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Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using PSO algorithm

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ABSTRACT

Waste collection widely depends on the route optimization problem that involves a large amount of expenditure in terms of capital, labor, and variable operational costs. Thus, the more waste collection route is optimized, the more reduction in different costs and environmental effect will be. This study proposes a modified particle swarm optimization (PSO) algorithm in a capacitated vehicle-routing problem (CVRP) model to determine the best waste collection and route optimization solutions. In this study, threshold waste level (TWL) and scheduling concepts are applied in the PSO-based CVRP model under different datasets. The obtained results from different datasets show that the proposed algorithmic CVRP model provides the best waste collection and route optimization in terms of travel distance, total waste, waste collection efficiency, and tightness at 70–75% of TWL. The obtained results for 1 week scheduling show that 70% of TWL performs better than all node consideration in terms of collected waste, distance, tightness, efficiency, fuel consumption, and cost. The proposed optimized model can serve as a valuable tool for waste collection and route optimization toward reducing socioeconomic and environmental impacts.

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1. Introduction

Managing waste is a major concern across the world due to its direct effect on the environment. Rapid urbanization and every day human activities produce a large amount of waste from residential, commercial, or industrial areas all over the world. These activities impact climate by increasing the emission of different greenhouse gases (GHGs). The environment quality is rapidly deteriorating with the concerns of solid waste issues (Manaf et al., 2009; Moh and Manaf, 2014). Accumulation of CO_2 in the atmosphere is showing an increasing pattern of approximately 2 ppm per year (Budzianowski, 2012). Currently, CO_2 in the atmosphere is reaching approximately 390 ppm, which leads to global warming (Budzianowski, 2016). The rapid growth of urbanization and population along with the environmental concern have created a critical situation for waste management (Poser and Awad, 2006; Zhang and Huang, 2014; Cioca et al., 2015; Pérez-López et al., 2019; Hua et al., 2017). Every step of waste management should be performed effectively to solve the solid waste problems.

Among all steps of waste management, waste collection from waste generation center to waste management center, i.e., waste collection route, is an important issue (Kanchanabhan et al., 2010). If waste is not collected properly, then nuisance may occur in the waste generation area (Hua et al., 2017). The typical process of waste collection involves vehicles starting from the depot and traveling in fixed routes to collect waste by visiting all locations, which cost a large amount of budget. This process causes wastage of resources because of traveling to empty a bin that is not full yet. Moreover, given a fixed schedule and route of collection and no real-time information of bin status, a bin is not emptied sometimes, although it is full before the scheduled day. This scenario eventually creates a problem (Johansson, 2006). For an efficient waste collection, the collection route needs to be optimized in such a way that considers all the mentioned scenarios. Waste-collecting cost can be reduced if the bin waste level status is known prior to collection. An algorithm is needed for the decision on an optimized waste collection route instead of collecting garbage in a predefined route (Kuo et al., 2012). This route optimization method can save travel distance and minimize the number of vehicles, which in turn

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reduce labor cost, fuel cost, operation time, and GHG emission (Son and Louati, 2016; Gilardino et al., 2017; Mahmuda et al., 2017; Nowakowski, 2017). The route optimization cannot be effective with the conventional waste collection process given no any real-time information about bin status. A waste collection route needs to be designed on the basis of the waste status of smart bin data to ensure efficiency of waste collection.

In considerable research, the waste collection problem of an area has been designed on the basis of the vehicle-routing problem (VRP), which finds an effective collection route (Bautista et al., 2008). However, vehicle capacity has been disregarded. To solve this problem, Dantzig and Ramser (1959) considered vehicle capacity constraint in the VRP, which was named as capacitated VRP (CVRP). Waste collection has been modeled in CVRP approach with different algorithms and software (Kuo et al., 2012; Liu and He, 2012a; McLeod and Cherrett, 2008). Nevertheless, limited experiments have been conducted with smart bin technologies for waste collection and route optimization (Rada et al., 2010; Kristanto et al., 2016; Mamun et al. 2016).

This study introduces an efficient waste collection and route optimization process based on the data from smart waste bins. Smart bin is assembled with different sensors described in the paper of Mamun et al. (2015), which gives the real-time waste condition of the bin. In the current study, particle swarm optimization (PSO) is applied in a CVRP model to solve the routing problem. A number of local improvement algorithms are also applied to improve the PSO performance. The objective of this study is to verify the feasibility of the proposed method for waste collection and route optimization in terms of collection trucks, distance, efficiency, fuel consumption, and cost.

2. Overview of waste collection optimization

Solid waste collection optimization has been studied widely for the last few decades (Swapan and Bidyut, 2015; Khanh et al. 2017; Mahmuda et al. 2017). Every country has to deal with the management of its generated waste. Different optimization approaches have been applied to make the collection system efficient, such as reducing traveling distance, time, cost, and emission. In this section, a brief overview of the related algorithms and solid waste collection technologies is described.

2.1. Optimization algorithms

The algorithms applied in solid waste collection optimization are categorized as conventional, heuristic, and meta-heuristic. In conventional approaches, mathematical programming, 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. The limitations of these methods are ineffectiveness for small-scale problems, in which they require numerous components to be considered for optimization; thus, the solution approaches become complicated. These approaches were common at the beginning of solid waste optimization research.

Heuristic approaches have become popular to overcome the complexity of conventional approaches. In case of optimization problems, conventional approaches require considerable computational time. These problems are minimized using heuristic approaches. For example, Faccio et al. (2011) applied nearest neighborhood search algorithm for waste collection optimization. Bautista and Pereira (2006) and Sahoo et al. (2005) used greedy algorithm for collection optimization. However, these techniques lack precision and require a long execution time in collecting solid waste (Viotti et al., 2003). Thus, a new optimization technique is required for efficient collection optimization.

