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A GENETIC ALGORITHM FOR THE INTEGRATED WAREHOUSE LOCATION, ALLOCATION AND VEHICLE ROUTING PROBLEM IN A POOLED TRANSPORTATION SYSTEM

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In this paper, we address the integrated location, allocation, and routing problem in the framework of a pooled transportation system. We assume that many enterprises with familiar customers aim to share their logistical means. Two collaborative scenarios are proposed and solved. A genetic algorithm based on Clarke and Wright's savings heuristic is proposed to solve the different considered scenarios. A comparison is established between collaborative and noncollaborative scenarios to assess the impact of the proposed pooled transportation system. The obtained computational results indicate that the collaborative scenarios outperform the noncollaborative scenario. The total annual transportation cost is reduced by approximately 28% to 54% in the collaborative scenarios. Furthermore, the collaborative scenarios may reduce the number of required vehicles and increase the average fill rate of the used vehicles. It is worth noting that the proposed genetic algorithm solves efficiently adapted benchmark instances from the literature.

Keywords: Genetic Algorithm, Pooled Transportation System, Saving Heuristic, Vehicle Routing, Horizontal Collaboration.

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1. INTRODUCTION

Global competition has increased urban traffic congestion, and increased carbon dioxide (CO_2) emissions have pressured companies to look for efficient transportation methods with low costs, minimal environmental impacts, and low turnaround times. However, the increased delivery frequency, which is supposed to improve customer service and reduce inventory costs, leads to low vehicle utilization (i.e., incomplete loading), which increases the transportation costs incurred by fuel and road taxes (Lozano *et al.,* 2013; Pomponi *et al.,* 2015). This consequently increases CO_2 emissions and traffic congestion. One of the solutions proposed by researchers to overcome these challenges is collaborative logistics. Collaboration occurs when two or more entities form a coalition and exchange or share physical and/or informational resources to make decisions or generate benefits from activities that they cannot do individually (Audy *et al.*, 2012). Simatupang and Sridharan (2002) defined a *collaborative supply chain* as a scenario when "two or more independent companies work jointly to plan and execute supply chain operations with the greatest success than when acting in isolation". Successful cooperation between partners requires commitment, trust, information sharing (Singh and Power, 2009), and a fair allocation of benefits (Hacardiaux and Tancrez, 2018).

The load factor is an index of the utilization of the available cargo capacity; according to the European Environment Agency, on average, cargo trucks are only 50% loaded (Abate, 2014). This shows significant room for improvement. Nevertheless, increasing the load factor would reduce the volume of freight traffic, thus reducing transportation costs and CO_2 emissions.

Adopting a pooled transportation system between companies with similar products and joint customers is an attractive solution for increasing the load factors of cargo trucks. A pooled transportation system involves cooperation between independent supply chains to build a shared supply chain network while sharing their available transportation and warehousing resources. Pooled logistics impose the sharing of depots and vehicles. Thus, this paradigm may yield decreased warehousing and transportation costs compared to classic logistics. Although pooled logistics can increase vehicle utilization and reduce CO_2 emissions, developing a pooled network is complex. It must include the locations of shared facilities, the assignment of each company to these facilities, and the routing of the distribution vehicles.

Theoretically, the pooled transportation problem is closely related to the classic vehicle routing problem (VRP), in which the total cost of a vehicle departing from a company's depot, delivering the required quantities to its customers, and

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then returning to the depot is minimized. However, unfortunately, the classic VRP is a nondeterministic polynomial (NP)-hard problem; i.e., no known polynomial-time algorithms exist to solve it.

Indeed, the VRP generalizes the traveling salesman problem (TSP) and the bin packing problem, which -are also known as NP-hard (Garey and Johnson, 1979). As cargo vehicles are often underutilized, companies intervening in the same distribution area and selling compatible products may find it profitable to share their distribution resources and depots to optimize their distribution networks.

This work, therefore, aims to simultaneously solve the warehouse location problem, the allocation of companies to the selected depots, and the routing problem. The objective is to minimize the total transportation cost from collaborative companies to the depots and from depots to the customers. In this paper, two different collaborative scenarios are proposed. A genetic algorithm (GA) is then developed and modified to solve each corresponding scenario. The proposed GA uses Clarke and Wright's savings (CWS) algorithm to assess the fitness of each chromosome. Finally, the performance of the GA is tested on modified benchmark instances from the literature concerning the VRP.

The remainder of this paper is organized as follows. First, a literature review is presented in Section 2. Then, a description of the problem is detailed in Section 3. After that, the methods used to solve the proposed problem are described in Section 4. The obtained results are then displayed and discussed in Section 5. Finally, conclusions and future research directions are provided in Section 6.

2. LITERATURE REVIEW

A collaborative supply chain is a business partnership between two or more companies to achieve common goals. Depending on its structure, it is classified as either vertical, horizontal, or lateral collaboration (Simatupang and Sridharan, 2002).

- Vertical collaboration: This type of collaboration occurs between actors or partners working at different levels of the supply network (Cruijssen, 2006). Some examples of the applications of vertical collaboration are related to the inventory routing problem (Archetti *et al.,* 2007, Savelsbergh and Song, 2008) and the production routing problem (Adulyasak *et al.,* 2015).
- Horizontal collaboration: The European Union (Union, 2001) defined horizontal collaboration as "concerted practices among companies operating at the same level(s) in the market." According to Simatupang and Sridharan (2002) and Moutaoukil, Derrouiche *et al*. (2012), horizontal collaboration involves the collaboration of two or more competing or unrelated organizations at the same level (e.g., between suppliers, manufacturers, and distributors) in a supply network to share their information or resources. The goal is to reduce costs and/or improve services (Pérez-Bernabeu *et al.,* 2015). Horizontal collaboration has been applied to the collaborative VRP of carrier collaboration and the lane-covering problem of shipper collaboration (Danloup *et al.,* 2013).
- Lateral collaboration: This paradigm combines vertical and horizontal collaboration to increase flexibility (Simatupang and Sridharan, 2002).

The collaboration between partners in a supply chain can take place at different planning levels, as follows (Gonzalez-Feliu and Morana, 2011).

- *Transactional collaboration*: This level involves the standardization and coordination of administrative operations and exchange techniques.
- *Informational collaboration*: This level relates to a mutual exchange of information. Examples of this type of collaboration include sales, stock levels, and delivery dates.
- *Decisional collaboration:* This level concerns collaboration at different planning horizons, namely:
  - *Operational planning:* concerned with daily operations that are shared or coordinated, such as freight transportation.
  - *Tactical planning*: also called middle-term planning, which involves several decisions such as sales forecasts, shipping operations decisions, quality control, and production management. Trust between the collaborators is essential at this stage.
  - *Strategic planning*: related to long-term planning. Decisions at this level include network design, facility location, finance, and production planning.

Habibi *et al*. (2018) classified decisions at each level regarding collaboration in the supply chain as follows.

- Operational planning involves delivery scheduling, routing, and vehicle assignment.
- Tactical planning focuses on determining inventory levels, delivery frequencies, and cost and benefit allocation.
- Strategic planning focuses on defining the number and locations of facilities, the number of required vehicles, decisions on whether to enter a coalition and partner selection.

Researchers have identified two types of horizontal collaboration: shipper and carrier collaboration. Shipper collaboration considers multiple shippers and a single carrier and is realized by consolidating the shippers' shipments to be offered to the carrier. Carrier collaboration considers how to provide opportunities for less-than-truckload (LTL) carriers to reduce the costs associated with fleet operation, decrease lead times, increase asset utilization, and enhance overall service levels (Li *et al.*, 2016).

Verdonck *et al*. (2013) classified horizontal carrier collaboration into two main approaches: sharing customer orders and sharing vehicle capacities. Sharing customer orders concerns all states where the collaborating carriers share, combine, or exchange customer orders or requests, but each carrier's fleet remains unchanged (Fernández *et al.*, 2018). In this approach, carriers may enjoy increased capacity utilization, improve their asset repositioning capabilities, and reduce the total incurred transportation costs due to enhanced transportation planning. In addition, when sharing vehicle capacities, capital investments may be divided among partners, and vehicle utilization may be improved. Therefore, capacity sharing is a suitable alternative to order sharing, especially in environments where private order information cannot be shared among collaborating partners.

