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An aided decision framework based on optimisation and game theory for a green and shared vehicle routing problem

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Abstract: We introduce an aided decision framework for co-opetition, i.e., collaboration of competitor companies, in food distribution by considering the economic and environmental advantages of it. We show the benefits and issues related to co-opetition of the retailing companies in food distribution networks. The mathematical model indicates major financial and environmental improvements through increasing the filling rate of the trucks and reducing the number of trucks used in the logistics network as a result of co-opetition of the companies. The results are based on a case study of a food distribution network serving three retailers. This paper provides practical facts which might be useful for the logistics managers of the food retailing companies. The sustainable environmental benefits of co-opetition through the lens of cooperative game theory are investigated.

Keywords: food distribution; collaboration; co-opetition; economic; environmental.

1. INTRODUCTION

A way for improving the filling rate of vehicles is the collaboration of companies through sharing the vehicles used for transporting their goods (Newing, 2008), as a form of inter-organisational collaboration in the supply chain (Barratt and Oliveira, 2001; Wagner et al., 2002). The phenomenon of cooperation among competing firms as a form of collaboration, known as co-opetition (Bengtsson et al., 2010), has gained considerable attention by academics and practitioners in the last decade. Co-opetition can be used as a solution for collaborative transportation management in logistics networks when the companies who share trucks are seen as competitors, i.e., they provide the same types of products to the final consumers in the market. Although different examples of co-opetition are introduced in marketing and manufacturing literature (see Bengtsson and Kock (2000); Hingley et al. (2015); Osarenkhoe (2010)), in logistics and supply chain management areas the co-opetition is not elaborated appropriately and documented cases of co-opetition in supply chain and logistics are scarce.

This paper is studying a vegetable distribution network, in which three retailers are cooperating by sharing trucks distributing vegetables from the DC (Distribution Centre) to their stores and on the other hand compete on the sold items to the final consumers. The research devel-

ops a framework for co-opetition in food distribution by considering distribution planning based on reducing emissions and also reducing costs. The first component of this framework is based on a mixed integer linear programming (MILP) model optimizing both indicators through centralized planning. Second, meaning several sharing strategies, we investigate saving costs for each retailer in order to highlight the taken advantage of co-opetition.

The paper is organised as follows. Section 2 presents the problem statement, while Section 3 discusses the mathematical model for optimising the environmental and economic performance of the network based on different distribution planning proposals. The used cost sharing mechanisms are presented in Section 4. The distribution network is introduced in the case study section, which is Section 5. The results of the analysis are discussed in Section 6. Section 7 concludes the paper. Most of the publications on improving truck utilisation in logistics and supply chain management focus on the economic dimension. The induced environmental improvements are started to be considered in recent works. Vehicle Routing Problems (VRP) incorporating CO₂ emissions are studied by Özener (2014); Pérez-Bernabeu et al. (2015); Sanchez et al. (2016). Özener (2014) studies a VRP where transportation and environmental costs are optimised and induces allocations in terms of these costs and CO₂ emissions for up to 50 players. The paper's input data are however randomly generated. Pérez-Bernabeu et al. (2015) find a median of 23% of CO₂ emissions reduction for the Multidepot VRP (MDVRP), by using classical MDVRP benchmark

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instances, which are also randomly generated. Sanchez et al. (2016), similarly as Özener (2014), incorporate environmental costs in the optimisation of the VRP with time windows (VRPTW), before computing allocations and emissions reductions according to the Shapley value. Their instances draw from Solomon’s library (Solomon, 2003).

Providing CO₂ emissions based on real-life data are still lacking in game theory-based co-opetition approaches, with the notable exception of Zhu et al. (2016). The VRPs accounts in the literature incorporating CO₂ emissions use mostly randomly generated data for those costs, e.g. Özener (2014); Pérez-Bernabeu et al. (2015); Sanchez et al. (2016). Assessments using simulated data may not reflect the actual emissions reductions that could be implemented by competitive companies. The current article aims to fill this gap by incorporating environmental costs within the optimisation and producing reliable gaps based on ground collected dataset in the food distribution.

