Waste Management 119 (2021) 1–10

Contents lists available at ScienceDirect

Waste Management

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

Optimisation of waste clean-up after large-scale disasters

Cheng Cheng [a,b,c], Rui Zhu [c,*], Alysson M. Costa [d], Russell George Thompson [a,b]

[a] The Department of Infrastructure Engineering, The University of Melbourne, VIC 3010, Australia
[b] Center for Disaster Management and Public Safety, The University of Melbourne, VIC 3010, Australia
[c] Future Urban Mobility IRG, Singapore-MIT Alliance for Research and Technology, 1 CREATE Way, #09-02 CREATE Tower, Singapore 138602, Singapore
[d] School of Mathematics and Statistics, The University of Melbourne, VIC 3010, Australia

A R T I C L E I N F O

Article history:
Received 25 May 2020
Revised 11 September 2020
Accepted 14 September 2020

Keywords:
Disaster waste clean-up
Temporary disaster waste management site
Location selection
Buildings demolition arrangement
Mixed integer programming

A B S T R A C T

Disaster waste clean-up after large disasters is one of the core activities at the recovery stage of disaster management, which aims to restoring the normal functioning of the disaster affected area. In this paper we considered a waste clean-up system consists of (i) demolition operation, (ii) collection of waste from customer nodes to temporary disaster waste management sites (TDWMSs), (iii) processing at TDWMSs, and (iv) transportation of the waste to final disposal sites in the recovery of disasters. A multi-objective *mixed integer programming* model is developed to minimise the total clean-up cost and time. Three different approaches are developed to solve the problem, which are tested with artificial instances and a real case study. Results of artificial instances indicate that the models developed can be used to obtain close to optimal solutions within an acceptable computing time. Results of the case study can facilitate the decision-makers to develop the waste clean-up with minimised total cost and clean-up time by selecting the right location of TDWMSs and setting up the proper waste clean-up schedule.

1. Introduction

Large natural disasters draw the public particular concerns when they are happening and during the response stage which comprises evacuation and relief. After the disaster, recovery measurements aim at restoring the normal functioning which has been affected. Waste management is one of the core activities in the recovery stage, focusing on collecting, reducing or recycling, and final disposal of the remaining waste. Debris removal activities in the recovery stage are time-consuming, expensive and difficult (Zhang et al., 2019) because of the huge amount of the waste generated during the disaster, which can be several orders of magnitude larger than the usual waste generation. In many cases, this is due to the necessity of demolishing compromised buildings. For instance, during the 2008 Wenchuan earthquake, 6,945,000 rooms collapsed and 5,932,500 rooms were severely destroyed (Xiao et al., 2012), which generated 381 million tonnes of waste approximately.

To support the management of lager amount of waste generated after disasters, the modelling of disaster waste management system (DWMS) is needed (Zhang et al., 2019). The disaster waste management problem can be modelled as a reverse logistic problem (Hu and Sheu, 2013), which can be mathematically formulated using objective functions, decision variables and constraints. Depends on the focus of researches, the mathematical model are usually different. In the previous research, Cheng and Thompson (2016), Kim et al. (2014), and Fetter and Rakes (2012) focused on the decision of the location of temporary disaster waste management sites (TDWMSs). Takeda et al. (2015) made the decision on the route plan of disaster waste disposal. In Onan et al. (2015), both the location selection of temporary storage facilities and planning for the collection and transportation were considered as decision variables. In terms of the objectives, different objectives are considered, such as minimization total cost (Hu and Sheu, 2013; Onan et al., 2015), minimising risk (Hu and Sheu, 2013; Onan et al., 2015), and psychological impacts (Hu et al., 2019; Hu and Sheu, 2013). However, there is few research considered the total time as the objective, which can affect the progress of the recovery of disaster affected area and increase potential risky to public and environmental health (Brown et al., 2011a). In our study, we will make decision on the location of TDWMSs and waste collection and transportation route plan by minimising the total clean-up cost and time. Furthermore, we will also include the decision on the arrangement of destroyed building demolish in our model, which haven't been address in the literature. The demolition of damaged buildings plays an important role in the clean-up since it affects the waste generation in collection and transportation stage, which have impacts on total waste clean-up cost and time.

* Corresponding author.
E-mail address: rui.zhu@smart.mit.edu (R. Zhu).

https://doi.org/10.1016/j.wasman.2020.09.023
0956-053X/

To summary, we focus on large disasters which require extensive manpower to demolish damaged architectures in the recovery stage of disaster management. Thus, the waste clean-up system we considered consists of (i) demolition operation, (ii) collection of waste from customer nodes to TDWMSs, (iii) processing at TDWMSs, and (iv) transportation of the waste to final disposal sites. We incorporate the problem into a Mixed Integer Programming (MIP) framework, which allows TDWMSs to process waste clean-up in two continuous stages, i.e., the scheduling of damaged buildings demolition and the subsequent scheduling of collection and selection of transportation routes. The complexity of the problem limits the straightforward application of black-box solvers for large scales instances. Therefore, we also propose a decomposition approach that firstly solves the building demolition arrangement problem and secondly addresses the two-echelon waste clean-up problem.

We test our approaches with small, medium, and large-scale artificial instances to compare their performance. Furthermore, we conduct a case study focusing on the 2009 Black Saturday Bushfires in Victoria, Australia. The remainder of this paper is structured as follows. Section 2 presents a detailed description of the problem. Section 3 demonstrates a mathematical formulation of the problem. Section 4 investigates the case study and artificial instances generation. Then, Section 5 summarises the numerical results. Finally, Section 6 draws the conclusion.

2. Problem description

The reverse disaster waste management system involves four major operations: demolition of destroyed buildings (demolition), collection of waste from demolished buildings to TDWMSs (collection), processing of waste in TDWMSs (processing), and transportation of waste from TDWMSs to the final disposal sites (transportation). TDWMSs are facilities where waste can be temporarily stored, reduced, sorted, and processed before final disposal (FEMA, 2007). They can help to improve the flexibility of operations, facilitate recycling and reduce waste, which has been applied in many cases (Alziari et al., 1981; Amato et al., 2020, 2019; Brown and Milke, 2016; Karunasena et al., 2012; Oh and Kang, 2013; Rafee et al., 2008). The establishment of these facilities can also shorten waste collection time. The processing of waste in the TDWMSs can include waste separation, compression, and transfer from collection vehicles to transportation vehicles depends on the composition of waste generated in disasters. The operation of waste separation in TDWMSs are context dependent since the waste composition of different disasters vary a lot (FEMA, 2007). Fig. 1 describes the relationship between the operations in the waste clean-up system. Demolition precedes the other operations to make waste available for collection. However, it does not mean that the collection can only start when all demolition tasks are completed. Alternatively, the collection operation can start whenever there is waste available. Similarly, the processing work can begin immediately after the first waste collection trip. Ultimately, transportation operations can commence when waste has been processed in TDWMSs.

After large-scale disasters, the number of demolition machines is limited; therefore, arrangements need to be made for the demolition of the destroyed buildings, with the consideration of the demolition times required for each destroyed building. Notably, the efficiency of destruction affects the whole waste clean-up system as well as the recovery of the disaster affected area. In the two-echelon waste clean-up problem, we choose candidates among the available TDWMSs and then decide the waste flows, which determines two important attributes: (i) the amount of waste to be collected at each demolished building and transported to each selected TDWMSs, and (ii) the amount of waste to be transported from each chosen candidate to each final disposal site.

Fig. 1 provides a simple demonstration of the problem. A depot is used to park vehicles used in the system, which is also all the vehicles' initial origins and final destinations on each working day. Damaged buildings that have been demolished become customers with determined waste to be collected. In the figure, nodes 1, 3, 5, and 6 are available customers. Collection vehicles transport waste from these nodes to the selected TDWSM. Due to the large waste generation from each building, each customer node (demolished building) requires multiple services to collect all its waste. For example, $0 \rightarrow 1 \rightarrow a \rightarrow 1 \rightarrow 3 \rightarrow a \rightarrow 3 \rightarrow c \rightarrow 0$ is a possible route for a collection vehicle. After processing, the waste is transported from selected TDWMSs to final disposal sites by transportation vehicles.

