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Balancing partner preferences for logistics costs and carbon footprint in a horizontal cooperation

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Abstract Horizontal cooperation in logistics has gathered momentum in the last decade as a way to reach economic as well as environmental benefits. In the literature, these benefits are most often assessed by aggregating all demand and then optimizing the supply chain at the level of the coalition. However, such an approach ignores the individual preferences of the participating companies and forces them to agree on a unique coalition objective. Companies with different (potentially conflicting) preferences could improve their individual outcome by diverging from this joint solution. In order to prevent such individualistic behaviour, we propose an optimization framework that explicitly accounts for the individual partners' interests. In the models presented in this paper, all partners are allowed to specify their preferences regarding the decrease of logistical costs versus reduced CO_2 emissions. Consequently, all stakeholders are more likely to accept the solution, and the long-term viability of the collaboration is improved. The contribution of our work is threefold. First, we formulate a multi-partner multi-objective location-inventory model. Second, we distinguish two approaches to solve such a multi-partner multi-objective optimization problem, each focusing primarily on a single dimension. The result is a set of Pareto-optimal solutions that support the decision and negotiation process. Third, we propose and compare three different solution techniques to construct a unique solution which is fair and efficient for the coalition. Our numerical experiments not only confirm the potential of collaboration but — more importantly — also reveal valuable managerial insights on the effect of dissimilarities between partners with respect to size, geographical overlap and operational preferences.

Keywords Horizontal Collaboration · Individual Partners' Preferences · CO_2 Emissions · Location-Inventory Model · Multi-Objective Optimisation

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1 Research context and motivation

To remain competitive in today's demanding markets, it is no longer sufficient to solely operate at minimum cost (Saad, Rahim, and Fernando, 2016). Companies are under pressure to deliver high customer service levels while at the same time respecting environmental sustainability. Encouraged by public incentives and the emergence of carbon taxes, more and more companies integrate emissions targets into all levels of decision-making (Hovelaque and Bironneau, 2015). The low average vehicle loading rates — currently between 57% and 68% in EU-28 countries (Creemers, Woumans, Boute, and Beliën, 2017; Vargas, Patel, and Patel, 2018) — show huge potential for improving the sustainability of logistical networks. At the same time, maintaining high delivery frequencies is crucial to remain competitive.

A promising avenue to improve the efficiency as well as the sustainability of the logistical operations is to engage in a collaboration. In this paper, the focus is on horizontal cooperation, which is defined as *"multiple companies (potentially competitors), operating at the same level of the supply chain, that join forces with the aim of improving their overall efficiency"* (Cruijssen, 2006). Through active sharing of vehicles and facilities, companies can achieve substantial economies of scale. This leads to more efficient vehicle loading rates and a reduction in total kilometres driven, which positively impacts the operational costs as well as the carbon footprint of the collaborating companies (Hacardiaux and Tancrez, 2020).

A key challenge when modelling and analyzing collaborative environments is that companies often differ significantly in size, resulting in unbalanced coalitions, while remaining independent entities with different (potentially conflicting) preferences, in particular regarding the cost versus the carbon footprint of the logistical network and all joint operations. Surveys on companies wishing to collaborate show that they do not only focus on economic benefits but are also looking for sustainability improvements, and that they do not give the same priority to the different benefits (Aloui, Hamani, Derrouiche, and Delahoche, 2021; Verstrepen, Cools, Cruijssen, and Dullaert, 2009). Targets regarding CO_2 emissions reductions vary substantially among companies (Hopkins, Haanaes, Balagopal, Velken, Kruschwitz, and Arthur, 2011). For instance, Coca-Cola aimed to reduce its emissions by one-fourth by 2020, the same year by which Unilever aimed to cut them in half (Yang, Zhang, and Ji, 2017). In case of cooperation, such companies with dissimilar priorities would need to compromise and the joint logistical network would be impacted.

In the literature, this challenge is most often circumvented with two premises: authors focus on the improvement in one dimension and consider the coalition as a unanimous deciding entity. Existing research typically relies on the assumption that all partners agree on a unique objective. A minimization of the total logistics costs is typically assumed. Furthermore, customer demands and the preferences of the collaborating partners are aggregated and the identity and independence of the partnering companies are ignored (Defryn, Sörensen, and Dullaert, 2019). Consequently, the optimal solution at the coalition level can be sub-optimal at the individual partner level. This discrepancy creates an incentive for the partners to behave opportunistically and diverge from the proposed solution to improve their individual outcome. A partner with dominating influence might gear the collaborative solution towards its priorities. For example, an environmentally conscious company might use its influence to push for opening more costly distributions centers to reduce distances and carbon emissions (such dynamics are discussed in Section 6). This potential mismatch between individual partner and coalition objectives jeopardizes the long-term stability, and thus success, of the collaboration, and need to be understood and balanced.

In this context, this paper is the first that presents an extensive study on multi-objective multi-partner logistics collaborations, as we look at collaborations with multiple objectives (costs and CO_2 emissions reductions in this paper) while explicitly accounting for the influences of the coalition partners and for differences in their individual preferences. Our main contributions are in the exploration of this problem, in the proposition of a decision support system for this setting and in the derivation of managerial insights. Decision support is provided through a multi-objective framework that introduces five different approaches to find a fair and efficient solution both on a collaborative and individual partner level. Simple proportional rules, that are commonly applied in practice, are used to allocate costs and emissions directly to the partners. The first two solution approaches generate a set of Pareto-optimal solutions that can support the negotiation and decision-making process. The other three approaches help companies to highlight a unique solution based on predefined criteria. To support the presentation and show the working of our framework, it is applied and validated on a multi-objective location-inventory problem that designs the joint supply network. Computational experiments compare the five approaches and allow us to derive valuable managerial insights for strategic and tactical decision support, particularly during the initialization phase (when the collaboration is set up), including partner selection.

The remainder of the paper is structured as follows. Section 2 contains a literature review and positions the contribution of our paper. In Section 3, the problem setting and the multi-objective and multi-partner collaborative location-inventory model are presented. The first two multi-objective solution approaches that rely on the construction of a Pareto frontier are discussed in Section 4. The other three approaches, aimed at finding a unique solution, are introduced in Section 5. In Section 6, experimental results are presented and relevant managerial insights are derived. Finally, Section 7 concludes our paper and presents ideas for future research.

2 Related literature

Due to its practical importance and promising benefits, collaboration in logistics has attracted the interest of the research community over the last decade. Existing studies mainly focus on collaborative transport or distribution systems, where the main motivation for companies to cooperate is an increased efficiency of the vehicle fleet operations and thus a lower logistical cost (Gansterer and Hartl, 2018; Verdonck, 2017). Despite the potential environmental and economical benefits, the sharing of distribution centers or joint inventory management policies have not received much attention from the research community. While location-inventory problems have been explored and analyzed substantially (Daskin and Maass, 2019; Farahani, Rashidi Bajgan, Fahimnia, and Kaviani, 2015; Melo, Nickel, and Saldanha-Da-Gama, 2009), their application in a horizontal cooperation context is novel. Verdonck, Beullens, Caris, Ramaekers, and Janssens (2016) analyze the benefits of cooperative facility location in a horizontal carrier cooperation. Solving the joint location-allocation problem leads to an average reduction in facility opening and distribution costs of 9.1%. Tang, Lehuédé, and Péton (2016) determine optimal locations for regional distribution centers in a collaborative distribution network. Makaci, Reaidy, Evrard-Samuel, Botta-Genoulaz, and Monteiro (2017) empirically study the sharing of warehouses among different companies to identify, among others, the KPIs and uncertainty sources. Hacardiaux and Tancrez (2018) present a location-inventory model and demonstrate average savings of around 22% in terms of facility opening, transportation, cycle inventory, ordering and safety stock costs when setting up a collaboration.

A limited number of papers consider carbon footprint reductions associated with the collaborative location-inventory model. Hacardiaux and Tancrez (2020) analyze the impact of several market and partner characteristics (e.g. vehicle capacity, periodical facility opening cost, inventory holding cost, demand variability) on the reduction of cost and CO_2 emissions when collaborating. Stellingwerf, Laporte, Cruijssen, Kanellopoulos, and Bloemhof (2018) analyze the economic and environmental benefits of joint route planning and vendor-managed inventory in the context of collaborative food logistics. Results show significant savings in costs, emissions, distance and travel time, and demonstrate the advantages of vendor-managed inventory in the case under study. Ouhader and El Kyal (2017) propose a multi-objective optimization model, including both facility location and routing decisions, that maximizes costs reduction and job creation subject to a constraint on CO_2 emissions. Unlike the work presented in this paper, existing contributions focus exclusively on coalition objectives and the individual preferences of partners are ignored.

Despite its inherent multi-objective nature, horizontal logistics collaboration has mainly been studied from a single-objective perspective in the literature (Defryn et al, 2019). Typically, the collaborative scenario is simulated by aggregating the customers' demand of the different partners, and a single-objective optimization model is then solved at the level of the coalition. For the cooperation to be viable and ensure significant collaborative savings in the long run, the individual partner preferences need to be taken into account (Defryn et al, 2019).

A growing body of research exists on multi-objective optimization in various logistics domains. A general overview of relevant literature can be found in Ehrgott (2005), Caramia and Dell'Olmo (2008) and Deb (2014). More specifically, multi-objective applications have been developed for vehicle routing problems (Jozefowiez, Semet, and Talbi, 2008), facility location problems (Farahani, SteadieSeifi, and Asgari, 2010) and inventory management (Tsou, 2008). The consideration of multiple objectives in a horizontal cooperation context, however, is a novel research domain. Kimms and Kozeletskyi (2017) develop a multi-objective optimization model for the travelling salesman problem (TSP) with horizontal cooperation. Their goal is to simultaneously minimize travelling costs and maximize the partner utility consequential to order assignment. In line with Kimms and Kozeletskyi (2017), Defryn and Sörensen (2018) solve a multi-objective collaborative TSP aimed at minimizing both the total distance travelled and the customer time window violations. Wang, Zhang, Assogba, Liu, Xu, and Wang (2018) present a vehicle routing model which minimizes both the operating costs and the number of vehicles in the context of collaborative customer and vehicle sharing. Soysal, Bloemhof-Ruwaard, Haijema, and van der Vorst (2018) model an inventory routing problem analyzing collaborative benefits in terms of multiple objectives, i.e., emissions, driving time and total logistics cost. While all cited papers consider multiple objectives on the coalition level, none of them accounts for individual partner preferences.