2. PROBLEM STATEMENT

In this section, we describe the studied problem before formulating its VRP based mixed-integer model. We consider the problem of co-opetition between shippers/retailers (or carriers if the transportation activity is subcontracted) in a logistics origin-destination network. Here origin is a supplier and destination is a customer. Two variant formulations are developed: an isolated scenario where each shipper (retailer) only serves the set of its affiliated customers/stores and a centralised collaboration based scenario where a centralised authority constructs a solution for all shippers at once and then allocates costs and profits on them. To show the benefits of the collaboration, we perform a case study of 3 retailers distributing vegetables from a central distribution centre (supplier) to their own warehouses called her customers. The data is collected through conducting interviews and also reviewing the documents of the companies. The data gathered about the operations of the company is modelled to identify the optimal solutions for distribution considering the cost and emission as main parameters.

In Danloup et al. (2015), we proposed a mixed-integer linear programming model, which minimises total CO₂ emissions. We propose two extensions in the present paper. First, adding to total CO₂ emissions, we consider the total transportation cost. Second, we include in the total transportation cost the penalty fees when the window time is not respected. By doing it we can see the effects of co-opetition based strategies for reducing emissions on the total cost of transportation in food distribution networks.

Problem description. The purpose of the collaborative shippers/retailers is to group their shipments such that to propose a full truckloads shipment to a carrier. The description of the problem is given by the following sets:

- i/ \mathcal{O} : the origin nodes or the suppliers.
- ii/ \mathcal{D} : the destination nodes or the customers. Suppliers and customers are considered to be distinct ($\mathcal{O} \cap \mathcal{D} = \{\emptyset\}$).
- iii/ \mathcal{A} : the possible connections between \mathcal{O} and \mathcal{D} . There are three possible arcs: arcs between suppliers, be-

tween customers, and arcs going from suppliers to customers. The sets \mathcal{O} , \mathcal{D} , and \mathcal{A} define the problem graph $G = (\mathcal{O} \cup \mathcal{D}, \mathcal{A})$.

- iv/ \mathcal{V} : the set of heterogeneous vehicles. Each vehicle of \mathcal{V} has a capacity Q , starts at a supplier node and ends its route at a customer.
- v/ \mathcal{K} : the set of commodities.

The demand requests are defined by three elements: a pair of $(o, d) \in \mathcal{O} \times \mathcal{D}$, a commodity of $k \in \mathcal{K}$, and the related volume of k . For each commodity and a pair of nodes, there is only one request. All requests can be split between several vehicles.

Two kinds of time windows are taken into account. First, on the supplier side, time windows are hard. The vehicle visiting a given supplier has to arrive in the corresponding time slot, otherwise if arriving before, it has to wait. For the customers, the time windows are soft. A vehicle can’t arrive before the minimum hour but it can wait. It can arrive after the maximum hour, but a penalty fee has to be paid. The penalty cost we choose is the transportation cost from the supplier to the customer concerned. This penalty cost is also linear to the probability of refusing the vehicle. To do that, we consider two delays, A^{max} and L^{max} . If the vehicle arrives before A^{max} , the probability of refusing the vehicle is null. If the vehicle arrives between A^{max} and L^{max} , the probability increases linearly from 0 to 1. And if the vehicle arrives after L^{max} , the probability of refusing the vehicle is 1. This probability is represented in the model by a penalty coefficient. The service time in a supplier or a customer is linear with the quantity of products to load or unload.

The problem’s aim in our study is to compare the benefits of collaboration when minimizing the CO₂ emission due to transport and when minimizing costs. The emissions are relative to the load factor of the vehicle and the distance travelled (Pan et al., 2013; EcoTransIT World Initiative, 2022). The costs are the addition of transportation costs, linear to the distance, and the penalty fees. We do not minimize both costs and emissions at the same time.

Assumptions. The main assumptions we consider in the isolated routing problem are:

- (1) Each retailer r solely considers the set of its affiliated suppliers O_r and customers D_r in the optimisation.
- (2) The transportation and environmental costs of each retailer result from his own optimisation.

Concerning the centralised routing problem, the considered assumptions are:

- (1) All suppliers $O = \cup_r O_r$ and customers $D = \cup_r D_r$ are considered in the optimisation formulation.
- (2) The allocation of the transportation and environmental costs among retailers are made according to the mechanisms of cooperative game theory by a central authority, i.e., the optimiser.

