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A moment-based Optimization Model for Designing the Supply Chain of Dairy Products: Data-driven and Sustainable Approach

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Abstract: This study presents a moment-based optimization model for designing a sustainable, data-driven supply chain for perishable dairy products. The proposed multi-objective model integrates economic, environmental, and social dimensions of sustainability and addresses the inherent uncertainty in demand through a machine learning forecasting approach. The supply chain network includes producers, distributors, and retailers, with the aim of minimizing total costs and carbon emissions while maximizing job creation. A novel moment-based reformulation is introduced to enhance computational tractability, allowing the model to be efficiently solved using state-of-the-art optimizers such as Gurobi. Additionally, a CNN-based algorithm is employed for route optimization and fitness evaluation, improving decision-making under dynamic and uncertain conditions. The model's performance is validated using a real-world case study from the dairy industry, demonstrating its effectiveness in achieving sustainable supply chain objectives under varying demand scenarios and operational constraints. Comparative analyses with metaheuristic methods like NSGA-II further highlight the robustness and efficiency of the proposed approach.

Keywords: Sustainable supply chain, Perishable dairy products, Demand prediction, multi-objective optimization, CNN-based routing.

1. Introduction

Supply chain management involves approaches used to effectively integrate suppliers, warehouses, and stores to produce the appropriate amount of goods, distribute them in the right quantity, at the right time, and place, while minimizing costs (Carcano et al. 2005; Wang 2025). Supply chain management focuses on strategic, tactical, and operational activities. Strategic activities include long-term planning and issues like designing and configuring a multi-level supply chain. Tactical activities focus on short-term and long-term supply policies and material flow, while operational activities, in the short term, determine transportation capacity and optimize daily allocation of customer demand to retailers, distribution centers, or production locations (Hosseinitabar et al. 2024; Laínez et al. 2008). Coordination of supply, production, and distribution in the supply chain includes the integration of all processes related to the supply of goods, production, and distribution of products to minimize costs and increase the overall efficiency of the supply chain (Hosseinitabar et al. 2024; Jain et al. 2025). Various parameters in the supply chain can affect the system's costs, such as the type of product, inventory policies, demand type, the structure of the supply chain, and others. Considering the high costs of inventory management and the crucial importance of inventory control systems in the supply chain, inventory management is regarded as one of the most critical issues in trade and industry. This importance becomes even more significant in the case of perishable goods due to their specific conditions (Mirabelli et al. 2022; Rafiei et al. 2018).

In general, a perishable good is defined as a product that loses its value over time, such as dairy products, fruits, vegetables, medicines, blood, etc. In today's competitive market, providing appropriate solutions for better management of perishable goods' demand seems essential. Spoilage of goods, in addition to causing economic loss for businesses, leads to customer dissatisfaction and increases environmental waste and pollution (Mustafa et al. 2024; Yavuz et al. 2024). Many perishable goods lose their quality or are completely wasted due to inefficient transportation processes. Through better planning and control of transportation activities, it is possible to reduce the spoilage and loss of freshness of goods (Liu et al. 2021; Li et al. 2025). Moreover, by coordinating, providing accurate information, and continuously monitoring perishable products, the transportation schedule can be quickly updated before or during transportation to preserve the freshness and quality of products and prevent their loss, resulting in more transparent and efficient supply chains (Biuki et al. 2020; Lejarza et al. 2020). In today's competitive market, finding suitable solutions for better management of perishable goods' demand is essential. Spoilage of goods not only causes economic losses for businesses but also results in customer dissatisfaction and environmental waste and pollution. Therefore, considering sustainability in the design of supply chains for perishable products is of great importance. The sustainability approach consists of three aspects: economic, environmental, and social (Liu et al. 2021; Yavari et al. 2019). Many perishable goods lose their quality or are entirely wasted due to inefficient transportation processes. Through better planning and control of transportation activities, the spoilage and freshness loss of goods can be reduced. Additionally, by coordinating, providing accurate information, and continuously monitoring perishable products, the transportation schedule can be quickly updated before or during the transportation to preserve the freshness and quality of products and prevent their loss. This results in more transparent and efficient supply chains (Mejjaouli et al. 2018; Can Atasagun et al. 2024). On the other hand, one of the significant problems in designing supply chains is estimating supply chain demand. The uncertainty in demand affects inventory management, order planning, and production quantities, causing various challenges in the supply chain. Demand prediction plays a critical and vital role in supply chain management. A good demand forecast can neutralize the bullwhip effect, reduce losses, and increase profits. One of the methods for demand prediction is to use a data-driven approach and machine learning algorithms (Mediavilla et al. 2022; Rahman Mahin et al. 2025). Based on what has been discussed, the aim of this research is to present a data-driven hybrid model for modeling a sustainable supply chain for perishable dairy products. In other words, this research presents a multi-objective model to minimize the supply chain costs for perishable products and minimize the delivery time based on the product's shelf life. The proposed supply chain includes a producer, distributor, and retailer, where the products produced by the producer are transferred to the distributor and finally sold by the retailer. The objective functions considered in this model include minimizing supply chain costs. The second objective is to minimize the cost of carbon dioxide emissions as an environmental sustainability factor, and the third objective is to maximize the number of jobs created in the supply chain. Given the uncertainty in supply chain demand, the proposed model uses machine learning to predict demand. The structure of this research is as follows: Section 2 reviews previous studies on the supply chain of perishable products and demand forecasting approaches. In Section 3, the proposed mathematical model is presented, including the problem description, assumptions, the proposed mathematical model, and research methodology. Section 4 discusses the demand prediction approach and related machine learning algorithms. Section 5 presents the results of the hybrid model and analyzes the model's performance using a numerical example. Finally, Section 6 presents the conclusions of the research.

2. Literature Review

Designing an efficient and sustainable supply chain for perishable goods, particularly dairy products, is a critical challenge for both industry and academia. The inherent perishability of these products introduces immense complexity, requiring integrated planning that synchronizes supply, production, and distribution activities to minimize spoilage and cost while maximizing freshness and customer satisfaction. Furthermore, rising consumer demand, stringent quality standards, and increasing pressure for sustainable operations necessitate models that go beyond traditional cost minimization to include environmental and social objectives. This review synthesizes existing literature on integrated supply chain models, highlighting key advancements in handling perishability, uncertainty, and multi-objective optimization, thereby establishing the foundation and necessity for the proposed data-driven, sustainable model for the dairy industry. The foundation of supply chain design literature is built upon integrated mathematical models that seek to synchronize various echelons and functions. Early work by researchers like Kazemi et al. (2018) and Rabbani et al. (2016) established multi-objective frameworks for multi-level networks, aiming primarily to minimize total costs—encompassing transportation, inventory, production, and shortages—while improving service levels. A common thread among these studies, including Wang (2021) and Cheng et al. (2019), is the acknowledged computational complexity of such integrated models. This complexity invariably necessitates the employment of advanced metaheuristic algorithms, such as Non-dominated Sorting Genetic Algorithm (NSGA-II) and Particle Swarm Optimization (PSO), to find near-optimal solutions within a feasible timeframe. These foundational models successfully highlight the trade-offs and interdependencies within a supply chain but often lack specific mechanisms to address the critical issue of product perishability, which is a defining characteristic of the dairy industry and a major source of cost and waste. A significant and highly relevant evolution in the literature addresses the unique challenges posed by perishable products and uncertainty. Studies by Ahmadi et al. (2019) and Chan et al. (2020) explicitly incorporate product perishability into their models, expanding the objective function to include maximizing product quality upon delivery and minimizing spoilage costs. This focus is crucial, as evidenced by Ali et al. (2021), who identified inadequate cold storage infrastructure as a primary cause of customer dissatisfaction in India's dairy industry. Concurrently, to cope with the inherent uncertainties in demand and supply, researchers like Alavidoost et al. (2021) adopted fuzzy optimization approaches, while others like Liu et al. (2021) integrated environmental concerns by adding objectives to minimize carbon emissions. This body of work demonstrates a clear shift from purely economic models towards more holistic frameworks that balance cost, quality, and sustainability, which are all essential considerations for a modern dairy supply chain.

The most recent research trends focus on enhancing supply chain resilience and leveraging data-driven techniques for improved decision-making. Scholars like Abbasian et al. (2023) and Foroozesh et al. (2022) are designing robust networks capable of withstanding disruptions through strategies like dynamic pricing, multiple sourcing, and robust probabilistic programming to handle epistemic uncertainties. Parallel to this, the adoption of Machine Learning (ML) is emerging as a powerful tool to reduce uncertainty at its source. Feizabadi (2022) and Rekabi et al. (2023) demonstrate that ML methods, including neural networks and quadratic regression, significantly outperform traditional forecasting methods, thereby mitigating shortage risks and improving overall supply chain performance. These cutting-edge approaches in resilience and data-driven analytics provide a strong rationale for developing a novel moment-based optimization model that can effectively tackle the specific challenges of the dairy sector.Recent research highlights the pivotal role of data-driven methodologies in optimizing sustainable supply chain design across various industries. In the realm of perishable goods, Arabyesbani et al. (2024) and Flores-Siguenza et al. (2025) employ robust optimization and fuzzy optimization integrated with Life Cycle Assessment, respectively, to design cold chains that mitigate uncertainty and environmental impact, with applications in livestock and the dairy industry. Extending this to strategic advantage, Kumar et al. (2024) argue from a Resource-Based View that big data analytics enhance a supply chain's innovative capability, which is a critical source of sustainable competitive advantage, particularly in the food sector. The focus on coordination and multi-objective modeling is evident in the work of Belghand et al. (2025), who develop a novel buy-back contract for a symbiotic supply chain using a fuzzy and data-driven approach, while Yao et al. (2025) use data-driven marketing to compare government subsidy strategies for optimal decision-making in a green duopoly. Finally, Jafarian et al. (2025) demonstrate the integration of these themes, designing a multi-echelon pharmaceutical supply chain that simultaneously addresses sustainability, resilience, and digitalization through a multi-stage machine learning model. Collectively, these studies underscore a paradigm shift towards leveraging data analytics, artificial intelligence, and fuzzy systems to solve complex, multi-objective problems in modern supply chains.

