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Cold chain management in hierarchical operational hub networks

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Abstract

This paper proposes a multi-objective mixed-integer linear programming to model a cold chain with complementary operations on a hierarchical hub network. Central hubs are linked to each other in the first level of the network and to the star network of the lower-level hubs. As for a case study, different hub levels provide various refreshing or freezing operations to keep the perishable goods fresh along the network. Disruption is formulated by the consideration of stochastic demand and multi-level freshness time windows. Regarding the solution, a genetic algorithm is also developed and compared for competing the large-sized networks.

Keywords: Cold chain management (CCM), Hierarchical hub location problem, Operational hub, Perishable goods, Freshness time window

1. Introduction

The ultimate quality of a product is remarkably affected by how well organized logistics and transportation facilities have been managed. In perishable food industries, improper logistics can be the cause of up to one-third of spoilage (Rockefeller, 2013). Frozen foods such as fish, meat and poultry are identified as highly perishable foods, and continuous monitoring of temperature supports the real-time evaluation of product quality and specifies the remainder of its shelf life. It is well known that using a high-quality logistics system, the planners can achieve these goals.

The meat distribution crisis during the COVID-19 pandemic in the United States and prolonged waiting time of trucks to unload their goods into a distribution center validate the importance of an efficient distribution network and the lack of a proper one in today's fresh product distribution industry (ABC News, 2020).

This has motivated the academic and real business worlds to determine the concept of cold chain management (CCM) (Singh et al., 2017). CCM is defined as a series of managerial decisions taken in a supply chain (SC) to enhance customer value, including the temperature control operations for the perishable products

[⋆] Fully documented are available in the elsarticle package on Address.

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(Bogataj et al., 2005). Determining the location and type of operations for each facility is up to the hub location problems (HLPs) (Farahani et al., 2013).

HLP concerns the movement of goods, people, or information between origin-destination (O-D) demand nodes. Hubs in a network are facilities that consolidate, link, and switch nodes for flow between O-Ds. Although there are several studies on HLPs available in the existing literature, the consideration of both cold chain requirements and specificities of perishable products have yet to be matured. To the best of the authors' knowledge, there is no single study covering HLP mathematical modeling of the CCM concept.

Hub facilities in a network can reduce the transportation cost of each pair of nodes by considering a routing cost discount factor, α, between hubs (Yaman, 2009). In a hub, freights from various origins to a similar endpoint are consolidated into one shipment. There are single or multiple allocations of hub settings in the models (Alumur et al., 2012). In the former, one hub node connects to both the origin and the destination of the cargo, meaning the flow from its origin to the hub facility and then from that facility to the destination. In the latter, the freight circulates along the two assigned hub facilities located between the origin and destination. In this study, the design of the network considers the single allocation setting. The goal is to select P hubs among a group of predetermined demand nodes in order to minimize the transportation cost under indivisible demand; i.e. each demand node is assigned to a single hub facility.

The task of designing a network needs to pay specific attention to the perishable nature of goods, such as fruits, vegetables, seafood, meat, and dairy products, as it impacts both production and distribution activities (Amorim et al., 2012). The deterioration of these products may start in the early stages of production and span across the distribution system before reaching the customers. Perishability issues not only impact the company financially but may also result in customer dissatisfaction. It is worthy to mention that these products have a freshness time window about which all distributors are concerned (Tsiros and Heilman, 2005). Various cold chain operations, such as refreshing or freezing (depending on the product), are applied during transportation to avoid exceeding this window. For instance, in the transportation process of seafood with containers or airtight bags, it is suggested to freeze the products several times to avoid spoilage. This also works for frozen fruit and vegetables. Naturally, hubs, serving as gathering points of products, are the best place to provide the extra operations required for keeping the products fresh.

Kuo and Chen (2010) concede that a food cold chain logistics system includes three temperature monitoring categories; frozen food (below $-18°$C), chilled food ($-2°$C to $+7°$C), and fresh food (18°C constantly). They also categorize the transportation vehicles into equipped (e.g. refrigerated trucks) and non-equipped vehicles (e.g. ambient temperature trucks). In a logistics system with the equipped vehicles, the temperature can be kept constant during travel times. On the other hand, the non-equipped transportation system requires applying at least two complementary operations (i.e. refreshing and freezing operations) in the consolidation warehouses or hubs. Considering that the non-equipped system is more cost effective, we consider such a food cold chain in our HLP.

As this study is motivated by managing cold chain operations for frozen food industries, we consider a hierarchical hub network (Lin and Chen, 2004) with two level hubs distinguishing central hubs from low-level hubs. In the central hubs, both refreshing and freezing complementary operations can be performed whereas in the low level, only refreshing is allowed. We restrict the set of operations of the hubs due to underlying distribution times and costs. Figure 1 displays a hierarchical operational hub network with 15 demand nodes and five hubs, in which two of them are central hubs (hubs number 1 to 4, respectively).

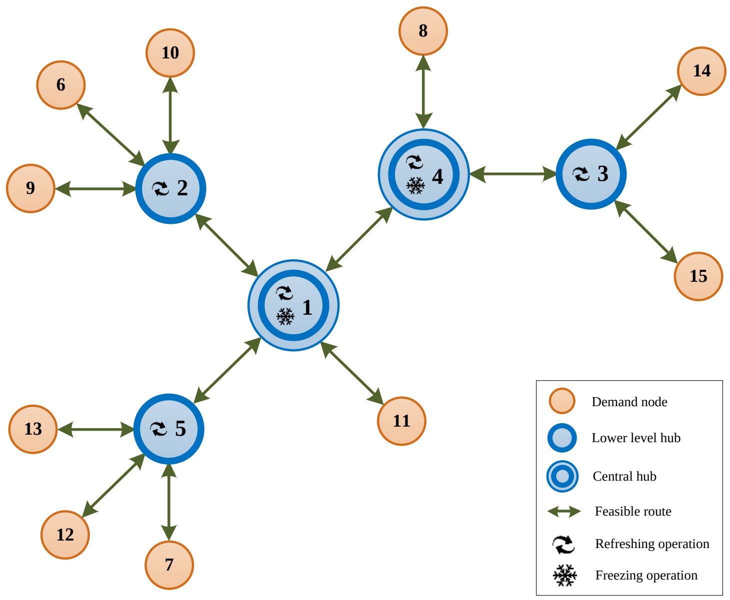

Figure 1: Hierarchical operational hub network with 15 nodes and five hubs, two of which are central hubs

In a cold chain, freshness is a primary concern for customers when buying a perishable product (Wu et al., 2018). Therefore, a complementary operations satisfaction rate is defined for the freshness of goods in every flow based on applied operations. The freshness of goods is traced along the network. Our model also examines the effectiveness of each freezing and refreshing operation. Besides freshness, (predetermined) delivery time windows significantly affect customer satisfaction, and consequently, are considered in the design of our hierarchical operational hub network (Wang et al., 2017). These windows must include loading, unloading and processing times at demand nodes and hubs. Minimizing total cost, optimizing delivery time, and providing a reliable distribution network are the main elements of any supply chain systems (Albashabsheh and Stamm, 2019; Hamdan and Diabat, 2020; Sabahi and Parast, 2020). While minimizing transportation time and cost is achievable through the traditional hierarchical hub location model, having a reliable distribution network is essential to define novel HLPs to handle the network uncertainties (An et al., 2015; Mohammadi et al., 2014).

The contribution of this paper to the literature is the inclusion of cold chain requirements in HLP models that considers both refreshing and freezing operations. Furthermore, we are the first to model the occurrence of disruptions in a cold chain network in which the demand of a pair of nodes is stochastic, and multiple freshness time windows are considered. Demand disruption will be mitigated by including stochasticity in the approach, while the freshness is maintained by the consideration of multiple time windows. Three levels of freshness time windows are introduced to apply the operations more precisely in the hubs. In a disruption situation, even when the operations are properly applied, the lack of suitable transportation vehicles could lead to ineffective refreshing operations. Since in our model the vehicles are assumed to not have refrigeration equipment, the probable disruption is mitigated by controlling the transportation time between each pair of nodes and matching them against the freshness time windows.

Several new HLPs are introduced to comply with the above features. To evaluate the effectiveness of the approach, a few examples are provided. Sensitivity analysis is conducted on the main parameters of the cold chain (such as discount factor, freshness time window, size of the network, and operations costs), delivering managerial insights. Finally, developing a solution algorithm based on the Genetic Algorithm and comparing its performance with a modified Feasibility Pump is another type of the contributions of the current study.

The rest of the paper is organized as follows: Section 2 reviews the most relevant studies available in the literature regarding HLP models and CCM. Section 3 introduces the base formulation of the proposed models, both under deterministic and stochastic settings. Section 4 develops realistic numerical examples to assess the validity and applicability of the models. Lastly, final remarks are presented in Section 6.

2. Literature review

HLPs are a dominant field of network design. In contrast to general network design problems in which the demand is supplied by a facility, the consideration of user to user/facility demands makes the HLPs more distinct and valuable (Ortiz-Astorquiza et al., 2018; Karimi-Mamaghan et al., 2020). Since the first introduction by O'Kelly (1987) and an evolutionary step by Campbell (1994), HLPs have been extensively studied (see the detailed survey studies in O'Kelly and Miller (1994); Alumur and Kara (2008); Campbell and O'Kelly (2012); Farahani et al. (2013); Laporte et al. (2015); Torkestani et al. (2016)). The studies acknowledge a variety of additional considerations in a hub network design, such as travel time and latest arrival time (Kara and Tansel, 2001), capacity-limited and queuing system in hubs (Rodriguez et al., 2007), measuring reliability (Kim and O'Kelly, 2009), incapacitated hubs (Contreras et al., 2011; Gelareh and Nickel, 2011), vehicle routing problem (Rodríguez-Martín et al., 2014), competitive and duopoly market (Mahmutogullari and Kara, 2016), mobility features for facilities (Bashiri et al., 2018), and green HLP (Dukkanci et al., 2019). Despite such valuable considerations in the HLPs, no research stream can be found on the treatment of perishable goods in hub networks. As a result, we review the relevant studies in two separate streams; 1) hierarchical setting of HLPs, aiming at finding important features of the hub network; 2) cold chain requirements for perishable goods flowing in the network.

2.1. Hierarchical hub location problems

The hierarchical HLP is a common type of hub problem introduced by Chou (1990). In a hierarchical HLP, facilities/users are interrelated in a top-down or bottom-up approach at various levels. To enhance the basic hierarchical HLP model, Lin and Chen (2004) propose a time-constrained hierarchical hub-and-spoke network design problem to provide a time-guaranteed delivery system and minimize operational costs by ascertaining the truck size and their trip schedules. Later, Yaman (2009) emphasizes the cost efficacy of the hierarchical hub models and proposes mixed integer programming (MIP) models by introducing a discount factor between the hubs and considering delivery time windows between every pair of nodes. They note that the routing cost between two hub nodes can be discounted at a rate (discount factor) to demonstrate the savings thanks to the hubs operations. In their model, the central hubs are fully connected to lower-level hubs by a single allocation design and are introduced as fully connected central hubs.

Table 1 summarizes the most important features considered in recent hierarchical HLP studies. As can be seen, the majority of the studies propose deterministic models. The main reason for this can be traced back to the potential drawbacks of traditional hub models. Based on the literature, although hub networks can provide a cost-efficacy network to cover a large group of the distant customers, its hub centers are vulnerable to disruptions (Rushton et al., 2014; Wonnacott, 1996). However, Farahani et al. (2013) concede that the consideration of uncertainty or stochasticity is more realistic. Managing unexpected events in strategic plans can be performed by formulating the problem before the events occur with a robust optimization approach (Hosseini-Motlagh et al., 2016; Meraklı and Yaman, 2016) and after the events by making strategic decisions about emergency plans (Zhan et al., 2020; Van Hui et al., 2014). The performance of a supply chain deeply relies on the efficient management of logistics decisions and operations (Wang et al., 2016). The studies on hub-and-spoke networks found that using robust optimization to establish a resilient network can deal with uncertainty both before and after disruption (Hsu and Wang, 2013; Yang and Chiu, 2016). Typically, the underlying HLP models define three indices which express the links between demand nodes, hubs, and central hubs. The majority address a single cost-related objective. Although the majority of the studies in HLP address a single cost-related objective, the literature demonstrates the importance of time-dependent transportation cost (Lo and Szeto, 2009; Szeto and Lo, 2008; Sun et al., 2018; Ghaffarinasab, 2020) in various HLP problems. For instance, in the public health field, by considering the impacts of road traffic emissions, noise, and accidents on public health and medical cost, (Jiang and Szeto, 2015) utilize an artificial bee colony algorithm to propose a sustainable multi-objective network design framework to incorporate the time-dependent transportation cost. Contrarily to the consideration of fixed costs and operational costs, costs associated with delivery time windows are still scarce in the HLP models from the literature. Furthermore, the literature analyzed with respect to the solution approach illustrates that the heuristic algorithms seem more applicable in HLPs. The main reason may be rooted in the complexity of the problem regarding large-scale networks. Chen (2010) designs a tabu search algorithm to deal with complexity in determining the types of vehicles, vehicle routing, and their schedules, simultaneously. In another study, Fazel Zarandi et al. (2015), by comparing the performance of the simulated annealing algorithm and iterated local search algorithm on a hierarchical HLP, stress the applicability of the model on finding a near-optimal solution. In light of the complexity involved in determining different types of hub locations, allocations, the requested operations, and the delivery time constrains, we believe that applying meta-heuristic algorithms to HLP models will lead to near-optimal solutions in acceptable computational times.

