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Cold-Chain Resilience for Perishable Dairy: A Simulation-Based Sourcing, Inventory, and Location Decisions

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ABSTRACT

Perishable food cold chains face significant challenges arising from product perishability, temperature-control requirements, high logistics costs, and environmental concerns. The geographical dispersion of customers and the time and temperature requirements of dairy products make it challenging to determine appropriate distribution centre locations and coordinate sourcing and inventory decisions while simultaneously achieving cost efficiency, timely delivery, and reduced carbon emissions. This study aims to optimize the cold chain distribution network of Nada Company, a dairy producer in Riyadh, Saudi Arabia, serving customers in Oman. The study employs AnyLogistix, integrating Greenfield Analysis, Network Optimization, and simulation to determine suitable distribution centre locations, evaluate network performance, and support strategic distribution network decision-making. Greenfield Analysis initially identified three potential locations in Sohar, Salalah, and Samail, while Network Optimization determined that retaining two distribution centres in Sohar and Salalah provided a more efficient configuration. Compared with the Greenfield configuration, the optimized network reduced transportation costs from \$2.13 million to \$1.84 million and CO_2 emissions from 949,784 to 821,524, while maintaining the same total flow and demand fulfilment. The findings demonstrate that integrating network optimization and simulation can support more efficient and sustainable cold chain network design and evidence-based distribution decisions, providing a practical decision-support framework for perishable dairy products.

1. Introduction

1.1 Research Background

Perishable products such as dairy, meat, fruits, and vegetables play a vital role in global food systems. However, their limited self-life and sensitivity to environmental conditions present significant challenges for supply chain management (SCM). These goods require precise handling and temperature control at every stage, as even minor deviations in storage or transportation can lead to spoilage. Inefficient logistics in handling perishable products not only results in food waste but also

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contributes to economic losses and environmental issues, such as increased carbon emissions and excessive resource consumption in food production [1, 2]. According to the Food and Agriculture Organization (FAO), approximately one-third of all food produced globally is wasted due to improper handling and transportation of perishable goods [3].

As consumer demand for fresh products rises, businesses face mounting pressure to maintain product quality while balancing cost, delivery speed, and inventory efficiency. Meanwhile, poor logistics management can lead to customer dissatisfaction, financial losses, and increased waste [4, 5]. Additionally, sustainability concerns are becoming more prominent, with the cold chain responsible for transporting perishable goods contributing around 3.5% of global emissions, while the entire food production system accounts for nearly 40% [6]. This has led cold supply chains to integrate sustainable practices to offset greenhouse gas emissions and curb their carbon footprint [7]. In response, businesses must enhance operational efficiency while adopting greener practices, such as energy-efficient refrigeration, optimized transportation routes, and waste reduction strategies. Effective SCM, supported by technology and collaboration with third-party logistics (3PL) providers, is crucial in ensuring the availability of perishable goods while mitigating economic and environmental risks [8, 9]. Such coordination is also important for mitigating broader operational and financial risks across supply-chain activities [10].

One of the most pressing issues in perishable food SCs is cost management, as logistics costs constitute a significant portion of total expenses. For instance, U.S. business logistics costs reached $2.3 trillion in 2022, representing 9.1% of gross domestic product of the nation [11]. While these figures vary across industries and regions, they highlight the need for efficient logistics strategies to prevent unnecessary financial burdens. Furthermore, the time-sensitive nature of perishable goods demands rapid and reliable distribution. Delays in transportation or inadequate handling can result in significant product losses, reducing profitability and exacerbating food insecurity. Meanwhile, increasing regulatory pressures and consumer expectations for sustainability compel businesses to adopt environmentally friendly SC practices [12]. However, the adoption of green supply chain practices can be constrained by several key barriers, including technological limitations, insufficient government support, financial constraints, and gaps in awareness and knowledge [13].

To address these challenges, companies are increasingly outsourcing logistics operations to 3PL providers and optimizing the locations of distribution centers (DCs). 3PL providers offer specialized services, such as temperature-controlled storage and transportation, which help maintain product integrity, extend shelf life, and enhance SC efficiency. By leveraging the expertise of 3PL companies, businesses can improve inventory management, reduce operational costs, and enhance overall SC resilience [14]. Additionally, strategic DC placement plays a crucial role in perishable food SC optimization. The strategic placement of DCs does more than merely influence the capital expenditure associated with establishing hub facilities [15]. By reducing travel distances and shortening response times, such positioning drives greater cost-effectiveness, bolsters supply chain operations, and advances environmental sustainability [16].

This study focuses on optimizing the cold chain distribution network for perishable products by determining the optimal number and location of DCs while balancing cost efficiency, lead time reduction, and sustainability. As a case study, we examine Nada Company, a dairy producer in Riyadh, Saudi Arabia, which outsources its distribution to Oman. Given the perishability of dairy products, the company relies on 3PL providers to manage refrigerated transportation and storage, ensuring product freshness and minimizing waste. The objective is to identify the best DC location in Oman to enhance distribution efficiency while reducing costs and environmental impact. Using real-world data from Nada Company, including product shelf life, demand patterns, and customer distribution, we develop an optimized logistics model that integrates cost, time, and sustainability considerations.

1.2 Literature Review

Cold chain networks and logistics are essential for ensuring the safe and efficient transportation of perishable products, such as dairy, meat, fruits, and vegetables, which are highly sensitive to temperature fluctuations. The structure of these networks typically consists of multiple echelons, including production facilities, DCs, and end customers. The complexity of managing perishable supply chains arises from the need to maintain product quality while optimizing costs and minimizing wastage [17]. Studies highlight that effective network design directly impacts product freshness, shelf life, and customer satisfaction [18].

Cost minimization and profitability are critical objectives in the design and management of perishable supply chains. Several cost components must be considered, including transportation, cold storage, and inventory holding. In a sustainable SC of perishable products, Rahal and Elloumi [19] aimed to minimize total costs while considering environmental and social impacts. It had been implemented in the case of dates in the Kebeli region of Tunisia, providing a decision-making tool that balances economic, environmental, and social objectives. Liu *et al.,* [20] proposed a model considering location-inventory-routing for perishable. the main objectives were maintaining the freshness of perishable products at the highest level while minimizing economic costs. Makkar [21] studied a two-stage SC coordination problem for perishable products under uncertain costs and demand information, aiming to minimize total procurement and distribution costs by integrating procurement and distribution decisions, considering inventory carrying costs due to the perishable nature of products, and applying fuzzy set theory to handle uncertainties. Musavi and Bozorgi-Amiri [22] presented a novel sustainable hub location-vehicle scheduling model to optimize the total transportation costs, freshness, and quality of foods. Ahmadi Malakot *et al.,* [23] examined a green SC model for perishable goods, aimed to maximize profits by optimizing sales levels under uncertainties in manufacturing costs and prices. The model considered backorders and the perishable nature of products, providing insights into the trade-offs between profitability and environmental impact.