3. Modelling

3.1. Assumptions

The study proposes three important assumptions for the modelling of the problem described in Section 2: (i) Waste is available to be collected at each damaged building when the demolition

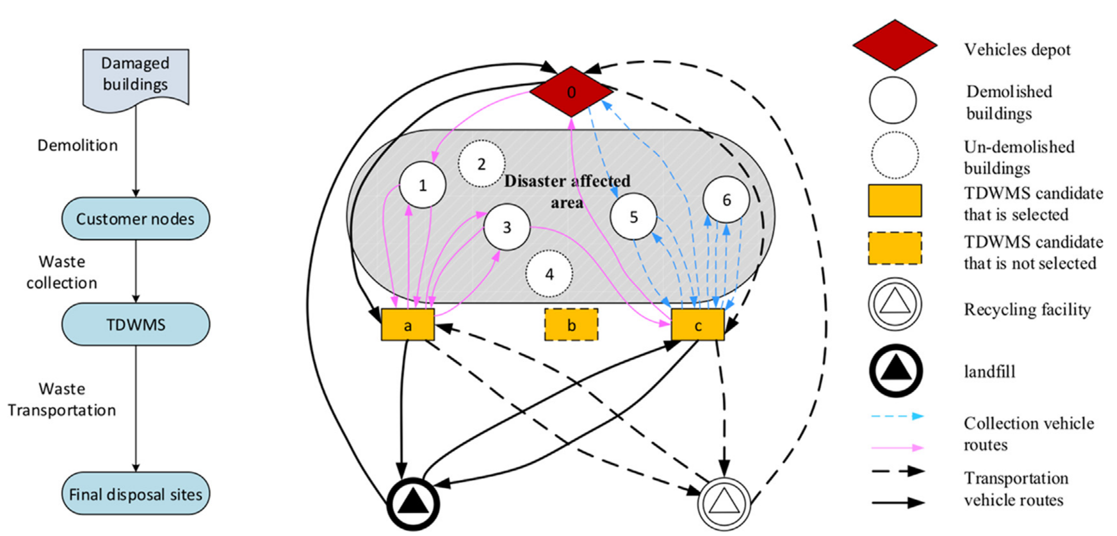

Fig. 1. Illustration of the waste clean-up problem.

starts. Besides, the waste generated at each customer node during each day of the demolition period is assumed to be the same. It means that in the demolition period of a building, $m = M/t$ is the fraction of waste generated every day, where M is the total amount of waste generated from the building and t is the number of days required to demolish this building; (ii) In the system, we assume that the recyclable waste is collected by recycling facilities from TDWMSs after separation. Thus, in the second echelon, we only need to deal with the landfill waste; (iii) In both the collection and transportation stages, each vehicle can only provide service to one node in each trip.

3.2. Integrated model (A1)

In this section, we develop the mathematical model for the problem described in Section 3.1 using mixed integer programming (MIP). Readers interested to MIP are referred to books (Kaufmann and Henry-Labordère, 1977; Pochet and Wolsey, 2006). In our problem, a graph $G = (N, A)$ is defined to describe the problem, in which N is a set of nodes and A is a set of arcs associated with the nodes. More specifically, $\{0\}$ denotes the depot, $C = \{1, 2, \ldots, n\}$ is the set of customer nodes, $J = \{n+1, n+2, \ldots, n+m\}$ is the set of TDWMS candidates, $F_1 = \{n+m+1\}$ denotes a hazard waste disposal facility, $F_2 = \{n+m+2\}$ denotes recycling facility, $F_3 = \{n+m+3\}$ denotes a landfill, $F = F_1 \cup F_2 \cup F_3$, $N_1 = C \cup J$, $N_2 = J \cup F$, $N = C \cup J \cup F$, and A is the set of arcs $(i,j), \forall i,j \in N$.

The graph considers the following parameters.

φ_{ij}: distance between node i and node j, $\forall i,\ j \in N,\ i \neq j$
c_{ij}: cost of travelling arc (i,j), $\forall i \in C,\ j \in J$
E_j: fixed cost for building the TDWMS j, $\forall j \in J$ (unit: AUD)
O_j: operation cost of TDWMS $j \in J$ (unit: AUD/d)
W_i: total demand of customer node $i \in C$
t_i: time required to demolish a customer node $i \in C$
m: number of demolition machines
K: set of available collection vehicles in a day
K': set of available transportation vehicles in a day
Q: the capacity of each collection vehicle
Q': the capacity of each transportation vehicle
v: collection vehicle speed
v': transportation vehicle speed
R: total working time of a vehicle in a day (unit: min)
T: set of days in the clean-up period
τ_j: capacity of TDWMS $j \in J$
η: waste recycling rate

It also defines of the following variables.

x_{id}: binary variable equals to 1 if the demolition of customer $i \in C$ starts in day $d \in T$, otherwise 0
y_{id}: binary variable equals to 1 if there is waste generated from customer $i \in C$ in day $d \in T$, otherwise 0
γ_{id}: the amount of total waste either demolished or not that has not been cleaned at customer $i \in C$ at the end of day $d \in T$ ($\gamma_{id} \geq 0$)
D_{id}: amount of waste available to be collected in customer $i \in C$ in day $d \in T$ including the waste generated in this day ($D_{id} \geq 0$)
r_{id}: the amount of waste that is available but have not been collected in customer $i \in C$ at the end of day $d \in T$ ($r_{id} \geq 0, r_{i0} = 0$)
s_d: binary variable equals to 1 if clean-up operations have finished at the end of day $d \in T$, otherwise 0
ω_j: binary variable equals to 1 if TDWMS $j \in J$ is open, otherwise 0
α_{ijd}: number of trips between node i and node j in day $d \in T$, $i,j \in N,\ i \neq j$ ($\alpha_{ijd} \geq 0$)
z_{ijd}: the amount of waste collected from customer $i \in C$ and sent to TDWMS $j \in J$ in day $d \in T$ ($z_{ijd} \geq 0$)
σ_{jd}: the amount of waste left in TDWMS $j \in J$ at the end of day $d \in T$ ($\sigma_{jd} \geq 0, \sigma_{j0} = 0$)
β_{jld}: number of trips between node j and node l in day $d \in T$, $j, l \in N_2$ ($\beta_{jld} \geq 0$)
f_{jld}: the amount of waste transported from TDWMS $j \in J$ to final disposal site $l \in F$ in day $d \in T$ ($f_{jld} \geq 0$)
μ_j: operation cost of TDWMS $j \in J$ ($\mu_j \geq 0$)

The model can be written as:

$$\min \sum\nolimits_{j\in J} \omega_j E_j + \sum\nolimits_{j\in J} \mu_j + \left(\sum\nolimits_{j\in\{0\}\cup J} \sum\nolimits_{i\in C} \sum\nolimits_{d\in T} \alpha_{jid} c_{ji} + \sum\nolimits_{i\in C} \sum\nolimits_{j\in J} \sum\nolimits_{d\in T} \alpha_{ijd} c_{ij} + \sum\nolimits_{j\in J} \sum\nolimits_{(1)d\in T} \alpha_{j0d} c_{j0}\right) + \left(\sum\nolimits_{l\in\{0\}\cup F} \sum\nolimits_{j\in J} \sum\nolimits_{d\in T} \beta_{ljd} c_{lj} + \sum\nolimits_{j\in J} \sum\nolimits_{l\in F} \sum\nolimits_{d\in T} \beta_{jld} c_{jl} + \sum\nolimits_{l\in F} \sum\nolimits_{d\in T} \beta_{l0d} c_{l0}\right) \quad (1)$$

$$\min\ |T| - \sum_{d\in T} s_d + 1 \quad (2)$$

Constraints:

$$\sum_{d\in T} x_{id} = 1, \quad \forall i \in C \quad (3)$$

$$y_{id} = \sum_{d'=\max\{1,\ d-t_i+1\}}^{d} x_{id'}, \quad \forall i \in C \quad (4)$$

$$\sum_{i\in C} y_{id} \leq m, \quad \forall d \in T \quad (5)$$

$$\gamma_{id} = W_i - \sum_{j\in J} \sum_{d'=1}^{d} z_{ijd'}, \quad \forall i \in C, d \in T \quad (6)$$

$$y_{id} \frac{W_i}{t_i} + r_{id-1} = r_{id} + \sum_{j\in J} z_{ijd}, \quad \forall i \in C, d \in T \quad (7)$$

