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RESEARCH ARTICLE **Open Access**

Integrated Optimization of Facility Location, Inventory Control, Fleet, and Routing in the Supply Chain of Perishable Products Using a Hybrid Simulation-Based Optimization Approach

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Abstract
The supply chain of perishable products is highly complex due to the short lifespan of the products. Therefore, it is essential to utilize flexible tools to comprehensively evaluate various issues in the supply chain, such as location, inventory, and logistics. The aim of this research is to present a hybrid simulation-based optimization approach, combining discrete event and agent-based modeling, to optimize facility location, inventory control, fleet composition, and routing in the supply chain of perishable products. The optimization process is carried out using metaheuristic algorithms. As a case study, the supply chain of one of the largest dairy producers in the country is considered. Due to the high production and demand for ice cream, this product is selected as the perishable product in the supply chain analysis. The results show that the integrated optimization of the research subject leads to significant improvements in product waste reduction, shorter order processing and delivery times, and a reduction in the fleet size.

Keywords: Supply Chain, Perishable Products, Agent-Based Modeling, Discrete Event Simulation, Optimization, Metaheuristics

Introduction

In recent years, demand for fresh, high-quality products with short shelf lives has increased significantly. Due to high competition in this market, consumers place great importance on the freshness of these products (Liu et al., 2021). Waste is an inseparable part of perishable supply chains, as products become unsuitable for consumption after their predetermined lifespan has passed. Currently, approximately one-third of the world's total food production, equivalent to 1.3 billion tons, is wasted. In the United States, about 15% of perishable products are wasted due to transportation issues (Ferguson & Ketzenberg, 2005). In Australia, these losses are estimated at around 10 million dollars (Martin, 2015). In emerging countries, the rate of perishable product wastage is even higher than in developed countries. For example, in China, over 25% of perishable products are wasted due to transportation, storage, and sales problems. (Nikounam Nazemi et al., 2023).

To solve these problems, inventory control, transportation route optimization, and improving the efficiency of perishable product supply chain operations are essential. Generally, facility location, inventory control, and routing are three key topics in managing the supply chain of perishable products (Liu et al., 2021). Since the quality of perishable products changes during

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storage and distribution processes, any optimization in this area will lead to improvements in the performance of the perishable supply chain (Fahmy et al., 2023). One of the challenges in managing perishable supply chains is controlling carbon gas. In emerging economies, simultaneously meeting the demand for perishable products and controlling carbon emissions is challenging. In perishable supply chains where carbon emissions are not a priority, the optimization of facility location, inventory control, and routing remains a serious problem, leading to low profitability in the supply chain (Kuo, 2011) and (Mihajlović et al., 2019).

The aim of this research is to design a hybrid agent-based and discrete event simulation model and use a simulation-optimization approach to determine facility locations, inventory control, and routing. The main research question is how to optimize facility locations, inventory control, fleet composition, and routing using a hybrid agent-based and discrete event simulation model combined with metaheuristic methods and a simulation-optimization approach.

To implement and evaluate the designed model for optimizing facility location, inventory control, and fleet composition, the supply chain of one of the largest dairy producers in the country was selected as a case study. Due to the high production and demand for ice cream and its perishable nature, the ice cream supply chain was specifically analyzed. The hybrid simulation model was implemented using the AnyLogic simulation software, and metaheuristic algorithms were used to optimize the model through the OptQuest optimization package.

This research is structured as follows: First, previous studies are reviewed. Then, the research methodology, the construction of the hybrid agent-based and discrete event simulation model, and the simulation-optimization approach are presented. Next, the designed model is implemented in one of the largest dairy producers in the country, and the results are provided. Finally, conclusions and future research directions are presented.

Background

Research on integrated optimization and decision-making in perishable product supply chain management has grown significantly. Over 50% of the research conducted in this field over the past 15 years has been published in the last five years (Mirabelli & Solina, 2022). This research focuses on production and distribution planning, inventory control, routing, and facility location. This section reviews recent studies in this field.

Many studies have examined inventory control as one of the key challenges in perishable product supply chain management and have emphasized its crucial role in reducing waste within the supply chain (Liu et al., 2021). Lacomme et al. (2018) explored simultaneous production and transportation planning in the perishable supply chain. In their research, a perishable product was considered, and the fleet composition for product transportation was varied (Lacomme et al., 2018). Moreira et al. (2019) investigated a combined production and routing problem in a multi-product perishable supply chain. In this study, a time window for product delivery was considered, and metaheuristic algorithms were used to solve the problem. Qiu et al. (2019) optimized an integrated production, routing, and inventory control policy using Ant colony optimization modeling. Violi et al. (2020) examined the agricultural product supply chain under uncertainty from the perspective of inventory control and routing and used a rolling horizon algorithm to solve the problem. Biuki et al. (2020) proposed a model to integrate facility location, routing, and inventory control problems in the perishable product supply chain. The multi-objective model was developed using mixed-integer programming. Due to the large problem size and its NP-Hard nature, they used a hybrid approach combining genetic algorithms and swarm algorithms to solve the model. Distribution planning under uncertainty in demand and disruptions in perishable product supply chains was studied by Suryawanshi and Dutta (2021). The supply chain disruptions were related to the supply of raw materials from suppliers.

Jouzdani and Govindan (2021) presented a model to minimize costs, energy consumption, and traffic congestion in the dairy product supply chain. In this research, the product's lifespan was considered probabilistically, and the dependence of product quality on vehicle refrigeration efficiency was accounted for. The researchers used mathematical programming to optimize the problem. Liu et al. (2021) studied the perishable product supply chain from the perspective of facility location, inventory control, and routing. This research focused on emerging markets, and mathematical modeling was used for integrated optimization.

With the growing application of machine learning algorithms in optimization problems, Ahumada et al. (2022) used deep reinforcement learning and Q-learning algorithms to propose an optimal inventory control policy in the pharmaceutical supply chain. To evaluate the optimal policy adopted by the reinforcement learning algorithm, the problem was also solved using probabilistic integer programming with CPLEX and genetic algorithms, and the results were compared.

