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**Article**

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# A fair multi-commodity two-echelon distribution problem

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## ABSTRACT

In the context of a short and local supply chain of fresh produce in the public sector, we introduce a fair multi-commodity two-echelon distribution problem. A decision maker has to decide on the planning of the first-echelon collection trips of commodities from suppliers to distribution centers equitably and on the second-echelon delivery routes of commodities from the centers to customers. In addition to the classic objective of minimizing the total transportation cost in vehicle routing problems, the goal is to make sure that all suppliers receive an equitable service with regard to their profits. This is done by introducing fairness measures into the problem as a set of constraints. We use two widely used inequality metrics from the literature and present a novel problem-specific equity measure as well. We model the problem as a mixed-integer program using an arc-route-based formulation and suggest a matheuristic to solve the problem. Through numerical experiments, we analyze the performance of our matheuristic on a series of generated instances and on the instances of a French fresh produce supply chain from the literature. We evaluate the efficacy of the three used fairness schemes with regard to a series of key performance metrics and investigate the strengths and weaknesses of the different fairness measures. Moreover, we study the trade-off between enforcing fairness and optimizing transportation costs to come up with insights for the managers of the supply chain.

## 1. Introduction

Traditionally, minimizing cost has been the main objective in vehicle routing problems (VRPs). However, focusing only on optimizing costs does not always lead to implementable decisions in practice, especially when more than one actor is involved in a logistics system. As a consequence, in recent decades there has been an increasing interest in incorporating other metrics and performance measures into the equation among researchers in the stream of VRPs. In a recent survey, Vidal et al. (2020) discuss categories of emerging objectives and their integration into VRP varieties as extra objectives or sets of constraints. One of these metrics is *equity* or *fairness* (in the rest of this paper we use these two words interchangeably). The definition of equity in decision making processes can be broad, as it is dependent on how the decisions affect individuals/actors. Identifying a basis for comparison and target groups for fairness leads to defining equity and proper metrics for evaluating the performance of an equity-oriented system (Balcik et al., 2011). In VRPs, equity can be interpreted as a fair distribution of resources, tasks/duties, and costs/gains. The main categories of equity criteria in routing literature are service equity (in public and non-profit organizations), workload balance (in the private sector), and collaborative planning (in the logistics sector) (Vidal et al., 2020).

Offering equitable services to customers is one of the main goals in the public and non-profit sector. The literature of VRPs includes

many studies with a focus on applications of routing, public transportation, home health care, and food/supply distribution, to name a few, under fairness objectives. The end users/customers are generally the primary target group to be served by some routes in these applications. However, in the context of public organizations, there can also be applications in which suppliers/producers should be provided with a fair service, but they are not. Gu et al. (2022) describe such a case in a local and short supply chain with a two-echelon network of collection and delivery of fresh fruits and vegetables, which is supported by the local authorities of the department of Isère in France. In this network, fresh products (also referred to as commodities) are collected from farmers (also referred to as suppliers) and transported on direct trips to distribution centers for consolidation, and then delivered from the centers to customers (school canteens and supermarkets) on routes. A customer can be visited more than once. The daily operations of this network are managed by a central decision maker, i.e. Isère's authorities in collaboration with an association of farmers. In spite of a governmental initiative, there may be some farmers who rarely supply products. This happens due to the fact that some of the farmers are located farther away from the distribution centers than the others (Gu et al., 2022) and also because the primary goal of the distribution network is to minimize the transportation costs.

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In this paper, we address the issue of service inequity for suppliers in the above-mentioned supply chain. We introduce a fair multi-commodity two-echelon distribution problem, which decides on the daily planning of the first-echelon collection trips of commodities from suppliers to distribution centers equitably, and on the second-echelon delivery routes of commodities from the centers to customers. The objective is to keep the total transportation cost at a minimum, while respecting the maximum availability of commodities at the suppliers and vehicle capacities, and satisfying the equity measure. This problem is an extension of the problem studied by Gu et al. (2022). These authors model the problem at hand with an arc-based formulation and propose a heuristic sequential approach that decomposes the two-echelon problem into two subproblems associated with each echelon, and then solves the subproblems sequentially. In order to model multiple commodities required by customers for their solution method, Gu et al. (2022) use a *customer–commodity* pair associated with each commodity in a customer's demand. In other words, a customer is equivalent to a combination of customer–commodity pairs.

We model our problem as a mixed-integer program (MIP) using an arc-route-based formulation and include a service equity measure for suppliers as a set of constraints. We first formulate this set of constraints by applying two commonly used inequality indexes from the literature (relative range and Gini coefficient) and then design our own equity measure proportional to the supply of suppliers and profits of commodities. Unlike Gu et al. (2022), we do not consider customer–commodity pairs when modeling the demand of customers, as it can result in a large number of combinations when the number of customers and commodities grow. Moreover, as solution method, we take a different approach than Gu et al. (2022)'s, that solves their two-echelon problem in a sequential manner. For our problem, we design a matheuristic that jointly optimizes the first and second echelons. We leave the decisions on the first-echelon collection trips to a default solver. We generate a pool of feasible second-echelon routes heuristically and pass it to the solver, which will then decide on both daily collection and delivery plans. We evaluate the performance of our matheuristic on randomly generated instances of Gu et al. (2022) and the realistic instances from the French department of Isère. For benchmarking, we first relax the fairness constraints to fall back to the problem studied by Gu et al. (2022) and compare our results with theirs. We then investigate the efficacy of our equity measure versus the relative range and Gini coefficient metrics with regard to reducing inequity among suppliers as well as optimizing the cost in terms of several key performance indicators (KPIs).

We study the effect of service equity for suppliers on the network to draw some managerial insights. When no fairness is enforced, our matheuristic on average provides solutions with less total transportation costs than the best known costs for the instances, while the solution times are substantially faster, sometimes in an order of magnitude, than the total run times known from the literature. The numerical experiments also show that guaranteeing a fair collection of commodities from suppliers can result in an increase in the total transportation cost on average. However, for each instance group there is a sweet spot beyond which enforcing fairness becomes increasingly expensive.

The rest of the paper is organized as follows. In Section 2, we provide a review of the related works in the literature. Section 3 presents the problem description and formulation as well as the three fairness measures. We illustrate the elements of our matheuristic in Section 4. The results of our numerical experiments are discussed in Section 5. We conclude the paper with some remarks and future avenues in Section 6.

## 2. Literature review

The problem studied in this paper is related to the stream of two-echelon VRPs in which (i) a distribution network is divided into two echelons and first-echelon and second-echelon vehicles are in charge of picking up commodities from suppliers/depots and delivering them

to end customers, respectively, (ii) transshipment facilities/distribution centers are used to merge and prepare collected commodities for further shipments, and (iii) the goal is to plan a set of routes in the first and second echelons of the network, such that the total transportation cost of the network is minimum and the demands of customers are satisfied. Cuda et al. (2015) and Sluijk et al. (2023) are the most recent survey papers on two-echelon VRPs. Moreover, two-echelon problems are also part of a larger body of literature, i.e. freight transportation problems with intermediate facilities. These facilities can be either satellites or cross-docks (Guastaroba et al., 2016) and their primary role in the distribution network is not as inventory but rather as transfer locations. The decision on the design and scheduling of routes in such problems are midterm decisions and related to tactical planning of distribution networks.

Cross-docking is a strategic distribution approach in logistics. Cross-docks are intermediate or transshipment facilities where freight or products arrive on inbound vehicles, get sorted and consolidated, and then depart on outbound vehicles to be delivered to the final destinations. There is already a vast body of literature on the operations of cross-docks from both academic and practical points of view (for example see the survey papers by Ladier and Alpan (2016) and Van Belle et al. (2012)). Some of the operational decisions for cross-docks are routing and scheduling of the inbound and outbound vehicles. One important aspect of cross-dock operations is synchronization between inbound and outbound vehicles (Soriano et al., 2023). Given that we consider a local agri-food transportation network, we follow the problem setting studied by Gu et al. (2022). In this setting, the commodity collections in the first-echelon are performed before the deliveries to the customers in the second-echelon. Therefore, we do not consider synchronization at cross-docks. Interested readers can refer to a recent survey by Soriano et al. (2023) that discusses vehicle routing problems with transfers or cross-docks in the literature as part of the family of vehicle routing problem with synchronization. Another interesting study is the review paper by Lahyani et al. (2015), which discusses the literature of cross-dock systems as a taxonomy of rich vehicle routing problems.

In our underlying problem, the supply and demand of commodities are considered explicitly. Similar to the study by Gu et al. (2022), the commodities can be collected from any origin that offers them, consolidated in intermediate locations, and delivered to customers. In other words, the setting is a many-to-many distribution system. Another study that deals with more than one commodity in a two-echelon network with satellite synchronization is the paper by Jia et al. (2023), which considers customers' demands for two commodities provided by two distinct origins (suppliers/depots). These two commodities should be delivered simultaneously by only one vehicle in the second echelon. In a recent work by Dellaert et al. (2021), it is mentioned that their two-echelon distribution problem is a multi-commodity distribution system. However, the authors consider a one-to-one origin–destination flow of items. The commodities required by customers are provided from unique suppliers/depots, consolidated in intermediate facilities, and then delivered to customers via synchronization processes between the first and second echelons. In other words, a commodity in such context refers to a specific depot–customer combination. We refer the reader to the survey by Sluijk et al. (2023) for further studies that treat commodities as unique depot–customer pairs with satellite synchronization in two-echelon distribution systems.

Vidal et al. (2020) list equity as one of the emerging objectives in the stream of VRPs. Equity can be interpreted as a fair distribution of resources, tasks/duties, and costs/gains. Therefore, the main categories of equity criteria in the literature are service equity (in public and non-profit organizations), workload balance (in the private sector), and collaborative planning (in the logistics sector) (Vidal et al., 2020). Humanitarian logistics (survey paper on the applications of multicriteria optimization: Gutjahr and Nolz (2016)) and relief routing (review paper: Balcik et al. (2011)) are two groups of VRPs that deal with

service equity. An example of humanitarian logistics in the literature is the study by Eisenhandler and Tzur (2019), which introduces the humanitarian pickup and distribution problem. This problem focuses on daily logistics operations of a food bank that collects donated food from suppliers and distributes it among welfare agencies. The authors combine a measure of effectiveness of the operation and a measure of equity of allocations to agencies via the Gini coefficient, borrowed from economics, in the objective function. In the context of relief routing, Huang et al. (2012) study last-mile distribution of supplies in a humanitarian relief chain from a distribution center to aid recipients. Efficacy, efficiency, and equity metrics are incorporated as alternative objective functions in their model. Workload balance (equity) focuses mostly on fair allocations of workloads and balancing resource utilizations in VRPs. In a survey paper, Matl et al. (2018) review and analyze different ways of incorporating equity metrics for workloads in biobjective VRPs. These metrics are related either to the tour length (distance/duration) or to the demand served per tour. Matl et al. (2019) later extend prior studies to incorporate various workload resources. In the logistics sector, collaborative planning occurs in VRPs when carriers enter into a partnership to increase their efficiency (Gansterer and Hartl, 2018) and share resources, costs, or profits fairly (Guajardo and Mikael Rönnqvist, 2016). In the stream of collaborative transportation, a recent study on a multi-depot VRP by Soriano et al. (2023) incorporates a profit fairness metric into the set of constraints. They calculate the profit in a current solution compared to a stand-alone solution per depot. There are some studies that combine workload balance and collaborative planning. For example, Mancini et al. (2021) consider workload and profit equity metrics in the constraints in a multi-period VRP of a collaborative transportation setting.

How to formulate equity/fairness mathematically and incorporate it into optimization problems are some of the questions that are often discussed in the Operations Research literature (see survey papers: Karsu and Morton (2015), Barbati and Piccolo (2016) and Chen and Hooker (2023)). In a recent survey on fairness measures for optimization problems, Chen and Hooker (2023) classify well-known equity criteria into four main groups of (i) fairness for disadvantaged, such as Rawlsian maximin and leximax measures, (ii) inequality-based metrics such as relative range, relative mean deviation, coefficient of variation, and Gini coefficient, (iii) group parity measures, such as demographic parity, and (iv) metrics combining efficiency and fairness, be it classical methods, such as proportional fairness, or threshold methods. Since we aim at reducing inequity among suppliers in terms of their profits, we choose two of the most commonly used inequality measures, namely relative range and Gini coefficient, to incorporate fairness into our underlying problem. Relative range, defined as the difference between the maximum and minimum of outcomes and normalized by the maximum outcome, is widely used as it is easy to understand and implement. Being the best known income/wealth inequality index, the Gini coefficient is defined either as proportional to the area between the Lorenz curve and the diagonal line of perfect equality or as one half of the average value of pairwise absolute deviations of all outcomes normalized by the average outcome (Chen and Hooker, 2023). The Gini coefficient takes values between and including zero and one, where a value of zero denotes perfect equality among outcomes. We also design our own fairness measure that is constructed as a guaranteed share of profit per supplier proportional to their supply and the profits of commodities.

The concept of fairness places our problem at the intersection of collaborative planning and service equity. On the one hand, securing a fair share of the profit per supplier relates the problem to the equity category of collaborative planning. On the other hand, the underlying problem is inspired by a case study of the pickup and delivery of fresh produce in a short agri-food supply chain in which not all suppliers always provide products due to a transportation cost minimization objective (Gu et al., 2022). As this distribution system is managed by

local authorities of the French department of Isère, introducing the fairness for suppliers links the problem to the service equity category.

