Journal of Cleaner Production 364 (2022) 132571

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

A dynamic location-arc routing optimization model for electric waste collection vehicles

Sahar Moazzeni [a], Madjid Tavana [b,c,*], Sobhan Mostafayi Darmian [d]

[a] Department of Industrial Engineering, Shiraz University of Technology, Shiraz, Iran
[b] Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, USA
[c] Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, Paderborn, Germany
[d] Department of Industrial Engineering, University of Kurdistan, Sanandaj, Iran

ARTICLE INFO

Handling Editor: Prof. Jiri Jaromir Klemeš

Keywords:
Location-arc routing
Electric vehicles
Waste collection
Metaheuristic algorithms
Pandemic outbreak

ABSTRACT

Waste collection management plays a crucial role in controlling pandemic outbreaks. Electric waste collection systems and vehicles can improve the efficiency and effectiveness of sanitary processes in municipalities worldwide. The waste collection routing optimization involves designing routes to serve all customers with the least number of vehicles, total traveling distance, and time considering the vehicle capacity. This paper proposes a dynamic location-arc routing optimization model for electric waste collection vehicles. The proposed model suggests an optimal routing plan for the waste collection vehicles and determines the optimal locations of the charging stations, dynamic charging arcs, and waste collection centers. A genetic algorithm and grey wolf optimizer are used to solve the large-sized random generated NP-hard location-arc routing problems. We present a case study for the city of Edmonton in Canada and show the grey wolf optimizer outperforms the genetic algorithm. We further demonstrate the total number of waste collection centers, charging stations, and arcs for dynamic charging needed to ensure a minimum required service for electric vehicles throughout Edmonton's entire waste collection system.

1. Introduction

The global pandemic of coronavirus disease has disrupted life and caused distressing economic and social activities worldwide. The Municipal Waste Management (MWM) systems have been impacted drastically by the pandemic due to changes in population and consumption patterns, business closures, staff shortages, healthcare waste disposal, and restrictions on waste collection points, among others. Due to the coronavirus epidemic and the global effort to break the chain of the outbreak, street cleaning has become an essential task for many municipalities worldwide (Tripathi et al., 2020). Running street cleaning and sweeping operations has come at a high cost to local governments and municipalities. Given the identification of mutated strains of the virus that have raised concerns about global re-emergence, studies are needed to understand the impact of street cleaning and sweeping on reducing total suspended solids and associated pollutant wash-off from urban streets. Although several studies have examined the effects of the pandemic on the people and society, it is imperative to study further the challenges and innovations for effective MWM during and post-pandemic (Sharma et al., 2020). Sarkodie and Owusu (2020) have found that waste has increased significantly during the pandemic due to intensifying production and consumption caused by panic buying and increased usage of single-use products. The increased use of personal protective equipment, plastic-packaged food, and disposable utensils has also impacted plastic dependency, increased fossil fuel consumption (Vanapalli et al., 2020), and a new energy dependency and environmental crisis (Hof et al., 2017). One of the most effective strategies to manage energy dependency and ecological crisis is using electric vehicles to reduce fossil fuel consumption and develop the necessary infrastructure to create smart cities (Erdelić and Carić, 2019). The electric vehicle demand has risen dramatically over the past decade due to changing environmental regulations, improved batteries, availability of charging stations, and price comparability with internal combustion engine vehicles (Chen et al., 2017; Lin et al., 2016; Zhang et al., 2019).

The MWM activities are grouped into generation, collection, transportation, transformation, and disposal stages (Ghiani et al., 2012).

* Corresponding author. Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA, 19141, United States.

E-mail addresses: sahar.moazzeni@gmail.com (S. Moazzeni), tavana@lasalle.edu (M. Tavana), sobhan.mostafayi@gmail.com (S. Mostafayi Darmian).

https://doi.org/10.1016/j.jclepro.2022.132571
Received 2 August 2021; Received in revised form 15 May 2022; Accepted 2 June 2022
Available online 9 June 2022

Electric vehicles collect and transport solid waste, recyclables, and organics to recycling centers for transformation and disposal facilities. Waste collection and transportation costs account for 60–80% of the total MWM costs (Babaee et al., 2019). Moreover, waste collection operations and transportation are costly city services and should be managed efficiently in Canada (Farahbakhsh, 2019). The critical issues for using electric waste collection vehicles during the pandemic are the clean-up operation, landfill identification, waste disposal, and the minimization of the risk of spreading viral infections while determining suitable locations for charging the vehicles and reducing the required time for power supply (Raeesi and Zografos, 2020). Finally, obtaining optimal vehicle routes for cleaning operations can directly reduce cost and save energy. The clean-up operations spread throughout the municipality, and it is impossible to determine specific points/nodes for receiving urban services. Thus, designing and implementing an arc routing model is necessary to determine optimal vehicle routes (Laporte et al., 2019). The central premise of this paper is to develop a mathematical optimization model to coordinate decisions related to the location of waste collection centers and charging facilities with the optimal routing of vehicles and energy consumption objectives in pandemic outbreaks. For this purpose, the mathematical optimization model considers minimizing the establishment cost of various facilities, the operational costs of waste collection activities subject to facility location, arc routing, and charge-calculation constraints. The secondary premise of this paper is to provide an efficient algorithm to obtain reliable solutions in real-world dimensions. However, the existing commercial software cannot solve large-sized numerical instances because the location-arc routing is an NP-hard problem (Albareda-Sambola and Rodríguez-Pereira, 2019). Therefore, the best approach is to apply a meta-heuristic algorithm. In this paper, a genetic algorithm (GA) and a grey wolf optimizer (GWO) are used to solve large-sized instances, followed by numerical comparisons to analyze the performance of the algorithms.

2. Literature review

2.1. Municipal waste management and pandemic outbreaks

The spread of coronavirus has caused many problems, including challenges regarding solid waste management in small and large urban municipalities worldwide (Haque et al., 2020). While the food waste generation trend has decreased during the coronavirus outbreak due to increased awareness of the environmental consequences (Burlea--Schiopoiu et al., 2021), personal protective equipment consumption, like face masks and gloves, has increased substantially, increasing solid waste production (Haji et al., 2020). Therefore, municipalities worldwide have introduced contingency plans to improve solid waste collection efficiency since improper waste management increases the spread of the disease (World Health Organization, 2020). Several studies have recently examined the issue of solid waste collection management from different perspectives, including strategy design, collection and disposal methods, environmental effects of waste disposal, and collection challenges (Das et al., 2021a, 2021b). One of the essential activities in solid waste collection operations is the proper management of the transport fleet, including vehicle routing, which directly impacts the reduction of cost and destructive environmental effects and increment of operations speed (D. Chen et al., 2020). For this purpose, Babaee Tirkolaee et al. (2021) presented an optimization model for collecting solid medical waste and designing a transportation network based on sustainability criteria.

Kargar et al. (2020) studied the waste management problem in the Coronavirus outbreak in the form of a reverse supply chain where waste collection and transportation operations in different categories are formulated as a linear multi-objective optimization model. Tirkolaee et al. (2020) developed a location-allocation model for urban waste collection, which was then used by Tirkolaee et al. (2021) to solve the sustainable location-routing problem for solid waste collection. Government agencies must modify their past plans to suit the coronavirus outbreak situation that Valizadeh et al. (2021) investigated as a bi-level optimization model. Zaeimi and Rassafi (2021) examined municipal consideration costs and destructive environmental effects reduction. The results showed the tremendous impact of waste collection operations on increasing the harmful ecological effects. Electric vehicles have been recognized as one of the best approaches for achieving sustainable development goals in waste collection operations (Boss, 2005). Therefore, developing the necessary infrastructure to use electric vehicles for general day-to-day driving and municipal waste collection can play an essential role in reducing costs and adverse environmental impact, especially during a pandemic outbreak. Despite the importance of electric vehicles, the use of electric vehicles for waste collection and transportation during pandemic outbreaks has not been fully investigated. The model proposed in this paper can be considered as a pivotal point in developing new research streams and achieving useful results in alleviating the harmful impact of environmental disasters and pandemic outbreaks.

2.2. Arc routing for electric vehicles

Routing problems are studied in two contexts: arc routing and node routing. In arc routing problems, the critical service activity is to cover the arcs, and in node routing, the vital service activity is to cover the nodes in a transportation network. While arc routing focuses on the traversal of edges, in node routing, the arcs are of interest only as the paths connecting the nodes. The first formal formulation of capacitated arc routing problem (CARP) was introduced by (Golden and Wong, 1981), and a comprehensive bibliography of arc routing is provided by (Mourão and Pinto, 2017). Different operational applications of arc routing include waste collection (Kiilerich and Wøhlk, 2018; Nossack et al., 2017), money collection (Constantino et al., 2017), postal and newspaper delivery (Chang and Yen, 2012; Corberán et al., 2011), outdoor activities like cycling (Souffriau et al., 2011; Verbeeck et al., 2014), post-disaster operations (Akbari and Salman, 2017a, 2017b), road cleaning and marking (Dussault et al., 2013; Huang and Lin, 2012; Lannez et al., 2015), meter reading (Eglese et al., 2015), security patrol routing (Shafahi and Haghani, 2015; Willemse and Joubert, 2012), and mobile van mapping problem (Vansteenwegen et al., 2010).

Despite the widespread application of arc routing in urban management and the importance of using electric vehicles in urban transportation, only Fernández et al. (2020) studied electric vehicles in the context of arc routing. They presented an integer linear mathematical model that considered dynamic charging, a branch-and-cut algorithm for exact solutions, and a heuristic algorithm for solving large-size problems. However, they did not consider charging facilities in their model.

2.3. Electric vehicle routing and charging facilities

Integrating decisions related to routing and charging facility locations can effectively reduce the costs in the entire system (Erdelić and Carić, 2019). If the location of a charging facility is determined optimally, the total distance traveled by vehicles to receive the charge and consequently the total costs will be reduced. The location of the charging facilities and electric vehicle routing is a dependent problem that cannot be solved in isolation (Schiffer et al., 2019). However, few studies have examined the two problems concurrently (Dascioglu and Tuzkaya, 2019). Location decisions are primarily concerned with battery swapping stations or charging stations, while automotive industries have recently considered dynamic charging technology (T. Chen et al., 2020). Li et al. (2018) proposed a bi-level programming model to determine public recharging infrastructures. Zuo et al. (2019) presented a mathematical optimization model considering a convex non-linear charging function. The application of electric vehicles in finding the best routes

for home health care is studied by Erdem and Koç (2019).

Yang and Sun (2015) proposed the first formulation of the electric location routing problem (ELRP) to determine the location of battery swapping stations and electric vehicle routing. Their results were later improved by Hof et al. (2017). Schiffer and Walther (2018) also developed an approach to determine electric vehicle routing simultaneously and charging facility locations under uncertain customer patterns. Arias, Sanchez, and Granada (2018) studied the impact of charging stations and electric vehicles routing on the power distribution system for a merchandise transportation application using a mixed-integer non-linear mathematical model. Paz et al. (2018) extended the multi-depot vehicle routing problem into a multi-depot ELRP, studied two energy supply technologies, plug-in recharging and battery swapping, and solved the problem for small-size instances. Zhang et al. (2019) studied the impact of stochastic demand on this problem to minimize the total cost of stations and routing. Liu et al. (2019) developed a new model without dummy nodes by considering different objective functions. To the best of our knowledge, dynamic charging has not been studied in ELRP.