Many researchers have investigated carrier collaboration. For example, He *et al*. (2018) studied collaboration between carriers with some of their orders to reduce the influences of shippers' stochastic demands and transportation costs. Verdonck *et al*. (2016) discussed the sharing of distribution centers (DCs) with collaborating organizations in their presented approach for horizontal carrier collaboration. They focused on deciding which DCs to open and how to allocate the quantity of product flowing to each open DC to minimize the logistics cost between the partnering companies. The authors classified this problem as a facility location problem under cooperation and concluded that DC sharing may reduce costs by up to 21.6%. Furthermore, Ftouh *et al*. (2020) reviewed structured classification types for carrier collaboration problems.

Verdonck *et al*. (2013) presented a review of solution methods based on two operation planning approaches: order sharing and capacity sharing. They focused on the operational level of horizontal collaboration between carriers. Amer and Eltawil (2015) performed a literature review on quantitative models for the successful implementation of horizontal collaboration. They classified the literature into conceptual, empirical, and mathematical research. Regarding the empirical research, the authors listed empirical studies on horizontal collaboration in supply chain networks by giving each study's location, sector, purpose, and methodology. For mathematical research, the authors presented research related to mathematical approaches with different types of decisions and the importance of horizontal collaboration. Then, the authors proposed a framework for integrating sustainability into a collaborative supply chain strategy for meeting customer and stakeholder expectations while focusing on long-term environmental effects. Gansterer and Hartl (2017) classified the literature on the collaborative VRP into centralized and decentralized collaborative planning approaches with and without auctions. The central decision-maker should complete the relevant information in centralized collaborative planning.

In contrast, decentralized collaborative planning appears when the decision-maker does not have complete relevant information. Chen *et al*. (2017) conducted a systematic literature review and a quantitative bibliometric analysis on supply chain collaboration for sustainability. The review revealed trends in supply chain collaboration. One trend shows that research has moved from upstream collaboration to combining upstream and downstream collaboration. Another trend is that research has broadened to include other elements for collaboration, such as relationships and shared responsibilities. The third trend shows increasing attention to economic and environmental issues. However, the authors reported that there is a lack of consideration regarding the social issues of sustainability. Basso *et al*. (2019) conducted a survey on practical issues related to implementing horizontal collaboration. Ferrell *et al*. (2019) reviewed existing horizontal collaboration research. Pan *et al*. (2019) performed an extensive review of horizontal collaborative transport methods and classified the previous studies according to their horizontal collaborative transport solutions and implementation issues. Gansterer and Hartl (2020) retained the classification of their previous literature review published in 2017. Nevertheless, they focused on recent findings, identified research gaps, and reported more than 40 relevant articles published in the last three years alone.

Independent of the classification of collaborative supply chains, many approaches have been used to enhance their performance indicators over those of noncollaborative supply chains. Specifically, heuristic and simulation approaches have been deployed. Moutaoukil *et al*. (2012) performed a large-scale revision and introduced a conceptual framework for implementing a pooling supply chain as a horizontal collaborative logistics strategy. Furthermore, the same authors of this latest paper mentioned that logistic systems must satisfy the economic, ecological, and societal levels of sustainable development (Moutaoukil *et al.*, 2013). Therefore, to address these three levels of sustainable development, a simulation approach with different scenarios was developed to reduce CO_2 emissions in the framework of a pooled logistic system. Ferdinand, Kim *et al*. (2014) proposed a GA for a collaborative service network in which one service center is operated and shared by companies with low demand. Saif-Eddine *et al*. (2019) proposed an improved GA for the integrated inventory, location and routing problem and studied the effect of vehicle capacity on the total supply chain cost by solving two instances with 10 and 30 customers. Ouhader and Elkyal (2016) studied a model for a pooled distribution supply chain (SC). They developed a multisourcing and multiproduct 2E-LRP in which routes can end at different depots from the starting depot. A mixed-integer linear model was proposed for the problem. The authors focused on a single objective, optimizing the cost, and then evaluated other metrics, such as the carbon emission rate. Ouhader and El Kyal (2017) proposed a bi-objective mathematical model to minimize total transportation costs and CO_2 emissions in a horizontal collaborative supply chain framework. The authors simultaneously considered facility location and vehicle routing decisions in their model. Another study performed by (Ouhader, 2020) adopted a multiobjective approach that focused on the balance between the economic and environmental impacts resulting from adopting horizontal collaboration among shippers. Nataraj *et al*. (2019) proposed a metaheuristic algorithm for the location routing problem in different collaborative scenarios. (Zouari, 2019) proposed seven pooling scenarios between three companies and evaluated each based on its transportation cost, greenhouse gas emissions, congestion, use of resources, and delivery times. Quintero-Araujo *et al*. (2019) proposed a hybrid metaheuristic algorithm for integrated facility location and routing decisions. Three scenarios were solved: noncooperative, semi-cooperative, and fully cooperative situations. These scenarios were evaluated based on two aspects. The first aspect was the total cost, which comprises the opening cost of the depot, vehicle costs and routing costs. The second aspect concerned CO_2 emissions. Wang, Yuan *et al*. (2020) proposed a decomposition optimization method to solve a collaborative two-echelon multicenter VRP based on a state–space–time (CTMCVRP-SST) network. Achamrah *et al*. (2020) proposed two simulation models to evaluate the advantages and disadvantages of sharing pallets in a collaborative supply chain. The first model was a noncollaborative supply chain in which each producer managed its pallets. In contrast, the second model was a collaborative supply chain in which producers shared empty pallets. The results showed that collaboration between producers could reduce transportation and inventory costs. Kao *et al*. (2021) proposed a two-stage model including decisions about supply chain design and virtual machine allocation in cloud computing environments. The objective of the first level is to minimize the total cost, carbon emissions, and transportation lead time. The second level aims to minimize the physical machines' energy consumption and power waste.

As reported in many research studies, the implementation of collaborative supply chains demonstrates a significant benefit. Cruijssen (2006) showed that using more flexible and developed logistical strategies is more efficient than traditional strategies for helping transportation sectors achieve their economic and environmental goals. Xu *et al*. (2012) showed that supply chain pooling can result in reductions in both transportation costs and carbon emissions and that an increase in the carbon tax rate gives enterprises more incentive to implement such a pooling scheme. Pan *et al*. (2014) applied the pooling concept to a collection of small and medium-sized Western French food suppliers serving the same retail chain. They demonstrated the efficiency of pooling through a comparison between the existing transport organization scheme and various pooling scenarios. The computational results of Ouhader and El Kyal (2018) showed that a collaborative approach could reduce transportation costs, the number of vehicles used, and CO_2 emissions and indirectly minimize both nuisance and traffic congestion levels in cities. Mangina *et al*. (2019) stated that pooling could increase efficiency and reduce road freight transport emissions.

A list of the most important published papers about horizontal collaboration is presented in Table 1. The proposed methodology and the type of decision level (strategic, tactical, and/or operational) of each paper are specified in this table.

Table 1. Analysis of Research on Horizontal Collaboration and Pooled Logistics

Author/Year	**Research Focus**	**Methodology**	**Decision Level**		
			Strategic	Tactical	Operational
Ergun *et al.*, 2007	Truckload shipper collaboration.	Greedy heuristic			X
Krajewska *et al.*, 2008	Studying cooperation among freight carriers to share requests in a pickup and delivery problem with a time window and analyzing the profit margin resulting from horizontal collaboration among carriers.	Adaptive large neighborhood search heuristic for routing problems Cooperative game theory for profit allocation		X	X
Bahinipati *et al.*, 2009	Assessing the level of collaboration between partners.	Analytic hierarchy process–fuzzy logic model (AHP–FLM)	X		
Ballot and Fontane, 2010	Reducing transportation CO2 emissions through the pooling of supply chain networks.	Mathematical equations	X		
Hernández *et al.*, 2011	Carrier-carrier collaboration for small- to medium-sized less-than-truck-load carriers.	Branch-and-cut algorithm			X
Gonzalez-Feliu and Grau, 2012	Proposed a framework for logistic pooling and an ex-ante evaluation to compare collaboration and noncollaboration scenarios.	Simple heuristic			X

