A multi-objective location-routing model for dental waste considering environmental factors

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Abstract
Nowadays, the amounts of infectious medical waste (IMW) have surged considerably so waste management has become a critical emergency in many developing countries. However, most large medical waste generation centers (MWGC) are equipped with treatment facilities, small MWGC faces the waste management problem. It reveals the significance of having a proper program for small health centers. This is an indisputable difficulty that governments bordered because it imposes great costs on societies, also the environmental problems caused by improper treatment are irreparable. To attend to all the essential aspects of the problem, this paper recommended a location-routing model with four objective functions to minimize the total costs, environmental pollution, the risk imposed on the population around disposal sites, and the total violation from the expected arrival time. Considering a multi-period problem with a maximum acceptable delay plays a key role to connect the assumptions to the real-world problem. In addition, for solving mathematical models based on case studies, the role of uncertainty is undeniable. The demand for dental waste treatment is not definite and is changed based on the different conditions thus fuzzy chance-constrained programming is proposed for this problem to tackle the uncertainty. The revised multi-choice goal programming method is considered to solve the model and a real case study for dental clinics in Babol city of Iran is investigated to illustrate the validation of the proposed model. The results indicate that the solution method can create a balance between four objective functions. Finally, sensitivity analyses are performed for some parameters to analyze the behavior of the objective functions.

Keywords Location-routing · Dental Waste · Mathematical Model · Fuzzy chance-constrained programming · Goal programming · Environmental considerations

1 1. Introduction

Increasing the generation of infectious medical wastes is a result of the growing population, urbanization, and rising living standards (Kapukaya et al., 2019). In addition, the transportation dangers of hazardous wastes caused the issue of IMW treatment has become a serious
A crisis. Large MWGCs such as hospitals produce a wide range of IMWs (Shareefdeen, 2012). These wastes, even in small quantities, can cause widespread health problems for medical staff, patients, and the community (Mardani et al., 2020). For instance, researchers proved the consequences of improper waste management affected by human immunodeficiency viruses (HIV) on the medical staff (Marinković et al., 2008). Recently, with the advent of the corona pandemic, the treatment of IMW signifies a global challenge for government officials that needs special attention (Sazvar et al., 2021).

From the environmental aspect, some researchers focused on deploying carbon-free emerging technologies such as drones for their last-mile delivery operations in routing problems (Farajzadeh et al., 2020; Moadab et al., 2022). Waste management has been a pressing issue for developing nations as it involves environmental and economic aspects which must be propounded, simultaneously (Thakur et al., 2021), (Argoubi et al., 2020). Ineffective programs in the treatment of IMW waste and the lack of transportation approaches in an acceptable time lead to unauthorized disposal and dangerous environmental problems such as water pollution, soil contamination, and production of significant amounts of toxic and non-toxic wastes (Harijani et al., 2017). The economic aspects help to assess the financial position of the waste disposal companies and also cover the pricing policy of the organizations (Thakur et al., 2021). In addition, indirect economic consequences of IMW could be very influential, for instance, the reduction of disease and healthcare costs, improvement of environmental quality, and enhancement of related business volumes (Rajadurai et al., 2021). Due to the various dimensions, numerous problems have been defined in research on the issue of waste management.

Determining the location of the disposal site is a substantial step of IMW problems because the results of this decision will appear in the long term and it will have striking effects on societies (Asefi et al., 2015). The government leads the decision on the location of the disposal sites to overcome the obnoxious effects and guarantee cost-effectiveness. Moreover, the decision about the waste collection routing based on the government-approved locations is crucial to reducing the logistics cost (Ma et al., 2021). Alongside the importance of finding the best tour for carrying infectious waste to disposal sites, selecting a suitable site with enough capacity is essential. Therefore, the problem is defined as a location-routing problem (LRP).

Most of the large MWGCs have on-site equipment and often carry out the treatment process. These facilities are expensive, also many hospitals and medical centers do not have enough capacity to consider these facilities, so LRPs of infectious wastes are more critical for small medical centers. Dental clinics are one of the MWGCs that do not have a specific waste management system. Generated waste in dental clinics is often infectious and needs to be treated. This is more challenging in unpredictable situations such as the COVID-19 pandemic due to the high risk of spreading the disease (Queiroz et al., 2020). Therefore, systematic mathematical models can be effective to forecast the pandemic trends and manage the situation (Khalilpourazari & Hashemi Doulabi, 2021). More importantly, the space and equipment of small dental clinics are not proper for considering suitable equipment.

Considering the real challenges that developing countries interface to treat the infectious wastes, a multi-objective and multi-period mathematical model is developed based on a case study in Babol city of Iran. Minimizing the total cost, environmental pollution, the risk of disposal sites, and deviation from expected arrival time are investigated as objective functions to suggest a model regarding all the necessary aspects of an IMW problem. The recommended model aims to consider all the dental clinics that might generate infectious wastes and every possible disposal site to treat wastes in Babol. For illustrating more realistic conditions, the multi-vehicle problem is assumed with different speeds and costs.
The remainder of the paper is organized as follows. In Sect. 2 a survey on related research is provided. Section 3 describes the research methodology, the proposed model, linearization, and solution method. Section 4 explains the computational results based on the case study. In Sect. 5, sensitivity analysis is considered for effective parameters. Finally, Sect. 6 presents conclusions about the findings of the research and future directions.

2 Survey on related research

In recent years, a significant number of IMW problems are developed and in some of them LRP in supply chains and waste management systems has been investigated (Drexl & Schneider, 2015). For the first time, Wang et al., (2018) defined the LRP problem as an extension of the classic routing problem that integrates the strategic and operational decisions by facility location problem (FLP) and vehicle routing problem (VRP), respectively (Erkut et al., 2008; Tirkolaee et al., 2020). VRP is the developed concept of the traveling salesman problem that seeks to supply the node’s demand subject to vehicle capacity constraints through designing the optimal route (Validi et al., 2020). The purpose of LRPCs is to find an optimal solution for allocating facilities and finding the optimal route, simultaneously, instead of considering the two problems separately (Drexl & Schneider, 2015). A review of the previous literature has been done to examine the location-routing issues in IMW’s problems and classify important objectives and assumptions.

As one of the pioneering research, Zografros & Samara (1989) stated that IMW’s problems are the issue of finding a suitable location and considering the optimal route for waste transfer. They developed the appropriate solution as a comprehensive LRP. Ghezavati & Morakabatchian (2015) investigated a multi-objective location-routing model for a real case study related to a petrochemical special economic zone located in Khuzestan (Iran). The considered objectives were minimizing total costs and total risks of population along routes and near treatment sites. The waste collection system was improved by a fuzzy customer satisfaction level presented during the optimization process. Ardjmand et al., (2016) worked on a new stochastic model for the transportation and allocation of hazardous materials. The presented model aimed to minimize the total cost and risk of routing facilities and transportation. They applied Genetic Algorithm (GA) to solve the model. To clarify the role of environmental aspects, (Toro et al., 2017) uncovered the important effect of greenhouse emissions by proposing a bi-objective problem concerning minimizing operating costs and environmental impacts. They considered the epsilon-constraint method to solve the mathematical model. Zhao & Ke (2017) introduced a bi-objective model for explosive waste management. The objective functions were minimizing total cost and risk to optimize the combination of location, inventory management, and vehicle routing. A case study has been developed in China and solved based on the TOPSIS method to test the applicability of the proposed methodology.

In recent articles, researchers supposed more realistic assumptions based on case studies for IMW’s problems. Considering a case study of 107 hospitals in Thailand, and with respect to infrastructure, geology, and environmental criteria, Wichapa & Khokhajaikiat (2018) evaluated global priority weights using a fuzzy hierarchical analysis process. They examined a new multifunctional FLP model using the analytic hierarchy process and fuzzy goal programming. The vehicle routing problem for the case study was solved using a hybrid GA, GA, and local search. Asgari et al., (2017) suggested a multi-objective location-routing problem with three objectives to minimize the treatment and disposal facility undesirability, costs, and the
risk associated with the transportation of wastes. An effective memetic algorithm is developed and tested in a case study in Singapore. Mahmoudsoltani et al., (2018) discussed unknown hazards by assuming three types of hazards which are accident, population, and environmental. A decision-making structure problem of location-routing IMW’s presented. They used three well-known algorithms, including the non-dominated sorting GA II, the strength Pareto evolutionary algorithm II, and the multi-objective evolution algorithm to solve the problem. Based on a case study in Turkey, a mathematical model of a mixed-integer programming profit-based is developed by Aydemir-Karadag (2018). The main objective of waste management is considered cost-effective by collecting, transporting, treating, and disposing of waste. Khalilpourazari & Pasandideh (2021) offered a new robust mathematical model for designing an efficient flood evacuation plan in disasters which takes a set of potential locations for establishing evacuation shelters with limited capacities. The main goals considered maximizing the number of rescued people and total cost. They implemented the robust model on real-world data from 2011 Japan’s destructive tsunami. Concerning the importance of developing models to design effective blood supply chains in emergency situations, Khalilpourazari and Hashemi Doulabi (2022) proposed a multi-objective transportation location inventory routing formulation for an emergency blood supply chain network based on a case study in Iran. In addition, two flexible uncertain models are proposed to provide risk-averse and robust solutions for the problem. To tackle uncertainty in planning issues, Hashemi Doulabi & Khalilpourazari (2022) recommended a state-variable model to formulate a two-stage stochastic weekly operating room planning problem with an exponential number of scenarios. The aim considered minimizing the sum of the fixed opening cost of operating rooms and the expected overtime costs. Asefi et al., (2019) integrated waste management includes a review of the activities and processes of collection, transportation, treatment, recycling, and disposal of municipal solid waste. A case study in Tehran is investigated and a step-by-step heuristic method within the frames of two meta-heuristic approaches (variable neighborhood search and simulated annealing) is presented. Osaba et al., (2019) formulated a model for drug logistics by collecting pharmaceutical waste based on a case study in Bizakia, Spain to minimize the total cost of transporting. The problem has been analyzed by a discrete and improved bat algorithm.

