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Sustainability of the Supply Chain for Perishable Products from Economic, Environmental, and Social Perspectives Using a Hybrid Simulation Approach

Mehdi Sohanian[1], Reza Ehtesham Rasi[2*], Reza Radfar[3]

1-*Ph.D. Candidate, Department of Industrial Management, Faculty of Management and Economics, Science and Research, Islamic Azad University, Tehran, Iran.*

2- Department of Industrial Management, Faculty of Management and Economics, Islamic Azad University, Qazvin Branch, Qazvin.

3- Department of Industrial Management, Faculty of Management and Economics, Science and Research, Islamic Azad University, Tehran, Iran..

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Abstract

purpose: Sustainability in the supply chain is one of the important issues in this field, which has generally received less attention than other aspects of production due to its complexity. The study and research were conducted with the aim of investigating and improving the sustainability of the supply chain of perishable products. The sustainability examined in this study was carried out with a comprehensive view of environmental, economic and social issues and with a simulation approach.

Methodology: The case study is one of the largest dairy factories in Iran, which used a combination of the discrete-event agent base model and fuzzy analysis for modeling. After examining the current situation by simulating the impact of economic and social factors, in this study, items related to personnel retention were considered and how their positive impact on the factory production rate and production number was examined as an optimal scenario. In terms of environmental sustainability, the proposed scenario shows a decrease in traffic and an increase in service time.

Findings: The results show that simultaneous assessment of the supply chain using sustainability components leads to a significant improvement in product delivery time and a reduction in carbon emissions. In addition, it was found that environmental components conflict with economic and social components in some objectives, such as the level of supply chain service.

*Corresponding Author: *rezaehteshamrasi@gmail.com*

1. Introduction

Sustainable Supply Chain Management (SSCM) refers to the transparent and strategic integration of economic, environmental, and social goals of organizations, carried out in a coordinated process. Considering other dimensions of supply chain sustainability, alongside the economic aspect, helps managers design strategies for the long-term survival and success of the organization and provides a comprehensive view of the supply chain process. Sustainable supply chain management includes technologies that go beyond delivery, cost control, and inventory management technologies. As mentioned, sustainable supply chain management encompasses economic, social, and environmental sustainability aspects. Therefore, the concept of sustainable supply chain management is broader than that of green supply chain management, with green supply chain management being a subset of sustainable supply chain management (Farahani et al., 2009).

In the environmental goal of the supply chain, the organization seeks to reduce environmental risks and improve efficiency by controlling resource management processes and reducing the harmful environmental impacts of the supply chain. In the social goal, increasing safety, improving the physical and psychological health of employees, and enhancing social adaptability are the focus. The economic goal also emphasizes profitability and financial performance improvement (Beske-Janssen, Johnson & Schaltegger, 2015).

Perishable product supply chains differ fundamentally from those of other products, including significant and continuous changes in product quality from the early stages of the supply chain to the final stages (Bloemhof and Soysal, 2017). In many cases, the quality of perishable products, especially fresh foods and dairy products, is not stable and deteriorates over time until it reaches zero (Osvald and Stirn, 2008). Furthermore, one of the issues in managing perishable product supply chains is that storing large volumes of these products in warehouses has three major negative impacts: (1) if the products spoil, supply chain costs increase, (2) the waste of perishable products has environmental impacts, and (3) the quality of these products deteriorates immediately after production (Aghaei Fishani et al., 2022).

The main focus of many studies on perishable product supply chains has been the economic aspect of the chain, with less attention given to the social and environmental dimensions (Moreno-Camacho et al., 2023). In this study, after reviewing the literature, a research gap was identified in two ways. As mentioned, the research conducted in this field has been more about examining economic variables and less attention has been paid to environmental and social variables. In addition, the modeling carried out with a mathematical approach has been carried out and simulation models have been less considered. Therefore, in this study, an attempt has been made to use the discrete agent-based factor simulation approach and fuzzy analysis as a simulation approach to have a comprehensive look at the sustainability variables in the supply chain of perishable products.

2. literature review

Ensuring the achievement of predefined objectives in the economic, environmental, and social dimensions and improving them is one of the primary goals of supply chain sustainability (Fathi, Karimi & Saen, 2022). In the supply chains of perishable products, quality control in production, inventory management, and pricing policy selection are recognized as critical concerns (Buisman, 2019). Below is a review of recent studies conducted in the field of supply chain sustainability for perishable products.