$$r_{i|T|} = 0, \quad \forall i \in C \quad (8)$$

$$z_{ijd} \leq \alpha_{ijd} Q, \quad \forall i \in C, j \in J, d \in T \quad (9)$$

$$\sum_{j\in\{0\}\cup J} \sum_{i\in C} \alpha_{jid} \frac{\varphi_{ji}}{v} + \sum_{i\in C} \sum_{j\in J} \alpha_{ijd} \frac{\varphi_{ij}}{v} + \sum_{j\in J} \alpha_{j0d} \frac{\varphi_{j0}}{v} \leq \sum_{i\in C} \alpha_{0id} R, \quad \forall d \in T \quad (10)$$

$$\sum_{i\in C} \alpha_{0id} = \sum_{j\in J} \alpha_{j0d}, \quad \forall d \in T \quad (11)$$

$$\sum_{j\in J} \alpha_{ijd} = \sum_{j\in J\cup\{0\}} \alpha_{jid}, \quad \forall i \in C,\ d \in T \quad (12)$$

$$\sum_{i\in J\cup\{0\}} \alpha_{jid} = \sum_{i\in C} \alpha_{ijd}, \quad \forall j \in J,\ d \in T \quad (13)$$

$$\sum_{i\in C} \alpha_{0id} \leq |K|, \quad \forall d \in T \quad (14)$$

$$\sum_{j\in J} \sum_{d\in T} z_{ijd} = W_i, \quad \forall i \in C \quad (15)$$

$$(1-\eta)\sum_{i\in C} z_{ijd} + \sigma_{jd-1} = \sigma_{jd} + \sum_{l\in F} f_{jld}, \quad \forall j \in J, d \in T \tag{16}$$

$$\sigma_{j|T|} = 0, \quad \forall j \in J \tag{17}$$

$$f_{jld} \le \beta_{jld} Q', \quad \forall j \in J, l \in F, d \in T \tag{18}$$

$$\sum_{l\in\{0\}\cup F} \sum_{j\in J} \beta_{ljd}\frac{\varphi_{lj}}{v'} + \sum_{j\in J}\sum_{l\in F}\beta_{jld}\frac{\varphi_{jl}}{v'} + \sum_{l\in F}\beta_{l0d}\frac{\varphi_{l0}}{v'} \le \sum_{j\in J}\beta_{0jd}R, \quad \forall d \in T \tag{19}$$

$$\sum_{j\in J}\beta_{0jd} = \sum_{l\in F}\beta_{l0d}, \quad \forall d \in T \tag{20}$$

$$\sum_{l\in F}\beta_{jld} = \sum_{l\in F\cup\{0\}}\beta_{ljd}, \quad \forall j \in J, d \in T \tag{21}$$

$$\sum_{j\in J\cup\{0\}}\beta_{ljd} = \sum_{j\in J}\beta_{jld}, \quad \forall l \in F, d \in T \tag{22}$$

$$\sum_{j\in J}\beta_{0jd} \le |K'|, \quad \forall d \in T \tag{23}$$

$$\sigma_{jd} \le \omega_j \tau_j, \quad \forall j \in J, d \in T \tag{24}$$

$$(1-\eta)\sum_{i\in C}\sum_{d\in T} z_{ijd} = \sum_{l\in F}\sum_{d\in T} f_{jld}, \quad \forall j \in J \tag{25}$$

$$s_d \le 1 - \frac{\gamma_{id}}{W_i}, \quad \forall i \in C, d \in T \tag{26}$$

$$s_d \le 1 - \frac{\sigma_{jd}}{\tau_j}, \quad \forall j \in J, d \in T \tag{27}$$

$$\mu_j \ge (|T| - \sum_{d\in T} s_d + 1)O_j - |T|O_j(1-w_j), \quad \forall j \in J \tag{28}$$

Eq. (1) is the objective function of the problem, which aims to minimise the total cost. It contains four parts, the first part is the establishment cost of TDWMSs, the second part is TDWMSs operation cost, and the last two parts denote waste collection cost and waste transportation cost, respectively. The collection cost includes travelling expenditures from the depot or TDWMSs to customer nodes, from customer nodes to TDWMSs, and from TDWMSs to the depot. The transportation cost consists of cost for travelling from final disposal sites or the depot to TDWMSs, from TDWMSs to final disposal sites, and from final disposal sites to the depot. Eq. (2) is the second objective function aiming to minimise waste clean-up time.

Constraints (3) allow that each customer node is demolished once and only once. Constraints (4) compute the value of variables y_{id}. Constraints (5) ensure the maximum number of the demolition machines used on each day is not exceeded, and Constraints (6) calculate the total amount of waste that has not been cleared in each customer node, including waste either demolished or not. Constraints (7) are the flow balance in each customer node for each day. The above constraints make sure that the waste generated in a day plus the available waste left in the previous day equals to the amount waste to be collected at the end of the day plus the amount of waste that has been cleared at each customer.

Then, Constraints (8) ensure that all waste at customer nodes is cleared at the end of the period. Constraints (9) are capacity constraints on collection vehicles. Constraints (10) compute the aggregated maximum daily operation times for collection vehicles. Note that these constraints are approximations, which should not be considered as the limitation of operation times for every single collection vehicle. Constraints (11)–(13) are degree constraints to ensure the continuity of collection vehicle routes. Constraints (14) ensure that the number of collection vehicle used in each day is less than the available number of collection vehicles. Constraints (15) make sure all the waste in each customer node is collected. Constraints (16) are the flow balance of TDWMSs for each day, which is similar to the structure of the flow balance constraints of customer nodes.

Furthermore, constraints (17) ensure that all the waste stored in each TDWMS is cleared at the end of the given period. Constraints (18) make sure the capacity of transportation vehicles not exceeded. Constraints (19) avoid the transportation vehicles exceeding their aggregated daily working times. Similar to Constraints (10), we cannot guarantee the work time limitation of each single transportation vehicle. Constraints (20)–(22) are degree constraints to ensure the continuity of transportation vehicle routes. Constraints (23) regulate that the number of transportation vehicles used in one day is no more than the maximum available number. Constraints (24) ensure that a TDWMS cannot be used if it is closed and its capacity will not be exceeded. Constraints (25) guarantee all the waste stored in each TDWMS is cleared at the end of the period. Constraints (26)–(27) make the s_d variable equalling to 1 when there is no waste left either in customer nodes or in TDWMSs. Finally, Constraints (28) compute the operational cost for TDWMSs.

3.3. Decomposition approach (A2)

The problem is decomposed into two hierarchical sub-problems for an explicit presentation. In the first sub-problem (SP1), the objective is to assign customer nodes to demolition machines and minimising the total time required for demolition. Then, the sequence of customers that have been designated for a machine is random since it will not affect the final result. In the second sub-problem (SP2) is the two-echelon waste clean-up problem. A new set of M and two more sets of variables are introduced to formulate SP1:

M: the set of available demolition machines;
σ_{im}: a binary variable equalling to 1 if the demolition of customer $i \in C$ is assigned to demolition machine $m \in M$, otherwise 0;
p: the total time required to finish the demolition work.

Given these parameters, the model reads:

$$\min \; p \tag{29}$$

$$\sum_{m\in M}\sigma_{im} = 1, \quad \forall i \in C \tag{30}$$

$$\sum_{i\in C}\sigma_{im} t_i \le p, \quad \forall m \in M \tag{31}$$

After solving SP1, the value of $\sigma_{im}, \forall i \in C, m \in M$ and p can be obtained. By randomly scheduling the sequence of customers that have been assigned for each machine, the value of variables $y_{id}, \forall i \in C, d \in T$ can be determined, acting as the input of SP2. In SP2, the objectives are the same as those in A1 with Constraints (6)–(28). To improve the results and test the efficiency of the decomposition approach, the solution obtained for each instance in A2 is used as an initial feasible solution, while solving the integrated model with y_{id} again as decision variables (A3). Comparison of the results is made in Section 5.1.

4. Empirical evaluation

4.1. Study area

Bushfire in Victoria, Australia has been a catastrophe for a long history. There were about 30 severe bushfires in the history that took people's lives and burned significant acreage of land. Besides, a single bushfire can generate hundreds or even thousands of tons of waste to be removed for post-disaster reconstruction and rebuild of the economy (Brown et al., 2011b).

