

A Hybrid Optimization-Simulation Approach for Supply Chain Network Design under Uncertainty and Highly Perishable Environments

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Abstract—Designing and managing logistics and supply chain networks for perishable products requires careful consideration of product quality degradation over time due to environmental conditions and processing delays. This study proposes a Hybrid Optimization-Simulation (HOS) framework that combines a Mixed-Integer Linear Programming (MILP) model with a Discrete Event Simulation (DES) to design a cost-efficient and quality-preserving distribution network for floral products. The MILP model incorporates a Time-Temperature Sum (TTS) constraint to account for product perishability, while the simulation model evaluates the network's operational feasibility under dynamic conditions. A case study of the floriculture supply chain, involving growers, hubs, and retailers, is used to validate the proposed approach's performance. The results show that the deterministic MILP achieves the lowest total cost of \$163,418, but does not account for uncertainty. In contrast, the proposed HOS outperforms the typical Simulation-Based Optimization (SBO) by 4.78% in total cost and achieves a much shorter computation time. In addition, the HOS framework can produce logistics and supply chain network configurations that balance cost efficiency and quality assurance, providing a robust tool for supply chain design in highly perishable environments.

Index Terms—Perishable Products, Mixed Integer Linear Programming (MILP), Simulation, Hybrid Optimization Approach

I. INTRODUCTION

The design of logistics and supply chain networks for perishable products presents distinct challenges due to the rapid deterioration of product quality over time. In supply chains, handling products such as cut flowers, freshness is a critical performance measure, and quality degradation is heavily influenced by

factors such as temperature exposure and delays during transportation and processing. As these factors interact dynamically, traditional logistics planning approaches that focus solely on cost minimization often fail to maintain acceptable service levels or reduce spoilage.

A typical cut flower supply chain offers a representative example of this complexity, in which flowers are cultivated in geographically dispersed regions and routed through distribution hubs for processes such as bouquet-making before reaching retailers. These processes often require the timely combination of different flower types, further complicating logistics coordination. The perishability of flowers, typically measured in vase life, requires that strategic decisions—such as facility placement, flow routing, and process allocation—explicitly account for product quality through the supply chain.

Conventional optimization techniques such as Mixed-Integer Linear Programming (MILP) have been extensively used in supply chain network design. However, these models often rely on static approximations and do not adequately capture the dynamic nature of quality decay. In contrast, simulation models can incorporate time-dependent and uncertain elements such as transport variability and temperature fluctuations, providing more realistic evaluations of operational performance. Nonetheless, simulation alone lacks the prescriptive capabilities of optimisation in determining optimal network configurations.

To bridge this gap, Hybrid Optimization-Simulation (HOS) approaches have emerged, combining the prescriptive strength of optimization with the descriptive richness of simulation. A notable contribution in this area is the model developed by De Keizer et al. [1], who combined an MILP with DES to design logistics networks for cut flowers. Their approach used simulation feedback to iteratively adjust product-deterioration constraints in the MILP, enabling the design to reflect real-world operational conditions such as uncertain supply, processing delays, and variable transport temperatures.

Building upon this framework, the present study adopts an HOS approach to the supply chain network design. This research also emphasises the importance of incorporating time-temperature-sum quality metrics into strategic decision-making. This study also makes four additional contributions beyond previous studies. Firstly, a modified HOS approach is proposed to tradeoff between degrading product quality and the customer's service level, subject to minimising total costs. Secondly, it extends the HOS methodology by varying the levels of uncertainty in the simulation model to improve the realism and robustness of supply chain performance evaluations. Thirdly, it introduces OptQuest, an optimization tool embedded in ARENA, as a benchmarking tool to evaluate and validate the MILP and HOS solutions using metaheuristic-based search techniques. This dual-layered validation provides greater confidence in the effectiveness of the proposed network designs, especially under dynamic and uncertain conditions. Finally, this research contributes a practical implementation of the HOS approach by developing and constructing the hybrid framework in a real-world simulation platform. This demonstrates how theoretical optimization-simulation integration can be operationalized effectively, offering actionable insights for decision-makers in perishable supply chains. These advancements support the development of more resilient and empirically grounded logistics networks for perishable products.

As a result, the research contributes to the growing body of literature that seeks to enhance supply chain resilience and efficiency in environments characterized by high perishability and operational uncertainty.

II. LITERATURE REVIEW

This literature review section begins by examining prior related studies on perishable products in supply chain network design, followed by discussions of optimization, simulation, and hybrid methodologies, particularly those focused on process allocation and product quality degradation.

A. Perishable Products in Supply Chains

Perishable products such as fresh food and cut flowers are inherently vulnerable to quality degradation, which significantly complicates supply chain planning and execution. These products are highly sensitive to environmental conditions—particularly time and temperature—making quality preservation a critical objective throughout transportation, storage, and processing. Managing the flow of perishables requires not only timely delivery but also specialized handling protocols and temperature-controlled logistics. Musavi and Bozorgi-Amiri [2] emphasized the importance of freshness in their sustainable hub location-vehicle scheduling model,

which incorporated both product perishability and environmental impact through CO₂ emissions. Their approach illustrated how sustainability goals and quality preservation could be jointly addressed in strategic supply chain decisions. Similarly, Rong et al. [3] developed a framework for integrating food quality degradation into an MILP model. Their study focused on modeling the deterioration of food products over time and incorporating this into production and distribution planning. By doing so, they bridged the gap between quality control and logistical decision-making in food supply chains. Next, Pasha et al. [4] further advanced this domain by modeling quality as a function of both time and temperature in a two-echelon distribution system. Their work demonstrated how product quality could be monitored dynamically to influence both inventory control and network design decisions. Agustina et al. [5] experimented on the production-distribution planning for perishable products, emphasizing that shelf-life dynamics and cold-chain responsiveness were central to efficient network design. These contributions highlighted that perishable supply chains cannot be effectively managed without incorporating the physical decay processes into the decision-making framework.

B. Optimization in Perishable Supply Chains

A wide range of optimization techniques has been applied to enhance the performance of supply chains dealing with perishable products. Mathematical modeling is essential for its prescriptive power and ability to find globally optimal solutions under defined constraints. These mathematical models are especially useful for determining optimal facility locations, inventory policies, and routing decisions under resource and time constraints. In the context of perishables, these models must also account for the limited shelf life and quality degradation that affect the economic value of goods over time. For instance, Mohebalizadehgashti et al. [6] developed a multi-period, multi-product, multi-echelon MILP model for a green meat supply chain in Southern Ontario that simultaneously minimizes total cost and CO₂ emissions while maximizing capacity utilization, using the augmented ϵ -constraint method to obtain Pareto-optimal solutions. They further incorporated the decision tree analysis to assess the impact of demand and purchasing cost uncertainty, offering decision-makers balanced trade-offs for sustainable perishable supply chain design. Mohammadi et al. [7] addressed routing optimization in agri-food supply chains, where timely delivery was essential to minimize quality losses. Their hybrid algorithm sought to reduce both operational costs and perishability-driven losses, demonstrating the dual objectives often presented in such networks. A particularly notable contribution is by De Keizer et al. [1], who formulated an MILP to

design a distribution network for cut flowers. This model incorporated a Time-Temperature Sum (TTS) constraint to ensure product quality thresholds were met across the supply chain. Their framework enabled decision-makers to assess the trade-off between cost efficiency and product freshness, particularly in networks with multiple product types and processing stages. Collectively, these studies have reinforced the relevance and adaptability of optimization methods in addressing the unique challenges of perishable product distribution. Then, Shirzadi et al. [8] addressed optimization in perishable supply chains by developing a green inventory-routing model with simultaneous pickup and delivery that integrates postharvest biological behavior, greenhouse gas emission control, and reverse logistics. Their bipolar fuzzy optimization framework incorporated freshness and ripeness into pricing and satisfaction while managing uncertainty in quality and holding costs, offering a more comprehensive solution than previous models that considered these factors separately.