2.2. Cold chains and perishable goods

Cold chain management as a strategic decision-making area seeks desirable service levels at minimum cost through required planning activities (van der Vorst, 2000). Although the main application of the concept is in the food industry (Kuo and Chen, 2010), it may also be applied to pharmaceutical products (Bishara, 2006a), vaccines (Duijzer et al., 2018), blood (Ramezanian and Behboodi, 2017) or other perishable products (Zhang and Lam, 2018). The relevant studies address two main issues: *cold chain temperature monitoring* and *cold chain logistics*. In the first issue, several studies regarding RFID or tracking systems can be found (e.g. Chen and Shaw (2011)) that provide tactical solutions for the problem. However, the literature lacks models providing strategic solutions such as network design. There are only a few works on the second issue (e.g. Singh et al. (2017)), also proposing tactical solutions (rather than strategic), such as managing freezing and refreshing operations in the facilities.

Supply chain network design (SCND) is an attractive area of research in both the academic and real business worlds (Jahani et al., 2018, 2019). Govindan et al. (2017) concede that an FLP can be identified as a type of SCND once it comes in the context of supply chain modeling. The vast literature on the SCND techniques covers a broad range of approaches considering operational and disruption risks as well as delivery time windows (Fattahi et al., 2017; He et al., 2019). In addition to the SCND models, other network design techniques also shed light on the perishability features. Table 2 reports some recent articles in which the perishability features have been considered. The examples have been selected as a result of having warehouses or distribution centers similar to hub nodes in the proposed networks. The result of the table explicitly reveals that organizers need to consider the disruption risk or the uncertainty in the network design stage. Moreover, the deliberation on the studies affirms the importance of taking delivery time restrictions into account.

Another feature in the models is the freshness or quality of the goods. Ma et al. (2018) confirm the suitability of the MIP method to model a supply chain network for managing the quality of the food. The model prescribes whether each facility can provide a specific level of temperature. The application of perishable product studies in various field such as inventory management, revenue management, production management and vehicle routing management presents its importance in industry and academia (see column ”Field” in Table 2). Cold chain management is also an essential component of the global pharmaceutical supply chain (Bishara, 2006b), food supply chain (Mercier et al., 2017), and vaccine supply chain (Lin et al., 2020). Based on this table, the common method to handle difficulties regarding the distribution of perishable products is using immediate delivery system and seasonal delivery plans. However, in many cases, covering distant customers within the freshness time window is impossible.

Aravindaraj et al. (2020) asserted that despite the large production of perishable food products in India, there is not much study has been done on the cold storage industry. Moreover, the literature specifies that designing a suitable distribution network is an essential factor for any supply chain to the degree that

Table 1: Literature review summary of recent hierarchical HLPs

Author(s) (year)	Main objective(s)		Variables		Allocation	Capacity	Model	Solution approach	Main contribution
	Definition	No.	Type	Indices					
Lin and Chen (2004)	FC,TC,OC	SO	Det	3	SA	LC	Binary	Implicit enumeration algorithm	Determining the fleet size and schedules in a time-constrained network
Thomadsen and Larsen (2007)	TC	SO	Det	2	MA	LC	Binary	Branch-and-price algorithm	Application of hierarchical HLP in designing fully interconnected telecommunication network.
Yaman (2009)	TC	SO	Det	3	SA	UC	MIP	Branch-and-bound*	Locating a predetermined number of hubs and central hubs to minimize the total routing cost
Chen (2010)	TC, OC	SO	Det	3	MA	LC	Binary	Tabu search	Designing a heuristic approach to find a near-optimal solution for time-definite common carrier operation planning problem
Lin (2010)	FC, TC	SO	Det	3	MA	LC	Binary	Implicit enumeration algorithm	Designing a directed network where operating cost is minimized by considering the service time and operations restrictions
Sahraeian and Korani (2010)	TC	SO	Det	3	SA	UC	MIP	Branch-and-bound*	Proposing a heuristic method to minimizing the total cost for assigning nodes to their top-level hubs with predetermined cover radius
Chi et al. (2011)	FC,TC	SO	Det	2	SA	LC	Binary	Genetic algorithm	Proposing a new model of hierarchical HLP to provide a responsive and effective humanitarian relief network for disaster condition
Alumur et al. (2012)	FC,TC	SO	Det	2	SA	UC	MIP	Branch-and-bound*	Performing sensitivity analysis to illustrate that the locations of airport hubs are less sensitive to the cost parameters compared to the locations of ground hubs in improving the service quality
Davari and Fazel Zarandi (2012)	TC	SO	Fuzzy	3	SA	UC	Binary	Variable neighborhood search	Applying heuristic method to the single allocation hierarchical HLP with fuzzy demands to manage uncertainty in demand
Saboury et al. (2013)	TC	SO	Det	3	SA	UC	Binary	Hybrid heuristics	Applying the hybrid heuristic method to find the optimal hierarchical hub network in fully interconnected telecommunication industry
Rieck et al. (2014)	FC,TC,OC	SO	Det	3	SA	LC	MIP	Genetic algorithm	Extending hierarchical HLP and pick-up and delivery problems for companies that provide their services through hub networks
Fazel Zarandi et al. (2015)	TC	SO	Det	3	SA	UC	Binary	Heuristic algorithm	Highlighting the applicability and efficiency of meta-heuristic methods in solving hierarchical HLPs due to their complexity
Dukkanci and Kara (2017)	TC	SO	Det	2	SA	UC	Binary	Heuristic algorithm	Proposing a heuristic algorithm to indicated the locations and allocate the demand in the hub covering problem with a service time bound
Torkestani et al. (2018)	FC,TC,OC	SO	Sto	3	MA	LC	MIP	Heuristic algorithm	Proposing a robust hierarchical hub network under a site- and time-dependent disruption probability
Zhong et al. (2018)	FC,TC	SO	Sto	3	SA	LC	MIP	Genetic and Tabu search algorithm	Application of a meta-heuristic algorithm to design a multi-level hub network and determine the integration location of urban and rural public transport hub
Khodemani-Yazdi et al. (2019)	FC,TC,MR	BO	Sto	3	MA	LC	MIP	NSGA-II and hybrid simulated annealing algorithm	Application of a meta-heuristic algorithm in solving a bi-objective hierarchical HLP to minimize the total cost and maximize route length
Song and Teng (2019)	CP	SO	Det	2	SA	LC	Binary	Genetic algorithm	Proposing a hybrid hierarchy to have higher CP
Ma et al. (2020)	TC	SO	Det	3	SA	UC	MIP	GUROBI default method	A multi-modal hierarchical HLP with time restriction to improve the efficiency and balance the cargo flow of the China railway network
Ghaffarinasab (2020)	TC	BO	Det	2	SA	UC	MIP	Tabu search heuristic	Proposing a heuristic solution approach for solving a bi-objective star HLP
This study	**TC, OC, DT**	**MO**	**Sto**	**3**	**SA**	**UC**	**MIP**	**Genetic algorithm**	**Applying a genetic algorithm to solve multi-objective hierarchical HLPs to minimize total cost and maintain the freshness of products in operational centers**

* Not specific solution approach is noted in these studies. So, default approach, i.e. branch-and-bound, is considered.

Acronyms: FC: Fixed cost, OC: Operation cost, TC: Transportation cost, MR: Maximum route length, DT: Delivery times, SO: Single-objective, BO: Bi-objective, CP: Coverage performance, MO: Multi-objective, Det: Deterministic, Sto: Stochastic, SA: Single allocation, MA: Multiple allocation, LC: Limited capacity, UC: Un-capacitated

Table 2: Example of supply chain studies considering the perishability features.

Author(s) (year)	Field	Delivery time window	Product	Variable type	Uncertain parameter	Model	Freshness Strategy
Hwang (2004)	Set-covering location	✓	Perishable	Sto	Availability of centers	Binary	–
Feng and Xiao (2006)	Pricing and capacity allocation		Perishable	Sto	Price	MIP	–
Law and Wee (2006)	Production-inventory planning	✓	Perishable	Det	–	MIP	Immediate delivery
Cai et al. (2008)	Manufacturing	✓	Perishable	Sto	Processing time	Binary	–
Chew et al. (2009)	Inventory allocation and pricing		Perishable	Sto	Demand	Integer	Immediate delivery
Chen et al. (2009)	Scheduling and vehicle routing	✓	Perishable food	Det	–	MIP	Penalty cost of late delivery
Boysen (2010)	Zero-inventory cross docking	✓	Food	Sto	Flows	Binary	Refrigerated outbound trucks
Ahumada and Villalobos (2011)	Production planning and distribution	✓	Perishable agricultural	Sto	Freshness	Integer	Short-term planning in the harvest season
Amorim et al. (2012)	Production planning and distribution	✓	Perishable	Det	–	MIP	Differentiating holding costs depending on shelf-life
Gunpinar and Centeno (2016)	Vehicle routing problem	✓	Blood	Sto	Processing time	MIP	Using fully equipped blood-mobiles
Zahiri et al. (2017)	Supply chain network design		Pharmaceutical	Sto	Demand	MIP	Multi-period pharmaceutical network design
Ma et al. (2018)	Cold chain management	✓	Fruit	Det	–	MIP	Scheduling of the inter-modal network of refrigerated containers
Wang et al. (2019)	Supply chain management		Food	Det	–	MIP	Refrigerated transportation
Wei et al. (2019)	Vehicle routing problem	✓	Food	Det	–	MIP	Using cold storage and periodical distribution in cold chain distribution
Lin et al. (2020)	Cold chain management		Vaccine	Sto	Adverse event	MIP	The retailer's inspection at the end of transportation
Hamdan and Diabat (2020)	Supply chain network design	✓	Blood	Sto	Demand	MIP	Minimum time of delivering blood to hospitals
This study	**Hierarchical HLP**	✓	**Perishable**	**Sto**	**Demand**	**MIP**	**Complementary operations at hubs**

almost 30 percent of the total price of products has a direct relationship with transportation costs (Apte and Viswanathan, 2000; Rahmanzadeh Tootkaleh et al., 2014). The consideration of uncertainty and disruption is also a common concern in recent modeling approaches (Boysen, 2010; Gunpinar and Centeno, 2016; Zahiri et al., 2017; Hamdan and Diabat, 2020; Akbarpour et al., 2020). For instance, Ahumada and Villalobos (2011) consider the quality or freshness of agricultural food as the uncertain parameter of their MIP model and introduce some metrics, such as shelf life, color, grade, external appearance, and texture, to quantify the quality. They point out that a trade-off between the freshness and the transportation cost should be made.

Taking both Table 1 and Table 2 into consideration, we acknowledge that hierarchical hub networks with special equipment at hub nodes are beneficial for the flow of perishable products. To sum up, the superiority of the proposed model over the existing one relies on a robust transportation network for perishable goods by means of operational hub centers in a cold chain that includes delivery time restrictions and product freshness levels with stochastic demand. To handle the complexity of the problem, our solution approach converts the multi-objective function into a single one, which will be discussed in detail in the following section.

