Optimized approach for collaborative last-mile delivery

A Thesis

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by

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Dedication

This thesis is dedicated to my family for their unwavering support and encouragement throughout this journey.

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Abstract

Spyridon Motsenigos, M.Sc. in Data and Computer Systems Engineering, Department of Computer Science and Engineering, School of Engineering, University of Ioannina, Greece, 2025.
Optimized approach for collaborative
last-mile delivery.
Advisor: Konstantinos E. Parsopoulos, Professor.

Last-mile delivery is one of the most critical and cost-intensive stages of the logistics chain. Factors such as traffic congestion, high customer expectations, and sustainability concerns make efficient last-mile delivery a key challenge for logistics service providers (LSPs). Collaborative delivery models have emerged as a promising solution, allowing multiple carriers to share resources and reduce inefficiencies. To address ownership challenges, some models involve the use of collaboration points, where goods can be transferred between vehicles of different LSPs.

The present thesis investigates the application of metaheuristic optimization techniques to minimize the cost of the routing process by strategically determining the optimal locations for collaboration points in the Two-Echelon Vehicle Routing Problem with Collaboration Points (2E-VRP-CP). The employed approach, based on the Particle Swarm Optimization (PSO) method, determines the optimal coordinates for collaboration points, aiming to minimize total travel distance and operational costs. The algorithm is tested on multiple problem instances with varying parameter sets to evaluate its performance in comparison to existing collaborative routing strategies. Experimental results are statistically analyzed and demonstrate that the proposed approach can significantly improve efficiency, paving the way for more sustainable and cost-effective last-mile delivery solutions. The research contributes to the growing field of collaborative logistics by providing insights into how collaboration points can improve last-mile delivery operations, achieving significant economic gain.

Εκτεταμενη Περιληψη

Σπυρίδων Μοτσενίγος, Δ.Μ.Σ. στη Μηχανική Δεδομένων και Υπολογιστικών Συστημάτων, Τμήμα Μηχανικών Η/Υ και Πληροφορικής, Πολυτεχνική Σχολή, Πανεπιστήμιο Ιωαννίνων, 2025.
Βελτιστοποιημένη προσέγγιση για συνεργατική παράδοση τελευταίου μιλίου.
Επιβλέπων: Κωνσταντίνος Ε. Παρσόπουλος, Καθηγητής.

Η παράδοση τελευταίου μιλίου (last-mile delivery) αποτελεί ένα από τα πιο κρίσιμα και δαπανηρά στάδια της εφοδιαστικής αλυσίδας. Παράγοντες όπως η κυκλοφοριακή συμφόρηση, οι υψηλές προσδοκίες των πελατών καθώς και ανησυχίες για την βιωσιμότητα καθιστούν την αποδοτική διανομή τελευταίου μιλίου βασική πρόκληση για τους παρόχους υπηρεσιών εφοδιαστικής αλυσίδας (Logistics Service Providers - LSPs). Τα συνεργατικά (collaborative) μοντέλα διανομής έχουν αναδειχθεί ως μία πολλά υποσχόμενη λύση, επιτρέποντας σε πολλαπλούς παρόχους να μοιράζονται πόρους και να μειώνουν τις αναποτελεσματικότητες. Για να αντιμετωπίσουν ζητήματα ιδιοκτησίας, ορισμένα μοντέλα περιλαμβάνουν τη χρήση σημείων συνεργασίας (collaboration points), όπου τα αγαθά μπορούν να μεταφέρονται μεταξύ οχημάτων διαφορετικών LSPs.

Η παρούσα διπλωματική εργασία μελετά τη χρήση μεταυρετικών τεχνικών βελτιστοποίησης για την ελαχιστοποίηση του κόστους της διαδικασίας δρομολόγησης, μέσω του στρατηγικού προσδιορισμού των βέλτιστων τοποθεσιών των σημείων συνεργασίας στο πρόβλημα δρομολόγησης δύο επιπέδων με σημεία συνεργασίας (Two-Echelon Vehicle Routing Problem with Collaboration Points - 2E-VRP-CP). Η προτεινόμενη προσέγγιση βασισμένη στην μέθοδο της βελτιστοποίησης σμήνους σωματιδίων (Particle Swarm Optimization - PSO), προσδιορίζει τις βέλτιστες συντεταγμένες των σημείων συνεργασίας, με σκοπό την ελαχιστοποίηση της συνολικής διανυθείσας απόστασης και του λειτουργικού κόστους. Ο αλγόριθμος εφαρμόζεται σε πολλαπλά σενάρια προβλημάτων υπό διαφορετικά σύνολα παραμέτρων, προκειμένου να

αξιολογηθεί η απόδοσή του σε σύγκριση με τις υπάρχουσες συνεργατικές στρατηγικές δρομολόγησης. Τα πειραματικά αποτελέσματα αναλύονται στατιστικά και αποδεικνύουν ότι η προτεινόμενη προσέγγιση μπορεί να βελτιώσει σημαντικά την αποδοτικότητα, ανοίγοντας τον δρόμο για πιο βιώσιμες και οικονομικά αποδοτικές λύσεις παράδοσης τελευταίου μιλίου. Η έρευνα συμβάλλει στο συνεχώς αναπτυσσόμενο πεδίο της συνεργατικής εφοδιαστικής, παρέχοντας χρήσιμες γνώσεις για το πώς τα σημεία συνεργασίας μπορούν να βελτιώσουν τις διαδικασίες παράδοσεις τελευταίου μιλίου, επιτυγχάνοντας έτσι σημαντικά οικονομικά οφέλη.

Chapter 1

Introduction

1.1 Objectives

The Vehicle Routing Problem (VRP), introduced by Dantzig and Ramser in 1959 [1], is one of the most extensively studied problems in operations research and combinatorial optimization. It is formulated as a generalization of the "Travelling Salesman Problem", which seeks to find the optimal routes for a fleet of vehicles to serve a set of customers while minimizing the total distance traveled. Over the years, numerous variants of the VRP have been proposed, including the Capacitated VRP (CVRP), VRP with Time Windows (VRPTW), dynamic VRPs, and VRPs with multiple depots, among others [2]. Nevertheless, real-world complexities such as urban congestion and environmental concerns require more advanced extensions of the problem.

The Two-Echelon Vehicle Routing Problem (2E-VRP) is an extension of the classical VRP that uses intermediate facilities to introduce an additional level of transportation. As defined by Crainic *et al.* [3], the first echelon is responsible for the transportation of goods from central depots to these intermediate facilities. The second echelon, in turn, handles the delivery of goods to the final customers. Both problems share similar challenges and aim to minimize the total distribution cost across all routes.

The rapid growth of e-commerce and urbanization has led to significant challenges in last-mile delivery, the final and often most complex stage of the supply chain. Last-mile delivery is responsible for transporting goods from distribution hubs to end customers. However, it remains the most costly and inefficient part of the supply chain, accounting for up to 75% of total logistics costs as underlined by Gevaers *et al.* [4]. These inefficiencies stem from factors such as traffic congestion, customer expectations, fragmented deliveries, and environmental concerns [5]. As customer expectations for faster and more affordable delivery continue to rise, logistics service providers (LSPs) need to adopt more innovative approaches to optimize their operations.

A promising solution to this end is the collaboration between last-mile service providers, in which multiple LSPs share resources such as vehicles, distribution centers, and routing information, in order to enhance efficiency. Relevant research [6] indicates that a collaborative last-mile delivery network can reduce the total distance covered by vehicles, thereby reducing the associated costs. However, traditional collaborative logistics models often require asset sharing, which can lead to challenges related to ownership disputes, control, and coordination. To address these concerns, a recent study [7] proposed a two-echelon vehicle routing model with collaboration points (2E-VRP-CP), where second-echelon vehicles exchange goods at predefined collaboration points (CPs) instead of relying on sharing distribution centers or satellites. While this model improves flexibility and reduces infrastructure dependencies, the placement of CPs remains arbitrary, limiting its overall efficiency.

In collaborative last-mile delivery models with collaboration points, a critical factor is the selection of their locations. The placement of CPs affects both the total distribution cost and the individual cost of the participating logistics service providers. Pingale *et al.* [7] demonstrated that even small changes in the position of the collaboration points can lead to different outcomes in terms of cost for both the whole distribution network and individual LSPs. However, existing studies have treated CP locations as arbitrary or predetermined, instead of strategically optimized. This creates a research gap in determining CP locations strategically in order to minimize total distribution costs. The solution to this problem improves cost and operational efficiency in real-world applications of collaborative logistics models.

The present thesis aims to enhance the 2E-VRP-CP model by integrating Particle Swarm Optimization (PSO), an efficient nature-inspired metaheuristic algorithm, to determine the optimal locations for the collaboration points. PSO simulates swarming behavior and has been widely used in vehicle routing and logistics optimization, exhibiting remarkable ability to efficiently explore large solution spaces and find near-optimal solutions in reasonable computation time [8]. Leveraging PSO enables the minimization of overall distribution costs, the reduction of travel distances, and the enhancement of last-mile delivery efficiency.

The proposed approach is evaluated on test cases where we consider two LSPs, each operating a distribution center, two intermediate facilities (satellites), and a fleet of first- and second-echelon vehicles. Each LSP serves six customers. The delivery of the goods to customers can be completed either directly by the assigned LSP's vehicles or by the other LSP's vehicles after an exchange of goods at a collaboration point. The evaluation is based on different instances of varying parameter configurations. The solutions obtained by the commercial CPLEX solver are used as the baseline for comparisons. Experimental results for the optimized approach are statistically analyzed and compared to the results of the standard 2E-VRP-CP model. The efficiency of the suggested algorithm is assessed, and an optimized solution with all vehicle routes and the locations of CPs is obtained for every problem instance. Finally, useful managerial insights are derived to enhance operational efficiency in practical cases

1.2 Structure of the Thesis

The present thesis comprises four chapters and is organized as follows: Chapter 2 provides the necessary background information. This includes a brief overview of basic concepts of last-mile delivery and the vehicle routing problem, as well as the employed PSO algorithm. Chapter 3 analyzes the proposed approach, while Chapter 4 is devoted to the experimental results and the conclusion of the thesis.

Chapter 2

Background Information

2.1 Two-Echelon Vehicle Routing Problem

Dantzig and Ramser [1] introduced the classic Vehicle Routing Problem in 1959 under the name "Truck Dispatching Problem". They formulated it as a generalization of the "Travelling Salesman Problem" that aimed to determine the optimal routes for a fleet of vehicles to serve a set of customers while minimizing the total distance traveled. Later, Clarke and Wright [9] expanded the problem by utilizing multiple vehicles with varying capacities to serve the customers. This work is considered to have established the VRP in its widely known form.