Table 1reviews the most relevant studies exploring the application of electric vehicles in arc routing problems.

2.4. Research gap

The literature review shows that although several studies have examined MWM in the context of a pandemic outbreak, some essential health aspects are neglected (Van Fan et al., 2021). In addition, environmental pollution caused by road cleaning operations with trucks running on fossil fuel has not been addressed adequately in the literature. We study the infrastructure for using electric vehicles to fill these gaps. Furthermore, there is a need to construct various charging facility types suitable for all-electric vehicles capable of accommodating different technologies such as dynamic charging. However, locations with multiple charging technologies have not been studied adequately in the literature. Although integrated location-arc routing models for electric vehicles improve efficiency in urban areas, they are still in their infancy and have not been studied widely. More specifically, the integration of decisions related to the location of waste collection centers, activation of various charging facilities, and vehicle routing for carrying out road cleaning operations is the aspect of our study. The novelties of this research can be summarized as follows:

- We develop an integrated optimization model for MWM and road cleaning during pandemic outbreaks. Most MWM studies have investigated waste collection problems as node-based routing (Cheng et al., 2021; Tirkolaee et al., 2021). Node-based routing assumes that demand is concentrated on nodes rather than arcs. However, in some applications like road cleaning, demand is distributed along streets (Kokane et al., 2021; Delle Donne et al., 2021; Tordecilla et al., 2021).
- We propose a location-arc routing model for electric vehicles. Electric vehicles are emerging technologies that can significantly reduce the adverse impact of pandemics in smart cities (Costa and Peixoto, 2020). In addition, they can reduce the dependency on fossil fuel consumption and help achieve sustainability goals in municipalities.
- We simultaneously consider charging station locations and suitable arcs for dynamic charging. To the best of our knowledge, dynamic charging in the arc routing problems has not been studied as a viable technology for decreasing the charging time of electric vehicles.
- We consider demand splitting an alternative strategy to decrease the service cost and time, especially when the number of available vehicles is limited or some arcs are in high demand.
- We solve the problem using two population-based metaheuristic algorithms due to the NP-hardness of the location-arc routing problems. We use the Grey Wolf algorithm as an efficient meta-heuristic to discover a more streamlined alternative and compare its performance with GA as a well-known approach in the field.

3. Problem description

This paper considers an optimization model for Location Arc Routing Problems (LARPs) to collect municipal waste and clean roads during the pandemic. The location component of the model determines the optimal location of the waste collection centers, charging stations, and the arcs for dynamic charging. The routing component of the model determines the optimal vehicle routes considering one-way and two-way streets, collecting waste, and clearing the routes. Integrating arc routing with location decisions aims to reduce the time required to charge the vehicles. The integrated framework allows the vehicles to spend the least amount of time and distance to be charged to perform their tasks effectively. Fig. 1 shows an overview of the problem structure in this paper.

Fig. 1 shows the final output of the model, including the location of waste collection centers, charging stations, and dynamic charging arcs, as well as the routes for each vehicle, to effectively perform its waste collection and cleaning tasks. An important consideration in electric vehicles is the charge consumption function based on the vehicles' technical conditions and the urban environment. Since electric vehicles use lithium batteries, the charging may be impacted non-linearly by various parameters such as traffic and arc distances. In this paper, an energy reduction function is developed as follows.

$$f(a,k) = \beta_0 + \beta_1 Traffic + \ldots + \beta_n Traffic^n + CR_k \sqrt{Dist_a^3} \tag{1}$$

where $\beta_0 + \beta_1 \text{Traffic} + \ldots + \beta_n \text{Traffic}^n$ is a regression structure for predicting traffic that is calculated using historical data from the Traffic Control Center, $\sqrt{\text{Dist}^3}$ is a non-linear non-absolute ascending function for the dependency between distance and energy consumption. An electric vehicle traveling 100 km continuously will need more charge than five 20 km intervals. Finally, CR_k is the amount of energy consumption of vehicle k per unit distance. Eq. (1) can determine the energy consumption along arcs. We use the location-arc routing formulation proposed by Lopes et al. (2014) as the initial mathematical model and further expand it according to the requirements of the problem under investigation in this study. Some of the changes include but are not limited to improving the constraints, removing the sub-tours (Constraint

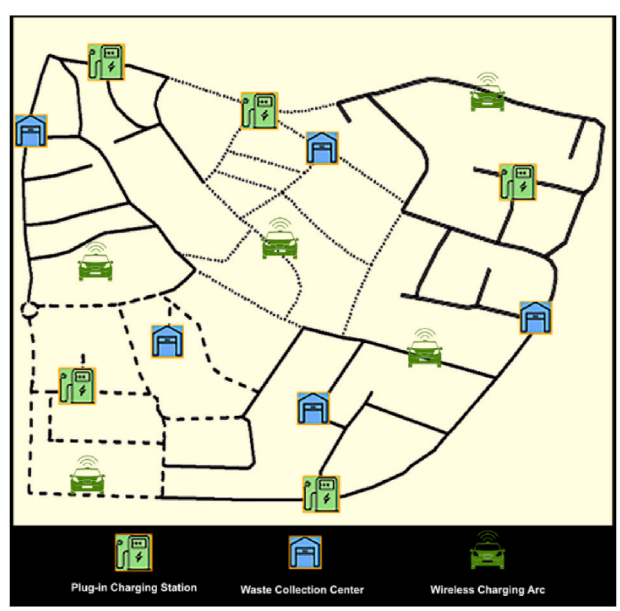

Fig. 1. An overview of the problem structure.

(8)), using electric vehicles, and calculating their charge (e.g., Constraints (18) to (22)).

This paper has several unique features. First, we propose a new constraint to eliminate the sub-tour since modeling the arc-routing problem is complex. Second, we also consider demand splitting as an alternative strategy. These contributions can reduce the service cost and time in real-world problems, especially when the number of available vehicles is limited or some arcs are in high demand (more than the capacity of one vehicle). Furthermore, the electric vehicle utilization and calculation of the charges are among other contributions of this paper.

Sets	
V	Set of vertices
$A = \{(i,j) \mid i,j \in V, i<j\}$	Set of arcs
$R \subseteq A$	Set of demand arcs that need to be cleaned
J	Set of potential vertices for establishing waste collection centers
K	Set of vehicles
$C \subseteq V$	Set of potential charging stations on vertices
$H \subseteq A$	Set of potential arcs for dynamic charging
Parameters	
C_a	Service cost of $a \in R$
TC_a	Traversal cost of $a \in A$
D_a	Demand of $a \in R$
f_m	Establishment cost of potential waste collection center $m \in J$
e_k	Fixed cost of vehicle k
Q_k	Capacity of vehicle k
b_m	Capacity of potential waste collection center $m \in J$
L	Maximum number of established waste collection centers
PC_i	Cost of establishing a charging station on vertex $i \in C$
CW_a	Cost of providing arc $a \in H$ with dynamic charging
Dis_a	Traversal time of arc $a \in A$
$f(a,k)$	Charge consumption function of vehicle k in case of traversing arc $a \in A$
$g(a,k)$	Recharging function of vehicle k in case of traversing the dynamic charging arc $a \in H$
LB	Minimum amount of vehicle charge
M	A sufficient large number
Decision variables	
x_{ak}	The number of times arc $a \in A$ is traversed by vehicle k
Z_m	Equals to one if potential waste collection center $m \in J$ is established
w_{km}	Equals to one if vehicle k is allocated to waste collection center $m \in J$
d_{ak}	The amount of demand of arc $a \in R$ met by vehicle k
y_{ak}	Equals to one if arc $a \in R$ is serviced by vehicle k
$\delta^+(S)$	For any subset S of vertices, the set of arcs leaving S
$\delta^-(S)$	For any subset S of vertices, the set of arcs entering S
$L(S)$	For any subset S of vertices, the set of arcs with both extremities in S
when S has just one member, $\delta^+(v)$ is used instead of $\delta^+(\{v\})$	
EP_i	Equals to one if a charging station is established on vertex $i \in C$
EW_a	Equals to one if potential arc $a \in H$ is selected for dynamic charging
CH_{kal}	The percentage of remaining energy of vehicle k after traversing arc $a \in A$ in the lth traverse
PH_{kil}	The percentage of charged energy for vehicle k at charging station on vertex $i \in C$ in the lth traverse

$$Min\ ELARP = \sum_{m\in J} f_m Z_m + \sum_{i\in C} EP_i PC_i + \sum_{a\in H} EW_a CW_a + \sum_{a\in A}\sum_{k\in K} x_{ak} TC_a + \sum_{a\in R}\sum_{k\in K} y_{ak} C_a + \sum_{k\in K}\sum_{m\in J} w_{km} e_k \tag{2}$$

s.t.

$$\sum_{a\in\delta^+(i)} x_{ak} + \sum_{a\in\delta^+(i)} y_{ak} = \sum_{a\in\delta^-(i)} x_{ak} + \sum_{a\in\delta^-(i)} y_{ak} \quad i \in V,\ k \in K \tag{3}$$

$$\sum_{a\in R} d_{ak} \le Q_k \quad k \in K \tag{4}$$

$$\sum_{k\in K} d_{ak} = D_a \quad a \in R \tag{5}$$

$$x_{ak} \ge y_{ak} \quad a \in R,\ k \in K \tag{6}$$

$$y_{ak} d_a \ge d_{ak} \quad a \in R,\ k \in K \tag{7}$$

$$\sum_{a\in\delta^+(S)} x_{ak} + \sum_{a\in\delta^+(S)} x_{ak} \ge 2y_{(p,q)k} - M(1-w_{km}) \quad \begin{array}{l} k \in K, \\ (p,q) \in A \\ S \subseteq V/\{m\} \end{array} \tag{8}$$

$$\sum_{k\in K} y_{ak} \ge 1 \quad a \in R \tag{9}$$

$$\sum_{a\in R}\sum_{k\in K} d_{ak} \le b_m Z_m \quad m \in J \tag{10}$$

$$w_{km} \le Z_m \quad m \in J,\ k \in K \tag{11}$$

$$Z_m \le M \sum_{k\in K} w_{km} \quad m \in J \tag{12}$$

$$\sum_{a\in R} y_{ak} \le M \sum_{k\in K} w_{km} \quad k \in K \tag{13}$$

$$M \sum_{a\in R} y_{ak} \ge \sum_{k\in K} w_{km} \quad k \in K \tag{14}$$

$$d_{ak} \ge y_{ak} \quad a \in A,\ k \in K \tag{15}$$

$$\sum_{m\in J} w_{km} \le 1 \quad k \in K \tag{16}$$

$$\sum_{a\in\delta^+(m)} y_{ak} \ge 1 - M(1-w_{km}) \quad k \in K,\ m \in J \tag{17}$$