Case Study	Sustainability			Demand Prediction		Objective Function		Perishability	Paper
	Social	Environmental	Economical	Machine Learning	Time Series	Multi Objective	Single Objective		
						✓		✓	Kazemi et al. (2018)
							✓		Alavidoost et al. (2021)
								✓	Rabbani et al. (2016)
✓							✓		Wang (2021)
				✓			✓		Cheng et al. (2019)
							✓	✓	Ahmadi et al. (2019)
	✓	✓	✓			✓		✓	Chan et al. (2020)
		✓	✓				✓	✓	Liu et al. (2021)
						✓		✓	Ali et al. (2021)
✓				✓	✓			✓	Feizabadi (2022)
				✓		✓		✓	Rekabi et al. (2023)
		✓	✓			✓		✓	Abbasian et al. (2023)
						✓		✓	Foroozesh et al. (2022)
✓						✓		✓	Jaigirdar et al. (2023)
		✓	✓	✓			✓	✓	Arabyesbani et al. (2024)
		✓	✓	✓		✓		✓	Kumar et al. (2024)
		✓	✓			✓		✓	Flores-Siguenza et al. (2025)
			✓	✓		✓			Belghand et al. (2025)
	✓	✓	✓	✓		✓		✓	Jafarian et al. (2025)
		✓	✓	✓			✓		Yao et al. (2025)
✓	✓	✓	✓	✓		✓		✓	This Paper

Based on the conducted studies, this paper introduces a novel moment-based optimization model for designing a sustainable, data-driven supply chain for perishable dairy products. The key innovation lies in its hybrid approach that integrates machine learning for demand forecasting with a multi-objective mathematical model addressing economic, environmental, and social dimensions of sustainability. Unlike traditional models that rely on binary variables for facility location and allocation, the proposed framework uses a moment-based reformulation to transform the problem into a more tractable form solvable by state-of-the-art optimizers like Gurobi. This reformulation replaces binary constraints with moment-based bounds, leading to a second-order conic program that improves computational efficiency while maintaining solution quality. Additionally, the model incorporates dynamic pricing, traffic-aware routing, and shelf-life constraints to reduce waste and emissions, and leverages a CNN-based algorithm for route optimization. The result is a comprehensive, scalable, and computationally efficient framework that enhances both the sustainability and resilience of dairy supply chains under uncertainty. The research methodology of present study is as figure 1.

Figure 1. *Research Methodology*

3. Proposed Model

This study focuses on the supply chain of perishable food items under a resilience strategy aimed at reducing disruptions in traffic conditions related to time windows, considering the shelf life of perishable products. This includes dynamic pricing and transportation policies to minimize costs as well as environmental impacts. For this purpose, we consider a supply chain of perishable food items that includes production centers (PCs), distribution centers/warehouses (DCs/W), and retailers. Through this supply network, products are transferred from PCs to DCs and from DCs to retailers. There are various routes for transportation to retailers, which are susceptible to traffic disruptions. Each route starts from candidate DCs and returns to candidate DCs after delivering the product to one or more retailers. Different vehicles with varying capacities can be used for transportation. If an order is received at the start of period (t), it expires at the beginning of period (t+LFp), where LFp denotes the product's shelf life. Therefore, this research will focus on designing a multi-objective resilient and sustainable supply chain model for perishable dairy products. Initially, the proposed model is developed based on resilience and sustainability approaches in three aspects: economic, social, and environmental. Additionally, demand forecasting will be conducted using a machine learning algorithm.

Indices:

N	Set of available routes
R	Set of retailers
P	Set of products
T	Set of time periods
V	Set of vehicles
D	Set of potential locations
M	Set of PCs (production centers)

Parameters:

FC_{mt}	Fixed cost of opening PC m in period t
FC_{dt}	Fixed cost of opening DC d in period t
FC_{dmt}	Fixed cost of allocating DC d to PC m in period t
FC_{ndt}	Fixed cost of allocating retailer r to DC d in period t
SC_{mdvt}	Transportation cost from PC m to DC d with vehicle v in period t
SC_{drvt}	Transportation cost from DC d to retailer r with vehicle v in period t
CHI_{dt}	Inventory holding cost at DC d in period t
PC_{pmt}	Production cost of product p at PC m in period t
CF_{vt}	Fuel cost for vehicle v considering traffic conditions in period t
RE_{mt}	CO2 emission rate due to the opening of PC m in period t
RE_{dt}	CO2 emission rate due to the opening of DC d in period t
RE_{pdt}	CO2 emission rate due to storing product p in DC d in period t
RE_{pmdvt}	CO2 emission rate due to transporting product p from PC m to DC d with vehicle v in period t
RE_{pdrvt}	CO2 emission rate due to transporting product p from DC d to retailer r with vehicle v in period t
RE_{vrt}	CO2 emission rate for restarting vehicle v at retailer r in period t

RE_{pmt}	CO2 emission rate due to producing product p at PC m in period t
MD_{prt}	Maximum demand for products p at retailer r in period t
MS_{drvt}	Maximum allowable speed considering traffic conditions on routes from DC d to retailer r in period t
Ds_{dr}	Distance between DC d and retailer r
C_v	Capacity of vehicle v
CD_d	Capacity of DC d
CP_m	Capacity of PC m
PE_{rpt}	Demand elasticity of retailer r for product p in period t
STL_{rvt}	Late service time for retailer r in period t by vehicle v
STE_{rvt}	Early service time for retailer r in period t by vehicle v
LST_{rvt}	Last service time for retailer r in period t by vehicle v
EST_{rvt}	First service time for retailer r in period t by vehicle v
RCF_{vdrt}	Fuel consumption rate for vehicle v when delivering product from DC d to retailer r under traffic conditions in period t
M	Large number (used in mathematical models)
RVD_{ndt}	Value of 1 if route n goes to DC d in period t, otherwise 0
RVR_{nrt}	Value of 1 if route n goes to retailer r in period t, otherwise 0
LF_p	Shelf life of product p
SD_{dt}	Number of jobs created in DC d in period t
SP_{mt}	Number of jobs created in PC m in period t

Variables:

SL_{rvt}	Service level of retailer r with vehicle v in period t
AT_{vrt}	Arrival time of vehicle v at retailer r in period t
DT_{vrt}	Departure time of vehicle v from retailer r in period t
AD_{rpt}	Actual demand of retailer r for product p in period t affected by pricing
Xpd_{pmdvt}	Amount of product p transferred from PC m to DC d with vehicle v in period t
Xr_{pdrvt}	Amount of product p transported from DC d to retailer r with vehicle v in period t
Xp_{pmt}	Amount of product p produced at PC m in period t
I_{pdt}	Inventory level of product p at DC d in period t
SP_{prt}	Maximum selling price of product p at retailer r in period t
USP_{prt}	Selling price of product p at retailer r in period t
IL_{prt}	Inventory level of product p at retailer r in period t
OD_{dt}	1 if DC d is open in period t, otherwise 0
OP_{mt}	1 if PC m is open in period t, otherwise 0
γ_{rdt}	1 if retailer r is assigned to DC d in period t, otherwise 0

δ_{dmt}	1 if DC d is assigned to PC m in period t, otherwise 0
μ_{vnt}	1 if vehicle v is selected for route n in period t, otherwise 0
Y_{nrvt}	1 if route n is used by vehicle v delivering to retailer r in period t, otherwise 0
Z_{nt}	1 if route n is selected in period t, otherwise 0

3.1. Optimization Model

$$Min\ Z_1 = \sum_{m=1}^{M}\sum_{t=1}^{T} FC_{mt}.OP_{mt} + \sum_{d=1}^{D}\sum_{t=1}^{T} FC_{dt}.OD_{dt} + \sum_{d=1}^{D}\sum_{m=1}^{M}\sum_{t=1}^{T} Fc_{dmt}.\delta_{dmt} + \sum_{r=1}^{R}\sum_{d=1}^{D}\sum_{t=1}^{T} Fc_{rdt}.\gamma_{rdt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{t=1}^{T} PC_{pmt}.Xp_{pmt} + \sum_{P=1}^{P}\sum_{d=1}^{D}\sum_{t=1}^{T} CHI_{dt}.I_{pdt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{mdvt}.Xpd_{pmdvt} + + \sum_{p=1}^{P}\sum_{d=1}^{d}\sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{drvt}.Xdr_{pdrvt} + \sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{n=1}^{r\cup d}\sum_{v=1}^{V}\sum_{t=1}^{T} Y_{nvvt}.CF_{vt}.RCF_{vdrt}.\frac{Ds_{dr}}{Ms_{drvt}} \tag{1}$$

$$Min\ Z_2 = \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{t=1}^{T} Ds_{dr}.Ms_{drvt}.\big(RE_{vrt} + Xpd_{pmdvt}.RE_{pmdvt} + Xdr_{pdrvt}.RE_{pmdvt}\big) + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{t=1}^{T} RE_{pdt}.I_{pdt} + \sum_{m=1}^{M}\sum_{t=1}^{T} RE_{mt}.OP_{mt} + \sum_{d=1}^{D}\sum_{t=1}^{T} RE_{dt}.OD_{dt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{t=1}^{T} RE_{pmt}.Xp_{pmt} \tag{2}$$

$$Max\ Z_3 = \sum_{d=1}^{D}\sum_{t=1}^{T} SD_{dt}.OD_{dt} + \sum_{d=1}^{D}\sum_{t=1}^{T} SP_{mt}.OP_{mt} \tag{3}$$