(Behzadi et al,2017) explored the design of an agricultural product supply chain using a bi-objective mathematical model. They specifically studied the two-level supply chain for mushroom supply. However, they did not explicitly address the perishability of the products. The results indicated that the supply chain could increase its profitability by 11% while simultaneously reducing environmental impacts by 28% (Banasik et al., 2017). In another study, (Sazvar et al. 2018) proposed a multi-objective linear programming model that considered all three dimensions of sustainable food supply chain design. Using the AUGMECON method, they optimized three deterministic objectives: total cost, total greenhouse gas emissions, and social health. The results showed that shifting supply chains toward organic food products could result in social impacts up to four times better than conventional chains. Similar patterns were observed regarding environmental aspects, emphasizing the importance of organic food products (Sazvar et al., 2018). (Yavari and Zaker, 2019) designed a sustainable supply chain network for perishable products. Their model considered the resilience of an integrated two-level chain under power outages. They proposed a bi-objective mathematical model to minimize total supply chain cost and total CO2 emissions, solving the model using the LP-metric method. They studied a four-level dairy supply chain in Iran, and comprehensive analysis showed that chain integration and product lifespan improvements could lead to 21% reductions in total cost and 25% reductions in total emissions (Yavari & Zaker, 2019). In another paper, (Yakavenka et al, 2019) proposed a multi-objective sustainable supply chain network design model for all three sustainability dimensions. They used mathematical modeling to conduct a case study on a fresh fruit supply chain to examine the perishability issue. They also considered transportation using refrigerated containers and proposed the model under deterministic parameters. Their study analyzed environmental and social impacts through total CO_2 emissions and total transportation time. Their analysis revealed that optimizing total cost could increase delivery times by 111%, while optimizing delivery time not only increased total cost by 22.62% but also worsened the emissions objective by 34.52% (Yakavenka et al., 2020). (Biuki et al ,2020) developed a mixed-integer multi-objective programming model for the location-routing-inventory control problem in a sustainable perishable product supply chain network, considering demand uncertainty. They applied a combination of genetic algorithms and particle swarm optimization to solve several stochastic test problems to analyze the impact of various model parameters. The results showed that decisions related to facility location, particularly production centers, play a very important role in the sustainability of the chain. Moreover, the analyses indicated that transitioning to a more sustainable supply chain involves decentralization, and sustainability could be achieved with minimal economic costs in the supply network (Biuki et al., 2020).(Jouzdani and Govindan ,2021) explored the design of a sustainable supply chain for perishable products using multi-objective mathematical programming. In this study, product lifespan uncertainty was explicitly modeled using a Weibull random variable, and perishability was influenced by the use of refrigerated vehicles as a decision-making variable. They also examined various types of vehicles and products. This research considered the dairy product supply chain as a case study and examined the interactions between economic, social, and environmental dimensions, known as the "triple bottom line." The results showed that focusing on the economic aspect in highly perishable products could increase environmental impacts by up to 120%, and in highly congested road networks, social impacts could increase by up to 51%. However, a 15% reduction in the economic dimension could improve the sustainability of the supply chain design by up to 150% (Jouzdani & Govindan, 2021). Abbasian et al. (2023) developed a bi-objective mathematical model for evaluating the supply chain of perishable food products while considering sustainability dimensions. In this study, in addition to reducing total costs and CO_2 emissions, a dynamic pricing strategy is used to deal with disruptive events. One of the key features of the proposed model is considering the impact of route disruptions and traffic conditions on product spoilage. To solve this bi-objective nonlinear optimization model, an innovative hybrid method using genetic algorithms was developed (Abbasian et al., 2023). (Pan and Shan ,2024) presented a comprehensive framework for optimizing production, location, and inventory issues in the supply chain of perishable products, considering sustainability dimensions. They applied a hybrid heuristic method to solve this problem (Pan & Shan, 2024).

As observed, most of the research conducted in the evaluation of perishable product supply chain sustainability has used mathematical modeling and heuristic algorithms, and to the authors' knowledge, a hybrid simulation approach has not been employed so far. Very few studies have used simulation tools combined with heuristic methods to derive optimal combined solutions in perishable product supply chains, focusing only on the economic goal of the supply chain, with little consideration of other sustainability dimensions (Soysal et al., 2018; Onggo et al., 2019). This study aims to fill this identified research gap by utilizing the flexibility of hybrid simulation approaches and simulation-based optimization.

3. Research Methods

To construct a simulation model for the perishable product supply chain and evaluate its sustainability, it is necessary to select an appropriate approach for the simulation. Simulation approaches are classified into three categories based on the level of detail required. Discrete-event simulation is applied to operational-level problems and requires incorporating a high level of detail. Dynamic system modeling, in contrast to the previous method, is suitable for strategic-level problems, and most issues in this domain require considering lower levels of detail. Agent-based modeling offers high flexibility and a bottom-up approach, covering a wide range of problems from operational to strategic levels (Figure 1).

If the processes of a system have dynamics and time dependencies, they are candidates for modeling through the agent-based approach. The three main components of the agent-based simulation approach are (Macal, 2010):

1. Defining the agents, their characteristics, and behaviors
2. The way agents interact and communicate
3. The environment

Due to the wide application of agent-based modeling in simulating various systems and the diverse characteristics of agents in each of them, no comprehensive definition of an agent has yet been established (Macal, 2010). However, generally, three key features are widely accepted as essential characteristics of an agent: **autonomy**, **memory**, and the **ability to interact** (Macal, 2014).

3.1. Identification of Agents in the Perishable Product Supply Chain

Based on the characteristics of agents in the research conducted by Macal in 2014, the agents of the perishable product supply chain in this study are identified as follows (Macal, 2014):

1. Supplier Agent
2. Factory Agent
3. Cold Storage Agent
4. Order Processing Agent
5. Vehicle Agent
6. Distributor Agent

The characteristics and interactions of these agents will be described further in the following sections. It shows in figure 2.

3.1.1. Supplier Agent

Milk is considered the most crucial raw material in the dairy industry. Therefore, daily milk requirements are sent from contracted farms to the factory agent. To determine the input data for the supplier agent, the type of vehicles and the share of each type of vehicle from the total incoming milk are calculated using available data in the system. Then, the distribution function for the milk entry rate by vehicle is derived from the entry intervals of the vehicles.

3.1.2. Factory Agent

The factory agent is responsible for product production. The raw materials needed for product manufacturing are sent from the supplier agent to the factory agent. It is worth noting that the milk sent by the supplier agent may be rejected for various reasons, such as contamination, the presence of chemicals, low-fat content, etc., and its quality may be rejected with a probability of a percent. If the milk is approved by the quality control unit, it will be transferred to the factory tank to enter the pasteurization process and then the production lines.

The factory agent has different production lines for various ice cream product groups, each with different cycle times (Cl) and packaging sizes (Pl). Given the need to examine the constraints of production lines and the requirement for a granular-level perspective in modeling the factory agent, the behavior of this agent will be implemented through discrete-event simulation. The logic for implementing the production of each of the production lines is shown in Figure 3.

3.1.3. Warehouse (Cold Storage) Agent

The products produced by the factory agent are stored in the warehouse (cold storage) agent and are then sent to the distributor agents. The cold storage agent manages the inventory levels of products in all storage facilities. The factory agent monitors these inventory levels to effectively manage production and product dispatch. If the inventory levels in different cold storages indicate a need for production and dispatch, the products will be sent to the cold storages based on their priority.

3.1.4. Distributor Agent

The distributor agents are located in provincial centers. These agents register a specific number of orders for various products based on the demand in their region. A notable aspect of this agent is its seasonal behavioral differences. During the first six months of the year, the demand is higher than during the last six months.

3.1.5. Order Processor Agent

After the order is registered by the distributor agent, the order processor agent is responsible for processing the order and coordinating dispatch, considering the inventory in the various warehouses. If dispatching the received order is possible, the following actions are performed by the order processor agent:

- A vehicle is selected based on the volume of the distributor's order. If no vehicle is available, the order is suspended until a vehicle becomes available.
- Once a vehicle is called, the scheduling for visiting the warehouses to load all the items in the order is performed.
- The destination (the location of the distributor agent) is communicated to the vehicle.