$$CH_{kal} \le CH_{kbl'} - f(a,k) + PH_{kil} + g(a,k).EW_a + M(1-y_{ak}) + M(1-y_{bk}) \quad \begin{array}{l} k \in K, i,j \in V, \\ a \in \delta^+(i), a \in \delta^-(j), b \in \delta^+(j), \\ l \in \{1,\ldots,x_{ak}\}, l' \in \{1,\ldots,x_{ak}\} \end{array} \tag{18}$$

$$CH_{kal} \ge CH_{kbl'} - f(a,k) + PH_{kil} + g(a,k).EW_a - M(1-y_{ak}) - M(1-y_{bk}) \quad \begin{array}{l} k \in K, i,j \in V, \\ a \in \delta^+(i), a \in \delta^-(j), b \in \delta^+(j), \\ l \in \{1,\ldots,x_{ak}\}, l' \in \{1,\ldots,x_{ak}\} \end{array} \tag{19}$$

$$LB \le CH_{kal} \le 1 \quad k \in K,\ a \in A, l \in \{1, \ldots, x_{ak}\} \tag{20}$$

$$\sum_{k \in K} \sum_{l \in L} PH_{kil} \le M.EP_i \quad i \in V, \tag{21}$$

$$EP_i \le M.\sum_{k \in K} \sum_{l \in L} PH_{kil} \quad i \in V, \tag{22}$$

$$\begin{aligned} &Z_m, w_{km}, y_{ak}, EP_i, EW_a \in \{0,1\} \\ &x_{ak}, d_{ak}, \delta^+(S), \delta^-(S), L(S) \in Z^+ \\ &0 \le CH_{kal}, PH_{kil} \le 1 \end{aligned} \quad \begin{aligned} &k \in K, a \in A, m \in J, i \in V, \\ &l \in \{1, \ldots, x_{ak}\} \end{aligned} \tag{23}$$

The objective function minimizes the sum of the establishment cost of waste collection centers, charging stations on vertices, dynamic charging along arcs, traversing arcs, and servicing costs. Constraint (3) ensures continuity, which means the number of arcs entering a vertex equals the number of arcs leaving it. Constraint (4) is associated with the capacity of vehicles. Constraint (5) (along with Constraint (15)) ensures that the total demand met by all vehicles must be equal to the total customers' demand. Providing service to a required arc is possible only when it is traversed. A demand arc should be traversed at least once specified in constraint (6). Constraint (7) states that a required arc can be serviced when it is allocated to a vehicle. Constraint (8) ensures each route is started from a waste collection center and ends at the waste collection center. Constraint (9) requires that each arc should be served by at least one vehicle.

In contrast to the previous studies in the literature, the assumption that the waste collection centers, or the so-called depots, are uncapacitated is corrected in this paper according to actual conditions. Constraint (10) guarantees the amount of demand met by vehicles does not exceed the capacity of the relevant waste collection center. Constraints (11) to (17) confirm the relationships between establishing waste collection centers, allocating routes to them, and allocating required arcs to vehicles. Constraints (18) and (19) calculate the amount of charge remaining in each vehicle after traversing each arc. The energy of each vehicle along each arc should be within a predetermined range that is guaranteed by Constraint (20). Constraints (21) and (22) ensure that vehicles are to be recharged at the established charging stations.

3.1. Estimation model of waste generation

The hedonic models have been used to determine time series independent parameters (Sopranzetti, 2015). These models were developed to provide coefficients of independent variables with higher levels of complexity by providing measurement errors and separating the demand parameter into the independent variables. In this research, several significant factors affecting waste generation in different streets, including the traffic load, number of shopping outlets, offices, residential buildings, distance from recreation centers and parks, cultural maturity of residents, number of health and medical centers, and the number of active urban bins are studied (Ben-Ameur and Kerivin, 2005). In other words, population density depends on the number of shopping outlets, residential buildings, health and medical centers, and active urban bins. Therefore, population density is calculated in the population estimation. Different transform structures have been presented for hedonic models, including linear, semi-log, and Box-Cox structures. In this paper, the Box-Cox structure is used due to its comprehensive structure compared to other structures. Generally speaking, the transfer function of the Box-Cox structure can be expressed as Eq. (24).

$$X^\lambda = \begin{cases} \dfrac{X^\lambda - 1}{\lambda}, & \lambda \ne 0,\ X > 0 \\ \ln X, & \lambda = 0 \end{cases} \tag{24}$$

Therefore, demand prediction can be made through the following equation.

$$D = X^\lambda \beta + \varepsilon \tag{25}$$

where X is the vector of variables, β is the coefficient of variables, λ is the transfer parameter of the Box-Cox structure, and $\varepsilon \sim N(0, \sigma^2)$ denotes the computation error. Appropriate choice of λ and β can greatly contribute to lowering error levels, leading to a more accurate estimation of the demand level. The following logarithmic probability function can be used to determine an appropriate value for these parameters (Sopranzetti, 2015).

$$\ln L(\beta, \sigma^2, \lambda | y) = -\frac{1}{2\sigma^2}(z - X\beta)'(z - X\beta) - \frac{n}{2}\ln(2\pi\sigma^2) + (\lambda - 1)\sum_{i=1}^{n} \ln(y_i) \tag{26}$$

where y_i is to the real demand in the i th sample, z is calculated using a normal distribution function, and n is the total number of samples. Accordingly, appropriate values of λ and β can be determined by the logarithmic likelihood function based on the maximum likelihood estimation.

4. Solution method

Like facility location and arc routing problems, the LARP is known as an NP-hard problem, difficult to solve large-sized instances with exact methods (Lopes et al., 2014). Meta-heuristic algorithms can be used to overcome this difficulty in large real-world problems. An important issue in selecting an appropriate meta-heuristic algorithm is comparability with nature and the functional structure to find the final solutions. The population-based meta-heuristic algorithms have better performance than other algorithms in these problems (Corberán et al., 2021). GA is the state-of-the-art for LARPs (Amini et al., 2020). The paper also proposes a GWO to solve the problem and compare the obtained solutions through numerical and statistical analyses. The authors find the most suitable method to solve the case study.

4.1. Solution representation

In this paper, a greedy algorithm is used to design an efficient solution representation because it is difficult to obtain a feasible solution for the LARP through random assignment. The greedy approach initializes the GA's solution by satisfying constraints in this paper. The developed algorithm is as follows:

a. Generate a random number called B, from $[1, L]$.

   Let L = *4* and $B = 2$.

b. Generate a matrix with size $1 \times |J|$.

   Let $J = 5$.

c. Generate positive random numbers from $[0, 1]$ for each cell of the generated matrix in step 2.

0.52	0.28	0.37	0.47	0.88

dSelect the B larger numbers and set them to 1. Other numbers should be set to 0.

1	0	0	0	1

So, facilities 1 and 5 are selected as depots.

Steps a through d ensure that the location of the waste collection facility is feasible.

e. Generate a matrix with size $1 \times |R|$.
f. Generate positive random numbers from [0, B] for each cell of the generated matrix in step 5. Then update the generated numbers based on the ceiling function.

Let $R = 15$.

0.14	1.85	0.63	1.47	0.18	1.55	0.34	1.23	0.76	0.58	0.48	1.29	0.37	1.57	1.17

⬇

1	2	1	2	1	2	1	2	1	1	1	2	1	2	2

Based on the order of the selected depots in Step d, the above matrix can be updated to the following matrix.

1	5	1	5	1	5	1	5	1	1	1	5	1	5	5

For instance, based on the above matrix, arc 1 is assigned to depot 1, and arc 2 is assigned to depot 5.

f. Find all of the vertices located on the shortest path between each selected depot and each vertex and save it as set H_{ij}.
g. This step assigns vehicles to the depots using integer random generated array. For example, in the following matrix, vehicle 1 is assigned to depot 1, vehicle 2 is assigned to depot 5, and vehicle 3 is not used (based on constraints 9, 11, 12, and 16).

1	5	0

Therefore, Each assigned arc to the related depot is served by a separate vehicle that is assigned to the depot (based on constraints 13 and 14).

h. Based on the randomly generated two-dimensional array ($|K| \times |A|$) with values in [0,1], it is possible to determine the amount of demand of arc $a \in R$ met by vehicle k based on constraints (5, 7, and 15). It should be noted that the sum of the randomly generated numbers in each column should be equal to one. Moreover, If an array in step (g) is equal to zero, the related row in the two-dimensional array ($|K| \times |A|$) should be zero.
i. Each vehicle starts from a depot and traverses the arcs located on the shortest path between the depot (H_{ij}) and the internal vertex of the assigned arc. Then the arc is served, and a two-dimensional array ($|K| \times |A|$), that generates (x_{ak}), get value based on the constraints (6 and 17). Finally, the vehicle traverses the arcs located on the shortest path between the external vertex of the assigned arc and the depot. Each vehicle travels continuously without any sub-tours (based on constraints 3 and 8).
j. The merging method proposed by (Lopes et al., 2014) is applied to merge the routes for fewer used vehicles.
k. Like steps c and d, the recharging stations on vertices and arcs to be electrified are determined.

In this way, it is ensured that charging stations and dynamic charging arcs are feasibly located.

l. The remaining energy of vehicles is calculated based on the recharging stations on vertices and arcs to be electrified that are available on each route (based on constraints 18 and 19).

Each solution that violates the constraints related to vehicle capacity and the remaining energy will be rejected to obtain feasible solutions (based on constraints 4, 10, and 20 to 22).

4.2. Genetic algorithm

GA is an evolutionary meta-heuristic algorithm inspired by the biological evolution process, applied to solve different arc routing problems (Arakaki and Usberti, 2018; Lacomme et al., 2006). Generally, a solution for the optimization problem should be coded as an array, called a chromosome, and a set of solutions, called a population (generation), evolves toward better solutions. Each solution has an associated fitness, calculated based on the objective function. The evolution in the GA is an iterative process that typically starts from a population of randomly generated chromosomes. The chromosomes with better fitness value are more likely to survive to the next generation. Consequently, the algorithm converges to an optimal or near-optimal solution. Bio-inspired operators such as mutation, crossover, and selection are commonly used to obtain the next generation in each GA's iteration (Darmian et al., 2021). In this paper, after initializing solutions, we apply the tournament selection operator in which we select a random sub-group from the population. Then the solutions with the highest fitness are selected to create a mating pool. Genetic operators, including crossover and mutation, are then applied successively to the mating pool to create a new set of solutions (offspring). The size of the population and mating pool in GA is defined by pop_size and mpool_size, respectively. Furthermore, the probability of crossover and mutation operation is defined by crossover_prob and mutation_prob successively.

- *Crossover operator:* This operator is a two-point crossover with a repair of infeasible solutions. We take care of duplicating a value corresponding to the eliminated edges in new solution arrays for the repair mechanism during the crossover operator. In such a situation, duplicated values are changed to the nearest possible value.
- *Mutation operator:* This operator randomly selects an element in the solution array of an offspring generated by the crossover operator and changes its value. The mutation operator also takes care of duplicating a value corresponding to the eliminated edges in a new solution array.

