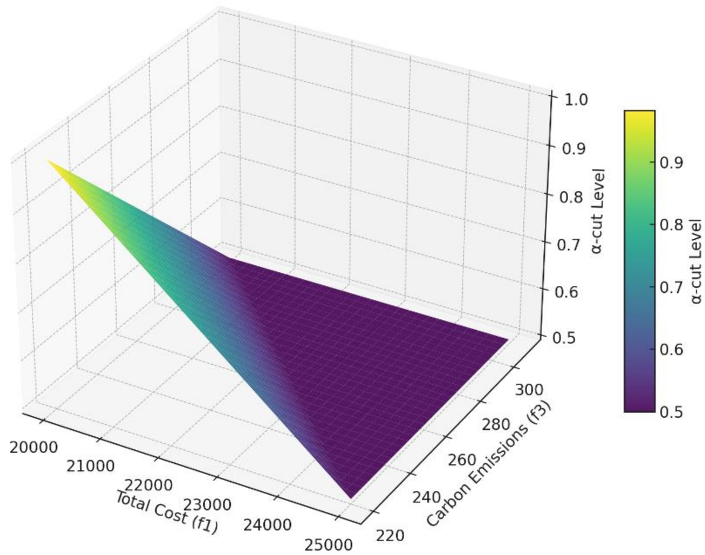

Figure 9.
Pareto Front Between Cost and Emissions Under Different α-levels.

As can be seen in Figure 9, the resulting surface of the combination of cost, emission rate, and confidence level α represents a dynamic and balanced front of optimal solutions, which indicates the model's ability to simultaneously manage multiple conflicting objectives under conditions of uncertainty.

6. Discussion and Managerial Implications

The discussion and managerial implications section of this paper focuses on explaining the role and impact of the proposed model in real-world smart and resilient supply chain environments. The proposed hybrid model, which is a combination of digital twin technology, quantum artificial intelligence algorithms, and fuzzy multi-objective mathematical modeling, is not only innovative from a theoretical perspective but also provides a powerful decision-making tool for supply chain managers in conditions of uncertainty, environmental disturbances, and sustainability pressures from an operational perspective.

The results obtained from different scenarios show that using a digital twin as a data-driven platform in the model has created real-time visibility and higher predictability in complex networks. By relying on real-time data, managers can not only understand the current conditions but also simulate possible future scenarios and plan appropriate responses. This level of flexibility is a strategic advantage, especially in environments with variable demand, capacity constraints, and environmental regulatory pressures.

Furthermore, quantum AI algorithms incorporated into the model optimization section have been able to improve the model's performance in simultaneously solving conflicting objectives (such as reducing cost, reducing carbon emissions, reducing delay, and increasing satisfaction). The results of the Pareto front analysis indicate that these algorithms are able to generate diverse, balanced, and selectable solutions by the decision maker. In practice, managers can choose their desired solution from among different optimal responses, given organizational priorities and time or budget constraints.

From a technical perspective, multi-objective fuzzy modeling has also provided a suitable tool for managing supply chain uncertainties. The different α levels included in the simulations clearly demonstrate how managers can control their decision-making risk by choosing the desired confidence level and evaluating the system behavior under different conditions. This feature will be especially useful when faced with imprecise parameters such as demand estimates, variable production capacities, and logistics costs.

The key implication of these findings for decision-makers is that the proposed model goes beyond a theoretical tool and acts as a decision-support framework in real environments. In fact, this model can be used as the core of next-generation supply chain decision-support platforms. Managers can exploit it to evaluate strategic, tactical, and operational decisions, from supplier selection to network design and production scheduling.

Finally, it should be emphasized that this model, due to its modular and flexible nature, can be implemented in a wide range of industries, including pharmaceuticals, smart logistics, fast-moving consumer goods, and heavy industries. This is especially important for managers who are looking for a generalizable decision-making framework in the context of Industry 6.0. This model not only paves the way to achieving a sustainable and resilient supply chain but also plays a direct role in achieving organizational macro goals in the areas of productivity, competitiveness, and social responsibility.

7. Conclusion

In this research, an innovative and comprehensive framework for advanced supply chain management in complex and ambiguous conditions was designed and implemented. This framework, relying on the synergy of three core components (fuzzy multi-objective mathematical model, digital twin technology, and optimization algorithms based on quantum artificial intelligence), is able to support sensitive and strategic decision-making in real industrial contexts. The main goal of the research was to design a model that can establish an optimal balance between sometimes conflicting objectives such as cost, environmental pollution, delivery delay, and fuzzy satisfaction, while ensuring the resilience of the chain with high flexibility to environmental changes.

