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An Integrated Approach Using a Collaborative Strategy for Sustainable Cities Freight Transportation: A Case Study

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Abstract

In recent years, the increasing freight transportation activities has caused extensive economic, environmental and social impacts on society. Therefore, it becomes necessary for logistics company to find high-performance strategies to enhance their sustainability. Collaboration between companies appears as one of the promising solution that improves the freight transport efficiency of modern cities. Existing studies on collaborative transport did not sufficiently account for sustainability aspects and they mainly discuss the independent planning of decision-making problems with economic objectives. However, collaboration an integrated decision-making process can significantly ameliorate the effectiveness of urban transportation systems. This study addresses the issue of sustainable freight transportation planning by formulating and solving a collaborative and integrated two-echelon inventory, location and routing problem (2E-CILRP). The 2E-CILRP is formulated as a multi-objective integer programming model that minimizes logistics costs, CO_2 emissions and accident rate. A hybrid heuristic based on machine learning is also introduced to solve the studied problem. The proposed approach combines k -means clustering and genetic algorithms. Comparison of the obtained results with those provided with exact method reveals that the developed approach is more efficient and more practical for designing integrated and collaborative networks with large-sized data. A case study of four agri-food SMEs in France is investigated in order to demonstrate the sustainable benefits of the developed optimization approach. The obtained results suggest that the developed approach can significantly reduce the level of CO_2 emissions, logistics costs and accident rate caused by transportation in cities.

Keywords: Collaborative City Logistics; Integrated Planning; Sustainable Freight Transport; Mixed-Integer Linear Programming; Heuristic

1. Introduction

The logistics service networks are important components that allow the supply chain to achieve a variety of objectives, ranging from low cost to high responsiveness, and improve its overall profitability and competitiveness (Javid and Azad, 2010; Chen et al., 2017). In fact, the design and management of the logistics networks are critical issues in any supply chain optimization due to their crucial role in the development of society and the protection of environment (Comi and Savchenko, 2021; Muñoz-Villamizar et al., 2021; Kermanshah et al., 2020; Mahmoudi et al., 2019; Kiba-Janiak et al., 2021). Thus, to remain competitive in today’s growing market, companies should implement efficient strategies for designing and managing their distribution networks for sustainable cities. In this direction, logistics collaboration between companies can considerably increase their logistics operations efficiencies and strengthen the city’s growth in socio-environmental terms (Russo et al., 2021; Vargas et al., 2020; Strulak-Wójcikiewicz and Wagner, 2021). In logistics networks, collaboration can be horizontal or vertical. The first type occurs when logistics stakeholders at different levels of the supply chain, such as the manufacturers, distributors, carriers and retailers, pool their resources and performance information to enhance the operational efficiency (Ferrell et al., 2020; Dolati Neghabadi et al., 2021; Ferrero et al., 2018). However, the second type involves companies at the same level of the supply chain performing similar activities. These enterprises can benefit from economies of scale by working together, e.g. cooperation between two wholesalers (Pan et al., 2019).

Recently, interest in collaborative practices has gained momentum, and many studies have been conducted to find solutions that can increase the effectiveness of freight transportation operations through horizontal collaboration (Soysal et al., 2018; Akyol and De Koster, 2018). Indeed, by pooling resources, customers are delivered to closer distribution centres, which reduces the travelled distances and transportation costs (Habibi et al., 2018). Moreover, companies can make sustainable savings by increasing transport fleet fill rates, and reducing fixed costs, empty trips and fuel consumption. This mode of collaboration has been widely applied during the last years in several decision problems, especially in the vehicle routing problem (Wang et al., 2021).

Location-allocation, inventory management and vehicle routing problems are major issues emerging in the distribution network design and planning.

Traditionally, these decisions were addressed sequentially or independently. They were also approached before vehicle routing and inventory management (Aloui et al., 2021b). The literature proved that the integrated planning decisions have a major impact on the overall supply chain success in terms of cost, quality and service time due to the great interdependence between the various problems (Farias et al., 2020; Nagy and Salhi, 2007; Liu and Lin, 2005). Although the integration of planning decisions has gained momentum in the last years, collaborative and integrated planning research is in its infancy. In fact, few recent studies have developed integrated models for the collaborative network design and planning. More recently, in preliminary work (Aloui et al., 2021a), the two-echelon collaborative inventory-location-routing problem (2E-CILRP) with environmental considerations has been modelled for the first time. In the 2E-CILRP, the transportation providers cooperate to optimize their location, inventory and routing decisions. In other words, they determine the distribution centres to be opened, customer and supplier allocation, routes and quantity of goods to be stocked in each period. However, the growing socio-environmental concerns have led companies to focus more on integrating economic, environmental and social objectives in the global performance assessment. To the best of our knowledge, the 2E-CILRP under sustainability considerations has not yet been addressed in the literature. To fill this gap, in this study, planning decisions are integrated and three sustainability dimensions are evaluated in the two-echelon collaborative logistics network design. For this purpose, a description and formulation of the problem using a mixed integer linear programming are presented. Besides, due to the NP-hard nature of the considered problem, a new hybrid approach with modified k -means clustering and genetic algorithm is proposed to solve large-scale 2E-CILRP. Moreover, a case study of agri-food SMEs in France is studied to show the sustainable benefits of the developed optimization approach on both society and environment.

The remainder of this paper is organised as follows. Section 2 provides a review of the relevant works dealing with the integrated and collaborative planning and the inventory-location-routing problem. The 2E-CILRP is described and modelled in Section 3. Section 4 depicts the developed solution methodology to solve the 2E-CILRP. The computational results are presented in Section 5. Finally, Section 6 concludes this study and provides some future research directions.

2. Literature review

There are many rich review studies about collaborative freight transportation planning. For instance, we can cite (Aloui et al., 2021b; Gansterer and Hartl, 2018; Pan et al., 2019; Verdonck et al., 2013; Guajardo and Rönnqvist, 2016; Cleophas et al., 2019). This research domain is still developing and the number of research works dealing with it has increased during the last decade to achieve better performance of existing systems and attain sustainability goals (Mahmoudi et al., 2019). This section presents a brief state-of-the-art related to this issue. It includes four parts. The first part examines the collaborative strategy in independent urban transport planning. The second focuses on the literature about the integrated and collaborative planning problems to assess the existing state-of-the-art knowledge. On the other hand, the third part reviews the literature on the classical ILRP as well as some variants of the problem. Finally, the fourth part presents the main contributions of this paper with respect to the current literature.

2.1. Collaborative and independent urban planning

The logistics network planning problem has been a main research subject for almost a century (Zheng et al., 2019). It concerns decision making at different levels. For instance, the strategic level decisions implicated in the distribution network planning problem are the location of facilities and the allocation of customers and suppliers. The tactical level decision is mainly the inventory management, while the operational planning is related to the vehicle routing problem (Yavari et al., 2020).

However, the collaborative logistics network design problem has received very little consideration in the literature. For instance, Tang et al. (2016) have addressed the problem of locating urban consolidation centers in a multi-period collaborative distribution network for horticultural products in France by minimizing transportation costs and facility opening costs. Also, Fernández and Sgalambro (2020) have investigated the collaborative hub location problem by proposing a MILP to minimize the freight distribution costs. Recently, Mrabti et al. (2020) have studied the two-echelon collaborative distribution network design problem using multiobjective optimization of emissions and costs.

In the last few years, several studies dealing with collaborative routing problems in urban areas have been published (Cleophas et al., 2019; Aloui et al., 2021b; Yadav and Karmakar, 2020). For example, Montoya-Torres

et al. (2016) have investigated the collaborative routing problem in urban logistics. The authors have evaluated the economic and environmental benefits of collaborative freight transport in the city of Bogotá, Colombia. Similarly, Muñoz-Villamizar et al. (2019) have assessed the environmental and operational impact of the implementation of electric vehicle fleets in collaborative urban freight distribution. Yao et al. (2019) analyzed the performance of collaboration in urban logistics by considering profit and CO_2 emission aspects. Moutaoukil et al. (2012) have solved the vehicle routing problem with time windows in order to study the impact of last-mile delivery under environmental concerns. Mancini et al. (2021) have introduced the collaborative consistent vehicle routing problem with workload balance. In addition, Wang et al. (2021) have investigated the issues of collaboration between logistic operators in the two-echelon collaborative multi-depot and multi-period vehicle routing problems from the economic perspective. Furthermore, Dolati Neghabadi et al. (2021) have discussed the impacts of operational constraints on the effectiveness of city freight pooling. Very recently, Strulak-Wójcikiewicz and Wagner (2021) have shown the benefits of vehicle sharing in sustainable urban goods transport.

2.2. Collaborative and integrated planning

The traditional optimization method is generally used to approach sequentially the different decisions in order to impose the solution obtained from one level to the next one in the hierarchy of decisions. Although this technique is very intuitive and simple to apply, many studies have shown that it may lead to sub-optimal decision-making (Guerrero et al., 2013; Darvish and Coelho, 2018; Nagy and Salhi, 2007). For this reason, several researchers have focused, in recent years, on the integration of different decisions in order to improve the global efficiency of logistics networks. Although integrated planning is in its early stages in the field of collaborative logistics, few studies have attempted to integrate two or three decision problems, such as Location-Routing Problem (LRP), Inventory-Routing Problem (IRP), Location-Inventory Problem (ILP) and Inventory-Location-Routing Problem (ILRP), in a collaborative environment.