Pan *et al.,* 2013	Investigated the environmental impact of supply chain pooling and analyzed the transportation cost.	Mixed-integer linear programming	X		
Taieb *et al.,* 2014	Studied the impact of the pooling of means and resources in logistics networks.	Mathematical programming	X		X
Yang *et al.,* 2015	Considered the collaborative distribution between two logistics service providers (LSPs) with the objective of reducing costs and delivery times.	Mathematical models		X	X
Montoya-Torres *et al.,* 2016	Compared the allocation and routing decisions in collaborative and noncollaborative scenarios.	MILP models for single-depot VRP and for allocation problems	X	X	X
Kaewpuang *et al.,* 2017	Collaboration between small shippers to share their own vehicles and create a vehicle pool.	Integer programming and stochastic programming models Cooperative game theory		X	X
Quintero-Araujo *et al.,* 2017	Studied the horizontal collaboration concept in integrated facility location and routing decisions and compared the noncollaborative scenario with two cooperative scenarios.	Biased randomization with a variable neighborhood search (BR-VNS) algorithm	X		X
He *et al.,* 2018	Carrier collaboration with parts of orders to reduce the stochastic order of shipper and transportation costs.	Hybrid ant colony optimization (ACO) heuristics			X
Habibi *et al.,* 2018	Studied the collaborative hub location problem in which two distribution networks collaborate to determine the best location of a hub to serve their nodes.	Mathematical formulation	X	X	X
Debroy and Sarmah, 2019	Carrier collaboration by sharing unused vehicle capacity and deciding how much to share.	Algorithms			X
Dolati, Espinouse *et al.,* 2021	Formulated a pooled problem called the multi-depot VRP (MDVRP) and focused on compatibility constraints in which the network cannot be fully pooled.	Binary matrix to model compatibility in the allocation phase Simulated annealing and variable neighborhood search algorithms for routing	X	X	X
Jerbi, Jribi *et al.,* 2022	Studied supply chain pooling strategies to reduce CO2 emissions.	Discrete event simulation	X		
This study	Investigated the saving in transportation costs when adopting a pooled transportation approach suitable for large-size instances.	Genetic algorithm (GA) and Clarke & Wrights Saving (CWS) Heuristic.	X		X

3. PROBLEM DESCRIPTION

In this section, a special case of a pooled logistic problem is considered. We assume that many enterprises aim to share their depots and transportation fleets to distribute their products to their common customers. We assume that each enterprise should be assigned to only one depot. Consequently, a set of enterprises is assigned to each depot. Hence, a routing problem should be solved for each depot. Certainly, the solution of the assignment problem at the first level affects the solution of the routing problem at the second level. We note that it is possible to not use some depots. Thus, the considered problem is an integrated location, allocation and routing problem (ILARP). The main questions concern which enterprise is assigned to which depot and what routes are taken by the vehicles in each used depot. The main difference between this problem and the classic ILARP is that one customer can be visited more than one time since he or she may have orders from different enterprises. The core components of the considered distribution network are as follows.

- E: set of enterprises.
- D: set of depots.
- C: set of customers.
- $DEMAND_{ce}$: demand of customer c from enterprise e.
- CAP_d: capacity of depot d.
- CAP_LV: capacity of large vehicles.
- CAP_SV: capacity of small vehicles.
- $COST\_LV$: transportation cost per km for large vehicles from enterprises to depots.

- $COST\_SV$: transportation cost per km for small vehicles from depots to customers.
- $DIST_{ij}$: Euclidean distance from node *i* to node *j* in km.
- NT_e: number of trips from enterprise *e* to its assigned depot *d*.
- *F*: frequency of a route per year.
- *TC*: total annual transportation cost.
- TC_FL: total annual transportation cost of the first level.
- TC_SL: total annual transportation cost of the second level.
- NR_d: number of routes from depot *d*.
- RD_{dr}: distance of route *r* from depot *d* in km.
- *NV*: total number of required small vehicles.
- CM_{dr}: cumulative demand of the customers served by route *r* of depot *d*.
- *FR*: average vehicle fill percentage.

3.1 Assumptions

1. Each enterprise should be assigned to only one concentration depot.
2. Direct shipment from enterprises to customers is not allowed.
3. At the first level, the large vehicles start at an enterprise, visit one depot, and then return to the same enterprise. At the second level, the small vehicles start at a depot, visit one or more customers, and then return to the same depot.
4. Connections between depots are not allowed.
5. The number of days of separation between two consecutive deliveries is constant.
6. A vehicle's capacity fits the demand of any customer. If the customer's demand is greater than the vehicle's capacity, the demand of this customers is duplicated as much as needed to fit with the capacity of the vehicle.
7. Each customer's demand is satisfied.
8. Vehicles are homogeneous with predefined capacities.
9. The number of vehicles is not specified in advance.
10. The distance matrix is symmetric; i.e., the distance from node *i* to node *j* is equal to the distance from node *j* to node *i*.
11. The cost per km for the small and large vehicles is a linear function of the Euclidean distance.

The considered problem is a two-echelon location routing problem that has two levels. At the first level, products are shipped from the enterprises to the depot. The products are then distributed to the customers from these selected depots. This is an NP-hard problem because it combines the facility location problem (FLP) and the vehicle routing problem (VRP), which are both NP-hard problems. Decisions are made at both strategic and operational levels. The assignment of depots to enterprises and the locations of the depots are strategic decisions, whereas the routing strategy to distribute products from the selected depots to customers is an operational decision. Once a depot is selected and assigned to firms, customer demands are delivered from this assigned depot. The costs involved in this problem to be optimized include the annual cost of transporting products from firms to their assigned depots (i.e., *TC_FL*) and the annual cost of routing from the assigned depots to customers (i.e., *TC_SL*). The total annual transportation cost, *TC,* is therefore equal to the sum of these two costs.

$$TC = TC\_FL + TC\_SL. \tag{1}$$

The Euclidian distance from node *i* to node *j*, *DISTij*, is calculated as:

$$DIST_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{2}$$

where x and y are the x-coordinates and y-coordinates of nodes i and j, respectively.

First Level:

$$NT_e = \left\lceil (F \times (\sum_{c=1}^{C} DEMAND_{ce}))/CAP\_LV \right\rceil \quad (3)$$

$$TC\_FL = \sum_{e=1}^{E} (2 \times (COST_{LV}) \times (NT_e) \times (DIST_{e\,d_e})) \quad (4)$$

where d_e represents the depot assigned to enterprise e.

Second Level:

$$TC\_SL = F \times COST\_SV \times \sum_{d \in D} \sum_{r=1}^{NR_d} RD_{dr} \quad (5)$$

$$NV = \sum_{d \in D} NR_d \quad (6)$$

$$\mathrm{FR}=100 \times \frac{\sum_{d \in D} \sum_{r=1}^{NR_d} \frac{CM_{dr}}{CAP_{SV}}}{NV} \quad (7)$$

The number of trips required to deliver the demand from each enterprise to its assigned depot using large vehicles is calculated using Equation (3). Equations (4) and (5) calculate the total annual costs of the first and second levels, respectively. The number of required small vehicles and the average fill rate of each small vehicle are calculated using (6) and (7), respectively. Although the problem can be solved in two separate steps (i.e., the assignment of depots to enterprises and then the VRP from each selected depot), this method may lead to a suboptimal solution when compared with the integrated approach, which simultaneously handles both tasks. In this paper, the integrated problem of depot location, assignment and vehicle routing is solved in a pooled transportation system.

3.2 Descriptions of Scenarios

Three scenarios are examined to determine whether a pooled transportation system can reduce the transportation costs of potential collaborating companies. We first consider a noncollaborative scenario, and then we introduce two collaborative scenarios. Detailed descriptions of these scenarios are given in the following subsections.

3.2.1 Noncollaborative Scenario

In this noncollaborative scenario (NCS), each company has its own depot and fleet of vehicles to distribute its products. This scenario is commonly used by companies and is likely to produce long-distance routes. Therefore, this scenario is expected to provide the worst results in terms of travel distance and time (Montoya-Torres *et al.*, 2016). An NCS example involving three enterprises, four depots, and three customers is illustrated in Figure 1.