Song and Zhengyang (2023) studied integrated optimization of facility location, inventory control, and routing in the perishable product supply chain. In this research, a three-level supply chain, including suppliers, distributors, and retailers, was considered, and mixed-integer programming was used to solve the problem. Partovi et al. (2023) examined a two-level perishable product supply chain to optimize facility location, inventory levels, and routing. The number of warehouses and their locations in the first level and the number of retailers in the second level were the decision variables. Fuzzy goal programming was used in this study to extract the combined policy. The trade-offs between economic and environmental variables in the perishable product supply chain were examined by Sun et al. (2023). This study integrated production, inventory, and routing optimization in the perishable product supply chain and used a particle swarm optimization algorithm to derive the optimal solution. Heidari et al. (2021)

According to the authors of this study, an integrated approach to facility location, inventory control, routing, and fleet composition in the perishable product supply chain has not yet been thoroughly examined. Furthermore, few studies have utilized simulation tools and combined them with metaheuristic methods to derive optimal combined solutions in the perishable product supply chain (Soysal et al., 2018) and (Onggo et al., 2019). Additionally, based on a review of the literature by the authors of this study, hybrid simulation approaches have not been applied to analyze the perishable product supply chain. This research aims to address this research gap by leveraging the flexibility of hybrid simulation approaches and metaheuristic methods.

Method

To carry out the simulation-based optimization process in the supply chain of perishable products, the appropriate simulation approach must be adopted. There are three simulation approaches for modeling real-world systems, each suited to the level of detail required. Discrete event simulation is applicable to operational-level issues and requires a high level of detail. In contrast, system dynamics modeling is suitable for strategic-level problems, where lower levels of detail are often necessary. Agent-based modeling offers high flexibility and a bottom-up perspective, making it suitable for covering a wide range of issues, from operational to strategic levels (Figure 1).

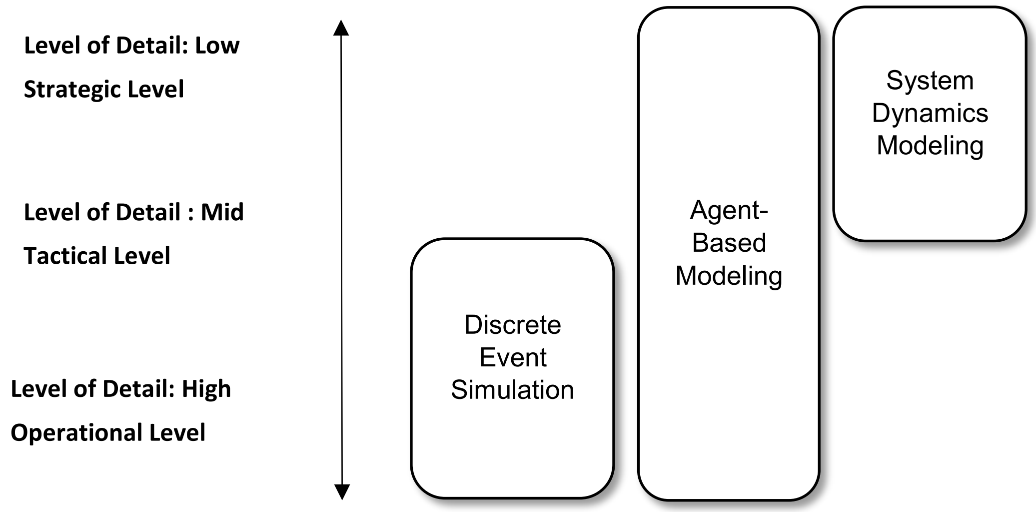

Figure 1. *Different Simulation Approaches*

When the processes of a system exhibit dynamics and time dependencies, they are candidates for modeling using the agent-based approach. The three main components of the agent-based simulation approach are:

1. Defining agents, their characteristics, and behaviors
2. Defining the interactions and communications between agents
3. The environment

Due to the widespread use of agent-based modeling in simulating various systems and the different characteristics of agents in each of them, a comprehensive definition for an agent has not yet been provided (Macal, 2010). However, three key features are commonly accepted for an agent: autonomy, memory, and the ability to interact (Macal, 2014).

Identifying the Agents in the Perishable Supply Chain

Based on the characteristics of agents outlined in the study by Macal in 2014, the agents in the perishable supply chain identified for this research are as follows:

1. Supplier agent
2. Factory agent
3. Warehouse (Under zero storage) agent
4. Order processing agent
5. Vehicle agent
6. Distributor agent

The characteristics and interactions of these agents will be discussed further.

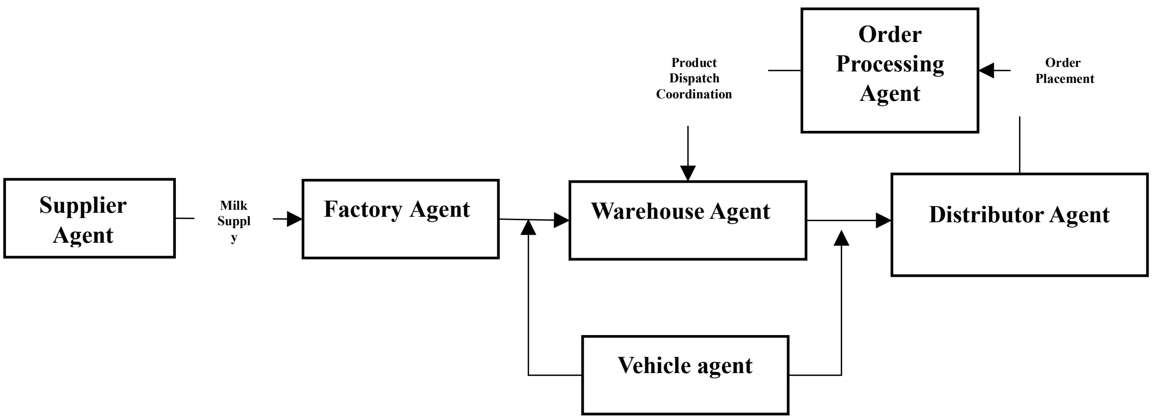

Figure 2. *Interaction of Identified Agents in the Perishable Supply Chain*

Supplier Agent

Milk is considered the most critical raw material in the dairy industry. Therefore, the required amount of milk is delivered daily from contracted farms to the factory agent. To determine the input data related to the supplier agent, the type of vehicles and the share of each in the total milk deliveries were calculated using existing system data. Then, the distribution function of milk delivery rates was calculated by analyzing the intervals between vehicle arrivals.

Factory Agent

The factory agent is responsible for producing the product. The raw material (milk) required for production is delivered from the supplier agent to the factory agent. It is important to note that the milk received from the supplier may be rejected due to various reasons such as contamination, the presence of chemicals, low fat content, etc., and its quality might be rejected with a probability of "a" percent. If the milk passes the quality control unit's approval, it is transferred to the factory's storage tanks for pasteurization and then directed to the production lines.