Both isolated and centralised variants of the food delivery problem solve the same mathematical formulation. Only the set of considered suppliers and customers differ. For the cooperative case, a centralised planning is imposed. Collaborative decisions are performed by a central author-

Symbol	Meaning
\mathcal{O}	Suppliers set
\mathcal{D}	Customers set
\mathcal{V}	Vehicles type set
\mathcal{K}	Products set
E_{Empty}^v	CO ₂ emissions per km from an empty vehicle of v type
E_{Pallet}^v	CO ₂ emissions per km per pallet added in a v type vehicle
C_{KM}^v	Cost per km per vehicle of type v
Q_v	Capacity of a v type vehicle
P	Penalty fee
M	A sufficiently large constant
d_{ij}	Distance between nodes i and j
t_{ij}	Time between nodes i and j
q_{ij}^k	Quantity of products k to deliver from node i to j
A_i^{min}	Minimum arrival time at i
A_i^{max}	Maximum arrival time at i
L_i^{max}	Maximum arrival time at site i after when the penalty fee is full
u_i^v	Loading/Unloading time at site i for vehicle v
x_{ij}^v	Boolean variable set to true if v travels between nodes i and j
y_{ij}^{vk}	Quantity of k type product transported in the vehicle v between i and j
s_{ij}^v	Boolean variable set to true if v is affected to a request between i and j
z_{ij}^{vk}	Quantity of k type product of the request (i, j) in v
a_i^v	Arrival time of the vehicle v at node i
b_i^v	Departure time of the vehicle v at node i
w_i^v	Waiting time of vehicle v at site i
m_i^v	1 if vehicle v arrives after the first limit A_i^{max} at customer i
l_i^v	1 if vehicle v arrives after the second limit L_i^{max} at customer i
f_i^v	Probability of refusing the vehicle v at customer i
g_{ij}^v	Coefficient of the penalty cost if vehicle v making a delivery between supplier i and customer j is late

Table 1. Notations.

ity with full information. In the following are the major assumptions related to the mathematical formulation.

- (1) The set of served suppliers of each vehicle's route have to be visited at once before starting to deliver to any customer.
- (2) Vehicles begin and end their routes at the same depot.
- (3) The total duration between any two points of each vehicle's route does not exceed a pre-set limit.

3. MATHEMATICAL MODELING

This section pins down the mixed-integer linear programming formulation of the routing problem. The model notations are listed in Table 1.

The formulation is as following

$$\text{Min} \sum_{i \in \mathcal{O} \cup \mathcal{D}} \sum_{j \in \mathcal{O} \cup \mathcal{D}} \left(\sum_{v \in \mathcal{V}} (E_{Empty}^v d_{ij} x_{ij}^v + \sum_{k \in \mathcal{K}} E_{Pallet}^v d_{ij} y_{ij}^{vk}) \right) \quad (1)$$

$$\text{Min} \sum_{i \in \mathcal{O} \cup \mathcal{D}} \sum_{j \in \mathcal{O} \cup \mathcal{D}} \sum_{v \in \mathcal{V}} (C_{KM}^v d_{ij} x_{ij}^v) + \sum_{i \in \mathcal{O}} \sum_{j \in \mathcal{D}} \sum_{v \in \mathcal{V}} g_{ij}^v d_{ij} P \quad (2)$$

The model's first objective (1) is to minimize the total CO₂ emissions. These emissions are additions to the emissions of the empty vehicles, plus the surplus emissions due to the loads. The second objective function (2) is set to minimize the total transportation cost and the penalty fees. In this problem, we minimize emissions or costs but not both at the same time. There is a positive correlation between both objectives, but it is not linear due to the presence of penalty fees in (2), and the incremental nature of emissions in function of the number of used pallets in (1).

The constraints of the problem are:

$$\sum_{v \in \mathcal{V}} \left(\sum_{j \in \mathcal{O}} y_{ij}^{vk} + \sum_{j \in \mathcal{D}} y_{ij}^{vk} - \sum_{j \in \mathcal{O}} y_{ji}^{vk} \right) = \sum_{j \in \mathcal{D}} q_{ij}^k, \forall i \in \mathcal{O}, \forall k \in \mathcal{K} \quad (3)$$

$$\sum_{v \in \mathcal{V}} \left(\sum_{i \in \mathcal{O}} y_{ij}^{vk} + \sum_{i \in \mathcal{D}} y_{ij}^{vk} - \sum_{i \in \mathcal{D}} y_{ji}^{vk} \right) = \sum_{i \in \mathcal{O}} q_{ij}^k, \forall j \in \mathcal{D}, \forall k \in \mathcal{K} \quad (4)$$

Constraint (3), respectively (4), imposes that quantities of products a supplier has to supply, resp. a customer has to receive, are respected.

