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Designing a sustainable logistics network for hazardous medical waste collection a case study in COVID-19 pandemic

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ABSTRACT

The process of collecting and transporting hazardous medical waste poses a potential threat to the environment and public safety. Furthermore, the waste management system faces higher transportation costs due to the increasing human activities related to rapid population growth. The absence of an efficient and safe logistics network for the timely collection and transportation of hazardous wastes may have negative effects on the environment and public health. Therefore, more sustainable transportation of hazardous waste services is a necessity This paper attempts to design a sustainable network for hazardous medical waste collection services during the COVID-19 pandemic. An electric medical waste collection vehicle routing problem is introduced to construct optimal routes and rosters for a fleet of electric vehicles as well as cover their choice of charging technologies, times and locations. This problem allows us to minimize the health risk of hazardous medical waste while providing cost-effective, zero-emission waste management logistics. Therefore, this problem covers environmental and economic objectives to achieve sustainable development. An effective heuristic that covers adaptive large neighbourhood search and a local search is designed to deal with the complex problem. A series of extensive computational experiments is carried out using real-life benchmark instances to assess the performance of the algorithm. A sensitivity analysis is also conducted to investigate the effect of multiple charger types on the cost and risk objectives. The experiment results indicate that mixed-use of different charger types can reduce the total energy cost and transport risk compared to the case of using only a single charger.

1. Introduction

The demand for health activities has increased owing to the growth in population and rising chronic diseases, ageing population of older people, etc. World Health Organization (2019). The amount of medical waste produced by health institutions such as hospitals, research centres, and laboratories is increasing each year in parallel with this rate (Greenhealth, Waste, 2020). Although the majority of medical wastes are deemed to be non-hazardous waste, 20% of which is considered hazardous waste material that has been exposed to infection, chemicals or toxicity (World Health Organization, 2018). These types of wastes are low in proportion; however, they are a critical group that entails high risks. It can involve harmful contagious microorganisms that contaminate patients, healthcare staff and the general public. Furthermore, the volume of medical waste generation increased significantly worldwide due to the diagnosis and treatment of the COVID-19 pandemic (United Nations Environment Programme (UNEP), 2020; Singh et al., 2020). In 2018, the average amount of hazardous waste per hospital bed per day in developed countries was 0.5 kg, while this figure is 0.2 kg on average in developing countries. However, in 2020, a patient with COVID-19 can generate up to 3.4 kg of waste per day (Asian Development Bank, 2020).

Medical waste management includes the processes of collection, separation, storage, transportation, processing, and disposal of wastes produced in health institutions. These processes should be operated very carefully in order to minimize the risks and control the infectious epidemic. Adequate and appropriate handling of medical wastes can contribute to the public health consequences and reduce the negative impact on the environment. For this reason, good management of waste is critical for protecting human and environmental health (WHO, 2014; Das et al., 2021). The global medical waste management worth was $14.17 billion in 2020, and this figure rises at a compound annual growth rate of 2.6% in 2021. The growth of the market is expected to be $18.2 billion at a compound annual growth rate of 6% in 2025 (Business Research Company, 2021).

The cost of waste collection and transport operations accounts for more than 70% of the municipal solid waste management system. Moreover, diesel fuel consumption constitutes a large part of the transport and collection costs (Tavares et al., 2009). In this regard, it is

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crucial to design a cost-effective solution to provide waste collection services. In this way, it can be ensured that the waste collection efficiency is increased and the tax rates paid are reduced (Boskovic et al., 2016).

The transport sector is a crucial component of social and economic development challenges. However, the global transportation sector is a major pollutant, emitting approximately 7.3 billion metric tons of CO_2 emissions. A large part of the transport is usually made to ICEVs, which have severe effects on human health, environmental quality, etc. Medium and heavy trucks are carrying freight account for more than one-fifth of transport emissions (Statista, 2021; EPA, 2021). Increasingly, countries worldwide are looking for new strategies to improve social and ecological conditions while considering individual mobility. Sustainable road transport entails three pillars economic efficiency, environmental stability, and social equity (Schwaab and Thielmann, 2002). Furthermore, to accomplish the Paris Agreement's goals to limit global temperature, this sector should operate in a more sustainable way and energy-efficient manner (United Nations Climate Change (UNCC), 2020). The use of electric vehicles (EVs) in the transportation sector emerged as a global strategy to reduce emissions and was met with government support. For instance, Deutsche Post DHL has allocated seven billion euros for the electric fleet over the next ten years. Similarly, UPS announced an order for 1000 EVs to be used in logistics operations within a few years (Anon, 2021; UPS, 2020). New research has shown that EVs provide more than a 10% cost advantage over diesel vehicles. It is predicted that this cost advantage will reach 50% by 2030, together with the improvement and cheapening of battery technology (Amol et al., 2021).

The need to design the routes of EVs has introduced a new research field, and the new problem defined as the electric vehicle routing problem that attracts increasing attention from the scientific circles (Moghdani et al., 2021). In order to manage an EV fleet efficiently, disadvantages of them such as their limited range, long charging times, a limited number of charging stations, and availability of charging infrastructure need to be considered in planning. These limitations increase the complexity of the planning problem and turn it into a combinatorial optimization problem.

This paper aims to optimize the waste collection and transportation operations utilizing a fleet of EVs instead of internal combustion engine vehicles (ICEVs). This problem is called the electric medical waste collection vehicle routing problem (EMWCVRP). The new problem is concerned with optimizing hazardous medical waste collection operations in a sustainable way. Considering that sustainable transportation includes more than one target, such as air pollution, public health, safety, operating efficiency of the transportation system, environmental protection and economic vitality, etc. UN (2019), the proposed problem becomes important in this respect. Therefore, the new problem considers different objectives with two different mathematical models of these goals. While one of these objectives is the energy cost of vehicles, the other purpose is the risk of transporting hazardous waste. The new problem extension also considers multiple types of hazardous medical waste, multiple charger types, vehicle-station compatibility, and heterogeneous electric vehicle fleet. This problem extension has not been studied before in the hazardous waste management framework. To deal with the problem, an efficient solution algorithm employing the adaptive large neighbourhood search (ALNS) and a local search heuristic is developed in this sense. Furthermore, several numerical experiments on real-life instances are conducted to examine the performance of the algorithm and to investigate the effect of multiple charger types on the cost and risk objectives.

The rest of this paper is structured as follows: Section 2 reviews an overview of related research literature. Section 3 describes and explains the EMWCVRP and formulates two different mathematical models. Section 4 presents the proposed heuristic approach. Section 5 addresses the results of the numerical experiments and analyses. Lastly, Section 6 concludes the paper and discusses future research.

2. Literature review

This section provides the most relevant literature on medical waste management and the electric vehicle routing problem (EVRP) since the EMWCVRP incorporates the features of these two complex problems.

2.1. A brief literature review on medical waste collection problems

Zografros and Samara (1989) addressed the hazardous waste location-routing problem with a single type of waste. The authors applied a goal programming model to minimize disposal and routing risks and travelling time. List and Mirchandani (1991) studied the same problem with multiple types of hazardous waste and treatment technology. The proposed model covers three objectives is to minimizing total risk, transportation cost, and total risk equity. Nema and Gupta (1999) proposed an integer model to deal with the selection of routes, hazardous waste treatment, and disposal facilities. The proposed function for transportation risk is defined as dependent on the volume and property of the hazardous wastes and the probability of accident of the vehicle and the exposed population. The capacity of trucks and interactions among wastes were not taken into account in the model.

Alumur and Kara (2007) developed a model for a hazardous waste location-routing problem to minimize the total cost and transportation risk regarded as population exposure. The model takes into account a series of decisions such as the locations and technologies of treatment centres, locations of disposal centres, routing of different types of waste with compatible technologies and routing of the generated waste residues to disposal centres. The authors applied their model to a case study in Turkey. Samanlioglu (2013) studied the same problem, considering three objective functions in the model developed. These objectives can be counted as total operating cost, total fixed costs of treatment, disposal and recycling centres and the transportation risk defined as the work of Alumur and Kara (2007). The author used a lexicographic weighted Tchebycheff approach to solve the problem. Both works utilize geographic information system (GIS) software to obtain information on population.

Shih and Chang (2001) studied the collection of infectious medical waste (in Tainan City, Taiwan) and modelled it as a periodic vehicle routing problem. The authors developed a two-phase solution method to optimize the routing and scheduling decisions as to the problem. Hamdi et al. (2010) studied the vehicle routing problem with conflicts (VRPC) aiming to minimize the travelling cost of routes for the different hazardous compatible materials. The authors developed an iterated local search (ILS) metaheuristic to solve it. Paredes-Belmar et al. (2017) proposed a new approach to tackle the hazardous material collection problem. The objective is to minimize the transportation cost and the risk of exposure, which is measured by the total population influenced by the route in case of an accident. The authors also considered the capacity of homogeneous trucks and multiple wastes can be loaded in the same truck with the parameters of waste compatibility and risk dominance. The integer programming method was applied to Santiago, Chile's the transportation network of wastes.

Mantzaras and Voudrias (2017) developed a nonlinear model for the infectious medical waste management system. The objective of this study is to minimize the total transport, disposal, collection treatment and disposal costs, altogether. The authors also applied a GIS-based methodology to determine the locations of candidate sites, such as treatment facilities and transfer stations. Zhao et al. (2016) addressed regional hazardous waste management systems and proposed a multi-objective mixed-integer linear programming (MILP) formulation. The objective of the formulation is to minimize total cost and risk in decisions related to transportation and location. The authors applied an augmented ε-constraint, an augmented weighted Tchebycheff, and a weighted-sum approaches to explore efficient solutions. It was concluded that the last approach did not yield high quality of solutions in contrast to the first two approach. Zhao and Ke (2017) studied

Table 1
A summary of waste management/collection problem studies.

