Int. J. Production Economics 276 (2024) 109342

Contents lists available at ScienceDirect

International Journal of Production Economics

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

A Bi-objective location-routing model for the healthcare waste management in the era of logistics 4.0 under uncertainty

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ARTICLE INFO

Keywords:
Location-routing problem
Healthcare waste management
Logistics 4.0
Electric autonomous vehicle
Fuzzy theory

ABSTRACT

The purpose of this study is to apply Industry 4.0-based technologies to improve the management of infectious healthcare waste considering location-routing problem and population risk under uncertainty. To achieve this, a decision support system is developed and implemented utilizing a bi-objective mixed-integer linear programming (MILP) model. The bi-objective MILP model improves the performance of the healthcare waste management by applying Industry 4.0 technologies, including electric autonomous vehicles, information sharing system, internet of things (IoT), Global Navigation Satellite System (GNSS), and RFID-tagged waste bags. We develop a multi-objective solution approach by integrating the lexicographic and TH methods. The validity of the model has been established through its implementation in seven hospitals in the city of Karaj, Iran. The results denoted significant improvements in waste collection efficiency, route optimization, and the reduction of contamination risks.

1. Introduction

In a time of increased worldwide connectivity, the threat of health crises has never been greater. These crises can originate from natural pandemics, biological terrorism, or other microbial hazards (Zeng et al., 2023). Despite growing awareness of the risks, it appears that our social infrastructure is unprepared to deal with them (Tin et al., 2022), leaving us open to attacks that could have severe consequences. In the event of a bio- or infectious disease outbreak, healthcare facilities embody the first line of defense in containing the spread of the disease and minimizing its effects (Govindan et al., 2020). Although these facilities play a crucial role in the treatment and control of infectious diseases, they present a significant challenge when it comes to managing the large quantities of infectious waste they generate (Zangrillo et al., 2020; Budak and Ustundag, 2017). As evidenced by the recent pandemic, current infectious waste management systems are ineffective (Chen et al., 2021a,b). It is imperative that infectious waste be managed with the utmost care and precision because it poses serious health risks to entire communities if it is allowed to serve as a vehicle for the spread of disease. In 2009, many residents of Gujarat became hospitalized just because of a deficiency in healthcare waste management (Dadhaneeya et al., 2023).

Current methods of waste collection are at the heart of the problem. Human collectors and drivers are crucial to the success of traditional models of waste collection, but they face challenges in the form of excessive waste production, insufficient collection routes, and a lack of data-driven approaches to improving waste collection points. Worse yet, these people are themselves often exposed to toxic materials (Andrade et al., 2017). These inefficiencies not only increase the risk of infection, but also put extra strain on the supporting systems, resulting in less-than-ideal use of available assets. Inspired by the Fourth Industrial Revolution, Logistics 4.0 is an incremental improvement in the logistics industry (Tang and Veelenturf, 2019). There may be less friction in

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https://doi.org/10.1016/j.ijpe.2024.109342
Received 4 January 2024; Received in revised form 25 June 2024; Accepted 16 July 2024
Available online 25 July 2024

integrating new systems, more automation, and more reliance on data-driven methods of decision-making as a result of this shift. Autonomous trucks have the potential to significantly alter the waste management industry if placed in this context. Self-driving vehicles have the potential to improve environmental sustainability by lowering emissions and fuel consumption, and they also reduce risks to public health by preventing people from coming into contact with potentially infectious waste. Although Logistics 4.0 technologies are available, this does not guarantee that they will be used to their full potential. We need to make the most of the available technology to guarantee that they can be easily incorporated into our existing waste management system. As a result of the amalgamation, a sturdy, effective, and long-lasting structure should emerge, one that can weather any public health crisis that may arise.

Infectious waste management is a very important area of research (Nosrati-Abarghooee et al., 2023; Govindan et al., 2022), but further efforts are needed to close the gap between the theoretical and practical advantages of Logistics 4.0 for the safe and efficient disposal of infectious waste from hospitals and other healthcare facilities. Recent literature also highlights that despite the relatively slow adoption of digitalization in the field of medical waste management, there is an increasing need for this service, necessitating the development of additional proposals to enhance the current infrastructure (Mohamed et al., 2023). This study, therefore, aims to model a decision support system (DSS) that optimizes Logistics 4.0's contribution to the subject. By shedding light on this topic, the authors hope to pave the way for a future in which our society is resilient in the face of health crises and better prepared to deal with the complexities of health emergencies, thereby protecting the security and welfare of its entire population. This study is expected to serve as a symbol of desire, illuminating modern technology's potential to pave the way toward a safer, greener future while drawing attention to pressing issues. This is especially important in an era when collection and processing chains of healthcare waste have become increasingly complex. In this vein, this paper provides several contributions, which can be summarized as follows:

- Developing a practical DSS based on a mixed-integer linear programming (MILP) model to manage healthcare infectious waste by applying Industry 4.0-based technologies;
- Utilizing location-routing problem, population risk concept, electric autonomous vehicles, information sharing system, internet of things (IoT), Global Navigation Satellite System (GNSS), and RFID-tagged waste bags in the structuring of the presented MILP model;
- Developing a hybrid multi-objective solution approach to solve presented bi-objective MILP model under uncertainty;
- Validating the presented model through its implementation at the pilot level using data from seven hospitals in Karaj, Iran.

The rest of this study is structured as follows. The related literature is reviewed in Section 2. Section 3 deals with the problem statement and proposed model. The case study and discussion are included in Sections 4 and 5, respectively. Section 6 is allocated to managerial implications. Finally, the conclusion is presented in Section 7.

2. Literature review

This section will examine previous investigations to gain a better understanding of the rationale and trajectory that led to the achievement of the goals outlined in this paper.

2.1. Healthcare waste management

Hospital material management, service system design, pharmaceutical supply chain, service delivery, and environmentally conscious practices adoption are just a few of the recent topics of interest in healthcare logistics and supply chain management (Benzidia et al., 2019). However, healthcare waste management demands more attention (Singh et al., 2022). Successful handling of both medical and non-medical waste is a crucial aspect of healthcare logistical operations due to its distinct characteristics that differentiate it from other industries or sectors (Tilahun et al., 2023). Managing waste flows presents a multitude of challenges encompassing economic, public security, and environmental and public health considerations (Dadhaneeya et al., 2023; Sharma et al., 2020, 2021). A large amount of the waste generated is non-hazardous domestic waste, but approximately 10%–25% involves infectious medical waste, which poses an unacceptable risk to the health of the society and environment (Benzidia et al., 2019). The management of these flows includes a variety of activities such as sorting, collection, transportation, and storage (Luo and Liao, 2022), and healthcare organizations are required to adopt methods that adhere to regulatory, environmental, and security standards (Benzidia et al., 2019). Healthcare waste is globally recognized as the second most hazardous category, surpassed only by radioactive materials (Das et al., 2021). This waste, which includes sharps, anatomical remains, blood, chemicals, pharmaceuticals, and medical apparatus, is primarily produced by healthcare establishments such as hospitals, clinics, and laboratories (Nikzamir and Baradaran, 2020). If mismanaged, it poses a severe risk to public health, a concern that escalates during infectious disease outbreaks, during which waste volume increases significantly (Govindan et al., 2021). The COVID-19 pandemic, instigated by the SARS-CoV-2 virus, exacerbated the generation of healthcare waste due to heightened hospital admissions and the widespread use of personal protective equipment (Chowdhury et al., 2022). The daily average medical waste generation from May 2020 to August 2020 in a case-studied city was above 125% more than 2019, the year before the pandemic, due to increased testing and treatment that took place after the outbreak began (Luo and Liao, 2022). This surge necessitates bolstered waste management to curb virus transmission (Chowdhury et al., 2022; Das et al., 2021). Annually, mismanaged medical waste contributes to millions of deaths, including a substantial number of children (Singh et al., 2022). The pandemic has amplified this threat, highlighting the need for protective measures for waste management personnel. COVID-19-related waste, particularly from infected patients and healthcare providers, is deemed infectious and demands specialized handling (Das et al., 2021; Mekonnen et al., 2021).

Infectious healthcare waste can dramatically increase due to any pandemic presenting significant management challenges (Tushar et al., 2023; Hantoko et al., 2021), and all rampant health crises will easily increase healthcare wastes. Even when a shared health service to be provided for a group of people is restricted to an isolated area, an estimate of waste generation (kilogram) from quarantined patients is 0.3 multiplied by the number of people in the quarantine. In case test kits or vaccinations are required, the estimated waste increases per each individual involved (Chowdhury et al., 2022). To minimize the negative effects of these wastes, an effective healthcare waste management is needed. Healthcare waste management is, however, a multifaceted system made up of multiple divisions that work together to carry out an array of processes (Feibert and Jacobsen, 2015). Improving a sector's logistics performance now necessitates paying close attention to the management of logistics human resources that support these flows (Benzidia et al., 2019). In this system, drivers and waste collectors, who are in direct contact with contaminated materials, face increased infection risks, potentially exacerbating community spread. Here understanding the survival time of microbes is crucial to understand the importance of an effective waste management. The microorganism's longevity ranges even up to a few days, influenced by the substrate and environment (Barandongo et al., 2023; Morgan et al., 2022). Its persistence in healthcare settings raises the risk of transmission, underscoring the importance of proper waste handling (Dihan et al., 2023).