S.t:

$$SD_{dt}.OD_{dt} \leq 1 \qquad \forall d,t \tag{4}$$

$$SP_{dt}.OP_{dt} \leq 1 \qquad \forall d,t \tag{5}$$

$$Xp_{pmt} = \sum_{d=1}^{D}\sum_{v=1}^{V} Xpd_{pmdvt} \qquad \forall m,p,t \tag{6}$$

$$I_{pd(t-1)} + \sum_{m=1}^{M}\sum_{v=1}^{V} Xpd_{pmdvt} = \sum_{v=1}^{V}\sum_{r=1}^{R} Xdr_{pdrvt} + I_{pdt} \qquad \forall p,d,t \tag{7}$$

$$\sum_{d=1}^{D}\sum_{v=1}^{V} Xdr_{pdrvt} + IL_{pr(t-1)} = AD_{prt} + IL_{prt} \qquad \forall p,r,t \qquad (8)$$

$$\sum_{p=1}^{P} I_{pdt} \leq CD_d.OD_{dt} \qquad \forall d,t \qquad (9)$$

$$\sum_{p=1}^{P} Xp_{pmt} \leq CP_m.OP_{mt} \qquad \forall m,t \qquad (10)$$

$$I_{pd(t-1)} \leq \sum_{r=1}^{R}\sum_{t'\geq t}^{t'\leq(t+LF_p)} AD_{prt'}.\gamma_{rdt'} \qquad \forall p,d,t \qquad (11)$$

$$IL_{pr(t-1)} \leq \sum_{t'\geq t}^{t'\leq(t+LF_p)} AD_{prt'} \qquad \forall p,r,t \qquad (12)$$

$$\sum_{m=1}^{M} Xp_{pm(t-1)} \leq \sum_{t'\geq t}^{t'\leq(t+LF_p)} AD_{prt'} \qquad \forall p,t \qquad (13)$$

$$\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D} Xpd_{pmdvt} \leq C_v.\mu_{vnt} \qquad \forall v,n,t \qquad (14)$$

$$\sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{r=1}^{R} Xdr_{pdrvt} \leq C_v.\mu_{vnt} \qquad \forall v,n,t \qquad (15)$$

$$\sum_{p=1}^{P}\sum_{v=1}^{V} Xdr_{pdrvt} \leq M.\gamma_{rdt} \qquad \forall r,d,t \qquad (16)$$

$$\sum_{p=1}^{P}\sum_{v=1}^{V} Xpd_{pmdvt} \leq M.\delta_{dmt} \qquad \forall m,d,t \qquad (17)$$

$$\gamma_{rdt} \leq OD_{dt} \qquad \forall r,d,t \qquad (18)$$

$$\delta_{dmt} \leq OD_{dt} \qquad \forall d,m,t \qquad (19)$$

$$\delta_{dmt} \leq OP_{mt} \qquad \forall d,m,t \qquad (20)$$

$$\sum_{d=1}^{D} \gamma_{rdt} \leq 1 \qquad \forall t,r \qquad (21)$$

$$\sum_{m=1}^{M} \delta_{dmt} \leq 1 \qquad \forall t,d \qquad (22)$$

$$AD_{prt} = MD_{prt} - PE_{prt}.USP_{prt} \qquad \forall p,r,t \qquad (23)$$

$$USP_{prt} = \left(USP_{pr(t-1)} - \frac{SP_{prt}}{LF_p}\right).\left(1 - \sum_{d=1}^{D} \gamma_{rdt}\right) + SP_{prt}.\left(\sum_{d=1}^{D} \gamma_{rdt}\right) \qquad \forall p, r, t \qquad (24)$$

$$SL_{rvt} \leq \frac{1 + 0.15.\left(\frac{DT_{vrt} - AT_{vrt}}{C_v}\right)^4 - STL_{rvt}}{LST_{rvt} - STL_{rvt}} \qquad \forall r, v, t \qquad (25)$$

$$SL_{rvt} \leq \frac{STE_{rvt} - 1 + 0.15.\left(\frac{DT_{vrt} - AT_{vrt}}{C_v}\right)^4 - STL_{rvt}}{STE_{rvt} - EST_{rvt}} \qquad \forall r, v, t \qquad (26)$$

$$\sum_{n=1}^{r \cup d} Z_{nt}.RVR_{nrt} \leq 1 \qquad \forall r, t \qquad (27)$$

$$Z_{nt} \leq \sum_{d=1}^{D} RVR_{nrt}.OD_d \qquad \forall n, t \qquad (28)$$

$$DT_{vrt} \leq AT_{vrt} + \sum_{d=1}^{D} \frac{DS_{dr}}{MS_{drvt}}.\left(1 + 0.15\left(\frac{DT_{vrt} - AT_{vrt}}{C_v}\right)^4\right) + M.(1 - Y_{nvrt}) \qquad \forall v, r, t, n \qquad (29)$$

$$DT_{vrt} \geq AT_{vrt} + \sum_{d=1}^{D} \frac{DS_{dr}}{MS_{drvt}}.\left(1 + 0.15\left(\frac{DT_{vrt} - AT_{vrt}}{C_v}\right)^4\right) + M.(1 - Y_{nvrt}) \qquad \forall v, r, t \qquad (30)$$

$$AT_{vrt} \geq STL_{rvt} \qquad \forall v, r, t \qquad (31)$$

$$DT_{vrt} \leq STE_{rvt} \qquad \forall v, r, t \qquad (32)$$

$$\sum_{n=1}^{N} \mu_{vnt} \leq M.Z_{nt} \qquad \forall n, t \qquad (33)$$

$$\sum_{r=1}^{R} Y_{nvrt} \leq M.\mu_{vnt} \qquad \forall v, n, t \qquad (34)$$

The developed mathematical model includes three objective functions. The first objective function (1) aims to minimize the total supply chain cost, which includes fixed facility opening costs, fixed allocation costs, production costs, inventory holding costs, transportation costs, and vehicle costs depending on traffic conditions and fuel consumption. The second objective (2) represents minimizing the total amount of CO2 emissions, which includes CO2 emissions due to traffic conditions, transportation between facilities, as well as emissions from storing products in DCs, facilities, and production processes. The third objective function indicates the number of job opportunities created in the supply chain. In the proposed model, constraints (4) and (5) represent the maximum allowable job opportunities created in each period for production and distribution centers, respectively.Constraints (6) to (8) indicate that the amount of input and output for the facilities must be balanced. Constraints (9) and (10) represent the inventory capacity limits for distributors and the production capacity limits, respectively. Constraints (14) and (15) ensure vehicle capacity limits. Constraints (11) to (13) prevent overproduction and excessive inventory storage, which reduces the amount of expired food products. Constraints (16) and (17) ensure that the flow between unassigned pairs is zero. According to constraints (18) to (20), the allocation must be assigned to the established facilities. Constraint (21) (and constraint (22)) ensures that a retailer (distributor) can be assigned to only one distributor (producer) at most. Constraints (23) and (24) are used to demonstrate the dynamic pricing mechanism, which depends on product shelf life and the price sensitivity of demand. Overall, these constraints show the relationship between demand, price, dynamic pricing function, and the shelf life of products. On the other hand, constraint (24) shows the dependency of each DC's service on retailer demand, which occurs during allocation. Constraints (25) to (32) represent the retailer's service level within the time window, where t(X) is a function of t0, the start time of the trip, k, the vehicle capacity, and x, the travel time. These constraints indicate the service level based on traffic conditions at the time of arrival and departure and highlight the best service level for retailers, considering the randomness of service times for the first and last services. Constraints (29) and (30) calculate the time for each node to assign a vehicle transporting products along the routes, with distances determined by the vehicle's speed. The upper and lower bounds of the time windows, which determine the service level provided by the retailer, are represented by constraints (31) and (32), respectively.

3.2. Moment-based reformulation

To bridge the LO and MIO approaches, a moment-based approach was proposed by Zinchenko et al. (2008) for radiotherapy optimization. In this section, we proposed a moment-based reformulation for our model which is easily solvable on the state-of-the-art solvers like Gurobi, CPLEX, Mosek. In supply chain design problem, such as the problem targeted in this paper, binary variables are used for two purposes 1- Selection/location: indicator variables which are one if a facility is located, opened, or selected. 2- Allocation/assignment: indicator variables which are one if a facility is assigned to another facility. There are several approaches to split these two problems although these problems are related to each others. In this paper first, we try to address selection/location variables by using moment-based approaches. Generally, constraints for selection/location have the following general form:

$$\sum_{i=1}^{n} x_{ij} d_{ij} \leq C_j . y_j \tag{35}$$

Also, we have one constraint like:

$$\sum_{j=1}^{m} y_j \leq P \tag{36}$$

Variables x_{ij} is continuous and usually represents production, inventory or service. Variables y_j are binary and accounting for selection or location decisions. Following figure 2 shows a histogram representing the above constraint. Red curve shows the upper bound enforced by binary variables. The dashed line shows a solution sample for production.

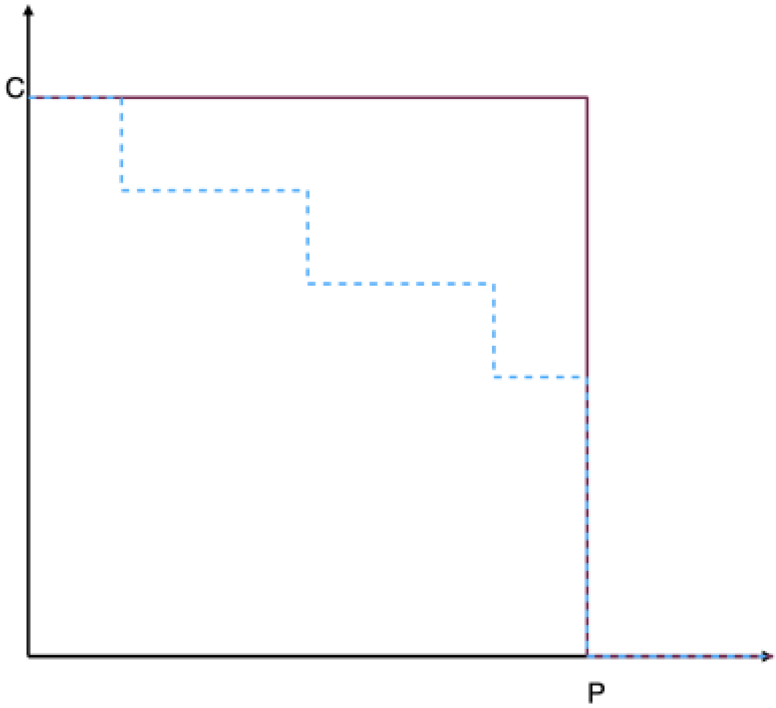

Figure 2. *histogram representing*

In the moment-based reformulation instead of using binary variables to enforce this upper bound we want to use moments of function. Let f_1 be the production function and f_2 be the upper bound function (red line). We denote first and second moment of a function by $\mu_1(f)$ and $\mu_2(f)$, respectively. Thus, we can add the following constraints to model instead of the binary constrains as follows:

$$\mu_1(f_1) \leq \mu_1(f_2)$$
$$\mu_2(f_1) \leq \mu_2(f_2) \tag{37}$$

The first constraint a linear constraint and the average of production should be bounded by the average of the upper bound function. However, the second constraint leads to a second-order conic constraint as follows:

$$\sqrt{\sum_{i=1}^{n} x'^2_i} \leq \mu_2(f_2) \tag{37}$$

Although this is a nonlinear constraint, there are polynomial time algorithms to solve this kind of problems and solver like Gurobi can solve second-order conic problems efficiently. After solving we the moment-based model, one can calculate the value of binary problem by rounding. Then the assignment/allocation part of the model is a simple assignment problem which can be solved easily. Thus, the steps of algorithm are as figure 3.