As a solution strategy for the problem at hand, we present a matheuristic that optimizes the first and second echelons jointly, by solving an arc-route-based formulation of the problem over a pool of feasible second-echelon routes and leaving the decisions on the first-echelon collection trips to a default solver. As the closest study to ours, Gu et al. (2022) propose a heuristic sequential approach that decomposes the arc-based formulation of their problem into two subproblems associated with each echelon, and then solves the subproblems sequentially. In their sequential technique, the first-echelon subproblem is modeled as a mixed-integer linear program and solved to optimality. The second-echelon subproblem is solved by an adaptive large neighborhood search. These two approaches are then combined to provide a solution for the complete two-echelon problem. In order to model multiple commodities required by customers, unlike our solution approach, Gu et al. (2022) use a customer–commodity pair associated with each commodity in a customer’s demand, which can result in a large number of combinations when the number of customers and commodities grow. For the same problem as in Gu et al. (2022), preliminary results of an exact branch-price-and-cut algorithm on a subset of the small instances of Gu et al. (2022) are provided in a report by Petris et al. (2022). In the PhD thesis by Gu (2019) (Chapter 5), a metaheuristic approach, referred by the author as an integrated optimization approach, is presented that uses several operators to improve the solutions of the collection and delivery subproblems used in the sequential approach of Gu et al. (2022). This heuristic has been tested only on the generated instances of Gu et al. (2022) and the results reported denote an average percentage improvement of up to 0.65% over the best known solutions from the original sequential metaheuristic used in Gu et al. (2022).

According to the survey paper by Sluijk et al. (2023), there are two studies in the literature of two-echelon VRPs that suggest and use matheuristics as solution methods for their corresponding problems. One work is by Wang et al. (2017), which provides a matheuristic for a two-echelon capacitated VRP in a distribution network with a single depot and a set of satellites and a set of customers. This technique relies on solving an arc-route-based formulation of the problem, given a set of previously generated second-echelon routes via a variable neighborhood search. In a similar setting to Wang et al. (2017)’s, Amarouche et al. (2018) present a matheuristic for their two-echelon VRP. Their iterative technique is composed of two elements: a neighborhood search to generate feasible first and second-echelon routes, and a set-covering formulation of the problem to recombine the routes. In addition to these two papers, in a recent study, Dumez et al. (2023) also propose a matheuristic for a two-echelon VRP for a distribution network with forward and reverse flows, one depot per echelon (two depots in total), a set of satellites, and a set of customers. Their matheuristic is an iterative two-phase heuristic that operates on decomposing the problem into two subproblems; one subproblem per echelon. It finds routes for each subproblem with a large neighborhood search associated with the underlying echelon while fixing the other echelon. The resulting routes for the first and second echelons are then recombined through a route-based formulation to find a better solution for the problem. These three studies deal with single commodities. For further details on different exact and heuristic solution approaches for two-echelon VRPs, we refer to the thorough review by Sluijk et al. (2023).

### 3. Problem

In this section, we describe the problem at hand and present a formulation.



### 3.1. Description

The problem we study in this paper is about managing the distribution system of commodities centrally within a two-echelon short supply chain in which commodities are picked up from suppliers, consolidated at distribution centers, and then delivered to customers. The collection and delivery operations are done on a daily basis.

Suppliers provide commodities, more specifically fresh fruits and vegetables, up to given available quantities at a price. In the first echelon, the commodities are transported from the suppliers to distribution centers on direct trips. The collection of supply from a supplier can be split by both commodity and quantity. Therefore, it is possible that a supplier is visited by more than one vehicle. In the second echelon, the commodities are consolidated at and delivered from distribution centers to customers on routes that are sequences of customers. Transfers between two suppliers and direct deliveries from suppliers to customers are prohibited. Neither in the first echelon nor in the second echelon, transfers between distribution centers are allowed.

Following the problem definition by Gu et al. (2022), we consider that the direct trips of the first echelon between suppliers and distribution centers are implemented by an unlimited fleet of capacitated homogeneous vehicles. In the rest of the paper, we refer to the first-echelon vehicles as *trucks*. There is also an unlimited fleet of capacitated homogeneous vehicles stationed at each distribution center that operates the second-echelon routes and can transport any group of commodities. We keep referring to the second-echelon vehicles as *vehicles* in the rest of paper. The (first-echelon) trucks and (second-echelon) vehicles may have different capacities. The demand of a customer can be split by commodity but not by the quantity of each commodity. This means that it is allowed to visit a customer in the second echelon multiple times, but the demand for a single commodity has to be delivered in a single visit. For an illustration of the structure of the two-echelon distribution network, see Gu et al. (2022).

The goal of the central decision maker is to find a daily plan that optimally details the collection and delivery operations of commodities in order to satisfy the total demand in the network, while minimizing the total transportation cost and respecting maximum availability of commodities at suppliers, the capacity of the vehicles, and the fairness constraints for the suppliers.

### 3.2. Formulation

Let  $\mathcal{G} = (\mathcal{V}, \mathcal{A})$  be a directed graph.  $\mathcal{V} = S \cup D \cup C$  is the set of vertices, where  $S = \{1, \dots, |S|\}$  is the set of suppliers,  $D = \{|S| + 1, \dots, |S| + |D|\}$  represents the set of distribution centers, and  $C = \{|S| + |D| + 1, \dots, |S| + |D| + |C|\}$  is the set of customers.  $\mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2$  is the set of arcs, where  $\mathcal{A}_1 = \{(j, j') | j \in S, j' \in D\}$  is the set of first-echelon arcs between suppliers and distribution centers, and  $\mathcal{A}_2 = \{(j, j'), (j', j) | j \in D, j' \in C\} \cup \{(j, j') | j, j' \in C, j \neq j'\}$  is the set of second-echelon arcs between distribution centers and customers as well as those between customers. There is a non-negative cost associated with each arc in set  $\mathcal{A}$ , denoted by  $c_{jj'}$  for  $(j, j') \in \mathcal{A}$ . The specifications associated with the three actors involved in this problem are as follows.

Suppliers provide a set of commodities  $\mathcal{M}$ . Each supplier  $s \in S$  offers a maximum available quantity  $O_{sm} \in \mathbb{N}_0$  of commodity  $m \in \mathcal{M}$ . Let  $\mathcal{M}_s = \{m \in \mathcal{M} | O_{sm} > 0\}$  be the set of commodities a supplier offers. The commodities are directly transported to the distribution centers by a fleet of homogeneous trucks with capacity  $Q^S \in \mathbb{N}$ . The collected supply from a supplier can be transferred by more than one truck, as the supply can be split by both commodity and quantity. In other words,  $O_{sm}$  can be split as well. The cost per truck traveling from supplier  $s$  to distribution center  $d$ , regardless of the load, is  $\bar{c}_{sd}$ .

Each customer  $i \in C$  requests a quantity  $D_{im} \in \mathbb{N}_0$  of commodity  $m \in \mathcal{M}$ . Associated with each customer, there is set  $\mathcal{M}_i = \{m \in \mathcal{M} | D_{im} > 0\}$  of commodities that the customer requires. For the sake of customer convenience, the demand of a customer with multiple commodities (Gu

et al., 2022) can be delivered by more than one vehicle, if the demand is split by commodity. However, the demand per commodity, i.e.  $D_{im}$ , cannot be split. We assume that at each distribution center there is a fleet of homogeneous vehicles with capacity  $Q^D \in \mathbb{N}$  for deliveries to customers. The delivery of commodities to customers in the second echelon is done via routes that start from distribution centers, visit at least one customer, and end at the same starting distribution centers. Therefore, our second-echelon routes are sequences of locations. Let  $K$  be a set of second-echelon feasible routes and  $\sigma_{ik}$  is a binary parameter specifying whether customer  $i$  is on route  $k \in K$ . Associated with each route  $k \in K$ , there is a parameter  $\gamma(k)$ , which represents the distribution center which the route starts from and ends at, as well as a cost  $c_k$ , which is the total distance traversed on route  $k$ , i.e. the summation of  $c_{jj'}$  of the arcs on the route.

The commodities are palletized. Therefore, the supply and demand are integer, and we use unit and pallet interchangeably. Each commodity  $m \in \mathcal{M}$  has a profit  $\pi_m$ , per unit. A logistics provider operates the distribution centers and makes decisions on the collection of commodities from suppliers to the centers as well as on the delivery of commodities to customers from the centers. In other words, the decision maker looks for a collection and delivery plan in which each customer's demand is satisfied and the maximum available quantities at suppliers and the truck and vehicle capacities are taken into consideration. Moreover, in this plan each supplier should have a fair share of the profit and the total cost of transportation is minimum.

Based on the arc-based model from Gu et al. (2022), we model our problem using a route-based formulation in the second echelon and a set of fairness constraints. Let  $x_{sd}^1 \in \mathbb{N}_0$  be the number of trucks traversing arc  $(s, d) \in \mathcal{A}_1$  and  $q_{msd} \in \mathbb{N}_0$  be the quantity of commodity  $m \in \mathcal{M}_s$  collected from supplier  $s \in S$  and transported to distribution center  $d \in D$  in the first echelon. On the other hand, for the second echelon, let  $y_{mik} \in \{0, 1\}$  be a binary variable indicating whether commodity  $m \in \mathcal{M}_i$  is delivered to customer  $i \in C$  on route  $k \in K$ , if customer  $i$  is on route  $k$ , i.e.  $\sigma_{ik} = 1$ , and  $\theta_k \in \{0, 1\}$  be another binary variable specifying whether route  $k \in K$  is selected. The problem is then formulated as a MIP with all variables and parameters summarized in Table 1. The model is as follows:

$$\min \sum_{(s,d) \in \mathcal{A}_1} \bar{c}_{sd} x_{sd}^1 + \sum_{k \in K} c_k \theta_k \quad (1)$$

$$\text{s.t.} \quad \sum_{\substack{k \in K: \\ \gamma(k)=d}} \sum_{\substack{i \in C: \\ \sigma_{ik}=1 \wedge \\ m \in \mathcal{M}_i}} D_{im} y_{mik} = \sum_{\substack{s \in S: \\ m \in \mathcal{M}_s}} q_{msd}, \quad m \in \mathcal{M}, d \in D \quad (2)$$

$$\sum_{m \in \mathcal{M}_s} q_{msd} \leq Q^S x_{sd}^1, \quad s \in S, d \in D \quad (3)$$

$$\sum_{d \in D} q_{msd} \leq O_{sm}, \quad s \in S, m \in \mathcal{M}_s \quad (4)$$

$$\sum_{\substack{k \in K: \\ \sigma_{ik}=1}} y_{mik} = 1, \quad i \in C, m \in \mathcal{M}_i \quad (5)$$

$$\sum_{\substack{i \in C: \\ \sigma_{ik}=1}} \sum_{m \in \mathcal{M}_i} D_{im} y_{mik} \leq Q^D, \quad k \in K \quad (6)$$

$$y_{mik} \leq \theta_k, \quad i \in C, m \in \mathcal{M}_i, k \in K : \sigma_{ik} = 1 \quad (7)$$

$$x_{sd}^1 \in \mathbb{N}_0, \quad (s, d) \in \mathcal{A}_1 \quad (8)$$

$$q_{msd} \in \mathbb{N}_0, \quad (s, d) \in \mathcal{A}_1, m \in \mathcal{M}_s \quad (9)$$

**Table 1**

Notation.

Sets	
$S$	The set of suppliers, index $s$
$D$	The set of distribution centers, index $d$
$C$	The set of customers, index $i$
$\mathcal{V} = S \cup D \cup C$	The set of all vertices, i.e. actors
$\mathcal{A}_1$	The set of arcs between suppliers and distribution centers in the first echelon
$\mathcal{A}_2$	The set of arcs between distribution centers and customers as well as those between customers in the second echelon
$\mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2$	The set of all arcs, index $(j, j')$
$\mathcal{M}$	The set of commodities, index $m$
$\mathcal{M}_s \subseteq \mathcal{M}$	The set of commodities offered by supplier $s \in S$
$\mathcal{M}_i \subseteq \mathcal{M}$	The set of commodities required by customer $i \in C$
$K$	The set of second-echelon feasible routes, index $k$
Parameters	
$c_{jj'}$	The cost of traversing arc $(j, j') \in \mathcal{A}$ , between two vertices $j, j' \in \mathcal{V}$
$\bar{c}_{sd}$	The cost per truck travelling from supplier $s \in S$ to distribution center $d \in D$
$\pi_m$	The profit of commodity $m \in \mathcal{M}$ , per unit
$Q^S$	The capacity of trucks collecting commodities from suppliers and transporting them to distribution centers
$Q_{sm}^{\max}$	The maximum available quantity of commodity $m \in \mathcal{M}$ offered by supplier $s \in S$
$Q^D$	The capacity of vehicles delivering commodities from distribution centers to customers
$D_m$	The demand of customer $i \in C$ for commodity $m \in \mathcal{M}$
$c_k$	The travel cost of route $k \in K$
$\gamma(k) \in D$	The distribution center from which route $k \in K$ starts and ends at
$\sigma_{ik}$	A binary parameter indicating whether customer $i \in C$ is on route $k \in K$
Variables	
$x_{sd}^1 \in \mathbb{N}_0$	Number of trucks traveling on arc $(s, d) \in \mathcal{A}_1$
$q_{msd} \in \mathbb{N}_0$	Quantity of commodity $m \in \mathcal{M}_s$ picked up at supplier $s \in S$ and transported to distribution center $d \in D$
$y_{mik} \in \{0, 1\}$	It takes value 1 if commodity $m \in \mathcal{M}_i$ is delivered to customer $i \in C$ on route $k \in K$ with $\sigma_{ik} = 1$ ; and 0 otherwise.
$\theta_k \in \{0, 1\}$	It takes value 1 if route $k \in K$ is chosen; and 0 otherwise.

$$y_{mik} \in \{0, 1\}, \quad i \in C, m \in \mathcal{M}_i, k \in K : \sigma_{ik} = 1 \quad (10)$$

$$\theta_k \in \{0, 1\}, \quad k \in K \quad (11)$$

$$\text{Fairness constraints.} \quad (12)$$

The objective function (1) aims at minimizing the total transportation costs of the first and second echelons. Constraints (2) make sure that enough quantity of each commodity is transported to a distribution center in order to satisfy the demand of the customers served on the routes from that center. Constraints (3) enforce the capacity limit of trucks transporting commodities from a supplier to a distribution center in the first echelon. They also make certain that there is enough number of trucks for collecting commodities from the supplier to the distribution center. Constraints (4) guarantee that the total quantity of a commodity transported from a supplier to distribution centers does not violate the maximum available quantity of the commodity at the supplier. Constraints (5) make sure that the demand of a customer for a commodity is delivered on exactly one second-echelon route. Constraints (6) state that total quantity of customers' demands served on a second-echelon route cannot exceed the vehicle capacity. Constraints (7) emphasize that a commodity is delivered to a customer on a route, only if that customer is on the route and the route is chosen. Constraints (8)–(11) define the decision variables. Note that the binary decision variable  $\theta_k$  can be defined as a real-valued variable in  $[0, 1]$ . However, as it will always take an integer value in the optimal solution, we leave it as integer for clarity's sake. Constraints (12) guarantee a certain share of the total profit for each supplier to secure a minimum level of fairness among all suppliers. We will present the formulations of the two classic equity measures and our designed measure in the next section.

