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IoT-based smart bin allocation and vehicle routing in solid waste management: A case study in South Korea

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ABSTRACT

Increasing waste generation has become a real challenge because of population growth and rapid urbanization. Given this, most waste bins get overfilled easily because of the improper management of waste and the irregular cleaning of waste bins. The internet of things (IoT) is a remarkable modern technology that offers powerful resolutions to modernize traditional systems. In this study, the filling level of waste bins is considered in conjunction with IoT-based waste bins. This paper develops an integrated IoT-based smart bin allocation with a central monitoring system (CMS) and enhanced vehicle routing algorithm in solid waste management. This article proposes the time-dependent penalty concept to waste management authorities if these waste bins are not emptied in time after becoming full. To obtain the solution with faster execution time, an intelligent variable neighborhood search with ant colony optimization method (VNS- ACO) is developed. The proposed model is illustrated with some numerical data, and a sensitivity analysis is established with some parameters. Furthermore, the superiority of our developed VNS-ACO algorithm is established through testing on some traveling salesman problem (TSP) instances in the traveling salesman problem library (TSPLIB). Results have been compared with an advanced version of genetic algorithm (GA) and ACO methods.

1. Introduction

For community health and hygiene, cities must properly maintain environmental sanitation. In many communities, waste bins are kept without proper monitoring until they are overflowing, which results in environmental pollution. In smart cities, waste bins need to be monitored and controlled to ensure a healthy and clean environment. Nowadays, municipal authorities are giving serious attention to the use of advanced technologies in waste collection. They make decisions on optimal route planning and scheduling for collecting waste, as described by Huang and Lin (2015) and (Nuortio et al., 2006). However, they have not considered IoT-based waste bins. Until now, no researchers have developed a waste management technique considering IoT-based waste bins with vehicle routing. In this study, we also considered the time-dependent penalty concept as a prod to waste management authorities if the waste bins are not emptied in time after becoming full. This penalty incentivizes waste management authorities to clean the waste bins in time to avoid the penalty and results in effectively keeping environments clean.

Currently, our environment is being polluted by the rapid creation of global waste. According to a recent report of World Bank (Schrader-King and Liu, 2018), it is expected that global waste will grow by 70 percent by 2050 unless immediate monitoring and control are taken of waste management. Because of the increasing rate of global population and urbanization, the volume of waste produced globally is expected to rise to 3.4 billion tons within the next three decades. The use of modern IoT-based technologies can pave the way for better monitoring and control of waste as compared to the traditional approach. Pardini et al. (2020) presented a hardware and software approach to waste management to be part of a waste management process.

Some researchers have formulated waste collection problems mathematically and solved models with different techniques. The mathematical model for vehicle routing to collect municipal solid waste was presented by (Beltrami and Bodin, 1974). In 2012, Wang et al. (2012) developed a model for municipal solid waste (MSW) management using a fuzzy-stochastic programming approach. Levis et al. (2013) proposed

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an Integrated solid waste management modeling framework to collect waste from the curb to the final disposal by minimizing cost or and environmental impacts. Angelelli and Speranza (2002b) considered a model in which collection vehicles use immediate facilities for unloading waste along their routes. In another research paper, Angelelli and Speranza(2002a) considered an algorithm that was used to measure the operating costs of three different waste collection systems. Hauge et al. (2014) considered an industrial waste collection problem and solved it by routing technique. Rabbani et al. (2020) developed a routing model and decision-making techniques in industrial waste management. Recently, Rathore and Sarmah (2021) developed a mathematical model on municipal solid waste collection systems and applied it to the supply chain mechanism. In our model, we consider three types of IoT-based waste bins for collecting waste. We also describe different scenarios considering different types of vehicles to collect different types of waste.

Hemmelmayr et al. (2014) presented a research article on integrated waste bin allocation and vehicle routing in solid waste management. In this article, however, they considered bin allocation cost and routing cost separately and did not consider smart waste bins. Vicentini et al. (2009) developed a model on sensitized waste collection containers for content estimation and collection optimization but have not considered any other new advanced web-based information systems. Sinha et al. (2015) proposed a smart waste bin that can contribute to a clean and hygienic environment to build a smart city. Zeb et al. (2019) proposed an IoT-enabled smart waste bin management system for smart cities. A wireless sensor network-based smart bin was proposed by (Ramson and Moni, 2017). Very few researchers developed their work in IoT-based smart bin areas. Marques et al. (2019) developed an IoT-based smart cities infrastructure architecture and applied it to a waste management technique. Nidhya et al. (2020) implemented an ERS algorithm for a smart waste management system.

Given the possibilities of ongoing technological advances, real-time monitoring and automated control of waste disposal could be applied to this challenging area that needs urgent attention by the research community. The traditional approach of monitoring waste bins is a very inefficient way of waste management that is not in agreement with smart city requirements. Recently, advanced IoT algorithms have been able to boost information technology to a large extent. In this study, our waste management model considered three types of waste bins: bins for food waste, bins for general waste, and bins for recyclable waste. Also, this study considered different scenarios for waste collection and discussed these situations with cost analyses. Some sensitivity analyses concerning different parametric values are also illustrated in this model. Soft computing (SC) is a widely used technique in the current research of optimization. Nowadays, SC is used to design complex real-world problems and it is a part of artificial intelligence. To be specific, evolutionary computing techniques are parts of SC. ACO is one of the most popular evolutionary approaches for designing and solving complex optimization problems at present. ACO is versatile and can be applied globally. Its versatility gives it strong distributed computing capability and it has been successfully applied to handle different kinds of optimization problems. Karadimas et al. (2007) solved a conventional municipal solid waste collection model with ACO. The VNS algorithm has been proved to be successful in solving a variety of combinatorial problems. A VNS algorithm is used with the motivation of obtaining a near-optimal solution with better computational efficiency and with the motivation of providing efficient solutions for large instances in less computational time. Delgado-Antequera et al. (2020) & Molina et al. (2019) implemented a VNS algorithm to solve the waste collection problem. A hybridized metaheuristic approach of PSO-SA is proposed by Sarbijan and Behnamian (2022) to solve the multi-fleet feeder vehicle routing problem. This algorithm is compared with VNS, ACO, and PSO. Kyriakakis et al. (2021) proposed a hybrid algorithm of the Ant Colony System-Variable Neighborhood Decent and the Max-Min Ant System-Variable Neighborhood Decent to solve the cumulative capacitated vehicle routing problem. The authors consider only classical strategies to build the VNS. Our research fills this lacuna by introducing comparison-based heuristic strategies in the improvement section in VNS. ACO is used to generate an initial solution for VNS, and a modified local search is implemented to improve the performance of VNS. However, none of the researchers implemented any hybridized algorithm to solve the waste management problem to achieve faster execution of emptying full bins. In this study, waste bin allocation and routing problems (WBARP) is mathematically formulated to minimize the total costs, including bin allocation cost, driver wages, routing cost, and waste bin penalty cost, subject to the constraints. Our research motivation relates to enhancing the efficiency and effectiveness of the conventional heuristic to solve this type of NP-hard problem. We solved the problem using an hybridized VNS-ACO algorithm and showed that our algorithm works better than conventional methods.

This paper presents the design and implementation of an IoT-based Arduino Uno microcontroller working with the ultrasonic sensors that detect the level of waste in the waste bins placed in different locations. The sensors display the status information of the bins as “filled,” “half-filled,” or “empty” on an LCD screen at regular intervals and send this information to the CMS. This operation is performed using a microcontroller, a Wi-Fi module, and ultrasonic sensors. The above process helps to automate waste bin monitoring and control. Experimental results demonstrate a promising solution to waste management. Several tests can be performed to evaluate the system’s performance. The proposed IoT-based waste bin system will help to keep smart cities clean.