Besides, there is a scarcity of workers with extensive knowledge in logistics (Klumpp, 2018), especially for infectious waste handling. This adds risk of infectious transmission and environmental hazards. According to the paper presented by Lemma et al. (2022), only less than half of waste handlers in certain countries had sufficient knowledge of safe waste logistics. For example, in Zambia, according to a recent study (Leonard et al., 2022), staff members who are directly responsible for waste disposal are not given adequate training in healthcare waste management. The level of healthcare waste knowledge was not found to be safe enough; previous training for healthcare professionals was either inadequate or not conducted on a regular basis. A separate study noticed that even among workers who were informed about healthcare waste risks, a significant proportion of them were not considering this knowledge in their daily practices (Djam et al., 2023).

The integration of autonomous, driverless vehicles in waste logistics could potentially reduce the risks of infectious transmission, marking a significant step forward in modernizing healthcare waste management systems. Thus, by examining the intersection of healthcare waste management and modern logistics, we can identify opportunities for innovation and improvement in the handling of infectious waste, ultimately contributing to a safer and more sustainable healthcare system.

2.2. Logistics 4.0 in healthcare waste management

The adoption of Industry 4.0 technologies throughout the supply chain enhances performance across multiple areas, including Procurement 4.0, Manufacturing 4.0, Logistics 4.0, and Warehousing 4.0 (Govindan et al., 2022; Kannan et al., 2023). Modern logistics principles, known as Logistics 4.0, are grounded in the Fourth Industrial Revolution (Chen et al., 2021a,b). Logistics 4.0 has resulted in significant advancements in the field of waste management (Zhang et al., 2023). By programmable applications enabling the collection and dissemination of real-time data, the use of IoT has significantly improved waste management practices (Govindan et al., 2024). This enables the automation of waste management at various stages of any supply chain, leading to increased efficiency and effectiveness (Zhang et al., 2023). It is worth noting that many businesses have already begun to integrate Industry 4.0 technologies into their supply chain operations (Bai et al., 2020; Bhattacharya et al., 2024; Frank et al., 2019; Govindan, 2024; Kannan et al., 2024) and waste management (Kannan et al., 2024), but there is still a lack of research that takes an operations management perspective on the use of Logistics 4.0 in organizational waste management and supply chains (Zhang et al., 2023). The critical field of healthcare waste management, in particular, has lagged far behind the modernization trend. An examination of medical waste logistics practices reveals that many countries are experiencing difficulties and have yet to find effective solutions to their healthcare waste management problems (Görçün et al., 2023).

According to the literature on Logistics 4.0, digitalization, automation, and data-driven applications have resulted in a significant transformation in supply chain management (Heilig et al., 2020; Sorkun, 2020). The aforementioned advancements are critical in addressing the numerous challenges associated with waste management, including collection, transportation, and disposal (Borchard et al., 2022), particularly for infectious healthcare wastes. The use of advanced technologies such as the IoT, self-driving cars, and GNSS is a distinguishing feature of modern logistics operations (Joubert et al., 2020). Technological advancements have facilitated improved communication, automation, and waste management process optimization (Anjum et al., 2022; Hannan et al., 2015).

The IoT is used in healthcare waste management to enable real-time monitoring and tracking of waste streams in order to ensure adherence to regulatory compliance and environmental safety standards during the waste collection, transportation, and disposal processes (Mohamed et al., 2023). The transportation of infectious healthcare waste presents unique challenges; however, autonomous vehicles, which are commonly used in modern logistics, offer a promising solution (Gao et al., 2021). The availability of automated vehicles creates a potential pathway to transform transport systems, including several aids such as better health and safety concerns, reduced congestion and environmental issues, and increased mobility choices and economic benefits (Luca et al., 2023). While not a recent development, autonomous vehicles are expected to be among the most revolutionary technologies ever (Fritschy and Spinler, 2019). Utilization of these vehicles has significant benefits for healthcare systems (Pourrahmani et al., 2020); since no operator is involved, the risk of infection transmission is minimum.

RFID technology is important in the logistics context (Ullah and Sarkar, 2020). The Republic of Korea has recently adopted the use of RFID bags for healthcare waste tracking purposes. This implementation enables the tracking of waste at the product level, starting from its origin at the hospital and continuing until its disposal at the designated site (Mohamed et al., 2023). Waste management enterprises possess the capability to efficiently exchange information pertaining to the collection of refuse through the utilization of label scanning technology. In contrast to the prevalent utilization of portal websites within the United States, a significant proportion of nations continues to depend on human labor for the management of medical waste (Mohamed et al., 2023).

The literature on modern logistics in the domain of hazardous waste management strongly supports the proposed optimization model. The preceding statement emphasizes the transformative potential of Industry 4.0 technologies in improving healthcare waste management and its operational efficiency, environmental sustainability, and health-related outcomes. Following that, this paper will deepen our understanding by developing a problem statement that includes the potential benefits and challenges of utilizing cutting-edge logistics to design a healthcare waste management DSS with enhanced operational efficiency. Still, in addition to the significant financial costs and time investment associated with providing high-quality healthcare services, establishing and maintaining a dependable medical waste logistics system is a significant undertaking (Görçün et al., 2023). Thus, it is very important to provide a practical structure to optimize decisions related to healthcare waste management, because in addition to reducing costs, it leads to reducing harmful environmental effects such as air, soil, and water pollution, and prevents the spread of diseases and infections.

3. Problem statement and proposed model

In this paper, an optimal network is configured for healthcare waste management by applying Industry 4.0 technologies. An application has been used to share information between collection centers and hospitals. Hospitals share information about their waste with collection centers through the application. By running the proposed model using the obtained data, optimal decisions are made, including the optimal number of vehicles, the routes assigned to each vehicle, the estimated time of vehicles arriving at the hospitals, and the amount of waste allocated to each vehicle. Drivers transporting infectious healthcare waste are always at risk. The use of autonomous vehicles can solve this problem. On the one hand, the application shows the location of vehicles to users using the GNSS. On the other hand, as mentioned, the proposed model calculates the estimated time of the vehicles arriving at the hospitals. Therefore, hospitals can accurately estimate the arrival time of vehicles at hospitals and reduce vehicle waiting time. It should be noted that waste is delivered to vehicles in bags equipped with RFID tags. The overall structure of the examined network is presented in Fig. 1. In general, using Industry 4.0 and an application to share information in healthcare waste management has many advantages. Some of the most important ones are listed below:

- The amount of waste to be collected from hospitals has already been announced by the hospitals in the application. Therefore, there is no uncertainty in the amount of produced waste. In other words, the use of application increases transparency and reduces uncertainty.
- Lack of proper planning will increase the waiting time for vehicles to be loaded in hospitals. This application reduces the waiting time for

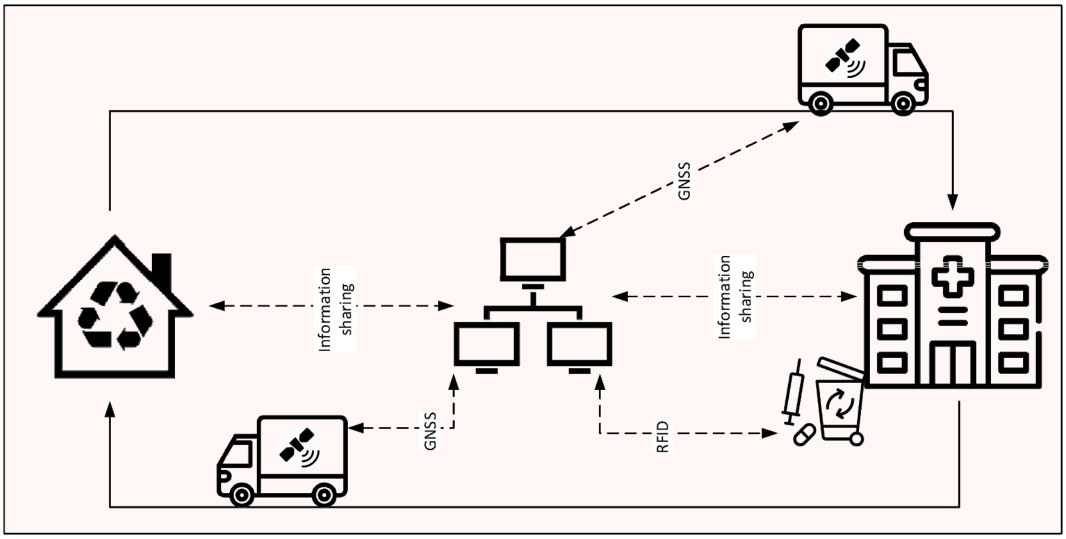

Fig. 1. The overall structure of the examined network.

vehicles in the hospital. In addition to minimizing costs, reducing waiting time decreases the risk of spreading infections and diseases.

- The use of GNSS technology enables the tracking of vehicles and increases the security of the transportation system.
- The use of bags equipped with RFID tags leads to the amount of waste produced by hospitals in different periods being easily traceable. In other words, this technology provides valuable information to users and decision-makers.