To the best of our knowledge, Defryn et al (2019) are the only authors which describe and investigate the inclusion of individual partners preferences in collaborative logistical planning. In their paper, they propose a framework that allows for differences in individual partner preferences while assuring maximal synergy creation through collaboration. Our research work differs from theirs by developing a multi-objective framework both at the coalition and at the individual partner level, accounting for preferences in both costs and CO_2 emissions reductions, and accounting for the individual partners' influence on the collaboration. Consequently, in this paper, there is no need for coalition partners to agree on a single coalition objective, contrary to the assumptions made by Defryn et al (2019). Furthermore, our methodology is tested and validated on a collaborative location-inventory problem. Finally, we consider an a priori stated preference articulation with respect to the effect of the collaboration on both objectives. In other words, we analyze the current stand-alone situation for each individual partner to state their preferences in advance. Again, this approach differs from Defryn et al (2019), in which an a posteriori preference articulation is assumed.

Based on our literature review, we conclude that multi-objective approaches in horizontal logistics cooperation research is scarce. Moreover, the focus is on cost-minimizing routing or distribution partnerships, and only the coalition level is typically considered. Since collaborating companies remain independent entities with potentially conflicting goals, there is a need for more multi-objective, multi-partner models that account for the individuality of the partners and their preferences. Accounting for this research gap, this paper has the following academic and managerial contributions. We develop a multi-objective framework accounting for the individuality of partners in terms of their costs-emissions preferences and their influence weights. Applying one of our five solution approaches, we generate either a Pareto front or a unique solution depending on the preferences of the coalition partners. The proposed framework provides quantitative decision support and managerial insights for practitioners implementing and managing horizontal partnerships in terms of supply chain network design and partner selection.

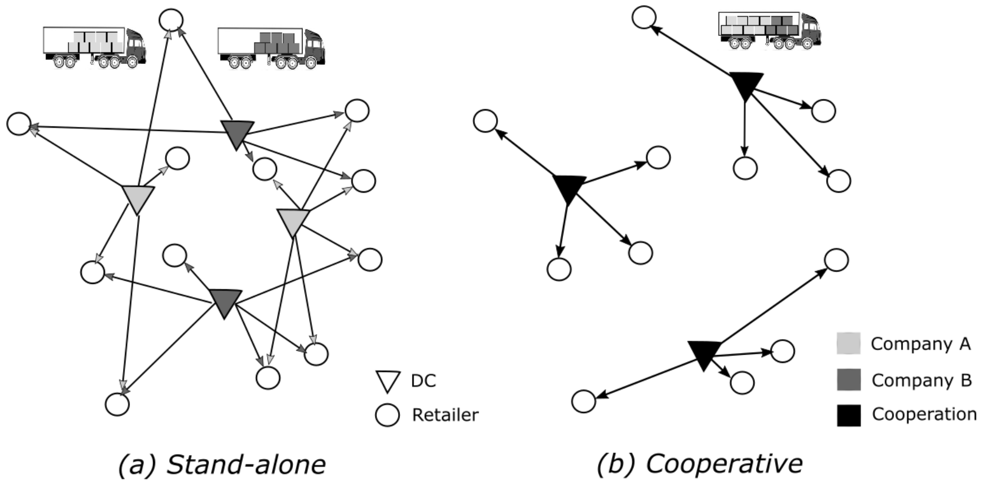


Fig. 1: Illustration of the delivery networks of two independent stand-alone companies (a), and of the joint delivery network of these companies when they are cooperating (b).

3 The multi-objective collaborative location-inventory problem

In this section, we start by formally introducing the multi-objective collaborative location-inventory problem. We then formulate both objectives, the minimization of logistics costs and the minimization of CO_2 emissions, and finally we present our multi-objective collaborative location-inventory model. In Hacardiaux and Tancrez (2020), a first insight is provided on the environmental benefits of horizontal cooperation using a single-objective location-inventory model. In this paper, the model of Hacardiaux and Tancrez (2020) is significantly extended to a multi-objective optimization framework that integrates the individual partner preferences, and leads to very different solution approaches.

3.1 A formal problem definition

We are given a set of companies that are willing to engage in a horizontal collaboration. Each company produces one specific product in their own central plant. As illustrated in Figure 1(a), each company currently has their own (set of) distribution centers (DCs), from where they distribute their product to a group of retailers.

We assume that each individual company has independently optimized its distribution network given its preferences regarding costs and CO_2 emissions. Each company has opened an optimal number of DCs, chosen their location and allocated the retailers. Cycle inventory is also considered, in particular choosing the right shipment sizes for each transport. To satisfy the uncertain demand during the lead time (which is proportional to the traveled distance) safety stocks are kept at every DC.

Motivated by potential reductions in logistics costs and CO_2 emissions, the companies consider setting up a joint supply network in which they *share their DCs and vehicles*, as illustrated in Figure 1(b). The following advantages can be expected (Hacardiaux and Tancrez, 2020):

- As DCs are shared by the cooperating companies, the total number of DCs is likely to reduce (from 4 to 3 DCs in Figure 1), while each company's product will probably be delivered from more DCs (from 2 to 3 DCs in Figure 1).
- The vehicle loading rates will improve due to the bundling of goods from multiple companies for a shared customer.

Table 1: Overview of mathematical notations.

Sets and indices:	
$D = \{1, \dots, n_D\}$	Potential distribution center (DC) locations, indexed by d.
$R = \{1, \dots, n_R\}$	Retailers, indexed by r.
$I = \{1, \dots, n_I\}$	Companies, indexed by i.
Parameters:	
F	Periodical fixed cost for opening a DC, in €/period.
T	Transportation cost per km for a vehicle, in €/(km·vehicle).
D_{dr}	Distance between DC d and retailer r, in km.
H_r^i	Unit inventory holding cost at retailer r for a product of company i, in €/(item·period).
h_d^i	Unit inventory holding cost at DC d for a product of company i, in €/(item·period).
C	Vehicle capacity, in items/vehicle.
K_d^i	Fixed cost at DC d for placing an order to the plant of company i, in €/order.
z_α^i	Standard normal deviation associated with service level α^i at retailers, for company i.
LT_{dr}	Lead time between DC d and retailer r, in periods.
LT_d^i	Lead time between the central plant of company i and DC d, in periods.
λ_r^i	Mean demand for products of company i at retailer r, in items/period.
Λ_r	Mean demand for all products at retailer r, in items/period, i.e., $\Lambda_r = \sum_i \lambda_r^i$.
Λ^i	Mean demand for products of company i for all retailers, in items/period, i.e., $\Lambda^i = \sum_r \lambda_r^i$.
Λ	Mean total demand for all companies and all retailers, in items/period, i.e., $\Lambda = \sum_r \Lambda_r$.
σ_r^i	Standard deviation of the demand for products of company i at retailer r, in items/period.
ϵ^e	CO_2 emissions emitted by an empty vehicle in kg/km.
ϵ^f	CO_2 emissions emitted by a fully loaded vehicle in kg/km.
Q_{dr}	Total shipment size (for all companies) from DC d to retailer r (decided a priori), in items/vehicle.
Decision Variables:	
y_d	$\begin{cases} 1, & \text{if DC } d \text{ is opened,} \\ 0, & \text{otherwise.} \end{cases}$
x_{dr}	$\begin{cases} 1, & \text{if DC } d \text{ serves retailer } r \text{ (for all products),} \\ 0, & \text{otherwise.} \end{cases}$
v_{1d}^i, v_{2d}^i	Auxiliary variables for company i and DC d.

- The total distance travelled will decrease for two reasons: retailers are delivered from a potentially closer DC, and the improvement of the loading rate will reduce the number of vehicles travelling (per time period).

Although products from different companies are stored in the same facilities, companies keep their own cycle inventory and safety stock. We assume direct deliveries and single sourcing, meaning that all the products delivered to a specific retailer come from a single DC, even if these products originate from different partners.

3.2 Logistics costs and CO_2 emissions

The goal of the coalition is to design a supply chain network that balances the interests of all partners, relative to their two objectives: minimizing the logistics costs and the CO_2 emissions. In this section, we formulate the costs and emissions of an individual partner in the coalition (using the mathematical notations listed in Table 1). Each individual partner aims to minimize its own share of costs and emissions in the coalition. As detailed below, to share the total logistics costs as well as the total CO_2 emissions of the cooperation among partners, we apply *proportional rules* based on the quantity of products shipped by each partner. In practice, proportional allocation methods are most commonly used due to their simplicity and the fact that their transparent calculation and interpretation facilitate communication among partners (Guajardo, 2018).

3.2.1 Objective 1: Minimizing logistics costs

The logistics costs is composed of facility opening costs, transportation costs and inventory costs. A detailed description of these cost components can be found in Hacardiaux and Tancrez (2018). To share the facility costs, a proportional *volume-based rule* is used such that each partner pays for the fraction of the DC it is storing its products in. Regarding the transportation costs, we use a *separate deliveries weighted allocation rule*, where, in a similar manner, each partner pays for each vehicle proportionally to the volume its products occupy in it (Frisk, Göthe-Lundgren, Jörnsten, and Rönnqvist, 2010). The transportation cost allocation is thus different for each retailer ($\frac{\lambda_r^i}{\Lambda_r}$). Finally, as each company has its own cycle inventory and safety stock, the inventory costs can be directly allocated to a specific partner. The share of the logistics costs for a partner i in the cooperation, noted $Cost^i_{CO}$, can thus be expressed as follows.

$$Cost^i_{CO} = \frac{\Lambda^i}{\Lambda} \sum_d F\, y_d + \sum_r \frac{\lambda_r^i}{\Lambda_r} \sum_d T\, D_{dr}\, \frac{\Lambda_r}{Q_{dr}}\, x_{dr} + \sum_{d,r} \sqrt{2\, K_d^i\, h_d^i\, \lambda_r^i}\, x_{dr} + \sum_{d,r} H_r^i\, \frac{Q_{dr}}{2}\, \frac{\lambda_r^i}{\Lambda_r}\, x_{dr}$$
$$+ \sum_d h_d^i\, z_\alpha^i\, \sqrt{LT_d^i} \sqrt{\sum_r (\sigma_r^i)^2 x_{dr}} + \sum_{d,r} H_r^i\, z_\alpha^i\, \sigma_r^i\, \sqrt{LT_{dr}}\, x_{dr} \quad (1)$$

The terms of equation (1) represent, for company i, its share of periodical facility opening costs, its share of transportation costs (Λ_r/Q_{dr} gives the number of shipments per period to a retailer r), its cycle inventory and ordering costs at DCs (assuming an EOQ inventory structure), its cycle inventory costs at retailers, its safety stock costs at DCs and its safety stock costs at retailers (to reach service level α). The inventory-location models we present in this paper thus include strategic location decisions as well as tactical allocation and inventory decisions, as it has been shown in the literature that inventory decisions may impact location decisions (Atamtürk, Berenguer, and Shen, 2012; Farahani et al, 2015; Melo et al, 2009; Schuster Puga, Minner, and Tancrez, 2019; Shen, Coullard, and Daskin, 2003; Tancrez, Lange, and Semal, 2012). Moreover, including shipment size decisions (inventory related decisions) is important to be able to reveal the improvement of the loading rate of vehicles when collaborating.