	Objective		Risk	Fleet comp.		Waste type		Location	TW
	Single	Multi	function	Single	Multi	Single	Multi		
Zografros and Samara (1989)		+	+	+		+		+	
List and Mirchandani (1991)		+	+	+		+		+	
Nema and Gupta (1999)		+	+	+		+		+	
Alumur and Kara (2007)		+	+	+			+	+	
Samanlioglu (2013)		+	+	+			+	+	
Shih and Chang (2001)		+		+		+			
Hamdi et al. (2010)	+			+			+		
Paredes-Belmar et al. (2017)		+	+	+			+		
Aydemir-Karadag (2018)	+			+			+	+	
Mantzaras and Voudrias (2017)	+				+			+	
Zhao et al. (2016)		+	+	+			+	+	
Zhao and Ke (2017)		+	+	+		+		+	
Babaee Tirkolaee and Aydın (2021)		+	+	+		+		+	
Eren and Tuzkaya (2021)		+		+		+			
Ghannadpour et al. (2021)		+	+	+			+		
This study	+	+	+		(EV) +		+		+

explosive waste management and defined environmental risk as a volume-based risk assessment approach. The authors proposed a bi-objective model, through which the optimization of route and facility locations as well as the inventory risks are taken into account. Furthermore, a TOPSIS-based solution procedure was applied to convert the bi-objective formulation to a single objective model. Aydemir-Karadag (2018) dealt with the hazardous waste location-routing problem to solve a real case study in Turkey. The author aims to maximize the profit of the hazardous waste management (HWM) system for the long-term planning horizon. In addition, the proposed model also incorporates several aspects of HWM system such as multiple wastes, waste-to-technology compatibility and electricity generation from the waste. Babaee Tirkolaee and Aydın (2021) developed a bi-objective MILP for medical waste management services. While one of the objectives is the minimization of total costs, the other objective is total risk exposure that is imposed by the transportation and disposal of the waste. Eren and Tuzkaya (2021) addressed the medical waste collection problem to maximize safety and minimize the total travelled distance. The authors used the safety score which was determined for 15 hospitals with more than 20 beds in Istanbul during the Covid-19 pandemic (Eren and Tuzkaya, 2019). In addition, the membership function approach was applied in the multi-objective traveller salesman problem (TSP). Ghannadpour et al. (2021) addressed sustainable healthcare waste collection routing problem with homogeneous vehicles that are equipped with an internal combustion engine. The economic, environmental, and social dimensions of sustainable development goals have been taken into account as the objectives of the problem. The type measured the social risk and weight of waste, the impact of disease and disease transmission probability, and the vehicle arrival time. In addition, the authors presented a multi-objective self-adaptive evolutionary algorithm (MOSEA) to solve problem of a healthcare waste transportation company in Iran.

Table 1 summarizes the mainstream on waste management/collection problem studies. Most of the existing studies on HWM have considered the environmental impact indirectly and several constraints have been defined to minimize the use of greenhouse gas (Hannan et al., 2020; Ghannadpour et al., 2021). The main purpose of these definitions is to minimize the environmental effects of conventional ICEVs. However, increasing concerns about the negative environmental impacts of transportation activities have directly affected the research of new vehicle technologies. Moreover, efficient, safe, and environmentally-friendly objectives in the context of vehicle routing problems (VRPs) gain increasing attention from the scientific community (Bektaş et al., 2019). Therefore, the electric vehicle routing problem (EVRP) has emerged as a topic that has started to be studied in the last decade. It aims to minimize environmental concerns while considering the technical limitations of these vehicles.

2.2. A brief literature review on sustainable vehicle routing problems

Erdoğan and Miller-Hooks (2012) first considered a green VRP in which alternative fuel vehicles (AFVs) are refuelled at alternative fuel stations. Thus, the charging duration of AFVs is constant. Schneider et al. (2014) proposed the EVRP with time windows in which homogeneous EVs were utilized instead of AFVs. These studies aim to minimize the total energy cost of vehicle routes. Furthermore, these studies assumed that EVs depart from the charging stations (CSs) with a full battery charge. Contrary to the full charge policy in the previous studies (Erdoğan and Miller-Hooks, 2012; Schneider et al., 2014), the partial charge policy was taken into account in the later studies (Keskin and Çatay, 2016; Bac and Erdem, 2021). In other words, EVs can leave the CS with a partially charged battery. Moreover, in several studies (Hof et al., 2017; Soysal et al., 2020) assumed the battery swapping options. The depleted battery is removed from the EV at battery swap stations and replaced with a fully charged battery. In parallel with the developing technology related to EVs and their battery, research is also underway on how to charge them conveniently. There are several ways to charge a battery. Keskin and Çatay (2018) assumed that CSs are equipped with three different types of chargers: normal, fast, and super-fast. Several studies also addressed the EVRP with the heterogeneous fleet. Some studies (Hiermann et al., 2016; Erdem and Koç, 2019) considered different types of EVs with different load capacity, energy consumption, etc. Some studies (Goeke and Schneider, 2015; Masmoudi et al., 2021) also regarded a fleet mixing problem in which EVs and conventional vehicles are utilized.

In terms of the energy consumption, most of the studies on EVRP considered that it is related to the travelled distance. Unlike these studies, Goeke and Schneider (2015) proposed a more comprehensive energy consumption function that is comprised of air resistance, rolling resistance, and gravitational forces. Furthermore, Murakami (2017) used a nonlinear function to compute the energy consumption based on the load, vehicle, and actual road network parameters. In terms of the charging functions, one can classify the assumptions into two groups: studies employing linear and non-linear charging functions. In the first group employing a linear charging function, the battery is assumed to be charged at a constant rate at the station. In the second group, the charging process is represented as a non-linear charging function and it is approximated by means of a piece-wise linear function (Montoya et al., 2017).

Sustainable waste management proposes taking a series of measures to reduce the consumption of natural resources. In this way, it is aimed to reduce waste and minimize the harmful effect on the environment. In the current studies on medical waste collection management, a number of restrictions/formulas have been defined to minimize the environmental impact, namely greenhouse gases. These definitions have been proposed to minimize the environmental impact of ICEVs. There is an increasing interest worldwide to use more environmentally friendly vehicles instead of using these conventional vehicles. In 2015, UN adopted the seventeen global goals (a.k.a sustainable development goals SDGs) that aim to shift the world on a more sustainable path (UN, 2019). The 10 SDGs with a wide variety of 12 direct and indirect targets are related to the transport sector (UNECE, 2019; Hannan et al., 2020). Therefore, from this perspective, sustainable transport should not be ignored.

2.3. Scientific contributions and structure of the paper

In contrast to the aforementioned problems, this paper focuses on collecting and transferring hazardous medical wastes from a wide range of medical centres (hospitals, laboratories, dental clinics, etc.) to a landfill site employing an environmentally friendly way. None of the existing problems involves all the aspects of this problem variant to our best knowledge. This paper attempts to take simultaneous routing, scheduling, and charging decisions considering the risk of hazardous medical wastes. In terms of the objective function, the majority of the studies aim to minimize total shipment cost of ICEVs. Several studies also involve inventory and facility construction costs. On the other hand, the proposed models consider the total energy costs of a heterogeneous fleet of EVs. Furthermore, due to the potentially harmful nature of the multiple waste, the developed risk function depends on the waste's transportation time, type, and volume. The majority of works ignore the waste's transportation time. In terms of the constraints, working and service time windows, partial charge policy, multiple charger technologies, and vehicle-station compatibility are taken into account in this sense. All of the aforementioned studies used ICEVs for the waste collection services. Hence, a more sustainable operation of waste collection can be achieved using zero-emission logistic vehicles. For this reason, it is necessary to develop a meta-heuristic algorithm for the electric medical waste collection vehicle routing problem (EMWCVRP) that allows us to minimize the risk of medical waste while providing cost-effective, zero-emission waste management logistics.

The contributions of this paper are as follows. First, the EMWCVRP with time windows, vehicle-station compatibility, and multiple hazardous medical wastes and their transfer risks is introduced. Second, two mixed-integer programming models are mathematically formulated for the problem. One is the single objective model that aims to design optimum routes for EVs considering the total cost. The other aims to plan EVs by taking into account transportation costs and risks. Third, an effective ALNS-based heuristic is developed to solve these models. Fourth, a new set of real-life size benchmark instances is generated to the assess method's solution quality and to provide several managerial insights.

3. Problem description and formulation

3.1. Problem description

The electric medical waste collection vehicle routing problem (EMWCVRP) considers the collection of different types of multiple hazardous medical wastes from geographically scattered districts while minimizing energy costs as well as their transfer risks. The entire transfer risk is directly related to transportation time, the type and amount of waste, transmissibility and severity of medical waste. The problem involves a set of medical centres with known amount of multiple hazardous wastes, time windows, and service durations. A heterogeneous fleet of EVs carries out the collection activities with different load and battery capacities as well as different battery charging durations. The collection activities must be performed within the given time windows. Similar to this, a time interval is also set for EVs, and during this working period medical wastes must be picked up from centres. The state of charge (SoC) decreases proportionally with the distance travelled. In the problem, EVs can depart from the landfill (depot), and CSs with a partially charged battery return the landfill with a low-level or empty battery. Since the maximum safety standards are required for the collection of hazardous materials, EVs are prevented from using several urban CSs. For this reason, EV-CS compatibility is also taken into account in this framework.

Fig. 1 presents a small-size example that consists of eight medical centres, two CSs, and a landfill. A heterogeneous fleet of EVs collects infectious, pathological, sharps, and chemical-pharmaceutical wastes from these medical centres. The percentage values symbolize the SoC of EVs. In this example, EV 1 arrives at CS 1 with a 40% battery level and departs from it with a fully charged battery. While EV3 does not use any CS, EV2 departs from CS2 with a partially charged battery. Moreover, EVs leave the landfill with a required certain amount of energy level to perform all the assigned tasks. It is assumed that the landfill is only equipped with a Level 2 (fast) charger. EVs can use Level 2 (fast) and Level 3 (super-fast) multiple charger options at CSs with a usage fee depending upon the charger type.

3.2. Notation

An instance of the EMWCVRP involves a set of medical centres B, a set of stations S, and a set of EVs K. $\{0, n\}$ refers to the two copies of the landfill node that indicates the starting and ending route of an EV. Multiple visits of CSs are allowed; thus, it is represented S' as the set of CSs along with their copies. The set of charger types is represented by an F. Two different types of chargers are taken into account $F = \{1, 2\}$. $f = 1$ refers to Level 2 charger whereas $f = 2$ corresponds to Level 3 charger. It is assumed that medical centres produce four types of hazardous medical waste, $M = \{1, 2, 3, 4\}$. These are infectious, pathological, sharps, and chemical-pharmaceutical wastes. Let $N = B \cup S'$, $N_0 = N \cup \{0\}$, $N_n = N \cup \{n\}$, and $N_{0,n} = N \cup \{0, n\}$. Then the problem at hand can be defined by a complete directed graph $G = (N_{0,n}, A)$, where there is a set of arcs $A = \{(i, j) : i, j \in N_{0,n}, i \neq j\}$.

