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Improving a multi-echelon last mile delivery system by effective solution methods based on ant colony optimization

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A B S T R A C T

The Covid-19 pandemic has significantly impacted consumer behavior and commerce, prompting a shift towards online goods and services. The surge in demand has led to inefficiencies and disruptions, especially in the last-mile delivery (LMD) process. Because of the LMD, the final stage of the supply chain, plays a crucial role in transporting goods from businesses to consumers, challenges such as the cost inefficiencies of direct home delivery have underscored the need for innovative solutions. In this study, the collection delivery points (CDPs) approach was adopted instead of direct home delivery. It focuses on addressing these challenges by adopting service points as dynamic CDPs and handling the problem as a dynamic location routing problem (DLRP). Two solutions approaches are proposed, to select candidate depots strategically and determine efficient route configurations, to aim to minimize travel distance. One of them is a two-phased hierarchical method that starts with clustering and continues with an Ant Colony Optimization (ACO) based-hybrid algorithm, and the other one is based solely on an ACO-based hybrid algorithm. The performance of these approaches is evaluated on modified benchmark instances from the literature. It has been observed that the ACO based-hybrid algorithm is more successful in terms of total travel distance, and if an evaluation is made in terms of the number of routes, it is recommended that the results of the two-phased hierarchical method should also be considered. Furthermore, a real word case study was conducted with the proposed methods and the results were compared from different perspectives. The results corroborate the findings regarding benchmark instances, thereby providing additional validation to the results obtained.

1. Introduction

With the Covid-19 pandemic, sheltering in place and social distance rules have forced consumers to turn to online goods and services, which has also affected consumer behavior and the nature of current commerce. In particular, the lockdown decisions taken to stop the spread of the virus have affected people's shopping habits and the retail industry and current supply chain models (Sarkis, 2020) and accelerated the trend towards e-commerce and m-commerce (Guthrie et al., 2021; Wang et al., 2020). Before the pandemic, there were a limited number of local and/or global cargo and logistics companies that e-commerce platforms partnered with. Generally, all shipment operations have been carried out through these companies according to the agreements made. As a result of the unexpected increase in e-commerce and m-commerce volumes, it has been observed that the supply chain has reached the breaking point at the stage of reaching the final consumer due to insufficient responsiveness and flexibility. The excessive demand that came with the pandemic made the current model no longer working and the search for more flexible modes began (Paul et al., 2021). Since the current supply chain models, which are fragile, could not show enough flexibility against this unexpected trend, serious slowdowns and disruptions were experienced in the entire especially last-mile delivery (LMD) process (Bhatti et al., 2020).

LMD constitutes the final leg of the supply chain, aiming to deliver the consumer's order either directly to the recipient's residence or to a designated collection delivery point (CDP). It represents the ultimate phase in the delivery service from

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business to consumer, facilitating the transport of consignments from the business entity to consumers, either through direct home delivery or at a CDP (Gevaers et al., 2011). In direct home delivery, situations such as the fact that there is usually only one package per house (due to economies of scale), the difficulty of couriers in finding the home address, and the consumer not being at home both make the process difficult and create a disadvantage in terms of cost (Lin et al., 2020). On the other hand, CDPs can reduce the carrier's cost because they collect customer requests at a single delivery point. It can also help avoid transportation costs and additional costs resulting from unsuccessful delivery attempts (Janjevic et al., 2019). In order to eliminate these disadvantages, two types of CDP, called 'parcel lockers' and 'service points', are generally identified in the literature within the scope of CDP. Parcel lockers are personalized unattended delivery points with a locking system located in a specific area. They can often be found in public areas, shopping malls or busy urban areas. Couriers or delivery personnel can drop off packages using these locking systems. Recipients can then pick up their packages themselves from these locked points. Service points generally refer to a delivery point designated by a particular business or service provider. This could be a convenience store, branch, gas station or similar facility. A parcel locker usually includes storage units equipped with automatic locking systems (sometimes called automatic parcel locker), is generally preferred to be in public areas and can be available 24/7. In contrast, service point generally refers to the physical location of a business, belongs to a specific business or service provider, and can generally only provide service during business hours (Molin et al., 2022).

In this study, since an e-commerce platform wants to get rid of the problems caused by establishing stationary distribution locations that do not allow enough flexibility when delivering its products to its customers, high fixed costs, and costs arising from customer dissatisfaction, service points are preferred as CDPs and the problem is addressed as a dynamic location routing problem (DLRP). Because DLRPs involve determining the lowest-cost set of the depot, vehicle fleet, and route configurations over a planning horizon in a time period r (Laporte & Dejax, 1989). The problem addressed is determining the alternative delivery points closest to the geographical locations where customer demands are intense, selecting the candidate depot or depots among these delivery points, and planning the shipment from these candidate depot locations to the delivery points. In this model, candidate depot determined among the candidate delivery points can be selected differently for each data set. The main goal is to minimize the total travel distance. In the study, two solutions are proposed for the location problem in which temporary depots are determined and the routing problem that arises during the shipment from the determined temporary depots to the delivery points. The first is a hierarchical method in which the depot location determination and routing problem is addressed based on the clustering method, and the second is an ant colony-based hybrid algorithm in which the two problems are addressed simultaneously. Their performance is evaluated based on 36 benchmark instances that adapted to our problem from the dataset presented by Zhou et al. (2018). Furthermore, we applied these approaches to a real case study of an e-commerce company.

The main contributions of this paper can be summarized as follows:

- We proposed a new multi-echelon LMD system to avoid the cost of direct home delivery and fixed depot locations.
- Two metaheuristic solution approaches are proposed, the ACO based-hybrid algorithm and the two-phased hierarchical method, for solving large instances.
- The effectiveness of these proposed approaches was validated on benchmark instances modified to our problem.
- Furthermore, we applied the proposed approaches on a real word LMD problem, and the results were compared from different perspectives.

The rest of this paper is organized as follows. Section 2 includes a relevant literature review. In Section 3, details of the problem and the proposed multi-echelon LMD system are given. The proposed solution approaches are detailed in Section 4. In Section 5, computational experiments are given to reveal the performance of the proposed approaches. Section 6 exhibits our experimental case study using real-world data and the findings are discussed. Finally, conclusion is given in Section 7.

2. Literature review

2.1 LMD problem

Recent studies in the literature indicate that as online shopping and e-commerce habits become widespread around the world, consumers' expectations for fast, reliable and effective delivery have increased, and parallel to this, increasing parcel volumes are causing problems such as traffic congestion and, pollution in urban areas (Deutsch & Golany, 2018; Boysen et al., 2021; Kiba-Janiak et al., 2021; Molin et al., 2022). It is observed that the motivation of the studies presented in the literature is based on these and similar reasons. These studies were carried out with the aim of researching innovative methods for the LMD process generally taking into account technological innovations, mitigating the environmental impacts of LMD and designing different distribution structures.

Weltevreden (2008) presented a study that pioneered the discussion of parcel locker or service points alternative by presenting the details of the strengths and weaknesses of parcel lockers and service points alternatives in different aspects to the literature. Accordingly, both parcel lockers and service points are advantageous in terms of paying when collecting parcels. It is stated that parcel lockers are more advantageous in terms of opening hours, requiring time for collecting parcels, and anonymity when receiving the parcel. Conversely, it is emphasized that service points are more advantageous in terms of payment options, storing capability, using public space, sensitivity to crime and vandalism, opportunity to combine the collection of the parcel with other shopping activities, ease of using the service. Another comprehensive study addressing the research on preferences of parcel lockers or service points, which is one of the important problems of LMD, was presented by Molin et al. (2022). They investigated consumers' preferences for receiving parcels ordered online to better understand how consumers may prefer using pick-up points, including home delivery, service point, and parcel locker alternatives. The findings indicate that changes in prices significantly affect preferences. Research focusing solely on the parcel locker problem is presented by Deutsch and Golany (2018). They addressed the problem of selecting parcel locker facilities in the optimal number, location and size, focusing on LMD with parcel lockers. Another research on determining the most suitable locations of parcel lockers was also presented by Lin et al. (2020). On the other hand, Kedia et al. (2020) studied the service points alternative as collection and delivery points. These studies focus on the delivery points of the LMD process.