A bi-objective MILP model is formulated to structure the proposed network. In the following, the assumptions of the proposed model are presented:

- The investigated network is multi-period and multi-item.
- The location of collection centers is determined by the model.
- Multi-depot, capacitated, and split-pickup vehicle routing problem is considered.
- Autonomous vehicles are heterogeneous.
- The focus of the proposed model is on the hazardous (infectious) waste.
- The time distance among hospitals depends on the time period index. In other words, traffic is considered in the proposed model.
- Electric autonomous vehicles are used to collect waste.
- Each vehicle departs from a collection center and finally returns to that collection center.
- Vehicles are fully charged in the collection centers.
- Each vehicle is allowed to visit each hospital at most once per time period.
- Each purchased vehicle must be assigned to one collection center.
- Finally, $k = 1$ is considered as the collection center.

The proposed bi-objective MILP model is given below:
Mathematical Model.

Indices

$w \in \{1, 2, \ldots, W\}$:	Infectious waste type.
$a \in \{1, 2, \ldots, A\}$:	Autonomous vehicle type.
$i \in \{1, 2, \ldots, I\}$:	Collection center.
$j \in \{1, 2, \ldots, W\}$:	IoT technology.
$\hat{k}, k \in \{1, 2, \ldots, K\}$:	Hospital.
$t \in \{1, 2, \ldots, T\}$:	Time period.

Parameters

Φ^{CL}_{wi}:	The capacity of the collection center i to process the type w infectious waste.
Φ^{AV}_{a}:	The capacity of the type a autonomous vehicle.
δ_{wkt}:	The amount of the type w infectious waste generated in the hospital k in time period t.
ϑ^{IoT}_{ij}:	The cost of applying the type j IoT technology at the collection center i.
ϑ^{CL}_{i}:	The cost of establishing the collection center i.
ϑ^{AV}_{a}:	The cost of supplying the type a autonomous vehicle.
α^{IoT}_{j}:	The average energy required to process, record and transmit data by the type j IoT technology.
α^{AV}_{a}:	The average energy required to travel one unit of distance by the type a autonomous vehicle.
EP:	The price of one unit of energy.
β^{PR}_{wi}:	The cost of processing one unit of type w infectious waste at the collection center i.
β^{DT}:	The average cost of recording, recalling, and processing the data associated with infectious waste at the collection centers.
μ^{CL-HP}_{ik}:	The geographical distance among the collection center i and the hospital k.
$\mu^{HP}_{\hat{k}k}$:	The geographical distance among the hospital k' and the hospital k.
$\lambda^{HP}_{a\hat{k}kt}$:	The time required to travel the route among the hospital k' and the hospital k by the type a autonomous vehicle in time period t.
λ^{CL-HP}_{aikt}:	The time required to travel the route among the collection center i and the hospital k by the type a autonomous vehicle in time period t.
θ^{AV}_{a}:	The maximum distance that the type a autonomous vehicle can travel if it is fully charged.
κ_{kt}:	The average time required to load the waste at the hospital k in time period t.
ξ_{w}:	The volume of the type w infectious waste.
$\varpi_{\hat{k}k}$:	The population living on the route among the hospital k' and the hospital k.
BM:	A big number.

Variables

χ^{CL}_{i}:	1 In case of establishing the collection center i; 0 otherwise.
χ^{IoT}_{ij}:	1 In case of applying the type j IoT technology at the collection center i; 0 otherwise.
χ^{AV}_{a}:	1 In case of supplying the type a autonomous vehicle; 0 otherwise.
$\chi_{a\hat{k}kt}$:	1 In case of traveling the route among the hospital k' and the hospital k by the type a autonomous vehicle in time period t; 0 otherwise.
γ_{ai}:	1 In case of allocating the type a autonomous vehicle to the collection center i; 0 otherwise.
Q_{akt}:	The estimated time of arriving the type a autonomous vehicle to the hospital k in time period t.
U_{wakit}:	The amount of type w infectious waste collected from the hospital k and shipped to collection center i by the type a autonomous vehicle in time period t.
Y_{wakt}:	The amount of type w infectious waste in the type a autonomous vehicle when arriving the hospital k in time period t.

3.1. Objective functions

The first objective function minimizes the total costs of the network. These costs include the cost of establishing collection centers, the cost of applying IoT technology in collection centers, the cost of supplying electric autonomous vehicles, the cost of processing healthcare waste in collection centers, the cost of recording, recalling, and processing the data, and the cost of energy consumption by IoT technology and vehicles. This objective function is as follows:

$$\min Z_1 = \sum_{i} \vartheta_i^{CL} \times \chi_i^{CL} + \sum_{i,j} \vartheta_{ij}^{IoT} \times \chi_{ij}^{IoT} + \sum_{a} \vartheta_a^{AV} \times \chi_a^{AV} + \sum_{w,a,k,i,t} \beta_{wi}^{PR} \times U_{wakit} + \sum_{w,a,k,i,t} \beta^{DT} \times U_{wakit} + \sum_{w,a,k,i,j,t} EP \times \alpha_j^{IoT} \times \chi_{ij}^{IoT} \times U_{wakit} + \sum_{a,\hat{k}>1,k>1,t} EP \times \alpha_a^{AV} \times \mu_{\hat{k}k}^{HP} \times \chi_{a\hat{k}kt} + l. \tag{1}$$

The second objective function minimizes the population exposed to infection from healthcare waste. Below is this objective function:

$$\min Z_2 = \sum_{w,a,\hat{k},k,t} \varpi_{\hat{k}k} \times \chi_{a\hat{k}kt} \times Y_{wakt} \tag{2}$$

subject to:

All waste generated in the hospitals must be collected by vehicles. This process must be implemented in all time periods. Constraint (3) guarantees this:

$$\sum_{a,i} \mathrm{U}_{\mathrm{wakit}} \geq \delta_{\mathrm{wkt}} \quad \forall \mathrm{w,k,t} \tag{3}$$

Constraint (4) states that if a collection center is established, we should use exactly one type of IoT technology in that center. The following is this constraint:

$$\sum_{j} \chi_{ij}^{\mathrm{IoT}} = \chi_i^{\mathrm{CL}} \quad \forall \mathrm{i} \tag{4}$$

If a collection center is not established, that collection center should not collect the waste. This condition is considered in constraint (5) as follows:

$$\sum_{w,k,a} \mathrm{U}_{\mathrm{wakit}} \leq \mathrm{BM} \times \chi_i^{\mathrm{CL}} \quad \forall \mathrm{i,t} \tag{5}$$

Constraint (6) expresses that if a vehicle enters a hospital, it must leave the hospital after loading the waste. The following is this constraint:

$$\sum_{\hat{k}} \chi_{\mathrm{a\hat{k}kt}} = \sum_{\hat{k}} \chi_{\mathrm{ak\hat{k}t}} \quad \forall \mathrm{a,k,t} \tag{6}$$

Visiting hospitals is possible when vehicles are purchased. This condition is satisfied by constraint (7) as follows:

$$\sum_{\hat{k}} \chi_{\mathrm{a\hat{k}kt}} \leq \chi_{\mathrm{a}}^{\mathrm{AV}} \quad \forall \mathrm{a,k,t} \tag{7}$$

Constraint (8) elucidates that if a vehicle has not been purchased, that vehicle is not allowed to be assigned to a collection center. Below is constraint (8):

$$\sum_{i} \gamma_{\mathrm{ai}} \leq \chi_{\mathrm{a}}^{\mathrm{AV}} \quad \forall \mathrm{a} \tag{8}$$

One of the conditions for collecting healthcare waste from hospitals is that vehicles are purchased and assigned to a collection center. Another condition is that the vehicles visit the hospitals. These conditions are considered in constraints (9) and (10), respectively. The following are these constraints:

$$\sum_{w,k} \mathrm{U}_{\mathrm{wakit}} \leq \mathrm{BM} \times \gamma_{\mathrm{ai}} \quad \forall \mathrm{a,i,t} \tag{9}$$

$$\sum_{w,i} \mathrm{U}_{\mathrm{wakit}} \leq \mathrm{BM} \times \sum_{\hat{k}} \chi_{\mathrm{a\hat{k}kt}} \quad \forall \mathrm{a,k,t} \tag{10}$$

The amount of healthcare waste in each vehicle before entering the hospitals and the collection center is calculated by constraints (11) and (12), respectively. It should be noted that sub-tour elimination is caused by these constraints. Below are these constraints:

$$Y_{wakt} + (1 - \chi_{a\hat{k}kt}) \times BM \geq Y_{wa\hat{k}t} + U_{wa\hat{k}it} \quad \forall w, a, \widehat{k}, k > 1, i, t \tag{11}$$

$$Y_{wa1t} \geq \sum_{k} U_{wakit} \quad \forall w, a, i, t \tag{12}$$

Constraint (13) controls that the vehicles are not loaded beyond their capacity. This constraint is as follows:

$$\sum_{w} Y_{wa1t} \times \xi_w \leq \Phi_a^{AV} \quad \forall a, t \tag{13}$$

The capacity control of collection centers is done by constraint (14) as follows:

$$\sum_{a,k} U_{wakit} \leq \Phi_{wi}^{CL} \quad \forall w, i, t \tag{14}$$

Each vehicle can travel a maximum distance, if it is fully charged. The distance traveled by each vehicle should not exceed the maximum defined distance. Constraint (15) handles this issue as follows:

$$\sum_{\hat{k}>1,k>1} \mu_{\hat{k}k}^{HP} \times \chi_{a\hat{k}kt} + \sum_{i,k>1} \mu_{ik}^{CL-HP} \times \gamma_{ai} \times (\chi_{a1kt} + \chi_{ak1t}) \leq \theta_a^{AV} \quad \forall a, t \tag{15}$$