$$\sum_{j \in \mathcal{O}} y_{ij}^{vk} + \sum_{j \in \mathcal{D}} y_{ij}^{vk} \geq \sum_{j \in \mathcal{O}} y_{ji}^{vk}, \forall i \in \mathcal{O}, \forall v \in \mathcal{V}, \forall k \in \mathcal{K} \quad (5)$$

$$\sum_{i \in \mathcal{O}} y_{ij}^{vk} + \sum_{i \in \mathcal{D}} y_{ij}^{vk} \geq \sum_{i \in \mathcal{D}} y_{ji}^{vk}, \forall j \in \mathcal{D}, \forall v \in \mathcal{V}, \forall k \in \mathcal{K} \quad (6)$$

Constraint (5), resp. (6), is derived from the flow conservation constraint for the supplier side, resp. the customer side. The quantity of products in a vehicle v after leaving a customer, resp. a supplier, has to be lesser or equal, resp. greater or equal to the quantity in the vehicle before arriving to the site. The difference corresponds to the quantity unloaded in case of a customer node, or the quantity loaded in case of a supplier node.

$$\sum_{j \in \mathcal{O}} x_{ij}^v + \sum_{j \in \mathcal{D}} x_{ij}^v \leq 1, \forall i \in \mathcal{O}, \forall v \in \mathcal{V} \quad (7)$$

$$\sum_{j \in \mathcal{D}} x_{ij}^v \leq 1, \forall i \in \mathcal{D}, \forall v \in \mathcal{V} \quad (8)$$

$$\sum_{j \in \mathcal{O}} x_{ji}^v \leq 1, \forall i \in \mathcal{O}, \forall v \in \mathcal{V} \quad (9)$$

$$\sum_{i \in \mathcal{O}} x_{ij}^v + \sum_{i \in \mathcal{D}} x_{ij}^v \leq 1, \forall j \in \mathcal{D}, \forall v \in \mathcal{V} \quad (10)$$

Constraints (7) and (8) impose that vehicles do not split after leaving a node. Constraints (9) and (10) impose that each vehicle when arriving at a site has a unique origin node.

$$Q_v x_{ij}^v \geq \sum_{k \in \mathcal{K}} y_{ij}^{vk}, \forall i, j \in \mathcal{O} \cup \mathcal{D}, \forall v \in \mathcal{V} \quad (11)$$

$$\sum_{v \in \mathcal{V}} z_{ij}^{vk} = q_{ij}^k, \forall i \in \mathcal{O}, \forall j \in \mathcal{D}, \forall k \in \mathcal{K} \quad (12)$$

$$\sum_{j \in \mathcal{D}} z_{ij}^{vk} \leq \sum_{j \in \mathcal{O}} y_{ij}^{vk} + \sum_{j \in \mathcal{D}} y_{ij}^{vk} - \sum_{j \in \mathcal{O}} y_{ji}^{vk}, \forall i \in \mathcal{O}, \forall v \in \mathcal{V}, \forall k \in \mathcal{K} \quad (13)$$

$$\sum_{i \in \mathcal{O}} z_{ij}^{vk} \leq \sum_{i \in \mathcal{O}} y_{ij}^{vk} + \sum_{i \in \mathcal{D}} y_{ij}^{vk} - \sum_{i \in \mathcal{D}} y_{ji}^{vk}, \forall j \in \mathcal{D}, \forall v \in \mathcal{V}, \forall k \in \mathcal{K} \quad (14)$$

$$M s_{ij}^v \geq \sum_{k \in \mathcal{K}} z_{ij}^{vk}, \forall i \in \mathcal{O}, \forall j \in \mathcal{D}, \forall v \in \mathcal{V} \quad (15)$$

$$s_{ij}^v \leq M \sum_{k \in \mathcal{K}} z_{ij}^{vk}, \forall i \in \mathcal{O}, \forall j \in \mathcal{D}, \forall v \in \mathcal{V} \quad (16)$$

Constraints (11) to (16) are relative to the requests allocation to the vehicles. Constraints (12) to (14) ensure that the requests are respected. Constraints (15) and (16) ensure that a request is assigned to a truck.