In addition, the design of the process was inspired by studies with various perspectives on the problem, focusing on the LMD process generally, technologically or structurally. Gdowska et al. (2018) addressed a different issue, assuming that occasional couriers are free to reject assignments for the first time and took probability of acceptance into consideration. They proposed a bi-level methodology to solve the professional delivery fleet matching and routing problem with stochastic occasional couriers that emerged with this assumption. An alternative urban delivery method is presented to literature by Charisis and Kaisar (2019). They proposed a mathematical model with the goal of optimizing LMD, incorporating handcarts or self-pick-up methods by establishing a network of small logistics centers. The model considers constraints such as delivery deadlines, maximum allocation distance, and the number of customers. Janjevic et al. (2019) proposed a non-linear model that includes location decisions to integrate collection and delivery points into the design of omni-channel distribution networks and considers changes in demand patterns with their placement, and in addition, a heuristic solution method for solving large-scale problems. Orenstein et al. (2019) introduced the concept of the flexible parcel delivery problem. They assume that each customer is inclined to accept self-service only from a specific set of lockers, such as those within walking distance, and offer a mixed-integer programming model along with a metaheuristic to address the resulting combined assignment and routing challenge. Schwerdfeger and Boysen (2020) introduced the dynamic location model of mobile parcel lockers, suggesting that lockers have the capability to shift locations throughout the day. The primary goal was to minimize the count of mobile lockers while guaranteeing service to all customers and they optimized the locker positions, ensuring accessibility to customers within a predefined range. Guerrero-Lorente et al. (2020) proposed a mixed integer programming model for the network design problem of a parcel carrier managing online orders from omni-channel retailers. The proposed model aims to optimize the strategic design of urban distribution networks by integrating customer preferences, maximum walking distance and the impact of the channel on customer preference. Janjevic et al. (2021), slightly different from his previous research (Janjevic et al., 2019), focused on the multi-echelon location routing problem (LRP) encountered in the operating environment of contemporary e-commerce last mile distribution systems, and presented an integrated omni-channel modeling framework that addresses strategic last mile design in e-commerce. Liu et al. (2021) introduced a two-echelon LRP with mixed vehicles and mixed satellites, addressing the complexities of a multi-modal LMD system. They proposed a hybrid immune algorithm, demonstrating its effectiveness through performance comparisons with a non-dominated sorting genetic algorithm-II and a hybrid particle swarm optimization. In addition to these studies, Mangiaracina et al. (2019) examined LMD studies by categorizing them according to their methods, focusing on the main factors affecting the cost of LMD and what innovative solutions are offered to reduce these costs. In discussing research on LMD, Kiba-Janiak et al. (2021) focused on the perspectives of specific stakeholder groups, such as receivers and shippers, and they evaluated them in terms of sustainability, organization and technology areas. They determined the research fields as organization, technology, sustainability, optimization, crowdsourcing & crowdshipping, cooperation and behavior regarding sustainable LMD in the urban e-commerce market. In another review study, Boysen et al. (2021) systematically examined existing and innovative last mile concepts, with a special emphasis on the decision problems that need to be solved during the installation and operation of each concept.

Many different systems are designed for LMD in the literature, and within these systems, different problems that take into account different environmental conditions and constraints are focused on. Our study is like Zhou et al. (2019) in terms of addressing the LMD structure. They addressed the LMD problem as a bi-level LRP and proposed a method that hybridized genetic algorithm and simulated annealing algorithms for the solution. In our study, it was considered the service points that will serve as CDPs in the LMD problem may vary depending on each order. In other words, as orders in a certain region differ, different service points may become active for each order. Therefore, determining the location of CDPs problem is discussed from the dynamic location routing problem (DLRP) perspective, where the location and allocation problem and vehicle routing problem are discussed together. In this context, studies in the literature addressing the DLRP were also examined.

2.2 DLRP

The location allocation problem (LAP) is finding a set of the optimum number of new facility locations meeting customer demand to minimize the cost of transportation from facilities to customers and facility operating costs (Azarmand & Neishabouri, 2009). The vehicle routing problem (VRP) is aimed to determine a set of routes that start and end at a particular node to serve particular customers considering total traveling distance (Baker & Ayechew, 2003). LRP is an integrated problem type that aims to solve these two problems simultaneously (Nagy and Salhi, 2007). The aim is to allocate the best facility locations considering especially the routes of the vehicles that serve the demand points from the facility locations, and the other problem constraints. The best facility location is where the total cost of opening the facility and routing is the minimum. Both LAP and VRP are NP-hard problems therefore, LRP is in the NP-hard problem class too (Ferdi and Layeb, 2018).

The emergence of the LRP concept with the integrated approach of LAP and VRP almost parallels the growth of international trade, which requires distribution efficiency (Hassanzadeh et al., 2009). Many studies have been published with LRP, which has been popular since the early 1980s. The first study to comprehensively review and classify these studies was presented by Min et al. (1998). Similarly, Nagy and Salhi (2007) also classified the LRP problem and examined the studies in the literature according to variants. Prodhon and Prince (2014) examined in detail the publications that were not addressed in the studies of Nagy and Salhi (2007) and later presented them to the literature, according to the class of the problem and the constraints they addressed. Based on these studies, it can be concluded that LRP has many variants under very different constraints, and a wide variety of methods have been introduced to the literature for their solution. Hassanzadeh et al. (2009) emphasized that future potential LRP studies will be in stochastic LRPs, time windows LRPs, DLRPs and LRPs with multiple objective classes.

Our paper is in the DLRP class in literature. Nagy and Salhi (2007) stated that modeling LAPs that contain VRPs with short planning intervals as DLRPs is more compatible with real-life problems. Based on this view, we considered modeling the real-life LRP problem that emerged in the Covid-19 period in the most accurate way in this paper.

Although DLRP is a very important area of the LRP, there are a limited number of studies presented in the literature (Nadizadeh & Nasab, 2014). The first study that brought the concept of DLRP to the literature was presented by Laporte and Dejax (1989). In this study, LRP was handled dynamically by considering multiple planning periods, and so both locations and routes could be changed in each period. Nadizadeh and Nasab (2014) handled the DLRP under the constraints that the fuzzy customer demands in each time and depots and heterogeneous vehicle fleets which have a limited capacity. The objectives of the problem are minimizing the total cost of opening depots and routing the vehicles. Li and Keskin (2014) addressed the patrol route problem of state troopers and modeled the problem as a DLRP to increase petrol efficiency on highways. Also, they stand out for considering the time window constraint in the LRP and aim to maximize the benefit of critical location coverage while minimizing the cost of stopping locations, vehicle utilizations, and route/travel. Gao et al. (2016) studied and dynamically modeled LRP under environmental conditions including random and cyclic traffic factors. Bozorgi-Amiri and Khorsi (2016) considered uncertain conditions in demand, travel time and cost parameters of humanitarian relief logistics LRP. They modelled LRP multi-objective (minimizing the maximum number of shortages among the affected areas in all periods, the total travel time, and sum pre- and post-disaster costs) and dynamically. Memari et al. (2020) modelled the air and ground ambulance LRP which emerges after a disaster case dynamically. Their bi-objective model minimizes the operational costs along with the rate of human loss and the critical time spent before the medical treatment considering fuzzy traveling times and patient demands.

In these reviewed DLRP studies, various exact algorithms such as mixed-integer programming model applying the ε-constraint method, augmented e-constraint approach were presented for solution of the small-scaled problems. For realistic instances or real cases, various solution approaches were developed based on heuristic and/or metaheuristic algorithms such as greedy search, ant colony optimization, and genetic algorithms. In addition, it is noteworthy that the proposed solution approaches for large-scaled problems are multiphase, hierarchical or decomposition based (Nadizadeh & Nasab, 2014; Li and Keskin, 2014). Indeed, it is more practical to consider LRP as two sub-problems, routing and locating. But in our opinion, it is important to resolve the LRP in one step to deal with it dynamically. Because the aim is to find the best temporary location for each scenario, rather than finding the routes according to the most suitable locations for different scenarios as in the studies summarized above. Therefore, in this study, unlike various studies in the literature, a hybrid algorithm based on ant colony optimization that offers a solution for large-scaled DLRP was developed considering the locating and routing problem simultaneously.

3. Problem description

The proposed LMD system for an e-commerce platform is illustrated in Fig. 1. Accordingly, the LMD starts from a main depot. CDPs are determined as contracted gas stations, markets, florists, etc., which are called service points in the literature. Since the LMD is planned to be done in multi-echelon (delivery from the main depot to L-CDP, delivery from L-CDP to S-CDP when necessary, and customer pick-up of the product from the CDP determined by him/her), some of the CDPs are named 'Local CDP or L-CDP' and some are named 'Satellite CDP or S-CDP'. A dynamic structure was designed, as whether CDP will be L-CDP or S-CDP will change in each delivery period.