Constraints (16) and (17) calculates the estimated time of vehicles arriving at the hospitals and collection centers, respectively. Below are these constraints:

$$\mathrm{Q}_{\mathrm{akt}} + \mathrm{BM} \times (1 - \chi_{\mathrm{a\hat{k}kt}}) \geq \mathrm{Q}_{\mathrm{a\hat{k}t}} + \kappa_{\mathrm{\hat{k}t}} + \lambda_{\mathrm{a\hat{k}kt}}^{\mathrm{HP}} \quad \forall \mathrm{a}, \widehat{\mathrm{k}}, \mathrm{k} > 1, \mathrm{t} \tag{16}$$

$$\mathrm{Q}_{\mathrm{a1t}} + \mathrm{BM} \times (1 - \chi_{\mathrm{ak1t}}) \geq \mathrm{Q}_{\mathrm{akt}} + \kappa_{\mathrm{kt}} + \lambda_{\mathrm{aikt}}^{\mathrm{CL-HP}} \times \gamma_{\mathrm{ai}} \quad \forall \mathrm{a,i,k} > 1, \mathrm{t} \tag{17}$$

3.2. Linearization process

In the proposed model, the terms $\chi_{ij}^{IoT} \times U_{wakit}$ and $\gamma_{ai} \times \chi_{a\hat{k}kt}$ in the first objective function, the term $\chi_{a\hat{k}kt} \times Y_{wakt}$ in the second objective function, and the term $\gamma_{ai} \times \chi_{a\hat{k}kt}$ in the constraint (15) have led to the creation of a mixed-integer nonlinear programming (MINLP) model. In this section, we intend to convert the presented MINLP model into a MILP one by linearizing the nonlinear terms. For this end, we define three auxiliary variables and replace them with nonlinear terms. The new variables are presented in Table 1.

Note that the variables ϕ_{wakijt} and $\upsilon_{wa\hat{k}kt}$ are inherently integer, and the variable $\eta_{ai\hat{k}kt}$ is inherently binary. But according to Rossit et al. (2020), it is better to define these variables as continuous variables to reduce the complexity of the model. Defined auxiliary variables replace nonlinear terms. Therefore, the first objective function, the second objective function, and the constraint (15) are converted to Eqs. (18)–(20), respectively. The following are Eqs. (18)–(20):

Table 1
Auxiliary variables applied in the linearization process.

Nonlinear term	Auxiliary/linearization variable	Variable type
$\chi_{ij}^{IoT} \times U_{wakit}$	ϕ_{wakijt}	Continuous and positive
$\gamma_{ai} \times \chi_{a\hat{k}kt}$	$\eta_{ai\hat{k}kt}$	
$\chi_{a\hat{k}kt} \times Y_{wakt}$	$\upsilon_{wa\hat{k}kt}$	

$$\min Z_1 = \sum_i \vartheta_i^{CL} \times \chi_i^{CL} + \sum_{i,j} \vartheta_{ij}^{IoT} \times \chi_{ij}^{IoT} + \sum_a \vartheta_a^{AV} \times \chi_a^{AV} + \sum_{w,a,k,i,t} \beta_{wi}^{PR} \times U_{wakit} + \sum_{w,a,k,i,t} \beta^{DT} \times U_{wakit} + \sum_{w,a,k,i,j,t} EP \times \alpha_j^{IoT} \times \phi_{wakijt} + \sum_{a,\hat{k}>1,k>1,t} EP \times \alpha_a^{AV} \times \mu_{\hat{k}k}^{HP} \times \chi_{a\hat{k}kt} + \sum_{a,i,k>1,t} EP \times \alpha_a^{AV} \times \mu_{ik}^{CL-HP} \times (\eta_{ai1kt} + \eta_{aik1t}), \tag{18}$$

$$\min Z_2 = \sum_{w,a,\hat{k},k,t} \varpi_{\hat{k}k} \times \upsilon_{wa\hat{k}kt}, 28 \tag{19}$$

$$\sum_{\hat{k}>1,k>1} \mu_{\hat{k}k}^{HP} \times \chi_{a\hat{k}kt} + \sum_{i,k>1} \mu_{ik}^{CL-HP} \times (\eta_{ai1kt} + \eta_{aik1t}) \leq \theta_a^{AV} \quad \forall a,t \tag{20}$$

Now we have to express the relationship between the auxiliary variables and the variables that led to the creation of the nonlinear term. The relationship between variables ϕ_{wakijt}, χ_{ij}^{IoT}, and U_{wakit} is given in constraints (21) to (23). Constraints (24) and (25) express the relationship between variables $\eta_{ai\hat{k}kt}$, $\chi_{a\hat{k}kt}$, and γ_{ai}. Also, the relationship between variables $\upsilon_{wa\hat{k}kt}$, $\chi_{a\hat{k}kt}$, and Y_{wakt} is defined in constraints (26) to (28). The following are constraints (21) to (28):

$$\phi_{wakijt} \geq U_{wakit} + BM \times \left(\chi_{ij}^{IoT} - 1\right) \quad \forall w,a,k,i,j,t \tag{21}$$

$$\phi_{wakijt} \leq U_{wakit} \quad \forall w,a,k,i,j,t \tag{22}$$

$$\phi_{wakijt} \leq BM \times \chi_{ij}^{IoT} \quad \forall w,a,k,i,j,t \tag{23}$$

$$1.5 \times \eta_{ai\hat{k}kt} \leq \chi_{a\hat{k}kt} + \gamma_{ai} \quad \forall a,i,\hat{k},k,t \tag{24}$$

$$\eta_{ai\hat{k}kt} + 1.5 \geq \chi_{a\hat{k}kt} + \gamma_{ai} \quad \forall a,i,\hat{k},k,t \tag{25}$$

$$\upsilon_{wa\hat{k}kt} \geq Y_{wakt} + BM \times (\chi_{a\hat{k}kt} - 1) \quad \forall w,a,\hat{k},k,t \tag{26}$$

$$\upsilon_{wa\hat{k}kt} \leq Y_{wakt} \quad \forall w,a,\hat{k},k,t \tag{27}$$

$$\upsilon_{wa\hat{k}kt} \leq BM \times \chi_{a\hat{k}kt} \quad \forall w,a,\hat{k},k,t \tag{28}$$

3.3. Multi-objective solution approach

Researchers use multi-objective decision-making methods to solve mathematical programming models with multiple objectives. Methods such as LP-metric, goal programming, lexicographic, and so forth are among the most well-known methods in this field (Zandkarimkhani et al., 2020). The type of method chosen depends on the nature of the multi-objective model; each method suffers from disadvantages as well as advantages. An intelligent combination of these methods can lead to the structuring of an effective multi-objective solution approach. In this vein, this paper integrates the lexicographic optimization method presented by Aghaei et al. (2011) and the TH method provided by Torabi and Hassini (2008) to develop an efficient multi-objective solution approach to solve the presented bi-objective MILP model. The lexicographic method is an effective way to find the lower and upper bounds of objective functions (Govindan et al., 2023). On the other hand, the TH method is a suitable means to convert a multi-objective model to a single-objective one by considering the weight for the objective functions, solving the model under uncertainty, and providing the Pareto solution set (Tavana et al., 2023). Therefore, by integrating these two methods, an efficient two-stage approach has been developed, which is given below:

Stage 1. Lexicographic method

In this stage, we employ the lexicographic method to calculate the lower and upper bounds of objective functions in our bi-objective model. This stage consists of four steps, which are presented below:

Step 1.1. In this step, we optimize the mathematical model for the first objective function. The optimal value calculated for the first objective function (i.e., Z_1^*) is considered as the lower bound of the first objective function (i.e., ZL_1).

Step 1.2. In this step, the mathematical model is optimized for the second objective function. The optimal value calculated for the second objective function (i.e., Z_2^*) is considered as the lower bound of the second objective function (i.e., ZL_2).

Step 1.3. In this step, we add the constraint $Z_2 \leq ZL_2$ to the set of constraints and optimize the model for the first objective function. The optimal value calculated for the first objective function is the upper bound of this objective function and is denoted by ZU_1.

Step 1.4. Similarly, in this step, the constraint $Z_1 \leq ZL_1$ is added to the set of constraints and the model is run to optimize the second objective function. The optimal value calculated for the second objective function is considered as the upper bound of this objective function and is denoted by ZU_2.