During the past 35 years, there have been many extremely damaging events in Victoria, such as the "Ash Wednesday" fires in February of 1983 and 'Black Saturday' fires in 2009. Both resulted in destruction of a large number of buildings, loss of fencing and livestock with severe impact on regional economies. The other two significant bushfires were the 2003 Eastern Victorian Alpine fires that burned through 1.3 million hectares and the 2006–2007 forest fires in the Great Divide that burned over 1.2 million hectares (Australia, 2010). The latest fire was the 2019–20 Australian bushfire season which is known as the Black Summer. The fires burnt an estimated 0.186 million km^2, destroyed more than 5900 buildings and killed at least 34 people (Schweinsberg et al., 2020; Ulpiani et al., 2020).

The study investigates in the Kinglake region (Fig. 2), which was severely affected by the 2009 "Black Saturday" bushfires that almost all the residential buildings were destroyed. Kinglake is a town in Victoria, Australia, 46 km north-east of Melbourne's Central Business District. It had a population of 1347 at the 2011 Census. It was the most damaged region of the state in the 2009 'Black Saturday' bushfires.

4.2. Estimation of input data for the case study

4.2.1. Customer nodes

The location of each destroyed building presents a customer node. The amount of the waste generated from each customer is estimated based on Rawson (2015), which estimates that the average disaster waste generation from a residential building is 170.1 tonnes. It indicated that even the best waste estimation methods have a 30% error (FEMA, 2007). This means that the waste generated from each customer is between 120 and 220 tonnes theoretically. Therefore, the total waste of each customer is randomly generated in this range. The other important information is the time for demolishing a general residential building, which can be estimated by inspecting the disaster sites usually. It has already suggested that the demolition time is ranging from 1 to 14 days for the customers in this specific area (Brown et al., 2010), which is thus used in the study straightforwardly.

4.2.2. TDWMSs candidates

TDWMSs have two properties of *location* and *capacity*. The selection of TDWMS candidates has been addressed by many studies. For example, Grzeda et al. (2014) applied binomial cluster analysis and GIS to select TDWMSs before disasters. In Kim et al. (2014), a model to select optimised location for TDWMSs is developed. Cheng and Thompson (2016) used Boolean Logic and GIS for determining suitable locations for TDWMSs. The candidate's selection method we use is the one developed in Cheng and Thompson (2016), which is clear and easy to follow. Based on this method, suitable locations of the candidates have been obtained, which contains 125 customers, 8 TDWMS candidates, and 1 depot (Fig. 3). There is also one final disposal site around 80 *km* away from the study area.

The capacity is calculated by using an established method (Tabata et al., 2017) with Equation (32). In the equation, Gis the capacity of the candidate, a is the floor area of the candidate, ρ is the relative volume-weight of the disaster waste (m^3/t), and h is the height for stacking the disaster waste (m).

$$G = \frac{a \times h}{\rho} \tag{32}$$

To determine the capacity construction cost and operation cost for TDWMS, we consulted staffs involved in the recovery of the Black Saturday Bushfire. However, the answers are inconclusive.

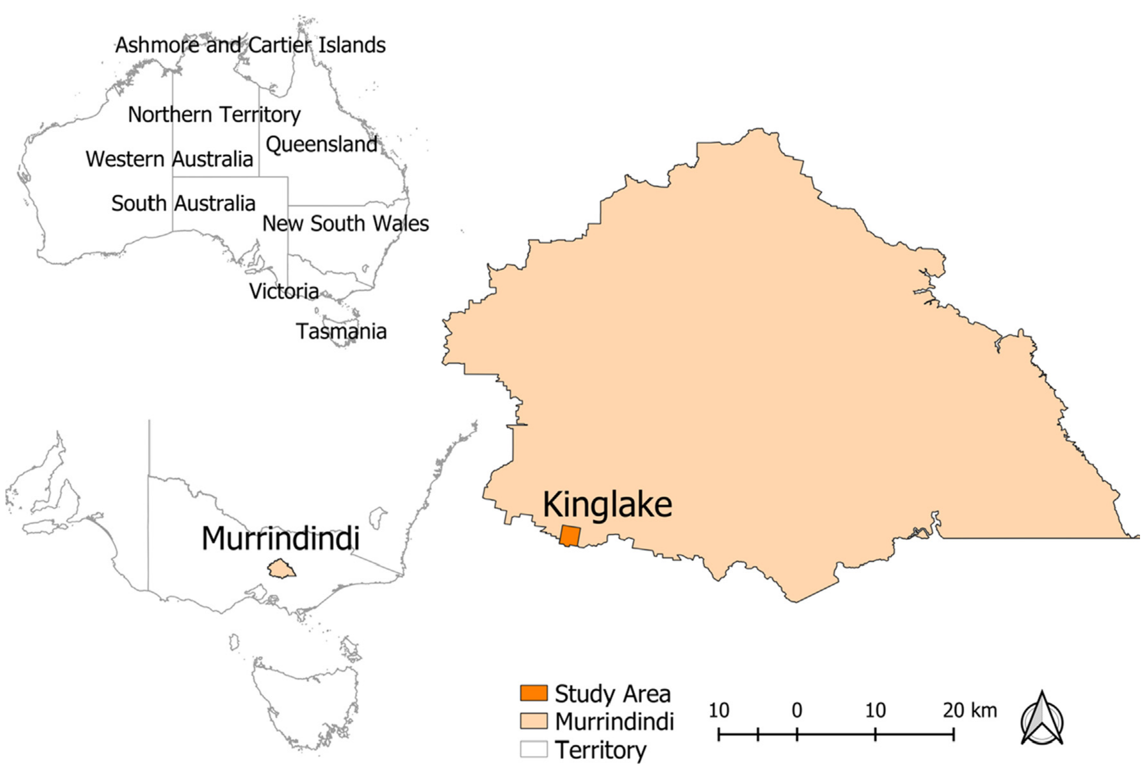

Fig. 2. Study area is in the Kinglake town, which locates in Murrindindi, Victoria, Australia.

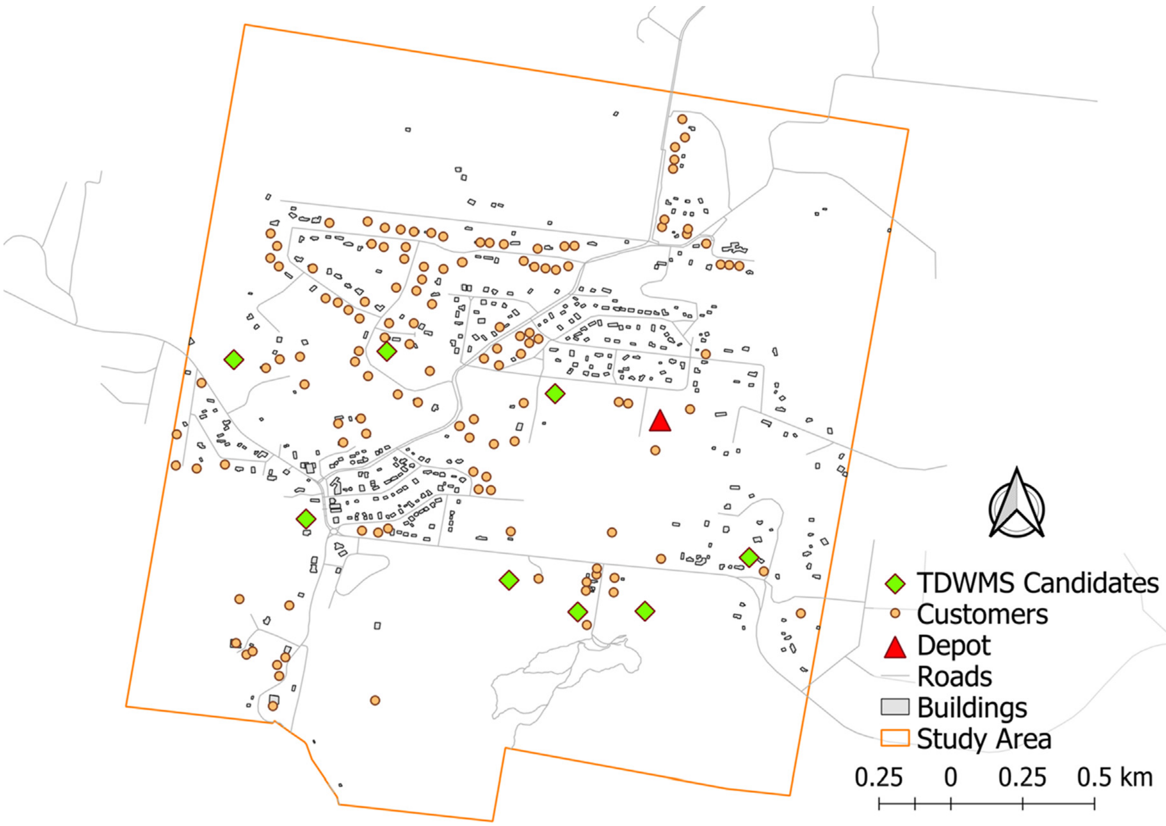

Fig. 3. There are 125 customers, 8 TDWMS candidates, and 1 depot in the Kinglake town.

