Les Cahiers du GERAD ISSN: 0711–2440

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G–2025–78

November 2025

La publication de ces rapports de recherche est rendue possible grâce au soutien de HEC Montréal, Polytechnique Montréal, Université McGill, Université du Québec à Montréal, ainsi que du Fonds de recherche du Québec – Nature et technologies.

Dépôt légal – Bibliothèque et Archives nationales du Québec, 2025
– Bibliothèque et Archives Canada, 2025

The publication of these research reports is made possible thanks to the support of HEC Montréal, Polytechnique Montréal, McGill University, Université du Québec à Montréal, as well as the Fonds de recherche du Québec – Nature et technologies.

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Collaborative routing orchestration for organic food distribution

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November 2025
Les Cahiers du GERAD
G–2025–78

Abstract : This paper investigates the *Collaborative Routing Orchestration for Organic Food Distribution Problem* (CRO-FDP), a two-echelon collaborative distribution network setting inspired by a regional organic food network in Québec, Canada. The CRO-FDP integrates hub selection, vehicle routing, and synchronization decisions under tight time constraints to coordinate multiple producers and food banks sharing logistics resources. We develop a mixed-integer model and a *time-expanded* reformulation that jointly capture routing and timing decisions across a discretized planning horizon. A dedicated *Relax–Solve–and–Fix* matheuristic leverages this reformulation to efficiently solve realistic instances beyond the reach of standard formulations. Computational experiments demonstrate that the time-expanded model consistently yields feasible and near-optimal solutions for medium and large instances, outperforming the compact formulation. Results reveal significant efficiency and sustainability gains: collaborative pooling and hub usage reduce total travel distance by up to 1,000 km—an average decrease of 28%—and lower fleet requirements while maintaining service quality. These findings emphasize the strategic value of orchestration and hub-based collaboration for enhancing the environmental and economic performance of regional food distribution systems.

Keywords : Location-routing problem; collaborative distribution; organic food network; regional distribution systems; two-echelon logistic networks

1 Introduction

1.1 Motivation

The organic food sector has experienced significant growth over the last decade, driven by increasing consumer demand for locally sourced products and a growing awareness of sustainable food systems. According to the 2025 FiBL report on The World of Organic Agriculture, global retail sales of organic food exceeded €135 billion in 2023, representing a sustained annual growth rate of about 5% over the past decade (Willer & Schlatter, 2025). This evolution has intensified the need to strengthen the production, aggregation, and distribution capacities of organic producers and organizations to enhance food security and foster regional economic resilience.

Organic food distribution has distinctive operational challenges that differ from conventional logistics and require tailored solutions (Baez et al., 2020; Melkonyan et al., 2020). Unlike conventional products, organic goods often require strict segregation throughout the supply chain, particularly during transport and packaging, necessitating dedicated warehouses and vehicles. Transportation typically involves smaller, fragmented batches, which directly contrasts with the consolidated shipments common in conventional logistics (Melkonyan et al., 2020).Small and medium producers often lack adequate transport and storage infrastructure, resulting in high logistics costs (Baez et al., 2020; Etemadnia et al., 2015; Todorović et al., 2018). Organic products generally have a shorter shelf life and are highly perishable, demanding efficient and timely delivery as well as precise temperature control to maximize food quality and reduce waste (Albrecht & Steinrücke, 2017; Nguyen et al., 2019; Yadav et al., 2022). Together, these factors contribute to higher per-unit logistics costs and limited economies of scale. Overcoming these challenges requires an integrated approach that reflects the collaborative nature of regional organic food systems. Collaborative logistics has been shown to enhance efficiency and sustainability in agri-food supply chains (Wang et al., 2023; Zhou et al., 2024), while recent studies emphasize the need for integrated models that jointly address collaboration and sustainability in logistics decision-making (Nematollahi et al., 2021; Nguyen et al., 2019).

1.2 Problem statement

The proposed problem is grounded in the business case of the Consultation Table of Organic Food in the Laurentides (TCBL) region in the Province of Québec, Canada. The TCBL, a non-profit organization, aims to build a prosperous organic food sector by uniting and supporting diverse local companies and organizations, including growers, producer groups, retailers, restaurants, and regional food banks. These members are typically small, geographically dispersed, and face logistical challenges due to limited bargaining power with traditional logistics providers, who are generally not interested in small and specialized deliveries (Tongarlak et al., 2016). As an orchestrator, the TCBL must design an effective and efficient collective organic food distribution network that connects both commercial and food security organizations. This involves coordinating numerous heterogeneous entities, managing the transport of multiple commodities with specific weight, volume, handling, and timing constraints (Abbas et al., 2023), and addressing the challenge of small shipment sizes often below a single vehicle's capacity. Accordingly, orchestration decisions must integrate hub selection, fleet dimensioning, and detailed routing while maintaining service-level compliance and operational feasibility within a cooperative rather than competitive framework, a key distinction from traditional commercial logistics problems (Nematollahi et al., 2021; Cerulli et al., 2024).

This paper formalizes this context as the *Collaborative Routing Orchestration for Organic Food Distribution Problem* (CRO-FDP). The CRO-FDP models a two-echelon distribution network that integrates location and routing decisions across interconnected echelons (Ben Mohamed et al., 2020). Although related to the Two-Echelon Location–Routing Problem (2E-LRP), it differs structurally since only the second echelon involves location decisions (transfer hub activation), while both echelons include routing components, as in the Two-Echelon Vehicle–Routing Problem (2E-VRP, Cuda et al.

(2015)). The problem considers simultaneous facility location and vehicle routing decisions (Jacobsen & Madsen, 1980) with temporal coordination and perishable-goods constraints, resulting in a tightly coupled multi-level optimization structure. Similar to recent two-echelon and collaborative distribution studies (Kim et al., 2021), the CRO-FDP explicitly accounts for coordination and resource sharing among independent actors. The challenge is compounded by the need to synchronize product availability and delivery schedules within limited available time to fulfill the transportation—a requirement inherent to perishable food logistics (Jiang et al., 2018; Wang et al., 2021). The problem therefore encompasses three interconnected decision layers: the activation of transfer or consolidation hubs, the allocation of commodities to these hubs, and the routing and scheduling of vehicles with appropriate precedence. To the best of our knowledge, this study is the first to jointly integrate these three decision layers within a unified optimization approach specifically designed for collaborative organic food distribution.

1.3 Contribution

This paper makes three key contributions to the field of collaborative logistics and distribution network design, with a particular focus on sustainable regional food systems.

- We introduce the *Collaborative Routing Orchestration for Organic Food Distribution Problem* (CRO-FDP), a two-echelon collaborative distribution problem inspired by the operational context of the TCBL network. The CRO-FDP integrates resource pooling, synchronization, and hub-based coordination among multiple producers, combining features of the 2E-LRP and 2E-VRP while remaining distinct through its orchestration role and time-sensitive, multi-actor setting.
- We develop a mixed-integer optimization model that jointly determines hub activation, commodity allocation, and routing schedules within an integrated decisional process. To address the combinatorial complexity of the problem, we propose a time-expanded reformulation coupled with a dedicated *Relax–Solve–and–Fix* matheuristic capable of efficiently solving medium and large instances.
- We conduct computational experiments using TCBL data to assess the benefits of collaborative orchestration. Results show notable efficiency and sustainability gains: pooling and hub utilization reduce total travel distance by up to 1,000 km—an average decrease of 28%—and lower fleet requirements while maintaining service quality.

The remainder of this paper is structured as follows. Section 2 reviews the related literature on two-echelon distribution, collaborative routing, and perishable food logistics. Section 3 presents the problem setting and the mathematical model. Section 4 details the proposed solution approach. Section 5 discusses the computational experiments and managerial insights, and Section 6 concludes with key findings and directions for future research.

2 Literature review

2.1 Collaborative distribution

Collaboration among logistics players is increasingly recognized as a crucial strategy to enhance operational efficiency, reduce costs, and mitigate environmental impact (Audy et al., 2010; McLaren et al., 2002; Vargas et al., 2018). Horizontal collaboration, involving cooperation between organizations at the same supply chain echelon, has demonstrated significant benefits, including improved facility utilization and reductions in transportation costs (Ferrell et al., 2019; Padmanabhan et al., 2023). For instance, studies have shown that order sharing can lead to notable decreases in transportation expenses, ranging from 5% to over 15%, and flexible horizontal logistics collaboration coupled with adequate cost allocation strategies can yield even greater savings (Cruijssen et al., 2007; Vanovermeire et al., 2013).

Despite the compelling benefits, the successful implementation and long-term sustainability of collaborative transportation solutions present considerable challenges (Pan et al., 2019). Practical applications often fall short of achieving anticipated performances, with many initiatives failing in their early stages due to factors such as a lack of stakeholder participation and reluctance to alter existing satisfactory systems (Do et al., 2019; Karam et al., 2021).

A significant motivator for logistics collaboration is the prospect of cost savings, which places considerable research emphasis on designing fair and reasonable cost allocation mechanisms (Liu & Cheng, 2020; Santos et al., 2020; Vanovermeire et al., 2013). Various methods have been explored to ensure equitable distribution of benefits and costs among collaborators, with the Shapley value being widely utilized for its fairness in attributing contributions from each participant (Guajardo & Rönnqvist, 2016; Ciardiello et al., 2021).

In non-profit oriented contexts, collaboration among supply chain members becomes a key component for achieving organizational objectives (Çiğdem Ataseven et al., 2020; Xu et al., 2022). Such "umbrella" organizations—centralizing decisions, information, and resource allocation—enhance efficiency and resilience (Chatain & Plaksenkova, 2018; Gualandris & Klassen, 2018; Roehrich et al., 2023; Vaillancourt, 2017; Cornforth et al., 2014). In organic food chains, Nematollahi et al. (2021) show that coordination benefits all members by resolving channel conflicts. Similarly, the TCBL, as orchestrator of the CRO-FDP, coordinates hub use, allocation, and routing synchronization.

