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Multi-period two-echelon location routing problem for disaster waste clean-up

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ABSTRACT

Waste clean-up after a disaster is one of the most critical tasks in the response stage of disaster management. We develop a model to minimise the cost and duration of disaster waste clean-up considering using Temporary Disaster Waste Management Sites (TDWMSs), which can store and process waste before it is sent to the final disposal sites. The problem that arises can be seen as a Multi-Period Two-echelon Location Routing Problem (MP-2ELRP) in which the main decisions are the location of the TDWMSs and the routing of vehicles in both echelons. In this paper, we propose both a mixed-integer program and a Genetic Algorithm (GA) to model and solve the problem. Computational tests indicate: (i) the performance of proposed GA is robust; (ii) the use of TDWMSs can reduce both total waste clean-up cost and duration; and (iii) the capacities of TDWMSs have a significant impact on the total waste clean-up time and duration.

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Disaster waste management; two-echelon location routing problem; MIP; genetic algorithm; greedy algorithm

1. Introduction

Disasters can generate a large amount of waste and debris (Baycan 2004; Brown, Milke, and Seville 2011b; Xiao, Xie, and Zhang 2012; Ishimura, Takeuchi, and Carlsson 2014). The generated volume from a single event can reach 5–15 times the annual waste normally produced by affected communities (Brown, Milke, and Seville 2011b). The clearance, removal, and disposal of such large amounts of debris are costly and time-consuming operations. Indeed, they account for about one-fourth of disaster recovery costs (FEMA 2007) and can last for many years (Brown, Milke, and Seville 2011b).

The disaster management cycle consists of several stages, including mitigation, preparation, response and recovery (UNISDR 2009). Waste clean-up occurs in the last two stages, with the cleaning of roads in the response phase (Fetter and Rakes 2012) and the removal of debris from affected areas in the recovery phase (FEMA 2007). In the response stage of disaster management, the goal of waste clean-up is to open blocked roads to ensure the

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routes for rescue, evacuation, and relief are accessible. In the recovery stage, the major task of disaster waste management is cleaning all the waste generated in disaster affected area to make sure the recovery operations go well. The modelling of open blocked routes during the response stage has been addressed by Sakuraba et al. (2016); Pramudita, Taniguchi, and Qureshi (2014); Özdamar, Aksu, and Ergüneş (2014); Çelik (2015); Sahin, Kara, and Karasan (2016); Berktaş, Kara, and Karaşan (2016). In this research, we focus on the disaster waste clean-up in the response stage, which includes a large amount of waste removal operations.

Planning complex removal operations requires proper coordination between collection, processing and disposal of waste. To improve the efficiency of the overall process, one study suggested establishing temporary disaster waste management sites (TDWMSs) (FEMA 2007), which can be used to temporarily store and process the waste. Thus, it is vital to achieve a dynamic re-balance, particularly when final disposal sites are far away from the collection points or when they have limited capacities. The other study proposed a simple mathematical model to decide on the location of TDWMSs, the assignment of collection points to TDWMSs, and the choice of the recycling technologies (Fetter and Rakes 2012). However, the model has an ambiguous capability in optimising the disaster waste clean-up. Therefore, our study aims to improve the efficiency of waste clean-up in the response stage of disaster management by minimising the total cost and duration of waste clean-up considering the optimisation of disaster waste clean-up. Essentially, we need to solve a two-echelon location routing problem (2E-LRP) with multiple periods, which include optimising the collection routes between disaster affected areas, the TDWMSs and transportation routes between TDWMSs and the final disposal sites, and the location selection of TDWMSs for the whole waste clean-up period.

To achieve this, the main challenge is providing cycles between TDWMSs without visitation of the depot, which is associated by the determination of routes in the presence of TDWMSs. To tackle this problem, we propose new linear constraints that are able to capture this feature and incorporate them into a full mixed-integer program. We also develop fast heuristics to obtain feasible solutions within acceptable computation time for large scale problems.

The rest paper is structured as follows. Section 2 presents a literature review. Section 3 provides detailed description of the problem. Section 4 presents the core of the proposed mathematical formulation. Section 5 summarises the developed heuristic algorithms and Section 6 discusses the case study and instance generation. The following section analyses the computation results. Conclusions are presented in Section 8.

2. Literature review

In this section, we review previous disaster waste clean-up strategies (Section 2.1), summarise the research focused on the optimisation of waste clean-up in the disaster recovery (Section 2.2), and discuss the methods used to solve 2E-LRP (Section 2.3).

2.1. Disaster waste clean-up strategies

The choice of an appropriate disaster waste clean-up system is case-dependent, especially after disasters in which many different stakeholders are involved. The usage (or not)

Table 1. Comparison of disaster waste management systems in different instances.

Instance	Strategies	Remarks	Reference
Hanshin-Awaji Earthquake	Some governments use TDWMSs	The sort of waste can facilitate management; The method for waste transportation should be improved; The choose and use of heavy construction machines is important in TDWMSs	Nakamichi and Inoue (1995)
Cedar & Paradise fires, 2003	Bin program; Property clearing program; Two temporary recycling facilities	Average recycling rate was about 54%; Total cost of waste management reduced to a large extent	County of San Diego (2005)
Flood in 2000 in the USA	Door-to-door garbage collection on a fee-for-service basis	Catastrophic flooding in 2000 and the implementation of a 'garbage tax' increased pressure on the city to improve garbage collection	Kruks-Wisner (2006)
Victoria Bushfire, 2009	A central contract was signed to clean-up	A small percentage of metal and most concrete were recycled; Waste was collected to four existing landfills and one new landfill directly	Brown, Milke, and Seville (2011c)
Hurricane Katrina, 2005	Kerbside collection; On-site separation; Applied TDWMSs	Demolition waste sent to disposal sites directly	Brown and Milke (2011)
2010 Canterbury and 2011 Christchurch Earthquakes	Established facilities; Specifically for disaster waste; Waste separated in TDMWS	Different systems for different waste sources	Brown and Milke (2012)
L'Aquila Earth-quake, 2009	Waste separated in TDMWS when it was handled by Civil Protection Department but changed to on-site separation when the municipality took the responsibility	Waste management works were separated into three categories according to the severity of building damage	Brown et al. (2010)
Samoan Tsunami, 2009	Individual government and international NGOs involved	No overall coordination and waste management strategy from the international community; Not include separation before collection; Most of the waste ended in landfill	Brown, Milke, and Seville (2011d)
Marmara earthquake, Turkey	Recycling plant; 17 Dump sites	High level of reinforcement, bars in the demolition waste causes operational problems in plant; Illegal dumping at coastal line	Karunasena et al. (2009)
2014 South Carolina storm	A TDWMSs set up before the storm events	Use experienced storm clean-up contractors; Recycled wood waste	Emerson (2014)

of intermediate facilities such as TDWMSs is a central aspect of differentiation between different strategies.

Table 1 presents a brief review of the different strategies used in the literature and highlights the main aspects of the existing approaches. Situations in which TDWMSs were used present higher recycling rates. The 2003 Cedar & Paradise fires waste clean-up is a proper example of high recycling rates that can be obtained in these cases. The report indicated that more than 50% of the waste could be recycled. Generally, on top of the increasingly recycling rates, TDWMSs have some other advantages, including improving the flexibility of operations and reducing the volume of waste as well as shortening waste collection times (FEMA 2007). In Section 7.3, the performance of two different disaster waste clean-up systems (with and without TDWMSs) are compared.

2.2. Modelling in disaster waste management

Disaster waste management modelling is necessary to improve the efficiency of disaster waste clean-up in the recovery stage (Cheng, Zhang, and Thompson 2018). In general, the problem in disaster waste management can be described using a reverse logistics system (Hu and Sheu 2013) which includes logistics activities such as location of TDWMSs and route planning in waste collection and transportation (Zhang et al. 2019). Hu and Sheu (2013) proposed a mathematical model to minimise environmental and operational risk, and psychological trauma experienced by residents in a disaster waste management system. In a recent paper published by the same author, traffic impacts is added as another objective in the model (Hu et al. 2019). However, in both papers, the selection of TDWMSs location was not considered in the model. To select candidates for TDWMSs, Cheng and Thompson (2016) proposed a land use suitability assessment method. Fetter and Rakes (2012) developed a decision model TDWMSs location selection with recycling incentives to support disaster debris cleanup operations. In addition to the decision of TDWMSs location, Onan, Ülengin, and Sennaroğlu (2015) also included the assignment of customer nodes between TDWMSs.

Regarding the route planning in disaster waste management, most models addressed routing planning by focusing on the response stage, which aim to open blocked roads to support evacuation, rescue and relief. For example, Pramudita, Taniguchi, and Qureshi (2014) proposed a model to minimise waste clean-up cost in the response phase by optimising waste transportation routing considering the blocked access by waste. Çelik (2015) developed a model to determine the sequence to clean roads to satisfy relief demand. Sahin, Kara, and Karasan (2016) also aimed to provide emergency relief supplies to disaster-affected regions as soon as possible by unblocking roads after disasters. Furthermore, Berktaş, Kara, and Karaşan (2016) used a model to minimise the total time spent to open blocked roads to reach all the critical nodes.

2.3. Relevant solution methods for 2E-LRP

Table 2 summarises methods for the 2E-LRP from different studies. Both exact algorithms and heuristics algorithms have been applied to solve the problem in different papers. In general, exact algorithms can only solve small instance problems (Crainic, Sforza, and Sterle 2011). Thus, most of the papers applied tailored or generalist heuristic algorithms to solve this problem. The Greedy algorithm is normally used to generate initial solutions. For example, Nguyen, Prins, and Prodhon (2012) applied three greedy randomised heuristics to generate initial solutions, which were improved by two variable neighbourhood descent procedures. Heuristics such as Tabu-search, the genetic algorithm, and local search are usually applied for improving initial solutions. Nguyen, Prins, and Prodhon (2010) and Wang et al. (2017) developed local search algorithm to improve initial solutions. Dalfard, Kaveh, and Nosratian (2013) introduced hybrid genetic algorithm and simulated annealing for solution improvement. To solve multiple objective problems, the non-dominated sorting genetic algorithm (NSGAII) based on heuristics are the typical used (Wang et al. 2020b). For instance, two recent paper proposed NSGA-II based algorithms to solve a collaborative two-echelon multi-centre vehicle routing problem (Wang et al. 2020b) and a green logistics location-routing problem with eco-packages (Wang et al. 2020a).

Table 2. A summary of papers on 2E-LRP formulation.