3. Model formulation

In this section, we formulate the problem systematically by employing the notation described in Table 3. The model is proposed in terms of a single allocation hierarchical operational hub for a cold chain (hereafter called the HOH-CC model) which is presented in two main streams. First, we assume that the model is not inflicted with disruption. Then, in the second approach, the model is extended to cope with disruption. In contrast with the existing hierarchical HLP models, where hub nodes at different levels provide similar services, our model's hubs offer different services for perishable goods. The main assumptions of the HOH-CC model are summarized as follows (c.f. Table 1 for justifying and referencing these assumptions):

- A three-level hub network shown in Figure 1 is considered in the model, including nodes (I), hubs (H), and central hubs (C).
- A single allocation hub problem is studied where the non-hub nodes are linked to exactly one hub.
- A central hub cannot be linked to a demand node.
- There is no capacity limitation in the network.
- The number of hubs (P) and central hubs (P_c) are predetermined.
- There is a cost discount factor between the central hubs denoted by α_c and between the remaining hubs by α_h.
- There is a time reduction factor between the hubs which is considered by α'_h for the hubs and α'_c for the central hubs.
- There is a predetermined delivery time window (β) between every pair of linked nodes.

- The flow from a node to its own location is null, and the associated cost and time are zero ($w_{ii} = 0$, $c_{ii} = 0$ and $t_{ii} = 0$). No goods are transferred through the model's routes.

- Symmetric cost matrix, i.e. the unit transportation cost from node i to node j is equal to the unit transportation cost from node j to node i ($c_{ij} = c_{ji}$).

- Symmetric time matrix, i.e the arrival time from node i to node j equals to that from node j to i ($t_{ij} = t_{ji}$).

3.1. *Deterministic model (without uncertainty; HOH-CC model)*

In the first model, demand is constant, and the freshness time window is assumed to be fixed for all flows. Based on FSIS (Food Safety and Inspection Service) safety and security guidelines for transportation and distribution of meat, poultry, and egg products[1], it is highly recommended that transportation vehicles, containers, and conveyances should be designed for food transportation and that they should be restricted to a single commodity to reduce the risk of cross-contamination from previous cargoes. To meet this importance, the proposed model provides the optimal transportation system for single-type food. However, index f has been added to the variables that can be affected by food type. We introduce the model in five main steps. First, the assignment variables and the relevant constraints are defined in Section 3.1.1. Next, the flow of goods is investigated in Section 3.1.2. Section 3.1.3 presents the delivery time variables and constraints. The cold chain requirements are added into the model through Section 3.1.4. Lastly, we outline the objective function of the MILP model in Section 3.1.5. Sets of indices, parameters, and decision variables used in the model are introduced in Table 3.

3.1.1. *Assignment*

The location-allocation constraints of the model are formulated as follows:

$$\sum_{j \in H} \sum_{k \in C} X_{ijk} = 1 \quad \forall i \in I \tag{1}$$

$$X_{ijk} \leq X_{jjk} \quad \forall i \in I, j \in H \backslash \{i\}, k \in C \tag{2}$$

$$\sum_{g \in H} X_{jgk} \leq X_{kkk} \quad \forall j \in H, k \in C \backslash \{j\} \tag{3}$$

$$\sum_{j \in H} \sum_{k \in C} X_{jjk} = P \tag{4}$$

[1] https://www.fsis.usda.gov/shared/PDF/Transportation_Security_Guidelines.pdf

Table 3: Nomenclature

Sets of indices	
I	Set of nodes $(i = 1, ..., I)$
H	Set of feasible locations for hub nodes which is a subset of I $(H \subseteq I)$
C	Set of feasible locations for central hubs which is a subset of H $(C \subseteq H)$
Sn	Set of possible scenarios in the model affected by disruption $(sn = 1, ..., Sn)$
F	Set of foods $(f = 1, 2, \dots)$ Here, this is single-food distribution network (f=1)
General parameters	
P	The number of hubs to be opened
P_c	The number of central hubs to be opened
w_{ij}	Amount of goods that flowed from node $i \in I$ to node $j \in H$
c_{ij}	Unit transportation cost from node $i \in I$ to hub node $j \in H$ once node i has been linked to hub j
Cr_{jf}	Fixed cost of refreshing operation in hub $j \in H$ for perishable product f
Cf_{kf}	Fixed cost of freezing operation in hub $k \in C$ for perishable product f
α_h	Cost discount factor used between the hubs
α_c	Cost discount factor used between the central hubs
α'_h	Time reduction factor used between the hubs
α'_c	Time reduction factor used between the central hubs
ψ_{sn}	Probability of occurrence of scenario sn
Assignment variables	
X_{ijk}	Equals 1 if node $i \in I$ is linked to lower-level hub $j \in H$, which has been linked to central hub $k \in C$, and 0 otherwise.
Flow balance variables	
$f1_{ijk}$	Amount of goods that flowed from node i to lower-level hub j, passing through central hub k
$f2_{ikl}$	Amount of goods that flowed from node i to central hubs k, passing through another central hub l $(k \neq l)$
Delivery time variables	
At_k	Arrival time when all flows from hubs and demand nodes linked to central hub k arrives at k
Rt_l	Release time, i.e. the time at which all flow coming from nodes and hubs linked to l can leave the central hub towards their destinations
Delivery time parameters	
t_{ij}	Travel time between nodes i and j
r_i	Time when all flows starting from node i are ready to transmit
Pt_{jf}	Complementary operation processing time in hub j
Pt_{kf}	Complementary operation processing time in central hub k
Lt_i	Loading time in node i
Ut_i	Unloading time in node i
Dt_{is}	Delivery time upper limit between every pair of nodes
β	Delivery time window between every pair of nodes

Table 3: Nomenclature-Continued

Cold chain variables	
Z_{is}	Equals 1 when a refreshing or freezing operation is needed during the transportation of goods from node i to node s, and 0 otherwise
R_{isj}	Equals 1 if a refreshing operation is needed in hub j when the flow between pair of nodes (i, s) passes through hub j, and 0 otherwise
F_{isk}	Equals 1 if a freezing operation is needed in central hub k when the flow between pair of nodes (i, s) passes through central hub k, and 0 otherwise
Sr_{is}	Complementary operations satisfaction rate of goods' freshness resulting by using refreshing or freezing operations on a flow between pairs of nodes (i, s)
Cold chain parameters	
Ft_f	Freshness time window between every pair of nodes
Rs_f	Refreshing satisfaction rate
Fs_f	Freezing satisfaction rate
M	Large value used for defining some constraints

$$\sum_{k \in C} X_{kkk} = P_c \tag{5}$$

$$X_{kjk} = 0 \quad \forall j \in H, k \in C \backslash \{j\} \tag{6}$$

$$X_{ijk} = \{0, 1\} \quad \forall i \in I, j \in H, k \in C \tag{7}$$

The single allocation assumption is ensured by Constraints (1), which confirm that each demand node is linked to only one lower-level hub and one central hub. Constraints (2) state that demand node i, hub j and central hub k can be linked if hub node j and central hub k are linked. Constraints (3) declare that hub j can be linked to central hub k if the node k is selected as a central hub. Constraints (4) and Constraints (5) force the number of hubs and central hubs to be equal to predetermined values. Constraints (6) declare one of the main assumptions that a central hub cannot be linked to a demand node. Constraints (7) define the allocation of binary values for X in any combination of nodes and hubs.

3.1.2. Flow balance

In order to model the traffic between the nodes, two kinds of flow variables are introduced in the HOH-CC model. One causes the flow of goods to agree between hubs and central hubs (i.e. $f1_{ijk}$) and the other one determines the flow among central hubs (i.e. $f2_{ikl}$). The model also satisfies the triangle inequality for all nodes. The following constraints define the limitation of flow between the nodes:

$$f1_{ijk} \geq \sum_{s \in I \setminus \{j\}} (w_{is} + w_{si})(X_{ijk} - X_{sjk}) \quad \forall i \in I, j \in H, k \in C \setminus \{j\} \tag{8}$$

$$\sum_{l \in C \setminus \{k\}} f2_{ikl} - \sum_{l \in C \setminus \{k\}} f2_{ilk} = \sum_{s \in C} w_{is} \sum_{j \in H} (X_{ijk} - X_{sjk}) \quad \forall i \in I, k \in C \tag{9}$$

$$f1_{ijk} \geq 0 \quad \forall i \in I, j \in H, k \in C \tag{10}$$

$$f2_{ikl} \geq 0 \quad \forall i \in I, k \in C, l \in C \setminus \{k\} \tag{11}$$

The amount transferred from node i to hub j and then to central hub k is calculated in Constraints (8). The flow balance between central hubs is formulated in Constraints (9). Constraints (10) and (11) assure that the flow variables are non-negative.

3.1.3. Delivery time window

One main objective of designing hub networks is the implementation of just-in-time delivery. Delivery time is the summation of travel time between two pairs, loading and unloading time, and potential complementary operation processing time based on the delivery time window. In this regard, we control the arrival and release time of flow in central hubs. Constraints (12) calculate the latest arrival time at central hub k (At_k) and Constraints (13) formulate the release time at the next central hub l (Rt_l). Constraints (14) confirm that the delivery time between each pair of linked nodes is restricted to a predetermined delivery time window (β). Constraints (15) and (16) assure non-negativity of the variables.

$$At_k \geq \sum_{j \in H} (r_i + Lt_i + t_{ij} + Pt_{jf} + \alpha'_h t_{jk} + Pt_{kf}) X_{ijk} \quad \forall i \in I, k \in C \tag{12}$$

$$Rt_l \geq At_k + (\alpha'_c t_{kl} + Pt_{lf}) X_{kkk} \quad \forall l \in C, k \in C \tag{13}$$

$$Rt_l + \sum_{j \in H} (\alpha'_l t_{lj} + Pt_{jf} + t_{ji} + Ut_i) X_{ijl} \leq \beta \quad \forall i \in I, l \in C \tag{14}$$

$$At_k \geq 0 \quad \forall k \in C \tag{15}$$

$$Rt_l \geq 0 \quad \forall l \in C \tag{16}$$

3.1.4. Cold chain requirements

Up to this point, the model includes the main concept of a single location-allocation hub network problem noted in the relevant literature (see the allocation mode in the studies listed in Table 1). However, a cold chain requires several refreshing and freezing operations. Hereafter, we introduce several variables and parameters aimed at modeling a cold chain. In the proposed cold chain, the refreshing and freezing operations are offered in every hub node to guarantee the freshness of perishable goods delivered in demand nodes. Regarding the temperature control of the cold chain, we assume that the lower-level hubs only perform refreshing operations, while central hubs provide both refreshing and freezing ones. We also assume that the transportation system is working with a sufficient number of delivery vehicles (with ambient temperature) to manage cold logistics.

To ensure the minimum freshness of goods, we control travel times (Dt_{is}) between each pair of nodes and check whether a refreshing or freezing operation is required. When the travel time surpasses the freshness time window of goods (Ft_f), a refreshing or freezing operation is applied (with the help of R_{isj} and F_{isk} variables, respectively). We assume that there is a common sense of quality or freshness of the products in the cold chain named as complementary operations satisfaction rate, which can be calculated for every pair of nodes (Sr_{is}) and is directly dependent upon the complementary operations. Figure 2 clarifies the dependence of the customer complementary operations satisfaction rate based on the delivery time. As depicted, if the delivery time is shorter than the freshness time limit, the network will not apply any complementary operations therefore, the customer complementary operations satisfaction rate for that pair of nodes would equal to zero. In case the complementary operations can extend the freshness time limit and delivery time can meet this extended limit, then of the customer complementary operations satisfaction rate would be calculated based on the applied operations. Finally, if the delivery time is over the extended freshness time limit, even complementary operations will not be able to preserve food freshness; therefore, the customer complementary operations satisfaction rate would be equal to zero.