2.2 Organic food supply chain

The distribution of organic food products presents unique and complex challenges that distinguish them from conventional food items due to their perishable nature and stringent requirements for maintaining quality and safety throughout the supply chain (Baez et al., 2020; Melkonyan et al., 2020). Unlike conventional food, organic goods often necessitate strict segregation during transport and packaging, requiring dedicated infrastructure and vehicles. This leads to smaller, fragmented batches and higher per-unit logistics costs, impacting economies of scale (Baez et al., 2020). These characteristics underscore the need for collaborative pooling and hub-based coordination to restore economies of scale and ensure timely deliveries.

A critical challenge in organic food distribution stems from the inherent perishability and short shelf life of its products (Osvald & Stirn, 2008; Song & Ko, 2016). This demands efficient and timely delivery, as well as precise temperature control to maximize quality and minimize waste (Nguyen et al., 2019). Mismanagement in the cold chain can lead to significant capital loss and food deterioration (Aung & Chang, 2013; Han et al., 2021). Consequently, maintaining continuous product integrity from harvest to final consumption necessitates strict adherence to time windows and complex synchronization across the entire supply chain (Albrecht & Steinrucke, 2018; Jiang et al., 2018). This temporal coordination challenge is explicitly addressed in the CRO-FDP, which integrates due times and product release constraints.

Small and medium-sized producers in the organic sector often face challenges in accessing appropriate vehicles, warehouse facilities, and distribution infrastructures, which contributes to significant logistical costs and limits their negotiation power with traditional logistics providers (Baez et al., 2020; Etemadnia et al., 2015; Tongarlak et al., 2016). Intermediate and short food supply chains have been proposed as more sustainable alternatives to global networks (Renkema & Hilletofth, 2022), while collaboration also supports improvements in quality and safety (Naspetti et al., 2011). Food waste, in particular, emerges as a significant problem, primarily due to inefficiencies in handling, storage, and cold chain infrastructure (Yadav et al., 2022). Food banks play a key role in mitigating food waste by connecting surplus supply with those in need, highlighting the importance of optimizing interactions between donors, food banks, and agencies (Zhou et al., 2024). The CRO-FDP incorporates these actors through coordinated hubs, optimized allocation, and synchronized routing.

2.3 Two-echelon location–routing problems

The literature on two-echelon location–routing problems (2E-LRPs) can be divided into two main approaches: hierarchical and simultaneous (Ben Mohamed et al., 2023). In the hierarchical approach, location decisions are made at a strategic level and routing at a tactical one, whereas the simultaneous approach optimizes both decisions jointly to capture their interdependence. Due to the temporal constraints imposed by the perishable nature of organic food and the coordination required among members, the CRO-FDP adopts a simultaneous approach, integrating facility location and vehicle routing decisions within a unified optimization setting.

In practice, the temporal gap between strategic location and operational routing decisions has narrowed significantly. Emerging logistics paradigms such as on-demand warehousing, mobile hubs, ship-from-store systems, and truck–drone coordination exemplify the need for continuous and dynamic reconfiguration of distribution networks (Ben Mohamed et al., 2023; Faugère et al., 2020; Hübner et al., 2022; Moshref-Javadi et al., 2021). These developments underline the growing relevance of integrated approaches that optimize location and routing decisions simultaneously to achieve system-wide efficiency and responsiveness.

The Two-Echelon Location-Routing Problem (2E-LRP) arises when location decisions incorporate an intermediate facility. Fueled by the expansion of e-commerce, 2E-LRPs have attracted increasing attention, with models accounting for platform costs, capacity limits, and hierarchical routing structures. Sterle (2010) first defined the two-echelon Capacitated LRP in an urban context, proposing three mixed-integer programming formulations that differ in vehicle tracking. Subsequent studies (Contardo et al., 2012; Schwengerer et al., 2012) developed exact and heuristic methods to solve such problems, while more recent works extended these formulations to include time windows and flexible due dates (Mirhedayatian et al., 2021; Darvish et al., 2019). Unlike traditional 2E-LRPs, the CRO-FDP situates transfer hubs within the second echelon and enforces synchronization between interconnected routes, adding a temporal and collaborative dimension.

While most 2E-LRPs consider a single type of operation, the problem becomes a 2E-LRP with simultaneous pickup and delivery (Yıldız et al., 2023) when both operations occur at the same customer. Fewer studies consider distinct pickup and delivery operations across echelons, including multi-product formulations by Rahmani et al. (2016) and direct delivery settings by Azizi & Hu (2020). do C. Martins et al. (2021) further explores precedence relationships between pickup and delivery customers. Nevertheless, these contributions generally treat the two flows independently and do not address the synchronization of timing and capacity across echelons, which is central to collaborative orchestration.

In a city logistics context, Gückel et al. (2025) examine the orchestration between logistics service providers, showing that collaboration leads to savings of 26%. However, synchronization between echelons was not considered. Tight synchronization constraints were recently modeled by Escobar-Vargas & Crainic (2024), who proposed a time-expanded formulation to better manage timing dependencies. Despite significant progress on 2E-LRPs, the combination of location, routing, and synchronization decisions remains largely unexplored. To the best of our knowledge, Mirhedayatian et al. (2021); Escobar-Vargas & Crainic (2024) are the only works addressing synchronization across both echelons. The CRO-FDP extends this emerging research stream by embedding synchronization in a collaborative setting and demonstrating the computational advantages of a time-expanded reformulation on realistic regional instances.

3 Problem description and mathematical model

3.1 Problem description

In the *Collaborative Routing Orchestration for Organic Food Distribution Problem* (CRO-FDP), we consider a two-echelon distribution network composed of producers (members), transfer hubs, and clients or food banks, coordinated through a central depot (dummy in our network representation) where all vehicle routes start and end. Each transportation request, referred to as a commodity, corresponds to a specific product flow with a defined origin (member), destination (client or food bank), and quantity. Furthermore, according to the service-level agreement between each member and its clients, each commodity has a time at which it is available at its origin for pickup and a due time for delivery at its destination. While these time constraints are respected, each commodity can be served by a single vehicle or by multiple vehicles through hubs.

We define a hub as a transfer or consolidation facility that can be activated within the network to enable collaborative resource sharing. Although activating a hub entails minor adaptation and handling costs, it facilitates vehicle transfer and shipment pooling among members. Hubs primarily serve as intermediate transshipment points for short-term consolidation of commodities. No long-term storage or transformation occurs at these sites; hence, synchronization between incoming and outgoing vehicles is essential to meet delivery due times and preserve product freshness. Key decisions — the activation of hubs and the coordination of inter-vehicle transfers — are binary, strongly interdependent, and together contribute to the combinatorial complexity of the problem.

The distribution system operates with a homogeneous fleet of vehicles that can pick up commodities from members and deliver them to clients, potentially using the intermediate hubs. Each vehicle has a limited capacity, a maximum operation time, a fixed cost per route, and a variable cost per distance traveled. The goal of the CRO-FDP is to determine optimal vehicle routes and hub utilization that minimize total operational cost while satisfying vehicle capacity and time constraints. This collaborative setting is formally captured in the next section through a mixed-integer programming formulation (denoted FM), which integrates hub activation, vehicle routing, and temporal synchronization decisions into a unified optimization approach.

3.2 The FM model

In this section, we formalize the *Collaborative Routing Orchestration for Organic Food Distribution* problem as a mixed-integer linear programming model that jointly captures the location and routing decisions while effectively managing synchronization and commodity precedence constraints. This model enables the integrated optimization of resource allocation and logistical flows, ensuring efficient and timely delivery of perishable goods. To achieve this, we use continuous decision variables to determine which vehicle serves each commodity transport request, and at what time. It explicitly tracks both vehicle and commodity flows, providing a detailed temporal and spatial representation of logistics operations.

In the mixed-integer programming (MIP) formulation, denoted by FM we assume that there is a finite set L of identical vehicles that can transport goods across the network.Also, we denote by K the finite set of commodities (transport requests), indexed by $k \in K$. Each commodity has an origin, available time, destination, and due time, denoted by o_k, o_k^t, d_k and d_k^t, respectively. There are four types of nodes: the *origins* given by the set $\mathcal{O} = \{o_1, \ldots, o_k\}$, the *destinations* $\mathcal{D} = \{d_1, \ldots, d_k\}$, *hubs* H and finally the dummy depot node Δ. The set of non-depot nodes is denoted by $N = \mathcal{O} \cup \mathcal{D} \cup H$, which is completed by the depot to form the set of all nodes $\overline{N} = N \cup \{\Delta\}$.

Consider the complete directed graphs (N, A) and $G = (\overline{N}, \overline{A})$ on N and $\overline{N}$ respectively. That is

$$A = \{(m,n) \in N \times N : m \neq n\}, \quad \overline{A} = \left\{(m,n) \in \overline{N} \times \overline{N} : m \neq n\right\}.$$

To simplify the model presentation, we denote by $A_{n\to*}$ or $A_{n\to*}$ the set of arcs whose origin is node $n \in \overline{N}$ and by $A_{*\to n}$ or $A_{*\to n}$ the set of arcs whose destination is node $n \in \overline{N}$. Putting an overline over any of these sets indicates that the depot node Δ is a permissible origin or destination. We will also denote by a^+ and a^- the head and tail of the arc $a \in \overline{A}$. That is, if $a = (m,n)$ then $a^+ = n$ and $a^- = m$.

To each arc $a \in A$ we associate a travel time $\tau_a > 0$ to traverse it, which includes the service time at the arrival node. Travel time to and from the dummy depot node is assumed to be zero. Each vehicle has a total travel time W_ℓ after which it must have completed its tour.

On this structure we define the following decision variables: first, for each $h \in H$ we let $y_h \in \{0, 1\}$ denote the choice of opening hub h. The binary variable $f_a^{k\ell}$ takes the value of 1 if commodity $k \in K$ goes through arc $a \in A$ on vehicle $\ell \in L$. The flow of vehicles is regulated by the binary decision variables x_a^ℓ, which takes the value 1 if and only if vehicle $\ell \in L$ uses arc $a \in \overline{A}$. The binary decision variable $u_{hk}^{\ell\ell'}$ takes the value 1 if a commodity $k \in K$ is transferred from vehicle $\ell \in L$ to another vehicle $\ell' \in l$ at hub $h \in H$.