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

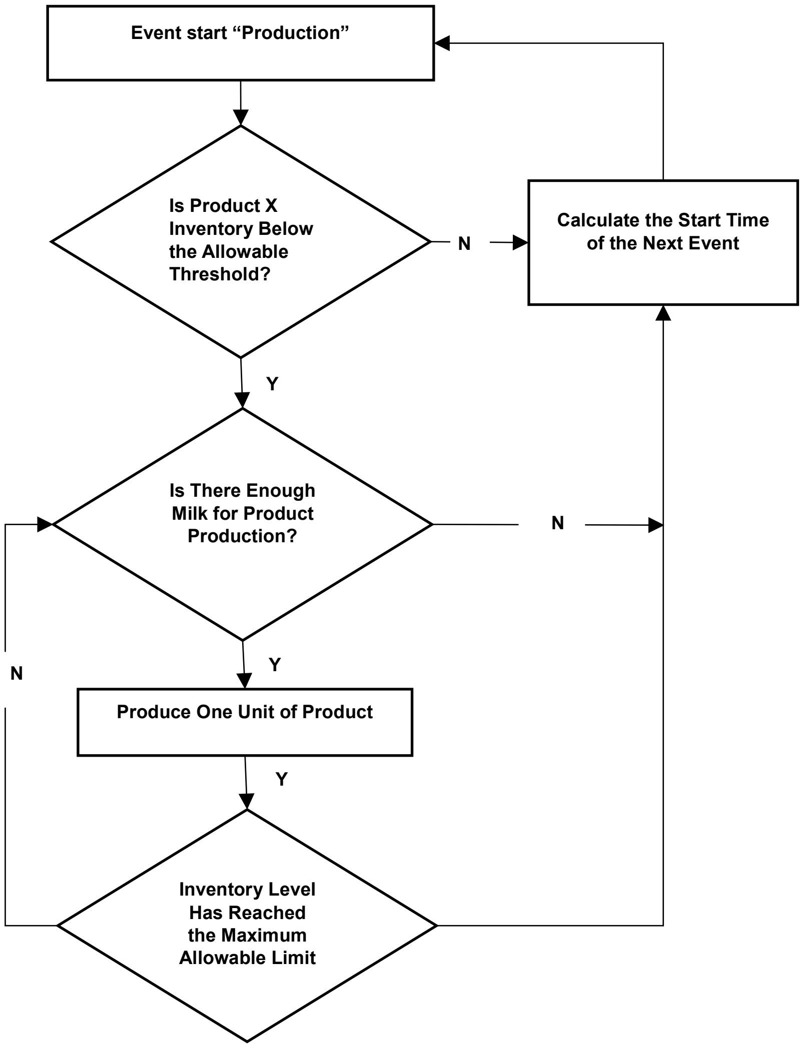

Figure 3. *Discrete Event Algorithm for Factory Agent's Production Lines*

Once the desired product is produced on the factory agent's production lines and packaged according to the required quantity, a carton of the product is transferred to the loading section for delivery to the warehouse (Under zero storage). The factory agent monitors the inventory levels of products in all warehouses to manage production and determine how to dispatch products. If production and shipment to warehouses are necessary based on the inventory levels in various cold storage facilities, products will be dispatched to the warehouses in order of priority.

Warehouse (Under zero storage) Agent

The products produced by the factory agent are stored by the warehouse agent, from where they are later dispatched to the distributor agents.

Distributor Agent

Distributor agents are located in provincial centers. These agents register a specified number of product orders based on the demand in their respective provinces. A notable characteristic of the distributor agents is the variation in their behavior across different seasons. Specifically, their behavior differs in the first six months of the year compared to the second six months, with higher demand during the first half of the year.

Order Processing Agent

After the distributor agents place their orders, the order processing agent is responsible for processing the order and coordinating the dispatch based on the inventory levels at different warehouses. If the order can be dispatched, the order processing agent performs the following actions:

- A vehicle is selected that matches the volume of the distributor agent's order. If no vehicle is available, the order will be held until one becomes available.
- Once the vehicle is called, a plan is created for how the vehicle will visit the warehouses to load all the ordered items.
- The vehicle is provided with the destination (the distributor agent's location).

Once the order is finalized, and the vehicle is called, the necessary information such as the loading plan and destination is sent by the order processing agent to the vehicle agent, which then proceeds with loading and departs toward the destination.

Vehicle Agent

Product transportation in the agent-based simulation model of this research is carried out by the vehicle agent. After being called by the order processing agent and receiving information about the loading process and destination, the vehicle agent behaves according to the state diagram designed for it (Figure 4) in the simulation model.

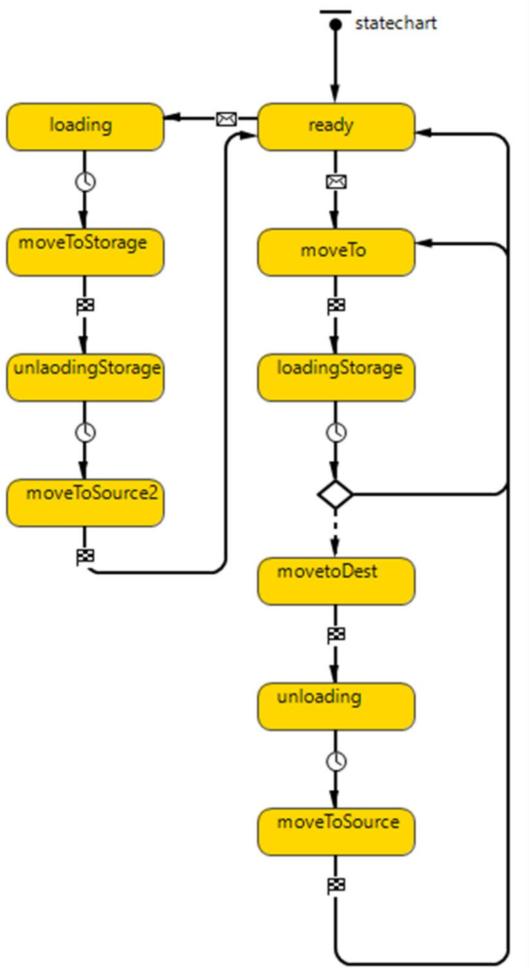

Figure 4. *State Diagram of the Vehicle Agent*

Based on the state diagram, the vehicle agent initially remains in the "ready" state. The agent transitions to the next state when it receives a message either from the factory agent, indicating the need to transport products to cold storage, or from the order processing agent, instructing it to load products from warehouses and head toward the distributor agent.