Optimizing the location of DCs is crucial, as it significantly influences both transportation expenses and operational efficiency [24]. Pan *et al.,* [25] aimed to minimize total costs by determining the optimal number and locations of DCs, allocating retailers to these DCs, and optimizing vehicle routes for product deliveries. The model incorporated factors such as product perishability, inventory holding costs, and transportation expenses. Dutta and Shrivastava [26] focused on designing an optimal SC network for perishable products, specifically in the milk industry, under conditions of demand, supply, and process uncertainties. Their objective was to minimize the total SC cost by determining optimal facility locations and shipment decisions while considering potential disruptions in transportation routes and facilities. Abbasi *et al.,* [27] designed a reliable hub-and-spoke network considering disruption risks and product perishability to minimize the cost and time of the SC network and simultaneously, optimize the decisions in location, number, and fortification of main and backup hubs and DCs, and the inventory of perishable products. One of the key findings of this study was that disruption of hubs and DCs affected product perishability because the storing and distribution conditions and requirements were not met under facilities disruption.

Additionally, 3PL providers play a vital role in reducing logistics costs through economies of scale, route optimization, and advanced fleet management technologies [28]. Outsourcing logistics to 3PLs allows companies to focus on their core operations while benefiting from reduced transportation and storage expenses. Demircan and Özcan [29] aimed to investigate the warehouse location selection of 3PL cold chain suppliers and provided a new perspective of warehouse selection in cold chain logistics since cold chain warehousing and transportation prevent the product spoiled and organizations can save their funds and time by having effective cold chain management. Karagiannis *et al.,* [30] optimized the network of a 3PL company to minimize the warehouse and distribution cost for both forward and reverse logistics. They employed a MILP model to select the optimal warehouse location and the product inventory. The results showed a 10.8% reduction in warehousing and distribution costs.

Timely delivery is a fundamental requirement in perishable supply chains, as delays can lead to product deterioration and financial losses. Researchers emphasize the trade-off between fast delivery and cost efficiency, where companies must optimize transportation routes and vehicle scheduling to ensure reliability. In this regard, Wei *et al.,* [31] focused on minimize the time products spend in the SC to reduce spoilage and ensure freshness upon delivery in perishable products. By integrating production scheduling with efficient routing and inventory management, the research aims to streamline operations, thereby reducing lead times and enhancing the overall responsiveness of the SC for perishable goods. Hashemi *et al.,* [32] modeled the SC as a queuing system, considering factors such as storage capacity and waiting room capacity. with the goal of minimizing waiting times and improving customer satisfaction. By determining optimal values for these capacities, the research seeks to reduce lead times and ensure timely replenishment of perishable goods. The implementation of an (S-1, S) ordering policy aimed to maintain inventory levels that prevent stockouts and minimize delays, thereby enhancing the speed and reliability of the SC. Tu *et al.,* [33] investigated the implementation of a time-based multiple pricing policy within supply chains handling perishable products, to reduce the time products remain in inventory by adjusting prices dynamically based on their remaining shelf life. By offering price reductions as products approach their expiration dates, their policy aimed to accelerate sales, thereby minimizing the duration products spend in the SC. This strategy not only helped in reducing potential wastage due to spoilage but also ensures that consumers receive fresher products. Wu *et al.,* [34] proposed a real-time robust optimization scheme for perishable supply chains to minimize delays and inefficiencies by creating a virtual replica of the SC that allows for continuous monitoring and optimization. Gkiotsalitis and Nikolopoulou [35] introduced the pickup and delivery problem with cross dock for perishable goods, aiming to minimize delivery times for perishable products by incorporating cross-docking facilities into the SC. Cross-docking allowed vehicles to exchange goods at a central point, thereby shortening delivery routes and reducing transportation times. The model considered operational constraints such as time windows, vehicle capacities, and the synchronization of vehicles at the cross dock, all tailored to the specific requirements of perishable goods that should not endure long trips.

Sustainability has become a key focus in cold chain logistics, particularly concerning carbon emissions from refrigerated transportation. The use of energy-intensive cooling systems in vehicles and warehouses significantly contributes to greenhouse gas (GHG) emissions [36]. Researchers have explored strategies such as route optimization, fuel-efficient vehicles, and alternative refrigeration technologies to mitigate environmental impact. Musavi and Bozorgi-Amiri [22] introduced an innovative hub location-vehicle scheduling model aimed at optimizing total CO2 emissions, aligning with environmental sustainability goals. Liu *et al.,* [20] developed a model that integrates both freshness and carbon emission factors in the location-inventory-routing decisions for perishable products. Their study assessed product quality, economic costs, and carbon footprint, with the primary objective of maximizing freshness while simultaneously minimizing costs and emissions. Cold chain outsourcing to 3PL providers can also support sustainability efforts by leveraging shared logistics networks, thereby reducing empty truck trips and improving vehicle utilization [31]. Daghigh *et al.,* [37] focused on designing a 3PL network to reduce overall costs and greenhouse gas emissions. Their multi-objective model incorporated sustainability considerations while ensuring equitable access to products and job creation. Leylaparast *et al.,* [38] explored a three-tier agricultural SC, emphasizing the vital role of 3PL providers in delivering fresh products before expiration and promoting eco-friendly packaging solutions. Additionally, sustainable DC location selection involves factors such as proximity to renewable energy sources, effective insulation for cold storage, and integration with urban logistics networks [39]. Le *et al.,* [40] analyzed site selection for cold storage warehouses, highlighting its impact on lowering emissions, enhancing resource efficiency, and fostering responsible SC practices.

Despite the growing body of research on perishable food supply chains, limited attention has been given to the integrated optimization of cold chain distribution networks that simultaneously considers distribution center location, sourcing decisions, inventory policies, logistics costs, lead time, and environmental sustainability. Furthermore, although simulation and optimization have been applied jointly in logistics research to evaluate operational performance and support decision-making [17], their application to cold-chain network design remains relatively limited. This is especially true when it comes to outsource distribution of dairy goods beyond state boundaries. The problem here is the perishable nature of the products, the geographical spread of the consumer base, and the use of outsourcers for delivering the goods. Balancing cost-effectiveness, timely deliveries, availability of the products, and sustainability of cold chain operations presents a challenge for businesses.