Finally, the following continuous variables are used to track time, ensuring that the precedence constraints are fulfilled. Decision variable e_n^ℓ denotes the arrival time of vehicle $\ell \in L$ at node $n \in \overline{N}$, while d_n^ℓ corresponds to the departure time of vehicle l from node n.

We seek to minimize the total cost of transport, which consists of three parts: the cost of using a hub, the fixed cost of using (hiring) a vehicle, and the variable routing cost:

$$min \sum_{h \in H} C_h y_h + \sum_{\ell \in L} \sum_{a \in \overline{A}_{*\to\Delta}} C_l x_a^\ell + \sum_{\ell \in L} \sum_{a \in A} C_a^\ell x_a^\ell. \tag{1}$$

Here, C_h is the cost of opening hub $h \in H$, C_ℓ is the cost of using vehicle $\ell \in L$ and C_a^ℓ is the cost of moving vehicle ℓ across arc $a \in A$.

In the FM model there are four types of constraints: hub and transshipment constraints, flow constraints, commodity and vehicle synchronization constraints and finally capacity constraints.

Hub and transshipment constraints

$$u_{hk}^{\ell\ell'} \leqslant y_h \qquad \forall h \in H, \forall k \in K, \forall \ell, \ell' \in L \tag{2}$$

$$\sum_{a \in \overline{A}_{*\to h}} f_a^{k\ell} + \sum_{a \in \overline{A}_{h\to *}} f_a^{k\ell'} \leqslant u_{hk}^{\ell\ell'} + 1 \qquad \forall h \in H, \forall k \in K \forall \ell, \ell' \in L \tag{3}$$

We can only transfer commodities between different vehicles at a hub, which is the content of (2). On the other hand, (3) says that a commodity k can only be transferred from vehicle ℓ to vehicle ℓ' at hub h if $u_{hk}^{\ell,\ell'} = 1$.

Origin-destination commodity flows

$$\sum_{\ell \in L} \sum_{a \in A_{*\to d_k}} f_a^{k\ell} = 1 \qquad \forall k \in K \tag{4}$$

$$\sum_{\ell \in L} \sum_{a \in A_{o_k\to *}} f_a^{k\ell} = 1 \qquad \forall k \in K \tag{5}$$

$$\sum_{a \in A_{*\to n}} f_a^{k\ell} - \sum_{a \in A_{n\to *}} f_a^{k\ell} = 0 \qquad \forall \ell \in L, \forall n \in N \backslash \{o_k, d_k\}, \forall k \in K \tag{6}$$

$$\sum_{a \in \overline{A}_{*\to n}} x_a^\ell - \sum_{a \in \overline{A}_{n\to *}} x_a^\ell = 0 \qquad \forall \ell \in L, \forall n \in N \tag{7}$$

$$f_{ak}^\ell \leqslant x_a^\ell \qquad \forall k \in K, \forall \ell \in L, \forall a \in A \tag{8}$$

$$\sum_{a \in \overline{A}_{\Delta\to *}} x_a^\ell \leqslant 1 \qquad \forall \ell \in L \tag{9}$$

$$\sum_{\ell \in L} \sum_{a \in \overline{A}_{*\to n}} x_a^\ell \leqslant 1 \qquad \forall n \in N \tag{10}$$

$$\sum_{\ell \in L} \sum_{a \in \overline{A}_{*\to h}} x_a^\ell \leqslant y_h \qquad \forall h \in H \tag{11}$$

Constraints (4)–(5) ensure that commodity $k \in K$ departs from its origin and arrives at its destination. Flow conservation at non-hubs nodes is assured by (6). The flow conservation for every vehicle at every node is given by (7). Constraint (8) says that a commodity can be taken across arc a by vehicle ℓ only if that vehicle actually travels across the arc. Constraint (9) states that a vehicle can only depart the depot once, while (10) means that every node can be visited by at most one vehicle. Finally, constraint (11) states a vehicle can only visit those hubs that have been selected.

Synchronization between vehicles and commodities Recall that a^+ and a^- denote the head and tail of the arc a. We denote by M a sufficiently large constant.

$$e_h^\ell - d_h^{\ell'} \leqslant M(1 - u_{hk}^{\ell\ell'}) \qquad \forall k \in K, \forall \ell, \ell' \in L, \forall h \in H \tag{12}$$
$$d_{a^-}^\ell + \tau_a - e_{a^+}^\ell \leqslant M(1 - x_a^\ell) \qquad \forall \ell \in L, \forall a \in \overline{A} \tag{13}$$
$$e_n^\ell \leqslant d_n^\ell \qquad \forall \ell \in L, \forall n \in N \tag{14}$$
$$e_\Delta^\ell \geqslant d_\Delta^\ell \qquad \forall \ell \in L \tag{15}$$
$$e_{d_k}^\ell \leqslant d_k^t \qquad \forall k \in K, \forall \ell \in L \tag{16}$$
$$d_{o_k}^\ell \geqslant o_k^t \qquad \forall k \in K, \forall \ell \in L \tag{17}$$

Because M controls differences between time steps in (12) and (13), it must be chosen much larger than the time horizon T.

The condition (12) is the synchronization constraint at hubs when commodities are transferred. Vehicle time consistency is ensured through constraints (13). These constraints also serve as sub-tour elimination. Constraints (14)–(17) ensure that the times when commodities become available and when they are due is respected.

Vehicle capacity and time

$$e_\Delta^\ell - d_\Delta^l \leqslant W_l \qquad \forall \ell \in L \tag{18}$$
$$\sum_{k \in K} q_k x_a^\ell \leqslant Q_l \qquad \forall \ell \in L, \forall a \in A \tag{19}$$

Constraint (18) ensures that the total travel time of a vehicle does not exceed the working time of the vehicle. The capacity of each vehicle is enforced by (19).

3.3 Valid inequalities

In the context of a homogeneous fleet, the FM formulation introduces significant symmetry due to the vehicle index (ℓ). Since all vehicles have the same usage cost, swapping one vehicle for another yields the same objective value. One way to reduce this symmetry is by adding a lexicographic constraint, which enforces an order in the use of vehicles. In other words, vehicle $\ell = 2$ cannot operate unless vehicle $\ell = 1$ is already in use. This order is determined by the departure from the dummy depot. Taking into account our notation from above, the constraint can be written as follows:

$$\sum_{a \in \overline{A}_{\Delta \to *}} x_a^\ell \leqslant \sum_{a \in \overline{A}_{\Delta \to *}} x_a^{\ell-1} \qquad \forall \ell \in L \setminus \{1\}\,. \tag{20}$$

Further, since all solutions must use at least one vehicle to fulfill all transportation requests, the use of the first vehicle can be made mandatory. This corresponds to adding the following constraint to the FM model:

$$\sum_{a \in \overline{A}_{\Delta \to *}} x_a^1 \geqslant 1 \tag{21}$$

These constraints eliminate symmetry by enforcing a specific order of vehicle utilization, thereby reducing equivalent solutions and improving the solver's efficiency.

4 Reformulation and solution method

The complexity and size of the problem means that commercial solvers struggle to find feasible solutions in the real-life instances that we are interested in. Therefore, we propose a 'Relax, Solve, and Fix' procedure. For this we reformulated organic food distribution problem with MIP model that uses a time-expanded network. Here, time decisions are given jointly with flow decisions. The planning horizon is split into discrete time intervals. We name this new formulation TE.

4.1 The TE formulation

The TE model is defined on a time-expanded network whose physical network $(\overline{N}, \overline{A})$ is the same as for the FM model, see subsection 3.2. Recall that $\overline{N} = N \cup \{\Delta\}$ where Δ is the dummy depot.

For the time-expanded formulation, the time horizon is discretized into a finite number of periods. Specifically, let δ be the interval length. There are η discrete time intervals, so the total horizon runs from time 0 to time $\eta\delta$. Let $T = \{0, \delta, 2\delta, \ldots \eta\delta\}$ be the set of indices for the time intervals.

Therefore, the time-expanded network is given by the nodes $\overline{N}^E = \overline{N} \times T$, with $N^E = N \times T$ representing the non-depot time expanded nodes. Given a time-expanded node $\nu = (n, t) \in \overline{N}^E$ we will refer to n as the *physical component* and write $p_\nu = n$ and to t as the *time component* of the node, also denoted t_ν.

We define two types of arcs on the time-expanded nodes. First, let τ_{mn} be the travel time from node m to node n. We assume that each τ_{mn} is an integer multiple of δ. The *diagonal* arcs are those that start at the physical node m at some time and end at the physical node n at τ_{mn} units later, provided that this later time is still within the time horizon. That is, they model the movement of a vehicle from m to n in time τ_{mn}. Define the set of all diagonal arcs to be :

$$A^D = \left\{\left((n,t),(m,t+\tau_{nm})\right) : n,m \in \overline{N}, t \in T,\ t + \tau_{mn} \leqslant \eta\delta\right\}.$$

We also define arcs that correspond to a vehicle waiting at a node for one time period:

$$A^W = \{((n,t),(n,t+\delta)) \forall n \in N, t \in T \setminus \{\eta\delta\}\}.$$

The latter set of arcs can be written as the disjoint union of sets $A^{(n)}$ for $n \in N$. Here, $A^{(n)}$ is the set of time-expanded arcs that wait at node n, i.e. that are of the form $((n,t),(n,t+\delta))$. Finally we denote by A^H the union of $A^{(h)}$ for $h \in H$, that is the set of all waiting arcs at a possible hub location.

The *time-expanded graph* is $G^E = (N^E, A^E)$ where $A^E = A^D \cup A^W$ is the set of all time-expanded arcs. We denote by $\overline{G}^E$, $\overline{A}^D$ and $\overline{A}^W$ the sets of arcs obtained by replacing N by $\overline{N}$ in the above definitions, i.e. when the dummy depot node is included.

On the time-expanded graph we define the following binary variables: y_h takes the value of 1 if hub $h \in H$ is used. x_a^ℓ takes the value of 1 if vehicle $\ell \in L$ passes through the time-expanded arc $a \in \overline{A}^E$ (i.e. ℓ waits at node n if $a = ((n,t),(n,t+\delta))$ is a waiting arc and moves from m to n if $a = ((m,t),(n,t+\tau_{m,n}))$ is a diagonal arc.) Finally, $f_a^{k\ell}$ takes the value of 1 if commodity $k \in K$ travels through arc $a \in A^E$ in vehicle $\ell \in L$.