The model investigates the satisfaction rate for refreshing and freezing operations separately (i.e. by employing Rs_f and Fs_f). The cold chain operational constraints are defined as follows:

$$Dt_{is} \geq r_i + X_{ijk}t_{ij} + X_{sjk}t_{sj} \quad \forall i \in I, s \in I\backslash\{i\}, j \in H, k \in C \tag{17}$$

$$\begin{aligned} Dt_{is} \geq & r_i + X_{ijk}t_{ij} + \alpha'_h(X_{ijk} + X_{sgk} - 1)(t_{jh} + t_{gs}) + X_{sgk}t_{sg} \\ & \forall i, s \in I, i \neq s. \quad j, g \in H, j \neq g. \quad k \in C \end{aligned} \tag{18}$$

$$\begin{aligned} Dt_{is} \geq & r_i + \sum_j \big((t_{ij} + \alpha'_h t_{jk})X_{ijk}\big) + \alpha'_c t_{kl}\big(\sum_j X_{ijk} + \sum_g X_{sgl} - 1\big) + \sum_g \big((t_{sg} + \alpha'_l t_{gl})X_{sgl}\big) \\ & \forall i, s \in I, i \neq s \quad j, g \in H, j \neq g \quad l, k \in C, l \neq k \end{aligned} \tag{19}$$

$$Dt_{is} - Ft_f \geq M(Z_{is} - 1) \quad \forall i, s \in I \tag{20}$$

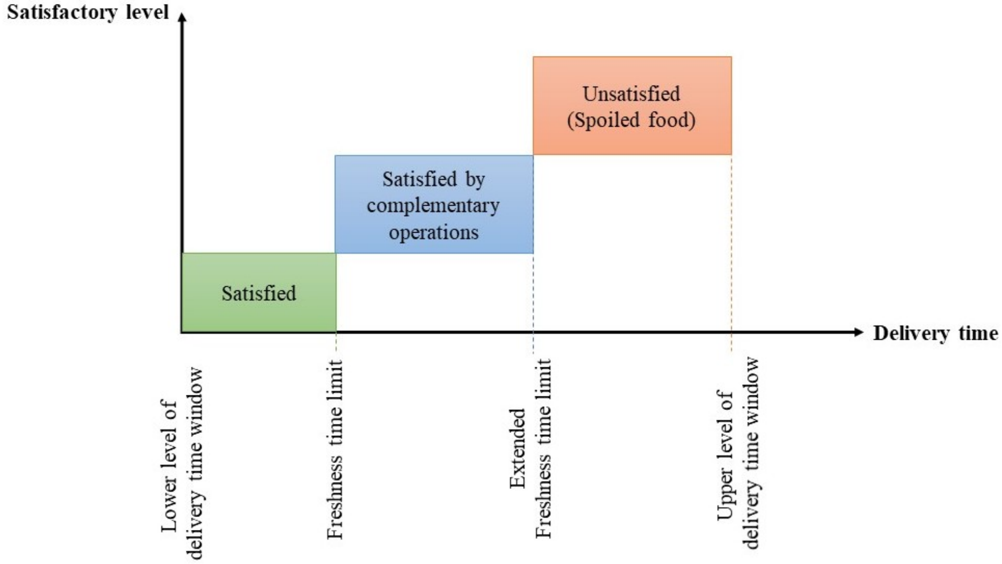

Figure 2: Step-wise satisfaction level based on delivery time.

$$Dt_{is} - Ft_f \leq M(Z_{is}) \quad \forall i, s \in I \tag{21}$$

$$F_{isk} \leq \sum_{j \in H} X_{ijk} + \sum_{g \in H} X_{sgk} \quad \forall i, s \in I, \quad k \in C \tag{22}$$

$$R_{isj} \leq \sum_{k \in C} X_{ijk} + \sum_{k \in C} X_{sgk} \quad \forall i, s \in I, \quad j, g \in H \tag{23}$$

$$\sum_{k \in C} F_{isk} + \sum_{j \in H} R_{isj} = Z_{is} \quad \forall i, s \in I \tag{24}$$

$$Sr_{is} = Fs_f \sum_{k \in C} F_{isk} + Rs_f \sum_{j \in H} R_{isj} \quad \forall i, s \in I \tag{25}$$

$$F_{isk}, R_{isj}, Z_{is} = \{0, 1\} \quad \forall i, s \in I, \quad j \in H, \quad k \in C \tag{26}$$

Constraints (17) limit the delivery time of each pair of nodes (i, s) which have been assigned via a common lower-level hub j. If the pair of nodes (i, s) includes two different lower-level hubs and a common central hub, the delivery time is limited by the constraints (18). Moreover, if the pair of nodes (i, s) includes two different central hubs, the delivery time is determined by Constraints (19) that otherwise will be non-active. Constraints (20) and (21) state that an extra operation is required when it takes more time to transmit the goods between the nodes (i, s) than the freshness time window will allow. Constraints (22) and (23) determine the type of operation (refreshing or freezing) needed at lower-level and central hubs. Constraints (24) ensure that if an extra operation is required in a hub, only one of the refreshing or freezing operations is performed. The overall satisfaction rate achieved from the implemented operations is calculated by Constraints (25).

The spoilage rate in our cold chain depends on the difference between the delivery time of each pair of nodes (Dt_{is}) and the freshness time window (Ft_f). Therefore, let us define a penalty cost per time unit (Pl) for calculating the spoilage cost in the model. This unit cost will be different depending on the types of goods transferred in the network. For instance, vital goods such as pharmaceutical products will have a larger unit penalty cost than agricultural products. Equation (27) calculates the spoilage cost in the model.

$$\text{Spoilage cost} = Pl. \sum_{i\in I}\sum_{s\in I}(Dt_{is} - Ft_f) \quad ; if \quad Dt_{is} > Ft_f \tag{27}$$

3.1.5. Objective function

It is evident that the HOH-CC is NP-hard, since the p-hub median problems are NP-hard (Kara and Tansel, 2003). The proposed objective function of the current study is multi-objective function including. In order to simplify the optimization, we convert our multi-objective optimization model into a single objective problem by using a weighted sum method. The objective function of the proposed model can be defined in two subcategories. The minimization part attempts to minimize the total transportation cost (first component in Equation (28)), delivery time (second component in Equation (28)), and operational cost associated with the refreshing and freezing operations (fourth component in Equation (28)). The second part tries to maximize the satisfaction rate of customers regarding goods' freshness (third component in Equation (28)).

For coping with the multi-objective function, we define four positive scalar weights (i.e. P_1 to P_4 while $\sum_{i=1}^{4} P_i = 1$) to present the single objective function of the model in Equation (28). Moreover, to handle the maximization terms, the negative coefficient of the weight P_3 has been included in the Equation (28). As the overall objective function is a minimization problem, the use of a negative coefficient of the weight P_3 indicates that the satisfaction rates should be maximized in the optimization algorithm.

The overall HOH-CC model reads:

$$\begin{aligned} Min \quad & P_1\Big(\sum_{i\in I}\sum_{s\in I}(w_{is}+w_{si})\sum_{j\in H}c_{ij}\sum_{k\in C}X_{ijk} \\ & + \sum_{i\in I}\sum_{s\in I}\sum_{k\in C\setminus\{j\}}\alpha_h c_{jk} f1_{ijk} + \sum_{i\in I}\sum_{k\in C}\sum_{l\in C\setminus\{k\}}\alpha_c c_{kl} f2_{ikl}\Big) \\ & + P_2\sum_{i\in I}\sum_{s\in I}Dt_{is} - P_3\sum_{i\in I}\sum_{s\in I}Sr_{is} + P_4\Big(\sum_{i\in I}\sum_{s\in I}\sum_{j\in H}R_{isj}Cr_{jf} + \sum_{i\in I}\sum_{s\in I}\sum_{k\in C}F_{isk}Cf_{kf}\Big) \end{aligned} \tag{28}$$

3.2. Classic hierarchical hub model

As stated in the literature review section, the previous hierarchical hub problems do not include the concepts of cold chains. We call such problem as the classic hierarchical hub (CHH) and can be defined by ignoring the cold chain-related constraints of Section 3.1.4. The objective function of CHH only includes the minimization of transportation costs as well as the minimization of the total delivery times.

Therefore, the CHH model is defined as follows:

$$
\begin{aligned}
Min \quad & P_1\Big(\sum_{i\in I}\sum_{s\in I}(w_{is}+w_{si})\sum_{j\in H}c_{ij}\sum_{k\in C}X_{ijk}+\sum_{i\in I}\sum_{s\in I}\sum_{k\in C\setminus\{j\}}\alpha_h c_{jk}f1_{ijk} \\
& +\sum_{i\in I}\sum_{k\in C}\sum_{l\in C\setminus\{k\}}\alpha_c c_{kl}f2_{ikl}\Big)+P_2\sum_{i\in I}\sum_{s\in I}Dt_{is}
\end{aligned}
\tag{29}
$$

Subject to the constraints (1) - (19), (27).

3.3. Model affected by disruption

In this section, uncertainty is considered the demand that will trigger the model HOH-CC and is hereafter determined as HOH-CC-D. Farahani et al. (2013) concede that the main parameter of a network problem affected by disruption is demand. It is common to rely on scenario analysis for contemplating demand disruption in hierarchical network models (Lin and Chen, 2004). We originate several scenarios for the potential demand and consider different flows between each pair of nodes to assess the effects of disruption. The second parameter with uncertainty is the freshness time window which is highly related to the origin demand node. The third parameter is the effectiveness of cold chain operations, which means that freezing and refreshing operations may be unsuccessful in preventing the deterioration of goods. In this situation, the model should avoid ineffective operations. With a slight abuse of notation, only the modified version of the constraints and the objective function of model HOH-CC-D are presented hereafter.

3.3.1. New flow balance constraints

Stochastic demands are considered in the model by applying different scenarios (Sn refers to the number of scenarios) for the flow balance constraints introduced in Section 3.1.2, as follows:

$$
f1^{sn}_{ijk}\geq\sum_{s\in I|\{j\}}(w^{sn}_{is}+w^{sn}_{si})(X_{ijk}-X_{sjk})\quad\forall i\in I,j\in H,k\in C\setminus\{j\},sn\in Sn \tag{30}
$$

$$
\sum_{l\in C\setminus\{k\}}f2^{sn}_{ikl}-\sum_{l\in C\setminus\{k\}}f2^{sn}_{ilk}=\sum_{s\in C}w^{sn}_{is}\sum_{j\in H}(X_{ijk}-X_{sjk})\quad\forall i\in I,k\in C,sn\in Sn \tag{31}
$$

$$
f1^{sn}_{ijk}\geq 0\quad\forall i\in I,j\in H,k\in C,sn\in Sn \tag{32}
$$

$$
f2^{sn}_{ikl}\geq 0\quad\forall i\in I,k\in C,l\in C\setminus\{k\},sn\in Sn \tag{33}
$$

3.3.2. New cold chain constraints

The HOH-CC model could only accept a specific freshness time window (Ft_f), whereas in the new HOH-CC-D, we consider a multi-level freshness time window stated in Equation (34) to cope with the disruption affecting the cold chain. By adding this equation, the travel time of every pair of nodes is compared to multi-freshness time windows to ensure that the complementary operations will keep the goods fresh. If the travel time between origin i to destination s (Dt_{is}) is shorter than the refreshed product lifetime (Ft_f2), the model will apply refreshing operation to keep the product fresh. If the travel time is longer but shorter than the frozen product lifetime (Ft_f3), the model will apply a freezing operation to keep the product fresh. Subsequently, if the travel time is longer than the frozen product lifetime, complementary operations cannot prevent deterioration, so no operation will be done.

$$\begin{cases} if \quad Ft_f1 \leq Dt_{is} \leq Ft_f2 & \text{Do refreshing operation} \\ if \quad Ft_f2 < Dt_{is} \leq Ft_f3 & \text{Do freezing operation} \\ if \quad Ft_f3 < Dt_{is} & \text{None of the operations can prevent deterioration} \end{cases} \tag{34}$$

Constraints (20) and (21) in the HOH-CC model are converted to Constraints (35) to (38) in the new model. Constraints (35) state that if the delivery time between a pair of nodes is greater than the lower bound of the freshness time window (Ft_f1), a complementary operation will be required ($Zop_{is} = 1$). Constraints (36) to (38) determine the type of complementary operation, which can be refreshing ($Z1_{is} = 1$) or freezing ($Z2_{is} = 1$) or none ($Z0_{is} = 1$). Constraints (39) and (40) determine the optimal hub nodes for the related operations. Constraints (41) and (42) assure that only one operation is implemented in the corresponding route. The overall satisfaction rate achieved from either refreshing or freezing operations is calculated by Constraints (43).

$$Dt_{is} - Ft_f1 \leq M.Zop_{is} \quad \forall i, s \in I \tag{35}$$

$$Dt_{is} - Ft_f2 \leq M.Z0_{is} \quad \forall i, s \in I \tag{36}$$

$$Dt_{is} - Ft_f3 \leq M.(Z0_{is} + Z2_{is}) \quad \forall i, s \in I \tag{37}$$

$$Dt_{is} - Ft_f3 \leq M.(Z0_{is} + Z2_{is} + Z1_{is}) \quad \forall i, s \in I \tag{38}$$

$$\sum_{k \in C} F_{isk} = Z2_{is} \quad \forall i, s \in I \tag{39}$$

$$\sum_{j \in H} R_{isj} = Z1_{is} \quad \forall i, s \in I \tag{40}$$

$$\sum_{k \in C} F_{isk} + \sum_{j \in H} R_{isj} = 1 \quad \forall i, s \in I \tag{41}$$

$$Z0_{is} + Z1_{is} + Z2_{is} = Zop_{is} \quad \forall i, s \in I \tag{42}$$

$$Sr_{is} = Rs_f * Z1_{is} + Fs_f * Z2_{is} \quad \forall i, s \in I \tag{43}$$

3.3.3. New objective function

The objective function of the new model (i.e HOH-CC-D) is defined when minimizing the expected value of the previous four weighted objective functions, introduced in Equation (28), under the potential occurrence of all scenarios. The overall HOH-CC-D model is formulated as follows:

$$\begin{aligned} Min \quad & \sum_{sc \in Sn} \psi_{sn} \Big(P_1 (\sum_{i \in I} \sum_{s \in I} (w_{is}^{sn} + w_{si}^{sn}) \sum_{j \in H} c_{ij} \sum_{k \in C} X_{ijk} \\ & + \sum_{i \in I} \sum_{s \in I} \sum_{k \in C \setminus \{j\}} \alpha_h c_{jk} f1_{ijk}^{sn} + \sum_{i \in I} \sum_{k \in C} \sum_{l \in C \setminus \{k\}} \alpha_c c_{kl} f2_{ikl}^{sn}) \\ & + P_2 \sum_{i \in I} \sum_{s \in I} Dt_{is} - P_3 \sum_{i \in I} \sum_{s \in I} Sr_{is} + P_4 (\sum_{i \in I} \sum_{s \in I} \sum_{j \in H} R_{isj} Cr_{jf} + \sum_{i \in I} \sum_{s \in I} \sum_{k \in C} F_{isk} Cf_{kf}) \Big) \end{aligned} \tag{44}$$

Subject to Constraints (1) to (43).