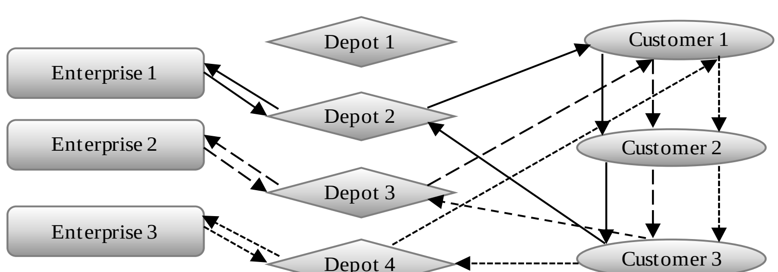

Figure 1. Noncollaborative scenario (NCS)

3.2.2 Collaborative Scenario (Type 1)

This type of collaborative scenario represents a strict collaborative scenario, denoted as an SCS. Each enterprise must collaborate with another to share a joint depot and their fleets of vehicles. An example of an SCS involving three enterprises that share only one depot to deliver their products to three joint customers is shown in Figure 2.

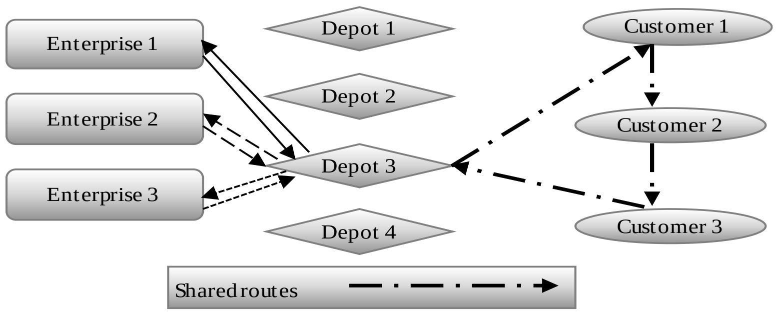

Figure 2. Strict collaborative scenario (SCS)

3.2.3 Collaborative Scenario (Type 2)

In a free collaborative scenario (FCS), enterprises can share a depot and fleets of vehicles with other enterprises or operate their supply chains individually. For example, Figure 3 illustrates an FCS in which enterprise 1 has its own depot and fleet of small vehicles, whereas enterprises 2 and 3 share depot 3 and a joint fleet of small vehicles.

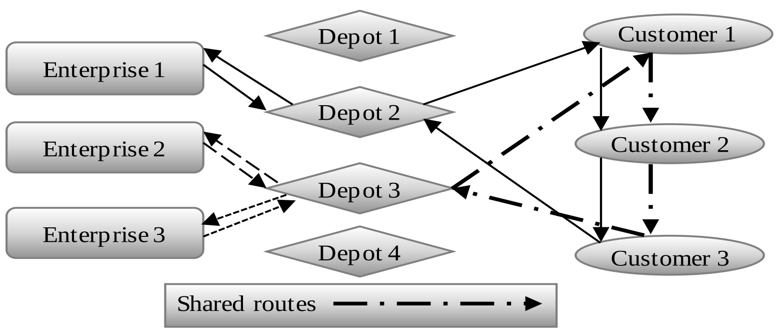

Figure 3. Free collaborative scenario (FCS)

3.3 An Illustrative Example

The example summarized in Figure 4 illustrates depot assignment to enterprises and vehicle routing in both collaborative and noncollaborative scenarios. The required distances between nodes and customer demands are shown in Tables 2 and 3, respectively. The components of this example are as follows:

- Two enterprises (E1 and E2).
- Three depots (D1, D2, and D3).
- Three customers (1, 2, and 3).
- Two types of vehicles (small and large).
- Small vehicles deliver products from depots to customers with an assumed capacity of CAP_SV = 10.
- Large vehicles deliver products from each enterprise to a depot and have a capacity of CAP_LV = 40.
- The route frequency per year F=100.

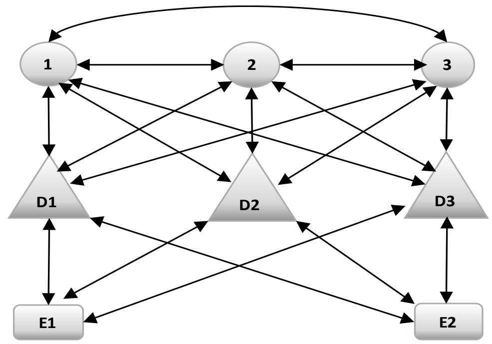

Figure 4. Distances between the nodes of the illustrative example

Table 2. Distances between the Required Nodes

From	To	Distance
E1	D1	2.00
	D2	2.24
	D3	2.83
E2	D1	2.83
	D2	2.24
	D3	2.00
D1	C1	1.00
	C2	1.41
	C3	2.24
D2	C1	1.41
	C2	1.00
	C3	1.41
D3	C1	2.24
	C2	1.41
	C3	1.00
C1	C2	1.00
	C3	2.00
C2	C3	1.00

Table 3. Demand of Customers

Enterprise no.	Demand		
	Customer 1	Customer 2	Customer 3
1	4	6	1
2	3	3	2

All feasible routes and the related costs of the NCS are shown in Table 4. The total costs of E1 and E2 are 1113.00 and 840.40, respectively. Thus, TC = 1953.4; this solution is presented in Figure 5. E1 delivers its demand to D1 in one shipment using a large vehicle. From D1, two small vehicles are needed to deliver products to customers since CAP_SV = 10, and the total demand of the three customers from enterprise 1 is equal to 11. On the other hand, E2 delivers its demand to D2 in one shipment using one large vehicle and needs only one small vehicle to deliver its products to customers.

All feasible routes and their related costs in the strict collaboration scenario are summarized in Table 5; in the optimal solution, detailed in Figure 6, TC = 1542.16. In this scenario, only one depot, D2, is used. Each enterprise delivers its product with its own fleet of large vehicles to the shared depot in one shipment. As each customer's demand from both enterprises is collected in D2 to be delivered by a common fleet of small vehicles, only two small vehicles are needed to deliver products to customers.

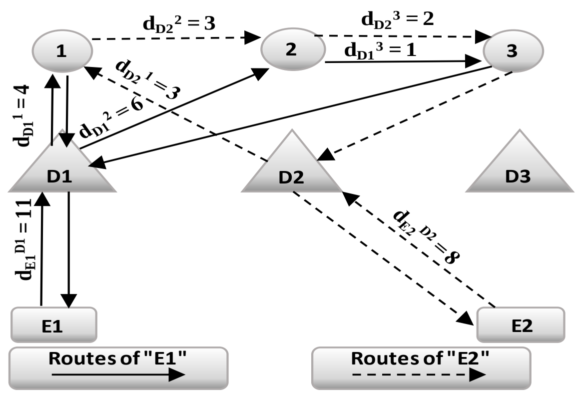

Figure 5. The optimal solution of the NCS of the illustrative example

Table 4. Solution for the NCS of the Illustrative Example

Depot	Enterprise 1							Enterprise 2				
	Route 1	Route 2	Route 3	Cost route 1	Cost route 2	Cost route 3	TC	Route 1	Route 2	Cost route 1	Cost route 2	TC
D1	E1-D1-E1	D1-1-2-D1	D1-3-D1	448.00	341.00	448.0	1237.00	E2-D1-E2	D1-1-2-3-D1	452.80	524.0	976.8
	E1-D1-E1	D1-1-3-D1	D1-2-D1	448.00	524.00	282.0	1254.00	-	-	-	-	-
	E1-D1-E1	**D1-2-3-D1**	**D1-1-D1**	**448.00**	**465.00**	**200.0**	**1113.00**	-	-	-	-	-
D2	E1-D2-E1	D2-1-2-D2	D2-3-D2	501.76	341.00	282.0	1124.76	**E2-D2-E2**	**D2-1-2-3-D2**	**358.40**	**482.0**	**840.4**
	E1-D2-E1	D2-1-3-D2	D2-2-D2	501.76	482.00	200.0	1183.76	-	-	-	-	-
	E1-D2-E1	D2-2-3-D2	D2-1-D2	501.76	341.00	282.0	1124.76	-	-	-	-	-
D3	E1-D3-E1	D3-3-2-D3	D3-1-D3	633.92	341.00	448.0	1422.92	E2-D3-E2	D3-3-2-1-D3	320.00	524.0	844.0
	E1-D3-E1	D3-3-1-D3	D3-2-D3	633.92	565.00	282.0	1480.92	-	-	-	-	-
	E1-D3-E1	D3-2-1-D3	D3-3-D3	633.92	465.00	200.0	1298.92	-	-	-	-	-