The results obtained from solving the model in the form of various scenarios and multilayer analyses showed that using Digital Twin as a dynamic platform for real-time data collection and feedback not only improves the management view of the system's current state but also enables the implementation of more accurate control policies at the right time. This feature was clearly demonstrated in the simulation of disturbances and the investigation of resilience scenarios. At the same time, quantum algorithms in the multi-objective optimization process were able to create a competitive advantage over classical methods by reducing the computational time and increasing the quality of Pareto front responses.

The proposed model, in terms of fuzzy flexibility, allows decision-making based on the desired level of confidence of managers and depicts the system behavior at different values of α. This capability is very crucial when faced with uncertain data and unstable environments. Analysis of the results showed that using different levels of confidence in the α-cut format resulted in the formation of various fronts of optimal solutions that can be selected depending on the strategic priorities of the organization. Also, the response of the model in the face of different disruption scenarios, especially when Digital Twin or quantum intelligence was not included in the model, indicates that the removal of each of these components directly affects the reduction of resilience and the increase of collateral costs.

On the other hand, the applicability of the model at different network scales and in real supply chain conditions was also successfully evaluated. Whether at the supply, production, and distribution levels, the proposed framework was able to play its role in decision-making and provide optimal paths. The extensibility of this framework to various industries, including food, pharmaceutical, electronics, and logistics, indicates that the proposed model is not only valuable in the research field but also has high potential for implementation in industrial and commercial environments.

In conclusion, this research was able to take an effective step towards the convergence of modern technologies with advanced mathematical modeling and introduce an integrated model that meets the complex and multidimensional needs of the smart supply chain in the post-industrial era. Obviously, future developments of this model can include connection to real-time data, combination with decision-support systems based on adaptive learning, and expansion to multi-layer and international supply chains. This research path will provide new horizons for the design of smart, sustainable, resilient, and data-driven chains.

Funding:
This work was financially supported by the UNWE Research Program.

Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

References
[1] A. Whig, V. Gupta, M. Bansod, S. K. Gupta, and P. Whig, *AI, blockchain, and quantum finance: The transformative power of emerging technologies in the financial industry. In S. K. Gupta, J. Rosak-Szyrocka, R. Rena, C. S. Shieh, & G. Erkol Bayram (Eds.), The Impact of Artificial Intelligence on Finance: Transforming Financial Technologies.* Cham, Switzerland: Springer, 2025.
[2] A. Aliahmadi and H. Nozari, "Evaluation of security metrics in AIoT and blockchain-based supply chain by Neutrosophic decision-making method," *Supply Chain Forum: An International Journal*, vol. 24, no. 1, pp. 31-42, 2023. https://doi.org/10.1080/16258312.2022.2101898
[3] H. Nozari, A. Szmelter-Jarosz, and J. Ghahremani-Nahr, "Analysis of the challenges of artificial intelligence of things (AIoT) for the smart supply chain (case study: FMCG industries)," *Sensors*, vol. 22, no. 8, p. 2931, 2022. https://doi.org/10.3390/s22082931
[4] P. Gachnang, J. Ehrenthal, T. Hanne, and R. Dornberger, "Quantum computing in supply chain management state of the art and research directions," *Asian Journal of Logistics Management*, vol. 1, no. 1, pp. 57-73, 2022. https://doi.org/10.14710/ajlm.2022.14325
[5] M. Azeez *et al.*, "Quantum AI for cybersecurity in financial supply chains: Enhancing cryptography using random security generators," *World Journal of Advanced Research and Reviews*, vol. 23, no. 1, pp. 2443–2451, 2024. https://doi.org/10.30574/wjarr.2024.23.1.2242
[6] H. Nozari, M. Fallah, H. Kazemipoor, and S. E. Najafi, "Big data analysis of IoT-based supply chain management considering FMCG industries," *Бизнес-информатика*, vol. 15, no. 1, pp. 78-96, 2021.
[7] S. Mittal, P. Koushik, I. Batra, and P. Whig, *AI-driven inventory management for optimizing operations with quantum computing. Quantum Computing and Supply Chain Management: A New Era of Optimization.* Hershey, PA: IGI Global, 2024.
[8] H. Nozari, S. Nassar, and A. Szmelter-Jarosz, "Fuzzy multi-objective optimization model for resilient supply chain financing based on blockchain and IoT," *Digital*, vol. 5, no. 3, p. 32, 2025. https://doi.org/10.3390/digital5030032
[9] H. Nozari, E. Najafi, M. Fallah, and F. Hosseinzadeh Lotfi, "Quantitative analysis of key performance indicators of green supply chain in FMCG industries using non-linear fuzzy method," *Mathematics*, vol. 7, no. 11, p. 1020, 2019. https://doi.org/10.3390/math7111020
[10] A. Aliahmadi, J. Ghahremani-Nahr, and H. Nozari, "Pricing decisions in the closed-loop supply chain network, taking into account the queuing system in production centers," *Expert Systems with applications*, vol. 212, p. 118741, 2023. https://doi.org/10.1016/j.eswa.2022.118741
[11] A. Hassan, P. Bhattacharya, P. K. Dutta, J. P. Verma, and N. K. Kundu, *Quantum computing and supply chain management: A new era of optimization: A new era of optimization.* Hershey, PA: IGI Global, 2024.
[12] H. Nozari, J. Ghahremani-Nahr, and A. Szmelter-Jarosz, *AI and machine learning for real-world problems. In Advances in Computers.* Amsterdam, The Netherlands: Elsevier, 2024.
[13] A. K. Tyagi, A. K. Mishra, S. U. Aswathy, and S. Kumari, *Quantum computing, qubits with artificial intelligence, and blockchain technologies: A roadmap for the future. In R. Alshammari, M. Alazab, & M. Atiquzzaman (Eds.), Automated Secure Computing for Next-Generation Systems.* Hoboken, NJ, USA: Wiley, 2024.
[14] H. Nozari, J. Ghahremani-Nahr, and A. Szmelter-Jarosz, "A multi-stage stochastic inventory management model for transport companies including several different transport modes," *International Journal of Management Science and Engineering Management*, vol. 18, no. 2, pp. 134-144, 2023. https://doi.org/10.1080/17509653.2022.2042747