In an attempt to bridge this knowledge gap, this research proposes a cold chain distribution model that integrates these aspects and provides insights into how the optimal number of distribution centers in Oman and their locations can be determined considering logistics costs, lead times, demand satisfaction, and CO_2 emissions. In order to achieve this objective, AnyLogistix software will be used to combine Greenfield Analysis, Network Optimization, and simulation methods. All of the information needed to conduct this analysis, including the shelf life of the products, customer demand patterns, locations of customers, and other logistic aspects, will be obtained from Nada Company that is a milk producer in Riyadh, Saudi Arabia and outsources the distribution of its products in Oman to its customers via 3rd party logistics providers.

The remainder of this study is structured as follows. Section 2 describes the problem statement and case study. Section 3 presents the methodology and discusses the results. Finally, Section 4 concludes the study and provides directions for future research.

2. Problem Statement

The optimization of cold chain is under study specifically for perishable products. As given previously, there is a significant need for perishable products daily. Each perishable product has specific conditions for each type of product depending on the company such as, precooling mode, refrigerated transportation mode, temperature, and humidity. In establishing the logistics network, the primary objective is establishing the costs associated with low temperature DCs and transport modes from origin to the destination. Meanwhile, pre-cooling stations, DCs, storage cost and transportation cost should be considered. So, outsourcing the management of logistics operations to a 3PL company is important to optimize the flow of products from the company to the customers where these products have been transmitted to the warehouses. The need for refrigerated transportation modes to move the shipments and products from one place to another is a significant thing to avoid perish. The products are combined, stored, and sent to the final customers or distribution centers. These perishable products must be stored in DCs that must deliver them before ending their lifetime.

The purpose of this research is to minimize both cost and time of the network, considering sustainability aspects which in this case, focus on minimizing CO2 emission from transportation. Delivering shipments on time with product freshness and high quality will lead to customer satisfaction.

2.1 Case Study

In this article, Nada Company, based in Riyadh, Saudi Arabia, is selected as a case study for its dairy production operations. The logistics network consists of three echelons, illustrated in Figure 1: Nada Company, DCs, and customers in Oman. The primary objective of this study is to determine the optimal location for DCs in Oman.

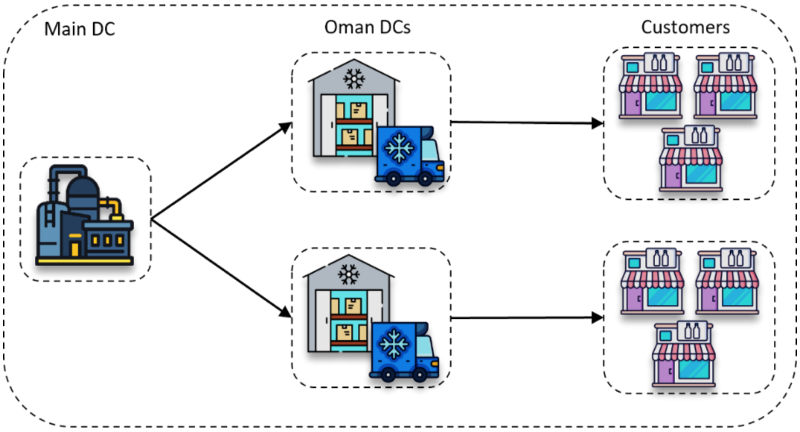

Fig. 1. Logistics network for 3PL company

Due to the considerable distance between the company and Oman, products are outsourced to DCs in Oman to ensure proper handling under controlled conditions, including low temperatures and specific humidity levels, to prevent spoilage. Instead of direct deliveries, products are first transported from the company's main DC to Oman's DCs before being distributed to customers. This outsourcing strategy minimizes perishability, reduces costs, and ensures product safety and quality while lowering waste. However, temperature fluctuations occasionally occur, necessitating regular maintenance of refrigerated trucks and containers at all key points within the 3PL network.

Table 1 presents the customers in each governorate, while Figure 2 maps their locations. This study examines ten different perishable products, each with their own shelf life and demand, as detailed in Table 2.

Table 1
Customers

Governorate	State
Muscat	Muscat, Muttrah, Amerat, Bawshar, Seeb and Quriyat
Dhofar	Shaleem, Thumrait, Salalah, Thumrait, Mirbat, Taqa, Mazounah, Sadah, Muqshin, Rakhyut, Dhalkut and Hallaniyat Islands
Musandam	Khasab, Daba, Bukha and Madha
Buraymi	Buraimi, Muhadha and Sinainah
The Dakhiliyah	Nizwa, Bahla, Manah, Adam, Izki, Samail, Bidbid and Al Hamara
The North Batinah	Sohar, Shinas, Liwa, Saham, Al Khaburah and Al Suwaiq
The South Batinah	Barka, Musana'ah, Rustaq, Awabi, Nakhal, Wadi Al Ma'awil
The South Sharqiyah	Sur, Al Kamil wa'l Wafi, Ja'alan Bani Bu Ali, Ja'alan Bani Bu Hassan and Masirah
The North Sharqiyah	Ibra, Mudhaibi, Qabil, Bidiyah, Wadi Bani Khalid, Dima wa'l Ta'een
The Dhahirah	Ibri, Yanqul, Dhank
The Wusta	Haima, Duqm, Al Jazer and Mahwat

Demand for these products follows a periodic pattern, requiring shipments to be made before their expiration dates to ensure timely delivery and product freshness. Since demand is directly related to the population of each city, Muscat, for example, has higher demand compared to Duqm due to its larger population. All required data for this study were collected through interviews with Nada Company representatives. The planning horizon for this case study is one year.

Table 2
Shelf Life and Demand of Products

Products	Shelf life (days)	Demand (pcs)	Order Interval (days)
Fresh Labneh	10 days	400	Uniform 5-7
Laban	10 days	Uniform 500-2000	Uniform 6-9
Greek Yoghurt	14 days	Uniform 350-500	Uniform 10-13
Fresh Yoghurt	14 days	Uniform 350-500	Uniform 10-14
Protein Milk	21 days	Uniform 450-900	Uniform 10-20
Iced Coffee	21 days	Uniform 500-700	Uniform 13-20
Fresh Juice	30 days	Uniform 500-800	Uniform 15-25
Turkish Labneh	30 days	Uniform 350-400	Uniform 20-27
Cooking Cream	6 months	Uniform 450-700	Uniform 30-70
Tomato Paste	1 year	Uniform 500-1000	Uniform 60-300

Fig. 2. Location of customers in Oman

3. Methodology and Results

This study utilizes the anyLogistix (ALX) simulation and optimization packages to design the SC, identify optimal DC locations, and enhance network performance by evaluating various sourcing and inventory policies under disruption scenarios. Among the various tools available for simulating SC behaviour under risk, ALX has proven highly effective in analyzing risk and resilience in supply chains [41]. Through network optimization, ALX facilitates the identification of optimal site locations and attributes, considering factors such as demand, capacity, seasonal variations, product types, customer locations, road networks, fixed and variable costs, and inventory management. By utilizing ALX, dynamic modelling of SC behaviour can be achieved, allowing for the examination of the impact of changes in design, ordering, and transportation regulations [42].