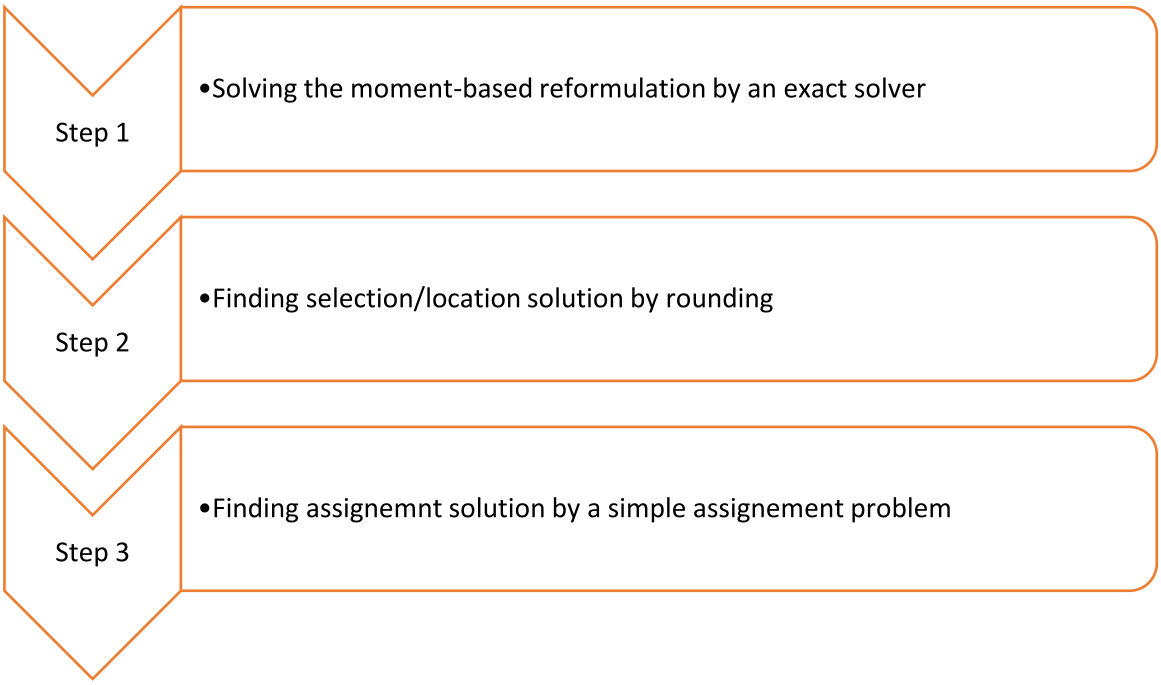

Figure 3. *Steps of algorithm*

4. Solution Methodology and Computational Results

Considering the different storage conditions for products in Ofogh Kourosh stores, various refrigerators are available for storing these products. Their storage capacity, based on the different storage capacities of these products in various warehouses, has been considered as a fuzzy number according to expert opinion, as shown in Table 1.

Table 1. *Capacity for different products*

Product	Capacity	Product	Capacity	Product	Capacity
Milk	(1000, 1400, 1850)	Cream	(750, 1125, 1500)	Cheese	(1000, 1375, 1700)

4.1. A CNN-based algorithm for route optimization

In this research, the optimal number and suitable route for facilities are determined with the goal of maximizing the coverage of retailers. The route's fitness refers to the intrinsic desirability of the target site based on compatibility and incompatibility criteria. In this study, a multi-criteria evaluation method is used to calculate route fitness. First, the values for each criterion are calculated for each route. After standardizing and assigning weights to each, the final fitness is obtained using the weighted linear combination method. The greater the distances in the incompatibility criteria, the higher the desirability of a safe route. To achieve this, the values of each criterion are standardized in ascending order using the following equation.

$$D_{new} = \frac{d_{near} - \min(d)}{\max(d) - \min(d)} \tag{38}$$

On the other hand, shorter distances in the compatibility criteria will result in greater desirability for a route. In this case, the values of the criteria will be standardized in descending order using the following equation.

$$D_{new} = \frac{\max(d) - d_{near}}{\max(d) - \min(d)} \tag{39}$$

The weight of each criterion indicates its importance and value relative to other criteria. To calculate the weights, tables were prepared based on the deep learning method with CNN architecture.

Table 2. *The weight of each criteria*

Criterion	Weight	Sub-criterion	Weight
Compatible	0.5	Cost	0.445
		Time	0.262
		CO2	0.152
		Economic	0.089
		Job	0.052
Incompatible	0.5	Transportation	0.5
		Product Shortage	0.25
		Spoiled Products	0.25

As mentioned at the beginning of this section, the weighted linear combination method has been used to integrate compatibility and incompatibility criteria. Based on the final table of criteria and sub-criteria weights, the route fitness for each route is calculated. These route fitness values are used in the secure route selection stage as specific information for the research.

$$SS = \sum W_i \,.\, C_i + \sum W_j \,.\, I_j$$

In the above equation, SS represents the route fitness. Wi and Wj are the weights of each criterion, and Ci and Ij are the compatibility and incompatibility criteria, respectively.Considering that the CNN algorithm can be adapted to the conditions of the research problem, changes have been made to the problem-solving method, and the routing and allocation model has been designed according to its specific rules. To this end, the optimization of the supply chain process, the determination of optimal routes, and the allocation of demand are performed. Figure 4 shows how each factor's objective function result is evaluated. Any factor that satisfies all three constraint values can move to the next stage, which is the proposed network update. Before updating, its value is compared with the value of the other factor's function, and the factor with the minimum value is allowed to update the CNN. Otherwise, its result will be unacceptable. This stage must also be examined for the other factor, and the authorized factors will proceed to the update stage.

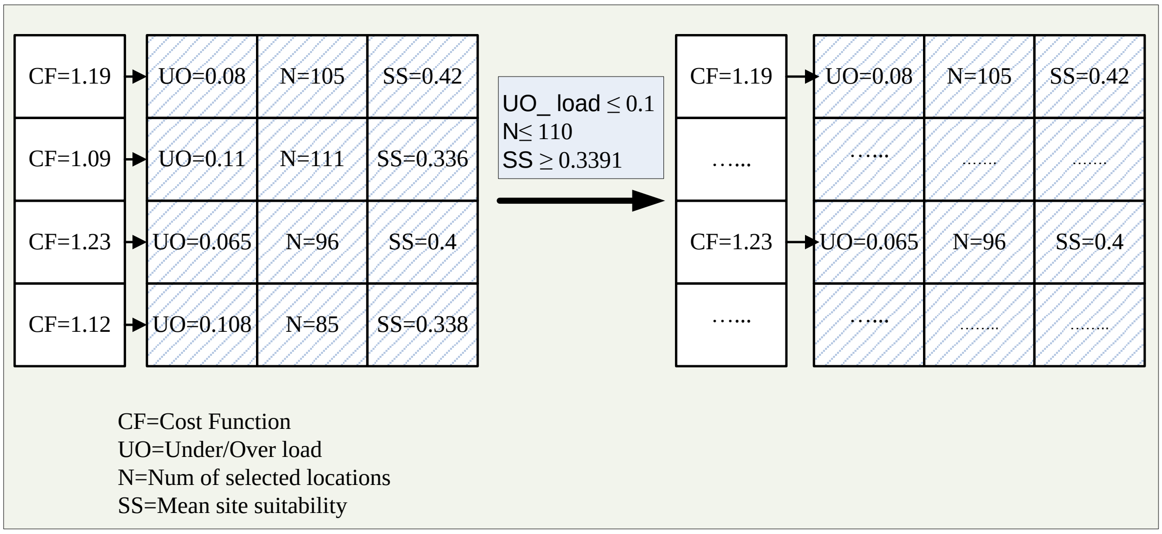

Figure 4. *each factor's objective function result*

The aim of the optimization process is to find the best combination of N routes such that, in addition to having the lowest cost (best desirability), they also satisfy the problem's constraints. In the first three steps, the goal is to generate a solution and evaluate its quality based on the objective function. In the final step, which is the most important part of the CNN algorithm, the goal is to record these solutions for future steps and assist in improving problem-solving by other agents in subsequent iterations. By performing these operations, the optimization process is completed. At the beginning of the model-solving process, an equal amount is allocated to all safe routes. The only difference between the safe routes during the selection phase in the first step is their heuristic values. As mentioned, the combination of safe routes is evaluated by the objective function; therefore, the agents tend to select routes with the highest desirability based on their exploratory nature. As a result, with successive selections of better routes by the agents, more pheromone is placed on them. According to the points discussed in the recent section, the objective function value of an agent is acceptable if the agent satisfies all three constraints. In this case, the value is recorded, and if another agent also reaches this stage, a comparison is made. Ultimately, the proposed algorithm, named the CNN-based supply chain optimization algorithm, is suggested for solving the problem, and its pseudocode is shown in the table 3.