In fact, the LRP combines the decisions about the location of distribution centers, the allocation of customers and suppliers and the vehicle routing. Ouhader and El Kyal (2017) have studied the two-echelon Location-Routing Problem (2E-LRP) to evaluate the synergies of horizontal collaboration and the combination of the operational and strategic planning in urban freight

transport. The authors have proposed a multi-objective MILP model to optimize logistics costs, minimize CO_2 emissions and increase the created job opportunities. The results of their study have revealed that horizontal collaboration can reduce substantially CO_2 emissions and increase the transportation cost savings. However, such collaboration may minimize the number of the created job opportunities. Consequently, [Ouhader and El Kyal \(2020\)](#) have recently focused on how to balance both economic and environmental concerns in a collaborative strategy using the ϵ -constraint method. However, despite the complexity of this problem, the exact method has been used to solve only small instances of the model using a commercial solver. The single-echelon and mono-period collaborative LRP has been studied by [Quintero-Araujo et al. \(2019\)](#) and [Nataraj et al. \(2019\)](#) to design urban distribution networks. The authors have proposed multiple scenarios with different levels of collaboration. These scenarios have been solved using metaheuristics to minimize the distribution costs and evaluate a posteriori the CO_2 emissions. Combining inventory management and vehicle routing decisions results in a complex optimization in logistics known as the IRP. The latter has been investigated by [Stellingwerf et al. \(2018\)](#) in the case of temperature-controlled food distribution. The authors have suggested a MILP to evaluate the economic and environmental advantages of horizontal collaboration in a single-echelon and multiple time period IRP. From a similar perspective, [Soysal et al. \(2018\)](#) have addressed this problem in a collaborative context between suppliers of perishable products by taking into account environmental impacts and uncertainty of demand. In the studies of [Soysal et al. \(2018\)](#) and [Stellingwerf et al. \(2018\)](#), the models have been solved by the exact method using the CPLEX solver and no heuristics were proposed to solve the large-scale problems. Recently, in [\(Fardi et al., 2019\)](#), a Mixed Integer Programming (MIP) formulation and metaheuristic algorithms have been developed to solve the single-echelon and collaborative IRP. As for the LIP models, their objective is to determine both the storage plans at the distribution centers (DCs) and the location allocation decisions ([Zhang and Unnikrishnan, 2016](#); [Zheng et al., 2019](#)). In the collaborative logistics literature, this problem has been dealt with only once by [Hacardiaux and Tancrez \(2020\)](#). The authors have introduced a Mixed Integer Quadratic Program (MIQP) to address the LIP and evaluate the environmental benefits of horizontal collaboration while satisfying uncertain demands. This model has been validated on small instances using the CPLEX solver. However, these research works have generally focused on combining two planning decisions.

They have evaluated only the economic and environmental dimensions of sustainability. Recently, due to the necessity of incorporating inventory and routing decisions in the design of logistics networks, [Aloui et al. \(2021a\)](#) have conducted a preliminary study where the 2E-CILRP has been modelled, using a MILP formulation, and solved by the CPLEX solver. In this study, only logistics costs and CO_2 emissions have been evaluated and just small-sized instances have been tested.

2.3. Inventory-location-routing problem

Different cases of the ILRP have been dealt with in the literature. The ILRP with one echelon, involving a set of depots and a set of retailers, has been studied by [Guerrero et al. \(2013\)](#) and [Zhang et al. \(2014\)](#). In fact, it has been modelled using MILP formulation, by minimizing strategic as well as tactical and operational costs. On the other hand, it has been solved by exact and approximate methods. Likewise, [Yavari et al. \(2020\)](#) have examined the multi-period and mono-echelon ILRP for perishable products under road disruptions at certain periods. The problem has been modelled using MILP, by maximizing the total profit, and solved applying a genetic algorithm.

The two-echelon ILRP with a single manufacturer/supplier has been discussed in several works. For example, [Hiassat et al. \(2017\)](#) and [Rafie-Majd et al. \(2018\)](#) have addressed it in the case of a perishable product. They have solved this problem by applying a genetic algorithm and lagrangian relaxation algorithm that minimizes the total costs. Similarly, [Saif-Eddine et al. \(2019\)](#) have investigated the ILRP with a single supplier and following an inventory strategy at the customers. The problem has been formulated, by optimizing the total supply chain cost, and solved with an improved genetic algorithm. [Saragih et al. \(2019\)](#) have examined a heuristic method to solve the two-echelon ILRP (2E-ILRP) in which one supplier, a set of depots and a set of customers have been considered. The main objective of this study is to determine the location of the depots, the allocation of retailers to the opened depots, the inventory in the different logistic entities and the routing of the vehicles from the depots to the retailers by minimizing the total cost. More recently, [Wu et al. \(2021a\)](#) have studied the multi-period two-echelon ILRP by taking into account time windows at retailers and vehicle fuel consumption. To solve this problem, the authors have developed a hybrid two-stage metaheuristic approach to reduce the total costs. Although cost efficiency is a prerequisite for sustainable performance, it is insufficient for achieving

Table 1: Overview of the related literature on collaborative and integrated planning, and the ILRP

Paper	Logistics cooperation	Network echelons	Decision problem			Evaluated sustainability			Suppliers	Solution approach
			Location	Inventory	Routing	Economic	Environmental	Social		
Tang et al. (2016)	✓	3	✓	-	-	✓	-	-	Multiple	Exact
Fernández and Sgalambro (2020)	✓	1	✓	-	-	✓	-	-	Multiple	Heuristic
Mrabti et al. (2020)	✓	2	✓	-	✓	✓	✓	-	Multiple	Exact
Montoya-Torres et al. (2016)	✓	1	-	-	✓	✓	✓	-	Multiple	Heuristic
Muñoz-Villamizar et al. (2019)	✓	1	-	-	✓	✓	✓	-	Multiple	Exact
Yao et al. (2019)	✓	1	-	-	-	✓	✓	-	Multiple	Heuristic
Moutaoukil et al. (2012)	✓	1	-	-	✓	✓	✓	✓	Multiple	Exact
Mancini et al. (2021)	✓	1	-	-	✓	✓	-	-	Multiple	Heuristic
Wang et al. (2021)	✓	2	-	-	✓	✓	-	-	Multiple	Heuristic
Dolati Neghabadi et al. (2021)	✓	1	-	-	✓	✓	-	-	Multiple	Heuristic
Strulak-Wójcikiewicz and Wagner (2021)	✓	1	-	-	-	-	-	✓	Multiple	Exploratory
Ouhader and El Kyal (2017)	✓	2	✓	-	✓	✓	✓	✓	Multiple	Exact
Soysal et al. (2018)	✓	1	-	✓	✓	✓	✓	-	Multiple	Exact
Stellingwerf et al. (2018)	✓	1	-	✓	✓	✓	✓	-	Multiple	Exact
Quintero-Araujo et al. (2019)	✓	1	✓	-	✓	✓	✓	-	Multiple	Heuristic
Nataraj et al. (2019)	✓	1	✓	-	✓	✓	✓	-	Multiple	Heuristic
Fardi et al. (2019)	✓	1	-	✓	✓	✓	-	-	Multiple	Heuristic
Ouhader and El Kyal (2020)	✓	2	✓	-	✓	✓	✓	-	Multiple	Exact
Hacardiaux and Tancrez (2020)	✓	2	✓	✓	-	✓	✓	-	Multiple	Exact
Aloui et al. (2021a)	✓	2	✓	✓	✓	✓	✓	-	Multiple	Exact
Guerrero et al. (2013)	-	1	✓	✓	✓	✓	-	-	Single	Heuristic
Zhang et al. (2014)	-	1	✓	✓	✓	✓	-	-	Single	Heuristic
Yavari et al. (2020)	-	1	✓	✓	✓	✓	-	-	Single	Heuristic
Hiassat et al. (2017)	-	2	✓	✓	✓	✓	-	-	Single	Heuristic
Rafie-Majd et al. (2018)	-	2	✓	✓	✓	✓	-	-	Single	Heuristic
Saif-Eddine et al. (2019)	-	2	✓	✓	✓	✓	-	-	Single	Heuristic
Saragih et al. (2019)	-	2	✓	✓	✓	✓	-	-	Single	Heuristic
Wu et al. (2021a)	-	2	✓	✓	✓	✓	-	-	Single	Heuristic
Karakostas et al. (2020)	-	1	✓	✓	✓	✓	✓	-	Single	Heuristic
Zhalechian et al. (2016)	-	2	✓	✓	✓	✓	✓	✓	Multiple	Heuristic
Biuki et al. (2020)	-	3	✓	✓	✓	✓	✓	✓	Multiple	Heuristic
The current paper	✓	2	✓	✓	✓	✓	✓	✓	Multiple	Heuristic

sustainability objectives (Lin et al., 2014). In fact, there are very few studies that have incorporated social and environmental concerns in integrated decisions optimization. For instance, Karakostas et al. (2020) have focused on the green ILRP to optimize CO_2 emissions and the total cost. They have developed a general variable neighborhood search-based framework to address this problem. Zhalechian et al. (2016) have examined the two-echelon ILRP for a sustainable closed-loop supply chain by taking into account the CO_2 emission, wasted energy and the negative impacts on economic development. Recently, Biuki et al. (2020) have addressed the multi-echelon ILRP of perishable products to design sustainable logistics networks. They have also developed a multi-objective mixed integer programming under carbon tax policy and two hybrid metaheuristics to solve this problem.

2.4. Research gap and contributions of the study

A comparative overview of the existing research works and the present one is presented in Table 1. From the latter, we notice that although the related studies have addressed several collaborative transportation planning issues, they suffer from the following problems: (i) Collaboration as a strategy applied to optimize configurations has not been extensively studied in the context of the integrated two-echelon logistics network planning; (ii) most studies dealing with integrated planning have used only commercial solvers to solve small-scale problems, but they have ignored large-scale problems; (iii) minimal attention has been paid to the three sustainability objectives in integrated logistics network planning; (iv) existing ILRP studies have rarely considered multiple suppliers and ignore the collaboration in different echelons.

To fill this research gap, The main contributions of this study are summarized as follows: (i) implementating logistical collaboration between Less Than Truckload (LTL) carriers in the two-echelon ILRP; (ii) proposing a multi-objective model to design collaborative and sustainable two-echelon logistics networks by minimizing the total cost, CO_2 emissions and accident risk; (iii) performing an exact resolution and proposing a hybrid heuristic based on k -means clustering and genetic algorithms to efficiently solve the large-scale 2E-CILRP by taking sustainability explicitly into consideration.