If a message is received from the factory agent, the agent's state changes to "move To Storage" (moving towards the specified cold storage) followed by "unloading Storage" (unloading the products at cold storage) and then returns to its origin. If the message is from the order processing agent, the agent transitions to the "move To" state (moving towards the listed warehouses) and then to "loading Storage" (loading products). This cycle continues until the loading schedule is complete, after which the vehicle moves toward the destination (the distributor agent) as specified in the order ("move To Dest") and, after unloading the products ("unloading"), returns to its origin ("move To Source").

The cooling system of the vehicle agent is subject to failure. In the event of such a failure, if the repair time or the time to reach the destination exceeds *t* hours, all loaded products on this agent are considered waste.

Agent Positioning and Routing on the GIS Map

One of the capabilities of the agent-based modeling approach in the AnyLogic simulation software is the ability to connect the simulation model to GIS maps and use data from the OSM (OpenStreetMap) server. By utilizing the data from this system, it is possible to implement various routing algorithms, such as Dijkstra's algorithm.

Dijkstra's algorithm is a greedy algorithm used for routing. In this algorithm, the set X is initialized as {s}, where dist{s} is set to zero and the distances of all other vertices in the graph are set to infinity (∞). In each step, all edges $e = (v, w)$, where one end is in X ($v \in X$) and the other is in V-X ($w \in V-X$), are considered. Then, the edge that minimizes the value of $dist[v] + l_{vw}$ is selected. Subsequently, 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. Figure 5 illustrates how the hybrid agent-based and discrete event simulation model connects with the GIS map and how its outputs are utilized.

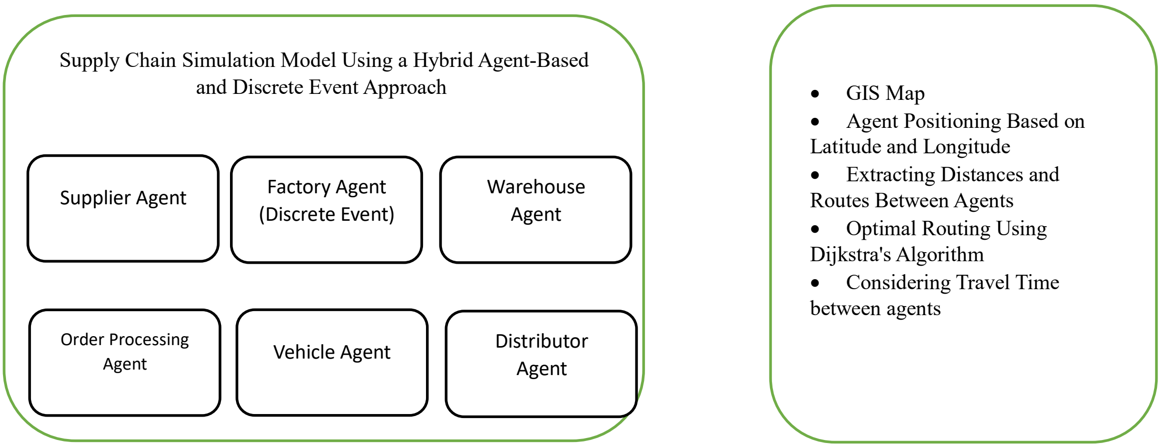

Figure 5. *Interaction between the Hybrid Simulation Model and the GIS Map*

Simulation-Optimization Method

The term simulation-optimization refers to techniques used to optimize parametric stochastic problems (Gosavi, 2019). In this method, the input values of the simulation model are selected as decision variables in such a way that a specific objective is optimized. In most cases, in simulation-optimization methods, a hybrid simulation model is combined with metaheuristic algorithms, and by determining the values of the decision variables and the objective function and conducting iterative processes, the optimal values are derived.

The following figure illustrates how metaheuristic algorithms interact with the simulation model in the simulation-optimization method.

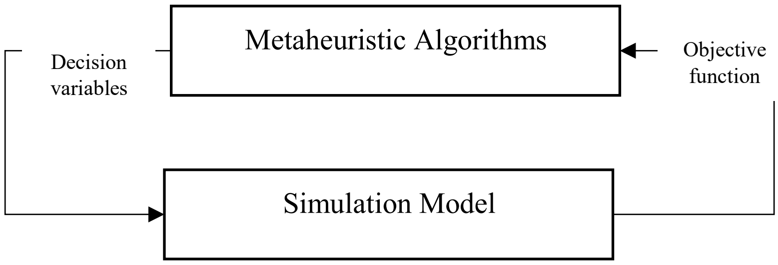

Figure 6. *Simulation-Optimization Approach*

In this research, the facility location problem related to product storage, inventory control, fleet composition, and routing can be modeled as a discrete parametric problem. The objective function for the optimization problem i s expressed by equation (1).

$$Min\ Z = \sum_k (H_k \times C_{hk}) + \sum_k (B_k \times C_{bk}) + \sum_k (L_k \times C_{lk}) + \sum_i (O_i \times C_o) + \sum_i D_i \quad (1)$$

In this formulation:
C_{hk}: Holding cost for product k
H_k: Total amount of product k held during the simulation model execution
C_{bk}: Shortage cost for product k
B_k: Total shortage of product k during the simulation model execution
C_{lk}: Waste cost for product k
L_k: Number of wasted products of type k during the simulation model execution
C_o: Carbon emission cost
O_i: Total carbon emissions by fleet i during the simulation model execution
D_i: Maintenance and depreciation cost of fleet i during the simulation model execution
Decision variables for the optimization problem are:
x_j: Construction of a warehouse at candidate location j (0 or 1)
N_i: Number of fleet type i (integer)
S_{jk}: Maximum inventory level of product k in warehouse j
s_{jk}: Minimum inventory level of product k in warehouse j
For the optimization problem, there will be constraints as follows:

$$\sum_j x_j \le U \quad (2)$$

$$s_{jk} < x_j \times S_{jk} \qquad \forall j.k \quad (3)$$

U represents the maximum number of candidate locations considered for warehouse construction. The second constraint states that the maximum inventory level must always be greater than the minimum inventory level required for reorder. Equation (3) ensures that if no warehouse is allocated at candidate location j, the inventory levels S_{jk} and s_{jk} will be zero.