### 3.3. Fairness constraints

We now present three formulations of the fairness constraints (12).

#### 3.3.1. Relative range

In the first formulation, we use the *relative range* scheme from the literature. As an inequality index, the idea behind the relative range is

to reduce the relative deviation between the maximum and minimum profits for the suppliers. In other words, the goal is to minimize

$$\frac{\max_{s \in S} \{ \sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd} \} - \min_{s \in S} \{ \sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd} \}}{\max_{s \in S} \{ \sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd} \}}.$$

Although this metric is nonlinear, it can be linearized by applying auxiliary variables (Chen and Hooker, 2023).

Let  $\pi_{\min} = \min_{s \in S} \{ \sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd} \}$  and  $\pi_{\max} = \max_{s \in S} \{ \sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd} \}$ . Then, the relative range metric for the problem at hand can be formulated as the following groups of constraints:

$$\sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd} \geq \pi_{\min}, \quad s \in S \quad (12-R1)$$

$$\sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd} \leq \pi_{\max}, \quad s \in S \quad (12-R2)$$

$$\pi_{\max} - \pi_{\min} \leq (1 - \alpha) \pi_{\max}, \quad (12-R3)$$

$$\pi_{\max}, \pi_{\min} \geq 0. \quad (12-R4)$$

with  $\alpha \in [0, 1]$  adjusting the desired level of fairness. Then, the MIP formulation consists of objective function (1) and constraints (2)–(11), plus fairness constraints (12-R1)–(12-R4).

#### 3.3.2. Gini coefficient

The second formulation of fairness constraints uses the Gini coefficient, which is one of the most well-known inequality measures in the literature. One definition of the Gini coefficient is half of the average value of the absolute deviations between all pairs of suppliers' profits divided by the average profit, i.e.

$$\frac{\sum_{s \in S} \sum_{s' \in S} \left| \sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd} - \sum_{m \in \mathcal{M}_{s'}} \sum_{d \in D} \pi_m q_{ms'd} \right| / 2}{|S| \sum_{s \in S} \sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd}}.$$

Since the absolute values of differences between the profits of pairs  $(s, s')$  and  $(s', s)$  are the same, this metric can be written as:

$$\frac{\sum_{s \in S} \sum_{s' \in S: s < s'} \left| \sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd} - \sum_{m \in \mathcal{M}_{s'}} \sum_{d \in D} \pi_m q_{ms'd} \right|}{|S| \sum_{s \in S} \sum_{m \in \mathcal{M}_s} \sum_{d \in D} \pi_m q_{msd}}.$$

The value of the Gini coefficient varies between zero and one. The closer its value to zero, the less inequality there is among the suppliers with regard to their profits. The Gini coefficient is a nonlinear metric

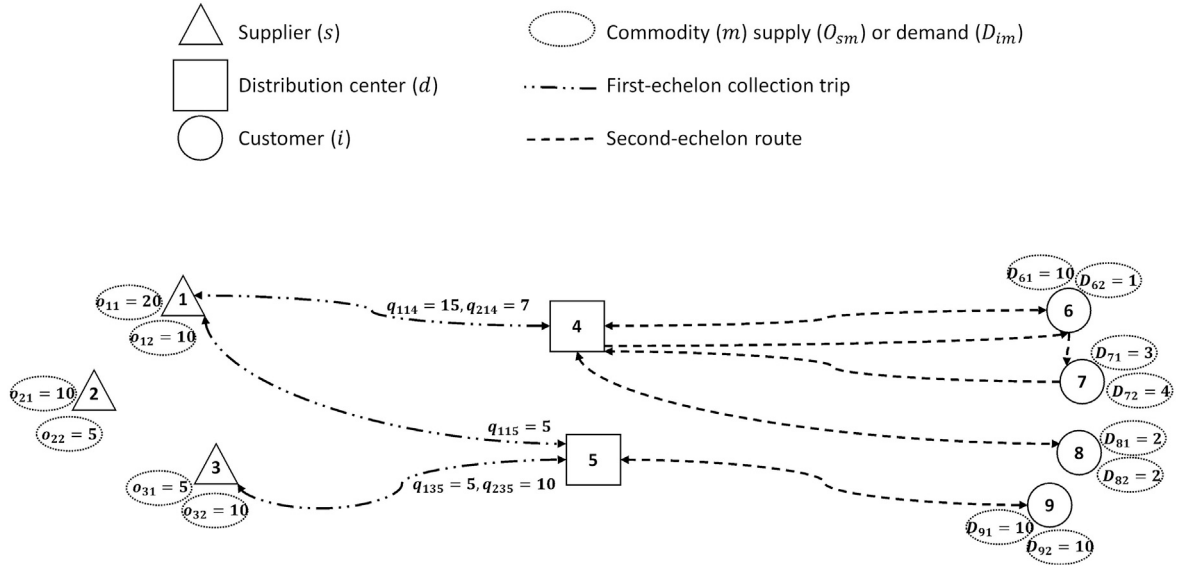


Fig. 1. An example of an unfair solution of the problem.

which can be linearized using a change of variable (Chen and Hooker, 2023). Let  $\pi_{s,s'}$  be a variable that satisfies  $\pi_{s,s'} \geq \left| \sum_{m \in \mathcal{M}_s} \sum_{d \in \mathcal{D}} \pi_m q_{msd} - \sum_{m \in \mathcal{M}_{s'}} \sum_{d \in \mathcal{D}} \pi_m q_{ms'd} \right|$ , for  $s, s' \in S : s < s'$ . Then, the Gini metric for our problem can be rewritten as:

$$\pi_{s,s'} \geq \sum_{m \in \mathcal{M}_s} \sum_{d \in \mathcal{D}} \pi_m q_{msd} - \sum_{m \in \mathcal{M}_{s'}} \sum_{d \in \mathcal{D}} \pi_m q_{ms'd}, \quad s, s' \in S : s < s' \quad (12-G1)$$

$$-\pi_{s,s'} \leq \sum_{m \in \mathcal{M}_s} \sum_{d \in \mathcal{D}} \pi_m q_{msd} - \sum_{m \in \mathcal{M}_{s'}} \sum_{d \in \mathcal{D}} \pi_m q_{ms'd}, \quad s, s' \in S : s < s' \quad (12-G2)$$

$$\sum_{s \in S} \sum_{s' \in S : s < s'} \pi_{s,s'} \leq (1 - \alpha) |S| \sum_{s \in S} \sum_{m \in \mathcal{M}_s} \sum_{d \in \mathcal{D}} \pi_m q_{msd}, \quad (12-G3)$$

$$\pi_{s,s'} \geq 0, \quad s, s' \in S : s < s', \quad (12-G4)$$

with  $\alpha \in [0, 1]$  implying the minimum acceptable Gini coefficient. Therefore, the MIP comprises (1)–(11), plus the new fairness constraints (12-G1)–(12-G4).

### 3.3.3. Our equity measure

Since suppliers in the case study we consider are quite heterogeneous, we notice that classic fairness measures may not be fully adequate. Specifically, as some suppliers are inherently smaller than others, they will constitute a bottleneck for classic fairness measures like the range or the Gini index since they can never contribute as much to the system as suppliers that have more or more valuable produce. To alleviate this issue, we explicitly consider the available supply of each farm in our measure.

We now present our own equity measure. Let for each supplier  $s$ ,  $F_s$  be the supplier's share of the total supply of commodities in the network, calculated as  $F_s = \sum_{m \in \mathcal{M}_s} O_{sm} / \sum_{s' \in S} \sum_{m \in \mathcal{M}_{s'}} O_{s'm}$ . Then in order to serve suppliers equitably, we make sure that each supplier has a guaranteed percentage of the total profit proportional to their available supply. To do so, we define our fairness constraints as the following:

$$\alpha F_s \sum_{m \in \mathcal{M}_s} \sum_{i \in C} \pi_m D_{im} \leq \sum_{m \in \mathcal{M}_s} \sum_{d \in \mathcal{D}} \pi_m q_{msd}, \quad s \in S. \quad (12-O1)$$

Therefore, the new MIP formulation of the problem at hand involves objective function (1), constraints (2)–(11), and constraints (12-O1).

Given that we have introduced a new equity measure, we now investigate the theoretical aspects of our proposed metric through a

group of eight axiomatic properties that are commonly known for the classical fairness measures, especially for inequality indexes. Following a discussion by Matl et al. (2018) on these criteria with regard to allocating workloads to agents, we start by defining the vector of allocations in our case. Denoted by  $\mathbf{q}$ , this vector is a vector of the collected and transported supplies from all suppliers:

$$\mathbf{q} := ([q_{msd}]_{m \in \mathcal{M}_s, d \in \mathcal{D}})_{s \in S}.$$

Next, we present our fairness objective as

$$I(\mathbf{q}) := \min_{s \in S} \hat{\alpha}_s,$$

where  $\hat{\alpha}_s$  is defined by

$$\hat{\alpha}_s := \frac{\sum_{m \in \mathcal{M}_s} \sum_{d \in \mathcal{D}} \pi_m q_{msd}}{F_s \sum_{m \in \mathcal{M}_s} \sum_{i \in C} \pi_m D_{im}}.$$

The goal is to find a vector of collections,  $\mathbf{q}$ , that maximizes equity, i.e.  $\max I(\mathbf{q})$ , or, equivalently, maximizes  $\alpha$  in Constraints (12-O1).

With these definitions, we now analyze our measure with regard to the eight axiomatic characteristics discussed by Matl et al. (2018). None of the fairness criteria they investigate satisfies all the properties. Three out of eight axioms hold for our suggested fairness metric: *Transitivity* (Axiom 2), *Population Independence* (Axiom 4), and *Monotonicity* (Axiom 7).

### 3.4. An illustrative example

An example of the problem is depicted in Fig. 1. There are three suppliers, i.e.  $S = \{1, 2, 3\}$ , denoted by triangles, two distribution centers, i.e.  $D = \{4, 5\}$ , denoted by squares, and four customers, i.e.  $C = \{6, 7, 8, 9\}$ , denoted by circles. There are two commodities  $\mathcal{M} = \{1, 2\}$  with profits  $\pi_1 = 1$  and  $\pi_2 = 2$  per unit. The capacity of the (first-echelon) trucks,  $Q^S$ , and (second-echelon) vehicles,  $Q^D$ , are assumed to be both equal to 10. The maximum available quantity of commodities offered by each supplier,  $O_{sm}$ , and the demand of each customer for commodities,  $D_{im}$ , are listed next to the corresponding entity inside dotted ellipses. One feasible solution for this distribution network is presented in the figure with three first-echelon collection trips and four second-echelon routes depicted in dashed arrows with dots and dashed arrows, respectively. Given the demands of the customers that need to be satisfied via distribution centers 4 and 5 and the available supply of commodities at suppliers 1 and 3, focusing solely on minimizing the total transportation cost of the network leaves supplier 2 disconnected

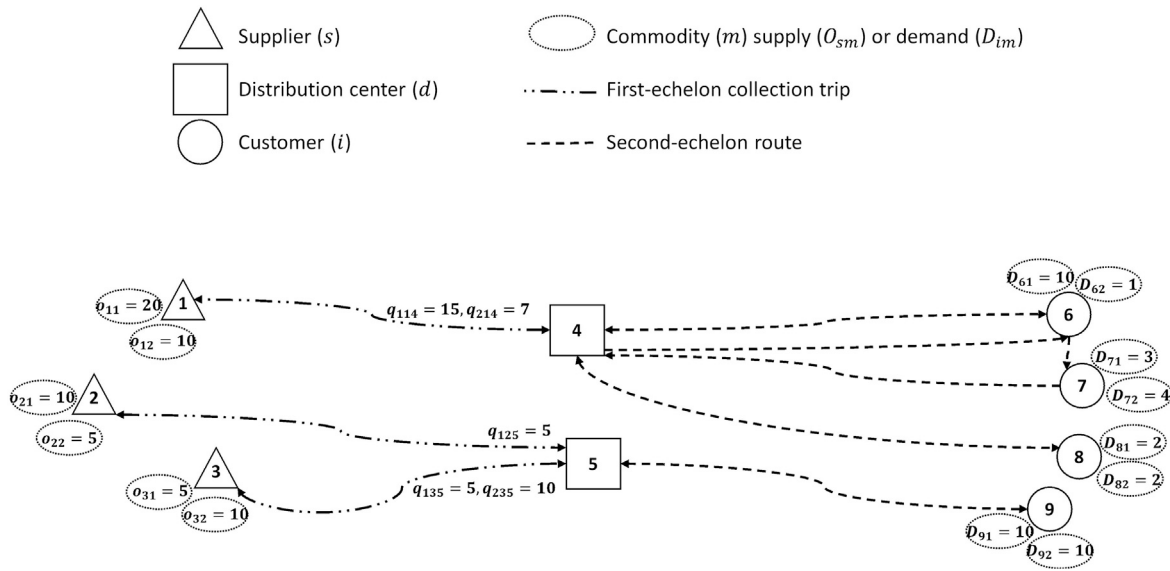


Fig. 2. An example of a solution of the problem when fairness is enforced.

from the network. The quantities of collected commodities from suppliers 1 and 3 transported to distribution centers 4 and 5 are denoted above the corresponding first-echelon collection trip. Note that given the capacity of the trucks, this means that for performing the collection trip between supplier 1 and distribution center 4, three trucks, the collection trip between supplier 1 and distribution center 5, one truck, and the collection trip between supplier 3 and distribution center 5, two trucks are needed. Imposing fairness through a set of constraints can (probably) circumvent the issue of excluding supplier 2. A feasible solution in which supplier 2 is connected to the network and gains a profit is displayed in Fig. 2. To compare these two solutions in terms of profit equity, we calculate the profits of suppliers in each solution and then use the three fairness measures discussed in the previous sections. In the solution of Fig. 1, the profits of suppliers 1, 2, and 3 are 34 (maximum), 0 (minimum), and 25, respectively. On the other hand, in Fig. 2 the profits of suppliers 1, 2, and 3 are 29 (maximum), 5 (minimum), and 25, respectively. Therefore, the relative range for the first solution is 1 and for the second solution is 0.8. The Gini coefficient of the first solution is 0.38 and for the second solution is 0.27. For our suggested fairness measure, the suppliers' share of the total supply in the network are  $F_1 = 0.50$  and  $F_2 = F_3 = 0.25$ , and since all three suppliers have both commodities available, the total profit of the network's demand for their commodities is 59. Since the profit of supplier 2 in the first solution is zero, our fairness measure evaluates to  $\alpha \times 0.25 \times 59 \leq 0$ , i.e. to  $\alpha = 0$  guaranteed share of profit. In the second solution, supplier 2's profit is 5, which is the minimum. Therefore, our metric evaluates to  $\alpha \times 0.25 \times 59 \leq 5$ , i.e. to maximum  $\alpha = 0.34$  guaranteed share of profit.

