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16. Abstract:
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INTEGRATE AUTONOMOUS DELIVERY VEHICLE INTO SUSTAINABLE URBAN LOGISTICS PLANNING AND OPTIMIZATION: ECONOMIC AND ENVIRONMENTAL EVALUATION

Final Report

By

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DISCLAIMER

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EXCUTIVE SUMMARY

The last mile problem of E-grocery Distribution comprises one of the most costly and highest polluting components of the supply chain in which companies deliver goods to end customers. To reduce transport cost and fuel emissions, a new element of ground-based delivery services, autonomous delivery vehicles (ADVs), is included in the E-grocery distribution system for improving delivery efficiency. Thus, the objective of this study is to optimize a two-echelon distribution network for efficient E-grocery delivery, where conventional vans serve the delivery in the first echelon and ADVs serve delivery in the second echelon. The problem is formulated as a two-echelon vehicle routing problem with mixed vehicles (2E-VRP-MV) with a nonlinear objective function, in which the total transport and emission costs are optimized. This optimization is based on the flow assignment at each echelon and to realize routing choice for both the van and ADV. A two-step clustering-based hybrid Genetic Algorithm and Particle Swarm Optimization (C-GA-PSO) algorithm is proposed to solve the problem. Computational results of up to 21, 32, 50, and 100 customers show the effectiveness of the methods developed here. At last, the impacts of the layout of the depot-customer and customer density on the total cost are analyzed. This study sheds light on the tactical planning of the multi-echelon sustainable E-grocery delivery network.

1. INTRODUCTION

1.1. Overview

Population density, increase in number of vehicles day by day due to the availability of rideshare and delivery services, are resulting in extensive traffic congestion in urban metropolitan cities. It can also be said that e-commerce are a growing contributor to traffic congestion in urban areas. E-commerce has grown over the last couple of years, with the revolution of digital technology. In addition, e-commerce has a significant effect on the economy of any country in the world and gives much room for innovation in this sector, which is likely to improve overall economic efficiency. An essential component of e-commerce is the last-mile delivery, which refers to the last leg of the delivery system where distribution of goods from the local distribution centers to the customers. According to a report by Mckinsey and Company, nearly 25 percent of customers are willing to pay a significant amount for the chance of same-day or instant delivery. As younger consumers are more inclined to prefer same-day and instant delivery over regular delivery, and this share is likely to increase (McKinsey & Company 2016). The last-mile delivery of parcels has some adverse effects of transport on congestion, safety, and pollution in dense urban areas, as demand for the same-day and instant delivery rises at a rapid rate that is expected to hit a combined market share of 20-25 percent by 2025 (McKinsey & Company 2016). According to the MHI Annual Industry Report, by the end of 2050, urban freight is projected to rise by 40 percent, which means that the number of trucks will rise, contributing to congestion in residential and downtown areas as goods are being transported and delivered by trucks mostly (MHI 2020). If delivery vehicles get stuck due to heavy traffic, companies spend more on fuel and labor, and congestion costs as much as 2 to 4 percent of urban GDP (Tomorrow. Mag 2019). In reality, last-mile delivery is seen as the costliest part of the distribution process. The cost of the last mile can be as much as 28 percent of the cost of the entire supply chain, according to the Council of Supply Chain Management Professionals.

Most innovative concepts concentrate on delivering the products to the customer with the aid of electric and autonomous vehicles to reduce last-mile congestion and costs. Some of the first autonomous delivery ideas include the use of unmanned drones that have drawn attention due to Amazon's announcement as they plan to use drones to deliver goods to customers. For now, drones are not very cost-effective and not publicly accepted. In addition, the drones have some drawbacks, and the application of this technology is not accepted for flying in populated areas (Ansys 2020). As a solution to this, various companies in the supply chain and logistics organizations are dealing with the last-mile delivery robots for congested urban environments, as shown in **Fig.1**. These are the sidewalk delivery robots that deliver products to customers without a delivery person's intervention. These robots can either be dropped off from a truck to deliver goods to the customers or can also be dispatched from micro-hubs within communities. This poses enormous challenges in determining how these robots will be deployed in suburban and densely populated areas where trucks, cars, bikes, pedestrians and, more travel in different directions at different times. One of the most known automated delivery robots are the Starship (created by founders of Skype) and Dispatch (created by researchers from MIT and University of Pennsylvania). These robots can be used for delivering small packages, grocery, laundry, pizza and many more. Similar to drones, these sidewalk delivery robots are faster in delivering customer’s orders to their doorstep and the flexibility of choosing a convenient delivery time. The delivery cost of parcels in the delivery robots are somewhat less than the drones which is an additional benefit. But, delivery robots have a shorter range in distance covered and sometimes, obstacles on the road can be problem from them.

Figure 1: Delivery robot

Source: https://www.wired.com/story/nuro-dominos-pizza-delivery-self-driving-robot-houston/

1.2. Problem Statement

Fast and cost-efficient delivery of goods ordered online to customers is an unmet problem that many companies are facing with. To bridge the last mile to customers, new technologies are needed. One technology-driven opportunity that has recently received much attention is the deployment of autonomous delivery vehicles (ADVs) to support parcel delivery. An important advantage of an ADV compared to a regular delivery van is that it can operate without an expensive human driver. Another advantage is that ADVs can travel on congested roads without significant delay by using the sidewalk. ADVs also referred to as delivery robots, have the potential to reduce urban emissions for the last-mile delivery to customers as ADVs are powered by batteries.

However, although several companies, including Amazon, Kroger, and Walmart, are currently running practical trials to investigate the use of ADVs for parcel delivery (as shown in **Table 1**), there are several inherent limitations to the successful use of ADVs, such as low speed and limited capacity. Sensitivity analysis between ADVs capacity and total costs indicate a strong relationship—the overall cost will decrease with the increased number of compartments in an ADV [1]. Additionally, as ADV is battery-powered, the range of an ADV likely remains limited, compared to a regular, fuel-based delivery van. A conventional delivery van, on the other hand, has a longer range and a greater capacity. Currently, conventional vans perform the majority of urban logistical activities. However, their long-range delivery and large-volume gas consumption may produce high emissions. Therefore, to take the advantages of ADV and van, one way is to allow them to collaborate with each other. A combined van-ADV delivery system (V-ADV) can be used in E-grocery logistics planning to enhance the delivery efficiency and overcome their respective drawbacks. In other words, we can combine the advantages of conventional vans (large volume and low cost) with the advantages of the ADVs (low emissions and flexibility).

Table 1: Parameters of ADVs currently used in some companies

Company	Name	Product Specification	Testing Area	Delivery Item	Travel Lane
Nuro	R1	[1]1500 pounds (680 kgs), 25 mph, half the width of a Toyota Corolla	Arizona, Houston	Groceries from Kroger, pizza from Domino's	Sidewalk
Neolix		[2]1 m width, volume 2.4 cum, speed 50 km/h, 100 km cruising range	China		
Refraction AI	REV-1	[3]ADV-cycle, 4-foot tall 80 pounds, 15 mph, 16 cubic feet	Ann Arbor, Michigan	Food	Sidewalk/Bike lane
Amazon	[4] Scout		Washington		Sidewalk
Udelv	Newton	[5] 60 mph, 800+ lbs capacity	Oklahoma	Walmart	
Baidu	[6] Apollo 3.5		San Francisco	Walmart	
Marble	Eat 24	[7] 4 feet tall, travels 3–4 mph and can hold up to four grocery bags	San Francisco		Sidewalk
Starship		[8] 20 pounds of cargo, delivery radius of 3 to 4 miles and can travel a maximum speed of 4 mph	College campuses	Food	Sidewalk
Teleretail	Aito/Pulse	[9] 33 inches wide, weighing up to 77 lbs	Switzerland		Sidewalk

Source: [1] http://www.digitaljournal.com/tech-and-science/technology/startup-nuro-s-self-driving-vehicle-bypasses-usa-safety-rules/article/566652;
[2] https://www.forbes.com/sites/davidsilver/2019/06/04/neolix-accelerates-the-autonomous-delivery-rush/#3fec3dfc95a8;
[3] https://www.iottechtrends.com/autonomous-delivery-vehicle-bicycle/;
[4]https://www.theverge.com/2019/8/9/20798604/amazon-scout-robot-delivery-irving-southern-california-expansion-prime;
[5] https://www.udelv.com/
[6] https://venturebeat.com/2020/03/04/silc-technologies-raises-12-million-for-long-range-lidar-sensors/
[7] https://www.roboticsbusinessreview.com/rbr/marble_delivery_robots_yelp_eat24/
[8] https://talkbusiness.net/2016/04/starship-land-drone-being-tested-at-university-of-arkansas-for-final-mile-delivery/
[9] https://www.bdcnetwork.com/thyssenkrupp-tests-self-driving-robot-%E2%80%98last-mile%E2%80%99-delivery-elevator-parts

