Journal of Optimization in Industrial Engineering

Vol.18, Issue 1, Winter & Spring 2025, 223-232

Research Article

Medical goods distribution and pharmacological waste collection by plug-in electric vehicles with load-dependent energy consumption: Shuffled frog leaping algorithm

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https://doi.org/10.71720/joie.2025.1184399

Received: 18 September 2024
Revised: 01 February 2025
Accepted: 13 February 2025

Abstract

The transportation sector, is the undeniable foundation of economic and industrial development. Despite the importance of transportation to global life, it is considered dangerous for the world since it is one of the hugest consumers of petroleum products. These days, with the objective of reducing fixed and economical costs of vehicles, fuel costs, and gas emissions, most transportation systems are planning to have simultaneous pickup and delivery systems. The amount of emissions depends mainly on the amount of fuel consumed, the type of fuel, the mileage travelled, and the amount of load in that distance. Using alternative energy sources is one way to decrease greenhouse gas emissions and environmental pollution. On the other hand, the amount of fuel consumption of the vehicles is dependent on the amount of their load and it is necessary to consider their load in the planning. Hence, the work presented in this paper is focused on a medical goods distribution problem with pharmacological waste collection by plug-in hybrid vehicles considering the amount of energy consumption depends on the load of the vehicle. The problem has been modelled as a mixed integer linear programming with the aim of properly finding the route of all the vehicles with the objective of minimizing the economic costs and fuel costs of vehicles. GAMS software was used for model validation and by solving it in small size, its validity has been confirmed. Due to the complexity of this problem, the shuffled frog leaping algorithm is used for solving large-size instances. Then, the used algorithm is compared with a hybrid genetic algorithm and simulated annealing algorithm. Finally, the results obtained from the comparison of the exact solution and meta-heuristic algorithms showed that the proposed algorithm has a good performance in terms of solution quality and runtime.

Keywords:
Plug-in vehicle routing;
Energy consumption;
Shuffled frog leaping algorithm;
Pickup and delivery

Citation:
Behnamian, J., & Kiani, Z. (2025). Medical goods distribution and pharmacological waste collection by plug-in electric vehicles with load-dependent energy consumption: Shuffled frog leaping algorithm. *Journal of Optimization in Industrial Engineering*, 18(1), 223-232. https://doi.org/10.71720/JOIE.2025.1184399

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1. Introduction

Medical equipment and goods are an important part of the treatment process. Medical centers get the equipment they need from companies that produce or distribute equipment. Considering that a significant part of the costs of any organization is related to the costs of transportation and movement of equipment and facilities, one of the biggest concerns of the distribution and procurement unit is always to deliver the goods to the customers at the lowest possible cost and in the shortest possible time. For this reason, today the topics related to transportation and routing of vehicles have been given more attention than before and organizations try to minimize transportation costs by eliminating unnecessary tours, optimal use of existing facilities, and improving vehicle routes, in addition to increasing flow and reducing travel time. Regarding the distribution of medical equipment, due to the importance of this equipment in medical centers, it is important to deliver this equipment to the centers at the right time. Currently, the main companies that supply medical equipment and hospitals, and the companies that produce and distribute the equipment are rated and show which companies have the right activity and price. Also, rating the brands has created suitable competition among the companies. With this introduction, it can be claimed that understanding the importance of the role of the transportation system and its effect on the performance of companies leads to the use of the vehicle routing problem to achieve optimal distribution routes with the lowest cost. Therefore, due to the competitiveness of the logistics network, companies that can deliver orders to medical centers in a reasonable time and at a lower cost and gain their satisfaction will be more successful. On the other hand, with the rapid development of industry and economy, transportation is one of the main sources of carbon emissions. According to the published statistics, the amount of carbon emissions in China's transportation industry constitutes almost one-fifth of the total social emissions. China bears social responsibilities and pressures to reduce the emission of polluting gases and save energy. Hence, achieving low-carbon logistics is an important part of a low-carbon economy (Wang et al., 2024). With this concern, it can be said that compared to conventional cars, electric cars have many advantages such as almost zero carbon emission, high energy efficiency and less pollution (Xia et al., 2024). Because the problem investigated in this research is completely a problem in the real world, it should be noted that current limitations such as the lack of sufficient charging stations in cities and roads limit the use of all-electric cars. On the other hand, the problems with these vehicles are that their batteries don't hold much energy, and they take a long time to recharge. Therefore, plug-in hybrid cars have been used in this research. In addition, since electric vehicles have a limited energy source and their fuel consumption depends on the amount of cargo they carry, it is important to consider the vehicle's load when planning. The mentioned cases have necessitated the need for a planned and documented routing system with environmentally friendly vehicles. Such a system can find the set of optimal routes for the distribution of goods between medical centers, taking into account the existing limitations and delivering the goods on time, in addition to reducing the total cost of distribution or the total time taken for service, the amount of carbon emission can be minimized.