Formulation	Algorithm	Reference
No Mathematical Formulation	Tree-Tour Heuristic	Jacobsen and Madsen (1980)
Two-index ILP	No solution algorithm	Laporte and Nobert (1988)
No Mathematical Formulation	Tabu-search Heuristic	Boccia et al. (2010)
Three-index MILP	Heuristics (Greedy, local search, and Tabu-list)	Nguyen, Prins, and Prodhon (2010)
One-index, two-index, and three index MILP	XPRESS MIP Solver	Crainic, Sforza, and Sterle (2011)
Two-index MILP	Branch-and-Cut, Large-Neighbourhood Search	Contardo, Hemmelmayr, and Crainic (2012)
Three-index ILP	Heuristics (Greedy, learning process, path relinking, and variable neighbourhood descent)	Nguyen, Prins, and Prodhon (2012)
Three-index MILP	Heuristics (Hybrid genetic algorithm and simulated annealing)	Dalfard, Kaveh, and Nosratian (2013)
Three-index MILP	Heuristic	Rahmani, Oulamara, and Cherif (2013)
No Mathematical Formulation	Heuristics (Local search)	Rahmani, Cherif-Khettaf, and Oulamara (2015)
Two-index MILP	Heuristics (Large neighbourhood based)	Breunig et al. (2016)
Three-index MILP	Cplex solver for small instance, Heuristics (Nearest neighbour, Best Sequential Insertion, and Hybrid Clustering)	Rahmani, Ramdane Cherif-Khettaf, and Oulamara (2016)
Three-index MILP	Heuristic	Vidovic et al. (2016)
ILP	Multi-phase hybrid heuristics	Wang et al. (2017)
MILP	Heuristic (dynamic programming, improved K-means clustering, and improved NSGAII)	Wang et al. (2020b)
MILP	Heuristic (Clarke–Wright saving method-based NSGAII and Lagrangian relaxation)	Wang et al. (2020a)

Notes: ILP = Integer Liner Programming, MILP = Mixed Integer Liner Programming.

To sum up, the majority of papers related to disaster waste management modelling didn't consider the decision of location of TDWMSs and route planning in waste collection and transportation together, especially in the recovery stage of disaster management. One paper that considered both TDWMSs location selection and waste collection and transportation assumed that the waste generated from each customer node is more than the capacity of collection vehicles (Cheng et al. 2021). Therefore, there is no need to consider the sequence of visiting customers for collection stages in a single vehicle route, which makes the problem much easier to formulate and solve. However, in many disasters, the capacity of vehicles is larger than the waste generation demand from each customer node. In this case, developing a model to solve the problem which captures the aforementioned features in disaster waste clean-up is necessary. Furthermore, none of the algorithms developed for 2E-LRP considered long operational time, which is an important capability since our model operates long duration of the clean-ups. To bridge the gap, we propose a mathematical model to solve the waste clean-up problem for the whole response stage of disaster management considering: (i) the location selection of TDWMSs; (ii) the routing of waste collection between waste generation nodes and selected TDWMSs; (iii) cycles of collection vehicles between TDWMSs without visitation of the depot; and (iv) the routing of waste transportation between TDWMSs and final disposal sites.

3. Problem description

In this section, we analyse the differences between disaster waste clean-up and periodic municipal waste management collection (Section 3.1), and describe the specifications of the waste clean-up problem investigated in this paper, positioning it within the existing literature (Section 3.2).

3.1. Differences between municipal solid waste management and disaster waste clean-up

A typical municipal solid waste (MSW) management system includes demand points that can be either residential or commercial buildings, transfer stations which can provide reduction, separation, or recycling operations to waste, and final disposal sites that can be recycling facilities, landfill sites, or incinerators. At the first sight, it might seem that MSW collection and transportation methods could be directly applied to disaster waste clean-up. There is abundant literature, since the MSW management has already been studied extensively (Lu et al. 2015).

There are, nevertheless, significant differences between MSW management and disaster waste clean-up (Fetter and Rakes 2012). The volume of the waste to be collected is probably the main difference. Because of the huge volume of waste generated from disasters, the capacity of local municipalities can be exceeded and, thus, additional contractors that are not a part of the MSW management are needed. In addition, in MSW collection, the location and amount of waste are known while in the aftermath of a disaster, the quantity and location of waste are unknown and estimation methods are not accurate. This affects the selection of TDWMSs and the arrangement of clean-up vehicles.

The standards to deal with disaster waste are also different in two scenarios. Disaster waste usually results in mixtures, which makes it difficult to comply with municipal solid waste separation and disposal protocols followed under normal conditions. Normally, there can be policy waivers in order to reduce the duration of disaster waste clean-up operations (Brown, Milke, and Seville 2010a). Furthermore, in MSW management, waste transfer stations are permanent facilities which are determined when the system is designed, while in recovery situations, TDWMSs are temporary facilities that have to be established after disaster happens. Indeed, although TDWMS candidates are identified before disasters, it is an operational decision to use either one or all of them. The last additional difference is that after the clean-up of disaster waste, the selected TDWMSs should be restored to allow their previous use to be resumed (FEMA 2007).

The differences between the two types of waste management systems make disaster waste clean-up an unique problem from the conventional MSW problem. When considering TDWMSs, the disaster waste clean-up problem can be seen as a two-stage process. In the first stage, waste is collected from waste generation nodes and sent to the TDWMSs. In the second stage, they are transported to final disposal sites from TDWMSs, after necessary treatments such as separation and compression.

3.2. Problem definition

To differentiate between the problem demonstrated in this research and the problem that has been addressed in Cheng et al. (2021), we classify disasters into small disasters and large disasters according to the amount of waste generated at the demand nodes. We assume that in small disasters, the waste generated from each demand node is generally smaller than the capacity of a collection vehicle. In large disasters, the waste generated from a single demand node is much larger than the capacity of collection vehicles. The focus of Cheng et al. (2021) is large disasters, while our aim is to solve the waste clean-up problem for small disasters. The complete process of small disaster waste clean-up can be seen as a reverse two-echelon routing problem.

The Two-Echelon Routing Problem (2ERP) has been rigorously defined and described as a two-echelon, synchronised, scheduled, multi-depot, multiple-tour, heterogeneous vehicle routing problem with time windows (Crainic, Ricciardi, and Storchi 2004). The first application of 2ERP can be traced back to the 1980s, in the context of newspaper distribution (Jacobsen and Madsen 1980). There is a systematic review on 2ERPs (Cuda, Guastaroba, and Speranza 2015), which classified the problem into three categories: the two-echelon location routing problem (2E-LRP), the two-echelon vehicle routing problem (2E-VRP), and the truck and trailer routing problem (TTRP). In 2E-LRP, the satellites to be opened have to be selected from a set of possible candidates. In comparison, the set of satellites has been determined in 2E-VRP. In a TTRP, transportation is organised as a set of trucks and trailers that need to satisfy the following requirements. A subset of customers should be served by a truck alone, and the rest of customers can be visited either by a truck alone or a vehicle (a truck or a trailer). According to this classification scheme, the problem described in this paper belongs to the 2E-LRP since we include location selection for TDWMSs in our problem.

In this study, rather than the delivery of freight to customers, the goal is to collect waste from waste generation nodes, which are defined as customer nodes in classical VRP. The first echelon comprises the links between waste generation points (customers) and TDWMSs (satellites). The second echelon connects the TDWMSs (satellites) and final disposal sites (depots), and those connecting pairs of TDWMSs (satellites). Besides, the vehicle depot, a parking site for collection vehicles, is also considered. In the 2E-LRP, the decisions involve the TDWMSs locations connecting the first echelon (in which waste is collected from waste generation points) to the second echelon (in which waste is sent to the landfills). According to a well developed notation (Laporte 1988; Crainic, Sforza, and Sterle 2011), the 2E-LRP in this study is a challenge because location decisions have to be made in the first echelon and routes are allowed in both echelons.

Like in most 2E-LRP, here we take into account the maximum route durations and the capacity of both vehicles and location facilities. Additionally, the problem has some significant features that have seldom been considered in the literature. Firstly, the problem is a multi-period problem since the huge quantities of the waste require a long collection horizon. This implies that some sort of waste inventory management must be implemented to model the problem properly. Moreover, sub-routes forming cycles including a TDWMS can be feasible. Therefore, this is the most challenging modelling issue for this problem. The use of sub-cycles without including the depot has been considered in the case of so-called Lasso solution for the VRP with delivery and pick-ups (Gribkovskaia, Halskau, and Myklebost 2001; Hoff et al. 2009). In a Lasso solution, the first customers on the route can be visited twice. On the first visit, only the delivery demands are performed to create more available space on the vehicle. On the way, back to the depot, the same customers are visited the second time to perform the pick-up service. In our case, sub-cycles starting and ending at the same TDWMS or paths starting and ending at different TDMWS are allowed since visiting to a TDWMS has an effect of renewing the capacity of the vehicle.

Colour online, B/W in print

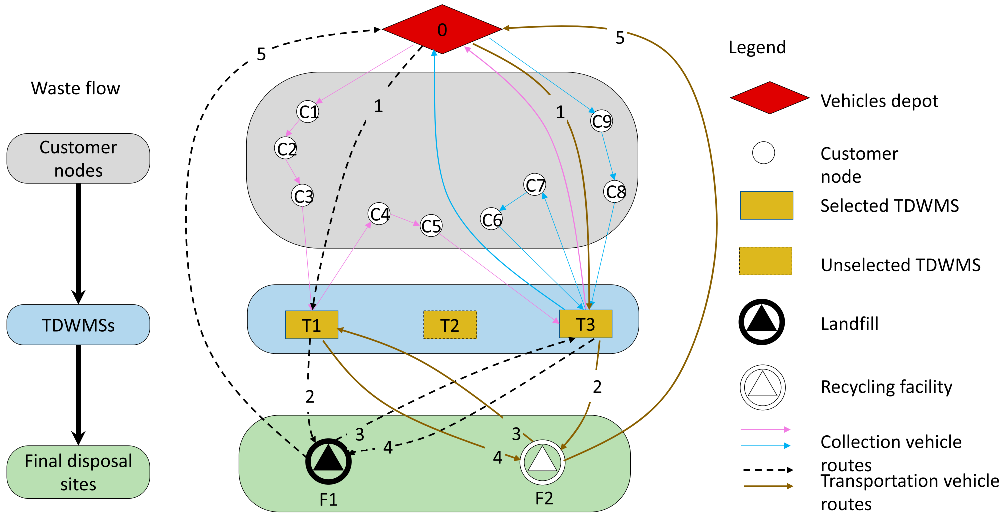

Figure 1. Disaster waste management system.

