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How horizontal cooperation can help companies achieve a robust supply chain

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Année académique : 2023-2024
ingénieur de gestion, à finalité spécialisée

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Summary

The main goal of the present paper is to understand how horizontal cooperation can help companies to develop a robust supply chain where the principal source of uncertainty is demand. For that matter, a robust collaborative location-inventory model, formulated as a conic quadratic mixed-integer program (CQMIP) has been developed to include both strategic and operational decisions. The model can be solved by optimization software packages. Different stages of the supply chain (DCs, transportation and retailers) are considered. Several main costs have been integrated: DCs opening cost, order cost at DCs, cycle inventory cost at DCs, safety stock costs at DCs, transportation cost, cycle inventory cost at retailers and safety stock costs at retailers. The loading rate in cooperation is another important objective of the horizontal cooperation. Computational experiments have been carried out to include 49 retailers, 2 companies and 5 scenarios. In total, 576 experiments are conducted to assess the impact of robustness over the benefits of the joint supply chain. The results of our experiments show that horizontal cooperation from a robust perspective leads to significant cost savings for all the stages of the supply chain. When demand becomes less predictable, we observe a decreasing average synergy value of 34.43%, 32.44% and 32.21% for companies of the same sizes that choose to cooperate. Also, companies with high fixed facility cost, low order cost and high unit holding cost benefit more from the cooperation. Smaller companies have better loading rate while larger companies benefit more in cooperation. Additionally, the greater the difference in company size, the less beneficial the collaboration, with the average synergy value falling from 29.21% to 23.37%.

The paper is structured as follows. Sect.2 is the literature review on robust optimization. This section introduces the concept of robust optimization, provides examples on robust optimization supply chain design, describe the current state of the collaborative supply chain design literature review and identify the current gaps. Sect.3 presents the robust collaborative location-inventory model and its notations, its strategic and operational decisions and the CQMIP formulation. Sect.4 presents the computational experiments, the single scenario configuration, the synergy value analysis, the benefits of cooperation for the various stages of the supply chain (DCs, transportation and retailers) impacted by robustness and discusses the findings from additional experiments. Sect.5 conclude the paper.

Acknowledgments

I would like to express my sincere gratitude to my supervisor Jean-Sébastien Tancrez, for his support and guidance throughout the master thesis.

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1. Introduction

Over the past few decades, horizontal cooperation has emerged as an interesting avenue for companies seeking to enhance the efficiency of their logistical operations (Hacardiaux & Tancrez, *2022*). For LSPs (i.e. logistics service providers), horizontal cooperation has increased significantly and has become an important organizational form (Schmoltzi, & Wallenburg, *2011*). In this regard, many LSPs engage in horizontal cooperation to access tangible and exploitable resources, such as well-structured transportation networks or warehouse infrastructure (Raue & Wieland, *2015*). These resources directly impact LSP's firm performance (Raue & Wieland, *2015*).

The definition of horizontal cooperation for both Hacardiaux & Tancrez (*2020*) and Schulz & Blecken (*2010*) is aligned with the definition provided by the European Union, which defines horizontal cooperation as "concerted practices among companies operating at the same level(s) in the market" (Union, E., *2001*). Furthermore, as outlined by Cruijssen et al. (*2007*), horizontal cooperation has to be between two or more firms that are active, at the same level of the supply chain and perform a comparable logistics function on the landside. Pérez-Bernabeu et al. (*2015*) additionally assert that these companies can either be competing or unrelated suppliers, manufacturers, retailers, receivers, or logistic service providers that share information, facilities, or resources with the goal of reducing costs and/or improving service. Finally, horizontal cooperation usually involves load consolidation centers (i.e. distribution centers), conjoint route planning, and purchasing groups (i.e. retailers) (Pérez-Bernabeu et al., *2015*).

Several benefits can be leveraged from having a joint supply chain. In terms of financial benefits, Schulz & Blecken (2010) suggest that horizontal cooperation increase the company's productivity for core activities, reduces costs for non-core activities, reduces purchasing costs, offers better quality of service and protects company's market share. Hacardiaux & Tancrez (*2022*) add that loading rates are also improved since vehicles are shared. The total number of trips required is reduced, thereby reducing transportation costs (Hacardiaux & Tancrez, *2022*). In their study, Hacardiaux & Tancrez (*2022*) posit that horizontal cooperation yields substantial savings, with an average cost reduction of 22.4% across all stages of the supply chain (DCs, transportation, retailers). The results presented by Pérez-Bernabeu et al. (*2015*) indicate that horizontal collaboration can reduce costs by an average of 5% to 90% when customers are distributed geographically with respect to their transport service providers. Based on the results provided by Hacardiaux et al. (2024), collaboration between companies offering the same product type leads to substantial logistics cost reductions (24.3% and 26.3%, on average, for functional and innovative products, respectively).

The main goal of the present paper is to understand how horizontal cooperation can help companies to develop a robust supply chain where the principal source of uncertainty is demand. For that matter, a robust collaborative location-inventory model, formulated as a conic quadratic mixed-integer program (CQMIP) has been developed to include both strategic and operational decisions. The model can be solved by optimization software packages. Different stages of the supply chain (DCs, transportation and retailers) are considered. Several main costs have been integrated: DCs opening cost, order cost at DCs, cycle inventory cost at DCs, safety stock costs at DCs, transportation cost, cycle inventory cost at retailers and safety stock costs at retailers. The loading rate in cooperation is another important objective of the horizontal cooperation. Computational experiments have been carried out to include 49 retailers, 2 companies and 5 scenarios. In total, 576 experiments are conducted to assess the impact of robustness over the benefits of the joint supply chain. The results of our experiments show that horizontal cooperation from a robust perspective leads to significant cost savings for all the stages of the supply chain. When demand becomes less predictable, we observe a decreasing average synergy value of 34.43%, 32.44% and 32.21% for companies of the same sizes that choose to cooperate. Also, companies with high fixed facility cost, low order cost and high unit holding cost benefit more from the cooperation. Smaller companies have better loading rate while larger companies benefit more in cooperation. Additionally, the greater the difference in company size, the less beneficial the collaboration, with the average synergy value falling from 29.21% to 23.37%.

The paper is structured as follows. Sect.2 is the literature review on robust optimization. This section introduces the concept of robust optimization, provides examples on robust optimization supply chain design, describe the current state of the collaborative supply chain design literature review and identify the current gaps. Sect.3 presents the robust collaborative location-inventory model and its notations, its strategic and operational decisions and the CQMIP formulation. Sect.4 presents the computational experiments, the single scenario configuration, the synergy value analysis, the benefits of cooperation for the various stages of the supply chain (DCs, transportation and retailers) impacted by robustness and discusses the findings from additional experiments. Sect.5 conclude the paper.

2. Literature review

Optimization affected by parameter uncertainty has long been a focus of the mathematical programming community (Bertsimas et al., *2011*). In the field of optimization, robust optimization is an approach to optimization under uncertainty, in which the uncertainty model is not stochastic, but rather deterministic and set-based (Bertsimas et al., *2011*). Robust optimization is popular because of its computational tractability for many classes of uncertainty sets and problem types (Gorissen et al., *2015*). Gorissen et al. (*2015*) add that robust optimization is very useful in practice, as it adapts to the available information and leads to computationally tractable formulations. For Alonso-Travesset et al. (*2022*), robust optimization seeks to incorporate a degree of robustness to uncertainty in the input data.

The term 'robust optimization' encompasses several approaches that aim to protect the decision maker from parameter ambiguity and stochastic uncertainty (Gabrel et al., *2014*). The main paradigm relies on worst-case analysis: a solution is evaluated using the realization of the uncertainty that is most unfavorable (Gabrel et al., *2014*). Gorissen et al. (*2015*) add that RO (i.e. robust optimization) does not assume that probability distributions are known, but rather that uncertain data reside in the so-called uncertainty set. Furthermore, basic versions of RO assume "hard" constraints, i.e., violation of the constraints cannot be allowed for any realization of the data in the uncertainty set. Alonso-Travesset et al. (*2022*) define a robust solution as one that remains optimal, feasible, or at least acceptable under any realization of the uncertainties. Alonso-Travesset et al. (*2022*) add that it is common to define an uncertainty set that includes all realizations.