Thiriet et al., (2020) identified the number of micro-scale Anaerobic digestion sites and their capacities to present a model for minimizing the distance of biological waste and its transport, taking into account system constraints. A geographic system information method for preparing the mixed-integer linear program model implemented in France. Concerning the city’s preference to transform its infrastructure based on sustainability guidelines and practices, Torkayesh et al., (2021) developed a multi-criteria evaluation model based on type-2 neutrosophic numbers to identify contributing factors to failure in the adoption of the Internet of Things and blockchain in smart Medical waste management systems. Results of a case study in Turkey indicated that training for different stakeholders, market acceptance, transparency, and professional personnel are the main failure factors in the adoption of smart technologies. Tirkolaee et al., (2022) formulated mixed-integer linear programming for a sustainable periodic capacitated arc routing municipal solid waste management problem. Minimization of the total cost, total environmental emission, workload deviation, and maximization of citizenship satisfaction were considered as main objectives. A hybrid multi-objective optimization algorithm, namely, MOSA-MOIWOA is designed based on a multi-objective simulated annealing algorithm and multi-objective invasive weed optimization algorithm. Rabbani et al., (2019) developed a multi-objective mathematical model for hazardous industrial waste management that covers integrated decisions at three levels: location, vehicle routing, and inventory control. Methodologically, a new approach that combines
the GA of adverse ranking and Monte Carlo simulation to overcome the problem of stochastic hybrid optimization is presented in this research. In addition, uncertainty about some parameters is assumed in this multi-period planning. Markov et al., (2020) suggested a non-linear mixed-integer routing problem in which a heterogeneous constant amplitude is used to collect recyclable waste from large containers. The purpose of this research model is to minimize the emergency cost of waste collection, routing costs, and the expected cost of incorrect routing. To solve the problem, an adaptive large neighborhood search algorithm was integrated with a purposeful prediction model. Tirkolaee et al., (2021) proposed a new mixed-integer linear programming model to formulate the LRP for medical waste management due to the epidemic condition. The goals are assumed to reduce total travel time, overall window breaks, and the total risk of environmental infection imposed on people around disposal sites. To deal with uncertainty, the fuzzy chance limited scheduling approach is implemented. A real case study in Sari, Iran has been investigated to test the performance of the model. A bi-objective mixed-integer linear programming for the management of IMW during the COVID-19 outbreak was proposed by Govindan et al., (2021). The objectives considered minimizing the total costs and risks of the population’s exposure to pollution. Infectious and non-infectious medical waste is managed based on realistic assumptions including time window-based green vehicle routing problems, vehicle scheduling, vehicle failure, split delivery, population risk, and load-dependent fuel consumption. To solve the problem, a fuzzy goal programming approach was developed, and the performance of the model and solution approach is assessed using data related to medical waste production in Tehran.

To have a better overview of IMW management problems, the reviewed articles are briefly presented in Table 1. The main information of each article including the type of objective functions, mathematical modeling, environmental aspects, critical constraints, period, type of waste, case study, and solution method are briefly reviewed.

### 2.1 Research gap

The literature review indicates the importance of attention to various aspects of IMW’s location-routing problems. As it is clear, these issues have different dimensions economic, and environmental, so considering only one aspect can decrease the efficiency of the defined problem. Due to the emphasis on the importance of various aspects of IMW’s problems, most of the researchers focused on multi-objective programming. Since the healthcare system has a limited capacity, predicting the pandemic’s future trend is essential to avoid overload (Khalilpourazari et al., 2021). Based on reviewed articles, the need for treating IMW is increasing especially during high-risk pandemics as a result, societies will be faced with significant costs. In addition, the problem of treatment and waste disposal are affiliated with private and government organizations. Given this issue, the cost is always one of the most effective dimensions to define the problem and the authors pay special attention to reducing costs.

Based on the literature review, greenhouse emissions and environmental hazards types are mentioned as environmental problems. As the research area gets narrowed down, there are fewer articles that pay attention to the environmental problems caused by traffic congestion. In the studies conveyed, no article paid special attention to the importance of environmental pollution caused by traffic. One of the most important problems of infectious waste is the risk of spreading on the routes, and this risk increases on busy roads so the second goal in the proposed problem implies environmental pollution caused by traffic.
| Author          | Year | Objective                                                                 | Period | Location/ Allocation/ Routing | Environmental aspects | Waste type                      | Case study | Solution method                  |
|-----------------|------|----------------------------------------------------------------------------|--------|-------------------------------|-----------------------|----------------------------------|------------|----------------------------------|
| Zografros et al.| 1989 | • Minimize disposal risk  
• Minimize routing risk  
• Minimize travel time | S      | L/R                           | –                     | Hazardous materials     | –                      | • Goal programming  |
| Erkut et al.    | 2008 | • Minimize the greenhouse effect  
• Minimize the final disposal at the landfill  
• Maximize the energy recovery  
• Maximize the material recovery  
• Minimize the total cost | S      | L/A                           | *                    | Municipal solid waste  | Greece     | • Lexicographic  
• Minimax approach  
• MSW planning  |
| Ghezavati et al.| 2015 | • Minimize the total cost  
• Minimize the risk of crowded places along the transportation route and disposal centers | S      | L/R                           | –                     | Hazardous industrial waste | Iran       | • An algorithm based on complex integer programming  |
| Author          | Year | Objective                                                                 | Period | Location/ Allocation/Routing | Environmental aspects | Waste type           | Case study | Solution method            |
|-----------------|------|---------------------------------------------------------------------------|--------|------------------------------|-----------------------|----------------------|------------|-----------------------------|
| Ardjmand et al. | 2016 | • Minimize the total cost  
• Minimize the risk of facility routing and transportation | S      | L/A                          | –                     | Hazardous material   | –          | • Genetic algorithm         |
| Asgari et al.   | 2016 | • Minimize treatment facility undesirability  
• Minimize costs related to the problem  
• Minimize the transportation risk | S      | L/R                          | –                     | Various types of wastes | Singapore | • Memetic algorithm         |
| Toro et al.     | 2017 | • Minimize operational costs  
• Minimize environmental effects | S      | L/R                          | *                     | –                    | –          | • Epsilon-constraint method |
| Zhao et al.     | 2017 | • Minimize total cost  
• Minimize total risk | S      | L/R                          | *                     | Explosive waste      | China      | • Mixed-integer programming |
| Wichapa et al.  | 2018 | • Minimize the total cost  
• Maximize the priority weight of all candidate municipalities | S      | L/R                          | –                     | Infectious waste     | Thailand   | • Genetic algorithm, goal programming |
| Author          | Year | Objective                                                                 | Period | Location/Allocation/Routing | Environmental aspects | Waste type          | Case study | Solution method                          |
|-----------------|------|---------------------------------------------------------------------------|--------|------------------------------|-----------------------|---------------------|------------|-----------------------------------------|
| Mahmoudsoltani et al. | 2018 | • Minimize the total cost<br>• Minimize total risk                        | S      | L/R                          | *                     | Hazardous material | Iran       | • NSGA-II<br>• SPEA-II<br>• MOEA/D     |
| Aydemir-Karadag  | 2018 | • Maximize profits                                                       | S      | L/R                          | –                     | Hazardous waste    | Turkey     | • Rolling horizon basis through the objective function of net present value<br>• Stepwise heuristic<br>• Variable neighborhood search<br>• Hybrid VNS<br>• Simulated annealing<br>• Bat algorithm<br>• Evolutionary algorithm<br>• Evolutionary simulated annealing |
| Asefi et al.     | 2019 | • Minimize the total cost                                                | S      | L/R                          | –                     | Municipal solid waste | Iran       | • Stepwise heuristic<br>• Variable neighborhood search<br>• Hybrid VNS<br>• Simulated annealing<br>• Bat algorithm<br>• Evolutionary algorithm<br>• Evolutionary simulated annealing |
| Osaba et al.     | 2019 | • Minimize the total transportation costs                                | S      | R                            | –                     | Pharmacological waste | Spain      | • Stepwise heuristic<br>• Variable neighborhood search<br>• Hybrid VNS<br>• Simulated annealing<br>• Bat algorithm<br>• Evolutionary algorithm<br>• Evolutionary simulated annealing |
| Rabbani et al.   | 2019 | • Total cost minimization<br>• Transportation risk minimization<br>• Depot location risk minimization | M      | L/R                          | –                     | Hazardous wastes    | -          | • NSGA-II<br>• Monte Carlo simulation |
| Author          | Year | Objective                                                                 | Period | Location/ Allocation/ Routing | Environmental aspects | Waste type       | Case study | Solution method                                      |
|-----------------|------|-----------------------------------------------------------------------------|--------|--------------------------------|-----------------------|------------------|------------|------------------------------------------------------|
| Thiriet et al.  | 2020 | • Minimize the total payload distances                                      | M      | *                              | Biowaste              | France           | • Geographic Information System                       |
|                 |      |                                                                             |        |                                |                       |                  |            | • Branch and cost                                     |
|                 |      |                                                                             |        |                                |                       |                  | • Large adaptive local search                         |
|                 |      |                                                                             |        |                                |                       |                  | • Branch and cut                                       |
| Markov et al.   | 2020 | • Minimize the total cost                                                   | M      | R                              | Recyclable waste      | Switzerland      | • Fuzzy goal programming                              |
|                 |      |                                                                             |        |                                |                       |                  |                                                       |
| Govindan et al. | 2021 | • Minimize the total costs                                                  | M      | L/R                            | Medical waste         | Iran             | • Weighted goal programming                           |
|                 |      | • Minimize the risk of the exposed population                               |        |                                |                       |                  |                                                       |
| Tirkolaee et al.| 2021 | • Minimize the total travel time                                             | M      | L/R                            | Medical waste         | Iran             | • Weighted goal programming                           |
|                 |      | • Minimize the total violation of time windows                               |        |                                |                       |                  |                                                       |
|                 |      | • Minimize the disposal sites risk                                           |        |                                |                       |                  |                                                       |
| Author                  | Year | Objective                                                                 | Period | Location/Allocation/Routing | Environmental aspects | Waste type       | Case study | Solution method                                                                 |
|-------------------------|------|---------------------------------------------------------------------------|--------|------------------------------|----------------------|------------------|------------|--------------------------------------------------------------------------------|
| Khalilpourazari and Pasandideh | 2021 | • Maximize the number of rescued people • Minimize the total cost         | S      | L/R                          | –                    | –                | Japan      | • Genetic Algorithm-III • Multi-Objective Dragonfly • Multi-Objective Grey Wolf Optimizer • Multi-Objective Multi-Verse Optimizer |
| Khalilpourazari and Hashemi Doulabi | 2022 | • Minimizes the total costs of the supply chain • Reduce the transportation time | M      | L/R                          | –                    | –                | Iran       | • Flexible Robust Fuzzy Chance Constraint Programming • Flexible Fuzzy Chance Constraint Programming |
| Tirkolaee et al.         | 2022 | • Minimize the total cost • Minimize the total environmental emission • Minimize workload deviation • Maximize the citizenship satisfaction | M      | R                            | *                   | Solid waste      | -          | • MOSA-MOIWOA that designed based on a multi-objective simulated annealing algorithm and multi-objective invasive weed optimization algorithm |
| Author           | Year | Objective                                                                 | Period | Location/ Allocation/ Routing | Environmental aspects | Waste type    | Case study | Solution method                      |
|------------------|------|----------------------------------------------------------------------------|--------|-------------------------------|----------------------|--------------|------------|---------------------------------------|
| Present research | 2022 | • Minimize total costs                                                    | M      | L/R                           | *                    | Dental waste | Iran       | • Revised multi-choice goal programming |
|                  |      | • Minimize the environmental pollution                                    |        |                               |                      |              |            |                                        |
|                  |      | • Minimize the risk imposed on the population around disposal sites        |        |                               |                      |              |            |                                        |
|                  |      | • Minimize the total violation from the expected arrival time             |        |                               |                      |              |            |                                        |