3.2.2 Objective 2: Minimizing CO_2 emissions

To account for the CO_2 emissions, we focus on transportation and use the formula proposed by Pan, Ballot, and Fontane (2013), which is commonly accepted in the literature (Danloup, Mirzabeiki, Allaoui, Goncalves, Julien, and Mena, 2015; Moutaoukil, Neubert, and Derrouiche, 2015; Ouhader and El Kyal, 2017). This formula also has the advantage of accounting for the vehicle loading rate, which is an important factor of improvement when cooperating. To allocate the CO_2 emissions among partners, we apply the *polluter-pays principle* (Kellner and Otto, 2012). CO_2 emissions are divided proportionally to the usage of the vehicles (it is also a volume-based rule, as expressed by the fraction $\frac{\lambda_r^i}{\Lambda_r}$). This method for the allocation of emissions is frequently applied by practitioners as it is efficient and easy to understand (Leenders, Velázquez-Martínez, and Fransoo, 2017). The share of CO_2 emissions produced by a partner i in the cooperation, noted $Emis^i_{CO}$, can be expressed as follows.

$$Emis^i_{CO} = \sum_r \frac{\lambda_r^i}{\Lambda_r} \sum_d \; [\epsilon^e \frac{\Lambda_r}{Q_{dr}} + (\epsilon^f - \epsilon^e) \frac{\Lambda_r}{C}]\; D_{dr}\; x_{dr} \quad (2)$$

The share of CO_2 emissions for company i, due to deliveries to its retailers, is composed of baseline emissions from an empty vehicle, to which emissions proportional to the vehicle load are added. In the first part of equation (2), the CO_2 emissions emitted by an empty vehicle per km (ϵ^e) are simply multiplied by the number of trips. Then, the CO_2 emissions related to the vehicle load ($\epsilon^f - \epsilon^e$) are multiplied by the volume of products expressed in full vehicles. To get the total CO_2 emissions of the supply chain, these emissions per km are multiplied by the distance, and summed for all deliveries to retailers.

3.3 Multi-objective collaborative location-inventory model

In this section, we present our multi-objective collaborative location-inventory model. Equations (1) and (2) provide two criteria, $Cost^i_{CO}$ and $Emis^i_{CO}$, that need to be minimized for each partner in the cooperation, leading to a multi-objective and multi-partner optimization model with $2\,n_I$ objectives. The model aims to determine the number and locations of the joint DCs, the allocation of the flows, as well as inventory decisions regarding the shipment sizes and the safety stocks. Moreover, the model directly allocates the costs and the CO_2 emissions to the specific partners. It is formulated as a *conic quadratic mixed integer program*, which has the advantage to be solvable by commercial optimization softwares. Similarly to Atamtürk et al (2012) and Hacardiaux and Tancrez (2020), the non-linearity in the logistics costs is moved to the constraints using auxiliary variables v^i_{1d} and v^i_{2d}. Specifically, in $Cost^i_{CO}$ (equation (1)) the term $\sum_{d,r} \sqrt{2\,K^i_d\,h^i_d\,\lambda^i_r}\,x_{dr}$ is replaced by $\sum_{d,r} \sqrt{2\,K^i_d\,h^i_d}\,v^i_{1d}$, and the term $\sum_d h^i_d\,z^i_\alpha\,\sqrt{LT^i_d}\,\sqrt{\sum_r (\sigma^i_r)^2 x_{dr}}$ is replaced by $\sum_d h^i_d\,z^i_\alpha\,\sqrt{LT^i_d}\,v^i_{2d}$, while constraints (5) and (6) are added. In the final model, the objectives are linear and the constraints are either linear or conic quadratic. Our multi-objective multi-partner collaborative location-inventory model is formulated as follows.

$$
\begin{aligned}
\min \quad & Cost^i_{CO} && \forall i && (3)\\
\min \quad & Emis^i_{CO} && \forall i && (4)\\
\text{s.t.} \quad & \sum_r \lambda^i_r\,(x_{dr})^2 \le (v^i_{1d})^2 && \forall d, i && (5)\\
& \sum_r (\sigma^i_r)^2\,(x_{dr})^2 \le (v^i_{2d})^2 && \forall d, i && (6)\\
& \sum_d x_{dr} = 1 && \forall r && (7)\\
& x_{dr} \le y_d && \forall d, r && (8)\\
& v^i_{1d}, v^i_{2d} \ge 0 && \forall d, i && (9)\\
& x_{dr}, y_d \in \{0,1\} && \forall d, r && (10)
\end{aligned}
$$

Equations (3) minimize the share of logistics costs of each partner and equations (4) minimize the share of CO_2 emissions of each partner in the cooperation ($2\,n_I$ objectives). Constraints (5) and (6) define the auxiliary variables v^i_{1d} and v^i_{2d}, giving the model its conic quadratic mixed integer program form (using $x_{dr} = x^2_{dr}$ and $y_d = y^2_d$). Constraints (7) ensure that each retailer is assigned to exactly one DC (single sourcing). Constraints (8) ensure that a retailer can be served by a DC only if the latter is opened. Constraints (9) impose non-negativity on the auxiliary variables, while constraints (10) enforce the binary nature of decision variables x_{dr} and y_d. Note that the shipment size decision, Q_{dr}, is not treated as a variable when solving our model, but rather as a parameter. We will show in Section 4 that Q_{dr} can be computed a priori, before solving the model, in a way that depends on the approach used to solve model (3)-(10).

4 Multi-objective optimization frameworks

Our multi-objective collaborative location-inventory model is challenging to solve due to the number of objectives, which is equal to the number of partners in the cooperation times two, $2\,n_I$. In this way, the objectives are multiple in two dimensions: the logistics costs vs. the CO_2 emissions on one hand, the multiple partners on the other hand. In this section, we present two approaches to solve our multi-objective model, where each approach tackles the problem starting from one of the two dimensions in order to generate a specific Pareto frontier.

Even though only one solution is chosen in practice, generating these Pareto fronts provides useful insights into the trade-off between costs and emissions on the one hand and between the partners interests on the other hand. The cost effect of striving for a particular emissions level (and vice versa) can be analyzed, next to the balance of the partners benefits in various collaborative network solutions. Ultimately, this allows collaborative partners to reflect on their preferences and engage in negotiations on the costs-emissions strategy of the collaboration.

4.1 Articulation at the coalition level

In the first approach, we tackle the multi-objective problem by aggregating the individual partners, considering the coalition as a whole. In other words, we look at the problem as if the coalition was one homogeneous decision entity (Hacardiaux and Tancrez, 2020; Tang et al, 2016; Verdonck et al, 2016). The shares of all partners are added up, leading to two objectives: the total coalition costs and the total coalition emissions. Compared to (3)-(4), $\forall i$ is replaced by $\sum_i$ (and the equation is simplified), leading to the following objectives.

$$\min \sum_i Cost^i_{CO} \tag{11}$$

$$\min \sum_i Emis^i_{CO} \tag{12}$$

4.1.1 Solution method

As part of our framework, various solution techniques for multi-objective optimization (e.g., an ϵ-constraint method) could be used to tackle the remaining bi-objective model and construct the Pareto frontier. When applying our framework to the cooperative inventory-location model, we chose the weighted sum method for reasons that will appear at the end of this subsection (a priori computation of Q_{dr}), with a varying weight β, which reflects the relative importance of logistics costs versus CO_2 emissions for the cooperation (Kim and de Weck, 2005; Marler and Arora, 2010). Both objectives are combined and the following model is obtained.

$$\begin{aligned} \min \quad & \sum_i Cost^i_{CO} + \beta \sum_i Emis^i_{CO} \\ \text{s.t.} \quad & (5)-(10) \end{aligned} \tag{13}$$

The weight β is referred to as the costs-emissions weight, and reveals *how important CO_2 emissions are compared to logistics costs for the collaboration.* A small β means that the cooperation is mainly focused on costs, while a large β reveals a higher environmental attention. The parameter β can be interpreted as the monetary cost of CO_2 emissions. It can for example be related to carbon taxes or company reputation. The use of this weight solves the problems of nature and proportionality between both objectives, as they were originally expressed in euros and kilograms of CO_2.

As noted in Section 3.3, the shipment size Q_{dr} can be computed prior to solving the model. Differentiating expression (13) (using equations (1) and (2) for $Cost^i_{CO}$ and $Emis^i_{CO}$) with respect to Q_{dr}, equaling the resulting expressions to zero, and accounting for the vehicle capacity, we find the following closed-form formula for the shipment size.

$$Q_{dr} = \min\left(C, \sqrt{\frac{2\,(T + \beta\,\epsilon^e)\,D_{dr}\,\Lambda_r}{\sum_i H^i_r\,\lambda^i_r/\Lambda_r}}\right) \tag{14}$$

Note that, as β is part of this equation, the ability to compute Q_{dr} a priori is thus tied to the use of the weighted sum method. This is the reason why it is the preferred method to tackle the cooperative location-inventory model with the two objectives (11)-(12).

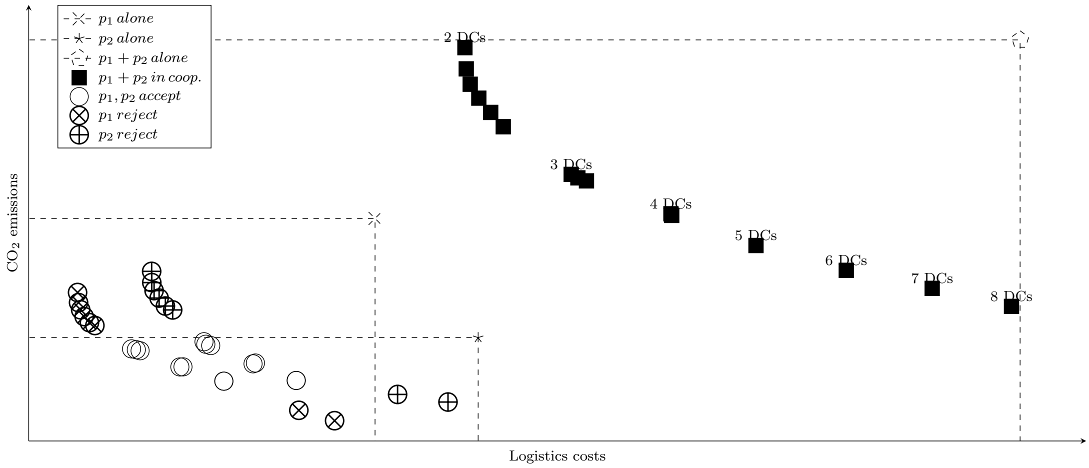


Fig. 2: Balancing the logistics costs and the CO_2 emissions on an illustrative case with two companies $p1$ and $p2$: optimal solutions for the stand-alone companies ($\times$ and $\star$) and sum of these two (dashed circle); Pareto front for the cooperation, varying β ($\blacksquare$); and allocated shares for both companies of each Pareto front solution ($\bigotimes$, $\bigoplus$, $\bigcirc$)

4.1.2 Pareto front

Varying the value of β in model (13), the Pareto front balancing costs and CO_2 emissions at the coalition level can be computed. Figure 2 (black squares) represents this Pareto front for an illustrative case with two partner companies. The first solution on the left of the frontier is obtained by only minimizing the total logistics costs ($\beta = 0$). For increasing values of β, we observe a reduction in CO_2 emissions caused at first by changes in the inventory policy. More specifically, the shipment size, and thus the vehicles' loading rate, is progressively increased, reducing the number of shipments and the CO_2 emissions, but increasing the inventory costs. Then, the CO_2 emissions are further decreased by opening additional DCs, which have a major impact on costs (additional facility opening costs) and CO_2 emissions (reduced travelled distances).