3. Problem description and model formulation

3.1. Problem statement

Compared to the traditional 2E-ILRP in which the functioning of companies is relatively independent, the 2E-CILRP is defined to optimize a two-echelon distribution network through collaboration and resource sharing. In fact, it can effectively improve the loading rate of the transport means and improve the effectiveness of the logistics network operation. In this study, the considered two-echelon distribution network is composed of a set of suppliers, a set of distribution centres and a set of customers in urban areas to be served. Fig.1 depicts the logistics network before and after collaboration. The 2E-

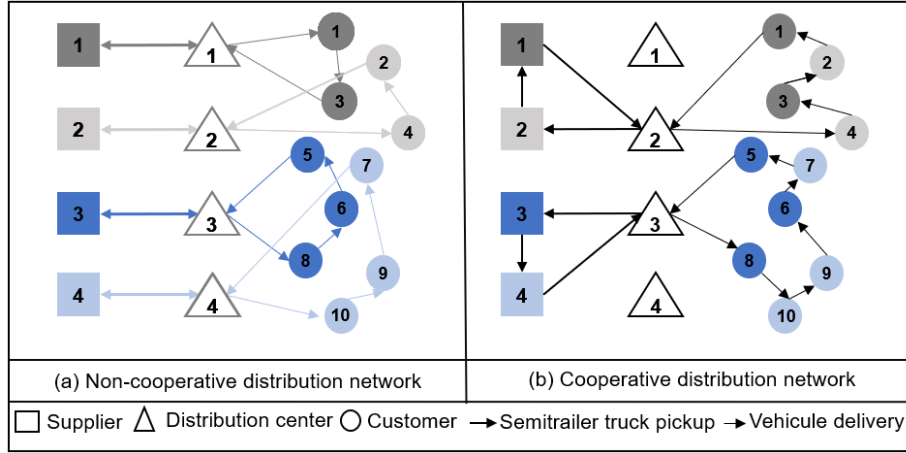


Figure 1: The distribution network before and after collaboration.

CILRP is formally defined in this study as a complete graph $G = (V, E)$ where V denotes the set of nodes including the set of customers $I = \{1, \dots, N_{Customers}\}$, the set of potential distribution centers $D = \{1, \dots, N_{DCs}\}$ and the set of suppliers $J = \{1, \dots, N_{Suppliers}\}$ and $A = \{(i, j): i, j \in V; i \neq j\}$ is the set of edges that includes the delivery and pickup arcs. Each customer has a non-constant and deterministic demand q_{ij}^t from one supplier j at each period $t \in T = \{1, \dots, N_{periods}\}$. For regulatory constraints in urban cities, the customers are served by a homogeneous fleet of light vehicles with a fixed capacity Qv and a fixed cost Fv . On the other hand, customer i can be visited no more than once by one of the vehicles and served from only one distribution center where demands must be consolidated. In this case, direct transport from supplier to customer is not possible. Each potential

distribution $d \in D$ has a storage capacity C_d and a fixed cost FO_d when it is open. To transport goods between suppliers and distribution centers, a homogeneous fleet of semitrailer trucks with a fixed capacity Qs and a fixed cost Fs is used in the first echelon.

The aim of the studied problem is to determine the distribution centres to be opened, the customers and suppliers assignment, the routes as well as the inventory quantity in each period to minimize the total cost of the CDs opening, routing and storage and to reduce the CO_2 emissions and the accident rate so that the final customer demands will be met during each time period.

The model sets, parameters and decision variables of this paper are presented in Table 2.

3.2. Sustainability indicators

In the related literature, performance assessment of the transport systems is based essentially on the economic indicators (Aloui et al., 2021b). However, in this study, we take into account the triple bottom-lines of sustainability. From the economic perspective of sustainability, we consider the different costs related to the use of distribution centres and transport means, the storage of products in the distribution centres and the transport activities. From the environmental point of view, we take into account the CO_2 emissions resulting from transport activities and distribution centres functioning. On the other hand and from the social perspective, we consider the accident rate caused by transport.

3.2.1. Cost calculation

The cost function, in model formulation, is calculated by adding the fixed costs (C_F) of opening distribution centres and operating transport means, the inventory cost (C_I) and the transport cost in the first and second level (C_T) by applying Equation (1).

$$C = C_F + C_I + C_T \quad (1)$$

The fixed costs are calculated by summing the costs of purchasing the transport means and the opening costs of the selected installations (Equation (1)).

$$C_F = \sum_{d \in D} y_d FO_d + \sum_{t \in T} \sum_{d \in D} \sum_{j \in J} x_{d,j}^t Fs + \sum_{t \in T} \sum_{d \in D} \sum_{i \in I} x_{d,i}^t Fv \quad (2)$$

Table 2: Notations and definitions used in the mathematical modelling.

Notation	Description
Sets	
J	Set of suppliers
D	Set of distribution centers
I	Set of customers
$A1, A2$	The set of arcs of the pickup and delivery routing
T	Set of planning periods
Parameters	
C_d	Storage capacity of the distribution center d
FO_d	Fixed cost of the distribution center d
EC_d	Average energy consumption of the distribution centre d
Qs	Semitrailer truck loading capacity
Qv	Vehicle loading capacity
Fs	Semitrailer truck operating cost
Fv	Vehicle operating cost
Ts_E	Fuel consumption rate by an empty semitrailer truck (L/Km)
Ts_L	Fuel consumption rate by a fully-loaded semitrailer truck (L/Km)
Tv_E	Fuel consumption rate by an empty vehicle (L/Km)
Tv_L	Fuel consumption rate by a fully-loaded vehicle (L/Km)
c_I	Unit cost of storage in distribution centre ($\text{€}/Kg$)
c_f	Fuel price per litre ($\text{€}/L$)
e_F	Fuel to CO_2 emissions factor ($Kg CO_2/L$)
e_c	CO_2 emitted by unit energy consumption ($Kg CO_2/kwh$)
A_c	Number of accidents per year
$d_{i,j}$	Distance between two nodes i and j : $i, j \in J \cup D \cup I$
q_{ij}^t	Demand of customer i from supplier j in the period t
Decision variables	
y_d	Equal to 1 if the distribution center d is open 1; otherwise 0
z_{id}^t	Equal to 1 if the node i is assigned to the center d ; otherwise 0, $i \in I \cup J, d \in D$
Q_{jd}^t	Quantity delivered by supplier j to the center d in the period t
I_{jd}^t	Inventory level of product j in the center d at period t
$x_{i,j}^t$	Equal to 1 if the arc($i;j$) is traversed in period t by a vehicle/semitrailer truck 1; otherwise 0
$f_{i,j}^t$	Semitrailer truck/vehicle load on the arc ($i; j$) if a semitrailer truck/vehicle travels directly from the node i to the node j in the period t , $(i, j) \in A1 \cup A2$

The inventory cost is calculated with the multiplication of the inventory amount in each period by the unit inventory cost (Equation (3)).

$$C_I = \sum_{t \in T} \sum_{d \in D} \sum_{j \in J} c_I I_{jd}^t \quad (3)$$

Finally, to compute the transport costs, the formula proposed by [Pan et al. \(2014\)](#) is used. Indeed, this cost depends principally on the semitrailer truck/vehicle load and the travelled distance (see Equation (4)). In the first part of Equation (4), the fuel consumption of an empty vehicle/semitrailer truck (Tv_E) is simply multiplied by the number of the used vehicle/semitrailer truck. In the second part, the fuel consumption related to the vehicle/semitrailer truck load ($Tv_L - Tv_E$) are multiplied by the volume of products expressed in full vehicle/semitrailer truck. To obtain the total transport costs, the amount of fuel consumed per *km* is multiplied by the distance and the fuel price and summed for all deliveries and pickups.

$$C_T = \sum_{t \in T} \sum_{(i,j) \in A1} d_{ij} c_f [x_{ij}^t Ts_E + (Ts_L - Ts_E) \frac{f_{ij}^t}{Q_s}] + \sum_{t \in T} \sum_{(i,j) \in A2} d_{ij} c_f [x_{ij}^t Tv_E + (Tv_L - Tv_E) \frac{f_{ij}^t}{Q_v}] \quad (4)$$

3.2.2. Emissions calculation

As mentioned above, the CO_2 emissions result from the means of transport (E_t) and the distribution centres functioning (E_f). Therefore, the total emissions of the distribution network are quantified by summing these two components using Equation (5).

$$E = E_t + E_f \quad (5)$$

To calculate the CO_2 emissions, we use the approach proposed by [Pan et al. \(2014\)](#). This method is largely employed in collaborative transport planning ([Hacardiaux and Tancrez, 2020](#); [Ouhader and El Kyal, 2017, 2020](#); [Aloui et al., 2021a](#)). It has the advantage of taking into account vehicle/semitrailer truck loading rates, which is an important factor of improvement when cooperating. The CO_2 emissions due to the transportation depend on the weight loaded by the vehicle/semitrailer truck, the vehicle/semitrailer truck capacity and the travelled distance. To determine the total transportation CO_2 emissions, we add up the collection and delivery emissions using Equation

(6).

$$\begin{aligned}
E_t = & \sum_{t \in T} \sum_{(i,j) \in A1} d_{ij} e_F [x_{ij}^t T s_E + (T s_L - T s_E) \frac{f_{ij}^t}{Q_s}] \\
& + \sum_{t \in T} \sum_{(i,j) \in A2} d_{ij} e_F [x_{ij}^t T v_E + (T v_L - T v_E) \frac{f_{ij}^t}{Q_v}]
\end{aligned} \tag{6}$$

To estimate the emissions generated by the operation of distribution centres, we utilize the same approach applied in [Aloui et al. \(2021a\)](#). This approach is based on the reports [ADEME \(2005, 2010\)](#) where the CO_2 emissions are estimated using a fuel conversion factor e_c for the consumed energy (See Equation (7)).

$$E_c = \sum_{d \in D} e_c EC_d y_d \tag{7}$$

3.2.3. Accident rate calculation

Modelling social considerations is a complex task that was not given great attention in the literature ([Pan et al., 2019](#)). In this paper, the social dimension is represented by the risk rate related to traffic accidents. Indeed, previous studies have shown that this rate depends principally on the travelled distance ([Abdullahi et al., 2021](#)). To do this, we adopt the formula proposed by ([Palšaitis and Petraška, 2012](#)) to estimate the accident rate A_r per thousand kilometers (Equation (8)).

$$A_r = \frac{Ac \ 1000}{Distance \ 365} \tag{8}$$

As can be seen in Equation (8), distance is inversely proportional to accident rates. Therefore, we estimate the accident rate A for the travelled distance d_{ij} from nodes i and j with respect to the reference distance d_{ref} . Finally, the accident rate A is calculated by applying Equation (9).

$$A = \sum_{t \in T} \sum_{(i,j) \in A1 \cup A2} A_{ref} \frac{d_{i,j}}{d_{ref}} x_{i,j}^t \tag{9}$$