In addition, metaheuristic approaches have been widely used to handle complex, nonlinear problems that traditional solvers may struggle with, particularly under time constraints or in large solution spaces. Pan et al. [9] introduced a hybrid metaheuristic optimization for multi-echelon perishable supply chains, improving computational efficiency and robustness under uncertainty. More recently, reinforcement learning has emerged as a promising approach, enabling the learning of adaptive decision-making policies through interaction with dynamic environments, a capability that is especially useful for real-time control and routing in uncertain supply chains.

C. Simulation in Supply Chain Modeling

While MILP optimization models offer prescriptive decision-making tools, they often rely on static assumptions that may not capture the full complexity and uncertainty of real-world perishable supply chains. In contrast, simulation provides a powerful means to evaluate system performance under dynamic and stochastic conditions. Discrete Event Simulation (DES) is particularly effective in modeling time-dependent processes such as transport delays, machine breakdowns, and fluctuating demand—all of which can significantly impact product freshness and delivery reliability. For example, Nakandala et al. [10] incorporated simulation to evaluate their optimization outcomes, allowing them to assess quality performance under variable transport conditions. Their approach provided critical insights into how operational uncertainties affected quality-related metrics, which were often overlooked in deterministic models. Sel and Bilgen [11] developed a simulation-supported decision-making framework

for the beverage industry, combining MILP-based heuristics with DES to evaluate operational feasibility. Their framework was capable of adapting to machine failures and uncertain production rates using a rolling horizon planning approach. This integration allowed for more accurate forecasting and responsiveness in high-variability environments. Ásmundsson et al. [12] applied simulation modeling to analyze and improve supply chain performance, focusing on identifying bottlenecks, testing alternative policies, and evaluating operational changes in a risk-free environment. Then, Gaukler [13] demonstrated that integrating time-temperature history data into simulations significantly enhanced the accuracy of logistics decision-making for perishable foods. In summary, these studies have shown that simulation is an essential complement to optimization, particularly for perishable goods that are highly sensitive to real-time disruptions. It allows researchers and practitioners to test logistics configurations before implementation, improving both reliability and service performance.

D. Hybrid Optimization–Simulation Approaches

Hybrid Optimization–Simulation (HOS) approaches have emerged as a promising methodology for tackling the complexity of perishable supply chain design and operation. These approaches leverage the strengths of both optimization—providing optimal or near-optimal solutions under defined constraints—and simulation, which evaluates system performance under realistic, variable conditions. For example, Sel and Bilgen [11] implemented a hybrid method by combining MILP-based heuristics with simulation in the beverage industry. Their rolling-horizon approach enabled sequential decision-making while responding dynamically to changes in system status. Ding et al. [14] proposed an HOS approach using a Multi-Objective Genetic Algorithm (MOGA) and Discrete Event Simulation (DES) to design production-distribution networks under uncertainty. Their model simultaneously optimized network structure, operational strategies, and control parameters while capturing dynamic and stochastic system behavior. Ko et al. [15] developed an HOS framework for third-party logistics providers (3PLs), combining a genetic algorithm for network design with simulation to evaluate warehouse capacity and service time under uncertain demand and processing variability. Such hybrid frameworks are particularly valuable for perishable products, where operational realities like spoilage, temperature sensitivity, and time constraints play a critical role. By integrating both planning and evaluation layers, HOS approaches can offer a more comprehensive and practical solution for managing uncertainty and ensuring quality in perishable supply chains. Then, Abbasian et al. [16] developed a bi-objective hybrid optimization method incorporating location, inventory, and routing

decisions for a perishable food supply network, and addressed resiliency and sustainability under disruption-risk conditions.

Most existing optimization models for perishable supply chains focus primarily on deterministic environments and cost-minimizing objectives, neglecting the influence of real-world uncertainties such as process time variation, buffering delays, and fluctuating temperature conditions that directly affect the product freshness and the service level performance. As a result, this study tries to fill the gap by integrating a Discrete Event Simulation (DES) with a Mixed-Integer Linear Programming (MILP) model to capture the dynamic effects of uncertainty on product quality through Time-Temperature Sum (TTS) constraints.

III. PROBLEM DESCRIPTION AND OPTIMIZATION MODEL

A. Problem Description

This study focuses on the cut-flower supply chain, from growers to retailers, with floricultural clusters (such as auctions and traders) in between. These clusters are where flowers are collected, processed into bouquets, and sent to retailers. The model builds upon the conceptual framework proposed by De Keizer et al. [1], who analyzed the distribution network of cut flowers in the Netherlands.

In this supply chain network, growers deliver flowers to auction centers at scheduled times. At the auction, traders buy the flowers and arrange delivery to their facilities. After that, the flowers are processed into bouquets and delivered to retailers. Flowers that are not sold or processed in time are thrown away because they no longer meet customer requirements. Traders can also buy flowers directly from growers, skipping the auction, but the time and quality limits still apply.

A key decision in designing this network is where to do the bouquet-making. Since bouquets take up more space than single flowers, it may seem better to make them close to the retailer. However, doing all processing in one place (centralized) can reduce costs. On the other hand, bringing flowers from different locations together may cause delays. This can lead to a loss of quality if the flowers are not combined on time. So, the location of bouquet-making must balance transport costs and the risk of quality degradation.

The quality of flowers is measured by their vase life, where Tromp et al. [17] as how many days the flowers can stay fresh in a vase at room temperature (usually 20°C). Quality loss is calculated using the Time-Temperature Sum (TTS) model. It depends on

the starting vase life (A) and the Time Temperature Sum (TTS), which shows how temperature and time affect the flowers during transport and storage. The formula is: $VL = A - TTS$, where $TTS = \sum_i time_i * temperature_i$. i is the process in the supply chain. TTS adds up the effect of time and temperature at each stage in the supply chain. A higher TTS indicates a shorter vase life. As each retailer has a service level requirement, which means a certain percentage of flowers must meet a minimum vase life, the network design must find the best locations and product flows to keep costs low while meeting these quality rules.

Each grower supplies one type of flowers or green ornamentals, representing specialized production. There are five flower types (Alstroemeria, Lilium, Tulipa, Gerbera, and Rosa) and two ornamental types (Pittosporum and Ruscus). Ten retailers (see Fig. 1) are included in the model, each placing demand for bouquets that are mono-type (single flower type) or mixed-type (combination of flowers and greens). Table I presents the bill of materials for mono and mixed bouquets, specifying the required input quantities of each flower type and their available supply from growers. The differentiation between these bouquet types introduces synchronization challenges, particularly for mixed bouquets that require the timely availability of all input components. Nine potential hub locations (see Fig. 2) are included as intermediate facilities capable of storing (buffering) and performing bouquet-making processes. Hubs also differ in buffer durations and processing times, reflecting differences in operational efficiency. All nine hubs have identical unit cost parameters. Each hub requires a fixed installation cost of \$10,000, and an additional fixed cost of \$5,000 for installing the bouquet-making process. The variable processing cost is \$1 per unit. Transportation costs and temperature during transport are calculated based on time and shipment type (flowers or bouquets), with additional consideration of whether the transport is cooled or non-cooled. When the transport time is longer than 6 hours, the cooled transport (7 °C) is used in which is more expensive than non-cooled transport (14 °C) (see Table IV). There are 10 retailers (see Fig. 3), each responsible for receiving a mix of mono and mixed bouquets based on their demand and quality requirements. These retailers set specific service-level targets and required vase-life thresholds that the network must meet to ensure customer satisfaction. As a result, the network design must find the best locations and product flows to keep costs low while meeting these quality rules. The input data are shown in Tables I-IV and Figs 1-3.