#### 4. Solution approach: A matheuristic

As Sluijk et al. (2023) point out, solving midsize two-echelon VRPs can be computationally expensive. Solving a problem like ours is even more challenging due to the presence of multiple distribution centers, the number of suppliers and customers, and the explicit consideration of multiple commodities. Therefore, we solve the problem at hand heuristically. We design a matheuristic in which the first and second echelons are jointly optimized. A scheme of the matheuristic is presented in Fig. 3. We first generate a (heuristic) pool of feasible second-echelon routes and pass it to the model. We then solve the model containing all the first-echelon variables and the second-echelon

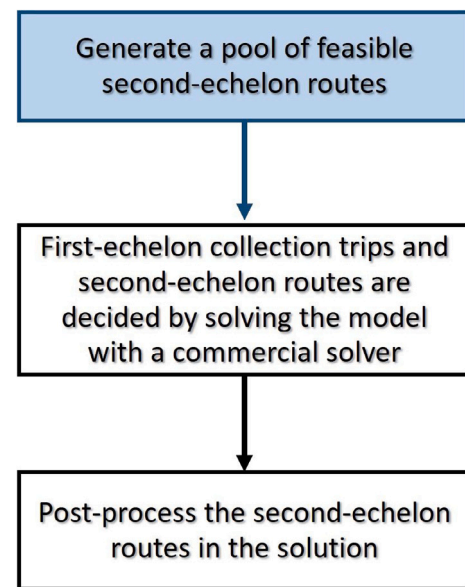


Fig. 3. The general scheme of our matheuristic.

heuristic route pool via a commercial solver (CPLEX) to decide on the first-echelon collection trips and second-echelon routes. Since the second-echelon routes are generated heuristically, it is possible for some customers to be on a selected route in the solution, but no commodity is actually delivered to those customers. Therefore, as the final step, we update the route and its cost by excluding such customers. We refer to this step as post-processing the second-echelon routes in the solution.

##### 4.1. Second-echelon route generation

Generating the set of all routes becomes computationally intractable for realistic instances. Therefore, we present a heuristic technique that



**Algorithm 1:** Estimation of the current available capacity of a route.

---

```

1 Data: route  $r_k$ ; the portion of customers' demands,  $\beta\%$ ; the vehicle capacity,  $Q^D$ 
   Result:  $\underline{Q}_{curr}^D(k)$ 
2  $\underline{Q}_{curr}^D(k) \leftarrow Q^D$  /* initialize the available capacity */
3 for  $i' \in C : \sigma_{i'k} = 1$  do
4   if  $\underline{Q}_{curr}^D(k) < \beta \sum_{m \in \mathcal{M}_{i'}} D_{i'm}$  then
5     set  $\underline{Q}_{curr}^D(k) \leftarrow -\infty$ 
6     break
7   else
8     find  $\tilde{\mathcal{M}}_{i'} \in \arg \max_{\mathcal{M}'_i \subseteq \mathcal{M}_{i'}} \{ \sum_{m \in \mathcal{M}'_i} D_{i'm} : \sum_{m \in \mathcal{M}'_i} D_{i'm} \leq \underline{Q}_{curr}^D(k) \}$  /* a subset of customer's commodities that fills
       the available capacity the most */
9     if  $\sum_{m \in \tilde{\mathcal{M}}_{i'}} D_{i'm} \geq \beta \sum_{m \in \mathcal{M}_{i'}} D_{i'm}$  then
10      set  $\underline{Q}_{curr}^D(k) \leftarrow \max(0, \underline{Q}_{curr}^D(k) - \sum_{m \in \tilde{\mathcal{M}}_{i'}} D_{i'm})$  /* update the available capacity */
11    else
12      set  $\underline{Q}_{curr}^D(k) \leftarrow -\infty$ 
13      break
14    end
15  end
16 end

```

---

constructs a pool of feasible second-echelon routes, while avoiding duplicates in the pool. In our case, a route is a sequence of customers to be visited by a vehicle which departs from and returns to the same distribution center. We consider a limit on the number of generated routes to circumvent the problem of exploding the MIP size for the solver. Moreover, the demand of a customer for multiple commodities can be split by commodity but not by quantity in the second echelon. Hence, to exclude very long and suboptimal routes, which will probably not be selected by the model, we estimate the current available capacity of route  $k \in K$ , denoted by  $\underline{Q}_{curr}^D(k)$ . The calculation of the current available capacity of the route is described in Algorithm 1.

The information the algorithm requires are the route, the minimum portion of customers' demands that should fit on the route, i.e.  $\beta\%$ , and the vehicle capacity, i.e.  $Q^D$ , in the second-echelon (line 1). Note that  $\beta$  is a hyperparameter of the matheuristic. We initialize the available capacity with vehicle capacity (line 2). Next, for every customer  $i' \in C$  on route  $k$ , i.e.  $\sigma_{i'k} = 1$ , we iteratively (lines 3–13) verify whether the available capacity is less than  $\beta\%$  of the total demand of the customer (line 4). If yes (lines 4–6), we declare the remaining capacity insufficient by setting it to  $-\infty$  and break out of the loop (lines 5–6). If no (lines 7–13), we then find a subset of customer's commodities that fills the available capacity the most (line 8). If the demand of this subset is at least as big as  $\beta\%$  of the total demand of the customer (lines 9–10), we update the available capacity by taking the maximum between zero and the demand of the commodity combination subtracted from the current available capacity (line 10). If that is not the case (lines 11–13), we announce the current remaining capacity insufficient by setting  $\underline{Q}_{curr}^D(k)$  to  $-\infty$  and stop the iteration (lines 12–13).

We then use this estimate in the following conditions when inserting a customer  $i \in C$  into the route:

- (a) Customer  $i$  is not added to the route, if the total minimum demands of the customers currently on the route plus the minimum demand of  $i$  violates the vehicle capacity, i.e. if

$$\sum_{\substack{i' \in C: \\ \sigma_{i'k}=1}} \min_{m \in \mathcal{M}_{i'}} \{D_{i'm}\} + \min_{m \in \mathcal{M}_i} \{D_{im}\} > Q^D.$$

- (b) Assume  $\underline{Q}_{curr}^D(k) > 0$ . Customer  $i$  is not added to route  $k$ , if the current remaining capacity is smaller than  $\beta\%$  of the total demand of the customer, i.e.  $\underline{Q}_{curr}^D(k) < \beta \sum_{m \in \mathcal{M}_i} D_{im}$ . Otherwise, customer  $i$  is not added to route  $k$ , if the demand of the subset of commodities that fills the current available capacity of the

route the most is smaller than  $\beta\%$  of the total demand of the customer. To formulate this part, assume  $\tilde{\mathcal{M}}_i \subseteq \mathcal{M}_i$  to be the subset of commodities with  $\tilde{\mathcal{M}}_i \in \arg \max_{\mathcal{M}'_i \subseteq \mathcal{M}_i} \{ \sum_{m \in \mathcal{M}'_i} D_{im} : \sum_{m \in \mathcal{M}'_i} D_{im} \leq \underline{Q}_{curr}^D(k) \}$ , then customer  $i$  will not be added to the route, if

$$\sum_{m \in \tilde{\mathcal{M}}_i} D_{im} < \beta \sum_{m \in \mathcal{M}_i} D_{im}.$$

If  $i$  is added to route  $k$ , then we update the remaining capacity as  $\underline{Q}_{curr}^D(k) \leftarrow \max(0, \underline{Q}_{curr}^D(k) - \sum_{m \in \tilde{\mathcal{M}}_i} D_{im})$ .

- (c) Customer  $i$  is not added to route  $k$ , if the insertion imposes a detour bigger than a small enough threshold  $\tau$ ,  $0 < \tau < 1$ , on the route cost. In other words, let  $\bar{c}_k(i)$  be the estimated travel cost of route  $k$  with the possibility of customer  $i$  being inserted in the cheapest position plus a random noise on the insertion cost drawn from interval  $[-\max N, \max N]$ , where  $\max N = \eta \max_{(j,j') \in A_2} \{c_{jj'}\}$  and  $\eta = 0.025$ . Then,  $i$  is not added to the route, if

$$\bar{c}_k(i) > (1 + \tau)c_k.$$

We recall that  $c_k$  is the cost of route  $k$  without customer  $i$ . Our route generation procedure is composed of two main phases: Phase 1, generating a set of feasible routes via a restricted enumeration to guarantee the feasibility of the MIP model; and Phase 2, enlarging the pool of routes in four sub-steps via a constructive heuristic, and destroy and repair operators. The details of the two phases are as follows.

**Phase 1** Restricted enumeration of single-customer and two-customer routes: From each distribution center, we produce routes with one and two customers on them. In both cases, we make sure that condition (a) mentioned above is respected. In case of two-customer routes, we consider two more conditions. We put two customers on a route, if (i) the distribution center closest to them is the same, and (ii) the distance between the two customers is not bigger than half of the largest distance between the second-echelon nodes, i.e. the distance between the distribution centers and customers, and between customers themselves. These routes will then be added to the pool of routes, which is initially empty.

**Phase 2**

- Step 1** Generating a base set of routes via a constructive heuristic: From each distribution center, we construct an initial set of routes by using the Savings algorithm from [Clarke](#)

and Wright (1964), while making sure that firstly condition (a) is respected and secondly condition (b) is respected with the current available capacity of routes estimated via Algorithm 1. We then improve these routes by applying a local search, namely a series of intra-route 2-opt moves (Lin, 1965), on them. These routes will then be used to construct more routes in Step 3.

- Step 2 Extending the base set of routes: Before adding the resulting routes from Step 1 to the pool, we try to extend them. For every route from Step 1, we go through the set of customers and for every customer that is not currently on the route, we check whether conditions (a) and (c) are respected. If so, we then insert the customer in the cheapest position possible on that route. The purpose of this step is to find customers that are not added to a route from Step 1 only because of condition (b), while visiting them will cause a very small detour (maximum 1% of the route cost, i.e.  $\tau := 0.01$  in condition (c)) on the route, and add those customers to the route, as the route is still good to serve at least the smallest demands of such customers without costing much. The materialized routes will be added to the pool afterwards.
- Step 3 Deduplicating the base set of routes: The routes in Step 1 are constructed from every distribution center and, therefore, customers can appear on multiple routes. To avoid operating on copies of the same customer, we deduplicate customers on the routes. To do so, we keep a customer on a route from a randomly chosen distribution center and remove it from the routes of other distribution centers. The resulting routes will then be utilized in the next step.
- Step 4 Constructing more routes by applying destroy and repair operators iteratively: Borrowed from the Large Neighborhood Search algorithm, we apply destroy and repair moves on the deduplicated routes from Step 3, iteratively to produce more routes that are diverse as well. In each iteration, we use two operators presented in Ropke and Pisinger (2006): the random removal and basic greedy insertion with a random noise on the insertion cost. We randomly remove a certain number (drawn also randomly between 20% and 50%) of customers and then insert back the removed customers into the routes by applying the basic greedy insertion with a random noise. We make sure that firstly condition (a) and secondly condition (b) with the current available capacity of routes estimated by Algorithm 1 are respected by the insertion. Similar to Ropke and Pisinger (2006), we calculate the noise by drawing a number from interval  $[-\max N, \max N]$  randomly, where  $\max N = \eta \max_{(j,j') \in \mathcal{A}_2} \{c_{jj'}\}$  and  $\eta = 0.025$ . At each iteration, we calculate the noise and add it to the insertion cost for deciding on which route to insert a customer. Note that there is a possibility that one or more customers cannot be inserted back into any route due to conditions (a) and (b). If this happens, i.e. there are some customers unserved on any existing route, we create empty routes from the distribution centers and start inserting the unserved customers into those routes via the basic greedy insertion operator with random noise, while still respecting conditions (a) and (b). At the end of each iteration of destroy and repair, we apply a series of intra-route 2-opt moves (Lin, 1965) on the constructed routes, until no further improvement is possible, and then we add the resulting routes to the pool. We apply destroy and repair operators for 100 iterations.

To avoid having multiple copies of the same route added to the pool, we check whether a route generated in Phase 1 or in Step 2 and Step 4

from Phase 2 already exists in the pool. If not, we then add the route to the pool. Moreover, before adding a route to the pool, we check the current size of the pool to avoid violating the limit on the number of routes generated.

## 5. Numerical experiments

In this section, we first evaluate the performance of our matheuristic in solving the multi-commodity two-echelon distribution problem by Gu et al. (2022), which is a special case of our problem with relaxed fairness constraints. We use the results from these authors as benchmarks. Next, we compare the efficacy of our proposed fairness measure with the relative range and Gini coefficient schemes from the literature through the lens of different KPIs. Finally, by activating the fairness constraints in our MIP model, we study the consequences of the level of equity enforced on both echelons' transportation costs and finish the section with some managerial insights.