3.3. Model formulation for 2E-CILRP

The model presented in this section relies on a recently-proposed 2E-CILRP formulation (Aloui et al., 2021a) in which three objective functions of minimizing costs (10), reducing CO_2 emissions (11) and minimizing accident rates (12) are considered.

$$\text{Minimize } C \quad (10)$$

$$\text{Minimize } E \quad (11)$$

$$\text{Minimize } A \quad (12)$$

3.3.1. Location-allocation constraints

Constraints (13) ensure that customers and suppliers can be assigned to a distribution center only if it is open. Constraints (14) force each customer (respectively supplier) to be assigned to only one distribution center. Constraints (15) and (16) guarantee that the capacities of the distribution centers are not exceeded. Constraints (17)-(22) eliminate the routes that do not start and finish at the same distribution center. They also allow allocating customers and suppliers. More precisely, constraints (17) and (18) ensure that arc (j, d) is traversed if and only if the supplier j is assigned to the distribution center d at time t . Similarly, constraints (20) and (21) eliminate the infeasible routes in the second echelon (Distribution centers-customers). Constraints (19) and (22) guarantee that the routes between two suppliers/customers are eliminated if they are assigned to two different distribution centers.

$$z_{id}^t \leq y_d \quad \forall t \in T, \forall i \in I \cup J, \forall d \in D \quad (13)$$

$$\sum_{d \in D} z_{id}^t \leq 1 \quad \forall t \in T, \forall i \in I \cup J \quad (14)$$

$$\sum_{j \in J} \sum_{i \in I} z_{id}^t q_{ij}^t \leq C_d z_d \quad \forall t \in T, \forall d \in D \quad (15)$$

$$\sum_{j \in J} Q_{jd}^t \leq C_d z_d \quad \forall t \in T, \forall d \in D \quad (16)$$

$$x_{dj}^t \leq z_{jd}^t \quad \forall t \in T, \forall j \in J, \forall d \in D \quad (17)$$

$$x_{jd}^t \leq z_{jd}^t \quad \forall t \in T, \forall j \in J, \forall d \in D \quad (18)$$

$$x_{jj'}^t + z_{jd}^t + z_{j'd'}^t \leq 2 \quad \forall t \in T, \forall j, j' \in J, \forall d, d' \in D \quad (19)$$

$$x_{di}^t \leq z_{id}^t \quad \forall t \in T, \forall i \in I, \forall d \in D \quad (20)$$

$$x_{id}^t \leq z_{id}^t \quad \forall t \in T, \forall i \in I, \forall d \in D \quad (21)$$

$$x_{ii'}^t + z_{id}^t + z_{i'd'}^t \leq 2 \quad \forall t \in T, \forall i, i' \in I, \forall d, d' \in D \quad (22)$$

3.3.2. Maximum level inventory policy constraints

Constraints (23) define the initial inventory level in the distribution centers. Constraints (24) calculate the stock level in the distribution centers at each planning period. Constraints (25) ensure that the inventory amount at each distribution center does not exceed the available storage capacity. Constraints (26) express that the amount of goods to be delivered to the distribution center d will never exceed its capacity for each planning period.

$$I_{jd}^0 = 0 \quad \forall j \in J, \forall d \in D \quad (23)$$

$$I_{jd}^t = Q_{jd}^t + I_{jd}^{t-1} - \sum_{i \in I} q_{ij}^t z_{id}^t \quad \forall j \in J, d \in D, t \in T \quad (24)$$

$$I_{jd}^t \leq C_d y_d \quad \forall j \in J, \forall d \in D, \forall t \in T \quad (25)$$

$$\sum_{j \in J} Q_{jd}^t \leq C_d y_d - \sum_{j \in J} I_{jd}^{t-1} \quad \forall d \in D, \forall t \in T \quad (26)$$

3.3.3. Constraints in the first echelon

Constraints (27) ensure that each supplier must be visited only once at most in each period. Constraints (28) and (29) ensure an equal number of incoming and outgoing arcs. Constraints (30) guarantee the flow conservation for the collection process. Constraints (31) ensure that the loaded quantity on the semitrailer will not exceed its capacity on the arc (i, j) . Constraints (32) guarantee that the semitrailer truck is empty when starting from an open distribution center.

$$\sum_{i \in J \cup D} x_{ij}^t \leq 1 \quad \forall t \in T, \forall j \in J \quad (27)$$

$$\sum_{j \in J} x_{dj}^t = \sum_{j \in J} x_{jd}^t \quad \forall t \in T, \forall d \in D \quad (28)$$

$$\sum_{i \in J \cup D} x_{ij}^t = \sum_{i \in J \cup D} x_{ji}^t \quad \forall t \in T, \forall j \in J \quad (29)$$

$$\sum_{i \in J \cup D} f_{ji}^t - \sum_{i \in J \cup D} f_{ij}^t = \sum_{d \in D} Q_{jd}^t \quad \forall t \in T, \forall j \in J \quad (30)$$

$$f_{ij}^t \leq Q_s x_{ij}^t \quad \forall t \in T, \forall i, j \in J \cup D \quad (31)$$

$$\sum_{j \in J} f_{dj}^t \leq 0 \quad \forall t \in T, \forall d \in D \quad (32)$$

3.3.4. Constraints in the second echelon

Constraints (33)-(38) concern the delivery process. They present conditions similar to those of the pickup process (27)-(28);

$$\sum_{i \in I \cup D} x_{ji}^t \leq 1 \quad \forall t \in T, \forall i \in I \quad (33)$$

$$\sum_{i \in I} x_{di}^t = \sum_{i \in I} x_{id}^t \quad \forall t \in T, \forall d \in D \quad (34)$$

$$\sum_{j \in I \cup D} x_{ji}^t = \sum_{j \in I \cup D} x_{ij}^t \quad \forall t \in T, \forall i \in I \quad (35)$$

$$\sum_{j \in I \cup D} f_{ji}^t - \sum_{j \in J \cup D} f_{ij}^t = \sum_{j \in J} q_{ij}^t \quad \forall t \in T, \forall i \in I \quad (36)$$

$$f_{ij}^t \leq Q_v x_{ij}^t \quad \forall t \in T, \forall i, j \in I \cup D \quad (37)$$

$$\sum_{i \in I} f_{id}^t \leq 0 \quad \forall t \in T, \forall d \in D \quad (38)$$

3.3.5. Other constraints

Constraints (39)-(43) specify the nature of each decision variable used in this modelling.

$$y_d \in \{0, 1\} \quad \forall d \in D \quad (39)$$

$$z_{id}^t \in \{0, 1\} \quad \forall t \in T, \forall d \in D, \forall i \in I \cup J \quad (40)$$

$$x_{ij}^t \in \{0, 1\} \quad \forall t \in T, \forall (i, j) \in A1 \cup A2 \quad (41)$$

$$f_{ij}^t \geq 0 \quad \forall t \in T, \forall (i, j) \in A1 \cup A2 \quad (42)$$

$$Q_{jd}^t, I_{jd}^t \geq 0 \quad \forall t \in T, \forall d \in D, \forall j \in J \quad (43)$$

4. Solution approach

The 2E-CILRP is a practical subject of logistics network optimization. Our model aims to find out the optimal location, the inventory and the routing of transport means while minimising costs, emissions and accident risk. As mentioned before, the ILRP is known as an NP-hard problem, which means that it is difficult for exact methods to find the optimal solutions

for large-scale problems within a reasonable computation time. Therefore, heuristics and meta-heuristics provide high quality solutions for large-scale instances (Goodarzian et al., 2021). The literature shows that hybrid approaches, including k -means clustering, can reduce the complexity of urban logistics networks and improve computational efficiency for large-scale problems (Defryn and Sörensen, 2017; Wang et al., 2021, 2020b). Therefore, a hybrid heuristic approach composed of a modified k -means clustering and a genetic algorithms is introduced to solve the 2E-CILRP. The flowchart of the proposed heuristic approach is shown in Fig. 2. The parameters used in this flowchart are described as follows: k is the number of clusters formed, Num_{gen} is the current number of generations, Pop is the population size of individuals and N_{max} is the maximum number of generations.

As depicted in Fig. 2, the proposed approach divides the problem into two steps. The first one consists in grouping and assigning customers and suppliers to the appropriate distribution centers using a modified k -means clustering algorithm. As costs, emissions and accident risk related to transportation are proportional to the travelled distance, the Euclidean distance is adapted to evaluate the similarities of the elements in each cluster. More precisely, customers geographically close to one another and with similar products are placed in the same cluster and assigned to the nearest distribution center. Then, based on the clustering and assignment results, the routing in both echelons and the inventory levels in the distribution centers are optimized by the genetic algorithm. Finally, the three considered sustainability objectives are evaluated and the best logistic configuration is obtained. The clustering procedure and the genetic algorithm are presented in detail in the following sub-sections.