Each $(i, j) \in A$ has two associated parameters: a distance c^d_{ij} and a travel time c_{ij}. The medical centres are serviced by using a limited and heterogeneous fleet of EVs. The battery and load capacities of EV $k \in K$ are Y_k and Q_k, respectively. EV $k \in K$ consumes energy at a rate of h_k based on unit travelled distance and charges energy at a rate of r_{fk} based on charger type. Each medical centre $i \in B$ is associated with a service time window $[\alpha_i, \beta_i]$, and a duration of service p_i. In addition, each EV $k \in K$ has a working time window $[\alpha_k, \beta_k]$. q_{im} denotes the produced waste type $m \in M$ produced at medical centre $i \in B$. Parameter e_{ik} be equal to 1 if EV $k \in K$ is allowed to visit CS $i \in S'$ and 0 otherwise. ϕ^c_f is the unit charging cost by using charger type $f \in F$ and ϕ^u_f is the usage cost of using charger type $f \in F$.

The following binary decision variables are first defined to formulate the mathematical models. Let x_{ijk} be equal to 1 if EV $k \in K$ travels on arc $(i, j) \in A$, and to 0 otherwise. Let binary variable v_k be equal to 1 if EV $k \in K$ is utilized, and to 0 otherwise. Let variable γ_{ik} be equal to 1 if EV $k \in K$ uses a Level 2 charger type at station $i \in S'$, and to 0; otherwise, EV uses a Level 3 charger. Let θ_{if} be equal to 1 if charger type $f \in F$ is used at CS $i \in S'$, and 0 otherwise. Now the following continuous decision variables are represented for the models. While y_{ik} tracks the SoC of EV $k \in K$ at node $i \in N_n$, g_{ik} specifies SoC of EV $k \in K$ when departing from station $i \in S'$. Variable ψ_{ikf} represents the amount of energy stored at station $i \in S'$ of EV $k \in K$ utilizing charger type $f \in F$. δ_{ik} specifies the charging time of EV $k \in K$ at CS $i \in S'$. u_{ikm} tracks the amount of waste type $m \in M$ carrying at node $i \in N_{0,n}$ by EV $k \in K$. Finally, t_{ik} denotes the time at which EV $k \in K$ starts service at node $i \in N_{0,n}$.

Single- and multi-objective mixed-integer linear programming formulations of the problem are presented in the following sections.

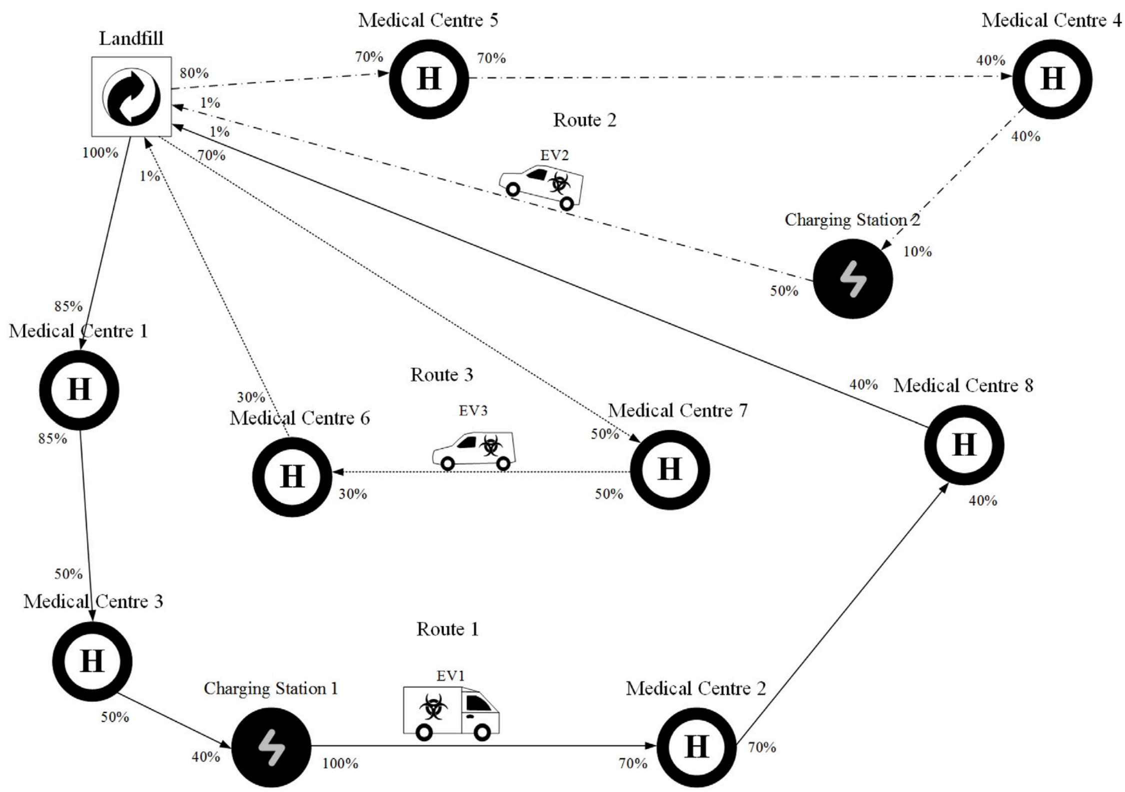

Fig. 1. An illustrative example.

3.3. Problem formulation

In this section, two models are presented for EMWCVRP. Section 3.3.1 provides the cost-oriented single objective model. The aim of Model 1 is to minimize the total costs, which consists of charging costs and station usage fees. On the other hand, Section 3.3.2 both considers the total costs and the risk of transporting medical wastes. The proposed risk function depends on the transport time, the type and amount of medical waste.

3.3.1. Model 1

This model aims to minimize the sum of energy costs and the total usage fee of CSs based on the charging types. The single-objective mathematical model is formulated as follows:

$$\text{Minimize} \quad \sum_{i\in S'}\sum_{f\in F}\phi_f^u\theta_{if} + \sum_{i\in S'}\sum_{k\in K}\sum_{f\in F}\phi_f^c\psi_{ikf} + \phi_1^c\Big(Y\sum_{k\in K}\sum_{j\in B}x_{0,j,k} - y_{n_k,k}\Big) \tag{1}$$

subject to

$$\sum_{j\in N_n, i\neq j} x_{ijk} = 1 \qquad k\in K, i\in B \tag{2}$$

$$\sum_{k\in K}\sum_{j\in N_n, i\neq j} x_{ijk} \leq 1 \qquad i\in S' \tag{3}$$

$$\sum_{i\in N_0}\sum_{j\in N_n, i\neq j} x_{ijk} \leq (|\,N\,|+1)v_k \qquad k\in K \tag{4}$$

$$\sum_{j\in B} x_{0,j,k} + \sum_{i\in N_n} x_{i,n,k} = 2v_k \qquad k\in K \tag{5}$$

$$\sum_{i\in N_0} x_{ijk} - \sum_{i\in N_n} x_{jik} = 0 \qquad k\in K, j\in B \tag{6}$$

$$\alpha_k \leq t_{jk} \leq \beta_k \qquad k\in K, j\in N \tag{7}$$

$$\alpha_j \leq t_{jk} \leq \beta_j \qquad k\in K, j\in N \tag{8}$$

$$t_{ik} + (c_{ij} + d_i)x_{ijk} \leq t_{jk} + \beta_k(1 - x_{ijk}) \qquad k\in K, i\in B\cup\{0\}, j\in N_n, i\neq j \tag{9}$$

$$t_{ik} + (c_{ij} + \delta_{ik})x_{ijk} + \leq t_{jk} + (\beta_k + r_{1k}Y_k)(1 - x_{ijk}) \qquad k\in K, i\in S', j\in N_n, i\neq j \tag{10}$$

$$u_{ikm} + q_{im}x_{ijk} \leq u_{jkm} + Q_k(1 - x_{ijk}) \qquad k\in K, i\in B, j\in N, m\in M \tag{11}$$

$$\sum_{i\in B}\sum_{m\in M} u_{ikm} \leq Q_k \qquad k\in K \tag{12}$$

$$y_{jk} \leq y_{ik} - c_{ij}^d\, h_k\, x_{ijk} + Y(1 - x_{ijk}) \qquad k\in K, i\in N_0, j\in N_n, i\neq j \tag{13}$$

$$y_{jk} \leq g_{ik} - c_{ij}^d\, h_k\, x_{ijk} + Y(1 - x_{ijk}) \qquad k\in K, i\in S', j\in N_n, i\neq j \tag{14}$$

$$y_{ik} \leq g_{ik} \leq Y_k \qquad k\in K, i\in S'\cup\{0\} \tag{15}$$

$$\sum_{f\in F}\psi_{ikf} = (g_{ik} - y_{ik}) \qquad k\in K, i\in S' \tag{16}$$

$$\sum_{f\in F} r_{fk}\psi_{ikf} = \delta_{ik} \qquad k\in K, i\in S' \tag{17}$$

$$\psi_{ik1} \leq Y_k \gamma_{ik} \quad k \in K, i \in S' \tag{18}$$

$$\psi_{ik2} \leq Y_k (1-\gamma_{ik}) \quad k \in K, i \in S' \tag{19}$$

$$\sum_{i \in S'} \sum_{k \in K} \psi_{ikf} \leq BigM \theta_{jf} \quad j \in S, f \in F \tag{20}$$

$$\sum_{j \in N_n, i \neq j} x_{ijk} \leq e_{ik} \quad k \in K, i \in S' \tag{21}$$