According to Shariatmadar et al. (*2022*), robust optimization does not require a specified probability distribution of the uncertain data. Instead, robust optimization restricts the uncertain variables to a set of possible values and then optimizes for the worst-case realization of the uncertain variables among these sets. Rahim et al. (*2022*) argue that when sufficient historical data is not available, then the RO approach proves to be the best robust and feasible solution uncertainty modelling techniques. However, according to Gabrel et al. (*2014*), overconservatism issues are paramount in robust optimization, where the set of uncertain parameters over which the worst case is computed must be chosen to achieve a trade-off between system performance and protection against uncertainty.

Robustness can be observed in different environments such as biology, economics, electricity, robotics and mechanics. It is defined as the ability of a system to maintain its internal functions and properties constant regardless of external perturbations (Escobar et al., 2023). In logistics, an important question is not only how to operate a system most efficiently but also how to design it in the presence of uncertainty (Gabrel et al., 2014). In this section, several robust model will be presented. Aghezzaf (2005) proposes a robust deterministic-based optimization model to generate capacity expansion programmes and warehouse location plans that are robust to uncertain realizations of future market demand. Aghezzaf (2005) defines scenarios where the only source of uncertainty is the demand. It is assumed that all parameters except demand are known and set. Ribas et al. (2010) propose three models for modelling the Brazilian oil supply chain. The oil chain comprises 17 refineries, 3 large petrochemical plants, 16 crude oil units, 50 intermediate products, 10 finished products, 13 terminals, and a logistics network consisting of 278 transport arcs in terms of road, water, rail, and pipeline modes. The author created 27 distinct scenarios, each representing a unique combination of stochastic parameters.

Salehi et al. (2019) present a mixed robust-stochastic model for blood supply in the event of an earthquake disaster in Tehran. The demand for blood is simulated using scenarios generated for the active faults in Tehran, considering the possibility of each scenario occurring and its consequences (Salehi et al., 2019). Cheng et al. (2021) utilize a robust two-stage optimization approach to address a plant location problem under demand uncertainty, while also considering plant disturbances. The location decision is made in the first stage, and in the second stage, the decision is postponed until the uncertainty is revealed. Demand uncertainty is characterized by uncertainty sets.

A robust two-stage stochastic optimisation model for perishable products is proposed by Harati et al. (2021). The model results show that, in a perishable product supply chain, the supply cost, installation cost, vehicle supply cost, and production cost represent 55%, 28%, 3%, and 14% of the total cost, respectively. The demand is determined by a set of scenarios denoted as S. Kumar Tarei et al. (2022) presents a mean-variance robust optimization model for a multi-echelon, multi-product, multi-modality supply chain in the oil sector. The model considers multiple decision variables for each step in the supply chain design problem (upstream, midstream and downstream). Decisions are made from both strategic and tactical perspectives. To account for the various uncertainties, the author opted to generate a range of scenarios with different values for the uncertain parameters to solve the model. Guan et al. (2022) present a hybrid robust and stochastic approach for managing various uncertainties in fresh products supply chain design, including transport costs, demand, and clearance rate.

(Qi et al., 2023) proposes a two-stage robust optimization model for the supply of basic necessities under uncertainty. The model addresses the location and pre-positioning problem. In the first stage, the model considers the location of secondary warehouses and the pre-positioning of stocks of items prior to the disaster. The second stage considers the distribution plans for pre-positioned relief items and the procurement strategy from third-party manufacturers to serve affected customers. To model demand uncertainty, uncertainty sets are used. Escobar et al. (2023) introduced a methodology for designing a supply chain that considers strategic and tactical decisions.

In the context of collaborative supply chain design, Verdonck et al. (2016) introduce a facility location problem formulated as a mixed integer linear programme where the total cost is composed of facility opening cost and transportation cost. A 21.6% cost savings have been achieved when DCs are shared. The optimization problem developed by Tang et al. (2016) consists of finding the locations of intermediate logistics facilities and assigning customers to these facilities according to one year of historical data. The collaborative distribution network considers 4 suppliers, 1 consolidation distribution center and 29 potential regional distribution centers. Habibi et al. (2018) study hub location problem in collaborative context of two distribution networks belong to different supply chains. He et al. (2017) create a framework to locate a joint DC using different social, economic and environmental criteria. Ouhader and El Kyal (2017) investigated the potential economic, environmental and social impact of horizontal cooperation, combining facility location and routing decisions in an urban context. A reduction of 23.14% and 8.45% have been observed for total cost and CO_2 emissions, respectively.

Hacardiaux & Tancrez (2022) introduce location and inventory decisions to assess the benefits of cooperation in a joint supply chain. Hacardiaux & Tancrez (2022) present a collaborative location-inventory model which minimizes facility opening and transportation costs, as well as inventory costs and safety stock costs at distribution centers and at retailers. An average cost reduction of 22.4% is observed across all stages of the supply chain. Similarly, Hacardiaux & Tancrez (2020) propose a location-inventory where one of the main contributions remains the assessment of CO_2 emissions reduction in a joint supply chain. Results show that horizontal cooperation reduces CO_2 emissions by 16% on average (Hacardiaux & Tancrez, 2020). Hacardiaux et al. (2022) present an extensive study on multi-objective multi-partner logistics collaborations. Hacardiaux et al. (2024) propose a cooperative location–inventory model which accounts for the innovativeness level of the partners' products and the individuality of partners in terms of their influence to adapt the collaborative supply chain according to their preferences. An average cost reduction of 24.3% and 26.3% is observed for functional and innovative products, respectively.

The present paper has two main contributions. To the best of our knowledge, no other work focuses on robust collaborative supply chain design that implements both location and inventory decisions for the different stages of the supply chain (DCs, transportation and retailers). For that reason, this paper intends to provide a robust collaborative model that implements both location and inventory decisions. The model will be solved with optimization software packages. The other contribution is the managerial insights to assess how horizontal cooperation can lead to a more robust supply chain.

3. Robust collaborative location-inventory model

Since the aim of this paper is to evaluate the impact of robustness on total cost reductions (i.e. the benefits) when companies cooperate by using a joint supply chain, we will be presenting in this section, the notations, the strategic and operational decisions, and the CQMIP formulation of the model. The mathematical model employed is deeply inspired by the collaborative location-inventory model developed by Hacardiaux et al. (*2022*). For the present paper, the model created by Hacardiaux et al. (*2022*) will be redesigned to account for its resilience when faced with changing demands. The robust collaborative location-inventory model developed for this study integrate scenarios.

a. Notations

Sets and Indices

- $D = \{1 \dots N_D\}$: Set of potential distribution center (DC) locations indexed by d.
- $R = \{1 \dots N_R\}$: Set of retailers indexed by r.
- $I = \{1 \dots N_I\}$: Set of companies wishing to collaborate indexed by i.
- $S = \{1 \dots N_S\}$: Set of scenarios indexed by s.

Parameters

- F_d: Fixed cost for opening DC d 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 holding cost at retailer r for product i in €/(item · period).
- h_d^i: Unit holding cost at DC d for product i in €/(item · period).

- C_{dr}: Vehicle capacity from DC d to retailer r in items/vehicle.
- K_d^i: Fixed cost at DC d for an order to the plant of company i in €/order.
- z_α: Standard normal deviation associated with service level.
- 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.
- P_s: Probability of scenario s.
- λ_r^{is}: Mean demand for product i at retailer r in scenario s, in items/period.
- Λ_r^s: Mean demand for all products at retailer r in scenario s, in items/period.
- σ_r^{is}: Standard deviation of the demand for product i at retailer r in scenario s, in items/ period.
- q_{dr}^{is}: Shipment size for product i from DC d to retailer r in scenario s, in items/vehicle.
- Q_{dr}^s: Total shipment size from DC d to retailer r in scenario s, in items/vehicle.