Golden, Magnanti, and Nguyen [10] introduced the term "Vehicle Routing Algorithms" to describe a class of heuristic algorithms they developed to solve VRP instances. They also presented various key aspects of the vehicle routing problem, including alternative system configurations (e.g., single or multiple depots), objective functions (e.g., minimization of total distance, total cost, delivery times, carbon emissions), and constraints (e.g., vehicle capacity, customer time windows). Due to the inherent complexity, solving large instances of the VRP with exact algorithms can be computationally infeasible. Therefore, numerous heuristic and metaheuristic algorithms have been developed to tackle this problem [11].

According to [12], the VRP can be formally defined as a graph-theoretic problem in which, $G = (V, A)$ is a graph consisting of a vertex set $V = \{0, 1, \ldots, n\}$ and an arc set A. Vertex 0 typically represents the depot, while the remaining vertices, $i = 1, \ldots, n$, denote the customers, each one associated with a known (constant or dynamic) demand d_i. Each arc $(i, j) \in A$ has an associated cost c_{ij}, denoting the travel cost between vertex i and vertex j.

The main objective of the VRP is to minimize the total cost, which is the sum of travel costs for all vehicle tours, by determining an optimal set of vehicle routes. Since a sequence of arcs represents a route, the cost of each route is computed by summing the costs of its constituent arcs. The constraints that must be satisfied are the following [12] :

1. Each route must start at the depot (vertex 0).
2. Each customer must be visited exactly once.
3. The total demand of the customers on a given route must not exceed the capacity of the vehicle that is assigned to that route.

A multitude of variants of the VRP have been proposed in the relevant literature. These include the Capacitated VRP (CVRP), VRP with Time Windows (VRPTW), dynamic VRPs, and VRPs with multiple depots, among other [2]. In the classical VRP, routes typically represent transportation channels from a depot directly to the customers, which implies the use of large-capacity vehicles. However, in urban environments, the utilization of such vehicles can lead to demanding challenges, including traffic congestion, increased air pollution, and limited mobility due to their large size compared to typical urban traffic.

To address these issues, Crainic *et al.* [3] introduced the concept of using intermediate facilities, also known as *satellites*. Thus, they formally introduced the Two-Echelon Vehicle Routing Problem (2E-VRP) where goods are first transported from depots to satellites using first-echelon vehicles and then distributed to the customers via second-echelon vehicles. Their study examined different variants of the 2E-VRP, including scenarios with multiple products, multiple depots, and time and synchronization constraints. Perboli et al. [13] introduced the first mathematical model of a 2E-VRP using only a single depot. Since then, the 2E-VRP has been applied in several real-life applications including city logistics, multimodal transportation, e-commerce distribution, and food retail product distribution [14].

A large number of 2E-VRP variants have also been adapted to different operational constraints and objectives. For example, Baldacci *et al.* [15] concentrated on capacity constraints in two-echelon systems. Another common extension to 2E-VRP models is the consideration of time window constraints [16, 17], as meeting scheduled delivery windows is crucial in many real-world applications. Additionally, synchronization constraints have been examined by Rahmanifar *et al.* [18], where first- and second-echelon vehicles must arrive simultaneously or within a short time window at satellites to ensure timely deliveries.

A more realistic approach is the incorporation of a heterogeneous fleet of vehicles [19] in which, large vehicles are used in the first echelon and smaller vehicles are assigned for the delivery of goods in the second echelon. In contrast, a homogeneous fleet consists of vehicles of the same capacity and cost. The second echelon usually refers to deliveries in urban areas, where vehicle traffic can pose serious challenges relevant to environmental pollution and city noise.

Following these developments, an extension of the 2E-VRP has recently emerged, namely the Electric 2E-VRP [20], where an electric fleet of vehicles is used in the second echelon. In such models, additional constraints related to battery capacity and charging station availability shall be considered, while the objective function may include the minimization of carbon emissions. Another recent variant of the 2E-VRP was proposed in Triantali *et al.* [21], incorporating the utilization of occasional drivers for last-mile delivery. These drivers may reject delivery assignments based on conditions such as the weight of goods to be delivered or the total distance to be traveled.

Despite the numerous variants of the VRP and 2E-VRP, several issues remain open, including carbon emissions and limited access for large vehicles in dense urban areas, which introduce additional challenges. To resolve these issues, collaborative logistics models have emerged to enhance sustainability and efficiency in the supply chain [22]. A common example is the horizontal collaboration that is widely adopted in the field of freight transportation. This is defined in Basso *et al.* [23] as cooperation between companies operating at the same level in the supply chain, aiming to reduce the total distribution cost compared to non-collaborative approaches. The most common form of horizontal collaboration in 2E-VRP involves the sharing of depots or satellites among multiple logistics service providers [7].

2.2 Last-mile delivery

Last-mile delivery is considered the final and most complex stage of the supply chain. Typically, it refers to the transportation of goods from a distribution center to all customer locations, and it involves demanding operational challenges. In other words, last-mile delivery is the process that begins when a shipment has arrived at a starting point in an urban area and ends with the delivery of that shipment to the customer's destination [24].

Although there are many stages in the supply chain, namely sourcing, manufacturing, storage, transportation, and last-mile delivery, the final stage is usually the most costly. According to Gevaers *et al.* [4], last-mile delivery accounts for between 13% and 75% of total supply chain costs. The total distribution cost is affected by factors such as traffic congestion, customer expectations, fragmented deliveries, failed delivery attempts, and environmental concerns [5]. Such difficulties can also impact the efficiency of last-mile delivery, which is crucial for companies.

Besides that, the rapid growth of the population in urban areas, the rise of e-commerce, as well as the need for faster delivery times have necessitated the development of effective and optimized solutions for last-mile logistics [25]. Logistics service providers (LSPs) aim to minimize overall distribution costs while simultaneously focusing on reducing negative environmental impacts and minimizing delivery times. To achieve this, companies are keen to develop and adopt innovative approaches and technologies.

Such an approach is based on the concept of multi-echelon distribution networks. In such networks, there is a first echelon where goods are transported in large quantities from the distribution centers to intermediate satellites using large vehicles. In the second echelon, goods are delivered to customers using smaller and environmentally friendly vehicles. Another contemporary promising approach is the pick-up point network, where customers participate in the delivery of goods by collecting them from predefined locations, thereby reducing the number of failed deliveries. Also, collaborative logistics networks, where cooperation involves members at the same level in the supply chain (horizontal) or at different levels (vertical), have emerged as effective alternatives for increasing operational efficiency [25].

Innovative approaches such as the aforementioned ones are necessary, as the increase in urban deliveries introduces numerous obstacles in transportation, such as air pollution, climate change, traffic congestion, accidents, and noise pollution among other [26]. Hence, the development of sustainable strategies is crucial for the well-being of urban areas. To face these problems, companies need to take action that will reduce delays and emissions. Such actions include optimizing the vehicle route in a way to avoid overlap between regions, selecting the best stopping points for the delivery, as well as placing parcels in the right position in the vehicle in order to be easily and quickly identified by the driver [27].

A newly adopted strategy is the collaborative last-mile delivery in which, LSPs cooperate among them by sharing vehicles or satellites, aiming to reduce total costs and environmental impact. This strategy can ameliorate the impact of urban-related problems, while increasing service quality and enhancing sustainability in last-mile delivery systems [22]. Collaborative models combined with different innovative technologies can become a cornerstone in building efficient last-mile delivery solutions.

2.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based, stochastic optimization algorithm inspired by the swarming behavior of particles. Introduced by R. C. Eberhart and J. Kennedy in 1995 [8], PSO has been widely adopted due to its simplicity and effectiveness in solving complex optimization problems. In PSO, a population, also called *swarm*, of candidate solutions, also known as *particles*, moves through the search space. Each particle adjusts its position based on its own findings as well as those of a subset of the swarm, called its *neighborhood*. When the position update for all particles is completed, the algorithm proceeds to the next iteration, and the process continues until a termination condition is met.

As described in [28], the process begins by initializing a swarm within the search space $X \subset \mathbb{R}^n$:

$$S = \{x_1, x_2, \dots, x_N\}, \tag{2.1}$$

where N is a user-defined parameter of the algorithm representing the number of particles. Each particle is defined as:

$$x_i = (x_{i1}, x_{i2}, \dots, x_{in})^T \in X, \quad i = 1, 2, \dots, N, \tag{2.2}$$

where n is the dimension of the optimization problem.

Each particle also has an adaptive velocity, which directs its movement through the search space:

$$v_i = (v_{i1}, v_{i2}, \ldots, v_{in})^T, \quad i = 1, 2, \ldots, N. \tag{2.3}$$

The velocity is updated by combining information obtained by the particle, i.e., its best position, with information obtained by the members of its neighborhood, i.e., the best position among them. The best position of each particle is stored as an n-dimensional vector:

$$p_i = (p_{i1}, p_{i2}, \ldots, p_{in})^T \in X, \quad i = 1, 2, \ldots, N. \tag{2.4}$$

The best positions of all particles are stored in a set P:

$$P = \{p_1, p_2, \ldots, p_N\}, \tag{2.5}$$

which contains the best positions discovered by the swarm during its run.

The neighborhood of each particle contains the indices of its neighbors, and for the i-th particle, it is defined as:

$$NG_i = \{i_1, i_2, \ldots, i_l\} \subseteq \{1, 2, \ldots, N\}. \tag{2.6}$$

There are various neighborhood topologies, two of them being widely recognized. The first is the fully connected topology in which, each particle i shares its best position with all other particles in the swarm and is defined as:

$$NG_i = \{1, 2, \ldots, N\}, \forall i. \tag{2.7}$$

This PSO variant is also known as the *gbest model*. The second one is the *ring* topology in which, the neighborhood of the i-th particle consists of its adjacent indices according to a radius r:

$$NG_i = \{i - r, \ldots i, \ldots, i + r\}. \tag{2.8}$$

The indices of the particles are recycled at the two ends, and this PSO variant is also known as the *lbest model*.

The particles update their positions according to the following scheme [28] :

$$v_{ij}^{(t+1)} = \chi \Big[v_{ij}^{(t)} + r_1 c_1 (p_{ij}^{(t)} - x_{ij}^{(t)}) + r_2 c_2 (p_{g_i j}^{(t)} - x_{ij}^{(t)}) \Big] \tag{2.9}$$

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)} \tag{2.10}$$

$$i = 1, 2, \ldots, N, \quad j = 1, 2, \ldots, n, \tag{2.11}$$

where g_i is the index of the best particle in the neighborhood of x_i; r_1 and r_2 are random numbers in [0,1]; c_1, $c_2 > 0$ are the cognitive and social parameters; and $\chi > 0$ is the constriction coefficient.