Once the order is finalized, and the vehicle is called with the necessary loading schedule and destination details, a message from the order processor agent is sent to the vehicle agent to initiate the loading process and proceed to the destination.

3.1.6. Vehicle Agent

Product transportation in the agent-based simulation model of this research is handled by the vehicle agent. After being called by the order processor agent and receiving the necessary loading and destination information, the vehicle agent behaves according to the state diagram established in the simulation model (Figure 4).

3.1.6. Vehicle Agent (Continued)

According to the state diagram, the vehicle agent initially starts in the ready state. The change of the vehicle's state to the next one is triggered by a message, which is sent either by the factory agent to move the produced products to the cold storage or by the order processor agent to load products from warehouses and transport them to the distributor agents.

- If a message is received from the factory agent, the vehicle’s state changes to moveToStorage to indicate movement toward the assigned cold storage. Then, it switches to unloadingStorage when unloading the products and eventually changes back to the moveToSource state, returning to the starting point.
- If the message is received from the order processor agent, the vehicle changes state to moveTo based on the list of warehouses provided. It then transitions to loadingStorage for loading the products. This process continues until the loading plan is completed. After that, the vehicle moves towards the destination (moveToDest) as specified in the order. Upon unloading the products at the destination, the vehicle returns to the source (moveToSource).

The cooling system of the vehicle agent is subject to failure. In case of a breakdown, if the repair time or the time taken to reach the destination exceeds t hours, all the loaded products in that vehicle are considered as waste.

3.2. Locating and Routing Agents on GIS Map

One of the capabilities of the agent-based modeling approach in AnyLogic simulation software is the ability to connect the simulation model to GIS maps and utilize data from OSM servers. By leveraging these GIS data, various routing algorithms, such as Dijkstra's algorithm, can be implemented.

Dijkstra's Algorithm is one of the greedy algorithms used in routing. The algorithm works as follows:

1. Initially, the set X is set to {s} (starting node), with dist[s] = 0 and dist of other nodes in the graph set to ∞.
2. At each step, all edges e = (v, w), where one end is in X (v ∈ X) and the other end is in V-X (w ∈ V-X), are considered.
3. The edge is selected that minimizes dist[v] + l_vw, where l_vw is the weight (or cost) of the edge.
4. Then, node w is added to X, and dist[w] is updated to dist[v] + l_vw.

In this research, Dijkstra's algorithm is used for optimal routing between agents. Figure 5 illustrates how the hybrid agent-based and discrete event simulation model is connected to the GIS map and how its outputs are utilized.

3.3. Simulation-Optimization Method

The term simulation-optimization refers to techniques used for optimizing parametric stochastic problems (Gosavi, 2015). In this method, the input values of the simulation model are selected in the form of decision variables in such a way that a specific objective is optimized. In most cases, in simulation-optimization, the created combined simulation model is integrated with metaheuristic algorithms, and by determining the values of decision variables and the objective function and performing the iteration process, optimal values are extracted. The diagram below shows the interaction between metaheuristic algorithms and the simulation model in the simulation-optimization method. (Figure 6)

In this research, the optQuest optimization package is used for simulation-based optimization. This optimization package utilizes a combination of metaheuristic algorithms, including genetic algorithms, taboo search, and simulated annealing, to optimize the objective function (Laguna, 2011). One of the advantages of using this optimization package is its integration with the AnyLogic simulation software, which results in faster optimization.

4. Results and discussion

In order to implement and evaluate the performance of the proposed combined agent-based – discrete event model, the supply chain of one of the largest dairy product manufacturers in the country has been considered as a case study. The required milk for the input of this supply chain is provided by suppliers through the vehicle weight percentages listed in Table 1.

To determine the statistical distribution function for the milk arrival at the factory, the arrival distances between milk transport vehicles were extracted from the available data in the system. Statistical fitting was performed using the EasyFit software. Based on the extracted data, the milk arrival distribution function is determined as Exponential(0.39). The histogram and the fitted distribution function are shown in Figure 7.

The ice cream production factory has 8 production lines, each producing a different group of products, as shown in Table 2.

There are 3 cold storage units for storing ice cream products, and their capacities are presented in Table 3. Cold storage unit number 3, due to storing other dairy products, will only be used in emergency situations and when the capacities of the central cold storage and cold storage unit number 2 are full.

Also, for transporting ice cream products, vehicles with the capacities provided in the table 4 are used:

To implement the ordering process for ice cream distributors in different provincial centers, orders recorded in the system for two periods— the first and second halves of the year— were extracted separately for each provincial center, and the corresponding probability distribution functions were fitted.

Figure 8 presents the view of the combined agent-based discrete event simulation model of the supply chain, with its connection to the GIS map. As mentioned, the simulation model was developed using the AnyLogic simulation software. The red agent represents the factory, the yellow agents represent the cold storage units, and the green agents represent the distributors.

5. **Results**

Before evaluating the sustainability dimensions in the current perishable product supply chain simulation model, it is essential to validate the combined simulation model. For this purpose, a comparison of the simulation model outputs with the data available in the system over a one-year period has been used. The results are presented in the table 5.

As the results indicate, for the four selected indicators used to evaluate the validity of the combined simulation model, the difference between the simulation model's output and the real-world data is less than 5%. Therefore, the assumption of the model's validity is confirmed. The simulation model's outputs for the current state are presented to allow for the comparison of the supply chain's performance in the sustainability scenarios. It is worth mentioning that the simulation model was executed for three and a half years, equivalent to 30,240 hours. (Figure 9,10,11)

The simulation model outputs indicate that the ice cream product has seasonal demand, and during periods of low demand, inventory levels increase, whereas during peak demand, inventory in some warehouses reaches zero. Additionally, Warehouses 1 and 2 cover a larger volume of ice cream production, while Warehouse 3 serves as a backup warehouse during special cases. It is worth mentioning that Warehouse 3 also handles other dairy products, and due to these products being considered within the scope of this study, this warehouse often has surplus capacity. The average time gap between receiving an order from distributors and the time of product unloading at the distributor location is one of the key indicators that determines the service level of the supply chain. The value of this indicator in the current state is presented in the figure 12.