The above problem is defined as the *Multi-Period Two-Echelon Location Routing Problem* (MP2ELRP) with multi-trips. The study has two objectives that minimise both the total cost and the total clean-up time. Figure 1 presents the problem in a schematic way. In the first echelon, collection vehicles start from the vehicle depot, collect waste from customers and unload this waste at a selected TDWMS. As mentioned above, multiple sub-trips can be performed before returning to the depot and several TDWMSs can be visited in a single complete route, such as the route $0 \rightarrow C1 \rightarrow C2 \rightarrow C3 \rightarrow T1 \rightarrow C4 \rightarrow C5 \rightarrow T3 \rightarrow 0$ (Figure 1). In the second stage, transportation vehicles are responsible for transporting waste from TDWMSs to the final disposal sites. In this echelon, transportation vehicles also start from the vehicle depot and travel to TDWMSs to provide service. Transportation vehicles may also take different routes on a single day depending on the route durations. The numbers on the transportation routes represent the sequence of routes for a transportation vehicle. For instance, a transportation vehicle may follow the route $0 \rightarrow T1 \rightarrow F1 \rightarrow T3 \rightarrow F1 \rightarrow 0$ (Figure 1).

4. Model formulation

In this section, we propose a simplified mixed integer program to formally describe the main characteristics of the problem approached in this paper. As expected, given the review above, this model can only be used to solve small instances. We, therefore, propose heuristics to solve the full problem emphasised above. We use a Genetic Algorithm (GA), and a Greedy Algorithm for the problem and the simplified model. This benefits for the simplicity of implementation and satisfactory capability in obtaining high-quality solutions for similar problems (Nguyen, Prins, and Prodhon 2010, 2012; Dalfard, Kaveh, and Nosratian 2013).

4.1. Assumptions

We assume that waste clean-up starts after the disaster, when residents have returned to their homes and take waste from their residences. This means that all the customers are available at the beginning of the process. As mentioned earlier, inventory management at TDWMSs is needed in order to ensure that their capacities are respected. These capacities constraints are validated at the end of each day.

4.2. Simplified model

Before solving the full problem proposed, we present solutions for a simplified problem. In this approximation, the second stage is not included. Thus, the problem is a *multi-period multi-trip*, *location routing problem*, which focuses on how to make a better arrangement of the first echelon of the full problem. Since even the classical location routing problem is an NP-hard problem, such a simplification is still a difficult optimisation problem. Based on the concept of classical LRP, the following decisions should be made.

- Determining the location and quantity of selected TDWMSs.
- Determining how much waste is to be carried back to each facility each day.
- Determining how many vehicles to use each day, considering the number of available vehicles.
- Determining the routes of each vehicle on a given working day.

In our specific problem, the following additional decisions are required.

- Determining which customers should be served each day.
- Determining the routes of each vehicle through all days in the planning horizon.

We propose a formal mathematical description of the problem presented above. We assume that road network and the amount of waste to be collected are known. Let $G = (N, E)$ be an undirected graph representing the area of interest. Let $N = \{0, 1, \ldots, n\}$ be the set of nodes, where each node represents a collection point, a TDWMS or the depot, i.e. $N = 0 \cup C \cup J$, where 0 represents the depot where trucks are originally parked, $C \subset N$ is the set of demand nodes and $J \subset N$ represents the candidate sites for temporary waste management facilities.

Each node $i \in C$ has an associated demand d_i representing the demand of waste to be collected at node i. Moreover, each node $j \in J$ has associated parameters o_j, p_j, and q_j representing the fixed cost of building TDWMSs, its daily operation cost and its capacity, respectively. We also define E as the set of links in the undirected network. For each edge $(i, j) \in E$ there are two associated parameters: c_{ij} denoting the cost associated with a vehicle traversing edge (i, j), and t_{ij} presenting the time a vehicle takes to traverse the edge. Finally, the problem also defines a set of vehicles. Each vehicle $k \in K$ has an associated capacity Q. These parameters are summarised in Table 3, along with a few additional parameters.

To model cycles between TDWMSs without visitation to the depot, we define a section as a subtour visiting collection points and starting at a depot or a TDWMS and finishing at a TDWMS or the depot. For example, in Figure 1, the vehicle tour $0 \rightarrow C1 \rightarrow C2 \rightarrow C3 \rightarrow T1 \rightarrow C4 \rightarrow C5 \rightarrow T3 \rightarrow 0$ contain three sections. The first section is $0 \rightarrow C1 \rightarrow C2 \rightarrow C3 \rightarrow T1$, $T1 \rightarrow C4 \rightarrow C5 \rightarrow T3$ is the second section, and $T3 \rightarrow 0$ is the third section. The numbering of route sections makes it possible for vehicles to visit TWDMSs more than once while tracking the source of waste unloaded in each TDWMS to make sure the capacity

Table 3. A summary of parameters and sets used in the formulation.

Parameters/sets	
N	set of nodes in the network ($N = 0 \cup C \cup J$)
0	node associated with the depot
C	set of demand nodes
d_i	demand associated with node $i \in C$
J	demand associated with node $i \in C$ set of TDWMSs candidate nodes
o_j	fixed cost of building facility $j \in J$
p_j	daily operation cost of facility $j \in J$
q_j	capacity of facility $j \in J$
E	set of edges
c_{ij}	cost associated with the traversal of arc (i, j)
t_{ij}	time to traverse of arc (i, j)
K	set of available vehicles
Q	capacity of vehicle $k \in V$
T	set of operation days
S	set of sections in one trip

Table 4. A summary of variables in the formulation.

x_{ijdks}	binary variable equals to 1 if arc (i, j), $i, j \in N$ is traversed by vehicle $k \in K$ in its sth section in the trip during day $d \in T$, otherwise 0
y_j	binary variable equals to 1 if TDWMS $j \in J$ is built, otherwise 0
z_{jd}	binary variable equals to 1 if TDWMS $j \in J$ opens on day $d \in T$, otherwise 0
μ_{jdks}	continuous variable representing the amount of waste vehicle $k \in K$ brings back to TDWMS $j \in J$ after its sth section in day $d \in T$
τ_i	continuous variable representing the time customer node $i \in C$ is visited
σ_{jd}	continuous variable representing storage of the waste in TDWMS $j \in J$ at the end of day $d \in T$
W_{jd}	the total amount of processed waste leaving TDWMS $j \in J$ on day $d \in T$

constraints for TDWMSs are not broken. Given this notation, we develop a mixed integer programming formulation for the problem with variables presented in Table 4.

The primary goal is to minimise the total clean-up cost:

$$\text{Min}: \sum_{i\in N}\sum_{j\in N}\sum_{d\in T}\sum_{k\in K}\sum_{s\in S}(c_{ij}x_{ijdks}) + \sum_{j\in J}(o_j y_j) + \sum_{d\in T}\sum_{j\in J}(p_j z_{jd}) \tag{1}$$

The objective function (1) contains three components: the first term minimises the cost of transportation from the waste generation points (customer nodes) to the TDWMSs. The second term refers to the total fixed charge for building the TDWMSs. The third term is associated with the cost of operating the TDWMSs.

Subject to degree constraints:

$$\sum_{i\in C} x_{0idk1} \le 1, \quad \forall d \in T, k \in K, \tag{2}$$

$$\sum_{i\in C}\sum_{s\neq 1, s\in S} x_{0idks} = 0, \quad \forall d \in T, k \in K, \tag{3}$$

$$\sum_{j\in J}\sum_{s\neq 1, s\in S} x_{j0dks} = \sum_{i\in C} x_{0idk1}, \quad \forall d \in T, k \in K, \tag{4}$$

$$\sum_{i\neq j, i\in N \sum_{d\in T}\sum_{k\in K}\sum_{s\in S}} x_{ijdks} = 1 \quad \forall j \in C, \tag{5}$$

$$\sum_{i\in N} x_{ijdks} = \sum_{i\in C\cup J} x_{jidks}, \quad \forall j \in C, d \in T, k \in K, s \in S, \tag{6}$$

$$\sum_{i\in C} x_{ijdks} = \sum_{i\in C\cup 0} x_{jidks+1} \quad \forall j \in J, d \in T, k \in K, s \in S. \tag{7}$$

Constraints (2) and (3) ensure that all vehicles start their trips at the depot. Constraint (4) balances the number of vehicles leaving the depot and the number of vehicles coming back from the TDWMSs. Constraint (5) ensures that each demand node will be visited once and only once. Applied with Constraint (6), it ensures that the number of vehicles leaving a certain node equals to the number of vehicles coming in that node. To modelling the sub-tours Constraint (7) starts a new section of the route when a TDWMS is visited.

Constraints on daily facility capacity

$$\sum_{i\in N}\sum_{j\in C} x_{ijdks} d_j = \sum_{j\in J} u_{jdks} \quad \forall d \in T, k \in K, s \in S, \tag{8}$$

$$\sum_{i\in C} M x_{ijdks} \geq u_{jdks} \quad \forall d \in T, k \in K, s \in S, \tag{9}$$

$$\sum_{k\in K}\sum_{s\in S} u_{jdks} \leq q_j - \sigma_{jd-1} + W_{jd} \quad \forall j \in J, d \in T, \tag{10}$$

$$\sigma_{jd} = \sum_{k\in K}\sum_{s\in S} u_{jdks} - W_{jd} + \sigma_{jd-1} \quad \forall j \in J, d \in T, \tag{11}$$

$$W_{jd} \leq \sigma_{jd-1} \quad \forall j \in J, d \in T. \tag{12}$$

Constraint (8) calculates the amount of waste brought back to TWDMS and Constraint (9) ensures the amount of waste cannot exceed the maximum capacity of the vehicle. Big M is a constant which can be the capacity of vehicles (Q). Constraints (10) and (11) ensure that the capacity of each TDWMS will not be exceeded and record the amount of waste stored at the end of each day. Constraint (12) ensures that the waste stored in a TDWMS at the end of the dth day will be cleared at the $(d+1)$th day.

Constraints on daily facility operation

$$\sigma_{jd} \leq M z_{jd} \quad \forall j \in J, d \in T, \tag{13}$$

$$y_j \leq \sum_{d\in T} z_{jd} \quad \forall j \in J, \tag{14}$$

$$M y_j \geq \sum_{d\in T} z_{jd} \quad \forall j \in J, \tag{15}$$

$$z_{jd} \leq z_{jd+1} \quad \forall j \in J, d \in T. \tag{16}$$

Constraint (13) ensures that they can be stored in a TDWMS j only when it is opened in a given day. The amount of waste stored at the end of the day cannot exceed its capacity. Big M is a constant, denoting the capacity of TDWMS j. Constraints (14) and (15) guarantee that a TDWMS can only be open if it is selected. Here, big M is the maximum waste clean-up duration. Constraint (16) ensures that TDWMSs should open everyday during the clean-up to make sure resources are used reasonably.