4.3. Grey wolf optimizer

The GWO is proposed by Mirjalili et al. (2014) based on the leadership hierarchy and hunting mechanism of grey wolves in nature. The GWO starts with a set of initial solutions, called grey wolf positions or search agents. Each solution (search agent) is denoted by $\vec{X}$. Based on the fitness value for each search agent α, β, and δ denote the first, second, and third best solution, respectively. Other solutions should be updated based on these best search agents. The updating mechanism of solutions in the next iteration (t+1) of the GWO is mathematically explained as follows, assuming $\vec{r}_1$ and $\vec{r}_2$ as the vector of random numbers between 0 and 1, and $\vec{a}$ as the vector of real numbers that decrease linearly from 2 to 0 through the algorithm's iterations.

$$\vec{A} = 2\vec{a}.\ \vec{r}_1 - \vec{a} \tag{27}$$

$$\vec{C} = 2\vec{r}_2 \tag{28}$$

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|,\ \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|,\ \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \tag{29}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\left(\vec{D}_\alpha\right), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\left(\vec{D}_\beta\right), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\left(\vec{D}_\delta\right) \tag{30}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{31}$$

The presented mathematical expressions (27–31) are developed based on the social structure of grey wolves. For more information regarding the GWO, one can refer to (Farughi et al., 2020). The pseudo-code of the GWO is presented in the Online Appendix (Figure A).

5. Computational results

This section reports on the numerical results for the case study of the city of Edmonton in Canada by presenting the randomly generated instances, evaluating the applicability of the model and relevant algorithms developed in this study, and offering several managerial insights through sensitivity. The presented mathematical model is solved using the CPLEX solver in GAMS 24.1 software, and the developed algorithms are coded in MATLAB R2016b. A personal computer powered by an Intel Core i7-640M CPU processing at 3.2 GHz with 16 GB of RAM is utilized to solve all numerical instances.

5.1. Generation of numerical instances

A connected direct graph $G(V,A)$ is generated where V denotes the graph vertices, and A refers to the arcs connecting different vertices to create a hypothetical geographical area for the numerical instances. Each vertex i has two characteristics xi and yi, which refer to the geographical longitude and latitude. These two geographic characteristics are randomly generated in the uniform interval of $U[10,1000]$. An array with the length $|V|$ is then generated, which cells representing the graph vertices with values in the range of $[0,100]$. The vertices with values smaller than 20 are supposed to indicate potential locations for establishing waste collection centers. The vertices with random values in the range of 20–30 indicated potential locations for establishing charging stations. The number of potential vehicles equals the sum of waste collection centers and charging stations. In addition, a two-dimensional array with the length $|A|$ is generated where the cells represent the graph arcs. The first-row cells have random values in the range of $[0,100]$, while the second-row cells have random values in the range of $\{0,1\}$. The arcs on the first row with values smaller than 30 are referred to as potential arcs for installing dynamic charging facilities.

In contrast, the arcs on the second row with a value of 1 are considered demanding arcs requiring cleaning operation. The demand for each arc is randomly taken from $[50,100]$ interval, using which the capacity of vehicles and the waste collection centers can be determined. For this purpose, the capacity of each vehicle and waste collection center is randomly generated within $[10,15]$% and $[20,30]$% of total demand, respectively. Travel cost per arc, charging station establishment cost per station, establishment cost of dynamic charging per arc, and waste collection center establishment cost for each center are randomly generated from the intervals $[60,100]$, $[120,150]$, $[150,200]$, and $[500,1000]$, respectively. Notably, the small-sized, medium-sized, and large-sized numerical instances differ in nothing but the numbers of vertices and arcs. The values of other parameters do not significantly impact the scale of the problem. It should be noted that the input data for the randomly generated problems are based on the uniform function in the mentioned intervals. These problems are intended to evaluate the model's performance and algorithms. They are independent problems with no relevance to the case study. Therefore, these numerical intervals are produced based on the authors' experiential knowledge and used only in numerical comparisons.

5.2. Solving the numerical instances by full enumeration

We identify all members of set S to solve the mathematical model using GAMS software (version 27.1.2). Therefore, the number of constraints increases rapidly with increasing the number of graph vertices, exponentially increasing the complexity of the problem. Set S contains different combinations of members of set V, and the total number of the members of set S is equal to different selections of the subsets of $\{1,\ldots,V\}$, which can be calculated by Eq. (32).

$$S = \left\{ \binom{|V|}{i} \right\} \quad i \in \{1,\ldots,I\}$$
$$|S| = \sum_{i\in\{1,\ldots,V\}} \binom{|V|}{i} \tag{32}$$

For instance, assuming three graph vertices, the total number of the members of set S is given by Eq. (33).

$$S = \{(1),(2),(3),(1,2),(1,3),(2,3),(1,2,3)\}$$
$$|S| = \binom{3}{1} + \binom{3}{2} + \binom{3}{3} = \frac{3!}{2!} + \frac{3!}{2!} + 1 = 7 \tag{33}$$

In general, the number of the members of set S is $(2^{|V|} - 1)$, which represents an exponential growth function. In other words, the mathematical model complexity increases non-linearly as more vertices are included. This implies that the mathematical model cannot solve numerical instances feasibly, even at small sizes. Figure B in the Online Appendix shows the number of set S members for different numbers of graph vertices.

Nevertheless, to verify the mathematical model, a small-sized numerical instance is generated. Once all members of set S are generated, the problem is solved using the CPLEX solver. A connected direct graph is assumed with eight vertices and 24 arcs. Vertices 2 and 4 are the potential locations for establishing waste collection centers, and vertices 1 and 8 are the potential places for charging stations. Arcs 5, 10, 15, 20, and 24 are the potential arcs for installing dynamic charging facilities. A graphical representation of the graph corresponding to this numerical instance is shown in Fig. 2.

It is assumed that all arcs require cleaning operations, and two vehicles should perform waste collection. Table 2 shows the establishment costs of waste collection centers, charging stations, and dynamic charging facilities. The capacities of vehicles 1 and 2 are respectively 1200 and 800. The capacities of waste collection centers 2 and 4 are 1700 and 1800, respectively. The per-arc demand and travel cost information are presented in Table 3.

Since the graph comprises six vertices, set S has 255 members, a part of which is presented in Table A in the Online Appendix. Based on a full enumeration of the members of set S, the mathematical model is solved

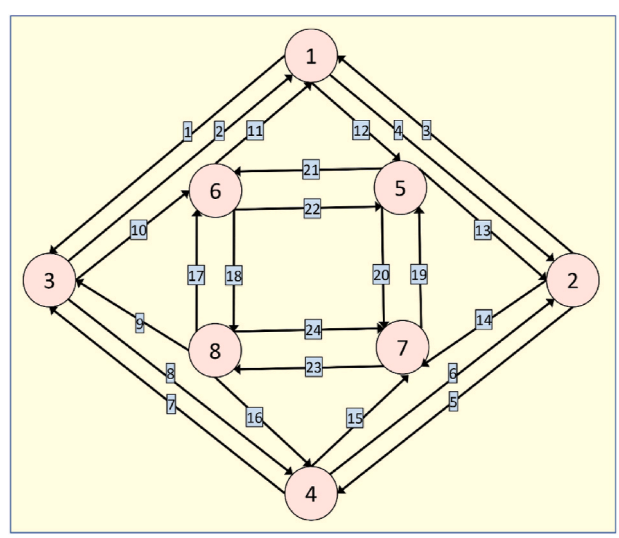

Fig. 2. Graphical representation of the numerical instance.

Table 1
A brief review of the most related papers.

Reference	Period	Tour	Dynamic charging	Location	Meta-heuristic	Exact	Application	Case study
Chow (2016)	M		N			✓	Road traffic	China
Campbell et al. (2018)	S	M	N		✓		W/A	N/A
(M. Li, Zhen, Wang, Lv and Qu, 2018)	M	M	N		✓	✓	W/A	N/A
(Y. Liu, Shi, Liu, Huang and Zhou, 2019)	S	M	N		✓		Powerline inspection system	China
Luo et al. (2019)	S	M	N		✓		Traffic patrolling routing	China
Yurtseven & Gökçe (2019)	S	M	N			✓	Waste collection	Turkey
Fernández et al. (2020)	S	M	Y		✓	✓	W/A	N/A
Campbell et al. (2021)	S	M	N			✓	W/A	N/A
This study	**S**	**M**	**Y**	✓	✓		**Waste collection**	**Canada**

Note: S: single period, M: multiple periods, W/A: without application, and N/A: not available.

Table 2
Establishment costs for different facilities.

Establishment cost	Potential dynamic charging arcs					Vehicles		Potential charging stations		Potential waste collection centers	
	24	20	15	10	5	2	1	8	1	2	4
	170	190	180	200	160	8	10	140	150	600	800

Table 3
Per-arc demand and travel cost information.

Arc	1	2	3	4	5	6	7	8	9	10	11	12
Demand	77	93	68	76	50	55	59	75	50	56	66	73
Arc	13	14	15	16	17	18	19	20	21	22	23	24
Demand	93	88	77	89	80	73	81	94	77	67	100	92

Table 4
Design costs of the waste collection network for the numerical instance.

Servicing cost	Traversal cost of arcs	Establishment cost of dynamic charging arcs	Establishment cost of charging stations	Establishment cost of waste collection centers
18	2745	530	290	1400

Table 5
The optimal level of the parameters of the proposed algorithms.

Problem size		Number of iterations	Population size (× chromosome length)	Transmittance rate	Mutation rate
small	*GA*	*320*	*1.3*	*0.7*	*0.15*
	GWO	*300*	*1.1*	-	-
Medium	*GA*	*550*	*1.7*	*0.7*	*0.21*
	GWO	*410*	*1.4*	-	-
Large	*GA*	*640*	*2*	*0.7*	*0.24*
	GWO	*500*	*1.9*	-	-

using the CPLEX solver. The values of the objective function are reported in Table 4.

Based on the numerical results, two collection centers are established, and both vehicles are used. Moreover, two charging stations are established, and three arcs are activated for dynamic charging. Fig. 3 demonstrates the assignment of different arcs to vehicles and the tour structures developed for each vehicle.

Fig. 3 shows that both vehicles are used at collection center 1, while only vehicle 1 is utilized at collection center 2. Since vehicle 2 enjoys dynamic charging, it utilizes dynamic charging arcs in both trips related to collection centers 1 and 2. However, vehicle 1 does not traverse any dynamic charging arcs and receives its required energy through charging stations. Table 7 presents the vehicle tours.

The routing structure of vehicle 1 from collection center 1 is such that it traverses arcs 14→23→16→15→23→9→1→12→21→11→3 and finally it returns to collection center 1. The routing structure of vehicle 2 from collection center 1 is such that it traverses arcs 3→1→10→18→17→22→21→18→17→22→20→19→13, and finally, it returns to collection center 1. The routing structure of vehicle 2 from collection center 2 is such that it traverses arcs 8→7→6→5→15→23→24→23→16, and finally, it returns to collection center 2. These results show the generated tours are all connected, with no sub-tour. Moreover, all arcs are served by the vehicles, indicating the proper performance of the mathematical model.