The methodology in ALX consists of three steps.

- Greenfield Analysis (GFA): GFA is used to identify the feasible locations for DCs and to develop a sourcing plan for different sites.
- Network Optimization (NO): The feasible network designed in the GFA can be converted into a NO model to identify the optimal number and location of new DCs, determine product flows, and evaluate sourcing options. This experiment includes various costs, such as production, transportation, closing, initial, and other related costs, that need to be minimized.
- Simulation (SIM): In the SIM experiment, different policies are defined over a time horizon, and performance of the model is analyzed through a wide range of Key Performance Indicators (KPIs), such as different costs, CO2 emissions, expected lead time, service level, and unfulfilled demands. Various events and disruptions can be incorporated into scenarios for "what-if" analysis, allowing the investigation of performance of the network under different conditions.

In this study, the process begins with the design of a GFA model to identify feasible locations for the required DCs. The selected DCs are then incorporated into the NO experiment to optimize costs, product flows, and maximize profit. In the simulation phase, sourcing and inventory policies are integrated into the model, and additional KPIs, such as service level and available inventory, are reported. Furthermore, disruptions are introduced to the model to analyze its resilience.

3.1 Greenfield analysis (GFA)

The SC is initially designed with the main DC serving as the primary hub. However, due to the significant distance between the main DC and some customers, which is critical for managing perishability, products are delivered to additional DCs. The first stage focuses on identifying feasible locations for new DCs using GFA. In this experiment, key data are input into the model, including product types, the geographical locations of the company and customers, and the demand for each customer.

Initially, the number of new DCs is set to three to identify feasible locations, after which the location or number of new DCs required to optimize the network is determined. The results suggest that new DCs should be located in Sohar, Salalah, and Samail. Figure 3 illustrates the new network structure, where all customers are sourced from these three DCs. This structure serves as the base input for the NO phase to optimize the DCs and flows.

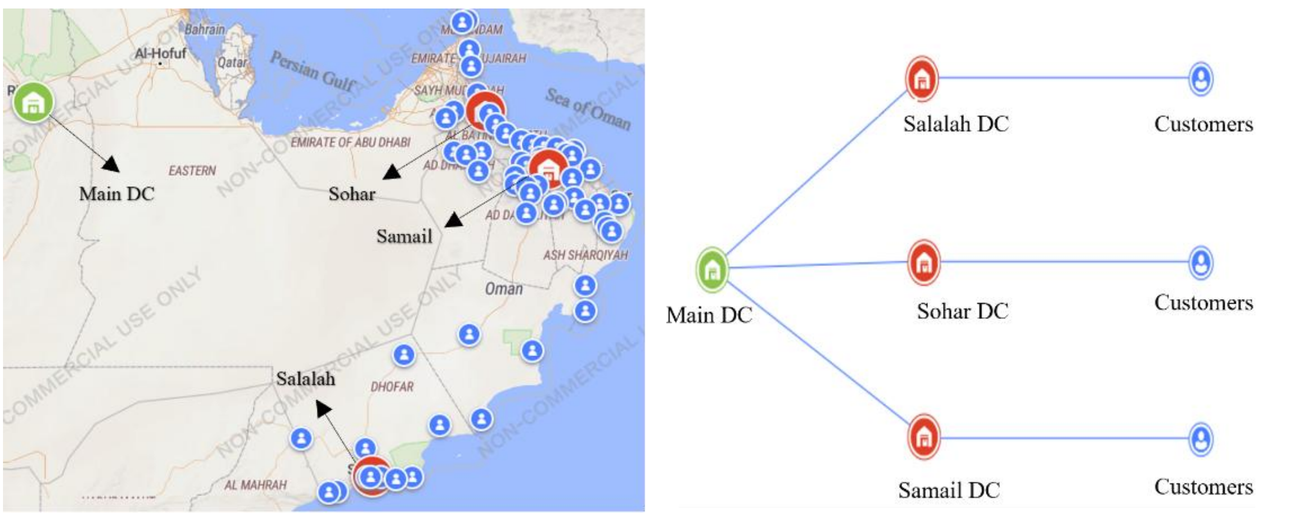

Fig. 3. GFA model

3.2 Network optimization (NO)

The feasible network designed in GFA, including initial solutions for the locations of new sites and product flow, is converted into the NO model to optimize the network, considering costs and additional model details, which are provided in Table 3. First, the output structure from GFA is implemented, and the results are illustrated in Table 4. This table includes total and transportation costs, CO_2 emissions, and demand fulfillment. The NO model, shown in the third column, presents the results after optimizing the number and location of DCs and the sourcing flow of demand. The results from Table 4 highlight the impact of transitioning from a manually configured network under GFA to an optimized structure derived from NO in ALX. In the GFA network, three DCs, Sohar, Salalah, and Samail, were preselected, and the demand flow between these DCs and customers was determined accordingly. However, in the NO model, the optimization model was allowed to determine the most efficient configuration, resulting in the retention of only Sohar and Salalah, while Samail was eliminated. Additionally, a new sourcing policy was applied to further optimize cost and efficiency.

Table 3
Other Data used in the NO Model

Parameters	Value
Initial Cost for DCs	$100
Other Costs for DCs	$10 per day
Outbound Shipment Processing Costs	$0.4-0.5
Fresh Labneh Production Cost	$1
Laban Production Cost	$2.31
Greek Yoghurt Production Cost	$1.3
Fresh Yoghurt Production Cost	$0.78
Protein Milk Production Cost	$1.09
Iced Coffee Production Cost	$2.06
Fresh Juice Production Cost	$1.49
Turkish Labneh Production Cost	$2.91
Cooking Cream Production Cost	$5.79
Tomato Paste Production Cost	$12.21
Fresh Labneh Production Cost	$4.6
Laban Production Cost	$6.1
Greek Yoghurt Production Cost	$5
Fresh Yoghurt Production Cost	$2.9
Protein Milk Production Cost	$3.3
Iced Coffee Selling Price	$5.2
Fresh Juice Production Cost	$4
Turkish Labneh Production Cost	$6
Cooking Cream Production Cost	$9
Tomato Paste Production Cost	$16
Transportation Cost	$1.2-1.5
CO_2 emission of Transportation	0.54-0.67
Truck 3 Ton Speed	100 km/h
Truck 5 Ton Speed	80-100 km/h