Subtour elimination constraints

$$\tau_i \geq \sum_{d \in T} \sum_{k \in K} x_{0idk1} \quad \forall i \in C, \tag{17}$$

$$\tau_i \leq \tau_j - \sum_{d \in T} \sum_{k \in K} \sum_{s \in S} x_{ijdks} + M(1 - \sum_{d \in T} \sum_{k \in K} \sum_{s \in S} x_{ijdks}) \quad \forall i \in C, j \in C. \tag{18}$$

Constraints (17) and (18) are used to eliminate sub-tours, which make sure a vehicle will only visit the next customer node when there is enough time. In Constraint (18), big M is the last time step of a day.

4.3. *Full problem modelling*

The model presented in the previous section captures the core features of the problem but does not include the second echelon. A full model of the problem is presented in Appendix.

5. Solution algorithm

We propose a GA to solve the two echelon problem formulated in the previous section. The main idea is to heuristically divide the decisions in this algorithm, in order to reduce the search space. This is achieved by setting up a chromosome encoding only the location decisions, i.e. the encoding vector has one binary slot for each TDWMS candidate site. This partial solution is completed heuristically and the obtained solution cost is used to estimate the individual fitness value. In the following, we describe the main algorithmic decisions associated with the GA in Section 4.2, and we discuss on the fitness evaluation procedure. In all algorithms presented, the notations are listed below.

n: number of generations,
m: number of individuals in each generation,
l: number of genes in an individual,
α: crossover rate,
β: mutation rate,
b: maximum cost can be used for the TDWMSs establishment,
c^M: maximum cost that can be used for the whole clean-up,
C: set of customer nodes,
J: set of TDWMSs candidates,
F: set of final disposal sites,
T^w: working hours a vehicle can provide a day,
K_1: set of collection vehicles,
K_2: set of transportation vehicles,
Q_1: capacity of collection vehicles,
Q_2: capacity of transportation vehicles,
r: recycling rate of the waste,
T_1^l: load time of collection vehicles,
T_1^{ul}: unload time of collection vehicles,
T_2^l: load time of transportation vehicles,

T_2^{ul}: unload time of transportation vehicles,
c: set of arc cost,
o: set of TDWMSs establishment cost,
p: set of TDWMSs operation cost,
q: set of TDWMSs capacity,
d: set of customer nodes demand,
D: set of arc distance,
σ: amount of waste stored in final disposal sites.

5.1. GA specialisation and parameters

The main routine used in our approach is presented in Algorithm 1, which receives the following input parameters:

$$geneticInput = \{n, m, l, \alpha, \beta, b, c^M, C, J, F, T^w, K_1, K_2, Q_1, Q_2, CT, r, T_1^l, T_1^{ul}, T_2^l, T_2^{ul}, c, o, p, q, d, D\}$$

In a nutshell, the method creates an initial random solution (line 1) and runs the main loop for the desired number of iterations (lines 3–49). In each iteration, individuals are evaluated that includes a call to the Greedy fitness estimator (lines 4–12) and they go through an elitist survival procedure (lines 13–16). Standard GA procedures are then applied to the population. Then, the individuals are subject to a roulette wheel selection (lines 17–29). Selected individuals then go (with probability α) through a one point crossover (lines 30–37). Each individual then goes (with a probability β) through a mutation stage, in which the status of one single gene is changed (lines 38–48). Finally, the best solution returns to the user when all iterations are completed (lines 50–52).

5.2. Fitness evaluator

In the GA described by Algorithm 1, individuals are evaluated in an approximative fashion in order to save computational time. This evaluation is described in Algorithm 2, which receives inputs from the main routine as the following parameters:

$$greedyInput = \{C, J, F, T^w, K_1, K_2, Q_1, Q_2, r, T_1^l, T_1^{ul}, T_2^l, T_2^{ul}, c, d, D, o, p, q\}$$

The evaluation algorithm first initialises its parameters according to the solution being assessed (lines 1–4). The idea of the procedure is to complete the solution given by the selected TDWMSs by finding collection (first echelon) and transportation (second echelon) routes for each day in the planning horizon.

The while loop in lines 5–16 is the core of the method and remains being executed while there are still customer nodes to be visited. When the loop is visited, a new day is added to the waste clean-up solution (line 6). For each given day, the available vehicles leave the depot and visit a series of customers and TDWMSs. The decisions on which customers should be visited by each vehicle and the order on which these visits should occur are taken within the CreateRoute call in line 13. The decisions on the second echelon routes are taken within the Stage2 call in line 15. The last call is also repeated after the collection ends and

Algorithm 1: Genetic Algorithm

input: geneticInput
$P_0 = m$ *individual randomly generated* (Each gene has 50% probability of getting set at 0);
$k = 0$;
while $k \leq n$ **do**
 (Evaluate);
 for $i \in P_k$ **do**
  $J = \{gene \in i \mid gene == 1\}$;
  if $\sum_{j \in J} o_j \leq b$ **then**
   $fitness_i = c^M - Greedy(greedyInput)$;
  else
   $fitness_i = 0$;
  end
 end
 (Select individual for next generation);
 $P_k\ =\ rank(P_k)$ *from largest to smallest according to fitness*;
 $k = k + 1$;
 $P_k\ =\ P_{k-1}(1:m)$;
 (calculate the selection rate for each individual in the population for the wheel selection);
 $sumFitness = \sum_{i=1}^{m} fitness_i$;
 $accumulateProb = 0$;
 for $i = 1 : m$ **do**
  $selectionProb_i = accumulateProb + fitness_i / sumFitness$;
  $accumulateProb = selectionProb_i$;
 end
 for $i = 1 : m/2$ **do**
  (Selection);
  for $j = 1 : 2$ **do**
   $r = rand(0, 1)$;
   $individual_j = \{i \in P_k | selectionProb_{i-1} < r \leq selectionProb_i\}$
  end
  (Crossover);
  $r_c = rand(0, 1)$;
  if $r_c \leq \alpha$ **then**
   $r_{pc} = rand(1, l)$ (l is number of genes in an individual);
   $temp_1 = concat(individual_1(1 : r_{pc});\ individual_2(r_{pc} - 1 : l))$;
   $temp_2 = concat(individual_2(1 : r_{pc});\ temp(r_{pc} - 1 : l))$;
   $P_k = [P_k;\ temp_1;\ temp_2]$;
  end
  (Mutation);
  $r_m = rand(0, 1)$;
  if $r_m \leq \beta$ **then**
   $r_{pm} = rand(1, l)$;
   for $j = 1 : 2$ **do**
    $temp_j = individual_j$;
    $temp_j(r_{pm}) = |temp_j(r_{pm}) - 1|$;
    $P_k = [P_k;\ temp_j]$;
   end
  end
 end
end
$bestIndividual = argmax\{fitness_i | i \in P_k\}$;
$J = \{gene \in bestIndividual \mid gene == 1\}$;
return $Greedy(greedyInput)$

Algorithm 2: Greedy

input: $C, J, F, T^w, K_1, K_2, Q_1, Q_2, r, T_1^l, T_1^{ul}, T_2^l, T_2^{ul}, c, o, p, q, d, D$

1 $C' = C$ *(assign all the customer nodes to C′)*;

2 $\sigma_j = \{0 \mid j \in J\}$;

3 $day = 0$;

4 $totalCost = 0$;

5 **while** $C' \neq \emptyset$ **do**

6     $day = day + 1$ *(start a new day)*;

7     $V_1 = K_1$;

8     $TDWMScapacity_j = \{q_j - \sigma_j \mid j \in J\}$;

9     $availableStorage =$ TRUE;

10   **while** $V_1 \neq \emptyset$ AND $availableStorage$ **do**

11         $k = k \in V_1$ *(choose any vehicle from the set of available vehicles)*;

12         $V_1 = V_1 - \{k\}$;

13         $availableStorage =$ CreateRoute($C', k, Q_1, T^w, T_1^l, \sigma, D, d, q, totalCost$);

14   **end**

15   Stage2($\sigma, J, F, K_2, T^w, T_2^l, T_2^{ul}, r, Q_2, c, totalCost$);

16 **end**

17 **while** $\sigma \neq \emptyset$ **do**

18   day=day+1;

19   Stage2($\sigma, J, F, K_2, T^w, T_2^l, T_2^{ul}, r, Q_2, c, totalCost$;

20 **end**

21 $period = day$;

22 $totalCost = totalCost + \sum_{j \in J} o_j + period \sum_{j \in J} p_j$;

23 **return** $totalCost$

while there is waste being processed in the TDWMSs (lines 17–20). The CreateRoute and the Stage2 routines are described in Algorithms 3 and 4, respectively.

Algorithm 3 decides in a route for a vehicle in the first echelon. After the parameters such as capacity and route time are initialised (lines 1–5), the main loop is repeated while the route duration has not been violated (lines 6–50). In lines 7–18, the nearest neighbour algorithm is implemented to decide on the first section of the collection route. The algorithm leaves this loop when there is no customer can be visited either because the capacity of the vehicle or the route duration limit has been violated. In lines 20–49, the algorithm decides on a TDWMS to visit. All TDWMSs with enough capacity are considered (line 20). If no TDWMS has enough capacity, no route is generated (line 48). Otherwise, a TDWMS is selected to empty the current vehicle (lines 22–46). In detail, the algorithm computes the route time length (lines 22–25). If it violates the maximum route length duration, the last visited node is removed iteratively until the constraint is respected. Then, in lines 39–46, the node demands, TDWMSs capacities and current position of the vehicle are updated.