Since there are limitations in the real world from medical centers or drug distribution centers, such as pharmaceutical waste and the need to collect them at the same time as the delivery of requested medical goods and load-dependent energy consumption, in order to be closer to reality, it is necessary to develop previous models in order to provide a more efficient model and an efficient algorithm to solve this problem quickly and optimally. In this regard, this paper deals with the medical goods distribution and pharmacological waste collection in real life. In this study, we consider small and medium-sized medical distribution companies that have an impact in their area. The main goal is to help them plan their daily delivery routes in a way that keeps costs low and uses less energy, while also taking real-life limitations into account. As mentioned earlier, air pollution is a big issue with shipping goods, so plug-in hybrid electric vehicles are being used for transportation. On the other hand, because electric batteries have a limited amount of energy, how much fuel this fleet uses depends a lot on how much they are carrying. Finally, this research looks at how using plug-in hybrid electric vehicles for delivering medical supplies and collecting wasted medications affects how much fuel is used, based on how much weight the vehicles carry. For this purpose, a mathematical model has been developed in this research, and since the proposed model can only be used to solve problems with small dimensions, a new algorithm called the shuffled frog leaping algorithm has been developed to solve problems with larger dimensions. In this research, the following questions are answered:

- What is the order of customer service?
- When does the vehicle deliver the goods to the customer?
- How much of the route does it use electricity and how much gasoline?
- How much should be the amount of loading of each vehicle in each route?
- How much cargo does it load from the depot and how much cargo does it return to the depot?
- What is the charge level or fuel level of the vehicle when it reaches customers and gas stations?

The following sections of the paper are as follows. Section 2 reviews the literature on the subject. Section 3 describes the problem and its mathematical modeling. Section 4 describes the proposed meta-heuristic approach which is the shuffled frog leaping algorithm. Section 5 reports the computational results, and finally, Section 6 discusses the final conclusions.

2. Literature Review

The challenge of figuring out the best paths and planning routes for vehicles is called Vehicle Routing Problems (VRPs). The first routing problem was introduced by Dantzig and Ramser in 1959 to help with organizing truck deliveries. By looking at more needs, different limits on generating routes, and the kinds of problems that come up, different types of VRPs have been created. For example, in the Capacitated Vehicle Routing Problem (CVRP), customers who need items are served by vehicles that can only carry a limited amount, ensuring that their needs are met without exceeding the vehicle’s capacity on each trip. The pickup and delivery in the VRP include both delivering items to customers and picking up items from them. The multiple depot VRP means there are several starting points (depots) where vehicles can begin or finish their routes. The VRP with time windows requires that services be provided to customers during specific time periods. The idea of a VRP with pickups and deliveries at the same time was first introduced by Min in 1989. He looked at the issue of sending and collecting books from a main library to 22 distant libraries. He grouped the customers together and solved the Traveling Salesman Problem (TSP) for each group. Osaba et al. (2019) looked at the practical problem of delivering drugs while also collecting medical waste. They studied the problem as a type of delivery challenge where multiple vehicles pick up and drop off items at the same time. They also looked at different costs for each route, roads that can’t be used, and limits on how much money can be spent. A new and better Bat Algorithm (DaIBA) was created to fix the problem. Recently, different types of VRPs with new uses have been discussed. For instance, by looking at the gas emissions from cars, people have thought about Green Vehicle Routing Problems (GVRP). The International Road Transport Union (IRU) reported that in 2004, traffic jams in the United States caused about 100 billion liters of fuel to be wasted, which is equal to 250 billion tons of CO_2. There are two main ways to reduce vehicle emissions: one is to focus on how much fuel vehicles use and plan their routes to save fuel. The other is to use eco-friendly vehicles.

Distribution companies want to use less fuel when delivering goods for two main reasons. First, using less fuel will lower their costs, which means they can make more money. The second reason is that using less fuel will lower the bad effects of greenhouse gases and air pollution. It's known that the cost of driving a vehicle on a road depends on several things. These factors can be grouped into two types. The factors in the first group, like how far you are going, how heavy your load is, how fast you are driving, the condition of the roads, how much fuel your vehicle uses for each mile, and the price of fuel, all affect your travel plans directly. The things in the second group don’t directly affect the travel schedule. They include tire and vehicle wear and tear, upkeep costs, driver pay, taxes, and so on. In comparison, the things in the first group are directly linked to how much fuel is used, so they can be seen as costs that change with fuel use. Also, if everything else stays the same, how much fuel is used mainly depends on how far you go and how much weight you're carrying. For example, it costs less to drive an empty vehicle than to drive a full one when going the same way and at the same speed (Xiao et al, 2012). Kara et al. (2007) suggested a way to calculate costs based on how far a vehicle travels and how much it carries for a problem called the Capacitated Vehicle Routing Problem. They proposed a mathematical model using integer linear programming that involves a certain number of binary variables and constraints, specifically $O(n^2)$, for pickup and delivery situations separately. Xiao et al. (2012) included the Fuel Consumption Rate (FCR) in the CVRP. This change allows researchers to focus on reducing fuel use while still considering how much weight the vehicles carry. A new method using a combination of exchange rules was proposed to solve the problem.