Table 3. *pseudocode of proposed algorithm*

Input data sets Initialize CSz, k, itr, (CSz: colony size; k= neighbourhood radius; itr: number of iterations; initial level of pheromone, Evaporating rate; local escape probability)

While n<itr

for $m \epsilon cs$

Step 1)

- If $\tau_m - \max_{n\epsilon cs}^{itr}(\tau_n) \geq EVR$
  - $\tau_m = \tau_m - EVR$

Step 2)

- if n=1
- Generate a layout
- else
- Call Selecting operator (tournament list)

Step 3)

- for i ∈ I
- if $OS_i < OP_i$
- O_i=min($D_{i,t}$;Out source capacity l)
- calculate Remained $D_{i,t}$

Step 4)

- find $MCIM_{i,j}$
- Generate Neighbor list considering neighbor radius (n^m)
  - $for\ k \in n$
    - $Part.route_k = \sum|internal\ travel| + |external\ travel|$ (for consecutive machin
- Find the Best Part routes in the X
- x_i= min(MA_j, Remained $D_{i,t}$, BS_i)
- calculate Remained $D_{i,t}$

Step 5)

- for i ∈ I
- if Remained $D_{i,t}$>0
  - if Machine Capacity=0
  - Set $L_{i,t}$
- Go step 3

Step 6)

- else
- Set b_i = Remained $D_{i,t}$

Step 7)

- Calculate OFV_m
- if $OFV_m \leq \min_{itr}(OFV)$
- $Tournament\ list_i = X_m$
- $OFV^{best} = OFV_m$
- $X^{best} = X_k{}^{itr}$
- call $Observation.operator$
- $\tau_m = 1 - \left(\frac{Tournament_{obj(m)}}{\underset{itr}{\text{sum}}(Tournament_{obj})}\right)\left(\frac{Observation(m)}{\underset{itr}{\text{sum}}(Observation)}\right)$

Step 8)

- else
- R=rand(1)
- if R≤ LEP
- $Tournament\ list_i = X_m$
- call $Observation.operator$
- $\tau_m = 1 - \left(\frac{Tournament_{obj(m)}}{\underset{itr}{\text{sum}}(Tournament_{obj})}\right)\left(\frac{Observation(m)}{\underset{itr}{\text{sum}}(Observation)}\right)$

Step 9)

- Check Stopping Criteria

End

In Figure 5, section 'a', both alpha and beta values, being equal, have the same effect on the generated solutions, such that the resulting costs are within a certain range and do not show much dispersion. With the increase in beta values, in sections 'b', 'c', and 'd', the dispersion of the solutions becomes quite evident. In this case, the solutions identified as the minimum are created purely by chance. On the other hand, increasing the beta value means placing more importance on the spatial fit of the demand points concerning the CNN parameter. Therefore, by keeping the alpha coefficient constant and increasing the beta coefficient, the probability of selecting routes with higher spatial fit increases. In this situation, the model selects product transfer and supply locations without regard to its previous route selections or the costs associated with those selections. Lower alpha parameter values cause less emphasis to be placed on previous solutions during each iteration, leading the model to randomly select a combination of safe locations in each iteration. The higher the beta coefficient, the greater the spatial fit of the selected routes. These changes are illustrated in Figure 6 for four different beta value scenarios.

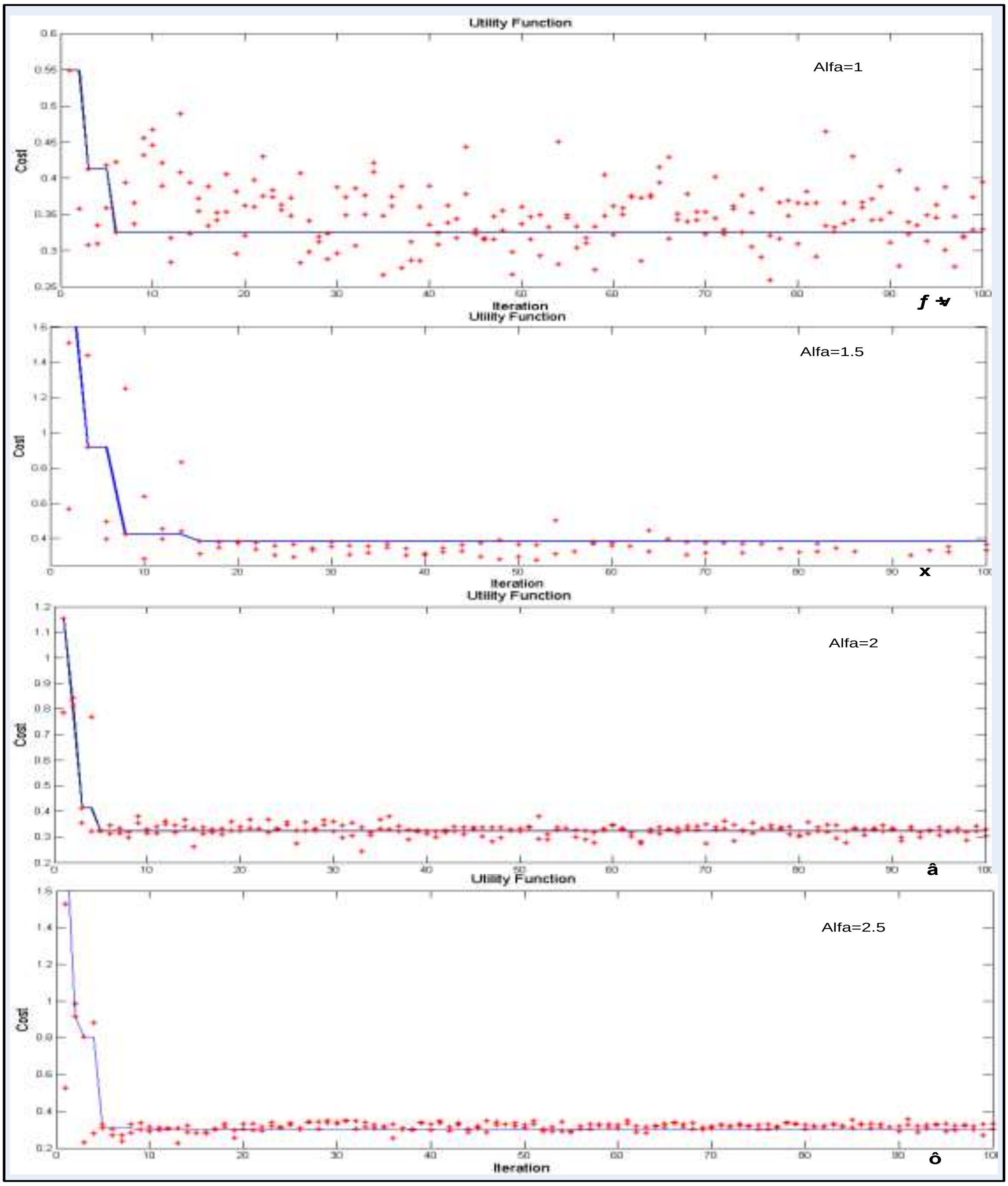

Figure 5. *Impact of Equal and Increasing Alpha and Beta Coefficients on Cost Dispersion and Solution Stability*

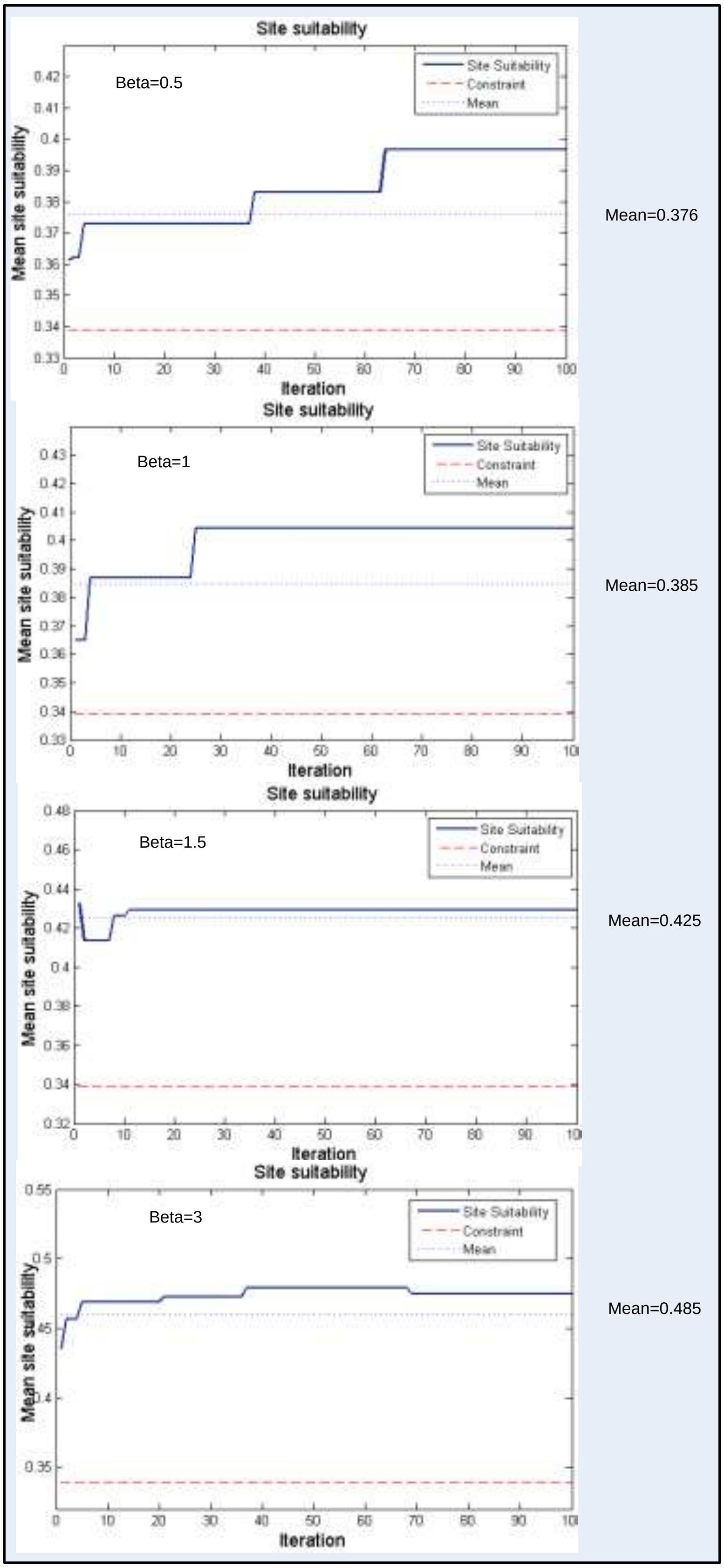

Figure 6. *Effect of Increasing Beta Coefficient on Spatial Fit of Selected Routes under Constant Alpha*

The alpha coefficient is used to preserve the good results obtained in each iteration for use by agents in subsequent iterations. In this section, the beta value is considered 0.5, and the results are examined by changing the alpha value. As the alpha value increases, the dispersion of solutions in terms of cost is reduced. This is shown in Figure 4. However, some of these solutions, due to the increased number of selected routes, occasionally cannot meet the route quantity constraint, which is why they are not selected. Another effect of increasing the alpha coefficient on the solutions in each iteration is that, due to the increased ability of CNN to select a route, the likelihood of routes selected in the early iterations being chosen by subsequent agents increases. This causes the costs of each agent in each iteration to converge gradually toward a specific value, preventing dispersion.