TABLE I
BILL OF MATERIALS AND SUPPLY DATA

	Type of Cut Flowers (flowers)				Type of Ornamentals (flowers)		
	Alstroemeria	Lilium	Tulipa	Gerbera	Rosa	Pittosporum	Ruscus
Mono Bouquet	-	-	15	-	-	-	-
Mixed Bouquet	3	3	-	3	5	4	4
Supply	6,450	6,450	15,000	6,450	10,750	8,600	8,600

TABLE II
BUFFERING AND PROCESSING TIME DATA

Hub	Buffering Time (Hours)	Processing Time (Hours)
Hub 1	8	5
Hub 2	3	4
Hub 3	5	3
Hub 4	5	3
Hub 5	5	3
Hub 6	5	3
Hub 7	5	3
Hub 8	9	4
Hub 9	12	5

TABLE III
CUSTOMER REQUIREMENT AND DEMAND DATA

Retailer	Required Product Quality (Days)	Service Level (%)	Demand (Bouquet)	
			Mono Bouquet	Mixed Bouquet
Retailer 1	8	90%	100	215
Retailer 2	8	95%	100	215
Retailer 3	8	90%	100	215
Retailer 4	8	95%	100	215
Retailer 5	9	95%	100	215
Retailer 6	9	95%	100	215
Retailer 7	9	90%	100	215
Retailer 8	9	95%	100	215
Retailer 9	8	90%	100	215
Retailer 10	8	90%	100	215

TABLE IV
TEMPERATURE AND TRANSPORTATION COST

From/To	Temperature		Costs/km/1,000 units of flower (\$)			
			Flower		Bouquet	
	<6 Hours	>6 Hours	<6 Hours	>6 Hours	<6 Hours	>6 Hours
Grower to Hub	14 °C	7 °C	1	1.2	-	-
Hub to Hub	14 °C	7 °C	0.5	0.9	2	2.4
Hub to Retailer	14 °C	7 °C	-	-	3	6.4

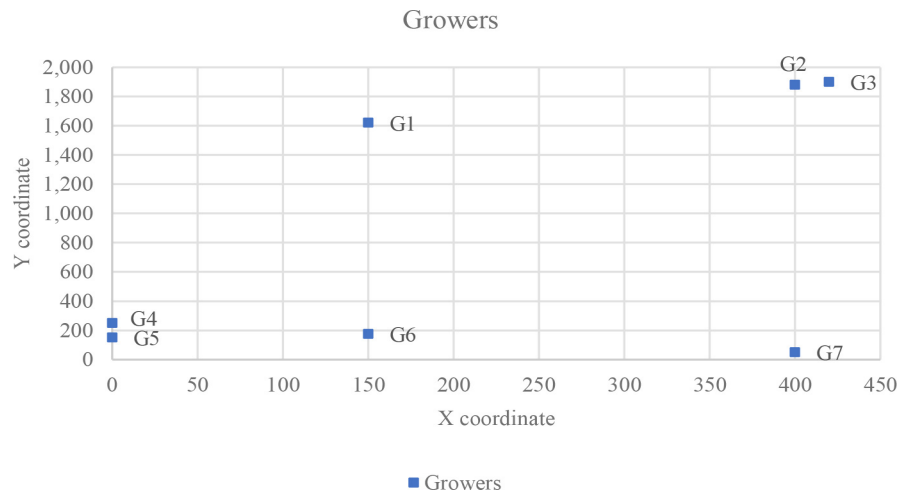


Fig. 1. Growers location coordinate

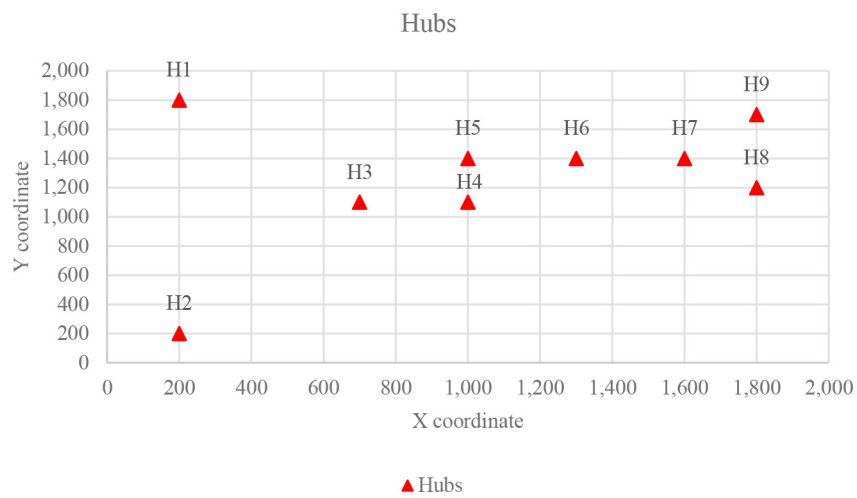


Fig. 2. Hubs location coordinate

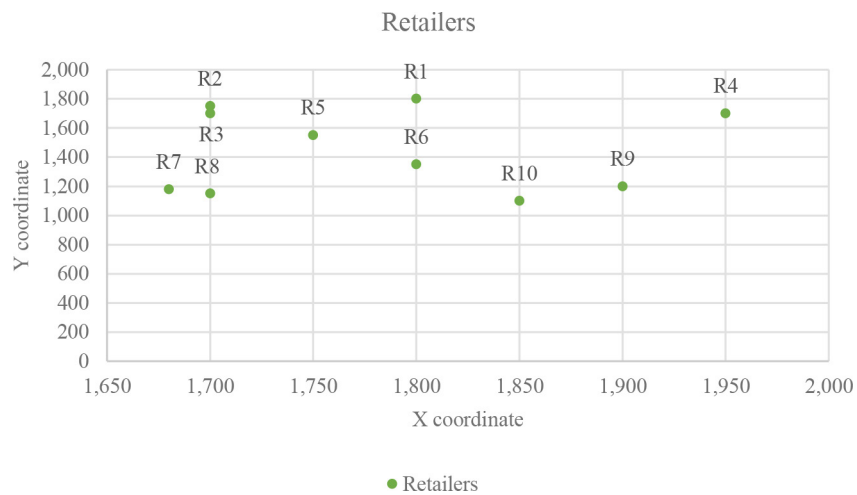


Fig. 3. Retailers' location coordinates

B. Problem Assumptions

The following are the assumptions that are imposed in the study:

- The initial vase life for each type of flower is 11 days.
- Capacities of hubs are assumed to be unlimited.
- Transporters are homogeneous with unlimited availability.
- Values of all parameters are deterministic while solving with the mathematical model.
- Values of all costs are always deterministic.
- Process time, buffering time, and temperature during the transport and processing can be uncertain in the simulation model, and they follow the normal distribution.

C. Mathematical Model

This section outlines the mathematical model developed for designing a logistics and supply chain network tailored to the distribution of perishable products. The MILP model aims to minimize the total costs of the network by determining optimal hub locations, assigning processes, and planning product flows.