4. Computational experiments

4.1. Data and experiment settings

In this section, we provide several numerical studies using the CAB dataset, introduced by O'Kelly (1987). Some data from a frozen food company have been added to the dataset to simulate a realistic cold chain. The company is assumed to distribute several kinds of frozen vegetables (such as baby beans, carrot, corn, and broccoli) and needs to apply complementary operations during the distribution of the products to keep them fresh. The temperature of the freezing operation performed in the central hubs is below $-18°$C and the refreshing operation is performed by changing the temperature of the product to less than $-2°$C. The transportation system does not require any freezing equipment and the maximum room temperature for any delivery trucks has been determined as 5°C. To comply with the above temperature requirements, a delivery time window ($\beta = 2760$min) and freshness time window ($Ft_f = 1500$min) allows the transportation system to manage the cold chain.

It is assumed that the company delivers the products to 10 demand nodes ($|I| = 10$ cities), and six of those are candidates for lower-level hubs ($|H| = 6$), whereas only two of the hubs could be central hubs ($|C| = 2$). The company has planned to open four hubs ($P = 4$) with one central hub at the most ($P_c = 1$).

All cost-discount and time-reduction factors between hubs and central hubs are assumed to have the same value of $\alpha_h = \alpha_c = \alpha'_h = \alpha'_c = 0.8$. We code and run all tests using a commercial optimization software (known as GAMS 23.6) on an Intel Core i5 CPU working with 2.53 GHz speed and 4 GB RAM.

4.2. Results and discussion

In this section, we compare the optimal solution delivered by the classic model (CHH) against the optimal solution given by the deterministic cold chain model (HOH-CC) on a single instance. We first investigate the configuration of the HOH-CC model. Figure 3 depicts the optimal hub network of the food cold chain and illustrates that node 4 has been selected as a central hub with freezing equipment. Nodes 7, 8, and 9 are the lower-level hubs. Hub 9 is the only one equipped with refreshing facilities (cf. Table 4).

Table 4: Numerical Case Study of the HOH-CC Model: Operations Required in Opened Hubs between Each Pair of Nodes.

Pair of nodes	Refreshing center	Freezing center
(3,8)	9	-
(10,3)	9	-
(10,8)	-	4
Other pairs	-	-

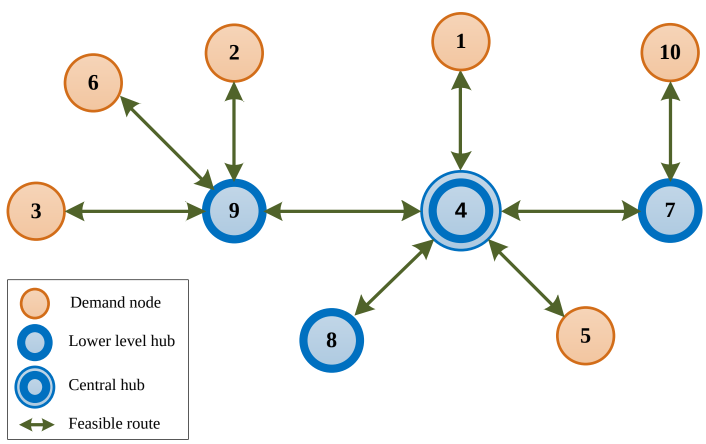

Figure 3: Numerical Case Study of the HOH-CC Model: Optimal Network Structure.

In order to assess the consideration of the cold chain's requirements, we compare the HOH-CC with the CHH model. Table 5 compares the total cost of two models, which includes spoilage, transportation, and operational costs for two settings: (1) the freshness time window (Ft_f) lower than the delivery time window (β); (2) Ft_f greater than β.

Naturally, the operational and spoilage costs only incur when the freshness time window is lower than the delivery time. The spoilage cost of the network is avoided in the HOH-CC model and incurs only by investing in the freezing or refreshing operations. Given that the transportation cost of both models and their network structure is the same, a great spoilage cost leads to a greater total cost for the classic model. It was concluded that the proposed model performs more efficiently when the the freshness time (f_t) is lower than the delivery time window between pairs of nodes (β).

Table 5: Numerical Case Study: Impact of Including Cold Chain Concepts ($k).

	Model	Total cost	Spoilage Cost	Transportation Cost	Operational cost
$Ft_f < \beta$	CHH	841,958	17,780	824,178	0
	HOH-CC	828,778	0	824,178	4,600
$Ft_f \geq \beta$	CHH	897,206	0	897,206	0
	HOH-CC	897,206	0	897,206	0

4.3. Sensitivity analysis of the CHH and HOH-CC models

Discount factors are significant parameters to determine how much of the cost and delivery times can be reduced in the network because of the hubs. The spoilage rate introduced in Equation (27) is calculated directly from the difference between the delivery times and the predetermined freshness time window. We first investigate the effect of discount factors, keeping $\alpha_h = \alpha_c = \alpha'_h = \alpha'_c = \alpha$ on the spoilage rate in our classic model (CHH). The results, demonstrated in Figure 4, validate the model by suggesting a smaller value for α and a better spoilage rate. The lowest cost discount factor (α) provides the most effective usage of the hubs in the network. The sensitivity analysis also confirms that increasing the discount factor yields a higher effect on large-size problems. Consequently, managers should make more efforts to build and sustain the cooperative work between hubs when the network is large.

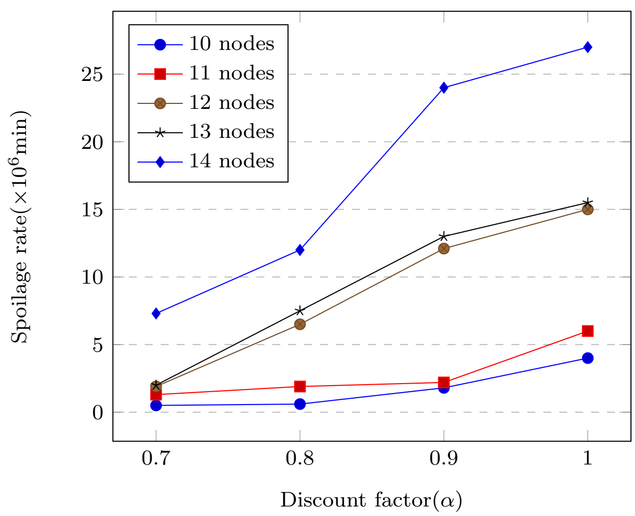

Figure 4: Numerical Case Study of the CHH Model: Effect of Discount Factor (α) on Spoilage Rate With Respect to Different Network Sizes.

Furthermore, we have investigated the effect of the discount factors (α) and the freshness time window (Ft_f) on the objective function of the frozen food company. As illustrated in Figure 5, as the discount factor decreases, the objective function values also decline significantly. This seems logical, as both the transportation cost and the delivery time-related objectives become less important, whereas the other elements of the objective function remain constant (see Equation (28)). On the other hand, less of an effect is observed on the objective function values as the freshness time window gets bigger. For $Ft_f \geq 2760$, the objective function values for each α remains steady because the freshness time window (Ft_f) is greater than the delivery time window (β), as we have observed in Table 5.

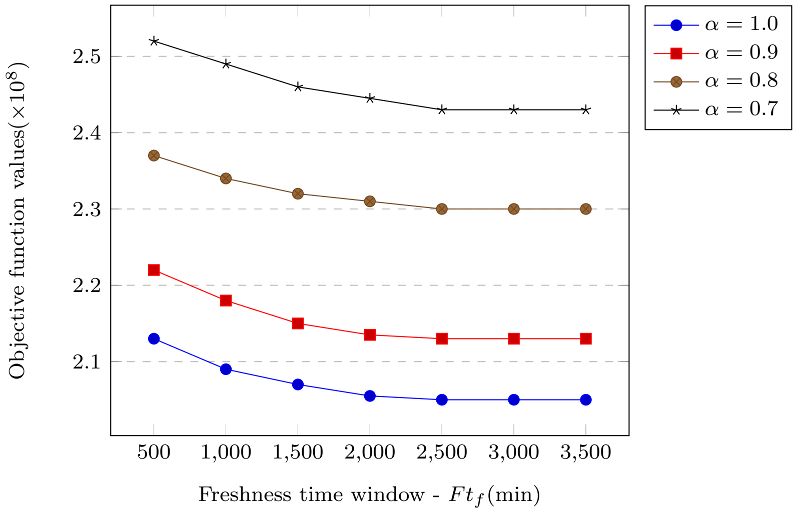

Figure 5: Numerical Case Study of the HOH-CC Model: Effect of Discount Factor (α) and the Freshness Time window (Ft_f) on the Objective Function.

Figure 5 depicts the result of the frozen food company network with 10 nodes. Additionally, Figure 6 illustrates that a shorter freshness time window would bring more costs in problems with larger network sizes than with smaller sizes. The trends of the plotted lines also demonstrate that in a larger network size (14 demand nodes), there is still an operational cost in the network, regardless of $Ft_f \geq \beta$. This means that for the goods having higher freshness time windows, the managers should set a higher optimal level of the delivery time window (here $\beta = 3000min$ for 14 demand nodes).

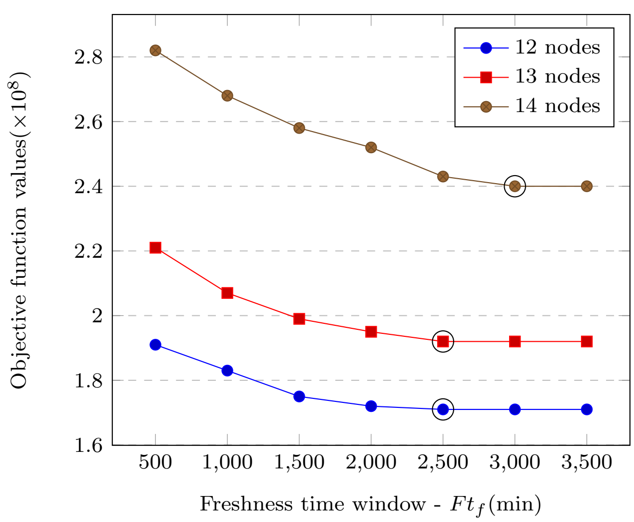

Figure 6: Numerical Case Study of the HOH-CC Model: Freshness Threshold With Respect to Different Network Sizes.

Operational cost contains the fixed cost of refreshing and freezing operations and plays a key role in establishing an efficient network. Figure 7 demonstrates that there is a threshold for refreshing fixed cost when we increase the fixed costs of freezing operations. For instance, when this cost is \$200k, increasing the refreshing fixed cost by \$200k would increase the objective function value. Nonetheless, in an instance where refreshing fixed costs is more than \$200k, the same objective function values will be unchanged. In managerial terms, this threshold means if organizers have budgeted \$200k for the freezing equipment of each central hub, they should spend less than \$200k for the refreshing equipment in the lower-level hubs. Figure 7 also illustrates that the threshold of the refreshing fixed cost should be increased for larger freezing fixed costs, accordingly.