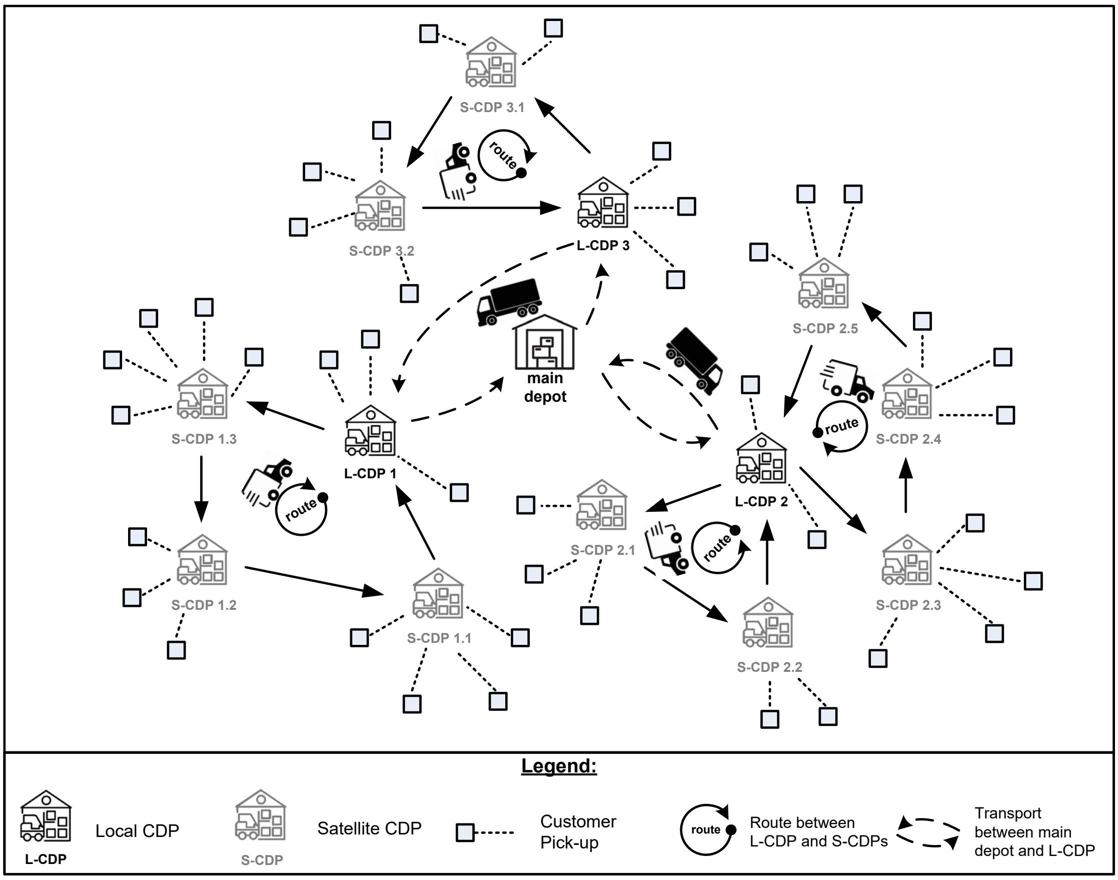

Fig. 1. Proposed multi-echelon LMD system

In this system, customers themselves determine which CDP they will receive their orders from. Therefore, how many customers will come to which CDP and the weight of the products to be delivered are known. Since the vehicles that will be distributed from L-CDP to S-CDPs have limited capacity, it is known that more than one route may occur at this distribution level. Accordingly, solutions to the following questions need to be sought:

- Which CDPs should be L-CDPs?
- Which ones will be selected as S-CDPs linked to the relevant L-CDP?
- Which will be L-CDP and S-CDP within the same route?
- What about routes created with capacity-limited vehicles.

While searching for answers to these questions, vehicles with different capacities will be used at both levels and the total distance at both levels will be minimized. Two different proposed solution methodologies are explained in detail in section 4.

4. Proposed solution approaches

4.1. ACO-based hybrid algorithm

4.1.1. Ant colony optimization

Inspired by the behavior of ants in nature, Ant Colony Optimization (ACO) was developed by Dorigo et al. (1991) and is a population-based meta-heuristic algorithm introduced to the literature. Ants can find the shortest path between their nest and food source and adapt to changes in the environment. Ants secrete a scent called pheromone in every path they pass. A pheromone is a chemical substance that enables ants to communicate. Ants make their route choices by following the smell of pheromones. The path where the pheromone is concentrated is more likely to be preferred. Since more passages will be on the short route, the amount of pheromone accumulated will also be higher. The accumulated pheromone helps the ants find their way back and the ants in the nest to find food sources. In ACO, accumulated pheromones are repeatedly updated, and path selection is made according to the updated pheromone amounts. This rule, which is effective in path selection, is called the transition rule (Dorigo et al., 1991).

- Transition Rule

In ACO, an ant (k) positioned at a node i selects the next node j to visit with a probability given by Eq. (1). In Equation (1), $\tau(i,u)$ shows the amount of pheromone between i and u node, $\eta(i,u)$ shows the inverse of the distance from point i to point u ($\eta_{ij} = 1/d_{ij}$), and $j_k(i)$ shows the points that ant k does not visit. α and β represent the relative importance of a trail and its attractiveness. This rule calculates the probability of choosing the paths to be taken. Therefore, the greater the amount of pheromone, the more likely the ant is to choose that path (Dorigo et al., 1996).

$$P_k(i,j) = \begin{cases} \dfrac{[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}}{\sum_{u \in j_k(i)}[\tau(i,u)]^{\alpha}[\eta(i,u)]^{\beta}} & \text{if } j \in j_k(i) \\ 0 & \text{other} \end{cases} \tag{1}$$

- Pheromone update

After all ants complete their tour, the pheromone amounts are updated. Initially, pheromones on all paths evaporate at a determined rate. Then, the amount of pheromone on the paths traveled by the ants is increased inversely proportional to the total distance traveled by the ant using that path. After a while, the amount of pheromone accumulated on the short path becomes more than on other paths. Pheromone updates are of two types: local and global (Dorigo et al., 1996).

Local pheromone updating prevents alternative solutions from being blocked and ensures that the ants coming from behind take different paths. After all ants complete their tour, the amount of pheromone evaporates at the determined rate. Then, the number of pheromones on the paths that each ant passes while completing its tour is increased according to Eq. (2).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}{}^{k}(t+1) \tag{2}$$

$\Delta\tau_{ij}{}^{k}(t+1)$is calculated by Equation (3):

$$\Delta\tau_{ij}{}^{k}(t+1) = \begin{cases} \dfrac{1}{L^{k}(t+1)} & \text{if ant k uses edge i– j in its tour} \\ 0 & \text{other} \end{cases} \tag{3}$$

ρ is the pheromone evaporation rate, and ρ ∈ (0, 1]. $\tau_{ij}(t)$ represents an amount of pheromone between nodes i and j at iteration t. $L^{k}(t+1)$ is corresponds to the total tour length of ant k.

Global pheromone update is best accomplished by adding pheromone to the edges of the tour after all ants have completed their tour. Global pheromone update is done according to Eq. (4).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}{}^{best}(t+1) \tag{4}$$

$\Delta\tau_{ij}{}^{best}(t+1)$is calculated by the following Eq. (5):

$$\Delta\tau_{ij}{}^{best}(t+1) = \begin{cases} \dfrac{1}{L_{best}(t+1)} & \text{if } i-j \text{ is part of the best solution} \\ 0 & \text{other} \end{cases} \tag{5}$$

$L_{best}(t+1)$, corresponds to the total length of the best tour in each iteration.

4.1.2. Local search

Local search is a heuristic algorithm that produces fast and good solutions to NP-hard optimization problems. LA starts with generating the initial solution according to the algorithm's structure, and new solutions are obtained according to the defined neighborhood relationship. This cycle continues until a solution considered optimal is found or for a certain number of iterations. In the OR heuristic, the main factor determining the solution's speed and quality is the neighborhood structure. The neighborhood structure is created by point or arc change movements (Gendrau & Tarantilis, 2010). We applied local search operators as in (Comert & Yazgan, 2023):

Reversion: Two nodes are randomly selected from the route, and these nodes between them are swapped in the reversion form.

Exchange: Two nodes are randomly selected from the route and are swapped.

Insertion: Two nodes are randomly selected, and the first customer is inserted behind the second customer.

In this paper, we propose an ant colony-based hybrid algorithm. A high-level summary of this algorithm for DLRP is provided in Algorithm 1.

Algorithm 1. ACO-Based Hybrid Algorithm for DLRP

```
Start
   Determine the number of ants, α, β and ρ parameters, number of CDPs, vehicle load capacity, load capacity of warehouses, shipment quantities to CDPs
   do
     for each ant
         Assign each CDP as depot respectively
         Determine a random initial CDP for each ant that is not assigned as a depot
         Determine the order of CDPs to be shipped next using Equation 1
         Assign CDPs to vehicles, taking into account the vehicle's load capacity constraint
       Calculate the total amount of demand met per kilometer for all vehicles
       Compare the best solution with the current solution and save if it is better
       Apply local search method
       Update pheromone using Equation 2 and Equation 3
       Compare the best solution with the current solution and save if it is better
     end for
   until the maximum number of iterations is satisfied
Finish
```

4.2. Two-phased hierarchical method

Another proposed solution methodology consists of two hierarchical phases and four steps, as shown in Fig. 2. At the first level, the first step begins with determining how many clusters the CDPs will be divided into, using the Elbow Method and Silhouette Score. After the number of clusters is determined, the second step is completed by dividing CDPs into clusters with the K-means algorithm. In the third step, an L-CDP is determined for each cluster using p-median. When these three steps are completed, the first phase is completed and the problem is divided into sub-problems. The routes between L-CDPs and S-CDPs is determined using the developed an Ant Colony Optimization Algorithm at the second phase.