For each solution of the Pareto front at the coalition level, the costs and CO_2 emissions can be shared among the partners using volume-based allocation rules (as described in Section 3.2). For each partner, the resulting trade-off between the costs and emissions share is illustrated in Figure 2 (empty circles). This allows to assess the solutions at the individual partner level. In particular, a partner could decide to reject a given solution because it violates rationality principles (Zolezzi and Rudnick, 2002). Two rationality principles are discussed in the following.

Individual rationality means that a partner will not accept a solution that is worse than its stand-alone situation. In other words, a partner will not accept to enter a cooperation that causes him to increase its costs or its CO_2 emissions. Only solutions that dominate all stand-alone solutions will be accepted by all partners. If no such solution exists, we can conclude that the collaboration will not be viable in the long run. In Figure 2, allocated individual shares above or on the right of the stand-alone solutions are deemed unacceptable and crossed. If a cooperative solution is rejected by at least one of the partners, this solution is inaccessible to the other partners even if acceptable for them individually (see crossed solutions $\bigotimes$ in the acceptable area in Figure 2). Since only individually rational solutions are considered, we can conclude, by definition, that *collective rationality* is also satisfied for the cooperation setting investigated here.

4.2 Articulation at the partner level

In the second approach, we tackle the multi-objective problem starting with the balance between the logistics costs and the CO_2 emissions. For each partner i in the coalition, these two objectives are added, accounting for its preferences regarding costs versus emissions using β^i. Similar to the β introduced in Section 4.1, β^i can be interpreted as the *monetary cost for company i of emitting one kilogram of CO_2*, and denotes the importance according to partner i of reducing the CO_2 emissions compared to reducing the logistics costs. It is referred to as the individual costs-emissions weight. The resulting sum, which aggregates the direct logistics costs and the indirect costs coming from CO_2 emissions, is referred to as the *augmented cost* (and noted *AugC*). Each partner i in the coalition aims to minimize its own augmented cost, leading to the following objectives.

$$\min \quad Cost^i_{CO} + \beta^i \, Emis^i_{CO} \qquad \forall i \tag{15}$$

In our approach, the individual costs-emissions weights β^i are supposed to be known. On the one hand, partnering companies might decide on any weight they see fit, either independently from their partners or within the context of a cooperative negotiation. On the other hand, these weights could be inferred from the stand-alone situation (before cooperation) if we suppose that each company has optimally designed its supply chain according to its individual preferences. Using this concept of *revealed preference articulation*, it is not necessary to ask the decision makers to explicitly express their individual preferences and avoids the use of untruthful information (Veldhuizen and Lamont, 2000).

4.2.1 Solution method

As in Section 4.1.1, in the context of our framework, the resulting multi-objective model can be solved with various techniques. When looking at our cooperative inventory-location model, we again apply a weighted sum approach. This time, the weights γ^i are used. They are referred to as the partner influence weights, as they reflect the relative influence of each partner in the coalition, i.e., *how important the reduction of the augmented cost of company i is compared to the reduction of the augmented cost of its partners*. The resulting model is the following.

$$\begin{aligned} \min \quad & \sum_i \gamma^i \left[Cost^i_{CO} + \beta^i \, Emis^i_{CO} \right] \qquad (16) \\ \text{s.t.} \quad & (5) - (10) \end{aligned}$$

As previously noted, the shipment size Q_{dr} can be computed a priori. Differentiating expression (16) (using equations (1) and (2) for $Cost^i_{CO}$ and $Emis^i_{CO}$), equaling the resulting expressions to zero, and accounting for the vehicle capacity, we find the following closed-form formula.

$$Q_{dr} = \min \left(C, \sqrt{\frac{2 \left[\sum_i \gamma^i \, \lambda^i_r \, (T + \beta^i) \, \epsilon^e \right] D_{dr}}{\sum_i \gamma^i \, H^i_r \, \lambda^i_r / \Lambda_r}} \right) \tag{17}$$

Similarly to Section 4.1.1, the ability to compute Q_{dr} a priori is tied to the use of the weighted sum approach, which determines γ^i (as noted earlier, the individual costs-emissions weights β^i are supposed to be decided by the company).

4.2.2 Pareto front

Varying the partner influence weights (γ^i), single-objective optimization models can be solved to generate the Pareto front, showing the trade-offs between the companies' augmented costs. Figure 3 shows the Pareto front for an illustrative case with two cooperating companies, where the first company gives priority to costs while the second company has a higher preference

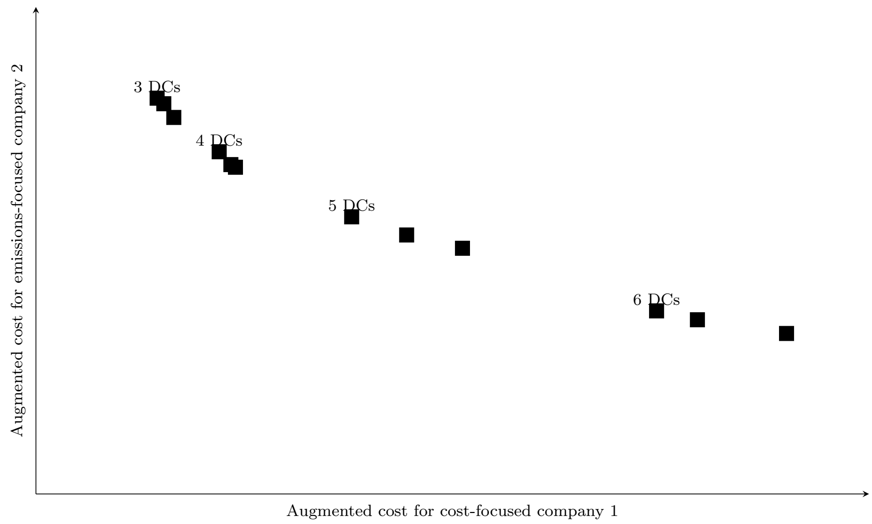


Fig. 3: Pareto front balancing the augmented costs of two cooperating companies (with $\beta^2 > \beta^1$). Each point represents a different value for γ^i

for CO_2 emissions ($\beta^2 > \beta^1$). The first solution on the left of the frontier is obtained by only minimizing the augmented cost of the cost-focused partner ($\gamma^1 > 0$ and $\gamma^2 = 0$), i.e., supposing that the first company has all the decision power in the cooperation. When the ratio γ^2/γ^1 increases, the emissions-focused company gets more power in the decision process. The locations of the DCs will be modified to get closer to its large customers. Moreover, as $\beta^2 > \beta^1$, the cooperation will become more environmentally friendly, and more DCs will be opened to reduce traveled distances. Finally, the last solution on the right of Figure 3 is the one that best accommodates the preferences of the emissions-focused company (with $\gamma^1 = 0$ and $\gamma^2 > 0$).

5 Identifying unique solutions

In Section 4, we proposed two approaches to reduce the multi-dimensionality of our model (3)-(10), leading to Pareto fronts that help decision-makers in designing a collaborative supply chain. The Pareto fronts balance the logistics costs and CO_2 emissions of the coalition (Section 4.1) or compromise the partners' augmented costs (Section 4.2).

In this section, as a complement to these results, we propose three different approaches to identify a unique solution that would be considered fair and efficient by every partner. The first two approaches use a value for either β or γ^i in order to generate a unique solution from the models provided in Section 4.1.1 and Section 4.2.1, respectively. The third approach aims to find a fair balance between the individual benefits that horizontal cooperation generates for the partners. For each of these three approaches, two methods are suggested, differing in terms of the way β and γ^i are calculated and in the viewpoint on fairness of individual partner benefits, respectively. These three approaches, with two calculation methods each, are presented in Sections 5.1, 5.2 and 5.3, respectively. They can be applied as a complement to the analysis of the Pareto fronts (Sections 4.1.2 and 4.2.2) to highlight solutions that are particularly relevant, and serve as a starting point for collaborative negotiations. Moreover, they have the advantage of being less computationally expensive in case the decision-makers prefer to bypass the Pareto fronts generation altogether. Furthermore, they can be scaled easily to settings with more than two companies whereas the complexity of the Pareto fronts representation increases significantly with the number of partners. Finally, in the context of a company looking to select a partner, unique solutions (rather than Pareto fronts) make it easier to compare potential partners and assess potential fit and benefits.

5.1 Costs-emissions weight β approach

In order to determine a unique solution for the model proposed in Section 4.1.1, without generating the Pareto front, the value of the costs-emissions preference weight β has to be fixed. For this, we rely on the known preferences of each partner, β^i, which can be inferred from their stand-alone supply chain (see Section 4.2). In order for β to be acceptable by all partners, each β^i is accounted for in proportion to the company's "importance". Two methods are presented here, which define importance based on the demand volumes of the partners or on their augmented costs, respectively. As discussed before, proportional techniques are the most commonly used in practice as they are simple, support communication purposes and do not require a substantial amount of data (Guajardo, 2018).

- *Volume weighted method (β_{Vol})*
  In the literature on collaborative transportation, allocation and aggregation techniques often rely on demand volumes (Guajardo and Rönnqvist, 2016). Following this common practice, in this first method, β is computed as the weighted average of the partner preferences (β^i), weighted by their demand volume, as follows.

$$\beta_{Vol} = \sum_i \beta^i \frac{\Lambda^i}{\Lambda} \tag{18}$$

- *Augmented cost weighted method (β_{AugC})*
  Next to demand volumes, stand-alone costs are also often used as a criterion for collaborative aggregation or allocation purposes (Guajardo and Rönnqvist, 2016). Accordingly, our second method computes β as the weighted average of the preferences β^i weighted by the stand-alone augmented cost. With $Cost^i_{SA}$ being the stand-alone cost of partner i and $Emis^i_{SA}$ its CO_2 emissions, the stand-alone augmented cost of partner i can be computed as $AugC^i_{SA} = Cost^i_{SA} + \beta^i\, Emis^i_{SA}$. The cooperation's preference weight β can then be derived as follows.

$$\beta_{AugC} = \sum_i \beta^i \frac{AugC^i_{SA}}{\sum_j AugC^j_{SA}} \tag{19}$$

While the volume weighted method (β_{Vol}) naturally favors the largest company, the augmented cost weighted method (β_{AugC}) favors companies with a larger stand-alone augmented cost, thus accounting for both logistics costs and CO_2 emissions.