Goeke et al. (2015) suggested a new way to plan routes for a mix of electric delivery vehicles and regular fuel-powered delivery vehicles. This method called the Electric Vehicle Routing Problem (EVRP) with Time Windows and Mixed Fleet (E-VRPTWMF), aims to improve vehicle routing. It uses a practical model to understand energy use based on speed, road incline, and how much cargo is being carried. They created a way to find solutions called Adaptive Large Neighborhood Search, which uses a local search method to help solve the problem. Zhang et al. (2015) suggested a model for a routing problem that focuses on reducing carbon emissions. They added costs of fuel and carbon emissions to the vehicle routing problem. They also developed a better version of a problem-solving method called RS-TS to find solutions for this model. Palmer (2007) suggested a quick way to measure fuel use for delivery trucks. He looked at how fast the truck goes and how that speed can help lower CO_2 emissions. The author found that using less fuel instead of just reducing the distance can lower CO_2 emissions by 5%. Koç et al. (2014) suggested a problem with pollution and routing that involves different types of vehicles and takes into account the number of vehicles in the fleet. Their objective function was to lower the total costs of keeping vehicles, as well as the costs of driving them, which includes fuel, CO_2 pollution, and driver wages. Poonthalir and Nadarajan (2018) suggested a way to plan routes for GVRP that save fuel, considering bi-objective and different speed limits. They suggested a model to reduce travel costs and fuel use by using goal programming. They also proposed a new method called Particle Swarm Optimization with a Greedy Mutation Operator and a changing acceleration coefficient to solve the problem. As mentioned before, another way to reduce CO_2 emissions is by using green vehicles. The EVRP is a version of the regular vehicle routing problem, but it involves vehicles that run on electricity instead of gasoline. Using electric vehicles for transportation helps cut down greenhouse gas emissions, supports companies in reaching their sustainability goals, and lowers operating costs. In gasoline and diesel cars, 75% of the energy is lost as heat and friction, and only 25% is used to move the wheels. In electric cars, only 20% of the energy is lost. However, having a small battery size, different ways to charge it, and a long-lasting battery make these problems really tricky. Many researchers are interested in these challenges, so more and more studies are being done on this topic. Conrad and Figliozzi (2011) studied the VRP using electric vehicles. In their idea, these vehicles could charge up at customers' locations, and this would add extra time to the overall trip. Their objective was to reduce the number of vehicles and keep costs low while considering distance, charging time, and service time. Schneider et al. (2014) introduced a new version of VRP that includes time limits and charging stations (E-VRPTW). In this version, vehicles can be recharged at any available charging station. They suggested a new method that mixes two techniques: a variable neighbourhood search and a tabu search. Mancini (2017) came up with a new type of routing problem called Hybrid-VRP (HVRP). He formulated this problem as a mixed integer linear programming and designed a method called Large Neighborhood Search to find optimal solutions.

Plug-in hybrid cars have two types of engines: one that runs on gasoline and another that runs on electricity from a rechargeable battery. These vehicles can use fossil fuel instead, so they don't have to go to charging stations (Hiermann et al, 2019). This is why researchers find plug-in hybrid vehicles interesting. Arslan et al. (2015) suggested a way to find the cheapest route for Plug-in Hybrid Electric Vehicles on a road network that has places to refuel and charge. They used dynamic programming as well as a quick way to find the shortest route to solve the issue. Hiermann et al. (2019) looked into how to manage a group of regular cars, plug-in hybrid cars, and electric cars. They combine a genetic algorithm with local and large search techniques to solve the problem. The findings show that using different types of vehicles together can greatly lower operating costs in many different price situations, compared to using only one type of vehicle.

Hospitals are using more advanced tools and technology for diagnosing, treating, and caring for patients. These medical devices have become an important part of providing health care. Managing medical and lab equipment is a way for hospitals to take care of their equipment. In recent years, there have been big improvements in how medical and lab equipment is managed, especially in areas like oversight, engineering, and maintenance (Noweir et al, 2013). Traditional methods of delivering services in hospitals can lead to big problems. These include poor control of supplies, expensive mistakes, interruptions in patient care, and higher treatment costs (Santana et al, 2014). Haji Baklu et al. (2018) did a study on the medical supply chain in Iran. The goal was to look into and assess how medical equipment is provided to schools and hospitals. The results show that there is a strong connection between how medical equipment is distributed and the supply chain. Improving how information is shared in the medical supply chain can make managing it better. Shipping costs are really important for the medicine industry. In the Netherlands, insurance companies now really need to consider which brand to buy. This has caused a lot of competition among medicine suppliers over prices. This competition has caused medicine suppliers and distributors to make much less profit. Making distribution networks is important for suppliers because it can lower shipping costs and make customer service better. Pharmaceutical companies need effective delivery systems to succeed in today's competitive market (Zhu and Ursavas, 2018). Zhu and Ursavas (2018) studied how to distribute products in the pharmaceutical industry. They proposed a branch and cut and looked to choose locations and routes at the same time to find a solution. The results showed that this method can offer solutions to real-life problems in a reasonable runtime. Behnamian and Kiani (2024) focused on medical goods distribution with pharmacological waste collection by plug-in hybrid vehicles with simultaneous pickup and delivery. They modeled this problem to minimize the costs of traveling and energy consumption. The authors also proposed the artificial bee colony algorithm to solve large-size instances.