Indices and sets:

$g \in G$ set of growers

$r \in R$ set of retailers

$i, j \in H$ set of hubs

$p, q \in P$ set of products (flowers and bouquets)

P_p set of input products for the process that produces product p (flowers)

Decision Variables:

Y_i hub open or not

Y_{ip} process producing product p installed at hub i or not (1 if $X_{ip} > 0$, 0 otherwise)

XG_{gip} quantity of product p transported from grower g to hub i (flowers)

XH_{ijp} quantity of product p transported from hub i to hub j (flowers/bouquets)

XR_{irp} quantity of product p transported from hub i to retailer r (bouquets)

X_{ip} quantity of product p produced at hub i (bouquets)

Auxiliary variables:

$ZH_{ijp} = TTSH_{ip} YH_{ijp}$

$ZR_{irp} = TTSH_{ip} YR_{irp}$

$Z_{iqp} = TTSH_{ip} Y_{ip}$

Parameters:

fc_i fixed costs for opening hub i (\$)

fc_{ip} fixed costs for installing the process producing product p at hub i (\$)

cg_{gip} unit transportation costs of product p from grower g to hub i (\$)

ch_{irp} unit transportation costs of product p from hub i to hub r (\$)

cr_{irp} unit transportation cost of product p from hub i to retailer r (\$)

c_{ip} unit production costs of product p at hub i (\$)

sup_{gp} supply of product by grower g to hub i (flowers)

dem_{rp} demand of product p by retailer r (flowers)

m_{pq} quantity of product p in one unit of product q (flowers)

tts_{gip} TTS for transporting product p from grower g to hub i (degree-days)

tts_{hijp} TTS for transporting product p from hub i to hub j (degree-days)

tts_{irp} TTS for transporting product p from hub i to retailer r (degree-days)

tts_{ip} TTS for producing product p at hub i (degree-days)

tts_{bip} TTS for buffer of product p at hub i (degree-days)

$maxtts_{rp}$ maximum TTS to have good quality of product p at retailer r (degree-days)

up_{ip} upper bound of $TTSH_{ip}$ (degree-days)

$$\min \sum_{i \in H} fc_i Y_i + \sum_{i \in H} \sum_{p \in P} fc_{ip} Y_{ip} + \sum_{g \in G} \sum_{i \in H} \sum_{p \in P} cg_{gip} XG_{gip} + \sum_{i \in H} \sum_{j \in H} \sum_{p \in P} ch_{ijp} XH_{ijp} + \sum_{i \in H} \sum_{r \in R} \sum_{p \in P} cr_{irp} XR_{irp} + \sum_{i \in H} \sum_{p \in P} c_{ip} X_{ip} \quad (1)$$

s.t.

$$\sum_{i \in H} XG_{gip} = sup_{gp} \quad \forall g, p \quad (2)$$

$$\sum_{i \in H} XR_{irp} = dem_{rp} \quad \forall r, p \quad (3)$$

$$\sum_{g \in G} XG_{gip} + \sum_{j \in H} XH_{jip} + X_{ip} = \sum_{j \in H} XH_{jip} + \sum_{r \in R} XR_{irp} + \sum_{q \in P} m_{gq} \quad \forall i \in H, p \in P \quad (4)$$

$$\sum_{g \in G} \sum_{p \in P} XG_{gip} + \sum_{j \in H} \sum_{p \in P} XH_{jip} + \sum_{p \in P} X_{ip} \leq [\sum_{g \in G} \sum_{p \in P} sup_{gp}] Y_i \quad \forall i \quad (5)$$

$$X_{ip} \leq \sum_{g \in G} sup_{gp} Y_{ip} \quad \forall i, p \quad (6)$$

$$Y_i \in \{0, 1\} \quad \forall i \quad (7)$$

$$Y_{ip} \in \{0, 1\} \quad \forall i, p \quad (8)$$

$$XG_{gip} \geq 0 \quad \forall g, i, p \quad (9)$$

$$XH_{ijp} \geq 0 \quad \forall i, j, p \quad (10)$$

$$XR_{irp} \geq 0 \quad \forall i, r, p \quad (11)$$

$$X_{ip} \geq 0 \quad \forall i, p \quad (12)$$

Equation (1) is to minimize total costs consisting of fixed location, process costs, transportation costs, and variable costs. Equation (2) ensures that the total amount of product p shipped from grower g to all hubs equals the grower's supply for that product. Equation (3) states that the total quantity of product p delivered from hubs to each retailer r must meet the retailer's demand. Equation (4) maintains the flow balance at each hub i for every product p . The total amount of product p entering the hub, whether from growers, other hubs, or as a result of local processing, must equal the amount leaving the hub, either to another hub, to a retailer, or to another process as an input. Equation (5) ensures that product flows through a hub only occur if the hub is opened. Equation (6) ensures that production can only take place if the

related process is installed. Equations (7) - (12) define binary and non-negative variables.

$$TTSR_{rp} = \sum_{r \in R} (TTS_{ip} + ttsr_{ip}) YR_{irp} \quad \forall i, p \quad (13)$$

Equation (13) calculates the total TTS for product p delivered to retailer r . This value represents the total exposure of a product to temperature over time from its point of origin until it reaches the retailer. Subsequently, there are 3 possible ways to get product to hub :

$$1. TTS_{ip}^{grower} = \sum_{g \in G} (tts_{gip} + ttsb_{ip}) YG_{gip} \quad \forall i, p \quad (14)$$

Equation (14) calculates the TTS of product p arriving at hub i when it is delivered directly from a grower g . This TTS includes the time-temperature exposure during transport from the grower to the hub and the buffering time at the hub.

$$2. TTS_{ip}^{hub} = \sum_{j \in G} (TTS_{jip} + tsh_{jip} + ttsb_{ip}) YH_{jip} \quad \forall i, p \quad (15)$$

Equation (15) represents the TTS of product p arriving at hub i when it is sent from another hub j . The total TTS includes the TTS already accumulated at hub j , the transport TTS between hubs j and i , and the buffer time at hub i .

$$3. TTS_{ip}^{process} = \sum_{q \in P_p} (TTS_{ip} + tsh_{ip} + ttsb_{ip}) Y_{ip} \quad \forall i, p \quad (16)$$

Equation (16) covers the case where product p is produced at hub i through a process. The TTS in this case includes the TTS of the input product q at hub i , the processing time at the hub, and the buffering time at hub i .

$$TTS_{ip} = \max[TTS_{ip}^{grower}, TTS_{ip}^{hub}, TTS_{ip}^{process}] \quad (17)$$

Equation (17) defines the TTS at hub i for product p . This value captures the maximum TTS among all possible ways product p can arrive at hub i .

$$(TTS_{ip} + ttsr_{ip}) YR_{irp} \leq \max tts_{rp} \quad \forall i, r, p \quad (18)$$

Equation (18) ensures that the total TTS for product p delivered to retailer r must be lower than or equal to the maximum allowance TTS at retailer r for product p .

$$(tts_{gip} + ttsb_{ip}) YG_{gip} \leq TTS_{ip} \quad \forall g, i, p \quad (19)$$

Equation (19) states that the sum of transport and buffering TTS from grower g to hub i is less than or equal to the maximum TTS at hub i .

$$(TTS_{jip} + tsh_{jip} + ttsb_{ip}) YH_{jip} \leq TTS_{ip} \quad \forall i, j, p \quad (20)$$

Equation (20) addresses the scenario where product p is transferred from hub j to hub i , including buffering time must be lower than or equal to the maximum TTS at hub i .

$$(TTS_{ip} + tsh_{ip} + ttsb_{ip}) Y_{ip} \leq TTS_{ip} \quad \forall i, p \quad (21)$$

Equation (21) ensures that TTS of the output product, which are TTS of input product q , processing time and buffering time at hub i should be less than or equal to maximum TTS at hub i .