$$x_{ijk} \in \{0,1\} \quad k \in K, i \in N_0, j \in N_n, i \neq j \tag{22}$$

$$v_k \in \{0,1\} \quad k \in K \tag{23}$$

$$\gamma_{ik} \in \{0,1\} \quad k \in K, i \in S' \tag{24}$$

$$t_{ik} \geq 0 \quad k \in K, i \in N_{0,n} \tag{25}$$

$$\delta_{ik} \geq 0, g_{ik} \geq 0 \quad k \in K, i \in S' \tag{26}$$

$$\psi_{ikf} \geq 0 \quad k \in K, i \in S', f \in F \tag{27}$$

$$y_{ik} \geq 0 \quad k \in K, i \in N_n. \tag{28}$$

Model 1 is a minimization problem with an objective function (1) covering three cost terms. The first term refers to the total usage fees of CS infrastructure. It depends upon the charger types at CS. The second term specifies the cost of energy charged along the routes. The last cost term corresponds to the amount of energy that has not been used en-route. It is calculated as the difference of SoCs between the departure from and the return to the landfill. Constraints (2) guarantee that each medical centre $i \in B$ is visited once, whereas constraints (3) guarantee that each CS copy $i \in S'$ is used at most once. In other words, constraints (2) enforce that the produced wastes of each medical centre are collected by an EV and constraints (3) mean that each CS copy does not need to be part of a solution. Constraints (4) prevent EVs from constructing empty routes. Hence, these constraints do not allow idle vehicle usage. Constraints (5) impose that each vehicle leaves the landfill (0) and returns to the landfill (n) at the end of route. These constraints guarantee that the routes of the EVs start and end at the landfill. Constraints (6) guarantee the flow conservation. Constraints (7) consider that the working time windows ($[\alpha_k, \beta_k]$) are respected. Constraints (8) the service starting time (t_{ik}) should be inside the time window ($[\alpha_j, \beta_j]$). Constraints (9) track EVs starting times at a node after leaving from the landfill or any medical centre. If the previously visited node is a station, constraints (10) consider the charging duration (δ_{ik}) instead of service duration (p_i) and track the starting times. Freight constraints are defined by (11) and (12). Constraints (11) track the load of EVs, and constraints (12) restrict the total load of waste never to exceed the capacity of EVs (Q_k). Charging constraints are given by (14)–(20). Constraints (13) and (14) keep track of SoC when an EV departs from a medical centre (y_{ik}) or CS (g_{ik}), respectively. Constraints (15) restrict the battery SoC of an EV (g_{ik}) to being smaller than the maximum battery capacity (Y_k). Constraints (16) and (17) compute the SoC of an EV and its corresponding charging duration, respectively. Constraints (18) and (19) decide the charger type for the charging of EV at CS. EV $k \in K$ can use either level 2 ($\gamma_{ik} = 1$) or level 3 ($\gamma_{ik} = 0$) charger at CS $i \in S'$. If charging takes place at CS $i \in S'$, constraints (20) keep track the used charging technology for the calculation of its usage fee. Here, BigM refers to a sufficiently big number. Constraints (21) state the EV-CS compatibility. That is to say, EVs can visit the allowed stations. Finally, constraints (22)–(28) set the domains of the decision variables.

3.3.2. Model 2

This model aims to minimize both the total energy costs and the risk of transporting medical wastes. The risk function is defined as a function of the wastes depending on the waste's transportation time, type, and volume. Let parameters o_m^s and o_m^l refers to the severity and likelihood of medical waste type $m \in M$. While the first parameter indicates the severity of medical waste on public health, the second parameter represents the probability of transmission of medical waste. Then, the multi-objective mathematical model of the problem is formulated as follows:

$$\text{Minimize} \quad Z_1 = \sum_{i \in S'} \sum_{k \in K} \sum_{f \in F} \phi_f^c \psi_{ikf} + \phi_1^c (Y \sum_{k \in K} \sum_{j \in B} x_{0_k,j,k} - y_{n_k,k}) + \sum_{i \in S'} \sum_{f \in F} \phi_f^u \theta_{if} \tag{29}$$

$$\text{Minimize} \quad Z_2 = \sum_{i \in B} \sum_{k \in K} (t_{n,k} - t_{i,k}) \sum_{m \in M} (q_{im})^{o_m^s} o_m^l \tag{30}$$

subject to (2)–(27). The multi-objective function of model 2 aims to minimize the total energy costs (29) and total risk (30), weighted by (μ) and ($1-\mu$), respectively. Employing the total risk function takes into account the transfer risk, which is then calculated as the transportation time of EVs ($t_{n,k} - t_{i,k}$), the amount of wastes transported (q_{im}), the disease probability of transmission (o_m^l) and the potential hazards of exposure (the severity o_m^s). All constraints mentioned above constraints (2)–(27) remain the same in both models.

4. Solution method

This section presents newly developed meta-heuristic algorithm that integrates a solution construction heuristic, ALNS, and a local search algorithm. The ALNS algorithm is initially proposed by Ropke and Pisinger (2006) and is an extension of LNS (Shaw, 1998). The basic principle of LNS is to exploit large neighbourhoods, which may involve high-quality solutions (Pisinger and Ropke, 2010). Many researchers have successfully utilized the ALNS algorithm to solve variants of VRPs (Pisinger and Ropke, 2007; Keskin and Çatay, 2016). The neighbourhood of a solution is acquired by removing several parts from the solution and reinserting these parts into the solution. In order to improve the incumbent solution, the algorithm uses a set of iterative remove and repair operators. At the end of each iteration, the past performance of operators is calculated/updated through a scoring mechanism. These operators to be applied on the solution are selected randomly based on their recorded scores. If the selected mechanisms provide high quality solutions, the scores of the mechanisms increase and mechanisms are more likely selected for the subsequent iterations. The new generated solution is accepted based upon a predefined acceptance criterion and the algorithm terminates when stopping condition is satisfied.

4.1. General framework

The framework of the extended ALNS is described in Algorithm 1. First, the sets of repair and destroy operators Ω^+ and Ω^-, the set of neighbourhood structures N_l ($l = 1, \dots, l_{max}$) used in the local search and temperature (T), and the maximum number of iterations (ω_{max}) are defined. The initial solution (S) is generated by utilizing a problem-specific procedure. Next, the initial temperature (T_0), the best solution (S^{best}), counter (ω) and the weights of repair and destroy operators (ρ^+ and ρ^-) are set at the beginning of the procedure. The cost of a solution (S) is represented by $f(S)$. If a generated new solution provides improvement $f(S'') \leq f(S')$, it is accepted ($S' \leftarrow S''$);

otherwise, it is accepted with a probability $e^{-(f(S'')-f(S'))/T}$, where the temperature T decreases over time.

Initially, all the operators have the same weight. At each ALNS iteration, a roulette wheel principle is used to select the destroy and repair operators. The algorithm uses the formulas $\rho_j^+/\Sigma_{i=1}^{N_k}\rho_i^+$ and $\rho_j^-/\Sigma_{i=1}^{N_k}\rho_i^-$ to dynamically updated the probabilities of repair and destroy methods, respectively. Once an iteration is completed, the weights are updated dynamically. The performance of weight of repair and destroy operators are tracked and measured by a scoring system. If an operator achieves a new overall best solution, the score (λ) of an operator is increased by η_1. If the new solution is better than the current solution, the score of an operator is increased by η_2. If the new solution is worse than the current solution, but it is accepted is increased by η_3. Otherwise, the score remains the same (η_4). Let k and m be indices of repair and destroy operators chosen in the last iteration of the ALNS, respectively. The algorithm updates the weights (ρ^+ and ρ^-) using the formulations $\rho_k^+ = \xi\rho_k^+ + (1-\xi)\lambda$ and $\rho_m^- = \xi\rho_m^- + (1-\xi)\lambda$. Here, $\xi \in [0,1]$ is the system parameter that determines how sensitive the weights are.

During the search procedure, the algorithm can accept the infeasible solutions. In other words, a solution may not respect the time-, load-, battery-, and compatibility-related constraints. To handle these violations that lead to infeasibility, a dynamic penalty mechanism is employed (Hof et al., 2017). Not only to improve the solution (S'), but also to eliminate the infeasibility, a local search procedure is employed within the algorithm.

Algorithm 1 The framework of the extended ALNS for problem

Input: Operators Ω^+ and Ω^-, the neighborhood structures N_l with $(l = 1, \ldots, l_{max})$, T_0 and ω_{max}
Generate an initial solution S
Initialize best solution $S^{best} \leftarrow S$
Initialize initial temperature $T \leftarrow T_0(c(S))$
Initialize the scores $\rho^+ \leftarrow (1,..,1); \rho^- \leftarrow (1,..,1)$
$\omega \leftarrow 1$
while $\omega \le \omega_{max}$ **do**
  Select destroy and repair operators $d \in \Omega^-$ and $r \in \Omega^+$ using weights ρ^+ and ρ^-
  Apply destroy and repair operators $S' \leftarrow r(d(S))$
  Apply local search $S'' \leftarrow$ Local Search(S', N_l)
  if $f(S'') \le f(S')$ **then**
    $S' \leftarrow S''$
  else
    Generate a random number $u \in [0,1]$
    if $u < e^{-(f(S'')-f(S'))/T}$ **then**
      $S' \leftarrow S''$
    end if
  end if
  if $f(S'') \le f(S^{best})$ **then**
    $S^{best} \leftarrow S''$
  end if
  Update ρ^+ and ρ^-
  Update the penalty factors
  $T \leftarrow T * \varepsilon$
  $\omega \leftarrow \omega + 1$
end while
Output: The best found solution (S^{best})

4.2. Initial solution construction

The initial solution is generated by utilizing a greedy construction heuristic (Bac and Erdem, 2021). Before constructing routes, several steps are achieved to arrange the visits in a certain way. These basic steps aim to decrease both the number of iterations and the run time in the improvement step. First, the visits are ranked in non-descending order in terms of their lower bound of the time windows. Second, the visits are ranked in ascending order considering their closeness to the landfill. These steps aim to collect the wastes with a minimum delay and energy. After these steps, the ordered visits are assigned to the vehicles with the largest capacity. Thus, the partially and temporarily constructed route is first created for each EV. Then, the energy consumption of each obtained route is considered, and the negative SoC is removed by inserting the nearest CS to the route. Each EV is expected to have enough charge level to return to the landfill. After updating the routes, the charging duration is calculated with a Level 2 charge type. EVs depart from the landfill with the necessary energy to complete their routes. In this way, unnecessary energy charging at the landfill is prevented from decreasing the total energy cost. Next, the schedule of each EV is constructed considering travelling time, given time windows and duration of services and charge. Finally, in case of infeasibility occurs related to the EV-CS compatibility, time, load and energy capacity constraints, each violation is added to the objective function as a penalty parameter.