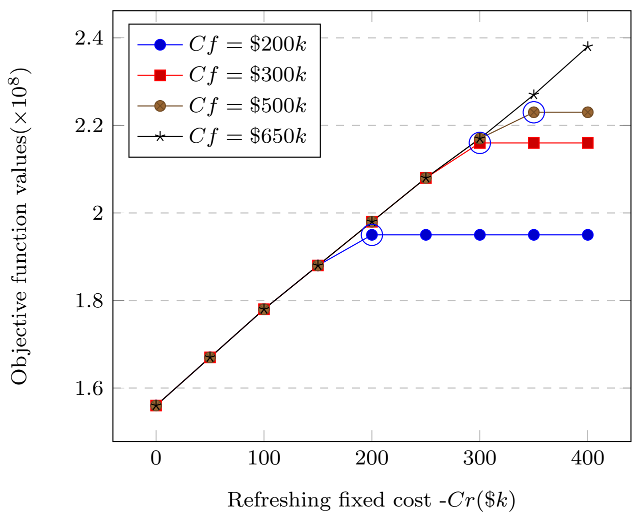

Figure 7: Numerical Case Study of the HOH-CC Model: Threshold of Refreshing Fixed Cost With Respect to Different Freezing Fixed Costs.

4.4. Computational considerations for the HOH-CC model

We run the HOH-CC model with several network sizes and numbers of central hubs investigating the network structure, computational gap, and running time. Hereafter, we assume that every demand node has the potential to become a lower-level or a central hub. Table 6 indicates that when the size of the instance increases, the number of central hubs should increase, correspondingly. For example, for instances over 15 nodes, more than four hubs should be targeted as central hubs to get a better gap and running time. Regarding such network sizes, we suggest the proposed solution developed in Section 4.5 for solving the HOH-CC-D model. The table also confirms that the total cost could be decreased by selecting more central hubs amongst every set of demand nodes.

Table 6: Numerical Case Study of the HOH-CC model: Different Network Sizes and Computational Gaps/Times.

# of nodes	# of central hubs	Opened hubs lower-level/central	Operations R*	F*	Cost($k)	Gap(%)	Time(s)
10	1	4,7,8,9/4	✓	✓	781,638	0.00	31
10	2	4,7,8,9/4,8	✓	✓	780,205	7.00	36
10	3	4,7,8,9/4,7,8	-	✓	744,687	5.30	51
10	4	1,4,7,9/1,4,7,9	✓	✓	743,856	8.40	7
11	1	4,7,8,9/4	✓	✓	911,097	3.66	66
11	2	3,4,6,7/4,6	✓	✓	924,922	9.90	8
11	3	4,7,9,11/4,7,11	✓	✓	863,156	6.03	468
11	4	1,4,6,7/1,4,6,7	-	✓	881,493	9.79	288
12	1	4,7,11,12/11	✓	✓	1,731,167	8.08	16
12	2	4,7,8,11/8,11	✓	✓	1,764,594	7.60	152
12	3	4,9,11,12/4,9,11	✓	✓	1,788,926	4.80	197
12	4	4,5,7,8/4,5,7,8	✓	✓	1,772,894	0.22	19
13	1	4,7,11,12/11	✓	✓	1,847,193	8.18	30
13	2	4,8,11,12/8,11	✓	✓	1,876,576	8.45	528
13	3	4,7,9,12/4,7,12	✓	✓	1,932,807	7.33	551
13	4	4,6,7,8/4,6,7,8	✓	-	1,955,471	2.60	40
14	1	5,7,11,12/11	✓	✓	2,421,765	7.83	46
14	2	1,5,11,12/5,11	✓	✓	2,523,219	9.63	820
14	3	1,4,7,12/4,7,12	✓	✓	2,568,868	8.79	789
14	4	1,4,7,8/1,4,7,8	✓	✓	2,586,832	0.7	145
15	1	5,7,11,12/11	✓	✓	2,660,395	7.14	88
15	2	-	-	-	-	-	-
15	3	-	-	-	-	-	-
15	4	1,4,7,8/1,4,7,8	✓	✓	2,908,999	2.42	457
16	1	-	-	-	-	-	-
16	2	-	-	-	-	-	-
16	3	-	-	-	-	-	-
16	4	4,8,12,13/4,8,12,13	✓	✓	2,987,382	9.89	126
17	1	-	-	-	-	-	-
17	2	-	-	-	-	-	-
17	3	-	-	-	-	-	-
17	4	1,4,7,17/1,4,7,17	✓	✓	5,172,282	9.95	148

* Complementary operations: Refreshing (R) and Freezing (F)

As an additional discussion on the proposed model, we conduct additional analyses by changing the freshness time potentially considering freezing (F+), and refreshing (R+) operations. The results are reported in Table 7.

Table 7: Analysis of additional operations during the distribution of various types of products with different freshness times

Freshness time	Freezing option	Refreshment option	Customer Satisfaction*	Total transportation cost ($*10^7$)	Refreshment cost	Freezing cost	Total Freezing and Refreshment Costs
1300	F+	R+	4100	8.895546	1400	1600	3000
1300	F+	-	5500	8.895546	0	4400	4400
1300	-	R+	3300	8.895546	2200	0	2200
1300	-	-	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
1500	F+	R+	2600	8.895546	400	1600	2000
1500	F+	-	3000	8.895546	0	2400	2400
1500	-	R+	1800	8.895546	1200	0	1200
1500	-	-	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
1600	F+	R+	2300	8.895546	700	1000	1700
1600	F+	-	3000	8.895546	0	2400	2400
1600	-	R+	1800	8.895546	1200	0	1200
1600	-	-	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
1800	F+	R+	1150	8.895546	600	200	800
1800	F+	-	1500	8.895546	0	1200	1200
1800	-	R+	1050	8.895546	700	0	700
1800	-	-	0	10.42207	0	0	0
2000	F+	R+	300	8.895546	200	0	200
2000	F+	-	500	8.895546	0	400	400
2000	-	R+	300	8.895546	200	0	200
2000	-	-	0	8.895546	0	0	0
2200	F+	R+	0	8.895546	0	0	0
2200	F+	-	0	8.895546	0	0	0
2200	-	R+	0	8.895546	0	0	0
2200	-	-	0	8.895546	0	0	0

* In this case, the complementary operations satisfaction rate for each pair of nodes could be 0 for no complementary operations, 300 for refreshing operations, and 500 for freezing operations.

The performed analysis confirms the following results:

1. Ignoring refreshing or freezing operations in the distributional hub network may lead to infeasible plans to deliver products to the customers, or to impose additional transportation costs on the solutions.
2. The freshness time window depends on the food products. The sensitivity analysis on the freshness time window with respect to operational costs illustrates that products with a lower freshness time will impose additional operation costs to ensure fresh product delivery to customers, as depicted in Figure

8, which demonstrates the model robust behavior.

3. Moreover, the sensitivity analysis demonstrates the effect of food types on dissatisfaction costs based on differences in the freshness time window. As illustrated in Figure 9, it can be observed that the proposed model can prevent customers' dissatisfaction cost due to delivery of non-fresh products. This will be much more important in special situations like pandemics.

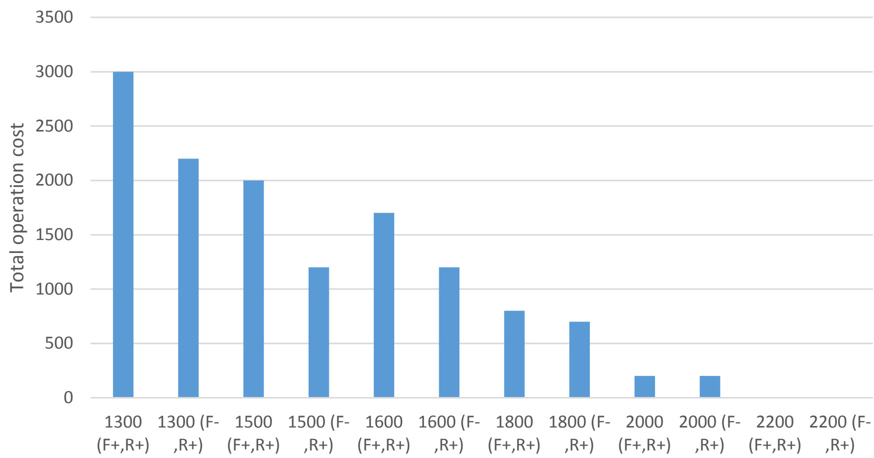

Figure 8: Analysis of freshness time as well as additional operations on total operation cost.

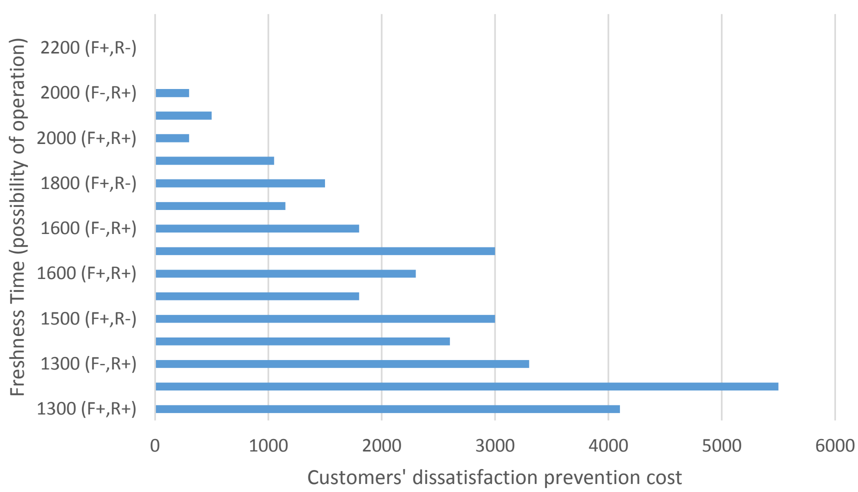

Figure 9: Analysis of freshness time as well as additional operations on customers' dissatisfaction cost.

4.5. Numerical examples for the HOH-CC-D model

As stated in Section 3.1.5, the HOH-CC-D model extends the HOH-CC model with scenarios. We first employ an exact approach to solve the model. Table 8 provides numerical examples solved by the GAMS software considering different network sizes and five demand scenarios. Considering a running time limit of 1800 seconds, the solver is not able to solve problems with more than 10 demand nodes. Naturally, the maximum network size of the optimally solvable HOH-CC-D is lower than the maximum instance size of the HOH-CC model (14 demand nodes - Table 6).

Table 8: Numerical Case Study of the HOH-CC-D model: Different Network Sizes and Computational Times using GAMS software.

# of nodes	# of central hubs	# of opened hubs lower-level/central	Spoilage Cost($)	Total Cost(k$)	Time(s)
10	1	1,4,7,9/ 4	64,085	929,523	531
10	2	1,4,7,9/ 4,7	57,729	901,532	1004
10	3	1,4,7,9/ 1,4,7	27,733	841,114	880
10	4	1,4,6,7/ 1,4,6,7	27,215	820,838	35
11	1	3,4,5,7/4	185,948	111,164	1006
11	2	-	-	-	-
11	3	-	-	-	-
11	4	1,4,6,7/1,4,6,7	137,771	937,345	88
12	1	4,7,8,11/11	514,979	1,871,519	1008
12	2	-	-	-	-
12	3	-	-	-	-
12	4	4,7,8,12/4,7,8,12	184,921	1,655,444	173
13	1	-	-	-	-
13	2	-	-	-	-
13	3	-	-	-	-
13	4	1,4,7,12/1,4,7,12	153,784	1,768,492	1009

Consequently, it is necessary to employ a heuristic approach to find near-optimal solutions in large-scale examples (Farahani et al., 2013; Dukkanci and Kara, 2017). Several solution methods have been developed for the NP-Hard hierarchical hub problems, such as the heuristic algorithm (Dukkanci and Kara, 2017; Saboury et al., 2013), the Tabu search (Chen, 2010), the Branch-and-price algorithm (Thomadsen and Larsen, 2007), and the genetic algorithm (GA) (Chi et al., 2011). Farahani et al. (2013) declare that GA is the most common and beneficial heuristic approach to solve NP-Hard HLP models in the literature. We resort to a GA method to solve our proposed optimization problem. The GA approach is a population-based heuristic search algorithm that explores the problem space to find a near-optimal solution with the help of simulating the mechanism of natural evolution (Rieck et al., 2014). In this study, we have used a single point crossover, a roulette wheel selection, and a one-point mutation for the applied genetic algorithm, so its complexity degree is $O(g(nm + nm + n))$, with g being the number of generations, n the population size, and m the size of each chromosome. The pseudo code presented in Algorithm 1 was coded in the MATLAB software.