The analysis of Clerc and Kennedy [29] provides a theoretical background that implies the following explicit relation of the parameters:

$$\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \tag{2.12}$$

where $\varphi = c_1 + c_2 > 4$. Based on this analysis, the default parameter set of $\chi = 0.729$ and $c_1 = c_2 = 2.05$ has emerged.

An important issue is to ensure convergence and that, after each update, the particles remain within the boundaries of the search space. This is achieved using a velocity limit on each particle:

$$-v_{\text{max}_j} \leq v_{ij} \leq v_{\text{max}_j}, \quad \forall i, j, \tag{2.13}$$

$$v_{\text{max}_j} = \alpha(u_j - l_j), \tag{2.14}$$

where $\alpha \in (0, 1]$ is the fraction of the search space a particle can explore and l_j, u_j are the lower and upper bounds for the j-th dimension of the search space. This restriction, along with the use of the constriction coefficient χ, provides convergent behaviour to the swarm. However, even in this case, a particle may violate the search space boundaries. Hence, an additional check is required to ensure that all its dimension components remain inside the bounds:

$$x_{ij}^{(t+1)} = \begin{cases} l_j, & \text{if } x_{ij}^{(t+1)} < l_j, \\ u_j, & \text{if } x_{ij}^{(t+1)} > u_j, \quad \forall i, j \\ x_{ij}^{(t+1)}, & \text{otherwise,} \end{cases} \tag{2.15}$$

The final step to complete a full iteration, consists of the evaluation of the new particle positions and the update of the best positions:

$$p_i^{(t+1)} = \begin{cases} x_i^{(t+1)}, & \text{if } f(x_i^{(t+1)}) < f(p_i^{(t)}), \\ p_i^{(t)}, & \text{otherwise,} \end{cases} \quad i = 1, 2, \ldots, N \tag{2.16}$$

The pseudocode of the PSO algorithm is presented in Algorithm 2.1.

Algorithm 2.1 PSO algorithm pseudocode

Input: search space X, constriction coefficient χ, cognitive and social parameters c_1, c_2, maximum velocity $v_{\max}$
$t \leftarrow 0$
$S^{(t)} \leftarrow$ **Initialize**(X) /* *initialize swarm* */
$V^{(t)} \leftarrow$ **Initialize**$(v_{\max})$ /* *initialize velocities* */
Evaluate$(S^{(t)})$ /* *swarm evaluation* */
$P^{(t)} \leftarrow S^{(t)}$ /* *update best positions* */
$x^* \leftarrow \text{best}(P^{(t)})$
while (termination condition does not hold) **do**
    $V^{(t+1)} \leftarrow$ **new_velocities**$(V^{(t)}, S^{(t)}, P^{(t)}, \chi, c_1, c_2)$ /* *velocity update* */
    $V^{(t+1)} \leftarrow$ **check_boundaries**$(V^{(t+1)}, v_{\max})$ /* *velocity clamping* */
    $S^{(t+1)} \leftarrow$ **new_positions**$(V^{(t+1)}, S^{(t)})$ /* *new position* */
    $S^{(t+1)} \leftarrow$ **check_boundaries**$(S^{(t+1)}, X)$ /* *boundary check* */
    Evaluate$(S^{(t+1)})$ /* *swarm evaluation* */
    $P^{(t+1)} \leftarrow$ **new_best_positions**$(P^{(t)}, S^{(t+1)})$ /* *update best positions* */
    $x^* \leftarrow \text{best}(P^{(t+1)})$
    $t \leftarrow t + 1$
end while
Return: overall best x^*

Chapter 3

Proposed Approach

3.1 Established Collaborative Last-Mile Delivery Approach

As already mentioned in Chapter 2, an efficient way to reduce costs in last-mile delivery is the collaboration among multiple LSPs. Notably, the idea of introducing collaboration points as locations where vehicles from different LSPs exchange goods in the second echelon, as depicted in Fig. 3.1, offers the advantage of avoiding prohibitive ownership issues that are met in shared logistics facilities. Relevant studies [7], which address the 2E-VRP-CP problem, provide sound evidence that the collaborative approach offers better efficiency and cost reduction when compared to either the classic non-collaborative approach or the collaborative approach with shared facilities [16].

More specifically, in [7] each LSP has exactly one distribution center (DC) and a predetermined number of satellites. Each customer of the network is assigned to an LSP and hence is associated with the corresponding DC of its LSP. Additionally, a fleet of first- and second-echelon vehicles with limited capacity is available for delivering goods to customers.

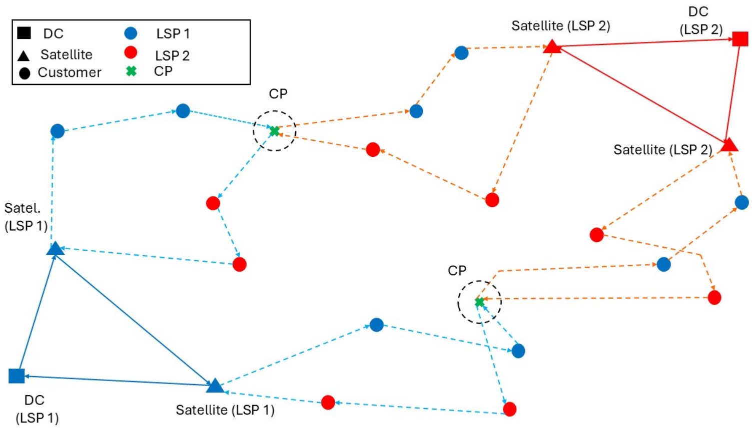

Figure 3.1: Example of delivery routes for the collaborative approach using collaboration points (green squares).

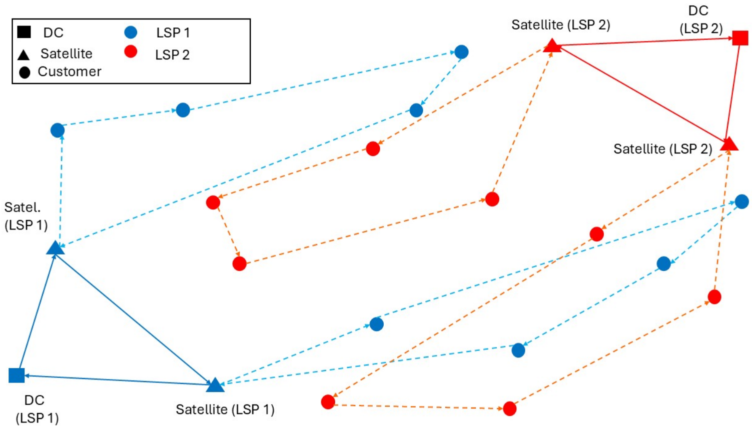

Figure 3.2: Example of delivery routes for the non-collaborative approach.

Each customer is assigned by its LSP to a satellite and to a first- and second-echelon vehicle, respectively. Thus, a first-echelon vehicle will serve its assigned customers by transporting their goods from the entrusted distribution center to the assigned satellite. Departing from the satellite, the goods reach the customer by the assigned second-echelon vehicle. If there is no collaboration between the two LSPs, all the involved transportation means and stations for a specific customer belong to the same LSP, as illustrated in Figure 3.2. The introduction of collaboration points apparently offers radical changes to the delivery routes.

In the collaborative approach, a second-echelon vehicle that is assigned to a satellite of a specific LSP can also serve customers from different LSPs. For this purpose, collaboration points are used, i.e., predetermined locations where two second-echelon vehicles of different LSPs meet and exchange goods. This way, a second-echelon ve-

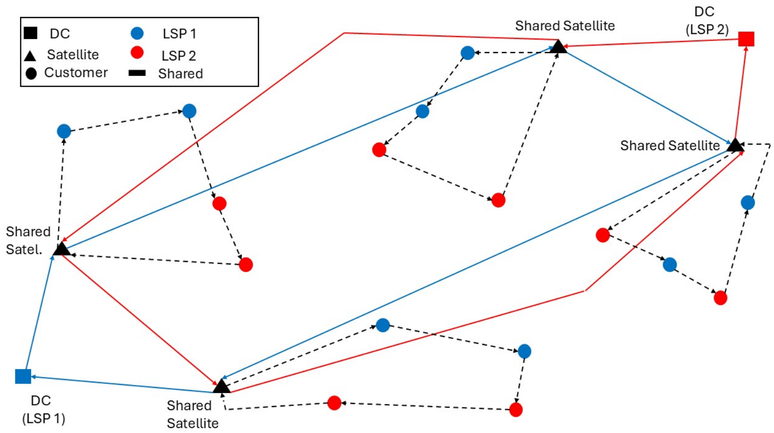

Figure 3.3: Example of delivery routes for the collaborative approach with shared facilities.

hicle of an LSP will primarily serve the customers who belong to the same LSP, and then, if necessary, it will visit a collaboration point to exchange goods with a corresponding vehicle of another LSP. Thus, customers may be served either by their own LSP's vehicles or by another LSP.

The collaborative approach can offer a significant reduction of up to 10% of the total distribution cost when compared with the non-collaborative approach [7]. These savings come from the lower cost in the second echelon, as this is the stage where the collaboration points are utilized. Additionally, there is a cost reduction of up to 9% when this approach is compared with the collaborative model of sharing logistics facilities depicted in Fig. 3.3. In some cases, the collaborative approach of sharing facilities may result in lower second-echelon costs when compared to the cooperative approach with collaboration points. However, even in such cases, the total cost in the first echelon is usually higher because the goods must be transported to every shared satellite of the transportation network.

3.2 Mathematical Model

The collaborative approach can be mathematically modeled in a mixed integer linear programming (MILP) problem as in [7] that will be extended with a sophisticated optimization approach to determine the locations of the collaboration points. While tackling the problem, certain assumptions are taken into consideration as described

Table 3.1: Notations of the model

Sets	Description
L	Set of the LSPs in the network, $L = \{1, 2, \dots, l\}$
D	Set of the DCs in the network, $D = \{1, 2, \dots, n_d\}$
S	Set of the satellites in the network, $S = \{n_d + 1, n_d + 2, \dots, n_d + n_s\}$
C	Set of the customers in the network, $C = \{n_d + n_s + 1, n_d + n_s + 2, \dots, n_d + n_s + n_c\}$
O	Set of the collaboration points in the network, $O = \{n_d + n_s + n_c + 1, n_d + n_s + n_c + 2, \dots, n_d + n_s + n_c + n_o\}$
D_l^i	i-th DC belongs to l-th LSP in the network, $l \in L, D_l \subset D$
S_l^i	i-th satellite belongs to l-th LSP in the network, $l \in L, S_l \subset S$
C_l^i	i-th customer belongs to l-th LSP in the network, $l \in L, C_l \subset C$
T	Set of the first echelon vehicles in the network, $D = \{1, 2, \dots, n_t\}$
V	Set of the second echelon vehicles in the network, $S = \{n_t + 1, n_t + 2, \dots, n_t + n_v\}$

below.