Base on the discussion, the construction cost of each TDWMS candidate is assumed to be ten times its capacity in Australia dollars (*AUD*) and the operation cost is assumed to be 100 *AUD/day*. The assumed data are not aimed to represent the real cost, but demonstrate the model developed in Section 3.2. The labour cost is not included since the data is not available in this case study but can be easily merged to the operation cost if the data is available in the further work. Table 1 summaries this information.

4.2.3. Other data

The model also requires other datasets to solve the problem, including a road network, operation cost of vehicles, recycling rates, the number of demolition machines, the number and capacities of collection and transportation vehicles. In particular the road network is collected from VicRoads,[1] which is used to create an uni-directional graph that has a topological relationship between edges (road segments) and nodes (vertexes of the segments) and weights are the distances of the edges. The collection and transportation costs are 5 *AUD/km* and 10 *AUD/km*, respectively (Yang et al., 2016). In our case, all the waste generated in the bushfire was categorised into a single waste classification by the Environmental Protection Agency of Australia to speed up the waste clean-up and minimise hazards to people and the environment (Brown et al., 2010). Thus, the amount of total volume to be recycled in our the case study is 0. Regarding demolition machines and vehicles, we assume 10 demolition machines are used to demolish the damaged buildings. The number of vehicles is chosen to be 25 in total according to (Brown et al., 2010). In this case, 10 vehicles are used for the collection work with a capacity of 10 tonnes and the reminder 15 vehicles take the responsibility to transport the waste with a capacity of 30 tonnes.

[1] The statutory road and traffic authority in the State of Victoria, Australia.

Table 1
The summary of the information about TDWMSs.

TDWMS candidates	Capacity (tonnes)	Establishment cost (AUD*)	Operation cost (AUD*/day)
126	400	4000	100
127	500	5000	100
128	600	6000	100
129	300	3000	100
130	800	8000	100
131	400	4000	100
132	800	8000	100
133	600	6000	100

* 1 AUD = 0.79 USD in the year 2009.

To decide the approach used to solve the problem of the case study area. We also generated artificial instances in small, medium, and large-scales to compare their performance.

4.3. Artificial instances

Artificial instances are randomly generated in a 2 km × 2 km grid which is the similar to the size of the case study area mentioned in Section 4.1. The locations of customer nodes, the depot and TDWMSs are randomly generated. The location of the landfill is defined as a 10 km × 10 km area far away from the other nodes. The demand and demolition time of a customer is generated by following the same rationale in the case study. Finally, four groups of the instances are generated with 10, 25, 50, and 100 customer nodes, respectively. Each group includes 10 different instances with the same configuration as summarized in Table 2. In small instances (with 10 customer nodes), the number of TDWMS candidates, demolition machines, collection vehicles, and transportation

Table 2
Configurations of four groups of the simulated instances, including the numbers of customer nodes, TDWMS candidates, demolition machines, collection vehicles, and transportation vehicles.

No. groups	Customer nodes	TDWMS candidates	Demolition machines	Collection vehicles	Transportation vehicles
1	10	3	2	2	2
2	25	3	3	3	3
3	50	5	3	4	6
4	100	8	8	8	12

vehicles are smaller compared to large-scale instances (with 100 customer nodes).

5. Numerical analysis

5.1. Analysis of the simulated instances

The model presented in this paper are solved by Gurobi Solver which uses branch-and-bound algorithm to solve MIP. Readers interested in branch-and-bound algorithm are referred to the paper (Clausen, 1999). In the solver, two parameter can be used to terminate it. The first one is the time limitation, as long as the running time (CPU) reaches the limitation the Solver will stop no matter a feasible solution is find or not. For example, in Table 3, no feasible results was obtained for instance 25-3 in A1 within the time limitation which is set to 3600 s. The other parameter is optimality gap. To understand optimality gap, we need to introduce the Solver Gap. Solver Gap is the percentage difference between the lower and upper objective bound, which defines the best and worst results we can get. The smaller the Solver Gap, the closer the result is to the optimised result. The Solver will terminate with an optimal solution when the Solver Gap is less or equal than the optimality gap. For instance, instance 10-2 in Table 3 obtained the optimised solution with a Solver Gap equals to 0.01 in 1425 s (less than the limitation time). In the integrated approach (A1), the optimality gap is set to 0.01% for all the instances. In the decomposition-model approach (A2), the limitation time is 3600 s for SP1 and SP2 in total. In A3, we used the integrated model (A1) to solve the problem initialised with feasible solutions obtained from the decomposition approach (A2). Both A1 and A2 have 3600 s to solve the problem. The objective considered in this section is to minimise the total cost. Table 3 summaries the results

Table 3
Numerical results of artificial instances.

Instances	Best known results (AUD)	A1				A2				A3			
		Gap to Best	Solver Gap	CPU (seconds)	P (days)	Gap to Best	Solver Gap	CPU (seconds)	P (days)	Gap to Best	Solver Gap	CPU (seconds)	P (days)
10-1	8.80×10^4	0.01%	1.18%	3600	40	0	0.53%	3600	40	0	0.70%	3600	40
10-2	9.12×10^4	0	0.01%	1425	40	0.22%	0	37	42	0	0	517	40
10-3	9.38×10^4	0	0	1434	43	0.03%	0.01%	104	43	0	0	1538	43
10-4	8.14×10^4	0	0.58%	3600	44	0.02%	0.58%	3600	44	0	1.90%	3600	44
10-5	8.90×10^4	0	1.05%	3600	44	0.01%	1.05%	3600	44	0	1.05%	3600	44
10-6	9.15×10^4	0	1.03%	3600	33	0.24%	1.02%	3600	35	0	1.02%	3600	33
10-7	8.66×10^4	0	0.01%	771	34	0.01%	0.01%	47	34	0	0	1586	34
10-8	8.04×10^4	0	0.01%	923	34	0.14%	0.01%	211	35	0	0.01%	516	34
10-9	8.74×10^4	0	0.84%	3600	48	0	0.53%	3600	48	0	0.53%	3600	48
10-10	9.86×10^4	0	1.97%	3600	35	0.53%	0.95%	3600	40	0	1.37%	3600	35
25-1	2.13×10^5	9.85%	11.47%	3600	128	0	0.21%	3600	71	0	1.70%	3600	71
25-2	2.20×10^5	15.06%	16.21%	3600	119	0	0	362	64	0	1.33%	3600	64
25-3	2.10×10^5	–	–	3600	–	0	0.22%	3600	70	0	1.56%	3600	70
25-4	2.21×10^5	5.48%	6.80%	3600	78	0	0	632	65	0	1.46%	3600	65
25-5	2.17×10^5	9.15%	10.91%	3600	127	0	0.43%	3600	70	0	3.44%	3600	70
25-6	2.18×10^5	8.63%	10.42%	3600	120	0	0.42%	3600	71	0	2.01%	3600	71
25-7	2.13×10^5	3.38%	5.16%	3600	114	0	0.01%	3600	63	0	1.42%	3600	63
25-8	2.02×10^5	–	–	3600	–	0	0.23%	3600	65	0	1.77%	3600	65
25-9	2.02×10^5	–	–	3600	–	0	0.47%	3600	64	0	1.81%	3600	64
25-10	2.06×10^5	–	–	3600	–	0	0.23%	3600	61	0	3.82%	3600	61
Instances	Best known results (AUD)	A1				A2				A3			
		Gap to Best	Solver Gap	CPU (seconds)	P (days)	Gap to Best	Solver Gap	CPU (seconds)	P (days)	Gap to Best	Solver Gap	CPU (seconds)	P (days)
50-1	4.26×10^5	–	–	3600	–	0	0.12%	3600	109	0	3.94%	3600	109
50-2	4.02×10^5	–	–	3600	–	0	0.11%	3600	92	0	4.00%	3600	92
50-3	4.26×10^5	–	–	3600	–	0	0.12%	3600	106	0	3.77%	3600	106
50-4	4.31×10^5	–	–	3600	–	0	0.23%	3600	116	0	4.46%	3600	116
50-5	4.07×10^5	–	–	3600	–	0	0.25%	3600	105	0	3.99%	3600	105
50-6	4.08×10^5	–	–	3600	–	0	0.37%	3600	94	0	4.24%	3600	94
50-7	4.22×10^5	–	–	3600	–	0	0.12%	3600	98	0	3.88%	3600	98
50-8	4.15×10^5	13.57%	17.44%	3600	150	0	0.01%	1296	96	0	4.51%	3600	96
50-9	4.13×10^5	–	–	3600	–	0	0.03%	3600	111	0	3.83%	3600	111
50-10	4.16×10^5	12.65%	16.42%	3600	140	0	0.82%	3600	114	0	4.30%	3600	114
100-1	9.25×10^5	–	–	3600	–	0	11.73%	3600	111	0	13.18%	3600	111
100-2	8.83×10^5	–	–	3600	–	0	11.19%	3600	125	0	12.65%	3600	125
100-3	9.09×10^5	–	–	3600	–	0	10.97%	3600	100	0	12.41%	3600	100
100-4	9.26×10^5	–	–	3600	–	0	12.21%	3600	101	0	13.68%	3600	101
100-5	9.17×10^5	–	–	3600	–	0	12.52%	3600	101	0	14.01%	3600	101
100-6	9.11×10^5	–	–	3600	–	0	11.05%	3600	110	0	12.67%	3600	110
100-7	9.51×10^5	–	–	3600	–	0	14.49%	3600	120	0	15.88%	3600	120
100-8	9.30×10^5	–	–	3600	–	0	12.74%	3600	107	0	14.14%	3600	107
100-9	9.41×10^5	–	–	3600	–	0	15.85%	3600	132	0	–	3600	132
100-10	8.92×10^5	–	–	3600	–	0	10.07%	3600	104	0	10.64%	3600	104