S: Single-period, M: Multi-period, L: Location, A: Allocation, R: Routing
The IMW problem has been investigated at various MWGCs. Nowadays, most large MWGCs such as hospitals are equipped with treatment facilities and the main problem is the treatment of infectious wastes in small MWGCs. A closer look revealed that the risk of transmitting different diseases through dental clinics is very high, especially under high-risk pandemics thus, dental clinics always face the IMW treatment problem (Peng et al., 2020). Due to the small amount of waste generated by dental clinics, many waste disposal companies are reluctant to cooperate with them. While disregarding collecting dental clinics’ waste can accelerate the spread of dangerous diseases. Improper treatment and disposal of dental waste can have irreversible environmental consequences. This is only because of the lack of appropriate planning for dental clinics in terms of the IMW collection, routing, and locating. Considering a comprehensive plan for the collection and treatment of IMW can be very helpful to solve this problem. A consummate location-routing plan can be economically acceptable for waste disposal companies and minimize both environmental risks and the spreading pollution risk.

To the best of our knowledge, there is no study yet dealing with the efficient treatment of IMWs with considering minimizing cost, environmental pollution, disposal site risk, and deviation from expected arrival time at the same time. Based on our review, each mentioned aspect is directly impressive in the economic, and environmental balance of IMW’s problem. In the present study, minimizing the total cost including routing and disposal sites cost is the first objective of the defined model. Concerning the importance of environmental issues, two objective functions have been considered to reduce environmental pollution and minimize the risk of disposal sites. In addition, waste disposal and treatment issues are time-sensitive therefore, the fourth goal is to minimize deviations from the expected arrival time. In the presented model, along with hypotheses such as facility capacity, types of vehicles, and limited travel time, the maximum allowable delay has been assumed to attention to the time sensitivities of the problem.

3 Methodology

This section describes the suggested methodology of the study to establish an efficient waste management system for dental clinics.

3.1 Problem description and mathematical model

The proposed model is considered as a network including the place of the depot, demand nodes (dental clinics), and pre-constructed disposal sites. The goal is to make location and routing decisions under a specific order so that the vehicle starts its tour from the depot, moves to the disposal sites after collecting the waste from dental clinics, and finally returns to the depot. Each demand node has its own expected arrival time that should be served. The objective functions are to simultaneously (i) minimize the total costs, (ii) minimize the environmental pollution caused by traffic congestion, (iii) minimize the total infection risk imposed on the population around disposal sites, and finally (iv) minimize the deviation from expected arrival time.

Figure 1 illustrates a hypothetical example of two possible routes to schematically describe the proposed network of the study. Two vehicles are considered to serve these 7 nodes (4 dental clinics, 2 disposal sites, and a depot). The first vehicle has one trip which is highlighted in green. The trip of vehicle 1 includes:
Fig. 1 A sample of vehicles tour for the dental waste problem

Depot → Dental clinic (2) → Dental clinic (1) → Disposal site (5) → Depot.
The second vehicle also has just one trip which is highlighted in red and consists of: Dental clinic (3) → Dental clinic (4) → Disposal site (6) → Depot.

The main assumptions of the problem are presented as follows:

- There is a set of nodes that are intended as dental clinics to visit.
- Each of the dental clinics has a specific demand.
- The model is considered a multi-period problem.
- Dental clinics must be visited once in each period.
- Each node in each period should be visited by only one vehicle.
- Vehicles start their tour from the depot node and return to that at the end of the tour.
- For each node, a maximum delay for the arrival time is defined.
- Different types of vehicles are provided for the route.
- For each vehicle, different speeds and costs, and specific capacity are considered.
- Candidate disposal sites are assumed for waste treatment and a different cost and capacity are defined for each of them.

The overall structure of the current research is presented in Fig. 2.

The mathematical notations of the proposed model including sets and indices, parameters, and decision variables are listed as follows: Sets and Indices.

| Symbol | Description |
|--------|-------------|
| $N$    | Set of nodes includes dental clinics, disposal sites, and depot $N=\{0, 1, 2, \ldots, n\}$ (0 represent the depot) |
| $R$    | Set of dental clinics $R=\{1, 2, \ldots, r\}$ |
| $G$    | Set of disposal sites |
| $K$    | Set of vehicles $K=\{1, 2, \ldots, k\}$ |
| $T$    | Set of time periods $T=\{1, 2, \ldots, t\}$ |
| $i$    | Index for each node defined in the node set ($i \in N$) |
| $j$    | Index for each node defined in the node set ($j \in N$) |
| $p$    | Index for each node defined in the node set ($p \in N$) |
Index for each vehicle defined in the vehicle set \((k \in K)\)

Index for each period in the time periods set \((t \in T)\)

**Parameters**

- \(D_{ij}\): Distance between node \(i\) and node \(j\)
- \(C_{ijk}\): Travel cost from node \(i\) to node \(j\) by vehicle type \(k\)
- \(V_k\): The average speed of the vehicle \(k\)
- \(F_{ij}\): Emission index of environmental pollution in the route from \(i\) to \(j\)
- \(C_{fk}\): Fixed cost for vehicle \(k\)
- \(W\): Vehicle capacity
- \(T_{max}\): Maximum available time for vehicles
- \(FX_i\): Fixed cost to use disposal site \(i\)
- \(C_{ait}\): The capacity of the disposal site \(i\) in the period \(t\)
- \(\tilde{D}_{mit}\): The demand of node \(i\) in period \(t\)
- \(L_{it}\): The expected arrival time to reach node \(i\) in period \(t\)
- \(P_{oi}\): Population size around disposal site \(i\)

**Decision variables**

- \(Y_{it}\): A binary variable which is 1 if disposal site \(i\) is visited in period \(t\); 0 otherwise
- \(X_{ijkt}\): A binary variable which is 1 if vehicle \(k\) travels arc \((i, j)\) by vehicle \(k\) at period \(t\); 0 otherwise
- \(Z_{kt}\): A binary variable which is 1 if vehicle \(k\) is used in period \(t\); 0 otherwise
- \(L_{W_{kt}}\): Amount of waste transported by vehicle \(k\) in period \(t\)
- \(U_{W_{it}}\): The amount of waste unloaded and treated at the disposal site \(i\) in the period \(t\)
- \(AT_{it}\): Arrival time at dental clinic node \(i\) in period \(t\)
- \(U_{it}\): The volume of transported waste from the first node to node \(i\). (to eliminate sub tours based on Miller–Tucker–Zemlin method)

**Objective functions**

Concerning the parameters and variables defined in the previous section, the following gives the mathematical model of the problem.

\[
\begin{align*}
\text{MIN } Z_1 &= \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} \sum_{t \in T} C_{ijk} \ast X_{ijkt} + \sum_{i \in N} \sum_{t \in T} F_{X_i} \ast Y_{it} \\
\text{MIN } Z_2 &= \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} \sum_{t \in T} F_{ij} \ast X_{ijkt} \\
\text{MIN } Z_3 &= \sum_{i \in G} \sum_{t \in T} P_{O_i} \ast Y_{it} \\
\text{MIN } Z_4 &= \sum_{i \in R} \sum_{t \in T} |AT_{it} - L_{it}| 
\end{align*}
\]
Four objective functions are considered in this research. The first part of the objective function (1) minimizes the transportation costs between existing nodes, and the second part reduces the fixed cost of visiting the disposal sites. In objective function (2), the minimization of environmental pollution caused by traffic is formulated. The third objective function (3) expresses minimizing disposal site risk. The objective function (4) minimizes the deviation from the expected arrival time for visiting nodes.