4.1. Clustering procedure

Clustering belongs to the family of unsupervised learning algorithms which consists of clustering a set of data according to specific criteria such as the distance function. It is one of the most efficient methods used to reduce the complexity of large-scale networks and improve computation time (Sever et al., 2018). The traditional clustering algorithms, such as k -medoids and k -means, have been widely adapted in vehicle routing and location problems (Meng et al., 2018; Rabbani et al., 2017; Wang et al., 2017, 2018, 2020a). In fact, the second algorithm is commonly used in the literature due to its of reproduction, wide application and ability to monitor the clustering operation. In this study, the k -means clustering procedure is adapted to assign

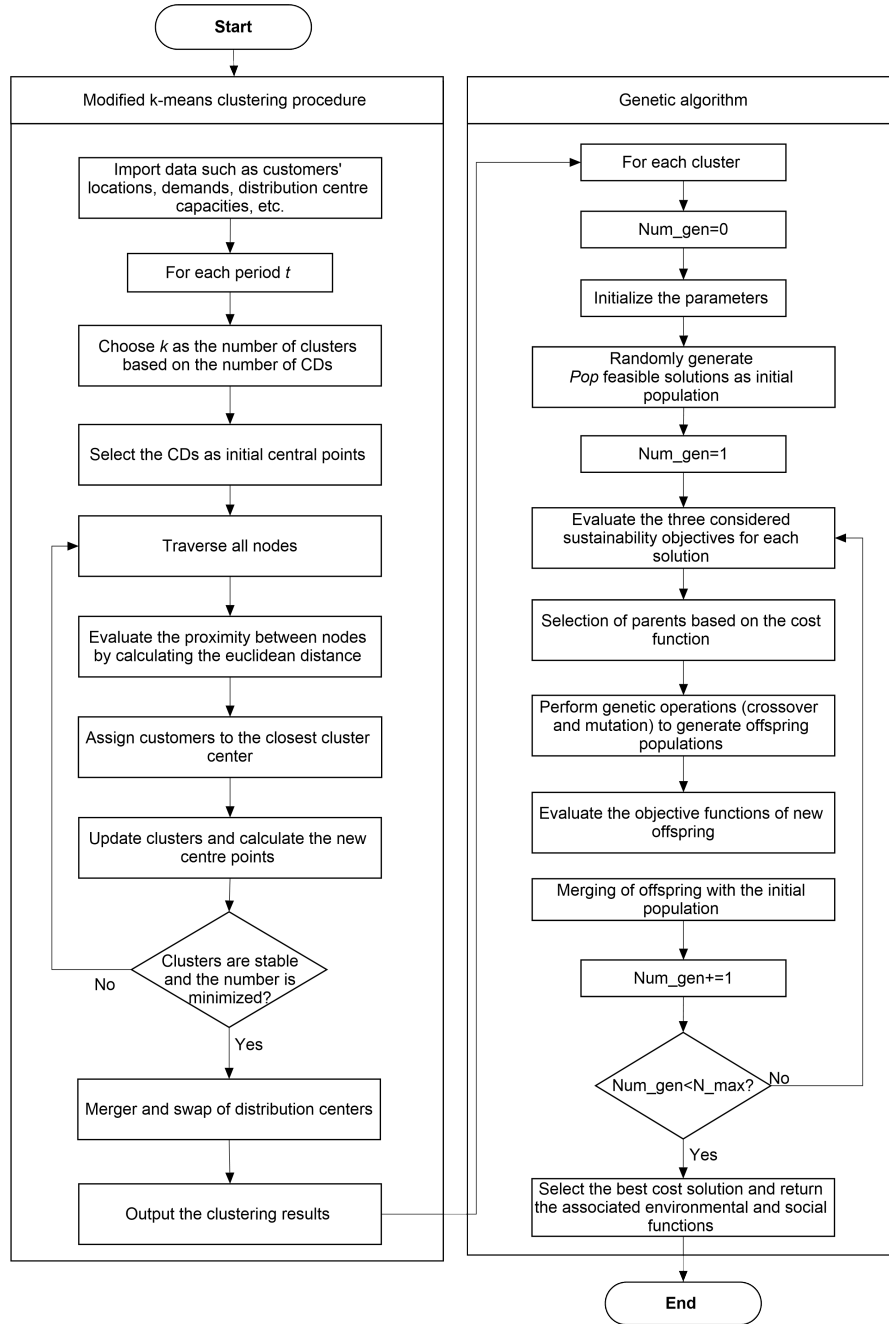


Figure 2: Flowchart of the proposed clustering-based approach to solve the 2E-CILRP.

customers and suppliers to the distribution centres according to the euclidean distance and product similarity. The pseudo-code of the modified k -means clustering algorithm is described in Algorithm 1.

Algorithm 1: MODIFIED_K_MEANS CLUSTERING ALGORITHM

Input: A set $I = \{I_1, I_2, \dots, I_{Nc}\}$ of customers data, $J = \{J_1, J_2, \dots, J_{Ns}\}$ of suppliers data, $D = \{D_1, D_2, \dots, D_{Nd}\}$ of DCs data and $P = \{1, 2, \dots, N_{per}\}$ of periodes

Output: Clustering and assignment results

```

1 for  $t = 1$  to  $P$  do
2   Select nodes coordinates, demand matrix and DCs capacities
3   Set  $k$  as the number of clusters on the basis of the number of DCs
4   Select the DCs as the initial central points of each cluster
5   repeat
6     for  $i = 1$  to  $I$  do
7       Calculate the distances between customer  $i$  and each
          center  $k$ 
8       Assign customer  $i$  to the closest and verified center point
9       Update the  $k$  clusters and calculate the new center points
10    end
11  until Maximum similarity is attained and the clusters are stable
12  Merging and swapping clusters to minimize the number of
     clusters
13 end
14 return Clusters results

```

As described in Algorithm 1, the geographical positions of suppliers, distribution centres, customers, the capacities of the distribution centres and the demands of the customers are imported to construct the datasets. Secondly, we define the number k of maximum clusters to be formed based on the number of the distribution centres that will be selected as k central points. Third, all elements are traversed and the distances between each element and the central points are calculated. Fourth, each element is assigned to the central points according to the proximity of distances and product similarity. In this step, the capacity constraints of the central points are checked. Fifth, the k clusters are updated and the new central points are calculated. The last three steps are applied until all customers will be assigned. Then,

we perform swap distribution centre location in order to avoid local optima. In addition, the clusters are merged by respecting the capacity constraints to minimize the number of distribution centres to be opened. The different steps of this algorithm are iterated until the formation of the clusters of all considered planning periods.

4.2. Genetic algorithm

The genetic algorithm, which was first announced in 1970s by [Holland et al. \(1992\)](#), is one of the approaches intensively applied to find good solutions to NP-hard optimization problems through its evolutionary process. In this study, a genetic algorithm is developed to deal with the routing and inventory problem. The pseudo code of the introduced algorithm is given by Algorithm 2. First, an initial population generation of *Pop* chromosomes is generated. Each chromosome should contain relevant information about the first echelon routing, the inventory plan and the second echelon routing plan at each period. The chromosome takes the form of a matrix with T rows and three strings that represent the pickup plan, the inventory in each distribution center and the delivery plan, respectively. To construct the routes, we apply a local search algorithm based on the nearest neighbor rules; the shortest distance. Then, the considered objectives are evaluated and a rank selection, relying on the economic function, is conducted. Then, the initial population is improved by two-point crossover and mutation operators in order to produce two offspring with a certain probability. This process will be continued until the maximum number of generations are attained. Finally, the best solution with low cost is selected .

5. Results, analysis and discussion

This section presents the computational experiments carried out to assess the effectiveness of the proposed approach in solving the 2E-CILRP and discuss managerial insights based on the real-world case study results. The heuristic was coded in Python 3. The MILP model was solved with IBM ILOG CPLEX 12.9.0 by normalizing and aggregating the three considered sustainability objectives, as discussed in [Aloui et al. \(2021a\)](#). All the experiments were solved in a PC running Windows 10 Home 64-bit with an Intel Core i5-10210U@ 1.6 GHz and 16 GB RAM.

To the best of our knowledge, there are no benchmark instances for the 2E-CILRP with sustainability concerns. Therefore, numerical tests on 13

Algorithm 2: GENETIC ALGORITHM

Input: Cluster data, maximum load transport fleet, set parameters

Output: Best solution

```
1 Generate the initial population
2 while  $Num_{gen} < N_{max}$  do
3   Evaluate the objectives function
4   Selection of parents based on the cost function
5   Realize two-point crossover and mutation operations
6   Generate the offspring populations and assess the objectives
    function
7   Combine offspring with the initial population
8 end
9 Select the best cost solution and assess the associated emissions and
    accident risk
10 return Best configuration
```

randomly generated small-scale and medium-scale instances are performed and a comparison between the heuristic and CPLEX results is carried out in Section 5.1 to evaluate the performance of the suggested approach. For each benchmark instance, the demands between each supplier-customer pair were randomly generated in the interval [1000,3000]. Similarly, the coordinates on the x-axis and y-axis of suppliers, customers and distribution centers are randomly generated in a square of size 200×200 . The distance between two nodes is calculated based on the Euclidean distance $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, where (x_i, y_i) are the coordinates of node i .

The parameter used in all computational experiments are derived from the literature and are listed in Table 3. For the proposed heuristic, the population size Pop and the maximum number of iterations N_{max} are 100 and 1000, respectively. The crossover and mutation probability are 0.8 and 0.05, respectively (Wang et al., 2018).

5.1. Experiments on small instances

The performance of the proposed heuristic is assessed by means of distance to solutions found by the CPLEX solver of the MILP model and computation time. For each instance, the best solutions found by the heuristic over 10 runs and the CPLEX results with a maximum CPU time of 3600

Table 3: Parameters setting for the numerical experiments

Parameter	Value	Unit	Source
EC_d	10000	kwh	ADEME (2010)
e_c	0.087	$kg\ CO_2/L$	ADEME (2010)
C_d	20000	Kg	Assumption
FO_d	6000	€	Wu et al. (2021b)
F_s	300	€	Soysal et al. (2018)
Q_s	20000	Kg	Soysal et al. (2018)
Ts_E	0.15	(L/km)	Hickman et al. (1999)
Ts_L	0.31	(L/km)	Hickman et al. (1999)
F_v	200	€	Soysal et al. (2018)
Q_v	10000	Kg	Soysal et al. (2018)
Tv_E	0.13	(L/km)	Hickman et al. (1999)
Tv_L	0.15	(L/km)	Hickman et al. (1999)
C_s	0.01	$\text{€}/Kg$	Stellingwerf et al. (2018)
e_F	2.66	$(kg\ CO_2/L)$	Tassou et al. (2009)
c_f	1.5	$(\text{€}/L)$	Aloui et al. (2021a)
A_c	2768	$(\text{€}/L)$	Mrabti et al. (2020)

seconds are reported. The computational results of 13 instances are summarized in Table 4. More specifically, the first five columns enumerate the characteristics of each instance. Columns 6, 7 and 8 present the total cost obtained by the CPLEX solver and the heuristic as well as the percentage gap between these two solutions, respectively. Columns 9, 10 and 11 show the total emissions obtained by the CPLEX solver, the total emissions found by the proposed heuristic and the solution quality deviation of the heuristic with the CPLEX solver, respectively. Columns 12 to 14 report the accident risk provided by the MILP model and the heuristic approach as well as the percentage gap between the latter solution and that of CPLEX, respectively. Columns 15 to 16 show the CPU time (in seconds) of the CPLEX solver and the proposed heuristic. The percentage difference between the solution of the proposed heuristic and the CPLEX solver is estimated as follows:

$$\%Gap = 100 \frac{Heuristic - CPLEX}{CPLEX}.$$

As shown in Table 4, the proposed heuristic can obtain solutions near to those obtained by the CPLEX solver in a much less computation time in the first ten instances. In fact, the cost gap is between -1.03% and 3.75%, with an average of 0.73%. The emissions gap ranges from 1.13% to 12.18%, with

Table 4: Summary of test results for the generated instances.