Algorithm 2 Local Search (Hansen et al., 2010)

Function Local Search(S', N_l)
$l \leftarrow 1$
while $l \le l_{max}$ **do**
  $S'' \leftarrow \arg\min_{y \in N_l(S')} f(y)$
  if $f(s'') < f(S')$ **then**
    $S' \leftarrow S''$
    $l \leftarrow 1$
  else
    $l \leftarrow l + 1$
  end if
end while
return The solution (S')

4.3. Removal and insertion operators

The framework of the extended ALNS adopted the basic operators by considering the rich constraint set of the problem (Keskin and Çatay, 2016, 2018).

- Visit removal: This operator randomly removes n visits from the randomly selected route. The value of n is based upon the number of visits that selected route. In other words, it is determined randomly from the minimum and the maximum number of jobs on the randomly selected route.
- Worst-distance removal: This operator removes the farthest visit, which is considered to be as the sum of distances from the preceding and following visit on the route.
- Worst-time removal: This aims to minimize the long wait and idleness of EVs. It calculates the difference between the service starting time (t_{ik}) and the lower bound of the time window (α_i) for each visit on the route, taking into account the scheduling decision.
- Heaviest load-based removal: This operator aims to reduce the transfer risks, which are defined by the amount of medical waste transported by EVs. The operator removes the medical centre that generates the highest amount of waste from the route.
- Route removal: This operator terminates the randomly selected route. The operator aims to decrease the number of EVs and costs.
- Station removal: This operator removes all the visited stations from the randomly selected route. In addition, the operator also eliminates the charging technology used by the selected route.
- Charge type removal: This operator randomly displaces the used charge type from the randomly selected route. If the cheaper/shorter charger option is feasible and causes less risk, charge type changes

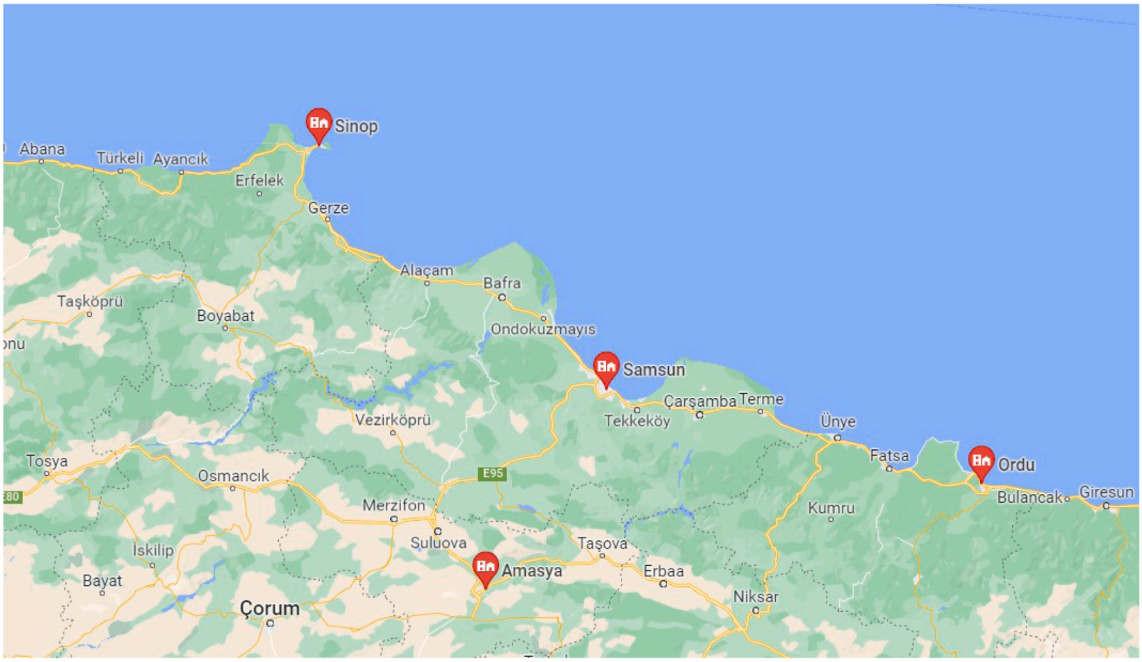

Fig. 2. A map of four cities (Google, 2022).

in this regard. Hence, the primary motivation of this operator is to decrease the transfer risks of EVs and their energy costs.

- Greedy insertion: This operator inserts visit i to the best position on the route considering the energy costs.
- Time-based insertion: The assignment of the visits to be inserted to the route to lead to minimum waiting is important in terms of both reducing the risk and using the cheaper charging technology of the EVs. Therefore, this operator inserts the visits to the route with minimum idleness.
- Load insertion: This operator checks the load of the EVs and inserts the visit to the best position to the corresponding route. In this way, the operator considers both the load capacity and the risk minimization.
- Station insertion: This operator controls SoC for each EV. It then takes each route one by one to eliminate the negative SoC. It inserts the nearest CS to the best position on the route. Next, the amount of energy required to return to the landfill is calculated for the EV. After this calculation, the charger type to be used is determined considering the schedule of the EV. Level 2 charger is initially assigned if it does not cause deviations in its schedule. In the other case, a Level 3 charger is used to eliminate scheduling violations.
- Charge type insertion: This operator determines the charger option (Level 2 or Level 3) to use on the route.

4.4. Local search

In the local search process, the variable neighbourhood descent (VND) algorithm (Hansen et al., 2010) is employed to both improve the solution and eliminate the possible violations of the constraints. The local search process depends upon the deterministic change of neighbourhoods (N_l, $l = 1, \ldots, l_{max}$). The VND algorithm uses the following operators:

- Vertical insertion and swap: These are two inter-route operators that aim to improve the objective of changing the visits' order. First, two different routes were selected randomly. Then, the swap operator replaces the two randomly selected visits, while the insert operator adds the randomly selected visits to the other job.
- Horizontal insertion and swap: These are two basic intra-route operators. They aim to improve the solution by modifying the position of the randomly selected route.
- Station insertion and removal: These are two basic components of the problem. These two versions are similar operators used in the previous step, adapted to local search.
- Charge technology insertion and removal: Similar to the operators used in the ALNS, these operators work with station insertion and removal to eliminate the infeasibility.

5. Computational experiments

In this section, the computational experiments are presented to assess the performance of the extended ALNS. All experiments were performed on a 3.4 GHz Intel Core i7 PC with 32 GB of RAM. CPLEX 20.1 optimizer was used to solve mathematically. A run-time limit of 7200 s was set for all instances.

The remainder of this section is structured as follows: Section 5.1 first presents newly generated benchmark instances and the parameter settings. Section 5.2 then analyses the performance of the extended ALNS on a set of small-, medium- and large-size instances. Moreover, Section 5.3 presents the analyses to explore trade-offs between energy cost and risk. Finally, Section 5.4 investigates the influence of different charging technology on the energy cost and risk.

5.1. Benchmark instances and parameter settings

A set of real-life benchmark instances is generated for the EMWCVRP. The data in these instances were collected using expert opinions and official reports (Minister of Environment, 2019, 2020) from the cities of Amasya, Ordu, Samsun, and Sinop in the Black Sea region of Turkey (see Fig. 2). The road network consisting of four cities and selected district centres is shown in Fig. 3. A wide range of medical centres (hospitals, laboratories, dialysis, dental clinics, etc.) is located in these 36 districts. These centres generate infectious, sharps, and chemical-pharmaceutical hazardous medical wastes. The amount of

Fig. 3. Road network of four cities.

these materials was calculated by considering the capacity of the medical centres and consultation with the experts. Each of the hazardous medical wastes has a harmful effect on human health. Hence, the transmission probability of disease and the potential hazard of exposure parameters are taken into account to minimize the medical waste-related risks. For each medical waste, these parameters are used and taken from the report (Sefouhi et al., 2013).

The landfill is located at Samsun. Two different types of heterogeneous EVs start services from this location and end at the same place. It is assumed that CS could be visited at public locations in each district. The distance between two locations is computed from using the real coordinates (Google, 2022). A small-, medium- and large-size data set with 32 benchmark instances are designed from each group. While small-size data sets involve 5 and 20 medical centres, large-size data sets comprise between 40 and 110 medical centres. Table A.1 in the Appendix summarizes the details of all instances.

Similarly, the technical specification of EVs used to transport medical waste are obtained from real-life settings (Mitsubishi, 2021; Ford E-Transit, 2021). While Type 1 EV has a maximum 200 km range and 2000 kg payload capacity, Type 2 vehicle has a 125 km range and 6000 kg payload capacity. Both of the vehicles can use both of the charger types at stations. Type 1 EV consumes 90 min for a full-charged battery using a Level 2 charger, whereas Type 2 EV needs 240 min. Furthermore, to fully charge using a Level 3 charger, a charger requires 43 and 45 min, respectively. The charging cost consists of both the fixed usage cost and the unit energy cost determined by the service provider according to the charger type (ZES, 2021). EVs can use only Level 2 charge during the night without usage fee at the landfill. Furthermore, due to the nature of the hazardous waste transported, large-size vehicles (Type 2) are prevented from using CS located at several densely populated urban locations. Hence, the EV-CS compatibility parameter is defined considering the mixed fleet features and location of CSs. The collection of waste requires a certain amount of time based upon the volume of waste and the location of medical centres. Thus, the duration of collection activities ranges from 20 to 60 min. Furthermore, the collection activities should be performed within a service time window. Similarly, each EV can work the working time slot, and overtime work is not allowed in this framework.

Several preliminary experiments are performed to fine-tune a set of correlated algorithm parameters. It yields high-quality results for ($\omega_{max} = |B| * 5000$) iterations, where $|B|$ is the number of medical centres. The score parameters are set η_1, η_2, η_3, and η_4 are 10, 6, 2, and 0, respectively. The cooling rate of heuristic (ε) and system parameters are 0.97 and 0.25, respectively.

5.2. Numerical results for Model 1

In this section, the efficiency of the proposed ALNS is investigated on the small-size instances. The heuristic solutions with the optimal or best-bound solution of the single objective MIP are compared and represented in Table 2. The name of the instance, objective, number of used EVs, as well as run time (in second) are indicated in the columns, respectively. The second to fourth columns refer to the single objective MIP results, whereas the fifth to seventh columns correspond to the ALNS results. The percentage deviation of the best-found solution of ALNS and the MIP results are reported in column Dev. (%).

