An Application of the Bi-Level Location Routing Problem for Post-Disaster Waste Collection

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ABSTRACT

This paper identified the disaster waste collection problem as a Bi-level Location Routing Problem with time windows. The upper-level problem is Temporary Disaster Waste Management Site (TDWMS) location problem. The lower-level problem is disaster waste collection problem, which is an extended VRP. The constraints considered include time windows, vehicle capacity, TDWMS capacity, which makes the problem complex to solve. To overcome the relevant challenges, three heuristic algorithms have been developed in MATLAB. The application of the methodology indicates that the algorithms can provide good results within acceptable computing time.

INTRODUCTION

The frequency and severity of disasters have increased because of climate change and the sharp rise in population levels. Every year, hundreds of natural disasters occur throughout the world and cause billions of dollar's damage. During last 10 years, there were 3906 disasters in total, resulting in 0.75 million lives being lost and 1.68 billion people were affected (Data source: EM-DAT1). The damage cost from these events was estimated to be

[1] EM-DAT: The CRED/OFDA International Disaster Database – www.emdat.be – Université Catholique de Louvain – Brussels – Belgium.

1284.9 US$ billion scaled to 2014 (Data source: EM-DAT). These data revealed the significance of improving disaster management, which can reduce the loss of disasters and shorten the recovery time.

Waste management is one of the most important activities in disaster management. There are many problems concerning waste clean-up aftermath of disasters such as the huge amount of waste generation, time-consuming and expensive waste collection and treatment (Swan, 2000). Generally, the waste removal process takes months, or even years to finish (Brown et al., 2011). After a disaster, it is likely to be a concern for some time since there exist many factors that make it a costly and complex operation. The cost mostly arises from waste collection and the transportation of waste to disposal sites. Costs from technical factors make up the cost of this process. There are three major factors to consider. Firstly, there is typically a limited space to establish appropriate temporary or final disposal sites. The second factor is the cost of providing necessary heavy vehicles and tools to execute the debris collection operation. The third factor is the transportation cost of waste disposal, which depends on vehicles' route choices to transport the waste to the temporary or final disposal sites. Routing problems are one of the most important issues in cost efficiency, considering that route choice greatly affects total travel costs that are incurred in the debris collection operation (Pramudita et al., 2014).

Besides the cost of disaster waste clean-up, environmental impacts are other significant issues. The initial reason is that environment and disasters are inextricably linked (Brown et al., 2011). On one hand, disasters lead to immediate physical damage to the environment. On the other hand, the rising of environment vulnerability increases the number and severity of disasters. Thus, the proper management of disaster waste is of great significant in terms of environment protection. Major environmental impacts happen in collection and disposal of disaster waste. Waste collection involved a lot of Heavy Duty Vehicles (HDV) activity. HDV are responsible for a disproportionate percentage of transport sector fuel consumption and Green House Gas (GHG) emissions due to heavier weight and greater miles travelled (Kodjak et al., 2015), although the number of them is relatively smaller comparing to other vehicles such as cars and buses. In addition to that, they are also a source of noise, which is another kind of environmental pollution. In terms of environment pollution in waste disposal side, the best way to reduce the pollution is to recycling the waste as much as possible. To address the problem, Temporary Disaster Waste Management Sites (TDWMS) are considered in the waste management system. They are locations where waste can be temporarily stored, reduced, sorted, and processed before final disposal in order to increase recycling and shorten waste clean-up time (FEMA, 2007). However, the establishment of TDWMS can also have environment impacts to the lands. Thus, it is important to decide the number and location of TDWMS in the upper level in order to minimize the environmental impacts of the whole waste clean-up system.

The combination of TDWMS location problem and waste collection routing problem will be the subject of this research. In order to address the problem in this research, a bi-level location routing problem (B-LRP) is applied to describe it. The upper-level problem is the TDWMS location problem, and the lower problem is the vehicle routing problem for post-disaster waste collection. On one hand, the location of TDWMS impacts the routing problem. On the other hand, the travel distance of the waste collection in the lower-level contributes a lot to the total environmental impact, which is the major objective in the upper level.

Given the limitation of time, only CO_2 emission is selected to reflect environmental impacts in the whole system.

The remainder of the document is structured as follows. Section 2 presents a model formulation for the problems. The third section is the algorithms developed to solve the problem. The next section gives a case study to apply the methodology. Following is results analysis section. The last section presents conclusions.

MODEL FORMULATION

To formulate the problem with a mathematical model, a graph, $G=(N, A)$, is defined as follows. A depot 0, a set of customer nodes $C=\{1, 2, ..., n\}$ and a set of TDWMS candidates $I=\{n+1, n+2, ..., n+m\}$ are identified as the vertexes of the graph G, so that $N=\{0\}\bigcup C\bigcup I$ and A is a set of arc $(i, j), \forall i, j \in N$. The following symbols are defined for the model:

K	Set of collection vehicles
Q	Capacity of collection vehicles (unit: tonnes)
$[S, E]$	Time window for collection vehicles and vertexes of the graph G (unit: minutes)
d_i	Demand of customer $i, i \in C$ (unit: tonnes)
CT_i	Capacity of TDWMS $i, i \in I$ (unit: tonnes)
TCT	Minimum total capacity of selected TDWMS (unit: tonnes)
D_{ij}	Distance of arc $(i, j), (i, j) \in A$ (unit: meters)
t_{ij}	Travel time of arc $(i, j), (i, j) \in A$ (unit: minutes)
ts_i	Service time of node i, $i \in N$ (unit: minutes)
ξ	CO_2 rate of waste collection vehicles (unit: Kg/m)
α_i	Fixed cost of TDWMS i (unit: AUD/day/facility)
e_i	CO_2 emission rate of TDWMS i (unit: Kg/day)
BT	Budget for TDWMS preparation and recovery (unit: AUD)
w_i	1, if TDWMS i is selected, 0, otherwise
x_{ijk}^{τ}	Times of vehicle k ($k \in K$) use arc $(i, j), (i, j) \in A$, $x_{ijk} \in \{0,1\}$
T	Disaster waste clean-up period
δ_{τ}	Binary variable that equals to 1 if the day τ $(\tau \in T)$ is used and 0 otherwise
U_{ik}^{τ}	Remain capacity of a collection vehicle k ($k \in K$) just before having served to node i ($i \in C\bigcup I$) in day τ
V_i^{τ}	Amount of waste storage in TDWMS i ($i \in I$) at day τ
ω_{ik}	Time when vehicle k ($k \in K$) arrives at node i ($i \in N$)
β	The minimum usage rate of vehicle's capacity

Following is the mathematical model M1:

Upper level problem:

Objectives:

$$\min \sum_{\tau \in T}\sum_{k \in K}\sum_{i,j \in N} \xi x_{ijk}^{\tau} D_{ij} + \sum_{i \in I} e_i w_i T \quad (1)$$

$$\min \sum_{\tau \in T} \delta_{\tau} \quad (2)$$

Suject to:

$$\sum_{i\in I}\alpha_i w_i \le BT \tag{3}$$

$$\sum_{i\in I} CT_i w_i \ge TCT \tag{4}$$

Lower level problem:

Objective:

$$\min \sum_{\tau\in T}\sum_{k\in K}\sum_{i,j\in N} D_{ij} x_{ijk}^{\tau} \tag{5}$$

Subject to:

$$x_{ijk}^{\tau} = \begin{cases} 1, Collection vehicle\ k\ travels\ from node i\ to\ node\ j\ ,\ i,\ j\in V \\ 0, Otherwise \end{cases} \tag{6}$$

$$\sum_{\tau\in T}\sum_{k\in K}\sum_{i\in N} x_{ijk}^{\tau} = 1, \forall j \in C \tag{7}$$

$$\delta_{\tau} = 1, \tau = 1 \tag{8}$$

$$\delta_{\tau} \le \delta_{\tau-1}, \forall \tau \in T/\{1\} \tag{9}$$

$$\sum_{k\in K}\sum_{i\in C} x_{0ik}^{\tau} = \sum_{k\in K}\sum_{j\in I} x_{j0k}^{\tau} \le |K|, \forall \tau \in T \tag{10}$$

$$\sum_{i\in N} x_{ihk}^{\tau} - \sum_{j\in C\cup I} x_{hjk}^{\tau} = 0, \forall h \in C, k \in K, \tau \in T \tag{11}$$

$$\sum_{i\in C} x_{ilk}^{\tau} - \sum_{j\in C\cup\{0\}} x_{ljk}^{\tau} = 0, \forall l \in I, k \in K, \tau \in T \tag{12}$$

$$0 \le \sum_{i\in C} x_{0ik}^{\tau} = \sum_{j\in I} x_{j0k}^{\tau} \le 1, \forall k \in K, \tau \in T \tag{13}$$

$$0 \le U_{ik} \le (1-\beta)Q, \forall i \in C, k \in K \tag{14}$$

$$U_{ik} - x_{jik}^{\tau} d_i \ge 0, \forall i,\ j \in C, i \ne j, k \in K, \tau \in T \tag{15}$$

$$U_{jk} - U_{ik} + Q x_{ijk}^{\tau} + (Q - d_i - d_j) x_{jik}^{\tau} \le Q - d_i, \forall i,\ j \in C, i \ne j, k \in K, \tau \in T \tag{16}$$

$$U_{ik} \ge d_i + \sum_{j\in C, j\ne i} d_j x_{ijk}^{\tau}, \forall i \in C,\ k \in K, \tau \in T \tag{17}$$

$$U_{ik} \le Q - (Q - d_i) x_{ijk}^{\tau}, \forall i \in C,\ j \in I, k \in K, \tau \in T \tag{18}$$

$$S \le \sum_{(i,\ j)\in A} x_{ijk}^{\tau}(t_{ij} + ts_j) \le E, \forall k \in K, \tau \in T \tag{19}$$

$$S \le \omega_{ik} \le E, \forall i \in N, k \in K \tag{20}$$

$$0 \le V_i^{\tau} \le CT_i * w_i, \forall i \in I \tag{21}$$

Equation (1) and (2) are the objectives of the upper-level problem which aim to minimize the total CO_2 emission. The first term of equation (1) is travelling cost and the second term is the cost of TDWMS establishment. Equation (3) is the total budget constraint for TDWMS establishment. Equation (4) ensures that the total capacity of selected TDWMS is no less than the minimum requirement. Equation (5) is the objective of the lower level problem which aims to minimize the total travel distance. Equation (6) is the value constraint of the variable x_{ijk}^{τ}. Equation (7) is a degree constraint to ensure that every customer node must be serviced once and only once. Equation (8) and (9) are value constraints for the variable δ_{τ}. Equation (10) is to make sure the number of collection vehicles used every day will not exceed the maximum number of collection vehicles. Equation (11) and (12) are degree constraints which make sure the continuity of collection vehicle route. Equation (13) is to ensure that every collection vehicle must leave and go back to the depot no more than once per day. Equation (14) makes sure that the load of a collection vehicle does not exceed its

capacity. Equation (15) is time window constraint for vehicles and vertexes in the graph. Equations (16) to (18) are well known Miller-Tucker-Zemlin (Miller et al., 1960) constraints eliminating the sub-tours, subject to the capacity restrictions. Equation (19) and (20) indicate that collection vehicles can only provide service within their time window.