Decision Variables

- $\mathrm{y_d} = 1$ if DC d is opened, 0 otherwise.
- $x_{dr}^s = 1$ if DC d serves retailer r in scenario s (for all products), 0 otherwise.
- v_{1d}^{is}, v_{2d}^{is} auxiliary variables for company i and DC d in scenario s.

b. Strategic and operational decisions

The robust collaborative location-inventory model incorporates both strategic and operational decisions. These two types of decisions are made sequentially. First the strategic decision and then the operational decision.

i. Strategic decisions

Strategic decision account for the first level of the supply chain (i.e. distribution centers). In the model, the strategic decision is made for the location of the distribution centers. The strategic decision is independent of the scenario and therefore will be the same for all scenarios. The location of DCs is made by the decision variable y^d. The strategic decision impacts the fixed facility cost of the joint supply chain which is formulated as follows:

$$\sum_d F_d y_d \tag{1}$$

ii. Operational decisions

The operational decision is responsible for the inventory allocation (i.e. which opened DC provides products to which retailer). The decision variable x_{dr}^{s} is used to represent operational decision and is dependent on scenarios. Scenarios are computed with P_s (i.e. the probability that a scenario s occurs) where $\sum_s P_s = 1$. In our case, the operational decisions account for different stages of the supply chain (transportation and retailers). In that sense, several main costs depend on operational decision (i.e. transportation cost, cycle inventory at retailers, cycle inventory at DCs, order cost at DCs and safety stock costs at DCs and retailers). The transportation cost accounts for all deliveries in the shared vehicles by the collaboration (Hacardiaux & Tancrez, 2022). The cost per delivery, T D_{dr} is multiplied by the number of deliveries per period, which is equal to the mean demand divided by the quantity of products a vehicle carries, $\frac{\Lambda_r^s}{Q_{dr}^s}$.

$$\sum_s P_s \sum_{d,r} T\, D_{dr} \frac{\Lambda_r^s}{Q_{dr}^s} x_{dr}^s \tag{2}$$

The cycle inventory at retailer r for company i in a scenario s depends on several terms. The unit holding cost (H_r^i), the average shipment size ($\frac{Q_{dr}^s}{2}$) and the delivery frequency of the vehicle ($\frac{\lambda_r^{is}}{\Lambda_r^s}$). The total cycle inventory cost at retailers is given by the following equation:

$$\sum_s P_s \sum_{d,r,i} H_r^i \frac{Q_{dr}^s}{2} \frac{\lambda_r^{is}}{\Lambda_r^s} x_{dr}^s \tag{3}$$

Likewise Hacardiaux & Tancrez (2022), the shipment size, Q_{dr}^s is not considered as a variable and it is computed a priori. The total shipment size is chosen to balance the transportation cost and the cycle inventory cost at retailers. Deriving the sum of the two costs, equaling it to zero, and accounting for the vehicle capacity (Hacardiaux & Tancrez, 2022).

$$Q_{dr}^{s} = \left(C_{dr}, \sqrt{\frac{2TD_{dr}\,\Lambda_r^s}{\sum_i H_r^i \frac{\lambda_r^{is}}{\Lambda_r^s}}} \right) \qquad \forall d, r, s$$

The cycle inventory and order cost at DCs for the cooperation is computed as follows:

$$\sum_{s} P_s \sum_{d,i} \sqrt{2K_d^i h_d^i\, v_{1d}^{is}} \tag{4}$$

Finally, the total safety stock costs at retailers and at DCs, for the collaboration is computed to consider the uncertainty in the demand. the demand follows a normal distribution and compute the safety stock level required to limit the probability of stockout, guaranteeing a (type 1) service level α (Hacardiaux & Tancrez, 2022). The unit holding cost is multiplied by the average safety stock, which is the standard normal deviation, z_{α}, times the standard deviation of the demand during the lead time, leading to the following formula (Hacardiaux & Tancrez, 2022).

$$\sum_{s} P_s \sum_{d,r,i} H_r^i z_{\alpha} \sigma_r^{is} \sqrt{LT_{dr}}\, x_{dr}^{s} + \sum_{s} P_s \sum_{d,i} h_d^i z_{\alpha} \sqrt{LT_d^i}\, v_{2d}^{is} \tag{5}$$

c. CQMIP formulation

The model is formulated as a conic quadratic mixed-integer program (CQMIP). The model can be solved with standard optimization software packages such as XPRESS. Several parameters and decision variables are sensible to the demand fluctuations. The parameters assumed to change for each scenario are λ_r^{is}, Λ_r^s, σ_r^{is}, Q_{dr}^s and P_s. Regarding the decision variables x_{dr}^s and the auxiliary variables $v_{1d}^{is}$and v_{2d}^{is} will be different for each scenario s. $v_{1d}^{is}$and v_{2d}^{is} are introduced to remove the non-linearities (7)-(8).

$$\begin{aligned} min \sum_d F_d y_d + \sum_s P_s \Bigg[\sum_{d,r} T\, D_{dr} \frac{\Lambda_r^s}{Q_{dr}^s} x_{dr}^s + \sum_{d,r,i} H_r^i \frac{Q_{dr}^s}{2} \frac{\lambda_r^{is}}{\Lambda_r^s} x_{dr}^s + \sum_{d,i} \sqrt{2K_d^i h_d^i}\, v_{1d}^{is} \\ + \sum_{d,r,i} H_r^i z_\alpha \sigma_r^{is} \sqrt{LT_{dr}}\, x_{dr}^s + \sum_{d,i} h_d^i z_\alpha \sqrt{LT_d^i}\, v_{2d}^{is} \Bigg] \end{aligned} \tag{6}$$

$s.t.$

$$\sum_r \lambda_r^{is} (x_{dr}^s)^2 \le \left(v_{1d}^{is}\right)^2 \quad \forall d, i, s \tag{7}$$

$$\sum_r \left(\sigma_r^{is}\right)^2 (x_{dr}^s)^2 \le \left(v_{2d}^{is}\right)^2 \quad \forall d, i, s \tag{8}$$

$$\sum_d x_{dr}^s = 1 \quad \forall r, s \tag{9}$$

$$x_{dr}^s \le y_d \quad \forall d, r, s \tag{10}$$

$$v_{1d}^{is}, v_{2d}^{is} \ge 0 \quad \forall d, i, s \tag{11}$$

$$x_{dr}^s, y_d \in \{0,1\} \quad \forall d, r, s \tag{12}$$

In the Eq. (6), the objective is to minimize the total costs for multiple stages of the supply chain (DCs, transportation and retailers) for all scenarios. The total cost is divided into several main cost components which are the DC opening cost, the transportation cost, the cycle inventory cost at retailers, the cycle inventory and ordering costs at DCs, safety stock costs at

DCs and retailers. The Constraints (7) – (8) defines the auxiliary variables $v_{1d}^{is}$and v_{2d}^{is}. Constraints (9) bound each retailer with at most one DC. Constraints (10) ensure that each retailer is served by an opened DC. Constraints (11) are the non-negativity constraints for both auxiliary variables v_{1d}^{is} and v_{2d}^{is}. Finally, Constraints (12) define x_{dr}^{s} and y^{d} as binary variables.

4. Computational results and analysis

This section examines the impact of robustness on the benefits of horizontal collaboration for a set of companies I, through a set of experiments, varying markets and partner characteristics. To provide a comprehensive evaluation of these benefits, it is necessary to undertake a comparison between the results of the robust collaborative model and those of a stand-alone case. The comparison will assist in determining whether it is more advantageous for a company to develop its own supply chain or to engage in collaborative efforts when demand changes. In that sense, Hacardiaux & Tancrez (*2022*) employ the synergy value to assess the financial benefits when companies cooperate. The synergy value is referred as the difference between the total stand-alone cost and the total collaboration cost divided by the stand-alone cost for all companies. The synergy value noted $SV(I)$ and developed by Hacardiaux & Tancrez (*2022*) is computed as follows:

$$SV(I) = \frac{[\sum_{i \in I} CostSA(i)] - CostCoop(I)}{[\sum_{i \in I} CostSA(i)]}$$

The set of all cooperating companies is noted I where each company $i \in I$. $CostSA(i)$ is the total cost for the stand-alone case for a company i. $CostCoop(I)$ is the total collaboration cost.

a. Experimental settings

Likewise Hacardiaux et al. (*2022*), the experiments are carried out to include two companies with the same size and market characteristics. The parameters that will be used throughout these experiments are summarized in Table 1. Forty-nine retailers locations are taken from the 49-node data set by Daskin (*2011*), which includes the 48 continental U.S. state capitals plus Washington DC (Hacardiaux et al., 2024). The retailers locations are also the possible locations for the distribution centers (Hacardiaux et al., *2024*). Distances are computed using the euclidean method (Hacardiaux & Tancrez, *2022*). The variability in the demand is introduced with the coefficient of variability noted CV. The service level follows a normal distribution and is fixed at 97.5 (z_α= 1.96). The transportation unit cost T equals 1 €/km. Two values are tested for each of the cost parameters F_d, K_d^i and H_r^i where $H_r^i = h_d^i$ (see Table *1*). The time horizon is one week. 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 plants to all DCs is fixed equal to the average lead time from all potential DC locations to all retailers (Hacardiaux & Tancrez, *2022*).