Given that the hybrid simulation model is connected to the GIS map, routing algorithms such as Dijkstra's algorithm can be utilized. In this research, after determining the decision variables using the optimization algorithm and entering them as parameters into the simulation model, the optimal fleet routes are calculated based on GIS map data at the start of the simulation model execution. As a result, the objective function value is computed in an integrated manner by the simulation model based on factors such as the allocated warehouse locations, inventory holding or shortages due to storage levels and maximum capacities at warehouses, product wastage, fleet movements, and consequently, carbon emissions.

The figure below illustrates the process of combined optimization for facility location, inventory control, fleet composition, and routing.

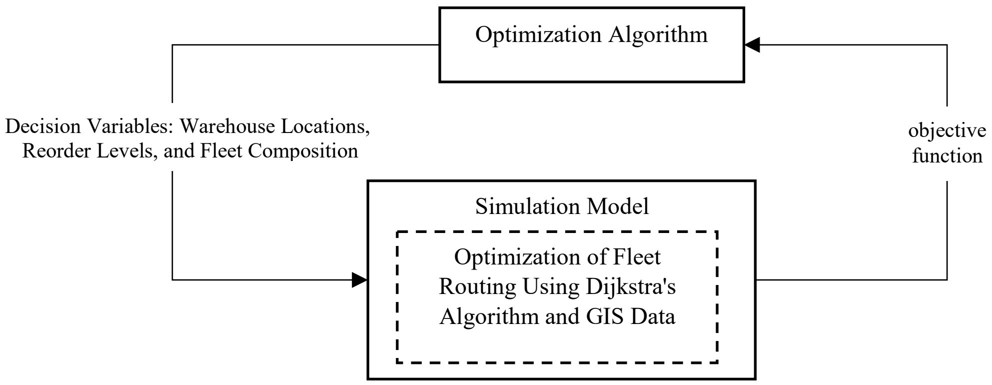

Figure 7. *Optimization of Facility Location, Reorder Levels, Fleet Composition, and Routing*

To establish the connection between the hybrid agent-based and discrete event simulation model developed in this research and metaheuristic algorithms, the optQuest optimization package was used. OptQuest, developed by optTek, is one of the leading packages for simulation-optimization. This optimization package combines metaheuristic algorithms such as scatter search, tabu search, and genetic algorithms, while also leveraging neural networks to determine the input parameters for the algorithms (Klijn, 2007).

Case Study

To implement and evaluate the performance of the hybrid agent-based and discrete event simulation model, the supply chain of one of the largest dairy producers in the country was selected as a case study, with a specific focus on ice cream for supply chain performance analysis. The data needed to build the hybrid simulation model and perform simulation-based optimization were extracted from the system's recorded data and interviews with experts.

Next, the supply chain of the case study used in this research will be introduced. Based on the analysis of the recorded data, it was found that the milk required for producing various ice cream products is supplied by the suppliers listed in Table 1, and delivered to the factory.

Table 1.
Weighted Percentage of Vehicle Types for Milk Inputs

Share of Total Input	Vehicle Type
2%	1500 Liters
5%	3000 Liters
20%	5000 Liters
40%	7000 Liters
33%	15000 Liters
10%	24000 Liters

To determine the statistical distribution function for the arrival of milk at the factory, the intervals between the arrivals of milk transportation vehicles were extracted from the system's recorded data. Statistical fitting was performed using the EasyFit software. Based on the extracted data, the arrival distribution of milk was determined to follow an Exponential(0.39) distribution. The histogram and the fitted distribution function are shown in Figure 6.

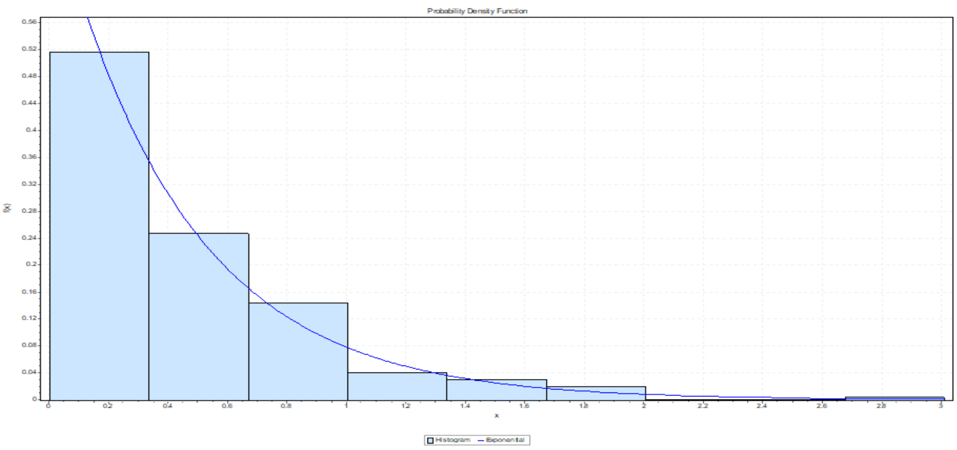

Figure 8. *Histogram and Fitted Function of the Arrival Rate of Milk Transport Vehicles*

The production facility has 8 different production lines, each designated for the production of various types of ice cream, categorized into 8 product groups. The specifications of these production lines are provided in Table 2.

Table 2.
Specifications of Ice Cream Production Lines

Production Line	Product Group	Product Name	Production Cycle Time (Seconds)	Required Milk (Liters)
1	1	Ice Cream Bar	37	0.16
2	2	Creamy Ice Cream	25	0.25
3	3	Cone / Biscuit / Cake	113	0.30
4	4	Cup Ice Cream	72	0.30
5	5	Magnum Ice Cream	89	0.40
6	6	One Liter Ice Cream	210	1.00
7	7	Five Liter Ice Cream	95	5.00
8	8	Special Ice Cream	135	0.50

The products produced by the factory are transferred to three cold storage facilities for storage, with the capacity of each and their storage priority listed in Table 3. Cold storage number 3 is primarily used for storing other dairy products and will only be utilized in critical situations when the central cold storage and cold storage number 2 have reached full capacity.

Table 3.
Specifications of Cold Storage Facilities for Ice Cream Storage

Name	Capacity (Cartons)	Storage Priority
Central Cold Storage Located at Factory	450,000 Packages	1
Cold Storage Number 2	250,000 Packages	2
Cold Storage Number 3	800,000 Packages	3

Additionally, ice cream products are transported using vehicles with the capacities listed in the following table.