In model M1, the general situation is considered, in which all customer nodes have the same time window with vehicles, depot, and TDWMS. However, customer nodes may not always available in the reality due to the particular function and location of each node. For example, it is better to collect waste from customer nodes that are close to major roads before or after peak hours to minimize the impacts on residents' normal life. Thus, different time windows are considered for each customer node. So that one more set of constraints is included in model M2, which can be described by Equation (22). $[s_i, e_i]$ is the time window of the node i.

$$s_i \le \omega_{ik}^{\tau} \le e_i, \forall i \in N, k \in K, \tau \in T \tag{22}$$

In both M1 and M2, the customer node can only be visited once. However, sometimes the VRP that allows split services, which is defined as Split Delivery Vehicle Routing Problem (SDVRP), can reduce the total travel distance by 50% (Archetti and Speranza, 2008). In order to find out how and in what situation SDVRP can benefit the system. One more model (M3) will be considered as well. In model M3, customer nodes can be visited more than once. Thus, another index should be added to the variable x_{ijk}^{τ}, which can be described by x_{ijka}^{τ}. It is also a binary variable, which is 1 if the vehicle k ($k \in K$) use arc (i, j), for the a*th* time in day τ, otherwise 0. In addition, one more variable y_{ika}^{τ} should be added in the model. It denotes the amount of waste vehicle k takes from the node i when it provides a*th* service to it in day τ. The constraints should be added are:

$$x_{ijka}^{\tau} = \begin{cases} 1, Collection vehicle\ k\ travels\ from node i\ to\ node\ j\ \ for\ the\ a th\ time\ in\ day\ \tau,\ i,\ j \in V,\ \tau \in T \\ 0, Otherwise \end{cases} \tag{23}$$

$$y_{ika}^{\tau} \le d_i \sum_{j \in C \cup I} x_{jika}^{\tau} \ \forall i \in C, k \in K, \tau \in T \tag{24}$$

$$\sum_{k \in K} \sum_{\tau \in T} \sum_{a \in A} y_{ika}^{\tau} = d_i, \forall i \in C \tag{25}$$

Equation (23) is value constraints of the variable x_{ijka}^{τ}. Equation (24) ensures a vehicle can take waste from a node for the a*th* time only when it provide a*th* service to it and the amount of waste is taken cannot exceed the demand of the node. Equation (25) is aim to make sure all the waste in a customer node should be clean-up at the end. For the other constraints, the only difference is that the variable x_{ijk}^{τ} changes to x_{ijka}^{τ}.

SOLUTION ALGORITHM

A lot of different algorithms have been applied for VRP related to waste management, such as Tabu search (Ma et al., 2012), Neighborhood search (Wy et al., 2013), Genetic algorithms (Gracia et al., 2014), Column generation (Shu et al., 2010), Branch-and-bound algorithm (Crainic et al., 2004). In the present study, heuristic algorithms have been proposed to address both the problems in the two levels. In the upper level, Genetic Algorithm (GA) is chosen to solve the problem. Since TDWMS location problem is a binary problem and GA is

the best choice for this kind of problem. In the lower level, the main problem is a routing problem. Greedy Algorithm is selected to get the initial solution because it is efficient and fast while Simulated Annealing (SA) is the choice to find the final results. In addition, according to the test of the problem, these algorithms can find good results within acceptable computing time.

Genetic Algorithm

A genetic algorithm (GA) is a search heuristic that simulates the process of natural selection, which generates solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. This heuristic is routinely used to generate useful solutions to optimization and search problems (Mitchell, 1998). In this research, it is applied to choose TDWMS in order to minimize the total cost, which consists of TDWMS establish cost and waste collection cost. Table 1 is the structure of GA. In this algorithm, there are 4 main inputs, namely maximum generation (n), population size (m), crossover rate (α) and mutation rate (β). The length of each individual equals the number of TDWMS candidates and each element in the individual stands for one TDWMS. If the element is 1, it means this TDWMS is selected, 0 otherwise. The natural evaluation operations considered are copy, selection, crossover, and mutation. In every generation, only the best individual is copied to the next generation. In addition, two individual are selected every iteration according to the selection probability, which is calculated according to the fitness value. Whether to conduct crossover or mutation depends on the crossover rate and the mutation rate. The most important variable of GA is fitness value, which is in inverse ratio to the total cost that calculated by the Greedy Algorithm.

