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Backtracking search algorithm in CVRP models for efficient solid waste collection and route optimization

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Waste collection is an important part of waste management that involves different issues, including environmental, economic, and social, among others. Waste collection optimization can reduce the waste collection budget and environmental emissions by reducing the collection route distance. This paper presents a modified Backtracking Search Algorithm (BSA) in capacitated vehicle routing problem (CVRP) models with the smart bin concept to find the best optimized waste collection route solutions. The objective function minimizes the sum of the waste collection route distances. The study introduces the concept of the threshold waste level (TWL) of waste bins to reduce the number of bins to be emptied by finding an optimal range, thus minimizing the distance. A scheduling model is also introduced to compare the feasibility of the proposed model with that of the conventional collection system in terms of travel distance, collected waste, fuel consumption, fuel cost, efficiency and CO_2 emission. The optimal TWL was found to be between 70% and 75% of the fill level of waste collection nodes and had the maximum tightness value for different problem cases. The obtained results for four days show a 36.80% distance reduction for 91.40% of the total waste collection, which eventually increases the average waste collection efficiency by 36.78% and reduces the fuel consumption, fuel cost and CO_2 emission by 50%, 47.77% and 44.68%, respectively. Thus, the proposed optimization model can be considered a viable tool for optimizing waste collection routes to reduce economic costs and environmental impacts.

1. Introduction

Solid waste management (SWM) is always a prime concern in every country. Solid waste collection (SWC) is one of the most challenging steps among all the operational steps of SWM. Municipal solid waste (MSW) is a major by-product of the urban lifestyle, which is rising even faster than urbanization (Hannan et al., 2015), and its quantity has been significantly increased due to the rapid population growth. Thus, the growth of population and urbanization, combined with growing environmental concerns, has created a critical situation such that the management or policy-makers must look for different sustainable means of effectively collecting and disposing of the mounting waste (Poser and Awad, 2006; Xue et al., 2015). It has also made SWC more delicate in terms of traffic congestion and fuel consumption and its subsequent cost, environmental pollution (greenhouse gas emission), etc. Moreover, a huge amount of the budget is spent on this sector. The concern regarding its efficiency has increased even more with the emerging modern era. In consequence of this concern, many municipalities (especially in industrialized nations) are forced to assess the cost-effectiveness and environmental impacts of their SWM systems, particularly waste collection route designs (Nuortio et al., 2006). Therefore, a number of studies have been conducted to reduce this expenditure. Economopoulou et al. (2013) described a software system to cut the annual capital investment and annual operating cost of MSW transportation, treatment and final disposal operation and achieve significant economic savings. Hence, with the proper study of SWC efficiency, cost in this sector can be cut by avoiding permanent adverse effects on the environment.

Management of solid waste is a multi-tasking process. It involves generation, source-separation, storage, collection, transfer and transport, processing and recovery, and disposal (Rada et al.,

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2010). Among all the steps of waste management, waste collection (from waste generation to the waste management centre, i.e., the SWC route) is the most important issue (Kanchanabhan et al., 2010). The typical process of waste collection involves vehicles that start from the depot; they travel in fixed routes to collect waste by visiting all locations, which consumes a large amount of the budget. While collecting waste, vehicles keep their engines running, even during the loading-unloading of waste bins, which results in huge consumption of fuel and greater emissions. Up to 70% of the total budget for SWM may be used for SWC, mainly for fuel consumption (Tavares et al., 2009); that has a substantial hazardous effect on the environment due to the consequent pollution emissions (Zsigraiova et al., 2013). This pollution has tremendous impacts, including an increasing pattern of CO_2 accumulation of approximately 2 ppm per year (Budzianowski, 2012, 2016). Therefore, by improving SWC, not only the total budget of SWM but also adverse effects on the environment can be improved tremendously.

Waste collection is a complex procedure for any municipality, especially in cities of developing countries, in terms of logistics, fuel and labour costs and air pollutant emissions (Malakahmad et al., 2014). In fact, SWM is a challenge for every municipality regardless of its economic condition. Malaysia is a Southeast Asian country with an upper middle income level. The Malaysian government has a very large budget for solid waste management. The budget of the Taman Beringin Transfer Station (TBTS), a solid waste transfer station, is approximately RM 30,000,000 per year for only simple operational costs (Budhiarta et al., 2012). Still, the level of waste management is unsatisfactory and dangerous (Periathamby et al., 2009). The local authorities must spend more than 50% of their operational budget for waste management, 50% of which is actually spent on the waste collection process (Manaf et al., 2009). Therefore, by improving the waste collection process, waste management can be made efficient and cost effective.

Previously, and even currently in most areas, solid waste collection is carried out without analysing demand, and the construction of the routes for collection is left to the drivers. Hence, it takes longer to collect garbage, and due to the absence of a proper monitoring system, many regions are commonly left out. This improper waste collection and transportation system makes the entire SWM process inefficient. The MSW collection cost is expressed as cost per tonne (Faccio et al., 2011); hence, it is a waste of resources to travel to empty a bin that is not full yet. If it is possible to identify the bins that are not full yet and can thus be emptied later, the waste collection route can be compressed, making it cost effective. Therefore, the need for a properly monitored waste collection system is growing with time, and studies concerned with finding proper solid waste collection and transportation are being conducted.

Researchers from all over the world have already conducted a number of studies on monitoring different steps of the waste collection process by applying modern technologies. For example, Mamun et al. (2015) developed a smart bin that monitors its waste status. A waste collection route can be made more efficient if it is designed to only empty the full bins based on the real-time waste statuses of smart bins. Again, the routing problem is computationally quite challenging, and in the case of large systems, optimal (exact) methods cannot be applied. Hence, comparatively new algorithmic approaches (e.g., heuristic and meta-heuristic) are applied in those cases to yield the most optimized result (Laporte et al., 2000). Thus, a proper algorithm is needed for the decision regarding an optimized waste collection route instead of collecting garbage in a pre-defined path. This route optimization method can conserve travel distance and minimize the number of vehicles, which reduces labour costs, fuel costs, operation time, greenhouse gas GHG emissions, etc.

To make solid waste collection more cost-effective, different optimization approaches have been applied, e.g., to reduce travel distance, time, cost, emissions, etc. In many research studies, the waste collection problem of an area is designed as a vehicle routing problem (VRP), which yields an effective collection route (Bautista et al., 2008). There are a number of constraints considered in these studies. The most common constraint is the vehicle capacity constraint. The solid waste collection route is modelled in such a way that the collected waste does not exceed the capacity of the vehicle. When a capacity constraint is considered in a VRP, it is named the capacitated vehicle routing problem (CVRP) (Dantzig and Ramser, 1959). In many studies, waste collection has been modelled in CVRP approaches with different algorithms and software (Kuo et al., 2012; Liu and He, 2012a; McLeod and Cherrett, 2008). There are various other constraints, e.g., time, regulatory, political, etc., that are taken into account in different studies. However, limited experiments have been conducted with smart bin technologies for waste collection and route optimization.