obtained from the three different approaches. The first column shows reference numbers of the instances. The second one presents the best result obtained from three different approaches. 'Gap to the best' is the difference between the result obtained from each approach and the best obtained result, 'Solver Gap' is the gap from the solver which is explained above, 'CPU' is the running time of the solver, and 'P' is the total time required to finish the clean-up.

In most of the small instances (with 10 customer nodes), A1 outperforms A2. However, it is difficult for A1 to get feasible solutions for 40% instances with 25 customer nodes, 80% instances with 50 customer nodes, and 100% instance with 100 customer nodes. A2 obtains a satisfactory performance in all instances regarding the ability of getting a feasible solution and the quality of solutions for medium- and large-scale instances. In comparison, A3 is the best approach since it always obtains the best solution. In small instances, A3 can improve the initial solution provided by A2. However, in larger instances, A1 is not able to improve the solution. Taking the 100-9 instance as an example, it is even unable to find a lower bound with the initial solution. The comparison of the solver gap of A2 and A3 indicates that solutions obtained from A2 are close to the optimal solutions. To confirm the performance of A2, one instance is selected from each group to run A1 for much longer time (36,000 s) when the initial solution has been obtained from A2 (running for 3600 s) by using the third approach. It shows that there is no further improvement in the solution, comparing to the results of A1 in the third approach that has the time limitation at 3600 s. The results also indicate that the sequences of customers that have been assigned to each machine are not significant regarding the minimisation of the total cost. Therefore, A2 is selected to solve the problem in the case study in Section 5.2.

5.2. Analysis of the case study

In the case study, the objectives are to minimise the total cost and the total clean-up time. In the literature, most multi-objective optimization problems are solved by converting multiple objectives into a single objective (Hu and Sheu, 2013) or using

Table 4
Numerical results of the case study.

	TDWMSs capacity 100% of the data provided in Table 1									
Scenarios	Parameter	Best known Result (AUD)	Objective: Minimize cost				Objective: Minimize time with cost constraint			
			Gap to best	Solver Gap	CPU (seconds)	P (days)	Gap to best	Solver Gap	CPU (seconds)	P (days)
CT 1-1	m = 10	1.22×10^6	0.82%	6.66%	3600	219	0	0	1480	87
	$\|K\|$ = 10	1.21×10^6	0.68%	6.38%	3600	210	0	0	2484	87
	$\|K'\|$ = 15	1.21×10^6	0.07%	5.87%	3600	187	0	0	1952	87
CT 1-2	m = 5	1.22×10^6	0.10%	6.46%	3600	218	0	0	1768	173
	$\|K\|$ = 10	1.22×10^6	0	5.71%	3600	186	0	0	2156	173
	$\|K'\|$ = 15	1.22×10^6	0	5.85%	3600	193	0	0	1502	173
CT 1-3	m = 5	1.23×10^6	0.05%	6.83%	3600	228	0	0	3600	182
	$\|K\|$ = 5	1.23×10^6	0.03%	7.20%	3600	239	0	0	3600	177
	$\|K'\|$ = 8	1.22×10^6	0.09%	6.06%	3600	209	0	0	2216	173
Scenarios	Parameter	Best known Result (AUD)	Objective: Minimize time				Objective: Minimize cost with time constraint			
			Gap to best	Solver Gap	CPU (seconds)	P (days)	Gap to bestSolver Gap		CPU (seconds)	P (days)
TC 1-1	m = 10	1.17×10^6	602.60%	0	1378	87	0	0.10%	3600	87
	$\|K\|$ = 10	1.17×10^6	601.11%	0	1232	87	0	0.09%	3600	87
	$\|K'\|$ = 15	1.17×10^6	534.45%	0	1443	87	0	0.10%	3600	87
TC 1-2	m = 5	$1.21E \times 10^6$	40.55%	0	666	173	0	3.73%	3600	173
	$\|K\|$ = 10	1.21×10^6	519.34%	0	613	173	0	3.83%	3600	173
	$\|K'\|$ = 15	1.21×10^6	63.75%	0	707	173	0	3.74%	3600	173
TC 1-3	m = 5	1.21×10^6	170.31%	0	832	173	0	3.70%	3600	173
	$\|K\|$ = 5	1.21×10^6	166.70%	0	949	173	0	3.63%	3600	173
	$\|K'\|$ = 8	1.21×10^6	33.66%	0	825	174	0	3.69%	3600	174
	TDWMSs capacity 50% of the data provided in Table 1									
Scenarios	Parameter	Best known Result (AUD)	Objective: Minimize cost				Objective: Minimize time with cost constraint			
			Gap to best	Solver Gap	CPU (seconds)	P (days)	Gap to best	Solver Gap	CPU (seconds)	P (days)
CT 2-1	m = 10	1.23×10^6	0	7.05%	3600	238	0.02%	0	1597	87
	$\|K\|$ = 10	1.21×10^6	0.11%	5.53%	3600	167	0	0	1837	87
	$\|K'\|$ = 15	1.22×10^6	0	6.56%	3600	214	0.02%	0	2235	87
CT 2-2	m = 5	1.23×10^6	0.09%	6.96%	3600	240	0	0	2154	173
	$\|K\|$ = 10	1.23×10^6	0.06%	6.56%	3600	223	0	0	3273	173
	$\|K'\|$ = 15	1.23×10^6	0.07%	6.59%	3600	214	0	0	3600	178
CT 2-3	m = 5	1.22×10^6	0.05%	6.53%	3600	209	0	0	2157	173
	$\|K\|$ = 5	1.22×10^6	0	6.51%	3600	213	0	0	2031	174
	$\|K'\|$ = 8	1.21×10^6	0.16%	5.55%	3600	185	0	0	3600	174
Scenarios	Parameter	Best known result	Objective: Minimize time				Objective: Minimize cost with time constraint			
			Gap to best	Solver Gap	CPU (seconds)	P (days)	Gap to best	Solver Gap	CPU (seconds)	P (days)
TC 2-1	m = 10	1.17×10^6	538.47%	0	1068	87	0	0.10%	3600	87
	$\|K\|$ = 10	1.17×10^6	551.69%	0	770	87	0	0.10%	3600	87
	$\|K'\|$ = 15	1.17×10^6	541.05%	0	1421	87	0	0.10%	3600	87
TC 2-2	m = 5	1.21×10^6	77.06%	0	621	173	0	3.77%	3600	173
	$\|K\|$ = 10	1.21×10^6	133.28%	0	614	173	0	3.79%	3600	173
	$\|K'\|$ = 15	1.21×10^6	48.39%	0	605	173	0	3.69%	3600	173
TC 2-3	m = 5	1.21×10^6	29.45%	0	857	173	0	3.88%	3600	173
	$\|K\|$ = 5	1.21×10^6	62.91%	0	857	173	0	3.69%	3600	173
	$\|K'\|$ = 8	1.21×10^6	28.98%	0	631	173	0	4.64%	3600	173