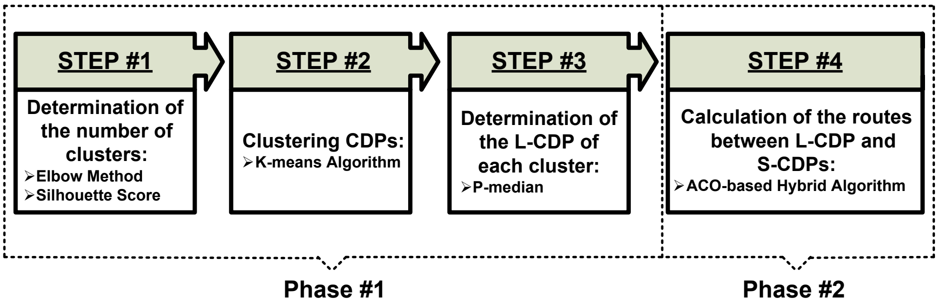

Fig. 2. Proposed hierarchical solution methodology

4.2.1. Phase #1

The first phase of the proposed hierarchical method consists of three separate steps. In STEP#1, the elbow method and silhouette scores (Kodinariya & Makwana, 2013; Rousseeuw, 1987), which are approaches that help in deciding the optimal value of the number of clusters k, were used.

After determining the optimal k number, CDPs are clustered using the k-means algorithm in STEP#2. *K-Means Algorithm* was introduced by MacQueen (1967). The assignment mechanism of this algorithm is one of the most widely used unsupervised learning methods, which allows each data to be included in only one cluster. The basic idea in this method is that the central point represents a cluster (Han & Kamber, 2001). One of the most used criteria to evaluate the K-Means clustering algorithm is the Sum of Square Error (SSE) criterion. The algorithm tries to identify k groups that will reduce the

SSE. The K-Means algorithm divides the data set consisting of n data into k clusters with k parameters determined by the user. Cluster similarity is measured by the average of the objects in the cluster, which is the center of gravity of the cluster (Xu and Wunsch, 2005). The pseudo-code for the K-Means algorithm is provided in Algorithm 2.

Algorithm 2. K-Means algorithm

```
Start
    Determine the number of clusters (k)
    Determine the number of clusters (k) as many center points
    do
        Include each data in the cluster by assigning it to the nearest center point
        Calculate the new center point of each cluster as the average of the data points belonging to that cluster
        Recalculate the new center points
    until the center points is not changed
Finish
```

After the CDPs are clustered, in the STEP#3, the L-CDP of each cluster is determined by the p-median method.

P-median method was first introduced to the literature by Hakimi in 1964. The P-median method is defined as selecting p facility locations from n demand locations and allocating demand points to these locations to minimize the demand-weighted average distance between demand points and the relevant facilities (Hakimi, 1964).

In the P-median model, facilities can only be located on nodes in the network. This thought may suggest that the solution could be more optimal. However, Hakimi (1965) proved that when the facilities to be opened in the p-median model are placed at the nodes in the network, there is at least one optimal result. Based on this feature, the number of potential solutions to a problem consisting of n nodes and p facilities to be opened can be shown by Eq. (6) below.

$$\binom{n}{p} = \frac{n!}{p!\,(n-p)!} \tag{6}$$

The notations of the P-median model are summarized as follows.

<u>Sets</u>

i Set of CDPs

j Candidate L-CDP locations

p Number of L-CDPs to be selected

<u>Parameters</u>

w_i Shipment amount of CDP *i*

d_{ij} Distance from CDP *i* and L-CDP *j*

<u>Decision Variables</u>

y_{ij} Take the value 1 if CDP *i* is assigned to L-CDP *j*, and 0 otherwise

x_j Take the value 1 if and only if L-CDP *j* is chosen, and 0 otherwise

The objective function and constraint equations of the P-median model are as follows (ReVelle and Swain, 1970):

$$\min Z = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i y_{ij} d_{ij} \tag{7}$$

$$\sum_{j=1}^{n} y_{ij} = 1 \qquad \forall_i \in \{1,2,3\ldots n\} \tag{8}$$

$$\sum_{j=1}^{n} x_j = p \qquad \forall_j \in \{1,2,3\ldots n\} \tag{9}$$

$$y_{ij} \le x_j \qquad \forall_i \in \{1,2,3\ldots n\},\ \forall_j \in \{1,2,3\ldots n\} \tag{10}$$

$$x_j = \{0,1\} \qquad \forall_j \in \{1,2,3\ldots n\} \tag{11}$$

$$y_{ij} = \{0,1\} \qquad \forall_i \in \{1,2,3\ldots n\},\ \forall_j \in \{1,2,3\ldots n\} \tag{12}$$

Eq. (7), the objective function, aims to minimize the shipment (w_i) weighted sum of the distances between L-CDP j and CDP i. Equation (8) ensures that each CDP is assigned to only one L-CDP. Eq. (9) ensures that there will be *p* number of L-CDPs to be selected among the CDPs. It refers to assigning shipping points to the L-CDPs selected in Eq. (10). Eq. (11) and Eq. (12) state that the decision variables should take integer values of 0 or 1.

4.2.2. Phase #2

In the second phase of the hierarchical method, the shortest distance routes between L-CDPs and S-CDPs are determined. At this stage of the method, the problem is designed as a capacitated vehicle routing problem (CVRP). The ant colony-based hybrid algorithm pseudo code for CVRP is provided in Algorithm 3.

Algorithm 3. ACO-Based Hybrid Algorithm for CVRP

```
Start
   Determine the number of ants, α, β and ρ parameters, number of CDPs, vehicle load capacity, and shipment quantities to CDPs.
   do
     for each ant
          Determine a random starting CDP for each ant
          Determine the order of CDPs to be shipped next using Equation 1
          Assign CDPs to vehicles, taking into account the vehicle's load capacity constraint
        Calculate total distance traveled (km) for all vehicles
        Compare the best solution with the current solution and save if it is better
        Apply local search method
        Update pheromone using Equation 2 and Equation 3
        Compare the best solution with the current solution and save if it is better
     end for
   until the maximum number of iterations is satisfied
Finish
```

5. Computational experiments

Computational experiments were conducted to evaluate the proposed approaches' performance in solving the multi-echelon LMD problem. The previously outlined solution, implemented in MATLAB, is executed on a computing system with an Intel Core i7 CPU running at 4.5 GHz and 16.00 GB of RAM.

Firstly, the test instances generated in this paper are presented in Section 4.1. In Section 4.2, the procedure for adjusting parameters for the proposed approaches is described. The performance of the proposed approaches is evaluated in Section 4.3. Finally, statistical tests are presented in Section 4.4 to compare the solutions of the proposed algorithms.

5.1. Test instances

In the problem addressed in the study, satellites are dynamic and can change in the data set. For this reason, there is no benchmark in the literature suitable for the problem we are addressing. In this study, we adapted the dataset presented by Zhou et al. (2018) to our problem. There are 36 instances in this dataset. These datasets are adapted based on one depot, n_s satellite station is dynamic and can change for each data set. Our customers determine their pick-up facilities, called CDPs, so we consider only n_c ={50, 100, 150, 200} customer data for our instances. This customer data represents the CDPs in our problem.

5.2. Parameter setting

The Taguchi method was used to determine our proposed ACO-based hybrid algorithm' best combination of parameters (Taguchi and Wu, 1979). Five parameters are defined. These are the number of iterations, the number of ants, α, β, ρ. Three levels of each parameter are considered. We used the same parameter levels and ranges as in (Comert and Yazgan, 2023). L18 orthogonal array was chosen by the number of parameters and levels. While setting the parameters, 36 test instances that we adapted to our problem were used and run 100 times. The levels of parameters' values for the tuning process are provided in Table 2.

Table 2
The tuning process of parameters and selected levels

Parameter	Level 1	Level 2	Level 3	Selected Level
The number of iterations	10	50	100	Level 3
The number of ants	10	100	1000	Level 1
α	0.1	0.5	1	Level 3
β	1	5	9	Level 3
ρ	0.01	0.065	0.65	Level 3

5.3. Results

Table 3 presents the results for all the 36 benchmark instances using the hierarchical method and ACO-based hybrid algorithm. Average results of the proposed methods correspond to the average solution obtained by ten runs, while the best corresponds to the best solution found of those ten runs. The first column contains the instance names. Column 2 shows the number of CDPs. Columns 3 and 6 indicate the number of L-CDP. Columns 4 and 7 report the best solutions obtained by the ACO-based hybrid algorithm and hierarchical method, respectively. In Columns 5 and 8, are the average solution values obtained for ACO-based hybrid algorithm and hierarchical method, respectively. The gap metric is defined as the percentage deviation of the solution by the ACO-based hybrid algorithm from the hierarchical method. The gap metric is defined as: Gap (value) = ((value (Hierarchical method) - value (ACO-based hybrid algorithm)) ⁄ value (ACO-based hybrid algorithm)) * 100. Value represents the best or the average total distances traveled and number of L-CDP found by each approach.