Equations (18), (20) and (21) are non-linear since they contain the products of binary and bounded non-negative variables. To eliminate multiplications of binary and bounded non-negative variables (18), (20) and (21), those equations translate to (22) - (25), (26) - (29) and (30) - (33), respectively:

$$ZR_{irp} + ttsr_{ip} YR_{irp} \leq \max tts_{rp} \quad \forall i, r, p \quad (22)$$

$$ZR_{irp} \leq YR_{irp} up_{ip} \quad \forall i, r, p \quad (23)$$

$$ZR_{irp} \leq TTS_{ip} up_{ip} \quad \forall i, r, p \quad (24)$$

$$ZR_{irp} \leq TTS_{ip} - (1 - YR_{irp}) up_{ip} \quad \forall i, r, p \quad (25)$$

$$ZH_{jip} + (tsh_{jip} + ttsb_{ip}) YH_{jip} \leq TTS_{ip} \quad \forall i, j, p \quad (26)$$

$$ZH_{jip} \leq YH_{jip} up_{jp} \quad \forall i, j, p \quad (27)$$

$$ZH_{jip} \leq TTS_{jp} \quad \forall i, j, p \quad (28)$$

$$ZH_{jip} \leq TTS_{jp} - (1 - YH_{jip}) up_{jp} \quad \forall i, j, p \quad (29)$$

$$Z_{iqp} + (tts_{ip} + ttsb_{ip}) Y_{ip} \leq TTS_{ip} \quad \forall i, p, q \quad (30)$$

$$Z_{iqp} \leq Y_{ip} up_{iq} \quad \forall i, q, p \quad (31)$$

$$Z_{iqp} \leq TTS_{jq} \quad \forall i, p, q \quad (32)$$

$$Z_{iqp} \leq TTS_{jq} - (1 - Y_{ip}) up_{iq} \quad \forall i, p, q \quad (33)$$

D. Simulation Model

The Discrete Event Simulation (DES) model, which is built in ARENA, is used to evaluate whether the logistics and supply chain network design meets customer requirements. The model follows the actual flow of individual products from growers to retailers and checks their quality upon delivery. Unlike the MILP model, the simulation captures detailed dynamics such as delays and temperature variations during transport and processing. For the base scenario, all uncertainties follow a normal distribution with their estimated means as the mean and standard deviations set at 7% of their means. However, different levels of each uncertainty will be further explored in the sensitivity analysis to assess their impact. The objective of the simulation is to test the feasibility of the network design proposed by the MILP model, with a focus on product quality. It simulates the real-world operation of the supply chain, including transport, buffering, and processing activities. The scope of the model covers the entire flow from the growers to the retailers, incorporating the effects of uncertainty in supply times, process durations, transport delays, and temperature conditions. It also evaluates whether products meet the minimum vase life required by each retailer.

The simulation model operates by tracing each product unit through the network. Each product is assigned key attributes such as current vase life, temperature exposure, and time spent at each stage. The model begins with growers generating daily supplies of flower types, which are transported to assigned hubs. At these hubs, products may be stored temporarily in buffers or processed into final forms, such as mixed bouquets. Bouquet-making processes

at the hubs begin only after all required input flows have arrived, in accordance with the proportions defined in the MILP solution. After processing, products are sent to retailers.

FIFO (First-In-First-Out) logic is used for buffering, and the model applies randomness to process durations, transport delays, and temperature conditions. It dynamically updates product quality using the degree-days model at each step. Each retailer specifies a minimum vase life and a target service level, which defines the percentage of deliveries that must meet the vase life requirement. At the end of a simulation run, the achieved service level for each retailer-product pair is computed by comparing actual delivery quality against these thresholds. The model is designed to be a terminating system, with 10 replications representing a 45-day operational cycle each. Across 10 replications, the variation in the objective value (total costs) is 3.68% relative to its mean.

E. Hybrid Optimization-Simulation Approach

This section introduces the HOS approach, which connects the MILP model with the simulation model. In this framework, as shown in Fig. 3, the MILP model is first used to generate an optimal network configuration that satisfies cost and quality constraints, including Time–Temperature–Sum (TTS) thresholds. The resulting solution—specifying facility locations, flow allocations, and process assignments—is then tested in the DES model to assess whether it meets the required service levels under operational uncertainty. The simulation captures real-world variability, such as delays and

temperature fluctuations, and calculates the actual vase life of delivered products. If the simulation indicates that quality targets are not met, the feedback is used to iteratively adjust the maximum TTS constraints in the MILP model based on required quality (β_{rp}) and realized quality (γ_{rp}): $\maxtts_{rp} * \gamma_{rp} / \beta_{rp}$. For example, if the realized quality, which is the actual service level obtained from the simulation is, 87% in an iteration, and the required quality (which is the required service level of the retailer is 95%) and $\maxtts_{rp}$ (which is the maximum TTS of product p at retailer r) is 100 degree-days and the Vase Life (VL) of 6 days, the new $\maxtts_{rp}$ would be $\frac{0.87}{0.95} * \maxtts_{rp} = 91.58$ degree-days. From $VL = A - \frac{1}{20} TTS$, A is the initial vase life (which is set at 11 days), so the new tightening VL would be 6.42 days. This VL duration exceeds the maximum of 6 days. Such an adjustment enables the system to accept higher-quality products by expanding the acceptance level for Vase Life (VL). As a result, the system will respond by finding an alternative route that is quicker and can accommodate a longer VL, but the cost could be higher than the route from the previous iteration.

This loop continues until the proposed network design satisfies both cost-efficiency and customer requirements under dynamic conditions. Although the MILP model ensures feasibility based on predefined constraints, the solution may become infeasible. A key reason for this infeasibility is that no available route or network configuration in the current solution can keep the TTS below the required maximum. This integration allows the strengths of both methods to be leveraged: MILP provides optimal planning, while DES ensures feasibility and robustness in execution.

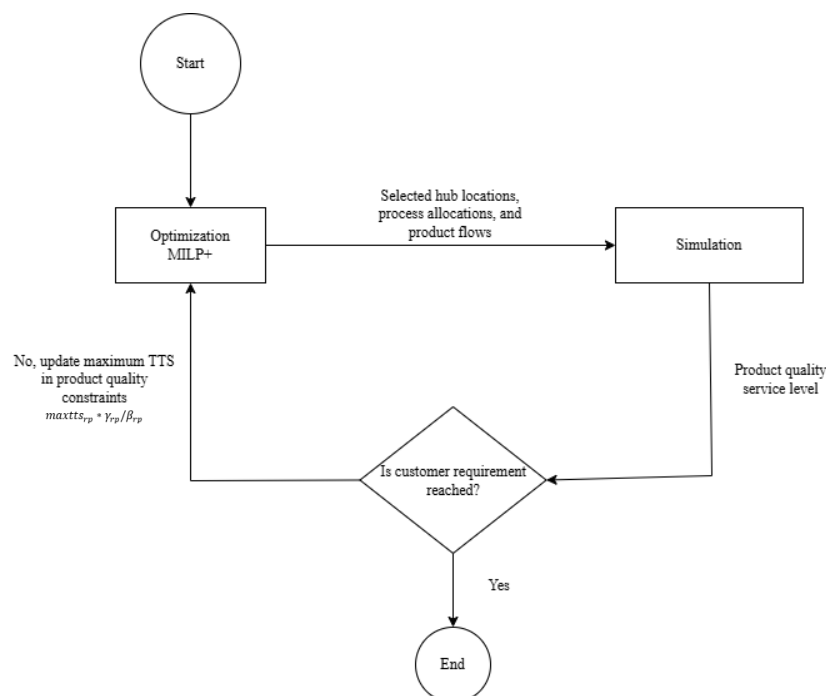


Fig. 3. HOS approach

F. Simulation-Based Optimization with OptQuest (SBO)

Simulation-Based Optimization (SBO) with OptQuest is a technique that combines DES with metaheuristic search algorithms to optimize decision variables within a stochastic environment. In this study, OptQuest—integrated within the ARENA simulation platform—is used to identify network configurations that minimize total costs while maintaining required service levels for customer requirements. The approach evaluates the performance of each solution through simulation runs, capturing the effects of randomness in processing times, buffering durations, and temperature conditions, which directly influence product freshness. OptQuest iteratively explores different combinations of hub selections and allocations of bouquet-making processes using heuristic methods. This method is particularly useful in complex systems where analytical models may not fully capture the operational dynamics, making it a practical tool for improving supply chain performance under real-world variability. In this research, SBO is used as a benchmark to assess and validate the performance of other proposed solutions.