We denote by o_k and d_k the origin and destination of commodity $k \in K$ in the time-expanded network. That is, $o_k = (o_k^P, o_k^T)$ and $d_k = (d_k^P, d_k^T)$, which means that commodity k becomes available at physical node o_k^P at time o_k^T and needs to be delivered to physical node d_k^P by time d_k^T.

Echoing the conventions from the FM model in subsection 3.2, we denote by $A_{n\to *}^E$ (respectively $A_{*\to n}^E$) the set of arcs starting (respectively ending) at a physical node $n \in \overline{N}$, that is the set of arcs coming out of (respectively ending at) a node of the form (n,t) for some $t \in T$. For a time-expanded arc $a \in A^E$ of the form $a = (\mu, \nu)$ we will also use the notation $\pi^+(a) = \nu \in N^E$ and $\pi^-(a) = \mu \in N^E$ to denote the (time-expanded) *head* and *tail* of a

Just as in the FM model, the total transport cost is to be minimized. It is composed of the cost of using a hub, the cost of using a vehicle and the travel time of a vehicle across an arc $a \in A^E$.

$$\min \sum_{h \in H} C_h y_h + \sum_{\ell \in L} \sum_{a \in A^D_{*\to\Delta}} C_\ell x^\ell_a + \sum_{\ell \in L} \sum_{a \in \overline{A_E}} C^\ell_a x^\ell_a \tag{22}$$

In the TE model there are three types of constraints: those concerning hubs and transshipment, those regarding origin-destination commodity flow and finally there are capacity constraints.

Hubs and transshipment constraints

$$\sum_{a \in \overline{A}^D_{*\to h}} x^\ell_a \leqslant y_h \qquad \forall h \in H, \forall \ell \in L \tag{23}$$

$$f^{k\ell}_a \leqslant x^\ell_a \qquad \forall k \in K, \forall \ell \in L, \forall a \in A^E \backslash (A^E_{o^P_k} \cup A^E_{d^P_k} \cup A^E_H) \tag{24}$$

Constraint (23) says that a vehicle can visit a hub only if that hub selected, while (24) is a linking constraint: a commodity can only travel on an arc if the a vehicle travels the arc, or the arc is a waiting arc at the commodity origin, destination or a hub node.

Origin-destination commodity flow

Recall that $o_k = (o^P_k, o^T_k)$ and $d_k = (d^P_k, d^T_k)$ denote the time-expanded origin and destination nodes of a commodity $k \in K$.

$$\sum_{\ell \in L} \sum_{\substack{a \in A \\ a^- = o_k}} f^{kl}_a = 1 \qquad \forall k \in K \tag{25}$$

$$\sum_{\ell \in L} \sum_{\substack{a \in A \\ a^+ = d_k}} f^{k\ell}_a = 1 \qquad \forall k \in K \tag{26}$$

$$\sum_{\ell \in L} \sum_{\substack{a \in A^E \\ a^- = \nu}} f^{k\ell}_a - \sum_{\ell \in L} \sum_{\substack{a \in A^E \\ a^+ = \nu}} f^{k\ell}_a = 0 \qquad \forall \nu \in N^E \backslash \{o_k, d_k\}, \forall k \in K \tag{27}$$

$$\sum_{\substack{a \in A^E \\ a^+ = \nu}} f^{k\ell}_a - \sum_{\substack{a \in A^E \\ a^- = \nu}} f^{k\ell}_a = 0 \qquad \forall k \in K, \forall \ell \in L, \forall \nu \in N^E \backslash (H \cup \{o_k, d_k\}) \tag{28}$$

$$\sum_{\substack{a \in \overline{A}^E \\ a^+ = \nu}} x^\ell_a - \sum_{\substack{a \in \overline{A}^E \\ a^- = \nu}} x^\ell_a = 0 \qquad \forall \nu \in N^E, \forall \ell \in L \tag{29}$$

$$\sum_{a \in \overline{A}^D_{\Delta\to *}} x^\ell_a \leqslant 1 \qquad \forall \ell \in L \tag{30}$$

Constraints (25)–(28) are the flow conservation constraints for the commodities: Equations (25) and (26) ensure that each commodity is generated at its origin time and location o_k and is delivered to its destination time and location d_k. Equation (27) ensures that as many commodities leave any node as enter, except for origin and destination nodes. Transfers between vehicles are controlled by (28): commodities may change vehicle only at hub nodes, in other words, if a commodity arrives at node, ν, on a vehicle, ℓ, it should leave on the same vehicle except if ν is a hub candidate node. Flow conservation for the vehicles is encoded by (29) while (30) means that a truck can only leave the depot once.

Capacity constraints Recall that a^+ and a^- are the (time-expanded) head and tail of an arc a and that t_ν denotes the time component of a time-expanded node ν.

$$\sum_{k \in K} q_k f^{k\ell}_a \leqslant Q_\ell \qquad \forall \ell \in L \forall a \in A^D \tag{31}$$

$$\sum_{a \in \overline{A}^E} (t_{a^+} - t_{a^-})\, x_a^l \leqslant W_\ell \qquad \forall l \in L \tag{32}$$

The capacity of each vehicle is enforced by (31), while (32) ensures that the working time of each vehicle is respected.

4.2 Preprocessing for the TE model

One of the main challenges of using a time-expanded network is that each discrete decision variable must be defined for every time step and vehicle, resulting in a very large number of binary variables. However, we can exploit specific temporal and structural characteristics of the problem to drastically reduce the number of flow variables $f_a^{k\ell}$.

Since the flow of each commodity $k \in K$ occurs only between its time-expanded origin node $o_k = (o_k^P, o_k^T)$ and destination node $d_k = (d_k^P, d_k^T)$, we can eliminate all flow variables corresponding to arcs $a \in A^E$ that cannot possibly carry commodity k. In other words, only arcs consistent with the commodity's availability, due time, and feasible travel duration are retained.

For example, if an arc starts before the commodity's release time or ends after its due time, it is unnecessary to define a flow variable for that arc. By applying a set of logical conditions, we can prefilter infeasible time–space arcs and restrict the domain of $f_a^{k\ell}$ to the feasible subset A_k^E. The following conditions (I–V) describe when an arc $((n,t),(n',t'))$ is excluded from A_k^E:

I) $t < o_k^T$ or $t = o_k^T$ and $(n,t) \neq (o_k^P, o_k^T)$
II) $t' > d_k^T$ or $t' = d_k^T$ and $(n',t') \neq (d_k^P, d_k^T)$
III) $n' \neq n$ and $n' = o_k^P$
IV) $n' \neq n$ and $n = d_k^P$
V) $t' + \tau_{(n',d_k^P)} > d_k^T$

Conditions I and II restrict arcs to those whose temporal components fall within the feasible interval between the commodity's release and due times. Conditions III and IV ensure that a commodity does not re-enter its origin node or depart from its destination node. Finally, condition V guarantees that a commodity only visits nodes from which it can still reach its destination within the remaining delivery window. This preprocessing step substantially reduces the number of binary flow variables in the TE model, improving tractability without affecting optimality.

4.3 Solution algorithm

We propose a 'Relax, Solve, and Fix' procedure to address the computational complexity of the TE model. Following Marshall et al. (2021), the relaxation aggregates consecutive time steps into coarser intervals, thus reducing the number of time-dependent decision variables while preserving temporal feasibility. The overall procedure, summarized in Algorithm 1, proceeds as follows:

Step 1. Construct the interval-based network and solve the corresponding relaxation, denoted the *Interval-Based MIP*, to obtain an initial lower bound (lines 2–3 of Algorithm 1).
Step 2. Check feasibility of the relaxed solution (lines 5–7)
Step 3. Construct the final solution: if the relaxed solution is feasible for the full TE model, it is optimal; otherwise, new feasible solutions are built using information extracted from the relaxed model (lines 9–15).

This approach provides a tractable way to combine lower- and upper-bound construction, balancing model accuracy and computational efficiency.

Algorithm 1 High-level description of the solution method.

Require: Base network $G = (N, A)$, Set of commodities K
Ensure: Dual bound LB, primal bound UB, feasible solution $\mathcal{S}$
$\mathcal{S} \leftarrow \varnothing$
Create a reduced network $G^\lambda = (N^\lambda, A^\lambda)$ ▻ subsubsection 4.3.1
Compute a LB from G^λ
Obtain S' from the relaxed model primal bound UB'
if S' is feasible **then** ▻ subsubsection 4.3.2
    $UB \leftarrow UB', S \leftarrow S'$
    return UB, LB, S
end if
Compute a new set of commodities K' from S'
Create a reduced network $G' = (A', N)$ from S'
Use RGCH to compute a primal bound UB_{RGCH} from K' ▻ subsubsection 4.3.3
Compute primal bound UB_{rubs} from $G' = (A', N)$ ▻ subsubsection 4.3.3
$UB \leftarrow min(UB_{RGCH}, UB_{rubs})$
Update S from UB
return UB, LB, S

4.3.1 Interval-based relaxation

To build the interval-based relaxation, we adapt the approach of Marshall et al. (2021), extending it to include both commodity and vehicle flows. This requires defining a consistent time partition across all nodes in the network.

In our interval-based relaxation, we divide the overall time horizon T into intervals I_j of fixed length and glue together all time-expanded nodes that have the same physical component and whose time component falls into the same interval. Recall that time advances in discrete steps of duration δ, giving the time horizon $T = \{0, \delta, 2\delta, \ldots, (\eta-1)\delta\}$. Thus, we choose the number of intervals λ and split T into intervals $I_j = [(j-1)\frac{\delta\eta}{\lambda}, j\frac{\delta\eta}{\lambda})$ for $j \in \{1, \ldots, \lambda\}$. For example, as shown in Figure 1, for the physical node n all the time expanded nodes, $[(n, 0), (n, \delta)]$, that are inside the time interval I_1 will be a single node in the interval-based relaxation.