Table 3
Average and best solutions for the ACO-based hybrid algorithm and hierarchical method

Instance	n_c	ACO-Based Hybrid Algorithm				Hierarchical Method			
		L-CDP Number		Total Distances		L-CDP Number		Total Distances	
		Best	Average	Best	Average	Best	Average	Best	Average
#1	50	6	6	34.14	36.1	4	5	37.17	39.2
#2	100	10	10	59.69	61.5	8	9	63.46	65.3
#3	50	10	10	38.69	40.7	8	9	41.86	43.9
#4	100	10	11	62.07	64.2	9	10	65.90	68.2
#5	100	7	7	55.54	57.6	6	6	59.19	61.25
#6	150	7	7	86.56	88.4	6	6	91.10	93.1
#7	100	8	9	63.38	65.1	7	8	67.25	68.9
#8	150	8	8	93.32	95.2	7	7	98.05	99.9
#9	150	9	10	87.86	89.8	7	8	92.43	94.5
#10	200	8	8	121.17	123.1	7	7	126.70	128.9
#11	150	10	11	86.94	92.5	7	9	96.63	100.4
#12	200	12	13	118.89	123.8	10	11	127.43	130.3
#13	50	7	7	31.81	33.5	6	6	34.78	36.5
#14	100	5	5	63.86	65.6	4	4	67.74	69.6
#15	50	9	10	39.06	41.2	8	9	42.23	44.4
#16	100	8	9	72.12	74.1	7	8	76.24	78.3
#17	100	8	8	66.45	68.4	7	7	70.41	72.4
#18	150	7	7	108.27	110.3	6	6	113.43	115.5
#19	100	10	10	60.34	62.5	9	9	64.13	66.2
#20	150	8	8	97.17	99.1	7	7	102.01	103.9
#21	150	8	8	89.22	91.2	7	7	93.84	95.9
#22	200	9	9	122.72	124.8	8	8	128.29	130.4
#23	150	10	12	94.39	99.4	9	10	102.24	107.3
#24	200	14	15	125.25	127.3	13	14	130.89	132.9
#25	50	7	8	41.91	43.4	6	7	45.16	46.7
#26	100	4	4	77.18	79.2	3	3	81.45	83.4
#27	50	8	10	42.21	44.3	6	8	45.48	47.6
#28	100	9	10	72.00	74.03	8	9	76.12	78.2
#29	100	5	5	60.48	62.5	4	4	64.27	66.3
#30	150	6	6	90.59	92.6	5	5	95.24	97.4
#31	100	9	10	64.54	66.5	8	9	68.45	70.4
#32	150	7	8	98.32	100.2	6	7	103.20	106.1
#33	150	10	10	94.04	96.1	9	9	98.78	101.4
#34	200	10	10	144.34	146.5	9	9	150.53	151.1
#35	150	10	12	97.37	102.4	9	10	105.30	108.3
#36	200	12	14	134.25	139.3	11	12	143.24	146.5
Average Gap%		**-14.4%**	**-13.2%**	**6%**	**5.6%**				

The ACO-based hybrid algorithm gave better results than the hierarchical method regarding total distances traveled in 36 test instances. In all 36 instances, the hierarchical method gave better results in terms of the number of L-CDP. Since increasing the number of L-CDP means increasing the number of routes between L-CDP and satellites, the hierarchical method has fewer routes. Also, average gap values confirm these results.

36 benchmark instances were solved with both solution methodologies and the obtained values are shown comparatively in the graphs in Fig. 3. When all graphs are evaluated in general, there are no contradictory results in the solution values obtained in different runs. This can be considered as one of the positive outcomes of selecting ACO in both solution methodologies.

When the graphs of benchmark instances # 1, 3, 13, 15 and 27, where nc = 50, are compared with the others, it is observed that the solution values obtained from both solution methodologies are closer to each other. On the other hand, when the graphs of benchmark instances #10, 12, 22, 24, 34 and 36, where nc = 200, are compared with the others, it is observed that the solution values obtained from both solution methodologies indicate values that are further away from each other. These two situations can be considered as an indication that as the problem size decreases, the success of both methods approaches each other, while as the size increases, the results differ.

Fig. 3. Comparative graphics of solutions by ACO-based hybrid and Hierarchical methodologies

5.4. Statistical tests

Paired sample t test was performed to compare the solutions illustrated in Table 3. First, we compared the solutions of the Hierarchical method and the ACO-based hybrid algorithm in terms of total distances traveled and number of L-CDP with paired sample t test. The null hypotheses are below. The test results are illustrated in Table 4 and Table 5 respectively.

Null Hypothesis 1: There is no significant difference between the solutions' means of the Hierarchical method and the ACO-based hybrid algorithm's solutions in terms of total distances traveled.

Null Hypothesis 2: There is no significant difference between the solutions' means of the Hierarchical method and the ACO-based hybrid algorithm's solutions in terms of number of L-CDP.

Table 4
Paired sample t test in terms of total distances traveled.

	Mean	Std. Deviation	Std. Error Mean	95% CI for mean difference		T-value	df	P-value
Best HA- Best HM	-4.84667	1.73106	.28851	-5.43237	-4.26096	-16.799	35	.000
Avg. HA- Avg. HM	-4.67000	1.28264	.21377	-5.10398	-4.23602	-21.846	35	.000

Table 5
Paired sample t test in terms of number of L-CDP

	Mean	Std. Deviation	Std. Error Mean	95% CI for mean difference		T-value	df	P-value
Best HA- Best HM	1.22222	.48469	.08078	1.05823	1.38622	15.130	35	.000
Avg. HA- Avg. HM	1.19444	.40139	.06690	1.05863	1.33025	17.855	35	.000

According to the results in Table 4, Null hypothesis 1 is rejected with %95 confidence interval. So, there is a significant difference between the solutions' means of the hierarchical method and the ACO-based hybrid algorithm's solutions regarding total distances traveled. The means of the hierarchical method's solution values are higher than the ACO-based hybrid algorithm's solution values, considering the negative mean difference interval. This means that the ACO-based hybrid algorithm is better than the hierarchical method in terms of total distances traveled.

The results in Table 4 indicate that null hypothesis 2 is accepted. However, the situation here indicates that the solution values of the hierarchical method are lower than those of the ACO-based hybrid algorithm. This means that the hierarchical method is better than the ACO-based hybrid algorithm in terms of the number of L-CDP. Therefore, the hierarchical method has less number of routes.

These options can be chosen according to the user's needs. If the user values the reduction in total distance traveled and can consider the costs of using vehicles for each route, ACO-based hybrid algorithm can be preferred. If the number of routes and, consequently, the costs of vehicles are significant, then the hierarchical method might be preferred. Here, the user's preference takes precedence.

6. Case study

This study discusses the LMD problem that occurs when an e-commerce company delivers its products to its customers. The problem addressed is determining the alternative CDPs closest to locations where customer demands are intense, selecting L-CDPs and S-CDPs from candidate CDPs and, planning the shipment from these L-CDPs to the S-CDPs. In the LMD model we propose, the L-CDPs determined between the CDPs can be selected differently for each data set. The dynamic structure of the problem emerges for this reason. The main goal is to minimize the total distance traveled. The company's shipments to the Marmara region will be planned. For this purpose, 81 CDPs (florist, market, cargo branch, etc.) in this region were determined. Products are shipped once in two days from the company's main depot in Gebze to L-CDPs. The average once in two days shipment quantity to be made to each candidate depot is known. Identical vans provide distribution and each of them can carry 175 boxes. They leave the L-CDPs with a reasonable capacity to deliver the orders to S-CDPs and return by following the determined route. Each S-CDPs can only be served by L-CDP and is visited by only one van.

The company's weekly shipment plan is divided into four, and the total shipment quantities to be made are given in Table 6. Weekly shipment quantities based on CDPs are given in Appendix A. We employ an ACO-based hybrid algorithm and hierarchical method to solve the LMD problem of the e-commerce company and compare their results.

Table 6
Weekly shipment quantities

Shipment No	Total Shipment Quantities
1	2114
2	2434
3	2963
4	3663

6.1. Results of ACO-based hybrid algorithm

In this subsection, the LMD problem is solved by the ACO-based hybrid algorithm according to the solution steps given in Section 4, and the results are presented.

In the proposed ACO-based hybrid algorithm, we used the same parameter values reported in Section 4. After solving the LMD problem by considering the quantities of the first shipment of the week, the L-CDPs and S-CDPs and, routes in Table 7 were determined, and the total kilometers of each route were given.