From the perspective of a freight transportation planning, this innovative concept creates a planning and optimization problem on last-mile delivery. This optimization problem involves volume assignment decisions and routing decisions. The volume assignment to both van and ADV need to be optimized to achieve the lowest logistics cost, while the routing decisions determine the sequence in which the customers allocated to each vehicle are visited. **Figure. 2** illustrates an example of such a network that freight delivered from the depot to the customers is managed by satellites. Thus, the transportation network is decomposed into two levels: the first echelon that connects the depot to the satellites and the second echelon bridging the satellites to the customers. In this example, four customers are designed to be served from one depot. There are two ways to serve customers. One way is to use traditional delivery van, as shown in Figure 2(a). The van departures from the depot, it visits all the customers and returns to the depot. Another way is to adopt V-ADV as shown in Figure 2(b). The delivery van departures from the depot, it visits all the satellites and returns to the depot on the first echelon. Then, the ADV departs from the satellite, it visits all the customer and return to the satellite on the second echelon. Here, we assume that the satellites are generated randomly from the customers. It can be seen that by serving four customers with an ADV instead of a van, the distance traveled by the van can be reduced while increasing the total travel distance. However, if the emission cost is considered (varied according to the distance), the total network cost might change.

Therefore, to better understand the related planning problems and potential benefits of the V-ADV, there is a need for new models to optimize the combined V-ADV two-echelon vehicle system. However, there lacks such a models and algorithms. Therefore, the present study aimed at filling this gap by developing a new formula to evaluate the performance of the V-ADV delivery system. To model the flow assignment and the route choice, we approach the modeling problem as a two-echelon vehicle routing problem with mixed vehicles (2E-VRP-MV) and use a clustering-based hybrid genetic algorithm (C-GA-PSO) to solve the 2E-VRP-MV.

Several numerical instances are also tested with different characteristics and sizes to verify the performance of the proposed C-GA-PSO, and the impact of layout of depot-customer and customer densities on the total cost are analyzed in the last section.

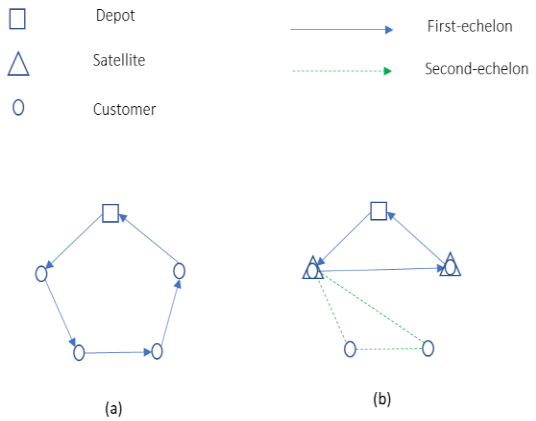

Figure 2: An example of a two-echelon delivery network with mixed vehicle

1.3. Research Objectives

To reduce transport cost and fuel emissions, a new element of ground-based delivery services, autonomous delivery vehicles (ADVs), is included in the E-grocery distribution system for improving delivery efficiency. Thus, the objective of this study is to optimize a two-echelon distribution network for efficient E-grocery delivery, where conventional vans serve the delivery in the first echelon and ADVs serve delivery in the second echelon. The problem is formulated as a two-echelon vehicle routing problem with mixed vehicles (2E-VRP-MV) with a nonlinear objective function, in which the total transport and emission costs are optimized. This optimization is based on the flow assignment at each echelon and to realize routing choice for both the van and ADV. A two-step clustering-based hybrid Genetic Algorithm and Particle Swarm Optimization (C-GA-PSO) algorithm is proposed to solve the problem. First, the end customers are clustered to the intermediate depots, named satellites, based on the minimized distance and maximized demand. To enhance the efficiency of resolving the 2E-VRP-MV-model, a hybrid GA-PSO algorithm is adopted to solve the vehicle routing problem. Computational results of up to 21, 32, 50, and 100 customers show the effectiveness of the methods developed here. At last, the impacts of the layout of the depot-customer and customer density on the total cost are analyzed. This study sheds light on the tactical planning of the multi-echelon sustainable E-grocery delivery network.

2. LITERATURE REVIEW

The literature review conducted aims at identifying all the approaches, methodologies and practices that have been applied so far in order to solve problems similar to the one addressed in the project. The study examined research conducted in the time previous to this study, with the goal of getting a better understanding on previous works conducted in the matter. This chapter is divided into two main subchapters: (a) studies related to city logistics and urban freight transport systems and (b) studies regarding the vehicle routing with autonomous vehicles.

2.1. Urban Logistics Studies

The last years many initiatives are being undertaken in order to make urban freight systems faster, safer and more reliable, and negate all the negative effects that can be associated with their operations. These initiatives vary from technical, organizational, regulatory and policy alterations that aim on improving their performance. More specifically, T. G. Crainic, et al. (2004) conducted a study in the domain of urban freight systems, proposing an organizational and technological framework for the integrated management of urban freight systems, while also identifying various important planning and operational issues encountered. In addition, they presented some corresponding to those issues operations research models, providing the exact formulation for one of them, which can help optimize the performance of these systems. M. Browne et al. (2005) worked on a project for the U.K. Department for Transport. The projects' main objective was the identification of the potential benefits from developing urban consolidation centers, as well the determination of the viability of this initiative. Moreover, G. Yannis et al. (2006) investigated the impacts of various regulations related to urban delivery traffic movements on urban areas. They developed traffic simulation models using data ranging from land uses, traffix mix, flows and capacities and delivery requirements for various types of services. The study concludes by stating that in order for such restrictions to be successful and provide significant improvements in urban areas, careful planning, adoption of supporting activities and gradual implementation are required. J. Muñuzuri et al. (2010) studied the ecological effects of urban freight systems. They developed a macroscopic simulation model in order to estimate a value for the ecological footprint of urban freight deliveries. The study concluded that the ecological footprint depends on the type of vehicles used, the distances travelled by them, their average speeds and the number of stops they make. Additionally, they analyzed urban freight policies in terms of their expected influence on costs and their contribution to the sustainability of the urban area. D. Patier and M. Browne (2010) proposed a framework for examining the effectiveness of initiatives in the field of urban logistics. Their objective was to develop a consistent methodology that can be applied in various types of city logistics experiments and pilot projects. The method considers both quantitative and qualitative performance measures, covering the economic, social, environmental effects of innovations. The study concludes by indicating that, given all the required data, the proposed methodology can provide a standardized approach that can be applied in all main types of urban freight innovations. L. K. Oliveira, et al. (2014) investigated the effects of utilizing urban logistics facilities for freight deliveries. They developed a simulation model that represents the operation of a ULS and then generated indicators to evaluate the performance of this space according to different operating configurations. The study concludes by indicating that this approach can provide many benefits in the operations of urban freight systems, such as reductions in truck trips made, waiting and delivery times and last mile costs. In addition, A. Alho et al. (2014) in their study focused on the analysis and modeling of logistics loading/ unloading bays. The developed model combines simulation and optimization techniques that take into account double-parking derived vehicle obstruction. The main goal of their study was the better understanding of the relation between the factors that lead to an optimized l/u bay system, mainly the number and location of bays, enforcement outcome and size of bays. E. Taniguchi (2014) discussed various aspects of city logistics systems. After presenting the multiple stakeholder involvement in the logistics process and their different objectives and perspectives, he focuses on the importance of collaboration between all parties for developing efficient and environmentally friendly urban freight transport systems. Later he describes the three main elements for effectively applying city logistics initiatives: (a) Application of innovative technologies of ICT and ITS, (b) Change in mind- sets of logistics managers, and (c) Public-private partnerships. JGV Vieira et al. (2015) examined the opinions of various stakeholders involved in the logistics operations. First, they investigated some logistical performance indicators adopted by the companies with the goal of developing a profile of companies that provide the best logistical performance in freight delivery. Additionally, they aimed at summarizing the opinions of shippers, LSPs and carriers regarding regulations and issues by conducting interviews and discussed the ways freight operators address these regulations and operate simultaneously and efficiently inside and outside megacities.