Along with other optimization problems, newly developed algorithms are also applied in solid waste collection optimization studies. Initially, conventional mathematical programming algorithms, such as linear programming (Kulcar, 1996) and mixed integer programming (Tung and Pinnoi, 2000; Badran and El-Haggar, 2006; Agha, 2006), have been applied for solid waste collection optimization. To overcome the limitations of these methods (that they are less effective for large-scale problems requiring more components to be considered for optimization, which makes the solution approach complicated), the heuristic approach has become popular because it can overcome the problem of huge computational time. Some popular and effective heuristic approaches are the nearest neighbourhood search algorithm (Faccio et al., 2011) and the greedy algorithm (Bautista and Pereira, 2006; Sahoo et al., 2005). However, these techniques lack precision and have longer execution times for the collection of solid waste (Viotti et al., 2003). The meta-heuristic approach is the most popular approach in recent years, yielding sufficiently good solutions for collection optimization even when there is incomplete information or limited computational capacity. This technique incorporates elements of biological evolution, the nervous system, intelligent problem-solving, etc. A few meta-heuristics approaches are popular, such as ant colony optimization (ACO) (Islam and Rahman, 2012; Liu and He, 2012a, 2012b), genetic algorithms (GAs) (Karadimas et al., 2007; Viotti et al., 2003), and particle swarm optimization (PSO) (Son, 2014; Kuo et al., 2012).

There is a number of software packages used in waste collection optimization. ArcGIS is a very commonly used software for solid waste collection optimization. Using this software, the real-time road conditions (traffic, blockage, etc.) can be optimized, and a route can be designed accordingly (Malakahmad et al., 2014; Shastri et al., 2014; Tavares et al., 2009; Khan and Samadder, 2016). With the development of technology, different technical devices, such as different sensors and systems (Mamun et al., 2015; Rovetta et al., 2009), RFID (Radio Frequency Identification) for solid waste bin and truck monitoring (Hannan et al., 2011), advanced image processing for bin waste-level detection, (Arebey et al., 2012) and vehicular ad-hoc networks (VANET) (Narendra et al., 2014), are becoming popular to make waste collection more efficient by making the communication easier between different collection components. Application of these technologies in waste bins makes it easy to make dynamic decisions on waste collection route design by taking its capacity (waste level) as a constraint.

However, very few studies have combined this technology with the best developed algorithms in solid waste collection research. Faccio et al. (2011) introduced a framework by using the traceable data from a smart bin and waste collection truck, both combined with a number of sensors with a heuristic approach in a simulation

Table 1
Literature on solid waste collection.

Method	Algorithm	Optimization	Use of GIS	Capacity constraint		Ref.
				Vehicle	Bin	
Convention	Mixed Integer Programming	Cost	No	Yes	No	Agha (2006)
	Mixed Integer Linear Programming		Yes	Yes	No	Anghinolfi et al. (2013)
	Linear Programming		No	No	No	Kulcar (1996)
Heuristic	Cluster-first-route-second	Distance	Yes	Yes	No	Otoo et al. (2014)
	Nearest neighbourhood		No	Yes	Yes	Faccio et al. (2011)
Meta-heuristic	Chaotic Particle Swarm Optimization	Waste quantity	Yes	Yes	No	Son (2014)
	Variable Neighbourhood Search thresholding	Cost	No	Yes	No	Nuortio et al. (2006)
	Tabu Search Method		No	Yes	No	Gómez et al. (2015)

environment. They considered different optimal replenishment levels and oversize risk parameters in their study to compare the collection route optimization results. Johansson (2006) also considered smart waste bins and designed dynamic scheduling and routing for waste collection. They showed a reduction in operational cost, travel distance and labour hours compared to the static fixed routing system. The following is a table that summarizes the modelling approaches applied in a few works in the literature for SWC route optimization. Table 1 clearly shows that most of the studies on SWC route optimization did not consider bin capacity or waste level. Thus, this study aims to fill the research gap with regard to the limited number of studies on SWC route optimization using real-time waste status data.

This study focuses on combining a newly developed meta-heuristic algorithm with a smart waste bin equipped with different sensors. The study is performed in a simulation environment. In this study, BSA is applied in a CVRP model along with the concept of smart bin data. A number of local improvement methods are also applied to improve the performance of BSA. The objective of the study is to find the feasibility of the proposed method for waste collection and route optimization in terms of distance, efficiency, fuel consumption, fuel cost and CO_2 emission. BSA is a simple optimization algorithm. It has already produced good results in different optimization problems. However, there is thus far no available literature on BSA in solid waste collection route optimization.

2. Methodology

To apply the proposed algorithm, this study develops a capacitated vehicle routing problem (CVRP) model in which the BSA algorithm is incorporated with the CVRP model to solve the route optimization problem. The BSA-based CVRP model uses data from smart bins to collect waste efficiently. Smart bins can obtain real-time waste data through a number of sensors, such as an ultrasonic sensor that provides the bin waste level, a load cell that measures the waste weight in the bin, etc. The bin also has a magnetic proximity sensor on its lid that provides information every time the lid is open (Mamun et al., 2015). All these sensors also help to monitor whether the particular waste bin has been emptied or not. Hence, real-time decisions can be made at the beginning of each collection process to collect waste from the most prioritized collection nodes and thus conserve travel distance, costs and emissions. The detailed CVRP model and BSA optimization algorithm are described below.

2.1. Capacitated vehicle routing problem model

The vehicle routing problem (VRP) addresses serving a set of customers in reduced travel distant routes by starting and returning at the depot (Ai and Kachitvichyanukul, 2009). CVRP is an extension of VRP with capacity constraints. CVRP in solid waste collection can be defined as collecting waste from a set of collection nodes (bins) by a homogenous or heterogeneous fleet of vehicles of fixed capacity that cannot be violated, each starting from and returning to the depot. The CVRP model is explained below, where n is the number of bins and k is the number of vehicles considered.

- A complete graph $G = (V, E)$, where $V=\{0, 1, \ldots n\}$ is a vertex (bin) set and E is the arc set. Here, 0 represents the depot.
- Vertices $i = 1,2 \ldots n$ correspond to the bins, where n is the number of bins to be visited. Each bin has a non-negative waste quantity c_i inside it.
- A set of homogenous vehicles $k = \{1, 2 \ldots K\}$, each with a capacity of C, is stationed at the depot for waste collection.
- A non-negative cost, d_{ij}, is associated with each arc $(i, j) \in E$ and represents the travel distance from bin i to bin j, where $i \neq j$.
- q_{ijk} represents the load of vehicle k while traversing arc (i, j).

To achieve the objective of the study, a number of constraints are considered to make the model more realistic. They are described below.

- All the vehicles start from and return to the depot;
- The depot also acts as the waste transfer facility;
- All the vehicles start at the same time from the depot;
- Each waste bin is visited by only one vehicle during each collection time;
- The cumulative waste of all the bins of a route must not exceed the maximum capacity of the vehicle assigned to it;
- The fleet of vehicles and the bins are homogenous;
- Traffic congestion is neglected during waste collection.

The current study considers both the capacity of the vehicles and the bins in the CVRP model. The CVRP model starts with a cluster of most prioritized bins. This cluster is formed prior to every collection by accessing the real-time waste data of bins. Bins that exceed a predefined threshold waste level (TWL) of their capacity are included in the cluster, and route optimization is performed for this cluster of bins for solid waste collection optimization.