Based on the above, it becomes clear that in both cases, high values of either alpha or beta prevent the model from reaching a satisfactory solution. The model has been run five times considering the values of these two parameters, and the results are shown in Tables 4 and 5.

Table 4. *Model Performance Under Varying Alpha Values (Beta Fixed)*

# of Locations	Convergence	Location	Abundance	Alpha	Number
94	0/2988	0/372	0/069	0/5	1
105	0/2914	0/342	0/071	1	2
96	0/395	0/355	0/073	1/5	3
109	0/33	0/359	0/0745	2	4
110	0/356	0/348	0/068	2/5	5

Table 5. *Model Performance Under Varying Beta Values (Alpha Fixed)*

# of Locations	Convergence	Location	Abundance	Alpha	Number
94	0/298	0/372	0/069	0/5	1
104	0/3670	0/382	0/066	1	2
95	0/3937	0/421	0/075	1/5	3
103	0/4328	0/442	0/071	2	4
107	0/4606	0/452	0/0704	2/5	5

In this research, the minimum final value of each combination of routes is considered as its evaluation criterion. However, due to the desire to further explore the problem space, the combination of the two parameters, alpha and beta, has been set to 0.5 and 1, respectively. Table 6 shows the results of the problem-solving using the proposed method. The solutions obtained by the proposed method are highly competitive in terms of the first and second objective function values.

Table 6. *Results of the problem-solving using the proposed method*

Method	Milk	Cream	Cheese
CNN	0.02	0.03	0.02
Deep Learning and SC Optimization	0.001	0.001	0.001
Pareto	0.04	0.03	0.04
Global programming	0.02	0.02	0.02

According to the table above, Figure 7 displays the values of the objective functions. The Pareto optimal solutions help the decision-maker select the most appropriate solution. For example, if the first objective function is prioritized, the decision-maker can choose the Min-Max or LP-metric method. Conversely, if the second objective function is prioritized, the decision-maker can choose the goal programming method to solve the problem.

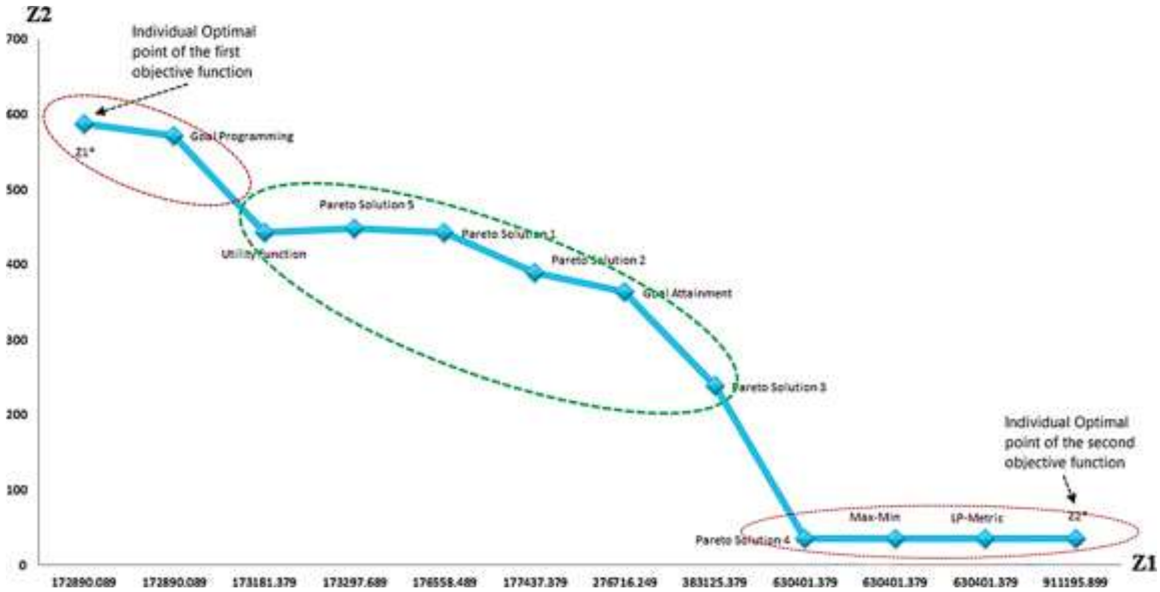

Figure 7. *the values of the objective functions*

Figure 8 shows the computation time of the lexicographic weighted Tchebycheff method compared to the proposed methods. The lexicographic weighted Tchebycheff method requires less computation time than the MODM method. The third Pareto optimal solution obtained using the lexicographic weighted Tchebycheff method is the best solution in terms of computation time.

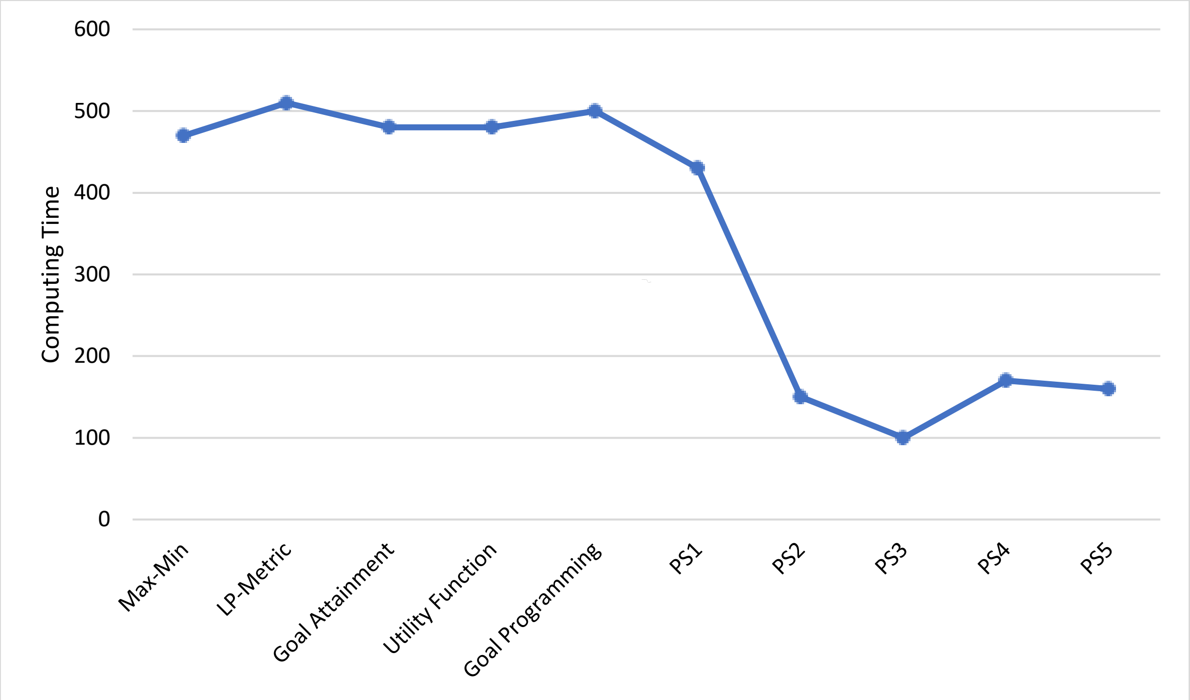

Figure 8. *computation time of the lexicographic weighted Tchebycheff method compared to the proposed methods*

An increase in demand leads to an increase in both objective functions, and a 50%+ increase causes the problem to become infeasible. Moreover, even a small change in demand results in changes in the values of both objective functions. An increase in mi reduces the values of the objective functions, and a 50% decrease makes the problem infeasible. The results obtained can reduce the total supply chain costs as well as the total CO2 emission costs.

4.2. Numerical Results

In this research, a multi-objective and multi-period mathematical model was considered, and the sustainable supply chain model for perishable dairy products, along with customer demand forecasting using a machine learning approach, was examined. The tools used in this study include mathematical programming models, a data-driven approach, and others for solving the problem under study. The model presented in this research was coded and solved using the NSGA-II metaheuristic algorithm in MATLAB software. The data and parameters used will be applied in the model using a numerical example.Here, the proposed model was coded using MATLAB software, and the written program was executed on a computer with a 2.3 GHz Core i7 processor and 4GB RAM. The execution time in all runs was less than 140 minutes. The model's validation was carried out through sensitivity analysis of some key parameters in the model, and the model's efficiency was also examined. To compare the efficiency of the NSGA-II metaheuristic algorithm, multiple examples in different categories and sizes were designed to evaluate the proposed model. The descriptions related to each category of problems are presented in the table 7.

Table 7. *Model Performance by Scale*

Size of Problems	# of Problems	m	d	r	p	t
Small	2	2	5‹7	5‹8	4	4
Medium	3	3‹5	9‹11‹14	10‹12‹15	5‹7	5‹7
Large	3	5‹7	17‹21‹25	18‹21‹25	7‹9	7‹9

For validation and solving the proposed model, 8 different approaches were considered based on the problem's indicators. The proposed model was designed for eight different scenarios. The model includes three objective functions based on a sustainability approach. In the developed model, the economic aspect (first objective function) seeks to minimize total costs, the environmental aspect (second objective function) aims to reduce carbon dioxide emissions, and the social aspect (third objective function) strives to increase job opportunities. The performance of the developed model, based on the problem's indicators, is shown in Table 7, A notable point in this table is the categorization of problem cases into three sections—small, medium, and large scales—for evaluating the performance of the developed model. Table 4-2 displays the performance of the developed model based on the problem's indicators, dividing the results of the NSGA-II metaheuristic algorithm according to the values of the first, second, and third objective functions.