Algorithm 1: Pseudo Code For the Genetic Algorithm With a Local Search.

Step 1: Generate the initial population.

Step 2: For each solution in the population set, do a local search.

Step 2.1: Find the optimal lower-level of allocations with the nearest facility method.

Step 2.2: Within the local search, repeat steps 2.2.1 to 2.2.3.

Step 2.2.1: Choose the central hubs randomly.

Step 2.2.2: Find the best higher-level allocation.

- Determine the best complementary operation.
- Determine the best hub for the related complementary operation.

Step 2.2.3: Calculate each objective function value of:

- Transportation cost.
- Delivery times.
- Complementary operations cost.
- Satisfaction rates.

Step 3: Perform crossover and mutation operations.

Step 4: Produce a new generation and go to step 2 until reaching a maximum generation.

Step 5: Stopping criterion.

In this study, two main parameters of the algorithm are analyzed, namely the number of population (*npop*) and number of generations (*iter*). So, an experimental design is conducted considering the objective function value as well as computational time. In the designed experiment, four levels are selected for each factor. (5,10,15,20) set is selected as the levels of *npop* and (25,50,75,100) as for the *iter*. Each experiment is replicated five times. According to the analysis of variance, shown in Figure 10, it is concluded that the *npop* is a significant parameter, while the *iter* is not statistically significant on the solution quality. Moreover, the main effect plot for the objective value in each level of *npop* and *iter* is depicted in Figure 11. Our analysis of the computational times and solution quality confirms that there is no significant difference between *npop*=10 and 15, while the *npop*=15 needs much more calculation time, so the *npop* is chosen as 10 and the *iter*, which is not significant statistically, is chosen as 50.

The instances of Table 8 have been solved by the new GA, and the results are shown in Table 10. There is a negligible difference between the results delivered by the algorithm and by the GAMS software in instances of small network sizes. Furthermore, the algorithm allows us to solve large network size instances. The opened hubs for the same small network sizes reported in Tables 8 and 10 demonstrate similar results for the

Factor Information

Factor	Levels	Values
npop	4	5, 10, 15, 20
iter	4	25, 50, 75, 100

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	15	0.259380	0.017292	1.84	0.048
Linear	6	0.198694	0.033116	3.52	0.004
npop	3	0.192773	0.064258	6.83	0.000
iter	3	0.005921	0.001974	0.21	0.889
2-Way Interactions	9	0.060686	0.006743	0.72	0.691
npop*iter	9	0.060686	0.006743	0.72	0.691
Error	64	0.601694	0.009401		
Total	79	0.861074			

Figure 10: Statistical analysis of designed experiment for tuning the algorithm parameters.

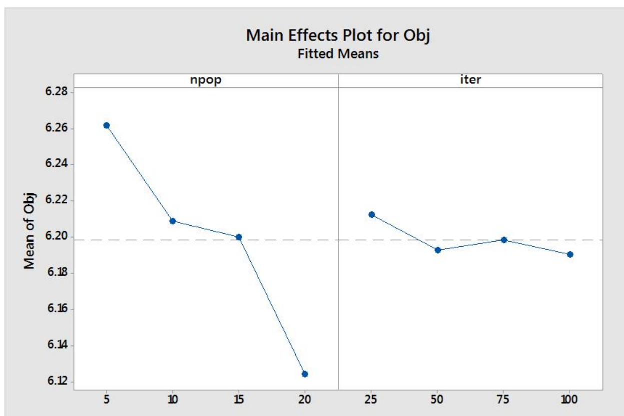

Figure 11: Main effect plot of algorithm parameters in each level on the objective function value.

GA approach and the exact optimization approach. Comparing the computational times presented in the last column of Table 8 with those of Table 10, it is clear that reasonable running times are achievable by the GA method.

Although the spoilage cost generated by the GA method (c.f. Table 10) is greater than that of GAMS on the HOH-CC-D model (c.f. Table 8), both are remarkably lower than the spoilage cost achieved by GAMS on the CHH model (c.f. Table 5). This makes it evident that the models equipped with the operations in hubs (i.e HOH-CC and HOH-CC-D) can more effectively restrain the deterioration rate of the goods in the network. This impact becomes more noticeable as the networks become larger. Moreover, the performance of the applied GA is compared to a heuristic algorithm (Modified Feasibility Pump). This algorithm, which has been proposed by Fischetti et al. (2005), is used to solve the MIP models and tries to find a proper feasible solution by solving some LP problems, iteratively. The algorithm starts with binary solutions extracted from linear programming, then enforces the model to achieve binary values for variables in a relaxed linear problem. The algorithm for our model is illustrated in Algorithm 2. GA algorithm performance has been compared with the modified feasibility pump, and the results are reported in Table 9. The results show that the GA algorithm has an average gap of 17 %, with an average time efficiency of 1082% compared with the feasibility pump algorithm. It confirms the superiority of the GA algorithm in finding a near-optimal solution in a reasonable time for the problem.

Table 9: Comparison of the GA algorithm's performance with the modified feasibility pump heuristic algorithm.

# of nodes	GA (ofv $*10^5$)	GA Time(s)	Feasibility Pump (ofv $*10^5$)	Feasibility Pump Time(s)	Solution Time Efficiency(%)	Gap (%)
8	5060.3	31.2	4546.7	**24.03**	-22.9	11.3
9	6045.6	**40.9**	5608.7	76.2	86.6	7.8
10	8777.3	**49.1**	6944.1	215.9	340.1	26.4
11	10264.7	**40.8**	8049.4	526.0	1189.0	27.5
12	20900.7	**52.7**	16231.2	1106.3	2000.5	28.8
13	21851.9	**84.9**	17317.3	1220.0	1337.0	26.2
14	27301.8	**88.1**	24315.2	1605.3	1722.9	12.3
15	30689.4	**178.0**	26484.7	1904.1	969.6	15.9
16	32664.8	**106.9**	29041.4	2202.3	1959.8	12.5
17	60241.7	**169.6**	54698.3	2270.1	1238.8	10.1
Average	-	-	-	-	1082.1	17.9

Algorithm 2: The modified Feasibility Pump Algorithm for the problem

Step1. Put $iteration = 0$ and solve LP relaxed problem. Let $X^*_{ijk}, Z^*_{is}, R^*_{isj}, F^*_{isk}$ to be their optimal values of relaxed decision variables;

Step2. Variables in the previous step will have a binary or real values, so construct a set of indices of variables with binary values (A_1), set of indices of variables with the rounded value of 1 (A_2), and set of indices of variables with the rounded value of 0 (A_3). Acquired values for $X^*_{ijk}, Z^*_{is}, R^*_{isj}, F^*_{isk}$ are considered as parameters ($\hat{X}^*_{ijk}, \hat{Z}^*_{is}, \hat{R}^*_{isj}, \hat{F}^*_{isk}$).

if $A_2 \cup A_3$ *is empty* **then**

  Return $X^*_{ijk}, Z^*_{is}, R^*_{isj}, F^*_{isk}$;

  Terminate algorithm.

end

while $iteration \leq MaxI$ **do**

  Let $iteration = iteration + 1$ and solve the following mathematical model ;

  $$\text{Min} \sum_{(i,j,s,k)\in A_3} (X_{ijk} + Z_{is} + R_{isj} + F_{isk}) + \sum_{(i,j,s,k)\in A_2} ((1 - X_{ijk}) + (1 - Z_{is}) + (1 - R_{isj}) + (1 - F_{isk}))$$

  s.t.: Original constraints.

  $$X_{ijk} = \hat{X}_{ijk}, Z_{is} = \hat{Z}_{is}, R_{isj} = \hat{R}_{isj}, F_{isk} = \hat{F}_{isk} \quad \forall (i,j,s,k) \in A_1$$

  $$(X_{ijk}, Z_{is}, R_{isj}, F_{isk}) \geq 0 \quad \forall i \in I, j \in H, k \in C, s \in I$$

  Update the sets of A_1, A_2, and A_3.

  if $A_2 \cup A_3$ *is empty* **then**

    Return $X^*_{ijk}, Z^*_{is}, R^*_{isj}, F^*_{isk}$;

    Terminate algorithm.

  end

end

if $iteration = MaxI$ **then**

  Fix the $R_{isj} = R^*_{isj}$ in the main model and solve the MIP model.

end

Table 10: Numerical case study of the HOH-CC-D model: different network sizes and computational times using the GA method.

# of nodes	# of central hubs	Opened hubs lower-level/central	Spoilage Cost($)	Total Cost(k$)	Time(s)
10	1	1,4,7,9/ 4	145,387	955,303	73
10	2	1,4,7,9/ 4,9	135,514	935,213	79
10	3	1,4,7,9/ 1,4,7	113,705	904,584	103
10	4	1,4,6,7/ 1,4,6,7	112,455	873,701	71
11	1	4,7,9,11/4	140,221	1,091,946	88
11	2	4,6,7,11/4,11	120,986	1,089,659	116
11	3	4,7,9,11/4,7,11	105,383	1,050,302	81
11	4	1,4,7,9/1,4,7,9	103,071	1,020,891	98
12	1	4,7,11,12/ 11	555,420	1,855,591	86
12	2	4,7,11,12/11,12	483,145	1,846,292	123
12	3	4,7,8,12/4,7,8	467,841	1,802,674	111
12	4	4,7,8,12/4,7,8,12	421,565	1,784,018	126
13	1	4,7,8,11/11	555,105	2,018,430	79
13	2	4,7,11,12/4,11	563,835	1,992,161	149
13	3	4,7,8,12/4,7,8	521,763	1,970,959	141
13	4	1,4,7,8/1,4,7,8	443,313	1,922,997	137
16	1	4,11,12,13/4	788,765	3,211,288	131
16	2	4,8,9,13/4,8	756,238	3,202,272	226
16	3	1,4,7,12/1,4,7	731,694	3,021,179	249
16	4	1,4,7,8/1,4,7,8	617,704	2,928,967	221
19	1	4,8,13,17/4	1,538,433	5,888,332	171
19	2	1,4,11,17/4,17	1,636,058	5,900,431	352
19	3	1,4,11,17/1,4,17	1,259,919	5,590,577	339
19	4	1,4,7,17/1,4,7,17	1,243,325	5,422,699	317
22	1	4,12,18,22/4	2,026,698	7,838,931	206
22	2	4,7,12,18/4,7	2,018,753	7,755,460	476
22	3	1,4,17,19/1,4,17	1,777,464	7,626,428	509
22	4	1,4,18,19/1,4,18,19	1,765,504	7,501,960	478
25	1	4,12,18,21/4	2,481,420	9,585,433	281
25	2	4,12,18,21/4,21	2,494,339	9,498,682	1059
25	3	1,4,8,18/1,4,18	2,269,800	9,160,403	663
25	4	1,4,18,19/1,4,18,19	2,104,488	9,027,061	770

To determine the efficiency of the solution for the HOH-CC-D model, which has been equipped with the cold chain operations, Figure 12 demonstrates a comparison between the HOH-CC-D model (i.e. equipped hub network) and the CHH model (i.e. non-equipped hub network).

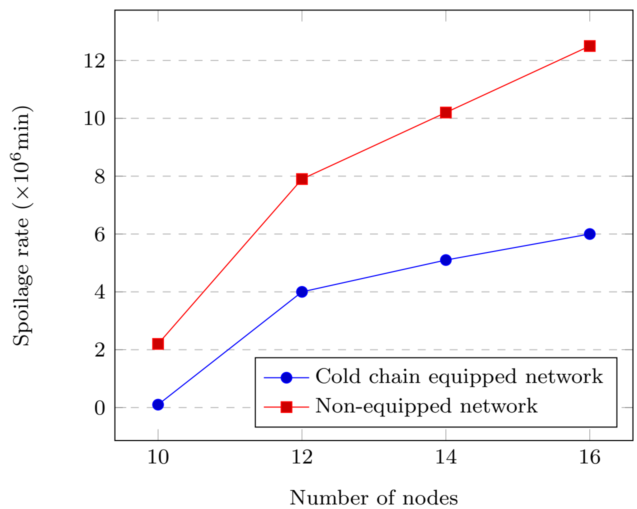

Figure 12: Numerical case study of the HOH-CC-D and CHH models: Comparing spoilage rates using the GA method.