Stage 2. TH method

In this stage, by applying the TH method, the developed bi-objective MILP model becomes a single-objective one. In the following, the TH method is presented in two steps:

Step 2.1. In this step, the membership functions of the objective function f (i.e., ψ_f) is calculated with the help of Eq. (29) as follows:

$$\psi_f = \begin{cases} 0 & Z_f < ZL_f \\ 1 & Z_f > ZU_f \\ \dfrac{ZU_f - Z_f}{ZU_f - ZL_f} & ZL_f \leq Z_f \leq ZU_f. \end{cases} \tag{29}$$

Step 2.2. In this step, the Model (30) is applied to transform the multi-objective model into a single-objective one. This model is as follows:

$$\begin{aligned} &\max \ell \times \sigma + (1-\ell) \times \sum_f \tau_f \times \psi_f \\ &\text{subject to:} \\ &\sigma \leq \psi_f \quad \forall f \\ &\text{System constraints.} \end{aligned} \tag{30}$$

where σ denotes the minimum satisfaction of objective functions, and ℓ shows its weight. Also, the weight of objective function f is displayed by τ_f. In the TH method, it is possible to value the objective functions by decision makers; the decision makers can set weights for the objective functions according to the conditions and strategies of their organization. In addition, in the TH method, a set of Pareto solutions can be provided by changing the weights of the objective functions. Note that the sum of the weights of the objective functions must be equal to one.

4. Case study

The most recent few years have posed a great challenge for healthcare waste systems. Difficulties were faced in effectively responding to the COVID-19 pandemic's generated infectious wastes (Chen et al., 2021a,b), so traditional systems surely need advancements to better respond to future health crises. The collection of healthcare waste in Iran is almost all traditionally managed; this approach, in addition to increasing costs and increasing the risk of contamination caused by infectious waste, has brought dissatisfaction to hospitals. Therefore, the government, specifically Iran's Ministry of Health and Medical Education (MHME), should plan to find a solution to this problem, with one option being cooperation with the private sector. In this vein, a knowledge-based company has provided an effective and sustainable solution for healthcare waste collection using Industry 4.0-based technologies. The company has proposed the use of electric autonomous vehicles to collect healthcare waste, as this would reduce air pollution, protect drivers from infectious contamination, and track vehicles online. Also, an application should be used to share data and information between the hospital and the collection centers. It should be noted that the wastes must be delivered from the hospitals in bags equipped with RFID tags. After collecting the data, the proposed model is run in GAMS software and the results will help decision makers to make optimal decisions in healthcare waste management. The solution proposed by Company ABC[1] demonstrates a notable emerging pattern in which medical logistics companies assume responsibility for medical waste disposal. Before the implementation of the project at the macro level, the company was required to implement the proposed model as a pilot study and to provide a detailed report of the model's performance and its obtained results. If the effectiveness of the presented model is confirmed at the pilot level, it will be decided to implement the project at the macro level. It should be noted that data from seven hospitals in Karaj city (the fourth most populous city in Iran) were used to validate the proposed model at the pilot level. Also, three potential collection centers, three types of infectious waste (i.e., metal, glass, and plastic), five vehicles, three potential IoT technologies, and four time periods have been considered for this purpose. Tables 2 and 3 demonstrates data associated with some parameters.

The amount of infectious waste generated at hospitals in each time period is reported in Table 2. For example, the number 13 in the second row of this table states that Shariati hospital produced 13 bags of infectious plastic waste in the first time period. Note that for simplicity in the formulation of the location-routing problem, hospital 1 ($k = 1$) is considered as the collection center and it is obvious that the amount of waste produced by it is zero as shown in Table 2.

First, using the proposed multi-objective solution approach, we structure the single-objective MILP model, which is given below:

Stage 1: Lexicographic method.

In the first stage, we apply the lexicographic method to calculate the lower and upper bounds of the objective function, which is presented in steps 1.1 to 1.4.

Step 1.1: The developed MILP model is run in GAMS software by CPLEX solver for the first objective function, and the optimal value of this objective function is $574,293. This value is considered as the lower bound of the first objective function (i.e., $ZL_1 = 574,293$).

Step 1.2: By running the model for the second objective function, the optimal value of this objective function is calculated as 1,249,026. In this way, the lower bound of the second objective function is determined (i.e., $ZL_2 = 1,249,026$).

Step 1.3: The constraint $Z_2 \leq 1,249,026$ is added to the system constraints and the model is optimized for the first objective function to calculate the upper bound of this objective function. By performing this operation, the value of ZU_1 was equal to $698,558.

Step 1.4: The constraint $Z_1 \leq 574,293$ is added to the system constraints and the model is optimized for the second objective function to calculate the upper bound of this objective function. By performing this operation, the value of ZU_2 was equal to $1,475,107.

Stage 2: TH method.

In this stage, the TH method is employed to transform the bi-objective MILP model into a single-objective one. These operations are presented in steps 2.1 and 2.2.

Step 2.1: By applying Eq. (29), the membership functions of the objective functions are determined, which are given in Eq. (31). This equation is as follows:

$$\psi_1 = \frac{698,558 - Z_1}{698,558 - 574,293}, \quad \psi_2 = \frac{1,475,107 - Z_2}{1,475,107 - 1,249,026}. \tag{31}$$

Step 2.2: In this step, the single-objective model is configured based on the structure provided in Eq. (30). Eq. (32) shows the single-objective model. It should be noted that the values of parameters ℓ, τ_1, and τ_2 are considered equal to 0.3, 0.6, and 0.4, respectively. The following is the single-objective model:

$$\max 0.3\times\sigma + 0.7\times(0.6\times\psi_1 + 0.4\times\psi_2)$$

subject to:

$$\sigma \leq \frac{698,558 - Z_1}{123,665}$$

$$\sigma \leq \frac{1,475,107 - Z_2}{226,081}$$

$$Z_1 = \sum_{i}\vartheta_i^{CL}\times\chi_i^{CL} + \sum_{i,j}\vartheta_{ij}^{IoT}\times\chi_{ij}^{IoT} + \sum_{a}\vartheta_a^{AV}\times\chi_a^{AV} + \sum_{w,a,k,i,t}\beta_{wi}^{PR}\times U_{wakit} +$$

$$\sum_{w,a,k,i,t}\beta^{DT}\times U_{wakit} + \sum_{w,a,k,i,j,t}EP\times\alpha_j^{IoT}\times\phi_{wakijt} + \sum_{a,\hat{k}>1,k>1,t}EP\times\alpha_a^{AV}\times\mu_{\hat{k}k}^{HP}\times\chi_{a\hat{k}kt} +$$

$$\sum_{a,i,k>1,t}EP\times\alpha_a^{AV}\times\mu_{ik}^{CL-HP}\times(\eta_{ai1kt} + \eta_{aik1t})$$

$$Z_2 = \sum_{w,a,\hat{k},k,t}\varpi_{\hat{k}k}\times\upsilon_{wa\hat{k}kt}$$

$$\text{Constraints}\,(3) - (14)$$

$$\text{Constraints}\,(16) - (17)$$

$$\text{Constraints}\,(20) - (28). \tag{32}$$

Table 2
The amount of generated infectious waste in hospitals.

δ_{wkt}		$t = 1$	$t = 2$	$t = 3$	$t = 4$
$w = 1$ (Plastic)	$k = 1$ (Collection center)	0	0	0	0
	$k = 2$ (Shariati hospital)	13	14	15	12
	$k = 3$ (Kamali hospital)	12	13	14	11
	$k = 4$ (Rajaei hospital)	14	15	16	13
	$k = 5$ (Alborz hospital)	14	15	16	14
	$k = 6$ (Madani hospital)	11	12	13	11
	$k = 7$ (Kosar hospital)	9	10	11	8
	$k = 8$ (Bahonar hospital)	10	11	12	9
$w = 2$ (Metal)	$k = 1$ (Collection center)	0	0	0	0
	$k = 2$	3	4	4	3
	$k = 3$	3	3	4	3
	$k = 4$	4	5	5	4
	$k = 5$	5	4	6	4
	$k = 6$	3	3	3	3
	$k = 7$	2	3	3	2
	$k = 8$	2	3	3	1
$w = 3$ (Glass)	$k = 1$ (Collection center)	0	0	0	0
	$k = 2$	5	7	8	5
	$k = 3$	5	6	7	4
	$k = 4$	6	7	8	5
	$k = 5$	7	8	9	6
	$k = 6$	4	5	7	4
	$k = 7$	4	5	6	3
	$k = 8$	4	5	6	4

Table 3
Data associated with geographic and time distance of nodes.

Parameters	Value	Unit
μ_{ik}^{CL-HP}	google.com/maps	Kilometer
$\mu_{\hat{k}k}^{HP}$		Kilometer
$\lambda_{a\hat{k}kt}^{HP}$		Minute

[1] The company name is changed to protect its anonymity.

The single-objective model is run by CPLEX solver in GAMS software. The GAMS code is given in the Appendix. The optimal values of decision variables and objective functions obtained from running the model in GAMS software are reported below:

- The optimal values of the objective functions 1 and 2 are 618,053 and 1,359,418, respectively.
- Collection center 2 should be established and type 2 IoT technology should be applied in this center.
- All vehicles should be purchased and assigned to collection center 2.
- The routes traveled by the electric autonomous vehicles in each time period are provided in Table 4.