Furthermore, the loading rate is also an important benefit of horizontal cooperation. In that sense, sixteen preliminary experiments are carried out to compute the optimal vehicle capacity for each cost parameter combination. The vehicle capacity will be referred as a theoretical percentage of retailers which are not constrained by the vehicle capacity (Table *1*, noted Cap%) (Hacardiaux & Tancrez, *2022*). For example, when Cap% = 10, the capacity is highly restrictive: the first ten retailers will not be limited by the capacity meanwhile 90% of the retailers will be constrained by the capacity (Hacardiaux & Tancrez, *2022*).

Five scenarios are considered where the base demand changes. The expected demand for each product and each retailer is randomly generated within the interval [50, 250]. The five scenarios are then multiplied by factors noted (f_s); they are: {0.5, 0.75, 1, 1.25, 1.5}. The demand for each product and each retailer varies for each scenario in the same manner. Furthermore, scenario probabilities (P_s) are computed following different approaches. The first probabilities configuration is {0, 0, 1, 0, 0} noted PSS (i.e. the single scenario probability). This configuration represents the likelihood that demand is known and predictable. The three main probabilities configurations are as follows: {0.02, 0.18, 0.6, 0.18, 0.02}, {0.1, 0.2, 0.4, 0.2, 0.1} and {0.2, 0.2, 0.2, 0.2, 0.2}. These probabilities configurations account for small, moderate and large error in the prediction of the demand which will be designated throughout the rest of the paper PS, PM and PL, respectively. Finally, two additional probabilities configurations will be considered in cases where companies have disparate sizes, they are: {0.02, 0.18, 0.4, 0.2, 0.2} and {0, 0.1, 0.3, 0.3, 0.3} and will be named PA and PB, respectively.

Overall, the parameter values, including the cost parameters, the six probabilities configurations and the stand-alone cases lead to 2 * 2 * 2 * 4 * 6 * 3 = 576 experimentations. The model is implemented in XPRESS and executed on 16 computers with 3.2 GHz and 16 GB of RAM. Computational experiments are stopped when the optimality gap is under 1% or when the computational time reaches six hours. The average optimality gap for stand-alone and cooperation are 0% and 5.16%, respectively. A detailed table of the gap for each cost parameter combination and for each probabilities configurations can be found in the appendices (see Table 5).

Parameter Setting	
Demand parameters	
CV	0.7
α	97.5%
z_α	1.96
Cost parameters	
Cap%	(10, 40, 70, 100)
F_d	(1000, 4000) €/week
K_d^i	(250, 1000) €/order
$h_d^i = H_r^i$	(0.25, 1) €/item · week

Table 1: Parameter values used for the computational experiments.

b. Single scenario configuration

In this section, the PSS configuration (i.e. single scenario probabilities configuration) is analyzed and will be compared with the other probabilities configurations (i.e. PS, PM and PL) in the managerial insights section.

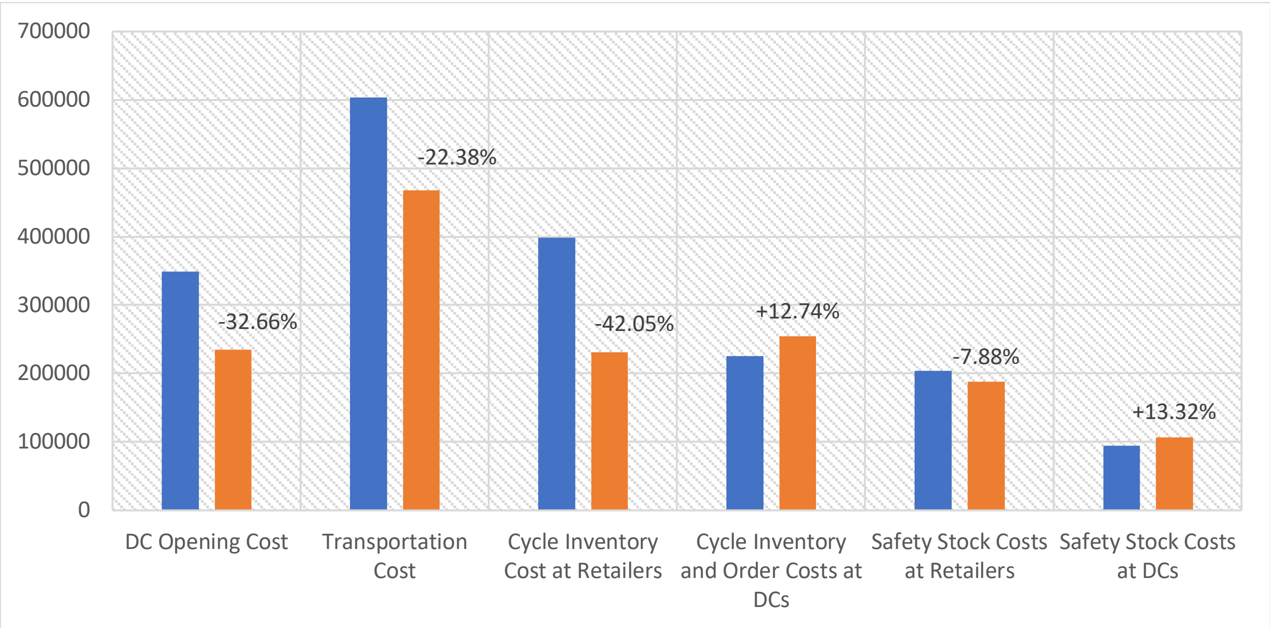


Fig.1: Repartition of the average total costs into each cost component when companies are stand-alone versus when they cooperate for the PSS configuration. The percentage are the average synergy value for each cost component.

In term of total cost reduction, the average synergy value for PSS is 20.89% which depicts significant cost reduction when companies cooperate. Regarding the individual instances, the synergy value varies from 11.87% to 28.22% depending on the parameter combinations. Several sources of benefits can be identified in all the stages of the supply chain (DCs, transportation and retailers).

Firstly, at DCs level, As seen in Fig.1, when companies cooperate, the DC opening cost is reduced by 32.66% on average. 3.68 DCs are opened on average, compared to 2.8 DCs for each stand-alone (5.65 in total for both companies). Each company that collaborates has access to more DCs while reducing the number of DCs compared to the total number of DCs for all companies. The DC opening cost contribute to 6.8% of the average synergy value (20.89%). However, the fact that each company has more access to DCs leads to an increase of 12.74% of the order cost and the cycle inventory at DCs. Also, in cooperation, the safety stock costs at DCs increase by 13.32%. Oder cost and cycle inventory at DCs account for 6.12% of the average synergy value meanwhile the safety stock costs at DCs account for 2.78%.

Secondly, at the transportation level, DCs are better distributed, reducing the distances to the retailers by 11.55% on average. Vehicles are also better loaded, the loading rate on average is also increased in collaboration going from 89.88% to 96.23% for the stand-alone and the collaboration, respectively. Furthermore, each company in the collaboration benefits from having a higher delivery frequency (+86% on average for each company and +5.71% in total) when vehicles are shared. The transportation cost is reduced on average by 22.38% and account for 6.82% of the average synergy value.