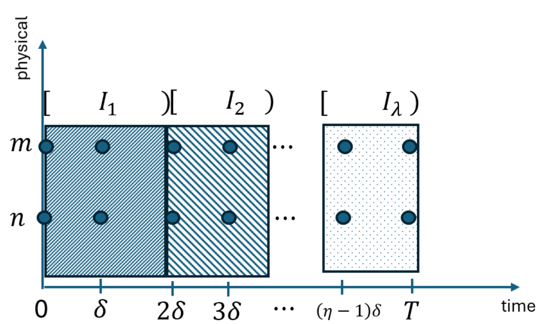


Figure 1: Interval-based time relaxation.

In this way we obtain a new set of time-expanded nodes

$$N^{(\lambda)} = \{(n, I_j) \colon n \in N,\ j \in \{1, \ldots, \lambda\}\}$$

(with the usual convention that $\overline{N}^{(\lambda)}$ includes the dummy depot node Δ among the physical nodes.

In this projection network, the waiting arcs are of the form $((n, I_j), (n, I_{j+1}))$, while the travelling arcs can be characterized as follows: for $m, n \in \overline{N}$ with $m \neq n$ we have $((m, I_i), (n, I_j)) \in A^{(\lambda)}$ if and only if there exist nodes in the full time-expanded networks that are connected by an arc and that are mapped to (m, I_i) and (n, I_j) respectively. Equivalently, $((m, I_i), (n, I_j)) \in A^{(\lambda)}$ if and only if there exist times $t_i \in I_i$ and $t_j \in I_j$ such that $((m, t_i), (n, t_j)) \in \overline{A}^D$. Note that this does not exclude the possibility that $i = j$: in the interval-based network, vertical arcs are possible (and occur between m and n if and only if the travel time from m to n is less than the duration $\frac{\eta\delta}{\lambda}$ of the intervals). The projection can be applied to the entire TE model, leading to the *interval-based model* which can be read off equations (22)–(32) by replacing N^E and A^E with N^λ and A^λ. In this way we obtain an MIP that we call the *interval-based relaxation*.

In order to accelerate the solution approach, we can perform pre-processing and symmetry breaking for the interval-based model as we did for the TE formulation in subsection 4.2. Moreover, we need to add subtour constraints. See Appendix A for details.

4.3.2 Feasibility check

The vehicle routes obtained from the interval-based relaxed model represent a feasible solution to the full TE model if and only if the routes respect the commodity times and the synchronizations at hubs are possible. In order to verify this, we introduce a linear program (LP) that attempts to undo the interval projection. The LP formulation is provided in Appendix A.

If the LP model (36)–(42) is feasible, we can assign visit times in the time-expanded model to each vehicle route and thus obtain a feasible solution to the full TE model. Moreover, the costs of the routes are the same in the interval-based relaxation and the full TE model. Therefore, in the case of feasibility we have found the optimal solution to the TE model.

4.3.3 Upper-bound solution construction

If the relaxed solution is not feasible for the full model, it can still provide valuable insights. Crucially, it reveals potential transfer points (hubs) and identifies the commodities that could benefit from such transfers. Also, the lower bound solution gives a set of arcs that may be used in the full solution. With this information, two different solutions can be obtained as follows. The first is a randomized greedy constructive heuristic (RGCH) and the second, called the *reduced upper bound solution* (RUBS) proceeds by restricting the arcs that can be used. Each of these solutions yields a corresponding upper bound.

Valid solution 1 The commodities are split into two groups: those that were transferred through a hub in the relaxed solution and those that weren't. For those commodities where a hub was used, a new set $\widetilde{K}$ of virtual origin–destination pairs is created by splitting the route of the commodity by hub. For example, if commodity k was transferred through a single hub h, then we have two transport requests: from o_k^P to h and from h to d_k^P. As presented on Figure 2 three new commodities are added to the list, one when commodity k_2 is halved, and two more when commodity k is divided into k_n,k_m and k.

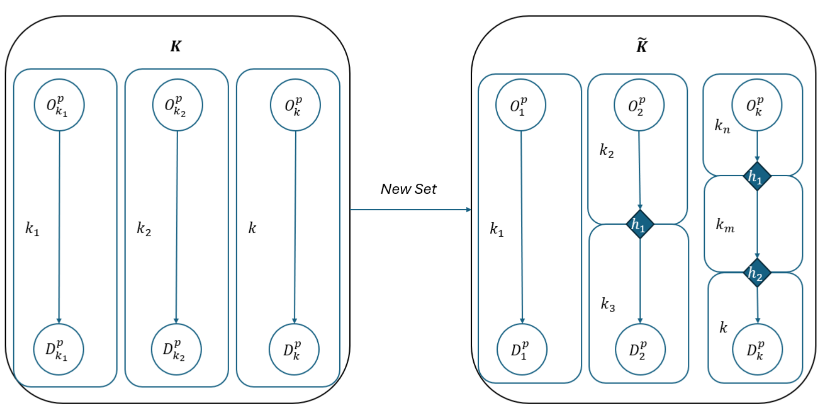


Figure 2: New set of commodities.

The available delivery time is distributed evenly to the new virtual commodities. For example, if the route was $o \to h_1 \to h_2 \to d$, then each virtual commodity receives a third of the originally available delivery time.

We now apply a Randomized Greedy Constructive Heuristic (RGCH) algorithm inspired by Ocampo-Giraldo et al. (2024) to this new set of commodities as presented in Algorithm 2. See Appendix B for a detailed description.

Algorithm 2 Randomized Greedy Constructive Heuristic (RGCH) algorithm.

Require: Set of overall commodities $\widetilde{K}$
Ensure: Solution routes R, primal bound UB
```
 1: let R ← ∅
 2: let K′ ← K̃
 3: while K′ ≠ ∅ do
 4:     Randomly select k from K′
 5:     Construct initial route r for k
 6:     remove k from K′
 7:     Compute feasible insertion set F_r
 8:     while F_r ≠ ∅ do
 9:         Greedily insert best commodity k̄ ∈ F_r into r
10:         Remove k̄ from K′
11:         Recompute feasible insertion set F_r
12:     end while
13:     Add r to R
14: end while
15: Compute solution cost UB from R
16: return UB, R
```

Valid solution 2 A second solution is obtained by restricting the original problem to a network obtained by removing any arc that was not traversed by any route in the interval-based relaxation solution (recall subsubsection 4.3.1). To further reduce the size of this model, a coarser time discretization is used, rounding up origin availability times and rounding down destination due times. Here, time intervals are of length 4δ instead of δ, and the solution is referred to as the *reduced upper bound solution* (RUBS).

5 Numerical experiments

In this section, we present the numerical experiments performed and the insights gained from solving the *Collaborative Routing Orchestration for Organic Food Distribution* using the proposed reformulation and solution algorithm. These experiments are conducted over a set of instances inspired from real data provided by the TCBL. The numerical experiments are divided into two parts: the first part evaluates the computational performance of the proposed solution algorithm, while the second focuses on practical implications and sensitivity analysis of key parameters.

5.1 Data description and instance generation

The TCBL is a non-profit organization that collaborates with various organic food producers and food banks within the Laurentides region of Quebec. The Laurentides is a vast administrative region northwest of Montreal, covering over 20,000 square kilometers and home to approximately 600,000 residents. From the TCBL, we collected information on 11 members spanning the entire food supply chain—from production to consumption—including farmers, food processors, wholesalers, retailers, and one food bank. These members collectively serve over 300 clients distributed across the Laurentides region and surrounding areas. Due to data confidentiality, the precise locations of these members have been obscured, but their relative geographical distribution is maintained to preserve the network's spatial characteristics.

Because modeling all 11 members and 300 clients is computationally demanding, we generate smaller, representative instances to evaluate the proposed methodology. We create diverse instances by varying the number of members and clients served. To preserve the network's spatial characteristics, we categorize the data into five geographical zones, each representing a major concentration of members and clients. Based on discussions with TCBL, three potential members that could serve as transfer hubs are identified; these three feasible hub locations are included in all instances. Figure 3 shows the geographical distribution of the 11 TCBL members and the five defined areas used to partition the data. The instance generation process begins by randomly selecting a subset of these areas, then populating them with a random selection of members and clients. Demand is assigned proportionally to the number of clients associated with each member in the selected region, while origin and due times are preserved. Following this procedure, we generate 100 instances, divided into three categories according to the number of origin–destination pairs to be served. Small-sized instances range from 8 to 20 origin–destination pairs, medium-sized instances include 21 to 40 origin–destination pairs, and large-sized instances contain up to 70 origin–destination pairs. Additionally, a subcategory captures the impact of geographical dispersion. Each subcategory is defined by the average distance between origin and destination nodes. The first category includes instances with closely clustered locations (short average travel distances), while the remaining categories correspond to increasingly dispersed geographical configurations (medium and long distances). Therefore, we define three distinct distance-based categories: short, medium, and long. Table 1 presents the number of origin–destination pairs, members, clients, and average travel distances for each instance type.

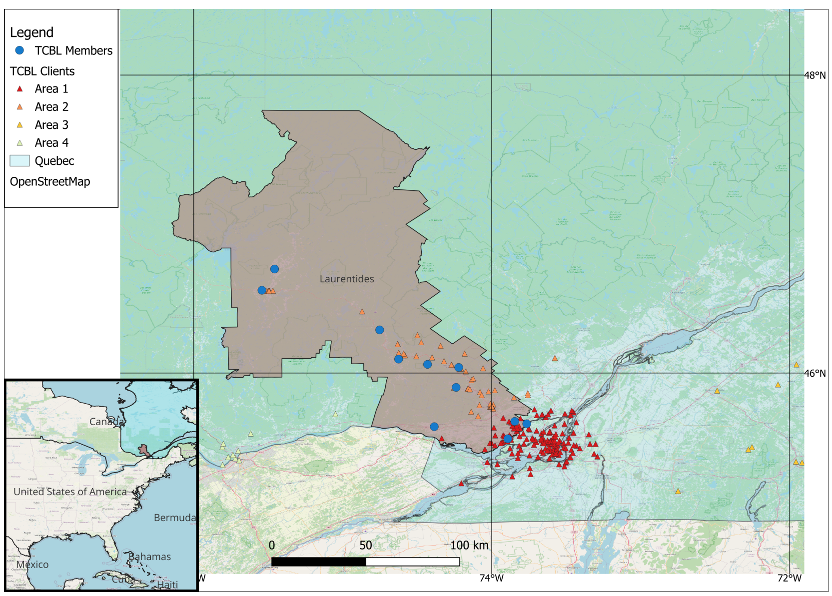


Figure 3: TCBL members and client distribution across five geographical areas.