Meta-heuristic approaches, which provide a sufficiently good solution for collection optimization even when incomplete information or limited computation capacity is given, are the most popular approaches in recent years. They incorporate biological evolution, nervous system, and intelligent problem solving. A few popular meta-heuristic approaches are ant colony optimization (Islam and Rahman, 2012; Liu and He, 2012b), genetic algorithm (GA) (Karadimas et al., 2007; Viotti et al., 2003), and PSO (Son, 2014). Recently, agent-based optimization model integrating GIS and backtracking search algorithm (BSA) applied in CVRP model are utilized for solid waste collection and route optimization, respectively (Swapan and Bidyut, 2015; Khanh et al., 2017). Although the performances are promising, however, the obtained results could not achieve optimized value due its continuous optimization problem. The PSO algorithm is a population-based meta-heuristic optimization method that simulates the social behavior of flocks of birds in searching for foods. This method has been used to optimize solutions for difficult problems. The PSO algorithm performs efficiently in route optimization. The basic step of PSO is that it produces a number of particles that are dragged toward the optimized value by a randomly initialized velocity. In every iteration, the algorithm keeps on a track of two best values: the value found by a particular particle (p_{best}) and the best solution found by the entire neighborhood (g_{best}).

ArcGIS is commonly used software for solid waste collection optimization. Real-time road conditions (e.g., traffic and blockage) can be optimized by using this software, and route can be designed accordingly. Considerable research (Malakahmad et al., 2014; Shastri et al., 2014) has applied GIS to determine an optimized route for waste collection. A 3D version of this software was used by Tavares et al. (2009) to determine the most fuel-efficient road. Aremu (2013) used Microsoft Office Excel add-in tool for waste collection optimization. Researchers have also utilized GPS (Arebey et al., 2009) and data mining for solid waste collection optimization (Revetria et al., 2011). However, all software applications are not up to the mark for solid waste collection optimization (Tavares et al., 2009).

2.2. Technologies used for waste collection

Advanced technologies and devices become popular for solid waste collection system. Different technical devices, such as 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), different sensors and systems (Mamun et al., 2015), and vehicular ad hoc network (Narendra et al., 2014), are used to communicate among different collection components to ensure efficiency of waste collection. Kuo et al. (2012) developed a CVRP-modeling concept along with a hybrid algorithm to determine an efficient waste collection route. However, smart bin waste data were not applied and implemented for their collection concept. In the current study, PSO algorithm is used in a CVRP model along with smart bin data from different sensors. These sensors update real-time waste data and bin condition in the server. The modified discrete PSO is modeled and compared its performance with other PSO models as well as BSA meta-heuristic optimization for the validation of the proposed development. The detailed methodology is explained in the next section.

3. PSO algorithm in a CVRP model

A CVRP model is developed on the basis of the present solid waste collection optimization problem. PSO algorithm is incorporated into the CVRP model to solve the route optimization problem. The PSO-based CVRP model uses smart bin data for efficient waste collection. Smart bin is equipped with a number of sensors that obtain real-time data, such as an ultrasonic sensor for providing bin waste level and a load cell for measuring the weight of the waste in the bin. Thus, real-time decision for waste collection is being provided, thereby saving travel distance and cost. The detailed CVRP model and PSO algorithm are as follows.

3.1. CVRP model

The basic concept of VRP is to serve a set of customers to find least total travel distant routes from starting to returning at the depot (Ai and Kachitvichyanukul, 2009). When vehicle capacity is considered, it becomes CVRP. CVRP in solid waste collection is defined as informing a set of collection nodes (bins) by a fleet of vehicles, and the vehicles start and return constraints at the depot. A smart bin sends its coordinate of location and waste status directly in the server through Zigbee. Thus, the CVRP model includes vehicle capacity and the waste level of bins. The model objective is to determine a viable route that minimizes distance or total cost with the following constraints:

- All vehicles start and return in the depot
- A waste bin is visited by only one vehicle every time;
- The total collecting capacity of a vehicle must not exceed its maximum;
- A bin is to be emptied as soon as it reaches its predetermined threshold waste level (TWL).

All vehicles and bins are assumed to be homogenous. The CVRP method starts with the smart bin data of a cluster of bins by accessing the bins that exceed the TWL of their capacity. Route optimization is then conducted by considering only that cluster of bins. The CVRP model is explained below, where *N* is the number of bin and *V* is the number of vehicle considered.

- A complete graph $G = (N, E)$, where N is the total bin set and E is the edge set of bins.
- $N = \{i\}$ is a set of homogenous bins, where $i = 0, 1, 2 \ldots n$ corresponds to the bins with a maximum capacity of c_max. Here, 0 is the depot.
- Each bin i possesses a nonnegative waste quantity, c_i.
- A set of homogenous vehicles $V = \{1, 2 \ldots k\}$ is available at the depot to collect waste, where the maximum capacity of each vehicle is C.
- A nonnegative distance cost d_{ij} is associated with each edge (i, j) $\in$ E and represents the distance from bins i to j, where $i \neq j$.

The decision variables of the model depend on vehicle capacity C and the waste quantity of the next bin, which are modeled as follows:

$$X_{ijk} = \begin{cases} 1, & \text{if vehicle k can travel from bin i to bin j} \\ 0, & \text{otherwise} \end{cases}, \tag{1}$$

$$Y_{ik} = \begin{cases} 1, & \textit{if bin i is visited by vehicle k} \\ 0, & \textit{otherwise} \end{cases} \tag{2}$$

The objective function to minimize total collection distance, Z is defined as follows;

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

To make the CVRP model realistic, the following constraints are considered:

$$\sum_{i=0}^{n} \sum_{V=1}^{k} X_{ijV} = 1, \quad \forall j = 1, 2, \ldots n \tag{4}$$

$$\sum_{j=1}^{n} \sum_{V=1}^{k} X_{0jV} = 1 \tag{5}$$

$$\sum_{j=1}^{n} q_{0jV} = 0 \quad \forall V = 1, 2 \ldots k \tag{6}$$

$$\sum_{i=1}^{n} \sum_{V=1}^{k} X_{i0V} = 1 \tag{7}$$

$$\sum_{i=1}^{n} c_i X_{ijV} \leqslant C \forall j = 0, 1 \ldots n; V = 1, 2, \ldots k \tag{8}$$

$$\sum_{i=0}^{n} \sum_{V=1}^{k} q_{jiV} - \sum_{i=0}^{n} \sum_{V=1}^{k} q_{ijV} = c_j \quad \forall j = 1, 2, \ldots n \tag{9}$$

$$\sum_{j=1}^{n} X_{ijV} = \sum_{j=1}^{n} X_{jiV} = Y_{iV} \quad \forall i = 0, 1, 2 \ldots n; V = 1, 2, \ldots k \tag{10}$$

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

$$X_{ijk} \in \{1, 0\}, \tag{12}$$

$$Y_{ik} \in \{1, 0\}. \tag{13}$$

Eq. (4) specifies that bin i is visited by not more than one vehicle k, whereas Eqs. (5) and (6) ensure that a truck starts from the depot and it does not carry any waste. Constraint (7) guarantees that, after visiting the last waste bin, a vehicle will reach the depot. Eq. (8) shows the collected bin that exceeds the TWL, in which capacity constraint is an important issue. Eq. (9) presents that the total amount of waste in a truck cannot exceed its maximum capacity. Constraint (10) indicates that a vehicle must fully empty all bins it visits. Therefore, the filled capacity of the vehicle will be equal to the summation of the waste amount of the visited bins. Constraint (11) shows that the distance of two nodes traveled back and forth is the same. Constraints (12) and (13) define the domain of the decision variable.