Thirdly, at the retailer level, less cycle inventory is needed. Since vehicles are shared, retailers carry less cycle inventory. On average, cycle inventory is reduced by 42.05% and it contributes to 8.78% of the average synergy value. Also, retailers carry less safety stock costs (-7.88%) when companies cooperate. This can be explained by the increased number of opened DCs available for each company of the cooperation but also by the reduced distances between DCs (-11.55%) since DCs are better distributed.

In conclusion, the cooperation between companies in the single scenario solutions brings a significant cost reduction (20.89%), each company has access to more opened DCs, DCs are better distributed, vehicles are better loaded, and retailers are more frequently delivered.

c. Managerial insights

In this section, the results of our experiments are analyzed based on the synergy value. This section begins with an analysis on the synergy value. Subsequently, the results for the various probabilities configurations (PS, PM, PL) are compared with PSS to derive insights for managerial practice. Finally, an analysis on additional experiments will be conducted to conclude the managerial insights.

i. Synergy value analysis

In our experiments, the average synergy value is 20.89%, 34.43%, 32.44% and 32.21% for PSS, PS, PM and PL, respectively. The synergy value varies significantly on the individual instances, depending on the parameter combination from 11.87% to 41.92%. The findings illustrate the significant cost savings that can be achieved through horizontal collaboration. Fig.2 shows the variation of the average synergy value for each probabilities configuration. The cost reductions are on average significantly increasing for all the probabilities configurations (+12.12% on average) compared to PSS.

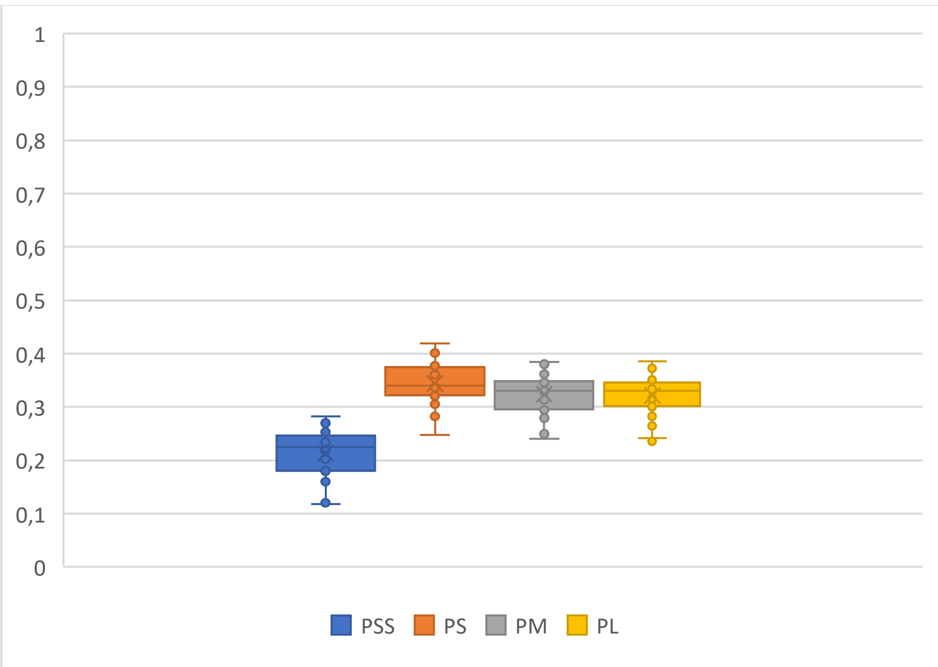


Fig.2: The average synergy value for each probabilities configuration (PSS, PS, PM and PL).

Several sources of benefits can be outlined. For each probabilities configuration, companies have access to more opened DCs and the total amount of DCs is lowered. The number of shared DCs on average is 4.78, 4.96 and 5.15 respectively for PS, PM and PL whereas in total without collaboration the number of DCs is 5.78. Vehicles are better loaded, the loading rate on average for each configuration is increased from 87% to 95.74% for standalone and collaboration, respectively. More vehicles are fully loaded in cooperation, the number of full vehicles has tremendously increased by 325.96% on average compared to PSS.

To further examine the close average synergy values across different probabilities configurations (PS, PM and PL), we conducted a more detailed analysis based on scenarios. The Fig.3 depicts the total costs for the five scenarios for each probabilities configuration (PS, PM and PL) compared to the expected costs.

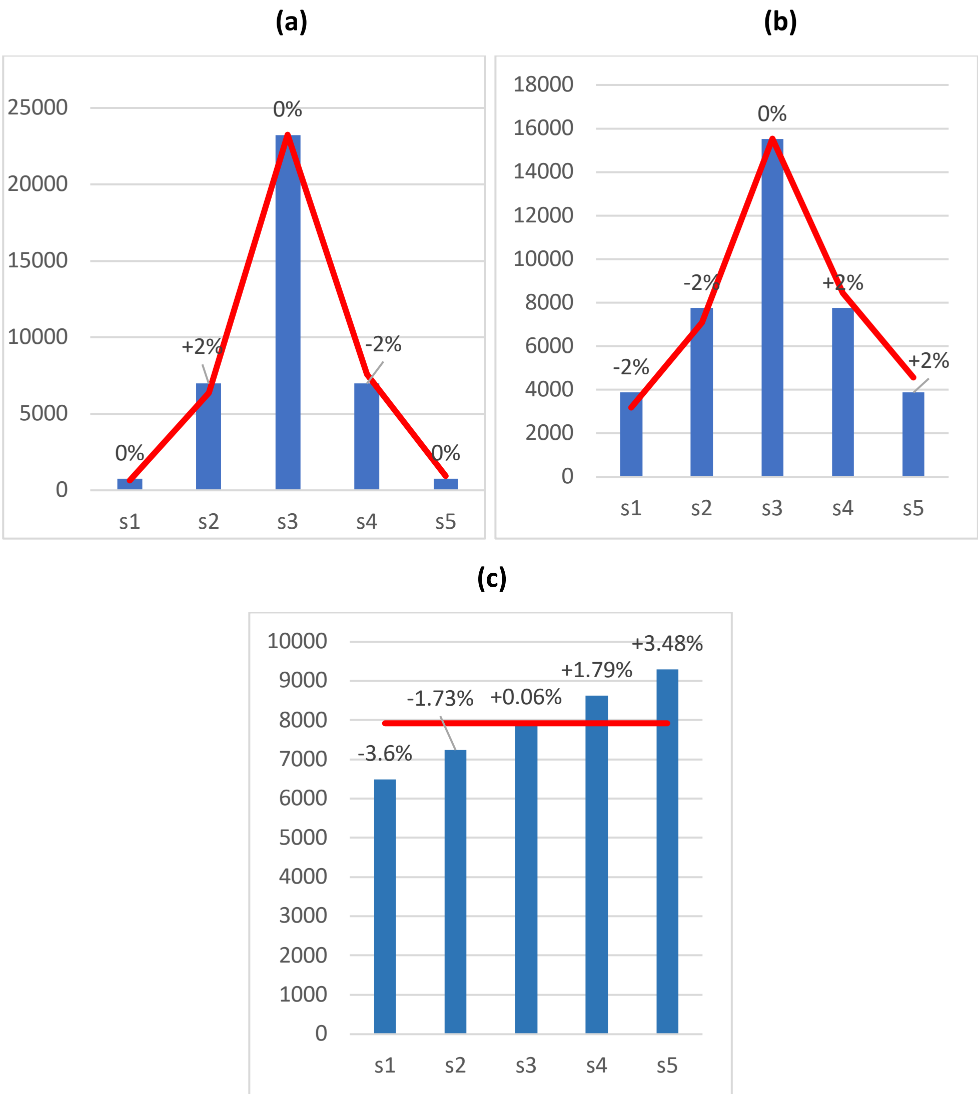


Fig.3: (a) the average total cost for each scenario and for the probabilities configuration (PS). (b) the average total cost for each scenario and for the probabilities configuration (PM). (c) the average total cost for each scenario and for the probabilities configuration (PL). The values are average over 32 instances (for each F_a, K_d^i, H_r^i and probabilities configuration). The red curve is the expected value for each probabilities configuration.