2.2. Vehicle Routing Problem with ADV

Many innovative concepts and technologies for people transportation and freight delivery have recently been developed to address the issues of excessive traffic, pollution, and high transportation costs in large urban areas. Different aspects of city logistics have been systematically reviewed by Neghabadi et al. (2019) [2]. Among those technologies that focus especially on freight transportation, electric vehicles-based freight transport [3–4], drone-based good delivery [5], deliver packages into car trunk [6], and truck-based autonomous robots [7], are mostly studied. Recently, a new type of delivery robot is tested in the State of Arizona. It carries a certain weight of groceries and can operate on sidewalks and crosswalks. However, few studies are related to the utilization of ADV in E-grocery delivery. Only two publications authored by Jennings and Figliozzi [8] and Boysen et al. [9] are closely related to the topic of this paper. Jennings and Figliozzi firstly discussed current regulations on autonomous delivery vehicles in the US and summarized the existing delivery devices and their capabilities. Besides, they estimated the number of customers and delivery time served by a special delivery van and an autonomous delivery robot. Nils Boysen et al. [9] proposed a scheduling procedure that determines the truck route along with the drop-off points of the robot. They formulated it as a truck and trailer routing problem that would minimize the number of late deliveries, which is a two-echelon vehicle routing problem (2E-VRP).

The 2E-VRP was initially proposed by González-Feliu et al. [10]. It has also been widely used by Teodor Gabriel Crainic et al. [11], Perboli et al. [12], Baldacci et al. [13], Santos, Mateus, and da Cunha [14], Grangier et al. [15], and Lin et al. [16]. All these studies have one common characteristic, which is that the transport cost is the only optimized objective, without considering the emission cost. Govindan (2014) proposed a two-echelon location-routing problem for the design of sustainable supply chain networks. This design considered vehicle type, load, and the environmental effect [17]. In another study of 2E-VRP led by Soysal (2015), the traveled distance, vehicle speed, vehicle type, load, and emissions were added [18]. However, only one kind of vehicles is considered. If considering more vehicles, 2E-VRP would be a generalization of the multi-depot VRP (MDVRP). The classical VRP deals with the optimal delivery route-designing problem, where there is only one central depot and one route, and the characteristics for each vehicle are the same [19]. This classical VRP has been expanded by considering the addition of real-life characteristics. One possible extension of this problem is the varying number of depots when there are more than two, thus the VRP is expanded to an MDVRP. The techniques that are most commonly used for solving an MDVRP include exact approaches, constructive heuristics, and metaheuristics.

However, nearly all these techniques are metaheuristics and heuristics, this is because within a reasonable computing time no exact algorithm can be guaranteed to have the optimal tours when there are a huge number of customers, also because of the NP -hardness of the problem [20]. For instance, Feliu et al. [21] and Baldacci [22] used an exact branch-and-cut algorithm to solve a 2E-VRP. As the sized data sets in reality are rarely, optimally solved by exact methods, the metaheuristics method becomes the only method of choice on most occasions [23], such as, genetic algorithm (GA) [24], tabu search [25], iterated local search [26], adaptive large neighborhood search [27], variable neighborhood search [28], hybrid heuristic algorithm [29].

3. METHODOLOGY

3.1. Problem Overview

In this two-echelon routing problem with mixed vehicles, the first echelon is the delivery route from the depot to the satellite by conventional van and the second echelon is the delivery route from the satellites to the customers by ADVs. A limited number of vehicles is set to travel at each level. The objective of our study is to minimize the total cost of travel and emission of the network. We assume that the sites of the satellites and customers are known, however, the customers are not allocated to any satellite in advance.

The 2E-VRP-MV is first reduced to a network graph W Here, there are three subsets of nodes: depots (P_O), customers (P_F), and satellites (P_S). We have $N = P_O \cup P_S \cup P_F, N_1 = P_O \cup P_S, N_2 = P_S \cup P_F$. Accordingly, the two-echelon delivery routes are distinguished: the first-echelon delivery route (i, j), $i, j \in N_1$ and the second-echelon route (i, j), $i, j \in N_2$. In the beginning, the delivery amounts to a satellite are not known and these amounts for each satellite are calculated after the customers are allocated to the corresponding satellites. A limited fleet of conventional vans V_{van} serve with the capacity of Q_{van} in the first- echelon and a limited fleet of ADVs V_{ADV} serve with the capacity of Q_{ADV} in the second-echelon, and $Q_{van} > Q_{ADV}$. Each satellite s_i is supposed to have its own capacity Z_{s_i}. The problem is how to allocate customers to the appropriate satellites at second-echelon and how to determine the van routes in the first-echelon and ADV routes in the second-echelon with a minimum total cost. Thus, the objective of this study is to minimize the total operational cost including the transportation and emission costs. In our model, the fixed costs of the van and ADV are not considered because we suppose that they are available in a certain number.

To summarize:

- Each vehicle is allocated at most one route.
- Each first-echelon trip must begin/end at the same open depot.
- Each second-echelon trip must begin/end at the same satellite.

- Each customer's demand cannot be split among different ADVs at the second echelon. In this way, each customer must be visited by one ADV.
- Each satellite's demand could be split among different vans at the first echelon and each satellite could be visited by two or more vans.
- The total requirements of the customers allocated to a satellite must not exceed the capacity of the satellite.

3.2. Mathematical Formulation

3.2.1. Parameters and variables

Parameters

$P_O = \{P_o\}$	Set of depots
$P_f = \left\{P_{f_1}, P_{f_2}, \dots, P_{f_{n_f}}\right\}$	Set of customers
$P_S = \left\{P_{s_1}, P_{s_2}, \dots, P_{s_{n_s}}\right\}$	Set of satellites
V	Set of vehicle types $\{V_{van}, V_{ADV}\}$
Q^{van}	Capacity of the van on the first level
Q^{ADV}	Capacity of the ADV on the second level
m^{van}	Number of the first-level vans
m^{ADV}	Number of the second level ADVs
$m_{s_k}^{ADV}$	Maximum number of the second-echelon tours starting from satellite s_k
n_s	Number of satellites
n_f	Number of customers
Z_k	Capacity of satellite k, $k \in P_S$
d_j	Demand from a customer j, $j \in P_F$
C_{ij}^{van}	Unit transport cost (per mile) per vehicle between the node i and j, $(i, j) \in N_1$
C_{ij}^{ADV}	Unit distance cost (per mile) per vehicle between the node i and j using, $(i, j) \in N_2$
φ_{ij}^{van}	Unit emission cost (per mile) per vehicle between the node i and j, $(i, j) \in N_1$

φ_{ij}^{ADV}	Unit emission cost (per mile) per vehicle between the node *i* and *j*, $(i,j) \in N_2$
H_k	Cost of handling operations of a unit of freight in satellite k
l_{ij}^{van}	Travel distance in the arc $(i,j) \in N_1$ in the first echelon
l_{ij}^{ADV}	Travel distance in the arc $(i,j) \in N_2$ in the second echelon

Decision Variables

x_{ij}	Number of vans traverses arc $(i,j) \in N_1$ in the first echelon
y_{ijk}^{ADV}	$\begin{cases} 1, \text{if an ADV traverses arc } (i,j) \\ \quad \in N_2 \text{ in the second} - \text{echelon} \\ \quad\quad \text{starting from satellite } k \\ 0, \text{otherwise} \end{cases}$
z_{kj}	$\begin{cases} 1, \text{if customer } j \text{ is allocated to} \\ \quad\quad \text{satellite } k, k \in P_S \\ 0, \text{otherwise} \end{cases}$
μ_{ij}^{van}	Flow traverses arc $(i,j) \in N_1$ in the first echelon
μ_{ijk}^{ADV}	Flow traverses arc $(i,j) \in N_2$ in the second echelon coming from satellite k