Table 4
Comparison of the NO Model and GFA Model

Parameters	GFA Network	NO Network
Total Flow	22,564,083	22,564,083
Profit	$47,246,529	$47,538,894
Demand Fulfilment	$11,282,041	$11,282,041
Transportation Costs	$2,125,694	$1,836,990
CO2 emission	949,784	821,524

A direct comparison between the two network configurations reveals significant improvements in cost efficiency and environmental performance without compromising demand fulfillment. Both networks maintain an identical total flow, ensuring that customer demand is met. However, the NO model achieves a higher profit compared to the GFA model. The total profit in the NO model exceeds the costs observed in the GFA configuration. A notable reduction in transportation costs further emphasizes the efficiency gains from NO. The NO model incurs transportation costs lower than those recorded in the GFA model. This reduction suggests that the optimized sourcing strategy and the elimination of an unnecessary DC contributed to a more streamlined and cost-effective logistics operation. Furthermore, the NO model significantly improves environmental performance, as evidenced by the reduction in CO2 emissions compared to the GFA configuration. This decline in emissions reinforces the advantage of optimizing network design in terms of sustainability.

3.3 Simulation (SIM)

The network with the two DCs, Sohar and Salalah, serves as the input for the simulation phase. The simulation experiment is designed in this SIM model to analyze the performance of the network under different scenarios and disruptions, focusing on more KPIs and detailed results. In this experiment, inventory and sourcing policies are incorporated into the converted NO model for the simulation phase.

The defined inventory policy in this network is the Min-Max with safety stock (s,S) policy. In this policy, products are ordered when the inventory level falls below a fixed replenishment point (s + safety stock). The ordered quantity is set so that the resulting inventory level reaches (S + safety stock). The values for each DC are provided in Table 5.

Table 5
Model Inventory policy for DCs

Object	s	S	Safety Stock
Main DC	250,000	500,000	650,000
Sohar DC	70,000	150,000	100,000
Salalah DC	70,000	150,000	100,000

The base scenario uses a network configuration with only the Sohar and Salalah DCs, determined through NO. The sourcing policy follows closest dynamic source policy, where products are delivered from the nearest available DC, while the inventory policy is Min-Max with safety stock to maintain inventory levels and prevent stockouts. This setup provides a baseline for evaluating alternative sourcing and inventory strategies.

The results in Table 6 show that demand fulfillment faced a backlog, with a portion of products delivered late. The service level is moderate, with a relatively high lead time, though variations in delivery performance are observed. The network remains profitable, and the transportation cost and CO2 emissions are within expected limits, indicating a balanced approach to logistics efficiency and sustainability.

3.3.1 Sourcing policies

In the first part of analysis, different source policies are designed, and results are illustrated in Table 6. Different sourcing and inventory policies are defined in this phase to analyze the performance of the designed network with different policies to find the best policy for sourcing and inventory. Performance of the network under three alternative sourcing policies, fastest dynamic source, most inventory dynamic source, and uniform split dynamic source—is analyzed in comparison to the baseline closest dynamic source policy. Each policy impacts fulfillment efficiency, service levels, transportation costs, and environmental sustainability differently, highlighting trade-offs in operational performance.

Table 6
Network Performance Under Different Sourcing Policies

KPIs	Basic network	Fastest (Dynamic)	Most Inventory	Uniform Sources
Demand Placed (Products) by Customer	11,402,549	11,402,549	11,398,684	11,397,272
Demand Received (Products)	22,959,749	22,959,749	22,905,884	23,163,298
Demand (Products Backlog)	11,342,831	11,342,831	11,338,351	11,164,888
Fulfillment Received (Products On time)	6,427,473	6,427,473	5,789,713	5,846,951
Fulfillment (Late Products)	4,970,776	4,970,776	5,603,842	5,543,425
Service Level by Products	0.567	0.567	0.564	0.572
ELT Service Level by Products	0.564	0.564	0.508	0.513
Lead Time	201	201	333	273
Max Lead Time	18.41	18.41	0.62	0.62
Mean Lead Time	0.16	0.16	0.28	0.44
Total CO2	2,013,337	2,013,337	4,071,700	7,475,259
Transportation Cost	4,479,357	4,479,357	9,054,462	16,618,307
Profit	23,318,457	23,318,457	18,390,14	11,213,343

The analysis of the sourcing policies reveals distinct differences in their performance compared to the baseline closest dynamic source policy. The fastest dynamic source policy, which directs customers to the DC capable of fulfilling their demand the quickest, shows similar results to the baseline closest dynamic source policy.

This indicates that prioritizing speed does not introduce inefficiencies compared to the closest dynamic source policy, and both approaches appear similarly balanced in terms of cost-effectiveness and environmental sustainability.

The most inventory dynamic source policy, where customers are served by the DC with the highest available stock, results in a lower service level and a significant reduction in on-time fulfillment compared to the baseline. This policy leads to more late deliveries and a longer lead time, showing that prioritizing inventory availability over speed and proximity can introduce fulfillment inefficiencies. Additionally, transportation costs and CO2 emissions rise substantially, indicating that this policy is less sustainable and more resource-intensive. The decline in profit further highlights the operational inefficiencies associated with this sourcing strategy.

The uniform split dynamic source policy, which evenly distributes customer demand across all DCs, leads to a higher service level than the baseline, but on-time fulfillment remains lower. The demand backlog is smaller, suggesting a more balanced distribution of demand, but fulfillment delays increase. Lead times are longer than in the baseline, which indicates that distributing demand evenly across multiple DCs may result in delays. Transportation costs and CO2 emissions are the highest among the policies, making this approach the least sustainable and most costly in terms of logistics. As a result, profits are significantly lower, indicating that the increased costs outweigh the benefits of a more evenly distributed demand.

In comparison to the baseline scenario, the closest dynamic source policy and the fastest dynamic source policy perform similarly in terms of fulfillment efficiency, lead times, and profitability. The most inventory dynamic source policy introduces inefficiencies, resulting in higher transportation costs, CO2 emissions, and lower profitability. The uniform split dynamic source policy achieves a slightly higher service level but at the cost of much higher transportation costs and environmental impact, making it the least efficient option. Overall, the closest dynamic source policy remains the most balanced approach in terms of logistics performance, cost, and sustainability.

3.3.2 Inventory policies

The analysis of different inventory policies considers service level, backlog, fulfillment, transportation costs, profitability, and lead time, revealing distinct performance variations. The study examines the Order-on-Demand policy and Reorder Quantity (RQ) policies under different initial stock levels and order quantities, respectively. The results of these investigations are summarized in Table 7.