Table 7
First shipment plan of the week (Determined L-CDP locations, routes and total kilometers)

L-CDP#	L-CDP Location	Vehicle No	Route	Total Km
#1	CDP11	1	CDP11-CDP16-CDP10-CDP77-CDP41-CDP54-CDP11	132
		2	CDP11-CDP34-CDP59-CDP39-CDP22-CDP17-CDP11	228
		3	CDP11-CDP26-CDP43-CDP11	55
#2	CDP79	1	CDP79-CDP63-CDP47-CDP21-CDP2-CDP46-CDP79	197
		2	CDP79-CDP80-CDP1-CDP33-CDP51-CDP31-CDP79	212
		3	CDP79-CDP27-CDP79	26
#3	CDP71	1	CDP71-CDP66-CDP19-CDP5-CDP55-CDP57-CDP37-CDP18-CDP71	204
		2	CDP71-CDP14-CDP81-CDP67-CDP74-CDP78-CDP6-CDP71	179
		3	CDP71-CDP50-CDP38-CDP40-CDP71	106
#4	CDP24	1	CDP24-CDP69-CDP29-CDP61-CDP28-CDP52-CDP60-CDP58-CDP24	217
		2	CDP24-CDP23-CDP44-CDP12-CDP62-CDP24	176
#5	CDP15	1	CDP15-CDP32-CDP3-CDP42-CDP68-CDP70-CDP7-CDP15	259
		2	CDP15-CDP64-CDP45-CDP35-CDP9-CDP48-CDP15	174
		3	CDP15-CDP20-CDP15	60
#6	CDP76	1	CDP76-CDP65-CDP30-CDP73-CDP56-CDP72-CDP13-CDP49-CDP76	280
		2	CDP76-CDP36-CDP75-CDP8-CDP53-CDP25-CDP4-CDP76	219
TOTAL KM				2724

As seen in Table 7, CDP11, 79, 71, 24, 15 and 76, which are the service points with the highest demand per kilometer according to the quantities in the first shipment, were determined as L-CDP. Three vehicles departed from the first, second, third, and fifth L-CDPs, two from the fourth and sixth L-CDPs, and products were delivered to all S-CDPs. As a result of the completion of the tours of the vehicles departing from the L-CDPs, a total of 2724 km was covered.

See Appendix B for detailed the second, third and fourth shipment plans of the week. After solving the LMD problem by considering the quantities of the second shipment, CDP 81, 27, 64, 40, 12, 57, and 70 and were selected as L-CDPs. Three vehicles departed from the first, second, third, and fifth L-CDPs, two from the fourth, sixth, and seventh L-CDPs, and products were delivered to all S-CDPs. For the third delivery of the week, CDP 77, 80, 48, 40, 12, 5, 36, and 10 and were determined as L-CDPs. Three vehicles departed from the first, second, fourth, and fifth L-CDPs, two from the third, sixth, seventh, and eighth L-CDPs. Finally the fourth delivery of the week, CDP 54, 46, 64, 50, 56, 5, 17, and 24 and were selected as L-CDPs. Three vehicles departed from the first, second, third, fourth, seventh, and eighth L-CDPs, two from the fifth and sixth L-CDPs. Also, the total travel distances of the plans obtained for the second, third and fourth shipments were calculated as 3037, 2961 and 2572 km, respectively.

6.2. Results of hierarchical method

In this subsection, the LMD problem is solved by the hierarchical method according to the solution steps given in Section 4, and the results are presented. First, considering their distance, 81 CDPs determined in the Marmara region are desired to be clustered. The first parameter to be specified here is the optimal number of clusters. Two different methods were used to determine the most appropriate number of clusters. One of these is the Elbow method. According to the Elbow method, dividing 81 delivery points into 2 clusters, considering their distance, gave the most appropriate result. The Elbow graph of CDPs is shown in Fig. 4.

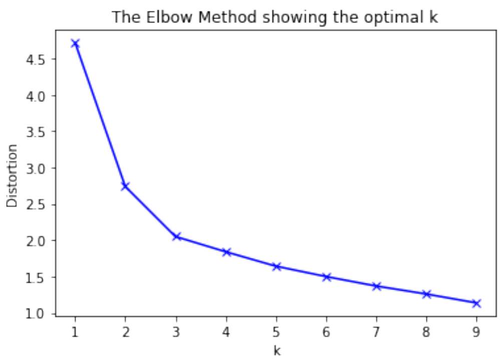

Fig. 4. The Elbow graph of S-CDPs

Table 8
Silhouette Score values

"k" Value	2	3	4	5	6	7	8	9
Silhouette Score	0.533	0.479	0.389	0.384	0.339	0.345	0.362	0.374

Another method used to determine the most appropriate number of clusters is Silhouette Score. Here, Silhouette Score values up to the number of clusters k = 2,…,9 are calculated as in the Table 8.
According to both methods, k = 2 was found to be the most appropriate value, and 81 CDPs were divided into 2 clusters according to the distance between each other. Clusters created k=2 using the K-Means algorithm are given in Table 9.

Table 9
CDPs divided into clusters using the K-Means algorithm

Cluster # 1	CDP3, CDP68, CDP6, CDP7, CDP9, CDP10, CDP74, CDP11, CDP14, CDP15, CDP16, CDP17, CDP18, CDP19, CDP20, CDP81, CDP22, CDP26, CDP32, CDP34, CDP35, CDP78, CDP70, CDP37, CDP71, CDP39, CDP40, CDP41, CDP42, CDP43, CDP45, CDP33, CDP48, CDP50, CDP51, CDP54, CDP57, CDP59, CDP64, CDP77, CDP66, CDP67
Cluster # 2	CDP1, CDP2, CDP4, CDP5, CDP75, CDP8, CDP72, CDP69, CDP12, CDP13, CDP21, CDP23, CDP24, CDP25, CDP27, CDP28, CDP29, CDP30, CDP31, CDP76, CDP46, CDP36, CDP38, CDP79, CDP44, CDP47, CDP49, CDP52, CDP80, CDP53, CDP55, CDP56, CDP58, CDP63, CDP73, CDP60, CDP61, CDP62, CDP65

Depot locations (L-CDPs) were determined using the P-Median method based on the weekly shipment quantities of Cluster #1 and Cluster #2, as shown in Table 10.

Table 10
Depot locations (L-CDPs) for Cluster #1

Week	L-CDPs for Cluster #1	L-CDPs for Cluster #2
1	CDP18	CDP79
2	CDP57	CDP5
3	CDP18	CDP79
4	CDP57	CDP5

After the L-CDPs were determined, the shipping routes from the L-CDP to the CDPs were created with the ACO-based hybrid algorithm. The routes and total travel distances for Cluster #1 and Cluster #2 are displayed in Table 11 and Table 12 respectively.

Table 11
Shipment plans of Cluster #1 (Determined routes and total kilometers)

L-CDP Location	Vehicle No	Route	Total Km
		First Shipment	
CDP18	1	CDP18-CDP48-CDP9-CDP35-CDP45-CDP18	392
	2	CDP18-CDP10-CDP17-CDP59-CDP39-CDP22- CDP18	199
	3	CDP18-CDP34-CDP41-CDP54-CDP81-CDP14-CDP18	292
	4	CDP18-CDP78-CDP74-CDP67-CDP37-CDP57-CDP19-CDP66-CDP40-CDP18	230
	5	CDP18-CDP50-CDP68-CDP51-CDP70-CDP42-CDP71- CDP18	212
	6	CDP18-CDP6-CDP26-CDP11-CDP16-CDP77- CDP18	302
	7	CDP18-CDP3-CDP43-CDP64-CDP20-CDP15-CDP32-CDP18	343
	TOTAL KM		1970
		Second Shipment	
CDP57	1	CDP57-CDP42-CDP68-CDP51-CDP50-CDP40-CDP66-CDP57	311
	2	CDP57-CDP19-CDP18-CDP71-CDP6-CDP26-CDP11-CDP57	311
	3	CDP57-CDP16-CDP77-CDP41-CDP54-CDP57	282
	4	CDP57-CDP81-CDP14-CDP78-CDP74-CDP67-CDP37-CDP57	245
	5	CDP57-CDP34-CDP59-CDP39-CDP22-CDP57	387
	6	CDP57-CDP17-CDP10-CDP45-CDP35-CDP57	470
	7	CDP57-CDP9-CDP48-CDP20-CDP64-CDP3-CDP57	441
	8	CDP57-CDP43-CDP15-CDP32-CDP7-CDP57	422
	TOTAL KM		2869
		Third Shipment	
CDP18	1	CDP18-CDP68-CDP50-CDP40-CDP66-CDP19-CDP18	173
	2	CDP18-CDP6-CDP71-CDP14-CDP81-CDP18	159
	3	CDP18-CDP54-CDP41-CDP77-CDP18	180
	4	CDP18-CDP16-CDP11-CDP26-CDP43-CDP18	243
	5	CDP18-CDP3-CDP64-CDP45-CDP18	282
	6	CDP18-CDP35-CDP9-CDP48-CDP18	340
	7	CDP18-CDP20-CDP15-CDP32-CDP7-CDP18	327
	8	CDP18-CDP42-CDP70-CDP51-CDP33-CDP18	286
	9	CDP18-CDP37-CDP78-CDP74-CDP67-CDP18	137
	10	CDP18-CDP34-CDP59-CDP39-CDP18	291
	TOTAL KM		2418
	Fourth Shipment		
CDP57	1	CDP57-CDP68-CDP51-CDP70-CDP42-CDP57	328
	2	CDP57-CDP32-CDP15-CDP7-CDP57	383
	3	CDP57-CDP20-CDP64-CDP3-CDP57	368
	4	CDP57-CDP43-CDP26-CDP11-CDP57	310
	5	CDP57-CDP16-CDP77-CDP57	283
	6	CDP57-CDP41-CDP54-CDP57	232
	7	CDP57-CDP81-CDP14-CDP78-CDP74-CDP67-CDP57	245
	8	CDP57-CDP37-CDP18-CDP71-CDP6-CDP57	175
	9	CDP57-CDP40-CDP50-CDP66-CDP19-CDP57	232
	10	CDP57-CDP34-CDP59-CDP57	328
	11	CDP57-CDP39-CDP22-CDP17-CDP57	435
	12	CDP57-CDP10-CDP45-CDP57	396
	13	CDP57-CDP35-CDP9-CDP57	429
	TOTAL KM		4144