**Constraints.**

\[ \sum_{j \in N} X_{ijkt} = \sum_{j \in N} X_{jikt} \quad \forall i \in N, i \neq j, k \in K, t \in T \quad (5) \]

\[ \sum_{j \in R} X_{0jkt} = Z_{kt} \quad \forall k \in K, t \in T \quad (6) \]

\[ \sum_{j \in N} \sum_{k \in K} X_{ijkt} = 1 \quad \forall i \in R, i \neq j, t \in T \quad (7) \]

\[ X_{ijkt} = 0 \quad \forall i \in G, j \in R, k \in K, t \in T \quad (8) \]
\[
\sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} X_{ijkt} \leq W \ast Z_{kt} \quad \forall k \in K, \ t \in T
\]  
\[U_{jt} - U_{it} \geq \tilde{D}_{m_it} - W \ast (1 - X_{ijkt}) \quad \forall i, j \in R, k \in K, t \in T \]  
\[\sum_{i \in R} \sum_{j \in N} \tilde{D}_{mit} \ast X_{ijkt} \leq W \quad \forall k \in K, t \in T \]  
\[L_{W kt} = \sum_{i \in R} \sum_{j \in N} \tilde{D}_{mit} \ast X_{ijkt} \quad \forall k \in K, t \in T \]  
\[U_{W it} = \sum_{j \in R} \sum_{k \in K} L_{W kt} \ast X_{ijkt} \quad \forall i \in G, t \in T \]  
\[U_{W it} \leq C_{ai} \ast Y_{iit} \quad \forall i \in G, t \in T \]  
\[\sum_{i \in \mathbb{N}} \sum_{j \in N} D_{ij} \ast X_{ijkt} \leq T_{\text{max}} \quad \forall k \in K, t \in T \]  
\[A_{T it} + \frac{D_{ij}}{V_k} \leq T_{\text{max}} \ast (1 - X_{ijkt}) + A_{T jt} \quad \forall j \in R, j \in R, t \in T, k \in K \]  
\[A_{T 0t} = 0 \quad \forall t \in T \]  
\[A_{T it} \leq L_{it} \quad \forall i \in R, t \in T \]  
\[Y_i, X_{ijkt}, Z_{kt} \in \{0, 1\} \quad \forall i, j \in N, k \in K, t \in T \]  
\[L_{W kt}, U_{W it}, A_{T it}, U_{it} \geq 0 \quad \forall i, j \in N, k \in K, t \in T \]

Constraint (5) examines the flow of nodes. Constraint (6) states that the tour starts from the depot. Constraint (7) indicates that all clinics must be visited once in each period. Constraint (8) states that vehicles cannot return to dental clinics from disposal sites. Equation (9) states that vehicles can travel on their assigned route. Constraints (10) and (11) are defined to remove sub-tours from clinical nodes by the Miller–Tucker–Zemlin method and ensure that there is only one solution corresponding to a given feasible tour (Bektas & Gouveia, 2014). Constraint (12) examines the maintenance of the capacity of each vehicle Constraints (13) and (14) are intended to examine the amount of waste collected by the vehicle and the amount of treated waste at each disposal site. Equation (15) is related to the capacity limit of each disposal site and ensures that each site has sufficient capacity for demands. Constraint (16) specifies the maximum possible time for each trip. Constraint (17) is intended to calculate the arrival time to each node. Constraint (18) states that the start time of the tour from the depot in each tour is equal to zero. Equation (19) is considered to limit the deviation from the expected arrival time, and the maximum allowable delay to reach each node is defined. Constraints (20) and (21) show the types of the variables.

### 3.2 Linearization of the model

In the proposed model, the objective function (4) and Constraint (14) are nonlinear. To simplify the model, linearization has been done. A new approach has been proposed to linearize the fourth objective function and to consider it as a constraint on the goal programming
method. First, to linearize the absolute value of the objective function, it is considered as Eq. (22), after simplifying Eq. (22), Constraints (23), and (24) are assumed. Constraint (25) shows the types of the variables. The maximum amount of $L_{it}$ is considered as an upper bound for linearization constraint.

$$\text{Min} = \sum_{i \in R} \sum_{t \in T} (A_{it} - L_{it})(2 \times A_{it} - 1) = \sum_{i \in R} \sum_{t \in T} 2 \times A_{it} \times AT_{Lit} - A_{it} + L_{it}$$ (22)

$$A_{it} - L_{it} \leq \max(L_{it}) \times AT_{Lit} \quad \forall i \in R, t \in T$$ (23)

$$A_{it} - L_{it} \geq \max(L_{it}) \times (A_{it} - 1) \quad \forall i \in R, t \in T$$ (24)

$$U_{it}, LA_{it} \geq 0, AT_{it} \in \{0, 1\} \quad \forall i, j \in N, k \in K, t \in T$$ (25)

Considering $A_{it} \times AT_{Lit}$ which is the multiplication of two decision variables, is a nonlinear part in Eq. (22), the linearization method of multiplying a binary variable and another variable has been used.

$$\sum_{i \in R} \sum_{t \in T} 2 \times LA_{it} - 2 \times L_{it} \times AT_{it} - A_{it} + L_{it}$$ (26)

$$LA_{it} \geq A_{it} - \max(L_{it}) \times (1 - AT_{it}) \quad \forall i \in R, t \in T$$ (27)

$$LA_{it} \leq A_{it} - \max(L_{it}) \times (1 - AT_{it}) \quad \forall i \in R, t \in T$$ (28)

$$LA_{it} \leq \max(L_{it}) \times AT_{it} \quad \forall i \in R, t \in T$$ (29)

Equation (22) is simplified to Eq. (26) then Constraints (27) to (29) are added to the main constraints of the problem.

Moreover, Constraint (14) in the model is nonlinear due to the multiplication of a positive continuous variable by a binary variable. To reduce the run-time, the constraint has been rewritten linearly and Equations (30) to (33) are added to the main constraints. The summation of the demands is considered an upper bound for linearization because $UW_{it}$, which is the amount of waste unloaded and treated at the disposal site $p$ in period $t$, could not exceed the amount of all demands.

$$UW_{it} = \sum_{j \in R} \sum_{k \in K} LX_{jikt} \quad \forall i \in F \cup G, t \in T$$ (30)

$$LX_{jikt} \leq \sum_{p \in P} \tilde{D}_{m_{pt}} \times X_{jikt} \quad \forall i \in F \cup G, j \in R, t \in T, k \in K, p \in R$$ (31)

$$LX_{jikt} \leq LW_{kt} \quad \forall i \in F \cup G, j \in R, t \in T, k \in K$$ (32)

$$LX_{jikt} \geq LW_{kt} \times \sum_{p \in P} \tilde{D}_{m_{pt}} \times (1 - X_{jikt}) \quad \forall i \in F \cup G, j \in R, t \in T, k \in K, p \in R$$ (33)

### 3.3 Fuzzy chance-constrained programming

Generally, no data on complex optimization problems can be considered certain. For instance, the amount of demand depends on its business conditions, and the duration of activities can affect by operating time especially manpower, equipment, and materials (Goli et al., 2021). In this research, to deal with the uncertainty and to develop a more realistic model, fuzzy
mathematical programming is considered. Zadeh (1978) recommended that in fuzzy linear programming, fuzzy coefficients can be viewed as fuzzy variables and constraints can be assumed as fuzzy events (Inuiguchi et al., 1993). Thus, by integrating the chance-constrained programming suggested by Charnes & Cooper (1959) and fuzzy measures including the possibility, necessity, credibility, and general, the chances of occurrence of fuzzy events can be measured.

The fuzzy method is based on strong mathematical concepts and due to the lack of need for accurate and sufficient information, this approach provides a more efficient model than other approaches including the probability approach that requires sufficient knowledge of the distribution of nonlinear parameters (Falcone & De Rosa, 2020; Khishtandar, 2019).

The expected value of a fuzzy number and its validity has a variety of fuzzy numbers, including triangular and trapezoidal numbers, giving the decision maker the ability to achieve minimum levels of confidence with chance constraints. By considering \( \tilde{\alpha} = (\alpha_1, \alpha_2, \alpha_3) \), \( \tilde{\beta} = (\beta_1, \beta_2, \beta_3, \beta_4) \) as a triangular fuzzy number, and trapezoidal fuzzy number, the membership function of the triangular fuzzy variable and trapezoidal fuzzy variable are presented in Eqs. (34) and (35).

\[
\mu(x) = \begin{cases} 
\frac{x-\alpha_1}{\alpha_2-\alpha_1} & \text{if } \alpha_1 \leq x \leq \alpha_2; \\
\frac{\alpha_3-x}{\alpha_3-\alpha_2} & \text{if } \alpha_2 \leq x \leq \alpha_3; \\
0, & \text{otherwise.}
\end{cases} 
\] (34)

\[
\mu(x) = \begin{cases} 
\frac{x-\beta_1}{\beta_2-\beta_1} & \text{if } \beta_1 \leq x \leq \beta_2; \\
1, & \text{if } \beta_2 \leq x \leq \beta_3; \\
\frac{\beta_4-x}{\beta_4-\beta_3} & \text{if } \beta_3 \leq x \leq \beta_4; \\
0, & \text{otherwise.}
\end{cases} 
\] (35)

The membership function curve of triangular fuzzy numbers and the trapezoidal fuzzy number are presented in Fig. 3.