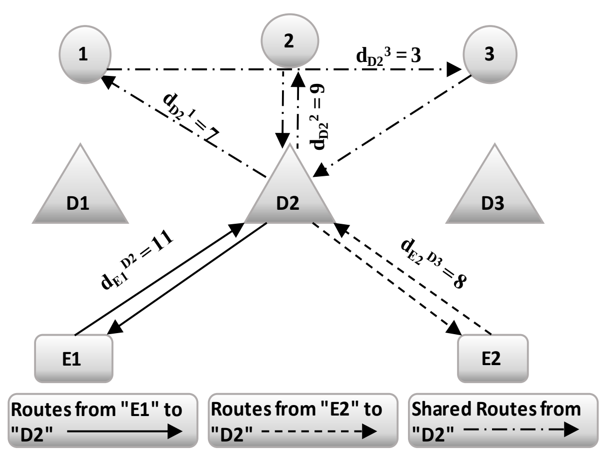

Figure 6. The optimal solution of the SCS of the illustrative example

Table 5. Solution for the SCS of the Illustrative Example

Depot	Enterprise 1 and Enterprise 2								
	Route 1	Route 2	Route 3	Route 4	Cost route 1	Cost route 2	Cost route 3	Cost route 4	TC
D1	E1-D1-E1	E2-D1-E2	D1-1-3-D1	D1-2-D1	448.00	452.80	524.00	282.00	1706.80
D2	**E1-D2-E1**	**E2-D2-E2**	**D2-1-3-D2**	**D2-2-D2**	**501.76**	**358.40**	**482.00**	**200.00**	**1542.16**
D3	E1-D3-E1	E2-D3-D2	D3-3-1-D3	D3-2-D3	633.92	320.00	524.00	282.00	1759.92

4. SOLUTION METHODS

On the one hand, exact methods for the pooled transportation problem are computationally expensive since this problem is NP-hard. Indeed, previous works that aimed to solve similar problems with exact methods only considered instances with small or medium sizes (Ouhader and Elkyal, 2016), where the number of nodes in the largest graph is only 58. On the other hand, a GA successfully solved larger instances in the case of the two-echelon location routing problem (Dalfard *et al.*, 2013), which is very similar to the problem considered in this paper. Indeed, the size of the graphs considered in this latest paper reaches 160 nodes. The solution to the two problems requires solving a location problem at the first level and a routing problem at the second level. Thus, a GA is proposed to solve each scenario described in Section 3.2. The assignment of the enterprises to the depots is presented as a chromosome. An initial population is generated, and the standard steps of selection, crossover and mutation are applied. The assessment of each chromosome requires solving as many VRP problems as the number of depots used. In this case, a single run of the genetic algorithm requires the intensive use of a VRP solver. Since the exact solution of the VRP is time-consuming, a very fast and efficient heuristic from the literature is used. A detailed description of the proposed GA is given in the following section.

4.1 Genetic Algorithm

GAs form a popular class of evolutionary algorithms that have shown the ability to solve large-scale NP-hard problems. In the 1970s, Holland John (1975) developed a GA to understand natural adaptive systems. GAs were then applied to optimization and machine learning in the 1980s (De Jong 1985, Goldberg and Holland 1988).

A GA starts by creating a set of solutions called a population. Then, a series of processes are performed in each population generation, including evaluating each individual, selecting individuals to be parents, and altering each individual or parent via genetic operators. A fitness function is used to evaluate each individual in a population for each generation. Genetic operators include crossover and mutation operators. Crossover operators cut and paste parts of two or more individuals to create a new individual, i.e., an offspring, with a certain crossover probability, whereas mutation operators make changes within a single individual with a specific mutation probability. Finally, each individual's fitness is evaluated, and the best individual survives to the next generation. The GA continues this process until a termination condition is met. Algorithm 1 gives a detailed description of a standard GA.

Several parameters must be considered when designing a GA, including the population size, number of generations, crossover probability, and mutation probability. Furthermore, the process of generating the initial population, the selection method, the genetic operators, the fitness function, and the termination conditions must be predefined.

Algorithm 1 Genetic Algorithm (GA)

1. Generate an initial population.
2. For each chromosome in the population, do:
   - Calculate the value of the fitness function.

   End for
3. While the stopping criteria is not satisfied:
   - Select parents for reproduction.
   - Perform crossover with a probability of p_c.
   - Perform mutation with a probability of p_m.
   - Repair offspring as necessary.

     For each offspring:
     - Calculate the fitness.
     - If an offspring’s fitness is better than that of the best solution, update the best solution.

     End for.
   - Select the best chromosome to be in the next generation.

   End while.
4. Return the best solution found.

4.1.1 Solution Representation

A vector of positions encodes each solution. Such a solution is called a chromosome. The elements within a chromosome are called genes. In our case, the number of genes in each chromosome represents the number of enterprises. Furthermore, the value of each gene is the selected depot for the related enterprise. A representative chromosome is shown in Figure 7, where there are five enterprises (E1, E2, E3, E4, and E5) and three depots (D1, D2, and D3). Here, D1 is assigned to E2 and E3; D3 is assigned to E1, E4, and E5; and D2 is not assigned to any enterprise.

D3	D1	D1	D3	D3
E1	E2	E3	E4	E5

Figure 7. Solution representation of a chromosome, where D is used to represent the depot assigned to each enterprise E

4.1.2 Generating the Initial Population

The first step in implementing a GA is the generation of an initial population. Here, the initial population is randomly generated. In the case of the SCS, we ensure that a depot is either assigned to at least two enterprises or ignored. In contrast, in the case of the NCS, we oblige that no depot is assigned to more than one enterprise.

4.1.3 Selection Methods

Selection methods are essential for obtaining better solutions in a population. During selection, two parents are selected from the population of a particular generation for reproduction. To ensure diversification, individuals with high fitness functions maintain some chance of being selected as parents. Many selection methods are available, including tournament selection, roulette wheel selection, stochastic universal sampling, and random selection (Talbi, 2009).

4.1.4 Crossover Operators

A crossover operator defines the extent to which the characteristics from parents' chromosomes are present in the generated offspring. For each parent, a random number is generated; if the random number is less than the predetermined crossover probability, the crossover is performed. Otherwise, no changes are made to the parents. Many crossover operators are used for performing crossover, including one-point, two-point, and uniform crossover operators (Talbi, 2009).

4.1.5 Mutation Operators

A mutation operator is a genetic operator that alters the characteristics of a single chromosome. The mutation of each gene of a chromosome depends on the mutation probability. Small mutation probability values are recommended [0.001, 0.01] (Talbi, 2009). Many mutation operators have been used to perform gene mutations, including insertion, swapping, and inversion (Talbi, 2009).

4.1.6 Repair Method

After crossover and mutation, the resulting chromosome may violate problem constraints; thus, a repair method must be applied to repair the chromosome. Here, three repair methods are applied. The first repairing method was applied to the NCS. In the NCS, as each enterprise has a unique depot, if any depot appears more than once in a chromosome, then this depot is replaced by another depot that does not exist in the chromosome. This process is repeated for all genes within a chromosome until each depot is assigned to only one enterprise. The second repairing method was applied to the SCS. In the SCS, each depot must be assigned to more than one enterprise; thus, if any depot appears only once in a chromosome, a repairing method attempts to make that depot appear more than once or ignore it to satisfy pooling. The third repairing method was applied to avoid exceeding the capacity of the depots: When multiple enterprises share a single depot, and the demand of their customers exceeds the capacity of that depot, the fitness value of such chromosomes is multiplied by a large number to exclude it from the future generation.

4.1.7 Chromosome Evaluation

Each chromosome is evaluated by calculating the total annual transportation cost, which is obtained as a sum of the cost of each of the two levels. At the first level, the annual cost of supplying products from enterprises to depots, i.e., TC_FL, is easily calculated. At the second level, the annual routing cost required for vehicles to deliver products from depots to customers, i.e., TC_SL, is computed using the CWS heuristic.

4.1.8 Chromosome Survival

The chromosome with the lowest calculated fitness value is selected to be passed to the next generation to ensure that the algorithmic performance is non-decreasing.