3.2.2 Model

2E-VRP-MV model

$$Min \sum_{i\in N_1}\sum_{j\in N_1} C_{ij}^{van} l_{ij}^{van} x_{ij} + \sum_{k\in P_S}\sum_{i\in N_2}\sum_{j\in N_2} C_{ij}^{ADV} l_{ij}^{ADV} y_{ijk}^{ADV} + \sum_{i\in N_1}\sum_{j\in N_1} \varphi_{ij}^{van} l_{ij}^{van} x_{ij} + \sum_{k\in P_S}\sum_{i\in N_2}\sum_{j\in N_2} \varphi_{ij}^{ADV} l_{ij}^{ADV} y_{ijk}^{ADV} + \sum_{k\in P_S} H_k \sum_{j\in P_F} d_j z_{jk} \quad (1)$$

Subject to

$$\sum_{j\in N_1} x_{oj} \le m^{van} \; \forall\, o \in P_O \quad (2)$$

$$\sum_{j\in P_S} x_{jk} = \sum_{j\in P_S} x_{kj} \; \forall\, k \in N_1 \quad (3)$$

$$\sum_{j\in P_F} y_{kjk}^{ADV} \le m^{ADV} \; \forall\, k \in P_s \quad (4)$$

$$\sum_{j\in P_F} y_{kjk}^{ADV} \le m_{s_k}^{ADV} \; \forall\, k \in P_s \quad (5)$$

$$\sum_{j\in P_F} y_{kjk}^{ADV} = \sum_{j\in P_F} y_{jkk}^{ADV} \; \forall\, k \in P_s \quad (6)$$

$$\sum_{i\in N_1} \mu_{ij}^{van} - \sum_{i\in N_1} \mu_{ji}^{van} = \begin{cases} \sum_{j\in P_F} d_j\, z_{jk} & j \text{ is not a depot} \\ \sum_{j\in F} -d_j & otherwise \end{cases} \quad \forall j \in N_1, i \ne j \quad (7)$$

$$\sum_{i\in N_2} \mu_{ijk}^{ADV} - \sum_{i\in N_2} \mu_{jik}^{ADV} = \begin{cases} z_{kj}\, d_j & j \text{ is not a satellite} \\ -\sum_{j\in P_F} d_j\, z_{jk} & otherwise \end{cases} \quad \forall\, j \in N_2, k \in P_s, i \ne j \quad (8)$$

$$\mu_{ij}^{van} \le Q^{van} x_{ij} \; \forall\, i,j \in N_1,\, i \ne j \quad (9)$$

$$\mu_{ijk}^{ADV} \le Q^{ADV} y_{ijk}^{ADV} \; \forall i,j \in N_2, k \in P_s,\, i \ne j \quad (10)$$

$$y_{ijk}^{ADV} \le z_{kj} \; \forall\, i \in N_2, j \in P_F, k \in P_s \quad (11)$$

$$y_{jik}^{ADV} \le z_{kj} \; \forall\, i \in P_S, j \in P_F, k \in P_s \quad (12)$$

$$z_{jk} = \sum_{i\in N_2} y_{ijk}^{ADV} \; \forall\, j \in P_F, k \in P_s \quad (13)$$

$$z_{jk} = \sum_{i\in P_s} y_{jik}^{ADV} \; \forall\, j \in P_F, k \in P_s \quad (14)$$

$\sum_{i \in P_s} z_{ij} = 1 \; \forall \; j \in P_F$ (15)
$y_{kjk}^{ADV} \leq \sum_{u \in N_1} x_{ku}, \forall j \in P_F, k \in P_s$ (16)
$x_{ij} \in Z^{+}, \forall \; i,j \in N_1$ (17)
$y_{ijk}^{ADV} \in \{0,1\} \; \forall i,j \in P_F \; k \in N_2$ (18)
$z_{kj} \in \{0,1\} \; \forall \; j \in P_F, k \in N_2$ (19)
$\mu_{ij}^{van} \geq 0 \; \forall \; i,j \in N_1$ (20)
$\mu_{ijk}^{ADV} \geq 0 \; \forall \; i,j \in N_2, k \in P_s$ (21)

Objective function (1) minimizes the total transportation cost by adopting V-ADV. Constraint (2) sets a van-number limitation on the first echelon. Constraint (3) ensures that the number of entering and leaving vehicles to each satellite is the same; when k=P_O, the first echelon begins and ends at the depot. Constraint (4) sets the limitation of the ADV number on the second echelon. Constraint (5) sets the limitation of the satellite capacity. Constraint (6) forces each route on the second echelon to begin and end at one satellite. Constraint (7) shows that the amount of delivery on each node on the first echelon should comprise the demand of this node, except for the depot where the amount of delivery should comprise the total requirements of the customers. Constraint (8) shows the flow balance at satellites on the second echelon, where the amount of delivery comprises the requirement (unknown) allocated to the satellites. Furthermore, constraints (7) and (8) forbid the sub-tours leaving from the depot or a satellite, respectively. The amount of flow received at each node equals to its demand. Constraints (9) and (10) place limitations to the capacity, for the first and second echelon, respectively. Constraints (11) and (12) indicate that a customer *j* is assigned to a satellite *k* only if it receives from the same satellite. Constraints (13) and (14) show that there is only one ADV serving each customer, and it imposes the limitation that an ADV travels from a satellite *k* to a customer *j* if the customer is allocated to that satellite. Constraint (15) ensures that each customer must be allocated to only one satellite. Constraint (16) shows a second echelon route starting from a satellite *k* only if a first echelon route has served it. Constraints (17) and (21) define the domains of the variables.

3.3. Mathematical Formulation

A two-stage method is adopted for the 2E-VRP-MV. First, we allocate customers to the satellites, thus decomposing the problem into several VRPs. Second, we address a multi-depot VRP. We propose a clustering-based hybrid genetic C-GA-PSO to solve the 2E-VRP-MV. The detailed steps are explained below. **Figure 3** shows the flowchart of the C-GA-PSOs.

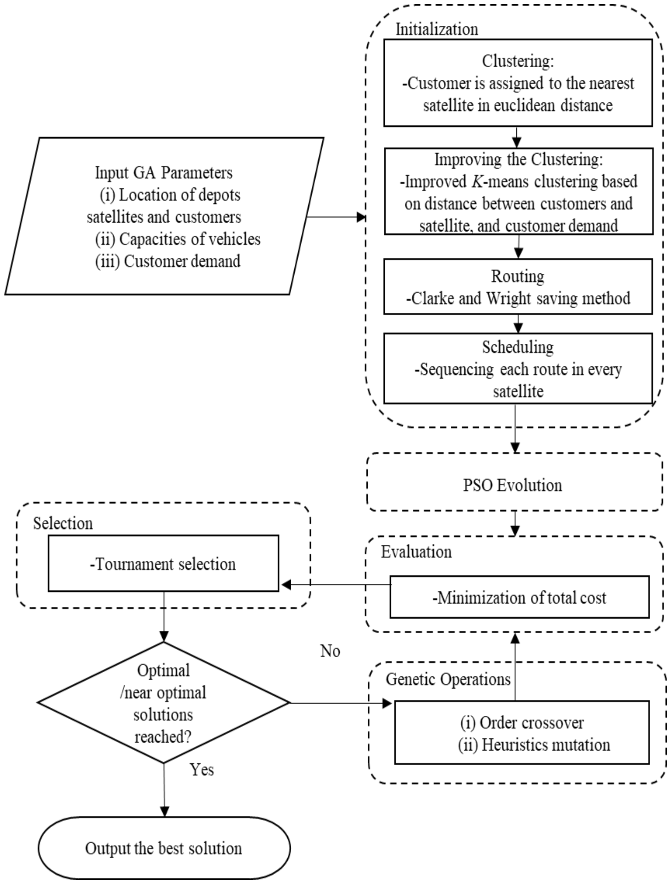

Figure 3: Flowchart of the C-GA-PSOs for 2E-VRP-MV

3.3.1. Initialization

Firstly, a path representation is used to encode the chromosomes for the solution of the 2E-VRP-MV, in which the customers are sequenced in order of a visit. To find a workable result for the optimization process, three basic steps: grouping, routing, and scheduling are generated. **Figure 4** shows an illustrative example. There are eight customers need to be visited by ADVs. The ADVs will require two routes to visit all the customers if the path representation for this example starts at $\boldsymbol{S_A}$ ***and*** $\boldsymbol{S_B}$. The first route starts from the satellite at $\boldsymbol{S_A}$ and then serves customers 3, 1, and 5. After it serves all the customer, the ADV returns to the satellite $\boldsymbol{S_A}$. In the same way, the second route starts from the satellite at $\boldsymbol{S_B}$, serves customers 4, 7, 6, and goes back to the satellite $\boldsymbol{S_B}$.