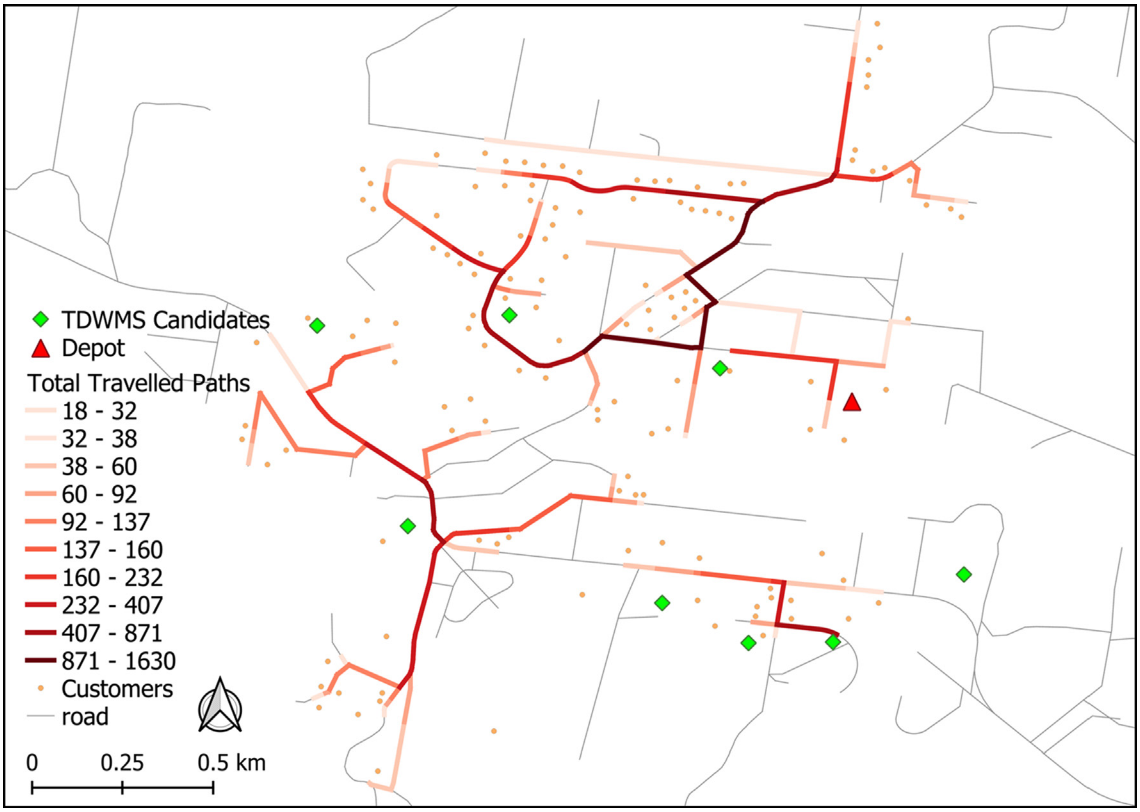

Fig. 4. Total number of trips travelled in the network in the entire clean-up period for waste collection stage.

heuristics algorithm such as non-dominated sorting genetic algorithm II (Onan et al., 2015) to solve the problem. However, both aforementioned methods cannot guarantee the quality of the results. In this study, to minimise both the cost and time, two sets of experiments are included. In the first one, the cost is minimised first, then the results are set as the initial solution to minimise the time with the constraint that the total cost cannot exceed the minimised cost (scenarios named as CT x-x). In the second set of the experiments, the priorities of the two objectives are exchanged, i.e., the time is minimised firstly and the cost is minimised with a time constraint secondly (scenarios named as TC x-x).

We also conducted sensitivity analysis to check the uncertainty of the results. The parameters selected for the analysis are the number of demolition machines (m), the numbers of collection vehicles ($|K|$) and transportation vehicles ($|K'|$), and the capacity of the TDWMS candidates. To test the uncertainty, each combination of parameters is repeated three times. The time limitation is 3600 s and the solver gap is 0.01% for all the experiments. Table 4 presents the results. The terms in this table are consistent with those in Table 3. The best-known result is the best result obtained from the two approaches regarding the total cost. The table is separated into two major parts according to the capacity of the TDWMS candidates (100% (scenarios named as CT 1-x or TC 1-X) versus 50% (scenarios named as CT 2-x or TC 2-x) of the original capacity). Two sets of the experiments are considered within each capacity, and three combinations of the parameters are included in each test group.

To check the feasibility of the solutions, we visualized the results using the shortest paths between origins and destinations (ODs) in GIS. To calculate the shortest paths between ODs, all the nodes in the network are mapped to the start or end points of the routes in the network. The visualization shows that the optimization results is feasible in the real network, which can be used to facilitate route planning in the post disaster waste management.

Fig. 4 shows the total number of trips travelled in the network in the entire clean-up period for waste collection from customer nodes to TDWMSs using the results from scenario TC1-1. The routes of the waste transportation cannot be show in the map since the final disposal sites are very far away from the case study area.

In terms of the multiple objectives (total clean-up time and total cost), the optimization results are feasible regarding the two objectives and they are not contradictory. The reason is that the second part of the total cost, which is the operation cost of TDWMSs, is related to the total clean-up time. However, they are not in line with each other because the operation cost is not the main contribution of the total cost. Thus, it cannot guarantee the total time is minimised by minimising the total cost especially when the results is not optimised. For example, when we minimise the total cost, the total time can reach 219 days in scenarios CT 1-1, while the actual minimised the total clean-up time is 87 days. To the contrary, if we minimise only the total time, we will get a total cost that is more than 6 times larger of the optimised total cost in scenarios TC 1-1. Therefore, the best approach is to minimise the total time first, then optimise the cost with the time constraint. Furthermore, by comparing the results obtained in different scenarios, total time highly depends on the number of demolition machines. The number of collection and transportation vehicles and the capacity of TDWMS has minor impacts on total cost and total clean-up time.

6. Conclusion

The study develops a reverse logistics system for post-disaster waste clean-up, aiming at minimising the cost and time involved in the system. The problem is formulated with a Mixed Integer Programming model. The proposed system is different from previous work in several ways. First, we solve the problem from a realistic and executable perspective, which considers the arrangement of buildings demolition and the location selection of TDWMSs. Second, the study concerns economic impacts on the waste clean-up, by incorporating the TDWMSs establish cost, operation cost, and waste collection cost into the model. This is particularly important for local governments and enterprises since they have to allocate reasonable amount of the budgets in advance. Third, the study also emphasizes on a timely post-disaster reconstruction by minimising the entire clean-up time with a minimization of the overall cost additionally. We also proposed two different models and three approaches to obtain an optimal result.