Through this review, it was found that the effect of load weight on energy consumption in the problem of medical supplies distribution and pharmaceutical waste collection using plug-in hybrid vehicles has not been studied in any of the research.

3. Problem Description and Mathematical Model

This paper considers a type of vehicle routing problem with simultaneous pickups and deliveries by plug-in hybrid electric vehicles considering the effect of load on energy consumption. There are three different types of nodes; a node represents the depot, a node that all vehicles start and end their routes. V_{cut} represents the hospitals, drug stores or health centres with demands for deliveries and pickups that all of them should be visited. V_{rec} represents the recharging stations that can be visited once or not at all. $z=\{fu, el\}$ show two types of energy sources: gasoline(fuel) and electricity. The assumptions of the model are as follows:

1. The number of deliveries and pickups that customers want is pre-deterministic.
2. The number of pickups can be none, less than, or more than the number of deliveries.
3. The distance, extra costs, and travel time between places are different and not the same in both directions.
4. The total cost of the edges in one path is not more than the highest cost allowed for that path.
5. The time spent at each center and the time to refuel at each station are mentioned.
6. The vehicle is assumed to have no waiting time for refueling.
7. Every vehicle at the station has a fully charged battery.
8. The total travel time for each vehicle is within the set limit.
9. All centers can send back their pharmaceutical waste to storage, as well as get the items they ordered.
10. The amount of deliveries and pickups for each vehicle is within what the vehicle can handle.
11. Each vehicle has a set amount of fuel and battery it can hold.
12. The energy used depends on how heavy the load is that the vehicle is carrying.

The following notations are used in the proposed model.

Notation

Sets

$V=\{0\}\cup V_{rech}\cup V_{cus}$	The set of all nodes
$z=\{fu, el\}$	The set of energy sources

Parameters	
$C_{\max}$	Maximum cost of each rout
$T_{\max}$	Latest time for coming back to the depot
Cap_k	Vehicle load capacity of each vehicle *k*
Q_{zk}	Capacity of energy sources type *z* for vehicle *k*
C_{ij}	Miscellaneous costs between vertices *i* and *j*
C_z	Cost rate for type *z* energy
t_{ij}	Traveling time over arc (*i*, *j*)
d_{ij}	Length of arc (*i*, *j*)
p_i	Service time at node *i*
$\rho_0(z,k)$	Fuel consumption rate of type z in vehicle k without load
$\rho^*(z,k)$	Fuel consumption rate of type z in vehicle k at maximum load
de_j	The amount of delivery demand to the customer *j*
pi_j	The amount of pickup demand at the customer *j*
M	A large enough number
Variables	
X_{ijk}	If arc (*i*, *j*) is used by vehicle *k*, = 0 otherwise
T_{ik}	Time to reach node *i* for vehicle *k*
Dl_{ij}	The amount of freight to be delivered to customers after node *i*
Pl_{ij}	The amount of cargo collected from customers before node *j*
L_{ijk}	The amount of load carried between the two *i* and *j* (kg)
y_{jzk}	The energy level of type z for vehicle k when arriving at node *j*
y'_{jzk}	The energy level of type *z* for vehicle *k* when arriving at the refueling station *j*

Based on the Behnamian and Kiani (2024), the problem can now be formulated as follows:

$$Min\ [\sum_{i\in V}\sum_{j\in V}\sum_{k\in K} C_{ij} * X_{ijk} + \sum_{i\in V}\sum_{j\in V}\sum_{k\in K}\sum_{z\in Z} C_z d'_{ijzk}(\rho_0(z,k) * X_{ijk} + \frac{\rho^*(z,k)-\rho_0(z,k)}{cap(k)} * L_{ijk})] \quad (1)$$