3.2. PSO algorithm

A discrete PSO (DPSO) algorithm has been used to improve the local route of solid waste bin location. The PSO is performed using binary numbers of the decision variable of whether a bin location is needed to be visited. The parameter selections of the PSO are generally set as a fixed value. However, conventional PSO exhibits the problems in iteration of being stuck in local minima. This study tunes the parameters as the inertial weight in every iteration changes in accordance with the average absolute value of velocity to avoid being stuck in local minima. Thus, in the process, the route of a solid waste bin is considered the order of bin locations. Subroutes are determined by considering vehicle capacity and bin waste level. The details of the PSO algorithmic steps are as follows:

Step 1: Initialization

a) The number of particles i, dimension size d, and the number of iterations t_max are set.
b) Parameter setting: The parameters are set along with the maximum, minimum, and step size of inertial weight.
c) A cluster of bins considering TWL is given.
d) Initial particles X_{id} are determined using sweep algorithm.
e) The initial velocity V_{id} of particles is randomly generated.

Step 2: For each particle X_{id}

f) A sub-route X^*_{id} that considers constraints is determined;
g) The fitness value Z_i is calculated in accordance with the objective function;
h) The particle best position is set as $X_{best_i} = X_{id}$, and the best fitness value is $p_{best_i} = Z_i$;
i) gbest is determined. If $p_{best_i} < gbest$, then $gbest = p_{best_i}$. Otherwise, gbest remains the same.

Step 3: For each iteration t,

j) The position X_{id} of each particle is updated;
k) The velocity V_{id} of each particle is updated;
l) A sub-route X^*_{id} that considers constraints is determined;
m) Routes are locally improved by applying local improvement algorithms;
n) The fitness value Z_i for new particles are determined in accordance with the objective function;
o) If $Z_i < p_{best_i}$, then $p_{best_i} = Z_i$ and $X_{best_i} = X_{id}$;
p) gbest is updated. If $p_{best_i} < gbest$, then $gbest = p_{best_i}$. Otherwise, gbest remains the same;
q) Steps (10)–(16) are performed until the maximum number of iteration is not met. If the maximum number of iteration is met, step (18) is conducted.

Step 4: Final solution

r) gbest is set as the final solution and the fitness value for the final optimized value.

Sweep algorithm is applied on the basis of the polar angles of bin node to determine initial particles. The particles are then taken as the sequences of bins in ascending order of their polar angle. Fig. 1 shows the operational flow of the developed PSO algorithm including the encoding and decoding of the particles. While determining the particles, the array is represented by a sequence of nodes from 0 to $(n-1)$, where n is the number of nodes. Initial velocity is also an array of randomly initialized n continuous numbers between the maximum and minimum values. The velocity (V) and position (X) update equations are given as follows:

$$V_i^{t+1} = \omega V_i^t + \varphi_1\beta_1(p^t_{best_i} - X_i^t) + \varphi_2\beta_2(g^t_{best} - X_i^t), \tag{15}$$

$$V_i^{t+1} = sig(V_i^{t+1}) = \frac{1}{1+exp^{(-V_i^{t+1})}}, \tag{16}$$

where i is the particle number, t is the iteration number, φ_1 and φ_2 are positive acceleration constants that control the influences of p_{best} and g_{best} on the search process and ω is inertia weight that influences the velocity of the particle. β_1 and β_2 are random values in the range of [0, 1] sampled from a uniform distribution.

This velocity is transformed to the continuous value between 0 and n using the following sigmoid function (17).

$$Sig(V^t_{id}) = \frac{n}{1+e^{-(V^t_{id})}} \tag{17}$$

$$X''^{t+1}_{id} = round(Sig(V^t_{id}) + (n-1)^*\sigma^*\beta) \tag{18}$$

$$X^{t+1}_{id} = \begin{cases} n-1, & \text{if } X''^{t+1}_{id} > n-1 \\ 0, & \text{if } X''^{t+1}_{id} < 0 \end{cases} \tag{19}$$

The position of particles is updated by Eqs. (13) and (14). Eq. (18) generates a discrete number using sigmoid function, standard deviation σ, and a random number β. Eq. (19) ensures the values to be between 0 and $n-1$. Particles are decoded from the updated position. When a tie exists, indexes according to the ascending sigmoid values are considered. Thus, a new particle is found and used to determine sub-routes in accordance with constraints. These sub-routes are then locally improved using four optimization algorithms. From these sub-routes, fitness value Z_i, particle best position X_{best_i}, best fitness value p_{best_i}, and final fitness value gbest are determined.