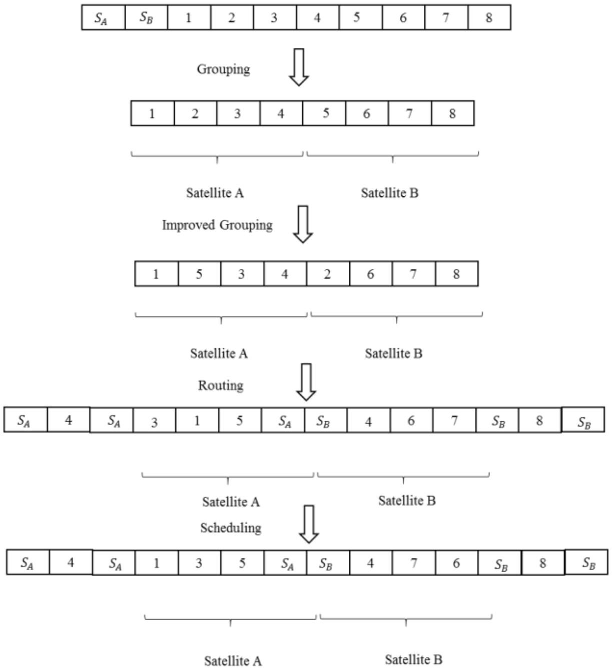

Figure 4: Chromosome representation and initial population

1) K-means clustering

The initial clustering of the customer is based on a simple distance-based rule.

Step 1: Determine the number of clusters, *k*.

Step 2: Initialization. Assign customer *i* arbitrarily to the centroid of each cluster.

Step 3: Cluster Assignment. For a customer location $(x_{P_{f_i}}, y_{P_{f_i}})$ and a cluster's centroid $(x_{P_{s_i}}, y_{P_{s_i}})$, the Euclidean distance between them is given by:

$$\theta(P_{f_i}, P_{s_i}) = \sqrt{\left(x_{P_{f_i}} - x_{P_{s_i}}\right)^2 + \left(y_{P_{f_i}} - y_{P_{s_i}}\right)^2} \qquad (22)$$

The assignment must be feasible with respect to the fleet-size restriction.

Step 4: Centroid update.

Step 5: Repeat step three and four until the assignment has not changed.

2) Improvement of k-means clustering

If the distance is the only factor to be considered when customers are clustered, we might not have the optimal clustering result. This is because customers that have smaller demand may be allocated to a cluster first, while the customers with larger demand have not allocated yet, which may lead to a generation of other clusters. An improved *k-means* algorithm is proposed to overcome this problem [30]-[32]. Two factors should be considered when customers are allocated to the nearest cluster - maximum demand and minimum distance; therefore, customers with bigger order will be allocated to the cluster first, then the customers with smaller order will be allocated to other clusters easily.

Step 1: Initialize k.

First, we have to specify the numeric value of *k* and then randomly select *k* objects from data as initial centers. Now we can select *k* satellites as initial centroid as the default value. This calculation is based on the demand ($\boldsymbol{d_i}$) of the customer and the capacity of the satellite ($\boldsymbol{Z_{s_i}}$) as:

$$k=\left\lceil \sum_{P_{f_i}\in P_F} d_{P_{f_i}} \Big/ Z_{s_i} \right\rceil \quad (23)$$

The initial k centroids are selected by sorting the customers based on their demand in their decreasing order: $d_{P_{f_1}} > d_{P_{f_2}} > d_{P_{f_3}} > d_{P_{f_i}}, P_{f_i} \in P_F$.

Step 2: Assign the customer.

Calculate the Euclidean distances between each customer to all the k centroids. Group all the customers P_{f_i} to the closest centroid j. Calculate a priority value to find the appropriate centroid j for P_{f_i}:

$$\delta_{P_{f_i}} = \theta(P_{f_i}, P_{s_i}) / d_{P_{f_i}} \quad (24)$$

The selected P_{f_i} that has the highest priority of having the centroid j, is allocated based on the constraint (10). If the constraint (10) is not satisfied, the selected P_{f_i} will be allocated to the next nearest centroid based on (10) and (23).

We used the Euclidean distance to calculate the distance between the customers and centroid as (21). The detailed algorithm is shown below.

An improved algorithm of *k-means* clustering

Input:

Coordinates (x_i, y_i)

Demands d_i

Customer P_{f_i}

Output:

k clusters

Procedure:

Calculate k using (23)

Select k satellites as the initial centroid

while each customer $P_{f_i} \in P_F$ is not converged

while P_{f_i} is not allocated

Sort the demand of customers from high to low and measure the Euclidean distance to each cluster k.

Assign the nearest centroid of P_{f_i} as m.

Group all unallocated requesters as G with m as their nearest centroid.

Calculate the priority value for $P_{f_i} \in$ G using (24).

Assign P_{f_i} to their nearest centroid based on the priority value without violating the vehicle's capacity.

Update z_{kj}

If P_{f_i} is not allocated, then the next nearest centroid will be chosen.

end if

end while

Update the new centroid based on the clusters generated before using

$x_j = \frac{\sum_{m=1}^{j} x_m}{n_j}$

and $y_j = \frac{\sum_{m=1}^{j} y_m}{n_j}$

where (x_j, y_j) represents the j^{th} centroid and n_j represents the number of customers in cluster j.

end while

---

3) Routing

We used the saving method of Clarke and Wright [33] to allocate the customers in the same group to several routes. The cost-saving regarded in our study is the distance traveled by the vehicles to serve the customers. A saving matrix S (P_{f_i}, P_{f_j}) is constructed for every two customers P_{f_i}, P_{f_i} in the same group first. Then, if the constraints of the vehicle-capacity are not violated, the customers with larger cost-saving values are assigned in the same route. Each customer P_{f_i} is allocated to a single satellite P_{s_i} only. The saving matrix is constructed as:

$$S\,(\boldsymbol{P}_{f_i}, \boldsymbol{P}_{f_j}) = \boldsymbol{D}\left(\boldsymbol{P}_{s_i}, \boldsymbol{P}_{f_i}\right) + \boldsymbol{D}\left(\boldsymbol{P}_{s_i}, \boldsymbol{P}_{f_j}\right) - \boldsymbol{D}\left(\boldsymbol{P}_{f_i}, \boldsymbol{P}_{f_j}\right)$$

4) Scheduling

The scheduling problem is solved by the nearest neighbor heuristic [34]. The principle of the nearest neighbor heuristic is to start randomly with the first customer. Then, the next customer is scheduled as close as possible to the previous customer from those unselected ones to generate the delivery sequence until all the customers are scheduled.

3.3.2. Application of GA-PSO to the given MDVRP

GAs emulates the mechanisms of natural selection by a procedure of randomized data exchange. GAs work by generating a population of numerical vectors called chromosomes. Each chromosome represents a possible solution to a problem. New chromosomes (solutions) are created by crossover or mutation. Solutions are then evaluated according to a fitness function. The fittest chromosome will survive, and the less fitting ones will be removed. The search process of GAs typically continues until a pre-defined fitting value is reached, or a set amount of computing time passes. When the number of iterations is large, GA-based algorithms provide better results than other algorithms. However, the GA algorithm will consume more time to reach the optimal solution due to the increasing number of iterations. The PSO algorithms provide better results than the other algorithms and in less time. However, the results may not be accurate due to the fast convergence rate, which may lead to local optimal solution. A hybrid of PSO and GA algorithms (GA-PSO), has shown better performance than the GA or the existing algorithms alone [35]-[38]. The overall procedure of the applied GA-PSO is described below.

Algorithm GA-PSO

Step 1 Initialize relevant parameters, such as the number of particles (*pop_size*), the number of PSO generations (*Max_k*), the maximum velocity of the particle v_{max}, the PSO weight coefficients (C_1 *and* C_2), generation number (*Max _Gen*), the crossover and mutation probabilities, length of the chromosome.
Step 2 Estimate the fitness function.
Step 3 Gen = 1.
Step 4 If Gen$\leq$ *Max _Gen*, turn to step 5, otherwise change to step 16.
Step 5 Sequence all individuals in descending order according to the fitness value.
Step 6 Delete 1/3 of the individual with the worst fitness value.
Step 7 Replicates the top 2/3 of the best-performing ones to form a new population.
Step 8 Let k = 1.
Step 9 If $k \leq Max\_k$, turn to step 10, otherwise, change to step 12.
Step 10 Update the individual's speed and position with the formula (25) and (26).
Step 11 k = k + 1, turn to step 9.
Step 12 The *pop_size* particles are ranked according to the fitness values.
Step 13 The crossover and the mutation operations are implemented respectively.