IV RESULTS AND DISCUSSION

This section presents the findings from the experiments using the MILP, Simulation-Based Optimization (SBO), and Hybrid Optimization–Simulation (HOS) approach. The goal is to evaluate how each method performs under uncertainty, especially in terms of cost, quality, and service level. The results are divided into three parts. First, the base scenario shows how the HOS model improves through multiple iterations. Then, a comparison is made between HOS, MILP (ideal case), and SBO to show their differences in both financial performance and the network structure. Finally, a sensitivity analysis is conducted to understand how different levels of uncertainty affect the network design and total costs.

A. Base Scenario's Results

This section presents the outcomes from applying three approaches—MILP, SBO, and Hybrid Optimization–Simulation (HOS)—under uncertainty set in the base case, where all uncertain parameters are set to fluctuate with a standard deviation at 7% from their means, normally distributed. Uncertainty is introduced in three key areas: processing time, buffering time, and temperature, all of which directly affect the freshness and quality of perishable products. The evaluation focuses on total cost performance while maintaining product quality and service-level requirements over a simulated 45-day operational period. The cost results and obtained service levels are summarized in Tables V–VII.

In the first iteration of HOS (see Table V), the total cost is \$186,827, comprising \$62,300 in production cost, \$84,527 in transportation cost, \$30,000 in hub fixed cost, and \$10,000 in process fixed cost. However, despite satisfying the mathematical constraints of the MILP model, this solution does not meet the required service levels in the simulation due to variability in process delay and temperature exposure affecting the vase life of flowers (see Tables VI–VII).

In response, the HOS framework is executed iteratively to refine the MILP solution by adjusting the Time-Temperature Sum (TTS) constraints. Over five iterations (see Table V), the total costs gradually increase—from \$186,827 in the first iteration to \$191,547 in the fifth iteration—as the model compensates for uncertainty by selecting more robust hub configurations and adjusting the transportation flows. While production and process costs remained constant across all iterations, changes in hub selection and route assignments led to variations in transportation and fixed hub costs. Notably, the hub fixed cost drops to \$20,000 during Iterations 3 and 4 due to fewer hubs being activated, though this is counterbalanced by higher transportation costs during those iterations.

TABLE V
COST OF THE HYBRID APPROACH IN THE BASE SCENARIO

Value (\$)	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Total Costs	186,827	188,173	189,645	189,645	191,547
Production Cost	62,300	62,300	62,300	62,300	62,300
Transportation Cost	84,527	85,873	97,345	97,345	89,247
Hub Fixed Cost	30,000	30,000	20,000	20,000	30,000
Process Fixed Cost	10,000	10,000	10,000	10,000	10,000

TABLE VI
ACTUAL VS. REQUIRED SERVICE LEVEL (MONO BOUQUET)

Retailer	Required Service Level (%)	Actual Service Level (%)				
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Retailer 1	90%	92.4%	94.6%	95.5%	95.5%	96.8%
Retailer 2	95%	91.6%	93.2%	96.8%	96.8%	97.2%
Retailer 3	90%	92.2%	94.3%	95.1%	95.1%	97.9%
Retailer 4	95%	91.4%	93.1%	95.4%	95.4%	96.1%
Retailer 5	95%	91.8%	92.7%	94.6%	94.6%	95.4%
Retailer 6	95%	92.7%	93.5%	95.7%	95.7%	96.2%
Retailer 7	90%	89.7%	91.6%	93.4%	93.4%	95.4%
Retailer 8	95%	90.1%	91.5%	93.7%	93.7%	95.3%
Retailer 9	90%	92.5%	94.8%	96.1%	96.1%	96.7%
Retailer 10	90%	91.9%	93.5%	96.7%	96.7%	97.6%

Note: Highlighted results show the unsatisfied service level at the retailers

TABLE VII
ACTUAL VS. REQUIRED SERVICE LEVEL (MIXED BOUQUET)

Retailer	Required Service Level (%)	Actual Service Level (%)				
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Retailer 1	90%	90.7%	91.2%	93.7%	93.7%	96.4%
Retailer 2	95%	89.4%	92.1%	94.5%	94.5%	96.1%
Retailer 3	90%	90.1%	91.9%	92.2%	92.2%	95.2%
Retailer 4	95%	84.3%	87.9%	92.6%	92.6%	95.5%
Retailer 5	95%	81.2%	85.3%	89.1%	89.1%	95.1%
Retailer 6	95%	83.8%	89.7%	92.5%	92.5%	95.6%
Retailer 7	90%	86.7%	89.4%	91.3%	91.3%	96.1%
Retailer 8	95%	89.8%	91.6%	94.5%	94.5%	96.6%
Retailer 9	90%	91.2%	92.4%	92.7%	92.7%	94.8%
Retailer 10	90%	87.1%	90.2%	93.5%	93.5%	94.7%

Note: Highlighted results show the unsatisfied service level at the retailers

B. Comparison of Hybrid Approach with MILP (ideal case) and SBO as a Benchmark

After analyzing the base scenario using the HOS approach, it is important to compare its performance with other commonly used methods. This helps assess whether the additional complexity and effort of the HOS framework yield better solutions for managing a perishable supply chain. Two other approaches are used for comparison: the MILP model under ideal conditions (without uncertainty) and SBO, which searches for an optimal or near-optimal solution under uncertainty but does not explicitly include perishability constraints. By comparing these three methods, we can better understand the trade-offs between cost, solution quality, and reliability in uncertain environments.

Table VIII shows the total costs and cost components for the MILP (ideal case), SBO, and Hybrid Optimization–Simulation (HOS) approaches. As expected, the MILP model produces the lowest total costs at \$163,418, with the production cost fixed at \$62,300, the transportation cost at \$61,118, the hub fixed cost at \$30,000, and the process fixed cost at \$10,000. However, this solution is created without considering any uncertainty. The SBO approach yields the highest total cost of \$201,172. While the production and process costs remain the same as the other methods, the transportation cost increased to \$98,872. In contrast, the HOS method shows total costs of \$191,547. This solution keeps the production and process costs constant at \$62,300 and \$10,000, respectively, and returns to using three hubs, resulting

in a hub fixed cost of \$30,000. However, the transportation cost increases to \$89,247, reflecting changes made to handle uncertainty while maintaining quality. Overall, Table VIII highlights how each approach allocates costs differently under uncertainty and how HOS offers a more balanced trade-off between cost and quality performance.