The numerical experiments are conducted using the instances from Gu et al. (2022), which we will briefly describe in the beginning of this section. All numerical tests are implemented in C# and run on a machine with a 1.8 Gigahertz AMD Ryzen 7 5700U CPU and 16 GB of RAM.

### 5.1. Instances

In the study by Gu et al. (2022), there are two categories of instances: randomly generated instances and case-study instances. From multiple sets of generated instances, Gu et al. (2022) chose three sets, referred to as  $\mathcal{S}$ ,  $\mathcal{S}_1^S$ , and  $\mathcal{S}_2^S$ , each containing 12 instances, to solve their compact model by CPLEX and by their proposed six sequential heuristics. The instances in these sets have either four or six suppliers, two distribution centers, and either 10, 15, 20, or 25 customers with locations built from the well-known Solomon (1987) instances, more specifically C101 instances. There are either two or three commodities in the network and customers demand commodities with the probability of either 0.6 or 1. The probability of 1 means that every customer has a demand for each commodity. The probability set to 0.6 means that the probability that a customer has a demand for a specific commodity is 60%. The capacity of trucks and vehicles in these instances are equal and set to either 150, 180, or 209 units. There are two groups of instances from the case-study category in Gu et al. (2022): school canteen instances; and supermarket instances. The case study was conducted by the local authorities of the French department of Isère to increase the volume of locally produced fresh fruits and vegetables sold through a short supply chain in that region of France. In the school canteen instances, there are either 54 or 61 suppliers offering at least one commodity. In all eight instances of this group, there are five distribution centers and 103 customers. The number of commodities in the network varies between five and eight. The capacity of trucks is 600 units and the capacity of vehicles is 1200 units. In the supermarket instances, the number of suppliers offering at least one commodity ranges from 45 to 61. In all 10 instances in this group, there are five distribution centers and 188 customers. Similar to the school canteen instances, the number of commodities in the network varies from five to eight. The capacity of trucks is 3000 units and the capacity of vehicles is 6000 units. For more details on these two instance groups selected for our numerical studies, we refer to Appendix.

Unless otherwise stated, the portion of customers' demands used in the calculation of the current available capacity and conditions in our route generation process, i.e.  $\beta\%$ , is set to 20% for the selected generated instances of Gu et al. (2022) and to 90% for the case-study instances of Isère. These values are chosen after preliminary experiments with different values ranging from 10% to 90%. The time limit for solving the selected generated instances and school canteen instances of the case-study is set to one hour. For supermarket instances of the case-study, however, the time limit for the solver is set to three hours. The vector of profits of commodities in the network is set to [10, 20, 15, 5, 10, 25, 15, 20] €/per pallet for commodities [one, two, three, ..., eight].

**Table 2**  
Result comparisons for generated instances.

Set	Instance	Gu et al. (2022)'s six heuristics		Our matheuristic					
		Best	T (s)	Solution				Route generation	
				Best	gap (%)	T (s)	Nb.Trucks & Nb.Routes	Nb.Routes	t (s)
$\mathcal{S}$	1	394.66	50	394.67	0.0	0.9	4 & 4	116	0.1
	2	579.52	58	586.37	1.2	1.7	7 & 8	60	<0.1
	3	470.77	59	470.77	0.0	2	5 & 5	76	<0.1
	4	512.50	89	510.91	-0.3	0.9	7 & 6	163	<0.1
	5	765.47	133	771.4	0.8	15.5	10 & 11	120	<0.1
	6	551.88	122	556.07	0.8	4	7 & 6	189	<0.1
	7	636.71	270	637.82	0.2	3.3	8 & 8	276	0.1
	8	1007.04	295	1018.1	1.1	9.4	14 & 13	209	0.1
	9	708.62	376	709.58	0.1	22.3	9 & 9	310	0.1
	10	818.57	141	800.58	-2.2	9.2	10 & 11	360	0.1
	11	1184.62	173	1184.71	0.0	23.8	15 & 16	336	0.2
	12	827.29	168	858.70	3.8	149.9	10 & 10	434	0.2
$\mathcal{S}_1^S$	1	406.52	48	406.53	0.0	0.8	4 & 4	116	<0.1
	2	562.34	57	580.71	3.3	0.9	7 & 8	60	<0.1
	3	437.98	70	437.97	0.0	1.4	5 & 5	76	<0.1
	4	533.43	96	533.46	0.0	1.0	7 & 6	163	<0.1
	5	784.05	134	787.66	0.5	3.3	10 & 11	120	<0.1
	6	554.73	152	572.81	3.3	6.1	7 & 6	189	<0.1
	7	668.5	255	662.8	-0.9	3.1	8 & 8	276	0.1
	8	1077.43	292	1092.62	1.4	41.2	13 & 13	209	0.1
	9	775.3	152	774.81	-0.1	30.5	8 & 9	310	0.1
	10	849.29	138	831.86	-2.1	7.0	10 & 11	360	0.1
	11	1258.91	164	1275.21	1.3	69.2	15 & 16	336	0.2
	12	894.56	164	896.15	0.2	9.2	10 & 10	434	0.1
$\mathcal{S}_2^S$	1	406.52	41	417.15	2.6	0.3	4 & 4	116	<0.1
	2	663.52	52	680.88	2.6	0.7	7 & 8	60	<0.1
	3	463.58	58	463.58	0.0	0.4	5 & 5	76	<0.1
	4	590.55	85	625.8	6.0	0.4	7 & 6	163	<0.1
	5	893.09	133	895.98	0.3	0.4	10 & 11	120	<0.1
	6	590.71	122	590.74	0.0	1.2	7 & 6	189	<0.1
	7	713.16	236	713.26	0.0	0.7	8 & 8	276	0.1
	8	1177.46	253	1231.69	4.6	2.5	13 & 13	209	0.1
	9	835	311	842.12	0.9	6.9	8 & 9	310	0.1
	10	881.02	175	925.49	5.0	4.6	10 & 11	360	0.1
	11	1367.61	147	1388.33	1.5	10.2	15 & 16	336	0.2
	12	939.52	151	1012.32	7.7	15.3	10 & 10	434	0.2
Average		-	150.6	-	1.2	12.8	8.7 & 8.9	-	-

## 5.2. Matheuristic performance analysis

We solve the selected instances of the multi-commodity two-echelon distribution problem with our proposed matheuristic and compare the results with the ones from Gu et al. (2022). For these analyses, we relax the fairness constraints in our model by setting the guaranteed percentage of suppliers' share, i.e.  $\alpha$ , to zero. Since there is no best heuristic, Gu et al. (2022) report the best results out of six heuristics, which they have run on an Intel(R) Core(TM) i7-4600U, 2.10 GHz with 16 GB of RAM, and give the total run time of all heuristics. In the following, we discuss the performance of the matheuristic for the generated instances and case-study instances.

**Generated instances.** The results of our approach along with the ones reported by Gu et al. (2022) on the three sets of (in total 36) generated instances are provided in Table 2. For each instance, the first two columns titled Best and  $T$  (s) present the best total cost among the six heuristics that Gu et al. (2022) applied and the total run time of those six heuristics in seconds. The next six columns display the performance of our proposed matheuristic. From these six columns, the first four are the KPIs associated with the solution. Columns Best and gap (%) show the total cost returned by the matheuristic and its percentage gap with the best result of Gu et al. (2022). Column  $T$  (s) for our matheuristic reports the total time in seconds, i.e. route generation time plus the CPU time of the solver, our approach took to provide a solution. Column Nb.Trucks & Nb.Routes presents the number of trucks and routes used in the first and second echelon of our solution, respectively. For these sets of instances, Gu et al. (2022) did not report

the number of trucks and vehicles used in their solutions. The last two columns are the KPIs associated with the route generation step of the matheuristic. Nb.Routes and  $t$  (s) denote the number of routes generated and the time our heuristic route generation scheme took.

From the numbers in Table 2, we note that on average our matheuristic returns a solution with a total cost within 1.2% of the best cost in Gu et al. (2022), about 12 times faster than Gu et al. (2022). Moreover, we find new best costs for five instances in this group of generated instances.

**Case-study instances.** In Tables 3 and 4, we report the results of our matheuristic and Gu et al. (2022)'s results for the school canteens and supermarket instances of the case study by the French department of Isère, respectively. The columns in these tables are the same columns associated with our matheuristic as the table for the generated instances. However, in addition to the two columns associated with the results from Gu et al. (2022) for the generated instances, Tables 3 and 4 contain one more column: Nb.Trucks & Nb.Vehicles, which reports the number of trucks and vehicles associated with the best result of Gu et al. (2022)'s six heuristics.

From both tables, we observe that our matheuristic provides a solution with a total cost of 7% and 1.5% in case of school canteen instances and supermarket instances, respectively, on average lower than the best costs reported by Gu et al. (2022). In addition, on average the total run times of the matheuristic are twice and 3.5 times faster than Gu et al. (2022)'s for school canteens and supermarket instances, respectively. Although our solution uses more trucks and routes in the first and second echelons on average compared to the best solutions

**Table 3**

Result comparisons for school canteen instances.

Instance	Gu et al. (2022)'s six heuristics			Our matheuristic					
				Solution				Route generation	
	Best	T (s)	Nb.Trucks & Nb.Vehicles	Best	gap (%)	T (s)	Nb.Trucks & Nb.Routes	Nb.Routes	t (s)
1	2877.15	12 123.68	41 & 16	2545.12	-11.5	3620.1	42 & 17	3004	20.1
2	2756.37	7941.12	41 & 14	2572.42	-6.7	3622.7	43 & 15	3010	22.7
3	2070.29	6757.6	33 & 9	1931.49	-6.7	3617.1	29 & 12	2787	17.1
4	2144.25	4618.24	35 & 8	2099.34	-2.1	3615.2	39 & 10	2699	15.2
5	2905.79	6159.37	46 & 11	2741.41	-5.7	3617.2	47 & 12	2872	17.2
6	2233.42	3970.63	38 & 8	2152.82	-3.6	3616.0	39&10	2764	16.0
7	2365.34	6928.82	41 & 10	2165.66	-8.4	3617.4	39 & 13	2834	17.4
8	2000.32	8746.92	34 & 9	1775.13	-11.3	3617.6	35 & 11	2747	17.6
Average	-	7155.8	38.6 & 10.6	-	-7.0	3617.9	39.1 & 12.5	-	-

**Table 4**

Result comparisons for supermarket instances.

Instance	Gu et al. (2022)'s six heuristics			Our matheuristic					
				Solution				Route generation	
	Best	T (s)	Nb.Trucks & Nb.Vehicles	Best	gap (%)	T (s)	Nb.Trucks & Nb.Routes	Nb.Routes	t (s)
1	6449.01	33 456.70	76 & 35	6256.68	-3.0	11 024.1	77 & 45	7902	224.1
2	6183.81	22 499.36	73 & 31	6181.01	0.0	11 003.2	73 & 42	7783	203.2
3	6168.55	33 718.74	73 & 34	5619.12	-8.9	11 009.2	73 & 45	7915	209.2
4	5351.62	49 915.48	84 & 37	5403.93	1.0	11 025.9	86 & 52	7940	225.9
5	4415.45	20 483.72	77 & 33	4625.91	4.8	11 007.7	76 & 44	7903	207.7
6	7037.98	30 045.25	95 & 43	6995.32	-0.6	11 063.5	98 & 59	8333	263.5
7	7847.62	71 251.28	108 & 49	7615.07	-3.0	11 076.8	109 & 58	8270	276.8
8	7954.41	46 509.08	105 & 48	7658.40	-3.7	11 040.9	106 & 56	8222	240.9
9	7436.06	45 285.77	93 & 44	7047.99	-5.2	11 033.7	95 & 53	8085	233.7
10	6449.01	31 680.10	76 & 35	6696.45	3.8	11 025.7	79 & 52	7882	225.7
Average	-	38 484.55	86 & 38.9	-	-1.5	11 031.1	87.2 & 50.6	-	-

reported by Gu et al. (2022), the matheuristic chooses trips and routes with minimum total transportation costs. We believe that the reason for this particular result of our technique is that, unlike the sequential heuristics of Gu et al. (2022) that decompose the problem into two subproblems associated with each echelon, the matheuristic optimizes the first and second echelons jointly. The matheuristic finds new best costs for all school canteen instances and for six out of 10 supermarket instances.

### 5.3. The choice of fairness measure

How to define a fairness measure has been a question that many studies with the focus on equity have faced in the literature. As we use two classic fairness metrics from the literature and also introduce our own equity measure, in this section we assess the adequacy of our metric versus the relative range and Gini coefficient with regard to achieving fairness in suppliers' profits and minimizing the cost in terms of two groups of KPIs. To do so, we run a series of numerical experiments on the generated instances of group  $\mathcal{S}$  and the school canteen instances with fairness being modeled by using one of these measures. The equity level, i.e.  $\alpha$ , varies from 0% to 100% with a step-size of 10%. The results are presented in Tables 5 and 6.

Both tables contain nine columns. The first column shows the equity level, i.e., the values of  $\alpha$ . For each value, there are groups of KPIs reported in two columns per fairness measure used. Column KPIs-Profit consists of maximum profit of suppliers (Max. Profit (€)), minimum profit of suppliers (Min. Profit (€)), average profit among suppliers (Avg. Profit (€)), standard deviation of suppliers' profits (STDEV.), number of suppliers with no profit (#Supp.No Profit), and the total time in seconds, meaning route generation plus the CPU time of the solver, our matheuristic took to return a solution (T(s)). Column KPIs-Cost includes total transportation cost of the network (Total cost), first-echelon cost (First-echelon cost), second-echelon cost (Second-echelon

cost), number of first-echelon trucks (Nb.Trucks), and second-echelon routes (Nb.Routes). Associated with each of these two groups of KPIs, there are three columns reporting the values of the KPIs for the relative range, Gini coefficient, and our own fairness measure. All numbers reported in Tables 5 and 6 are averaged over the instances of each corresponding instance group. For the values of  $\alpha$  where none of the instances in a group was solved by using a fairness metric, no number for the KPIs is reported.