Table 1. Algorithm 1- The general structure of Genetic Algorithm

Algorithm 1: GA(n, m, α, β)	
1:	Initialize generation 0;
2:	k←0;
3:	P_k← the n*th* population of m randomly generated individuals;
4:	**Evaluate** P_k
5:	**for** i=1:m
6:	**Function** greedy(P_k)
7:	**Return** totalCost(i)
8:	Fitness(i) ←maxcost- totalCost(i)
9:	Probability(i) = sum of probabilities + (fitness(i) / sum)
10:	**End for**
11:	Best-individual←P_k(max(Fitness), :)
12:	**k**←k+1
13:	**while** k<n+1
14:	**For i=1:2:m**
15:	**Selection**: Select two individual according to Probability
16:	**if** rand< α
17:	**do** crossover
18:	**end if**
19:	**if** rand< β
20:	**do** mutation
21:	**end if**
22:	**Repeat** Evaluate P_k
23:	P_k(min(Fitness), :)←Best-individual
24:	**k**←k+1
25:	**end while**
26:	**return**(Best-individual)

Greedy Algorithm

A greedy algorithm is an algorithm that follows the problem-solving heuristic of making the locally optimal choice at each stage (Cormen, 2009). In this algorithm, the inputs are customer set C, time window [E0, L0], vehicle set K, vehicle capacity Qc, TDWMS set F and TDMWS capacity SCi. The general structure of Greedy Algorithm shows in Table 2, which is developed for model M1. In each day, nodes are assigned to every vehicle. For each vehicle, the node that is closest to the current one is selected as the next node until the vehicle is full, then the vehicle goes to the closest TDWMS with enough capacity to unload the waste and start a new route until the end of the day. Then, a new vehicle starts to provide service to customer nodes until all vehicles are used or all selected TDWMSs are full. After that, a new day begins until all customer nodes are served. At the end, the total CO_2 emission will be calculated.

In model M2, time windows of each node should be considered when finding candidates for the next node in routing construction. Only nodes that are available when a vehicle arrives and satisfied the capacity limitation can act as the candidates for the next node. In model M3, candidates should meet time windows constraint. However, the demands of them do not need to be smaller than remain capacity of the vehicle. In addition, the route structure rule of model M1 is to select the closest candidate. In model M2 and M3, another rule will be considered, which is to choose the candidate that is first available. In these two models, these two route construction rules will be compared.

Table 2. Algorithm 2- The general structure of Greedy Algorithm

Algorithm 2: Greedy Algorithm (C, E0, L0, K, Qc, F, SC_i)	
1:	Initialize:
2:	B←C // assign all the customer nodes to B
3:	TDWMS storage S_j=0
4:	day=0
5:	**if** (｜B=0｜) // **B is empty**
6:	**Stop**
7:	**else //B is not empty**
8:	**do** day=day+1 **//Start a new day**
9:	**if** (｜K=0｜) //K is empty
10:	**return** to **line 4**
11:	**else** //Start a new vehicle k and Initialize k
12:	**do** T←E_0 //T is the current time, E0 is the open time of the depot
13:	Q←0 // Q is the current load of the vehicle
14:	r←0 //r is the last node the vehicle has visited
15:	**while** (Qc-Q>0)
16:	**do** Find nodes set E in B that satisfy d_i<= Qc-Q;
17:	**If** (E is not empty)
18:	**do** i= arg min {d_{rj}｜j∈E}
19:	T←T+t_{ri}+Lt //t_{ri}: travel time from r to j, Lt :load time
20:	Q←Q+di
21:	r←i
22:	B←B/i
23:	**end if**

```
24:                 end while
25:       Find nodes set Fc in F Fc={j | S_j+Q<=SC_j}
26:       j= arg min {d_rj | j∈Fc }
27:       Q←0
28:        r←j
29:       T←T+t_rj+ULt   // Ult :unload time
30:
31:         if T<L0 then   //check the route
32:
33:         do Assign the route to this vehicle and Return to step 3
34:         else
35:              Delete nodes in the route from the last one until T<=L0
36:              if (Q>=minLoad) t //aims to fully use the capacity of the vehicle
37:                 do assign this uncompleted route to the vehicles and then goes back to the
     depot
38:                       K=K/k
39:              Else
40:              Goes back to the depot directly
41:               K=K/k
42:             end if
43:         end if
44:     end if
45:   return to line 8
46:   end if
47:   Calculate total distance and total CO2 emission
```

Simulated Annealing

Greedy Algorithm is fast and it can always find a solution, however, the solution is always not optimized. To improve the solution, Simulated Annealing is chosen as the optimization algorithm. SA was independently described by (Kirkpatrick and Vecchi, 1983) and (Černý, 1985). It is a probabilistic technique for approximating the global optimum of a given function, specifically for problems where finding the precise global optimum is less important than finding an acceptable local optimum in a fixed amount of time. Simulated annealing interprets slow cooling as a slow decrease in the probability of accepting worse solutions as it explores the solution space. Accepting worse solutions is a fundamental property of metaheuristics because it allows for a more extensive search for the optimal solution.

Table 3. Algorithm 3- The general structure of Simulated Annealing

```
Algorithm 3: Simulated Annealing  (n, T0, Tmin, α)
1:   S_current←SolutionFromGreedy
2:   S_best←S_current
3:   T←T0
4:   While T> Tmin
5:   For 1=1: n
6:   do randomly exchange two nodes in S_current
7:   Si←solution after exchange
8:   if Time(Si)<L0 & LoadVeh<capVeh & TDWMSsto<capTDWMS  //Check constrains
9:       if cost(Si)< cost(S_current)
```