The triangular fuzzy numbers are more applicable to deal with data that are not accurate or precise (Li et al., 2012). Therefore, in this research, the Equation \( \tilde{X} = (X^p, X^m, X^o) \) is assumed as a triangular fuzzy number with the confidence level \( \rho \geq 0.5 \), concerning the confidence level of the fuzzy number versus the random number \( r \):

\[
Cr\{ \tilde{X} \leq r \} \geq \rho \iff r \geq (2\rho - 1)X^p + 2(1 - \rho)X^m 
\] (36)

![Fig. 3 The representation of fuzzy numbers. a Triangular membership function, b Trapezoidal membership function (Peykani et al., 2021)](image-url)
To convert the fuzzy chance-constrained programming model into a defuzzied model with definite values by comparing critical \( \rho \) values, Eqs. (36) and (37) are considered.

In the proposed model, based on real-world conditions, the uncertain parameter of the problem is demand \( \tilde{D}_{mi} \). Other parameters of the problem in the case study are estimated acceptably according to the questionnaire on different days. However, due to the unpredictable conditions of referring to dental clinics, the amount of demand for waste treatment is considered an uncertain parameter. To cope with uncertainty, \( \tilde{D}_{mi} = (D_{mi}^p, D_{mi}^m, D_{mi}^o) \) is assumed as independent triangular fuzzy numbers. In constraints (10) and (11), \( \tilde{D}_{mi} \) is defined as a score for each node and the volume of transported waste from the first node to node \( i \) is restricted to remove sub-tours from clinical nodes by the Miller–Tucker–Zemlin method. Therefore, these constraints are not systematic, and to be correct based on the MTZ method, we redefine them with \( D_{mi}^p \) as a score. Equations (10) and (11) are rewritten as Eqs. (38) and (39), respectively

\[
U_{jt} - U_{it} \geq D_{mi}^p - W \times (1 - X_{ijkt}) \quad \forall i, j \in R, k \in K, t \in T \quad (38)
\]

\[
D_{mi}^p \leq U_{it} \leq W \quad \forall i \in R, t \in T \quad (39)
\]

To reduce the complexity of the model, demand in the main constraints, Eqs. (12) and (13), is considered uncertain. These constraints ensure about maintenance of the vehicle’s capacity and indicate the amount of waste collected by the vehicles, respectively. Therefore, these constraints are sensitive to the amount of demand. Equations (12) and (13) are rewritten as Eqs. (40) and (41) based on a chance-constrained planning approach

\[
Cr \left\{ \sum_{i \in R} \sum_{j \in N} D_{mi}^* X_{ijkt} \leq W \right\} \geq \rho_{it}^1 \quad \forall k \in K, t \in T \quad (40)
\]

\[
Cr \left\{ LW_{kt} = \sum_{i \in R} \sum_{j \in N} D_{mi}^* X_{ijkt} \right\} \geq \rho_{it}^2 \quad \forall k \in K, t \in T \quad (41)
\]

Based on Eqs. (36) and (37), Eq. (40) is become definite and rewritten to Eq. (42). In addition, Eq. (41) is defined as two separate Eqs. (43) and (44)

\[
\sum_{i \in R} \sum_{j \in N} \left[ (2 \rho_{it}^1 - 1) D_{mi}^p \times X_{ijkt} + 2(1 - \rho_{it}^1) D_{mi}^m \times X_{ijkt} \right] \leq W \quad \forall k \in K, t \in T \quad (42)
\]

\[
LW_{kt} \leq \sum_{i \in R} \sum_{j \in N} \left( (2 \rho_{it}^1 - 1) D_{mi}^o \times X_{ijkt} + 2(1 - \rho_{it}^1) D_{mi}^m \times X_{ijkt} \right) \quad \forall k \in K, t \in T \quad (43)
\]

\[
LW_{kt} \geq \sum_{i \in R} \sum_{j \in N} \left( (2 \rho_{it}^1 - 1) D_{mi}^o \times X_{ijkt} + 2(1 - \rho_{it}^1) D_{mi}^m \times X_{ijkt} \right) \quad \forall k \in K, t \in T \quad (44)
\]

In Eqs. (31) and (33), the summation of the demands is determined as an upper bound for linearization. Thus, Constraints (31) and (33) are rewritten to Constraints (45) and (46), concerning \( D_{mi}^o \) as an upper bound

\[
LX_{ijkt} \leq \sum_{p \in P} D_{mi}^o \times X_{ijkt} \quad \forall i \in F \cup G, j \in R, t \in T, k \in K, p \in R \quad (45)
\]
\[ \prod_{jikt} \geq \prod_{t} \sum_{p \in P} Dm_{it}^{p} \gamma_{i} (1-X_{jikt}) \quad \forall \, i \in F \cup G, \, j \in R, \, t \in T, \, k \in K, \, p \in R \quad (46) \]

### 3.4 Revised multi-choice goal programming

Real-world problems often have different aspects, so decision-makers try to consider more than one aspect and define problems as multi-objective. Solving each aspect separately represents a specific answer, while by considering multi-objective approaches an overall optimal solution according to the decision-maker priorities will be achieved. This study utilized the Revised Multi-Choice Goal Programming (RMCGP) as a solution method; therefore, a brief background of the method is explained in the following.

Goal Programming (GP) is one of the most efficient approaches to multi-objective planning. This method was first introduced by Charnes et al., (1968) and after that, researchers extend it in various approaches to have more modified and efficient methods. It was considered in many previous related studies and showed appropriate performance (for instance see, Nayeri et al., 2020; Rezaei et al., 2020). GP and its extended approaches are utilized to solve many problems (Jones & Tamiz, 2016). In the classical GP, unlike linear programming, which maximizes or minimizes the goal, the deviations between the intended goals and the ideal results are minimized. Multi-choice goal programming is one of the approaches of GP introduced by Chang (2007). This method allows the decision-maker to set multi-choice aspiration levels for each goal to avoid underestimation of the decision. To consider the multi-choice aspiration levels of the model, multiplicative terms of binary variables are involved. This leads to model complexity and is not easily understood by industry participants. Chang (2008) revised this method and developed an alternative approach to formulating the multi-choice aspiration levels into two aspects. Firstly, the alternative approach does not involve multiplicative terms of binary variables, to have a more efficient Multi-Choice Goal Programming (MCGP) and it is also easily understood by the industrial participant. Secondly, the revised approach signifies a linear form of MCGP which can simply be solved by linear programming methods, not requiring the use of integer programming. The revised multi-choice goal programming has considerable advantages such as: (i) this method developed multiple targets rather than one target, (ii) this method is capable to incorporate the decision priorities in the problem, and (iii) the complexity of this approach is less than the other versions (Chang, 2008), (Jadidi et al., 2015). The parameters and variables of the RMCGP method are as follows:

| Symbol | Description |
|--------|-------------|
| \( g_{o,min}, g_{o,max} \) | The lower and upper bound of aspiration level for objective \( o \) |
| \( y_{o} \) | Continuous variable with a lower bound of \( g_{o,min} \) and upper bound of \( g_{o,max} \) |
| \( w_{o} \) | Weight of deviations from the goal for objective \( o \) |
| \( d_{o}^{+}, d_{o}^{-} \) | Positive and negative deviation from aspiration level of objective \( o \) |
| \( e_{o}^{+}, e_{o}^{-} \) | Positive and negative variation from upper or lower bound of aspiration level of objective \( o \) |
| \( \alpha_{o} \) | Weight of deviations from the upper or lower bound of aspiration level for objective \( o \) |
The configuration of the RMCGP has two cases based on the type of objective functions. The first case is “the more the better” formulated as Equations (47) to (51):

\[
\begin{align*}
\text{Min} &= \sum_{o \in O} [w_o \ast (d_o^+ + d_o^-) + \alpha_o \ast (e_o^+ + e_o^-)] \\
f_o(x) - d_o^+ + d_o^- &= y_o \quad o \in O \\
y_o - e_o^+ + e_o^- &= g_{o,\text{max}} \quad o \in O \\
g_{o,\text{min}} \leq y_o \leq g_{o,\text{max}} \quad o \in O \\
d_o^+ \cdot d_o^- \cdot e_o^+ \cdot e_o^- &\geq 0 \quad o \in O
\end{align*}
\]

The second case is called “the less the better” which is presented as Equations (52) to (56):

\[
\begin{align*}
d_o^+ \cdot d_o^- \cdot e_o^+ \cdot e_o^- &\geq 0 \quad o \in O \\
f_o(x) - d_o^+ + d_o^- &= y_o \quad o \in O \\
y_o - e_o^+ + e_o^- &= g_{o,\text{min}} \quad o \in O \\
g_{o,\text{min}} \leq y_o \leq g_{o,\text{max}} \quad o \in O \\
d_o^+ \cdot d_o^- \cdot e_o^+ \cdot e_o^- &\geq 0 \quad o \in O
\end{align*}
\]