Table 7
Network Performance Under Different Inventory Policies

KPIs	Order on-demand - Initial Stock			RQ - Order Quantities			
	100,000	200,000	300,000	1,000	5,000	10,000	20,000
Demand Placed (Products)	11,381,307	11,401,3	11,369,7	11,399,5	11,369,8	11,394,0	11,380,1
Demand Received	20,776,114	19,163,4	17,686,3	18,476,5	19,509,8	20,374,0	21,780,1
Demand (Products	9,472,332	7,753,81	6,727,09	6,669,63	7,541,46	8,284,96	9,784,14
Fulfillment Received	1,939,322	3,564,23	4,960,69	5,825,95	6,235,40	6,480,37	6,540,14
Fulfillment (Late Products)	9,435,566	7,829,24	6,405,40	5,565,68	5,130,07	4,908,66	4,833,18
Service Level by Products	0.174	0.319	0.444	0.514	0.550	0.571	0.577
ELT Service Level by	0.170	0.313	0.436	0.511	0.549	0.569	0.575
Lead Time	803	585	1,429	952	187	172	185
Max Lead Time	14.65	1.82	237.66	19.46	2.85	1.24	0.67
Mean Lead Time	0.62	0.48	0.45	0.38	0.14	0.12	0.12
Total CO2	6,823,027	6,532,81	5,655,42	6,136,37	2,509,05	2,183,65	2,012,55
Transportation Cost	15,245,025	14,587,6	12,619,4	13,709,9	5,591,19	4,862,31	4,479,05
Profit	13,296,338	17,922,8	22,605,6	14,652,2	22,613,1	23,368,6	23,468,2

3.3.2.1 Order-on-demand policy

This policy exhibits an increasing trend in service levels as the initial stock rises. A higher initial stock enhances demand fulfillment, reduces backlog, and boosts profitability. However, it also leads to higher transportation costs and CO2 emissions due to more frequent replenishment. Lead times are generally longer, as replenishment occurs only when demand arises, reducing delays in stock availability. The key trade-off in this policy is between higher product availability and the increased logistics costs and lead times caused by frequent replenishment.

- The impact of different initial stock levels is as follows:
- 100,000 initial stock: Low inventory levels lead to a high backlog, indicating an inability to meet demand.
- 200,000 initial stock: Inventory availability improves significantly, reducing backlog and ensuring better demand fulfillment.
- 300,000 initial stock: Further improvement in stock levels and backlog reduction, presenting the most balanced approach. However, maintaining higher initial stock levels may increase holding costs.

3.3.2.2 QR policy

In this policy, increasing the order quantity enhances service levels. Initially, smaller order quantities lead to higher backlog due to limited product availability. However, as order quantities increase, service levels and on-time fulfillment improve, demonstrating the efficiency of this approach. Additionally, CO_2 emissions and transportation costs decrease, while profitability rises.

The impact of different order quantities is as follows:

- Q = 1,000 and 5,000: Low inventory availability and a relatively high backlog suggest these quantities are insufficient to meet demand.
- Q = 10,000: Significant backlog reduction, but excessive inventory holding is observed in on-hand inventory.
- Q = 20,000: Achieves the highest stock availability and on-hand inventory. However, backlog issues persist, indicating that excessive stock alone does not fully resolve demand fulfillment challenges.

Inventory KPIs, including available inventory and backlog levels, provide critical insights into stock management and demand fulfillment (Figures 4 and 5). Based on the results, the RQ policy with an order quantity of 20,000 offers the best overall performance in terms of lead time, profitability, and sustainability. It improves service levels, reduces backlog, and strikes a balance between transportation costs and CO_2 emissions. However, backlog challenges remain. For a more balanced approach, a moderate RQ policy (Q = 10,000) or a well-calibrated Order-on-Demand policy (initial stock 300,000) delivers optimal results. These strategies provide strong performance across key metrics while mitigating excessive inventory holding and replenishment costs, ensuring operational efficiency and sustainable supply chain management.