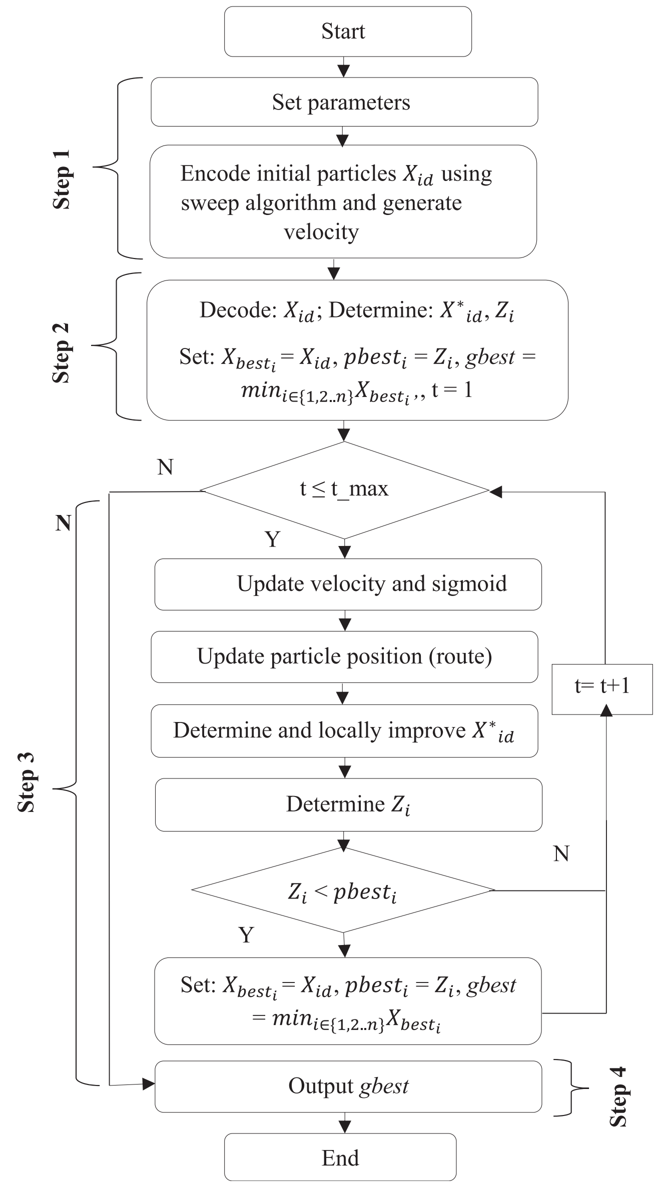

Fig. 1. Proposed PSO-based waste collection optimization model.

3.3. Local improvement algorithms

In this study, four algorithms are used to locally improve a route. Among these algorithms, two are used for inter-route improvement and the remaining two are implemented for intra-route improvement. A detailed illustration of all these algorithms is shown in Fig. 2.

*2-opt**: This algorithm is the first one applied for inter-route improvement. 2-opt∗ algorithm connects each link between two nodes of a sub-route that is broken and connected with nodes of another sub-route to find an optimal improvement. The complexity of 2-*opt** neighborhood is the order of $O(N^2)$, where N is the number of nodes.

Or-opt-1: This algorithm is a popular node exchange method for inter-route improvement. The idea is to relocate a node from one route to another adjacent route to improve the solution.
2-opt: This algorithm is commonly used for local improvement of intra-route. The algorithm structure allows reversing the existing path between two nodes *i* and *j* by replacing nonadjacent links ($i - 1, i$) and ($j, j + 1$) from the same sub-route with ($i, j + 1$) and ($i - 1, j$). The complexity of the move is $O(N^2)$, where *N* is the number of nodes.
Or-opt: This algorithm is also applied for intra-route improvement. The idea is to relocate one, two, or three consecutive nodes of the original sub-route with new edges without modifying the orientation. The complexity of Or-opt is $O(N^2)$, where *N* is the number of nodes.

3.4. TWL and scheduling model

This approach is used in the simulation to find the best TWL for different datasets. Scheduling of waste collection dataset for a hypothetical area is also used in the algorithm to validate the performance of the collection optimization. Thus, a wide range of renowned dataset is used and compared with other algorithms to validate the proposed algorithm. This study determines whether any improvement is incurred by using smart bin data rather than normal bin data to find the best TWL. The detailed steps for the best TWL are as follows:

a) Six datasets are tested.
b) Datasets consist of collection node from 32 to 100.
c) The simulation model considers TWL 0–90%. 0% represents collecting waste from all nodes.

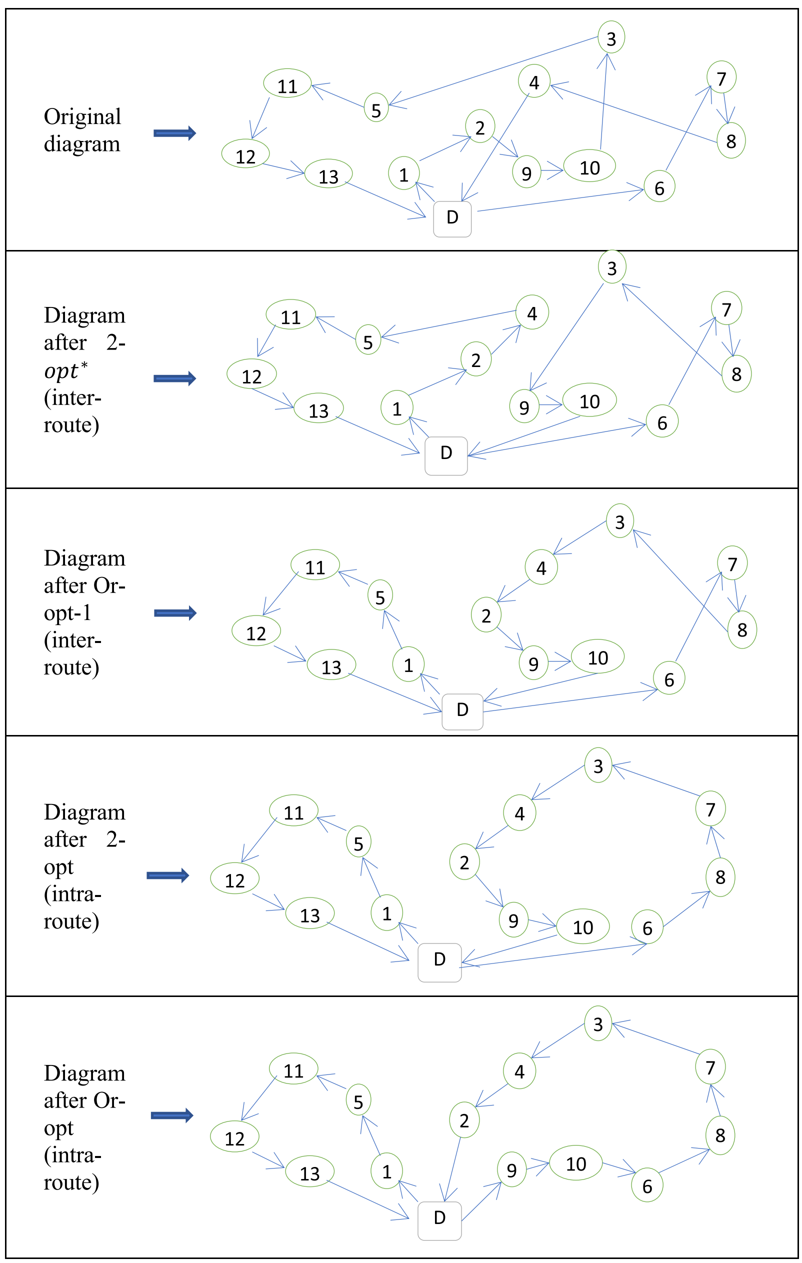

Fig. 2. Process flow of the local improvement algorithms.