Table IX presents the selected hub and process locations from each method. Both the MILP and the HOS solution choose the same configuration: Hubs 1, 2, and 7 are opened, and bouquet-making processes are installed at hubs 1 and 2. This configuration reflects a cost-efficient and quality-aware strategy. As shown in Table IV, the transportation cost for one bouquet is lower than transporting the equivalent volume of unassembled flowers (see Table IV). For example, a mixed bouquet requires multiple flower types, and transporting those individually incurs higher cumulative costs. In contrast, once these flowers are assembled into a single bouquet, they can be shipped as a single unit at a lower rate per bouquet. Therefore, the model favors performing the bouquet-making process early in the network—at hubs 1 and 2—near the growers. This reduces the total transportation cost by avoiding multiple flower shipments to downstream hubs. After assembly, the finished bouquets are sent to hub 7, which acts as a distribution hub. Table IX

indicates that the HOS method can maintain the original structure from the MILP model while still meeting customer requirements under uncertainty, through TTS refinement and simulation feedback. In contrast, the SBO solution activates hub 6 instead of hub 7 to reduce delivery cost and temperature exposure.

Table X shows the computation times from the three methods: MILP (ideal case), Simulation-Based Optimization (SBO), and Hybrid Optimization–Simulation (HOS). The MILP model requires only 5 seconds to compute because it operates under ideal, deterministic conditions and does not account for uncertainty or simulation feedback. In contrast, the SBO approach takes 5,842 seconds due to its reliance on multiple simulation runs and a metaheuristic search process to evaluate solutions under uncertainty. The HOS approach, which integrates optimization and simulation in an iterative feedback loop, requires 3,981 seconds—slightly less than SBO—because it begins with a MILP solution and refines it based on the simulation results. This makes HOS more computationally efficient than SBO while still addressing the uncertainty, offering a balanced trade-off between accuracy and efficiency in designing resilient supply chain networks for perishable products.

TABLE VIII
COST OF MILP, SBO, AND HYBRID APPROACH

Value (\$)	MILP (Ideal Case)	SBO	Hybrid Approach
Total Costs	163,418	201,172	191,547
Production Cost	62,300	62,300	62,300
Transportation Cost	61,118	98,872	89,247
Hub Fixed Cost	30,000	30,000	30,000
Process Fixed Cost	10,000	10,000	10,000

TABLE IX
OPTIMAL HUB AND PROCESS LOCATION OF MILP, SBO, AND HYBRID APPROACH

Location	MILP (Ideal Case)	SBO	Hybrid Approach
Hub Location	1,2,7	1,2,6	1,2,7
Process Location	1,2	1,2	1,2

TABLE X
COMPUTATION TIMES OF MILP, SBO, AND HYBRID APPROACH

Computation Performance	MILP (Ideal Case)	SBO	Hybrid Approach
Computation Time (Seconds)	5	5,842	3,981
Number of Iterations	-	22	5

Note: All models were run on a laptop with 13th Gen Intel(R) Core (TM) i7-13620H (2.40 GHz)

C. Sensitivity Analysis on the Uncertainty

This section looks into how different levels of uncertainty affect the results of the Hybrid Optimization–Simulation (HOS) approach. Five levels of uncertainty are tested: 0%, 3%, 7% (base scenario), 10%, and 15%, which are fluctuated from the means of all processing time, buffering time, and temperature under the normal distribution. Table XI and Fig. 4 show the total costs and cost breakdown at each level. When there is no uncertainty (0%), the total costs are \$163,418. As uncertainty increases, the total costs also increase. At a 3% uncertainty, the cost rises to \$183,873, and at a 7% uncertainty, it increases to \$191,547. When uncertainty reaches 10%, the cost is \$202,878. This increase is mostly due to a higher transportation cost, which goes from \$61,118 at 0% to \$90,578 at 10%. This happens because more effort is needed to keep products fresh and meet delivery times under uncertain conditions. Other cost components also change. The hub fixed cost increases from \$30,000 to \$40,000 when more hubs are opened to reduce travel distance and protect quality. Additionally, the number of iterations required by the HOS approach also increases with the uncertainty, as more feedback cycles between optimization and simulation are needed to adjust the TTS constraints and find a feasible solution that meets quality and service level requirements. At the 15% uncertainty level, the model becomes infeasible due to the absence of any viable routing configuration that can maintain

the TTS within the maximum allowable threshold. This indicates that, under such high variability in processing times, buffering durations, and temperature conditions, the network is unable to ensure product quality standards, as no available path satisfies the TTS constraints required to preserve the minimum vase life at the retailer.

Table XII shows the hub and process locations for each level of uncertainty. For 0%, 3%, and 7% levels, the selected hubs are 1, 2, and 7, with processes at hubs 1 and 2. However, when the uncertainty level rises to 10%, the model adds hub 6 to the network, resulting in four active hubs: 1, 2, 6, and 7, while still keeping the bouquet-making processes limited to hubs 1 and 2. As uncertainty increases, longer processing and buffering times, along with more variable temperatures, lead to higher TTS values, increasing the risk of product deterioration. By adding hub 6, the model reduces transportation distances for certain routes and distributes product flows across more facilities. This shows that as the uncertainty increases, the model adds more hubs to handle the extra delays and risks.

In summary, the HOS model adjusts the supply chain setup to deal with higher uncertainty. When there is more variation in process time, buffering, and temperature, the model changes the network by opening more hubs. These changes help protect product quality and service levels, even though they increase the total costs.

TABLE XI
RESULT OF THE SENSITIVITY ANALYSIS ON THE UNCERTAINTY

Value (\$)	Standard Deviation of Uncertainty				
	0%	3%	7% (base scenario)	10%	15%
Total Costs	163,418	183,873	191,547	202,878	Infeasible
Production Cost	62,300	62,300	62,300	62,300	-
Transportation Cost	61,118	81,573	89,247	90,578	-
Hub Fixed Cost	30,000	30,000	30,000	40,000	-
Process Fixed Cost	10,000	10,000	10,000	10,000	-
Number of Iterations	-	5	5	9	-

TABLE XII
OPTIMAL HUB AND PROCESS LOCATION ON VARIES UNCERTAINTY

Location	Standard Deviation of Uncertainty				
	0%	3%	7% (Base Scenario)	10%	15%
Hub Location	1,2,7	1,2,7	1,2,7	1,2,6,7	Infeasible
Process Location	1,2	1,2	1,2	1,2	Infeasible

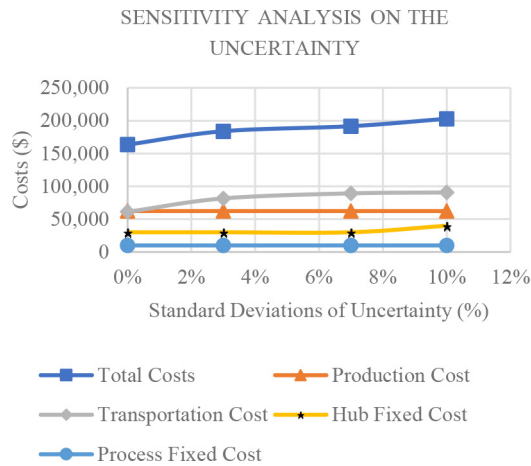


Fig. 4. Sensitivity analysis on the uncertainty

V. MANAGERIAL IMPLICATIONS

This study offered several important insights for supply chain managers handling perishable products such as cut flowers. Firstly, the proposed HOS approach demonstrated how integrating optimization with simulation could produce more resilient and quality-preserving logistics networks under real-world uncertainty. Managers can use this framework to balance cost efficiency with the required service level and product freshness, particularly when traditional optimization models fail to capture dynamic variability in processing time, buffering delays, and temperature fluctuations.

Secondly, the results highlighted the importance of carefully selecting hub locations and process allocations. When uncertainty is within manageable levels, the HOS approach can adjust the network configuration to preserve product quality while minimizing costs. However, when uncertainty exceeds a certain threshold—as observed at the 15% level in the sensitivity analysis—the model fails to find a feasible solution that satisfies quality and service level requirements. This outcome is particularly valuable for managers, as it signals the operational limits of the current supply chain design.