Therefore, the average order-to-receipt time is 143.4 hours (equivalent to 6 days). The total distance traveled by vehicles for order deliveries is 1,649,000 kilometers.

5.1. Evaluation of the Sustainability of the Perishable Goods Supply Chain from Economic, Social, and Environmental Perspectives

As mentioned, in order to evaluate the sustainability of the supply chain, it is necessary to consider the performance of the chain from economic, environmental, and social perspectives. One of the effects of focusing on the social aspects of the supply chain is the emphasis on employees, which, if handled properly, can lead to increased supply chain productivity and higher product output. Therefore, it can be stated that focusing on the social dimension of the supply chain will result in an improvement in the economic dimension of the supply chain (Duong, 2022).

Given the positive correlation between the social and economic dimensions of the supply chain, this study will first examine the optimization of supply chain sustainability from economic and environmental perspectives. Then, the environmental sustainability of the supply chain will be optimized.

5.1.1. Optimization of the Supply Chain from Social and Economic Perspectives

To assess the impact of social factors on the sustainability of the perishable goods supply chain, the impact of these factors on the increased production of the factory's production agent was examined. In the first step, by reviewing the literature and interviewing experts, factors that affect the increase in production from the social perspective were identified. Then, to quantify the impact of each of these factors, the fuzzy Delphi method was used. The social factors identified are as follows:

- Implementation of incentive and control systems to reduce employee absenteeism
- Occupational health and safety management system (OHSAS)
- Increasing job stability
- Enhancing employee capabilities through training programs
- Improving job motivation and employee satisfaction through solutions such as providing welfare facilities, incentive mechanisms, and creating communication channels with managers
- Establishing long-term working relationships and building mutual trust with suppliers

To quantify the impact of each identified factor, a five-point fuzzy triangular scale, as outlined in the table below, was developed. It should be noted that the ranges for the fuzzy triangular numbers were formulated based on expert opinions (Table 6).

To score the extracted indicators of social factors, interviews were conducted with 15 industry experts. Then, by using the fuzzy average of their opinions and finally defuzzification, the impact of each social factor on production increase was determined, as shown in the table 7.

Based on the extracted quantitative impact of social factors, the objective function and constraints for optimizing the sustainability of the supply chain based on economic and social factors are defined as follows:

1. Regarding social factors, the cost of implementing each of the extracted factors and its impact on increasing the production rate of the factory agent are incorporated into the objective function as binary variables. Therefore, if the optimization algorithm decides to utilize a social factor, its associated cost will be applied in the objective function, and the corresponding increase in the production rate of the factory agent will be reflected in the simulation model.
2. Regarding economic factors, production planning and inventory control are considered. In line with this objective, two costs—storage and product shortage (waiting time for the distributor agent to receive the product)—are included in the objective function. Thus, the optimization algorithm must adjust the maximum product holding levels and the start point for product production in such a way that the storage and product shortage costs are minimized.

As observed, social factors influence the economic components of the supply chain. With the explanations provided, the objective function for the optimization problem is defined as follows:

Objective Function

M_i : Inventory of product iii in the warehouse

CH_i : Holding cost of product iii in the warehouse

W_i :Total waiting time for the distributor agent to receive product iii

CW_i :Waiting cost for the distributor agent to receive product i

S_i :Use of social factor iii in the supply chain

CS_i :Cost of using social factor iii in the supply chain

$$Min\ z = \sum_i M_i \times CH_i + \sum_i W_i \times CW_i + \sum_i S_i \times CS_i$$

Constraints:

LL_i : Lower bound for the production of product iii by the factory agent

UL_i : Upper bound for the production of product iii by the factory agent

$$LL_i < UL_i \qquad \forall i$$

Considering the iterative process between the decision variable determination by the optimization algorithm and the objective function extraction from the simulation model outputs, other operational and logistical constraints are taken into account in the simulation model.

For optimization using the optQuest optimization package, the number of iterations is set to 10,000. Additionally, to avoid bottlenecks in the product delivery process to distributors due to the number of vehicles, a large number of vehicles is set in this scenario. It should be noted that in the next step, for optimizing environmental factors, the number and type of required vehicles will be optimized. The results of the optimization process are presented in the table 8.

Regarding the social components, the following factors have been selected by the optimization algorithm:

- Implementation of incentive and control systems to reduce employee absenteeism.
- Occupational Health and Safety Management System (OHSAS).

- Increasing personnel capabilities through training programs.
- Establishing long-term working relationships and mutual trust with suppliers.

To test the results of the optimization process, the new ordering levels and the selected social components are entered into the combined simulation model of the current status. The outputs of the combined simulation model with the optimized values are presented in figure 13.

As shown in Figure 13, the time between receiving an order and delivering it to the distribution agent has decreased from 143 hours to 96 hours, which is a reduction of approximately 2 days. Additionally, the objective function value has improved by 5% compared to the current model. The total kilometers traveled in the simulation model, considering both economic and social components, is 2,230,000 kilometers, which is an increase of 581,000 kilometers compared to the current model simulation.

As shown in the charts related to the inventory of Cold Storage 1 to 3, the inventory levels during periods of both decreased and increased demand have improved compared to the current status model. This improvement has led to a reduction in the service time from the factory to the distributor.(Figure 14,15,16)

5.1.2. Optimization of the Supply Chain from an Environmental Perspective

Following the optimization of the supply chain sustainability from the economic and social components, in this phase, the optimization of the supply chain sustainability from the environmental components is addressed. To this end, using the optimized decision variables related to the economic and social components from the previous phase, a new optimization problem is formulated with the focus on determining the number and type of vehicles required for product transportation. In this optimization problem, vehicle mileage, increased utilization rates, and reduced carbon emissions are considered. The objective function and constraints of the optimization problem are presented below.

Objective Function:

M_k : Number of vehicles of type k
C_k : Cost of vehicles of type k
W_i :Total waiting time of the distribution agent to receive product i
CW_i :Cost of waiting for the distribution agent to receive product i
C_o :Carbon emission cost
O_i :Total carbon emission by fleet iii during the simulation model execution

$$Min\ z = \sum_i (M_k \times C_k) + \sum_i (W_i \times CW_i) + \sum_i (O_i \times C_o)$$

Constraints:

There are no specific mathematical constraints to define within the optimization algorithm for this scenario. The operational constraints that affect the process have been implemented in the simulation model. These constraints are applied after the decision variables are entered into the simulation model, and their effects are returned to the optimization algorithm through the objective function. The annual costs related to maintenance, repairs, and capital idle time are also considered in the vehicle costs. Additionally, carbon emissions are included in the model by calculating the kilometers traveled by the fleet.