$$b_i^v + t_{ij} + w_j^v - a_j^v \leq M (1 - x_{ij}^v), \forall i, j \in \mathcal{O} \cup \mathcal{D}, \forall v \in \mathcal{V} \quad (17)$$

$$b_i^v + t_{ij} + w_j^v - a_j^v \geq -M (1 - x_{ij}^v), \forall i, j \in \mathcal{O} \cup \mathcal{D}, \forall v \in \mathcal{V} \quad (18)$$

$$a_i^v + u_i^v \sum_{j \in \mathcal{D}} \sum_{k \in \mathcal{K}} z_{ij}^{vk} = b_i^v, \quad \forall i \in \mathcal{O}, \quad \forall v \in \mathcal{V} \quad (19)$$

$$a_j^v + u_j^v \sum_{i \in \mathcal{O}} \sum_{k \in \mathcal{K}} z_{ij}^{vk} = b_j^v, \quad \forall j \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (20)$$

$$a_i^v \geq A_i^{\min}, \quad \forall i \in \mathcal{O} \cup \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (21)$$

$$b_i^v \leq A_i^{\max}, \quad \forall i \in \mathcal{O}, \quad \forall v \in \mathcal{V} \quad (22)$$

Constraints (17) to (22) are time windows constraints.

$$Mm_i^v \geq a_i^v - A_i^{\max}, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (23)$$

$$m_i^v \leq \frac{a_i^v}{A_i^{\max}}, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (24)$$

$$Ml_i^v \geq a_i^v - L_i^{\max}, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (25)$$

$$l_i^v \leq \frac{a_i^v}{L_i^{\max}}, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (26)$$

$$f_i^v \geq l_i^v, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (27)$$

$$f_i^v \geq \frac{a_i^v - A_i^{\max}}{L_i^{\max} - A_i^{\max}} - Ml_i^v, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (28)$$

$$f_i^v \leq m_i^v, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (29)$$

$$g_{ij} \geq f_j^v - (1 - s_{ij}^v), \quad \forall i \in \mathcal{O}, \quad \forall j \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (30)$$

$$g_{ij} \leq s_{ij}^v, \quad \forall i \in \mathcal{O}, \quad \forall j \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (31)$$

$$g_{ij} \leq f_j^v, \quad \forall i \in \mathcal{O}, \quad \forall j \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (32)$$

Constraints (23) to (32) are the constraints relative to the penalty fees. Constraints (23) to (26) are linearization constraints that calculate if a vehicle arrives late or not at a site. Constraints (27) to (29) calculate the probability of refusing a vehicle. And constraints (30) to (32) calculate the coefficient of the penalties regarding the probability of refusing a vehicle.

$$x_{ij}^v \in \{0, 1\}, \quad \forall i, j \in \mathcal{O} \cup \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (33)$$

$$s_{ij}^v \in \{0, 1\}, \quad \forall i, j \in \mathcal{O} \cup \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (34)$$

$$y_{ij}^{vk} \geq 0, \quad \forall i, j \in \mathcal{O} \cup \mathcal{D}, \quad \forall v \in \mathcal{V}, \quad \forall k \in \mathcal{K} \quad (35)$$

$$z_{ij}^{vk} \geq 0, \quad \forall i \in \mathcal{O}, j \in \mathcal{D}, \quad \forall v \in \mathcal{V}, \quad \forall k \in \mathcal{K} \quad (36)$$

$$a_i^v, b_i^v, w_i^v \geq 0, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (37)$$

$$m_i^v, l_i^v \in \{0, 1\}, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (38)$$

$$0 \leq f_i^v \leq 1, \quad \forall i \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (39)$$

$$0 \leq g_{ij}^v \leq 1, \quad \forall i \in \mathcal{O}, \quad \forall j \in \mathcal{D}, \quad \forall v \in \mathcal{V} \quad (40)$$

Constraints (33) to (40) give the restrictions and types of the decision variables.

4. COST SHARING

The framework of cooperative game theory provides several practical allocations to divide costs and profits across players for a target game, e.g. a business operation, a production planning, a delivery process, etc. In this subsection, we briefly review a number of basic game theoretic concepts of games with transferable utilities, before justifying our allocation choices.

A cooperative game $\Gamma(N, v)$ is described by two elements: a set of players $N = \{1, 2, \dots, n\}$, and a real-valued function $v : 2^n \rightarrow \mathbb{R}$, called the *characteristic function*, which satisfies $v(\emptyset) = 0$. A coalition can be any subset of players $C \subseteq N$. Its value is given by $v(C)$, which provides a

numerical indicator of the worth of the coalition if all members of C decide to cooperate together regardless of what the remaining players do. An *allocation* is a vector $x = (x_1, x_2, \dots, x_n) \in \mathbb{R}^n$ where $\sum_{i=1}^n x_i = v(N)$.