Table 2 indicates that the MIP finds only 5- medical centre instances to optimality. The extended heuristic can yield the same optimal solutions with longer computational time in these instances. On the other hand, the heuristic outperforms the MIP 10- medical centre instances in terms of computational time and the objective value. The MIP could not generate 15- and 20- medical centre instances of any feasible solution within a 7200 s run time. These results demonstrate that the ALNS algorithm is able to generate optimal solutions in a reasonable run time.

It is further evaluated the performance of the extended ALNS on medium- and large-size instances. The results of these experiments are presented in Table A.2 in Appendix. For each instance, the best-found solutions, the number of used EVs, and the total time of ten runs are reported in Table A.2. The average best solutions were calculated at 71.74 and 173.83 for medium- and large-size instances, respectively.

Fig. 4 represents the average percent contributions of each of the three-objective function cost components for each instance family. The total charge costs at the landfill, total charge en-route cost and total station usage fee are indicated as black, white line pattern and grey, respectively. It was computed on average that the initial charging cost constitutes 66% of the total energy costs and, the usage fee follows with 26%, the rest is the total charge en-route cost.

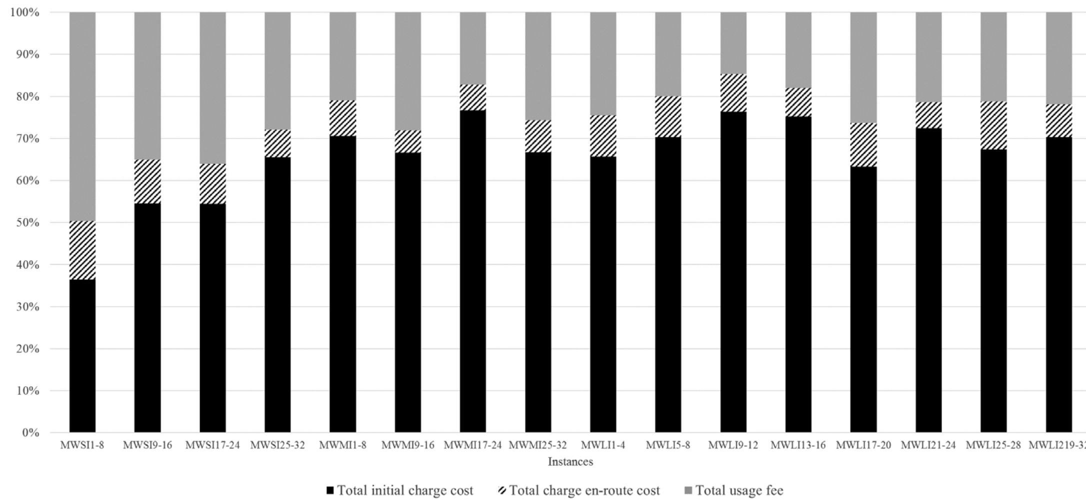

Fig. 4. Percentage of the objective of Model 1.

Table 2
Comparison of results on small-size instances.

Instance	MIP			Heuristic			
	Total energy cost	EVs	Total time	Total energy cost	EVs	Total time	Dev. (%)
MWSI1	72.70	4	<60.00	72.70	4	1080.77	0.00
MWSI2	47.41	4	<60.00	47.41	4	1077.95	0.00
MWSI3	32.46	2	<60.00	32.46	2	1040.47	0.00
MWSI4	89.13	2	<60.00	89.13	2	1072.26	0.00
MWSI5	77.24	2	<60.00	77.24	2	1177.08	0.00
MWSI6	15.97	3	<60.00	15.97	3	1097.05	0.00
MWSI7	62.74	2	<60.00	62.74	2	1044.14	0.00
MWSI8	33.59	2	<60.00	33.59	2	1157.26	0.00
MWSI9	164.96	5	7200.00	145.57	5	1349.72	−13.32
MWSI10	99.81	3	7200.00	89.80	4	1536.44	−11.14
MWSI11	13.66	3	7200.00	12.17	3	1382.86	−12.27
MWSI12	19.80	4	7200.00	17.40	4	1534.01	−13.78
MWSI13	48.20	5	7200.00	42.43	4	1483.62	−13.61
MWSI14	20.40	4	7200.00	19.24	4	1127.83	−6.02
MWSI15	101.01	4	7200.00	95.06	4	1212.56	−6.26
MWSI16	76.44	5	7200.00	72.01	4	1419.11	−6.15
MWSI17	-	-	7200.00	45.26	5	2148.14	-
MWSI18	-	-	7200.00	41.51	5	1840.64	-
MWSI19	-	-	7200.00	110.01	6	1729.90	-
MWSI20	-	-	7200.00	48.15	5	2192.73	-
MWSI21	-	-	7200.00	54.73	6	2146.13	-
MWSI22	-	-	7200.00	22.18	5	2054.55	-
MWSI23	-	-	7200.00	43.49	5	1895.25	-
MWSI24	-	-	7200.00	51.48	6	1681.45	-
MWSI25	-	-	7200.00	42.49	4	1822.64	-
MWSI26	-	-	7200.00	82.62	6	2272.98	-
MWSI27	-	-	7200.00	19.23	4	2939.81	-
MWSI28	-	-	7200.00	19.85	4	2141.85	-
MWSI29	-	-	7200.00	57.80	5	2080.32	-
MWSI30	-	-	7200.00	44.85	4	1953.37	-
MWSI31	-	-	7200.00	90.55	4	2036.36	-
MWSI32	-	-	7200.00	43.50	5	1971.61	-
Avg.			5415.00	54.46	4.13	1646.90	

5.3. Numerical results for Model 2

This section analyses the MIP of Model 2 by using the proposed ALNS. In order to explore the trade-offs between different objectives, i.e., the total energy cost and transfer risk, a series of experiments is conducted. Here, it is examined the effects of changing the relative weights of these objectives and acquiring an approximation to the Pareto optimal or non-inferior solutions. Figs. 5 and 6 indicate the trade-off curve of the two small-size instances. While the horizontal axis indicates total risk, the vertical axis shows the total energy cost. In these two figures, the competing objectives are observed. Each of the solutions on these figures represents a different combination of weights as the weight of the total energy cost decreases the total risk, which is defined according to the time of the EV, the type and weight of the load increases. The reason why the ascent in the total risk in Instance 8 is the increase in the number of used EVs for the solution in that weight combination. In other words, the new EV inserted into the solution caused an increase in transportation time.

Table 3
Comparison results on randomly selected instances.

Instance	Weights									
	1.00	0.00	0.75	0.25	0.50	0.50	0.25	0.75	0.00	1.00
	Z1	Z2	Z1	Z2	Z1	Z2	Z1	Z2	Z1	Z2
MWSI1	72.70	2.5E+18	211.27	1.8E+17	293.59	8E+17	211.27	2.5E+17	299.30	1.8E+17
MWSI3	32.46	3.1E+18	95.79	1.1E+17	121.22	1.1E+17	114.42	1.1E+17	149.07	1.1E+17
MWSI6	15.97	5.7E+18	39.41	2.9E+18	56.06	3.1E+18	60.19	2.9E+18	76.96	2.9E+18
MWSI8	33.59	9E+18	61.55	4.2E+18	61.55	4.2E+18	60.32	7.1E+18	136.55	4.2E+18
MWSI11	13.00	8.4E+23	40.92	4.2E+23	44.78	4.2E+23	65.84	7.2E+23	66.28	7.2E+23
MWSI12	19.80	2.3E+19	41.31	1.2E+19	43.42	1.2E+19	84.42	1.2E+19	86.59	1.7E+19
MWSI21	54.73	5.8E+19	57.27	4.0E+19	78.93	3.9E+19	79.35	3.8E+19	116.08	3.7E+19
MWSI23	43.49	2.6E+19	44.74	1.5E+19	49.25	1.4E+19	68.19	9.5E+18	68.19	9.5E+18
MWMI2	26.82	4.5E+23	34.24	2.2E+23	58.85	2.2E+23	63.05	2.2E+23	77.74	2.2E+23
MWMI4	123.76	6.1E+19	145.96	6.1E+19	149.34	7.0E+19	152.77	7.0E+19	155.54	7.0E+19
MWMI10	51.11	4.9E+19	78.30	2.4E+19	100.81	2.3E+19	101.03	2.3E+19	105.60	2.3E+19
MWMI15	26.56	4.2E+19	53.77	2.1E+19	53.77	2.1E+19	75.63	2.0E+19	75.63	2.0E+19
MWMI16	26.56	4.1E+19	58.26	2.0E+19	61.87	2.0E+19	77.62	2.0E+19	84.07	2.0E+19
MWMI21	44.66	6.6E+19	70.86	3.3E+19	74.28	3.3E+19	96.92	3.3E+19	99.73	3.3E+19
MWMI27	56.19	1.2E+20	105.04	5.8E+19	108.19	5.8E+19	132.63	5.6E+19	135.40	5.4E+19
MWMI31	103.00	1.4E+20	134.73	6.9E+19	142.39	6.9E+18	213.83	5.8E+19	215.40	5.7E+19
MWLI2	123.79	1.6E+21	184.33	8.0E+20	188.01	5.5E+20	217.21	5.2E+20	328.96	5.2E+20
MWLI7	127.74	2.5E+21	223.35	1.2E+21	224.50	1.2E+21	268.43	9.9E+20	268.43	9.9E+20
MWLI14	108.04	4.6E+23	238.94	2.3E+23	241.22	2.1E+23	281.55	2.0E+22	284.44	2.0E+22
MWLI23	144.57	6.7E+23	252.26	3.4E+23	253.88	3.3E+23	287.69	3.1E+23	291.70	2.9E+23
MWLI26	184.54	7.2E+25	258.70	3.6E+25	308.03	3.9E+25	257.63	3.5E+25	308.03	3.2E+25
Avg.	68.24	3.6E+24	115.76	1.8E+24	129.23	1.9E+24	141.43	1.7E+24	163.32	1.6E+24

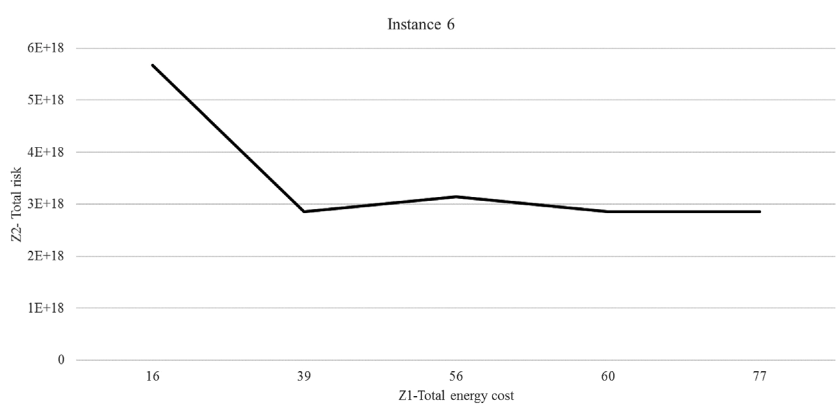

Fig. 5. Trade-off curve for instance 6.