To guide the algorithm toward optimizing the number and type of vehicles and avoid an excessive reduction in the fleet, the waiting costs for customers are also included in the objective function. This approach ensures the optimization algorithm is directed toward finding a balance between fleet costs, vehicle traffic, carbon emissions, and customer waiting costs.

The results of the environmental sustainability optimization process in the supply chain are presented in the table 9.

As observed, the optimization algorithm performed the process by altering the fleet composition and reducing the fleet size by 4 vehicles. After incorporating the new fleet specifications into the simulation model, it was found that the total distance traveled by the fleet decreased by approximately 5% (110,000 kilometers) compared to the simulation model with economic and social factors that shows in figure 17.

On the other hand, as shown in Figure 17, the time interval between receiving the order and delivering the order to the distributors has increased by 12 hours when considering the environmental factors, which is due to the change in the number and composition of the fleet. Therefore, it can be stated that incorporating environmental factors into the supply chain leads to reduced vehicle traffic but, on the other hand, increases the service time of the chain. However, when considering all related costs, the increase in service level is not significant compared to the improvements achieved in other dimensions of the supply chain.

6. Conclusion

This research aims to investigate supply chain sustainability with a comprehensive approach and factor-based modeling as a simulation method .The findings of this study involve the design of a combined simulation model and the use of a simulation-based optimization approach to evaluate and optimize the sustainability of the supply chain for perishable products. Unlike previous approaches, this research uses a combined agent-based – discrete event simulation approach to build the supply chain model. To assess the effectiveness of the designed model, a case study of one of the largest dairy product manufacturers in the country was considered. Due to the high production and demand for ice cream, this product was selected as the perishable product in the supply chain. Regarding the study of sustainability in terms of economic issues, the results of this study in the economic dimension are consistent with the research of (Behzadi et al,2017) and (Banasik et al., 2017). Also, the examination of sustainability in terms of environmental issues in this research is confirmed by research (Yakavenka et al, 2019) and (Yavari and Zaker, 2019) However, it should be noted that these studies are based on different modeling approaches. In the first phase, due to the positive correlation between economic and social factors, their impact on the factory's production rate and, consequently, the overall performance of the supply chain was evaluated. To quantify the impact of social factors, the fuzzy Delphi method was used, and through simulation-based optimization, the selection of social factors and the optimal levels of production and inventory management were determined. The results showed that improving the economic and social factors of the supply chain led to a 32% improvement in the service level of the chain and a 5% improvement in the objective function (costs of storage and product shortages). However, the total fleet traffic increased by 35%.

In the next phase, with the inclusion of environmental factors and the optimization of the fleet's number and composition, the total fleet traffic decreased by 5%, but the time between receiving an order and delivering the product to distributors increased by 12%. It was observed that the environmental factor is in conflict with the social and economic factors. However, the optimization of the sustainability factors in the supply chain of perishable products using a simulation-based optimization approach resulted in a 24% improvement in the supply chain performance compared to the current situation. Additionally, carbon emissions will decrease by 5%.

The combined simulation and simulation-based optimization approach used in this study can be applied to evaluate the sustainability of all supply chains. The following recommendations are suggested for the development of the model and future research:

- The impact of product carton size on the environmental factor of the supply chain
- Adding a customer agent to the current model and developing purchase behavior
- Adding a competitor agent and assessing the impact of competitors on the supply chain
- Using reinforcement learning algorithms to improve the economic factors of the supply chain

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Figure 1

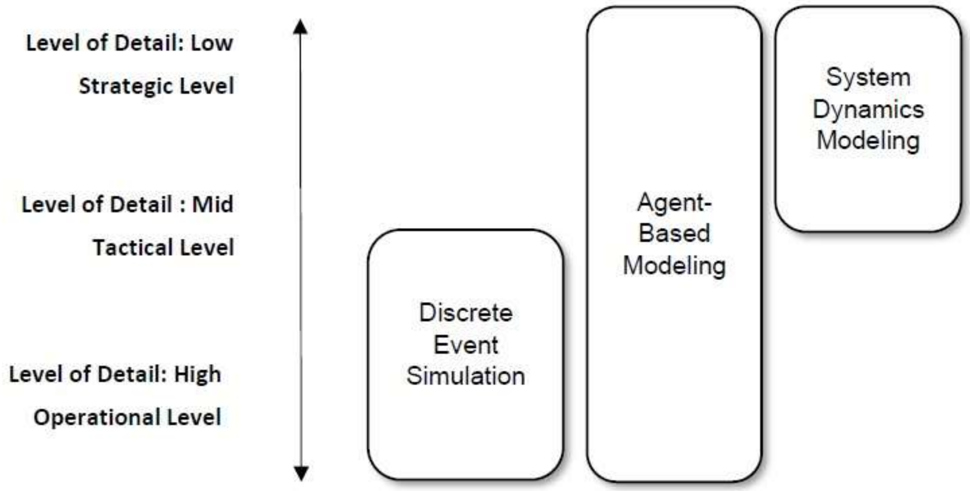

Figure 1. Different Approaches to Simulation

Figure 2

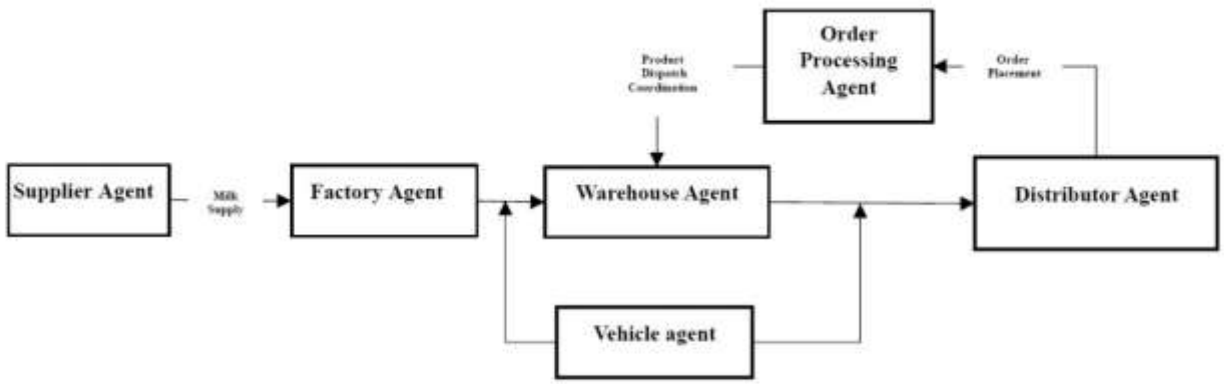

Figure 2. Interaction of Identified Agents in the Perishable Supply Chain

Figure 3.