4.1.9 Stopping Criteria

The GA terminates when the stopping criteria are met. The stopping criteria can be the maximum number of generations, the maximum CPU time, or any other prespecified parameter. The maximum number of generations is used in the proposed algorithm.

4.2 Clarke and Wright's Savings Algorithm

The Clarke and Wright savings (CWS) algorithm, which is commonly applied to generate fast and reasonable solutions to VRP problems, is selected to compute the routing cost of each chromosome. This heuristic utilizes an iterative procedure to calculate the distance savings obtained when customer nodes are combined rather instead of establishing a single route for each customer node (Clarke and Wright, 1964).

There are two versions of the CWS algorithm: a sequential version and a parallel version. The sequential version builds one route at a time until no more feasible merge option exists and then begins a second route until all nodes are included; the parallel version builds more than one route at a time. The pseudocode of the proposed parallel version of the CWS algorithm is detailed in Algorithm 2.

Algorithm 2 Clarke and Wright's Savings (CWS)

1. Calculate the distance ($DIST_{ij}$) from node *i* to node *j* for all nodes.
2. Using $S_{ij} = DIST_{i0} + DIST_{0j} - DIST_{ij}$, calculate the savings in terms of distance when customers *i* and *j* are grouped in a joint route instead of establishing a single route for each.
3. Sort the resulting savings pairs in descending order to create a “savings list.” The pair *(i,j)* with the greatest savings, S_{ij}, is chosen first for building routes.
4. For each pair of nodes *(i,j)* in the sorted list, if the vehicle capacity and the maximum allowed time are satisfied and if one of the following cases is satisfied, then combine nodes *i* and *j* into one route.
   4.1 Neither node *i* nor *j* exists in any route: create a new route containing both *i* and *j*. Go to step 5.
   4.2 One of the nodes (*i* or *j*) is located at either the beginning or end of an existing route (i.e., just after or just before the depot, respectively): add the node that does not exist in the route beside the existing node in the same route. Go to step 5.
   4.3 Nodes *i* and *j* are located in two different existing routes and are located at either the beginning or the end of a route: merge the two routes, and ensure that the two nodes are beside each other.
5. If all the nodes are covered, or all the pairs are explored, go to step 6; otherwise, go to step 4.
6. If any node is not included in any route, then create a new personal route for it.
7. Evaluate the total distance of each route.

5. RESULTS AND DISCUSSION

5.1 Algorithm Implementation and Data Generation

The proposed methodology was implemented in the C++ programming language using Microsoft Visual Studio 2010. Computational experiments were run on a PC with an Intel® core ™ i7-4720HQ processor at 2.6 GHz and 16 GB of memory. To evaluate the proposed scenarios, fourteen benchmark instances of the capacitated VRP with a single depot, described by (Christofides N 1979), were considered. These instances were modified to fit the requirements of the pooled transportation problem.

- Seven instances had only vehicle capacity constraints, whereas the other seven instances had capacity, maximum route time, and drop time constraints.
- The number of nodes ranged from 51 to 200 nodes.

The first node referred to the depot coordinates, and the remaining nodes were customer coordinates and the demand for each customer. To adapt these benchmark instances to suit this work, the numbers of enterprises and depots were first determined.

- The number of enterprises $|E| = 2 + 0.1 \times$ (number of nodes).

- The number of depots was randomly generated in the interval [$|E|$, $1.5\times|E|$].

Among the customers of the original instances, we randomly selected $|E|$ nodes to represent the enterprises and $|D|$ nodes to represent the depots. The remaining nodes were considered customers in the case of the pooled transportation system.

- The demand for each customer was randomly generated between [5, 25] units.
- CAP_SV = 140, 160, or 200 (as described in the original instances).
- $CAP\_LV = 4 \times CAP\_SV$.
- $F = 100/year$ (number of visits for each customer per year).
- The capacity of a depot was equal to the total customer demand divided by two.

The fourteen generated random instances and their corresponding constraints, numbers of nodes, numbers of enterprises, numbers of depots, small vehicle capacities, and depot capacities are summarized in Table 6. In addition, the utilized data are available upon request from the corresponding author.

Table 6. Characteristics of the Generated Instances

Instance no.	Constraints	No. of Nodes	No. of E	No. of D	Small Vehicle Capacity	Depot Capacity
1	C	51	7	9	160	1902
2	C	76	9	10	140	3797
3	C	101	12	12	200	7002
4	C	151	17	20	200	14716
5	C	200	22	32	200	23905
6	C, D	51	7	8	160	1945
7	C, D	76	9	10	140	3866
8	C, D	101	12	16	200	6570
9	C, D	151	17	21	200	14578
10	C, D	200	22	27	200	24884
11	C	121	14	18	200	9383
12	C	101	12	17	200	6327
13	C, D	121	14	18	200	9324
14	C, D	101	12	12	200	6849

C: capacity constraint,
D: distance constraint.

5.2 Performance Evaluation

Each scenario was evaluated using the objective function in Equation (1) for the total annual transportation cost. Then, other performance metrics were evaluated, including the number of vehicles used, the average fill rate of the vehicles, and the CPU time of each scenario.

5.3 Parameter Configuration of the Genetic Algorithm

Pilot-run experiments were conducted to determine the configuration of the GA parameters. Among these parameters were the maximum number of generations, population size, selection method, crossover operator, crossover probability, mutation operator, and mutation probability. In some of these pilot runs, we fixed the selection, the crossover and the mutation operators. In other runs, a random selection of the operators was considered. Experiments showed that the random selection of the operators yielded better results than the predefined ones. The cost reduction ranged between 2.8% and 26.8% in the FCS case due to dynamic selection. The FCS version was used in the pilot-run experiments since it enabled collaborative and noncollaborative solutions. Table 7 illustrates the selected parameters and the operators of the proposed GA.

Table 7. Parameters of the Proposed GA

Parameter	Method/Value
Maximum Number of Generations	200
Population Size	130
Selection Method	Tournament, roulette wheel, stochastic universal sampling, and random selection
Tournament Size	3
Crossover Operator	One-point, two-point, and uniform
Crossover Probability	0.9
Mutation Operator	Insertion, swapping, and inversion
Mutation Probability	0.01

5.4 Comparison Among the Proposed Scenarios

5.4.1 Total Cost Comparison

To assess the impact of the pooled transportation system, a comparison between the NCS and the two collaborative scenarios (the SCS and FCS) is stated. The resulting total annual transportation cost of each scenario and their improvement rates (in percentages) are displayed in Table 8. A graphical configuration of the achieved improvement is also demonstrated in Figure *8*. The collaborative scenarios (i.e., the SCS and FCS) provided savings from 29% to 53% in all cases. It is worth noting that significant savings were found when distance constraints were considered for the routes, as in instances 6–10 and 13–14. If the distance of the route is constrained, the vehicle cannot visit many customers, and its fill rate will be low. Thus, the collaboration will undoubtedly increase the fill rate and reduce the total number of routes required to cover the full demand.

Table 8. Total Annual Transportation Costs (TC) of the Proposed Scenarios

Instance no.	TC (SCS)	TC (FCS)	TC (NCS)	Gap (%) SCS vs. NCS	Gap (%) FCS vs. NCS
1	**273858.8**	277082.9	414722.9	**-33.97**	-33.19
2	617332.4	**602594.6**	883451.9	-30.12	**-31.79**
3	**801383.1**	819882.8	1294689	**-38.1**	-36.67
4	**1570296**	1618557	2509164	**-37.42**	-35.49
5	2647715	**2635548**	3771182	-29.79	**-30.11**
6	**284721**	285800.2	471975.3	**-39.67**	-39.45
7	**606786.8**	619841.8	1317823	**-53.96**	-52.96
8	745227.6	**731755.3**	1341940	-44.47	**-45.47**
9	**1637425**	1747076	3090836	**-47.02**	-43.48
10	2771732	**2707933**	5039435	-45	**-46.27**
11	1556581	**1548978**	2407306	-35.34	**-35.66**
12	798016.2	**793485.4**	1112689	-28.28	**-28.69**
13	1630427	**1594244**	2728717	-40.25	**-41.58**
14	831334.5	**828298.3**	1472728	-43.55	**-43.76**
Average	1198059.74	1200791.24	1989761.36	-39.07	-38.90