Table 4.
Specifications of Available Vehicles for Transporting Ice Cream Products to Warehouses and Provincial Centers

Name	Capacity (Cartons)	Quantity Available
Vehicle Type 1	900	6
Vehicle Type 2	1,300	6
Vehicle Type 3	2,500	15
Vehicle Type 4	3,800	15

As mentioned earlier, the cooling systems of vehicles tend to fail after covering certain distances. To extract and implement the logic for vehicle cooling system failures, data from the system on vehicle failures were collected and fitted using EasyFit software. The failure distribution of the cooling system follows a triangular distribution with a minimum parameter of 21,000 kilometers, a mode of 27,600 kilometers, and a maximum of 35,400 kilometers. As noted, if a vehicle with a cooling failure cannot reach its destination within 4 hours, all products on that vehicle will be considered waste.

Finally, to implement the ordering system for ice cream distributors in various provincial centers, the registered orders in the system, corresponding to the first six months and second six months of the year for each provincial center, were extracted, and their probability distributions were fitted.

Figure 7 provides an overview of the hybrid agent-based and discrete event simulation model for the supply chain, and its connection with the GIS map is illustrated. The red agent represents the factory, the yellow agents represent the cold storages, and the green agents represent the distributors.

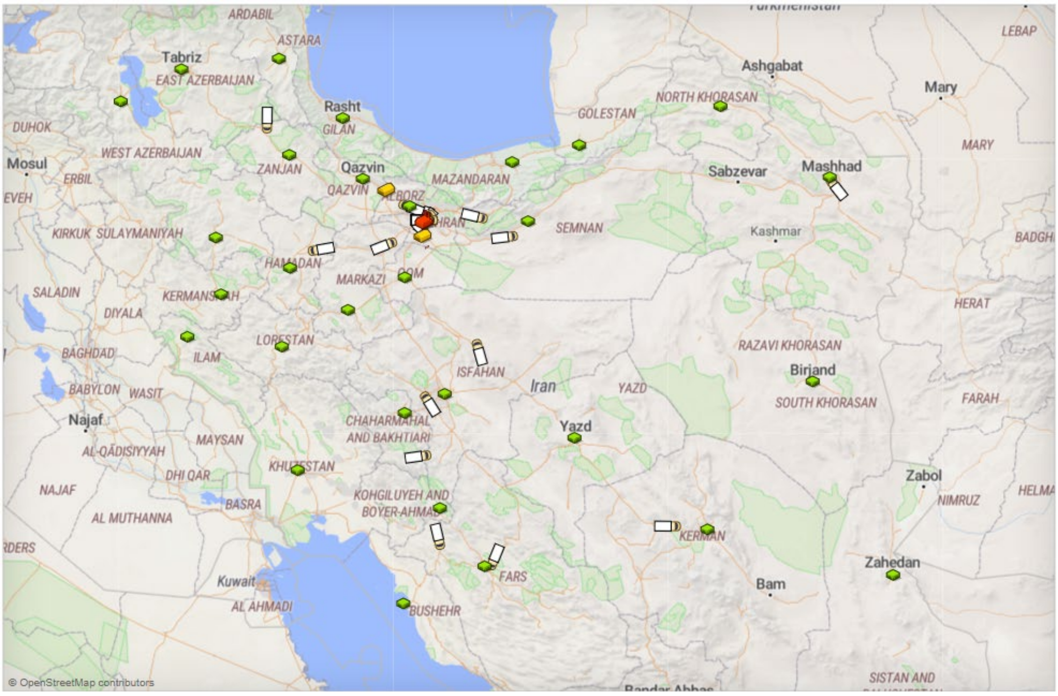

Figure 9. Implementation of Agents and Integration with the GIS Map

Finding

To utilize the created hybrid simulation model of the perishable product supply chain for analysis and improvement, the first step is to validate the hybrid simulation model. For the validation of the simulation model, a comparison of the simulation model's outputs with the actual data from the system over a one-year period was conducted. The results are presented in Table 4.

Table 5.
Criteria and Results of Validation for the Hybrid Simulation Model of the Perishable Supply Chain

Validation Criteria for Simulation Model	Simulation Model Value	Real-World Value	Difference
Number of Products Produced in One Year	111,487,306	112,365,147	0.7 percent
Number of Transportations for Delivering Products	774	779	0.8 percent
Number of Cooling Failures in Machinery	34	35	2.8 percent
Number of Cooling Failures Leading to Waste	27	26	3.7 percent

Given that the difference between the outputs of the simulation model and real-world data is less than 5%, the assumption of the simulation model's validity is confirmed. With the model's validation established, and to facilitate comparison between the current state and the optimized state, the simulation model's outputs for the current state are presented below. It is important to note that the simulation model was run for a period of three and a half years, equivalent to 30,240 hours.

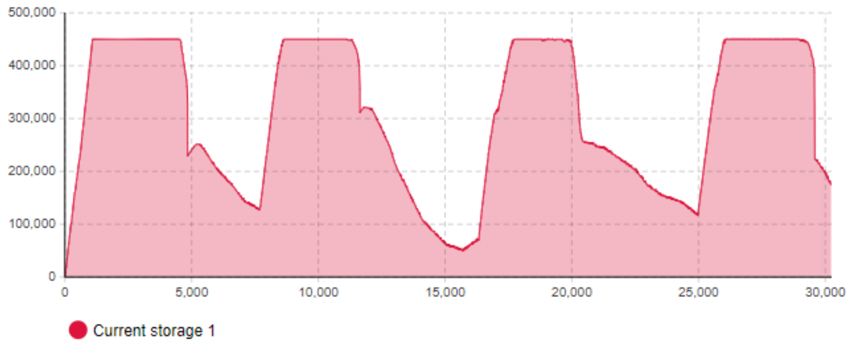

Figure 10. *Inventory of Cold Storage Number 2 in the Current State of the Simulation Model*