To the best of our knowledge, there is no research which impose a time-dependent penalty for the delay to serve a filled bin. The concept of neighboring bins is introduced to maintain the load constraint of a vehicle, and these are present under a certain radius from the last visited filled bin of a tour plan. In our proposed model, we consider the IoT-based smart waste bin system, which has the potential to detect the overflow of waste through an ultrasonic sensor. A time-dependent penalty is imposed on the waste management authority if filled bins are not emptied in time after becoming full. These smart waste bins can send messages to the CMS to avoid the penalty. After receiving the filled waste bins’ status, the CMS sends an appropriate vehicle to collect the waste, following the optimum path using our developed hybrid VNS-ACO algorithm. After collecting the waste from all the filled bins, the vehicle finds the nearest neighboring bins, which are not necessarily filled above a certain limit, and cleans those waste bins, too, if sufficient space is available for them to be emptied. By applying this idea to the vehicle routing technique, we can search for the shortest path to optimize the routing cost and clean the allocated bins as early and efficiently as possible. This model illustrates different scenarios, depending on different parameters, like vehicle types and driver availability under a budget limit. An intelligent hybrid VNS-ACO is developed to solve this waste management model numerically. In the computational experiments section, we analyze this model using realistic data. We chose 15 places in the Gwanak and Guro districts in Seoul, Korea. Additionally, according to the population of these areas, we generated an estimation of the amount of waste produced and considered the actual distances between waste bins placed in these areas. Different results are presented with our realistic input values and some of these results are depicted graphically. We also conducted sensitivity analysis with some important parameters. Our hybrid VNS-ACO algorithm is efficient for discrete optimization problems. To show the effectiveness of our developed algorithm, we tested it with some traveling salesman problem (TSP) instances from the traveling salesman problem library (TSPLIB), (Reinelt, 1991). Results are compared with an advanced version of genetic algorithm (GA) and ACO concerning total costs. Also, we show the efficiency of our algorithm with the analysis of variance (ANOVA) test.

This paper is structured as follows. In Section 1, a brief introduction and literature review are given. Section 2 provides a detailed description of the smart waste bin. In Section 3, our proposed mathematical model is discussed. We illustrate and describe in detail our developed hybrid VNS-ACO algorithm in Section 4. In Section 5, computational experiments are presented and managerial insights are discussed. We conclude the paper by discussing the importance of our research and the limitations and future scope of research in Section 6.

2. Smart waste bins

Our proposed model of an IoT-based smart bin system has the potential for detecting the overflow of waste bins (Fig. 1).

Detail configuration:

Ultrasonic sensors (USs): Ultrasonic sensors sense the distance between the closing lid of the smart bin and the level of waste within it. The continuously recorded data by USs is sent to a Wi-Fi module through the Arduino Uno system in real-time data from the smart bin's US sensor and is transmitted through the wireless module to a smart waste management application platform. The distance between the waste level of the bin and the lid of the bin is detected by the US sensor through a transmitter and receiver. The waste level calculation of the bin can be demonstrated in the following manner:

$$Vl_t = Vl_0 + R_{vl} \times Tm$$

Where, Vl_t is the velocity of sound at temperature at t^oC.

Vl_0 is the velocity of sound at temperature at 0^oC.

Tm is the temperature.

R_{vl} is the rate of change of velocity with per degree rise in temperature.

Distance $(Dt) = (Vl_t \times \text{ Time })/2$, where Time is the ping time from sensor.

Percentage filled $= 100 - (100/I) \times Dt$, where I is the height of the bin.

Arduino Uno: The Arduino Uno system is an automation system derived from the use of an Arduino Uno board; automation refers to the entire self-functioning system. The board itself acts as the "brain" or the central processing unit (CPU) for the entire apparatus. It controls the various interactions and synchronizations of the sensors.

Wi-Fi module: Internet access, through Wi-Fi, will be allocated to our system by ESP8266, which is known as a Wi-Fi module. The Wi-Fi module can communicate with any kind of microcontroller and can help in making the system wireless for remote access. Arduino Uno technology is among the leading technologies in transmitting devices in the IoT platform.

Servomotor: The servomotor is used to open and close the lids of waste bins and is controlled by the Arduino Uno technology, depending on the accessing mechanism. The servomotor mainly works by using a DC power supply.

Global system for mobile communication (GSM): This is a digital cellular technology used for transmitting mobile voice and text data. GSM digitizes and compresses data, then sends it through a channel.

Global positioning system (GPS): This technology obtains location information. Through this location information, our developed system can track the current location of where the smart bin is deployed.

Radio-frequency identification (RFID) reader: The RFID reader is used for authenticating the user. RFID is designed to enable readers to capture data from tags and transmit it to a computer system.

These kinds of sensors are very low-cost sensors. However, these sensors have acute sensitivity across wide ranges and have advantages such as long lifespans and less complexity to operate and maintain.

Working principle: Using an Arduino Uno board and sensors, we can automate the function of a normal waste bin, thereby turning it into a smart waste bin. By using the US, the smart waste bin can measure the amount of waste, and detailed information can be sent to the Arduino Uno board. As soon as the waste reaches a particular level set by the waste management authorities, the smart waste bin sends a notification to the municipal corporation for immediate cleaning of the waste bin. The Wi-Fi module is triggered from the Arduino Uno board and sends the real-time data to the central monitoring system to analyze the amount of waste that is within the waste bin.

3. Mathematical model

In this section, we present the smart waste collection problem occurring in a smart city where some IoT-based smart bins are placed in different locations around the city. Our problem consists of integrating the IoT-based smart bin allocation with vehicle routing for waste collection. This problem is called the waste bin allocation and routing

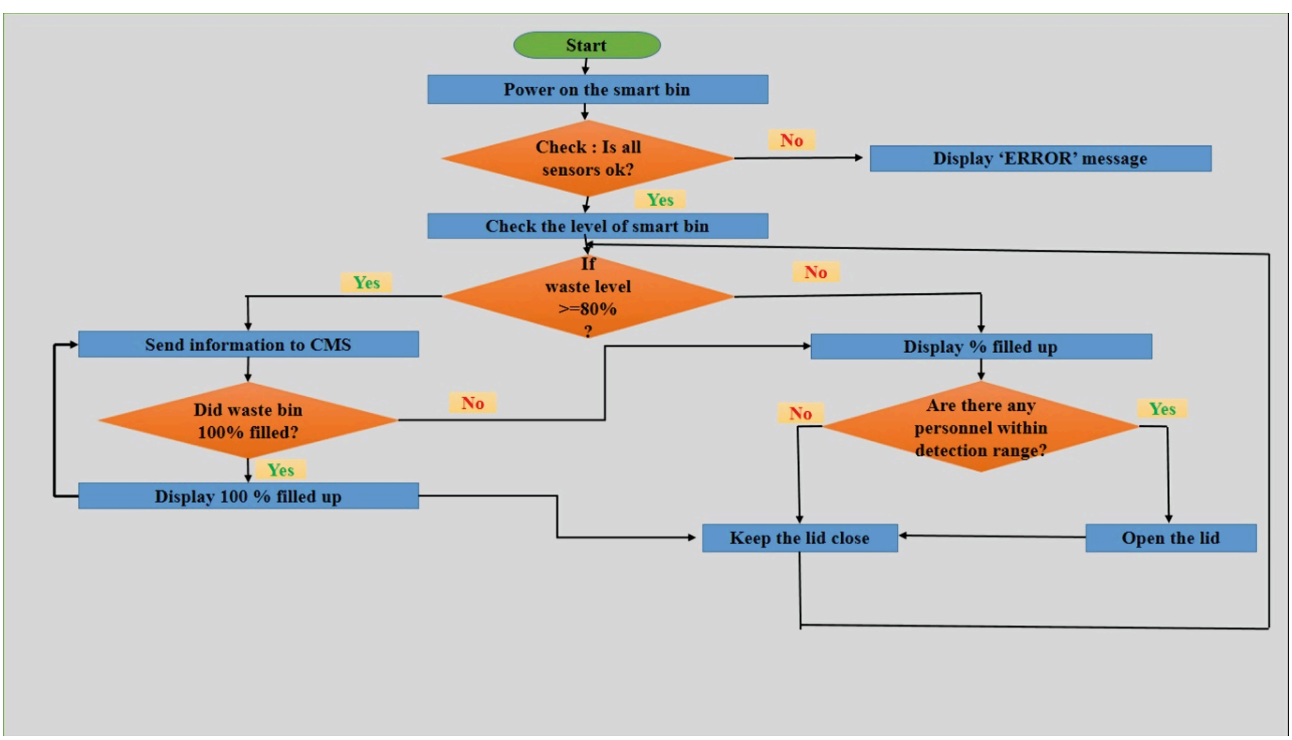


Fig. 1. Flowchart of IoT-based smart waste bin

problem (WBARP) and requires a balance between bin allocation costs and vehicle routing costs in an optimum measure. In many communities, waste bins get overfilled easily because no proper waste management system exists. Our proposed model eliminates this problem by sending alerts to cleaning authorities when smart bins are filled to a predefined TFL, say 80 percent. A time-dependent penalty cost to the waste management authorities is considered if smart bins are not emptied in time after filling to full capacity (100 percent). We developed a hybrid VNS-ACO technique, which will also search the neighboring bins' statuses at the time of cleaning the last filled (above 80 percent capacity) bin. The neighboring bins will be cleaned after emptying all filled (above 80 percent capacity) bins if space is available in the vehicle to hold the waste. To achieve the objective of this waste management model, some assumptions are considered to make the model more realistic.