The mathematical formulation of the model is presented below. The decision variables of the model depend on the vehicle capacity, C, and the waste quantity of the next bin to be visited. Decision variables are modelled in Eqs. (1) and (2) as follows.

$$X_{ijk} = \begin{cases} 1, & \text{if vehicle k traverses arc } (i,j) \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$Y_{ik} = \begin{cases} 1, & \text{if bin i belongs to the route of vehicle k} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

The objective function to minimize the travelling distance is defined in Eq. (3) as follows.

$$\min \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K} \mathrm{d_{ij}X_{ijk}} \tag{3}$$

Subject to

$$\sum_{j=1}^{n}\sum_{k=1}^{K} \mathrm{X_{0jk}} = 1 \tag{4}$$

$$\sum_{j=1}^{n} q_{0jk} = 0 \quad \forall \mathrm{k} = 1,2\ldots\mathrm{K} \tag{5}$$

$$\sum_{i=0}^{n}\sum_{k=1}^{K} \mathrm{X_{ijk}} = 1 \quad \forall \mathrm{j} = 1,2,\ldots\mathrm{n} \tag{6}$$

$$\sum_{j=1}^{n} \mathrm{X_{ijk}} = \sum_{j=1}^{n} \mathrm{X_{jik}} = \mathrm{Y_{ik}} \quad \forall \mathrm{i} = 0,1,2\ldots\mathrm{n}; \quad \mathrm{k} = 1,2,\ldots\mathrm{K} \tag{7}$$

$$\sum_{i=0}^{n}\sum_{k=1}^{K} q_{jik} - \sum_{i=0}^{n}\sum_{k=1}^{K} q_{ijk} = \mathrm{c_j} \quad \forall \mathrm{j} = 1,2,\ldots\mathrm{n} \tag{8}$$

$$\sum_{i=1}^{n} \mathrm{c_i X_{ijk}} \leqslant \mathrm{C} \quad \forall \mathrm{j} = 0,1\ldots\mathrm{n}; \quad \mathrm{k} = 1,2,\ldots\mathrm{K} \tag{9}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{K} \mathrm{X_{i0k}} = 1 \tag{10}$$

$$\mathrm{dist_{ij}} = \mathrm{dist_{ji}} \quad \forall \mathrm{i} = 0,1,2\ldots\mathrm{n}; \quad \mathrm{j} = 0,1,2,\ldots\mathrm{n} \tag{11}$$

Eqs. (4) and (5) specify that vehicle k will start the tour from the depot carrying no load. According to Eq. (6), each bin is visited by only one vehicle. Eq. (7) ensures the continuity condition. That is, if vehicle k enters a vertex, it must also leave the node. Eq. (8) ensures that the vehicle empties the bins visited, and Eq. (9) represents that the total collected waste from all the bins visited in a tour must not exceed the vehicle capacity. After the tour, the vehicle returns to the depot according to Eq. (10). Eq. (11) shows that the distance between two nodes is the same in both directions.

2.2. Backtracking Search Algorithm in the CVRP model

The Backtracking Search Algorithm (BSA) is a relatively new population-based meta-heuristic algorithm developed by Civicioglu in 2013. The BSA is a simpler and more effective evolutionary algorithm for optimization problems and has only one control parameter. Its simplified and unique structure has encouraged the solution of many complex real-world optimization problems (Niamul Islam et al., 2016). The BSA is a population-based optimization algorithm. It uses a large number of populations to find the optimized result by applying two unique concepts: the historical population and map matrix. For each movement, the historical population drags the solution towards the optimized result. It allows for exploration and exploitation of better solutions within a solution field to overcome the local minima trap. During the exploitation search, the map matrix refines the solution. Readers can find a clear explanation of the algorithm in Civicioglu (2013). In the present study, each population represents the string of a route starting and ending at the depot after visiting all the bins. The BSA is modified in this study to apply to waste collection optimization problems. The basic steps of this algorithm are explained below.

2.2.1. Step 1: Initialization

The BSA produces each individual of the initial and historical population based on a uniform distribution of boundary constraints using Eqs. (12) and (13).

$$\text{Initial population, } P_{n,d} \sim \cup(low_d, up_d) \tag{12}$$

$$\text{Historic population, } HisP_{n,d} \sim \cup(low_d, up_d) \tag{13}$$

$$\text{Fitness value, } Dist_{p_{n,d}} = f(p_{n,d}) \tag{14}$$

$$\text{Global best, } Dist_g = \min(Dist_{p_{n,d}}) \tag{15}$$

$$\text{Best population, } g_{best} = P_{n,d_{best}} \tag{16}$$

Here, $n \in \{1,2,3\ldots N\}$ and $d \in \{1,2,3\ldots D\}$, where N and D are the population size and problem dimension, respectively; $\cup$ is the uniform distribution; P_n and $HisP_n$ are the target individuals of the initial and historic population; and low and up are the boundary constraints. Population size is the number of routes considered, and dimension size is the number of bins to be emptied. $Dist_{p_{n,d}}$ represents the fitness value for the total population size, where $Dist_g$ evaluates the best fitness value among them, and the corresponding population is taken as the optimized population, g_{best}.

2.2.2. Step 2: Selection I

At the beginning of every iteration t, the historical population can be updated based on the 'if-then' rule while applying the following equation:

$$\text{If a} < \text{b, then } HisP := P|a,b \sim \cup(0,1) \tag{17}$$

where $:=$ presents the update operation. BSA has a memory. According to Eq. (17), the BSA designates a population belonging to a randomly selected previous generation as the historical population and remembers this historical population until it is changed. In the next step, the order of the individuals is changed by a random shuffling function according to Eq. (18).

$$HisP := permuting\ (HisP) \tag{18}$$

2.2.3. Step 3: Mutation + Crossover

The main difference between the proposed BSA model and the conventional model is in this stage. This stage combines two main steps of the original algorithmic form to produce a trial population during every iteration. The aim of this stage is to produce a trial population.

Mutant is the initial form of the trial population. To find mutant, the map matrix is introduced. To obtain the map matrix, the following equation is applied.

$$\text{Initial map matrix, } map_{1:N,1:D} = 1$$

$$\text{if a} < b|a,b \sim \cup(0,1), \text{ then for n from 1 to N do}$$

$$map_{n,u_{(1:\lceil mixrate.rand.D \rceil)}} = 0|u = permuting\ (\langle 1,2,3,\ldots D\rangle) \tag{19}$$

end

else

$$\text{for n from 1 to N do, } map_{n,randi(D)} = 0, \text{ end} \tag{20}$$

end

To obtain the trial population, mutant and offspring are found. The BSA's mutation process and the offspring finding for this study are performed according to Eqs. (21) and (22)

$$mutant = P + (map * F) * (HisP - P) \tag{21}$$

$$\mathrm{F} = \mathrm{d} * rndn$$

Here, F controls the amplitude of the search direction matrix ($HisP - P$), and d is the dimension of the problem. *rndn* is the built-in MATLAB function for generating normally distributed values (0–1).

$$Offspring = P + mutant \tag{22}$$

Unlike the conventional algorithm, the boundary condition of the BSA is used for the *Offspring* and for the trial population. The *Offspring* values are checked and updated according to the following equations.

$$\text{if } Offspring < 1 \text{ then } Offspring = 1$$
$$\text{if } Offspring > d \text{ then } Offspring = d$$

From this updated *Offspring*, the initial trial population, $T_{n,d}$, is found. As the node number of a bin is a real number, the *Offspring* values are sorted in ascending order to find the index value. This index value is set as the initial $T_{n,d}$. In case of a tie, the order is determined according to the ascending order of the mutant values for the respective *Offspring* values. By applying this initial $T_{n,d}$ in the CVRP model, a number of sub-routes are formed. Finally, by applying four local search methods in these sub-routes to improve the solution, the final $T_{n,d}$ is obtained.