\(f_o(x)\) indicates the objective function \(o\), and \(X\) is the decision vector. Since all objective functions are minimized, case two is considered to solve the model. Equation (52) represents the goal of the RMCGP which is minimizing the weighted summation of deviations from the aspiration level and the lower bound of the aspiration level. Equation (53) determines the positive and negative deviations from the aspiration level. Equation (54) calculates the positive and negative deviations from the lower bound of the aspiration level. Equation (55) ensures that aspiration levels are bound to the lower and upper bound. Equation (56) represents the characteristics of the variables. The mathematical model after application of the RMCGP is developed as follows:

\[
\begin{align*}
\text{Min} &= w_1 \ast (d_1^+ + d_1^-) + \alpha_1 \ast (e_1^+ + e_1^-) + w_2 \ast (d_2^+ + d_2^-) + \alpha_2 \ast (e_2^+ + e_2^-) \\
&\quad + w_3 \ast (d_3^+ + d_3^-) + \alpha_3 \ast (e_3^+ + e_3^-) + w_4 \ast (d_4^+ + d_4^-) + \alpha_4 \ast (e_4^+ + e_4^-) \\
f_1(x) - d_1^+ + d_1^- &= y_1 \\
y_1 - e_1^+ + e_1^- &= g_{1,\text{min}} \\
g_{1,\text{min}} \leq y_1 \leq g_{1,\text{max}} \\
f_2(x) - d_2^+ + d_2^- &= y_2 \\
y_2 - e_2^+ + e_2^- &= g_{2,\text{min}} \\
g_{2,\text{min}} \leq y_2 \leq g_{2,\text{max}} \\
d_o^+ \cdot d_o^- \cdot e_o^+ \cdot e_o^- &\geq 0 \quad o \in O
\end{align*}
\]
\[ f_3(x) - d_3^+ + d_3^- = y_3 \] (65)

\[ g_{3,\min} \leq y_3 \leq g_{3,\max} \] (66)

\[ f_4(x) - d_4^+ + d_4^- = y_4 \] (67)

\[ y_4 - e_4^+ + e_4^- = g_{4,\min} \] (68)

\[ g_{4,\min} \leq y_4 \leq g_{4,\max} \] (69)

\[ d_1^+, d_1^-, e_1^+, e_1^-, d_2^+, d_2^-, e_2^+, e_2^-, e_3^+, e_3^-, e_4^+, e_4^- \geq 0 \] (70)

Equation (57) minimizes the weighted positive and negative deviations from the aspiration levels and their lower bounds. Equation (58) to (59) determine the negative and positive deviations from related goals, and their lower bounds, and also ensure that aspiration levels are bound to their upper and lower bounds. Equation (70) represents the characteristics of the variables.

### 4 Computational results

This section investigates the validation of the proposed model using a real case study. The presented model is designed to treat the IMW according to the case study for seven dental clinics in Babol, Iran. The problem assumptions are defined based on the real condition and the data is collected as accurately as possible so that the results are practical. In the following, first, a complete description of the case study and the intended information is given, then the validation and output of the model with case study information are explained.

#### 4.1 Case description

As mentioned in the problem description, the considered problem has three parts, including a depot, dental clinics, and disposal sites. The model optimizes the locating and routing of vehicles, regarding the economic and environmental aspects. Based on the information from the case study, there are seven dental clinics in Babol, including (1) Labkhand, (2) Dr. Bakhradi, (3) Nikan, (4) Dr. Behnam Bustanara, (5) Dey, (6) Noshirvani, and (7) Zabihi. Also, three disposal sites for IMW treatment of (1) Rouhani hospital, (2) Shahid Beheshti hospital, and (3) Yahya Nejad hospital have been considered. Figure 4 indicates the location of the intended dental clinics and the disposal sites.

The main information of the case study is:

1. Due to the high risk of storage of IMW in clinics, the waste collection model is developed based on a daily period and weekly planning horizons.
2. Two types of vehicles with different speeds and costs are considered by examining the structure of waste transport vehicles. The vehicle’s capacity is assumed the same.
3. The distance between the nodes has been calculated using Google Maps.
4. Node 0 is the depot of the tour. Nodes 1 to 7 are assumed to the dental clinics, and nodes 8 to 10 are considered disposal sites.
5. Symmetrical triangular possibility distribution for demand (fuzzy parameter) is assumed. Thus, the most possible value of each imprecise parameter is defined based
Fig. 4 The location of the dental clinics and disposal sites
on analyzing data. According to the information of the dental clinics and considering the busy days of the week, a questionnaire was considered to determine the demand and volume of waste. Data were collected for two different weeks and then, using a simple numerical average, the amount of daily waste was estimated for each node. Then, the corresponding most pessimistic and optimistic values are considered by multiplying the most possible value by 0.8 and 1.2, respectively (Selim & Ozkarahan, 2008; Torabi & Hassini, 2008; Paydar & Saidi-Mehrabad, 2015).

(6) Due to the sensitivity of IMW to time and for more accurate planning, the expected time for waste collection from each dental clinic is assumed. The maximum allowable delay has been defined to minimize wasted travel time and excessive traffic. Also, the total time for each route is limited.

(7) For each disposal site, according to their conditions, a specific capacity is considered for each day of the week.

(8) A fixed cost is calculated to treat the waste at each disposal site. This payment varies for each site depending on the circumstances. Although in some cases the amount of waste can affect the cost of treatment, according to the real case, the amount of dental clinic waste is not large enough to consider the cost based on weight.

(9) Based on the second objective function, traffic congestion is considered an effective index for reducing environmental pollution. Transportation of IMW on busy routes with high traffic volume increases the risk of spreading especially in urban areas.

(10) According to the traffic information available on the sites http://news.mrud.irh and https://www.banikhodro.com, for each route, the volume of traffic per day in different hours was examined for two weeks. Then, the risk index is defined based on the traffic volume for each route.

(11) According to the definition of the third objective function to reduce the risk of spreading pollution in the disposal sites, for each location, the population index is estimated based on the region and demographic information (“Online traffic based on region.“).

In the following, vehicle information and facility information are shown in Tables 2 and 3, respectively.

| Table 2 | Details about vehicle types |
|---------|-----------------------------|
| Vehicle type | Vehicle speed (Km/h) | Cost per Km (1000 Rials) | Vehicle capacity (Kg) |
|-----------|------------------------|-------------------------|----------------------|
| 1         | 45                     | 1                       | 300                  |
| 2         | 30                     | 1.5                     | 300                  |

| Table 3 | Details about disposal sites |
|---------|-----------------------------|
| Disposal site | Fixed cost (1000 Rials) | Population index (person) |
|------------|---------------------------|---------------------------|
| Rouhani hospital | 450                       | 4000                       |
| Shahid Beheshi hospital | 500                       | 3000                       |
| Yahya Nezhad hospital     | 400                       | 2500                       |

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4.2 Results

The developed model with the parameters extracted from the case study is solved with Intel® Core™ i3 2410 CPU 4.00 GHz, 6.00 GB RAM, and CPLEX12.9 software. The weights assumed for RMCGP method are $W_1 = 0.4$, $W_2 = 0.2$, $W_3 = 0.2$, and $W_4 = 0.2$ which defined for objective functions one to four, respectively. These weights were set as the average of the values proposed by 5 experts from the waste management department in Babol (“Mazandaran University of Medical Sciences,” 2021). To obtain the upper bound $g_{k_{\text{max}}}$ and lower bound $g_{k_{\text{min}}}$ for the aspiration level of the RMCGP method, each objective is considered separately, and the other objective functions were considered as constraints in the model. Then, four single-objective models are solved. The presented model is implemented to attain the optimal solution structure for the case study to evaluate the performance and accuracy of the model. The RMCGP method is solved in 1212 s, which is a very acceptable time for a case study. The value of each objective function and the final value based on the RMCGP method are presented in Table 4. Table 5 indicates the optimal solution structure for the case study.

Table 4 indicates the results of each objective function separately can cause a significant increase in the deviation of the other objective functions from the ideal value. For instance,

| Objective | $Z_1$  | $Z_2$  | $Z_3$  | $Z_4$  |
|-----------|--------|--------|--------|--------|
| $Z_1$     | 5192.19| 24.6   | 39,000 | 321.18 |
| $Z_2$     | 5251.4 | 12.6   | 39,500 | 306    |
| $Z_3$     | 5541.5 | 28.1   | 33,000 | 311.85 |
| $Z_4$     | 5326   | 24.8   | 37,000 | 11.15  |
| RMCGP     | 5323.4 | 18.2   | 37,000 | 31.02  |

Table 5 indicates the optimal solution structure for the case study.

| Depot | Route | Depot | Vehicle | Time period |
|-------|-------|-------|---------|-------------|
| 0     | 7     | 0     | 1       | 1           |
| 0     | 1     | 6     | 9       | 1           |
| 0     | 2     | 3     | 7       | 1           |
| 0     | 1     | 6     | 9       | 2           |
| 0     | 1     | 3     | 7       | 3           |
| 0     | 2     | 4     | 5       | 3           |
| 0     | 5     | 4     | 3       | 4           |
| 0     | 1     | 6     | 8       | 4           |
| 0     | 7     | 6     | 1       | 1           |
| 0     | 5     | 10    |         | 2           |
| 0     | 2     | 4     | 5       | 1           |
| 0     | 1     | 3     | 6       | 6           |
According to the solution of $Z_1$, if only the cost objective function is considered, the deviation from the expected arrival time for visiting nodes has the worst value. According to the solution obtained from the goal programming method, the goals are as close as possible to their ideal values and the deviations are minimized so that an acceptable solution is gained considering the weight of the important goals.

As it is evident from Table 5, all dental clinics are visited in each period by two vehicles. The weight intended for the objective function of minimizing costs in RMCGP is assumed more important than other objectives in this scenario. Therefore, in the solution structure, the routes are assigned to minimize costs as much as possible. According to the solution structure presented in Table 5, considering the vehicle capacity, disposal sites capacity, and maximum delay, in 6 routes, the IMW is delivered to sites 10 since as presented in Table 3, the lowest fixed cost is assumed for disposal site 10 (Yahya Nezhad hospital). Considering Table 3, the fixed cost of disposal site 8 (Rouhani hospital) is less than 9 (Shahid Beheshti hospital), thus, it has been visited on 4 routes. While, because of the significant risk of the disposal site and the expected arrival time of site 8, site 9 with a higher fixed cost visited on 2 routes. Therefore, the chosen routes are not selected only based on transportation cost or risk, all the considered aspects are assessed to provide a better solution. For a more detailed analysis, the selection of vehicles on each route is examined. Table 6 represents the length of each of the routes traveled in the solution structure. In all periods, the type 1 vehicle is considered for a longer route because according to Table 2, this type of vehicle costs less per kilometer. In this way, it is clear from the choice of sites and selection of the vehicle that due to the higher weight of the cost reduction objective, more attention has been paid to reducing total cost.