The numerical results indicate that the integrated model (A1) can only be used to solve small-scale problems. The decomposed algorithm (A2) can address all the instances generated and achieve satisfactory results. The third approach A3, in which the solution getting from A2 is sent to A1 as the initial solution to improve the results, indicates that the solutions obtained from A2 are close to the optimal solutions. The results from the case study demonstrate that the best approach is to minimise the total time followed by the optimisation of the cost with the time constraint. Besides, the total time highly depends on the number of demolition machines. Furthermore, the results obtained from the case study can facilitate the local municipalities making decision. First, the location selection results of TDWMSs from the model can act as a good reference for the decision when they need set up TDWMSs for post-disaster waste management. Second, the estimated time and cost can help to set the budget and target clean-up period for the disaster management. Thirdly, the arrangement of building demolition and the schedule of each collection and transportation vehicle in each day can provide useful information for the decision-makers to develop the detailed waste clean-up plan.

Given the limitation of the available data regarding both quantity and quality, this work does not consider the different cost for different vehicles and the environmental impacts. We recommend integrating the selection of the number and type of vehicles and environmental impacts as well as total clean-up time and cost in the post disaster waste management with the consideration of the impacts of waste recycling rate as a worthwhile topic for the future research.

Declaration of Competing Interest

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

Acknowledgments

This research is supported by the National Research Foundation, Prime Minister's Office, Singapore under its Campus for Research Excellence and Technological Enterprise (CREATE) programme.

References

Alziari, S., Stepien, G., Durand, R., 1981. In vitro incorporation of (35S)-methionine in mitochondrial proteins of drosophila melanogaster. Biochem. Biophys. Res. Commun. 99, 1–8. https://doi.org/10.1016/0006-291X(81)91704-6.

Amato, A., Gabrielli, F., Spinozzi, F., Magi Galluzzi, L., Balducci, S., Beolchini, F., 2020. Disaster waste management after flood events. J. Flood Risk Manag. 13, 1–9. https://doi.org/10.1111/jfr3.12566.

Amato, A., Gabrielli, F., Spinozzi, F., Magi Galluzzi, L., Balducci, S., Beolchini, F., 2019. Strategies of disaster waste management after an earthquake: A sustainability assessment. Resour. Conserv. Recycl. 146, 590–597. https://doi.org/10.1016/j.resconrec.2019.02.033.

Australia, R., 2010. Summary of major bush fires in Australia since 1851. http://romseyaustralia.com/firesum.html.

Brown, C., Milke, M., 2016. Recycling disaster waste: Feasibility, method and effectiveness. Resour. Conserv. Recycl. 106, 21–32. https://doi.org/10.1016/j.resconrec.2015.10.021.

Brown, C., Milke, M., Seville, E., 2011a. Disaster waste management: A review article. Waste Manag. 31, 1085–1098. https://doi.org/10.1016/j.wasman.2011.01.027.

Brown, C., Milke, M., Seville, E., 2011b. Disaster waste management following the 2009 Victorian bushfires. Aust. J. Emerg. Manag. 26, 17 https://search.informit.com.au/documentSummary;dn=140450632768198;res=IELAPA.

Brown, C., Milke, M., Seville, E., 2010. Disaster Waste Management Case Study: 2009 Victorian Bushfires, Australia. http://ir.canterbury.ac.nz/handle/10092/5086.

Cheng, C., Thompson, R.G., 2016. Application of boolean logic and GIS for determining suitable locations for Temporary Disaster Waste Management Sites. Int. J. Disaster Risk Reduct. 20. https://doi.org/10.1016/j.ijdrr.2016.10.011.

Clausen, J., 1999. Branch and Bound Algorithms-principles and Examples. Dep. Comput. Sci. Univ. Copenhagen, pp. 1–30. https://doi.org/10.1.1.5.7475.

FEMA, 2007. Public assistance: debris management guide. Fed. Emerg. Manag. Agency [2007]. https://www.fema.gov/pdf/government/grant/pa/demagde.pdf.

Fetter, G., Rakes, T., 2012. Incorporating recycling into post-disaster debris disposal. Socioecon. Plann. Sci. 46, 14–22. https://doi.org/10.1016/j.seps.2011.10.001.

Grzeda, S., Mazzuchi, T.A., Sarkani, S., 2014. Temporary disaster debris management site identification using binomial cluster analysis and GIS. Disasters 38, 398–419. https://doi.org/10.1111/disa.12040.

Hu, Z.H., Sheu, J.B., 2013. Post-disaster debris reverse logistics management under psychological cost minimization. Transp. Res. Part B-Methodol. 55, 118–141. https://doi.org/10.1080/23249935.2019.1567618.

Hu, Z.H., Sheu, J.B., Wei, C., Hu, S.L., 2019. Post-storm debris removal considering traffic and psychological impacts. Transp. A Transp. Sci. 15, 1145–1174. https://doi.org/10.1080/23249935.2019.1567618.

Karunasena, G., Amaratunga, D., Haigh, R., 2012. Post-disaster construction & demolition debris management: a Sri Lanka case study. J. Civ. Eng. Manag. 18, 457–468. https://doi.org/10.3846/13923730.2012.699913.

Kaufmann, A., Henry-Labordère, A., 1977. Integer and Mixed Programming: Theory and Applications. Academic Press, New York.

Kim, J., Deshmukh, A., Hastak, M., 2014. Selecting a temporary debris management site for effective debris removal. https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1019&context=i3r2.

Oh, G.-J., Kang, Y.-Y., 2013. The status of flood wastes treatment and future tasks in South Korea. J. Mater. Cycles Waste Manag. 15, 282–289. https://doi.org/10.1007/s10163-013-0147-4.

Onan, K., Ülengin, F., Sennaroıjlu, B., 2015. An evolutionary multi-objective optimization approach to disaster waste management: A case study of Istanbul. Turkey. Expert Syst. Appl. 42, 8850–8857. https://doi.org/10.1016/j.eswa.2015.07.039.

Pochet, Y., Wolsey, L.A., 2006. Production Planning by Mixed Integer Programming. Springer, New York, Berlin. https://doi.org/10.1007/0-387-33477-7.

Rafee, N., Karbassi, A.R., Nouri, J., Safari, E., Mehrdadi, M., 2008. Strategic Management of Municipal Debris aftermath of an earthquake. Int. J. Environ. Res. 2, 205–214. https://doi.org/10.22059/IJER.2010.195.

Rawson, M., 2015. Disaster Waste Management Scoping Study. https://www.greenindustries.sa.gov.au/_literature_165438/Disaster_Waste_Management_Scoping_Study_-_final_report_(2016).

Schweinsberg, S., Darcy, S., Beirman, D., 2020. 'Climate crisis' and 'bushfire disaster': Implications for tourism from the involvement of social media in the 2019–2020 Australian bushfires. J. Hosp. Tour. Manag. 43, 294–297. https://doi.org/10.1016/j.jhtm.2020.03.006.

Tabata, T., Wakabayashi, Y., Tsai, P., Saeki, T., 2017. Environmental and economic evaluation of pre-disaster plans for disaster waste management: Case study of Minami-Ise, Japan. Waste Manag. 61, 386–396. https://doi.org/10.1016/j.wasman.2016.12.020.

Takeda, T., Mori, Y., Kubota, N., Arai, Y., 2015. A route planning for disaster waste disposal based on robot technology. In: IEEE SSCI 2014 2014 IEEE Symp. Ser. Comput. Intell. - RiiSS 2014 2014 IEEE Symp. Robot. Intell. Informationally Struct. Space, Proc. https://doi.org/10.1109/RIISS.2014.7009173.

Ulpiani, G., Ranzi, G., Santamouris, M., 2020. Experimental evidence of the multiple microclimatic impacts of bushfires in affected urban areas: the case of Sydney during the 2019/2020 Australian season. Environ. Res. Commun 2, 65005. https://doi.org/10.1088/2515-7620/ab9e1a.

Xiao, J., Xie, H., Zhang, C., 2012. Investigation on building waste and reclaim in Wenchuan earthquake disaster area. Resour. Conserv. Recycl. 61, 109–117. https://doi.org/10.1016/j.resconrec.2012.01.012.

Yang, Y., Perera, L., Thompson, R.G., Liu, Z., 2016. Determining optimal toll levels for city logistics. In: ARRB Conference, 27th, 2016, Melbourne, Victoria, Australia. https://trid.trb.org/view/1446701.

Zhang, F., Cao, C., Li, C., Liu, Y., Huisingh, D., 2019. A systematic review of recent developments in disaster waste management. J. Clean. Prod. 235, 822–840. https://doi.org/10.1016/j.jclepro.2019.06.229.