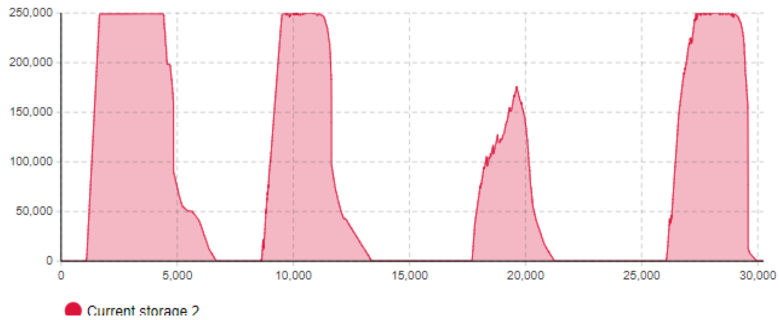

Figure 11. *Inventory of Cold Storage Number 2 in the Current State of the Simulation Model*

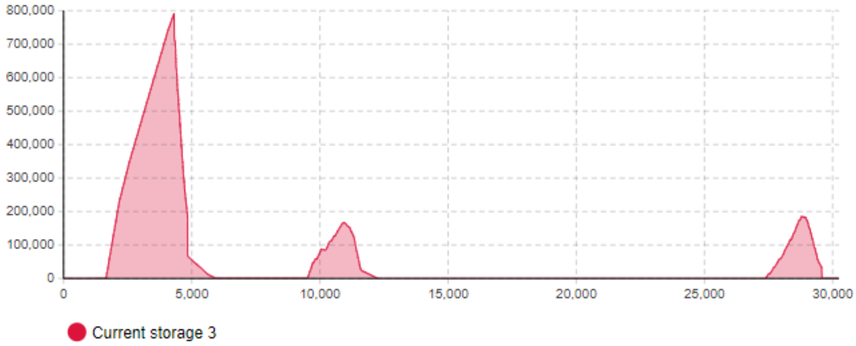

Figure 12. *Inventory of Cold Storage Number 3 in the Current State of the Simulation Model*

The outputs of the simulation model indicate that cold storages 1 and 2 handle the majority of ice cream production, while cold storage 3 acts as an auxiliary facility used in special circumstances. It is worth noting that cold storage 3 also stores other dairy products, which are beyond the scope of this research, and therefore it usually has excess capacity.

The trend of the charts related to ice cream storage reflects the seasonal demand for this product. During the colder six months of the year, inventory levels increase, while during periods of higher demand, the inventory levels decline significantly.

It is clear that the amount of ice cream stored is a critical factor in determining the time between receiving an order and delivering the product to the distributor agent. In the current state model, after distributor orders begin at simulation time 4320 hours, the total inventory in the cold storages can reach up to 50,000 packages of ice cream at certain intervals. Ultimately, after three and a half years of running the simulation model, the average time between receiving distributor orders and delivering the product to the distributor location was calculated to be 143.3 hours, which is approximately 6 days (see Figure 13).

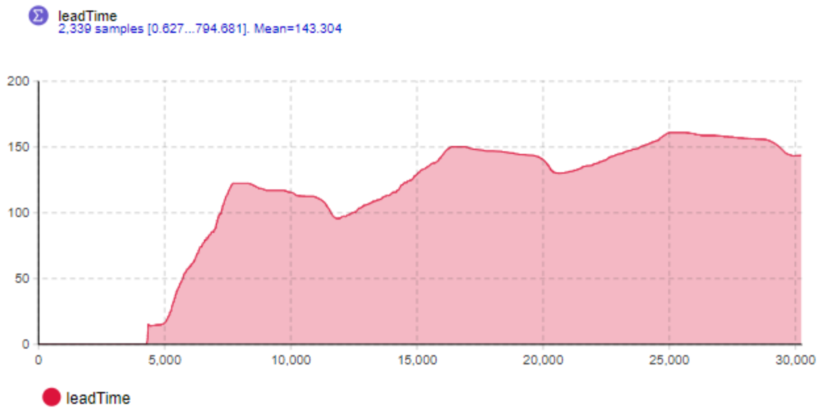

Figure 13. Average Time from Order to Product Receipt in the Current State of the Simulation Model

In the current state simulation model, over the course of the simulation run for 30,240 hours, a total of 1,624,000 kilometers was traveled to deliver the orders received by the distributor agents. During this period, there were 103 instances of vehicle failures, out of which 79 shipments (representing 3.3% of total production and a total of 240,000 packages) were discarded due to more than 4 hours passing after the vehicle breakdown (see Table 5).

Table 5.
Outputs of the Current State Simulation Model

Title	Distance Traveled by Fleet (Kilometers)	Number of Cooling Failures in Vehicles	Number of Cooling Failures Leading to Waste	Number of Product Wastage
Current State of Failures and Product Waste	1,624,000	103	79	240,694

As explained in the previous section, if the refrigeration unit of a vehicle fails, the ice cream product has a 4-hour window to either reach a cold storage facility or the sales representatives. Otherwise, the product becomes unusable and is classified as waste. One of the key solutions to reduce waste in the perishable supply chain examined in this research is the establishment of new cold storage facilities in various cities. Building these warehouses would reduce travel time, thereby lowering the likelihood of product waste. Additionally, reorder levels and inventory holding for various products become critical factors. The way products are dispatched to the new warehouses, as well as fleet composition and routing, are also affected.

For the reasons mentioned, this research focuses on the integrated optimization of warehouse location, inventory levels, fleet composition, and routing. Based on expert interviews, the cities of Isfahan, Hamedan, Mashhad, and Kerman were identified as candidate locations for new warehouses. These new warehouses would replace warehouse number 2 in the current state model. The order processing for distributor agents will be done such that the closest warehouse with available stock for the registered demand will fulfill the order. The capacity of the new warehouses, considering time and cost constraints, is set at 250,000 cartons of product.

It is important to note that the inputs for the optimization algorithm were extracted from system data and expert interviews. The settings for the optQuest optimization package are provided in Table 6.

Table 6.
Optimization Algorithm Settings for Simulation-Based Optimization

Specification	Value
Number of Iterations	10,000
Number of Model Replications per Main Iteration	Minimum: 30 Replications
	Maximum: 100 Replications
	Confidence Level: 80 percent
Duration of Simulation Model Execution per Iteration	30,240 hours

After entering the input values and configuring the settings for the optimization process, the optQuest package, aiming to minimize the objective function (Equation 1), determines the decision variables in the simulation model while taking into account the constraints defined by Equations 2 and 3. It should be noted that, in the first step, there are no restrictions on the number of candidate locations selected for warehouse construction. The outputs of the optimization process are provided in Table 7.