Assumptions

(I) Each time before collection, the smart waste bin's weight is checked with the TFL (80 percent of the bin's weight). If the fill level reaches the TFL, then an alert message is transmitted to the CMS so that the waste can be collected.

(II) The CMS sends appropriate vehicles from the depot when some waste bins are filled (above 80 percent capacity).

(III) All the empty vehicles start from the depot and collect waste from all filled (above 80 percent capacity) waste bins. From the last filled bin, the CMS will search neighboring bins and clean them if space is available in the vehicle to hold the waste. The collection vehicle will carry the collected accumulated waste to the nearest disposal center and return to the depot.

(IV) Each waste bin will be visited by only one vehicle during collection time.

(V) The cumulative waste in a vehicle per route must not exceed the maximum vehicle capacity.

(VI) The capacities of waste bins are homogeneous.

(VII) The capacities of vehicles are heterogeneous with different types but homogeneous with their own types.

(VIII) The average uniform speed of all vehicles is considered throughout the routing to avoid traffic congestion.

(IX) Each type of vehicle is available every time, but not drivers.

(X) Each driver can drive all types of vehicles.

(XI) In each place, we consider all types of waste bins side by side, i.e, waste bins b_{ki}, $\forall\, k = 1, 2, 3$ are placed in location i.

(XII) Cleaning more than one type of waste bin in the same location requires only one setup time.

Notations and abbreviations are presented in the Appendix.

In this WBARP model, a vehicle starts its journey from the depot after receiving a signal from the central monitoring system (CMS). This vehicle cleans the filled bin and its neighboring waste bins and unloads the accumulated waste at the nearest disposal center. Also, this vehicle follows the shortest route, using our developed VNS-ACO technique. The mathematical formulation is given below.

Total bin allocation cost:

$$B_{ac} = \sum_{k=1}^{3} C_{kb}|B_k| \tag{1}$$

Penalty cost of waste bin, b_{ki}, after filling to 100 percent capacity at time, t (in hours):

$$P_{ki}(t) = a + bt, a, b, t > 0, \forall b_{ki} \in B_p, k = 1, 2, 3, i = 1, 2, \cdots, u \tag{2}$$

In Eq. (2), a penalty cost of a waste bin means that if a waste bin is filled above 100 percent capacity, the waste management authority should pay a penalty for that. The formula for the penalty is a plus bt, and both a and b are two positive constants, with a being the fixed part (i.e., the minimum cost of the penalty) and b being the penalty cost linearly increasing with time t.

Total wages of drivers in T days:

$$Twd = S_l D_r T \tag{3}$$

The decision variables are as follows:

$$x_{ijh} = \begin{cases} 1 & \text{if a route is visited between node } i \text{ to node } j (i \neq j) \text{ in the undirected graph by a vehicle } h; h \in V_k, k = 1, 2, \cdots, 5 \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Scenario 1: Different vehicles to collect different types of waste.

Routing cost for collecting food waste from type-1 filled bins per trip.

$$Z_1 = \beta_0 r_1 \sum_{i \in B_{1f}^{+}} \sum_{j \in B_{1f}^{+}} d_{ij} x_{ijh}, i \neq j, h \in V_1 \tag{5}$$

Routing cost for collecting general waste from type-2 filled bins per trip.

$$Z_2 = \beta_5 r_2 \sum_{i \in B_{2f}^{+}} \sum_{j \in B_{2f}^{+}} d_{ij} x_{ijh}, i \neq j, h \in V_2 \tag{6}$$

Routing cost for collecting recyclable waste from type-3 filled bins per trip.

$$Z_3 = \beta_6 r_3 \sum_{i \in B_{3f}^{+}} \sum_{j \in B_{3f}^{+}} d_{ij} x_{ijh}, i \neq j, h \in V_3 \tag{7}$$

Routing cost for collecting waste from all types of neighboring bins per trip.

$$Z_{4k} = \beta_1 r_k \sum_{\left(i, j \in N^{+}[b_{kl}], b_{kl} \in B_{kf}\right)} d_{ij} x_{ijh}, i \neq j, h \in V_k, k = 1, 2, 3 \tag{8}$$

The objective function is to minimize the summation of bin allocation cost, routing cost, driver wages, and penalty cost over the time horizon, T, as follows:

$$Z = B_{ac} + Twd + \sum_{T} \left[\left(Z_1 + Z_2 + Z_3 + \sum_{k=1}^{3} Z_{4k} \right) + \beta_3 \sum_{b_{ki} \in B_p} P_{ki} \right] \tag{9}$$

Subject to:

$$\sum_{i\left(b_{ki} \in B_{kf}\right)} x_{d_0 ih} = 1, \forall h \in V_k, k = 1, 2, 3 \tag{10}$$

$$\sum_{i\left(b_{ki} \in B_{kf}\right)} l_{d_0 ih} = 0, \forall h \in V_k, k = 1, 2, 3 \tag{11}$$

$$\sum_{i\left(b_{ki} \in B_{kf} \cup N[b_{kl}]\right)} lb_{ki} \leq L_h, b_{kl} \in B_{kf}, \forall h \in V_k, k = 1, 2, 3 \tag{12}$$

$$\sum_{i=1}^{m} x_{d_i d_0 h} = 1, \forall h \in V_k, k = 1, 2, 3 \tag{13}$$

$$\sum_{i=1}^{m} l_{d_i d_0 h} = 0, \forall h \in V_k, k = 1, 2, 3 \tag{14}$$

$$\sum_{j \in B^{+}} x_{ijh} = \sum_{j \in B^{+}} x_{jih} = y_{ih}, \forall i \in B^{+}, i \neq j, \forall h \in V_k, k = 1, 2, 3 \tag{15}$$

$$x_{ijh} \in \{0, 1\}, i \neq j, \forall h \in V_k, k = 1, 2, 3 \tag{16}$$

In Eq. (8) and in Eq. (12), b_{kl} indicates the last filled bin in location l of type k being visited. In this scenario, constraint (10) confirms that, per trip, each vehicle starts its journey from the depot and then first visit a filled bin location. Constraint (11) ensures that the vehicle, h, will start its journey from the depot without any load. Constraint (12) states that the total collected waste from a set of waste bins must not exceed the maximum load capacity of a vehicle. Each vehicle will return to the depot after disposed of the collected waste to the disposal center;

constraints (13) and (14) maintain it. Constraint (15) indicates that location i is visited by the vehicle h and it ensures the continuity condition. That is if the vehicle h enters a node, it must also leave the node. Constraint (16) represents some binary variables.

Scenario 2: Same vehicle to collect general and recyclable waste with different compartments, and another vehicle for food waste.

Routing cost for collecting food waste from type-1 filled bins per trip.

$$Z_1 = \beta_0 r_1 \sum_{i \in B_{1f}^+} \sum_{j \in B_{1f}^+} d_{ij} x_{ijh}, i \neq j, h \in V_1 \tag{17}$$

Routing cost for collecting general and recyclable waste from type-2 and type-3 filled bins per trip.

$$Z_2 = \beta_2 r_4 \sum_{i \in B'^+_f} \sum_{j \in B'^+_f} d_{ij} x_{ijh}, i \neq j, h \in V_4 \tag{18}$$

Routing cost for collecting food waste from type-1 neighboring bins per trip.

$$Z_3 = \beta_1 r_1 \sum_{\left(i,j \in N^+[b_{1l}], b_{1l} \in B_{1f}\right)} d_{ij} x_{ijh}, i \neq j, h \in V_1 \tag{19}$$

Routing cost for collecting general and recyclable waste from type-2 and type-3 neighboring bins per trip.

$$Z_4 = \beta_1 r_4 \sum_{\left(i,j \in N^+[b_{2l}] \cup N^+[b_{3l}], b_{kl} \in B_{kf}\right)} d_{ij} x_{ijh}, i \neq j, h \in V_4, k = 2, 3 \tag{20}$$

The objective function is to minimize the summation of bin allocation cost, routing cost, driver wages, and penalty cost over the time horizon, T, as follows:

$$Z = B_{ac} + Twd + \sum_T \left[(Z_1 + Z_2 + Z_3 + Z_4) + \beta_3 \sum_{b_{ki} \in B_p} P_{ki} \right] \tag{21}$$