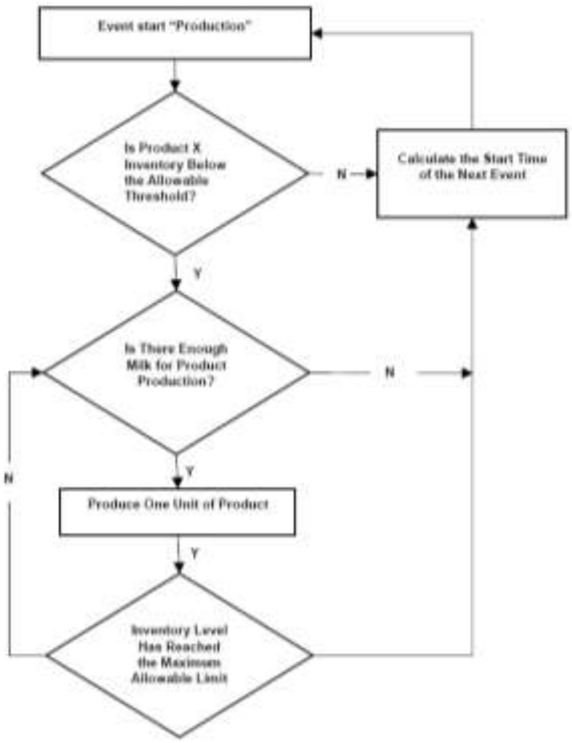

Figure 3. Discrete Event Algorithm for Factory Production Lines

Figure 4

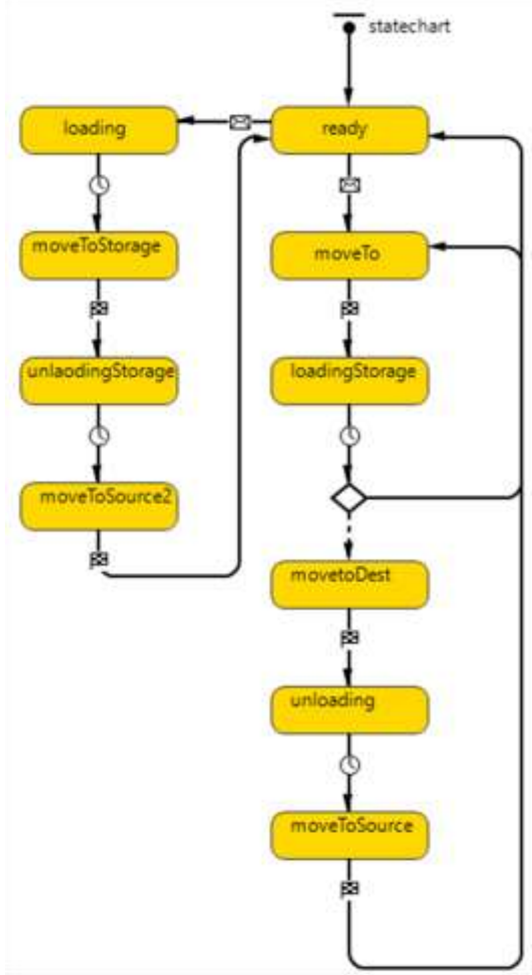

Figure 4. State Diagram of the Vehicle Agent

Figure 5

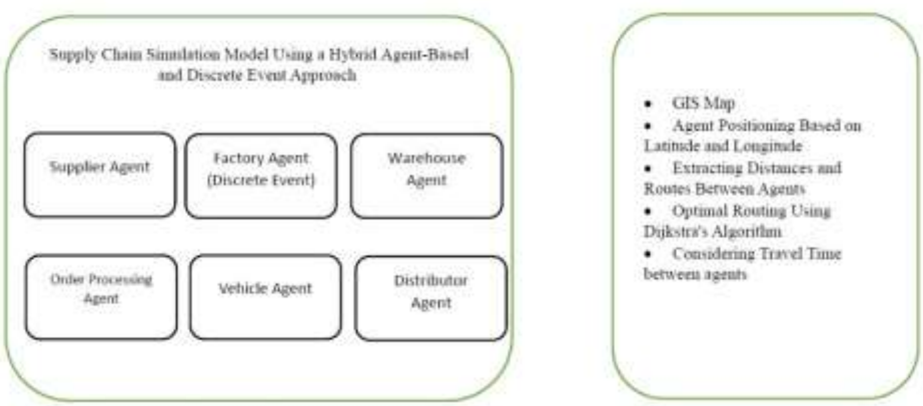

Figure 5. Interaction of the Combined Simulation Model and GIS Map

Figure 6

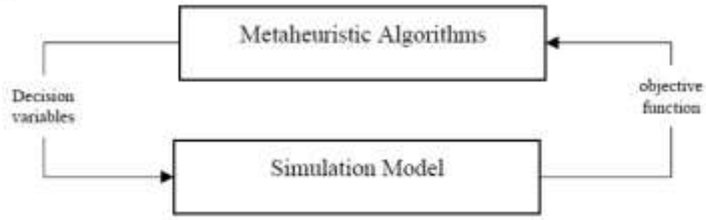

Figure 6. Simulation-Optimization Approach

Figure 7

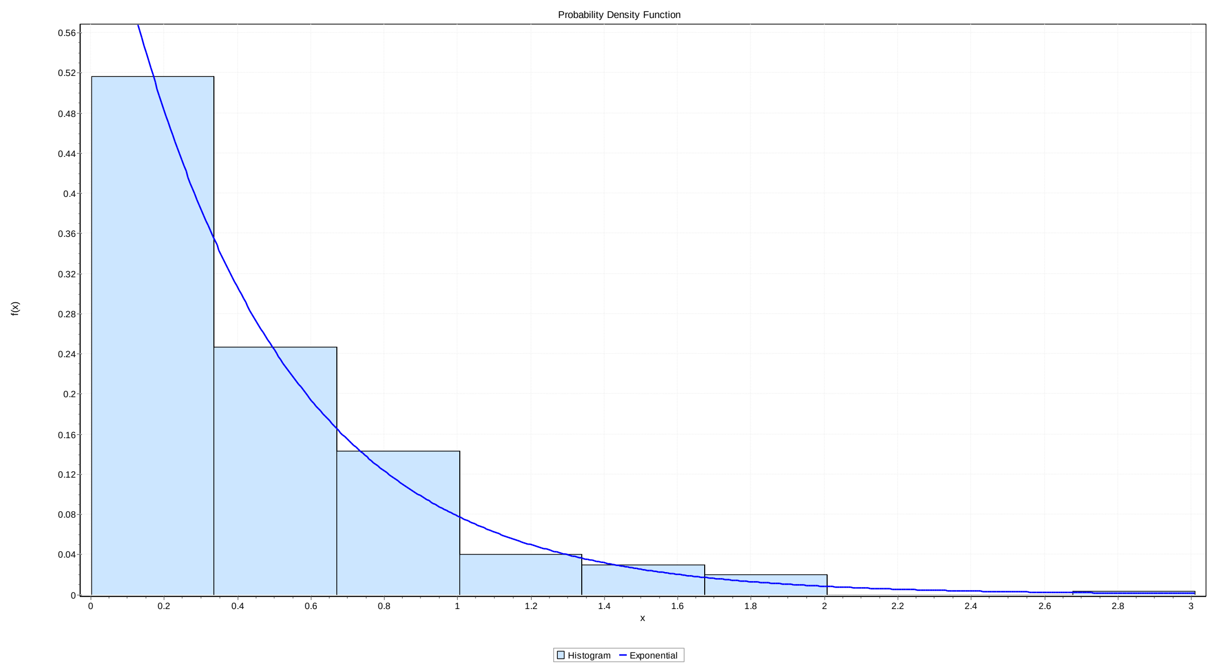