Assumption 1. There is a deterministic and known demand for each customer.

Assumption 2. Each customer can be visited exactly once, and goods cannot be delivered directly to them from distribution centers.

Assumption 3. Every first-echelon vehicle starts and ends its route at the same DC, through serving satellites and without visiting any collaboration point. Similarly, every second-echelon vehicle starts and ends its route at the same satellite, serving all its assigned customers, regardless of whether it visits a collaboration point.

Assumption 4. The DCs can cover the demand of all customers.

Assumption 5. A maximum of only two vehicles from different LSPs can meet at a collaboration point to exchange goods.

Assumption 6. A second-echelon vehicle starts its route by serving the customers of its own LSP. After that, the vehicle can visit a collaboration point to exchange goods and then serve the remaining customers of different LSPs.

Assumption 7. Each LSP owns one distribution center and two satellites that also have capacity constraints.

Assumption 8. A second-echelon vehicle can only visit one collaboration point once per route.

Assumption 9. Time and synchronization constraints typically apply but they are not considered in this study due to computation-time challenges.

The notations of the model are shown in Table 3.1.

The parameters of the model are shown in Table 3.2.

The decision variables of the model are shown in Table 3.3.

Table 3.2: Parameters of the model

Parameters	Description
C_{ij}	Cost for the transportation from node i to node j, $i, j \in D \cup S \cup C \cup O$
F_t	Fixed cost for every first echelon vehicle, $t \in T$
F_v	Fixed cost for every second echelon vehicle, $v \in V$
d_c	Demand of customer c in the network, $c \in C$
A_s	Capacity of satellite s in the network, $s \in S$
K_1	Capacity of first echelon vehicles
K_2	Capacity of second echelon vehicles
p_c	DC to which customer c is assigned, $c \in C$
M	A large constant used to ensure constraints hold under specific conditions

Table 3.3: Decision Variables of the model

Variables	Description
R_{ij}^t	1, if the first echelon vehicle t is traveling from node i to node j, $i, j \in D \cup S, t \in T$; 0, otherwise
X_{ij}^v	1, if the second echelon vehicle v is traveling from node i to node j, $i, j \in S \cup C \cup O, v \in V$; 0, otherwise
U_t	1, if the first echelon vehicle t is assigned to a route, $t \in T$; 0, otherwise
U_v	1, if the second echelon vehicle v is assigned to a route, $v \in V$; 0, otherwise
G_v^s	1, if the second echelon vehicle v is assigned to satellite s, $s \in S, v \in V$; 0, otherwise
Z_c^s	1, if the customer c is assigned to satellite s, $s \in S, c \in C$; 0, otherwise
N_c^t	1, if the customer c is assigned to the first echelon vehicle t, $t \in T, c \in C$; 0, otherwise
N_c^v	1, if the customer c is assigned to the second echelon vehicle v, $v \in V, c \in C$; 0, otherwise
B_{sv}^o	1, if second echelon vehicle v is assigned to satellite s and visits the collaboration point o, $s \in S, v \in V, o \in O$; 0, otherwise
P_{ij}^v	Number of goods transported by second echelon vehicle v from node i to node j, $i, j \in D \cup S \cup C \cup O, v \in V$;
W_i^t	Variables to avoid subtour in first echelon, $i \in S, t \in T$;
W_i^v	Variables to avoid subtour in second echelon, $i \in C \cup O, v \in V$;

The objective function of the model aims to minimize the total distribution cost, which consists of the transportation cost for each vehicle's route and a fixed cost for every vehicle used. It is defined as:

$$\sum_{t\in T}\sum_{i\in D\cup S}\sum_{j\in D\cup S} C_{ij}R_{ij}^t + \sum_{v\in V}\sum_{i\in S\cup C\cup O}\sum_{j\in S\cup C\cup O} C_{ij}X_{ij}^v + \sum_{t\in T} F_tU_t + \sum_{v\in V} F_vU_v \tag{3.1}$$

There are constraints for both the first and second echelons of the distribution network. Starting with the first echelon, we have the following constraints:

$$\sum_{n\in D\cup S} R_{nj}^t - \sum_{n\in D\cup S} R_{jn}^t = 0, \quad \forall j \in D\cup S,\ t\in T \tag{3.2}$$

This constraint ensures flow conservation in the first echelon.

$$\sum_{i\in S}\sum_{j\in D} R_{ij}^t = U_t, \quad \forall t \in T \tag{3.3}$$

Constraint 3.3 ensures that if a first-echelon vehicle is used, it must return to the depot where it started its route.

$$\sum_{s\in S} R_{p_cs}^t \geq N_c^t, \quad \forall c\in C,\ t\in T \tag{3.4}$$

Constraint 3.4 ensures that if a customer is assigned to a specific first-echelon vehicle and depot, then this vehicle must depart from that depot.

$$\sum_{c\in C} d_cN_c^t \leq K_1U_t, \quad \forall t\in T \tag{3.5}$$

This constraint ensures that the total demand assigned to a first-echelon vehicle does not exceed its capacity.

$$\sum_{t\in T} N_c^t = 1, \quad \forall c\in C \tag{3.6}$$

Constraint 3.6 ensures that each customer is assigned to a first-echelon vehicle.

$$M(2 - N_c^t - Z_c^s) + \sum_{z\in D\cup S} R_{sz}^t \geq 1, \quad \forall c\in C,\ s\in S,\ t\in T \tag{3.7}$$

Constraint 3.7 ensures that if a customer is assigned to a specific first-echelon vehicle and satellite, then this vehicle must visit that satellite.

$$R_{ij}^t = 0, \quad \forall i\in D_k\cup S_k,\ j\in D_l\cup S_l,\ k,l\in L,\ k\neq l,\ t\in T \tag{3.8}$$

This constraint ensures that transportation does not occur between distribution centers and satellites belonging to different LSPs.

$$\sum_{s\in S_k} Z_c^s = 1, \quad \forall c\in C_k,\ k\in L \tag{3.9}$$

This constraint ensures that each customer is assigned to a satellite that belongs to the same LSP as the customer.

The constraints related to the second echelon are as follows:

$$\sum_{n \in S \cup C \cup O} X_{nj}^{v} - \sum_{n \in S \cup C \cup O} X_{jn}^{v} = 0, \quad \forall j \in S \cup C \cup O, \ v \in V \tag{3.10}$$

This constraint ensures flow conservation in the second echelon.

$$\sum_{i \in C \cup O} \sum_{j \in S} X_{ij}^{v} = U_{v}, \quad \forall v \in V \tag{3.11}$$

Constraint 3.11 ensures that if a second-echelon vehicle is used, it must return to the satellite where it started its route.

$$\sum_{v \in V} N_{c}^{v} = 1, \quad \forall c \in C \tag{3.12}$$

Constraint 3.12 ensures that each customer is assigned to a second-echelon vehicle.

$$\sum_{z \in S \cup C \cup O} X_{cz}^{v} = N_{c}^{v}, \quad \forall c \in C, \ v \in V \tag{3.13}$$

This constraint ensures that if a customer is assigned to a second-echelon vehicle, that vehicle must visit that customer.

$$\sum_{s \in S} G_{v}^{s} = 1, \quad \forall v \in V \tag{3.14}$$

This constraint ensures that each second-echelon vehicle is assigned to a satellite.

$$\sum_{j \in C \cup O} X_{sj}^{v} = G_{v}^{s}, \quad \forall s \in S, \ v \in V \tag{3.15}$$

Constraint 3.15 ensures that if a second-echelon vehicle is assigned to a specific satellite, then this vehicle must depart from that satellite.

$$\sum_{s \in S} \sum_{o \in O} B_{sv}^{o} \leq 1, \quad \forall v \in V \tag{3.16}$$

Constraint 3.16 ensures that every second-echelon vehicle visits at most one collaboration point.

$$M(1 - B_{sv}^{o}) + \sum_{j \in C \cup O} X_{sj}^{v} + \sum_{i \in S \cup C} X_{io}^{v} \geq 2, \quad \forall v \in V, \ s \in S, \ o \in O \tag{3.17}$$

This constraint ensures that if a second-echelon vehicle is assigned to a satellite and must visit a collaboration point, it must do so starting from that satellite.

$$M(3 - Z_c^s - N_c^v - G_v^s) + \sum_{i \in S \cup C} X_{ic}^v \geq 1, \quad \forall v \in V,\ s \in S,\ c \in C \tag{3.18}$$

This constraint ensures that if a customer is assigned to a specific satellite and second-echelon vehicle, and the vehicle is also assigned to that satellite, then it must depart from that satellite and visit that customer.

$$M(3 - Z_c^s - N_c^v - G_v^h) + \sum_{o \in O} B_{hv}^o \geq 1, \quad \forall v \in V,\ c \in C,\ s, h \in S,\ s \neq h \tag{3.19}$$

Constraint 3.19 ensures that if a customer is assigned to a specific satellite and second-echelon vehicle, but the vehicle is assigned to a different satellite, it must first visit a collaboration point to exchange goods before visiting the customer.

$$\begin{gathered} M(4 - Z_c^s - N_c^v - G_v^h - B_{hv}^o) + \sum_{w \in C_k} X_{wc}^v + X_{oc}^v \geq 1, \\ \forall v \in V,\ o \in O,\ c \in C_k,\ k \in L,\ s, h \in S,\ s \neq h \end{gathered} \tag{3.20}$$

This constraint ensures that if the conditions of the Constraint 3.19 hold, then the vehicle carrying the necessary goods must visit the customer either directly from the collaboration point or after visiting another customer of the same LSP.

$$\begin{gathered} M(4 - Z_c^s - N_c^v - G_v^h - B_{hv}^o) + \sum_{w \in V} B_{sw}^o \geq 1, \\ \forall v \in V,\ o \in O,\ c \in C,\ s, h \in S,\ s \neq h \end{gathered} \tag{3.21}$$

Constraint 3.21 ensures that if a customer is assigned to a specific satellite and second-echelon vehicle, but that vehicle is assigned to a different satellite and visits a collaboration point, then another vehicle must depart from the customer's assigned satellite and reach the same collaboration point to exchange goods.

$$\sum_{c \in C} Z_c^s d_c = \sum_{v \in V} \sum_{j \in C \cup O} P_{sj}^v, \quad \forall s \in S \tag{3.22}$$

Constraint 3.22 ensures that the total demand of customers assigned to a satellite equals the total number of goods departing from that satellite.

$$\sum_{v \in V} \sum_{i \in S \cup C \cup O} P_{ic}^v - \sum_{v \in V} \sum_{i \in S \cup C \cup O} P_{ci}^v = d_c, \quad \forall c \in C \tag{3.23}$$