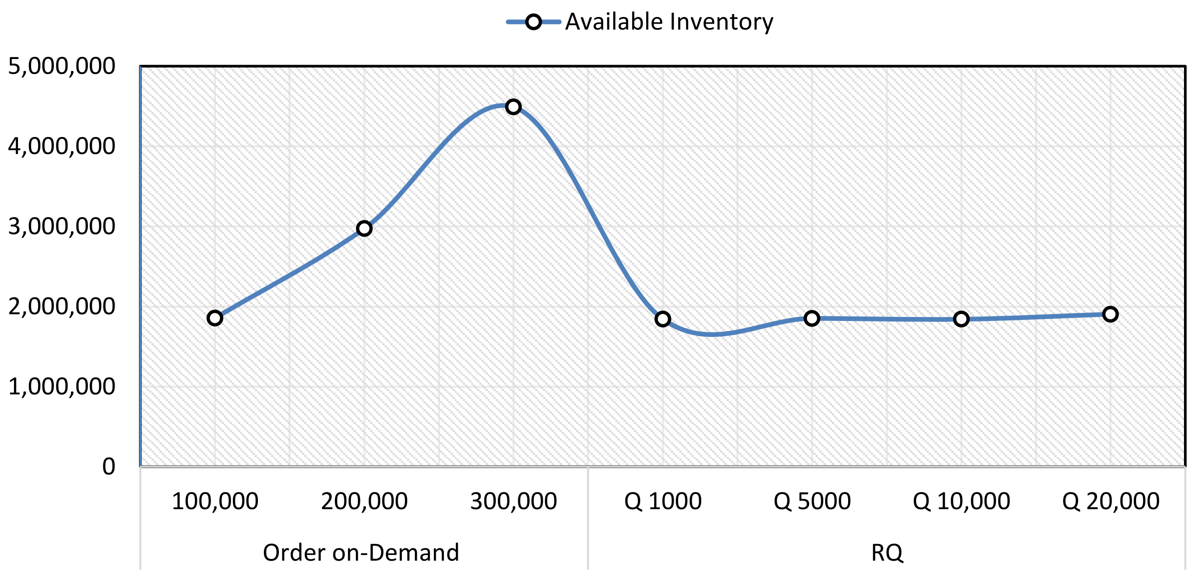

Fig. 4. Available inventory in inventory policies

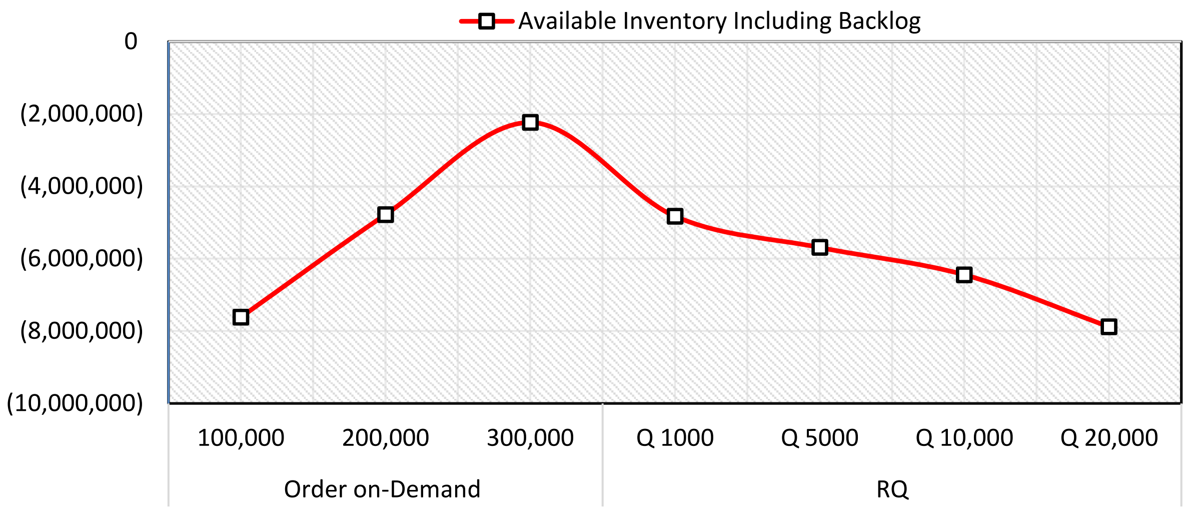

Fig. 5. Available inventory including backlog in inventory policies

3.3.3 Disruption scenarios

To assess the resilience of the SC network, two disruption scenarios were introduced:

Single-DC Operation: Each time, one DC was closed while the other remained operational for the entire planning horizon. This was tested separately for Sohar and Salalah DCs to evaluate their independent performance.

Single-DC with Increased Demand: In this scenario, only one DC remained operational, but customer demand was increased by 50% to test ability of the system to handle demand surges under restricted capacity. This was also tested separately for Sohar and Salalah.

As it can be inferred from Table 8, Operating with a single DC led to significant backlogs, with both Sohar and Salalah DCs accumulating nearly 11.88 million unfulfilled products. While both shipped around 11 million products, Sohar had slightly more late shipments. Sohar also outperformed Salalah in lead time, CO2 emissions, and transportation costs, resulting in higher profitability.

Under a 50% demand increase, backlog surged to 22.55 million products, while late shipments nearly doubled. Although fulfillment slightly improved, delays remained severe. Sohar maintained better efficiency, with lower lead times, CO2 emissions, and costs. However, higher demand boosted profits for both DCs, reaching $24 million for Sohar and $20.64 million for Salalah. These findings highlight efficiency of Sohar but also reveal the risks of relying on a single DC. A dual-DC strategy is essential to mitigate disruptions, reduce backlogs, and optimize costs while ensuring stable fulfillment.

The trade-offs among different disruption scenarios highlight the complex interplay between lead time, demand fulfillment, cost, and environmental impact. As shown in the Figure 6, shifting distribution operations to Sohar or Salalah alone significantly affects lead time, with Salalah exhibiting the highest delays. As shown in Figure 7, the increased demand scenarios further exacerbate this, particularly for Salalah, indicating its lower resilience under pressure. The backlog and demand received trends reinforce this, showing that while Sohar maintains a more stable fulfillment rate, Salalah struggles under higher demand. Moreover, Figure 8 reveals the cost and environmental implications of these disruptions, demonstrating that while Sohar may offer better fulfillment, it comes at a higher transportation cost and CO2 emissions, whereas inefficiencies of Salalah translate into increased delays and backlog. These insights emphasize the need for a balanced strategy that optimally distributes demand to mitigate risks while controlling costs and emissions.

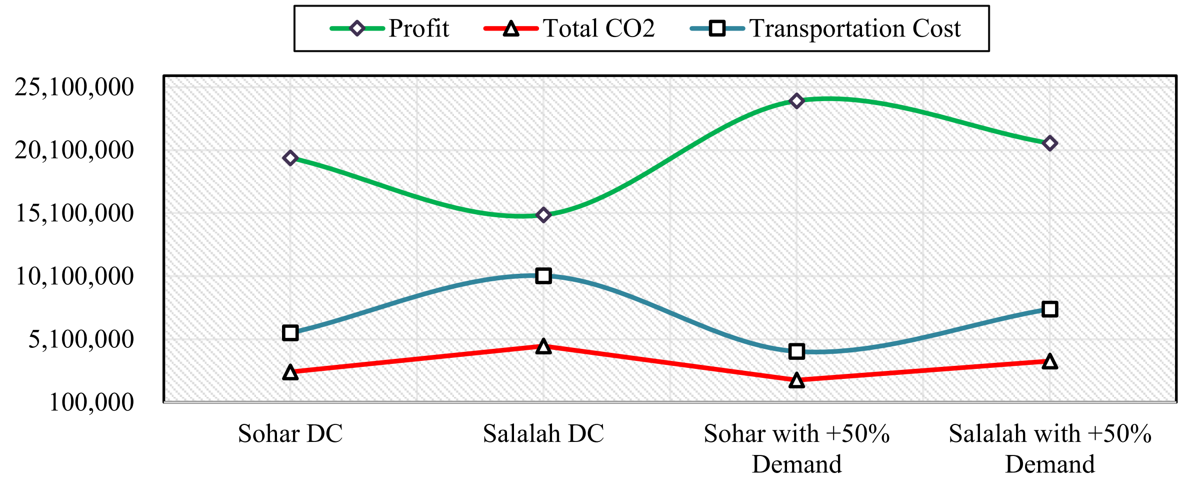

Fig. 6. Lead time in different disruptions

Table 8
Network Performance Under Different Disruption Scenarios

KPIs	Sohar DC	Salalah DC	Sohar with +50% Demand	Salalah with +50% Demand
Demand Placed (Products) by Customer	11,392,76	11,392,765	17,070,748	17,070,748
Demand Received (Products)	22,897,22	22,897,228	34,223,462	34,223,462
Demand (Products Backlog)	11,887,66	11,887,669	22,554,058	22,554,058
Fulfillment Received (Products On time)	5,018,749	5,464,397	5,242,611	5,707,116
Fulfillment (Late Products)	6,365,633	5,919,985	11,819,271	11,351,767
Service Level by Products	0.513	0.513	0.358	0.358
ELT Service Level by Products	0.441	0.48	0.307	0.335
Lead Time	120	220	120	220
Max Lead Time	0.57	0.62	0.84	1.47
Mean Lead Time	0.19	0.35	0.20	0.36
Total CO2	2,516,380	4,556,078	1,857,611	3,368,272
Transportation Cost	5,596,251	10,132,398	4,132,428	7,493,217
Profit	19,488,55	14,952,222	24,004,034	20,643,244