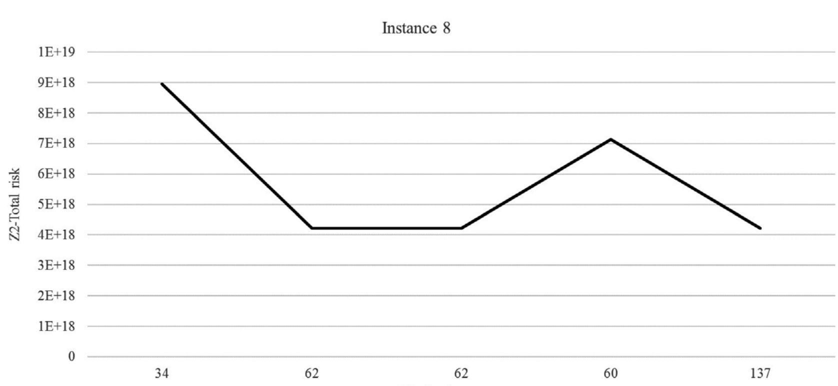

Fig. 6. Trade-off curve for instance 8.

Table 4
Results using only Level 2 charger.

Instance	Weights									
	1.00	0.00	0.75	0.25	0.50	0.50	0.25	0.75	0.0	1.00
	Z1	Z2	Z1	Z2	Z1	Z2	Z1	Z2	Z1	Z2
MWSI1	72.70	2.5E+18	121.06	1.9E+17	420.24	3.9E+18	231.06	2.9E+17	477.26	3.9E+18
MWSI3	32.46	3.1E+18	95.79	1.1E+17	74.52	1.1E+17	117.52	1.2E+17	149.07	1.1E+17
MWSI6	15.97	5.7E+18	39.41	2.9E+18	91.93	2.9E+18	63.41	3.3E+18	76.96	2.9E+18
MWSI8	33.59	9.0E+18	61.55	4.2E+18	61.55	4.2E+18	60.72	7.1E+18	289.36	4.2E+18
MWSI11	13.00	8.4E+23	40.92	4.2E+23	44.78	4.2E+23	66.20	4.2E+23	89.65	4.3E+23
MWSI12	19.80	2.3E+19	41.31	1.2E+19	43.42	1.2E+19	88.19	1.6E+19	90.01	1.7E+19
MWSI21	54.73	5.8E+19	57.27	4.0E+19	61.63	4.1E+19	83.49	4.7E+19	134.78	4.8E+19
MWSI23	43.49	2.6E+19	44.74	1.5E+19	49.25	1.4E+19	68.19	9.5E+18	68.19	9.5E+18
MWMI2	26.82	4.5E+23	34.24	2.2E+23	58.85	2.2E+23	63.05	2.2E+23	84.49	2.7E+23
MWMI4	124.69	6.2E+19	110.49	7.2E+19	110.74	7.3E+19	152.84	7.4E+19	119.14	7.3E+19
MWMI10	51.11	4.9E+19	78.30	2.4E+19	100.81	2.3E+19	101.03	2.3E+19	105.60	2.3E+19
MWMI15	26.56	4.2E+19	53.77	2.1E+19	53.77	2.1E+19	75.63	2.0E+19	75.63	2.0E+19
MWMI16	26.56	4.1E+19	58.26	2.0E+19	61.87	2.0E+19	82.74	2.0E+19	100.59	2.6E+19
MWMI21	44.66	6.6E+19	70.86	3.3E+19	74.28	3.3E+19	96.96	3.7E+18	102.69	3.9E+19
MWMI27	56.19	1.2E+20	105.04	5.8E+19	108.19	5.8E+19	138.88	5.8E+19	121.12	5.4E+19
MWMI31	103.00	1.4E+20	134.73	6.9E+19	142.39	6.9E+18	226.35	6.0E+18	166.68	5.8E+18
MWLI2	123.79	1.6E+21	184.33	8.0E+20	188.01	5.5E+20	246.19	6.1E+20	191.19	5.9E+20
MWLI7	127.74	2.5E+21	223.35	1.2E+21	224.50	1.2E+21	272.43	1.4E+21	244.64	1.3E+21
MWLI14	108.04	4.6E+23	238.94	2.3E+23	241.22	2.1E+23	284.24	2.3E+23	261.47	2.3E+23
MWLI23	144.57	6.7E+23	252.26	3.4E+23	253.88	3.3E+23	289.28	3.5E+23	267.62	3.5E+23
MWLI26	184.54	7.2E+25	258.70	3.6E+25	282.17	4.2E+25	257.63	3.5E+25	299.83	4.4E+25
Avg.	68.29	3.6E+24	109.78	1.8E+24	130.86	2.0E+24	146.00	1.7E+24	167.43	2.2E+24

Table 5
Results using only Level 3 charger.

Instance	Weights									
	1.00	0.00	0.75	0.25	0.50	0.50	0.25	0.75	0.00	1.00
	Z1	Z2	Z1	Z2	Z1	Z2	Z1	Z2	Z1	Z2
MWSI1	99.00	3.2E+18	211.27	1.8E+17	358.45	3.9E+18	211.27	2.5E+17	356.85	1.8E+17
MWSI3	49.51	3.3E+18	96.00	1.1E+17	121.22	1.1E+17	96.00	1.1E+17	158.47	1.1E+17
MWSI6	15.97	5.7E+18	50.72	2.9E+18	56.06	3.1E+18	60.19	2.9E+18	97.49	2.9E+18
MWSI8	48.41	9.0E+18	101.80	4.2E+18	101.80	4.2E+18	88.54	4.2E+18	197.34	4.2E+18
MWSI11	13.00	8.4E+23	88.10	4.2E+23	111.58	4.2E+23	65.84	7.2E+23	66.28	7.2E+23
MWSI12	19.80	2.3E+19	54.42	1.2E+19	57.76	1.2E+19	122.04	1.2E+19	86.59	1.7E+19
MWSI21	78.83	5.8E+19	79.35	4.0E+19	78.93	3.9E+19	79.35	3.8E+19	116.08	3.7E+19
MWSI23	67.87	2.6E+19	52.94	2.0E+19	57.23	1.4E+19	74.98	7.3E+19	81.47	7.3E+19
MWMI2	26.82	4.5E+23	34.24	2.2E+23	79.94	2.2E+23	86.54	2.2E+23	77.74	2.2E+23
MWMI4	196.70	6.1E+19	246.60	6.1E+19	196.89	7.0E+19	149.63	7.0E+19	151.25	7.0E+19
MWMI10	69.73	4.9E+19	124.59	2.0E+19	175.73	2.0E+19	185.95	2.0E+19	189.52	2.0E+19
MWMI15	26.56	4.2E+19	77.87	2.1E+19	82.64	2.1E+19	126.28	2.0E+19	126.28	2.0E+19
MWMI16	26.56	4.1E+19	87.24	2.0E+19	99.25	2.0E+19	173.62	2.0E+19	182.77	2.0E+19
MWMI21	44.66	6.6E+19	95.44	2.0E+19	87.62	2.0E+19	96.92	2.0E+19	99.73	2.0E+19
MWMI27	56.19	1.2E+20	138.75	5.7E+19	147.63	5.7E+19	132.63	5.6E+19	135.40	5.4E+19
MWMI31	186.88	1.4E+20	211.04	6.9E+19	219.65	6.9E+18	258.94	5.8E+19	259.66	5.7E+19
MWLI2	210.75	1.6E+21	289.36	8.0E+20	296.24	5.5E+20	305.24	5.2E+20	315.24	5.2E+20
MWLI7	210.10	2.5E+21	363.25	1.2E+21	360.09	1.2E+21	417.64	9.9E+20	423.27	9.9E+20
MWLI14	108.04	4.6E+23	337.96	2.3E+23	320.52	2.1E+23	378.69	2.0E+22	398.74	2.0E+22
MWLI23	151.06	6.7E+23	331.25	3.4E+23	322.52	3.3E+23	379.86	3.1E+23	355.27	2.9E+23
MWLI26	159.67	7.2E+25	288.92	3.6E+25	332.42	3.9E+25	289.45	3.5E+25	322.35	3.2E+25
Avg.	88.86	3.6E+24	160.05	1.8E+24	174.48	1.9E+24	179.98	1.7E+24	199.89	1.6E+24

Table 3 provides the results of different weighted objectives for the different sizes of randomly selected instances. For each instance, the best-known solution of 10 runs is presented in that table. The second and third columns show only the minimization of total energy cost (Z_1), while the last two columns indicate the optimization of the total transfer risk (Z_2). The last row of the table summarizes the average objective value with the different relative weight combinations. The results indicate that the total energy cost objective (Z_1), which consists of energy charging and station usage fees, increases as the weight of the risk (Z_2) objective rises. Since the total risk is defined as a function of time, the solution wants to reduce the transportation time for each EV so as to reduce the total risk. If vehicles have idle times in their schedules, the total energy cost of the solution may be the same. However, it is implausible that the cost will remain unchanged. Since EVs make an effort to transport heavy and more hazardous wastes to the landfill as soon as possible, this leads to reordering of visits in the route and schedule with a higher cost. In other words, minimizing the risk means increasing in the energy consumption of EVs.

5.4. Sensitivity analyses Model 2

This section examines the effect of multiple chargers on the multi-objective. In the previous section, it was assumed that all CSs are equipped with both types of chargers. This section assumes that the

Table 6
The number of chargers used.