As delineated in Figure 12, the spoilage rate in the cold chain-equipped network is reduced nearly by half. Moreover, the spoilage cost increases in larger network sizes as the delivery times for each pair of nodes get larger (see Equation (27)).

We also conduct another sensitivity analysis for investigating the effect of considering a multi-level freshness time window defined in our stochastic model. Herein, we calculate the number of ineffective freezing/refreshing operations incurred in the HOH-CC-D model by comparing the models considering single and multi-level freshness time windows. The analysis shows that the model with multi-level freshness time window can prevent ineffective operations in the hub nodes. Moreover, Figure 13 illustrates that a larger network yields more ineffective operations, which could be reduced by determining more central hubs in the network.

5. Comparisons and managerial implications

For highlighting the contributions of this study, we generally compare our results with the related findings provided in the prior literature. Table 11 demonstrates the comparisons in which we only focus on the practical (and not the solution or methodological) implications of our study and compare it with at least one set of similar results in recent publications.

Several main managerial implications can be drawn from this study. As the main implication in line with cold chain logistics operations, in our proposed model, there is no need to operate complementary operations inside the vehicles to keep the temperature of the products within a recommended temperature range. Given that in cold chain logistics companies transportation cost includes a major portion of the total cost compared with the production or inventory costs (Singh et al., 2017), in an effort to trim this cost, our model proposes

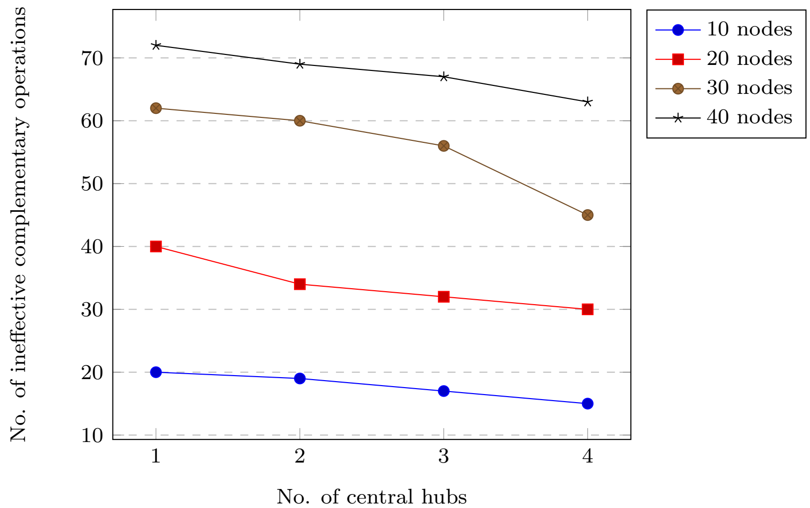

Figure 13: Numerical case study: Number of ineffective operations incurred using a single level freshness time window instead of a multi-level freshness time window in the HOH-CC-D model.

employing non-equipped vehicles for logistics. Therefore, depending on the perishable product, the cost of using any type of vehicles, and the distance between the network facilities, planners can employ any vehicles that maintain a constant temperature. For instance, unpasteurized milk has a short shelf life, and in any stage of the logistics chain, it cannot be stored for a long period. Accordingly, more expensive refrigerated trucks are required to ensure the maintenance of the freshness of the product, especially for long distances. In comparison with the consequent noticeable transportation cost, using our model with costs of freezing or refreshing operations in hubs would be more economical.

According to the recent effects of the Covid-19 pandemic on US meat supply, it has been discussed that the pandemic has significantly disrupted the food supply chain (ABC News, 2020). Empty grocery shelves were the direct result of the logistic and inventory insufficiency rather than food shortages. To point out the fundamental problem in the perishable food distribution system during the Covid-19 pandemic, it was reported that some perishable food manufacturers needed to pay for trucks to stay for days to unload their goods into a distribution center. Based on the applicability of hub networks in demand fluctuations and providing freezing and refreshing operations at hubs, our model demonstrates the compatibility of hubs to operate as efficient distribution centers that can mitigate the impact of pandemic-related demand disruptions.

As another implication, results highlighted that the settings for the freshness time window (Ft_f) and the delivery time window (β) between every pair of nodes are crucial in a cold chain to minimize/remove any spoilage. These parameters are highly related to the physical assets used in the given network that each has an optimum efficient working life. For instance, the thermal efficiency of trailers and containers diminishes throughout their useful life until the operator replaces them with a more modern unit. Our model optimizes the network and transmissions according to the existing physical assets in a planning horizon. Therefore, under reasonable settings for the working life of physical assets, our model would be able to provide practical

Table 11: Comparison of this study's results with the related findings provided in the prior literature

Main finding of this research	**Reference (this study)**	**Compared with another study**	**Characteristics of the study as per the finding**	**Remarks from the verification of this study**
No spoilage/waste by using refreshing and freezing operations at hubs	Section 4.2 - Table 5	Ma et al. (2018)	No waste by controling the freshness and quality of perishable food and trade-offs between transportation temperature and transport mode.	Transportation accompanied with refrigeration, which causes greater CO2 emissions.
Less spoilage/waste by using hubs with lower discount factors	Section 4.3 - Figure 4	Janssen et al. (2018)	Waste reduction in grocery stores for quickly perishable goods.	The waste is lower in the micro-periodic replenishment policy, which needs grocery retailers to be located close to their regional distribution centers for better collaboration (compared to lower discount factors in hubs).
Minimum total cost for perishable products with smaller freshness time windows	Section 4.3 - Figures 5 and 6	Chen et al. (2018)	Optimal freshness-keeping cost per unit of perishable product and per unit time is investigated.	A higher freshness-keeping cost is required to increase the storage time of perishable products.
Minimum total cost for networks with higher refreshing and freezing costs	Section 4.3 - Figure 7	Wang et al. (2019)	3 replenishment strategies (separate, joint leader-follower, and joint coalition of retailers) are discussed.	Minimum total cost gained for the network, but by using refrigerated transportation services.
Higher customer satisfaction by using refreshing and freezing operations at hubs	Section 4.4 - Table 7	Lin et al. (2020)	Inspect the quality of the vaccine by retailer (customer) in case of using a cold chain or non-cold chain.	Similar results (higher customer satisfaction by using cold chain), but with special decisions made by retailers.
Minimum spoilage rate and total cost in disruption situations	Section 4.5 - Table 10 and Figures 12	Maihami et al. (2019)	Minimize the deterioration costs for manufacturers and distributors in a probabilistic environment.	Similar results (both deterioration and total cost are minimized).
Lower number of ineffective complementary operations in hubs by using a multi-level freshness time window in disruption situations	Section 4.5 - Figure 13	Hamdan and Diabat (2020)	Minimizing the time and cost of delivering blood to hospitals after disruption.	Minimizing costs, but with no consideration of ineffective operations in blood collection centers and blood banks.

guidance for efficient product cold chain compliance.

As a theoretical implication, the results of considering an HLP model for a cold chain (HOH-CC model) demonstrates that the consideration of hub nodes instead of distribution centers in the models is more beneficial for the cold chains, as the hub facilities can serve demand nodes with a lower number of links. This helpful assumption not only develops an efficient cold chain but also helps managers in mitigating the number of disruptions occurring in the logistics system. Hubs are also loading and unloading, transshipment, and consolidation points in the network and can decrease the cost of inventories or establishing warehouses. Therefore, finding efficient hubs and allocating the demand nodes to them would be a helpful way to solve the issue of high inventory costs in the network redesigning process.

Our proposed hierarchical HLP model is applicable for distribution companies of perishable products facing high customer demand uncertainty. As every supply is dependent on a proper estimation of demand, the consideration of possible scenarios for the demand is crucial, especially for products with short shelf lives, such as food. Under this setting, companies must be prepared for the worst-case scenarios. Moreover, the quality or freshness of a perishable product can distort the demand. Although our model's multi-level freshness time window approach can maintain a desired quality level of excellence, the refrigeration equipment maintenance should be accurately arranged to ensure the least disruption on demand.

6. Conclusions and suggestions for future work

In this study, motivated by a case from a frozen food company, we introduce a hierarchical operational hub location problem for managing a cold chain of perishable products and configure an applicable distribution network. The respective mathematical model considers a complete network for central hubs that are connected to the other hubs. A discount factor on cost and time of flow between hubs is incorporated. Demand nodes are linked to the hubs with a single allocation strategy. Moreover, to be able to maintain the freshness of products at desirable level, hubs may also have additional services for perishable goods including refreshing and freezing operations. In the proposed MIP optimization model, these complementary operations are applied once the delivery time of each pair of nodes exceeds the freshness time window. As a consequence, the spoilage rate is reduced and the satisfaction rate, as well as freshness of goods, increases. Furthermore, to have a robust network in a disaster situation, the p-hub median problem is amended to a model affected by disruption. Both models with and without complementary operations are compared against each other. It is concluded that once the operations are applied, the total cost is reduced due to a significant decrease of the spoilage rate.

To the best of the authors' knowledge, most of the presented models in the literature did not consider the perishability feature of the transported good in designing hierarchical hub networks ((Lin and Chen, 2004; Wang et al., 2017; Dukkanci and Kara, 2017; Khodemani-Yazdi et al., 2019)). In fact, the proposed models did not support the freshness time window of products. Improper logistics can be the cause of up to one-third of spoilage in perishable food industries ((Rockefeller, 2013)). Without a freshness time limit, our findings support the results of the previous hierarchical hub location problem modeling presented by Yaman (2009); Alumur et al. (2012). By considering the freshness time limit, our findings supplement that using a high-quality equipped logistics system can help planners meet freshness time limits through the transportation network. The proposed model and algorithm in the present study have been moved forward to satisfy the freshness time limit beside satisfying basic hierarchical requirements. The proposed model and algorithm in the present study go beyond the satisfaction of basic hierarchical requirements and are capable of applying proper complementary operations on good flows that exceed freshness time limit in addition to minimizing travel time and travel cost to meet delivery time restriction.

Several sensitivity analyses are performed to investigate the validity of the model and draw some managerial insights. We realize that the lower the discount factors are, the lower the spoilage rate is. Furthermore, the freshness time window has a negative relationship to the total cost. For the freshness time windows that are longer than the delivery time windows, the spoilage and operational costs would be zero; however, in the large networks, the limits could increase correspondingly. Freezing and refreshing costs also have a threshold that determines the efficient investment for the fixed operational costs.

The proposed stochastic model is solved on larger networks by both the GAMS software and a customized genetic algorithm to address the computational burden. We observe that the genetic algorithm has a comparable result for the small network sizes and can comply with the medium-size networks by improving the running time and gap of the GAMS software's solutions. Beside the running time, our proposed GA algorithm is also capable of solving any large-size instances, whereas the exact optimization method of the GAMS solver cannot provide a solution in a reasonable time.

As a limitation for our study, in the temperature control levels, we remarked on two levels of operations to maintain the goods freshness level through refreshing and freezing operations, which could be extended according to Kuo and Chen (2010) as future research, with three or four operations (adding cooling and deeply freezing to the operations, for instance). As another limitation of this study, in the food types, we considered single-product transportation to meet FSIS guidelines, however, including multi-product distribution network as a potential future study direction can enhance the generalizability of the proposed model. Moreover, our proposed models are based on the incapacitated facilities in the network, while, according to Table 1, HLP models could consider limited facilities. In our model the cost of freezing and refreshing operations are fixed, but variable operational cost based on the volume or number of goods could be further examined.

Our proposed network will be able to manage the deterioration rate by applying freshness and freezing operations on goods if it is needed. Moreover, by considering stochastic demands of pair of nodes in the network, our model mitigates the catastrophic effects of disruption in the logistic network. The internet of things and all revolution regarding the industry 4.0 has lead to a significant change in the transportation industry, especially for perishable products. According to Bouzembrak et al. (2019), it is concluded that the IOT is going to be an effective technology for focusing on food safety as well as cold chain products' traceability and, finally, their quality monitoring. Considering such technologies and revolutions will lead to a significant improvement of the food transportation industry. As another direction for future work, novel recent multi-criteria decision-making can be employed for the solution approach regarding the proposed HLP problem (Zhang et al., 2020a,b).

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