From Table 5 we note that in case of the generated instances of group  $\mathcal{S}$ , all suppliers are already connected to the network and gain profit, even before the fairness measures are enforced, because of the demand structure. When the fairness constraints are imposed, i.e. starting from  $\alpha = 10\%$ , no major changes occur in any of the KPIs-Profit and KPIs-Cost until  $\alpha$  reaches 60% for the relative range, 90% for the Gini coefficient, and 70% for our measure. Regarding profit related KPIs, starting from  $\alpha = 60\%$ , the minimum profit starts increasing, while the maximum profit and consequently the standard deviation of profit start decreasing for the relative range. A similar trend can be observed from our measure starting from  $\alpha = 70\%$ .

Regarding cost related KPIs, the total transportation cost and first-echelon cost start increasing as of  $\alpha = 60\%$  for the relative range and as of  $\alpha = 70\%$  for our measure. Unlike these two measures, the Gini coefficient is rather slow in reacting to higher level of fairness enforced on the profits. Regardless of the measure, 100% fairness can only be achieved in one instance because the supply and demand structure of the other instances does not allow a perfectly balanced distribution of profits.

Table 6, relating to the school canteen instances, demonstrates that, unlike the generated instances, as soon as the fairness measures are enforced, i.e.  $\alpha = 10\%$ , the KPIs-Profit and KPIs-Cost start changing considerably for the relative range and our measure, while not much change happens in those KPIs for the Gini coefficient. Using the relative range or our measure guarantees that every supplier gains a profit,



**Table 5**Average performance of different equity measures for set  $\mathcal{S}$  of the generated instances.

\*\*\*1: Achieving full fairness by all three measures was possible only for one instance.

$\alpha$	KPIs-Profit	Equity measures			KPIs-Cost	Equity measures		
		Relative range	Gini coefficient	Our measure		Relative range	Gini coefficient	Our measure
0%	Max. Profit (€)	5579.2	5615.0	5615.0	Total cost	708.3	708.3	708.3
	Min. Profit (€)	3202.1	3310.8	3138.8				
	Avg. Profit (€)	4676.8	4676.8	4676.8		243.2	243.2	243.2
	STDEV.	1131.6	1081.0	1158.9		465.1	465.2	465.2
	#Supp.No Profit	0.0	0.0	0.0		8.8	8.8	8.8
	T (s)	19.6	20.7	20.2		8.9	8.9	8.9
10%	Max. Profit (€)	5548.8	5532.1	5601.3	Total cost	708.3	708.3	708.3
	Min. Profit (€)	3202.9	3355.8	3161.3				
	Avg. Profit (€)	4676.8	4676.8	4676.8		243.2	243.2	243.2
	STDEV.	1092.8	1017.5	1135.4		465.2	465.1	465.1
	#Supp.No Profit	0.0	0.0	0.0		8.8	8.8	8.8
	T (s)	17.8	19.6	20.5		8.9	8.9	8.9
20%	Max. Profit (€)	5615.0	5570.0	5612.5	Total cost	708.3	708.3	708.3
	Min. Profit (€)	3140.0	3166.3	3197.1				
	Avg. Profit (€)	4676.8	4676.8	4676.8		243.2	243.2	243.2
	STDEV.	1139.5	1123.4	1114.4		465.2	465.2	465.2
	#Supp.No Profit	0.0	0.0	0.0		8.8	8.8	8.8
	T (s)	18.0	20.2	20.3		8.9	8.9	8.9
30%	Max. Profit (€)	5566.7	5590.0	5601.7	Total cost	708.3	708.3	708.3
	Min. Profit (€)	3215.4	3165.0	3061.7				
	Avg. Profit (€)	4676.8	4676.8	4676.8		243.2	243.2	243.2
	STDEV.	1083.0	1146.5	1175.0		465.2	465.2	465.2
	#Supp.No Profit	0.0	0.0	0.0		8.8	8.8	8.8
	T (s)	19.3	11.5	18.6		8.9	8.9	8.9
40%	Max. Profit (€)	5566.7	5549.2	5601.7	Total cost	708.3	708.3	708.3
	Min. Profit (€)	3263.8	3204.2	3205.4				
	Avg. Profit (€)	4676.8	4676.8	4676.8		243.2	243.2	243.2
	STDEV.	1086.6	1071.9	1116.8		465.2	465.1	465.1
	#Supp.No Profit	0.0	0.0	0.0		8.8	8.8	8.8
	T (s)	16.6	18.1	17.4		8.9	8.9	8.9
50%	Max. Profit (€)	5582.1	5575.8	5594.2	Total cost	708.3	708.3	708.3
	Min. Profit (€)	3313.8	3265.4	3227.1				
	Avg. Profit (€)	4676.8	4676.8	4676.8		243.2	243.2	243.2
	STDEV.	1066.1	1066.1	1085.7		465.1	465.1	465.1
	#Supp.No Profit	0.0	0.0	0.0		8.8	8.8	8.8
	T (s)	14.9	18.8	18.6		8.9	8.9	8.9
60%	Max. Profit (€)	5577.5	5545.0	5580.8	Total cost	715.3	708.3	708.3
	Min. Profit (€)	3665.8	3256.7	3333.8				
	Avg. Profit (€)	4676.8	4676.8	4676.8		246.9	243.2	243.2
	STDEV.	899.4	1045.2	1040.1		468.4	465.1	465.2
	#Supp.No Profit	0.0	0.0	0.0		9.1	8.8	8.8
	T (s)	18.7	11.0	16.9		9.0	8.9	8.9
70%	Max. Profit (€)	5405.8	5549.2	5582.5	Total cost	717.9	708.3	715.3
	Min. Profit (€)	3877.9	3272.1	3646.7				
	Avg. Profit (€)	4676.8	4676.8	4676.8		252.3	243.2	246.9
	STDEV.	710.4	1046.8	889.7		465.6	465.2	468.4
	#Supp.No Profit	0.0	0.0	0.0		9.3	8.8	9.0
	T (s)	24.9	13.3	20.9		9.0	8.9	9.0
80%	Max. Profit (€)	5118.8	5568.3	5556.3	Total cost	731.1	708.3	719.8
	Min. Profit (€)	4203.8	3304.6	3820.8				
	Avg. Profit (€)	4676.8	4676.8	4676.8		264.0	243.2	253.6
	STDEV.	441.5	1046.1	782.8		467.1	465.1	466.2
	#Supp.No Profit	0.0	0.0	0.0		9.5	8.8	9.3
	T (s)	41.9	17.0	18.5		9.0	8.9	9.0
90%	Max. Profit (€)	4881.3	5473.8	5510.8	Total cost	750.7	714.5	735.7
	Min. Profit (€)	4418.8	3537.1	4224.6				
	Avg. Profit (€)	4676.8	4676.8	4676.8		269.0	244.7	265.7
	STDEV.	218.7	931.2	591.8		481.7	469.8	470.0
	#Supp.No Profit	0.0	0.0	0.0		9.5	9.0	9.5
	T (s)	53.4	20.0	32.0		9.0	9.0	9.0
100%***1	Max. Profit (€)	3010.0	3010.0	3010.0	Total cost	486.0	486.0	486.0
	Min. Profit (€)	3010.0	3010.0	3010.0				
	Avg. Profit (€)	3010.0	3010.0	3010.0		216.5	216.5	216.5
	STDEV.	0.0	0.0	0.0		269.5	269.5	269.5
	#Supp.No Profit	0.0	0.0	0.0		6.0	6.0	6.0
	T (s)	1.4	1.7	1.3		5.0	5.0	5.0

**Table 6**

Average performance of different equity measures for school canteen instances, if any instance solved.

<sup>r4</sup>: Achieving 20% fairness by the relative range was possible only for four instances.<sup>r2</sup>: Achieving 30% fairness by the relative range was possible only for two instances.<sup>s4</sup>: Achieving 90% fairness by the Gini coefficient was possible only for four instances.

$\alpha$	KPIs-Profit	Equity measures			KPIs-Cost	Equity measures		
		Relative range	Gini coefficient	Our measure		Relative range	Gini coefficient	Our measure
0%	Max. Profit (€)	11751.9	10305.0	11 751.9	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes	2269.8	2364.1	2269.8
	Min. Profit (€)	0.0	0.0	0.0		1022.6	1087.7	1022.6
	Avg. Profit (€)	2509.7	2509.7	2509.7		1247.2	1276.3	1247.2
	STDEV.	2684.7	2579.4	2684.7		39.0	39.9	39.0
	#Supp.No Profit	22.3	22.5	22.3		13.0	13.3	13.0
	T (s)	2254.7	3278.6	2278.8				
10%	Max. Profit (€)	5318.1	11373.1	10 318.1	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes	3043.6	2332.7	3048.6
	Min. Profit (€)	614.4	0.0	12.5		1814.3	1052.9	1821.9
	Avg. Profit (€)	2509.7	2509.7	2509.7		1229.3	1279.8	1226.7
	STDEV.	1488.3	2556.8	2026.4		60.4	39.5	60.5
	#Supp.No Profit	0.0	22.4	0.0		13.1	13.0	12.5
	T (s)	3617.9	3617.9	1694.7				
20%	Max. Profit (€)	4995.0 <sup>r4</sup>	9846.3	8231.9	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes	3168.9 <sup>r4</sup>	2326.0	3080.2
	Min. Profit (€)	1000.0 <sup>r4</sup>	0.0	20.0		1779.6 <sup>r4</sup>	1051.5	1906.5
	Avg. Profit (€)	2867.8 <sup>r4</sup>	2509.7	2509.7		1389.3 <sup>r4</sup>	1274.5	1173.7
	STDEV.	1350.0 <sup>r4</sup>	2507.4	1846.3		61.5 <sup>r4</sup>	39.3	60.6
	#Supp.No Profit	0.0 <sup>r4</sup>	22.3	0.0		15.8 <sup>r4</sup>	12.5	13.5
	T (s)	2778.0 <sup>r4</sup>	3236.0	1687.4				
30%	Max. Profit (€)	5000.0 <sup>r2</sup>	10913.8	8075.6	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes	3482.7 <sup>r2</sup>	2313.8	3062.1
	Min. Profit (€)	1500.0 <sup>r2</sup>	0.0	30.0		1855.1 <sup>r2</sup>	1101.9	1841.2
	Avg. Profit (€)	3975.7 <sup>r2</sup>	2509.7	2509.7		1627.6 <sup>r2</sup>	1212.0	1220.8
	STDEV.	1134.8 <sup>r2</sup>	2577.0	1802.7		61.5 <sup>r2</sup>	39.5	60.6
	#Supp.No Profit	0.0 <sup>r2</sup>	22.3	0.0		18.0 <sup>r2</sup>	13.4	12.8
	T (s)	2597.9 <sup>r2</sup>	3011.4	1465.2				
40%	Max. Profit (€)		10768.1	8318.8	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes		2293.4	3075.9
	Min. Profit (€)		0.0	26.9			1056.8	1877.1
	Avg. Profit (€)		2509.7	2509.7			1236.6	1198.8
	STDEV.		2494.0	1819.0			39.5	61.1
	#Supp.No Profit		21.9	0.0			12.9	13.0
	T (s)		2567.5	1971.2				
50%	Max. Profit (€)		9878.1	8796.9	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes		2377.8	3068.6
	Min. Profit (€)		0.0	36.9			1090.1	1844.1
	Avg. Profit (€)		2509.7	2509.7			1287.7	1224.5
	STDEV.		2271.5	1897.6			41.3	61.0
	#Supp.No Profit		20.6	0.0			13.3	13.1
	T (s)		3617.9	1105.9				
60%	Max. Profit (€)		7429.4	9067.5	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes		2455.4	3069.8
	Min. Profit (€)		0.0	41.3			1228.8	1840.9
	Avg. Profit (€)		2509.7	2509.7			1226.6	1228.8
	STDEV.		1901.7	1935.9			45.3	61.0
	#Supp.No Profit		17.1	0.0			13.3	13.8
	T (s)		3317.0	1500.5				
70%	Max. Profit (€)		6287.5	8146.3	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes		2622.1	3072.8
	Min. Profit (€)		0.0	52.5			1326.4	1870.1
	Avg. Profit (€)		2509.7	2509.7			1295.7	1202.6
	STDEV.		1510.5	1861.2			49.0	60.9
	#Supp.No Profit		11.8	0.0			14.8	13.4
	T (s)		3203.3	1388.0				
80%	Max. Profit (€)		5216.9	9787.5	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes		3027.9	3080.3
	Min. Profit (€)		0.0	35.6			1642.7	1898.6
	Avg. Profit (€)		2509.7	2509.7			1385.2	1181.7
	STDEV.		1099.1	1999.0			54.9	61.0
	#Supp.No Profit		6.4	0.0			14.8	13.8
	T (s)		3533.3	1110.1				
90%	Max. Profit (€)		4343.8 <sup>s4</sup>	9177.5	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes		3396.7 <sup>s4</sup>	3073.0
	Min. Profit (€)		375.0 <sup>s4</sup>	45.0			1878.2 <sup>s4</sup>	1836.8
	Avg. Profit (€)		3044.7 <sup>s4</sup>	2509.7			1518.5 <sup>s4</sup>	1236.3
	STDEV.		768.8 <sup>s4</sup>	1935.0			59.8 <sup>s4</sup>	61.5
	#Supp.No Profit		2.3 <sup>s4</sup>	0.0			17.0 <sup>s4</sup>	13.1
	T (s)		3619.3 <sup>s4</sup>	1186.9				
100%	Max. Profit (€)			9300.0	Total cost First-echelon cost Second-echelon cost Nb. Trucks Nb. Routes			3108.2
	Min. Profit (€)			48.1				1889.7
	Avg. Profit (€)			2509.7				1218.5
	STDEV.			1931.8				61.8
	#Supp.No Profit			0.0				13.4
	T (s)			1020.7				

therefore the minimum profit starts increasing, while the maximum profit and standard deviation start decreasing. Between these two metrics, the relative range enforces the fairness more aggressively by tapering the maximum profit more and more toward the minimum profit. As a consequence, there are fewer instances solved by the relative range when the value of  $\alpha$  increases, as the small suppliers cannot increase their quota any further to bring up the minimum due to small available supplies. At 20% only four out of eight instances, at 30% only two out of eight instances, and as of 30% none of the instances are solved. Our measure, on the other hand, can deal with different level of fairness imposed without flattening the maximum profit forcefully, while lifting up the suppliers with no profit by assuring a minimum share of total profit given the available supply of those suppliers.