Decision makers can plan their vehicles using the results presented in Table 4. Based on this, the routes assigned to each vehicle are determined in each time period. For example, from the first row of this table, it is deduced that vehicle 1 in time period 1 should go from collection center 2 to hospital 4 (Rajaei hospital) and then to hospital 2 (Shariati hospital), and finally return to collection center 2. In the same way, all routes can be analyzed. In addition, the information presented in Table 4 reveals that in time periods 1 to 3 we need all five vehicles, while in time period 4 vehicle 5 will not be used. Another noteworthy point is that collection center 2 is the starting and ending point of all vehicles in all time periods. This means that only collection center 2 is established.

- The estimated time of the vehicles arriving at the hospitals and established collection center is reported in Table 5.

The information presented in Table 5 is very important for both collection centers and hospitals. Before starting the waste collection operation, the information presented in this table is shared with the hospitals and the hospitals are informed about what time the vehicles will visit them. This enables hospitals to prepare waste before vehicles arrive, thereby reducing vehicle waiting times. For example, the number 32 in the first column of this table represents that vehicle 1 arrives at the hospital 4 in time period 1, about 32 min after leaving collection center 2. In this way, all the numbers in this table can be analyzed. In addition, due to the application of GNSS technology in vehicles, it is possible for users to monitor vehicles online. Therefore, by combining the results obtained from the model and online monitoring of vehicles, users can more accurately calculate the arrival time of vehicles to hospitals and collection centers.

Table 4
Routes traveled by electric autonomous vehicles.

Time period	Vehicle	Route
$t = 1$	$a = 1$	$i = 2\ (k = 1) \rightarrow k = 4 \rightarrow k = 2 \rightarrow i = 2$
	$a = 2$	$i = 2\ (k = 1) \rightarrow k = 7 \rightarrow k = 4 \rightarrow i = 2$
	$a = 3$	$i = 2\ (k = 1) \rightarrow k = 6 \rightarrow i = 2$
	$a = 4$	$i = 2\ (k = 1) \rightarrow k = 8 \rightarrow k = 3 \rightarrow i = 2$
	$a = 5$	$i = 2\ (k = 1) \rightarrow k = 5 \rightarrow i = 2$
$t = 2$	$a = 1$	$i = 2\ (k = 1) \rightarrow k = 8 \rightarrow k = 3 \rightarrow i = 2$
	$a = 2$	$i = 2\ (k = 1) \rightarrow k = 5 \rightarrow i = 2$
	$a = 3$	$i = 2\ (k = 1) \rightarrow k = 4 \rightarrow k = 6 \rightarrow i = 2$
	$a = 4$	$i = 2\ (k = 1) \rightarrow k = 3 \rightarrow k = 2 \rightarrow i = 2$
	$a = 5$	$i = 2\ (k = 1) \rightarrow k = 7 \rightarrow k = 4 \rightarrow i = 2$
$t = 3$	$a = 1$	$i = 2\ (k = 1) \rightarrow k = 5 \rightarrow k = 7 \rightarrow i = 2$
	$a = 2$	$i = 2\ (k = 1) \rightarrow k = 3 \rightarrow k = 2 \rightarrow i = 2$
	$a = 3$	$i = 2\ (k = 1) \rightarrow k = 4 \rightarrow k = 6 \rightarrow i = 2$
	$a = 4$	$i = 2\ (k = 1) \rightarrow k = 8 \rightarrow k = 3 \rightarrow i = 2$
	$a = 5$	$i = 2\ (k = 1) \rightarrow k = 4 \rightarrow k = 5 \rightarrow i = 2$
$t = 4$	$a = 1$	$i = 2\ (k = 1) \rightarrow k = 7 \rightarrow k = 5 \rightarrow i = 2$
	$a = 2$	$i = 2\ (k = 1) \rightarrow k = 8 \rightarrow k = 6 \rightarrow i = 2$
	$a = 3$	$i = 2\ (k = 1) \rightarrow k = 7 \rightarrow k = 4 \rightarrow i = 2$
	$a = 4$	$i = 2\ (k = 1) \rightarrow k = 3 \rightarrow k = 2 \rightarrow i = 2$

Table 5
The estimated time of vehicles arriving to nodes.

Q_{akt}		$t = 1$	$t = 2$	$t = 3$	$t = 4$
$a = 1$	$k = 1\ (i = 2)$	136	133	117	106
		$k = 2$	94	–	–
	$k = 3$	–	78	–	–
	$k = 4$	32	–	–	–
	$k = 5$	–	–	44	57
	$k = 7$	–	–	82	34
	$k = 8$	–	54	–	–
$a = 2$	$k = 1\ (i = 2)$	105	94	154	128
	$k = 2$	–	–	107	–
	$k = 3$	–	–	48	–
	$k = 4$	62	–	–	–
	$k = 5$	–	44	–	–
	$k = 6$	–	–	–	79
	$k = 7$	34	–	–	–
	$k = 8$	–	–	–	54
$a = 3$	$k = 1\ (i = 2)$	104	126	125	102
	$k = 4$	–	32	32	60
	$k = 6$	55	74	74	–
	$k = 7$	–	–	–	34
$a = 4$	$k = 1\ (i = 2)$	134	149	137	143
	$k = 2$	–	102	–	100
	$k = 3$	75	48	79	48
	$k = 8$	54	–	54	–
$a = 5$	$k = 1\ (i = 2)$	93	108	127	–
	$k = 4$	–	63	32	–
	$k = 5$	44	–	74	–
	$k = 7$	–	34	–	–

- The amount of waste collected by vehicles from each hospital in each time period is reported in Table 6.

The number 13 in the first row and first column of Table 6 states that vehicle 1 in time period 1 should collect 13 bags of type 1 waste (i.e., plastic) from hospital 2. Also, the results of this table show that vehicle 2 should pick up 3 bags of type 2 waste and 5 bags of type 3 waste from this hospital in time period 1 (See rows 20 and 40 of this table).

It is noteworthy that due to the permission of split-pickup, the wastes of a hospital may be collected by more than one vehicle. For example, the results presented in Table 5 reveal that the waste of hospital 4 in the first time period should be collected by vehicles 1 and 2. Perhaps the question arises for the reader, how many of each type of waste should each vehicle pick up? The answer lies in the results reported in Table 6. For instance, by examining Tables 2 and it is clear that hospital 4 produces 14, 4, and 6 bags of type 1, 2, and 3 waste in period 1, respectively. The results presented in Table 6 show that 14 bags of type 1 waste are collected by vehicle 2, and the remaining waste (i.e., 4 bags of type 2 waste and 6 bags of type 3 waste) must be collected by vehicle 1. Therefore, in the first time period, two vehicles visit hospital 4 at different times, and their arrival times are given in Table 5.

- The cumulative amount of each type of waste in each vehicle before that vehicle arrives at the hospital/collection center in different time periods is given in Table 7. For example, the number 13 in the first row of this table indicates that vehicle 1 has collected 13 bags of type 1 waste in time period 1 when it returns to the collection center.

The results of Table 7 provide useful information for users. The results of this table inform the user how many bags of each type of waste in each vehicle occur in each node. For example, suppose the user wants to know how many bags of each type of waste vehicle 1 has when it returns to the collection center in the first time period. The data presented at the intersection of rows 1, 13, and 28 with the first column of Table 7 provides this information to the user. That is, in the first time period, vehicle 1 enters the collection center with 13 bags of type 1 waste, 7 bags of type 2 waste, and 11 bags of type 3 waste. In this way, other results reported in this table can be analyzed.

Table 6
Amount of waste collected from hospitals by each vehicle in each time period.