5.3. Parameter setting in the proposed algorithms

Since the grey wolf algorithm operators are performed based on equations with specific parameters, the only controllable parameters in this algorithm include the number of population members (agents) and the number of iterations of the algorithm. GA has four key operators: population size, number of iterations, mutation rate, and transmittance rate. It is necessary to determine the optimal levels of these parameters for each algorithm to improve the performance of algorithms in solving different numerical examples. This research uses the experimental design method based on the response level method (RSM). The parameters of each algorithm are considered according to Table B in Online Appendix.

After performing the necessary tests by RSM method using Design Expert 12 software, the optimal levels of the parameters of the proposed algorithms are presented in Table 5.

5.4. Performance evaluation of the proposed algorithms

The heuristics and meta-heuristic algorithms guarantee a general optimal solution and only provide near-optimal solutions under an acceptable time (Darmian et al., 2020). In this section, the performance of the proposed meta-heuristics is compared with CPLEX solutions by solving some randomly generated problems. The CPLEX solver can solve numerical examples in small dimensions due to the high complexity of the mathematical model. Thus, seven numerical examples are randomly

Table 6
The comparison of numerical results obtained by solving random instances using CPLEX, GWO, and GA.

Instance	arc	Collection center	Charging station	Dynamic charging arc	CPLEX		GWO					GA				
					Objective function	CPU time (s)	Best	Ave	Worst	CPU time (s)	Optimality GAP %	Best	Ave	Worst	CPU time (s)	Optimality GAP %
1	20	2	2	5	1330	1316	1403	1541	2234	141	+5.49	1530	1619	2436	157	+15.04
2	22	2	2	5	1759	1544	1871	1979	2389	219	+6.37	2040	2138	2628	263	+15.97
3	26	3	2	6	2570	2137	2807	2828	3059	324	+9.22	3060	3083	3243	319	+19.07
4	28	3	3	6	2735	3996	2966	3089	3122	389	+8.45	3115	3368	3435	412	+13.89
5	30	4	3	7	2883	5816	3177	3230	3265	417	+10.20	3432	3392	3527	155	+19.04
6	32	4	4	7	3482	7941	3795	39801	4081	542	+8.99	4099	43384	4367	507	+17.72
7	34	5	4	8	N/A	>10000	3741	3756	3779	666	N/A	3966	4057	3968	712	N/A

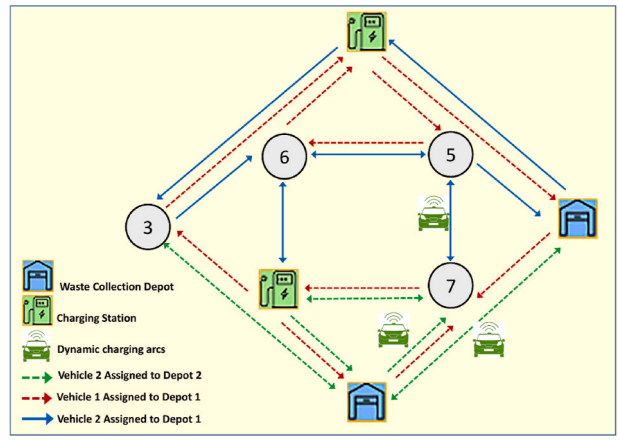

Fig. 3. Graphical structure of locating collection centers, charging stations, dynamic charging arcs, and vehicle routing.

generated. The CPLEX, GWO, and GA results are shown in Table 6.

The results of the meta-heuristic algorithms encompass the best, average, and worst solutions out of 10 independent runs. The CPLEX computational gap and the best solution of the algorithms in all numerical examples are less than 20%, indicating the suitable performance of the algorithms. Based on Table 6, CPLEX solves examples 1 through 6 within 10,000 s; however, it fails to solve example 7 due to the high complexity of the mathematical model.

In summary, the proposed algorithms perform well in solving small-sized problems. Sixty additional numerical instances are generated through the procedure described in Section 5.1 for further investigation into the proposed meta-heuristics performance. The results obtained from GA and GWO are investigated. The algorithms are compared based on the values of the objective function and run time. Table 7 shows the best solutions out of 10 independent runs of the algorithm.

Table 7 shows that the run time increases nonexponentially by increasing the numerical instance size. In other words, the run time grows in proportion to the increase of instances.

GWO achieves a shorter run time than GA in all numerical instances, indicating its run time superiority. When it comes to the value of the objective function, GA and GWO perform differently. The two algorithms obtained more-or-less the same solutions in the case of small-sized instances so that the computational gap is relatively small. As the size of numerical instances increases, the difference between solutions becomes more significant, and GWO shows larger capabilities to converge to a better solution. In fact, for all instances, GWO performs better and can solve real-world problems. Figures C and D in the Online Appendix demonstrate run time comparison and objective function comparison.

5.5. Statistical comparison between the proposed algorithms

In this section, statistical tests are conducted to compare GA and GWO and select a better algorithm to solve the case study. We begin with the Kolmogorov–Smirnov (K–S) test to verify normality of the data distribution. In this way, decisions are made on the choice of parametric or non-parametric tests. If the K–S test is rejected on a particular dataset, the data follows a normal distribution, justifying parametric statistical tests. On the other hand, a dataset that successfully passes the K–S test is non-normal, so non-parametric tests should be used to evaluate it properly.

Suppose the K–S test leads to significant results (i.e., p-value ≤ 0.05). In that case, the corresponding data is non-normally distributed, and non-parametric tests should be used to evaluate such data because being confirmed in the K–S test indicates the non-parametric nature of the data. The plots of K–S test results on all defined criteria are investigated,

Table 7
Obtained results of solving the numerical instances using different algorithms.

Number of arcs	Number of vertices	GA		GWO	
		objective function	Run time	objective function	Run time
80	20	5035	135	4127	110
90		4283	121	3269	90
100		4789	131	4164	103
110	25	8677	122	6242	105
120		12241	125	9067	102
130		9521	119	8279	99
140		12365	131	11139	94
150		18876	128	14520	114
160		19986	145	17531	124
170	30	15755	155	13942	109
180		13239	171	10424	142
190		13584	130	10867	110
200		8098	167	6229	147
210		9821	177	7440	146
220		10670	145	9042	103
230		15329	209	12462	147
240		14571	202	13246	168
250		15128	163	11374	141
260	35	9908	221	7128	155
270		23267	217	17761	174
280		34921	193	26455	165
290	40	114525	199	98728	156
300		90110	205	81180	179
310		78053	190	70957	166
320	45	90655	216	72524	193
330		118972	215	100823	157
340		97245	218	80367	181
350		86541	230	65068	164
360		121026	250	87069	178
370		127778	199	113077	168
380		195808	250	146125	195
390		190307	256	135933	192
400		159668	214	140059	189
410	50	112647	260	86651	227
420		193718	251	140375	181
430		156532	255	121342	179
440		177305	267	144150	227
450		195825	241	185558	172
460		139921	272	100662	240
470		183069	238	152557	208
480		347854	240	257669	188
490		326046	238	245147	208
500		296709	261	228237	204
510		216757	236	195276	168
520		203005	256	165044	210
530	60	162208	242	141050	216
540		316742	280	247454	247
550		255517	260	193573	216
560		228001	250	191060	198
570		226835	264	198978	230
580		239761	259	180271	234
590		158882	251	142979	209
600		187564	254	154841	183
610		115131	268	96748	204
620	60	187668	250	167560	223
630		283418	249	238166	222
640		254655	286	192920	232
650		164966	248	149969	194
660		277270	247	245371	213
670		251565	267	201252	238

Table 8
Results of Kruskal–Wallis tests for all criteria.

Criterion	Standard deviation	Run time	Objective function value
P-Value	0.147	0	0.161
Result	Accept the null hypothesis	*Reject the null hypothesis*	*Accept the null hypothesis*

and the results are presented here. The diagrams of the K–S test for all the defined criteria are shown in Figure E in the Online Appendix. The *p*-values corresponding to the normality tests on the objective function value, the run time, and the standard deviation are presented in Table C in the Online Appendix.

The final results of the normality test for the objective function, run time, and standard deviation are shown in Table C in the Online Appendix. None of the criteria exhibited normal distribution. Therefore, the two statistical populations should be compared through non-parametric tests. The Kruskal–Wallis test is used in this paper. The null hypothesis (H0) is the equality of the average values of the two statistical populations, while the alternative hypothesis (H1) refers to the latter's violation. The results of performing this test are presented in Table 8.

As shown in Table 8, GA and GWO are found to lead to two populations with equal average values in the objective function and standard deviation, indicating similar performance. However, the two algorithms exhibit significant differences in the run time. In this respect, the GWO is more efficient, as reported in Table 7. Therefore, we can conclude that GWO shows higher performance, making it the preferred method for solving real-world problems.

5.6. Sensitivity analysis

In this section, the numerical example presented in Section 5.2 is solved using the GWO, and numerical analyses are performed to evaluate the algorithm's sensitivity to changing the input parameters. Table 9 shows the computational gap between the objective function value of CPLEX and the GWO is 10.35%.

It should be noted that the solution provided by GWO is the best one among the ten independent runs. The demand values are changed 10%, 20%, and 50% to analyze the sensitivity of GWO. The results, along with the information on the network structure, the objective function values, the number of tours, and the number of facilities, are presented in Table 10.

Table 10 shows as the demand increases/decreases, the value of the objective function increases/decreases similarly. The number of tours also decreased/increased as the demand decreased/increased. In fact, the higher the demand, the more vehicles are activated. The number of collection centers, charging stations, and dynamic charging arcs are also affected by demand, and there is a direct relationship between them. These changes are quite logical and expected, which indicates the correct operation of GWO in solving the numerical examples.

6. Case study

Canada was one of the first countries to successfully take steps to reduce the rate of COVID-19 infection and subsequently reopen the country. Implementing programs to combat and prevent the spread of Coronavirus dramatically impacted Canada's economy, environment, and social activities with a positive impact on waste generation (Mofijur et al., 2021). One of the most significant changes is the increase in personal protective equipment (PPE) during and after the coronavirus pandemic (Adisesh et al., 2020). The reports from the waste disposal centers show changes in traffic and the use of care products have also impacted the business and economy in Canada (Richter et al., 2021). Studies by Richter et al. (2021) and Ikiz et al. (2021) confirm that, contrary to pre-Coronavirus conditions, from the summer of 2020 onwards, the waste generation rate was similar at different times of the year in Canada.

Moreover, the volume of medical waste generation (masks, gloves, empty containers of disinfectants) as municipal waste has increased significantly. In addition, the rate of generating medical waste related to home therapies has increased because fewer people visit hospitals and medical centers (due to fear of Coronavirus infection). It is important to note that the percentage of household waste separation has increased

Table 9
Optimality gap between GWO and CPLEX in randomly generated instance.