Algorithm 4, in turn, takes decisions on the second echelon routes. The available vehicles, waste to be collected in the TDWMSs and the set of TDWMSs are initialised in lines

Algorithm 3: CreateRoute

input: $C', k, J, Q, T^w, T^l, T^{ul}, \sigma, d, D, q, totalCost$

$enoughTime$ =TRUE;
$time = 0$;
$r = 0$ *(r is the last visited node which starts from the depot '0');*
$route_k = r$;
$currentLoad = 0$;
while $enoughTime$ **do**
    while $Q - currentLoad > 0$ AND $time < T^w$ **do**
        $candidateC' = \{i \in C' | d_i \leq capacity - currentLoad\}$;
        if $candidateC' \neq \emptyset$ **then**
            $i = argmin\{D_{ri} | i \in candidateC'\}$;
            $time = time + t_{ri} + T^l$;
            if $time < T^w$ **then**
                $currentLoad = currentLoad + d_i$;
                $r = i$;
                $route_k = (route_k, r)$;
            end
        end
    end
    (J' is the set of all TDWMSs with enough capacity to receive the waste carried by the current loaded vehicle);
    $J\prime = \{j \in J | \tau_j + currentLoad \leq q_j\}$;
    if $J\prime \neq \emptyset$ **then**
        $position = length(route_k)$;
        $r_1 = route_k[position]$;
        $j_1 = argmin\{D_{r_1 j} | j \in TDWMSavailable\}$;
        $time = time + t_{r_1 j_1} + T^{ul} + t_{j_1 0}$;
        if $time > T^w$ **then**
            $enoughTime$ = FALSE;
            while $time > T^w$ **do**
                $currentLoad = currentLoad - d_{r_1}$;
                $J\prime = \{j \in J | \sigma_j + currentLoad \leq q_j\}$;
                $position = position - 1$;
                $r_2 = route_k[position]$;
                $j_2 = argmin\{D_{r_2 j} | j \in J\prime\}$;
                $time = time - t_{r_1 r_2} - t_{r_1 j_1} - t_{j_1 0} + t_{r_2 j_2} + t_{j_2 0}$;
                $r_1 = r_2$;
                $j_1 = j_2$;
            end
        end
        $route_k = route_k[1 : position]$;
        $d_i = \{0 \mid i \in route_k\}$;
        $totalCost = totalCost + \sum_{(i,j) \in route_k} cost_{ij}$;
        $C' = C' - route_k$;
        $j = j_1$;
        $r = j$;
        $\sigma_j = \sigma_j + currentLoad$;
        $currentLoad = 0$;
    else
        return FALSE;
    end
end
return TRUE;

Algorithm 4: Stage2

input: $\sigma, J, F, K_2, T^w, T_2^l, T_2^{ul}, r, Q_2, c, totalCost$

$V_2 = K_2$;
$TDWMSdemand = \{\sigma_j(1 - r) \mid j \in J\}$;
$J\prime = J$;
$J\prime = \{j \in J | TDWMSdemand_j \geq Q_2\}$;
while $F \neq \emptyset$ AND $V_2 \neq \emptyset$ **do**
    $k = k \in V_2$ *(choose any vehicle from the set of available vehicles)*;
    $V_2 = V_2 - \{k\}$;
    $time = 0$;
    $r = 0$;
    $enoughTime$ =TRUE;
    while $enoughTime$ AND $F \neq \emptyset$ **do**
        $j = argmax\{TDWMSdemand_j | j \in J\prime\}$;
        $F = argmin\{D_{jf} | f \in F\}$;
        $time = time + t_{rj} + T_2^l + t_{jf} + T_2^{ul}$;
        $enoughTime = time \leq T^w$;
        if $enoughTime$ **then**
            $TDWMSdemand_j = TDWMSdemand_j - Q_2$;
            $totalCost = totalCost + c_{rj} + c_{jf}$;
            $r = f$;;
            $J\prime = \{j \in J | TDWMSdemand_j \geq Q_2\}$
        end
    end
end
$J\prime = J$;
while $F \neq \emptyset$ AND $V_2 \neq \emptyset$ **do**
    $k = k \in V_2$ *(choose any vehicle from the set of available vehicles)*;
    $V_2 = V_2 - \{k\}$;
    $J\prime = \{j \in J | TDWMSdemand_j > 0\}$;
    (F is the set of TDWMS with waste to be collected);
    (we assue that the final disposal sites always have enough space for all the waste, thus we always set the capacity of them to the total waste stored in TDWMSs and the storgae in the final facilities to 0);
    $Lstorage = \{0 | f \in F\}$;
    CreateRoute($J, k, F, Q_2, T^w, T_2^l, Lstorage, TDWMSdemand, D, \sum_{j \in J\prime} TDWMSdemand_j, totalCost$);
end
$\sigma = TDWMSdemand$;

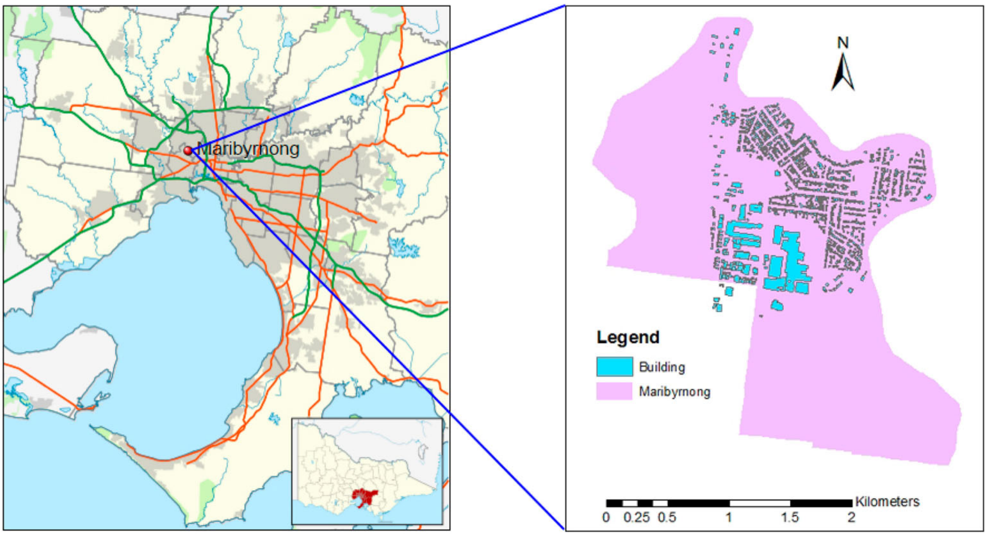

Figure 2. The location of the study area.

1–3, respectively. The rest of the algorithm decides on the routes between the TDWMSs and the final disposal sites. First, in lines 5–23, the vehicles are used to perform routes back and forth from the TDWMSs to the final disposal sites. When the waste stored at the TDWMSs becomes smaller than a full truck load, a routing approach similar to the one presented above is effected, treating the TDWMSs as customer nodes and the landfill as the final destination and calling the previous routing algorithm CreateRoute (line 31).

The approach described above can be easily changed to minimise the waste clean-up duration. In this case, the greedy algorithm described in Algorithms 2–4 is asked to return the number of periods needed as fitness value, instead of the cost. Clearly, a combination of objectives can also be easily implemented.

6. Empirical evaluation

To approximate realistic disaster waste clean-up instances, the study collected data covering Maribyrnong, which is a Melbourne suburb about 8 km northwest of the city's Central Business District as shown in Figure 2. Maribyrnong had a population of 10,165 in the 2011 Census. The area is bounded by the river that gives name to the suburb, being a flood hazard zone. Historically, this area experienced major floods in the years of 1906, 1916, 1974, 1983, 1987, 1993, 2000, 2005, and 2011. As an example, the flood of May 1974 resulted in an inundation of 4.2 m, which impacted on 3.85 km^2 of urbanised land and resulted in damage to 370 houses and businesses (SES 2018).

Although a significant number of floods have occurred in the study area, there are limited data related to post-flood waste management. In the following, we explain the rationale behind the procedures: (i) customer nodes locations and demands, (ii) TDWMSs candidate sites and capacities, (iii) final disposal sites locations, and (vi) vehicles quantities and capacities.

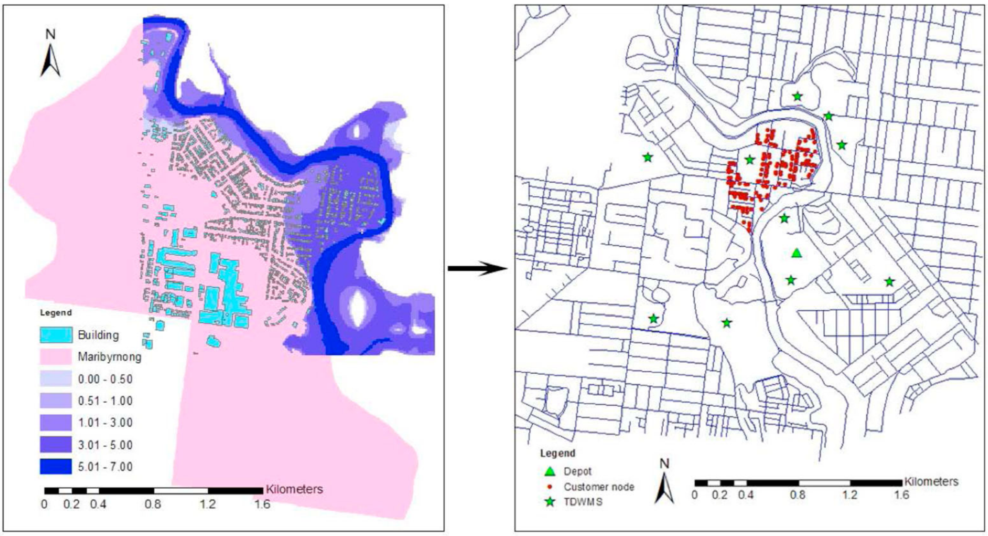

Figure 3. Inundation map and derived graph of the case study area.

Colour online, B/W in print

6.1. Main assumptions

Customer nodes: To generate customer node locations and demands, we used the MIKE21 model (Warren and Bach 1992) to simulate a flood and estimate the water depth in the affected area. Figure 3 depicts the inundation map of the study area, which contains 165 affected buildings. To simulate the waste demand in each building, we used formulas provided in Hirayama et al. (2010), which assume that 0.62 tons and 4.6 tons of waste are generated per household if the flood does not reach or reaches the floor level, respectively. These estimates are expected to have a 30% error (FEMA 2007).

TDWMSs candidate sites: According to FEMA (2007), existing disposal or recycling facilities close to the disaster affected area are ideal locations for TDWMSs. Other sites, such as parks, vacant lots, and sports fields are also feasible candidates. Using this criteria, 10 candidates of the TDWMSs were identified using the land suitability assessment method (Cheng and Thompson 2016). The capacity of each candidate was estimated by measuring the size of each site in ArcGIS 10.2.

Final disposal sites location: We used as landifill location, the position of the largest existing Melbourne landfill site.

Vehicles quantities and capacities: We assume two sets of vehicles. The first set, with smaller capacities, is used in the first echelon while the second set is used in the second echelon.

6.2. Base case study data

The base case study uses the simulated data which affected 165 buildings. Therefore, we consider the case with 165 customer nodes. The actual demand at each node is a random value obtained with the expression:

$$d_i = rand[0.7a,\ 1.3a],\ \forall i \in C \tag{19}$$

Table 5. Data related to candidate TDWMSs.