Several solution concepts have been devised in cooperative game theory to specify the allocation vector x , given a number of desirable properties, such as *stability*, *symmetry*, see Myerson (2013) for more details. The Shapley value is one of the main allocation mechanisms. Its formula states that each player i gets an allocation equal to a weighted sum of his marginal contribution $v(C \cup \{i\}) - v(C)$ across all possible subsets $C \subseteq N \setminus \{i\}$: $\phi_i(v) = \sum_{C \subseteq N \setminus \{i\}} \frac{|C|! (|N| - |C| - 1)!}{|N|!} (v(C \cup \{i\}) - v(C))$.

We have chosen to implement Shapley value due to its several advantages. First, the allocation is unique and always exists. This is an advantage compared to the core, which might be empty, and in case of existence non-unique. As players can have different preferences toward non-dominant allocations, uniqueness is a useful property to satisfy in coalitions. Secondly, the balanced contribution between players in Shapley's formula is closely related to the idea of fairness (Myerson, 1980). However, Shapley value lies generally outside the core set, i.e. the set of non-dominant allocations, unless the game is convex, see Shapley (1971). Vehicle routing processes do not usually satisfy convexity. To overcome this lack of stability, we also consider the Nucleolus allocation (Schmeidler, 1969). This solution has the advantage to be unique and always be part of the core set if it is non-empty. The Nucleolus is defined as the cost allocation that dominates all allocations x in terms of the excess vector, denoted as $e(x) = (e(C_1, x), \dots, e(C_m, x)) \in \mathbb{R}^m$, where m is the number of possible coalitions. We implement the Nucleolus by solving a sequence of linear programs in the sense of Fromen (1997), and by avoiding the common mistakes in its calculation (Guajardo and Jörnsten, 2015). Note that, proportional methods, although easier to implement, are empirically highly unstable (Guajardo and Rönnqvist, 2016). We include them for comparison matters.

5. CASE STUDY

We expect through this case study to improve the economic competitiveness and the environmental footprint of food supply chains. It is set in a global context characterized by an increase of food demands, a constant rise of global energy prices, and a pressure toward more environmentally friendly logistics practices, such as reducing greenhouse gas emissions. In practical terms, the case study has delivered a pilot to implement the previously described modeling/optimisation framework in the agri-food sector. Indeed, this framework is piloted across a food network to demonstrate how the new approaches can deliver real benefits. The expected outcome of the considered case study was to have identified a number of opportunities that the business is enthused to explore further, to have considered whether collaboration is an option worth pursuing and to have captured sustainability KPIs to feed into the modelling/optimisation if and when required.

In this case study, a company located in the UK distributes fruit and vegetables from its distribution center.

The company performs the packaging and warehousing of the products making them ready to be delivered to 27 retailer sites of the 3 food retailers (R1, R2, R3). Each retailer optimizes separately its vehicle routing to deliver its own retailer sites. The company will make retailers collaborating on sharing their trucks to optimise at the same time cost and CO₂ emissions. Improving truck utilization in the considered distribution network in this case study fits very well with the scope of the paper. It's a special case of the general considered network in the mathematical modeling where the number of suppliers here is equal to one. In this case study, customer orders are considered for the period from January to April 2013. The data file includes the inputs: dates of orders, requested volumes and amounts of each product and couple (supplier, customer), delivery sites, products' names.

6. EXPERIMENTAL STUDY

In this section, we conduct experiments to analyze the mathematical model and the sharing approaches introduced previously through the case study. The parameters' values used for the experiment are based on the case study: $E_{Empty}^v = 0.767$ kg/km; $E_{Pallet}^v = 1.104$ kg/km; $C_{KM}^v = 0.525$ €/km; $Q_v = 26$ pallets; $A_i^{max} - A_i^{min} = 3$; $L_i^{max} - A_i^{max} = 1$; $P = 0.91$. We use homogeneous vehicles. The distances between the sites are the "as the crow flies" distances. Firstly, we analyze the influences of the collaboration on the overall transportation costs, emissions, as well as the total number of trucks and their filling rates by comparing the results obtained when optimising each company individually with those obtained when the collaboration is taken place. By doing so, we are able to show the added value of explicitly including collaboration between competitor companies in the management decision-making in contrast to the traditional decision-making approach that considers each company individually. Secondly, we analyze the effectiveness of the cost-sharing strategies chosen in this study, where the overall cost and emissions are shared among the participant companies of the network. Table 2 presents the experimental results of the cost and emission indicators. It can be observed that, through the collaboration, the transportation cost is reduced by 28.57% to 33.87% in different months, while the emissions are decreased by 24.64% to 27.95%. The average reduction of the two indicators reaches 31.89% and 27.00%, respectively.