5.2 Partner influence weight γ^i approach

To find a unique solution using the model provided in Section 4.2.1, without generating the Pareto front, the value of every partner's influence weight γ^i has to be fixed. These weights characterize the influence of the companies on the final cooperative solution. To define them, we rely again on proportional techniques, using the demand volumes or the stand-alone augmented costs, similar to the computation of β described in Section 5.1.

- *Volume weighted method (γ^i_{Vol})*
  Demand volumes can be used to reflect the size and negotiation power of a company in the partnership (Cruijssen, Cools, and Dullaert, 2007b). In this way, a larger company will have higher impact on collaborative decisions. Based on this idea, the influence weight γ^i_{Vol} of partner i is computed as the ratio of its demand to the total demand of all partners.

$$\gamma^i_{Vol} = \frac{\Lambda^i}{\Lambda} \qquad \forall i \tag{20}$$

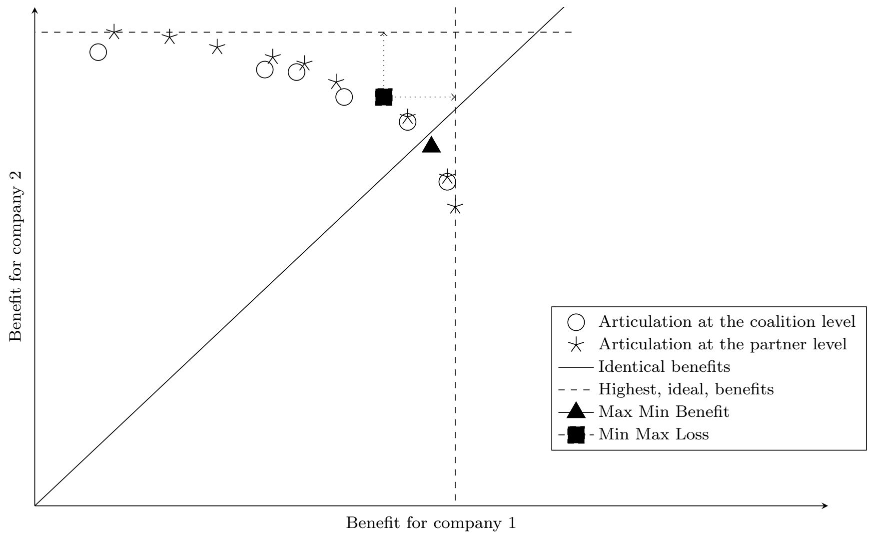


Fig. 4: Relative benefits from cooperation, in augmented costs, that can be achieved by two companies collaborating, for the solutions found applying the *articulation at the coalition level* and the *articulation at the partner level.*

– *Augmented cost weighted method* (γ^i_{AugC})
  In this second method, the augmented cost in the stand-alone case is used to reveal the influence of a partner. The partner influence weights, γ^i_{AugC}, are computed as the ratio of their stand-alone augmented cost to the total augmented cost of all partners.

$$\gamma^i_{AugC} = \frac{AugC^i_{SA}}{\sum_j AugC^j_{SA}} \qquad \forall i \tag{21}$$

The volume weighted method (γ^i_{Vol}) gives larger companies a higher impact on collaborative decisions, but does not account for the fact that economies of scale can be achieved through higher volumes, contrary to the augmented cost weighted method (γ^i_{AugC}) which accounts for it but may be less straightforward to apply as augmented costs may be uneasy to assess.

5.3 Partners benefits approach

The two previous approaches are based directly on the multi-objective models proposed in Section 4, balancing costs versus CO_2 emissions (Section 4.1) or balancing the augmented costs of the partners (Section 4.2). In this Section, we present a final approach that accounts for the benefits that collaboration generates for each individual partner. The relative benefit of cooperation for a partner i is computed as $(AugC^i_{SA} - AugC^i_{CO})/AugC^i_{SA}$, where $AugC^i_{SA}$ is the stand-alone augmented cost of partner i and $AugC^i_{CO}$ is its share of the cooperative augmented cost. The main motivation for a company to engage in a horizontal cooperation is to reduce *its own costs and CO_2 emissions*, i.e., decrease its individual augmented cost. In practice, a cooperation that leads to vastly different benefits among partners may be considered unfair, at least by those that benefit less. In the same vein, a collaborative supply network that is far from the ideal network for one company will likely result in dissatisfaction and threaten the long-term stability of the collaboration.

Figure 4 displays the relative benefits of each partner in an illustrative two company collaboration, for the solutions of the Pareto fronts as computed in Section 4, using articulation at the coalition level (see Section 4.1.1) or articulation at the partner level (see Section 4.2.1).

We observe a range of potential benefits for both companies. In isolation, the companies would choose very different collaborative networks, i.e., the two extreme points, leading to their ideal benefits. In what follows, we introduce two methods for selecting one solution from these solution sets, in order to guide decision makers. Both methods do not require the Pareto fronts to be known.

– *Maximizing the minimal partner benefit (MmBenefit)*
The first method aims at maximizing the lowest individual benefit a partner gets from cooperating. It will thus lead to a solution in which the company gaining the least gets as much as possible, and in which the benefits received by the different partners are as similar as possible. In Figure 4, this solution (represented by a triangle) is the one closest to the line with identical benefits for the partners. To find this solution, the following model is solved, maximizing the smallest benefit among partners (with $Benefit$ and $AugC^i_{CO}$ being variables and $AugC^i_{SA}$ being a parameter, computed a priori).

$$\max \quad Benefit \tag{22}$$

$$\text{s.t.} \quad Benefit \leq \frac{AugC^i_{SA} - AugC^i_{CO}}{AugC^i_{SA}} \qquad \forall i \tag{23}$$

$$AugC^i_{CO} = Cost^i_{CO} + \beta^i \, Emis^i_{CO} \qquad \forall i \tag{24}$$

$$Benefit \geq 0 \tag{25}$$

$$AugC^i_{CO} \geq 0 \qquad \forall i \tag{26}$$

$$(5) - (10)$$

Since this method leads to similar benefits among partners, it supports acceptance among partners and is in line with the premise of the *equal profit method* (Frisk et al, 2010). As such, it may be helpful in the early phases of a growing horizontal cooperation for communication and negotiation purposes (Verdonck et al, 2016). However, especially if partner characteristics and/or contributions are very dissimilar, it can be questioned whether an equal distribution of the benefits is desirable. Moreover, given its strive for more equal partner benefits, this method generally affects the average savings of the solution in a negative way. These specific cases will be numerically explored in detail in Section 6.

– *Minimizing the maximal partner loss (mMLoss)*
This last method is based on the statement that partners ultimately desire cooperative solutions which are as close as possible to their ideal cooperative solution from an individual perspective, i.e., the solution that maximizes their own benefit. Note that these solutions could be unacceptable as they might not comply with the individual rationality principle. The method aims at minimizing the maximum loss (dissatisfaction) of each partner, accounting for the cooperative solution that would be chosen individually, similarly to the idea behind the *Nucleolus* (Schmeidler, 1969). The solution that company i would select if it could decide alone for the cooperation (with an augmented cost noted $AugC^{i*}_{CO}$) is computed a priori (solving model (16) with $\gamma^i = 1$ and zero weights for other companies). The corresponding solutions for all partners are highlighted with the dashed lines in Figure 4. The method then finds the solution that minimizes the maximum difference in benefits with these previously computed solutions, as illustrated by the black square in Figure 4.

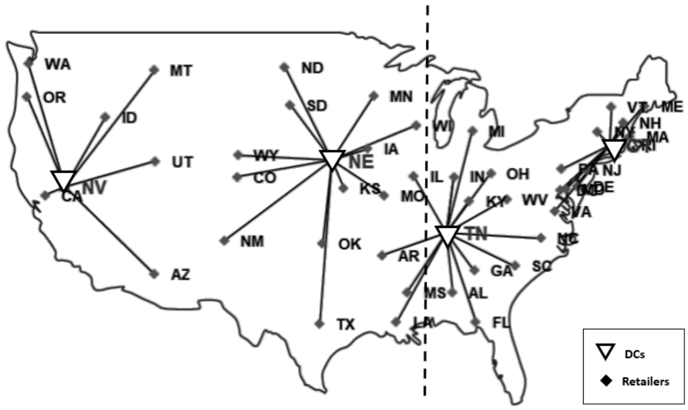


Fig. 5: Joint supply network for two collaborating companies with similar demand structures and costs-emissions preferences ($\beta^1 = \beta^2 = 3$), using the volume weighted β_{Vol} method (equation (18)). The dashed line distinguishes the eastern and the western cities (see Section 6.4).

The following model is solved, with $Loss$ and $AugC^i_{CO}$ being variables.

$$\begin{aligned}
\min \quad & Loss && && (27)\\
\text{s.t.} \quad & Loss \;\geq\; \frac{AugC^i_{CO} - AugC^{i*}_{CO}}{AugC^i_{SA}} && \forall i && (28)\\
& AugC^i_{CO} = Cost^i_{CO} + \beta^i\, Emis^i_{CO} && \forall i &&\\
& Loss \geq 0 && && (29)\\
& AugC^i_{CO} \geq 0 && \forall i && (30)\\
& (5) - (10) && &&
\end{aligned}$$

As the difference between the individually desirable solution and the cooperative solution is minimized, this approach will reduce the partners' willingness to leave the cooperation, and thus supports the long-term stability of the cooperation.

6 Computational Experiments

In this section, we present and discuss our experimental results in order to compare and validate all the approaches introduced in the previous sections. First, we introduce the experimental setting in Section 6.1. In Section 6.2, we discuss the working of both approaches presented in Section 4, that lead to Pareto fronts, relying on preference articulation at the coalition and at the partner level. In Section 6.3, we analyze the three approaches for finding unique solutions presented in Section 5. Finally, Sections 6.4 and 6.4 study collaborations among companies that are dissimilar in size (and therefore power) or have a different geographical demand distributions in order to derive some valuable managerial insights.

6.1 Experimental Setting

In our experiments, we focus on a cooperation between two companies (see Section 6.4 for cases with three companies notably), operating in the U.S. market. The retailer's locations are taken from the 49-node data set by Daskin (2011), which includes the 48 continental U.S. state capitals plus Washington DC. This data set is commonly used in the facility location literature (Jeon,

Table 2: Parameters values for the numerical experiments.