Figure 7. Histogram and the fitted distribution function of the milk carrier vehicle arrival rate.

Figure 8

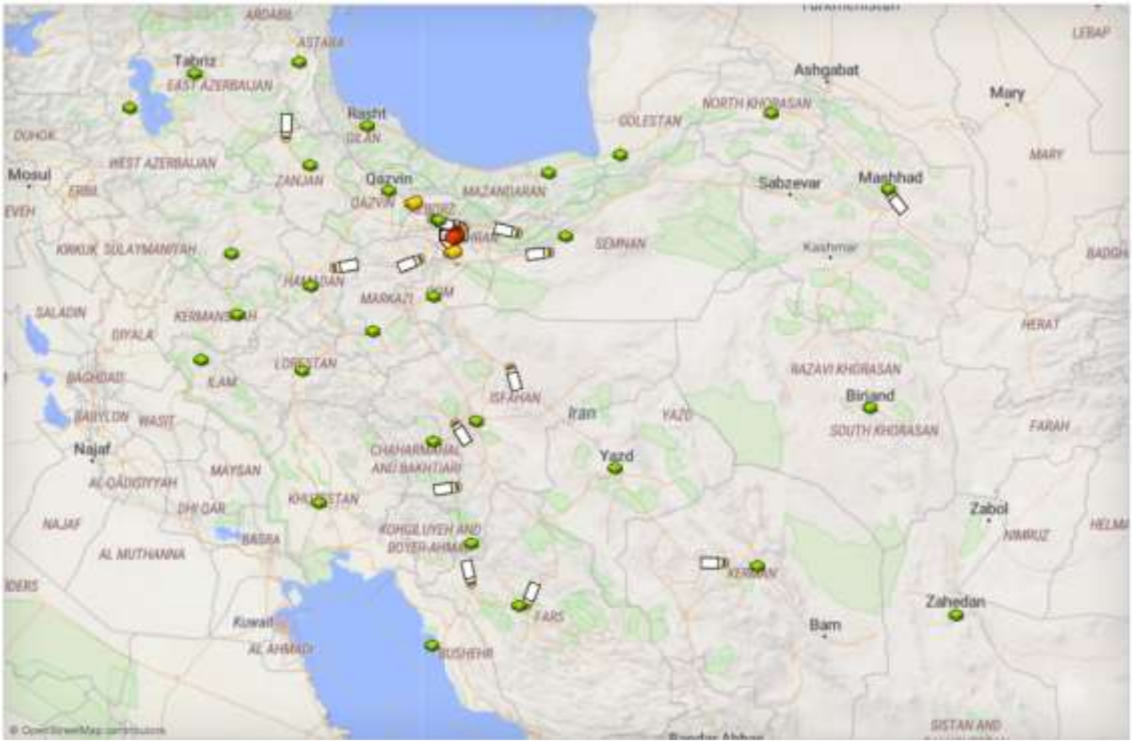

Figure 8. Implementation of agents and establishing connection with the GIS map.

Figure 9

Figure 9. Inventory of Warehouse 1 in the current state of the simulation model.

Figure 10

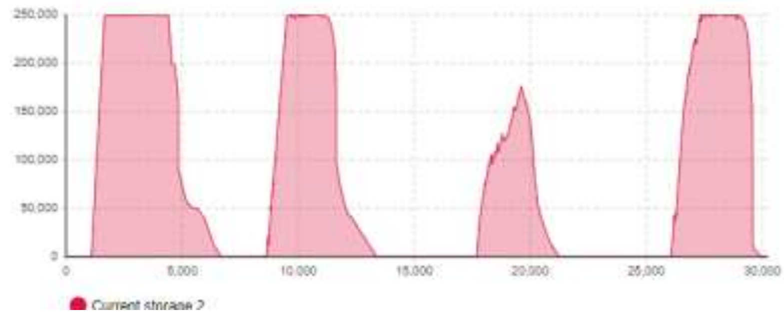

Figure 10. Inventory of Warehouse 2 in the current state of the simulation model.