This constraint ensures that each customer receives the exact number of goods they desire.

$$P_{ij}^v \leq K_2 X_{ij}^v, \quad \forall i, j \in S \cup C \cup O, \; v \in V \tag{3.24}$$

Constraint 3.24 ensures that the quantity of goods carried by a second-echelon vehicle must not exceed its capacity.

$$M(2 - \sum_{i \in S \cup C} X_{io}^v - \sum_{i \in S \cup C} X_{io}^m) + \sum_{i \in S \cup C} P_{io}^v \geq \sum_{j \in S \cup C} P_{oj}^m, \quad \forall o \in O, \; v, m \in V, \; v \neq m \tag{3.25}$$

$$M(2 - \sum_{i \in S \cup C} X_{io}^v - \sum_{i \in S \cup C} X_{io}^m) + \sum_{i \in S \cup C} P_{io}^m \geq \sum_{j \in S \cup C} P_{oj}^v, \quad \forall o \in O, \; v, m \in V, \; v \neq m \tag{3.26}$$

Constraints 3.25 and 3.26 ensure that if two second-echelon vehicles meet at a collaboration point, the exchange of goods is completed correctly by transferring them between the vehicles.

$$\sum_{i \in S \cup C \cup O} \sum_{v \in V} X_{io}^v \leq 2, \quad \forall o \in O \tag{3.27}$$

This constraint ensures that every collaboration point must be visited by at most two second-echelon vehicles to exchange their goods.

$$\sum_{i \in C \cup O} \sum_{j \in S} P_{ij}^v = 0, \quad \forall v \in V \tag{3.28}$$

This constraint ensures that each second-echelon vehicle returns empty to its departure satellite.

$$\sum_{c \in C} Z_c^s d_c \leq A_s, \quad \forall s \in S \tag{3.29}$$

Constraint 3.29 ensures that, for each satellite, the total demand of all its assigned customers does not exceed its capacity.

$$X_{ij}^v = 0, \quad \forall i \in C_k, \; j \in C_l, \; k, l \in L, \; k \neq l, \; v \in V \tag{3.30}$$

This constraint ensures that transportation does not occur between customers belonging to different LSPs.

$$W_i^t - W_j^t + n_s R_{ij}^t \leq n_s - 1, \quad \forall i, j \in S, t \in T \tag{3.31}$$

$$W_i^v - W_j^v + n_c X_{ij}^v \leq n_c - 1, \quad \forall i, j \in C \cup O, t \in T \tag{3.32}$$

Constraints 3.31 and 3.32 prevent subtours in the first- and second-echelon routes.

3.3 Proposed Optimized Approach

In the presented mathematical model, Pingale *et al.* [7] investigated the impact of varying CP locations by moving them along the line that connects the satellites of two different LSPs. Different results emerged from these experiments, both in terms of total transportation costs and individual costs for each LSP. Hence, the choice of collaboration point locations is crucial for the efficiency of each company, as well as for the overall efficiency of the collaborative network.

Obviously, real-world scenarios can rarely assume that CPs lie conveniently on straight lines between two satellites. Instead, there is a reasonable operational necessity for flexibility in the positions of the CPs, which should be able to lie potentially anywhere on the network map, unless hard constraints prohibit it (e.g., due to geographical or transportation constraints).

The present thesis addresses this issue by employing the PSO metaheuristic to determine strategically optimal locations of the collaboration points. The main goal remains the minimization of the total distribution cost across the collaborative network. PSO was specifically adopted over other evolutionary or stochastic algorithms for several reasons. First of all, PSO presents low parameter sensitivity. Specifically, PSO requires tuning of fewer parameters than Differential Evolution or Genetic Algorithm, making it more robust and easier to apply in practice. Moreover, PSO tends to converge faster towards optimal solutions in the search space compared to simulated annealing or Differential Evolution, which is crucial in the examined problem that requires solving the MILP model at each function evaluation. Additionally, PSO is characterized by its simplicity, as it handles continuous decision variables naturally and doesn't require encoding/decoding steps, unlike Genetic Algorithms. In this case, CP locations are represented as real-valued coordinates on a map, making PSO more suitable for this problem. Finally, PSO is widely and successfully applied in solving complex optimization problems, such as routing, facility location, and other logistics optimization problems, including the one presented in this thesis.

In our approach, the dimension coordinates of each particle of the swarm correspond to the actual coordinates of the collaboration points on a map grid. Thus, each particle represents a candidate position setting of the collaboration points. For each position setting, the MILP model is solved, offering the optimal total distribution cost that is achievable for the specific CP positions. This cost serves as the objec-

Algorithm 3.1 Swarm Evaluation - **Evaluate**(S)

Input: PSO swarm S, swarm size N
Output: particle values
Evaluate(S)
for $i = 1 \dots N$ **do**
  $(CP1, CP2) \leftarrow$ **get_CPs**(x_i) /* *Get Coordinates from particle* */
  Cost* $\leftarrow$ **solve_MILP_with_CPLEX**($CP1, CP2$) /* *CPLEX solution* */
  $f_i \leftarrow$ Cost* /* *function value assignment* */
end for
Return: $f_i, \forall i$

tive function value for the specific particle. The objective function (solution of the corresponding MILP problem) was computed with the state-of-the-art IBM CPLEX Solver [30], returning both the total distribution cost as well as the routes for all the employed vehicles.

Thus, the PSO algorithm iteratively searches for the best CP positions that minimize the total distribution cost by updating the positions of the particles. After the algorithm has finished, the best detected CP coordinates that correspond to the best detected solutions in terms of cost, are stored. The pseudocode of the evaluation function is presented in Algorithm 3.1.

As an example, consider a particle x_i with the following position values: $(17.54, 23.7, 19.97, 39.08)$. In this case, the coordinates of CP1 are $(17.54, 23.7)$ and the coordinates of CP2 are $(19.97, 39.08)$. These coordinates of the collaboration points (CP1, CP2), along with the other fixed parameters defined in this section, are the inputs to the MILP model. CPLEX is used to find the optimal solution of the model, which corresponds to the optimal total distribution cost obtained for these parameter settings (e.g., in our case, $Cost = 491.61$). This cost is then assigned as the objective function value for the specific particle x_i.

Chapter 4

Experimental Analysis

4.1 Implementation Details and Parameter Configuration

As described in the previous chapter, the PSO algorithm was used to enhance the solution of the 2E-VRP-CP problem. This part of the methodology was implemented in Python. Additionally, CPLEX was employed for solving the underlying MILP problem up to optimality at each objective function evaluation, which corresponds to a specific setting of the collaboration points.

To test our proposed approach, we conducted experiments on a set of five problem instances based on the information provided in [7]. The specific problem set was randomly generated according to the guidelines provided in [31], where customers and facilities are located within concentric circles of increasing radius, representing a multi-level urban area. Thus, the coordinates for DCs, satellites, customers, and CPs for each problem instance were aligned with those in [7]. In order to retain reasonable computation times, each problem instance consists of two distribution centers, four satellites, twelve customers, and two collaboration points, while the fleet comprises two first-echelon and four second-echelon vehicles for the whole collaborative network.

Table 4.1: Fixed and PSO parameter values for the studied model

Parameter	Value
Swarm Size	20,50
Neighborhood Topology	gbest, lbest
F_t	50
F_v	25
d_c	10
A_s	50
K_1	100
K_2	30
p_c	DC 1: for customers 8,10,12,14,16,18 DC 2: for customers 7,9,11,13,15,17
M	300

The parameters of the mathematical model retained the same values in all problem instances with the exception of the cost parameter, C_{ij}, which denotes the transportation cost between two nodes, and the network nodes which assumed map different coordinates. The values of the fixed parameters for the experiments are reported in Table 4.1.

Due to the heavy computational load required for CPLEX to optimally solve the MILP problem at each function evaluation of the PSO algorithm, it was decided to use a maximum computation budget of 1000 evaluations for PSO. Moreover, the number of independent experiments for each problem instance was set to 21 for the same reason. Regarding the PSO parameters, four different combinations were considered between swarm size and neighborhood type. The rest of its parameters were fixed. Nevertheless, a number of experiments were also conducted with varying velocities and restarting limits. However, the results were highly similar to or worse than those of the aforementioned configurations, so these combinations were not further studied. The parameter values for the PSO are also reported in Table 4.1.

4.2 Experimental Results

Table 4.2: Statistics of PSO

TP	Swarm Size (N)	Topology	Median	Mean	Std Dev.	Minimum	Maximum
1	20	gbest	**491.62**	**491.626**	**0.0133**	**491.61**	**491.652**
1	20	lbest	491.702	491.707	0.042	491.631	491.798
1	50	gbest	491.919	491.973	0.268	491.705	492.593
1	50	lbest	492.176	492.262	0.249	491.919	492.659
2	20	gbest	**489.235**	**489.235**	**0**	**489.235**	**489.235**
2	20	lbest	**489.235**	**489.235**	**0**	**489.235**	**489.235**
2	50	gbest	**489.235**	**489.235**	**0**	**489.235**	**489.235**
2	50	lbest	**489.235**	**489.235**	**0**	**489.235**	489.236
3	20	gbest	**504.224**	504.248	0.048	**504.223**	504.345
3	20	lbest	504.229	**504.231**	**0.009**	504.224	**504.256**
3	50	gbest	504.242	504.252	0.035	504.225	504.390
3	50	lbest	504.275	504.292	0.060	504.236	504.504
4	20	gbest	**503.238**	**503.238**	**0.006**	**503.228**	**503.255**
4	20	lbest	503.263	503.273	0.027	503.241	503.333
4	50	gbest	503.279	503.318	0.099	503.247	503.633
4	50	lbest	503.366	503.395	0.132	503.249	503.823
5	20	gbest	**496.175**	496.349	0.78	**496.175**	499.754
5	20	lbest	496.18	**496.225**	0.176	**496.175**	496.987
5	50	gbest	496.192	496.511	0.939	496.177	499.771
5	50	lbest	496.265	496.296	**0.09**	496.196	**496.501**

The obtained experimental results for each problem instance and parameter setting were statistically analyzed. More specifically, basic statistics were calculated for the total distribution cost, including the median, mean value, st. dev. minimum, and maximum. Table 4.2 reports these values for all five test problems.

Based on these statistics, it was observed that for Test Problems 1 and 4, the combination of a swarm size of 20 under the gbest neighborhood topology achieved the best performance, yielding the lowest mean and minimum costs. In Test Problems 3 and 5, the gbest topology with a swarm size of 20 also produced the best solutions.