	Servicing cost	Traversal cost of arcs	Establishment cost of dynamic charging arcs	Establishment cost of charging stations	Establishment cost of waste collection centers	Optimally GAP %
CPLEX	18	2745	530	290	1400	10.35
GWO	27	3073	596	334	1469	

Table 10
Changes in the objective function, number of tours, and number of facilities relative to changes in demand.

Demand changes (%)	Objective value	Tour	Collection center	Charging station	Dynamic charging arc
−50	3512	1	1	1	2
−20	3964	1	1	1	2
−10	5123	2	2	1	3
+10	5921	2	2	2	4
+20	6437	2	2	2	5
+50	7219	2	2	2	5

compared to pre-Coronavirus conditions, indicating public concern for saving the environment. In general, optimal waste collection and street cleaning management can help authorities manage their budget more effectively and plan waste collection and disposal services more efficiently.

The problem of municipal covid waste collection in Edmonton, Canada, is investigated in this case study. With a 1,461,000 population in 2020, the city of Edmonton is developed across an area of 767.85 km^2. The city is affected by many COVID-19 cases, similar to other metropolitan areas in North America. MWM in this city is currently performed through 10 active waste collection centers. Table D in the Online Appendix presents the MWM information about the city of Edmonton.

To properly collect municipal wastes during the COVID crisis, it is necessary to dedicate several waste collection centers for municipal wastes. The centers listed in Table D of the Appendix are considered potential locations for establishing waste collection centers. Given the relatively large number of electric vehicles utilized in Edmonton, the city has already been equipped with several charging stations, as detailed in Table E in the Online Appendix.

The listed stations in Table E in the Online Appendix are also considered potential stations for the electric vehicles, operating the waste collection to keep the electric vehicles powered consistently. Figure F in the Online Appendix shows the structure of the streets, intersections, potential locations for establishing waste collection centers, and potential locations for establishing charging stations.

The hedonic model described in Section 3.1. is used to estimate the demand along different streets (i.e., the amount of waste produced per 24-h period). For this purpose, we collect the data on traffic load, number of stores and shopping malls, number of administrative offices and service centers, number of residential buildings, distance from

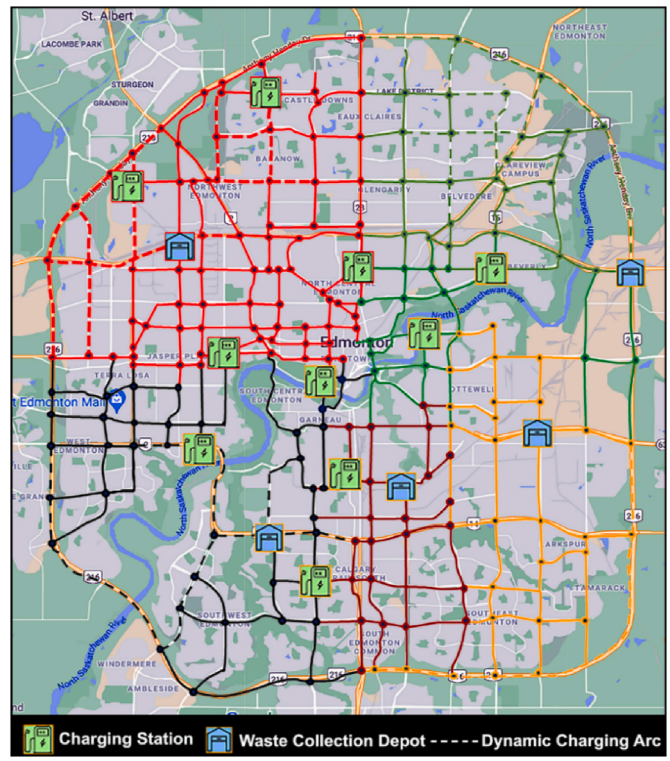

Fig. 5. Charging stations, waste collection depots, and arc routing logistics in Edmonton (Canada).

recreation centers and parks, number of hospitals and medical centers, and number of active urban bins along 30 main streets of Edmonton retrieved from (https://www.edmonton.ca). The average amount of waste generated in an annual interval daily is considered real data to obtain the daily pattern of the produced waste in each street. This way, the waste generation along other streets can be predicted.

After implementing the hedonic model using the data presented in Table F in the Online Appendix, the sensitivity of the log-likelihood function to the Box-Cox transfer parameter is determined. The amount of λ and the normality of the data are shown in Figures Gi and Gii in the Online Appendix, respectively. The average 24-h demand along each street in Edmonton can be estimated using a regression model with the

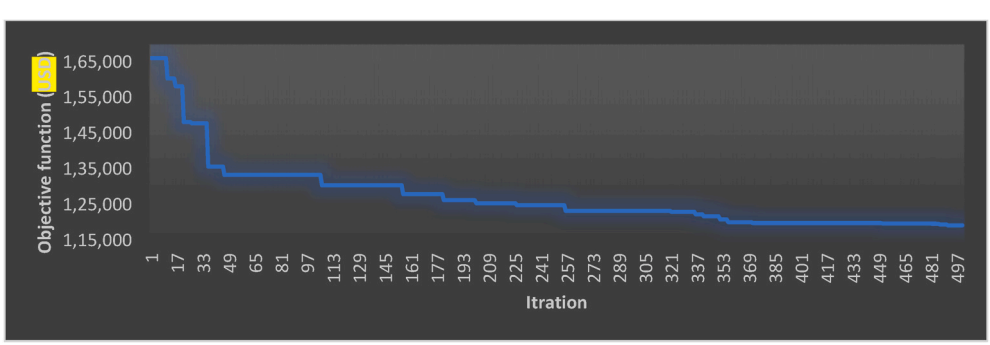

Fig. 4. Solutions convergence of GWO in solving the case study.

coefficients listed in Table G in the Online Appendix.

After solving the problem using GWO, solutions convergence is obtained, as shown in Fig. 4. The maximum number of iterations and the initial population size are 500 and 200, respectively.

Fig. 4 shows that GWO produced solutions with objective function values around 166,106 at initial iterations. The results improve significantly, and the final solution is obtained with the objective function value of 119,245 after 500 iterations by applying various operators in subsequent iterations. Decoding the solutions produced by the algorithm, we could see the locations proposed for establishing waste collection centers, charging stations, dynamic charging arcs, and arc routing across the city of Edmonton, presented in Fig. 5.

Fig. 5 exhibits five waste collection centers that are optimally required in Edmonton. Moreover, the algorithm determines ten charging stations and 41 dynamic charging arcs needed in the city so that electric vehicles have a minimum required level of charge during the entire waste collection process. The total cost of operating ten charging stations and five waste collection depots is estimated at $119,245 per day. Another important point is to investigate the efficiency of the solutions from a managerial point of view. Municipal managers seek to access the required information on the traffic load induced by waste management operations and clean-up of urban streets; hence, they can effectively plan the operations. In this paper, a numerical measure (L) is proposed to quantify the traffic wherein the deadheading is assumed as the primary parameter. Given that the deadheading can be evaluated using the variable x_{ak}, the measure L can be computed through the following procedure.

Step 1. calculate the deadheading for each tour k and store it in Dk.

Step 2. calculate an h-index for each tour k and store it in hk. Notice that a tour has an h-index if h arcs have at least h deadheadings.

Step 3. Calculate $P = \frac{\sum_k (D_k - h_k)^2}{M \times \sum_k D_k}$ where M is the number of tours for which $h_k \geq \alpha \times D_k$, and α is a number between 0 and 1 that is determined by experts, and its lower value implies greater attention to traffic management.

Notice that $0 \leq P \leq 1$, and P values smaller than 0.5 refer to the uniform traffic load in all tours, and P values above 0.5 refer to the heavy traffic load on one tour. Using this index, managers can make managerial decisions to improve urban transportation infrastructures. Indeed, in cases where $P \leq 0.5$, it is required to allocate human and financial resources to improve traffic structures uniformly overall routes. However, when the value of P exceeds 0.5, the traffic state of different tours should be investigated because there are chances that a particular area suffers from deeper infrastructural deficiencies.

Upon performing the required calculations for obtaining the traffic load in the proposed case study, we find $P = 0.71$, indicating an almost uniform traffic load in all tours. Therefore, the urban managers at Edmonton may plan for traffic in different parts of Edmonton uniformly.

An important point about the case study is the changes in the numerical results by changing the input parameters. Sensitivity analysis can provide the research users with various managerial insights by which they can make the best possible decisions for implementing the obtained results. For this purpose, two scenarios to analyze the algorithm's sensitivity to changes in demand per street and capacities of electric vehicles and waste collection centers are studied in this paper.

6.1. Scenario I: increasing/decreasing demand

Under this scenario, ± 50% changes in the demand per street in Edmonton are considered. After solving the problems by the proposed algorithm, the proposed number of waste collection centers, charging stations, dynamic charging arcs, and traffic load is obtained and presented in Table 11.

Table 11 shows that any change in the demand (decrease or increase) can significantly impact the main framework of locating various facilities for waste collection operations in Edmonton. One can effectively control the required number of facilities and the overall system costs by accurately monitoring and forecasting the demand. To sum up, we can conclude that demand control can affect the facility establishment cost.

6.2. Scenario II: decreasing capacities of waste collection centers and electric vehicles

As a necessity for limiting the outbreak of coronavirus across the city, promoting sustainable urban development, and saving fossil fuels, proper operation of the waste collection cannot be achieved unless the required capacities of the facilities and electric vehicles are well determined. Indeed, underestimating these capacities will increase the number of facilities and electric vehicles and, consequently, the overall system cost. In the case of exploiting centers and vehicles with high capacity, it will increase the cost and occupation of excessive physical space. This represents a significant problem in urban areas for realizing the sustainable development criteria and green cities. It is then more necessary to perform the required numerical analysis to evaluate the effect of this parameter on the obtained results. This section considers waste collection centers and electric vehicles with increased/decreased capacities at ten levels, and the required number of facilities and traffic load is obtained. It is worth mentioning that the percent decrease/increase in capacities presented in Table 12 are homogeneously applied to all facilities and electric vehicles.

Like changes in demand, changes in capacities of waste collection centers and electric vehicles directly impact the structure of services, affecting the cost level. With a 50% reduction in the capacity of all facilities and vehicles, it is necessary to use the maximum possible number of all facilities to meet demands. Therefore, one should pay good attention to different aspects of waste collection management and urban road cleaning, including the supply of required physical space for the facilities, to optimally control the coronavirus outbreak across the city.

Table 11
Effects of changes in the outputs of GWO in response to changes in demand.

Demand changes	Traffic load	Number of dynamic charging arcs	Number of charging stations	Number of waste collection centers
50%-	0.65	28	6	2
40%-	0.76	33	6	2
30%-	0.6	34	6	3
20%-	0.58	37	7	3
10%-	0.61	41	8	4
10%+	0.66	41	10	5
20%+	0.65	41	10	5
30%+	0.75	48	12	5
40%+	0.73	55	12	6
50%+	0.64	61	12	6

Table 12
Effects of changing the capacities of waste collection centers and electric vehicles on the outputs of GWO.