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d) Tightness is estimated for each dataset by calculating the amount of waste carried per unit vehicle capacity.
e) Comparison of tightness is conducted to determine any common pattern among all datasets on the basis of TWL.

Similarly, for scheduling, a dataset is considered from a hypothetical area for scheduling 1 week waste collection to show the improvement in a realistic scenario.

a) A mean waste generation rate along with a standard deviation is considered for a week.
b) Waste collection is conducted by considering 70% of TWL and visiting all nodes.
c) For high efficiency, TWL is adjusted in the model.
d) All nodes are not fixed for visiting in case of a route for another model.
e) Efficiency and tightness are estimated by calculating the amount of waste carried per unit distance.
f) Fuel consumption is calculated by

$$f_{consumption} = \frac{f_{total} - (f_{t,empty} + f_{t,full})}{W} \tag{20}$$

g) For cost calculation, the following equation proposed by Zsigraiova et al. (2013) is used:

$$Cost = \sum_k \sum_i \{LC_k t_{ik} + P_f fc_{idle,ik} t_{idle,ik} + (MC_k + P_f fc_{ik}) d_{ik}\}, \tag{21}$$

where LC_k is the specific labor cost of crew in vehicle k, t_{ik} is the total time spent by vehicle k in route i, P_f is the specific fuel cost, $fc_{idle,ik}$ is the specific fuel consumption in idling mode for vehicle k in route i, $t_{idle,ik}$ is the total time spent in idling mode by vehicle k in route i, MC_k is the specific maintenance cost for vehicle k, fc_{ik} is the specific fuel consumption in traveling mode for vehicle k route i, and d_{ik} is the distance traveled by vehicle k in route i. Here, the bases of fuel consumption are traveling distance and fuel consumption for unit waste collection only. Therefore, it is obtained by using Eq. (22).

$$Z^* FC^* P_f \tag{22}$$

Eq. (18) shows the minimization of total cost of the total waste collection route. Here, Z is the minimized route distance, FC is the fuel consumption per unit collected waste and P_f denotes the fuel price for unit distance of waste collection vehicle.

h) Different parameters for feasibility of implementing TWL over another model are compared.

For simplicity of design and ease of calculation, 10 units of distance value are considered 1 km and 1 unit of waste is considered 1 kg of garbage. A front-loader diesel waste collection truck (non-compaction) with a fuel efficiency of 0.89 (L/km) is considered for the model.

4. Results and discussion

The proposed algorithm is tested for a number of benchmark data with different sizes of bin nodes to validate its effectiveness and performance. The simulation is conducted in Matlab 8.3 on a computer with Intel Core i5 @ 3.20 GHz Processor with 2 GB RAM.

In our study, the parameters for DPSO are as follows: $\varphi_1 = \varphi_2 = 0.2$; $\beta_1 = 0.7$; $\beta_2 = 0.2$; the maximum swarm size and the maximum number of iteration are 50 and 120, respectively; the maximum and minimum inertial weights are taken as 0.9 and 0.3, respectively, with a step of 0.1. All simulation datasets used to test the algorithm can be found at http://www.coin-or.org/SYMPHONY/branchandcut/VRP/data/#V.

4.1. TWL in PSO algorithm for waste collection and route optimization

The main objective of this study is to optimize a waste collection route by implementing smart bin. This section deals with the improvement in waste collection and route optimization by applying the TWL concept in PSO. Six datasets of hypothetical area are considered for the simulation model, in which the vehicle sizes of four datasets are the same (100 units) and the vehicle sizes of the two other datasets are 140 and 400 units. This study does not focus on the optimization of bin number or bin size but on route to collect waste from a bin. Thus, a variable number of bins in every location are considered on the basis of the demand of that node. Demand in the dataset is considered the percentage of bin waste level. The maximum capacity of each bin is taken to be 10 units, and node demand is considered uniformly distributed in all bins. We consider five TWLs, namely, 60%, 70%, 75%, 80%, and 90%, in computing an efficient waste collection route. Waste bin exceeding a certain TWL needs to be collected immediately. Table 1 shows the obtained results, such as distance, improvement, total collected waste and its collection percentage, and the tightness of the system under different datasets, TWLs, nodes, vehicle capacities, and bins. The proposed algorithm shows impressive results on smart bin waste collection efficiency by applying the TWL. The obtained results also show that the best efficiency is generated from 70% to 75% of TWL for all datasets, which is above 95% of tightness. Therefore, if waste is collected between 70% and 75% of TWL, then good savings of distance can be obtained by collecting a high percentage of waste. If 80–90% of TWL is considered, then distance is decreased with the increase in TWL; however, in most cases, the waste collected percentage is less than 60% under all datasets, which will be inconvenient for waste collection vendors. Hence, the developed model gives an optimal decision at which the percentage of TWL, the best waste collection efficiency, tightness, and traveled distance and its improvement will occur. For example, in dataset No. 4, if waste is collected at 60% of TWL, then the highest tightness value is obtained; however, if we skip only two nodes, then the saving of travel distance and its improvement, the percentage of waste collection efficiency, and tightness are moderately good at 70% of TWL. At 70–75% of TWL, the developed system provides the most efficient and optimized values.

Fig. 3 shows the degree of variation in different parameters with the change in TWL. Fig. 3(a) and (b) show that, with the decrease in the numbers of nodes, route length is decreased; thus, only a few vehicles are needed. Fig. 3(c) depicts that, with the decrease in collection nodes, the total collected waste is decreased. Fig. 3(d) shows that, at 80–90% of TWL, the least vehicles and minimum travel distance are obtained; however, the tightness of this TWL range is also least. At 80–90% of TWL, the collected waste in all cases is below 70% of the total amount of waste. In fact, TWL is directly related to the number of vehicles, distance reduction, and collected waste. Therefore, waste collection and route will unnecessarily be optimized with the least cost routes. Nevertheless, Fig. 3 demonstrates that all the obtained results are fairly good at 70–75% of TWL in nearly all datasets.