Table 7.
Improved Values from the Simulation-Optimization Approach

Title	Optimization Algorithm Output
Selected Warehouse Location	Isfahan
Number of Vehicle Type 1	4
Number of Vehicle Type 2	5
Number of Vehicle Type 3	15
Number of Vehicle Type 4	13

The improved fleet composition compared to the current state shows a reduction of 5 vehicles. It is also important to note that the optimized values for the maximum inventory holding levels and the minimum reorder levels for various products were also determined by the optimization algorithm. These optimized values were then input into the simulation model of the current state to assess all decision variables and improvements in the system's performance. The outputs of the simulation model with the optimized values are presented below.

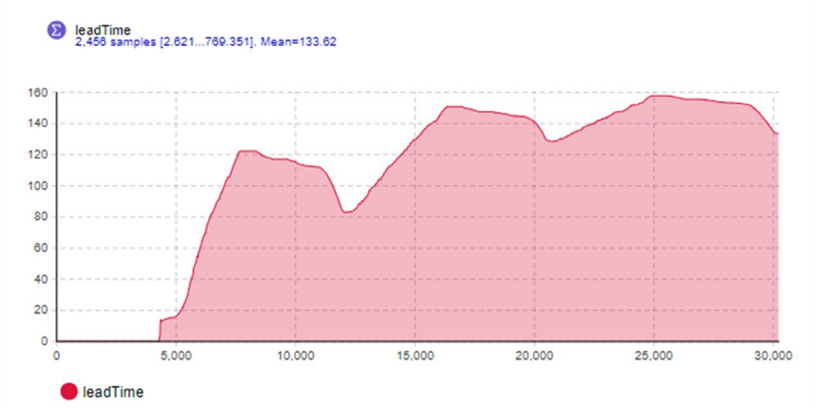

Figure 14. *Average Time from Order to Product Receipt in the Improved State*

As shown in Figure 14, the construction of a warehouse at the candidate location in Isfahan results in an average reduction of delivery time by 10 hours.

Figure 15. *Inventory of Warehouse Number 1 in the Improved State*

Figure 16. *Inventory of Warehouse Number 2 in the Improved State*

In Figures 15 and 16, it can be observed that due to the improvement in inventory levels by the optimization algorithm, the supply and consumption patterns have become more regular. A notable point is the 19% increase in kilometers traveled by the fleet, attributed to the establishment of the new warehouse, located approximately 450 kilometers from the factory. Consequently, the increased distance traveled by the fleet has led to a 21% rise in cooling system failures in vehicles. However, the construction of the new warehouse has resulted in a 59% reduction in product waste, equivalent to 140,000 units (Table 9).

Table 9.
Outputs of the Simulation Model with Improved Values

Title	Distance Traveled by Fleet (Kilometers)	Number of Cooling Failures in Vehicles	Number of Cooling Failures Leading to Waste	Number of Product Wastage	Reduction in Product Waste Compared to Current State
State of Failures and Product Waste with Improved Values from the Simulation-Optimization Approach	1,945,000	125	33	100,712	59%

The outputs of the simulation-based optimization process show that the objectives of reducing the kilometers traveled by the fleet and reducing carbon emissions are conflicting with the goal of minimizing product waste. However, the reduction in waste is significant enough that the optimization algorithm, despite the increase in kilometers traveled by the fleet, selects the decision variable corresponding to the construction of a new warehouse.

Conclusion

Thus, this research was conducted with the aim of an integrated examination of facility location, inventory control, fleet composition, and routing in the perishable product supply chain. Based on a review of previous studies, it was found that the simultaneous impact of these topics on the performance of the perishable product supply chain had not been thoroughly explored. To fill this gap, a hybrid simulation model for the perishable product supply chain was developed using agent-based modeling and discrete event simulation. The hybrid simulation approach allows for the modeling and analysis of all potential uncertainties in the supply chain. Moreover, connecting the agent-based model to GIS maps ensures that the data and constraints of the logistics system are grounded in real-world conditions.

In this research, a simulation-optimization approach was used to improve decision variables related to the construction of new warehouses, maximum and minimum inventory levels for order fulfillment, fleet composition, and routing. The AnyLogic software was used to build the simulation model, and the optQuest optimization package was employed for simulation-based optimization.

To implement the proposed method for integrated analysis, the supply chain of one of the largest dairy producers in the country was selected as a case study. Due to the high production and demand for ice cream, this product was chosen for in-depth analysis. In the first step, a hybrid agent-based and discrete event simulation model for this supply chain was developed, and after the model's verification and validation phases, the outputs of the current state simulation model were compared with those from the improved simulation model, optimized using the simulation-optimization approach. The objectives were to minimize product holding costs, shortages, waste, kilometers traveled by the fleet, and carbon emissions.

In the current state, the average time from receiving an order from distributors to delivering the product was calculated to be 143 hours. The fleet traveled 1,624,000 kilometers in total to transport products. During this period, there were 103 instances of vehicle cooling system failures, resulting in 79 shipments (equivalent to 240,000 packages) being wasted.

To improve supply chain performance, the construction of new warehouses, improved inventory levels, optimized fleet composition, and routing enhancements were considered. Four locations were selected for new warehouse construction. For routing optimization, Dijkstra's algorithm was used in the hybrid simulation model with GIS map data. After the simulation-based optimization process, it was found that constructing a new warehouse in Isfahan, along with inventory and routing optimizations, reduced the time to fulfill distributor orders by 10 hours. Additionally, the fleet was reduced by 5 vehicles, which led to lower maintenance and depreciation costs. Product waste was reduced by 51%, which equates to 140,000 units.

A comparison of the outputs from the current state simulation model and the improved simulation model shows that the goals of reducing waste and minimizing the kilometers traveled by the fleet are conflicting objectives in this perishable product supply chain. While the optimization process resulted in a 51% reduction in waste, it also led to a 19% increase in kilometers traveled by the fleet and a corresponding 21% increase in vehicle cooling system failures.

As seen, topics such as constructing new facilities, inventory level adjustments, fleet composition, and routing not only independently affect supply chain performance but also influence each other. Therefore, an integrated analysis of these topics is necessary in the context of perishable product supply chains.

The hybrid simulation-optimization approach developed in this research can be applied to other perishable product supply chains, such as those in agriculture, pharmaceuticals, and blood products. The following suggestions are made for future research and model development:

- Analyze the impact of adding other dairy products, such as milk and yogurt, to the supply chain model.
- Incorporate customer agents into the model and simulate purchasing behaviors.
- Add competitor agents to the model and analyze how customer behavior is influenced by competitors' performance.
- Use reinforcement learning algorithms to determine the optimal reorder levels.

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