Table 4.3: Wilcoxon rank-sum tests between gbest and lbest PSO for all test problems

TP	Swarm Size (N)	p-value	Stat. Diff. ($a = 0.05$)	Stat. Diff. ($a = 0.01$)
1	20	9.012×10^{-8}	✓	✓
1	50	0.000337	✓	✓
2	20	0.013218	✗	✓
2	50	0.428124	✗	✗
3	20	0.128029	✗	✗
3	50	0.001028	✓	✓
4	20	1.791×10^{-7}	✓	✓
4	50	0.005441	✓	✓
5	20	0.009924	✓	✓
5	50	0.007956	✓	✓

Nevertheless, some outliers were observed, leading to higher variability compared to the lbest neighborhood topology. Finally, in Test Problem 2, all parameter settings converged to nearly identical solutions, presenting insignificant differences across topologies and swarm sizes.

The observed performance differences of PSO suggest that the rapidly converging gbest PSO version can effectively solve the studied problem. The lbest version may offer better stability in some cases, but in general, it requires a higher number of function evaluations, which may not be necessary for this problem type. The outliers that were observed in some test cases also reveal a trade-off between exploration and exploitation in PSO.

The statistical significance of the observed performance differences was assessed using the Wilcoxon rank-sum test and it is reported in Table 4.3. For most test problems, the p-values confirmed significant differences between the gbest and lbest topologies, emphasizing the conclusion that the choice of neighborhood topology impacts the algorithm's performance. The exception was Test Problem 2, where the Wilcoxon rank-sum test indicated no significant difference between the two neighborhood topologies, being in full agreement with the identical results across parameter configurations. This finding indicates that for test problems with simpler structures, the impact of the neighborhood topology is negligible.

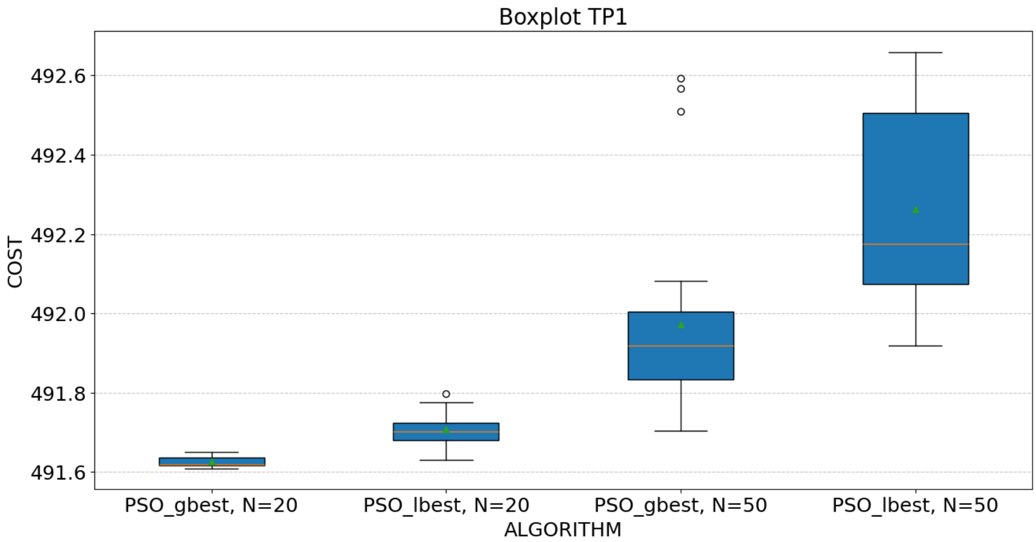

Figure 4.1: Boxplots of best solution cost achieved in 21 independent experiments for Test Problem 1

Overall, experimental results suggest that swarms of size 20 combined with the gbest topology yielded the most effective solutions in terms of minimizing the total distribution cost. Despite the fact that in some cases (Test Problems 3 and 5), the medians of this combination were higher than the ones obtained for the other settings, this configuration achieved the minimum cost values across the experiments. These observations are confirmed in Figures 4.1 - 4.5, which depict the boxplot representation of the distribution of solution costs for each test problem.

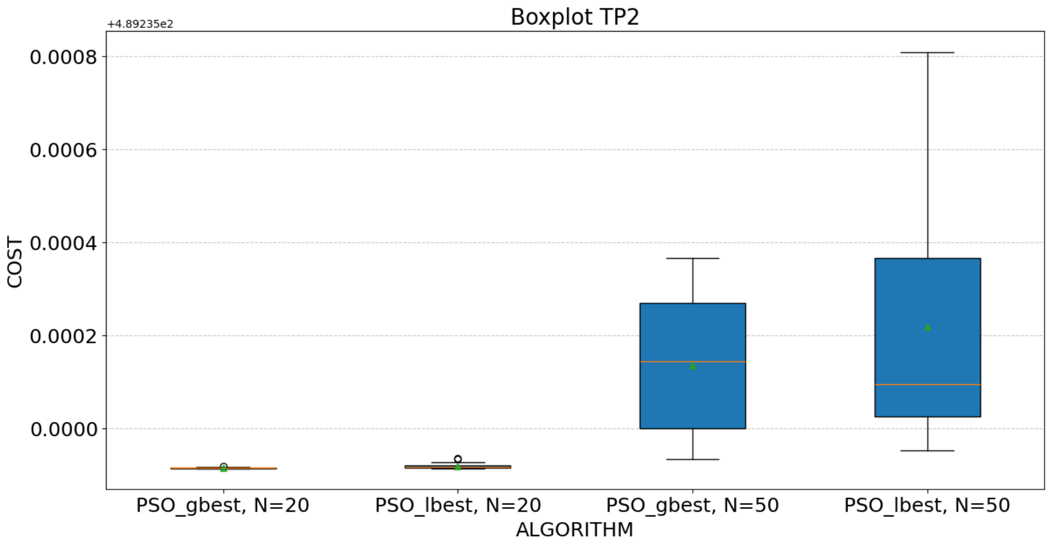

Figure 4.2: Boxplots of best solution cost achieved in 21 independent experiments for Test Problem 2

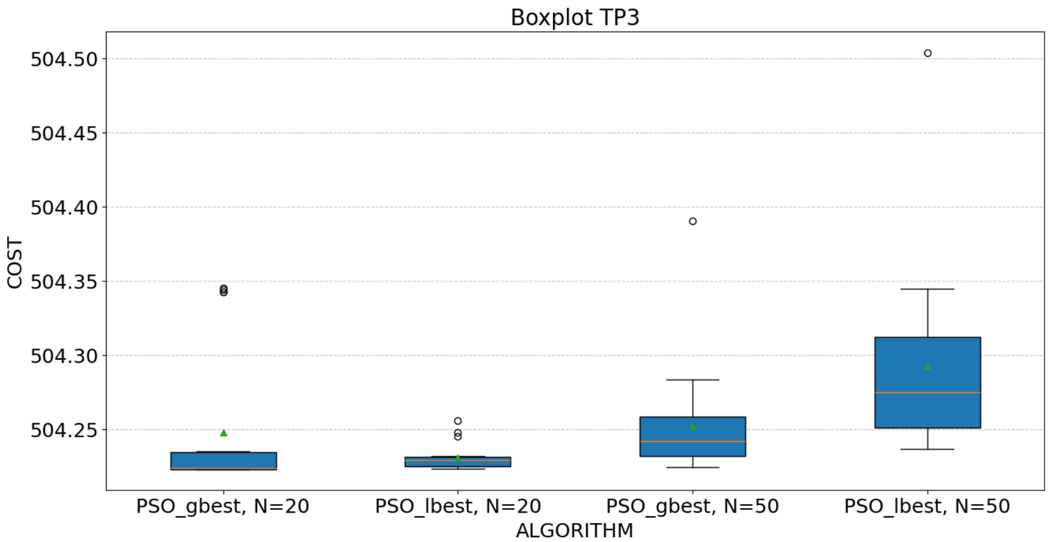

Figure 4.3: Boxplots of best solution cost achieved in 21 independent experiments for Test Problem 3

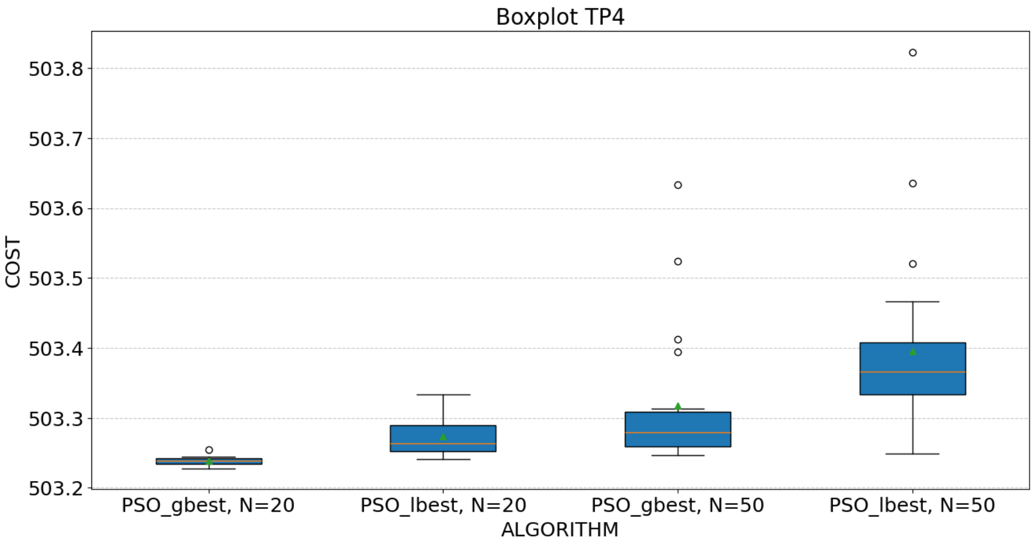

Figure 4.4: Boxplots of best solution cost achieved in 21 independent experiments for Test Problem 4

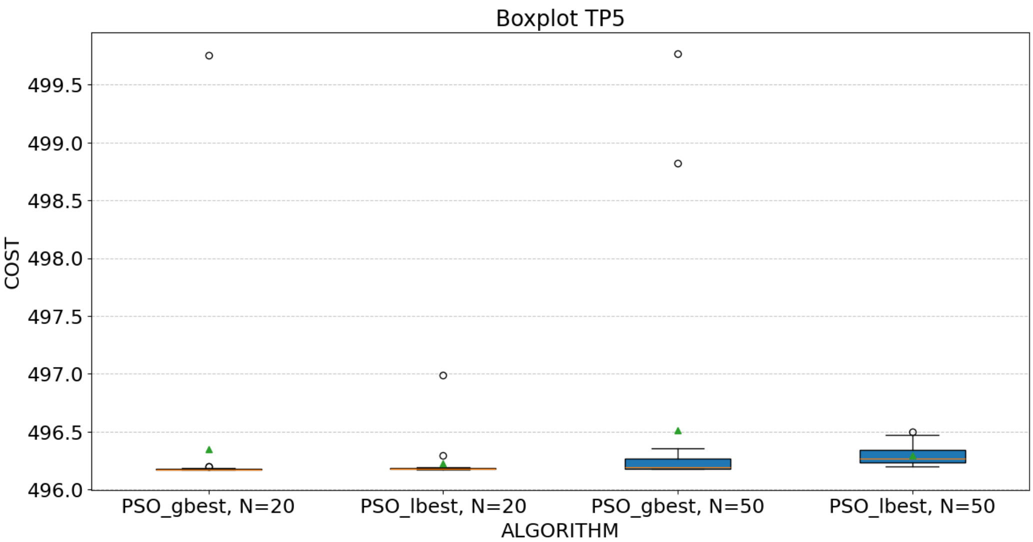

Figure 4.5: Boxplots of best solution cost achieved in 21 independent experiments for Test Problem 5