Step 14 Combine the evolved particles and new particles to generate new *pop_size* individual.
Step 15 Gen = Gen + 1, turn to step 4.
Step 16 Output the optimal solution and function value.

3.3.3. Enhancement

After initialization, new individuals on the next generation are created by enhancement. PSO is adopted to enhance individuals of the same generation. Here, the group constituted by the elites may be regarded as a swarm, and each elite corresponds to a particle in it (shown in Fig. 4). The enhancement operation tries to make the individuals more suitable to the environment after acquiring knowledge from the society. Also, the generated offspring will achieve better performance by using enhanced operation than those offspring by original elites.

In PSO, each particle represents a solution in search space and has a position represented by $\vec{y_i}$. They move with the velocity of each particle represented by a vector $\vec{v_i}$ and tend to find the best possible solution by changing the velocity according to rule inspired by bird flocking behavior. Each particle must maintain a memory of the last best-known position represented by $\vec{p_i}$. Also, the best position among all the particles obtained so far is represented by $\vec{p_g}$. At each time step *t*, by using the individual best position $\vec{p_i}(t)$ and global best position $\vec{p_g}(t)$, a new velocity for particle *i* is updated by

$$\vec{v_i}(t+1) = \vec{v_i}(t) + C_1\,\gamma_1(\vec{p_i}(t) - \vec{y_i}(t)) + C_2\,\gamma_2\,(\vec{p_g}(t) - \vec{y_i}(t) \qquad (25)$$

Where C_1 and C_2 are positive constants and γ_1 and γ_2 are uniformly distributed random numbers in [0,1]. Based on updated velocities, the position of each particle changes

$$\vec{y_i}(t+1) = \vec{y_i}(t) + \vec{v_i}(t+1) \qquad (26)$$

Based on formula (25) and (26), the population of particles tend to cluster together with each particle moving in a random direction.

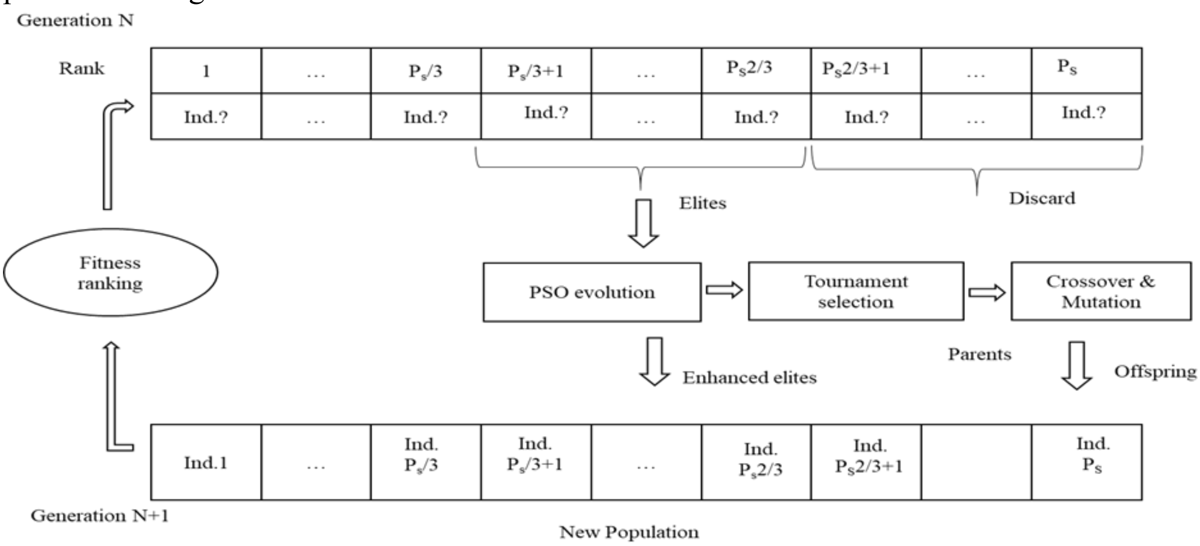

Figure 5: An enhancement procedure of operators' selection

3.3.4. Evaluation

Each solution in the population is evaluated using a measure of fitness to improve the solutions. The fitness measure we used is the objective function value in Eq. (1). Therefore, we found the best solution that corresponded to the lowest cost.

3.3.5. Selection

The parents are selected for mating and reproduction during each generation. We use the tournament selection [39] to generate offspring in the population. This selection strategy is based on fitness evaluation. The selection procedure is referring to [40].

Pseudo-code of tournament selection

func tournament_selection (pop, k):
best = null
for i=1 to k
ind = pop [random (1, N)]
    if (best == null) or fitness (ind) > fitness (best)
        best = ind
return best

3.3.6. Crossover

The crossover and mutation operations can ‘reshape’ the population, although tournament selection by itself generates a non-normal distribution, which makes the distribution to become more normal. The crossover operator adopted in our C-GA-PSOs is the modified order crossover based on classical order crossover (Gen and Cheng, 1997). The difference is that crossover points are selected in modified order crossover [41] instead of randomly selecting positions in a parent in classical order crossover. The modified ordered crossover behaves in the following way:

Parent 1

1	2	3	4	6	9	8	5	7

Parent 2

2	1	9	8	5	6	3	7	4

After position selection:

Parent 1

1	2	*	*	*	9	8	*	*

Parent 2

3	1	*	*	*	*	2	*	4

The generated pair of children are:

Children 1

1	2	5	6	3	9	8	7	4

Children 2

2	1	6	9	8	5	3	7	4

The Pseudo-code for the modified order crossover was as follows,

Pseudo-code of modified order crossover

Input: Parents $a_1 = [a_{1,1}, a_{1,2}, \dots, a_{1,n}]$ and $a_2 = [a_{2,1}, a_{2,2}, \dots, a_{2,n}]$
Output: Children $b_1 = [b_{1,1}, b_{1,2}, \dots, b_{1,n}]$ and $b_2 = [b_{2,1}, b_{2,2}, \dots, b_{2,n}]$
Initialize

- Initialize b_1 and b_2 being empty genotypes;
- Choose two crossover points p and q such that $1 \leq p \leq q \leq n$; $j_1 = j_2 = k = q+1$;

$i = 1$;
Repeat

if $a_{1,i} \notin \{a_{2,p}, \ldots, a_{2,q}\}$ **then** $b_{1,j_1} = a_{1,k}$; j_1++;
if $a_{2,i} \notin \{a_{1,p}, \ldots, a_{1,q}\}$ **then** $b_{2,j_1} = a_{2,k}$; j_2++;
k=k+1;
Until $i \leq n$

$$b_1 = [b_{1,1}, \ldots b_{1,p-1} a_{2,p}, \ldots, a_{2,q} b_{1,p} \ldots, b_{1,n-p}]$$

$$b_2 = [b_{2,1}, \ldots b_{2,p-1} a_{1,p}, \ldots, a_{1,q} b_{2,p} \ldots, b_{2,n-p}]$$

3.3.7. The heuristic mutation

A better offspring can be produced with a heuristic mutation operator - the neighborhood technique (Gen and Cheng, 1997).

4. EXPERIMENTATION

4.1. Computational Tests

The C-GA-PSOs code is implemented in MATLAB R2019a on Intel core 2 Duo (2.00 GHz), 6GB RAM PC. Test data is referring to the benchmark instances generated in [42] [43]. The first set of instances is obtained from the instances E-n22-k4, E-n33-k4, and E-n51-k5. The instances are generated by considering six pairs of randomly selected satellites from customers, the depot is internal to the customers' areas. Considering the realistic layout of the satellites, the second data set is also obtained from the instances E-n22-k4, E-n33-k4, and E-n51-k5, but we consider six pairs of the satellites randomly chosen between the customers, while the satellite is border random selected from the customers. The third data set is obtained from Crainic et al. (2010), which comprises 12 instances with 100 customers. All instance sets can be downloaded from the website of OR-Library. The characteristics of the benchmark tests are shown in **Table 2.** Per-mile CO2 emissions costs and energy costs for the van and ADV are calculated based on the formula proposed by Feng and Figliozzi [44], the unit handling cost is referring to [45]. Considering most packages are less than 5 lbs (2.3 kg), it was assumed that the ADV could carry up to eight customers. A fully charged ADV will go up to 100 miles before needing overnight recharging.