Changes in the capacity of facilities and vehicles	Traffic load	Number of dynamic charging arcs	Number of charging stations	Number of waste collection centers
50%-	0.71	56	14	10
40%-	0.69	51	14	10
30%-	0.58	51	14	8
20%-	0.67	47	11	6
10%-	0.71	47	11	6
10%+	0.77	41	10	5
20%+	0.69	41	10	5
30%+	0.73	41	10	4
40%+	0.59	33	7	3
50%+	0.66	33	7	3

Similar to Scenario I, the second scenario reflects the strong effects of the considered changes on the required numbers of waste collection centers and dynamic charging arcs, confirming the importance of properly estimating facility capacities based on actual demand. To sum up, proper management of this operation requires accurate estimation of the demand and highly precise determination of capacities for facilities and electric vehicles.

7. Managerial insights

One of the main problems with using electric vehicles is the lack of sufficient charging infrastructure in urban areas. Another problem with electric vehicles is the high purchase price. In addition, the spread of coronavirus and consequently the possibility of epidemics in the coming years can lead to a sharp increase in the use of vehicles in municipal services, including waste collection and road cleaning. This paper proposed a mathematical optimization model for locating charging stations with different technologies and vehicle arc routing for waste collection. However, implementing the model proposed in this paper is challenging due to (1) the lack of comprehensive technical knowledge in some countries to provide charging infrastructure, (2) limited electric vehicle companies, and (3) energy supply problems. Some knowledge-based companies and start-ups have succeeded in designing and making charging devices for electric vehicles, reducing the required time to charge vehicles.

Nevertheless, the lack of financial resources for research and development is one of the main problems in these companies and start-ups, which can be solved through government subsidies. In addition, allocating government budgets to leading start-ups and companies with electric vehicle production can create a competitive environment, increase competition, and reduce prices. As the cost of electric vehicles decreases, more people can purchase them, so the demand for charging services will increase. The charging infrastructure development can also increase the demand for electricity generation, which ultimately leads to an increase in the production capacity of power plants that often use fossil fuels—expanding the use of electric vehicles results in producing more bio-pollutants by power plants. One of the best ways to solve this problem is to invest in renewable energy sources, which have received attention recently. In many countries worldwide, suitable conditions are provided for energy production from renewable sources. Therefore, government resources, private sector investment, and public-private partnerships can be useful management solutions.

8. Conclusion and future research

This paper presents a new optimization model for efficiently and effectively managing the municipal waste collection problem and playing a crucial role in preventing the spread of coronavirus. The proposed optimization model locates the charging stations with different technologies and routing vehicles to collect waste through a location arc routing model. The objective function minimizes traversing arcs' total costs, establishing waste collection centers, charging stations, and dynamic charging lanes. The constraints include guaranteeing continuous routes, vehicle capacity, and vehicle charging by locating different charging stations optimally. Since the LARP is an NP-hard problem, GA and GWO are developed to solve some randomly generated numerical instances and a real-world case study in Edmonton, Canada. According to the literature review, several studies have examined urban waste management in the coronavirus outbreak; however, the problem is still considered a significant problem in controlling the Coronavirus crisis. In addition, the environmental pollution caused by road cleaning operations and the reduction in fossil fuel consumption has been less discussed. This study covered the research gap by investigating the necessary infrastructure for using electric vehicles. Moreover, the integration of the strategic and technical decisions related to locating waste collection centers, establishing charging stations with various technologies, and arc routing of vehicles to carry out road cleaning operations are other study contributions. A small-sized instance with random data is designed and solved with a CPLEX solver in a GAMS environment to evaluate the mathematical model. The sensitivity analysis is also performed under different conditions to evaluate the performance of the mathematical model. Moreover, Several small, medium, and large-sized instances are randomly generated and solved by GA and GWO. Computational results show that GWO and GA optimality gap is less than 20 percent in small-sized instances. Moreover, the numerical comparison between proposed algorithms indicated that GWO could solve the randomly generated instances about 18%–35% faster than GA, showing the superiority of GWO in terms of the run time. The statistical analyses show that GWO has a significantly better performance than GA from a run time perspective.

To summarize, GWO is selected as a higher-performing algorithm to solve the case study. According to the case study results, five waste collection centers, ten charging stations, and 41 dynamic charging arcs are required in Edmonton. The results of this paper can be used to manage waste collection problems in other countries. The sensitivity analysis performed in two scenarios shows a −50% to +50% change in demand, causing the number of dynamic charging arcs to increase from 28 to 61. This change also results in charging stations and waste collection centers rising from 6 to 12 and 2 to 6. In addition, a −50% to +50% change in the facility and vehicle capacities results in changes in the number of dynamic charging arcs, charging stations, and the number of waste collection centers to decrease from 56 to 31, 14 to 7, and 10 to 3, respectively. In conclusion, this paper could be duplicated in other countries to manage waste collection problems.

CRediT authorship contribution statement

Sahar Moazzeni: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Madjid Tavana:** Methodology, Writing – original draft, Writing – review & editing, Visualization. **Sobhan Mostafayi Darmian:** Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

Dr. Madjid Tavana is grateful for the partial support he received from the Czech Science Foundation (GĂCR19-13946S) for this research.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.132571.

References

Adisesh, A., Durand-Moreau, Q., Patry, L., Straube, S., 2020. COVID-19 in Canada and the Use of Personal Protective Equipment. Oxford University Press, UK.
Akbari, V., Salman, F.S., 2017a. Multi-vehicle prize collecting arc routing for connectivity problem. Comput. Oper. Res. 82, 52–68.
Akbari, V., Salman, F.S., 2017b. Multi-vehicle synchronized arc routing problem to restore post-disaster network connectivity. Eur. J. Oper. Res. 257 (2), 625–640.
Albareda-Sambola, M., Rodríguez-Pereira, J., 2019. Location-routing and Location-Arc Routing *Location Science*. Springer, pp. 431–451.
Amini, A., Tavakkoli-Moghaddam, R., Ebrahimnejad, S., 2020. A bi-objective transportation-location arc routing problem. Transport. Lett. 12 (9), 623–637.
Arakaki, R.K., Usberti, F.L., 2018. Hybrid genetic algorithm for the open capacitated arc routing problem. Comput. Oper. Res. 90, 221–231.

Arias, A., Sanchez, J., Granada, M., 2018. Integrated planning of electric vehicles routing and charging stations location considering transportation networks and power distribution systems. Int. J. Ind. Eng. Comput. 9 (4), 535–550.

Babaee Tirkolaee, E., Abbasian, P., Soltani, M., Ghaffarian, S.A., 2019. Developing an applied algorithm for multi-trip vehicle routing problem with time windows in urban waste collection: a case study. Waste Manag. Res. 37 (1_Suppl. l), 4–13.

Babaee Tirkolaee, E., Aydın, N.S., 2021. A Sustainable Medical Waste Collection and Transportation Model for Pandemics. Waste Management & Research, 0734242X211000437.

Ben-Ameur, W., Kerivin, H., 2005. Routing of uncertain traffic demands. Optim. Eng. 6 (3), 283–313.

Boss, A., 2005. Life Cycle Assessment of a Gas-Electric Hybrid Waste Collection Vehicle. Göteborg, Sweden.

Burlea-Schiopoiu, A., Ogarca, R.F., Barbu, C.M., Craciun, L., Baloi, I.C., Mihai, L.S., 2021. The impact of COVID-19 pandemic on food waste behaviour of young people. J. Clean. Prod. 294, 126333.

Campbell, J.F., Corberán, Á., Plana, I., Sanchis, J.M., 2018. Drone arc routing problems. Networks 72 (4), 543–559.

Campbell, J.F., Corberán, Á., Plana, I., Sanchis, J.M., Segura, P., 2021. Solving the length constrained K-drones rural postman problem. Eur. J. Oper. Res. 292 (1), 60–72.

Chang, T.-S., Yen, H.-M., 2012. City-courier routing and scheduling problems. Eur. J. Oper. Res. 223 (2), 489–498.

Chen, D., Pan, S., Chen, Q., Liu, J., 2020. Vehicle routing problem of contactless joint distribution service during COVID-19 pandemic. Transp. Res. Interdiscip. Perspect. 8, 100233.

Chen, T., Zhang, X.-P., Wang, J., Li, J., Wu, C., Hu, M., Bian, H., 2020. A review on electric vehicle charging infrastructure development in the UK. J. Morden. Power. Sys. Clean. Energy. 8 (2), 193–205.

Chen, Z., Liu, W., Yin, Y., 2017. Deployment of stationary and dynamic charging infrastructure for electric vehicles along traffic corridors. Transport. Res. C Emerg. Technol. 77, 185–206.

Cheng, C., Zhu, R., Costa, A.M., Thompson, R.G., Huang, X., 2021. Multi-period two-echelon location routing problem for disaster waste clean-up. Transportmetrica: Transport. Sci. 1–31.

Chow, J.Y., 2016. Dynamic UAV-based traffic monitoring under uncertainty as a stochastic arc-inventory routing policy. Int. J. Transport. Sci. Technol. 5 (3), 167–185.

Constantino, M., Mourão, M.C., Pinto, L.S., 2017. Dissimilar arc routing problems. Networks 70 (3), 233–245.

Corberán, Á., Eglese, R., Hasle, G., Plana, I., Sanchis, J.M., 2021. Arc routing problems: a review of the past, present, and future. Networks 77 (1), 88–115.

Corberán, Á., Fernández, E., Franquesa, C., Sanchis, J.M., 2011. The windy clustered prize-collecting arc-routing problem. Transport. Sci. 45 (3), 317–334.

Costa, D.G., Peixoto, J.P.J., 2020. COVID-19 pandemic: a review of smart cities initiatives to face new outbreaks. IET Smart Cities 2 (2), 64–73.

Darmian, S.M., Fattahi, M., Keyvanshokooh, E., 2021. An optimization-based approach for the healthcare districting under uncertainty. Comput. Oper. Res. 135, 105425.

Darmian, S.M., Moazzeni, S., Hvattum, L.M., 2020. Multi-objective sustainable location-districting for the collection of municipal solid waste: two case studies. Comput. Ind. Eng. 150, 106965.

Das, A.K., Islam, M.N., Billah, M.M., Sarker, A., 2021a. COVID-19 and municipal solid waste (MSW) management: a review. Environ. Sci. Pollut. Control Ser. 28, 28993–29008.

Das, A.K., Islam, M.N., Billah, M.M., Sarker, A., 2021b. COVID-19 pandemic and healthcare solid waste management strategy–A mini-review. Sci. Total Environ. 778, 146220.

Dascioglu, B.G., Tuzkaya, G., 2019. A Literature Review for Hybrid Vehicle Routing Problem *Industrial Engineering In the Big Data Era*. Springer, pp. 249–257.

Delle Donne, D., Di Tomaso, V., Duran, G., 2021. Optimizing leaf sweeping and collection in the Argentine city of Trenque Lauquen. Waste Manag. Res. 39 (2), 209–220.