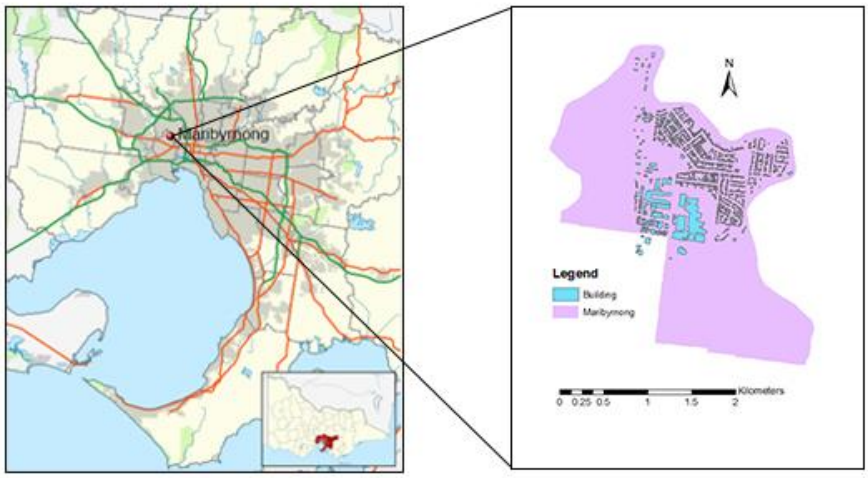
```
        S_current ← S_i
        if cost((S_i) < cost((S_best)
          S_best ← S_i
        end if
      elseif exp(cost(S_current) - cost((S_i))/T > rand
          S_current ← S_i
      end if
    end if
    T = T* α
    end while
    return (S_best)
```

In this case, the four inputs are iteration number, initial temperature, stop temperature, and cooling rate. The cross operation in this algorithm is to exchange two nodes in the results randomly, then check if the new result is feasible or not. If the new solution is feasible and better than the current solution, then replace the current solution with the new solution. Otherwise, accept the solution under a probability, which is determined by current temperature and the gap between current solution and the new solution. If the new solution is also better than the best solution, then assign the new solution to the best solution. Once reaching the maximum iteration, reduce the temperature until the temperature is lower than the minimum temperature. Finally, return the best solution.

CASE STUDY

Case study area

Flood is one of the most serious disasters that happened in Australia (Sam Amirebrahimi, 2015, Nafari et al., 2016). In the last 10 years there were about 20 floods. They always have significant impacts on affected areas. Take 2013 Eastern Australia floods as an example. Damage from severe weather and flooding amounted to at least 2.4 billion Australia dollars across the affected region. Houses were completely washed away and parts of Bundaberg's sewage network were destroyed. [2]



[2] https://en.wikipedia.org/wiki/Cyclone_Oswald

Figure 1. The location of the case study area

Thus, Maribyrnong is selected as the case study area in this research. Maribynong is a suburb of Melbourne, 8 km northwest of Melbourne's CBD, in Victoria, Australia. The City of Maribyrnong is its local government area, which is part of the River Ward. It had a population of 10,165 at the 2011 Census. The name of Maribyrnong is taken from the Maribyrnong River which bounds the suburb to the north and east. As a result, it is attacked by major floods in the years of 1906, 1916, 1974, 1983, 1987, 1993, 2000, 2005, and 2011. The flood of September 1906 is the largest one on record with a measured depth of water exceeding 4.65m above Australia Height Datum (AHD). The flood of May 1974 resulted in an inundation of 4.2m, which impacted on 385ha of urbanized land and resulted in damage to 370 houses and businesses.

Given the high risk of floods in Maribyrnong, it is reasonable to take it as the case study area in the present research.