Instance	Weights									
	1.00	1.00	0.75	0.75	0.50	0.50	0.25	0.25	0.00	0.00
	Level 2	Level 3	Level 2	Level 3	Level 2	Level 3	Level 2	Level 3	Level 2	Level 3
MWSI1	2	0	0	4	2	2	0	4	0	4
MWSI3	1	0	3	0	0	2	2	1	2	0
MWSI6	0	0	1	0	0	1	0	1	1	0
MWSI8	1	0	2	0	2	0	2	0	2	1
MWSI11	0	0	1	0	1	0	0	2	0	2
MWSI12	0	0	1	0	1	0	1	1	0	1
MWSI21	1	0	1	0	0	1	0	1	0	2
MWSI23	1	0	1	0	1	0	2	0	2	0
MWMI2	0	0	0	0	1	0	1	0	0	2
MWMI4	2	1	3	1	2	1	2	1	2	1
MWMI10	1	0	2	0	3	0	3	0	3	0
MWMI15	0	0	1	0	1	0	2	0	2	0
MWMI16	0	0	1	0	1	0	0	1	0	1
MWMI21	0	0	1	0	1	0	0	1	0	1
MWMI27	0	0	1	0	1	0	0	1	0	1
MWMI31	2	0	3	0	3	0	3	1	3	1
MWLI2	2	0	4	0	4	0	3	1	2	2
MWLI7	2	0	5	0	5	0	5	1	5	1
MWLI14	0	0	4	0	4	0	4	1	4	1
MWLI23	1	0	4	0	4	0	4	1	4	1
MWLI26	1	0	3	0	3	1	3	0	3	1
Avg.	0.81	0.05	2.00	0.24	1.90	0.38	1.76	0.90	1.67	1.10

stations are equipped with only one charger type and the results are compared to the best-found solutions mentioned in the previous section. Tables 4 and 5 present the computational results using only Level 2 and Level 3 chargers, respectively. When these tables are further investigated, using only a Level 3 charger, generally on average increases the total energy costs, but it does not lead to a lower-risk solution.

Furthermore, this expensive charging option may even cause vehicles to be idle. On the other hand, the use of Level 2, which is a cheaper charger option, increases the risk as it requires a long charging duration. When the travel time of the EVs is not enough to return to the landfill or to perform visits, the algorithm inserts a new EV into the solution, which increases the risk even more.

Table 6 shows the number of chargers used on different instances. The type of charger used in the best known solution found with each combination of relative weights is summarized in this table. When only the objective is defined related to the energy cost, there was little need for a Level 3 charger. In the other case, if the objective is only the risk, it turns out that it is used in every solution on average. Regarding the cost objective, the Level 2 charger is used more than the Level 3 type. In addition, there is more than a double increase in usage rate considering the risk-related objective. As a result, it is understood that using different charger types together is important, especially for risk minimization.

6. Conclusion

This paper has introduced the electric medical waste collection vehicle routing problem (EMWCVRP), in which a heterogeneous fleet of EVs collects hazardous medical wastes from geographically dispersed locations. The proposed study aims to minimize the energy cost, and the risk of transporting the medical waste, which is formulated depending on the duration of transportation, the severity, and the probability of the type of medical waste transported through these environmentally-friendly vehicles. Two different models with multiple products, multiple charging options, and vehicle-station incompatibility constraints are mathematically formulated. A hybrid solution based upon the ALNS extended with a local search is proposed. A set of different sizes of real-life instances is generated to examine the both models. The results indicate that the heuristic could solve small instances up to a size of 10 medical centres 5 EVs, and 4 CSs to optimality within a reasonable time. For larger instances, high-quality feasible solutions with up to 110 medical centres, 32 EVs and 10 CSs are obtained. The average results of Model 1 indicate that the initial charging cost accounts for 66% of the total energy costs, of which 26% is the station usage fee and the remainder is the total charge en-route cost.

Model 2 results indicated a large difference in the solutions between total energy cost and total risk objectives. Hence, it is crucial to determine the best alternative from the set of non-dominated solutions. The average results of the sensitivity analysis showed that the use of both chargers increased as the relative weight of the total risk objective increased in almost every solution.

In the future, the collected medical wastes can be processed in more than one facility and converted into electricity. Hence, the converted renewable energy can be used in these environmentally friendly vehicles. In addition, the problem can be extended, including the establishment costs of the new landfills and the periodic demands of the medical centres.

CRediT authorship contribution statement

Mehmet Erdem: Conceptualization, Methodology, Software, Data collection, Writing – original draft, Visualization, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix

See Tables A.1–A.2.

Table A.1
The characteristics of all instances.

Instance	Medical centre	EVs	CSs	Instance	Medical centre	EVs	CSs	Instance	Medical centre	EVs	CSs
MWSI1	5	3	3	MWMI1	24	10	6	MWLI1	40	18	8
MWSI2	5	3	3	MWMI2	24	10	6	MWLI2	40	18	8
MWSI3	5	3	3	MWMI3	24	10	6	MWLI3	40	18	8
MWSI4	5	3	3	MWMI4	24	10	6	MWLI4	40	18	8
MWSI5	5	3	3	MWMI5	24	10	6	MWLI5	50	20	8
MWSI6	5	3	3	MWMI6	24	10	6	MWLI6	50	20	8
MWSI7	5	3	3	MWMI7	24	10	6	MWLI7	50	20	8
MWSI8	5	3	3	MWMI8	24	10	6	MWLI8	50	20	8
MWSI9	10	5	4	MWMI9	28	12	6	MWLI9	60	22	8
MWSI10	10	5	4	MWMI10	28	12	6	MWLI10	60	22	8
MWSI11	10	5	4	MWMI11	28	12	6	MWLI11	60	22	8
MWSI12	10	5	4	MWMI12	28	12	6	MWLI12	60	22	8
MWSI13	10	5	4	MWMI13	28	12	6	MWLI13	70	24	8
MWSI14	10	5	4	MWMI14	28	12	6	MWLI14	70	24	8
MWSI15	10	5	4	MWMI15	28	12	6	MWLI15	70	24	8
MWSI16	10	5	4	MWMI16	28	12	6	MWLI16	70	24	8
MWSI17	15	6	4	MWMI17	32	14	6	MWLI17	80	26	10
MWSI18	15	6	4	MWMI18	32	14	6	MWLI18	80	26	10
MWSI19	15	6	4	MWMI19	32	14	6	MWLI19	80	26	10
MWSI20	15	6	4	MWMI20	32	14	6	MWLI20	80	26	10
MWSI21	15	6	4	MWMI21	32	14	6	MWLI21	90	28	10
MWSI22	15	6	4	MWMI22	32	14	6	MWLI22	90	28	10
MWSI23	15	6	4	MWMI23	32	14	6	MWLI23	90	28	10
MWSI24	15	6	4	MWMI24	32	14	6	MWLI24	90	28	10
MWSI25	20	8	5	MWMI25	36	16	8	MWLI25	100	30	10
MWSI26	20	8	5	MWMI26	36	16	8	MWLI26	100	30	10
MWSI27	20	8	5	MWMI27	36	16	8	MWLI27	100	30	10
MWSI28	20	8	5	MWMI28	36	16	8	MWLI28	100	30	10
MWSI29	20	8	5	MWMI29	36	16	8	MWLI29	110	32	10
MWSI30	20	8	5	MWMI30	36	16	8	MWLI30	110	32	10
MWSI31	20	8	5	MWMI31	36	16	8	MWLI31	110	32	10
MWSI32	20	8	5	MWMI32	36	16	8	MWLI32	110	32	10

Table A.2
Results on medium- and large-size instances.

Instance	Total energy cost	EVs	Total time	Instance	Total energy cost	EVs	Total time
MWMI1	26.82	6	3792.36	MWLI1	123.79	16	5339.60
MWMI2	22.72	5	2643.99	MWLI2	175.42	16	5960.22
MWMI3	21.42	5	2621.36	MWLI3	113.90	18	5805.22
MWMI4	123.76	7	2252.08	MWLI4	161.68	17	5542.50
MWMI5	27.90	6	3713.40	MWLI5	169.00	18	5942.00
MWMI6	123.80	6	3772.90	MWLI6	111.02	18	5825.90
MWMI7	47.61	6	2150.88	MWLI7	127.74	19	5818.70
MWMI8	48.05	6	3063.05	MWLI8	122.52	18	5224.30
MWMI9	49.30	7	3305.99	MWLI9	114.46	20	5376.90
MWMI10	51.11	7	3237.79	MWLI10	133.50	21	5979.90
MWMI11	46.03	6	3778.22	MWLI11	132.67	21	5269.40
MWMI12	106.38	6	2761.15	MWLI12	127.73	21	6000.50
MWMI13	62.20	8	2110.52	MWLI13	212.45	22	6051.74
MWMI14	67.62	9	3669.66	MWLI14	108.04	24	5794.61
MWMI15	26.56	6	2794.02	MWLI15	176.77	24	5679.40
MWMI16	26.56	6	3462.81	MWLI16	131.70	23	5971.10
MWMI17	78.18	10	3699.66	MWLI17	161.33	25	5336.20
MWMI18	77.69	10	3849.86	MWLI18	232.47	26	5357.50
MWMI19	89.33	11	3163.31	MWLI19	213.96	26	5874.80
MWMI20	44.54	8	2840.48	MWLI20	207.62	26	5453.22
MWMI21	44.66	8	4979.44	MWLI21	170.86	27	6203.64
MWMI22	81.80	12	4079.61	MWLI22	201.23	27	5558.91
MWMI23	31.69	8	2704.73	MWLI23	144.57	26	6242.92
MWMI24	120.87	10	3156.83	MWLI24	229.57	28	6111.62
MWMI25	154.25	12	4771.32	MWLI25	213.42	30	6298.15
MWMI26	129.98	13	5348.09	MWLI26	184.54	30	6220.51
MWMI27	56.19	14	2992.29	MWLI27	252.58	29	6471.04
MWMI28	148.67	16	5094.02	MWLI28	212.52	29	6377.55
MWMI29	87.82	13	3702.90	MWLI29	187.69	30	5932.61
MWMI30	97.00	15	5699.14	MWLI30	193.26	31	6367.11
MWMI31	103.00	14	4280.88	MWLI31	259.34	30	5999.97
MWMI32	72.26	15	5097.80	MWLI32	255.09	30	6325.74
Avg.	71.74	9.09	3580.95		173.83	23.94	5866.04

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