### 5 Sensitivity analyses and discussion

This section intends to investigate the accuracy of the behavior and performance of the recommended model. Sensitivity analysis is a method for changing the inputs of a statistical model in an organized way so that the effects of these changes on the output of the model can be predicted (Karrman & Allaire, 2009). Sensitivity analysis is done on some of the decision...
factors considered by decision-makers and the effective parameters of the model to evaluate the impacts of potential changes on the proposed solution structure. Several analyses and their effects on the final results are presented as follows.

5.1 Sensitivity analysis of the confidence level

To analyze the effects of confidence levels as a key parameter on the objective functions, a sensitivity analysis is performed. Different confidence levels are considered and the results are presented in Table 7) and Fig. 5.

| Objective | Confidence level($\rho_{it}$) |
|-----------|-----------------------------|
|           | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1     |
| $Z_1$     | 5199.85 | 5208.57 | 5212.32 | 5323.4 | 5332.41 | 5356.25 |
| $Z_2$     | 16.1 | 17.4 | 18.01 | 18.2 | 19.26 | 20.06 |
| $Z_3$     | 33,500 | 35,000 | 37,000 | 37,000 | 39,000 | 39,500 |
| $Z_4$     | 27.36 | 30.14 | 30.26 | 31.02 | 41.05 | 45.6 |
| RMCGP     | 0.24 | 0.25 | 0.27 | 0.29 | 0.32 | 0.41 |

Fig. 5 Sensitivity analysis of the objective functions against confidence levels
Table 7 and Fig. 5 indicate the increase in confidence levels affects the objective functions directly. The objective functions increase with various ranges of fluctuations in different intervals which means in all scenarios the amount of objective function worsens. It implies the considerable role of analyzing uncertainty to predict the changes. Therefore, with high confidence levels, more resources are needed to prevent failure in satisfying the demand.

### 5.2 Sensitivity analysis on objective weights of RMCGP

One of the most influential parameters that have significant effects on the solution of the problem is the parameters of the RMCGP method. Different scenarios for the weights of each objective function are considered to examine the influences of weight changes on the value of the objectives. In the previous section, the maximum weight is set for the total cost minimization objective but it does not mean that the economic aspects are always more important. However, the cost can always be effective in real-world issues, so different weights are considered for cost. Several weight scenarios have been considered according to the opinion of 5 experts to examine both low priority and high priority for all objective functions. In scenario 5, objective functions with equal weights are examined and the results are presented in Table 8.

A comparison between the first two scenarios reveals that a small change in the given weight to objective functions can cause a notable change in the final values of some objective functions. However, the other scenarios indicate that higher weight has a direct behavior with minimizing the objectives. Giving the more significant weight to one of the second or fourth objectives will change the final results in their favor. Compare to the other objectives, the third objective function is less sensitive to weights however based on scenarios 1, 2, 7, and 10, can demonstrate that the higher weights can give a better solution for each objective. In addition, in scenario 5 a balanced solution structure concerning all considered aspects is presented. So, it is indispensable that management should consider suitable weight based on decision-maker priorities to have better value for the objective function.

| Scenario | Considered weights for objectives | Objective values |
|----------|----------------------------------|------------------|
|          | \(W_1\) | \(W_2\) | \(W_3\) | \(W_4\) | \(Z_1\) | \(Z_2\) | \(Z_3\) | \(Z_4\) |
| 1        | 0.7     | 0.1     | 0.1     | 0.1     | 5202.7  | 18.6    | 39,000  | 56.22   |
| 2        | 0.6     | 0.1     | 0.1     | 0.2     | 5206.1  | 19.0    | 39,000  | 35.65   |
| 4        | 0.5     | 0.2     | 0.2     | 0.1     | 5220.2  | 15.4    | 37,500  | 62.56   |
| 3        | 0.4     | 0.2     | 0.2     | 0.2     | 5323.4  | 18.2    | 37,000  | 31.02   |
| 5        | 0.25    | 0.25    | 0.25    | 0.25    | 5230.01 | 16.9    | 35,500  | 31.13   |
| 6        | 0.2     | 0.1     | 0.1     | 0.6     | 5232.6  | 21.2    | 39,000  | 13.01   |
| 7        | 0.2     | 0.1     | 0.5     | 0.2     | 5233.36 | 22.45   | 34,500  | 32.56   |
| 8        | 0.2     | 0.2     | 0.1     | 0.5     | 5234.6  | 16.4    | 39,500  | 17.11   |
| 9        | 0.1     | 0.5     | 0.2     | 0.2     | 5332.65 | 15.01   | 38,500  | 35.24   |
| 10       | 0.1     | 0.6     | 0.2     | 0.1     | 5346.73 | 13.23   | 37,000  | 41.89   |
Table 9: Sensitivity analysis of the demand parameter

| Scenario | Demand’s change | Z₁       | Z₂       | Z₃       | Z₄       |
|----------|-----------------|----------|----------|----------|----------|
| 1        | + 10%           | 5227.2   | 15.5     | 37,500   | 38.27    |
| 2        | + 15%           | 5227.65  | 15.7     | 37,000   | 41.26    |
| 3        | + 20%           | 5229.32  | 16.1     | 37,500   | 43.59    |
| 4        | + 25%           | 5230.28  | 17.32    | 39,000   | 44.19    |
| 5        | + 30%           | 5233.14  | 17.95    | 39,500   | 45.69    |
| 6        | + 35%           | 5233.3   | 17.7     | 39,000   | 43.20    |
| 7        | + 40%           | Inf      | Inf      | Inf      | Inf      |

5.3 Sensitivity analysis based on demand parameter

The demand parameter has a direct effect on the final results of the problem. The amount of demand in each period, given the capacity available for each facility and vehicle, can make the problem infeasible so sensitivity analysis has been considered for changing demand. It can be examined to what extent the increase in demand is permissible and accountable for the intended case study. To test the performance of the problem, each scenario is considered a separate problem. According to Equations (57) to (70), each scenario was solved by revised multi-choice goal programming and the values of the objective function were obtained. The changes in the demand and the results are presented in Table 9.

Table 9 illustrates the increase of the demand up to 35% is responsive so the capacity of vehicles and disposal sites is sufficient. But as an interesting point, the problem becomes infeasible for the 40% increase in the demand. After investigating the issue, it became clear that the reason for the solution’s infeasibility is the lack of sufficient vehicle capacity. To accurately represent the sensitivity of objective functions to demand changes, the values of objective functions for each scenario have been shown in Fig. 6.

According to Fig. 6, the objective functions indicate the growth of the demand directly affects the objective function’s value and increases them. The waste management system cannot provide a solution for increasing demand by more than 35% because of vehicle capacity limitations. It indicates the undeniable role of vehicles in the dental clinic waste management network. To solve this difficulty, an extra vehicle can be considered then unpredictable demand can be treated to 40%.

5.4 Numerical examples

Since the investigated problem in this research comes from a real case study, there are differences in the model compared to the literature. To compare the case study with other instances, in total 6 random instances are generated. Table 10 compares the results of numerical examples with the case study and Fig. 7 indicates the changes in run-time for each scenario.

As it is evident from Fig. 7, the run-time for instances that are larger than the case study is considerably increased. This problem is defined based on a real case study and the solution method has acceptable run-time for the case study and small instances. While for large instances, it may be better to propose a metaheuristic algorithm to have a better run-time.
5.5 Managerial insight

This research presents a practical model for the IMW location-routing problem to minimize total costs, environmental pollution, disposal site risk, and deviation from expected arrival time based on the realistic assumptions of a case study. Regarding the characteristics of the research, it can give insights to the health organizations to manage the problem of IMW treatment in dental clinics efficiently. The results of the suggested model help decision-makers adopt a scenario that imposes the least economic and environmental risks. Some of the recommendations obtained from the result and sensitivity analyses of the case study are explained as follows:

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**Table 10** The detail of the instances

| No | N | R | G | K | T | CPU time | Z₁ | Z₂ | Z₃ | Z₄ |
|----|---|---|---|---|---|---------|----|----|----|----|
| 1  | 5 | 3 | 1 | 1 | 3 | 00:00:05 | 1231| 5  | 2400| 17.72|
| 2  | 7 | 4 | 2 | 1 | 4 | 00:00:07 | 1402.5| 9.3| 3700| 24.36|
| 3  | 8 | 5 | 2 | 2 | 5 | 00:09:10 | 4373.6| 15.34 | 8500| 22.15|
| (Case study) | 10 | 7 | 3 | 2 | 6 | 00:20:12 | 5323.4| 18.2 | 37,000| 31.02 |
| 4  | 15 | 12 | 3 | 3 | 6 | 03:12:54 | 6635.23| 18.6 | 45,500| 40.26 |
| 5  | 20 | 16 | 4 | 4 | 7 | 5:02:34 | 6953.35| 19.36 | 48,500| 56.32 |
| 6  | 25 | 21 | 4 | 5 | 9 | 10:25:43 | 7126.2| 25.58 | 50,000| 64.18 |

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Fig. 6 Sensitivity analysis based on demand change
(1) One of the essential factors in handling the generated waste and reducing its harmful effects in small cities is efficient planning for finding a location and proposing suitable routes. Infectious wastes can increase the danger of disease spread to people and medical staff, especially in small clinics because of the lack of treatment equipment. Hence, attempts to improve the performance of waste management can help managers to handle this waste improperly. At first, this process might have extra costs for the managers, but the decrease in risk of the IMW will reduce the cost in the long run. Moreover, controlling the disease can save many lives, and preserve the environment which is a more valuable result.

(2) Considering overcrowded routes with heavy traffic for transferring the IMW to disposal sites can lead to an increase in traffic congestion, besides the acceleration in the disease spread. In the case study, because of the weak transportation infrastructure, the problem of spreading infectious waste in traffic congestion is more critical. Finding the optimal route is a helpful key to tackling the problem. The transfers of infectious waste through less busy routes can reduce the risk of spreading IMW and it has a significant effect on reducing the volume of the traffic.