After looking at the total costs for each scenario, we observe that the total costs for each probabilities configuration is compensated through the five scenarios. Fig.*3.a* shows the average total cost for each scenario and for PS. In this case, scenario 4 (-2%) offsets the increase in total cost for scenario 2 (+2%). In Fig.*3.b*, scenarios 4 and 5 gain 2% compared to the expected costs, while the average total costs of scenarios 1 and 2 decrease by 2%. In Fig.*3.c*, for PL, the compensation is more significant. the cost reduction of scenarios 1 and 2 is 5.33%, which is compensated by scenarios 3, 4 and 5.
Several conclusions can be drawn, the greater the error in predicting demand, the higher the compensation would be. The compensation for PS, PM and PL is 2%, 4% and 5.33%, respectively. Also, the robust collaborative model is spreading the total costs into the five main scenarios for each parameters combination which is why for a specific parameter combination, we get close total costs therefore, close synergy values for different probabilities configurations.

ii. Distribution centers

The cost of opening DCs increases significantly as demand is less predictable. For small, medium and large error in prediction, the cost of opening DCs increases by 18.7%, 18.7% and 22.53% respectively compared to the PSS configuration and contributes to 9.49%, 10.43% and 8.93% of the synergy value compared to PSS with 7.68%. In terms of proportion, PM, PS and PL, in that order, have the most significant opening DCs cost on average with 21.6%, 20.28% and 18.41%, respectively. For each probabilities configuration, companies have access to more opened DCs and the total amount of DCs is lowered. They open on average 2.62, 2.5 and 2.56 DCs to share the fixed opening cost meanwhile independent companies use 3.43, 3.56 and 3.5 DCs in total for PS, PM and PL, respectively (see table *2*). DCs are better distributed. On average, compared to PSS, distances between DCs are reduced by 20.67%, 18.22% and 20.22% for PS, PM and PL, respectively. As seen in the Fig.*4*, compared to the single scenario configuration, safety stock costs at DCs increase progressively when the demand becomes less predictable. The average synergy value for safety stock costs at DCs is around 70% (70.87%, 70.43% and 69.68% for PS, PM and PL). The average synergy values for the cycle inventory and order costs at DCs for each probabilities configuration are 0.05%, -0.07% and -4.16% for PS, PM and PL, respectively. For cycle inventory and order costs at DCs, it is therefore better to have a separate supply chain when demand becomes less predictable. Compared to PSS, the cycle inventory and the order costs at DCs are significantly increasing from 14.81%, 16.46% and 19.21% for PS, PM and PL, respectively.

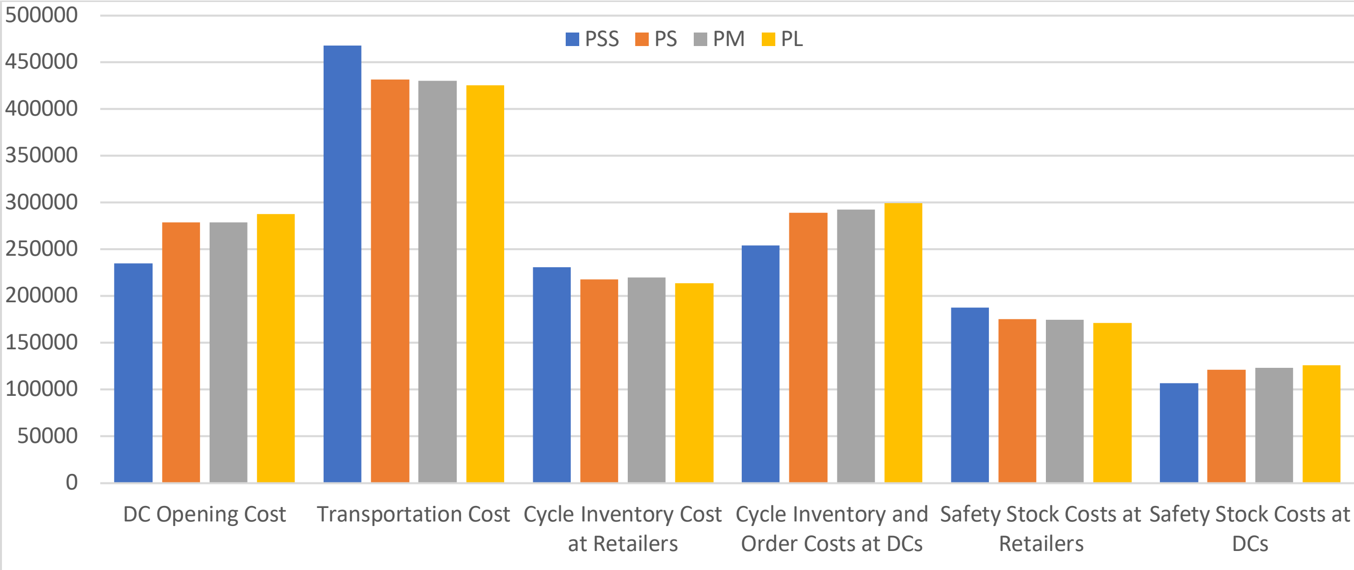


Fig.4: Repartition of the average total costs into each cost component for PSS, PS, PM and PL.

As seen in the Table 2, collaboration is more beneficial for companies with high fixed cost for opening DCs for each probabilities configuration. Also, companies that have a low order cost benefits more from the cooperation.

In conclusion, when demand changes, companies have more access to DCs, DCs are better distributed. Companies benefits more when the fixed facility cost is high and the order cost is low. When demand becomes more unpredictable, companies should not collaborate in term of cycle inventory and order costs at DCs.

Table 2: Average synergy value, average loading rate and average number of DCs for stand-alone and cooperating companies, when Fixed cost for DC opening (F_d) and Fixed cost for an order (K_d^i) are varied. The value on the table corresponds to PS (right|), PM (|center|) and PL (|left), respectively.

Parameters	F_d		K_d^i		*Avg.*
	1000	4000	250	1000	
Synergy Value	32.92 | 30.55 | 30.13	35.94 | 34.33 | 34.12	35.09 | 33.73 | 33.60	33.78 | 31.15 | 30.65	34.43 | 32.44 | 32.12
Number of DCs Alone	8.12 | 8.00 | 8.06	3.43 | 3.56 | 3.50	6.37 | 6.31 | 6.37	5.18 | 5.25 | 5.18	5.78 | 5.78 | 5.78
Number of DCs Coop	6.93 | 7.43 | 7.75	2.62 | 2.50 | 2.56	5.25 | 5.18 | 5.18	4.31 | 4.75 | 5.12	4.78 | 4.96 | 5.15

iii. Transportation

The transportation level has two main goals, First reduces the financial cost and secondly increase the loading rate as vehicle are shared in cooperation. In term of synergy value, the transportation cost is quite stable with an average synergy value of 29.19%%, 28.50% and 29.78% for PS, PM and PL, respectively. In terms of cost reduction, as seen in the Fig.3, the transportation cost is decreasing when demand is more unpredictable. Compared to PSS, the transportation cost is reduced by 7.79%, 8.13% and 9.16% for PS, PM and PL, respectively. This contribution can be explained in two ways. Firstly, in cooperation, since DCs are better distributed, the distances are reduced by 20.67%, 18.22% and 20.22% for PS, PM and PL compared to the PSS which leads to reduced transportation cost. Secondly, in cooperation, regardless of the unpredictability of the demand, the loading rate is always improved when companies decide to cooperate (+8.74%) on average. We observe that small to middle-sized companies (cap%=10 and cap%=40) tend to have the best loading rate in cooperation (99.89% and 99.00% for cap% = 10 and cap% = 40 respectively). Also, for each probabilities configuration, the average gap between loading rate alone and in cooperation is increasing when the vehicle capacity increase. For example, when Cap% = 10, the gap between alone and cooperation is not important (2.28%) but when Cap% = 100, the difference between alone and cooperation is significant (18.11%). The decreasing loading rate as cap% increases can be explained by a lower number of full vehicles in cooperation (-45.91% from cap% = 10 to cap% = 100).