Table 11 illustrates those seven vehicles for the first shipment, eight for the second shipment, ten for the third shipment, and thirteen for the fourth shipment completed the product distribution to all CDPs. The total distances traveled were calculated according to shipments as 1970, 2869, 2418, and 4144 km, respectively.

Table 12
Shipment plans of Cluster #2 (Determined routes and total kilometers)

L-CDP Location	Vehicle No	Route	Total Km
		First Shipment	
CDP79	1	CDP79-CDP72-CDP56-CDP73-CDP30-CDP65-CDP13-CDP49-CDP79	249
	2	CDP79-CDP12-CDP23-CDP44-CDP2-CDP63-CDP79	392
	3	CDP79-CDP21-CDP47-CDP25-CDP69-CDP29-CDP24-CDP62-CDP46- CDP79	123
	4	CDP79-CDP27-CDP80-CDP1-CDP31-CDP79	344
	5	CDP79-CDP38-CDP58-CDP60-CDP5-CDP55-CDP79	480
	6	CDP79-CDP52-CDP28-CDP61-CDP53-CDP8-CDP75-CDP36-CDP76-CDP79	381
TOTAL KM			1969
		Second Shipment	
CDP5	1	CDP5-CDP60-CDP58-CDP38-CDP2-CDP63-CDP5	332
	2	CDP5-CDP27-CDP79-CDP31-CDP80-CDP1-CDP5	321
	3	CDP5-CDP46-CDP44-CDP23-CDP62-CDP24-CDP29-CDP69-CDP5	355
	4	CDP5-CDP25-CDP12-CDP49-CDP13-CDP56-CDP72-CDP5	383
	5	CDP5-CDP21-CDP47-CDP73-CDP30-CDP65-CDP5	471
	6	CDP5-CDP4-CDP76-CDP36-CDP75-CDP8-CDP53-CDP61-CDP5	381
	7	CDP5-CDP28-CDP52-CDP55-CDP5	129
TOTAL KM			2372
		Third Shipment	
CDP79	1	CDP79-CDP8-CDP75-CDP36-CDP76-CDP4-CDP25-CDP79	449
	2	CDP79-CDP69-CDP29-CDP61-CDP53-CDP28-CDP52-CDP79	412
	3	CDP79-CDP55-CDP5-CDP60-CDP58-CDP79	318
	4	CDP79-CDP38-CDP46-CDP27-CDP79	158
	5	CDP79-CDP80-CDP1-CDP31-CDP79	118
	6	CDP79-CDP63-CDP2-CDP44-CDP79	159
	7	CDP79-CDP23-CDP62-CDP24-CDP12-CDP49-CDP13-CDP56-CDP79	357
	8	CDP79-CDP73-CDP30-CDP65-CDP72- CDP79	340
	9	CDP79-CDP21-CDP47- CDP79	170
TOTAL KM			2481
	Fourth Shipment		
CDP5	1	CDP5-CDP1-CDP80-CDP46-CDP5	260
	2	CDP5-CDP27-CDP79-CDP31-CDP5	292
	3	CDP5-CDP63-CDP2-CDP44-CDP5	293
	4	CDP5-CDP23-CDP62-CDP24-CDP29-CDP69-CDP5	299
	5	CDP5-CDP25-CDP4-CDP76-CDP36-CDP5	357
	6	CDP5-CDP75-CDP8-CDP53-CDP61-CDP5	315
	7	CDP5-CDP28-CDP52-CDP55-CDP5	129
	8	CDP5-CDP60-CDP58-CDP38-CDP5	154
	9	CDP5-CDP12-CDP49-CDP13-CDP56-CDP5	364
	10	CDP5-CDP72-CDP21-CDP47-CDP5	360
	TOTAL KM		2823

It is also apparent from Table 12 that six vehicles for the first shipment, seven for the second shipment, nine for the third shipment, and ten for the fourth shipment completed the product distribution to all CDPs. The total distances traveled were calculated according to shipments as 1969, 2372, 2481 and 2823 km, respectively.

6.3. Comparison of results

A weekly shipment plan was created with an ACO-based hybrid algorithm and hierarchical method, and the results obtained are summarized in Table 13. The columns ‘‘Gap %’’ indicate percentage difference with the result of the ACO-based hybrid algorithm and calculated as ((Total KM (Hierarchical method) - Total KM (ACO-based hybrid algorithm))∕Total KM (ACO-based hybrid algorithm)) ∗ 100. Examining the Gap value proves that the ACO-based hybrid algorithm performs better than the hierarchical method.

Table 13
Comparisons of the results in terms of total distances traveled

	Shipment 1		Shipment 2		Shipment 3		Shipment 4	
	HA	HM	HA	HM	HA	HM	HA	HM
Total KM	2724	3939	3037	5241	2961	4899	2572	6967
Gap %		0.45		0.73		0.65		1.71

HA: ACO-based hybrid algorithm, HM: Hierarchical method

When the findings obtained as a result of the solution of the case study according to two different methodologies are compared in terms of the number of routes, the results in Table 14 appear. In the solutions obtained with the two-stage hierarchical method, it is seen that the number of routes for the first three shipments is less than the ACO-based hybrid algorithm. We can attribute the reason for this to the fact that the two-phased hierarchical method distributes with fewer L-CDPs (only 2). However, it is seen that as the order amount increases, the difference decreases, and for the last shipment, the ACO-based hybrid algorithm distributes with fewer routes. It may be preferable to have a small number of routes due to a restriction on the number of vans to be used in daily delivery, a high fixed cost, etc. When the user decides which distribution plan to apply, taking into account the current order, we recommend that the two proposed solution approaches be taken into consideration.

Table 14
Comparisons of the results in terms of number of routes

	Shipment 1		Shipment 2		Shipment 3		Shipment 4	
	HA	HM	HA	HM	HA	HM	HA	HM
Number of Routes	16	13	18	15	20	19	22	23
Gap %		-18.75%		-16.65%		-5%		4.55%

7. Conclusion

In this study, a multi-echelon LMD system in which deliveries to a certain region are collected in a single warehouse called the main warehouse and distributed to CDPs from there is designed and this system is discussed from the DLRP perspective. Because CDPs are divided into L-CDP and S-CDP and will be assigned as L-CDP or S-CDP according to the order quantities in each delivery. Two different solution methods have been proposed to solve the problem. One of these is the ACO-based hybrid algorithm, which evaluates the entire delivery process in a single stage and produces a solution, and the other is the two-phased hierarchical method, which handles the delivery process at two hierarchical levels. ACO-based hybrid algorithm assigns CDPs as L-CDP or S-CDP according to the current order status, determines which L-CDP will be on the same route with which S-CDPs and determines the optimum routes. This method works dynamically depending on the status of the order. The two-phased hierarchical method clusters all CDPs according to their distance from each other and assigns the CDPs at the midpoints of these clusters as L-CDP. Therefore, it is not dynamic as it does not consider the status of the order at the first level. However, in the second stage, it determines the optimal routes considering the status of the order.

The performance of two different solution methods is evaluated based on 36 benchmark instances that adapted to our problem from the dataset presented by Zhou et al. (2018). Considering the results obtained from these experiments, it has been determined that in the all-benchmark instances with respect to both average and best solutions where the ACO-based hybrid algorithm is superior in terms of total distance traveled, it generally cannot show the same superiority in terms of the number of routes. Moreover, this superiority is statistically confirmed by the paired sample t test. According to this; it is recommended that the user who will implement a shipment plan decides by taking into account restrictions such as the status of fixed and variable costs and the number of available vehicles.