No.	Location	Total capacity (tonnes)	Capacity each day (tonnes)	Fixed cost/AUD
166	Maribyrnong Park	80	40	4000
167	Fairbairn Park	100	50	5000
168	Walter St. Reserve	120	60	6000
169	Public land	60	30	3000
170	Pipemakers Park	160	80	8000
171	Robert Barret Reserve	80	40	4000
172	Maribyrnong Reserve	160	80	8000
173	Aborfeldie Park	120	60	6000
174	Moonee Valley Transfer Station	100	50	5000
175	Fairbain Reserve	120	60	6000

in which a is the estimated waste generated (Hirayama et al. 2010) and a 30% relative error is considered.

As for the candidates of TDMWSs, they were obtained by visual inspection of the area map and are listed in Table 5, which contains the site location, the total estimated capacity (based on the site area), the daily processing capacity, and the installation costs. The processing capacity was estimated as half of the total capacity in each site. In terms of the cost of a candidate TDWMS, the fixed costs considered corresponded to land preparation and recovery costs, estimated at 20 AUD/m^2. The operation cost is assumed to be 500 AUD/day since the major cost in operating TDWMSs is the labour cost, which is not highly impacted by the capacity of TDWMSs in our case. However, if it considers more complex operations in TDWMSs that require expensive machines (e.g. compression), then the operation cost may depend on the capacity of TDWMSs. Figure 3 shows all the nodes considered in this study.

The network structure is obtained in ArcGIS 10.2 using road network data obtained from Vicroads (the statutory road and traffic authority in the State of Victoria, Australia). Collection variable costs are assumed to be 10 AUD/km and include drivers' salary and fuel consumption (Bumpus 2007). Finally, in the instances generated we considered two sets of trucks: 5 smaller trucks with capacities of 20 tons for the collection routes in the first echelon and 2 larger vehicles with capacities of 30 tons for the second echelon.

6.3. Artificial instances

In this section, two groups of instances are generated using the same rationale as the one explained above to address the following problems: (i) comparing the performance of developed heuristics algorithm proposed in Section 5 and the simplified MIP model developed in Section 3; and (ii) testing the robustness of the algorithm for the full problem and making decisions of algorithmic parameters for the case study.

First echelon instances: The first group contains data only for the first echelon and has seven instances. One of these instances has the original 165 customer nodes. For the remaining six instances, only part of the nodes of this original instance are considered. For the first of these partial instances, the first 10 nodes are considered. The second partial instance contains the first 20 nodes, and so on.

Complete instances: The second group of instances contains data for the complete problem. These instances have the same dimensions (1 depot, 165 customers, 10 TDWMSs candidates, and 1 final disposal site) as the original case study. Nevertheless, we randomly generate node locations in a 2.5 km by 2.5 km square.

Table 6. Results of mixed integer model and heuristics algorithms.

		Solver (Gurobi)			Heuristics		
Instance	Number of customer nodes	Obj	Solver Gap	CPU	Obj	Gap	CPU (s)
1	10	4864.7	0%	5 min	5067.4	4.00%	8.34
2	20	6987.7	13.40%	30 min	7128.7	1.98%	16.20
3	30	8901.4	14.50%	72 min	8425.7	−5.65%	23.53
4	40	10,169.5	15.60%	7 h	9796.5	−3.81%	30.52
5	50	12,070.5	14.80%	20 h	10,880.0	−10.94%	38.21
6	60	13,590.9	16.70%	38 h	11,981.0	−13.44%	54.05
7	165	NA	NA	48 h	20,125.0	NA	127.03

7. Computational results

Three experiments have been conducted to evaluate the performance of both the MIP model developed for the first echelon and of the GA presented for the complete problem. The first two experiments investigate the capability of the developed algorithms to obtain feasible solutions in a reasonable amount of time. The third experiment analyses the characteristics of the solution obtained for the case study in terms of the applicability and robustness.

7.1. Solution algorithms comparison for the simplified model (first echelon)

The GA was developed in MATLAB 2016b and Table 6 presents the computational performance in the Gurobi 6.5 solver with an operational system having an Intel Core I7-47700 @ 3.40HZ with 16GB RAM. The stopping criteria is a gap smaller than 20% for the Gurobi solver and 40 generations for the GA (with a population size of 20 individuals). Both algorithms were used to solve the seven first echelon instances described above, and the objective is to minimise the total cost. In the table, *CPU* is the computational time of the algorithms. The *Solver Gap* is the gap we get from the Gurobi solver versus the *Gap* of GA means the difference between the result obtained from GA and the solver.

It shows that, for Gurobi, *CPU* has a significant and non-linear growth with the increase of the number of the customer nodes, suggesting that this solution may be inapplicable and unpredictable if the size of the problem is remarkably large. In comparison, our developed GA has a much better performance in the same condition, resulting in a mild and almost linear growth. Notably, it only costs around 2 min even for the largest instance, having a compelling advantage when the solver has already spent 48 h but cannot find even a feasible solution for the first echelon of the problem. This means that our approach has achieved a significant improvement in computational complexity. In the other perspective, the optimal solution obtained from the GA is also better than the solver.

7.2. Complete instances

Each complete instance is solved 10 times for three different sets of algorithmic parameters (namely, population size and number of generations) (Table 7). In the table, the *Gap* is computed with respect to the best known solution value (i.e. the best result out of the 30 times repetitions of the algorithm), while *CPU* is the time required to solve the problem. The results suggest that the algorithms are robust because they have obtained similar and

Table 7. Results of artificial instances.

	Population size = 20, generation = 40		Population size = 40, generation = 20		Population size 100, generation = 80	
Instance	Aveg. Gap	Aveg. CPU (s)	Aveg. Gap	Aveg. CPU (s)	Aveg. Gap	Aveg. CPU (s)
1	0.57% ± 1.34%	104.39 ± 2.65	0.41% ± 1.31%	106.19 ± 1.78	0.54% ± 1.27%	100.53 ± 1.86
2	0.23% ± 0.71%	102.19 ± 2.00	0.02% ± 0.02%	104.02 ± 1.62	0.01% ± 0.02%	101.79 ± 1.82
3	0.32% ± 0.52%	100.37 ± 1.49	0.48% ± 0.80%	104.23 ± 2.42	0.19% ± 0.61%	98.24 ± 1.59
4	0.24% ± 0.66%	100.23 ± 1.27	0.29% ± 0.68%	104.89 ± 2.05	0.52% ± 1.64%	99.51 ± 1.69
5	0.56% ± 1.31%	104.26 ± 0.89	0.72% ± 1.33%	105.65 ± 0.83	0.80% ± 1.69%	103.44 ± 1.89
6	0.35% ± 0.57%	100.29 ± 0.81	0.47% ± 0.61%	107.21 ± 2.19	0.32% ± 0.70%	102.38 ± 3.14
7	0.48% ± 0.84%	95.71 ± 1.32	0.43% ± 0.66%	99.11 ± 0.61	0.35% ± 0.66%	97.68 ± 3.11
8	0.08% ± 0.27%	108.01 ± 1.86	0.44% ± 1.12%	110.51 ± 1.64	0.52% ± 1.37%	101.12 ± 1.96
9	0.10% ± 0.22%	108.92 ± 3.64	0.16% ± 0.25%	109.01 ± 2.06	0.40% ± 0.39%	105.33 ± 2.00
10	0.10% ± 0.17%	102.07 ± 2.20	0.33% ± 0.70%	107.02 ± 2.95	0.03% ± 0.11%	99.51 ± 1.35
Average	0.30% ± 0.76%	102.64 ± 1.20	0.37% ± 0.83	105.78 ± 3.50	0.37% ± 4.01%	100.95 ± 3.03

Table 8. Results of three different objective functions.

Scenarios	Scenario 1 (min total cost)	Scenario 2 (min total period)	Scenario 3 (min total distance)
Total time	10	4	5
TDWMS operation cost (AUD)	5000	12,000	10,000
TDWMS selected	[0,0,0,0,0,0,1,0,0,0]	[0,0,1,1,1,1,0,1,1,0]	[0,0,0,1,1,0,1,0,0,1]
TDWMS fixed cost (AUD)	8000	32,000	25,000
Total travel distance (m)	1,403,859	1,389,536	1,335,538
Travel cost (AUD)	14,038.59	13,895.36	13,355.38
Total cost (AUD)	27,038.59	57,895.36	48,355.38

acceptable solutions with small variations. It also shows that the *CPU* is reasonably short for a MP2ELPR, which *CPU* is comparable to simpler versions of the 2E-LRP (Prodhon and Prins 2014).

7.3. Case study results and analysis

In these experiments, we analyse different system configurations that were obtained by changing the objective function. The full case study is used and three different objectives are considered: (i) cost minimisation, (ii) clean-up duration minimisation, and (iii) travel distance minimisation.

Table 8 presents the main characteristics of the solutions obtained in these three simulations. As expected, given the very different nature of the objectives, the solutions are also very different structurally. When cost is minimised, a single TDWMS is open since the TDWMS is responsible for a large percentage of the clean-up expenses. When clean-up duration is minimised, the system then heavily relies on the TDWMSs to increase the time efficiency of the solution. Finally, some trade-off solution is obtained when route distance is the focus of the minimisation.

We also use the case study data to analyse the effectiveness of the TDWMSs in improving operational efficiency. The Greedy Algorithm proposed earlier is modified to obtain a solution that does not use TDWMSs. This solution is compared to the solution obtained with these intermediate facilities. Table 9 shows a side-by-side comparison of the main characteristics of the two solutions, by minimising the total cost including the disposal cost and

Table 9. Results comparison of the two systems.

	System 1 (no TDWMS)	System 2 (with TDWMSs)	Difference (System 2 – System 1)
Clean-up time at first echelon(days)	6	5	−1
Total clean-up period (days)	6	6	0
Total travel distance (m)	3,197,869	1,524,798	−1,673,071
Waste disposal cost (AUD)	20,277.10	14,193.97	−6083.13
Recycling revenue	0	5886.9	5886.9
Waste travel cost (AUD)	31,978.69	15,247.98	−16,730.71
TDWMS fixed cost (AUD)	0	15,000 ([1,0,0,1,0,0,1,0,0,0])	15,000
TDWMS operation cost (AUD)	0	9000	9000
Total cost (AUD)	52,255.79	47,555.05	−4700.74

Table 10. Experimental factors.

CV Number-TV Number	CV Capacity-TV Capacity (tonnes)
3–3	10–20
4–2	10–30
5–1	20–20
5–2	20–30
	30–30

the waste recycling revenue. It is clear that the system with TDWMSs can operate faster and at lower costs than its counterpart that does not use this type of facility.