2.2.4. Step 4: Selection II

This step compares the fitness values of the trial populations with the corresponding initial populations, and the population is updated based on that. The condition to update the population is shown below.

$$\text{if } Dist_{T_{n,d}} < Dist_{P_{n,d}} \text{ then } Dist_{P_{n,d}} = Dist_{T_{n,d}} \text{ and } P_{n,d} = T_{n,d}$$

From the updated population fitness value, the global fitness value, $Dist_g$, and the optimized population, g_{best}, are updated according to Eqs. (15) and (16). These steps are updated with every iteration.

When the number of iterations meets the maximum iteration t_max, g_{best} is taken as the optimized route with the optimized distance of $Dist_g$. To evaluate the effects of this optimized route, the variation in fuel consumption, cost and CO_2 emission is obtained from this optimized distance.

Fig. 1 shows the operational flow of the developed BSA, including the encoding and decoding of the particles.

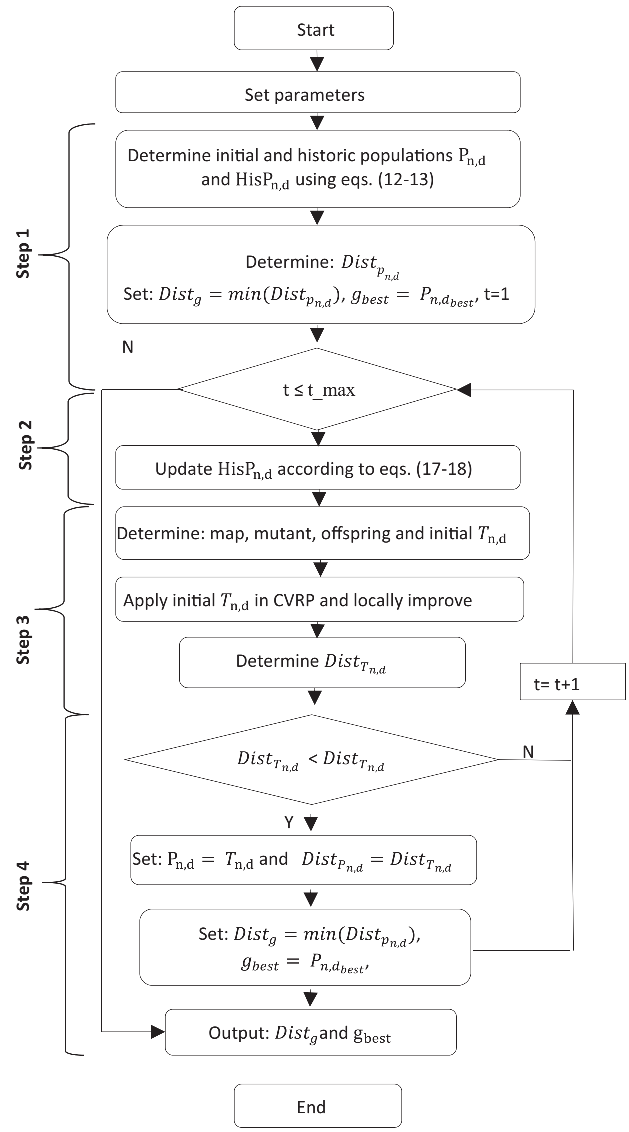

Fig. 1. Proposed BSA-based waste collection optimization model.

2.3. Local improvement of the trial population

The fundamental BSA model cannot find the optimized route. The routes found this way need to be locally improved. In this study, four local search methods are applied to find the improved routes. Among these, two methods are utilized for inter-route improvement, and the remaining two are implemented for intra-route improvement. A brief description, along with a figure (Fig. 2), where the dashed line shows the new route after improvement, is given below.

2-*opt**: This is the first local search method that is applied in trial routes. It is performed for inter-route improvement. Here, every connecting link of the nodes of the sub-routes is broken to connect with nodes from another sub-route to obtain improvement. The complexity of this method neighbourhood is $O(N^2)$, where N is the number of nodes. Fig. 2(a) is an illustration of the method.

Or-opt-1: For inter-route improvement, this method is applied next. It exchanges nodes between sub-routes. Here, every node from a certain sub-route is adjusted between two nodes from another sub-route to find an improved solution. Fig. 2(b) shows how the method works.

2-opt: This local search method is the most commonly applied method for locally improving a route. The 2-opt method replaces non-adjacent links $(i-1, i)$ and $(j, j+1)$ from the route with $(i, j+1)$ and $(i-1, j)$ by reversing the existing route between nodes i and j. The complexity of this neighbourhood method is $O(N^2)$, where N is the number of nodes. Fig. 2(c) shows its function.

Or-opt: This is the last local improvement method that is applied to upgrade the route. The method allows for relocating 1, 2 or 3 consecutive nodes from a route with new edges. Unlike 2-opt, it does not modify the orientation (Fig. 2(d)). The complexity of Or-opt is $O(N^2)$, where N is the number of nodes.

2.4. Threshold waste level and scheduling model

A threshold waste level approach is applied in this study to find its optimal value. This optimal threshold waste level (TWL) value is found from different datasets. The objective of this study is to obtain a range of filled percentages of waste collection nodes in which a considerable amount of waste can be collected by optimizing the waste collection route. To validate the performance of the proposed model, a scheduling of waste collection for four days is

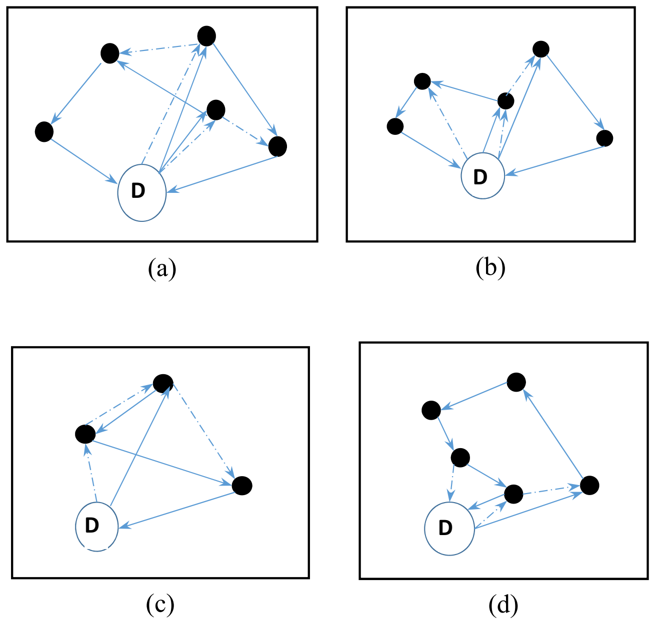

Fig. 2. Process flow of the local improvement methods (a) 2-*opt**, (b) Or-opt-1, (c) 2-opt, (d) Or-opt.

also performed for a dataset, taking it as a hypothetical area. Thus, the proposed model is applied in a number of renowned datasets to validate its performance by comparison with other already established algorithms. To obtain an optimal TWL value, this study considers some fixed waste node filled value for different datasets to find which TWL shows the most improved result using smart bin data compared to the conventional collection system, where no data are available. Detailed steps for finding the best TWL are as follows.