λ_r^i	$[0.75\pi_r; 1.25\pi_r]$ items/day	F_d	1000 €/day
CV	0.5	K_d^i	500 €/order
α^i	97.5%	$h_d^i = H_r^i$	0.05 €/item·day
z_α^i	1.96	ϵ^e	0.857 kg/km
T	1 €/km	ϵ^f	1.209 kg/km
C	2500 items		

Snyder, and Shen, 2006; Santiváñez and Carlo, 2018). All retailers' locations are considered to be possible locations for the DCs. This assumption is common and well-accepted in the facility location literature (see e.g. Atamtürk et al (2012); Shen et al (2003)). The 49 cities and the joint supply network for a specific collaboration are illustrated in Figure 5.

The parameter values, reflecting the characteristics of the two cooperating companies, are detailed in Table 2. These parameter values are used for both companies in all our experiments except for the companies' size and geographical distribution which differ in Sections 6.4 and 6.4 (i.e., demands λ_r^i differ). In order to highlight relevant insights, we assume that the companies share similar cost structures, but do not necessarily share the same costs versus emissions preferences ($\beta^i = 1, 3$ or 5 depending on the experiments). These three values are chosen to reflect a cost-focused company ($\beta^i = 1$), an emissions-focused company ($\beta^i = 5$), and a neutral company ($\beta^i = 3$). To illustrate, in our setting and for the stand-alone companies, these β^i parameter choices lead to the cost-focused company having a 20% lower cost but 35% more emissions than the emissions-focused company. Following Atamtürk et al (2012); Schuster Puga et al (2019), we use the city's population size divided by 1000 (noted π_r) as the baseline for the retailer's daily demand. To allow for variance in the dataset, a deviation of 25% is considered. For each company, the expected daily demand at a retailer, λ_r^i, is randomly generated within the intervals $[0.75\pi_r; 1.25\pi_r]$. The standard deviation of the demand is found applying a CV of 0.5 (normal distributions are assumed). The service level is set at 97.5%. A transportation cost of 1€/km is considered per vehicle. The vehicle capacity is fixed at a maximum of 2500 items per vehicle. The use of a DC involves a periodical facility opening cost of €1000. The order cost and the holding costs are €500 per order and €0.05 per item respectively (as in Atamtürk et al (2012); Schuster Puga et al (2019)). Lead times between DCs and retailers are directly proportional to the distance (assuming an average speed of 50 km/h). The order lead time from all DCs to all plants is fixed to the average lead time from all potential DCs to all retailers. The CO_2 emissions emitted by a vehicle are set to 0.857 kg/km for an empty vehicle (ϵ^e) and 1.209 kg/km for a full vehicle (ϵ^f). These values are obtained applying the formula proposed by Hickman, Hassel, Joumard, Samaras, and Sorenson (1999), considering a heavy-duty vehicle (maximum load of 25 tons) driving at a speed of 50 km/h, and ignoring the gradient of the road (Pan et al, 2013). Models are implemented in CPLEX and run on a 3.2 GHz computer with 8 GB of RAM. Problems are solved to optimality both for the stand-alone and the cooperation cases.

6.2 Pareto fronts analysis

To help decision-makers negotiate on the operational scope of the collaboration, our methods first display the alternative joint supply networks in the form of Pareto fronts. They can be computed using a preference articulation at the coalition level (Section 4.1) or at the partner level (Section 4.2). To illustrate these methods, the two collaborating companies, with similar demand structures, are supposed to have opposite costs-emissions preferences (otherwise the two companies would easily agree on their joint supply network). One company is focused on costs minimization ($\beta^1 = 1$) while its partner is focused on emissions reduction ($\beta^2 = 5$).

Figure 6 shows the resulting Pareto fronts for both preference articulations, at the coalition level and at the partner level, as well as the balance of the benefits in augmented cost that the partners get from cooperating (see Section 5.3). We observe that companies first have to decide whether to open 3, 4 or 5 DCs. Then, the decisions regarding the locations of these DCs as well as the loading rates of the vehicles will have an additional impact on the costs-emissions balance and on the individual augmented costs. Unsurprisingly, the results obtained with both preference articulations are not drastically different. They rather offer variations and a wider choice of alternative supply networks.

In Figure 6(c), we observe that no solution leads to perfectly equal relative benefits for both companies. This is not an exception related to this specific instance, and may be an impediment during the negotiation process. In this case, visualizing all possible alternative supply networks (and thus also the non-existing ones), in the form of Pareto fronts, may definitely be valuable. Interestingly, although collaboration is clearly beneficial for both partners, we see that benefits can vary between 20% and 29% for the cost-focused company and between 22% and 27% for the emissions-focused company. This disparity is a direct consequence of the difference in costs-emissions preferences for both partners.

In conclusion, using a preference articulation at the coalition level or at the partner level results in Pareto fronts offering a choice of optimal collaboration supply networks. These multiple collaboration solutions are valuable in the negotiation process and represent a first contribution of our paper.

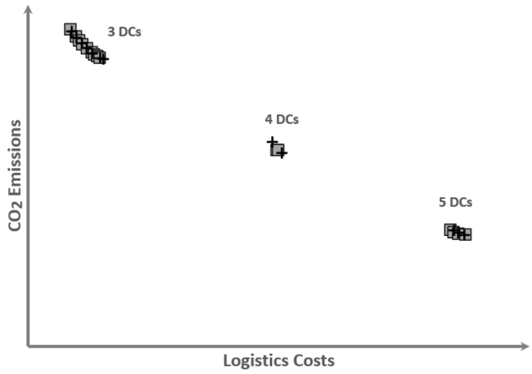
6.3 Impact of the individual costs-emissions preferences

To explore the impact of individual costs-emissions preferences (weight β^i), we perform additional experiments in which company 1 is set as a cost-focused company ($\beta^1 = 1$) while the other company's preference is altered. First, both companies are similar, being both cost-focused ($\beta^2 = 1$). Second, company 2 focuses more on CO_2 emissions ($\beta^2 = 3$). Third, company 2 is very environmentally conscious ($\beta^2 = 5$). For each scenario, we compare the unique solutions returned by each of the three approaches (six computation methods) introduced in Section 5. Note that, for the two methods of the partners benefits approach ($MmBenefit$ and $mMLoss$, Section 5.3), the shipment size Q_{dr} is computed using equations (17) and (20).

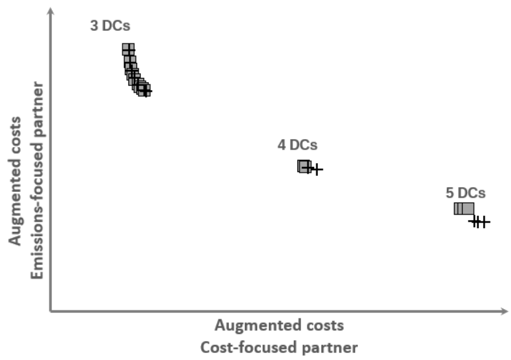
The results are summarized in Figure 7, showing the impact of the costs-emissions preference of the second company on the collaborative benefits for both companies. When the costs-emissions weights are the same for both companies ($\beta^1 = \beta^2 = 1$, first bar for each method), both companies are similar in all respects: cost parameters, demands and preferences. As a consequence, their costs and CO_2 emissions reductions from cooperating are very similar. The joint supply network is easily found and the various methods lead to nearly the same results.

With the increase of the second company's weight ($\beta^2 = 3$ then 5, second and third bar for each method), the relative benefit of the collaboration decreases as the companies have to compromise, accounting for different preferences. The cooperative solution becomes more environmentally friendly, with higher vehicle loading rates and in some cases the opening of additional DCs (with $\beta^2 = 5$ and the three methods β_{AugC}, γ^i_{AugC} and $MmBenefit$). Overall, the benefit decreases weakly for company 1 and more severely for company 2. For the cost-focused company 1, the decrease in the costs benefit (black bars) is compensated by an increase in the CO_2 emissions benefit (grey bars). In other words, the cost-focused company also benefits significantly from the reduction in CO_2 emissions enforced by the other partner. The notable exception to that are the instances where an additional DC is opened to satisfy the emissions-focused company 2 ($\beta^2 = 5$). The benefit for the cost-focused company drops significantly as the additional DC largely increases the cost of the network (and the CO_2 emissions reduction does not compensate for this loss).

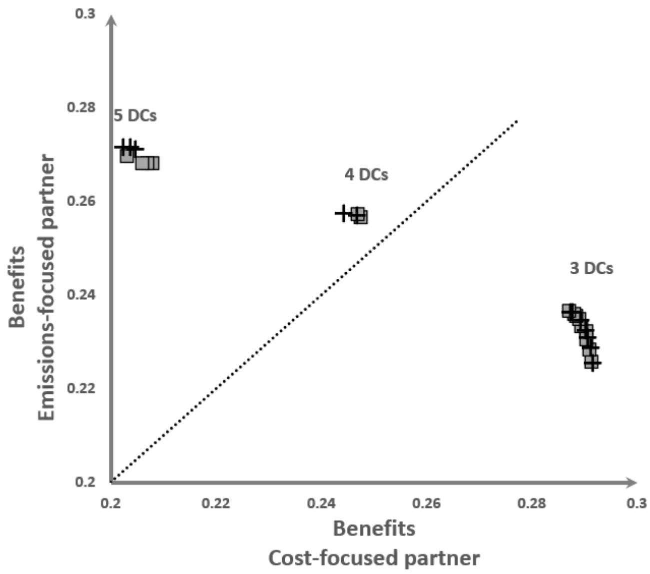
Looking at the second company, for which the costs-emissions weight increases, its benefits are decreasing more severely, deviating more and more from those of its partner. Moreover,



(a) Total coalition costs versus total coalition CO_2 emissions.



(b) Augmented costs for both partners.



(c) Relative benefits in augmented costs from cooperating, for both partners.

Fig. 6: Pareto fronts obtained using the articulation at the coalition level (□) and the articulation at the partner level (+) for companies with different costs-emissions preferences.

the share of profits actually linked to CO_2 emissions reductions (grey bars) is decreasing when the costs-emissions weight increases. Although this might seem counter-intuitive, it can easily be explained by the fact that we make use of stated preference articulation to determine the individual partner preferences. In other words, a company that prioritizes CO_2 emissions, will already have low CO_2 emissions when operating alone. The opportunities for decreasing the emissions even further when collaborating are thus limited, especially if the other partner (company 1 in this case) does not value CO_2 emissions reduction. In the special cases where the second company's strong preference for emissions reduction leads to the opening of an additional DC, the emissions indeed drastically decrease, but the benefit is cancelled out by the cost increase.