Figure 11

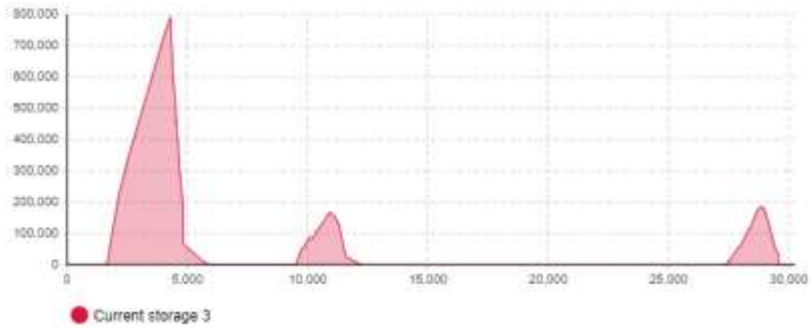

Figure 11. Inventory of Warehouse 3 in the current state of the simulation model.

Figure 12

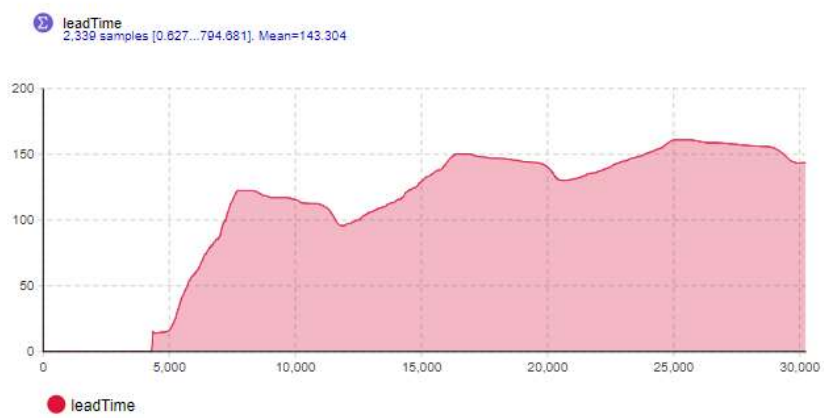

Figure 12. Average order-to-receipt time in the current state of the simulation model.

Figure 13

Figure 13. Average time from order to product receipt considering economic and social components in the simulation model

Figure 14

Figure 14. Inventory of Cold Storage No. 1, Current Status of the Simulation Model

Figure 15

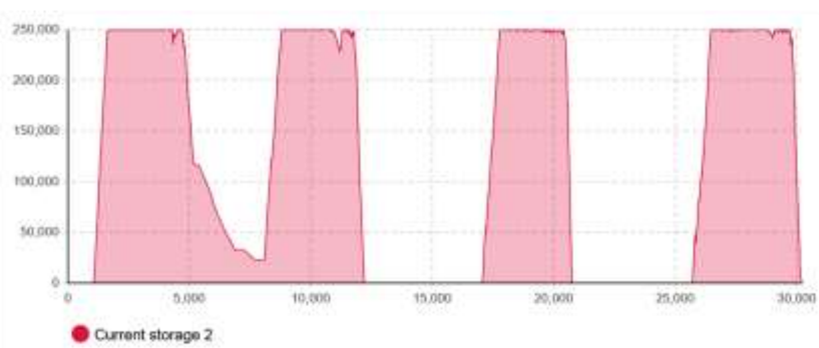

Figure 15. Inventory of Cold Storage No. 2, Current Status of the Simulation Model

Figure 16

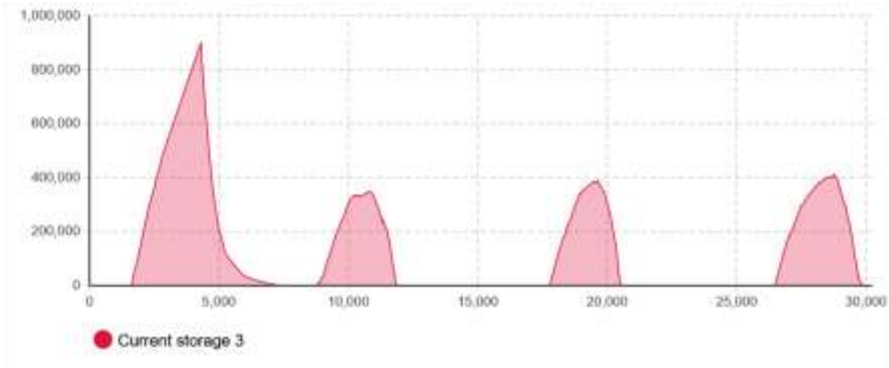

Figure 16. Inventory of Cold Storage No. 3, Current Status of the Simulation Model

Figure 17

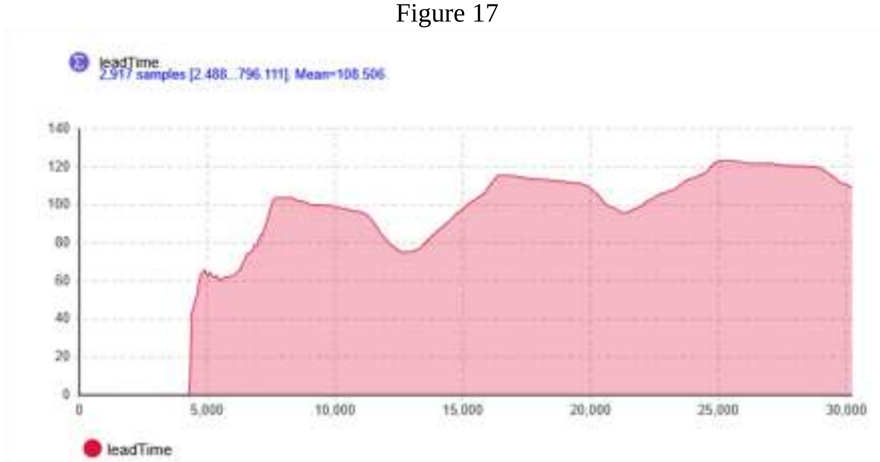

Figure 17. Average Time from Order to Product Receipt Considering Economic, Social, and Environmental Factors

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