The last set of experiments analyses the sensitivity of the solutions to various input parameters such as the TDWMSs capacities, and the number and distribution of vehicles. To investigate the impacts of the total capacity of TDWMSs, we consider the solutions in the first scenario (cost minimisation) in Table 8. In that solution, a single TDWMS is selected. We analyse the impact of varying the capacity of TDWMSs from 50 to 250 tonnes (in increments of 50 tones). We also consider different combinations of collection vehicles (CV) and transportation vehicles (TV) numbers and capacities (Table 10).

Figures 4–6 demonstrate the results of this analysis. In all figures, the *x*-axis shows the parameter combination in the form of a *X*-*Y*-*W*-*Z*, in which *X* is the number of CV, *Y* is the number of TV, *W* is the capacity of a CV and *Z* is the capacity of a TV. Figure 4 analyses the total travel distances for different combinations of the parameters. It indicates that the total travel distances can generally be reduced by increasing TDWMSs or vehicle capacities. In Figure 5, the same analysis is made when considering the total clean-up duration as the metric. For the parameters in these simulations, the TDWMSs capacities are the most important factor. Ultimately, Figure 6 replicates the experiment with the total cost as the objective function. In the last case, as for the total cost, TDWMSs capacities play an important role and the solutions are also sensitive to the size and quantity of the vehicles. Particularly, the heuristic nature of the algorithms might also play a role in the obtained results.

8. Implication, analysis and discussion

According to the results we obtained from the artificial instances, the MIP model we developed is feasible to solve the multi-period two-echelon location routing problem proposed for small disaster waste clean-up which have not been addressed in the literature. Furthermore, the developed heuristics algorithm is efficient and robust to solve large

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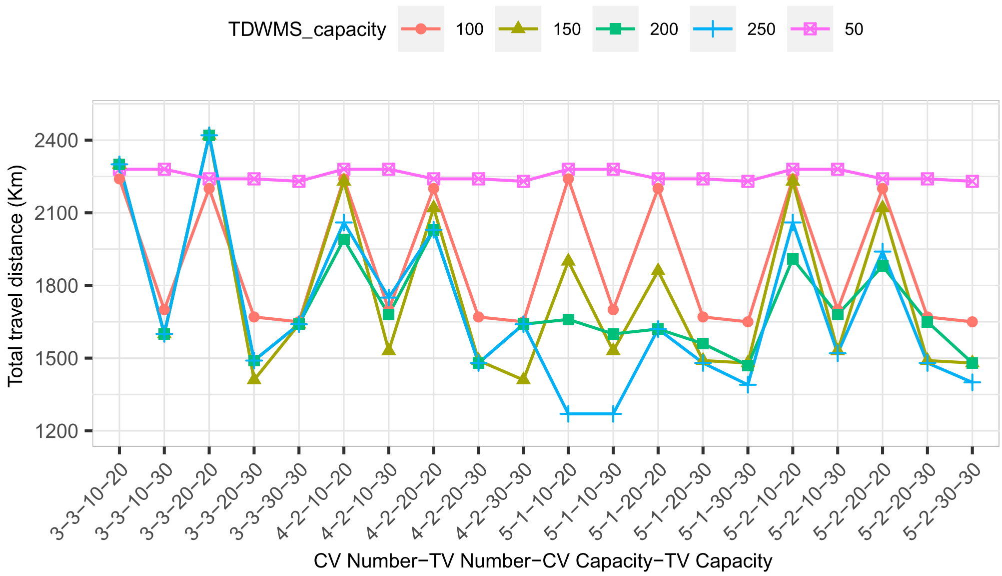

Figure 4. Impact of vehicle number, vehicle capacity and TDWMSs capacity on total travel distance.

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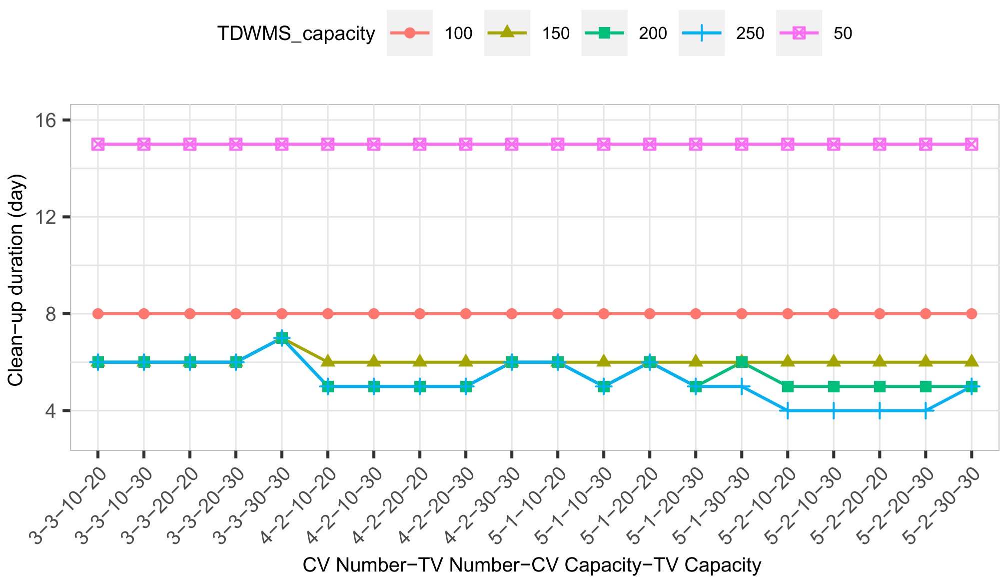

Figure 5. Impact of vehicle number, vehicle capacity and TDWMSs capacity on clean-up duration.

scale problems. Moreover, the developed algorithm can be flexibly modified for the waste clean-up system without TDWMSs.

The optimisation results considering different objectives in the case study area indicates that total waste clean-up cost and duration cannot be achieved at the same time. If the decision-makers want to clean the waste generated after disasters as soon as possible, more TDWMSs are needed. If the main objective of decision-makers is to minimise the total cost,

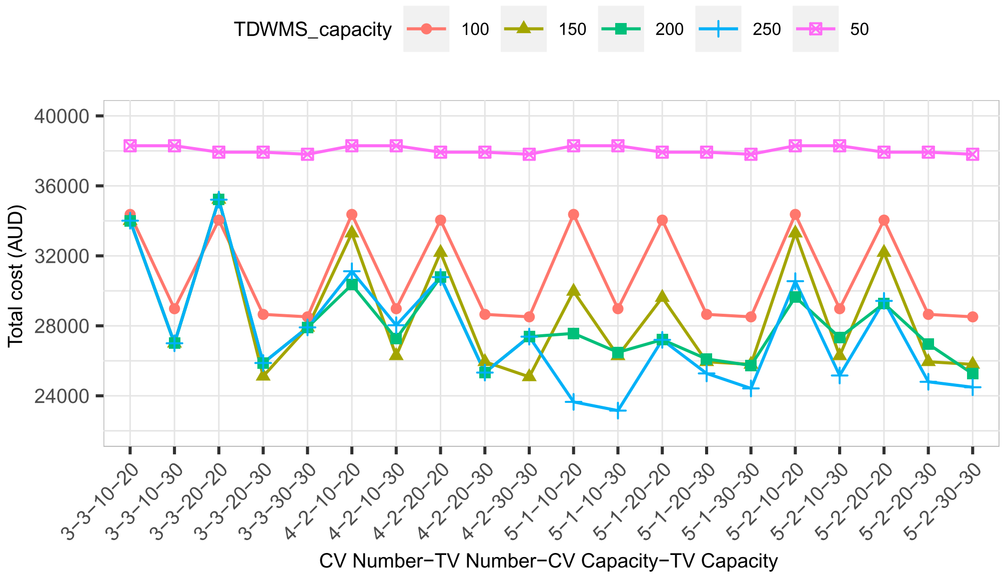

Figure 6. Impact of vehicle numbers, vehicle capacities and capacity of TDWMSs on total cost.

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they need to accept a longer waste clean-up duration. The obtained optimisation results can help decision-makers to make a balanced decision between the total clean-up time and duration. The comparison between waste clean-up system with and without TDWMSs confirmed that a disaster waste clean-up system considering TDWMSs can achieve both lower cost and shorter waste clean-up duration. The finding is in line with FEMA (2007), in which the authors claimed that TDWMSs is can make the disaster waste management system more efficient.

The results of the sensitivity analysis indicate the importance of TDWMSs capacity, which can affect both total travel distance, and total waste clean-up duration and cost. The capacity of vehicles only has an impact on total travel distance and total cost. Thus, the decision-makers can choose to improve the capacity of TDWMSs or vehicles based on their main goal of the post-disaster waste clean-up.

9. Conclusions

This paper investigates post-disaster waste clean-up operations, which can be seen as a multi-period two-echelon location routing problem. Our main objective is to analyse the effect of storage and processing facilities known as Temporary Disaster Waste Management Sites (TDWMSs). The use of these facilities gives origin to the two-echelon structure. In the first echelon, waste is collected from the demand locations and taken to the TDWMSs while, in the second echelon, waste is transferred from the TDWMSs to the final disposal sites.

We propose a mixed integer program to model the problem to determine where to locate the TDWMSs and the collection and transportation routes in the first and second echelon, respectively. The main innovation of the model is the use of original constraints that allow routes to contain cycles in the first echelon. These cycles are reasonable since trucks can revisit the TDWMSs multiple times on the same day without going back to the depot.

The model presented also accounts for TDWMSs capacities and waste inventory management. The model is able to solve small to mid-sized instances of the first echelon of the problem. These solutions are used to validate the performance of a GA that has been developed in our study. The heuristic algorithms are applied to instances derived from a case study. The data of the case study is generated to estimate demand locations and amounts as well as TDWMSs locations and capacities, according to strategies that have been proposed in the literature. Results obtained from different instances also indicated the robustness of the algorithm with respect to different parametric choices such as the population size.

From a more practical point of view, the analysis of the obtained solutions confirms that TDWMSs can help to reduce operational cost and waste clean-up duration. Moreover, we observe that operations can be highly sensitive to TDWMSs capacities and to the number and capacities of vehicles. The main contributions of this study are: (i) we developed a MIP model and heuristic algorithm to solve the complex MP2ELRP for waste management, and the test suggests that they are efficient, flexible and robust; (ii) we conducted a case study to confirm that the use of TDWMSs is more efficient in disaster waste management; and (iii) we designed scenarios analysis and sensitivity analysis to help decision-makers to propose an optimised waste clean-up plan.