Regarding the direct relationship between cap% and synergy value, we observe a correlation of 94.50% between these two variables which make us consider that larger companies (cap% = 100) tend to benefit more from cooperation (see table 3).

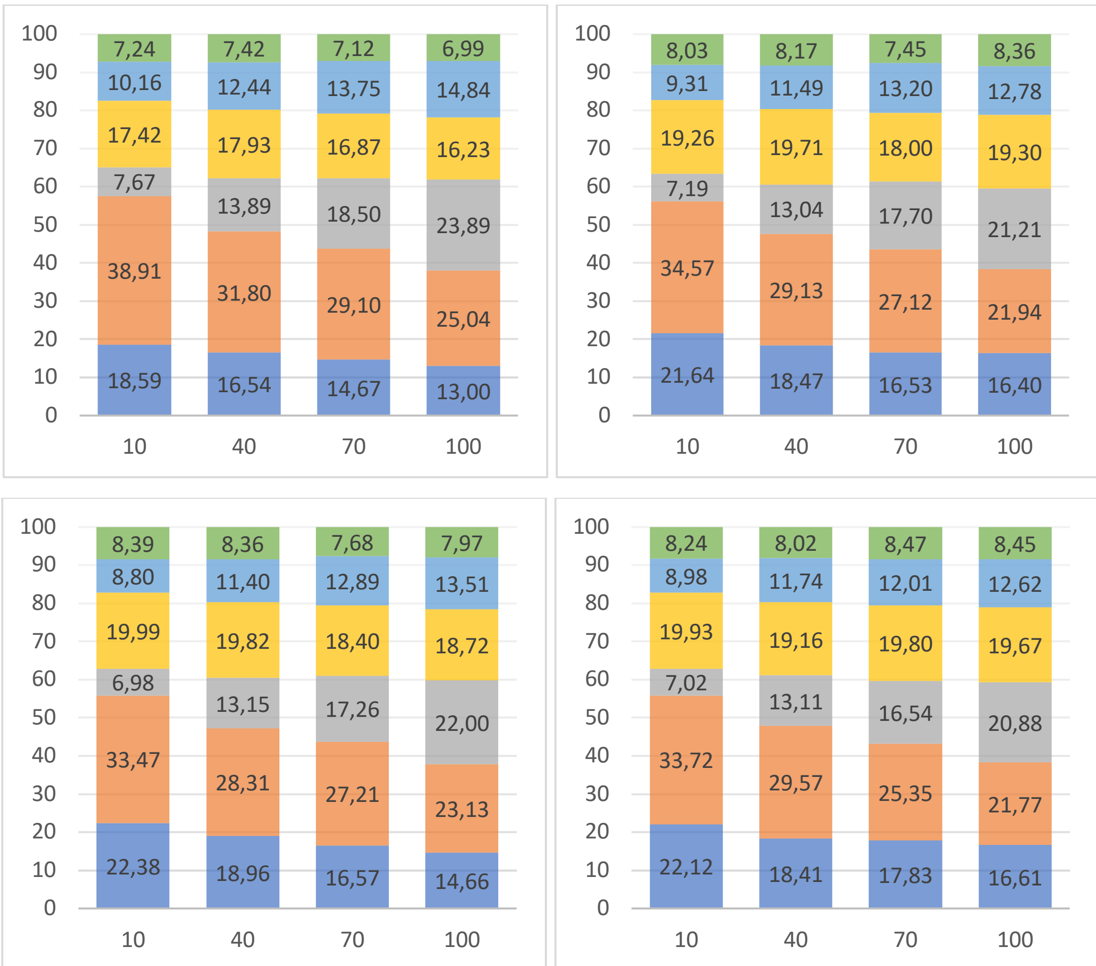
Table 3: Average synergy value, average loading rate and average number of DCs for stand-alone and cooperating companies, when the capacity percentage (cap%) is varied. The value on the table corresponds to PS (right|), PM (|center|) and PL (|left), respectively.

Parameters	*Cap%*				*Avg.*
	10	40	70	100	
Synergy Value	31.92 | 28.97 | 28.67	34.15 | 32.52 | 32.40	35.65 | 33.68 | 33.11	36.01 | 34.60 | 34.32	34.43 | 32.44 | 32.12
Number of DCs Alone	7.25 | 7.62 | 7.50	5.87 | 5.62 | 5.87	5.12 | 5.00 | 5.00	4.87 | 4.87 | 4.75	5.78 | 5.78 | 5.78
Number of DCs Coop	6.25 | 6.75 | 6.62	5.00 | 5.12 | 4.87	3.62 | 4.12 | 4.75	4.25 | 3.87 | 4.37	4.78 | 4.96 | 5.15

To further the discussions about cap%, Fig.5a, 5b, 5c and 5d depict the evolution of the synergy value and the portion of each cost component as a function of the cap% for each probabilities configuration. Fig.5a is used to compare the repartition of the costs with Fig.5b, 5c and 5d. As seen in Fig.5a, 5b, 5c and 5d, we observe that transportation cost in cooperation takes the biggest proportion of the total costs. For instance, for small companies (when cap% = 10), the proportion of the transportation costs tend to decrease when demand is less predictable (going from 38.91% of the total costs to 34.57%, 33.47% and 33.72 for PS, PM and PL, respectively). Overall, when demand is less predictable, the transportation costs tend to take less importance in proportion.

In conclusion, when demand is less predictable, transportation cost is reduced. Distances between DCs are shortened, the loading rate is increasing when companies cooperate, smaller companies benefit from cooperation by having better loading rate, larger companies tend to benefit more of the cooperation.

(a) (b)



(c) (d)

Fig.5: (a) repartition of each cost components based on cap% (10, 40, 70 and 100) for PSS. (b) repartition of each cost components based on cap% (10, 40, 70 and 100) for PS. (c) repartition of each cost components based on cap% (10, 40, 70 and 100) for PM. (d) repartition of each cost components based on cap% (10, 40, 70 and 100) for PL.

iv. Retailers

At retailer level of the supply chain, when the cooperation is pertained, retailers see their cycle inventory decreases when demand becomes unpredictable. Compared to PSS, cycle inventory is less needed (-5.65%, -5.00% and -7.57% for PS, PM and PL, respectively) (see Fig.3). In terms of synergy value, cycle inventory is quite stable with an average synergy value of 44.39%, 43.63% and 44.61% for PS, PM and PL, respectively.

Overall, companies with higher unit holding cost tend to benefit more from cooperation regardless of the changes in demand (36.33%, 32.93% and 32.53% for PS, PM and PL) (see table 4). When the unit holding cost H_r^i, increase from 0.25 to 1, the number of DCs accessible for retailers increases by 96% on average when companies cooperate.

Delivery frequency is also another benefits that companies gain from cooperation at retailer level. When companies cooperate, retailers are more often delivered. On average, when companies cooperate, retailers are visited 24 times more often when demand fluctuates meanwhile retailers are visited 9 times more often in total when companies does not cooperate compared to PSS. When vehicles are shared, products for each retailer are delivered in lower quantities but more frequently which reduce the need to have more cycle inventory at retailer level.

Regarding safety stock costs at retailer level, as seen in the Fig.3, safety stock costs decrease when the demand is less predictable. This can be explained by a higher number of DCs and reduced distances between DCs. Safety stock costs at retailers contribute to 3.76%, 3.70% and 4.36% of the average synergy value for PS, PM and PL, respectively.

In conclusion, when demand becomes less predictable, cycle inventory at retailers decreases, retailers are delivered significantly more frequently. Companies benefit more when the unit holding cost is high. Higher number of DCs and reduced distances in cooperation increase the safety stock costs.

Parameters	$h_d^i = H_r^i$		*Avg.*
	0.25	1	
Synergy Value	32.54 | 31.95 | 31.72	36.33 | 32.93 | 32.53	34.43 | 32.44 | 32.12
Number of DCs Alone	4.75 | 4.62 | 4.68	6.81 | 6.93 | 6.87	5.78 | 5.78 | 5.78
Number of DCs Coop	3.43 | 3.18 | 3.43	6.12 | 6.75 | 6.87	4.78 | 4.96 | 5.15

Table 4: Average synergy value, average loading rate and average number of DCs for stand-alone and cooperating companies, when the capacity percentage (cap%) is varied. The value on the table corresponds to PS (right|), PM (|center|) and PL (|left), respectively.

v. Additional results

Several conclusions can be drawn when companies of disparate sizes engage in cooperative activities. We observe an average synergy value of 29.21% and 23.37% for PA and PB respectively. The synergy values for each parameter combinations ranges from 14.67% to 40.78%. In cooperation, it can be observed that the average synergy value declines as the discrepancy in demand between the two companies increases.