The obtained results show the great effectiveness of waste collection based on the waste level in a bin by use of the developed PSO model. All the values of the simulated results show that the optimal TWL is between 70% and 75%. However, when applying this model in real case studies, the TWL value may vary by area because of waste management level decision, waste generation type, and waste collection components. For example, in case of dataset No. 2 (A-n46-k7), the collected waste at 75% of TWL is 20% more than that at 70% of TWL. However, if the waste genera-

Table 1
Obtained results by applying the TWL concept in PSO algorithm under different datasets.

No.	Datasets	Capacity of vehicle (unit)	Capacity of bin (unit)	TWL (%)	N	V	Distance (unit)	Improvement (%)	Total collected waste	Collected waste (%)	Tightness (waste/capacity)
1	A-n33-k5	100	10	0	32	5	661	0.00	446	100	0.89
				60	28	5	629	4.84	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	A-n46-k7	100	10	0	45	7	914	0.00	603	100	0.86
				60	38	7	895	2.08	496	82.26	0.71
				70	28	5	750	17.94	475	78.77	0.95
				75	22	4	634	30.63	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
3	A-n60-k9	100	10	0	59	9	1371	0.00	829	100	0.92
				60	41	8	1258	8.24	738	89.02	0.92
				70	38	8	1223	10.80	713	86.00	0.89
				75	31	6	1048	23.56	586	70.69	*0.98*
				80	29	6	979	28.59	517	62.36	0.86
				90	19	4	693	49.45	319	38.48	0.80
4	P-n40-k5	140	10	0	39	5	458	0.00	618	100	0.88
				60	34	4	417	8.95	547	88.51	*0.98*
				70	32	4	388	15.28	523	84.63	0.93
				75	25	4	352	23.14	439	71.04	0.78
				80	18	3	294	35.81	310	50.16	0.74
				90	12	2	232	49.34	219	35.45	0.78
5	B-n78-k10	100	10	0	77		1263	0.00	937	100	0.94
				60	54	9	1124	11.01	848	90.50	0.94
				70	43	8	1069	14.67	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*
6	P-n101-k4	400	10	0	100	4	705	0.00	1458	100	0.91
				60	81	4	616	12.62	1366	93.69	0.85
				70	70	4	564	20.00	1254	86.00	0.78
				75	62	3	545	22.70	1141	78.26	*0.95*
				80	55	3	494	29.93	1011	69.34	0.84
				90	33	2	351	50.21	587	40.26	0.73

tion rate in that area is higher in potential, then the waste bin may overflow. When 80% of the total generated waste is collected at 70% of TWL, the bin has a low probability to overflow. If the management finds that the waste generation rate in that area is less and chances of bins being overflown are less, then the model should be designed on the basis of 75% of TWL. Thus, the proposed model provides a diversity to adjust the parameters for obtaining the best decision for waste collection.

4.2. Scheduling for waste collection and route optimization

The purpose of scheduling is to improve waste collection efficiency and route optimization by use of the TWL concept. In this study, dataset No. 2 (A-n46-k7) is selected for scheduling for 1 week. For simulation, a random average waste generation rate ($\bar{x}$), standard deviation (σ), and a fixed mean inflow are considered. The waste generation is normally distributed among all waste bins, in which the average generation rate is 40% of the node capacity and the standard deviation is 25%. This generated waste is added with the waste that already exists in the bin.

The earlier results prove that the collection efficiency and optimization are good at 70–75% of TWL; thus, in this case, 70% of TWL is considered for scheduling purpose. The variable number of bins in each location with a capacity of 10 units based on the dataset demand is considered. The scheduling model is designed in such a way that the maximum cumulative waste capacity demand of 810 units cannot be exceeded. The advantage of the model is that generated waste is collected before it reaches the overflowing stage. However, at the current waste generation rate, if waste is not collected for three subsequent days, then it exceeds the total waste capacity of the area. Accordingly, 5 days per week scheduling are considered in this model, in which the total waste at the starting of the scheduling is 603 units. Tables 2 and 3 show the waste collection at 70% of TWL (model 1) and at every node (model) in terms of collected waste, distance, tightness, efficiency, fuel consumption, and cost. The waste generation pattern from the smart bin data indicates that the waste is collected every alternate day, except Sunday, at 70% of TWL, as if all bins are emptied to ensure no violence of the maximum total waste in that area. The obtained results show that, in all performance aspects including collected waste, distance, tightness, efficiency, fuel consumption, and cost Table 2, i.e., using TWL, is better than Table 3, i.e., node consideration.

Fig. 4 shows the performance of models 1 and 2 in terms of efficiency, tightness, number of vehicles needed for collection, fuel consumption, and overall cost. Fig. 4(a) shows that the scheduling by considering TWL presents high efficiency in terms of waste collected per distance. Although model 2 gives a better result in two days than that of model 1, the over efficiency performance of model 1 (0.91) is better than that of model 2 (0.86). The same pattern can be observed in terms of tightness in Fig. 4(b). In Fig. 4(c), model 1 requires more vehicles for 2 days only because it collects more waste on those days than model 2 does. In terms of fuel consumption and cost, model 1 constantly shows a better result than that of model 2. All the results imply that model 1 (scheduling by TWL approach) collects more waste by traveling less distance with