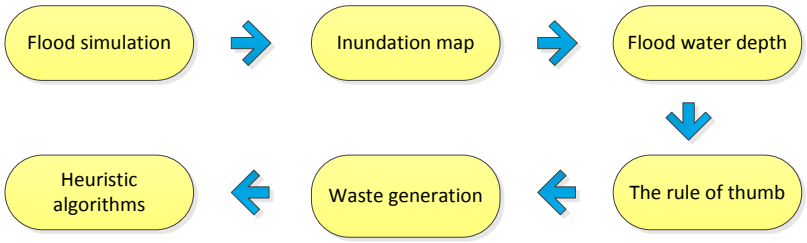


Figure 2. Customer nodes and waste generation estimation method

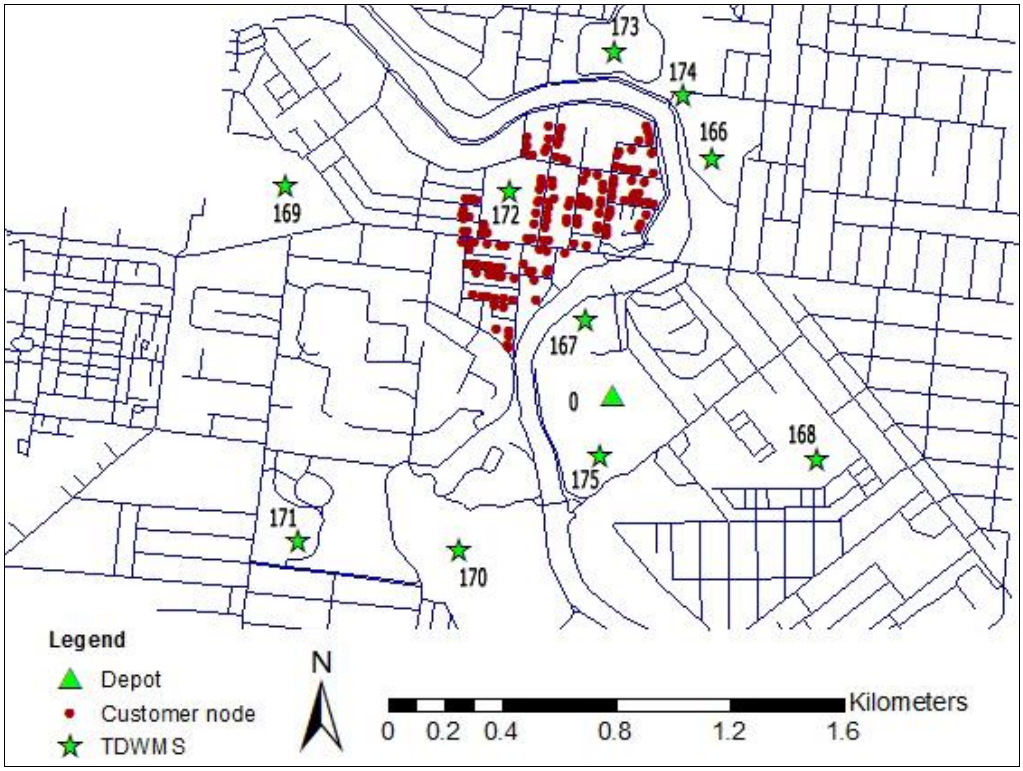


Figure 3. Nodes included in the instance

Although a significant number of floods have occurred in the case study area, there are limited data related to waste management post floods. Hence, most of the data required to run

the model were generated according to previous literature. Figure 2 shows the flow processes to finalise customer nodes and estimate waste generated from each node. In order to identify the inundation of each building in the case study area, a flood model, MIKE21, was applied to simulate a flood disaster. According to the simulation, 165 buildings flooded were identified as the customer nodes in the case study. In addition, 10 candidate TDWMS and 1 depot are identified using land suitability assessment method mentioned in (Cheng and Thompson, 2016). Figure 3 shows the nodes and road network considered in the case study area.

The waste generated at each customer node is calculated by applying the rule of thumb developed by Hirayama et al. (2010). In total, the demand of waste in the case study area is 651.4 tonnes. The capacity and CO_2 emission rate of each TDWMS depends on the size. Table 4 shows the size capacity and CO_2 emission rate.

Table 4. Data related to candidate TDWMS

No.	Location	Size /m^2	Capacity /ton	CO2 emission rate /Kg/d
166	Maribyrnong Park	180*100	40	3.60
167	Fairbairn Park	100*200	50	4.00
168	Walter St. Reserve	150*150	60	4.50
169	Public land	100*100	30	2.00
170	Pipemakers Park	180*180	80	6.48
171	Robert Barret Reserve	120*120	40	2.88
172	Maribyrnong Reserve	150*200	80	6.00
173	Aborfeldie Park	150*150	60	4.50
174	Moonee Valley Transfer Station	-	50	4.00
175	Fairbain Reserve	150*150	60	4.50

The distance between each pair of nodes is calculated in ArcGIS using road network data obtained from VicRoads (the statutory road and traffic authority in the State of Victoria, Australia). The number of available collection vehicles and the capacity of vehicles is assumed to be 5 and 20t respectively. The minimum total capacity of TDWMS was assumed to be 50t. The CO_2 emission of waste collection is 0.55Kg/km.

RESULTS ANALYSIS

Models comparison

This part compared the result of three different models mentioned in the second section. Model M1 is the original model without considering different time windows for customer nodes and split services. Model M2 includes specific time windows for customer nodes but do not allow split services. In model M3, split services are allowed and time windows are considered. In addition, two different routes construction rules are considered in the latter two models as well, namely, shortest distance (SD) and first available time (FAT).

Table 5 shows the results of different models. The results indicate that TDWMS no.7 is the best choice in all models no matter which route construction method is selected. The consideration of time windows for customer nodes increases total travel distance, total working time and also total CO_2 emission. However, the total clean-up period is still the same. In terms of different route construction methods, using shortest distance makes the total

travel distance much shorter while the application of first available time rule leads to a less total working time of vehicles. The longer the vehicles work the more impacts the clean-up will have in the disaster affected areas such as noise and traffic jams. Thus, the selection of route construction rules depends on what aspect of environment impacts is the major problem in the area. When it comes to the comparison of model M2 and M3, the results are different from literature (Archetti and Speranza, 2008) which recommended split service because it can save the total distance by 50%. In this research, the allowance of split service leads to a longer total travel distance using both route construction methods. In order to find out the impacts of TDWMS location, in the next section a sensitive analysis will be conducted.

Table 5. The results of different models

Model	M1	M2 (SD)	M2 (FAT)	M3(SD)	M3 (FAT)
TDWMS selected	[0000001000]	[0000001000]	[0000001000]	[0000001000]	[0000000100]
Total TDWMS capacity/t	80	80	80	80	80
Total travel distance /m	76247	99841	115838	100455	125661
Total working time /min	5086	10361	7849	11016	8348
Total clean-up period	9	9	9	9	9
Total CO_2 emission/kg	95.94	108.91	117.71	109.2503	123.11