(a) The model is applied to five datasets.
(b) The datasets consist of collection nodes from 32 to 77.
(c) The simulation study considered six TWL values between 0% and 90%. The value of 0% represents the conventional system of travelling to all collection nodes.
(d) Tightness is estimated for each dataset by calculating the amount of waste carried per unit vehicle capacity.
(e) Tightness values of all datasets, as well as the collection of a considerable amount of waste by travelling an optimized distance route by a reduced number of vehicles, are studied to obtain the best TWL.

Similarly, for scheduling, a dataset is considered from a hypothetical area for scheduling four days' waste collection to show the improvement in a realistic scenario. The efficiency of the model can be determined by its effectiveness over the conventional system after applying it in a more realistic scenario. To find the feasibility of the proposed model, scheduling is done for four days in a randomly generated hypothetical area with waste collection location co-ordinates and initial waste amounts. The assumptions considered here are described below.

(a) Waste is collected every alternate day.
(b) There is no collection during weekends.
(c) A fixed route is followed in the conventional system.
(d) Collections route may vary according to bin statuses in the proposed system.
(e) The depot and waste transfer facility are situated in the same location.
(f) After collecting each time, the waste amount for the next day is randomly generated considering a mean waste generation rate along with a standard deviation.
(g) Waste collection is performed considering both 70% TWL and visiting all the nodes.
(h) Efficiency and tightness are estimated by calculating the amount of waste carried per unit distance and the fill status of the vehicle after visiting all nodes.
(i) Fuel consumption is calculated according to the method proposed by Larsen et al. (2009) using Eq. (23) as follows.

$$f_{consumption} = \frac{f_{total} - (f_{t,empty} + f_{t,full})}{W} \tag{23}$$

Here, $f_{consumption}$ is the fuel consumption for collection (L/tonne); f_{total} is the total fuel consumption (L/day); $f_{t,empty}$ is the fuel consumption for driving an empty truck from the garage to the collection area and from the point of unloading to the collection area or garage (L/day); $f_{t,full}$ is the fuel consumption for driving a full truck from the collection area to the point of unloading (L/day); and W is the amount of waste collected (tonne/day).
(j) The collection cost is determined based on fuel consumption alone.
(k) The CO_2 emission value is also obtained according to the model by Lin (2010) using Eq. (24).

$$E_{CO_2} = W * D * \frac{EF_{fuel}}{F * W_{ave}} \tag{24}$$

Here, W is the total amount of municipal solid waste transported by one vehicle (kg), D is the distance travelled by the vehicle (km), EF_{fuel} is the CO_2 emission factor of fuel (kg CO_2/l), F is the fuel consumption rate (km/l), and W_{ave} is the average waste weight collected by all the vehicles (kg).

$$F = D/(f_{collection} * W)$$

$$W_{ave} = \frac{\sum W}{\text{no. of vehicles}}$$

3. Results and discussion

To validate the effectiveness and performance of the proposed algorithm, it has been tested for a number of benchmark data with different sizes of bin nodes. The simulation has been conducted in MATLAB 8.3 on a computer with an Intel Core i5 processor running at 3.20 GHz and 2 GB of RAM. The BSA is one of the simplest algorithms, as it requires only one parameter. Here, we have taken the dimension as the number of bins in each dataset. The maximum number of populations and maximum number of iterations are 50 and 120, respectively. All the simulation datasets that have been used to test the algorithm can be found at (http://www.coin-or.org/SYMPHONY/branchandcut/VRP/data/#V).

3.1. Algorithm performance

Based on the methodology described thus far, the Backtracking Search Algorithm (BSA) in the CVRP model is applied to evaluate the performance of the fundamental BSA without local algorithms and the proposed BSA model with the application of local algorithms. For this study, six datasets were used, with the number of nodes ranging from 15 to 71. For the fundamental BSA model, none of the datasets could achieve the best value, and with an increase in the number of nodes, the gap between the obtained value and the best known value increased, making this model inapplicable in collection route optimization. However, the proposed

BSA model achieved the best value for all datasets except for one. The gap between its value and the best value was very narrow for this problem instance. The results are summarized in the following table.

3.2. TWL in the BSA algorithm for waste collection and route optimization

The study is conducted to fulfil the main objective of optimizing the waste collection route by implementing smart bins. This section addresses the improvement in waste collection and route optimization by applying the TWL concept in the BSA. The model is applied in five datasets with a variation of the number of nodes between 32 and 77; four datasets have the same vehicle size of 100 units, and the other has 140 units. Due to the fluctuation of node demand in different problem instances, collection node capacities also fluctuated in this study. As this study did not focus on the optimization of the bin number or bin size but rather the route to collect waste from the bin, a variable number of bins in every location is considered based on the demand of that node. Demand in the dataset is considered as the percentage of node capacity. The maximum capacity of each bin is taken to be 10 units, and the demand of the node is considered to be uniformly distributed across all the bins. To compute an efficient waste collection route, we have considered five TWLs: 60%, 70%, 75%, 80% and 90%. Waste bins exceeding a certain TWL need to be collected. Table 3 shows the results obtained, such as total distance, improvement in distance, total collected waste and collection percentage, and the tightness of the system under different datasets, TWLs, nodes and vehicle and bin capacities, respectively. It is observed that the proposed model showed improved results when using the smart bin waste collection with TWLs. From the obtained results, it can be seen that the best tightness generated was for TWLs from 70% to 75% for all but one dataset with an optimized distance, which is above 95%; the exception also had a very good result of 86%. This problem instance (P-n40-k5) shows that the tightness value for a TWL of 0% is more than that for 75%. However, this model can result in collecting 78% of the total waste by travelling 22% less distance with a tightness reduction of only 2%. Thus, for all datasets, if waste is collected in between a 70% and 75% TWL,

Table 2
Obtained results from the application of the fundamental BSA and the proposed BSA to different datasets.

Dataset	N	Fundamental BSA		Proposed BSA		BKS
		Distance	Gap (%)	Distance	Gap (%)	
P-n16-k8	15	463	2.89	450	0.00	450
P-n23-k8	22	618	16.82	529	0.00	529
A-n33-k5	32	1285	94.40	661	0.00	661
P-n40-k5	39	942	105.68	458	0.00	458
E-n51-k5	50	1318	152.98	522	0.19	521
F-n72-k4	71	970	309.28	237	0.00	237

Where n is the number of collection points and BKS is the best known solution found thus far.