Unlike the relative range and our measure, the Gini coefficient does not guarantee a profit for every supplier, even if the value of  $\alpha$  starts increasing. That is why there are still suppliers with no profit even at  $\alpha = 90\%$ . Similar to the relative range, the Gini coefficient enforces equity among suppliers by depressing the maximum profit, but without lifting up all suppliers with no profit. Although the Gini coefficient starts assuring a profit for more suppliers at the higher values of  $\alpha$ , not all school canteen instances are solvable for those high values. At 90%, only four out of eight and at 100% none of the instances are solved by using the Gini coefficient. From the computational perspective, our measure seems more favorable, seeing that our matheuristic spends considerably less time to return a solution when using our measure, as this metric has the smallest T(s) among the three, no matter  $\alpha$ .

Regarding cost related KPIs, the total cost, first-echelon cost, and number of trucks start increasing as soon as fairness constraints are imposed by relative range and our measure. These values change relatively slowly when using the Gini coefficient, as this metric leaves 6.4 suppliers with no profit even at  $\alpha = 80\%$ . Overall, our measure guarantees a share of the network profit for all suppliers without artificially dampening the maximum profit. Moreover, the problem at hand is solvable no matter the value of  $\alpha$  in a shorter time, when using our metric.

In order to obtain an intuitive insight into how each fairness metric distributes the profits among the suppliers, we plot the Lorenz curve (Lorenz, 1905) of each measure for Instance 1 of school canteens in case of  $\alpha = 10\%$  as a representative instance. As a representation of inequality in a distribution, the Lorenz curve is a graph denoting the cumulative percentage of profit gained versus the cumulative population of suppliers, when they are sorted in an ascending order of profit. In a perfectly equitable solution,  $X\%$  of the suppliers should share exactly  $X\%$  of the profit, for any  $X$  between 0 and 100. This is denoted by the diagonal line in the figure. The resulting graphs are displayed in Fig. 4.

The Lorenz curves for both relative range and our measure are much closer to the equality line for different portions of the population compared to the Gini coefficient. This means the two metrics distribute the profit of satisfying the demand of the network among suppliers more equally, even if a low level of fairness is imposed. On the contrary, the Gini coefficient leaves up to 35% of suppliers with no profit. Between the relative range and our measure, the Lorenz curve from our measure is slightly closer to the line of equality than the one from the relative range. In conclusion, our measure facilitates shorter runtimes, is effective already at a low  $\alpha$  but also feasible at a large  $\alpha$ , and tends to encourage fairness by connecting more suppliers to the network rather than reducing the profits of large suppliers. Therefore, we continue using our suggested fairness metric in the remaining computational studies.

#### 5.4. The cost of fairness

Achieving fairness among suppliers imposes an extra cost on the logistics system, as every supplier must send a certain percentage of their share of supply to some of the distribution centers, which will probably result in a larger first-echelon transportation cost. It may also

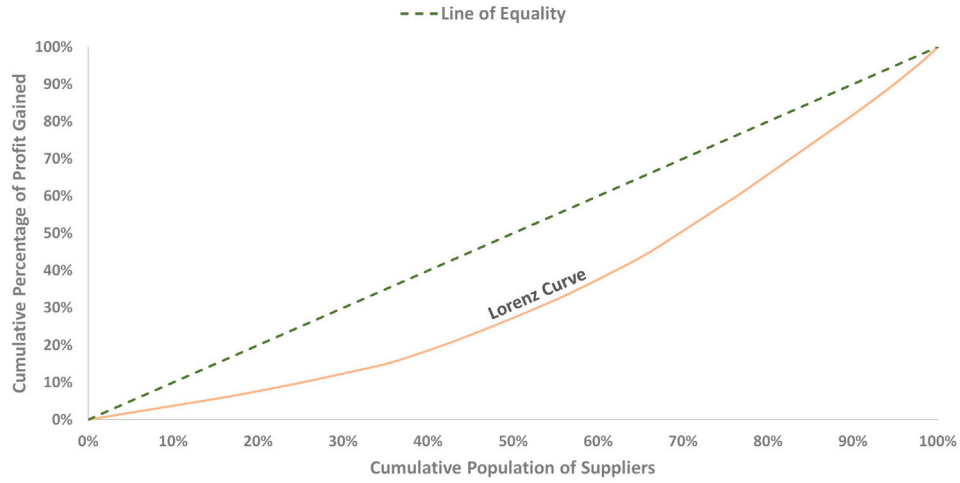
affect the second-echelon transportation cost, since the availability of commodities at certain distribution centers might change and hence different second-echelon routes might be selected.

From a managerial point of view, in order to study the trade-off between the level of equity enforced on the first echelon and the transportation costs, we vary the value of the guaranteed percentage of suppliers' share, i.e.  $\alpha$ , from zero to one (100%) gradually with a step-size of 0.1 (10%), for all instance groups. We then monitor the cost of fairness for the system, which demonstrates itself in relative changes in the total transportation, first-echelon, and second-echelon costs compared to the no-fairness case, i.e.  $\alpha = 0\%$ , averaged over the instances of each group. For these analyses, we keep the time limit of the solver at one hour for the generated instances and the school canteen instances. However, we also set the MIP gap of the solver to 10% for the school canteen instances. For supermarket instances, we increase the solver time limit to five hours and impose a MIP gap of 10%. The results are displayed in Figs. 5, 6, and 7.

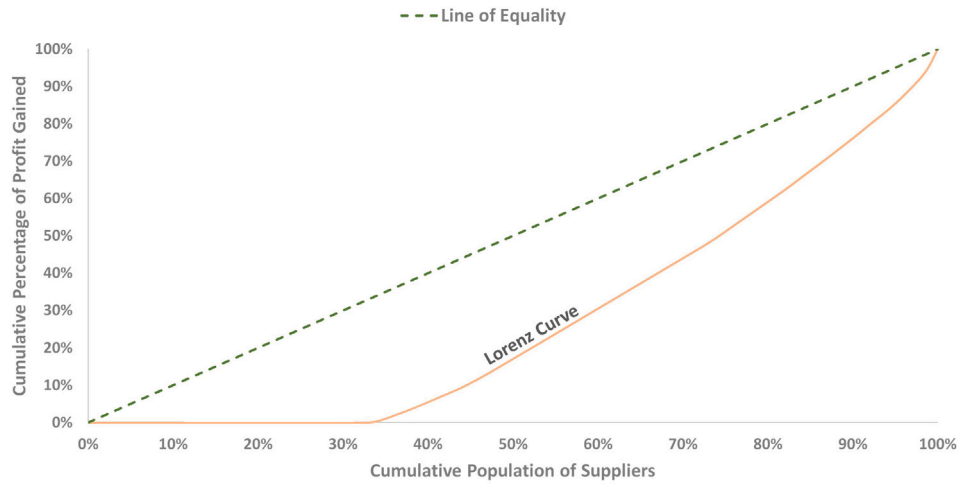
Figs. 5(a) and 5(b) present respectively average relative changes in the total transportation, first-, and second-echelon costs and in the number of trucks and routes used, for the generated instances. No instance of this group was solved with full fairness, i.e.  $\alpha = 100\%$ , therefore no number is reported in these two figures on  $\alpha = 100\%$ . We observe that there is no change in the costs and the number of trucks and routes on average from  $\alpha = 0$  to  $\alpha = 10\%$  for these instances. This means that the suppliers are served equitably and already connected to the distribution network providing commodities, even before the fairness constraints are enforced. This trend continues until  $\alpha = 60\%$ , meaning that 60% of the suppliers' share can be collected without imposing extra costs on the system. When collecting at least 70% of a supplier's share is enforced, the first-echelon cost and consequently the total transportation cost (Fig. 5(a)) starts increasing, on average. The second-echelon cost starts to slightly decrease (from  $\alpha = 80\%$ ). The number of trucks used in the first-echelon also starts to increase on average, when the system is required to collect at least 70% of the share from suppliers. The changes in the second-echelon cost and the number of second-echelon routes are both due to the fact that the supplies are distributed differently among the distribution centers, which might enable different choices for the second echelon, when  $\alpha$  is at least 70%. Therefore, to advise the managers of such supply chains on how equitable the collection of commodities from suppliers should be, the option of  $\alpha = 60\%$  is the cheapest and yet equitable level of service for the generated instances.

Figs. 6(a) and 6(b) depict the average relative changes in the total transportation, first-, and second-echelon costs and in the number of trucks and routes, respectively, for Isère's school canteen instances. We note that as soon as the fairness constraints are enforced, i.e. 10% of each supplier's share must be collected, the first-echelon and total transportation costs, and the number of trucks increase considerably, on average. After  $\alpha = 10\%$ , these KPIs reach a plateau. By ensuring an equitable collection of at least 10% of available commodities from suppliers, the allocation of supplies to the distribution centers changes as well. This can result in alternative routing plans for the second echelon and hence relative changes in both the second-echelon cost and the number of routes, on average, for these instances. Considering the relatively flat trend of the total transportation cost after  $\alpha = 10\%$ , we can conclude that there are two options to suggest to the managers of the supply chain. One option is no equitable service enforced at all, i.e.  $\alpha = 0$ , which results in a completely utilitarian collection of commodities from suppliers without making sure every supplier is connected to the distribution system. Another option is to have a completely egalitarian commodity collection plan from suppliers, i.e.  $\alpha = 100\%$ , which will result in collecting all the available quantities at the suppliers of the school canteen instances.

Figs. 7(a) and 7(b) respectively display the average relative changes in the total transportation, first-, and second-echelon costs and in the number of trucks and routes for Isère's supermarket instances. The



(a) Relative range.



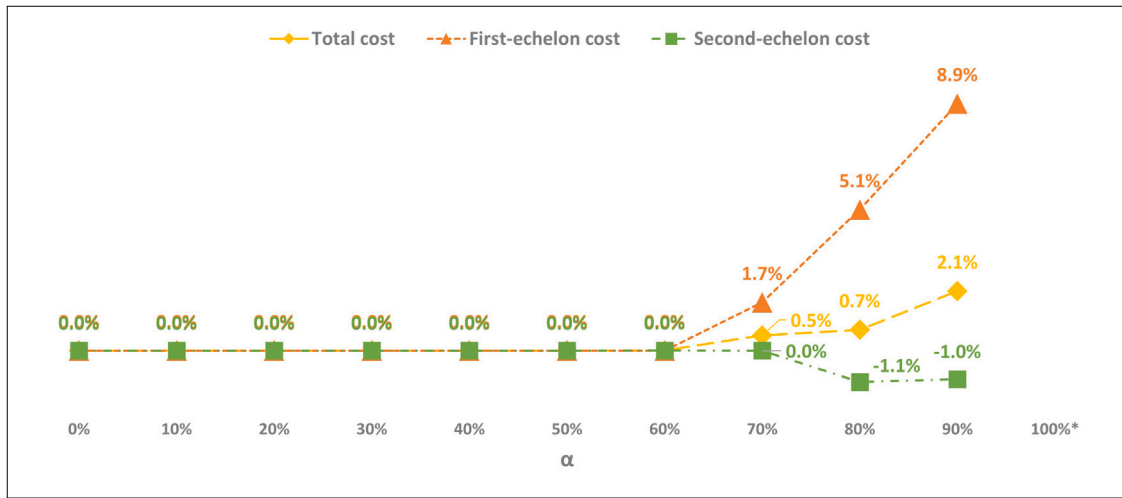
(b) Gini coefficient.



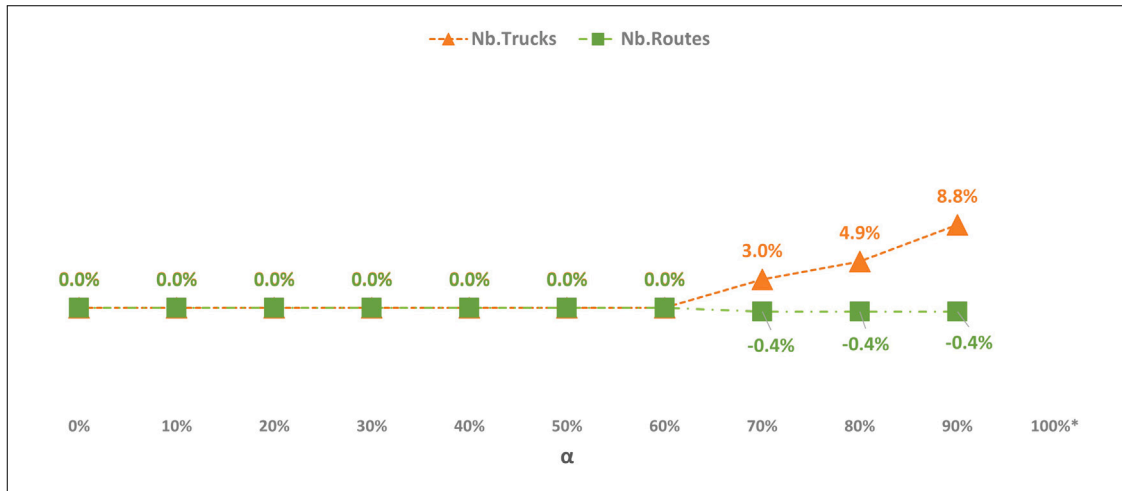
(c) Our measure.

Fig. 4. Distribution of profits among suppliers by three fairness metrics applied on Instance 1 of school canteens with  $\alpha = 10\%$ .