When the individual costs-emissions preferences differ, and companies become dissimilar, we also see in Figure 7 that the outcomes of the six computation methods of Section 5 diverge. To study this in more detail, we refer to Table 3, which presents, for each method, the benefits in augmented cost obtained in a cooperation between a cost-focused company 1 ($\beta^1 = 1$) and

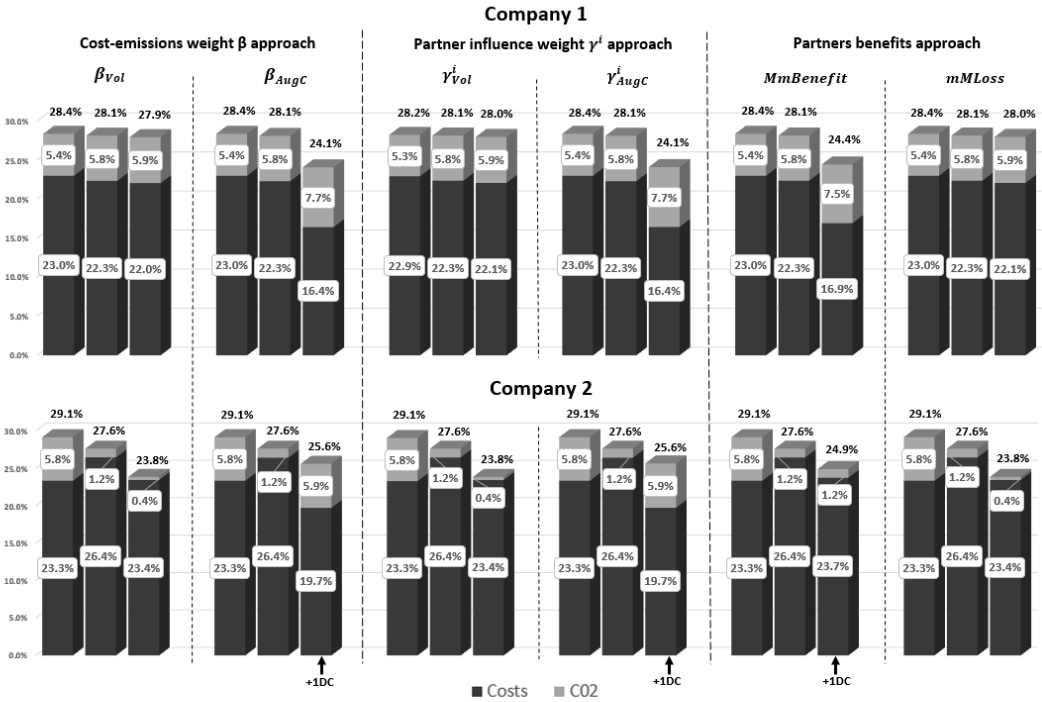


Fig. 7: Relative benefits in augmented cost from cooperating for cost-focused company 1 (first line) and company 2 with a changing costs-emissions preference (second line). Groups of three bars show the benefits obtained by each company when the costs-emissions weight increases for the second company ($\beta^2 = 1, 3, 5$). The weight does not change for company 1 ($\beta^1 = 1$). Each group of three bars, in the six columns, is for one of the six methods to propose a unique solution. Each bar is decomposed in terms of costs and CO_2 emissions reductions.

a very environmentally conscious company 2 ($\beta^2 = 5$). To underline the fact that the methods tend to have different strengths and weaknesses, Table 3 shows the benefits for each company, the average benefit revealing the global efficiency of the cooperation, the difference between the benefits unveiling the equity of the cooperation, and the difference with the ideal solution of a company (if it would decide alone for the cooperation). We see that the *volume weighted* methods (β_{Vol} and γ^i_{Vol}) lead to solutions with a high average benefit (25.9%), in which the cooperation as a whole benefits the most. However, these methods lead to a high disparity between partners (4.1%), clearly favoring the cost-focused company.

As touched upon earlier, the *augmented cost weighted* computation methods (β_{AugC} and γ^i_{AugC}) lead to the opening of an additional DC when the second company is very environmentally conscious ($\beta^2 = 5$). In general, these methods favor the emissions-focused company, leading to greener supply networks and larger CO_2 emissions reduction. However, as the emissions-focused company tends to have lower profits than its cost-focused partner, these methods counterbalance this negative impact, obtaining a lower average for the benefits but a lower gap between augmented costs reductions. In Table 3, we see that these methods, β_{AugC} and γ^i_{AugC}, lead to the higher benefit for the emissions-focused company 2 (25.6%), with a low difference with the benefit of company 1 (1.5%).

The method *maximizing the minimal partner benefit* ($MmBenefit$) further reduces the difference between the benefits of the partners (0.5%). As such, it allows to reach a solution where neither partner feels aggrieved. This is also the method that provides the highest minimum individual benefit (24.4%). To reach a sufficient benefit for the emissions-focused company 2, an additional DC is opened (as mentioned earlier). The main drawback of this method is that

Table 3: Relative benefits (in %) in augmented costs from cooperating for cost-focused company 1 ($\beta^1 = 1$) and emissions-focused company 2 ($\beta^2 = 5$), their average and their difference, as well as the highest difference with the ideal cooperative solution of each partner, as found by the six computation methods.

Method	**Costs-emissions weight**		**Partner influence weight**		**Partners Benefits**		*Average*
	β_{Vol}	β_{AugC}	γ^i_{Vol}	γ^i_{AugC}	$MmBenefit$	$mMLoss$	
Benef. Comp. 1	-27.9	-24.1	-28.0	-24.1	-24.4	-28.0	-26.1
Benef. Comp. 2	-23.8	-25.6	-23.8	-25.6	-24.9	-23.8	-25.0
Average	-25.9	-24.8	-25.9	-24.8	-24.7	-25.9	-25.3
Difference	4.1	1.5	4.2	1.5	0.5	4.2	2.7
Highest Diff. Ideal	3.2	4.4	3.2	4.4	4.1	3.2	3.7

it leads to a degradation of the average global savings level (24.7%). In short, $MmBenefit$ tends to prioritize partner equity at the cost of global efficiency. On the opposite, the method *minimizing the maximal partner loss* ($mMLoss$) leads to very different benefits (4.2%) but a more efficient supply network for the cooperation as a whole (25.9%). However, it minimizes the gap with the ideal solutions that companies would choose if they could decide alone for the cooperation (3.2%), and thus better guarantees that no partner is willing to leave the cooperation.

In conclusion, companies which are similar in terms of costs-emissions preferences have higher average benefits, while dissimilar preferences lead to lower and more disparate benefits. In addition, individual benefits from cooperation are mainly coming from an improvement of the objective which was less favored by the corresponding company. As such, a cost-focused company collaborating with an emissions-focused company will mainly enjoy significant CO_2 emissions reductions. This highlights again the importance of analyzing results (also) at an individual partner level. Finally, the choice of the solution method noticeably impacts the collaborative solution, the characteristics of the joint supply network, its costs and emissions. The various methods could favor a reduction in costs or in CO_2 emissions, one partner or the other, the reduction of the augmented cost of the cooperation as a whole or a smaller difference between individual benefits, or even a lower gap with the ideal cooperative solution of each partner. This gives a large set of options with clear features during the negotiation process of the collaboration.

6.4 Companies with different sizes

A significant part of the literature on horizontal cooperation considers coalitions of companies of a similar size (i.e., with similar demand). The reasons put forward to justify this assumption are an easier benefit distribution among partners and the elimination of power influence in the decision-making process (Cruijssen, Bräysy, Dullaert, Fleuren, and Salomon, 2007a; Hacardiaux and Tancrez, 2020; Vanovermeire, 2014). As our models consider the benefits distribution and the influence weights of the coalition partners, we can use them to analyze the impact on both coalition performance and individual benefits of having partners of different sizes in the coalition. For this, we run a new set of experiments where the first company is twice the size of the second company, while maintaining a similar total demand for the cooperation as previously. The demand rate λ^i_r is computed using the formula in Table 2, with π_r being the city's population size divided by 750 for the large company 1, and 1500 for the small company 2 (compared to 1000 for both companies previously). Three combinations of individual costs-emissions weights are tested, $\beta^1/\beta^2 = 3/3, 1/5$ or $5/1$, to illustrate companies with similar (3/3) or opposite (1/5 and 5/1) costs-emissions preferences. These new instances have been solved with the six computation methods proposed in Section 5, to get unique solutions for the

Table 4: Relative benefits (in %) from cooperating for a large company 1 and a small company 2, in augmented cost, logistics costs and CO_2 emissions, depending on their costs-emissions preferences β^1 and β^2.

	$\beta^1/\beta^2 = 3/3$			$\beta^1/\beta^2 = 1/5$			$\beta^1/\beta^2 = 5/1$		
	Coop.	Large C1	Small C2	Coop.	Large C1	Small C2	Coop.	Large C1	Small C2
Augm. costs	-26.8*	-16.8	-40.5	-26.6*	-16.5	-37.6	-22.8*	-16.2	-37.1
Logistics costs	-26.5	-16.3	-40.3	-32.3	-13.0	-52.3	-26.3	-21.5	-33.9
CO_2 emissions	-27.2	-17.7	-40.8	-24.3	-30.7	-6.6	-30.8	-7.2	-54.1

*For the partner influence weight and and partners benefits approaches, β_{Vol} (equation (18)) is used to compute the cooperative augmented cost.

collaboration. Table 4 provides the average results over the six methods, allowing us to focus on the insights related to the cooperative and individual benefits.

Analyzing Table 4, it directly appears that the relative benefits of both partners are very different, around 16% in augmented cost for the large company and between 37% and 40% for the small company. This is due to the fact that the large partner already has a more effective supply network before cooperating, thanks to better economies of scale. With equal costs-emissions weights ($\beta^1/\beta^2 = 3/3$), the costs and emissions of the large company are only 35% and 45% larger, respectively, while its demand volume is twice the volume of the small company. In particular, the average vehicle loading rate for the large company in the stand-alone case is already close to 90% (for the various costs-emissions weights combinations β^1/β^2). On the other hand, the small company, when cooperating, gets access to a larger number of DCs (for which they share the costs), better filled trucks (from 79% utilization rate in the stand-alone case to around 96% in the collaborative solutions) and more frequent deliveries (reducing inventory costs). Cooperation is therefore more beneficial, relatively, for the small company than for its larger partner. Companies thus best join forces with larger partners in order to fully exploit cooperation opportunities (as also stated in Verdonck, Ramaekers, Depaire, Caris, and Janssens (2019)).

However, the large company still benefits from a significant reduction of its costs and CO_2 emissions (around 16% in augmented cost). Even more interestingly, the large company is close to reaching the full potential of the collaboration, i.e., the maximum possible benefit, that a company would get deciding alone for the cooperation (for all β^1/β^2 combinations and with most methods). For example, with costs-emissions weights $\beta^1/\beta^2 = 1/5$, the results obtained with five of the six computation methods are very similar, with a relative benefit in augmented costs of 17.2% for the large company (37.4% for the small one), which is very close to its ideal cooperative solution (decided alone) with a benefit of 17.4%. The sixth computation method, which leads to other results, is the augmented cost weighted β_{AugC} method. It favors the small company even more, leading to a benefit of 39% for the small company and 13.3% for the large one. The high costs-emissions weight of the small company (artificially) skews the solution to favor it (even opening an additional DC). This β_{AugC} method should thus be avoided when companies are very dissimilar in terms of customer demand.