Table 3
Obtained results by applying the TWL concept in the BSA algorithm for different datasets.

No.	Datasets	Capacity of vehicle (unit)	Capacity of bin (unit)	TWL (%)	N	V	Distance (unit)	Improvement (%)	Total collected waste	Waste collected (%)	Tightness (waste/capacity)
1	A-n33-k5	100	10	0	32	5	661	0.00	446	100	0.89
				60	28	5	633	4.24	431	96.64	0.86
				70	25	4	585	11.50	392	87.89	0.98
				75	21	4	533	19.36	336	75.34	0.84
				80	17	3	457	30.86	252	56.50	0.84
				90	12	2	374	43.42	180	40.39	0.90
2	P-n40-k5	140	10	0	39	5	458	0.00	618	100	0.88
				60	35	5	441	3.71	588	95.15	0.84
				70	32	5	406	11.35	564	91.26	0.81
				75	26	4	359	21.62	480	77.67	0.86
				80	19	3	299	34.72	351	56.80	0.84
				90	12	2	232	49.34	219	35.44	0.78
3	A-n46-k7	100	10	0	45	7	914	0.00	603	100	0.86
				60	38	7	903	1.20	587	97.35	0.84
				70	28	5	753	17.61	475	78.77	0.95
				75	22	4	637	30.31	389	64.51	0.97
				80	18	4	548	40.04	313	51.91	0.78
				90	14	3	449	50.86	222	36.82	0.74
4	A-n60-k9	100	10	0	59	9	1402	0	829	100	0.92
				60	41	8	1253	10.63	738	89.02	0.92
				70	38	8	1237	11.77	713	86.01	0.89
				75	31	6	1052	24.96	586	70.69	0.98
				80	29	6	978	30.24	517	62.36	0.86
				90	19	4	693	50.57	319	38.48	0.80
5	B-n78-k10	100	10	0	77	10	1279	0.00	937	100	0.94
				60	54	9	1140	10.87	848	90.50	0.94
				70	43	8	1077	15.79	757	80.79	0.95
				75	27	6	732	42.04	495	52.83	0.83
				80	21	4	613	51.46	373	39.81	0.93
				90	11	2	346	72.60	189	20.17	0.95

a distance savings of up to 42% can be obtained by collecting a high percentage of waste with a minimized number of vehicles. For a TWL of 80–90%, with an increase of TWL, the distance is decreased; however, in most cases, the percentage of waste collected is the least for all datasets, which would not be convenient for the waste collection authority. Thus, at a 70–75% TWL, the developed system provides the most efficient and optimized values.

The variation of different parameters with respect to the change in TWL is shown in Fig. 3. The TWL is, in fact, directly related to the number of vehicles, distance reduction and collected waste. Fig. 3 (a) shows that, with the decrease in the number of nodes, the length of the route is decreased, thus resulting in fewer vehicles, as seen in Fig. 3(b). As with the increase in TWL, the number of collection nodes decreases, and the total collected waste is also reduced. Fig. 3(c) illustrates this pattern. At 80–90% of TWL, Fig. 3(d) shows that the fewest vehicles and the minimum travel distance are obtained; however, the tightness of these TWLs is also the least. Moreover, at a TWL of 80–90%, collected waste is lowest in all cases. Thus, it can be concluded that with the lowest-cost routes, it is not necessary that the waste collection and route be optimized. However, it is clear from Fig. 3 that in almost all datasets, all the obtained results are fairly good at a 70–75% TWL.

It can be seen from Fig. 3(d) that among all TWL values, tightness reaches the maximum value at 70% and 75% only with reduced distance routes. Nonetheless, in the case of the application of this model in real case studies, the TWL value may vary from area to area because of the waste management level decisions, waste generation type and waste collection components. For example, in the case of dataset (B-n78-k10), as seen from Table 2, the tightness values at the 70% and 90% TWLs are the same and are maximal. However, the 90% TWL collects a very small amount of waste compared to the 70% TWL, which ultimately makes the system unsuitable. Again, for (A-n60-k9), although the 75% TWL produces the best toughness value, according to the generation rate of waste in that area, waste can be collected considering a 70% TWL. If there is a potential for a higher generation rate, then a 70% TWL ensures a lower chance to overflow the waste bin, as using a 70% TWL collects almost 18% more waste than does using a 75% TWL in a more optimized route. Otherwise, it is better to collect considering a 75% TWL that provides a 25% optimized route, ensuring the best utilization of the waste collection vehicle. Hence, the model proposed in this study provides diverse choices for adjusting different parameters to obtain the best waste collection decision for an area.

3.3. Scheduling for waste collection route optimization

The scheduling of a waste collection route is conducted to show the improvement in waste collection efficiency when optimizing routes by applying the TWL concept. This study has applied dataset no. 2 (P-n40-k5) for the 4-day schedules. To make the waste generation condition stochastic, an average waste generation rate ($\bar{x}$), standard deviation (σ) and fixed mean inflow are considered for simulation. The waste generation is normally distributed among all the waste nodes. The average generation rate is taken as 20% of the node capacity, and the standard deviation is 50% of it. It is found that at TWLs of 70% and 75%, waste can be collected more efficiently by travelling an optimized route; for scheduling purposes, a 70% TWL is considered. However, for the conventional system, the initial optimized route is taken as the default route for every collection, as a fixed route is always considered in this system.

For simple design and ease of calculation, 10 units of distance are considered to be 1 kilometre (km), and 1 unit of waste is