Table 8. *optimal values of the objective functions for different scenarios with varying problem sizes*

Problems		Parameters					NSGA-II			Solution time
		m	d	r	p	t	Obj1 (Million)	Obj 2 (Thousand)	Obj 3 (Unit)	Time (Sec)
Small Scale	1	2	5	5	4	4	15.628	23.618	250	23/122
	2	2	7	8	4	4	18.749	28.225	274	28/653
Medium Scale	3	3	9	10	5	5	23.658	31.276	286	34/628
	4	3	11	12	5	5	31.562	38.485	298	44/325
	5	5	14	15	7	7	38.156	37.459	312	52/623
Large Scale	6	5	17	18	7	7	46.123	36.458	345	78/749
	7	7	21	21	9	9	64.325	36.967	386	109/132
	8	7	25	25	9	9	69.635	36.541	459	135/496

The results in Table 8 show the optimal values of the objective functions for different scenarios with varying problem sizes. Based on the results, it can be understood that as the size of the problem increases in different dimensions, the values of the first and second objective functions, which respectively represent the total supply chain costs and the amount of carbon dioxide emissions, increase. In other words, as the problem size and demand increase, the total supply chain costs rise. Additionally, with the increase in the number of established units, including production and distribution centers and the need for transportation between different centers to meet customer demand, the increase in carbon dioxide emissions is logical. However, due to the sustainability approach in the supply chain, the amount of carbon dioxide emissions initially increases, but from Scenario 5 onward, it stabilizes and reaches sustainability, indicating the supply chain's stability in terms of carbon dioxide emissions. Moreover, the value of the third objective function, which represents the number of job opportunities created, shows an upward trend as the problem size increases. In other words, as the number of established units increases, the number of job opportunities created throughout the supply chain also rises, which indicates the supply chain's sustainability in maintaining and developing job opportunities. Additionally, the performance of the developed model based on the problem's indicators and the model's execution time in each scenario to reach the optimal solution is shown in Table 7. The results show that as the problem size increases, based on the indicators, the model's solving time also increases. This is logical given the increased number of distribution and production centers, the model's complexity, and the increased number of iterations required to reach the optimal solution. The results related to the changes in the first, second, and third objective functions, as well as the solving time of the supply chain model based on the problem scenarios, are as follows:

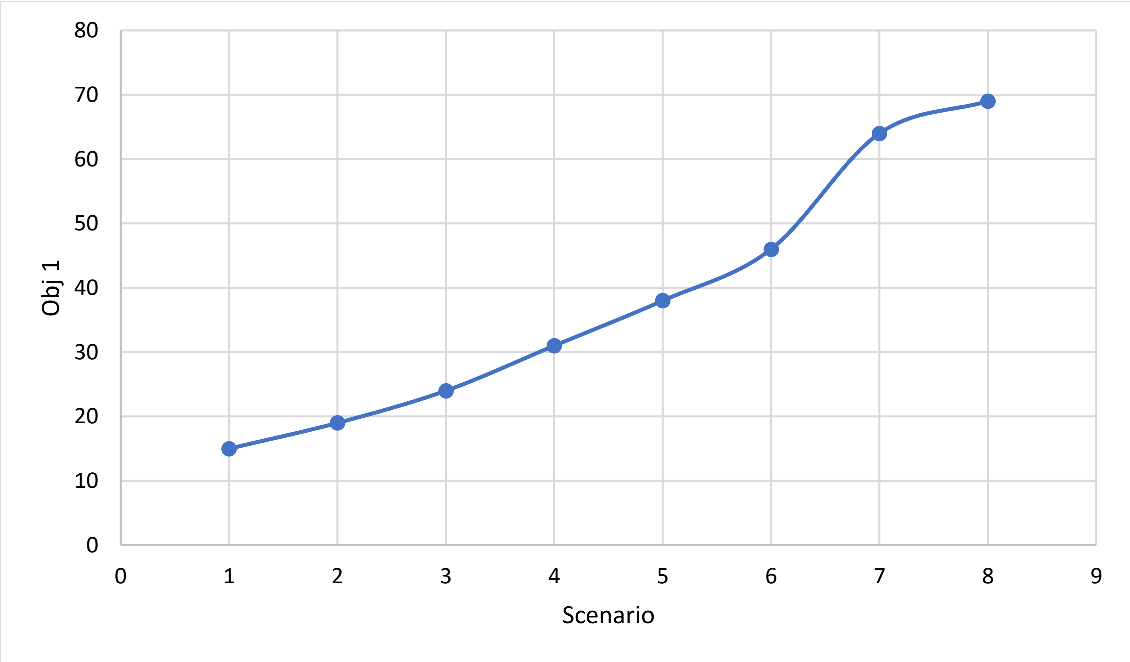

Figure 9. *Changes in the first objective function for each scenario*

Finally, according to Figure 9 it can be understood that with an increase in the problem size (in other words, with an increase in the number of established centers), the total supply chain costs in the first objective function show an upward trend. It is worth mentioning that in Figure 9, which illustrates the changes in the first objective function based on scenario values, the growth rate of the expected costs increases more sharply when transitioning from TP6 to TP7 (with changes in the indices and the establishment of various centers). However, after this point, the growth rate of the expected costs continues at a slower pace.

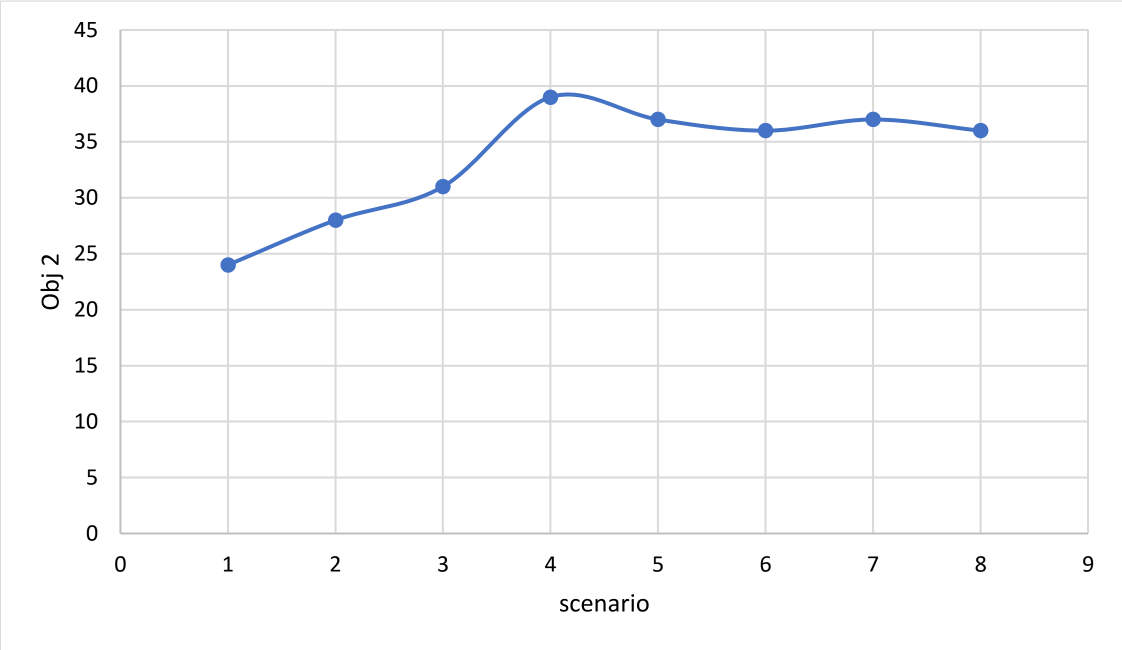

Figure 10. *Changes in the scecond objective function for each scenario*

Additionally, the changes in the second objective function, which represent the amount of carbon dioxide emissions, initially show an upward trend as the problem size increases, reaching its maximum at TP4 (figure 10). Afterward, the trend becomes relatively stable, indicating the stability of carbon dioxide emissions in the supply chain. In other words, the results of the stable trend in the second objective function after scenario 4 show that despite various disruptions in the supply chain, the model's performance is not significantly affected, and the model exhibits good stability. Furthermore, the changes in the third objective function based on the problem scenarios are illustrated in the figure 11.