Dussault, B., Golden, B., Groër, C., Wasil, E., 2013. Plowing with precedence: a variant of the windy postman problem. Comput. Oper. Res. 40 (4), 1047–1059.

Eglese, R., Golden, B., Wasil, E., 2015. Chapter 13: Route Optimization for Meter Reading and Salt Spreading *Arc Routing: Problems, Methods, and Applications*. SIAM, pp. 303–320.

Erdelić, T., Carić, T., 2019. A survey on the electric vehicle routing problem: variants and solution approaches. J. Adv. Transport. 2019, 5075671.

Erdem, M., Koç, Ç., 2019. Analysis of electric vehicles in home health care routing problem. J. Clean. Prod. 234, 1471–1483.

Farahbakhsh, S., 2019. Optimization of Waste Collection System at. University of Calgary.

Farughi, H., Tavana, M., Mostafayi, S., Santos Arteaga, F.J., 2020. A novel optimization model for designing compact, balanced, and contiguous healthcare districts. J. Oper. Res. Soc. 71 (11), 1740–1759.

Fernández, E., Leitner, M., Ljubic, I., Ruthmair, M., 2020. Arc Routing with Electric Vehicles: Dynamic Charging and Speed-dependent Energy Consumption.

Golden, B.L., Wong, R.T., 1981. Capacitated arc routing problems. Networks 11 (3), 305–315.

Haji, J.Y., Subramaniam, A., Kumar, P., Ramanathan, K., Rajamani, A., 2020. State of personal protective equipment practice in Indian intensive care units amidst COVID-19 pandemic: a nationwide survey. Indian J. Crit. Care Med.: Peer-Rev. Off. Pub. Indian. Soc. Critical. Care Med. 24 (9), 809.

Haque, M.S., Uddin, S., Sayem, S.M., Mohib, K.M., 2020. Coronavirus disease 2019 (COVID-19) induced waste scenario: a short overview. J. Environ. Chem. Eng., 104660

Hof, J., Schneider, M., Goeke, D., 2017. Solving the battery swap station location-routing problem with capacitated electric vehicles using an AVNS algorithm for vehicle-routing problems with intermediate stops. Transp. Res. Part B Methodol. 97, 102–112.

Huang, S.-H., Lin, P.-C., 2012. Multi-treatment capacitated arc routing of construction machinery in Taiwan's smooth road project. Autom. ConStruct. 21, 210–218.

Ikiz, E., Maclaren, V.W., Alfred, E., Sivanesan, S., 2021. Impact of COVID-19 on household waste flows, diversion and reuse: the case of multi-residential buildings in Toronto, Canada. Resour. Conserv. Recycl. 164, 105111.

Kargar, S., Pourmehdi, M., Paydar, M.M., 2020. Reverse logistics network design for medical waste management in the epidemic outbreak of the novel coronavirus (COVID-19). Sci. Total Environ. 746, 141183.

Kiilerich, L., Wøhlk, S., 2018. New large-scale data instances for CARP and new variations of CARP. INFOR Inf. Syst. Oper. Res. 56 (1), 1–32.

Kokane, P., Ashraf, M.A., Shinkar, V., 2021. Utilization of Geospatial Network Analysis Technique for Optimal Route Planning during COVID-19 Pandemic *COVID-19 Pandemic, Geospatial Information, and Community Resilience*. CRC Press, pp. 187–194.

Lacomme, P., Prins, C., Sevaux, M., 2006. A genetic algorithm for a bi-objective capacitated arc routing problem. Comput. Oper. Res. 33 (12), 3473–3493.

Lannez, S., Artigues, C., Damay, J., Gendreau, M., 2015. A railroad maintenance problem solved with a cut and column generation matheuristic. Networks 66 (1), 40–56.

Laporte, G., Nickel, S., Saldanha-da-Gama, F., 2019. Introduction to Location Science *Location Science*. Springer, pp. 1–21.

Li, M., Zhen, L., Wang, S., Lv, W., Qu, X., 2018. Unmanned aerial vehicle scheduling problem for traffic monitoring. Comput. Ind. Eng. 122, 15–23.

Li, Y., Zhang, P., Wu, Y., 2018. Public recharging infrastructure location strategy for promoting electric vehicles: a bi-level programming approach. J. Clean. Prod. 172, 2720–2734.

Lin, J., Zhou, W., Wolfson, O., 2016. Electric vehicle routing problem. Transport. Res. Procedia 12 (Suppl. C), 508–521.

Liu, H., Gao, B., Liu, Y., 2019. Battery swap station location routing problem with capacitated electric vehicles and time windows. In: Paper Presented at the 2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA).

Liu, Y., Shi, J., Liu, Z., Huang, J., Zhou, T., 2019. Two-layer routing for high-voltage powerline inspection by cooperated ground vehicle and drone. Energies 12 (7), 1385.

Lopes, R.B., Plastria, F., Ferreira, C., Santos, B.S., 2014. Location-arc routing problem: heuristic approaches and test instances. Comput. Oper. Res. 43, 309–317.

Luo, H., Zhang, P., Wang, J., Wang, G., Meng, F., 2019. Traffic patrolling routing problem with drones in an urban road system. Sensors 19 (23), 5164.

Mirjalili, S., Mirjalili, S.M., Lewis, A., 2014. Grey wolf optimizer. Adv. Eng. Software 69, 46–61.

Mofijur, M., Fattah, I.R., Alam, M.A., Islam, A.S., Ong, H.C., Rahman, S.A., Mahlia, T.M. I., 2021. Impact of COVID-19 on the social, economic, environmental and energy domains: lessons learnt from a global pandemic. Sustain. Prod. Consum. 26, 343–359.

Mourão, M.C., Pinto, L.S., 2017. An updated annotated bibliography on arc routing problems. Networks 70 (3), 144–194.

Nossack, J., Golden, B., Pesch, E., Zhang, R., 2017. The windy rural postman problem with a time-dependent zigzag option. Eur. J. Oper. Res. 258 (3), 1131–1142.

Paz, J., Granada-Echeverri, M., Escobar, J., 2018. The multi-depot electric vehicle location routing problem with time windows. Int. J. Ind. Eng. Comput. 9 (1), 123–136.

Raeesi, R., Zografos, K.G., 2020. The electric vehicle routing problem with time windows and synchronised mobile battery swapping. Transp. Res. Part B Methodol. 140, 101–129.

Richter, A., Ng, K.T.W., Vu, H.L., Kabir, G., 2021. Waste disposal characteristics and data variability in a mid-sized Canadian city during COVID-19. Waste Manag. 122, 49–54.

Sarkodie, S.A., Owusu, P.A., 2020. Impact of COVID-19 pandemic on waste management. Environ. Dev. Sustain. 1–10.

Schiffer, M., Schneider, M., Walther, G., Laporte, G., 2019. Vehicle routing and location routing with intermediate stops: a review. Transport. Sci. 53 (2), 319–343.

Schiffer, M., Walther, G., 2018. Strategic planning of electric logistics fleet networks: a robust location-routing approach. Omega 80, 31–42.

Shafahi, A., Haghani, A., 2015. Generalized maximum benefit multiple Chinese postman problem. Transport. Res. C Emerg. Technol. 55, 261–272.

Sharma, H.B., Vanapalli, K.R., Cheela, V.S., Ranjan, V.P., Jaglan, A.K., Dubey, B., Bhattacharya, J., 2020. Challenges, opportunities, and innovations for effective solid waste management during and post COVID-19 pandemic. Resour. Conserv. Recycl. 162, 105052.

Sopranzetti, B.J., 2015. Hedonic regression models. Handbook. Financial. Eco. Stat. 2119–2134.

Souffriau, W., Vansteenwegen, P., Berghe, G.V., Van Oudheusden, D., 2011. The planning of cycle trips in the province of East Flanders. Omega 39 (2), 209–213.

Tirkolaee, E.B., Abbasian, P., Weber, G.-W., 2021. Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak. Sci. Total Environ. 756, 143607.

Tirkolaee, E.B., Mahdavi, I., Esfahani, M.M.S., Weber, G.-W., 2020. A robust green location-allocation-inventory problem to design an urban waste management system under uncertainty. Waste Manag. 102, 340–350.

Tordecilla, R.D., Martins, L.d.C., Saiz, M., Copado-Mendez, P.J., Panadero, J., Juan, A.A., 2021. Agile Computational Intelligence for Supporting Hospital Logistics during the COVID-19 Crisis *Computational Management*. Springer, pp. 383–407.

Tripathi, A., Tyagi, V.K., Vivekanand, V., Bose, P., Suthar, S., 2020. Challenges, opportunities and progress in solid waste management during COVID-19 pandemic. Case stud. Chem. Environ Eng. 2, 100060.
Valizadeh, J., Hafezalkotob, A., Alizadeh, S.M.S., Mozafari, P., 2021. Hazardous infectious waste collection and government aid distribution during COVID-19: a robust mathematical leader-follower model approach. Sustain. Cities Soc. 69, 102814.
Van Fan, Y., Jiang, P., Hemzal, M., Klemeš, J.J., 2021. An update of COVID-19 influence on waste management. Sci. Total Environ. 754, 142014.
Vanapalli, K.R., Sharma, H.B., Ranjan, V.P., Samal, B., Bhattacharya, J., Dubey, B.K., Goel, S., 2020. Challenges and strategies for effective plastic waste management during and post COVID-19 pandemic. Sci. Total Environ. 750, 141514.
Vansteenwegen, P., Souffriau, W., Sörensen, K., 2010. Solving the mobile mapping van problem: a hybrid metaheuristic for capacitated arc routing with soft time windows. Comput. Oper. Res. 37 (11), 1870–1876.
Verbeeck, C., Vansteenwegen, P., Aghezzaf, E.-H., 2014. An extension of the arc orienteering problem and its application to cycle trip planning. Transport. Res. E Logist. Transport. Rev. 68, 64–78.
Willemse, E.J., Joubert, J.W., 2012. Applying min–max k postmen problems to the routing of security guards. J. Oper. Res. Soc. 63 (2), 245–260.
World Health Organization, 2020. Water, Sanitation, Hygiene, and Waste Management for the COVID-19 Virus: Interim Guidance, 23 April 2020.
Yang, J., Sun, H., 2015. Battery swap station location-routing problem with capacitated electric vehicles. Comput. Oper. Res. 55, 217–232.
Yurtseven, C., Gökçe, M.A., 2019. A novel arc-routing problem of electric powered street sweepers with time windows and intermediate stops. IFAC-PapersOnLine 52 (13), 2308–2313.
Zaeimi, M.B., Rassafi, A.A., 2021. Designing an integrated municipal solid waste management system using a fuzzy chance-constrained programming model considering economic and environmental aspects under uncertainty. Waste Manag. 125, 268–279.
Zhang, S., Chen, M., Zhang, W., 2019. A novel location-routing problem in electric vehicle transportation with stochastic demands. J. Clean. Prod. 221, 567–581.
Zuo, X., Xiao, Y., You, M., Kaku, I., Xu, Y., 2019. A new formulation of the electric vehicle routing problem with time windows considering concave non-linear charging function. J. Clean. Prod. *236*, 117687.