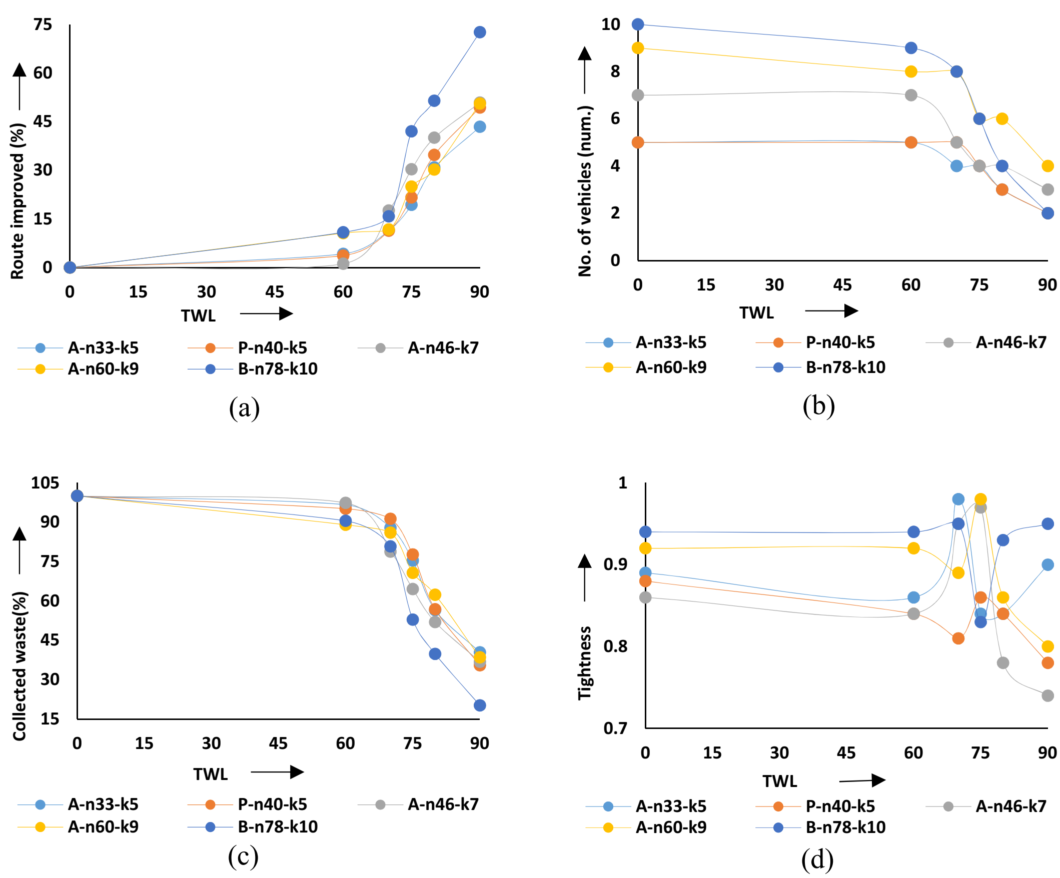

Fig. 3. Change of pattern in different TWL (a) route improvement, (b) no. of vehicles, (c) collected waste, and (d) tightness.

considered to be 1 kilogram (kg) of garbage. A front-loader diesel waste collection truck (compaction) with a fuel efficiency of 0.67 (L/km) is considered for the model. For estimating fuel (diesel) cost, the unit diesel cost is taken as MYR 1.6/l. While estimating CO_2 emissions, for diesel fuel, the CO_2 emission factor $EF_{fuel} = 2.67$ $kgCO_2/l$.

Tables 4 and 5 summarize the results for every collection day for both systems. It is found that the proposed model outperforms the conventional system in every parameter, e.g., distance, efficiency, fuel consumption, fuel cost and CO_2 emission. From Table 5, it is seen that the lowest amount is collected on day 2 (only 35%). However, as seen on the next collection day, the number of overflow nodes is only 2. A maximum of 9 waste collection nodes overflow on the next Monday due to the accumulation of waste over the weekend. Table 5 also summarizes the increase or decrease of the parameters compared to the conventional system.

The obtained result patterns over the collection time are illustrated in Fig. 4. It is found that the proposed optimization model

Table 4
Conventional model for solid waste collection and route optimization.

No.	Day	N	V	Collected waste (W)	Expected total waste for collection (kg)	Waste collected (%)	Distance (km)	Efficiency (W/distance)	Fuel consumption (l/kg)	Fuel cost (RM)	CO_2 emission ($kgCO_2$)
0	–	–	–	–	618	–	–	–	–	–	–
1	Monday	39	5	618	360	100	45.8	1.35	0.04	7.12	11.83
2	Wednesday	39	3	360	287	100	52.1	0.69	0.07	14.33	26.09
3	Friday	39	3	287	477	100	51.1	0.56	0.08	14.08	32.81
4	Monday	39	4	477	–	100	54.5	0.88	0.05	10.10	17.64
Total/average		–	15	1742	–	100	203.5	0.87	0.06	11.41	22.09

Table 5
TWL-based proposed model for solid waste collection and route optimization.

No.	Day	N	V	Collected waste (W)	Expected total waste for collection (kg)	Waste collected (%)	No. of overflown nodes	Distance (km)	Efficiency (W/distance)	Fuel consumption (l/kg)	Fuel cost (RM)	CO_2 emission ($kgCO_2$)
0	–	–	–	–	618	–	–	–	–	–	–	–
1	Monday	32	5	564	414	91.26	0	40.6	1.39	0.03	5.83	10.92
2	Wednesday	7	2	146	555	35.27	6	16.7	0.87	0.03	5.36	14.09
3	Friday	23	4	433	599	78.02	2	34.2	1.27	0.03	6.16	12.86
4	Monday	25	4	452	–	75.46	9	37.1	1.22	0.04	6.49	11.01
Total/average		–	15	1595	–	–	–	128.6	1.19	0.03	5.96	12.22
%		–	–	–	–	−8.61	–	−36.80	+36.78	−50.00	−47.77	−44.68

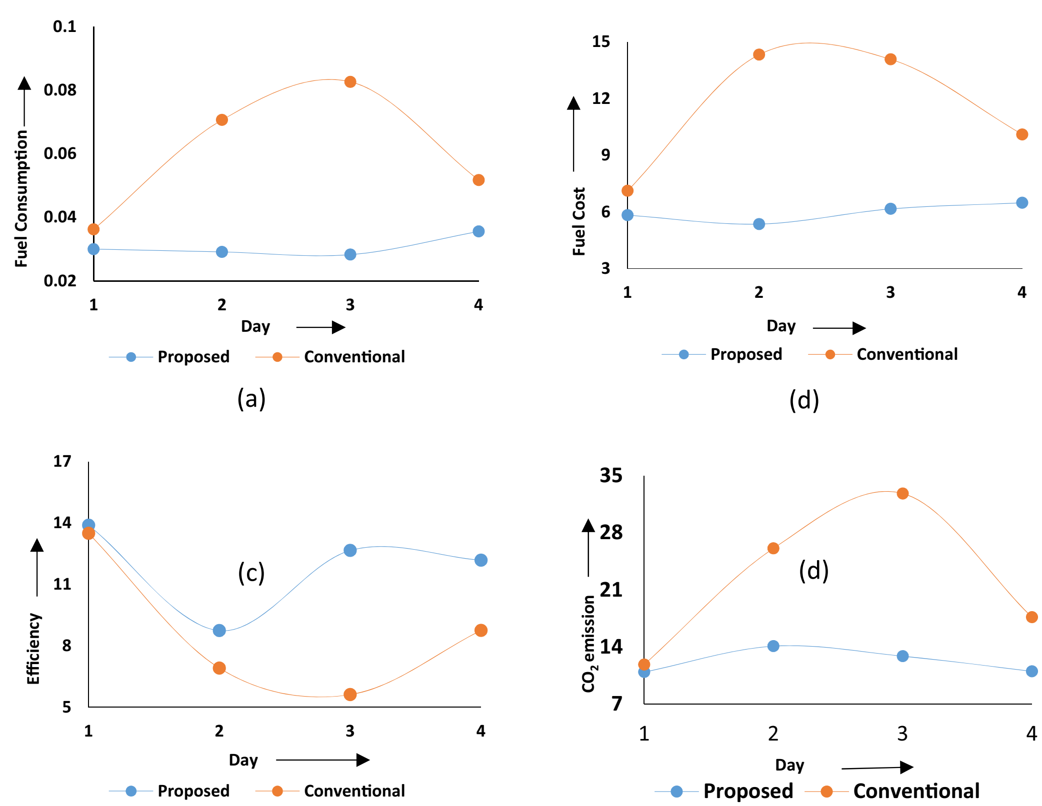

Fig. 4. Scheduling performance of the two systems in terms of (a) fuel consumption, (b) fuel cost, (c) efficiency, and (d) CO_2 emission.