Table 3 compares the number of trucks used and their filling rates in the collaborative solution to those without any collaboration activities. As expected, the collaborative model results in a smaller number of trucks and a higher filling rate for all tested instances, and, remarkably, the improvements are significant. It can be observed that, the number of trucks is reduced by 29.48% to 34.90%, and the filling rate is increased by 297.17% to 303.49%. The average decrease of all tested instances is 32.87%, while the fill rates have been augmented on average by 285.74%. The environment category shows similar trends, the average value reaches 33.16% and 277.84%, respectively. These results show that the co-opetition can substantially improve the above indicators.

Month	Indicator	No collaboration				Collaboration	Reduction (%)
		R1	R2	R3	Total	Total	
Jan	Transp.	32284.70	31021.78	63608.72	126915.20	83927	33.87
	Envir.	28121.08	28315.93	70907.79	127344.80	91932.79	27.81
Feb	Transp.	28944.90	27842.89	54557.36	111345.16	74155.86	33.40
	Envir.	25133.92	25378.93	60682.90	111195.75	80115.63	27.95
Mar	Transp.	31171.43	30122.22	59887.95	121181.60	82607.58	31.83
	Envir.	27084.19	27471.29	66183.44	120738.92	87286.44	27.71
Apr	Transp.	31171.43	30398.52	62372.04	123942.00	88532.02	28.57
	Envir.	27160.56	28474.38	69509.72	125144.66	94307.26	24.64
Total	Transp.	123572.46	119385.41	240426.07	483383.96	329222.46	31.89
	Envir.	107499.75	109640.53	267283.85	484424.13	353642.12	27.00

Table 2. Transport costs (€) and emissions (CO₂ eq Kg) of the retailers with and without collaboration.

Month	Indicators	objective	No collaboration	Collaboration	Gap (%)	
Jan	Number of trucks	transport	917	597	-34.90	
		envir.	917	603	-34.24	
	Filling rate	transport	5.44	21.62	+297.15	
		envir.	5.34	20.46	+283.18	
	Feb	Number of trucks	transport	808	528	-34.65
			envir.	808	535	-33.79
Filling rate		transport	5.26	20.94	+297.84	
		envir.	5.20	20.03	+285.27	
Mar	Nb of trucks	transport	871	587	-32.61	
		envir.	871	566	-35.01	
	Filling rate	transport	5.09	20.53	+303.49	
		envir.	5.09	19.47	+282.79	
Apr	Number of trucks	transport	899	634	-29.48	
		envir.	899	632	-29.70	
	Filling rate	transport	5.81	23.24	+300.05	
		envir.	5.80	20.95	+261.12	
Total of the number of trucks	transport	3495	2346	-32.87		
	envir.	3495	2336	-33.16		
Average of the filling rate	transport	5.40	20.83	+285.74		
	envir.	5.36	20.22	+277.24		

Table 3. Number of trucks and filling rates with and without cooperation.

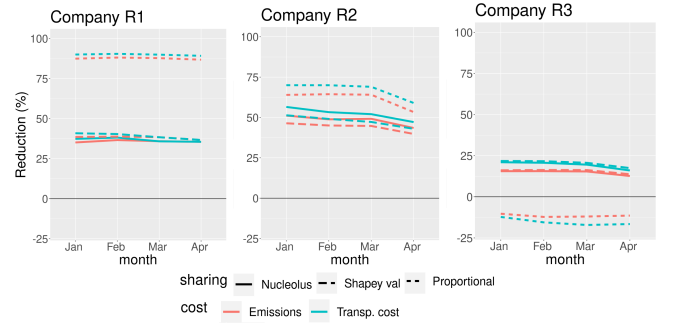


Fig. 1. The reduction rate for the transportation costs (blue color) and the CO₂ emissions (red color) using Shapley value (broken line), the Nucleolus (continuous line), and a proportional division for each retailer.

Fig. 1 shows in addition to the cost-sharing strategies of the Shapley value and the Nucleolus, a proportional division. This latter is based on the proportions of the product quantities each retailer delivers. It is simple to implement. For instance, the retailer R1 contributes to an average of 3.79% of the total product volume, leading to an impressive reduction of an average of 88.71%, when sharing the transportation and the CO₂ costs. In addition to yielding extreme divisions, proportional allocation is not stable. Indeed the retailer R3 reports losses for all months. Thus, R3 will not be favorable to collaborate if the proportional allocation is used. On the other hand, the cost-sharing strategies of the Nucleolus and Shapley value produce more balanced allocations with positive reductions for all retailers. All benefit significantly from the collaboration for an average of 38.6, 45.83, and 18% accounting for costs and emissions for respectively R1, R2, R3, and the Shapley Value.