U_{wakit}			$i=2$			
			$t=1$	$t=2$	$t=3$	$t=4$
$w=1$	$a=1$	$k=2$	13	0	0	0
$w=1$	$a=1$	$k=5$	0	0	0	14
$w=1$	$a=1$	$k=7$	0	0	11	0
$w=1$	$a=1$	$k=8$	0	11	0	0
$w=1$	$a=2$	$k=2$	0	0	15	0
$w=1$	$a=2$	$k=4$	14	0	0	0
$w=1$	$a=2$	$k=5$	0	15	0	0
$w=1$	$a=2$	$k=6$	0	0	0	11
$w=1$	$a=2$	$k=7$	9	0	0	0
$w=1$	$a=2$	$k=8$	0	0	0	9
$w=1$	$a=3$	$k=4$	0	0	0	13
$w=1$	$a=3$	$k=6$	11	12	13	0
$w=1$	$a=3$	$k=7$	0	0	0	8
$w=1$	$a=4$	$k=2$	0	14	0	12
$w=1$	$a=4$	$k=3$	12	13	14	11
$w=1$	$a=4$	$k=8$	10	0	12	0
$w=1$	$a=5$	$k=4$	0	15	16	0
$w=1$	$a=5$	$k=5$	14	0	16	0
$w=1$	$a=5$	$k=7$	0	10	0	0
$w=2$	$a=1$	$k=2$	3	0	0	0
$w=2$	$a=1$	$k=3$	0	3	0	0
$w=2$	$a=1$	$k=4$	4	0	0	0
$w=2$	$a=1$	$k=5$	0	0	6	4
$w=2$	$a=1$	$k=7$	0	0	3	0
$w=2$	$a=1$	$k=8$	0	3	0	0
$w=2$	$a=2$	$k=2$	0	0	4	0
$w=2$	$a=2$	$k=3$	0	0	4	0
$w=2$	$a=2$	$k=5$	0	3	0	0
$w=2$	$a=2$	$k=6$	0	0	0	4
$w=2$	$a=2$	$k=7$	4	0	0	0
$w=2$	$a=2$	$k=8$	0	0	0	1
$w=2$	$a=3$	$k=4$	0	5	5	4
$w=2$	$a=3$	$k=6$	3	3	3	0
$w=2$	$a=3$	$k=7$	0	0	0	2
$w=2$	$a=4$	$k=2$	0	4	0	3
$w=2$	$a=4$	$k=3$	3	0	0	3
$w=2$	$a=4$	$k=8$	2	0	3	0
$w=2$	$a=5$	$k=5$	5	0	0	0
$w=2$	$a=5$	$k=7$	0	3	0	0
$w=3$	$a=1$	$k=2$	5	0	0	0
$w=3$	$a=1$	$k=3$	0	6	0	0
$w=3$	$a=1$	$k=4$	6	0	0	0
$w=3$	$a=1$	$k=5$	0	0	9	6
$w=3$	$a=1$	$k=7$	0	0	6	3
$w=3$	$a=1$	$k=8$	0	5	0	0
$w=3$	$a=2$	$k=2$	0	0	8	0
$w=3$	$a=2$	$k=3$	0	0	7	0
$w=3$	$a=2$	$k=5$	0	8	0	0
$w=3$	$a=2$	$k=6$	0	0	0	4
$w=3$	$a=2$	$k=7$	4	0	0	0
$w=3$	$a=2$	$k=8$	0	0	0	4
$w=3$	$a=3$	$k=4$	0	7	8	5
$w=3$	$a=3$	$k=6$	4	5	7	0
$w=3$	$a=4$	$k=2$	0	7	0	5
$w=3$	$a=4$	$k=3$	5	0	0	4
$w=3$	$a=4$	$k=8$	4	0	6	0
$w=3$	$a=5$	$k=5$	7	0	0	0
$w=3$	$a=5$	$k=7$	0	5	0	0

Table 7
The cumulative amount of waste in the vehicles when arriving at hospitals.

Y_{wakt}			$t=1$	$t=2$	$t=3$	$t=4$
$w=1$	$a=1$	$k=1$	13	11	11	14
$w=1$	$a=2$	$k=1$	23	15	15	20
$w=1$	$a=2$	$k=4$	9	0	0	0
$w=1$	$a=2$	$k=6$	0	0	0	9
$w=1$	$a=3$	$k=1$	11	12	13	21
$w=1$	$a=3$	$k=4$	0	0	0	8
$w=1$	$a=4$	$k=1$	22	27	26	23
$w=1$	$a=4$	$k=2$	0	13	0	11
$w=1$	$a=4$	$k=3$	10	0	12	0
$w=1$	$a=5$	$k=1$	14	25	32	0
$w=1$	$a=5$	$k=4$	0	10	0	0
$w=1$	$a=5$	$k=5$	0	0	16	0
$w=2$	$a=1$	$k=1$	7	6	9	4
$w=2$	$a=1$	$k=2$	4	0	0	0
$w=2$	$a=1$	$k=7$	0	0	6	0
$w=2$	$a=2$	$k=1$	4	3	8	5
$w=2$	$a=2$	$k=2$	0	0	4	0
$w=2$	$a=2$	$k=4$	4	0	0	0
$w=2$	$a=2$	$k=6$	0	0	0	1
$w=2$	$a=3$	$k=1$	3	8	8	6
$w=2$	$a=3$	$k=4$	0	0	0	2
$w=2$	$a=3$	$k=6$	0	5	5	0
$w=2$	$a=4$	$k=1$	5	4	3	6
$w=2$	$a=4$	$k=2$	0	0	0	3
$w=2$	$a=4$	$k=3$	2	0	3	0
$w=2$	$a=5$	$k=1$	0	3	0	0
$w=2$	$a=5$	$k=4$	0	3	0	0
$w=3$	$a=1$	$k=1$	11	11	15	9
$w=3$	$a=1$	$k=2$	6	0	0	0
$w=3$	$a=1$	$k=5$	0	0	0	3
$w=3$	$a=1$	$k=7$	0	0	9	0
$w=3$	$a=2$	$k=1$	4	8	15	8
$w=3$	$a=2$	$k=2$	0	0	7	0
$w=3$	$a=2$	$k=4$	4	0	0	0
$w=3$	$a=2$	$k=6$	0	0	0	4
$w=3$	$a=3$	$k=1$	4	12	15	5
$w=3$	$a=3$	$k=6$	0	7	8	0
$w=3$	$a=4$	$k=1$	9	7	6	9
$w=3$	$a=4$	$k=2$	0	0	0	4
$w=3$	$a=4$	$k=3$	4	0	6	0
$w=3$	$a=5$	$k=1$	7	5	0	0
$w=3$	$a=5$	$k=4$	0	5	0	0

5. Discussion

In this research, by employing Industry 4.0-based technologies, a DSS based on a bi-objective MILP model was developed to manage the infectious healthcare waste. Then the applicability of the proposed model was evaluated using real world data. In this section, we intend to discuss the obtained results and analyze the outputs of the model. As can be seen, Table 4 provides the routes assigned to vehicles, and the arrival times of vehicles to nodes and the amount of waste collected from each node are presented in Tables 5 and 6, respectively. In addition, Table 7 reports the cumulative amounts of waste in each vehicle. The proposed DSS provides practical output for hospitals and waste collectors by integrating these results. For example, the first row of Table 4 shows the route assigned to vehicle 1 in time period 1. In the following, we describe the operations performed by vehicle 1 in the first time period using the information provided in Tables 5–7 Table 4 displays that vehicle 1 goes from the collection center to the hospital 4, and Table 5 shows that it arrives at this hospital 32 min later. Table 6 states that the vehicle picks up 4 and 6 bags of types 2 and 3 waste from this hospital, respectively. Obviously, before the vehicle enters this hospital, the cumulative amount of waste is zero. Next, the vehicle moves to hospital 2 (see Table 4). According to Table 5, the vehicle should visit the hospital 94 min after leaving the collection center. Table 7 shows that when the vehicle arrives at hospital 2, it carries a total of 4 bags of type 2 waste and 6 bags of type 3 waste. As reported in Table 6, hospital 2 delivers 13, 3, and 5 bags of type 1, 2, and 3 waste to the vehicle, respectively. Then, the vehicle departs to the collection center. The total travel time of this vehicle is 136 min, which can be seen in the first row of Table 5. This vehicle brings a total of 13 bags of type 1 waste, 7 bags of type 2 waste, and 11 bags of type 3 waste to the collection center (see Table 7). The route traveled by vehicle 1 in time period 1 along with the described information is depicted in Fig. 2.

Although the proposed model includes both strategic and operational decisions, its main application is decision-making at the operational level. In other words, the model is presented in a general structure. The proposed model is first implemented using historical data and strategic decisions such as setting up collection centers and purchasing vehicles. In the next time periods, the values of these variables

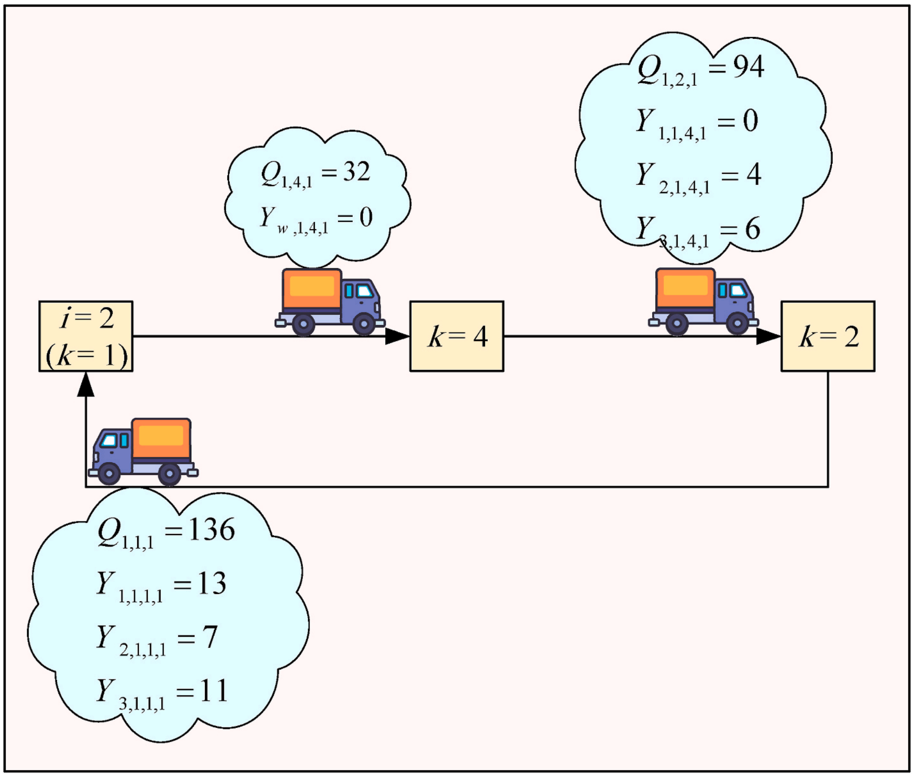

Fig. 2. The route allocated to the vehicle 1 in time period 1.

are considered fixed and operational decisions are optimized. For example, the results of the model implementation show that five vehicles should be purchased and collection center 2 should be established. Now if we want to plan for future time periods, we run the model with five purchased vehicles and an established collection center using new data. It should be noted that new data are uploaded in the system by hospitals. As long as the network capacity is responsive, we consider the strategic variables as fixed. However, if the amount of waste produced in the network increases significantly and if either the capacity of the collection center or vehicles are not responsive, strategic decisions should be modified and the model should be re-implemented for both strategic and operational decisions.