Future work will investigate alternative algorithmic methods for solving this problem, possibly with proof of optimally. One possibility is to use decomposition methods to decouple the two echelons and communicating via the information on the quantity of waste at each TDWMS at the end of each day.

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Appendix

To model the problem, two graphs G_1 and G_2 are defined. The first one is a graph $G_1 = (N_1, E_1)$, defined as follows. A depot 0, a set of customers nodes $C = \{1, 2, \dots, n\}$ and a set of candidate TDWMSs $J = \{n+1, n+2, \dots, n+m\}$ are identified as the nodes of the graph: $N_1 = \{0\} \cup C \cup J$, edges E_1 is the set of arcs (i, j), $\forall i, j \in N_1$. The second graph $G_2 = (N_2, E_2)$ is defined as follows. A depot 0, a set of candidates TDWMSs $J = \{n+1, n+2, \dots, n+m\}$, and the sets of final disposal sites $F = \{n+m+1, n+m+2, \dots, n+m+f\}$ are identified as the vertices of the graph G_2. So that $N_2 = \{0\} \cup J \cup F$, edges E_2 is the set of arcs (i, j), $\forall i, j \in N_2$. In addition, $N = N_1 \cup N_2$, $E = E_1 \cup E_2$. The following symbols are defined for the model: Parameters:

K : set of all vehicles,
$K1$: set of collection vehicles,
Q_1 : capacity of collection vehicles (unit: tonnes),
$[S_1, L_1]$: start time and end time of collection vehicles (unit: min),
$K2$: set of transportation vehicles,
Q_2 : capacity of transportation vehicles (unit:tonnes),
$[S_2, L_2]$: start time and end time of transportation vehicles (unit: min),
d_i : demand associated with node $i \in C$,
b : budget for total TDWMSs establishment (unit: AUD),
q_j : capacity of TDWMS j, $j \in J$ (unit: tonnes),
t_{ij} : travel time of arc (i, j), $(i, j) \in E$ (unit: tonnes),
γ_i : operating time in node i, $i \in \overline{N}$ (unit: min),
c_{ij} : cost associated with the traversal of arc (i, j),
p_j : daily operation cost of facility $j \in J$,
o_j : fixed cost of TDWMS j, $j \in J$ (unit: AUD),
r : recycling rate (unit: %),
T : set of clean-up periods that can be used.

Variables:

x_{ijdk_1} : binary variable equals to 1 if collection vehicle k_1, $(k_1 \in K_1)$ services node, j, $(j \in C)$ from i, $(i \in N_1)$ in day d, $d \in T$, otherwise 0,
α_{ijdk_2} : times of vechile k_2, $(k_2 \in K_2)$ use arc (i, j) in day d, $(d \in T)$,
y_j : binary variable equals to 1 if TDWMS j, $(j \in J)$ is selected and 0 otherwise,

U_{idk_1} : remaining capacity of a collection vehicle k_1, $(k_1 \in K_1)$ just after having served to customer, i, $(i \in C)$ in day $d, d \in T$

σ_{jd} : amount of waste stored in TDWMS j, $(j \in J)$ at the end of the day in day d, $(d \in T)$, $\sigma_{j0} = 0, \forall f,\ f \in F$

W_{jfdk_1} : amount of waste transported from TDWMS j, $(j \in J)$ to final disposal site f, $(f \in F)$ by vehicle k_2, $(k_2 \in K_2)$ in day d, $(d \in T)$

τ_{idk_1} : time when vehicle k, $(k \in K)$ arrives at node i, $(i \in N)$ in day $d, (d \in T)$,

δ_d : binary variable equals to 1 if all the waste has been cleared at the end of day d, $(d \in T)$.

Objectives:

$$\min \sum_{j \in J} p_j y_j (|T| - \sum_{d \in D} \delta_d + 1) + \sum_{j \in J} o_j y_j + \sum_{i,j \in N_1} \sum_{k_1 \in K_1} \sum_{d \in T} c_{ij} x_{ijdk_1} + \sum_{i,j \in N_2} \sum_{k_2 \in K_2} \sum_{d \in T} c_{ij} \alpha_{ijdk_2} \tag{A1}$$

$$\min |T| - \sum_{d \in T} \delta_d + 1 \tag{A2}$$

Subject to:

$$\sum_{j \in J} o_j y_j \leq b, \tag{A3}$$

$$\delta_d \leq \sum_{d'=1}^{d} \sum_{j \in C \cup J} \sum_{k_1 \in K_1} x_{ijd'k_1}, \quad \forall i \in C,\ d \in T, \tag{A4}$$

$$\sum_{d \in T} \sum_{j \in C \cup J} \sum_{k_1 \in K_1} x_{ijdk_1} = 1, \quad \forall i \in C,\ d \in T, \tag{A5}$$

$$\sum_{i \in C} \sum_{k_1 \in K_1} x_{0idk_1} = \sum_{j \in J} \sum_{k_1 \in K_1} x_{j0dk_1} \leq |k_1|, \quad \forall d \in T, \tag{A6}$$

$$\sum_{i \in N_1} x_{ijdk_1} = \sum_{i \in N_1} x_{jidk_1}, \quad \forall j \in N_1,\ d \in T,\ k_1 \in K_1, \tag{A7}$$

$$0 \leq \sum_{i \in C} x_{0idk_1} = \sum_{j \in J} x_{j0dk_1} \leq 1, \quad \forall k_1 \in K_1,\ d \in T, \tag{A8}$$

$$x_{ijdk_1} - y_j \leq 0, \quad \forall i \in C,\ j \in J,\ d \in T,\ k_1 \in K_1, \tag{A9}$$

$$0 \leq U_{idk_1}, \quad \forall i \in C,\ d \in T,\ k_1 \in K_1, \tag{A10}$$

$$x_{ijdk_1}(U_{idk_1} - d_j) \geq 0, \quad \forall i,j \in C,\ i \neq j,\ d \in T,\ k_1 \in K_1, \tag{A11}$$

$$S_1 \leq \tau_{idk_1} \leq L_1, \quad \forall i \in C,\ d \in T,\ k_1 \in K_1, \tag{A12}$$

$$\tau_{idk_1} + t_{ij} + \gamma_j - \tau_{jdk_1} \leq (1 - x_{ijdk_1})M, \quad \forall i,j \in C,\ i \neq j,\ d \in T,\ k_1 \in K_1, \tag{A13}$$

$$\sum_{j \in J} \sum_{k_2 \in K_2} \alpha_{0jdk_2} = \sum_{f \in F} \sum_{k_2 \in K_2} \alpha_{f0dk_2} \leq |K_2|, \quad \forall d \in T, \tag{A14}$$

$$\sum_{i \in N_2} \alpha_{ijdk_2} = \sum_{i \in N_2} \alpha_{jidk_2}, \quad \forall j \in N_2,\ d \in T,\ k_2 \in K_2, \tag{A15}$$

$$0 \leq \sum_{j \in J} \alpha_{0jdv_2} = \sum_{f \in F} \alpha_{f0dk_2} \leq 1, \quad \forall d \in T,\ k_2 \in K_2, \tag{A16}$$

$$\alpha_{jfdk_2} - My_j \leq 0, \quad \forall j \in J,\ f \in F\ d \in T,\ k_2 \in K_2, \tag{A17}$$

$$\tau_{idk_2} + t_{ij} + \gamma_j - \tau_{jdk_2} \leq (1 - \alpha_{ijdk_2})M, \quad \forall i,j \in J \cup F,\ d \in T,\ k_2 \in K_2, \tag{A18}$$

$$S_2 \leq \tau_{idk_2} \leq L_2, \quad \forall i \in J \cup F,\ d \in T,\ k_2 \in K_2, \tag{A19}$$

$$0 \leq \sigma_{jd} \leq q_j y_j, \quad \forall j \in J,\ d \in T, \tag{A20}$$

$$\sigma_{jd} = \sigma_{jd-1} - \sum_{k_2 \in K_2} \sum_{f \in F} W_{jfdk_2} + (1 - r) \sum_{k_1 \in k_1} \sum_{i \in C} x_{ijdk_1} (Q_1 - U_{idk_1}), \quad \forall j \in J,\ d \in T, \tag{A21}$$

$$\sigma_{j|T|} = 0, \quad \forall j \in J, \tag{A22}$$

$$W_{jfdv_2} \leq \alpha_{jfdk_2} Q_2, \quad \forall j \in J,\ f \in F,\ d \in T,\ k_2 \in K_2, \tag{A23}$$

$$\sum_{f \in F} \sum_{k_2 \in K_2} \sum_{d \in T} W_{jfdk_2} = (1 - r) \sum_{k_1 \in K_1} \sum_{i \in C} \sum_{d \in D} x_{ijdk_1} (Q_1 - U_{idk_1}), \quad \forall j \in J. \tag{A24}$$

Equation (A1) is the objective of the upper-level problem which aims to minimise the total cost of waste clean-up. The first term is TDWMSs operation cost and the second term is TDWMSs establishment cost. The last two terms are waste collection and transportation cost respectively. Equation (A2) is another objective which aims to minimise the total clean-up time. Constraint (A3) denotes that the total investment on TDWMSs cannot exceed the budget. Constraints (A4) make sure that δ_d can be 1 only when all the customer nodes have been served. Constraints (A5) are degree constraints to ensure every customer node must be serviced once and only once. Constraints (A6) are to make sure the number of collection vehicles used every day will not exceed the maximum number of available collection vehicles. Constraints (A7) are degree constraints which ensure the continuity of collection vehicle routes. Constraints (A8) ensure that every collection vehicle must leave and go back to the depot no more than once per day. Constraints (A9) ensure that a TDWMS can provide service to collection vehicles only when it is open. Constraints (A10) make sure that load on collection vehicles do not exceed their capacity. Constraints (A11) are non-linear constraints ensure that a vehicle will serve the next customer node only when it has enough capacity for it. Constraints (A12) and (A13) are time windows and subtours elimination constraints for the first stage. Constraints (A14) ensure the number of transportation vehicles used at any given day will not exceed the maximum number. Constraints (A15) are degree constraints which ensure the continuity of second waste transportation vehicle routes. Constraints (A16) make sure a transportation vehicle can not be used more than once per day. Constraints (A17) ensure that a TDWMS can provide service to transportation vehicles only when it is open. Constraints (A18) and (A19) are time windows and subtours elimination constraints for the second stage. Constraints (A20) avoid capacity violations at the TDWMSs. Constraints (A21) calculate the amount of waste stored in a TDWMS at the end of a day. Constraints (A22) ensure all waste will be cleared at the end of the planning period. Constraints (A23) ensure the capacity of transportation vehicles can not be exceeded. Constraints (A24) are waste input-output balance constraints for TDWMSs.