Subject to:

$$\sum_{i\left(b_{1i} \in B_{1f}\right)} x_{d_0 ih} = 1, \sum_{i\left(b_{ki} \in B_{kf}\right)} x_{d_0 ih} = 1, \forall h \in (V_1 \cup V_4), k = 2, 3 \tag{22}$$

$$\sum_{i\left(b_{1i} \in B_{1f}\right)} l_{d_0 ih} = 0, \sum_{i\left(b_{ki} \in B_{kf}\right)} l_{d_0 ih} = 0, \forall h \in (V_1 \cup V_4), k = 2, 3 \tag{23}$$

$$\sum_{i\left(b_{ki} \in B_{1f} \cup N[b_{1l}]\right)} lb_{1i} \leq L_h, b_{1l} \in B_{1f}, \forall h \in V_1 \tag{24}$$

$$\sum_{i\left(b_{ki} \in B_{kf} \cup N[b_{kl}]\right)} lb_{ki} \leq L_h, b_{kl} \in B'_f, k = 2, 3, \forall h \in V_4 \tag{25}$$

$$\sum_{i=1}^{m} x_{d_i d_0 h} = 1, \forall h \in V_1 \cup V_4 \tag{26}$$

$$\sum_{i=1}^{m} l_{d_i d_0 h} = 0, \forall h \in V_1 \cup V_4 \tag{27}$$

$$\sum_{j \in B^+} x_{ijh} = \sum_{j \in B^+} x_{jih}, \forall i \in B^+, i \neq j, \forall h \in V_1 \tag{28}$$

$$\sum_{j \in B^+} x_{ijh} = \sum_{j \in B^+} x_{jih}, \forall i \in B^+, i \neq j, \forall h \in V_4 \tag{29}$$

$$x_{ijh} \in \{0, 1\}, i \neq j, \forall h \in V_1 \cup V_4 \tag{30}$$

In this scenario, the above constraints have the same meaning as in Scenario 1.

Scenario 3: Same vehicle to collect all types of waste with different compartments.

Routing cost for collecting waste from all types of filled bins per trip.

$$Z_1 = \beta_4 r_5 \sum_{i \in B_f^+} \sum_{j \in B_f^+} d_{ij} x_{ijh}, i \neq j, h \in V_5 \tag{31}$$

Routing cost for collecting waste from all types of neighboring bins per trip.

$$Z_2 = \beta_1 r_5 \sum_{\left(i,j \in N^+[b_{1l}] \cup N^+[b_{2l}] \cup N^+[b_{3l}], b_{kl} \in B_{kf}\right)} d_{ij} x_{ijh}, i \neq j, \forall h \in V_5, k = 1, 2, 3 \tag{32}$$

The objective function is to minimize the summation of bin allocation cost, routing cost, driver wages, and penalty cost over the time horizon, T, as follows:

$$Z = B_{ac} + Twd + \sum_T \left[(Z_1 + Z_2) + \beta_3 \sum_{b_{ki} \in B_p} P_{ki} \right] \tag{33}$$

Subject to:

$$\sum_{i\left(b_{ki} \in B_{kf}\right)} x_{d_0 ih} = 1, \forall h \in V_5, k = 1, 2, 3 \tag{34}$$

$$\sum_{i\left(b_{ki} \in B_{kf}\right)} l_{d_0 ih} = 0, \forall h \in V_5, k = 1, 2, 3 \tag{35}$$

$$\sum_{k=1}^{3} \sum_{i\left(b_{ki} \in B_{kf} \cup N[b_{kl}]\right)} lb_{ki} \leq L_h, b_{kl} \in B_{kf}, \forall h \in V_5, k = 1, 2, 3 \tag{36}$$

$$\sum_{i=1}^{m} x_{d_i d_0 h} = 1, \forall h \in V_5 \tag{37}$$

$$\sum_{i=1}^{m} l_{d_i d_0 h} = 0, \forall h \in V_5 \tag{38}$$

$$\sum_{j \in B^+} x_{ijh} = \sum_{j \in B^+} x_{jih}, \forall i \in B^+, i \neq j, \forall h \in V_5 \tag{39}$$

$$x_{ijh} \in \{0, 1\}, i \neq j, \forall h \in V_5 \tag{40}$$

In this scenario, the above constraints have the same meaning as in Scenario 1.

4. Hybrid methaheuristic

Our problem size depends upon the number of waste bins allocated, the number of different types of vehicles used for collection, and the number of available drivers. Many researchers have implemented different metaheuristic techniques to address different combinatorial optimization problems in various fields. Benjamin and Beasley (2010) & Alves et al. (2012) have implemented metaheuristic techniques for waste collection, vehicle routing problems and leather nesting problems respectively. The vehicle routing problem (VRP) is a well-known optimization problem. Many algorithms exist to solve different types of VRPs. The backtracking search algorithm (BSA) is a population-based metaheuristic algorithm. Akhtar et al. (2017) used the BSA to solve the capacitated vehicle routing problem (CVRP). We developed an intelligent VNS-ACO algorithm for solving IoT-based smart bin allocation and vehicle routing model in solid waste management. Our hybrid VNS-ACO finds the nearest set of filled bins from the currently filled bin being visited. The nearest filled bins will be visited if their fill level reaches the pre-specified TFL, and after cleaning the filled bins, neighboring bins will be visited if sufficient space is available in the vehicle to hold the waste. Our developed algorithm is compared with an advanced version of genetic algorithm (GA) and ACO, which was proved to work better.

4.1. VNS

VNS is a metaheuristic method that exploits the idea of neighborhood change proposed by Mladenovic and Hansen (1997). VNS explores increasingly distant neighborhoods of the currently assigned solution and jumps from one to a new one if, and only if, an improvement was made. The VNS-based algorithm has been used several times successfully for solving a variety of large-scale combinatorial optimization problems because it becomes increasingly difficult to solve large problem instances with CPLEX (Wassan et al., 2017). de Armas et al. (2015) used the VNS algorithm for obtaining a near-optimal solution with a better computational efficiency for providing efficient solutions for large instances in less computational time. To escape from the local trap, the VNS technique performs the local search within several neighborhood structures (Wassan et al., 2017). VNS terminates once it reaches the maximum number of iterations. In this technique, the number of iterations and the maximum number of neighborhoods are considered as VNS parameters. The basic steps of VNS are as follows:

A. Set an initial solution X.
B. Select a set of neighborhood structures $N_k(X)$ with$k = 1,2,....,K_{max}$, used for searching the improved solution.
C. Main steps:
a) k = 1.
b) repeat
1. Shaking: Generate a point X' at random from the k^{th} neighborhood of$X(X' \in N_k(X))$;
2. Local search: Apply some local search method with X' as the initial solution and denote the obtained local optimum asX'';
3. Neighborhood change: If the solution X'' is better than X then $X = X''$ and continue the search with the current neighborhood structure;

Otherwise.

$k = k + 1$;

Until$(k = K_{max})$.

The neighborhood structures must work so that they prevent any infeasible solution.

4.2. VNS-ACO

4.2.1. Representation

A complete cycle of vehicle depot,(d_o), filled waste bins, neighboring bins, and disposal center represents a solution of ants. Therefore, a $(k + l + 2)$ dimensional integer vector,$X_i = (d_o, b_{1i'}, .., b_{2j}, ..., b_{3k}, b_{1,k+1}, .., b_{2,k+l'}, ..., b_{3,k+l}, d_{i''})$, is used to represent a vehicle depot, k the number of filled bins, l the number of neighboring bins and a disposal center to represent a solution, where d_o represents a vehicle depot, $b_{1i'}, .., b_{2j}, ..., b_{3k}$ represent a set of filled bins, $b_{1,k+1}, \cdots, b_{2,k+l'}, \cdots, b_{3,k+l}$ represent a set of neighboring bins and $d_{i''}$ represents a disposal center in the cycle. In this algorithm, an ant colony system is initially used to produce a set of paths (cycles) for routing which is a set of potential initial solutions for the VNS part.

4.2.2. VNS-ACO

In this VNS-ACO system (Fig. 3), initial solutions are generated by ACO. In ACO, $\tau_{i,j}$ represents the amount of pheromone that lies on the path between nodes i and j, maxiter represents the maximum iteration number of the ACO algorithm. n and $M = (k + l + 2)$ represent the number of ants or population size and number of nodes, respectively.

Pheromone initialization: As the aim of the WBARP is to minimize the total cost, i.e, minimize the bin allocation cost and routing cost, it is assumed that initial value of pheromone$\tau_{i,j} = \frac{1}{\sqrt{d_{ij}}}$, $\tau_{i,j}$ means the pheromone from node i to j.