Instance characteristics					Total costs			Total emissions			Accident risk			CPU time (s)	
ID	J	D	I	T	CPLEX	Heuristic	% Gap	CPLEX	Heuristic	% Gap	CPLEX	Heuristic	% Gap	CPLEX	Heuristic
I1	2	2	7	3	15224,73	15253,88	0,19	2769,28	2800,53	1,13	17,34	18,31	5,56	2,54	3,41
I2	3	3	7	3	8737,82	8784,11	0,53	1873,56	2101,84	12,18	18,12	20,45	12,85	33,08	4,65
I3	3	3	8	3	15815,57	16134,37	2,02	2973,38	3154,59	6,09	20,10	23,21	15,46	80,54	4,18
I4	3	3	9	3	8787,18	8848,07	0,69	2107,35	2216,78	5,19	20,38	21,74	6,68	134,54	12,84
I5	3	3	10	3	16105,25	16109,59	0,03	3120,34	3312,91	6,17	21,34	23,93	12,15	379,70	35,32
I6	3	3	12	3	17268,81	17363,34	0,55	3425,95	3836,25	11,98	27,85	33,69	20,98	954,23	32,12
I7	3	3	13	2	14977,92	14823,40	-1,03	2754,65	2932,69	6,46	17,20	19,79	15,05	1845,15	45,32
I8	3	3	13	3	16945,12	17044,94	0,59	3119,84	3475,64	11,40	23,62	28,73	21,61	2680,13	92,54
I9	3	3	14	3	16762,14	17360,66	3,57	3499,40	3831,46	9,49	27,14	33,34	22,86	3251,43	132,27
I10	4	4	15	3	23418,88	23467,00	0,21	4605,88	4839,77	5,08	30,63	33,57	9,60	3570,12	250,38
I11	4	4	17	3	33981,15	26805,04	-21,12	6955,41	6041,38	-13,14	61,42	57,57	-6,28	3600	386,64
I12	4	4	17	4	NA	32165,54	NA	NA	74315,34	NA	NA	61,43	NA	NA	421,54
I13	2	2	20	4	NA	28654,34	NA	NA	6431,54	NA	NA	59,31	NA	NA	432,76
Average					17093,14	18678,02	-1,25	3382,28	9176,21	5,64	25,92	33,47	12,41	1502,86	142,61

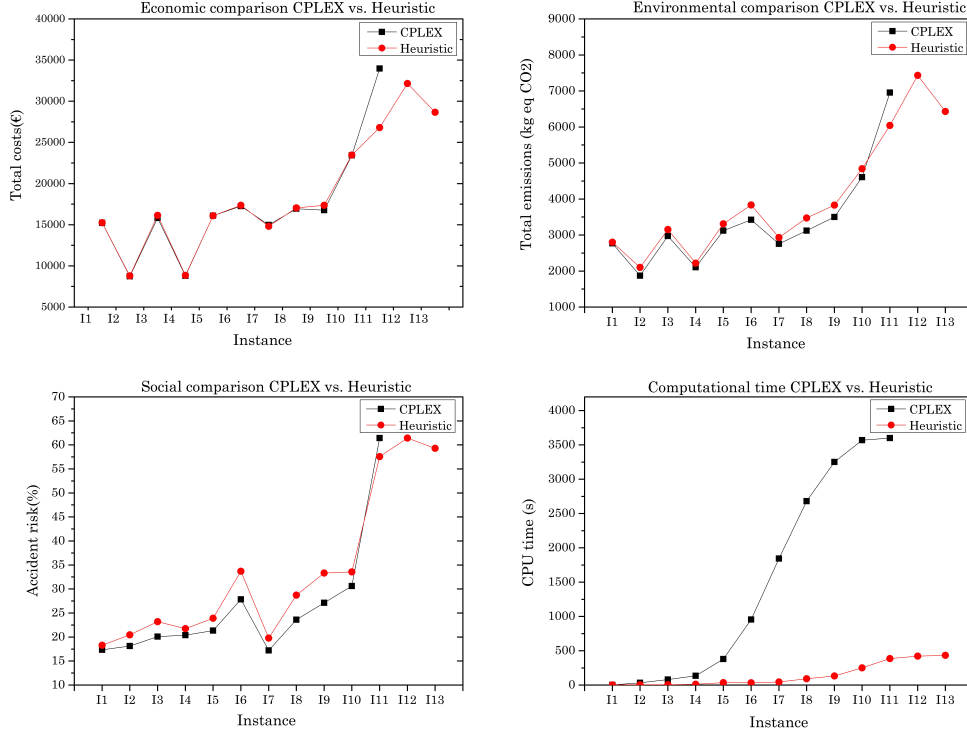


Figure 3: Performance of the proposed heuristic and the CPLEX solver

an average of 7.52%. Regarding the social aspects, the proposed heuristic provides feasible solutions with a gap varying between 5.56% to 22.86%, with

an average of 14.28% in the first ten instances. It is important to note that the solutions obtained by the heuristic approach are close to the optimal solutions for the instances I1 to I7, especially for the economic objective. For instance I11, our heuristic produces better solutions than CPLEX by almost 21% of the total costs, 13% of the total CO_2 emissions and 6% of accident risk. Moreover, it is obvious that the CPLEX solver cannot find any feasible solution for the instances I12 and I13 within a given time limit. From a computational efficiency perspective, the CPU time required for CPLEX solutions increases exponentially with the rise of the problem size, while the time of the heuristic is nearly linear, as shown in Fig. 3. Overall, the comparison results show that the proposed heuristic can rapidly find reasonably good and feasible solutions for 2E-CILRP problems as the gaps between the solutions are not significant. Consequently, our heuristic can be used to efficiently solve large problems in a reasonable time.

5.2. Performance evaluation on large-sized instances: Algorithm comparison

To verify and validate the effectiveness of the GA algorithm in the proposed approach, GA was compared with the most popular heuristic algorithms for solving logistic optimization problems, namely k -nearest neighbor algorithm (KNN) (Mohammed et al., 2017) and particle swarm optimization (PSO) (Chroua et al., 2021; Goksal et al., 2013). The algorithms were tested and compared using 10 different randomly generated instances with medium and large-size. In the computational experiments, the maximum iteration number was set to 10000 iterations for the KNN algorithm, personal and social learning confidences were fixed at 2, and an inertia weight was set to 0.8 for PSO algorithm. The comparison results are presented in Table 5.

As shown in Table 5, the proposed heuristic based on GA algorithm outperforms the other two algorithms in terms of total costs, emissions and accident risk in all tested instances. In fact, the average total costs of the proposed heuristic is lower than that obtained by the KNN and PSO algorithms by 2.73% and 8.16%, respectively. In terms of emissions, the GA-based heuristic allowed saving 8.16% of the total average emissions, compared with KNN algorithm, and 10.73% compared with PSO algorithm. In addition, the proposed algorithm can reduce the average accident risk by 3.37%, compared to KNN algorithm, and 8.43% compared to PSO. For computation performance, the proposed algorithm performs better than the KNN algorithm. In some cases, PSO algorithm finds lower quality solutions than those found

Table 5: Comparison results with two optimization algorithms

Instance	GA				KNN				PSO			
	Costs	Emissions	Risk	CPU	Costs	Emissions	Risk	CPU	Costs	Emissions	Risk	CPU
I1	8873,13	1910,94	15,53	36,05	9187,76	2243,37	17,46	41,87	9235,65	2276,43	18,03	37,49
I2	10974,83	2419,27	30,37	44,36	11499,62	2573,75	31,48	45,65	11643,66	2622,01	31,72	49,09
I3	11574,15	2800,87	37,55	46,32	12264,02	2991,01	38,32	51,43	11954,12	2875,33	37,99	51,80
I4	11813,21	3217,44	45,40	48,03	12839,68	3468,00	45,46	63,51	12887,01	3699,56	45,89	52,41
I5	12684,33	3568,83	52,72	62,40	12891,13	3939,68	52,93	72,11	12932,35	3712,89	53,01	61,19
I6	13007,05	3364,23	49,00	54,45	12989,39	3691,23	47,76	79,15	13010,79	3721,25	48,59	60,89
I7	16592,60	2957,43	23,10	70,43	16608,85	2986,56	23,67	86,49	16624,78	3015,13	24,27	66,89
I8	20128,25	4178,17	49,26	112,43	20011,85	4877,91	54,87	93,45	20128,64	4214,43	55,58	97,69
I9	20173,33	4540,15	54,46	128,54	21229,51	4780,15	56,50	136,11	21636,93	5869,46	71,94	116,11
I10	24798,85	7764,58	83,00	127,54	25321,43	8431,54	87,28	142,98	27497,98	9128,27	93,93	118,40
Average	15061,97	3672,19	44,04	73,06	15484,32	3998,32	45,57	81,28	15755,19	4113,48	48,10	71,19

by our algorithm with less computational time. Therefore, we can conclude that the GA-based heuristic is superior to both algorithms for integrated and collaborative optimization of two-echelon logistic networks.

5.3. Case study

In order to demonstrate the feasibility and effectiveness of the introduced optimization model in the real world, a case study of four French SMEs in the agri-food sector is discussed in this section. It consists of four companies (S1, S2, S3 and S4), four distribution centers (DC1, DC2, DC3 and DC4), 39 customers (C1 to C39) and 4 planning periods; each of which represents a week. The demand matrix for each client at each week is given in Table A.7. The companies in question are anonymized for confidentiality reasons. The geographical positions of each node are presented in Fig. 4 where colours are used to differentiate suppliers and their customers. For example, blue color represents supplier S1 and their customers. In the current situation, each company serves their customers independently of the others while, in a multi-period collaborative strategy, the companies share the means and resources to serve their customers in urban areas. The results optimization results obtained before and after collaboration of the three dimensions of sustainability, namely the total cost, total CO_2 emissions and accident risk, are summarized in Table 6. The location of distribution centers, the inventory management and the routing plans for each planning week are presented in Fig. 5 and Fig. 6, respectively.