Table 2: Characteristics of the benchmark tests

Set	No. of instances	Location of depot	n_s	n_f	m^{van}	m^{ADV}	Q^{van}	Q^{ADV}	Satellite distribution	Customer distribution
1	6	Internal of customers' area	2	21	1	4	1320	360	Random	Christofides and Eilon (1969) E-n22-k4 instance
1	6	Internal of customers' area	3	32	1	4	1320	360	Random	Christofides and Eilon (1969) E-n33-k4 instance
1	6	Internal of customers' area	2	50	1	5	1320	360	Random	Christofides and Eilon (1969) E-n51-k5 instance
2	6	Internal of customers' area	5	100	5	32	1320	140	Random	Crainic et al. (2010)
2	6	Internal of customers' area	10	100	5	35	1320	360	Random	Crainic et al. (2010)

3	6	Christofides and Eilon (1969) E-n22-k4 instance	2	21	3	4	1320	360	Border Random	Christofides and Eilon (1969) E-n22-k4 instance
3	6	Christofides and Eilon (1969) E-n33-k4 instance	2	32	3	4	1320	360	Border Random	Christofides and Eilon (1969) E-n33-k4 instance
3	6	Christofides and Eilon (1969) E-n51-k5 instance	2	50	3	5	1320	140	Border Random	Christofides and Eilon (1969) E-n51-k5 instance

The parameters of the C-GA-PSOs for the problems are: size of population = 25, number of iterations = 500, rate of crossover = 0.3, and rate of mutation = 0.2, number of particles=40, selection probability=1/3, inertia weight factor is a uniform random value between -8 and 8, the maximum velocity is 2.

4.2. Comparison of algorithms

We compare the performance of the C-GA-PSOs with HGA-2 (developed by William Ho et al. [46]) on set 1 and 2. Set 1 contains small instances with up to 50 customers and two or four satellites. **Table 3** contains the instance name and the number of satellites in Columns 1 and 2. Columns 3, 4, 5, and 6 show the performance of the C-GA-PSO, and Columns 7, 8, 9, and 10 show the performance of the HGA-2, providing for each heuristic the value of the best initial population, the computational time, the final best solution and the improvement rate. We find the best initial solutions produced by C-GA-PSOs are superior to those generated by HGA-2 in most of the instances except E-n33-k4-s4-, E-n33-k4-sl4-22, E-n33-k4-sl4-22, E-n51-k5-02-17, E-n51-k5-s 06-12, E-n51-k5-s11-19 for set 1. This phenomenon proves that both improvement rates of the C-GA-PSOs and the HGA-2 are low. Therefore, the improvement of the final result compared to the initial solution is limited.

Set 2 contains small instances with up to 50 customers and four or five satellites, which is shown in **Table 4**. The C-GA-PSOs finds the optimal solution for the instances where it is known. More precisely, four solutions that are slightly worse (E-n22-k4-s13-16, E-n22-k4-s19-21, E-n33-k4-s19-26, E-n33-k4-s22-26), the average solution quality of the C-GA-PSOs is better than the average solution quality of the HGA-2.

Table 3. Performance comparison of the algorithms for set 1

Set No. of instances	Num. of satellites	C-GA-PSO				HGA-2			
		Best initial population	CPU Time	Final best solution	Improvement rate a (%)	Best initial population	CPU Time	Final best solution	Improvement rate a (%)
E-n22-k4-s6-17	2	433.92	14.2	433.92	0.00%	435.19	13.8	435.19	0.00%
E-n22-k4-s8-14	2	78.42	11.9	69.17	11.80%	84.66	10.3	71.37	15.70%
E-n22-k4-s9-19	2	502.31	15.4	497.21	1.02%	503.2	15.6	500.67	0.50%

E-n22-k4-sl0-14	2	440.43	11.3	435.86	1.04%	440.63	11.3	434.63	1.48%
E-n22-k4-sll-12	2	431.47	11.3	440.89	7.09%	432.67	11.4	432.48	4.67%
E-n22-k4-sl2-16	2	121.87	15.1	105.94	13.07%	133.72	16.7	118.80	11.16%
E-n33-k4-sl-9	2	765.02	14.4	747.36	2.31%	767.76	16.5	760.83	0.9%
E-n33-k4-s2-13	2	752.79	13.4	723.45	3.9%	765.58	15.6	728.70	4.82%
E-n33-k4-s3-17	2	783.38	13.8	710.29	9.33%	771.31	14.9	710.49	7.9%
E-n33-k4-s4-5	2	862.36	13.2	813.15	5.71%	851.38	14.9	810.24	4.83%
E-n33-k4-s7-25	2	909.87	12.7	856.25	5.89%	865.51	12.4	841.86	2.73%
E-n33-k4-sl4-22	4	627.50	20.9	623.13	0.7%	636.98	25.5	620.39	2.6%
E-n51-k5-s02-17-46	2	770.94	21.7	732.54	4.98%	764.29	26.0	733.47	4.03%
E-n51-k5-02-17	2	659.61	18.2	626.39	5.04%	756.39	25.2	690.13	8.76%
E-n51-k5-s04-46	2	756.96	21.2	663.45	12.35%	716.73	24.9	684.50	4.50%
E-n51-k5-s 06-12	4	625.99	18.3	616.63	1.50%	626.78	22.3	626.78	0.00%
E-n51-k5-s 06-12-32-37	2	809.29	15.5	750.65	7.25%	778.28	20.7	758.34	2.56%
E-n51-k5-s11-19	4	667.47	20.1	644.95	3.38%	671.83	26.3	657.41	2.15%
E-n51-k5-s11-19-27-47	2	649.11	13.2	644.64	7.79%	687.67	19.4	651.34	5.82%
E-n51-k5-s27-47	2	697.66	15.7	672.68	3.58%	700.18	19.6	663.43	5.25%
E-n51 -k5-S32-37									

[a] Improvement rate= $(Best\ initial\ solution - Final\ best\ solution) / Best\ initial\ soluton$ *100%

Table 4. Performance comparison of the algorithms for set 2

instances	Num. of Satellites	C-GA-PSO avg.	HGA-2 avg.	% deviation	instances	Num. of Satellites	C-GA-PSO avg.	HGA-2 avg.	% deviation
E-n22-k4-s13-14	4	541.48	577.17	0.3569	E-n33-k4-s22-26	4	733.38	710.29	-0.2309
E-n22-k4-s13-16	4	551.20	547.82	-0.0338	E-n33-k4-s24-28	4	766.37	771.49	0.0512
E-n22-k4-s13-17	4	496.38	502.83	0.0645	E-n33-k4-s25-28	4	730.37	732.91	0.0254
E-n22-k4-s14-19	4	512.53	537.99	0.2546	E-n51-k5-s12-18	5	823.09	885.95	0.6286
E-n22-k4-s17-19	4	561.30	644.02	0.8272	E-n51-k5-s12-41	4	967.01	953.26	0.3569
E-n22-k4-s19-21	4	575.93	572.37	-0.0356	E-n51-k5-s12-43	4	914.94	1005.70	0.9076
E-n33-k4-s16-22	4	745.28	765.20	0.1992	E-n51-k5-s39-41	4	865.33	878.44	0.1311
E-n33-k4-s16-24	4	768.86	796.33	0.2747	E-n51-k5-s40-41	4	781.92	806.68	0.2476
E-n33-k4-s19-26	4	734.37	731.69	-0.0268	E-n51-k5-s40-43	4	919.55	943.77	0.2422

We tested the same procedure (C-GA-PSOs and HGA-2) on a larger data set with 100 customers. These instances present different realistic distribution of both customers and satellites. Given the complexity of the model, the involved number of constraints, and the large scale of the data set, it is not surprising that the solver takes a longer time to obtain a reasonable solution. On the other hand, an enhancement procedure of operator selection can help to reduce the computational time. **Table 5** presents the results of C-GA-PSO and HGA-2. The table contains the instance name and the number of satellites in Columns 1 and 2. Columns 3, 4, 5, and 6 show the performance of the C- GA-PSO, and Columns 7, 8, 9, and 10 show the performance of the HGA-2, providing for each heuristic the value of the best initial population, the computational time, the final best solution and the improvement rate. From the efficiency point of view, the CPU times of C-GA-PSO are less in the instances of 2EVRP-100-5-1b, 2EVRP-100-5-2, 2EVRP-100-5-2b, 2EVRP-100-5-3b, 2EVRP-100-10-1, 2EVRP-100-10-1b, 2EVRP-100-10-2b, and 2EVRP-100-10-3b, because of the usage of an enhancement procedure of operator selection, especially the size of the instances is more than 100 customers. From the results, we can see that the improvement rate is still limited to 7%.