S.t.:

$$\sum_{k\in K}\sum_{j\in V:(i,j)\in A} X_{ijk} = 1 \qquad \forall i \in V_{cus} \quad (2)$$

$$\sum_{k\in K}\sum_{j\in V:(i,j)\in A} X_{ijk} \le 1 \qquad \forall i \in V_{rech} \quad (3)$$

$$\sum_{j\in V:(i,j)\in A} X_{ijk} = \sum_{j\in V:(i,j)\in A} X_{jik} \qquad \forall i \in V, k \in K \quad (4)$$

$$\sum_{j\in V\setminus\{0\}} X_{0jk} \le 1 \qquad \forall k \in K \quad (5)$$

$$\sum_{j\in V\setminus\{0\}} X_{j0k} \le 1 \qquad \forall k \in K \quad (6)$$

$$\sum_{i\in V}\sum_{j\in V} c_{ij} X_{ijk} \le C_{\max} \qquad \forall k \in K \quad (7)$$

$$t_{0j} - M(1 - X_{0jk}) \le T_j \qquad \forall j \in V\setminus\{0\}, k \in K \quad (8)$$

$$T_{ik} + (t_{ij} + p_i) - M(1 - X_{ijk}) \le T_{jk} \qquad \forall j \in V\setminus\{0,i\}, i \in V, k \in K \quad (9)$$

$$pl_{0jk} = 0 \qquad \forall j \in V\setminus\{0\}, k \in K \quad (10)$$

$$dl_{i0k} = 0 \qquad \forall i \in V\setminus\{0\}, k \in K \quad (11)$$

$$\sum_{k\in K}\sum_{i\in V:(i,j)\in A} pl_{jik} - \sum_{k\in K}\sum_{i\in V:(i,j)\in A} pl_{ijk} = pi_j \qquad \forall j \in V\setminus\{0\} \quad (12)$$

$$\sum_{k\in K}\sum_{i\in V:(i,j)\in A} dl_{ijk} - \sum_{k\in K}\sum_{i\in V:(i,j)\in A} dl_{jik} = de_j \qquad \forall j \in V\setminus\{0\} \quad (13)$$

$$\sum_{k \in K} \sum_{i \in V \setminus \{0\}} pl_{i0k} = \sum_{i \in V \setminus \{0\}} pi_i \tag{14}$$

$$\sum_{k \in K} \sum_{j \in V \setminus \{0\}} dl_{0jk} = \sum_{j \in V \setminus \{0\}} de_j \tag{15}$$

$$dl_{jik} + pl_{ijk} \le Cap_k * X_{ijk} \qquad \forall i \in V, j \in V, k \in K, i \ne j \tag{16}$$

$$L_{ijk} = dl_{jik} + pl_{ijk} \qquad \forall i \in V, j \in V, k \in K, i \ne j \tag{17}$$

$$(\rho_0(z,k)*X_{ijk} + \frac{\rho^*(z,k)-\rho_0(z,k)}{cap(k)}*L_{ijk})*\mathrm{d}_{ijz} - (1-\mathrm{X}_{ijk})\mathrm{Q}_{zk} \le y_{izk} - y_{jzk} \le (\rho_0(z,k)*X_{ijk} + \frac{\rho^*(z,k)-\rho_0(z,k)}{cap(k)}*L_{ijk})*\mathrm{d}_{ijz} + (1-\mathrm{X}_{ijk})\mathrm{Q}_{zk} \qquad \forall i \in V, j \in V_{cus}, z \in Z, k \in K \tag{18}$$

$$(\rho_0(z,k)*X_{ijk} + \frac{\rho^*(z,k)-\rho_0(z,k)}{cap(k)}*L_{ijk})*\mathrm{d}_{ijz} - (1-\mathrm{X}_{ijk})\mathrm{Q}_{zk} \le y_{izk} - y'_{jzk} \le (\rho_0(z,k)*X_{ijk} + \frac{\rho^*(z,k)-\rho_0(z,k)}{cap(k)}*L_{ijk})*\mathrm{d}_{ijz} + (1-\mathrm{X}_{ijk})\mathrm{Q}_{zk} \qquad \forall i \in V, j \in V_{rech}, z \in Z, k \in K \tag{19}$$

$$y_{izk} \ge (\rho_0(z,k)*X_{i0k} + \frac{\rho^*(z,k)-\rho_0(z,k)}{cap(k)}*L_{i0k})*\mathrm{d}_{i0z} \qquad \forall i \in V \setminus \{0\}, k \in K, z \in Z \tag{20}$$

$$Q_{zk} - (\rho_0(z,k)*X_{ijk} + \frac{\rho^*(z,k)-\rho_0(z,k)}{cap(k)}*L_{ijk})*\mathrm{d}_{ijz} \ge y_{jzk} \qquad \forall i \in V \setminus V_{cus}, j \in V, k \in K, z \in Z \tag{21}$$