Path construction: To construct a path X_m for the *m-th* ant, the following are required:

a. Let $E = \{1, 2, ..., M\}$, $l = 1$ and $E' = \{2, 3, ..., M - 1\}$.

Node 1 and M in E represent d_o (vehicle depot), and disposal center, respectively.

b. x_{ml} = a random element from the setE'.

c.$i = x_{ml}$.

d. Let$E' = E' - \{i\}$.

e. Let node i be the present position of an ant. Then next node $j \in E'$ is selected by the ant with probability p_{ij} given by the formula$p_{ij} = \frac{\tau_{i,j}^{\delta_1}}{\sum_{j \in E'} \tau_{i,j}^{\delta_1}}$; where δ_1 is a user defined parameter which controls the relative importance of pheromone concentration. Roulette-Wheel selection process is used for the purpose.

f.$l = l + 1, i = j$.

g. If $l < (M - 1)$ go to step (d).

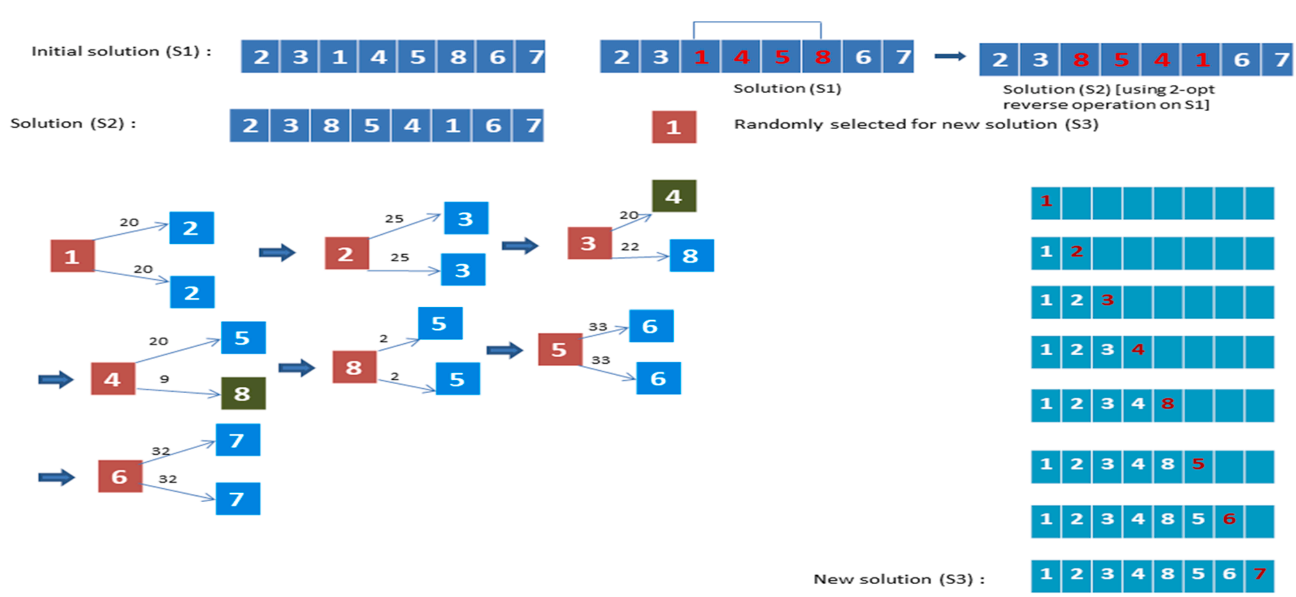


Fig. 2. Proposed local search in VNS

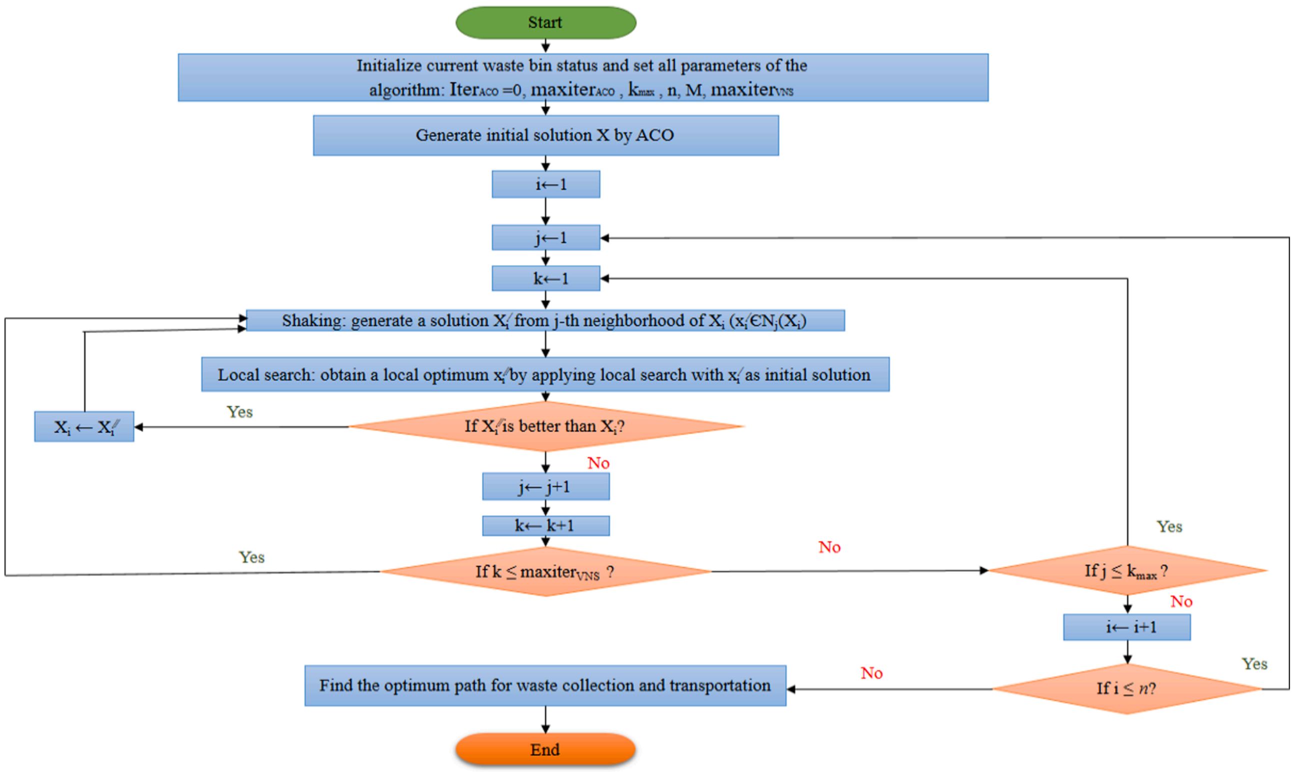


Fig. 3. Flowchart of VNS-ACO

n such paths are constructed for n different ants.

Pheromone evaporation: For evaporation of pheromone, the following formula is used.

$$\tau_{i,j} = (1-\rho)\tau_{i,j} \tag{41}$$

where ρ lies between [0, 1]. The constant,ρ, specifies the rate of pheromone evaporation, causing ants to forget previous decisions.

Pheromone updating: After the completion by all ants, pheromone is increased on the paths through which the ants have traveled. Depending upon the nature of the present problem, pheromone is updated using the following rules.

$$\tau_{i,j} = (1-\rho)\tau_{i,j} + \frac{\rho}{n}\sum_{i=1}^{n}\tau_{i,j}^{best} \tag{42}$$

where ρ represents the rate of evaporation and n the number of ants.

After obtaining an initial solution by ACO, we apply our VNS technique to achieve the optimum path for waste collection. Components of VNS include the initial feasible solution (from ACO), the shaking procedure, the local search for improving the solution, neighborhood change, and a terminating condition. Let $N_k(X)$ be a set of solutions in the *k-th* neighborhood of the solution,X. k_{max} is the maximum number of different neighborhood structures generated in the shaking phase. In this shaking phase, a solution is randomly taken from the *k-th* neighborhood structure to be used as an initial solution to find the improved solution in a local search. A local search rigorously finds the given neighborhood structure and compares each solution with the given solution obtained in the shaking phase and returns the best solution, and accordingly neighborhood changes take place. If a better solution is achieved, the above local search returns to the same neighborhood structure. Otherwise, the algorithm attempts to obtain a better solution from a different neighborhood structure, ($k = k+1$). We introduced a new comparison-based local search technique to improve the solution quality in Fig. 2. Initially, a solution is chosen for a local search, and a 2-opt reverse operation is applied to get a new solution. A heuristic search is applied based on these two solutions to get our expected final solution after the local search. After performing the local search from all the neighborhood structures, the algorithm stores the best-known solution and moves on to the next iteration. VNS procedure terminates once it reaches the maximum number of iterations. The number of iterations and the maximum number of neighborhoods generated are the VNS parameters.