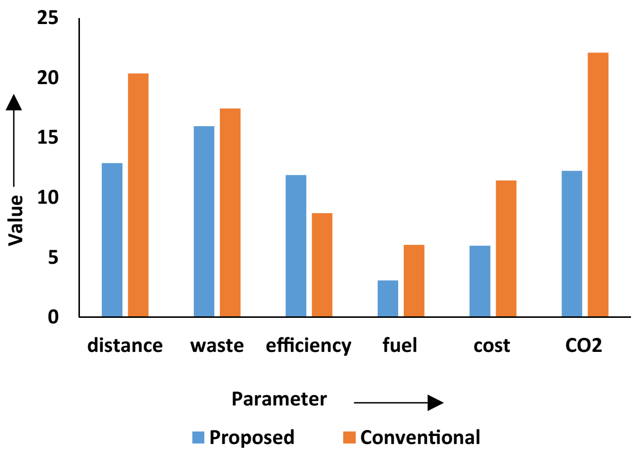

Fig. 5. Comparison of results of different parameters between the two systems after four days.

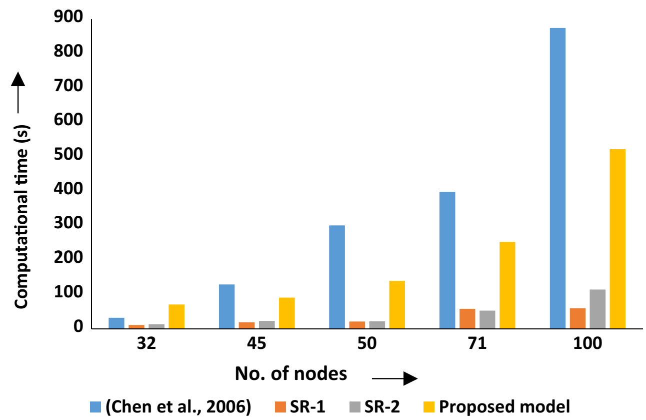

Fig. 6. Comparison of the computational time of the BSA with that of other algorithms for large-scale problems.

shows better results than the conventional system in every aspect. The differences between the values of the two models are very high. Fig. 4(a) shows that in the proposed model, the maximum fuel is consumed on day 4. Whereas in the conventional system model, it is on day 3. However, the difference between these two values is very high. The cost is highest on day 2 for the conventional system, whereas for the proposed system, the costliest collection day is day 2 (Fig. 4(b)). Fig. 4(c) proves that the proposed model is more efficient in terms of waste collected per unit distance than the conventional system. The lowest amount the proposed system carries is 8.75 kg per km; for the conventional system, it is 5.61 kg per km. In terms of CO_2 emission, it is clear from Fig. 4(d) how excessively the conventional model emits compared to the proposed system. Thus, it can be concluded from all the results that the proposed model collects 91.5% of the total generated waste by travelling less distance with the highest efficiency and less fuel consumption, fuel cost and CO_2 emission.

The proposed model performs better on each day. Fig. 5 gives an overview of the difference in these parameters between the two models. The values are adjusted to show the comparison between the two systems in the same illustration. It is seen that after four days, the proposed system has collected a greater percentage of waste by travelling a considerably shorter distance. It is, on average, more efficient and can conserve a greater amount of fuel, costs and emissions.

3.4. Comparison between the proposed algorithm and other algorithms

To assess the performance of the proposed BSA algorithm, the results of the five datasets are compared with established algorithms. This section also summarizes the results found from Ai and Kachitvichyanukul (2009). Chen et al. (2006) applied discrete particle swarm optimization (dPSO) along with simulated annealing (SA) to avoid being locally trapped and used the dataset for a waste collection system. Ai and Kachitvichyanukul (2009) also used the PSO algorithm to solve a CVRP model with two approaches. Both studies proposed two solution models, named SR-1 and SR-2, for two different dimension sizes. For locally improving the routes, in this study, three local algorithms (2-opt, 1-1 exchange and 1-0 exchange) were applied. However, the SR-2 model produces better results than does SR-1, which also fails to obtain the best value for problem instances exceeding a node number of 75. Table 6 summarizes the best results found after 10 runs of the proposed algorithm for each dataset. The results achieving the best value are presented in bold letters. Although the proposed model shows little error for the dataset as the number of nodes increases, the number of vehicles remains the same as the best known value. Nonetheless, model cannot outperform SR-1 and SR-2, but it shows better results than the other algorithm.

In terms of computational time, although the BSA cannot outperform SR-1 and SR-2, it outperforms the model proposed by (Chen et al., 2006) in all but one problem. Fig. 6 shows how the computational time differs for different models.

4. Conclusion

The study found a modified BSA algorithm in a CVRP model with smart bins to be feasible for solid waste collection route optimization. The developed CVRP model determines the optimized route for most prioritized solid waste collection nodes by minimizing the travel distance based on constraints and objective functions. The fundamental BSA is modified by applying a number of

Table 6
Comparison of the proposed algorithm with other algorithms.

Datasets	N	V	Chen et al. (2006)		Ai and Kachitvichyanukul (2009)				Proposed		BKS	e (%)
					SR-1		SR-2					
			Dist.	T(s)	Dist.	T(s)	Dist.	T(s)	Dist.	T(s)		
A-n33-k5	32	5	**661**	32.3	661	11	**661**	13	**661**	70.6	661	0.00
A-n46-k7	45	7	**914**	128.9	**914**	19	**914**	23	**914**	90.4	914	0.00
E-n51-k5	50	5	528	300.5	**521**	21	**521**	22	522	139.5	521	0.19
F-n72-k4	71	4	244	398.3	**237**	58	**237**	53	**237**	252.7	237	0.00
M-n101-k10	100	10	824	874.2	821	60	**820**	114	825	522.4	820	0.61

Where: N, No. of nodes; V, required No. of vehicles; Dist., Distance; T, computational time; BKS, best known solution; e, error between proposed methods solution and BKS.

local improvement algorithms. It is seen that the modified BSA algorithm can produce good results within a considerable time period, especially for problem instances under 50 nodes. Threshold waste level concepts are used in the BSA-based CVRP model under different datasets to find the best threshold level at which waste collection, route optimization and related efficiencies are optimal. Accordingly, different datasets are tested at 5 TWLs to determine the optimal waste collection TWL. The study shows that the proposed model improves different parameters by optimizing the waste collection route. The obtained results indicate that the developed system provides the most efficient and optimized values of travel distance, total waste, waste collection efficiency and tightness at TWLs of 70–75% for all the benchmark datasets. However, the scheduling concept is applied at 70% of TWL and at every node for collection and route optimization. Based on the obtained results for all aspects of performance, such as collected waste, distance, efficiency, fuel consumption, fuel cost and emission, the proposed model is found to be better than that of the conventional system. This method gives a diverse number of options for finding the most efficient TWL based on the waste generation pattern. Thus, it can be concluded that the proposed BSA-based CVRP model using the TWL concept provides the best waste collection and route optimization along with smart bin data implementation. However, a further study can be conducted with the same developed algorithms and models considering more constraints and uncertainties. In addition, a case study can also be piloted for the feasibility of real-world applications.

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