In this paper, we also applied two different methodologies developed for the proposed multi-echelon LMD system in real word instances of an e-commerce company involving 81 CDPs (florist, market, cargo branch, etc.) in the Marmara region. The results obtained support the results obtained from the solution of benchmark instances. The obtained outcomes substantiate the findings derived from the resolution of benchmark instances, fortifying the validity and reliability of the results.

The presented work can be extended in the future by adding time windows, heterogeneous vehicle fleets, and time-dependent travel time constraints to this problem.

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Appendix A Weekly shipment quantities

L-CDP Location	Shipment Quantity				L-CDP Location	Shipment Quantity				L-CDP Location	Shipment Quantity				L-CDP Location	Shipment Quantity			
	First	Second	Third	Fourth		First	Second	Third	Fourth		First	Second	Third	Fourth		First	Second	Third	Fourth
CDP1	42	39	60	59	CDP21	37	38	52	57	CDP41	36	46	51	69	CDP61	30	36	43	55
CDP2	30	30	42	45	CDP22	25	26	35	39	CDP42	40	45	57	68	CDP62	8	9	11	14
CDP3	29	28	41	42	CDP23	25	36	35	54	CDP43	29	30	40	46	CDP63	39	45	56	68
CDP4	24	24	33	36	CDP24	12	22	17	33	CDP44	33	32	47	48	CDP64	21	25	30	37
CDP5	19	20	27	30	CDP25	32	30	45	45	CDP45	36	44	50	66	CDP65	35	41	49	62
CDP6	43	39	61	59	CDP26	35	40	48	60	CDP46	33	37	46	56	CDP66	24	28	33	42
CDP7	41	45	58	68	CDP27	37	38	52	57	CDP47	30	35	42	53	CDP67	31	27	44	40
CDP8	15	11	21	16	CDP28	23	33	32	50	CDP48	35	31	50	47	CDP68	24	28	34	42
CDP9	36	42	51	63	CDP29	10	12	13	19	CDP49	21	24	29	37	CDP69	9	14	13	21
CDP10	35	35	50	52	CDP30	18	27	26	41	CDP50	18	21	25	32	CDP70	15	20	21	30
CDP11	15	24	20	36	CDP31	39	35	54	52	CDP51	24	21	34	31	CDP71	14	19	19	28
CDP12	18	29	24	43	CDP32	22	34	31	51	CDP52	32	34	45	51	CDP72	28	31	39	46
CDP13	19	19	27	28	CDP33	36	46	51	69	CDP53	21	21	29	32	CDP73	29	27	40	40
CDP14	19	21	27	32	CDP34	54	64	77	97	CDP54	33	43	46	64	CDP74	15	16	21	24
CDP15	16	22	22	33	CDP35	42	50	59	75	CDP55	36	43	50	65	CDP75	12	17	17	26
CDP16	42	50	60	75	CDP36	20	27	28	41	CDP56	18	22	25	33	CDP76	15	24	21	36
CDP17	24	30	33	46	CDP37	23	26	32	39	CDP57	12	15	16	23	CDP77	17	27	24	41
CDP18	12	16	16	24	CDP38	36	40	51	60	CDP58	29	28	40	42	CDP78	15	23	20	35
CDP19	26	23	36	35	CDP39	20	30	27	45	CDP59	34	42	48	63	CDP79	9	22	12	33
CDP20	35	38	48	57	CDP40	13	18	18	27	CDP60	29	29	41	44	CDP80	24	26	34	39
															CDP81	22	29	31	44

Appendix B- Detailed of the second, third and fourth shipment plans

L-CDP #	Second Shipment Plan				Third Shipment Plan				Fourth Shipment Plan			
	L-CDP Location	VN	Route (S-CDPs)	Total Km	L-CDP Location	VN	Route (S-CDPs)	Total Km	L-CDP Location	VN	Route (S-CDPs)	Total Km
#1	CDP81	1	CDP81-CDP54-CDP11-CDP77-CDP41-CDP81	93	CDP77	1	CDP77-CDP67-CDP74-CDP14-CDP81-CDP54-CDP77	152	CDP54	1	CDP54-CDP81-CDP14-CDP41-CDP54	60
		2	CDP81-CDP59-CDP39-CDP22-CDP34-CDP81	196		2	CDP77-CDP41-CDP34-CDP77	70		2	CDP54-CDP26-CDP43-CDP11-CDP54	93
		3	CDP81-CDP67-CDP14-CDP81	63		3	CDP77-CDP16-CDP11-CDP77	58		3	CDP54-CDP77-CDP54	41
#2	CDP27	1	CDP27-CDP21-CDP72-CDP56-CDP73-CDP47-CDP27	224	CDP80	1	CDP80-CDP46-CDP27-CDP79-CDP31-CDP80	104	CDP46	1	CDP46-CDP2-CDP63-CDP27-CDP46	98
		2	CDP27-CDP63-CDP2-CDP44-CDP46-CDP27	147		2	CDP80-CDP63-CDP2-CDP44-CDP80	174		2	CDP46-CDP80-CDP1-CDP31-CDP46	111
		3	CDP27-CDP80-CDP31-CDP79-CDP27	93		3	CDP80-CDP1-CDP80	35		3	CDP46-CDP79-CDP46	54
#3	CDP64	1	CDP64-CDP45-CDP35-CDP9-CDP48-CDP64	150	CDP48	1	CDP48-CDP20-CDP64-CDP3-CDP9-CDP48	171	CDP64	1	CDP64-CDP45-CDP35-CDP64	88
		2	CDP64-CDP10-CDP17-CDP16-CDP43-CDP3-CDP64	217		2	CDP48-CDP15-CDP32-CDP7-CDP48	147		2	CDP64-CDP9-CDP48-CDP20-CDP64	133
		3	CDP64-CDP20-CDP64	60		-	-	-		3	CDP64-CDP3-CDP15-CDP64	91
#4	CDP40	1	CDP40-CDP68-CDP50-CDP38-CDP58-CDP66-CDP40	159	CDP40	1	CDP40-CDP66-CDP38-CDP50-CDP68-CDP40	115	CDP50	1	CDP50-SCPD33-CDP70-CDP42-CDP50	172
		2	CDP40-CDP71-CDP18-CDP6-CDP26-CDP40	197		2	CDP40-CDP51-CDP33-CDP70-CDP42-CDP40	197		2	CDP50-CDP7-CDP32-CDP68-CDP50	230
		-	-	-		3	CDP40-CDP71-CDP6-CDP40	74		3	CDP50-CDP51-CDP50	33
#5	CDP12	1	CDP12-CDP25-CDP36-CDP75-CDP8-CDP53-CDP69-CDP24-CDP62-CDP12	287	CDP12	1	CDP12-CDP49-CDP13-CDP56-CDP72-CDP21-CDP12	123	CDP56	1	CDP56-CDP13-CDP65-CDP30-CDP56	149
		2	CDP12-CDP49-CDP13-CDP65-CDP30-CDP76-CDP4-CDP12	288		2	CDP12-CDP47-CDP73-CDP30-CDP65-CDP12	229		2	CDP56-CDP72-CDP21-CDP47-CDP56	102
		3	CDP12-CDP23-CDP12	58		3	CDP12-CDP23-CDP62-CDP12	85		-		-
#6	CDP57	1	CDP57-CDP55-CDP52-CDP28-CDP61-CDP29-CDP57	219	CDP5	1	CDP5-CDP60-CDP58-CDP52-CDP5	163	CDP5	1	CDP5-CDP60-CDP38-CDP66-CDP5	155
		2	CDP57-CDP5-CDP60-CDP19-CDP37-CDP78-CDP74-CDP57	263		2	CDP5-CDP55-CDP57-CDP37-CDP78-CDP18-CDP19-CDP5	205		2	CDP5-CDP52-CDP55-CDP57-CDP19-CDP5	188
#7	CDP70	1	CDP70-CDP42-CDP32-CDP15-CDP7-CDP70	186	CDP36	1	CDP36-CDP8-CDP53-CDP61-CDP28-CDP29-CDP24-CDP69-CDP36	271	CDP17	1	CDP17-CDP10-CDP16-CDP17	124
		2	CDP70-CDP33-CDP1-CDP51-CDP70	137		2	CDP36-CDP76-CDP4-CDP25-CDP75-CDP36	159		2	CDP17-CDP34-CDP59-CDP17	127
		-	-	-		-	-	-		3	CDP17-CDP39-CDP22-CDP17	102
#8	-	-	-	-	CDP10	1	CDP10-CDP22-CDP39-CDP59-CDP17-CDP10	195	CDP24	1	CDP24-CDP62-CDP12-CDP23-CDP44-CDP24	176
		-	-	-		2	CDP10-CDP26-CDP43-CDP35-CDP10	178		2	CDP24-CDP58-CDP28-CDP61-CDP29-CDP24	183
		-	-	-		-	-	-		3	CDP24-CDP69-CDP24	62
TOTAL KM				3037	TOTAL KM			2961	TOTAL KM			2572