Table 4.4 offers comparisons between optimal costs achieved by the proposed approach, and the costs reported in the relevant literature [7]. It is observed that the proposed PSO-based approach yielded better results than the established approach in [7] with arbitrarily placed collaboration points for each test problem, with cost savings ranging from 0.51% to 1.89% across all test cases. The proposed approach

Table 4.4: Comparison of results between existing and proposed approach

Test Problem	Proposed Best Cost	Proposed Worst Cost	Established Approach [7]	Difference Percentage
TP1	491.610	492.659	501.057	1.89%
TP2	489.235	489.236	491.763	0.51%
TP3	504.223	504.504	508.540	0.85%
TP4	503.228	503.823	512.1	1.73%
TP5	496.175	499.771	504.064	1.66%

presented better results, even in its worst-case solutions, for each test problem when compared to the existing approach. This highlights the stability and robustness of the proposed method. While absolute savings may appear modest, they acquire significant importance when applied to real-world logistics scenarios consisting of networks with thousands of nodes and deliveries. In such networks, even small reductions in total distribution cost may result in significant financial benefits. These improvements, which minimize total distribution cost and enhance network operational efficiency, emphasize the crucial role of strategically optimizing the locations of collaboration points instead of determining them arbitrarily in collaborative last-mile delivery systems.

The optimal solutions consisting of the routes for each test problem are depicted in Figures 4.6 - 4.10. Facilities owned by the first LSP and their corresponding first-echelon routes are coloured in blue, while those owned by the second LSP are coloured in red in order to be more distinguishable. Additionally, second-echelon routes are depicted with yellow and purple colors for vehicles departing from the first LSP's satellites and with orange and black colors for the remaining vehicles that are assigned to the second LSP's satellites. The locations of the arbitrarily placed CPs from the existing approach are also depicted (in black) for comparison with the optimal locations of the CPs obtained through the proposed approach, which are displayed in green.

The capacity of the satellites, as defined in Table 4.1 forced the first-echelon vehicles to deliver goods to both satellites of each LSP. In most test problems, the individual costs of LSPs were not perfectly balanced, reflecting real-world collaborative scenarios where companies prioritize mutual trust among collaboration members and the reduction of the total distribution cost. Besides, in such collaborative networks,

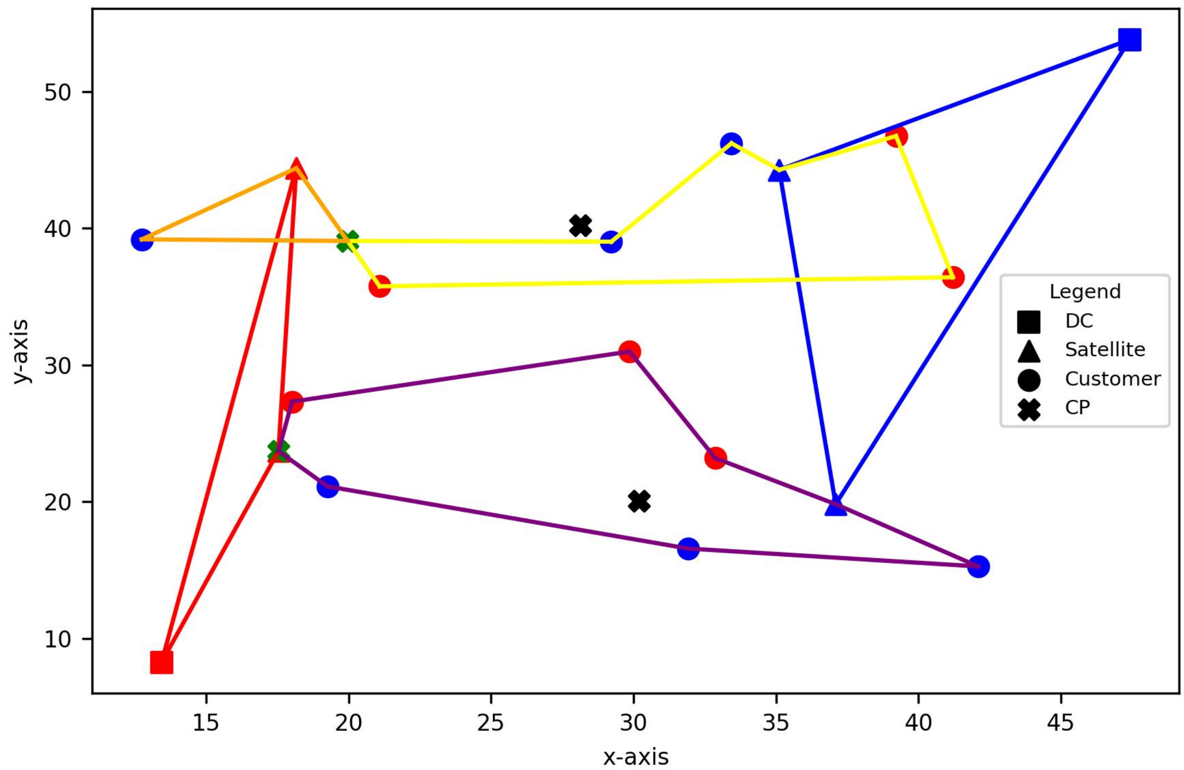

Figure 4.6: Optimal Solution for TP1, gbest topology and swarm size $N = 20$

the strategic placement of collaboration points may favor one LSP in certain instances and the other in other cases, depending on the locations of facilities and customers in the network. For example, in Test Problems 1 and 4, the location of a collaboration point was in a very close distance to an LSP's satellite. In another case, in Test Problem 2, the optimal solution did not require the utilization of both the collaboration points, and the delivery process was completed using only one CP. Nevertheless, in all cases the algorithm can offer solutions that minimize the total cost of the system.