The obtained results reveal that the proposed collaborative strategy affects positively the sustainability of transportation operations. Indeed, from

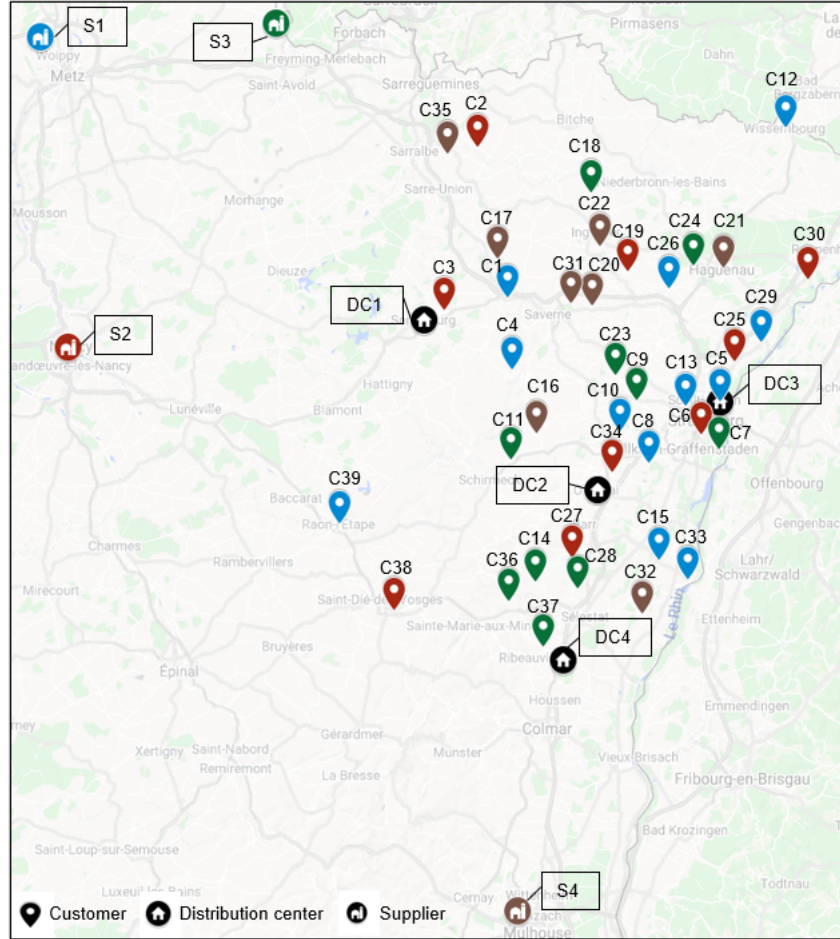


Figure 4: Suppliers, distribution centers and customers' locations in the case study.

Table 6: Summary of the results obtained in the initial and collaborative scenarios.

Sustainability Indicator	Integrated decisions planning		% Saving
	Initial	Collaborative	
Total costs (€)	35553,26	28422,48	20,06
Total CO_2 emissions ($Kg CO_2$)	6617,87	5534,64	16,37
Accident risk (%)	56,49	52,15	7,69

an economic point of view, the total cost decreases by 20.06% after collabora-

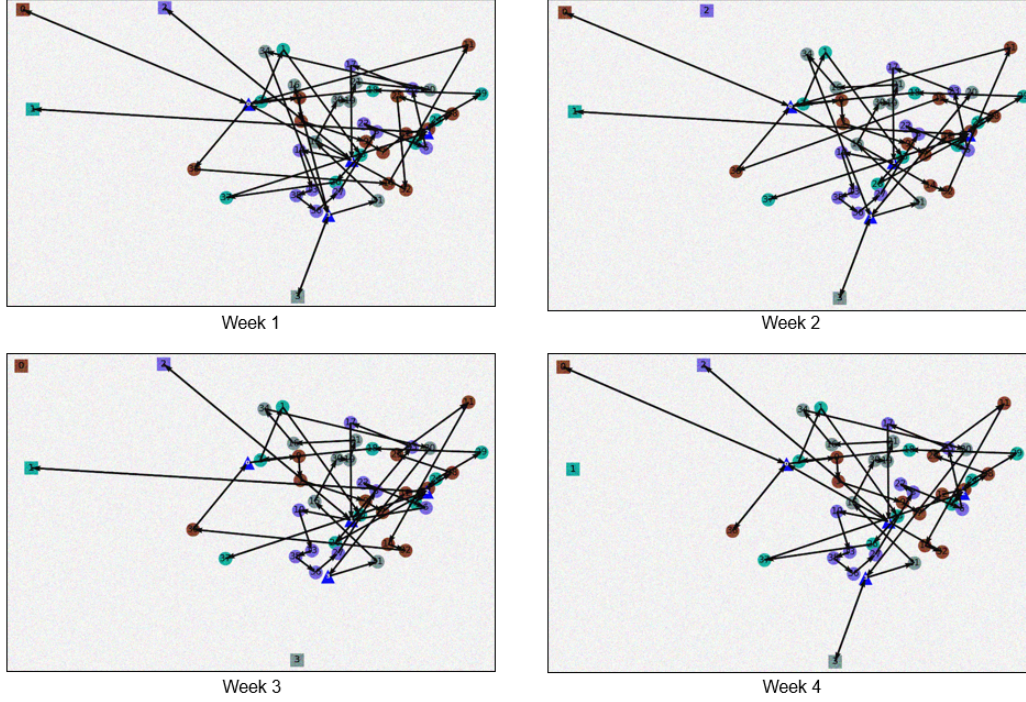


Figure 5: Initial distribution plan.

tion in 2E-ILRP. This reduction is due to the fact that collaboration between several companies can reduce the resources to be exploited. For example, in this case study, companies can benefit from resource sharing to minimize the number of distribution centres to be used and the number of routes through massification of flows, as shown in Fig. 6. From an environmental point of view, periodic cooperation can save CO_2 emissions to 16% through the sharing of distribution centres and the consolidation of goods. With regard to the assessed social dimension, the case study results show that joint planning reduces the risk of accidents by 7.69%, compared to the autonomous situation by reducing the total distance travelled in all periods. Through customer reallocation and joint route planning, these distances can be saved. Vehicle and semitrailer truck loading rates can also be increased to achieve economies of scale and reduce the number of vehicles in the city. In summary, the optimization of 2E-CILRP offers considerable benefits to logistics companies that wish to improve the sustainability of their logistics operations by reducing logistics costs, CO_2 emissions and accident risk.

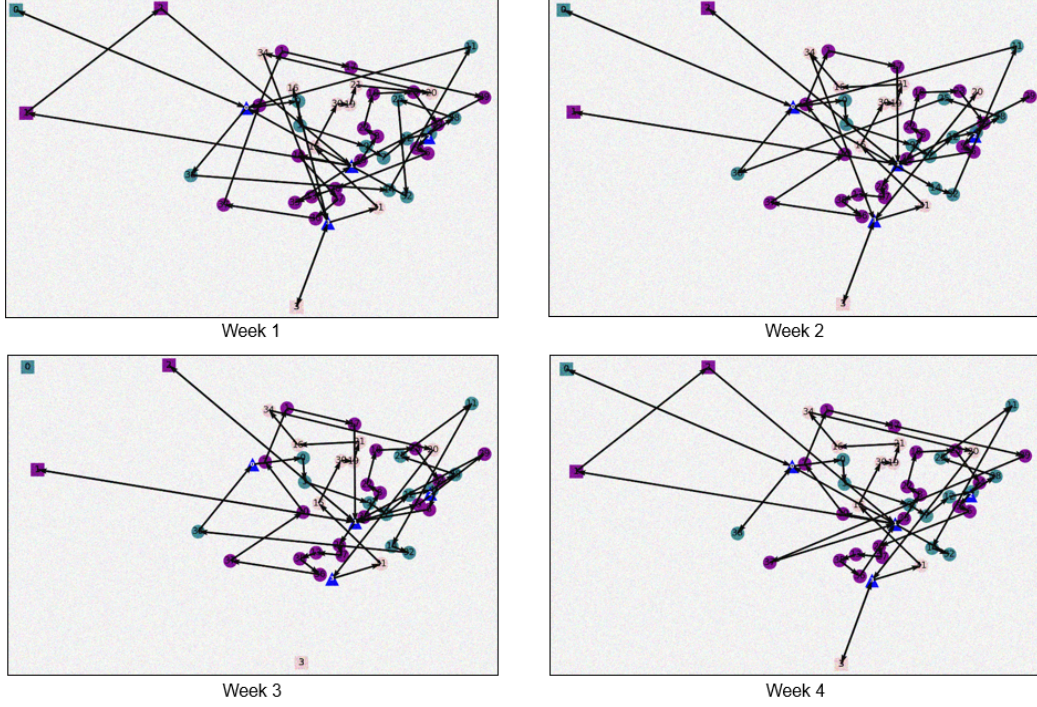


Figure 6: Distribution plan after collaboration.

5.4. Sensitivity analysis

As this paper discusses the collaboration and resource sharing in the inventory-location-routing problem, and as demands, distribution center capacities, vehicle and semitrailer trucks capacities are important input parameters, a sensitivity analysis is performed in this section to reveal the impact of varying these parameters on sustainability objectives and savings achieved by our model. For this reason, we considered multiplier coefficients for the base values of these parameters and varied these coefficients for different values. For example, the base capacities of vehicles and semitrailer trucks were multiplied by the following values: 0.8, 0.9, 1, 1.1, 1.2, 1.3. The results of the sensitivity analysis are presented in Table A.8 in Appendix A. Fig. 7 shows the savings in terms of costs, emissions and accident risk, compared to the autonomous situation in various scenarios.