6. Managerial implications

Integrating the technologies described in this study into Industry 4.0 brings about a new era of exceptional efficiency and sustainability in any business (Nasyiah et al., 2024) and also in the ever-changing field of healthcare waste management. By optimizing models that integrate these cutting-edge technologies, we not only demonstrate the significant progress we have made compared to traditional methods, but also highlight the remarkable versatility of these technologies, which extend far beyond their application in healthcare infectious waste management. This section explores the managerial consequences of implementing this model, emphasizing its practical benefits and its wider applicability to areas such as humanitarian logistics and supply chain management.

One of the serious challenges in the field of waste management, especially healthcare waste, is the uncertainty in the amount of waste produced by hospitals. With the emergence of a pandemic like COVID-19, this challenge becomes even more critical because the uncertainty of this parameter increases. This uncertainty stems from the lack of an information bridge between hospitals and collection centers to share data. The literature review shows that researchers use methods to deal with uncertainty such as stochastic programming (Govindan et al., 2022), fuzzy (Tirkolaee et al., 2021), robust optimization (Karimi et al., 2024), or a combination of them (Negarandeh and Tajdin, 2022) to control the uncertainty of this parameter. But in this research, to overcome this uncertain parameter, an information sharing system has been applied. In this way, the hospitals inform the collection centers about the amount of waste they have produced through this system, and the challenge of uncertainty for the collection centers is smoothed.

Furthermore, the incorporation of GNSS technology into the waste management infrastructure offers an unprecedented level of transparency in the logistics of waste collection. This technology enables healthcare facilities to enhance their preparedness for waste handoff by accurately forecasting the arrival time of collection vehicles. The high level of precision significantly enhances public health safety by reducing the risks associated with prolonged vehicle idling, such as the probability of cross-contamination. Besides, an innovative feature of our model is the integration of autonomous vehicles, which significantly reduce the probability of human exposure to dangerous waste. This measure enhances public health security and incorporates a social sustainability element by preventing waste collectors from coming into contact with infectious materials. Furthermore, our dedication to conserving the environment is evident in our transition to electric autonomous vehicles. Due to this alteration, the carbon emissions resulting from conventional waste disposal techniques will be significantly diminished, aiding in climate change mitigation, acheiving SDGs and supporting the goal of net-zero emissions (Govindan, 2023; Xu et al., 2024).

The model's adaptability and demonstrated efficacy render it well-suited for various applications, but it particularly excels in the realm of supply chain management and logistics for humanitarian organizations. The model's real-time information exchange and autonomous logistics capabilities can significantly improve operational efficiency and adaptability when there is a need to distribute resources quickly, efficiently, and securely. War zones and disaster relief operations are two instances of such circumstances. This model, moreover, with its demonstrated history of enhancing the management of infectious waste in terms of effectiveness, mitigating hazards, and promoting environmental sustainability, establishes the foundation for future research. Due to its scalability, the strategies and technologies of this system can be easily adapted to optimize supply chain and logistics operations in various industries, particularly those with volatile and uncertain demand. The innovative model we have developed, utilizing the capabilities of technology and Logistics 4.0 innovations, provides a promising opportunity to improve optimization methods in various important fields, as highlighted by distinguished scholars. Our paper proposes enhancements that can be employed by diverse groups tackling decision-making for various logistical challenges. The groups encompass, but are not limited to, humanitarian distribution plans (Eligüzel et al., 2023; Jafarzadeh-Ghoushchi et al., 2023), emergency resource allocation (Goli and Malmir, 2020), blood supply chains (Ala et al., 2024; Khalilpourazari et al., 2020), disaster operations management (Ali et al., 2020; Kebriyaii et al., 2021), organ transplant supply chains (Goli et al., 2023), rescue location-allocation decisions (Shaw et al., 2022), and vaccine supply chains (Lotfi et al., 2023). Every group adopts a distinct methodology for resolving these issues, yet they could all derive advantages from our recommendations. Our model can optimize their individual solutions by incorporating real-time data exchange, autonomous logistics, and improved coordination capabilities, resulting in increased efficiency, agility, and effectiveness. These domains can address the urgent requirements of modern complex and unpredictable environments by leveraging modern solutions, which provide unparalleled levels of efficiency and adaptability.

Last, but not the least, the integration of modern technologies and Logistics 4.0 innovations into healthcare waste management has broader managerial implications that go beyond mere operational efficiency improvements in medical facilities. They signify the commencement of a novel epoch in supply chain and logistics frameworks that are more intelligent, environmentally friendly, and resilient. This study not only demonstrates the feasibility and effectiveness of such a model, but also indicates that businesses in various industries should consider adopting similar technologies. The authors of the study aspire for future technological advancements to successfully surmount logistical challenges.

7. Conclusion

Applying Logistics 4.0 innovation in healthcare waste management leads to increasing public health safety and promoting environmental sustainability. By applying the mathematical programming tool, this study provided a transformative logistic solution in the field of infectious waste management, which is an important concern in the healthcare industry. The center of this transformation was based on the concept of reverse logistics, which includes cost-effective and efficient transportation of waste from hospitals to collection centers. For this purpose, a bi-objective MILP model was developed with the aim of minimizing total costs and population risk. In this study, electric autonomous vehicles equipped with GNSS technology were used to collect infectious waste, which brought several sustainability benefits, including reducing CO_2 emissions, intelligent tracking of vehicles, and increasing the safety and welfare of frontline workers. Another advantage of the proposed network was the use of the information sharing system to exchange information between collection centers and hospitals and deal with the uncertainty of the amount of waste produced by hospitals. In addition, this system shares the optimal decisions obtained from the implementation of the model with the hospitals in a comprehensible way, and informs the hospital users of the arrival time of the vehicles to hospitals. Therefore, the information sharing system has a significant effect in reducing the waiting time of vehicles in hospitals. IoT technology and RFID-tagged waste bags provide the possibility of storing information quickly and processing them in a safe way. The proposed model used the TH method to solve the presented bi-objective MILP model and created a balance between total costs and population risk. This study investigated the practicality and effectiveness of incorporating Logistics 4.0 technologies in real-life situations. It did so by conducting a case study that specifically examines the healthcare waste management system in Iran. The demonstrated success of the pilot project in Karaj city serves as evidence that the implementation of contemporary logistics solutions is viable and adaptable across various geographical settings, while also possessing the potential for expansion. The presented model has the potential to assist the healthcare industry in effectively and sustainably managing infectious waste, thereby mitigating its adverse environmental impacts.

Although the proposed model can solve challenges such as CO_2 emissions, uncertainty in the amount of produced waste, workers' safety, waiting time of vehicles in the hospitals, etc. in the healthcare industry, one of its limitations is that it is not possible to solve large size problems by GAMS software because the proposed model is NP-hard. Therefore, it is suggested to develop an efficient heuristic or meta-heuristic algorithm to solve the investigated problem in order to provide the possibility of solving large size problems. The current research includes collection centers and hospitals. Treating infectious wastes, recycling, and disposing of them are serious challenges in the healthcare industry. It is suggested to develop a comprehensive network in future research with the aim of optimizing decisions related to collection, treatment, recycling, and disposal centers in the era of Logistics 4.0. In this paper, information sharing system is used to control the uncertainty of generated waste. Combining information sharing system with prediction methods under uncertainty can improve the performance of the proposed model. In this regard, it is suggested to develop an efficient approach to estimate uncertain parameters in future researches by integrating information sharing system and the uncertain prediction methods provided by Mondal et al. (2024), Özmen (2023), and Özmen et al. (2017).

CRediT authorship contribution statement

Kannan Govindan: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Fereshteh Sadeghi Naieni Fard:** Writing – original draft, Validation, Software, Methodology. **Fahimeh Asgari:** Writing – original draft, Methodology, Conceptualization. **Shahryar Sorooshian:** Writing – original draft, Validation, Investigation, Formal analysis. **Hassan Mina:** Writing – original draft, Validation, Methodology, Data curation, Conceptualization.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijpe.2024.109342.

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