Finally, by comparing the HOS approach with MILP and SBO solutions, managers are better equipped to understand the trade-offs between cost, quality, and operational flexibility. This supports more informed strategic planning in perishable supply chains, especially in environments characterized by high uncertainty and tight quality requirements.

VI. CONCLUSION AND FURTHER STUDY

The study proposed a Hybrid Optimization–Simulation (HOS) approach for designing a logistics network for perishable products, focusing on a fresh floricultural supply chain. The HOS method combined a MILP model, which includes Time-Temperature Sum (TTS) constraints, with a DES model that tests

whether the network can maintain product freshness and meet the service level targets under uncertainty. The findings revealed that while the initial MILP solution could meet cost and quality requirements in a deterministic setting, it failed to maintain service levels when subjected to variability in processing time, buffering delays, and temperature exposure. Through iterative refinement, the HOS approach successfully adjusted TTS constraints and reconfigured network decisions—such as hub selection and product routing—to restore feasibility and ensure product freshness across all retailers. Compared to other methods, the HOS framework demonstrated a more balanced performance. While MILP could provide the lowest cost, it did not include any uncertainty. The SBO method accounted for uncertainty but required more computational effort and iteration cycles. In contrast, the HOS approach leveraged the strengths of both optimization and simulation, producing a feasible and quality-assured solution while maintaining reasonable computational efficiency.

The sensitivity analysis on different levels of uncertainty confirmed that as uncertainty increased, the total costs and complexity of the network also increased. The model responded by opening more hubs to keep the supply chain flexible and protect product freshness. Additionally, higher levels of uncertainty led to an increase in the number of required iterations within the HOS framework, as more adjustment cycles were needed to refine the Time-Temperature Sum (TTS) constraints and meet the quality and service level requirements. This iterative process allowed the model to gradually adapt the network configuration in response to dynamic conditions, demonstrating the capability of the HOS framework to handle uncertainty through repeated optimization and simulation feedback. However, beyond a certain level of uncertainty, the model could no longer generate feasible solutions, signaling the operational limits of the current supply chain design under extreme variability. These findings highlighted the usefulness of HOS for planning perishable supply chains in uncertain environments.

However, the proposed HOS model still has some limitations. It assumed unlimited hub capacity and homogeneous transporters, which might not reflect real-world operational constraints. In addition, the uncertainty in the simulation was only limited to the normal distribution, whereas real perishable supply chains may face non-normal or correlated variations. Furthermore, this framework focused solely on minimizing total costs without explicitly considering other objectives, such as waste reduction, environmental impact, or service responsiveness. Once these objectives are considered simultaneously, the problem becomes a multi-objective optimization problem.

Overall, the HOS framework proved effective in designing resilient supply chain networks that account

for both cost and quality under realistic conditions. It enabled decision-makers to plan logistics strategies that were not only efficient but also responsive to uncertainty. For further study, future work could explore other types of hybrid approaches to improve solution quality and computational performance. For example, combining metaheuristic algorithms with simulation or integrating reinforcement learning with optimization may help the model adapt faster to changing conditions. In addition, incorporating multi-objective optimization—such as minimizing both cost and number of disposed products—can offer a more complete view of trade-offs in decision-making. These improvements would enhance the flexibility and applicability of the framework in real-world perishable supply chains across different industries.

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REFERENCES

- [1] M. De Keizer, R. Haijema, J. M. Bloemhof, and J. G. A. J. van der Vorst, "Hybrid optimization and simulation to design a logistics network for distributing perishable products," *Comput. Ind. Eng.*, vol. 88, pp. 26-38, Aug. 2015.
- [2] M. Musavi and A. Bozorgi-Amiri, "A multi-objective sustainable hub location-scheduling problem for perishable food supply chain," *Comput. Ind. Eng.*, vol. 113, pp. 766-778, Nov. 2017.
- [3] A. Rong, R. Akkerman, and M. Grunow, "An optimization approach for managing fresh food quality throughout the supply chain," *Int. J. Prod. Econ.*, vol. 131, no. 1, pp. 421-429, Aug. 2011.
- [4] J. Pasha and P. Ghasemi, "A robust possibilistic programming approach for green closed-loop supply chain network design under hybrid uncertainty," *Comput. Ind. Eng.*, vol. 160, no. 107609, Oct. 2021.
- [5] D. Agustina, C. K. M. Lee, and R. Piplani, "Managing perishability in production-distribution planning: A discussion and review," *Flexible Serv. Manuf. J.*, vol. 25, no. 3, pp. 389-413, Sep. 2013.
- [6] F. Mohebalizadehgashti, H. Zolfagharinia, and S. H. Amin, "Designing a green meat supply chain network: A multi-objective approach," *Int. J. Prod. Econ.*, vol. 219, pp. 312-327, Jan. 2020.
- [7] Z. Mohammadi, F. Barzinpour, and E. Teimoury, "A location-inventory model for the sustainable supply chain of perishable products based on pricing and replenishment decisions: A case study," *PLoS One*, vol. 18, no. 7, no. e0288915, Jul. 2023.
- [8] S. Shirzadi, V. Ghezavati, R. Tavakkoli-Moghaddam, and S. Ebrahimnejad, "Developing a green and bipolar fuzzy inventory-routing model in agri-food reverse logistics with postharvest behavior," *Environ. Sci. Pollut. Res.*, vol. 28, no. 38, pp. 53103-53125, Mar. 2021.
- [9] L. Pan, M. Shan, and L. Li, "Optimizing perishable product supply chain network using hybrid metaheuristic algorithms," *Sustainability*, vol. 15, no. 13, no. 10711, Jul. 2023.
- [10] D. Nakandala, H. Lau, and J. Zhang, "Cost-optimization modelling for fresh food quality and transportation," *Ind. Manag. Data Syst.*, vol. 116, no. 3, pp. 564-583, Apr. 2016.
- [11] C. Sel and B. Bilgen, "A mixed integer linear programming model for the design of the capacitated multi-echelon, multi-product closed-loop supply chain," *J. Cleaner Prod.*, vol. 79, pp. 116-135, Aug. 2014.
- [12] Á. J. Ásmundsson, R. J. Linn, R. A. Jacobs, and E. L. Moore, "A practical approach to linking tactical and operational planning in the supply chain," *Decis. Sci.*, vol. 37, no. 4, pp. 559-582, Feb. 2006.
- [13] G. M. Gaukler, "The value of time and temperature history information for perishable food in logistics," *Int. J. Prod. Econ.*, vol. 259, no. 108885, May 2023.
- [14] H. Ding, L. Benyoucef, and X. Xie, "A simulation optimization method for supplier selection and order allocation," *Int. J. Prod. Econ.*, vol. 120, no. 1, pp. 171-182, Mar. 2009.
- [15] H. J. Ko, C. S. Ko, and T. Kim, "A hybrid optimization/simulation approach for a distribution network design of 3PLs," *Comput. Ind. Eng.*, vol. 50, no. 4, pp. 440-449, Aug. 2006.
- [16] M. Abbasian, Z. Sazvar, and M. M. Mohammadisiahroudi, "A hybrid optimization method to design a sustainable resilient supply chain in a perishable food industry," *Environ. Sci. Pollut. Res.*, vol. 30, pp. 6080-6103, Feb. 2023.
- [17] S. -O. Tromp, R. G. M. van der Sman, H. M. Vollebregt, and E. J. Woltering, "On the prediction of the remaining vase life of cut roses," *Postharvest Biol. Technol.*, vol. 70, pp. 42-50, Aug. 2012.



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