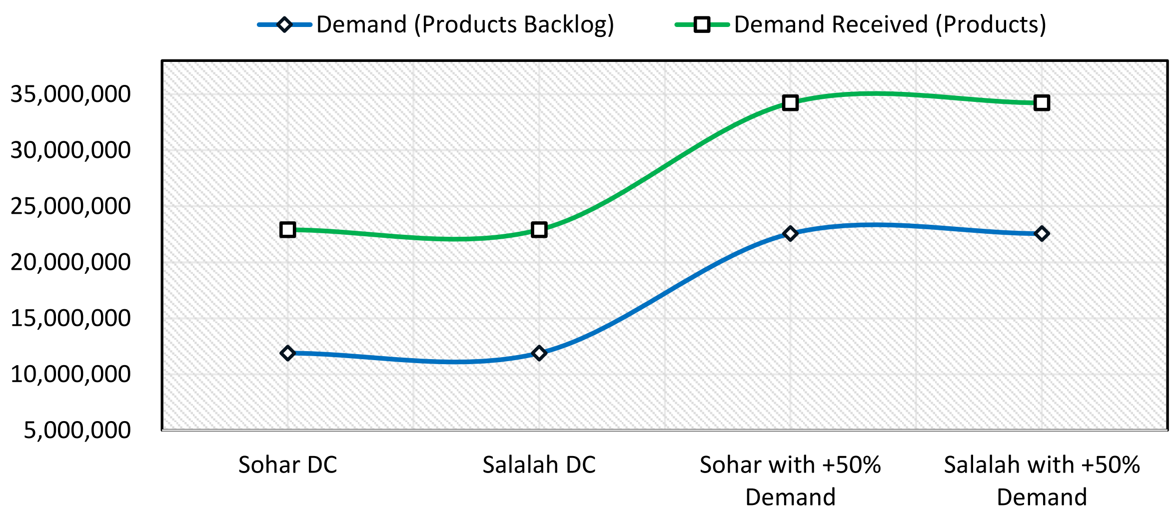

Fig. 7. Demand received and demand backlog in different disruptions

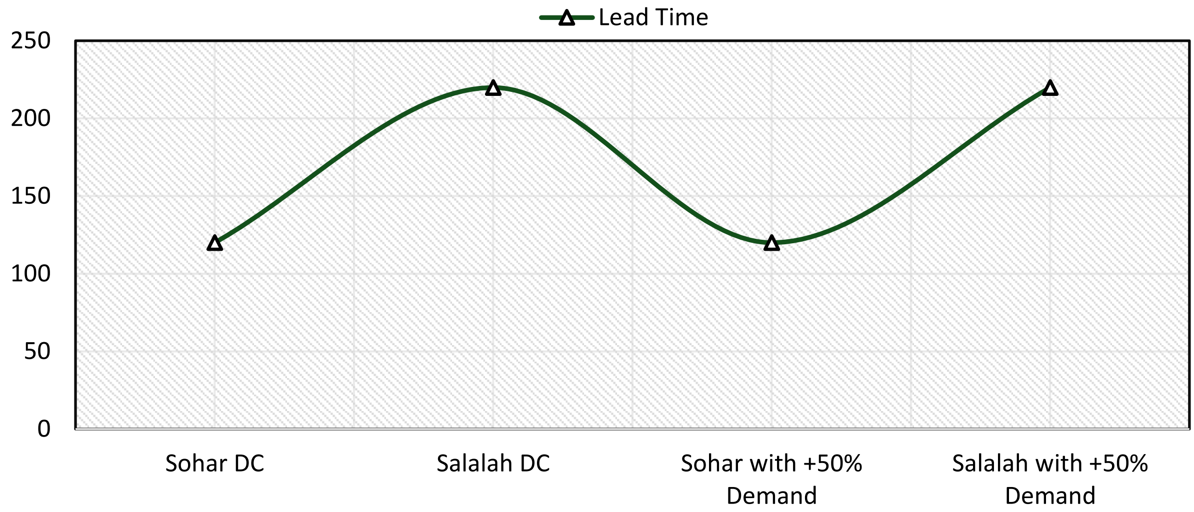

Fig. 8. Profit, transportation cost and total CO_2 emission in different disruptions

The results highlight the effectiveness of integrating network optimization and simulation in SC design to enhance cost efficiency, demand fulfillment, and sustainability. GFA identified Sohar, Salalah, and Samail as potential DC locations, but NO refined this configuration by removing Samail, leading to lower transportation costs and CO2 emissions while maintaining profitability. Simulation results demonstrated that sourcing and inventory policies significantly influence performance. The closest and fastest dynamic source policies provided the best balance between fulfillment, lead time, and sustainability, while the uniform split dynamic source policy was the least effective, increasing costs and emissions. Inventory policies revealed trade-offs between backlog reduction, cost efficiency, and service levels. The Order-on-Demand policy with higher initial stock improved fulfillment but raised costs. The RQ policy with larger order sizes struck a balance between service level and logistics efficiency. These findings emphasize the importance of selecting sourcing and inventory strategies aligned with operational priorities, ensuring a resilient and cost-effective SC.

4. Conclusions

This study demonstrates that integrating supply chain network optimization and simulation can improve the performance of outsourced dairy cold chain distribution. In response to the research objective, the results show that the optimized network should retain two distribution centers in Sohar and Salalah, while eliminating the initially identified Samail facility. This configuration reduced transportation costs from \$2.13 million to \$1.84 million and CO_2 emissions from 949,784 to 821,524 while maintaining the same total flow and demand fulfillment. Among the sourcing policies, the closest dynamic source policy provided the most balanced overall performance, while the reorder quantity policy with an order quantity of 20,000 showed strong performance across lead time, profitability, and sustainability. These findings confirm that coordinated network design, sourcing, and inventory decisions can improve the economic and environmental performance of perishable-product cold chains and provide practical support for logistics planning.

Future research can extend this study by incorporating more granular data, such as weather conditions or real-time demand fluctuations, to further refine optimization models. Additionally, exploring the integration of emerging technologies like blockchain for traceability or AI-driven demand forecasting could enhance SC resilience and sustainability. Testing the model with different product types and markets will offer broader applicability across industries dealing with perishable goods, further improving the versatility of optimization strategies.

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Conflicts of Interest
The authors declare no conflicts of interest.

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