Table 1: Number of OD pairs, members, clients, and average travel distances for each instance size category.

		OD pairs			Members			Clients			Avg. Distance (km)		
Size	Total	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Small	27	16	8	20	2	1	4	8	5	10	162	99	235
Medium	47	32	21	40	5	2	11	8	5	11	155	106	218
Large	26	53	42	70	6	4	11	9	7	11	158	108	195

5.2 Performance evaluation of the reformulation and solution method

In our first test, we compare the *FM* formulation with the proposed time-expanded reformulation *TE*. The experiments were carried out on an Intel Xeon Gold 6258R CPU @ 2.70 GHz with 15 GB of RAM. The mixed-integer formulations and the solution algorithm were implemented in Python 3.13 using the Pyomo modeling package and Gurobi 11.0 as the optimization solver. A time limit of 10,800 seconds (3 hours) was imposed on each run. The results, summarized in Table 2, show that the time-expanded reformulation significantly improves computational performance compared to the base model.

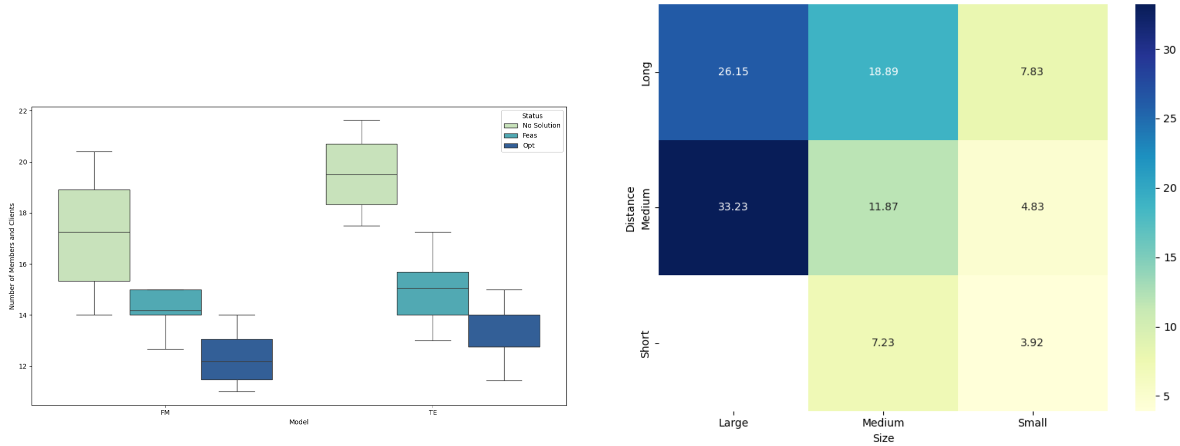
Table 2: FM vs. TE results. Feas indicates the number of instances where a feasible solution was found, while Opt indicates instances solved to optimality. The average time (Avg.T) is computed over optimal instances, and the average gap (Avg.G) over feasible but non-optimal ones.

		FM				*TE*			
Size	Total	Feas	Opt	Avg.T (s)	Avg.G (%)	Feas	Opt	Avg.T (s)	Avg.G (%)
Small	27	25	13	799.06	18.47	27	15	1449.89	10.21
Medium	47	8	1	7798.52	24.65	37	4	5734.13	20.44
Large	26	0	0	-	-	6	0	-	28.51
Total	100	33	14			70	19		

Over the 100 instances, the *TE* reformulation found feasible solutions in more than twice as many cases as the *FM* formulation and reached optimality in 19 instances, compared to 14 for *FM*. For small-sized instances, both models performed comparably, though *TE* required more computation time on average. The main difference appears in the medium and large instance categories. For medium-sized instances, *FM* solved only 8 of 47 instances (1 to optimality), whereas *TE* solved 37 instances (4 to optimality). Moreover, the average optimality gap among non-optimal solutions was smaller for *TE* (20.44%) than for *FM* (24.65%). For large instances, *FM* failed to find any feasible solution, while *TE* identified 6, though none to optimality. The number of origin–destination pairs strongly influences solver performance. However, even within a size category, performance varies notably between instances. This variability likely stems from additional factors such as the total number of network nodes and the distance between origins and destinations. For example, Figure 4a illustrates the solver status for both formulations as a function of the total number of nodes. As the network size grows, computational complexity increases for both models. Conversely, Figure 4b shows the average optimality gap for *TE* across different instance sizes and distance categories. Notably, instances with short average travel distances exhibit larger gaps due to the increased number of possible routing combinations. The above results indicate that the commercial solver performs well for small and some medium-sized instances, but struggles with larger cases due to the combinatorial explosion of time-expanded variables on the TE reformulation.

To further assess scalability, a second set of experiments evaluates the tailored solution algorithm. The corresponding results are reported in Table 3. The tailored algorithm identified feasible solutions for all instances and achieved optimality for most small cases (22 of 27) as well as several medium and large instances. The average gap among non-optimal solutions remained low for small instances (1.6%) and acceptable for medium (11.7%) and large (25.3%) instances. Regarding solution times, Figure 5a shows that average CPU time for medium and large instances is skewed by a few outliers. The distribution of optimality gaps (Figure 5b) reveals that several large instances still exhibit substantial residual gaps, suggesting that further improvements in the lower bound could enhance overall solution quality.

Overall, the time-expanded reformulation (*TE*) improves solvability over the base model (*FM*), especially for medium and large instances. While commercial solvers still face scalability limits, the proposed solution algorithm efficiently delivers high-quality solutions across all tested cases, confirming its practicality for collaborative organic food distribution.



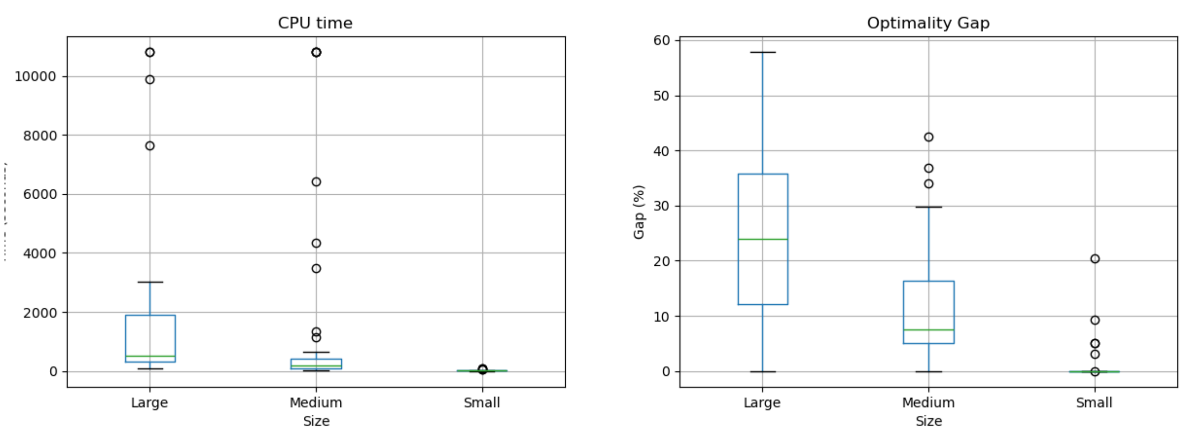
(a) Solution status by model and total number of members and clients.

(b) Mean optimality gap (%) by distance and instance size.

Figure 4: Commercial solver performance by instance size and distance.

Table 3: Performance of the tailored solution method. Avg.T reports the average time to solve the lower bound model ([subsubsection 4.3.1](#)), while Avg.G shows the mean optimality gap between upper and lower bounds.

Size	Total	Solution Method Solved	Optimality	Avg.T (s)	Avg.G (%)
Small	27	27	22	22.99	1.59
Medium	47	47	6	1432.48	11.70
Large	26	26	2	2193.55	25.30
Total	100	100	30		



(a) CPU time by instance size.

(b) Optimality gap by instance size.

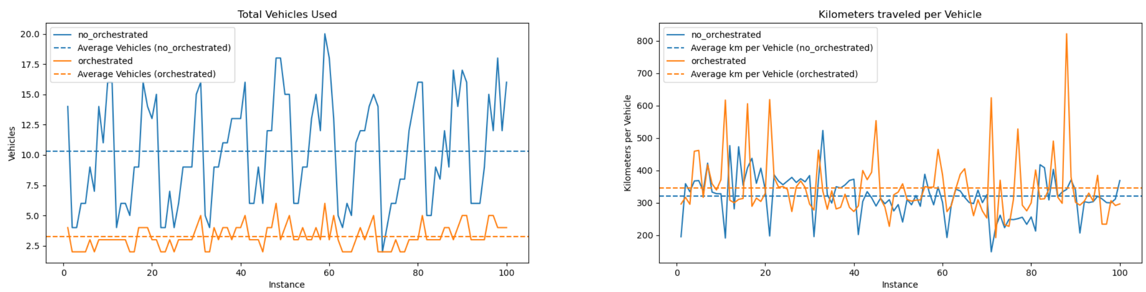
Figure 5: Computation time and optimality gap for the proposed solution method.

5.3 Results and managerial insights

This section presents the main numerical results and managerial implications of the proposed orchestration approach. We first quantify the efficiency gains achieved through collaboration and the use of transfer hubs, followed by sensitivity analyses assessing the effects of demand variability, delivery time flexibility, and transportation cost changes.

5.3.1 Impact of collaboration and resource pooling

We begin by evaluating the benefits of collaborative resource pooling among TCBL members. The non-orchestrated case, in which each member serves its own clients independently, is compared to the orchestrated scenario that enables full collaboration and joint routing (Figure 6).