Algorithm 1: Variable neighborhood search with ant colony optimization (VNS-ACO)

input: A set of given waste bins, B, with their current status,$iter_{ACO} = 0, maxiter_{ACO}, k_{max}, n, M, maxiter_{VNS}$.
output: An optimum path for waste collection and transportation.
Begin
set initial generation$iter_{ACO} = 0, maxiter_{ACO}, k_{max}, n, M, maxiter_{VNS}$;
initialize pheromone τ_{rs} $for r, s = 2, 3, \cdots, (M-1)$;
while ($iter_{ACO} \leqslant maxiter_{ACO}$) **do**
construct a path of n ants, i.e., n cycles
$X_i = (d_o, b_{1i'}, .., b_{2j}, ..., b_{3k}, b_{1,k+1}, .., b_{2,k+l'}, ..., b_{3,k+l}, d_{i''}, d_0), i = 1, 2, ..., n$ usingτ_{rs};
made pheromone evaporation by Equation (41);
update pheromone for all paths by Equation (42);
$iter_{ACO} = iter_{ACO} + 1$
end while
set initial solutions $X_i, i = 1, 2, \cdots, n$ by ACO
$i = 1$;
while ($i \leqslant n$) **do**
$j = 1$;
repeat
for k = 1 to $maxiter_{VNS}$ **do**
generate a solution X_i' from the $j-th$ neighborhood of X_i ($X_i' \in N_j(X_i)$);
apply proposed local search with X_i' as an initial solution to obtain a local optimumX_i'';
if (X_i'' is better than X_i) **then**
$X_i = X_i''$;
continue the search withN_j;
end if
else
$j = j+1$;
end else
end for
until($j \leqslant k_{max}$)
$i = i+1$;
end while
Find the optimum path for waste collection and transportation
End

5. Computational experiments

Our proposed algorithm was implemented in Python on a PC with an Intel Core i5 processor running at 3.2 GHz and 8 GB of RAM. The following data are used to illustrate the proposed model. $k^{'} = 1.0$ km,$C_{b1} = \$10$,$C_{b2} = \$8$,$C_{b3} = \$8$, ρ=0.03, $n = 80$, $q = 40$ km/hr, $SR_{t1} =$ 5 minutes, $SR_{t2} = 5$ minutes,$S_l = \$20$, $T = 5$ days, $a = \$10$, and $b = \$12$. The capacity of each type of bin = 40 kg, and the distances of d_0 from d_1 and d_2 (two disposal centers) are 6.4 km and 7.2 km, respectively.

We chose the Gwanak and Guro districts (Fig. 3) in Seoul, Korea, for the location of IoT-based waste bins. In these two districts, we selected fifteen places: (a) SNU Hospital in the Gwanak district, (b) Korea University Hospital in the Guro district, (c) factories in the Guro district, (d) Hallym University Hospital in the Gwanak district, (e) the multiplex at SNU Station in the Gwanak district, (f) a residential area in the Gwanak district, (g) an SNU dormitory in the Gwanak district, (h) Gwanak Mountain Park in the Gwanak district, (i) Doksan Park in the Gwanak district, (j) five high schools in the Guro district, (k) Gocheok Stadium in the Guro district, (l) assorted companies in the Guro district, (m) the Gwanak complex apartments in the Gwanak district (n) the Sillim multiplex in the Gwanak district, and (o) the Lotte department store in the Gwanak district. All these places have been taken from Google Maps, and their distances are written in Table 1 and shown in Fig. 4.

Regarding solution quality (total cost) and runtimes, Table 2 shows that our proposed VNS-ACO is effective in finding good-quality solutions within a reasonable time. An exact algorithm is implemented with Python and solved with CPLEX Optimizer 20.1, using the exact branch-and-cut algorithm. VNS-ACO is compared with the exact algorithm using the same parameters. A detailed routing sequence and costs are elaborated from subsection 5.1 to subsection 5.3. The results for VNS-ACO in Table 2 correspond to optimum cases in each scenario.

5.1. Scenario 1

In this scenario, we considered vehicles from the vehicle set V_1 to collect food waste, from vehicle set V_2 to collect general waste, and from vehicle set V_3 to collect recyclable waste. Unit traveling costs of each vehicle in V_1, V_2, and V_3 are \$1.25, and maximum load capacities of each vehicle in V_1, V_2, and V_3 are 300 kg.

Case 1: (No. of drivers = 3).

The waste management authority should have to pay a huge penalty because of the availability of fewer drivers, and the total cost over the time horizon, T, is \$2,624.76.

Case 2: (No. of drivers = 4).

The waste management authority should have to pay greater penalties because of the insufficient number of drivers, and the total cost over the time horizon, T, is \$2,268.81.

Case 3: (No. of drivers = 5).

We deduced that the optimal value of the total cost over the time horizon, T, is \$2,137.87. Optimum results for collecting all types of waste are presented in Table 3. In this case, total routing cost is \$1,153.52 and the total penalty cost is \$94.35.

Case 4: (No. of drivers = 6).

The waste management authority should have to pay more compared to Case 3, and the total cost over the time horizon,T, is \$2,200.48.

Case 5: (No. of drivers = 7).

The waste management authority should have to pay more money compared to previous cases, and the total cost over the time horizon,T, is \$2,288.16.

5.2. Scenario 2

In this scenario, we considered some vehicles from vehicle set V_1 to collect food waste, and other vehicles from vehicle setV_4, with different compartments, to collect general and recyclable waste. The unit traveling cost of each vehicle in V_1 is \$1.25, and the unit traveling cost of each vehicle in V_4 is \$1.45, and the maximum load capacities of each vehicle in V_1 are 300 kg and in V_4 are 400 kg, respectively.

Case 1: (No. of drivers = 2).

The waste management authority should have to pay a huge penalty because of the availability of fewer drivers, and the total cost over the time horizon,T, is \$2,438.82.

Case 2: (No. of drivers = 3).

The waste management authority should have to pay greater penalties because of the insufficient number of drivers, and the total cost over the time horizon,T, is \$2,083.14.

Case 3: (No. of drivers = 4).

We deduced that the optimal value of the total cost over the time horizon,T, is \$1,920.94. Optimum results for collecting all types of waste are presented in Table 4. In this case, total routing cost is \$952.51 and total penalty cost is \$178.43..

Case 4: (No. of drivers = 5).

The waste management authority should have to pay more money compared to Case 3, and the total cost over the time horizon,T, is \$2,010.14.

Case 5: (No. of drivers = 6).

The waste management authority should have to pay more money compared to previous cases, and the total cost over the time horizon,T, is \$2,100.02.

Table 1
Distance matrix of bins, depot, and two disposal centers

(i,j)	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o
a	0	6.5	8.2	4.7	1.4	3.4	0.6	3.5	3.9	11.5	9.1	5.2	2.3	2.6	3.4
b	6.5	0	1.7	2.1	6.1	3.2	7.1	3.6	2.9	5.1	2.6	1.4	5.9	4.1	3.5
c	8.2	1.7	0	3.6	7.7	4.9	8.7	5.2	4.5	3.5	1.1	3.1	7.5	3.9	3.5
d	4.7	2.1	3.6	0	4.1	1.9	5.3	2.7	2.2	7.2	4.7	1.6	3.8	2.1	1.4
e	1.4	6.1	7.7	4.1	0	3.3	1.7	3.9	3.7	11.1	8.7	4.9	0.9	1.9	2.6
f	3.4	3.2	4.9	1.9	3.3	0	3.9	0.7	0.6	8.2	5.8	1.8	3.5	1.5	1.8
g	0.6	7.1	8.7	5.3	1.7	3.9	0	4.1	4.5	12.1	9.7	5.7	2.7	3.1	4.1
h	3.5	3.6	5.2	2.7	3.9	0.7	4.1	0	0.6	8.2	6.1	2.1	4.1	2.2	2.6
i	3.9	2.9	4.5	2.2	3.7	0.6	4.5	0.6	0	7.7	5.4	1.5	4.2	2.2	2.3
j	11.5	5.1	3.5	7.2	11.1	8.2	12.1	8.2	7.7	0	2.4	6.3	10.9	9.1	8.6
k	9.1	2.6	1.1	4.7	8.7	5.8	9.7	6.1	5.4	2.4	0	3.9	8.4	6.7	6.1
l	5.2	1.4	3.1	1.6	4.9	1.8	5.7	2.1	1.5	6.3	3.9	0	4.9	2.9	2.6
m	2.3	5.9	7.5	3.8	0.9	3.5	2.7	4.1	4.2	10.9	8.4	4.9	0	2.1	2.3
n	2.6	4.1	3.9	2.1	1.9	1.5	3.1	2.2	2.2	9.1	6.7	2.9	2.1	0	0.9
o	3.4	3.5	3.5	1.4	2.6	1.8	4.1	2.6	2.3	8.6	6.1	2.6	2.3	0.9	0
d_0	4.8	2.5	3.9	2.9	4.6	2.1	5.9	2.1	1.4	6.1	4.0	0.8	4.7	2.9	2.8
d_1	9.8	4.2	3.6	6.6	9.2	6.9	10.2	6.6	6.4	2.2	2.5	5.4	9.7	7.7	7.6
d_2	2.1	7.1	8.7	5.9	0.9	3.9	2.1	4.6	4.7	11.8	9.5	5.9	1.1	2.5	3.6