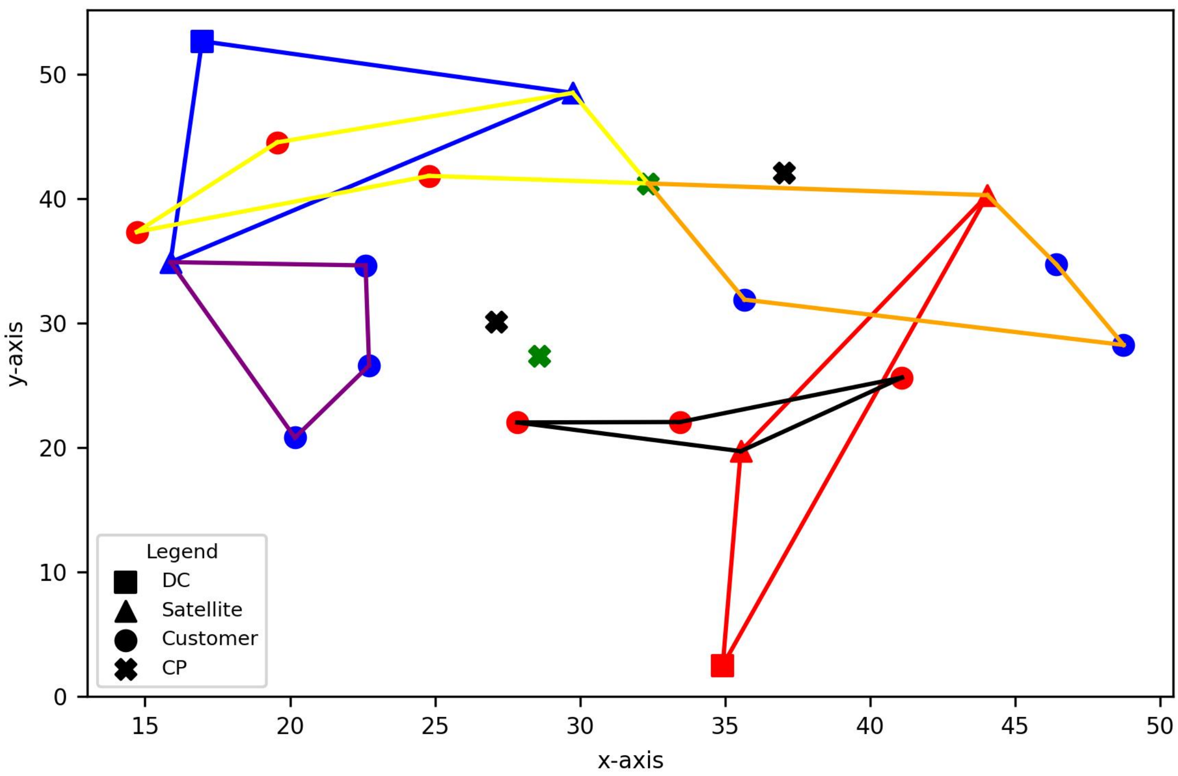

Figure 4.7: Optimal Solution for TP2, gbest topology and swarm size $N = 20$

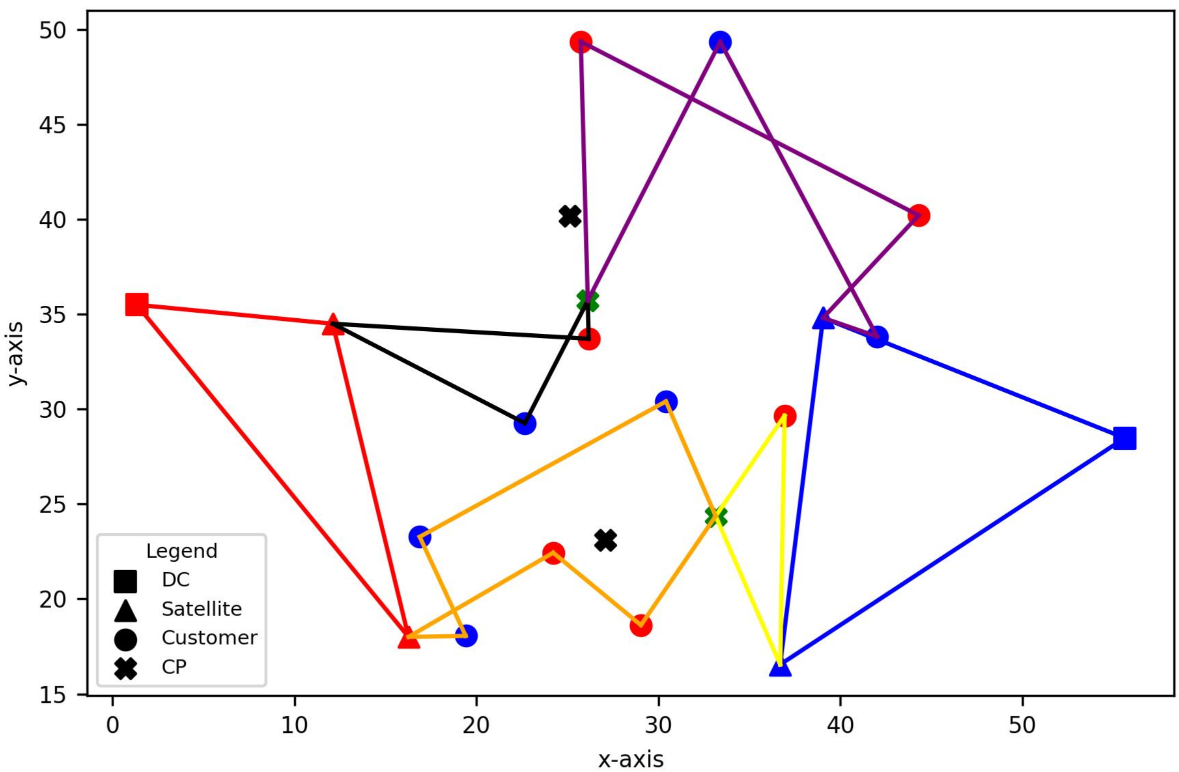

Figure 4.8: Optimal Solution for TP3, gbest topology and swarm size $N = 20$

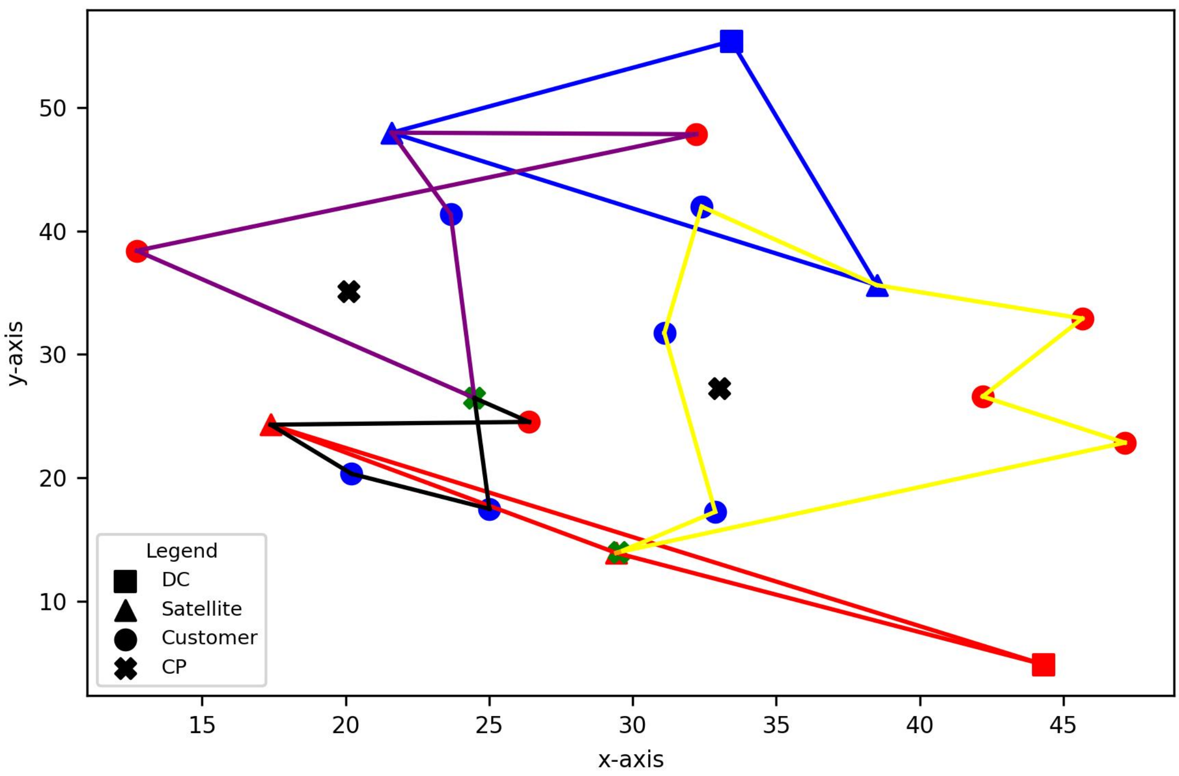

Figure 4.9: Optimal Solution for TP4, gbest topology and swarm size $N = 20$

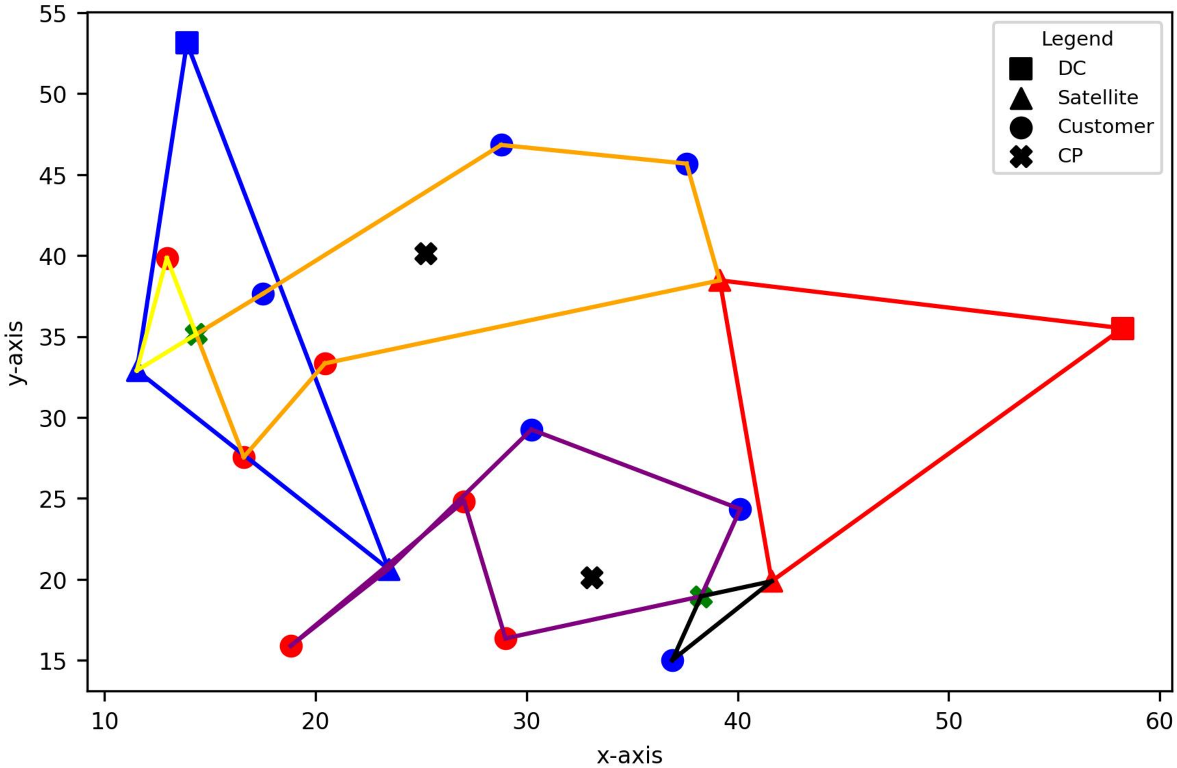

Figure 4.10: Optimal Solution for TP5, gbest topology and swarm size $N = 20$

4.3 Managerial Insights

From a managerial perspective, the proposed approach highlighted some crucial results. Firstly, it showed that even small changes in the locations of the collaboration points can have a great impact on total cost savings and optimization-based methods can offer an efficient way to determine these optimal positions. Moreover, it has been shown that a collaborative approach among LSPs, when utilizing collaboration points, can yield better results than the traditional collaborative approach with shared assets. As a consequence, LSPs avoid ownership and control issues that may arise, and by placing the location of the collaboration points strategically, they can build an effective and efficient relationship. Also, the fact that the individual costs of LSPs were not perfectly balanced creates a more trusting and harmonic collaboration between them, as they are not related on a strictly equal approach for each network, but they cooperate on a more flexible and long-term efficient approach based on the geographical specifications of each network.

In addition to cost savings and improved collaboration, the strategic placement of collaboration points also reduced unnecessary travel distances, resulting in lower fuel consumption and fewer kilometers traveled by vehicles. This resulted in reduced carbon emissions and less air pollution, which provides an environmentally friendly status in the collaborative network. Such consequences not only benefit the overall network efficiency but also enhance sustainability in city logistics, where congestion and emissions are major problems.

4.4 Conclusion

Nowadays, there is an increasing interest in meeting rising customer demands while maintaining efficient and sustainable logistics operations. Most companies aim to improve the quality of service they provide to their customers while simultaneously minimizing distribution costs. One promising approach is the collaboration among different Logistics Service Providers in the context of utilizing collaboration points for the exchange of goods. This approach exhibits lower distribution costs when compared to the classic non-collaborative model. However, the fact that the location of these points is arbitrarily determined limits the total cost savings. To tackle this, this thesis proposed a two-echelon vehicle routing problem with collaboration points, whose locations are optimally determined by using the PSO algorithm to obtain the coordinates that lead to minimum distribution costs.

The study validated the effectiveness of integrating PSO in this problem and found that the proposed approach yields better results and achieves cost savings of up to 2% compared to the existing approach. These findings demonstrated that strategically optimizing CP locations presents better results than arbitrarily setting them. Moreover, the proposed approach promotes sustainable logistics practices, as reducing unnecessary travel distances also decreases fuel consumption and carbon emissions, while minimizing total costs.

Despite these promising results, the accompanying computational demands (e.g., solving the MILP model with CPLEX at each function evaluation) make it challenging in large-scale problems. Future research can extend the proposed approach by modifying the model to include additional constraints (e.g., synchronization, time windows), thereby further leveraging the results of this study. Additionally, fairness considerations can be introduced to the model, so that the individual costs are as balanced as possible among the involved service providers.

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Short Biography

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