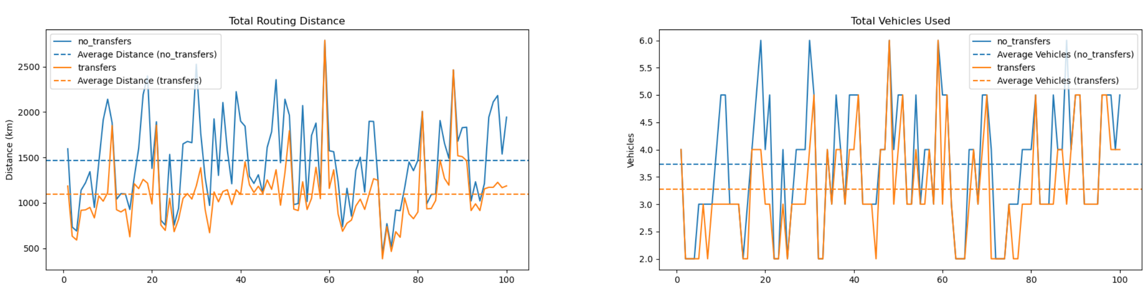
(a) Vehicles used. **(b) Kilometers traveled per vehicle.**

Figure 6: Orchestrated vs. non-orchestrated solutions.

Results reveal substantial efficiency gains from orchestration. On average, the orchestrated approach reduces the number of vehicles required to serve member demand by six (Figure 6a), showcasing a substantial improvement in logistical efficiency. Furthermore, orchestration optimizes resource utilization, increasing each vehicle's travel distance by 25 km, though this represents only an 8% increase in average travel time per vehicle (Figure 6b). This highlights a more efficient use of resources when members pool them, reducing the number of vehicles needed by 60% compared to each member serving their own demand, and contributing to more sustainable food logistics by lowering emissions and costs.

5.3.2 Role of transfers and hub utilization

Next, we isolate the effect of inter-vehicle transfers by comparing scenarios with and without hub use. In the no-transfer case, vehicles may serve multiple members but cannot exchange commodities between them. The results are presented in the Figure 7.



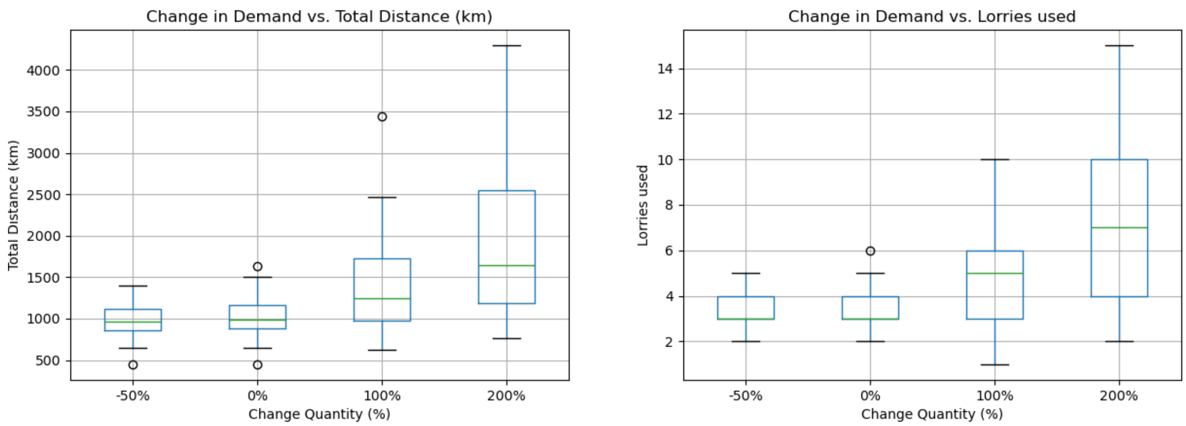
(a) Total distance traveled. **(b) Vehicles used.**

Figure 7: Transfers vs. no-transfer scenarios.

Allowing transfers through hubs yields additional improvements: the total distance traveled decreases by an average of 400 km (−28%), and up to 1 000 km in some instances (Figure 7a). Fleet size also declines as hubs facilitate load consolidation (Figure 7b). These results confirm that even limited hub activation enhances network efficiency and sustainability by reducing both empty travel and overall emissions.

5.3.3 Effect of demand variability

We now assess how fluctuations in demand volumes affect fleet size, traveled distance, and hub utilization. The demand analysis considers four scenarios: baseline (0%), low (−50%), high (+100%), and large (+200%) demand variations. This sensitivity test provides insight into how the collaborative network scales with volume. Figure 8 shows the distribution of the number of vehicles used and total distance traveled.



(a) Traveled distance. **(b) Vehicles used.**

Figure 8: Fleet use under demand-change scenarios.

An increase in demand necessitates the use of more vehicles to fulfill requirements. On average, two additional trucks are utilized when demand doubles the baseline case. Furthermore, this increased demand is reflected in a larger total distance traveled, particularly in scenarios with high demand (Figure 8a). The demand reduction scenario, however, has a minimal impact on the network configuration, primarily because the baseline scenario involves low demand that, in some cases, cannot be further reduced. As the quantity of commodities to be transported increases, the possibility of consolidation on each vehicle diminishes due to capacity constraints. Consequently, the average number of vehicles used in the solutions increases by two and four when the demand increases by 100% and 200%, respectively, as illustrated in Figure 8b. Also, as the number of vehicles required to meet demand grows, the total kilometers traveled by all trucks increases.

Hub utilization remains largely stable across demand levels (Figure 9), increasing only in a few high-demand instances. This stability indicates that once activated, hubs continue to play a central coordination role regardless of demand scale, confirming their structural importance in maintaining system efficiency.

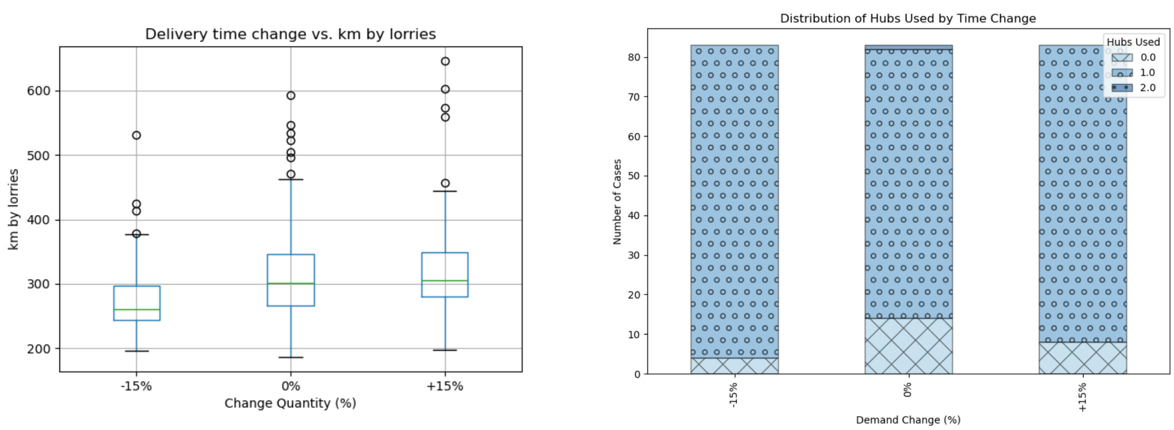
5.3.4 Influence of delivery time flexibility

This subsection explores the effect of tighter or more relaxed delivery time windows on route structure and fleet requirements. Delivery time flexibility is analyzed through three scenarios: baseline, tighter (−15%), and more relaxed (+15%) due times. Larger deviations were not tested due to infeasibility. Results are shown in Figure 10.

Results indicate that tighter delivery time windows lead to more direct routes and a larger fleet, even when demand remains constant, due to fewer consolidation opportunities. A 15% reduction in delivery windows shortens routes by about 50 km on average, whereas a 15% relaxation allows longer routes—up to 100 km more than the baseline (Figure 10a). Changes in time flexibility have little effect on hub utilization, with only slight increases in a few cases where no hub was used initially

(Figure 10b). This confirms that hub use is primarily driven by consolidation opportunities rather than delivery-time constraints.

Figure 9: Hubs used under demand-change scenarios.



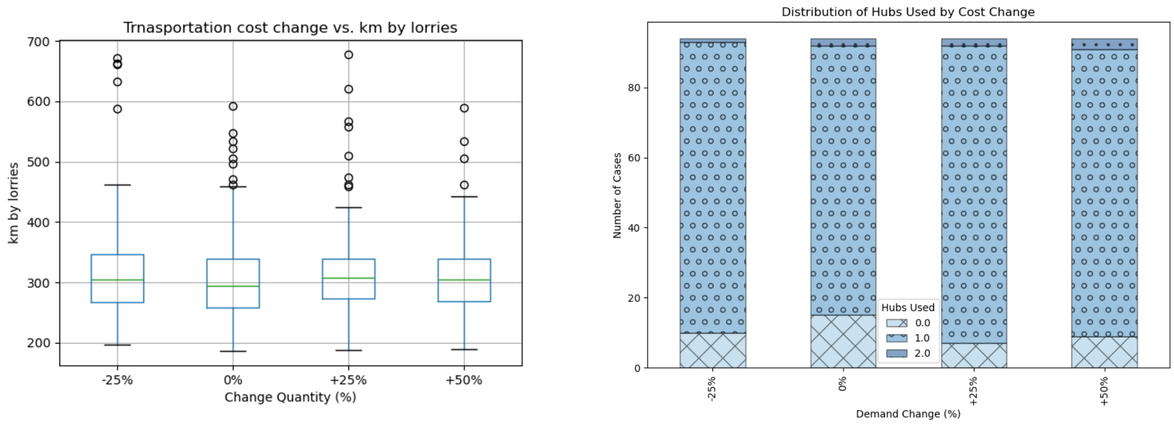
(a) Traveled distance. **(b) Vehicles used.**

Figure 10: Fleet use under delivery-time scenarios.

5.3.5 Sensitivity to transportation cost changes

Finally, we analyze the impact of transportation cost variations on routing and network configuration. The cost per kilometer is adjusted by ±50% relative to the baseline scenario, with results summarized in Figure 11.

Interestingly, changes in transportation cost have a limited effect on network structure. Even a 50% cost increase results in only marginal reductions in traveled distance and nearly identical fleet and hub utilization (Figure 11a). This stability highlights the robustness of the collaborative orchestration model, which mitigates cost sensitivity by optimizing shared resources and intermediate transfers. From a managerial standpoint, this suggests that once a collaborative system is established, it remains stable and economically viable even under fuel-price fluctuations.