Sensitive analysis

In this section, we repeated the algorithm for different TDWMS selection result (only one TDWMS was selected in each scenario. Figure 4 shows the results of total travel distance when TDWMS 166, 168, 171 or 173 was selected the total distance was shorter when split service was allowed for the route construction rule first available time. When the shortest distance was chosen as the rule to construct routes, the total travel distance was decreased when TDWMS 168, 170, 173, 174 or 175 was selected. The possible reason is that comparing to TDWMS 172 the TDWMS mentioned above are further from customer nodes, which benefit the total distance when split service is allowed in order to reduce the number of total routes. Figure 5 shows the results of total CO_2 emission, which is in direct ratio to total travel distance and total period needed. Thus, the trends are similar to the results of total travel distance. However, in Figure 6 which is the results of total working time, the trends are totally different. The advantage of TDWMS 172 is weak in terms of total working time especially using shortest distance rule. For instance, the total working time is shortest when 167 was chosen using shortest distance in M2. Thus, if the main goal of environmental impact control is to minimize the noise the result of TDWMS selection for the system will be different. Figure 7 is the result of period needed. It indicated that the allowance of split service can reduce the total clean-up period to some extent.

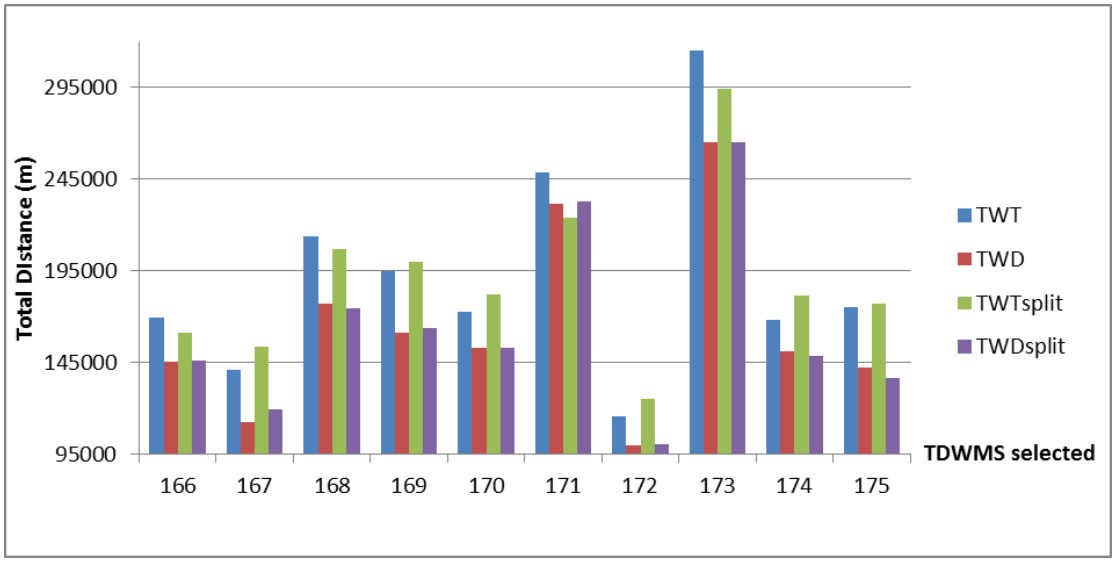


Figure 4. The results of total travel distance when different TDWMS was selected

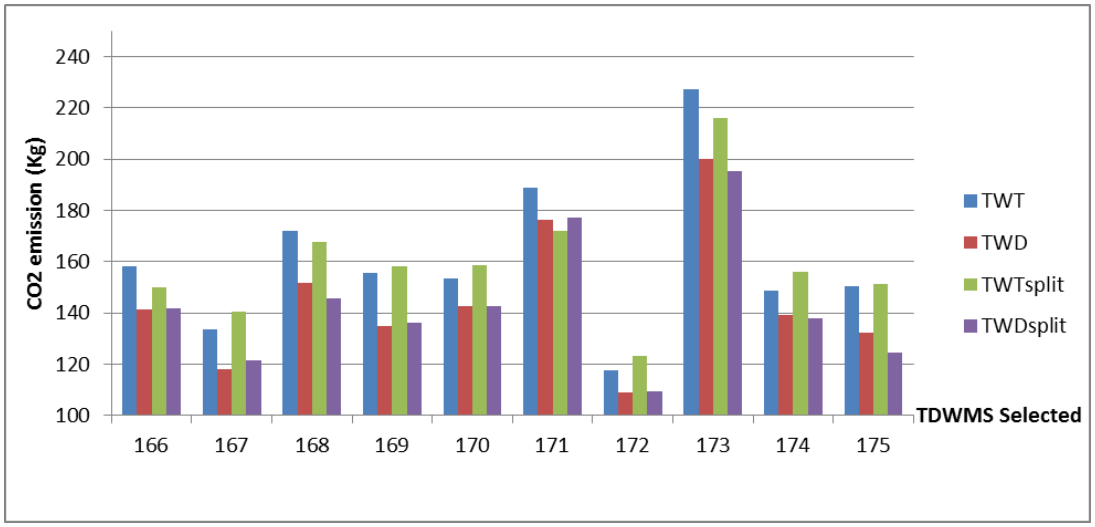


Figure 5. The results of total CO_2 emission when different TDWMS was selected

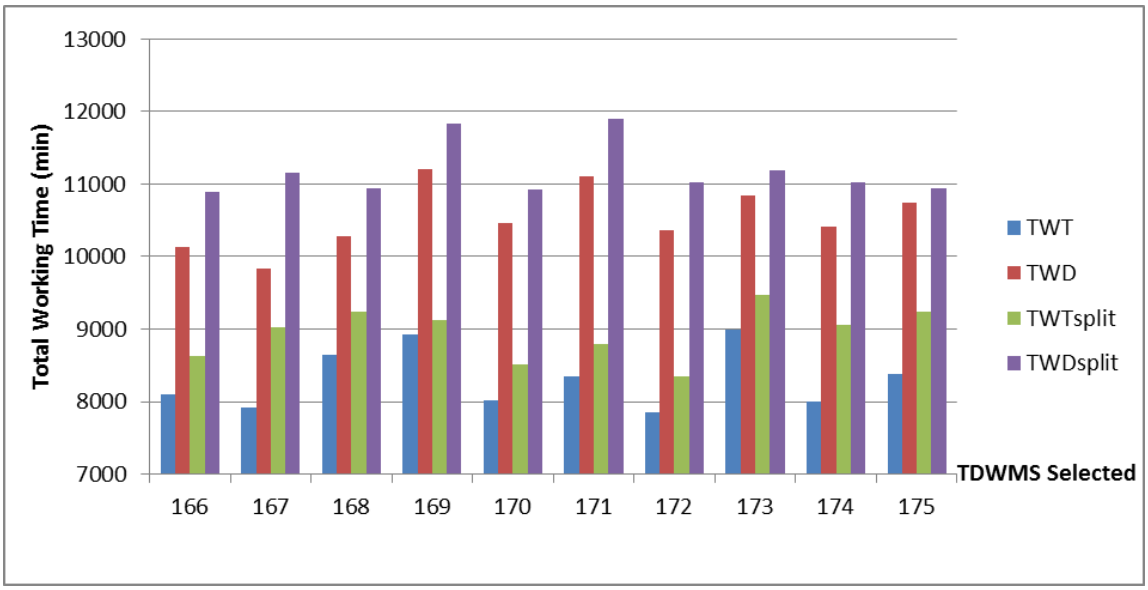