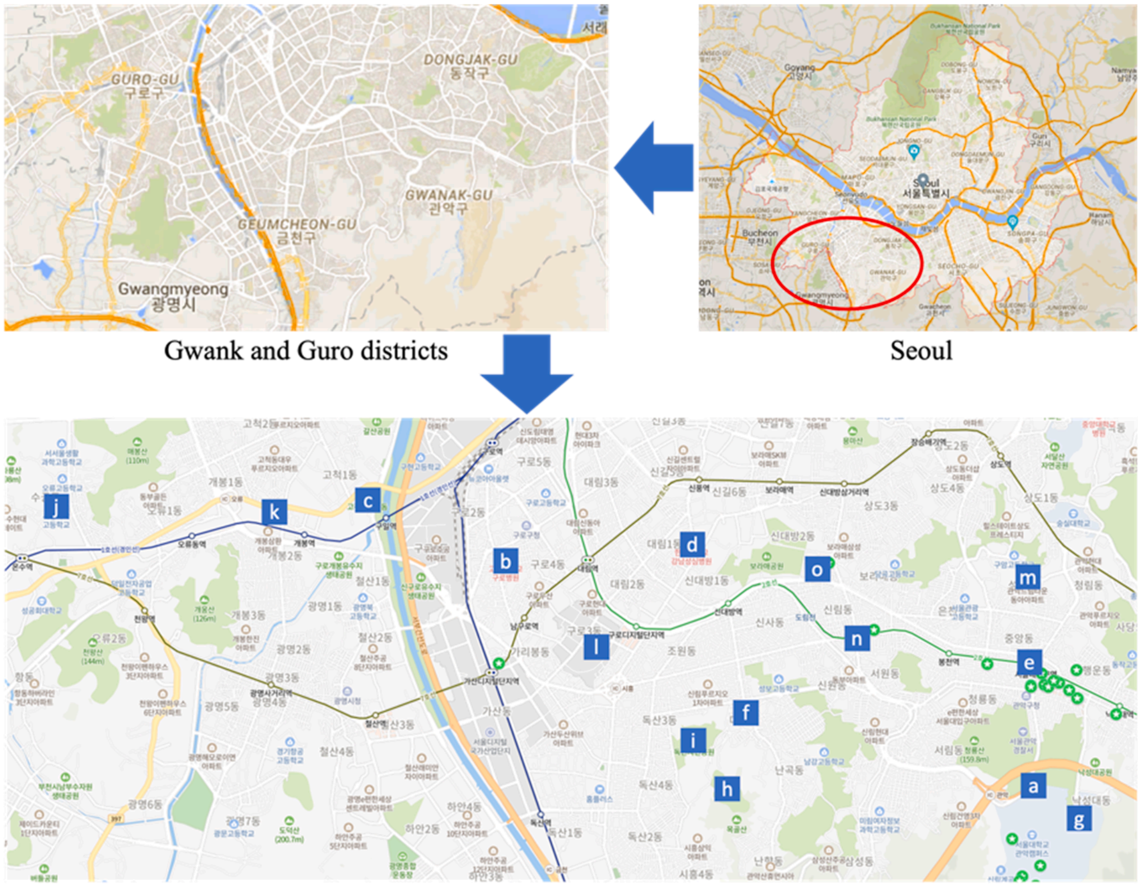


Fig. 4. Gwanak and Guro districts in Seoul

Table 2
Comparison of exact algorithm and VNS-ACO

Scenario	Waste type	Exact algorithm (Branh and cut)				VNS-ACO				Deviation	
		Routing cost ($)	Penalty cost ($)	Total cost ($)	Runtime (s)	Routing cost ($)	Penalty cost ($)	Total cost ($)	Runtime (s)	Total cost ($)	Runtime (s)
1	F	401.13	20.22	2133.20	495.43	373.13	22.80	2137.87	68.96	0.22 %	−86.08 %
	G	396.92	33.25			362.38	34.54				
	R	374.41	27.35			418.01	37.01				
2	F	390.24	26.93	1913.43	579.42	337.14	35.40	1920.94	92.65	0.39 %	−84.01 %
	G&R	544.52	181.5			615.67	143.03				
3	F&G&R	943.87	220.03	1853.80	648.85	916.50	262.00	1868.50	112.24	0.79 %	−82.70 %

5.3. Scenario 3

In this scenario, we considered vehicles from vehicle setV_5, with different compartments, to collect all types of waste. The unit traveling cost of each vehicle in V_5 is $1.55, and the maximum load capacity of each vehicle in V_5 is 450 kg.

Case 1: (No. of drivers = 2).

The waste management authority should have to pay greater penalties because of the insufficient number of drivers, and the total cost over the time horizon,T, is $2,077.68.

Case 2: (No. of drivers = 3).

We deduced that the optimal value of the total cost over the time horizon,T, is $1,868.50. Optimum results for collecting all types of waste are presented in Table 5. In this case, the total routing cost is $916.50, and the total penalty cost is $262.00.

Case 3: (No. of drivers = 4).

The waste management authority should have to pay more money compared to Case 2, and the total cost over the time horizon,T, is $1,956.74.

Case 4: (No. of drivers = 5).

The waste management authority should have to pay more money compared to previous cases, and the total cost over the time horizon,T, is $2,046.64.

5.4. Comparison of costs in different scenarios

In this subsection, in Fig. 5(a), we have considered the total cost in different scenarios concerning the different number of drivers. In this figure, we depicted several cases according to the number of drivers considered. The goal of our study is to fulfill the main objective of optimizing the waste collection and transportation route, with respect to total costs, by allocating the ideal number of drivers. In Scenario 1, Case 3 gives the total optimal cost considering five drivers. In Scenario 2, Case 3 gives the total optimal cost considering four drivers, but in Scenario 3, Case 2 gives the total optimal cost considering three drivers. Hence, Fig. 5(a) presents a comparative study of total costs, along with the

Table 3
Optimum results in Scenario 1 (Case 3)

Waste type	Days	No. of Trip	Bin location sequence/Bin location sequence (waste)	Routingcost ($)	Penaltycost ($)	Totalcost ($)
Food(F)	(1)	1	a → g → n → h → i → m → d → j	43.88	11.64	2137.87
		2	k → c → b → l → f → o → e → i	37.50		
	(2)	1	a → e → m → h → b → c → j	35.75		
		2	k → l → i → f → n → o → d → g	35.50		
	(3)	1	a → m → o → c → i → f → h	38.12		
		2	k → j → b → l → d → n → e → g	36.88		
	(4)	1	g → a → e → n → o → h → b → c	35.75		
		2	k → j → b → l → i → f → d → m	36.25		
	(5)	1	a → e → n → d → i → k	33.38		
		2	j → c → b → l → f → h → o → m → g	40.12	11.16	
General(G)	(1)	1	e → o → d → i → c → j	34.25		
		2	k → b → l → f → h → n → m → a → g	33.75		
	(2)	1	k → c → b → l → i → m → e	27.75		
		2	e → a → g → n → o → d → f → h → j	39.25	10.89	
	(3)	1	a → n → o → f → b → k → c → j	36.38		
		2	d → l → i → h → m → e → g	28.25		
	(4)	1	c → o → h → i → d → e → b	42.00	11.41	
		2	h → g → c → i → f → d → k → j	47.00	12.24	
	(5)	1	j → k → b → i → n → o → a	37.25		
		2	c → l → f → d → h → g → m → e	36.50		
Recyclable (R)	(1)	1	j → l → d → n → e → a → g	36.62		
		2	f → g → d → j → i → e → b → c → h	68.38	13.74	
	(2)	1	j → c → b → l → f → o → e	33.75		
		2	h → i → d → n → m → a → g → k	38.25		
	(3)	1	c → b → f → h → o → a → g	31.75		
		2	k → j → l → i → d → n → e → m	37.00		
	(4)	1	e → d → h → i → c → b → g → f	50.38	12.86	
		2	j → c → l → i → f → a → m	36.00		
	(5)	1	f → b → g → c → d → e → m	47.50	10.41	
		2	g → a → e → m → n → o → i → b → j	38.38		