(a) Traveled distance. **(b) Vehicles used.**

Figure 11: Fleet use under cost-change scenarios.

Overall, the results demonstrate that collaborative orchestration offers substantial operational and environmental gains. Pooling resources and enabling transfers through shared hubs reduce fleet size and travel distance without compromising service. The approach remains effective under varying demand, timing, and cost conditions, supporting both economic efficiency and sustainability in regional food distribution.

6 Conclusion

This study addressed a challenging distribution problem in the organic food sector, where a nonprofit entity orchestrates producers and food banks that share logistics resources under strict time constraints. The problem simultaneously involves hub selection, routing, and synchronization of heterogeneous vehicles serving time-sensitive deliveries. We formulated the problem as a mixed-integer program and introduced a time-expanded reformulation that discretizes the planning horizon and links routing and timing decisions. This reformulation underpins a tailored *Relax, Solve, and Fix* algorithm capable of solving realistic instance sizes that challenge standard solvers.

Computational experiments demonstrated the superior performance of the time-expanded model. It consistently found feasible and often optimal solutions where the compact model failed to do so. For medium instances, feasible solutions were obtained in nearly all cases, and optimality was reached in several. In large instances, feasible results were achieved even when the compact formulation failed. The algorithm delivered optimal or near-optimal solutions for small and medium cases and acceptable gaps for larger networks, confirming both efficiency and scalability.

Beyond computational performance, the results from Section 5.3 provide clear managerial insights. Pooling logistics resources reduced the total number of required vehicles by 60% on average, with an increase of only 8% of the average traveled distance by vehicle. This is translated into significant environmental and cost benefits. The integration of transfer hubs further improved efficiency—cutting distance by up to 1,000 km in some cases—while hub usage remained stable across demand and cost scenarios. Transportation-cost variations had little influence on fleet deployment or distance traveled, whereas tighter delivery windows required more direct routes and larger fleets, underscoring the trade-off between service quality and efficiency. Overall, these findings highlight the strategic value of collaborative orchestration and transfer hubs for sustainable regional food distribution.

Future research could extend this study in several directions. On the modeling side, the framework could be enriched by incorporating stochastic travel times and uncertain demand patterns to better capture the variability inherent in regional food logistics. Accounting for product perishability and temperature-control requirements would also make the model more representative of real-world organic food supply chains. On the algorithmic side, integrating learning-based or decomposition approaches could further enhance computational performance for larger instances. Finally, empirical validation through pilot implementations with regional food cooperatives or social enterprises would allow for an assessment of the environmental and economic impacts of orchestration in practice.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used Microsoft Copilot in order to make the writing clear. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

A Details on the interval-relaxation

A.1 Sub-tour elimination

In the interval-based relaxation, it is possible to create sub-tours on the flow of vehicles, because in the same time interval I_j a vehicle can go from n_1 to n_2 then and return to n_1. For this reason the following sub-tour elimination constraints are added to the model:

$$\sum_{\substack{a \in A^{(\lambda)} \\ a^- \in S, a^+ \notin S}} x_a^\ell \leqslant 1 \qquad \forall S \subset N^\lambda, \forall l \in L \tag{33}$$

A.2 Pre-processing

We can perform pre-processing for the interval-based model as we did for the TE formulation in subsection 4.2: we remove the flow variables on interval-based arcs of the form $((m, I_i), (n, I_j))$ $I_i = [t_1, t_1')$ and $I_j = [t_2, t_2')$ or $t_1 = (i-1)\frac{\delta\eta}{\lambda}$ and $t_1' = i\frac{\delta\eta}{\lambda}$ and $t_2 = (j-1)\frac{\delta\eta}{\lambda}$ and $t_2' = j\frac{\delta\eta}{\lambda}$ satisfying any of the following conditions:

(i) $m = d_k^P$ or $n = o_k^P$

(ii) $o_k^T + \tau_{(o_k^P, m)} + \tau_{(m,n)} + \tau_{(n, d_k^P)} > d_k^t$

(iii) $o_k^T + \tau_{(o_k^P, n)} \geqslant \min(i\kappa, j\kappa - \tau_{(m,n)})$

(iv) $\max(o_k^T + \tau_{(o_k^P, m)} + \tau_{(m,n)}, (i-1)\kappa + \tau_{(m,n)}, (j-1)\kappa) + \tau_{(n, d_k^P)} > d_k^T$

A.3 Symmetry breaking

The symmetry-breaking inequalities discussed in subsection 3.3 also hold for the interval-based relaxation. Moreover, further valid inequalities can be added to reduce the computational complexity. This family of inequalities removes solutions that do not make sense in the full model due to the existence of vertical arcs in the interval-based model.

$$\sum_{a \in A} \tau_a x_{((a^-, I_j), (a^+, I_j))} \leqslant \frac{\delta\eta}{\lambda} \qquad \forall j \tag{34}$$

$$o_k^T + \sum_{\ell \in L} \sum_{a \in A_k^\lambda} \tau_a f_a^{k\ell} \leqslant d_k^T \qquad \forall k \in K \tag{35}$$

A.4 LP to undo the interval projection

Let $P_\ell = \{n_1^\ell, \ldots, n_{r_\ell}^\ell\}$ be the ordered sequence of physical nodes that are visited by vehicle ℓ on a solution route. We can bind together commodities with the vehicles that pick them up from their origin and drop them off their destination respectively by the sets $\mathcal{O}$ and $\mathcal{D}$ as follows:

$$\mathcal{O} = \{(k,\ell) \in K \times L\colon k \text{ is picked-up by } \ell\}\,, \quad \mathcal{D} = \{(k,\ell) \in K \times L\colon k \text{ is delivered by } \ell\}$$

Further, we also define the set of transfers by

$$\mathcal{M}\left\{(h,k,\ell,\ell') \in H \times K \times L \times L\colon k \text{ is transferred from } \ell \text{ to } \ell' \text{ at } h\right\}.$$

Using this notation we introduce a linear program (LP) that attempts to undo the projection onto the intervals by finding times in the intervals of each element of P_ℓ so that the time constraints are respected. The LP model is defined by adapting constraints (12)–(17) with P_ℓ, $\mathcal{O}$, $\mathcal{D}$ and $\mathcal{M}$ obtained from the reduced model. Let $e_n^\ell \geqslant 0$ denote the arrival time of vehicle ℓ at physical node n, and let $d_n^\ell \geqslant 0$ denote the departure time of vehicle ℓ from physical node n.

$$\min \quad \sum_{\ell \in L} d_\Delta^\ell - e_\Delta^\ell \tag{36}$$

$$\text{s.t.} \quad e_h^\ell \leqslant d_h^{\ell'} \qquad \forall (h,k,\ell,\ell') \in \mathcal{M} \tag{37}$$

$$d_{n_i}^\ell + \tau_{(n_{i-1},n_i)} = e_{n_i}^\ell \qquad \forall i \in \{2,\ldots,r_\ell\}\ \forall \ell \in L \tag{38}$$

$$e_n^\ell \leqslant d_n^\ell \qquad \forall n \in P^\ell\ \forall \ell \in L \tag{39}$$

$$e_\Delta^\ell \geqslant d_\Delta^\ell \qquad \forall \ell \in L \tag{40}$$

$$e_{d_k^P}^\ell \leqslant d_k^T \qquad \forall (k,\ell) \in \mathcal{D} \tag{41}$$

$$d_{o_k^P}^\ell \geqslant o_k^T \qquad \forall (k,\ell) \in \mathcal{O} \tag{42}$$

B Details on the RGCH

Recall that the set of all commodities (virtual when a hub was used and original when a hub wasn't used) is denoted by $\widetilde{K}$. For $k \in \widetilde{K}$, let further $\widetilde{o}_k$ and $\widetilde{d}_k$ denote the time-expanded origins and destinations and $\widetilde{q}_k$ the quantity of that commodity to be transported.

The randomized greedy construction heuristic (RGCH) takes as input the commodities $\widetilde{K}$ and proceeds as follows: a commodity $k \in \widetilde{K}$ is selected at random and a two-node route from (o_k^P, o_k^T) to (d_k^T, d_k^T) initialized. For each commodity $\widetilde{k} \neq k$, the best insertion point of $\widetilde{k}$ in the current partial route and the cost is computed. The commodity $\widetilde{k}$ of least insertion cost is then optimally inserted into the partial route and $\widetilde{k}$ is removed from consideration.

This process is repeated until no more commodities can be feasibly inserted into the route and a new (empty) route is started. The RGCH terminates when all elements of $\widetilde{K}$ have been inserted into a route.

To evaluate if a commodity k' can be inserted into the route r we follow the procedure proposed by Masson et al. (2013). For every node i in r the *slack time* $\sigma_i(r)$ is the time that the visit to node i can be postponed without violating any of the constraints corresponding to the already inserted commodities. The *forward time* ϕ_i of a node i is now computed as the minimum of the slack times at i and all nodes visited after i in r.

Computing these times allows to quickly determine whether a new commodity k' can be inserted into the current partial route as follows: let T_1 denote the extra travel time to insert the origin o_k^P between points r_i and r_{i+1} of the route:

$$T_1 = \tau_{r_i,o_{k'}} + \tau_{o_{k'},r_{i+1}} - \tau_{r_i,r_{i+1}}$$

and similarly let T_2 denote the extra travel time required to insert d_k^P between points r_j and r_{j+1} in the route (of course $i < j$). Then, the insertion at r_i and r_j respectively is feasible (for the time constraints) if $T_j \leqslant \phi_i$ and $T_1 + T_2 \leqslant \phi_j$.

Similarly we check feasibility with respect to the capacity constraints by computing the smallest residual capacity of the vehicle at each node between r_i and r_j and comparing with $q_{k'}$.

If it is determined feasible, the extra cost of the insertion is computed as

$$I_k(i, j) = c(i, o_k) + c(o_k, i + 1) - c(i, i + 1) + c(j, d_k) + c(d_k, j + 1) - c(j, j + 1)$$

The routes obtained in this procedure are a feasible solution to the full problem and hence also yield an upper bound for the original optimization problem.

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