Month	Indicator	Shapley Value						Total
		R1		R2		R3		
		SV	%	SV	%	SV	%	
Jan	Transp.	19086.75	40.88	15089.69	51.36	49750.56	21.78	83927
	Envir	17279.99	38.55	15173.34	46.41	59479.46	16.11	91932.79
Feb	Transp.	17255.86	40.38	14161.32	49.13	42738.68	21.66	74155.86
	Envir	15379.87	38.80	13946.74	45.046	50789.02	16.30	80115.63
Mar	Transp.	19203.83	38.39	15896.47	47.23	47507.28	20.67	82607.58
	Envir	16683.89	38.4	15176.43	44.75	55426.12	16.25	87286.44
Apr	Transp.	19730.97	36.70	17331.23	42.99	51469.82	17.48	88532.02
	Envir	17199.12	36.68	17141.95	39.8	59966.19	13.73	94307.26
Total	Transp.	75277.41	39.08	62478.71	47.67	191466.34	20.36	329222.46
	Envir	66542.87	38.1	61438.46	43.96	225660.79	15.57	353642.12

Month	Indicator	Nucleolus						Total
		R1		R2		R3		
		Nucleolus	%	Nucleolus	%	Nucleolus	%	
Jan	Transp.	20218.18	37.37	13487.07	56.52	50221.81	21.04	83927
	Envir	18242.92	35.13	13834.69	51.14	59855.13	15.59	91932.79
Feb	Transp.	17900.04	38.16	13002.58	53.30	43253.22	20.71	74155.86
	Envir	15933.23	36.61	12979.87	48.85	51202.49	15.62	80115.63
Mar	Transp.	20003.7	35.83	14438.17	52.06	48165.76	19.57	82607.58
	Envir	17359.22	35.91	13957.25	49.19	55969.93	15.43	87286.44
Apr	Transp.	20093.86	35.54	16067.26	47.14	52370.92	16.03	88532.02
	Envir	17516.83	35.50	16088.66	43.5	60701.80	12.67	94307.26
Total	Transp.	78215.78	36.70	56995.08	52.26	194011.71	19.31	329222.46
	Envir	69052.2	35.77	56860.47	48.14	227729.35	14.80	353642.12

Table 4. Cost sharing of the transport costs and the emissions among the retailers according to the Shapley value and the the Nucleolus.

In Table 4, we analyze the effectiveness of the two cost-sharing strategies in more detail. It can be observed that both strategies result in cost and emissions reduction for each individual company. The average cost reduction of the companies with the Shapley value strategy are 39.08%, 47.67%, and 20.36%, respectively, while those with the Nucleolus strategy are 36.70%, 52.26%, and 19.31%, respectively. Regarding the emissions, the values are 38.10%, 43.96%, and 15.57% with the Shapley value strategy, and 35.77%, 48.41%, and 14.80% with the Nucleolus strategy, respectively. Although both allocations strategies are close enough to each other, we notice that the Shapley value is more balanced than the Nucleolus. Still, the Nucleolus has the advantage to be always in the core set of allocations. The sharing shows no increase in the indicators in any company, which indicates all participants can benefit significantly from the collaboration.

7. CONCLUSION

We investigated in this paper the benefits of co-opetition, i.e., collaboration of competitor retailers in food distribution networks to make saving costs and reducing CO₂ emissions. Food logistics is one of important sources of generating CO₂ emissions due to the large volumes and high pickup and delivery frequencies. Co-opetition of retailers in food supply chains will lead to reducing CO₂ emissions and transportation costs. Such collaboration could be in the form of sharing trucks by retailers, in order to increase fill rate of the vehicles and to reduce their empty running. With the framework of a case study, we were able to reduce in a central planning way the total CO₂ emissions and the total cost respectively by an average of at least 15.6%, resp. 20.4%. Moreover, this paper showed that, with a suitable cost-sharing strategy, all participants can benefit significantly from the co-opetition. One future direction could be to investigate a decentralized approach since total sharing information is not necessary accepted by all involved partners in the collaboration, using for instance smart contracts, blockchain technology, and digital tokens.

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