Table 5. Performance comparison of the algorithms on set 3

Set No. of instances	Num. of satellites	C-GA-PSO				HGA-2			
		Best initial population	CPU Time	Final best solution	Improvement rate (%)	Best initial population	CPU Time	Final best solution	Improvement rate (%)
2EVRP-100-5-1	5	1751.18	68	1746.81	0.25%	1785.95	67	1772.61	0.75%
2EVRP-100-5-1b	5	1337.91	67	1310.46	2.05%	1324.56	78	1290.67	2.56%
2EVRP-100-5-2	5	1583.35	59	1512.26	4.49%	1603.99	63	1571.74	2.0%
2EVRP-100-5-2b	5	1637.23	64	1587.01	0.25%	1701.86	71	1696.57	0.31%
2EVRP-100-5-3	5	1203.80	61	1140.96	5.22%	1162.44	56	1158.96	1.02%
2EVRP-100-5-3b	5	1090.88	57	994.81	7.1%	1026.32	69	993.82	4.1%
2EVRP-100-10-1	10	1238.94	58	1235.55	0.27%	1250.94	69	1232.21	1.5%
2EVRP-100-10-1b	10	1088.45	59	1083.3	0.47%	1103.65	65	1103.19	0.04%
2EVRP-100-10-2	10	1511.89	68	1490.15	1.44%	1434.25	68	1416.60	1.2%
2EVRP-100-10-2b	10	1456.06	52	1354.27	6.99%	1439.23	54	1403.09	2.51%
2EVRP-100-10-3	10	1179.18	65	1176.24	0.25%	1187.01	62	1176.78	0.86%
2EVRP-100-10-3b	10	1036.82	56	1027.21	0.93%	1025.42	66	1023.73	0.16%

4.3. Application and Output Illustration

We analyzed the solution results when adopting the above-proposed algorithm in terms of location of depot-customer and customer density. The experiment addresses instances with variable-density customer distributions and different depot locations. Two data sets with different customer density were generated for a total of 38 instances. In each data set, instances with 21, 32 and 50 customers, 2 and 4 satellites, and different depot locations were generated. The data set with low customer density (Table 6) was generated occasionally in a square [-100,100], X = 200 * rand (1, 19) - 100; Y = 200 * rand (1, 19) – 100. The data set with high customer density (Table 7) was generated occasionally in a square [-50, 50], X = 100 * rand (1, 19) - 50; Y = 100 * rand (1, 19) – 50. Two depot-location have been tested, and the depot is located inside the customer area, ± 25 units from the center of the square. The depot is located between 50 and 100 units beyond the lower frontier of the square (recall that the square is 200 x 200 units). In these two kinds of layout, the satellites were located around the customer sites. It can be seen from **Table 6** that when the customer density is low, the total costs are lower when the depot locates within the customer's area, except for the instances E-n33-k1-s2-7, E-n51-k1-s4-12, E-n51-k1-s4-16. With the increase of the customer density, the lowest costs are achieved when the depot locates outside of the customer's area. It can be explained by taking into consideration of package consolidation cost and emission cost for the conventional van and ADV. There was a break-even quantity of satellites when the number of customers increases.

Table 6. The impact of depot location on the total cost with low density customer

Instance	Number of satellite	Depot location (to the customer's area)	Total Cost	Depot location (to the customer's area)	Total Cost
E-n22-k1-s2-1	2	Internal	447.76	External	530.25
E-n22-k1-s2-2	2	Internal	379.12	External	534.58
E-n22-k1-s2-3	2	Internal	489.34	External	552.79
E-n22-k1-s2-4	2	Internal	390.44	External	528.42
E-n22-k1-s2-5	2	Internal	440.43	External	582.14
E-n33-k1-s2-6	2	Internal	434.35	External	563.98
E-n33-k1-s2-7	2	Internal	107.14	External	105.05
E-n33-k1-s2-8	2	Internal	629.97	External	846.15
E-n33-k1-s2-9	2	Internal	654.52	External	739.28
E-n33-k1-s2-10	2	Internal	610.20	External	705.04
E-n33-k1-s2-11	2	Internal	619.61	External	783.83
E-n51-k1-s4-12	4	Internal	741.05	External	741.01
E-n51-k1-s4-13	4	Internal	675.95	External	798.36
E-n51-k1-s4-14	4	Internal	685.64	External	824.71
E-n51-k1-s4-15	4	Internal	654.34	External	780.83
E-n51-k1-s4-16	4	Internal	810.07	External	802.68
E-n51-k1-s4-17	4	Internal	626.64	External	762.08
E-n51-k1-s4-18	4	Internal	668.19	External	813.97
E-n51-k1-s4-19	4	Internal	691.02	External	772.90

Table 7. The impact of depot location on the total cost with high customer density

Instance	Number of satellite	Depot location	Total Cost	Depot location	Total Cost
E-n22-k4-s6-17	2	Internal	447.76	External	403.25
E-n22-k4-sl0-14	2	Internal	379.12	External	534.58
E-n22-k4-s9-19	2	Internal	489.34	External	552.79
E-n22-k4-sll-12	2	Internal	393.07	External	393.78
E-n22-k4-sl2-16	2	Internal	440.43	External	582.14
E-n33-k4-sl-9	2	Internal	434.35	External	563.98
E-n33-k4-s2-13	2	Internal	119.28	External	108.01
E-n33-k4-s3-17	2	Internal	632.97	External	602.77
E-n33-k4-s7-25	2	Internal	623.48	External	593.52
E-n33-k4-sl4-22	2	Internal	578.55	External	530.69

E-n51-k5-s2-4-17-46	2	Internal	619.61	External	581.84
E-n51-k5-s02-17	4	Internal	736.12	External	747.52
E-n51-k5-s4-46	4	Internal	601.88	External	798.36
E-n51-k5-s6-12	4	Internal	764.58	External	740.60
E-n51-k5-s6-12-32-37	4	Internal	652.17	External	599.85
E-n51-k5-s11-19	4	Internal	749.29	External	715.03
E-n51-k5-s11-19-27-47	4	Internal	626.64	External	762.08
E-n51-k5-s32-37	4	Internal	691.02	External	772.90

5. CONCLUSIONS

This study provides a tactical planning view for an E-grocery delivery network when a traditional van and an ADV are combined in the last-mile delivery. We present a model for a 2E-VRP-MV to minimize transport and emission costs when adopting an ADV in the E-grocery delivery process. We proposed a C-GA-PSO for solving the problem and demonstrated the model's applicability using numerical studies based on the implementation of instance tests. It shows the best initial solutions produced by C-GA-PSOs are superior to those generated by HGA-2. We also developed a hybrid GA-PSO step that generates a high-quality solution to the problem within an acceptable computational time.

To further testify the effectiveness of the designed two-echelon delivery network assisted by ADV, we applied 2E-VRP-MV model and our solution algorithm to two scenarios that evaluate the impact of the customer density and the depot location on total costs. The results show that when the customer density is low and the depot is located inside the customer's area, the lowest costs are achieved. With the increase of the customer's density, the lowest costs for most of the instances are achieved when the depot is located outside the customer's area. It can be explained by the total system cost is influenced by consideration package consolidation cost and emission cost.

The capacity of the van and ADV, the weight of the customer order, the layout of depot-customer, the emission cost of the van, the handling cost and customer density are key factors for achieving minimum total cost. The instances generated from the sets 1, 2 and 3 present a distribution of the customers, which is quite different from the distribution in realistic applications in urban and regional delivery. Future research is required to test the model and algorithm in more realistic data set. Besides, the sensitivity analysis will be addressed between transport cost and emission cost. Other influential factors, such as the speed of the ADV will be involved in the model.

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