Finally, the observation provided in Section 6.3 is even stronger with companies of different sizes: when the partners have different costs-emissions preferences, each company benefits most in the non-priority objective. With costs-emissions weights $\beta^1/\beta^2 = 1/5$ for example, the large cost-focused company decreases its CO_2 emissions the most (30.7% vs. 13%), while the small emissions-focused company reduces its costs the most (52.3% vs. 6.6%). As a whole, the cooperation reduces its costs by 32.3% and its emissions by 24.3%, showing that the priority of the larger company for costs still clearly bends the cooperative solution. When both companies have similar sizes (configuration of Section 6.3 and Table 3, $\beta^1/\beta^2 = 1/5$), the benefits are more balanced, as the cooperation reduces its costs by 28.6% and its emissions by 29.3%.

In conclusion, the cooperation between a small and a large company leads to dissimilar benefits between them. The small partner has more incentive to cooperate as economies of scale due to the collaboration are larger while the company with a higher demand has more efficient supply network before cooperating. However, for the large partner, the costs and emissions reductions stay significant and are close to the maximum benefits reachable by the collaboration (i.e. full vehicles and an optimal number of DCs).

6.5 Three companies with different geographical demand distributions

In this section, we present the results of new experiments with three collaborating partners. Using those experiments, we discuss the impact of the geographical demand distribution. We assume that the demand for each company is no longer uniformly spread over all cities (while maintaining a similar total demand for the companies as previously). In the following experiments, the first company is based in the West, the second company in the Center and the third company in the East (see the dashed lines in Figure 8 for the limits of those regions). Each company gets half of its demand from its core region and one quarter from each other region. We consider companies with similar ($\beta^1/\beta^2/\beta^3 = 3/3/3$) or opposite ($\beta^1/\beta^2/\beta^3 = 1/3/5$ or $5/3/1$) costs-emissions preferences, and apply the six computation methods proposed in Section 5.

In these experiments with three partners, the individual benefits in augmented cost vary from 34.5% to 40% (depending on the partner, the computation method and the costs-emissions preferences). In comparison, a configuration with two partners and an East-West demand distribution leads to individual benefits going from 23% to 26% in augmented cost. As expected, increasing the number of partners in the collaboration raises the potential benefits (but the collaboration management complexity too). The cooperation is clearly attractive to a new entrant which profits from the totality of the augmented cost reduction. In contrast, the augmented cost reduction for previously existing partners adding a new partner equals the marginal gain, which tends to decrease with each newcomer.

The costs-emissions weight β approach (Section 5.1) leads for each preferences configuration ($\beta^1/\beta^2/\beta^3 = 1/3/5$ or $3/3/3$ or $5/3/1$) to a very similar costs-emissions weight β value, close to 3, as the partners are very similar in size. The same supply network and the same locations for 5 DCs are then found for the coalition, overlooking the difference in costs-emissions preferences β^i among partners (see Figure 8.a). On the opposite, the partner influence weight γ^i (Section 5.2) and partners benefits approaches (Section 5.3) account for this difference, leading to dissimilar supply networks, as illustrated in the three following examples. With preferences $\beta^1/\beta^2/\beta^3 = 3/3/3$, the γ^i_{Vol} method leads also to a solution with 5 DCs in slightly different locations compared to the costs-emissions weight β approach (Figure 8.b). The augmented cost of the western company (which is favored in the β approach as its main customers are more spread while those of other companies are mainly clustered) is increasing while it is decreasing for the center and the eastern companies. In conclusion, when companies have different geographical demand distributions, companies with a higher demand dispersion obtain higher benefits, as increased geographical coverage provides more cooperation opportunities (in accordance with Cruijssen et al (2007a), Guajardo and Rönnqvist (2015) and Verdonck et al (2019)). With preferences $\beta^1/\beta^2/\beta^3 = 1/3/5$, the $MmBenefit$ method proposes a solution with 4 DCs, and their locations are skewed towards the east (Figure 8.c). The difference between partners benefits is reduced to less than 1.7%, compared to 5.1% with the partner costs-emissions weight β approach. Using the $mMLoss$ method in a 5/3/1 preferences combination (Figure 8.d), the solution dominates, in terms of augmented costs, the solution found with the costs-emissions weight β approach. In this specific case, the increase in CO_2 emissions due to the opening of only 4 DCs is counterbalanced by the decrease in opening costs, leading to a smaller augmented cost for each partner and increasing the individual benefit between 0.5 and 1%.

In conclusion, when geographical spread and individual preferences differ, companies should prefer applying approaches that conserve these individual preferences as they allow to design a network that has different priorities (costs versus CO_2 emissions) in different regions.

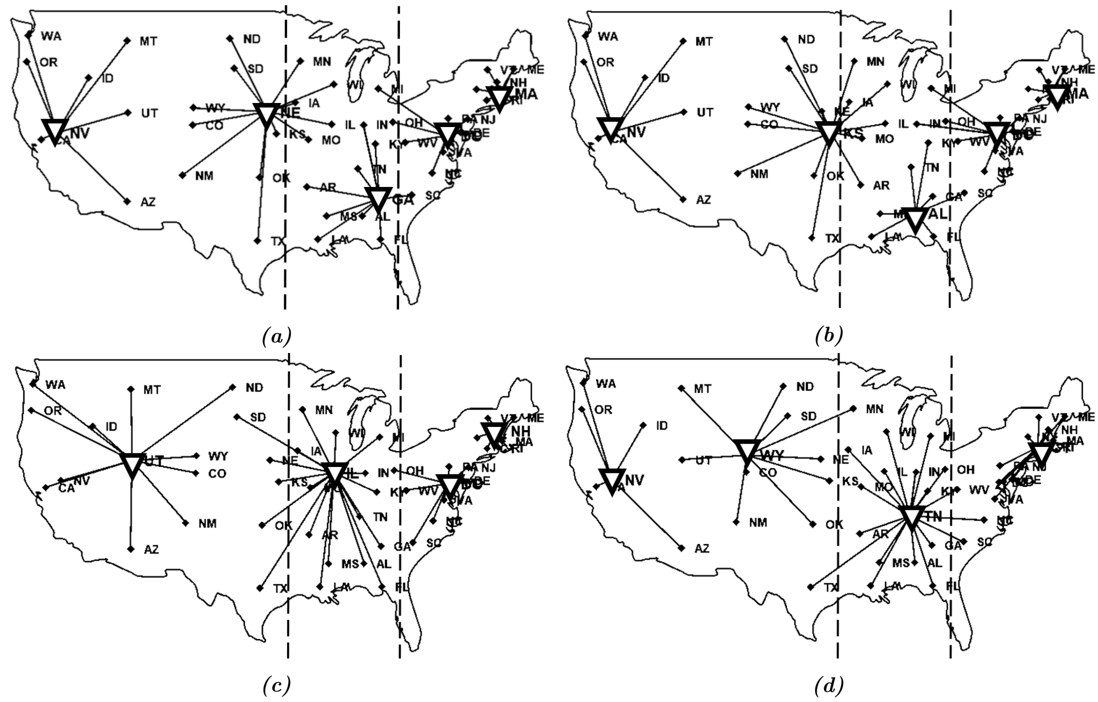


Fig. 8: Collaborative supply networks and DCs locations for three companies, found with the costs-emissions weight β approach in every individual preferences combinations (a); with the the γ^i_{Vol} method in a 3/3/3 preferences combination (b); with the $MmBenefit$ method in a 1/3/5 preferences combination (c); and with the $mMLoss$ method in a 5/3/1 preferences combination (d).

7 Conclusions

Horizontal collaboration is considered to be a promising avenue to improve the efficiency and sustainability of logistics services. Despite partners being independent entities, likely with different preferences, the majority of current research assumes that partners agree on a unique collaborative goal (most often the minimization of transportation costs). Our main goal in this research is to study how to navigate multiple objectives in collaborative logistics, how to help finding a joint supply network that is agreeable for all partners, and how it impacts collaboration benefits. For this, in Section 4, we develop a multi-objective multi-partner framework accounting for the influence weights of partners and for their individuality in terms of costs-emissions preferences. In order to inform the negotiation process, Pareto fronts can be generated to reveal the trade-offs between costs and emissions for the cooperation on the one hand (Section 4.1), and the augmented costs of the different partners on the other hand (Section 4.2). In Section 5, we propose three additional approaches to identify a unique, fair and efficient, solution: adding up the coalition's costs-emissions preference (Section 5.1), evaluating the partner influence weights (Section 5.2), or balancing the individual partner benefits (Section 5.3).

The proposed framework provides quantitative decision support for practitioners implementing and managing horizontal partnerships. Furthermore, it allowed us to various insight through numerical experiments (Section 6.1). First, collaboration remains beneficial for partners in all cases, even if their preferences, sizes or geographical demand distribution are different. Preference weight combinations do, however, impact the individual benefits of the partners, with dissimilar weights reducing the potential benefits (Section 6.2). Furthermore, when the partners have different costs-emissions preferences, they tend to benefit the most in the non-priority objective (Section 6.3). Second, the choice of the solution approach impacts the collaborative solution, rewarding either the partnership or a specific partner, favoring a reduction in costs or in emissions, and affecting the gap between individual benefits or with the ideal solution of each partner. Overall, the desirability of the solution reached by each approach depends on the context of the collaboration, the demand characteristics, the partners' preferences and influence (Section 6.3). Third, the importance of partner size is confirmed in Section 6.4. Comparatively smaller companies will tend to benefit more than larger companies which have better economies of scale when operating individually. Small companies thus best attract a large partner in order to enjoy savings associated with large volumes. However, the larger company may still bend the collaboration towards its costs-emissions preference and reach a cooperative set-up that is close to its ideal solution. Finally, broad geographical coverage increases the potential benefits of cooperation as observed in Section 6.4. When the geographical demand distributions and partners preferences are dissimilar, solution approaches accounting for the individual costs-emissions weights should be preferred.

To conclude, the following suggestions for further research can be made. One natural avenue is to include more complex allocation techniques from the literature (e.g. Shapley value) within our framework. Second, the multi-objective multi-partner approach could be applied to other collaborative settings besides the location-inventory model. According to Pan, Trentesaux, Ballot, and Huang (2019), research on intermodal collaborations should be enhanced, for example. Finally, it would be interesting to validate our framework with the use of real-life data. In practice, our work can be used to incentivize companies to consider the opportunity of collaborating with others, to foresee the collaborative benefits of a potential partner, or to support companies that are already engaged in a partnership to improve their synergy value.

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