Gap (%) SCS vs. NCS = 100× (TC (SCS) – TC (NCS))/TC (NCS)
Gap (%) FCS vs. NCS = 100× (TC (FCS) – TC (NCS))/TC (NCS)

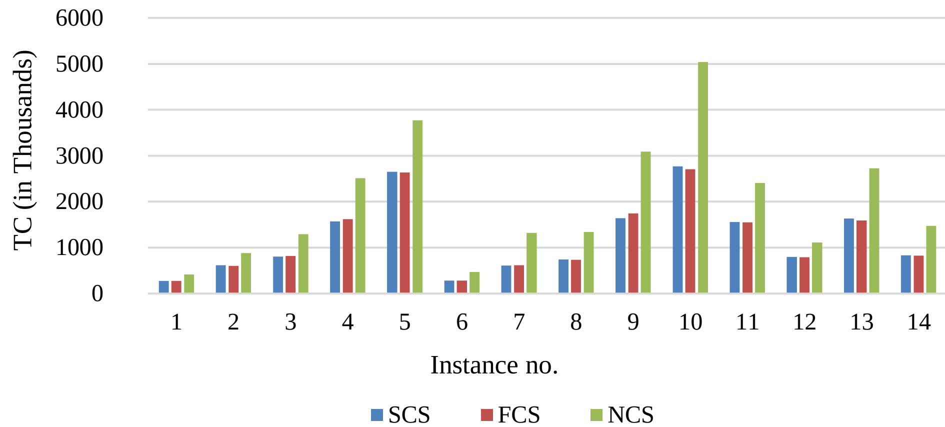

Figure 8. Total Annual Transportation Costs of the Proposed Scenarios

5.4.2 Allocation of Depots to Enterprises

The first step toward solving the integrated warehouse location and VRP was to allocate depots to enterprises. The resulting allocations for all instances are shown in Table 9, where the best chromosomes found by the GA are displayed. For the strict collaboration scenario (SCS), at least two enterprises were assigned to the same depot. In the free collaborative scenario (FCS), a depot could be assigned to one or more enterprises. Thus, each enterprise was free to collaborate or not collaborate with the remaining enterprises. The NCS requires that there is a unique depot for each enterprise.

Table 9. Allocation of Depots to Enterprises

Instance	Scenario	Best Chromosome	Instance	Scenario	Best Chromosome
1	SCS	5-4-4-2-5-2-5	8	SCS	15-15-1-6-1-1-6-6-6-1-6-15
	FCS	5-1-4-4-5-4-5		FCS	14-15-14-14-14-6-6-6-6-14-15-14
	NCS	5-4-2-1-8-3-7		NCS	10-0-3-14-9-15-1-4-6-8-57
2	SCS	3-7-8-7-3-8-8-3-3	9	SCS	9-1-11-9-9-1-9-1-11-1-11-11-11-1-1-9-11
	FCS	8-7-7-6-6-8-8-8		FCS	10-2-1-2-9-1-10-10-1-2-9-10-10-1-1-1-10
	NCS	3-7-8-9-4-6-0-5-2		NCS	9 1 10 7 8 14 20 19 5 3 15 2 13 11 4 6 0
3	SCS	0-0-1-1-1-0-1-6-6-0-6-6	10	SCS	18-4-18-5-4-5-4-4-18-5-9-9-18-5-18-4-18-5-23-23-5-18
	FCS	0-0-9-9-9-6-6-0-6-0-0-6		FCS	6-5-4-5-4-6-4-6-5-4-5-5-6-5-4-5-6-5-6-5-4-5
	NCS	1-3-10-0-11-2-6-4-5-8-9-7		NCS	18-5-1-4-17-10-20-9-25-6-8-0-2-7-15-21-23-24-19-26-12-11
4	SCS	11-10-11-11-10-1-1-1-1-10-10-10-11-1-9-9-1	11	SCS	4-1-1-1-0-4-4-0-4-0-1-4-4-1
	FCS	10-11-11-9-9-10-9-11-11-11-11-10-10-10-9-9-9		FCS	4-4-1-0-0-1-0-4-1-0-1-0-0-4
	NCS	9-2-11-17-7-13-5-19-3-16-10-14-12-4-0-6-1		NCS	4-0-1-5-8-11-13-2-12-10-7-9-6-3
5	SCS	28-9-31-31-9-31-31-5-31-5-28-9-9-31-31-31-5-5-9-31-31-31	12	SCS	10-9-10-9-10-9-11-9-11-10-11-10
	FCS	6-31-31-31-5-31-5-31-5-5-5-5-31-5-31-31-5-31-31-5-5-6		FCS	8-8-10-10-10-9-8-9-9-9-10-8
	NCS	18-29-17-28-7-30-20-24-9-4-8-25-12-2-16-31-21-14-23-6-10-0		NCS	10-9-3-12-15-11-5-8-13-1-16-14
6	SCS	5-4-4-2-5-2-5	13	SCS	4-1-4-4-0-0-1-1-4-4-1-4-4-1
	FCS	5-4-4-4-5-2-5		FCS	4-4-1-4-4-4-0-0-0-4-1-0-4-0
	NCS	5-4-2-1-7-3-0		NCS	4-5-6-14-0-9-10-3-2-12-7-1-11-8
7	SCS	8-7-7-7-8-4-8-8-4	14	SCS	9-11-11-8-8-8-11-8-11-8-9-8
	FCS	3-7-7-7-4-4-7-3-4		FCS	9-11-8-8-11-11-11-8-8-11-11-9
	NCS	1-7-4-0-8-6-3-2-5		NCS	8-9-0-10-4-11-2-6-7-3-5-1

5.4.3 Number of Vehicles and Average Fill Rate

The number of vehicles required to carry the total demand for each instance is displayed in Table 10. Although the number of used vehicles fluctuated between decreasing and increasing after adopting the collaboration mechanism, the average relative gap indicates a reduction of approximately 10% of the used vehicles in both cases: the FCS and SCS.

Table *11* presents the average vehicle fill rate in each instance. This latest indicator shows the significant impact of collaboration vs. noncollaboration. Indeed, the average fill rate of the vehicles jumped from 76.32% in the case of noncollaboration to approximately 86% in the case of collaboration (the SCS and FCS). The number of vehicles and the fill rate for each scenario are illustrated in Figure 9 and Figure 10, respectively.

Table 10. Variation in the Number of Vehicles

Instance No.	NV (SCS)	NV (FCS)	NV (NCS)	Gap (%) SCS vs. NCS	Gap (%) FCS vs. NCS
1	**27**	**27**	28	**-3.57**	**-3.57**
2	63	61	**60**	5	1.67
3	79	80	**76**	3.95	5.26
4	169	166	**157**	7.64	5.73
5	282	314	**254**	11.02	23.62
6	**29**	30	38	**-23.68**	-21.05
7	64	**61**	112	-42.86	**-45.54**
8	76	**74**	95	-20	**-22.11**
9	167	**163**	240	-30.42	**-32.08**
10	**294**	304	388	**-24.23**	-21.65
11	109	106	**103**	5.83	2.91
12	72	**70**	74	-2.7	**-5.41**
13	**113**	114	126	**-10.32**	-9.52
14	78	**76**	99	-21.21	**-23.23**
Average	115.86	117.57	132.14	-10.40	-10.36

Table 11. Variation of the Average Fill Rate

Instance No.	FR (SCS)	FR (FCS)	FR (NCS)	Gap (%) SCS vs. NCS	Gap (%) FCS vs. NCS
1	**88.08**	**88.08**	84.93	**3.7**	**3.7**
2	86.1	88.92	**90.4**	-4.76	-1.64
3	88.63	87.53	**92.13**	-3.8	-5
4	87.08	88.65	**93.74**	-7.1	-5.42
5	84.77	76.13	**94.11**	-9.93	-19.11
6	**83.84**	81.04	63.98	**31.03**	26.67
7	86.29	**90.54**	49.31	75	**83.61**
8	86.45	**88.79**	69.16	25	**28.38**
9	87.29	**89.44**	60.74	43.71	**47.24**
10	**84.64**	81.86	64.13	**31.97**	27.63
11	86.08	88.52	**91.1**	-5.5	-2.83
12	87.88	**90.39**	85.51	2.78	**5.71**
13	**82.51**	81.79	74	**11.5**	10.53
14	87.81	**90.13**	69.19	26.92	**30.26**
Average	86.25	86.56	77.32	15.75	16.41