$$y_{jzk} = Q_{zk} \qquad \forall j \in V, z \in Z, k \in K \tag{22}$$

$$X_{ijk} \in \{0,1\} \qquad (i,j) \in A, k \in K \tag{23}$$

$$Dl_{ij}, Pl_{ij} \ge 0 \qquad (i,j) \in A \tag{24}$$

$$L_{ijk} \ge 0 \qquad (i,j) \in A, k \in K \tag{25}$$

$$y_{jzk} \ge 0 \qquad j \in V, z \in Z, k \in K \tag{26}$$

$$T_j \ge 0 \qquad j \in V \tag{27}$$

The objective function (1) consists of two parts. The first part minimizes the total travel costs and the second part minimizes the total energy consumption cost depending on the vehicle load. Constraint (2) ensures that all customers are served exactly once. Constraint (2) ensures that there is a maximum of one follower after each refueling or charging station: one customer, station, or depot node. Constraint (4) ensures that a vehicle that enters a node must also leave the same. Constraints (5) and (6) guarantee that vehicles that are dispatched from the depot must eventually be returned. All vehicles start from a depot and return to it. Constraint (7) ensures that the total cost of each route does not exceed a maximum value. Constraints (8) and (9) are constraints related to the arrival time to each vertex. Restriction (8) also prevents the creation of a sub-tour. Constraints (10)-(15) indicate the amount of cargo in the vehicle at each node. Constraint (16) ensures that the amount of cargo carried does not exceed the capacity of the vehicle. Constraint (17) indicates the amount of load carried between nodes *i* and *j*. Constraints (18), (19), and (20) indicate the fuel/charge level of the vehicle when it reaches successive vertices. Constraint (21) indicates that the amount of fuel or charge remaining is proportional to the amount of energy consumed in the respective arc. Constraint (22) indicates that the *z*-type energy level reaches its full value after meeting the refueling or charging stations or going to the depot (the tank is full or the battery is fully charged). Constraints (22-27) represent the range of variables.

4. Shuffled Frog Leaping Algorithm (SFLA)

SFLA is a way of finding the best solutions by looking at a group of things, similar to how frogs look for food. A group of frogs jumping in a marsh. The swamp has several stones in different locations where the frogs can jump. The frogs want to quickly find the stone with the most food by getting better at sharing their information. The meme shows the location of the frogs. Frogs can communicate with each other and can get better at making memes by sharing information. Making memes better changes where a frog can jump by adjusting how far it hops. The group of virtual frogs is a population. The population is split into different groups that can grow and change separately and be explored in various ways. Frogs with better ideas need to do more to create new thoughts than frogs with less good ideas. To get an edge in making better memes, a triangular probability distribution is used to choose frogs. After a certain number of changes, information between groups of memes is shuffled. Shuffling makes memes better after they mix with ideas from other groups and helps culture grow in a way that isn't one-sided. Then, the local search and mixing process goes on until certain set goals are met (Lou et al., 2015).

In the SFLA, first, an initial population of *F* frogs is created randomly. For the d-dimensional problem, the position of the 'ith' frog is represented as $x_i = (x_{i1}, x_{i2}, \ldots, x_{id})$. Afterward, the frogs are sorted in descending order according to their fitness. Then the *F* frogs are divided into m memeplexes according to their fitness ordering, with n frogs at each memeplex (i.e., $F = m * n$), now there are *m* memeplex with n frogs in such a way that the first frog goes to the first memeplex, the second frog goes to the second memeplex, the mth frog goes to the mth memeplex, the $(m + 1)$th frog goes back to the first memeplex, and so on. The next step is constructing a sub-memeplex including q frogs for each memeplex. The main work of SFLA is to update the position of the worst-performing frog through iterative operation in each sub-memeplex. For this aim, a frog leaping algorithm is done at each memeplex. FLA improves a memeplex in detail as follows. At a memeplex with the size of n frogs, a sub-population including q frogs is chosen. It is reasonable to select the better frog's position with the higher probability in the sub-memeplex. Higher probability generated by a triangle probability distribution expressed in (28) is assigned to the frog with higher performance, according to which q frogs are selected out.

$$p_i = 2(m+1-i)/m(m+1) \qquad \forall i \tag{28}$$

Here, i is the number that shows the rank of the current frog based on how fit it is, listed from highest to lowest fitness. The group of q frogs is organized from the best to the worst based on how fit they are. In each small group of memes, p_B is the best position for a frog, and p_W is the worst position for a frog. Now we need to fix the worst frog position (p_W). Its place gets better by learning from the top frog in its group or from its own kind. In each small group, the new location of the worst frog is changed based on Equations (29) and (30).

$$U_q^{new} = p_W + s \tag{29}$$

$$S = r*(p_B - p_W) \quad S_{\min} \le S \le S_{\max} \tag{30}$$

where r is a random number in the range [0,1]. S_{min} and S_{max} are the minimum and maximum allowed changes in a frog's position, respectively. If the new position p_W is better than the old p_W, it replaces the old one. Otherwise, the best frog position of all memeplexes (p_X) is used and the calculation in Eqs (29) and (30) are repeated with the global best frog instead of p_X. If the improvement in this way cannot obtain a better position, by generating a random position the worst frog position would be replaced. The iteration continues for a predefined number of memetic evolutionary times within each memeplex, and then the whole population is mixed together in the shuffling process. Shuffling ensures that the cultural evolution towards any particular interest is free from bias. After shuffling, the searches for the optimal solution using the information in the independent memeplexes are again pursued. This local search and shuffling process continues until the defined convergence criterion is satisfied. In the following, the implementation details of the algorithm are described.