According to the results illustrated in Table A8, the variation in vehicles and semitrailer trucks capacities leads to a change in the sustainability objectives in both configurations (before and after the collaboration). In fact,

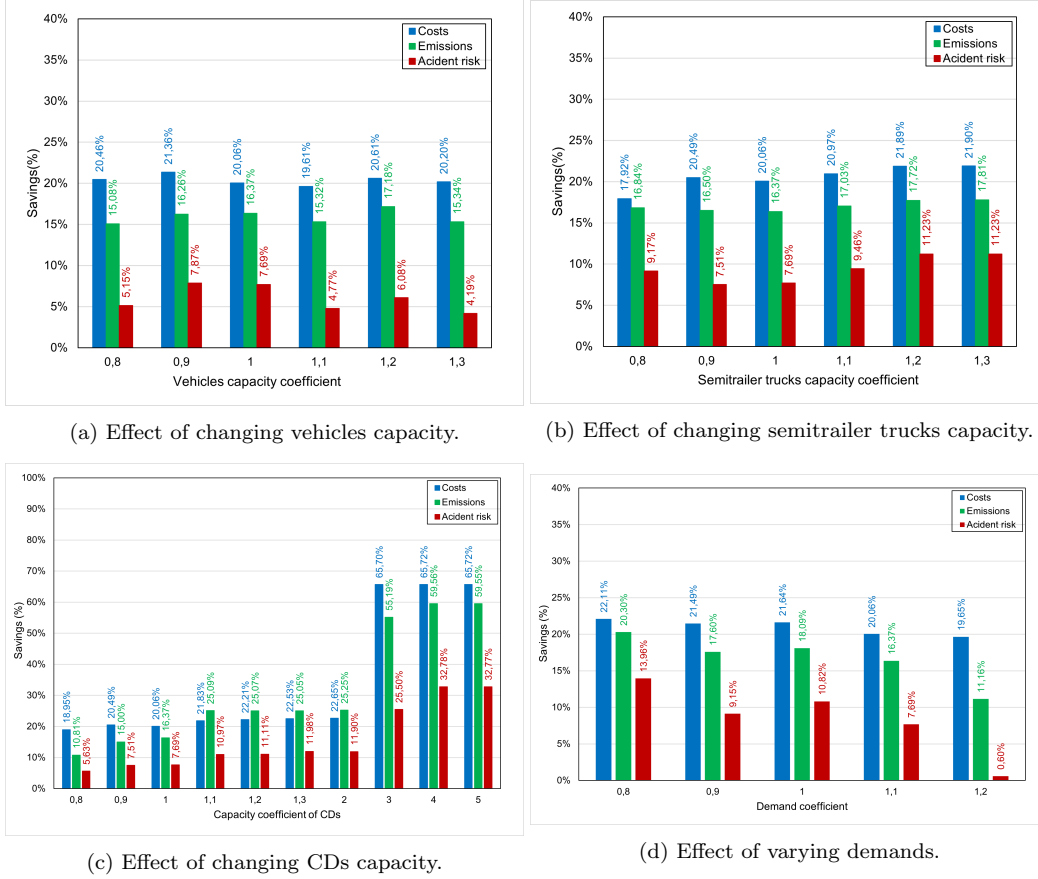


Figure 7: Impact of varying parameters on sustainability savings.

the use of transport means with high capacities allows minimizing total cost, emissions and accident risks. This reduction is due to the decrease of the number of trips by increasing the transport means loading rate. However, the decrease or increase of vehicles and semitrailer trucks capacities provides almost the same savings in the various scenarios. In addition, the results indicate that with an increase in distribution centers' capacities, the costs, emission levels and accident risks decrease continuously. Besides, as shown in Fig. 7, when the capacities exceed a certain value, the savings from co-operation compared to the non-collaborative case become significant. This finding can be interpreted by the reduction of the travelled distances and the number of used distribution centers as well as by the increase of the inventory

quantities by relaxing the distribution centers' capacities. For example, in the case where the capacities are multiplied by 3, our model opens only one distribution center and increases the amount of inventory in order to reduce the number of trips in the first echelon. As a result, the capacities of distribution centers have significant effects on the savings and decision making in general. Finally, we may deduce that high demand variation requires sending more products, which increases costs, emissions and accident risks. For the savings achieved through collaboration, the variation in demand impacts considerably the emissions and accident risk savings, as shown in Fig. 7. Nevertheless, the cost savings are very similar in most scenarios.

Through this analysis, we find that the distribution centers capacities and demands affect the resulting savings from the collaboration. Therefore, in order to achieve significant savings, decision-makers should adjust these parameters and choose high capacities values.

6. Conclusion

In the modern era, logistics network management by simultaneously addressing several challenges, such as integrated decision making and sustainability concerns, constitutes a major issue in the distribution network design. This study incorporated multi-period location, inventory, and routing decisions with an effective managerial strategy from a sustainable and efficient two-echelon transportation network. In fact, logistics collaboration was studied to analyze the effects of resource sharing on the sustainability of logistics networks. Firstly, a multi-objective model is developed to formulate the 2E-CILRP with the minimum logistic cost, CO_2 emissions and accident risk. Secondly, due to the complexity of the examined problem, a hybrid heuristic was suggested to solve large-scale problems. The heuristic combines a k -means clustering algorithm and a genetic algorithm. To evaluate the performance of the proposed heuristic, comparison of the obtained results with those provided with exact method on small and medium-sized instances was performed. Experimental findings showed that the heuristic is capable to generate good solutions in a reasonable computation time. Finally, a case study in French agri-food sector was discussed to evaluate the practical application of the proposed model and approach in the real world. The obtained results demonstrated that collaboration between companies is beneficial for reducing sustainability impacts. Comparing with the stand-alone situation, the sharing of resources and joint planning can achieve savings of almost 20%

in logistics costs, around 16% in resulting CO_2 emissions and also a decrease of nearly 8% in accident risk.

This study has some important managerial implications that can be summarized as follows: (i) this research can be used to highlight the importance of integrating strategic, tactical and operational decisions in the network design with sustainability performance evaluation; (ii) the proposed model and the solution approach can help logistics and transport decision-makers to design two-echelon and multi-period network; (iii) the sharing of resources, such as transportation means and distribution centers in multiple time periods, can improve the utilization of resources, achieve economies of scale, and reduce social-environmental aspects. However, there are several factors that can block its success and continuity, namely the compatibility of the products, the confidence, and the efficiency of information sharing between the stakeholders.

Although this study efficiently formulated and solved the 2E-CILRP for a sustainable transportation system, several suggestions are recommended for future research. Firstly, this work can be extended to incorporate multi-objective approaches (NSGA-II, MOPSO, etc.) to find Pareto efficient frontiers. Secondly, it is possible to integrate uncertainties and disruptions sources in the future development of the optimization model. Finally, the fair benefit-sharing mechanisms may be incorporated into the optimization approach to ensure the continuity and success of the collaborative strategy between participants.

Appendix A. Demand data and sensitivity analysis results

Table A.7: Customers' demand (Kg).

Customer	From supplier	Week 1	Week 2	Week 3	Week 4
1	1	1046	1183	1493	1907
2	2	144	1547	1304	705
3	2	1543	1015	258	1338
4	1	1969	116	1688	1341
5	1	432	1855	616	102
6	2	1842	1345	1888	413
7	3	1123	551	1002	239
8	1	759	659	122	465
9	3	789	863	1680	493
10	1	834	1723	507	1613
11	3	1718	751	629	895
12	1	955	1492	295	1433
13	1	1071	1729	269	155
14	3	303	952	1111	1249
15	1	1057	1849	301	1204
16	4	1372	1938	758	1433
17	4	1886	603	1599	1445
18	3	1247	255	1822	1644
19	2	1237	914	817	819
20	4	1695	1683	125	481
21	4	1436	1901	1432	1200
22	4	1947	1234	1288	868
23	3	609	1892	1500	1375
24	3	430	1932	1676	1507
25	2	1939	999	1664	159
26	1	1867	631	101	879
27	2	848	169	211	740
28	3	1028	952	653	696
29	1	1641	720	835	386
30	2	540	1424	967	508
31	4	1912	220	784	261
32	4	1222	1493	941	1094
33	1	160	1459	775	253
34	2	312	1452	1636	607
35	4	310	1956	971	1937
36	3	460	947	1418	174
37	3	511	611	629	1483
38	2	821	1922	1421	1867
39	1	321	303	600	1738

Table A.8: Sensitivity analysis results.

	Coefficient	Without collaboration			With collaboration		
		Costs (€)	Emissions (kg)	Accident risk (%)	Costs (€)	Emissions (kg)	Accident risk (%)
Vehicles capacity	0,8	36639,33	6772,21	59,68	29142,95	5750,69	56,61
	0,9	36218,75	6735,30	58,96	28481,27	5640,08	54,31
	1	35553,26	6617,87	56,50	28422,48	5534,64	52,15
	1,1	35114,83	6548,93	55,07	28228,54	5545,52	52,45
	1,2	34453,50	6438,95	52,70	27351,90	5408,08	49,50
	1,3	34028,93	6394,90	51,84	27155,10	5413,82	49,66
Semitrailer trucks capacity	0,8	35528,53	6958,50	61,82	29163,09	5786,81	56,15
	0,9	35924,83	6742,86	57,79	28563,10	5630,47	53,45
	1	35553,26	6617,87	56,49	28422,48	5534,64	52,15
	1,1	35536,96	6588,63	56,50	28084,67	5466,85	51,15
	1,2	35523,38	6564,20	56,50	27747,79	5400,70	50,15
	1,3	35511,89	6543,66	56,50	27735,23	5378,18	50,15
CDs capacity	0,8	28796,01	6025,19	58,34	35528,53	6755,28	61,82
	0,9	35924,83	6624,29	57,79	28563,10	5630,47	53,45
	1	35553,26	6617,87	56,50	28422,48	5534,64	52,16
	1,1	35390,27	7013,91	53,17	27663,41	5253,78	47,33
	1,2	35453,78	6922,54	52,47	27578,66	5186,91	46,64
	1,3	35435,88	6843,14	51,87	27452,37	5128,62	45,66
	2	35572,36	6751,70	51,18	27516,95	5046,67	45,09
	3	35572,37	6751,80	51,18	12200,98	3025,27	38,13
	4	35572,38	6751,90	51,18	12193,01	2730,68	34,41
	5	12193,02	2730,69	34,41	35572,39	6751,10	51,17
Demand	0,5	33634,54	5875,97	45,60	26196,47	4683,02	39,23
	0,7	33628,54	5954,72	45,60	26401,98	4906,66	41,43
	0,9	34711,39	6296,14	50,88	27199,85	5157,29	45,37
	1	35553,26	6617,87	56,49	28422,48	5534,64	52,15
	1,2	36669,32	6920,03	61,58	29464,47	6147,95	61,22

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