(3) By considering the time windows for service and assuming the limited travel time, timewasting on the route or at the time of service is prevented. This can have a positive effect on reducing the risk of IMW accumulation in dental clinics as it is removed from the clinics at specific times and periods.

6 Conclusion and future directions

Nowadays, the sudden increase in the amount of generated IMW is problematic because of inappropriate management and it can have significant negative effects on human health and the environment. IMW treatment in large medical centers is done on-site, but small medical centers such as dental clinics are always at risk of spreading infection due to improper treatment. Like every other country, Iran is dealing with this problem, so introducing an efficient strategy for managing this issue can be helpful for Iran. In addition, it can consider as an example for other countries with the same condition to use this approach so they would be able to control the IMW problem. Hence, designing an efficient location-routing plan is a necessity for dental clinics because of the high risk of disease spread especially
in a pandemic. In this regard, this study investigated a multi-objective mathematical model based on the realistic assumptions of dental clinics in Babol, to minimize the total cost, the disposal site risk, environmental pollution steam from traffic, and deviation from the expected arrival time. Real information based on the case study is collected for all the dental clinics in Babol and disposal sites with specific capacities are considered then, to solve the demand uncertainty problem, a fuzzy chance-constrained programming approach is proposed. Finally, the RMCGP approach is investigated to solve the proposed model. The following main conclusions are yielded:

(1) A developed mixed-integer mathematical model was suggested for the location-routing of the dental clinic’s IMW problem considering realistic assumptions such as multi-period planning and separate locations and different capacity for the disposal sites.

(2) The final results confirmed that the model can perform a balance between four considered objectives based on the decision maker’s preference. As a result, the importance of environmental aspects and deviation from arrival times should be considered as important as costs.

(3) To bring the issue closer to the real-world problem, demand uncertainty is considered and fuzzy chance-constraint programming is implemented. Also, by sensitivity analysis on the confidence level parameter, the demand changes are investigated.

(4) A real-life case study problem is implemented and a plan is presented. Furthermore, the results included the optimal planning in location and routing decisions with the optimal values of objective functions.

(5) The results of sensitivity analysis demonstrated that the objective functions are dependent on the weight of RMCGP. In addition, the feasibility of the solution is directly dependent on the demand. Unexpected demand can cause insusibility and it states the important role of vehicle capacity and the number of the considered vehicle.

(6) Paying attention to finding routes with less traffic index can have a positive effect on traffic congestion in urban areas. Therefore, in addition to the positive environmental aspect, the costs of urban traffic will also be indirectly reduced.

Besides its advantages, it is clear, that each paper has some limitations as well as other articles that may pave the way for future research. One of the limitations of the problem was collecting information accurately. For this purpose, the questionnaire method was used thus, to increase the accuracy of the information, the data was collected in several steps. The values were considered as averages of collected data to be more realistic. This method was considered for a small case study, however, in general, the data collection was very time-consuming as we tried to define them as close to reality as possible to be applied to the real-world problem.

Some helpful recommendations are suggested for future studies based on the main limitations of this research:

(1) Social issues such as job creation can be considered to design a sustainable network for IMW management.

(2) Large instances can be developed, and for solving the potential NP-hard problem heuristic or meta-heuristic algorithms can be proposed.
(3) Uncertainty for parameters for instance demand can be a future extension to manage unpredictable situations.

Appendix

See Tables 11, 12, 13, 14 and 15.

Table 11 Distance between all nodes (D_{ij}) Km

| Node | 0  | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 |
|------|----|----|----|----|----|----|----|----|----|----|----|
| 0    | 0  | 1.10 | 0.36 | 2.12 | 1.68 | 1.69 | 2.63 | 3.86 | 2.85 | 2.54 | 2.09 |
| 1    | 1.10 | 0  | 0.86 | 1.33 | 1.22 | 1.21 | 1.93 | 3.50 | 2.43 | 2.52 | 1.41 |
| 2    | 0.36 | 0.86 | 0  | 2.05 | 1.71 | 1.71 | 2.60 | 3.96 | 2.92 | 2.73 | 2.06 |
| 3    | 2.12 | 1.33 | 2.05 | 0  | 0.62 | 0.61 | 0.60 | 2.30 | 1.26 | 1.76 | 0.23 |
| 4    | 1.68 | 1.22 | 1.71 | 0.62 | 0  | 0.021 | 0.97 | 2.29 | 1.22 | 1.36 | 0.47 |
| 5    | 1.69 | 1.21 | 1.71 | 0.61 | 0.021 | 0  | 0.96 | 2.30 | 1.23 | 1.37 | 0.45 |
| 6    | 2.63 | 1.93 | 2.60 | 0.60 | 0.97 | 0.96 | 0  | 1.76 | 0.82 | 1.59 | 0.54 |
| 7    | 3.86 | 3.50 | 3.96 | 2.30 | 2.29 | 2.30 | 1.76 | 0  | 1.07 | 1.49 | 2.13 |
| 8    | 2.85 | 2.43 | 2.92 | 1.26 | 1.22 | 1.23 | 0.82 | 1.07 | 0  | 0.93 | 1.07 |
| 9    | 2.54 | 2.52 | 2.73 | 1.76 | 1.36 | 1.37 | 1.59 | 1.49 | 0.93 | 0  | 1.53 |
| 10   | 2.09 | 1.41 | 2.06 | 0.23 | 0.47 | 0.45 | 0.54 | 2.13 | 1.07 | 1.53 | 0  |

Table 12 Pollution index matrix for all nodes (F_{ij})

| Node | 0  | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 |
|------|----|----|----|----|----|----|----|----|----|----|----|
| 0    | 0  | 0.2 | 0.5 | 0.3 | 0.4 | 0.2 | 0.5 | 0.3 | 0.2 | 0.1 | 0.3 |
| 1    | 0.3 | 0  | 0.5 | 0.4 | 0.5 | 0.7 | 0.1 | 0.5 | 0.3 | 0.1 | 0.4 |
| 2    | 0.6 | 0.5 | 0  | 0.3 | 0.1 | 0.2 | 0.2 | 0.1 | 0.3 | 0.6 | 0.7 |
| 3    | 0.1 | 0.4 | 0.3 | 0  | 0.3 | 0.8 | 0.4 | 0.2 | 0.1 | 0.6 | 0.8 |
| 4    | 0.2 | 0.5 | 0.1 | 0.3 | 0  | 0.2 | 0.5 | 0.3 | 0.1 | 0.2 | 0.4 |
| 5    | 0.1 | 0.7 | 0.2 | 0.8 | 0.2 | 0  | 0.3 | 0.8 | 0.5 | 0.2 | 0.1 |
| 6    | 0.5 | 0.1 | 0.2 | 0.4 | 0.5 | 0.3 | 0  | 0.5 | 0.1 | 0.4 | 0.7 |
| 7    | 0.3 | 0.5 | 0.1 | 0.2 | 0.3 | 0.8 | 0.5 | 0  | 0.4 | 0.2 | 0.2 |
| 8    | 0.1 | 0.3 | 0.3 | 0.1 | 0.1 | 0.5 | 0.1 | 0.4 | 0  | 0.2 | 0.1 |
| 9    | 0.7 | 0.1 | 0.6 | 0.6 | 0.2 | 0.2 | 0.4 | 0.2 | 0.2 | 0  | 0.5 |
| 10   | 0.6 | 0.4 | 0.7 | 0.8 | 0.4 | 0.1 | 0.7 | 0.2 | 0.1 | 0.5 | 0  |
### Table 13 Capacity of the disposal sites during each period (Ca_{it}) Kg

| Period | Disposal site | 1 | 1 | 2 | 3 | 4 | 5 | 6 |
|--------|---------------|---|---|---|---|---|---|---|
| 1      |               | 400| 350| 400| 150| 400| 350| 400|
| 2      |               | 350| 450| 250| 200| 300| 150| 350|
| 3      |               | 350| 300| 300| 350| 450| 470| 350|

### Table 14 The expected arrival time to reach node i in period t (L_{ati})

| Period | Node (Dental clinics) | 1 | 1 | 2 | 3 | 4 | 5 |
|--------|-----------------------|---|---|---|---|---|---|
| 1      |                       | 4 | 6 | 9 | 5 | 3 | 10|
| 2      |                       | 10| 4 | 7 | 8 | 7 | 7 |
| 3      |                       | 7 | 3 | 4 | 4 | 3 | 6 |
| 4      |                       | 6 | 7 | 5 | 7 | 8 | 6 |
| 5      |                       | 10| 9 | 7 | 6 | 5 | 4 |
| 6      |                       | 4 | 5 | 6 | 11| 7 | 7 |
| 7      |                       | 9 | 7 | 10| 9 | 9 | 10|
| Period | Node (Dental clinics) | 1 | 2 | 3 | 4 | 5 | 6 |
|--------|----------------------|---|---|---|---|---|---|
| 1      | 56  70  84  40  50  60  56  70  84  48  60  72  48  60  72  60  75  90 |
| 2      | 52  65  78  56  70  84  36  45  54  52  65  78  48  60  72  48  60  72 |
| 3      | 56  70  84  44  55  66  44  55  66  44  55  66  40  50  60  56  70  84 |
| 4      | 40  50  60  44  55  66  52  65  78  52  65  78  60  75  90  56  70  84 |
| 5      | 48  60  72  40  50  60  52  65  78  56  70  84  56  70  84  48  60  72 |
| 6      | 44  55  66  48  60  72  60  75  90  60  75  90  36  45  54  60  75  90 |
| 7      | 48  60  72  52  65  78  48  60  72  48  60  72  60  75  90  52  65  78 |
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