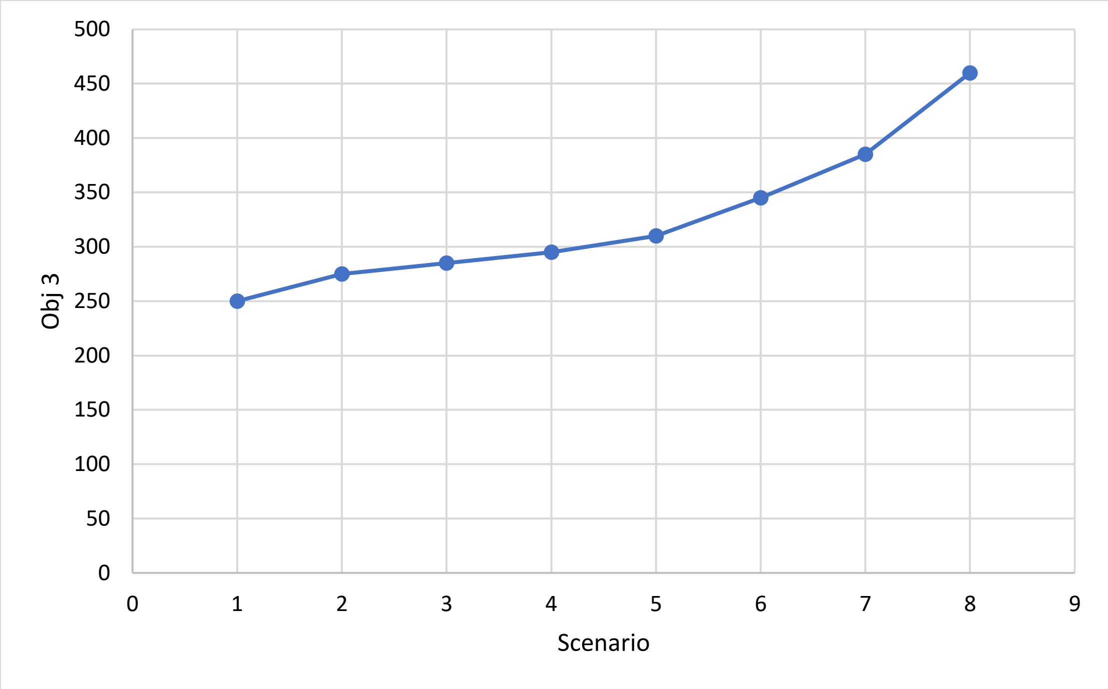

Figure 11. *Changes in the third objective function for each scenario*

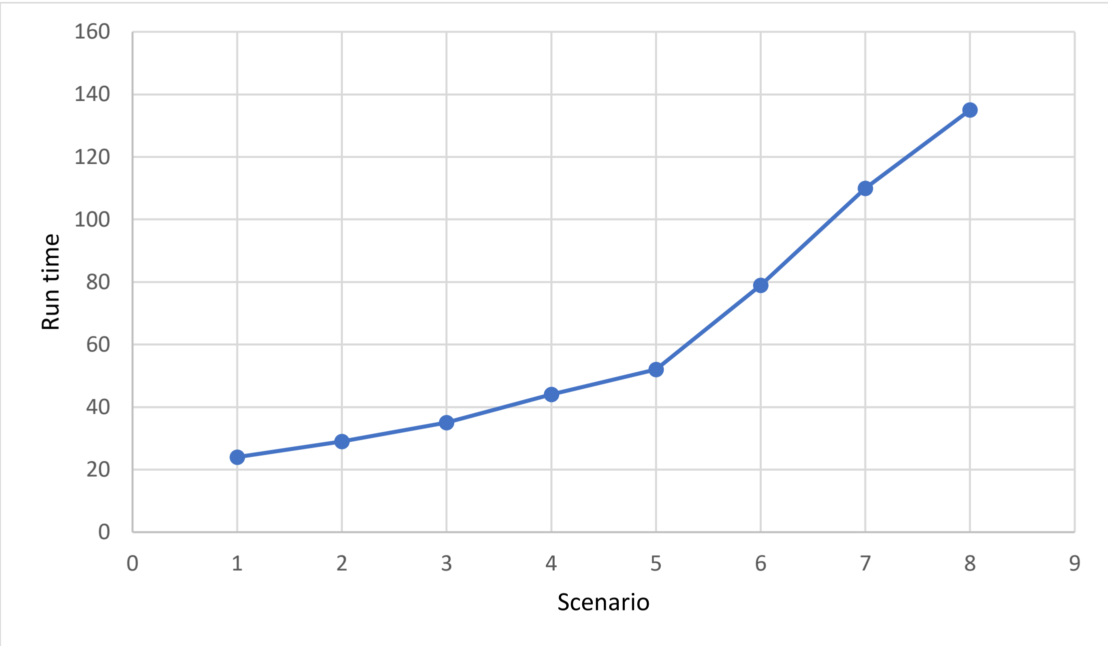

Figure 12. *Changes in the run time for each scenario*

In order to examine the impact of various parameters on the developed mathematical model, sensitivity analysis of different parameters based on varying parameter values in the developed model has been considered. This sensitivity analysis is based on the values of the objective functions and parameters, as follows:

Sensitivity analysis on MD_{prt} based on the first objective function:

According to the results of Table 9, in this section, the sensitivity analysis related to different product demand values in the market is performed based on the first objective function in the

NSGA-II metaheuristic algorithm. Based on the results, it can be understood that as product demand in the market increases, the value of the first objective function shows an upward trend, and the total supply chain costs increase.

Table 9. *Sensitivity Analysis of Market Demand on Obj1*

Row	MD_{prt}	Obj 1
1	50	16.658
2	100	18.526
3	150	23.541
4	200	24.638
5	250	28.547

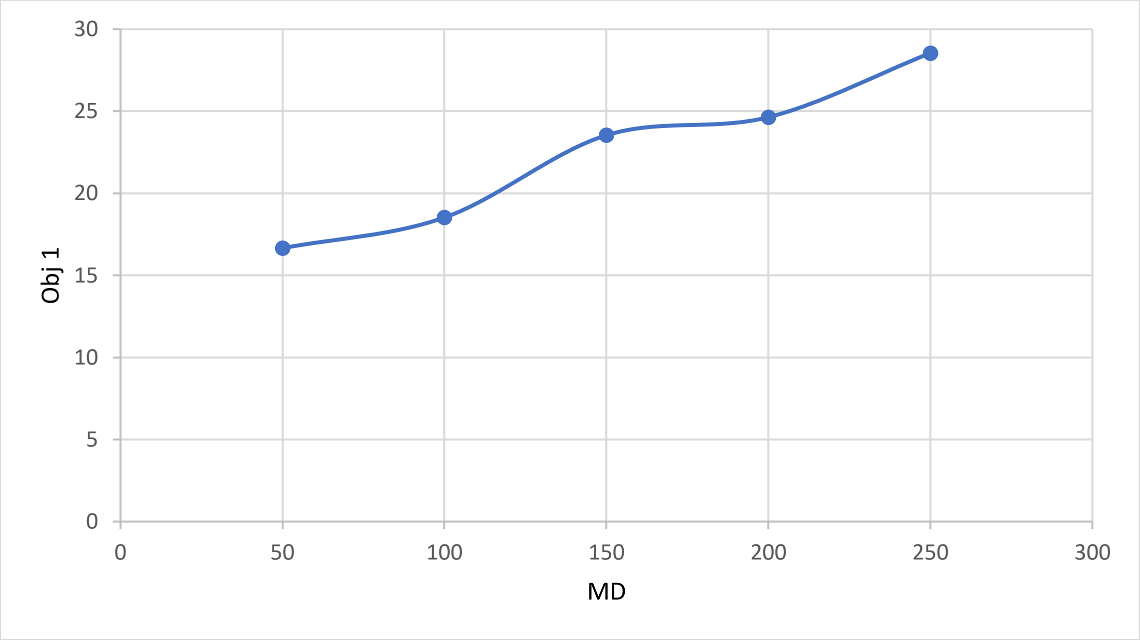

Figure 13. *Sensitivity Analysis of Market Demand on Obj1*

Sensitivity analysis on MD_{prt} based on the second objective function:

According to the results of Table 10, in this section, the sensitivity analysis related to different product demand values based on the second objective function is conducted using MATLAB software. Based on the results, it can be understood that as product demand increases, the value of the second objective function, which indicates the amount of carbon dioxide emissions, initially shows an upward trend, then reaches its maximum value, and stabilizes. In other words, the trend of this graph has two parts: the first part is an increasing and expected trend, where with the increase in demand, the carbon dioxide emissions rise due to the construction of new centers. However, in the second part of the graph, due to the reduction in stored products in distribution and production centers, the amount of carbon dioxide emissions follows a relatively stable and sustainable rate, which also indicates the sustainability of the proposed model with increasing demand.

Table 10. *Sensitivity Analysis of Product Demand on Obj2*

Row	MD_{prt}	Obj 2
1	50	23.618
2	100	25.681
3	150	27.345
4	200	26.931
5	250	26.983

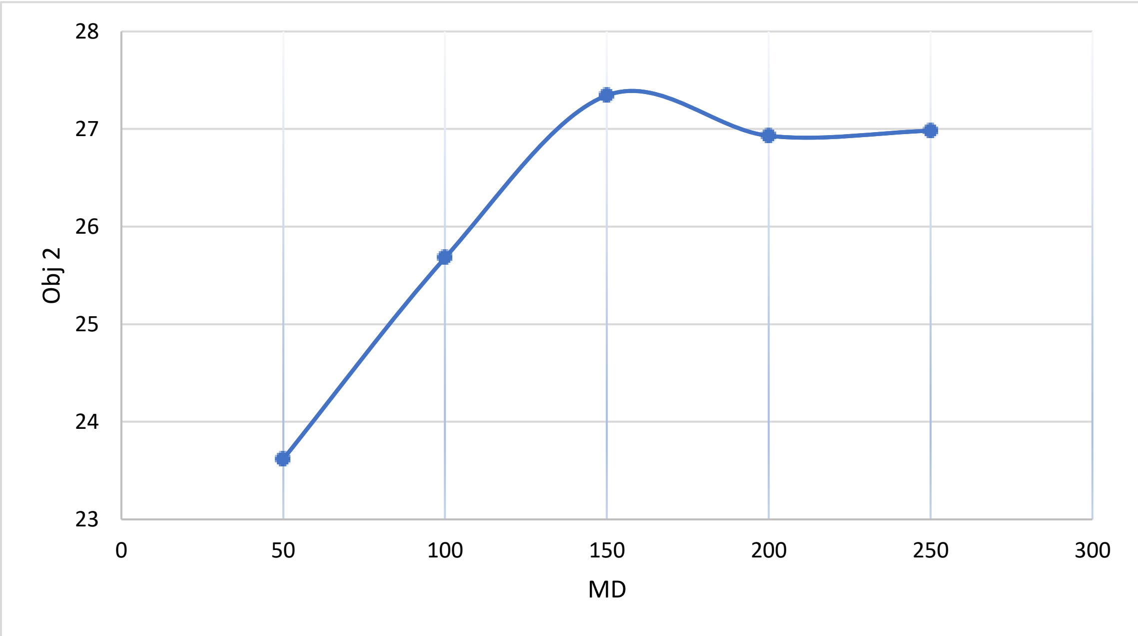

Figure 14. *Sensitivity Analysis of Product Demand on Obj2*

5. Conclusions

In conclusion, this study designed a data-driven, multi-objective model for a sustainable perishable dairy supply chain, integrating economic, social, and environmental dimensions. To address demand uncertainty, a machine learning approach was employed for forecasting, and the proposed model was subsequently solved using the NSGA-II algorithm in MATLAB, with its performance evaluated in a real-world dairy industry context. The results demonstrated that while rising demand causes increases in both the total cost and carbon emission objective functions—with an excess of 50% leading to infeasibility even minor demand fluctuations affect these objectives. Conversely, an increase in parameter mi reduced their values, though a 50% decrease also resulted in infeasibility. The model effectively reduces overall supply chain costs and carbon emission expenses. Furthermore, scalability analysis revealed that as the problem size grows, the costs and emissions initially rise due to expanded infrastructure and transportation needs; however, emissions eventually stabilize, underscoring the model's environmental sustainability. Simultaneously, the third objective function, social sustainability measured by created job opportunities, shows a consistent upward trend with network expansion, confirming the model's capability to enhance socioeconomic benefits while maintaining operational and ecological feasibility.

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