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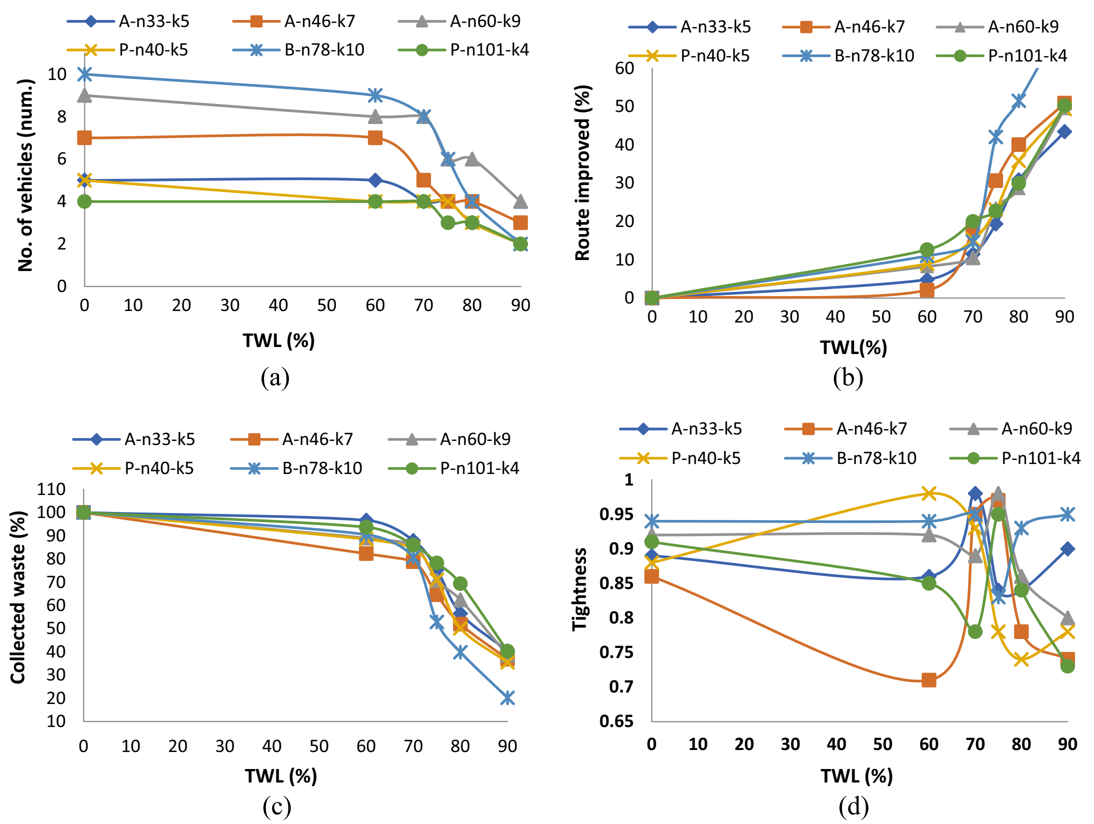

Fig. 3. Change in pattern at different TWLs (a) No. of vehicles (b) route improvement (c) collected waste (d) tightness.

Table 2
TWL-based model (model 1) for solid waste collection and route optimization.

N o.	Day	TWL	N	V	Collec ted waste (W)	Exp. total collected waste	Over flown condition	Dis tance	Tightness (W/capacity)	Efficiency (W/distance)	Fuel consumption	Cost
1	Monday	70	28	5	475	785	No	750	0.95	0.63	0.05	8.56
2	Wednes Day	70	43	8	748	725	No	1070	0.94	0.70	0.05	7.47
3	Friday	70	43	8	699	361	No	1045	0.87	0.67	0.05	6.16
4	Saturday	70	45	4	361	636	No	716	0.90	0.50	0.10	19.16
5	Monday	70	34	6	526	763	No	846	0.88	0.63	0.06	9.22
Overall		–	193	**31**	**2809**	–	–	**4427**	**0.91**	**0.63**	**0.06**	**10.11**

Table 3
Node-based model (model 2) for solid waste collection and route optimization.

No.	Day	n	V	Collected waste (W)	Expected total waste for next collection	Over flown condition	Distance	Tightness (W/capacity*V)	Efficiency (W/distance)	Fuel consumption	Cost
1	Monday	45	7	603	557	No	914	0.86	0.66	0.06	8.71
2	Wednesday	45	7	557	649	No	975	0.80	0.57	0.10	16.15
3	Friday	45	7	649	330	No	1005	0.93	0.65	0.06	9.02
4	Saturday	45	4	330	631	No	700	0.83	0.47	0.11	20.20
5	Monday	45	7	631	653	No	978	0.90	0.65	0.06	9.26
Overall		225	32	2770	–	–	4572	0.86	0.60	0.08	12.67

less numbers of vehicles, higher efficiency, and less fuel consumption and cost compared with model 2.

4.3. Comparison of the proposed and previous algorithms

The generated results are compared with the results obtained by Wang et al. (2004), Chen et al. (2006), and Kuo et al. (2012) to evaluate the algorithm performance. All such studies have applied their proposed methods to solve the CVRP. Wang et al. (2004) conducted their experiment by use of GA. They applied 2-opt algorithm to locally update the GA solution. Chen et al. (2006) applied DPSO along with simulated annealing (SA) to avoid being locally trapped. They found results only by applying SA. Kuo et al. (2012) used a dataset for waste collection system. They applied a hybrid algorithm that consisted of PSO and GA to conduct their study. The obtained results with PSO in CVRP model are also compared with the recently developed meta-heuristic modified backtracking search algorithm in CVRP model (Mahmuda et al., 2017) for waste collection route optimization. Table 4 summarizes the best results found after 10 runs of the proposed algorithm for