4.1. Solution representation

To keep the SFLA algorithm simple, we use a basic way to represent solutions. Suppose there are n customers and m charging stations that k vehicle routes visit. The arrangement of (m+n+k-1), the total number of places to visit (m+n), and the number of vehicles (k) are used to create the first possible route or solution. Numbers bigger than (m+n) are seen as separators. The series of nodes in between two separators is the order of customers that a vehicle will visit. The choices about which locations to visit, the order of visits, how much load is carried between different points, and the time it takes to get to each point all come from this set of data. To find out how much electric fuel and how much fossil fuel is used in each direction, make a table. This table should have two rows and a number of columns that is equal to the number of path points plus one. Next, we give each node on the path described in the earlier chromosome a column. If the distance between point i and point j is 1, we generate random numbers for this column that add up to one. This helps us understand how much of the distance is covered by electric fuel and how much is covered by fossil fuel.

4.2. Initial solution

A first solution is generated by assigning one customer to each of the m routes, one at a time. The customer is chosen by chance. The customer is placed in the location that costs the least to connect them to the current delivery routes. The steps above are done again and again until all customers are served. First, an initial solution is created. Then, the cost for each solution is calculated. The solution with the lowest cost becomes known as the best solution, and its cost is kept as the best value.

4.3. Local search

Most meta-heuristic methods work by moving from a current solution to a nearby solution and checking how much the results change. A neighborhood operator helps find a new solution, called x_{new}, from the current solution, which is x. In this study, we use three types of neighbor structures.

- ***Swap structure:*** This operator picks two positions, i and j, at random in the solution vector and swaps the customers in those positions.
- ***Insertion structure:*** This operator works by randomly picking two places, i and j, where i is different from j, and moving the customer from place i to place j. In the nearby structure where we are adding something, the arrangement of the parts is important. We pick two parts, take the first one out, and place it after the second one.
- ***Reversion structure:*** This operator involves picking two random positions, i and j. It moves a customer from position i to position j and also changes the order of the points in between.

5. Computational Results

In this section, we detail the experimental results of our proposed algorithm and the hybrid genetic algorithm and simulated annealing algorithm (GA-SA) as a competitor algorithm.

5.1. Evaluation metric

Relative percentage deviation (RPD) is a way to measure how well the algorithm is working. It is calculated using Equation (31), where Alg_{sol} represents the results from a certain algorithm (either A or B), and $Min_{A,B}$ is the smallest value of $\{Alg_A, Alg_B\}$.

$$RPD = \frac{Alg_{sol} - Min_{A,B}}{Min_{A,B}} \tag{31}$$

5.2. Numerical results

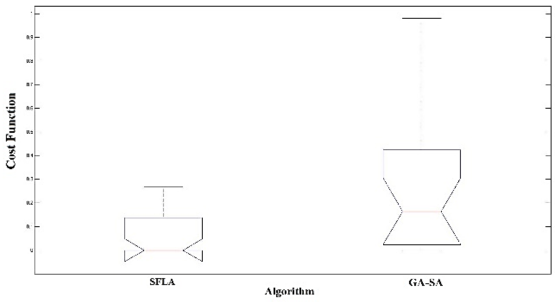
To see how well the SFLA algorithm works, we need to compare it with other similar methods. The SFLA method is being compared to the GAMS output and hybrid GA-SA. The table below shows the results of solving various problems of different sizes.

Table 1
Comparison of our two algorithms on best results and run time

0	Problem size	GAMS Cost Function	GAMS Runtime	SFLA Cost Function	SFLA Runtime	GA-SA Cost Function	GA-SA Runtime
Small	8*2*3	0	10.2	0.19401	25.0	0.60349	8.3
	10*2*3	0	557.1	0.18685	54.4	0.39448	9.2
	12*3*4	0	1373.6	0.14505	71.4	0.38290	8.5
	14*3*5	0	4907.1	0.10740	89.5	0.04745	63.7
Medium	27*3*6	-	-	0.14456	67.7	0	130.7
	36*4*6	-	-	0.26614	43.9	0	122.2
	50*5*8	-	-	0	102.7	0.31006	147.2
	60*6*8	-	-	0	100.4	0.19148	136.6
	70*6*10	-	-	0	133.0	0.13684	104.7
	80*6*11	-	-	0	66.6	0.06922	288.5
	90*8*12	-	-	0	84.0	0.71788	299.2
	100*8*15	-	-	0	186.7	0.48507	308.4
Large	110*10*15	-	-	0.12960	229.1	0	355.2
	115*10*20	-	-	0.10667	136.3	0	356.3
	125*10*20	-	-	0.11748	164.5	0	229.2
	135*10*20	-	-	0	212.7	0.05766	308.6
	145*12*20	-	-	0	228.4	0.45205	360.5
	155*14*20	-	-	0	322.9	0.98089	508.6
	176*14*25	-	-	0	184.2	0.32309	529.3
	186*14*30	-	-	0	216.9	0.04823	380.9
	Average	**-**	**-**	**0.069888**	**136.5**	**0.260043**	**232.7**