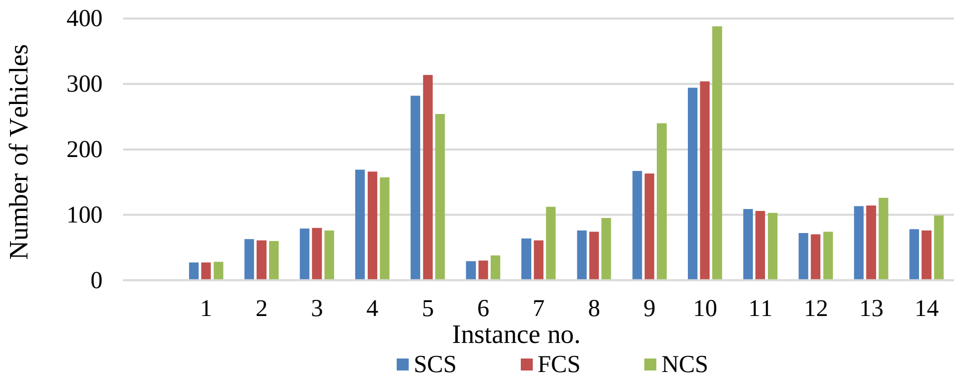

Figure 9. Number of vehicles in each scenario

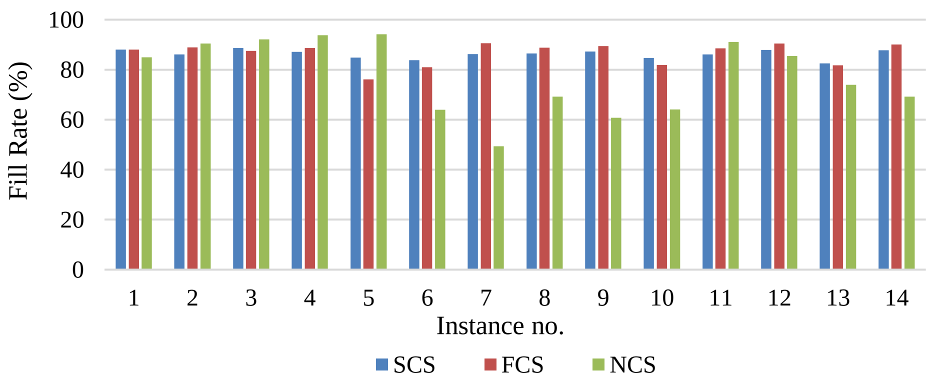

Figure 10. Average vehicles fill rates (in percentages)

5.5.4 CPU Time

The computational time of an optimization algorithm is commonly used to assess its performance. The resulting CPU times in seconds for the 200 iterations of the proposed genetic algorithm are displayed in Table 12 and summarized visually in Figure 11. All the tested instances are solved in a reasonable time under the three considered scenarios.

Table 12. Comparison of the CPU Time in seconds

Instance No.	**SCS**	**FCS**	**NCS**
1	**77.865**	81.306	134.874
2	**96.936**	106.615	182.351
3	**126.449**	146.526	263.273
4	**207.231**	282.86	473.828
5	**316.078**	486.014	786.795
6	**100.728**	102.339	173.608
7	**123.821**	135.329	240.409
8	**162.73**	188.325	317.13
9	**246.815**	335.469	556.885
10	**367.668**	527.625	899.996
11	**214.13**	264.852	443.5
12	**185.289**	212.498	362.83

Instance No.	SCS	FCS	NCS
13	**226.507**	276.397	466.449
14	**191.702**	216.524	393.588

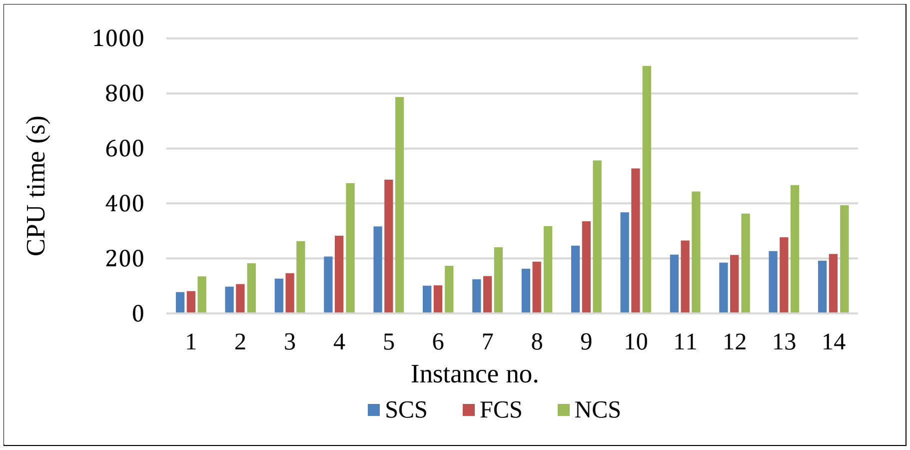

Figure 11. CPU time (s)

5.4.5 Discussion

When implementing a pooled transportation system, the results indicate that the collaborative scenarios outperformed the noncollaborative scenario. The total annual transportation cost for the collaborative scenarios was reduced by 38.1% for instances with only vehicle capacity constraints. On the other hand, a maximum reduction (53.96%) was observed for instances with vehicle capacity and distance constraints. Furthermore, the number of depots used for the collaborative scenarios is fewer than that used in noncollaborative scenarios. A further decrease in costs is expected if the fixed cost of opening a depot is considered in the objective function. In addition, the average vehicle fill rate increased, and the average number of vehicles decreased. Indeed, Table 10 and
Table *11* show that if the average vehicle fill rate for the NCS is high, the number of vehicles could be fewer than those used in collaborative scenarios. However, when the average fill rate of the NCS is low and almost less than 75%, as in distance-constrained instances, the fill rate of the collaborative scenarios increases, reducing the number of used vehicles by 45.5%.

Although the results show that implementing a pooled transportation system is encouraging, partners must overcome challenges and implementation issues before collaborating. Recent research surveyed and classified some of the challenges related to horizontal collaboration. (Pan *et al.*, 2019) discussed several implementation issues related to horizontal collaboration regarding the decisions on the mechanism of exchanging requests, gain and information sharing, organization, and management and governance issues. According to a review by (Serrano-Hernández *et al.*, 2017), the challenges of implementing horizontal collaboration also include maintaining a relationship of trust, finding a suitable partner, sharing profits/losses, and establishing a suitable framework.

6. Conclusions and Future Work

This work aims to determine whether a pooled transportation system can enhance the performance of collaborative enterprises. Three main key performance indicators are used to compare the collaborative and noncollaborative scenarios: the total annual transportation cost, the number of used vehicles, and the average fill rate. A common approach is used to solve the different considered scenarios. This approach employs a genetic algorithm that solves the integrated warehouse location and routing problems. The final solution includes an assignment of the depots to the enterprise and a routing plan from each depot to the final customers. To assess the fitness of each chromosome, the well-reputed Clark and Wrights saving algorithm is used to solve the VRP problem at each depot. Fourteen benchmark instances from the literature were adapted and modified to suit the proposed problem. One noncollaborative scenario and two collaborative scenarios were compared (i.e., the NCS and the SCS and FCS, respectively) to evaluate the potential cost savings achieved by employing a pooled transportation system. In the NCS, each enterprise had its own depot and fleet of vehicles. In the SCS, at least two enterprises needed to share a depot and vehicle routing; in the FCS, enterprises were free to share or not share depots and vehicles. The results show that implementing a pooled transportation system may reduce the total annual transportation costs of the collaborative scenarios by more than 28% in all instances; a maximum reduction of 53.96% was achieved when capacity and distance constraints were included. A maximum reduction of 45.5% was observed in the number of vehicles. The average vehicle fill rate was also improved, especially when the vehicle fill rate under the NCS was almost less than 75%. Moreover, the number of visited customers per vehicle was reduced using the collaborative scenarios due to the cumulative demand of joint customers. Future work will be conducted to consider the heterogeneous fleet version and the time widow constraints for the customers.

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