(a) Change in total transportation cost, and first- and second-echelon routing costs.



(b) Change in number of trucks and routes used.

Fig. 5. Average relative changes compared to  $\alpha = 0\%$ , when guaranteed share of profits of suppliers, i.e.  $\alpha$ , varies — Generated instances.  
100%\*: At  $\alpha = 100\%$  no instance was solved.

numbers are present until  $\alpha = 90\%$ , as for full equity, i.e.  $\alpha = 100\%$ , one of the instances was not solved. We see that imposing fairness does not significantly increase routing costs until the 90% level, when the total transportation cost goes up by 5% on average. Overall, the supermarket instances do not seem to react strongly to the enforcement of equity, maybe because most (all) suppliers are already connected to the distribution network in any case due to the demand structure.

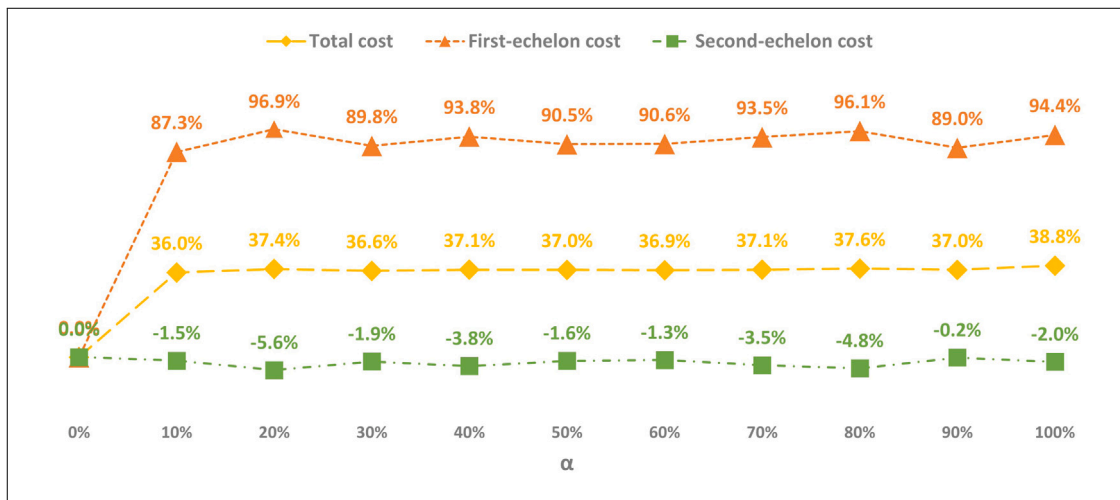
## 6. Conclusion

In this paper, we have addressed the issue of service inequity for suppliers (farmers) in a short agri-food supply chain in the public sector. This supply chain is designed in two echelons: In the first echelon, commodities (fresh fruits and vegetables) are collected from suppliers on direct trips and transported to distribution centers for consolidation. In the second echelon, the commodities are distributed from the centers to customers on routes. A customer can be visited more than once. Local authorities and an association of farmers are in charge of the daily operations of this network. Not all suppliers are, however, connected to the distribution network, as some of them are located farther away than the others. Therefore, we have introduced

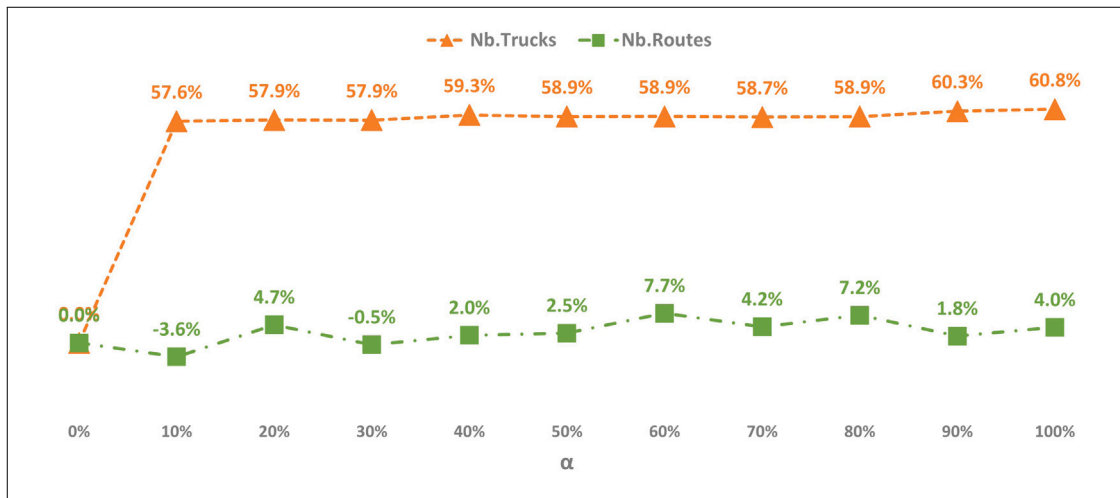
a fair multi-commodity two-echelon distribution problem that decides on the daily planning of first-echelon equitable collection trips and second-echelon delivery routes.

To model the problem, we have used an arc-route-based formulation with a service equity measure for suppliers, defined as a set of constraints proportional to their supplies and the profits of commodities. We have suggested a matheuristic to jointly optimize the first and second echelons. The decisions on first-echelon collection trips are left to a default solver and we have designed a heuristic route generation procedure to construct a pool of feasible second-echelon routes to be passed to the solver. The daily collections and delivery plans are then both decided by the solver. We have evaluated our solution method on a series of generated instances and on the instances of a French short agri-food supply chain from the literature.

The numerical results illustrate that our matheuristic on average provides solutions for the special case without fairness with less total transportation costs than the best known costs for the instances in times substantially faster, sometimes in an order of magnitude, than the total run times known in the literature. It also finds several new best costs for some of the instances.



(a) Change in total transportation costs and first- and second-echelon routing costs.



(b) Change in number of trucks and routes used.

Fig. 6. Average relative changes compared to  $\alpha = 0\%$ , when guaranteed share of profits of suppliers, i.e.  $\alpha$ , varies — School canteen instances.

We have defined the fairness metric dependent on suppliers' available supplies. The reason is that if the same share is collected from every supplier regardless of the available supply, it is possible that some suppliers will be simply unable to provide the share as they have less available supply. We then assess the efficacy of our equity measure versus the relative range and Gini coefficient metrics from the literature with regard to reducing inequity among suppliers as well as optimizing the cost in terms of several key performance indicators. The results indicate that our measure facilitates shorter runtimes and encourages fairness by connecting more suppliers to the network instead of aggressively reducing the profits of large suppliers.

Moreover, by using our suggested fairness measure, we have studied the trade-off between guaranteeing an equitable service for suppliers and optimizing the total transportation cost. The results demonstrate that overall there is a minimum level for fair collections that leads to an equitable service for suppliers, while keeping the relative increase in the total transportation cost low, on average. This level can help decision makers with the planning of first-echelon fair collection trips and second-echelon delivery routes. In conclusion, if most (or even all) suppliers are connected to the distribution network, our results indicate that raising the fairness level does not cost the logistics provider much

for low levels of equity. However, imposing the highest levels of fairness results in a significant increase in the total transportation costs, on average.

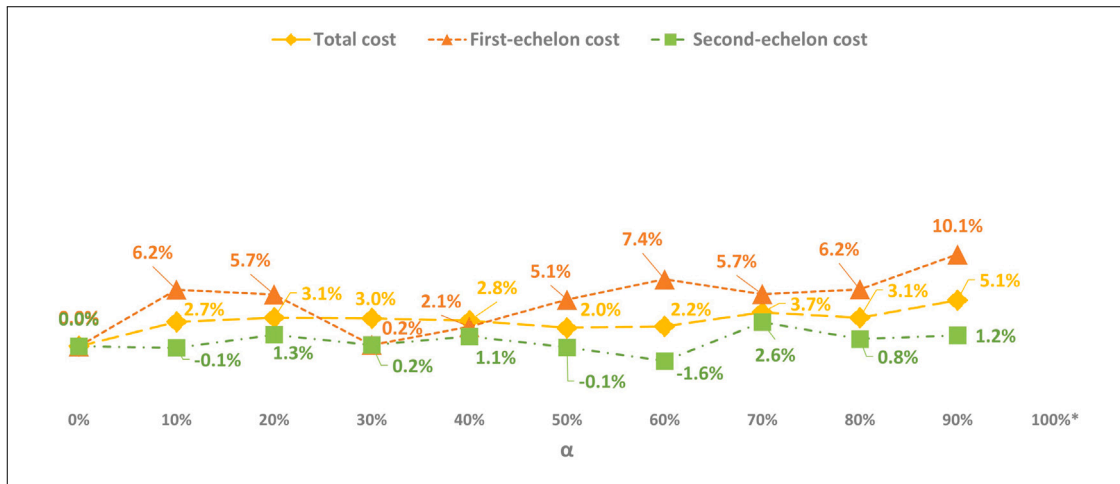
The demand in the second echelon is assumed to be static and known in advance. A future study can look into how to plan fair collection of supplies in the first echelon, when the demand becomes known dynamically or is stochastic in the second echelon. Another research question worth investigating is how to serve farmers equitably, if the first-echelon collection trips are required to be consistent and/or if the customers have time windows in the second echelon.

#### Declaration of competing interest

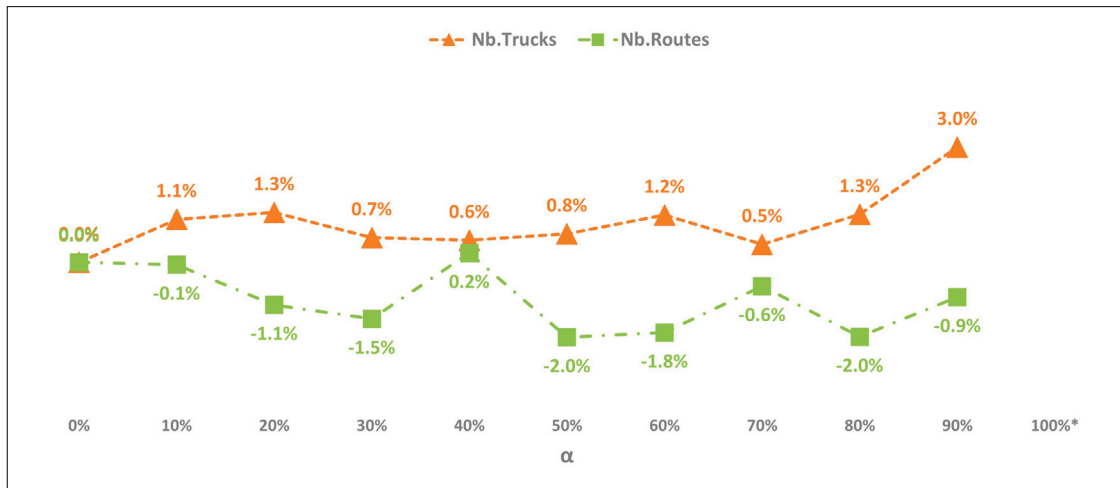
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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(a) Change in total transportation cost, and first- and second-echelon routing costs.



(b) Change in number of trucks and routes used.

**Fig. 7.** Average relative changes compared to  $\alpha = 0\%$ , when guaranteed share of profits of suppliers, i.e.  $\alpha$ , varies — Supermarket instances.  
100%\*: At  $\alpha = 100\%$  one instance was not solved.

**Table A.7**

Gu et al. (2022) generated instances solved in their study by a commercial solver and by their six sequential heuristics —  $|D| = 2$ .

Set	ID	$ S $	$ C $	$ M $	Probability	Truck & vehicle capacity
$\mathcal{S}$	1	4	10	2	0.6	150
	2	4	10	2	1	180
	3	4	10	3	0.6	209
	4	4	15	2	0.6	150
	5	4	15	2	1	180
	6	4	15	3	0.6	209
	7	4	20	2	0.6	150
	8	4	20	2	1	180
	9	4	20	3	0.6	209
	10	6	25	2	0.6	150
	11	6	25	2	1	180
	12	6	25	3	0.6	209
$\mathcal{S}_1^S$	1	4	10	2	0.6	150
	2	4	10	2	1	180
	3	4	10	3	0.6	209
	4	4	15	2	0.6	150
	5	4	15	2	1	180
	6	4	15	3	0.6	209
	7	4	20	2	0.6	150
	8	4	20	2	1	180
	9	4	20	3	0.6	209
	10	6	25	2	0.6	150
	11	6	25	2	1	180
	12	6	25	3	0.6	209
$\mathcal{S}_2^S$	1	4	10	2	0.6	150
	2	4	10	2	1	180
	3	4	10	3	0.6	209
	4	4	15	2	0.6	150
	5	4	15	2	1	180
	6	4	15	3	0.6	209
	7	4	20	2	0.6	150
	8	4	20	2	1	180
	9	4	20	3	0.6	209
	10	6	25	2	0.6	150
	11	6	25	2	1	180
	12	6	25	3	0.6	209

**Table A.8**

Gu et al. (2022)'s school canteen instances solved in their study by their six sequential heuristics — Truck capacity: 600 units; Vehicle capacity: 1200 units.

ID	$ S $	$ D $	$ C $	$ M $
1	61	5	103	8
2	61	5	103	7
3	61	5	103	6
4	61	5	103	5
5	61	5	103	6
6	61	5	103	5
7	61	5	103	6
8	54	5	103	7

**Table A.9**

Gu et al. (2022)'s supermarket instances solved in their study by their six sequential heuristics — Truck capacity: 3000 units; Vehicle capacity: 6000 units.

ID	$ S $	$ D $	$ C $	$ M $
1	61	5	188	6
2	61	5	188	5
3	61	5	188	6
4	54	5	188	7
5	45	5	188	5
6	58	5	188	6
7	61	5	188	8
8	61	5	188	7
9	61	5	188	7
10	61	5	188	6

## Appendix. Details of instances

The details of the generated instances and case-study instances from Gu et al. (2022), which we use for our numerical experiments, are summarized in Tables A.7–A.9.

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