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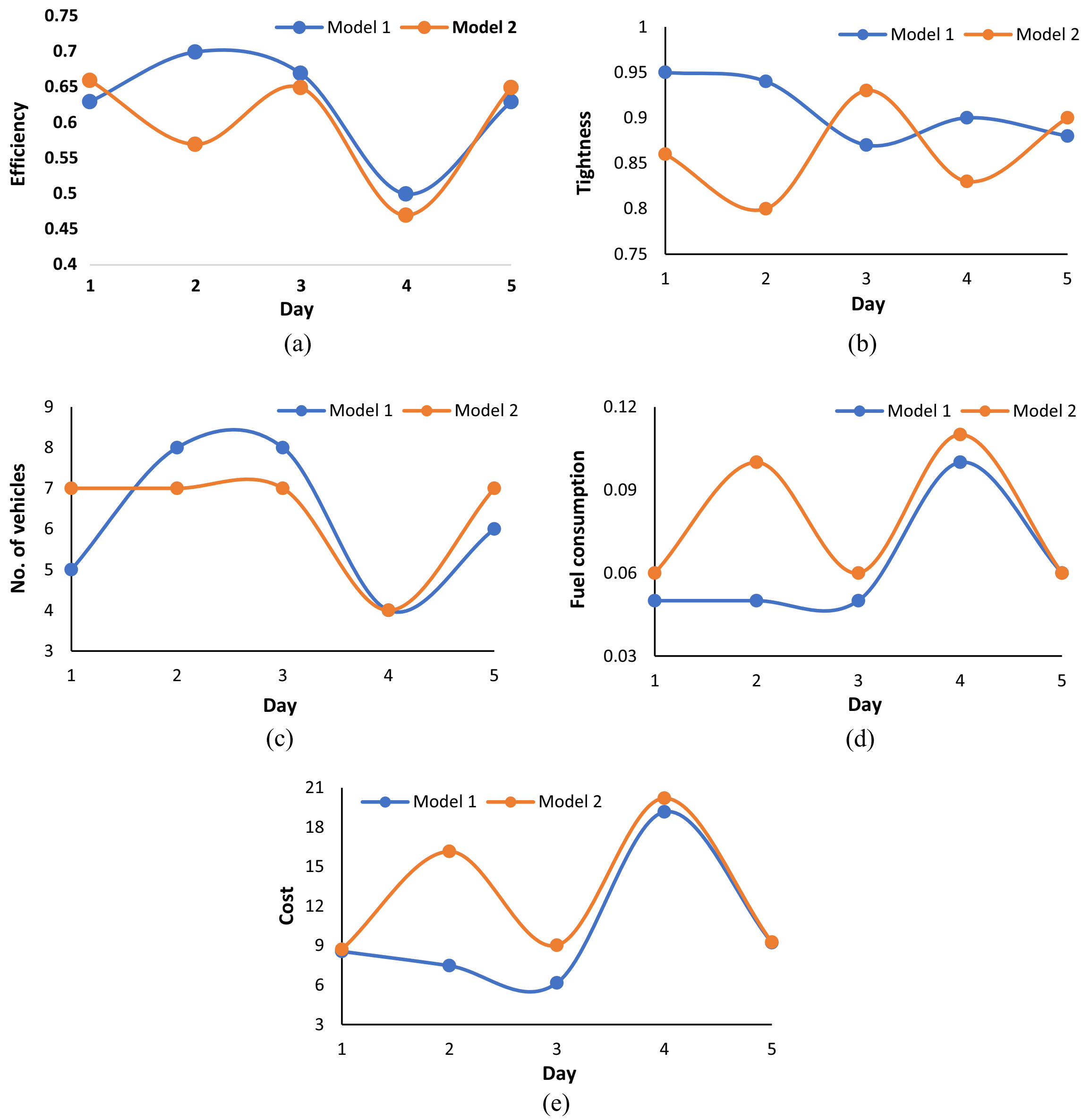

Fig. 4. Scheduling performance of models 1 and 2 in terms of (a) efficiency, (b) tightness, (c) numbers of vehicles, (d) fuel consumption, and (e) fuel cost.

Table 4
Comparison of the proposed algorithm and other algorithms.

Datasets	N	V	Wang et al. (2004)		Chen et al. (2006)		Kuo et al. (2012)		Mahmuda et al. (2017)		Proposed		BKS	e (%)
			Dist.	T(s)	Dist.	T(s)	Dist. (Ave ± stdev)	T(s)	Dist.	T(s)	Dist.	T(s)		
A-n33-k5	32	5	**661**	39.6	**661**	32.3	661 ± 8.9	20.64	**661**	70.6	**661**	27.6	661	0.00
P-n40-k5	39	5	–	–	–	–	458 ± 10.7	40.26	–	–	**458**	82.4	458	0.00
A-n46-k7	45	7	928	136.4	**914**	128.9	–	–	**914**	90.4	**914**	51.1	914	0.00
E-n51-k5	50	5	531	289.6	528	300.5	521 ± 19.29	88.09	522	139.5	**521**	264.1	521	0.00
A-n60-k9	59	9	1360	295.5	**1354**	308.8	–	–	–	–	1371	452.75	1354	1.26
M-n101–k10	100	10	836	992.1	824	874.2	824 ± 82.0	388.32	825	522.4	832	975.1	820	1.44

Note: N, No. of nodes; V, required No. of vehicles; Dist., Distance; T, computational time; Ave, average solution; stdev, standard deviation; BKS, best known solution; e, error between the proposed method solution and best value.

each dataset. The computational time of this algorithm in comparison with that of other algorithms is not very high. Although the algorithm shows an increase in error with the increase in the number of nodes, the tightness does not increase with it. The number of vehicles remains the same with best known values, although its optimized distance is more than them. Although the proposed algorithm cannot outperform PSO and GA, it shows a better result than those of other algorithms in case of the datasets of nodes of approximately 50. The proposed model achieves optimized result for four out of six datasets, whereas, model proposed by Wang et al. (2004) achieves in one, Chen et al. (2006) in three and Mahmuda et al. (2017) in two only. Thus, it is seen that the proposed model provides better solution than that of the models in small instances.

5. Conclusion

This study proposes a modified PSO algorithm in a CVRP model to check the feasibility of smart bin in solid waste collection and route optimization. The developed CVRP model determines the optimized route for solid waste collection by minimizing travel distance and total cost on the basis of specific constraints and objective function. The PSO is developed by applying numbers of local improvement algorithms that consider some specific constraints, such as vehicle capacity and bin waste level under different algorithmic steps for converting binary into an array of waste collection node. TWL and scheduling concepts are used in the PSO-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 five TWLs to check the workability of smart bin and determine optimal waste collection efficiencies. The proposed algorithm gives an impressive result on waste collection and route optimization. The obtained results show that the developed system provides the most efficient and optimized values of travel distance, total waste, waste collection efficiency, and tightness at 70–75% of TWL for all benchmark datasets. The scheduling concept is applied at 70% of TWL and at every node to find the collection and route optimization. The obtained results in all performance aspects, such as collected waste, distance, tightness, efficiency, fuel consumption, and cost, present that model 1, i.e., using TWL, is better than model 2, i.e., node consideration. This method gives a diverse amount of options to find the most efficient TWL in accordance with waste generation pattern. Thus, the proposed PSO-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 a large number of constraints and uncertainties in historical data. Also, in future, the proposed model can be implemented in real-world scenario by developing more smart bins to validate feasibility.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.wasman.2017.10.019.

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