Figure 6. The results of total working time when different TDWMS was selected

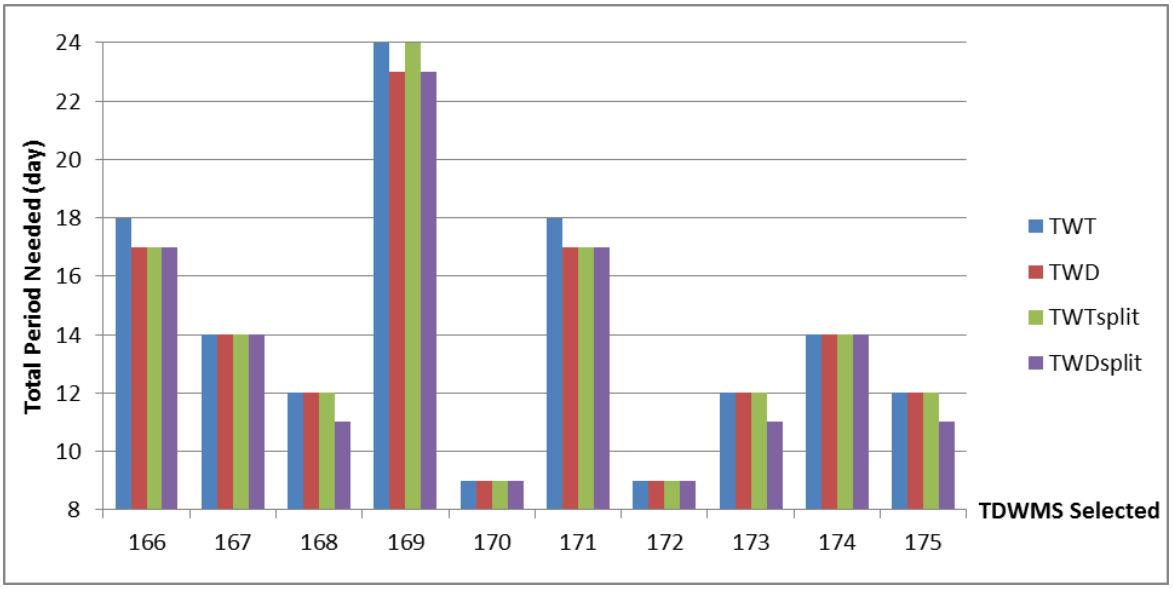


Figure 7. The results of total period needed when different TDWMS was selected

CONCLUSION

In this paper, we identified the waste collection problems post-disasters, which can be regarded as Bi-level Location Routing Problem (B-LRP). In order to solve this problem, three heuristic algorithms have been developed in MATLAB. The Genetic Algorithm is applied to solve the upper-level problem, which is a location problem. Greedy Algorithm is used to find the initial solution of the lower-level problem, which is an extended VRP. Simulated Annealing is conducted to optimize the initial solution in order to find a satisfying result. In addition, the methodology was applied to a case study area in Maribyrnong, a town in Victoria, Australia, that suffered from several serious floods. The application of the proposed methodology shows that the three algorithms can provide good results within acceptable computing time.

The present paper is different from research in this area in several ways. Firstly, different time windows for customer nodes are considered as a set of constraints in the models. In addition, different formulation models and route construction methods are compared to find the most suitable solution method in different situation. Furthermore, a sensitive analysis was analysed to identify the impacts of TDWMS location on the allowance of split service.

Given the limitation of the time, in this paper, we have not considered the difference of CO_2 emission when the load of a vehicle is different, which can make a big difference for heavy duty vehicles. The considering of this factor is of great interesting for the future research.

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