As it is clear from Table 1, the proposed algorithm has been able to obtain results close to the output of GAMS (as the optimal output of the proposed model) in a much shorter time in the small dimensions of the problem. Also, in this size, the quality of the SFLA algorithm is clearly better than the hybrid algorithm, which, of course, is obtained in more runtime than the GA-SA algorithm. In medium and large dimensions, the superiority has been completely with the SFLA algorithm, because the quality obtained from the algorithm has been clearly improved under the influence of the appropriate design of the local search embedded in it, and these operators have greatly contributed to the quality of the results at the same time as their simplicity and low time complexity and while in GA-SA, the convergence time in large dimensions is much longer due to the inherent slowness in the genetic algorithm, and at the same time, the quality of the objective function is lower than the SFLA algorithm. The next result is the increase in runtime in all methods by increasing the size of the solved problems, which is obvious and is due to the exponential nature of the runtime, and this growth is clearly evident in the runtime of GAMS.

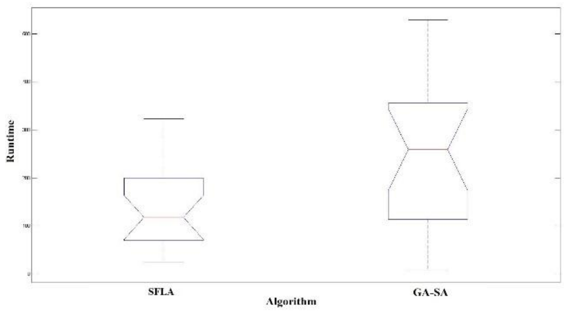
In the following, the significance of the difference between the algorithms was checked with the non-parametric Kruskal-Wallis test. The Kruskal-Wallis H test is a simple method used to find out if there are significant differences between two or more groups that do not rely on any specific mathematical assumptions. As shown in Figures (1) and (2), the results indicate the significant difference in runtime and the quality of the solutions obtained from the two algorithms, so that our algorithm was able to obtain good results in less runtime.



Kruskal-Wallis ANOVA Table

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	714.03	1	714.025	5.58	0.0182
Error	4275.97	38	112.526		
Total	4990	39			

Fig. 1. Kruskal-Wallis test for cost function



Kruskal-Wallis ANOVA Table

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	518.4	1	518.4	3.79	0.0515
Error	4811.6	38	126.621		
Total	5330	39			

Fig. 2. Kruskal-Wallis test for runtime

6. Conclusion and Future Research

One of the most important issues in the world today is air pollution caused by vehicles, which can be reduced by optimally planning the movement of vehicles in large areas such as public transportation or freight centers, reducing the use of diesel vehicles and replacing them with Electric or hybrid vehicles helped reduce this pollution. In this research, by solving a routing problem, an attempt has been made to design a suitable program for vehicles in medical equipment distribution companies. In this regard and in order to prevent the emission of greenhouse gases from hybrid vehicles with simultaneous pickup and delivery, it was considered that both activities can be performed at the same time when the vehicle leaves the depot and returns. Due to the existing limitations in the use of all-electric vehicles, such as the lack of proper charging stations, hybrid vehicles are used that have the ability to change the fuel mode. In this situation, if there is no charging station, the vehicle can change to normal fuel mode and drive to the charging station or the next customer with this fuel. On the other hand, to make the problem more realistic, it was assumed that the amount of energy consumed is directly related to the amount of vehicle loading. Also, time is considered as an influencing factor on customer satisfaction and company success. For this purpose, a mathematical model was first designed for the problem, and then the shuffled frog leaping algorithm was used to solve the problem in large dimensions. Finally, the efficiency of the proposed algorithm was compared with the hybrid genetic algorithm and simulated annealing algorithm. The results were analyzed using the non-parametric Kruskal-Wallis test. According to the resulting p-value, it was concluded that the null hypothesis, which was the equality of the groups' averages, was rejected, and it can be concluded that the proposed algorithm has a better performance in obtaining better objective function values (less cost) in less time. According to the limitations of the current research, the following areas are suggested to the researchers for doing new work:

- Integration of the model with the location model for locating charging stations,
- Considering multi-objective problems and other goals such as customer satisfaction, and
- Using other meta-heuristic algorithms to solve this problem.

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