In terms of proportion, as illustrated in Fig.6, the distribution of each cost component remains relatively stable regardless of the size of the companies that are engaged in collaborative efforts. However, in comparison to the stand-alone case, several cost components appear to vary.

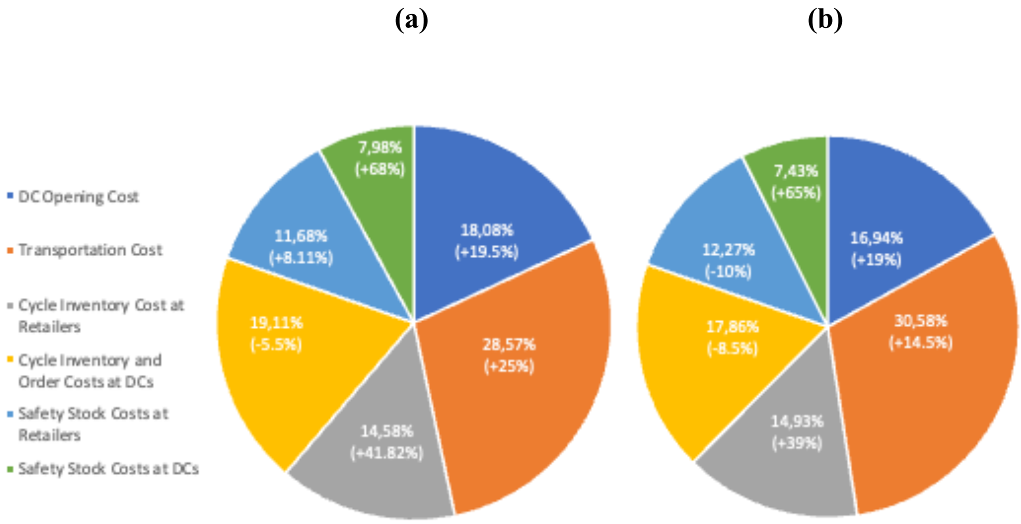


Fig.6: (a) Repartition of each cost component for PA. (b) Repartition of each cost component for PB. The percentages in parentheses are the average synergy value for each cost component.

At DC level, in cooperation with companies of different sizes, companies have access to more DCs while reducing the total number of opened DCs. Companies that cooperate share on average 4.78 and 4.25 DCs compared to 5.63 and 5.19 in total when companies do not cooperate for PA and PB, respectively. The average synergy value for DC opening cost remains roughly the same regardless of the size of the companies cooperating (19% and 19.5% for PA and PB, respectively).

In cooperation, the average synergy value for order and cycle inventory costs decreases (from -5.5% to -8.5% for PA and PB, respectively). Companies that cooperate benefit significantly more in safety stock costs with an average synergy value of 68% and 65% for PA and PB respectively.

At the transportation level of the supply chain. A notable decline in the average synergy value for the transportation cost can be observed going from 25.70% to 14.51% for PA and PB respectively (see Fig.*6*). This significant decrease can be explained by the increase in distances (+65.34% from PA to PB) which imply that DCs are poorly distributed when the discrepancy between two companies becomes larger. Compared to stand-alone case, the number of full vehicles is significantly decreasing when companies with different sizes cooperate (-289% and -328% for PA and PB in that order).

Meanwhile at retailer level, the size of companies that cooperate have an impact on safety stock costs. The discrepancy in demand between the two companies in question has been observed to result in a decline in the average synergy value of safety stock costs, with a decrease going from 8.11% to -10%.

Retailers are on average less visited when companies have different sizes, the number of deliveries significantly decrease compared to stand-alone case (-147% and -153% for PA and PB respectively). As the discrepancy between companies become larger, retailers tend to carry less cycle inventory in cooperation. As illustrated in Fig.*6*, For retailers, the cycle inventory is the same proportionally while the average synergy value is decreasing going from 41.82% to 39% (for PA and PB respectively).

In conclusion, when companies of different sizes decide to cooperate, it is still beneficial for companies to cooperate, companies have access to more DCs while reducing the total number of DCs, DCs are poorly distributed compared to the stand-alone cases, retailers are less visited, safety stock costs at retailers decline when the discrepancy between both companies increase. Finally, as the discrepancy in demand between the two companies increase, the cooperation becomes less beneficial.

5. Conclusion

The main objective of this paper is to assess the impact of robustness over the benefits that horizontal cooperation can provide to companies. For that matter, a robust collaborative model has been developed involving strategic and operational decisions. The model is developed to consider the different stages of the supply chain (DCs, transportation and retailers) and is formulated as a conic quadratic mixed-integer program (CQMIP) (see Sect.*3c*). Different main costs have been integrated: DCs opening cost, order cost at DCs, cycle inventory cost at DCs, safety stock costs at DCs, transportation cost, cycle inventory costs at retailers and safety stock costs at retailers. The loading rate is another important objective of the horizontal cooperation. Computational experiments have been carried out to include 49 retailers, 2 companies and 5 scenarios. The average optimality gap for stand-alone and cooperative are 0% and 5.16%, respectively (see Sect.*4*).

In (Sect.*4a*), a detailed analysis of the single scenario configuration have been performed to help infer valuable managerial insights. For the different probabilities configurations, we observe in Sect.*4b*, an average synergy value of 20.89%, 34.43%, 32.44% and 32.21% for PSS, PS, PM and PL, respectively.

(Sect.*4c.i*) shows that the more unpredictable the demand, the higher the compensation would be. The compensation for PS, PM and PL is 2%, 4% and 5.33%, respectively. Also, the robust collaborative model is spreading the total costs into the five main scenarios for each parameters combination which is why for a specific parameter combination, we get close total costs therefore, close synergy values for different probabilities configurations.

In (Sect.*4c.ii*, *4c.iii* and *4c.iv*), the four main probabilities configurations (i.e. PSS, PS, PM and PL) are compared to assess whether having a robust supply chain through collaboration is beneficial for companies. Several conclusions have been drawn. At DC level, companies have more access to DCs, DCs are better distributed. Companies benefits more when the fixed facility cost is high, and the order cost is low. Distances between DCs are shortened, the loading rate is increasing when companies cooperate, smaller companies benefit from cooperation by having better loading rate, larger companies tend to benefit more of the cooperation. Retailers are delivered significantly more frequently. Companies benefits more when the unit holding cost is high.

Finally, additional results (Sect.*4c.v*) have been carried out to analyze the impact of companies of different sizes cooperating. When companies of different sizes decide to cooperate, it is still beneficial for companies to cooperate even though companies with the same size tend to benefit more of the cooperation when demand fluctuates, companies have access to more DCs while reducing the total number of DCs, DCs are poorly distributed compared to the stand-alone cases and retailers are less visited.

6. Appendices

Parameters	F_d		H_r^i		K_d^i		*Cap%*				*Avg.*
	1000	4000	0.25	1	250	1000	10	40	70	100	
PSS	0	0	0	0	0	0	0	0	0	0	0
PS	7.60	3.96	4.65	6.92	4.36	7.21	4.06	7.25	6.67	5.15	5.78
PM	8.62	5.79	5.17	9.23	5.23	9.18	6.22	8.32	6.57	7.70	7.20
PL	8.48	5.25	5.49	8.24	4.81	8.92	7.64	8.39	5.75	5.68	6.86
PA	8.08	6.06	6.39	7.75	4.63	9.51	7.12	7.53	7.48	6.15	7.07
PB	4.58	3.50	3.93	4.18	2.08	6.17	3.01	4.10	3.52	5.82	4.06

Table 5: Average gap percentage for different cost parameters and different probabilities configuration.

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