[15] M. Singh, P. Bhardwaj, R. Bhardwaj, and S. Narayan, *Quantum advancements in logistics: Transforming operations through integrated quantum computing. In P. K. Dutta, P. Bhattacharya, J. P. Verma, A. Chopra, & N. Kundu (Eds.), Quantum Computing and Artificial Intelligence in Logistics and Supply Chain Management.* New York: Chapman & Hall/CRC, 2024.

[16] P. Whig, R. Remala, K. R. Mudunuru, and S. J. Quraishi, *Integrating AI and quantum technologies for sustainable supply chain management. Quantum computing and supply chain management: A new era of optimization*. Hershey, PA: IGI Global, 2024.

[17] A. Bakhshi Movahed and A. Bakhshi Movahed, *Sustainable cities based on artificial intelligence of everything (AIoE), in Artificial Intelligence of Everything and Sustainable Development, H. Nozari, Ed.* Singapore: Springer, 2025.

[18] H. Abdi and H. Nozari, *AIoE-enhanced multi-objective optimization for sustainable bioprocesses in smart bioreactors, in Artificial Intelligence of Everything and Sustainable Development, H. Nozari, Ed.* Singapore: Springer, 2025.

[19] M. Shoaib, S. Zhang, H. Ali, M. S. Ahmad, and M. A. Khan, "Integrating circular economy while adopting digital twin for enhancing logistics efficiency: A hybrid Fuzzy Delphi-FUCOM based approach," *International Journal of Logistics Research and Applications*, pp. 1-43, 2025. https://doi.org/10.1080/13675567.2025.2451750

[20] E. Arteaga-Cabrera, C. Ramírez-Márquez, E. Sánchez-Ramírez, J. G. Segovia-Hernández, O. Osorio-Mora, and J. A. Gómez-Salazar, "Advancing optimization strategies in the food industry: From traditional approaches to multi-objective and technology-integrated solutions," *Applied Sciences*, vol. 15, no. 7, p. 3846, 2025. https://doi.org/10.3390/app15073846

[21] N. Sasikaladevi, *Hybrid deep learning framework for grape plant disease identification and meta-agnostic visualization, in Artificial Intelligence of Everything and Sustainable Development, H. Nozari, Ed.* Singapore: Springer, 2025.