Table 4
Optimum results in Scenario 2 (Case 3)

Waste type	Days	No. of Trip	Bin location sequence/Bin location sequence (waste)	Routingcost ($)	Penaltycost ($)	Totalcost ($)
Food(F)	(1)	1	d → b → h → n → m → a → j	30.50		1920.94
		2	k → c → l → i → f → o → e → g	32.12		
	(2)	1	e → a → n → f → b → c → k → j	33.88		
		2	i → h → l → d → o → m → g	26.75		
	(3)	1	e → m → n → o → d → f → h → k	34.38		
		2	j → c → b → l → i → a → g	35.00		
	(4)	1	c → o → m → e → a → i → h	35.38		
		2	k → j → b → l → d → f → n → g	37.88	12.64	
	(5)	1	k → l → i → f → n → o → d → g	35.50	11.06	
		2	a → e → m → h → b → c → j	35.75	11.70	
General(G) & Recyclable(R)	(1)	1	a(G&R) → m(G) → o(R) → d(G) → f(G&R) → i(G&R) → c(R) → b(R) → l(G)	47.42	14.12	
		2	j(G&R) → k(G) → l(R) → h(G&R) → n(G&R) → e(G&R) → g(G&R)	42.92	12.34	
		3	f(G&R) → i(G&R) → d(R) → o(G) → b(G) → c(G) → k(R) → m(R)	42.48	10.22	
	(2)	1	g(G) → a(R) → n(R) → d(G&R) → b(G) → k(G&R) → j(G&R)	39.00		
		2	l(G&R) → i(G&R) → n(G) → o(G&R) → m(G&R) → e(G&R) → a(R)	27.98		
		3	k(G) → b(G) → c(G&R) → j(R) → h(G&R) → f(G&R) → g(R)	49.16	16.24	
	(3)	1	k(G) → j(G&R) → b(R) → l(G&R) → f(R) → n(G) → m(G&R) → a(R) → g(G)	44.22	12.12	
		2	g(R) → n(G&R) → f(G) → i(G&R) → b(G&R) → k(R)	36.98		
		3	a(G) → e(G&R) → i(R) → h(G&R) → d(G&R) → c(G&R) → o(G&R)	45.10	14.14	
	(4)	1	h(G&R) → f(G&R) → l(G&R) → d(R) → m(G&R) → e(G) → a(G&R)	31.32	10.84	
		2	g(G&R) → e(R) → n(R) → o(G) → d(G) → i(R) → c(G&R)	41.32	10.26	
		3	g(R) → n(G) → o(R) → i(G) → b(G&R) → c(R) → k(G&R) → j(G&R)	41.90	11.25	
	(5)	1	k(G&R) → b(G&R) → l(G) → i(G) → f(R) → o(G) → a(R)	35.67		
		2	g(G) → e(R) → m(R) → n(G&R) → d(G) → h(G&R) → c(R) → j(G&R)	47.42	15.28	
		3	a(G) → g(R) → f(G) → i(R) → l(R) → c(G) → o(R) → m(G) → e(G&R)	42.48	16.22	

number of available drivers in different scenarios. In Fig. 5(b), we depicted the total routing cost and total penalty cost, scenario-wise, for the optimum results, using a bar diagram. From this figure, we showed that Scenario 1 creates more routing cost but less penalty cost. Scenario 2 results in a lower routing cost than that of Scenario 1, but results in a higher penalty cost. Scenario 3 results in the lowest routing cost, compared with the other two scenarios, but results in the highest penalty cost compared with the other two scenarios.

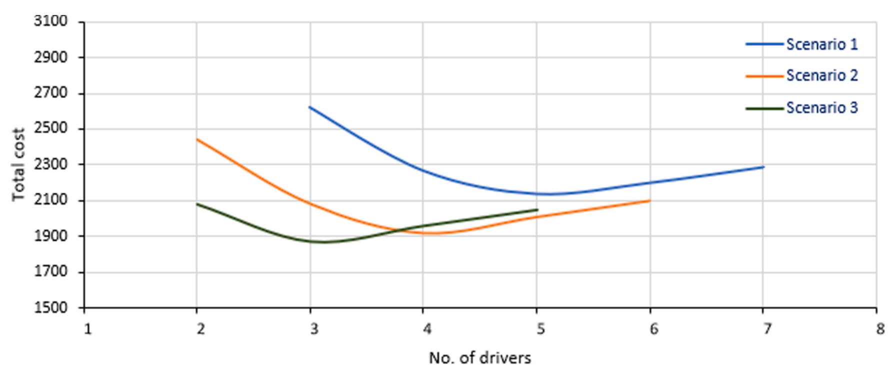
5.5. Performance test of VNS-ACO

5.5.1. TSPLIB instances

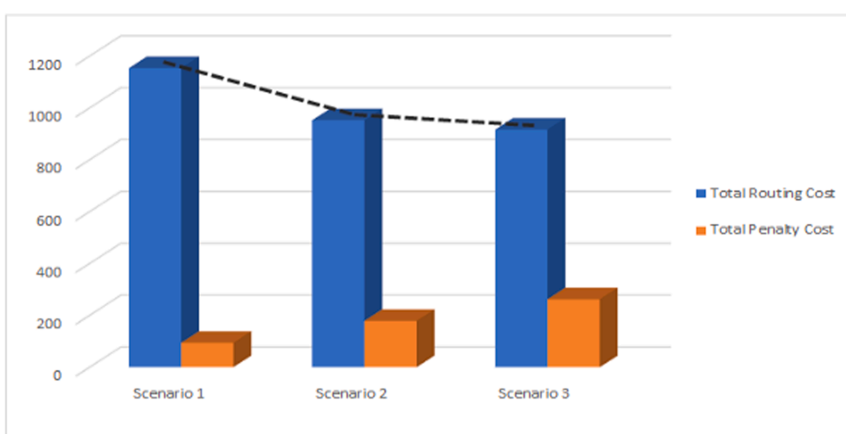
To judge the effectiveness and feasibility of the proposed hybrid algorithm (VNS-ACO), we applied it to 25 standard benchmarks using

Table 5
Optimum results in Scenario 3 (Case 2)

Waste type	Days	No. of Trip	Bin location sequence/Bin location sequence (waste)	Routingcost ($)	Penaltycost ($)	Totalcost ($)
Food(F),General(G)&Recyclable (R)	(1)	1	h(R) → i(F&G) → f(F&G) → o(R) → m(G&R) → a(F&R) → c(F&G)	43.24	11.88'	1868.50
		2	k(F) → j(R) → b(G&R) → l(F&R) → d(F&G) → n(G) → e(R) → g(F&G)	45.72	15.94	
		3	j(F,G&R) → k(F,G&R) → l(G) → i(R) → h(F&G) → d(F&R)	46.96	17.24	
		4	a(G) → g(G&R) → f(R) → o(G) → n(F&R) → m(F) → e(F) → b(F&R) → c(G)	50.84	20.22	
	(2)	1	g(G&R) → a(G) → e(F,G) → m(F,R) → o(G) → d(F) → i(F) → c(R) → k(R)	45.26	14.96	
		2	j(F,G) → b(G,R) → l(F,G) → f(R) → h(F) → n(F,R) → m(G,R)	42.94	10.92	
		3	d(G,R) → f(F,G) → h(G,R) → n(G) → m(F) → a(F,R) → b(F) → j(R)	50.06	16.68	
		4	c(F,G) → l(R) → i(R,G) → k(F) → j(F,G) → d(G) → o(R) → e(R) → g(F)	59.68	21.86	
	(3)	1	i(F,G) → d(G,R) → n(F,R) → e(R) → m(G) → a(F,G) → h(R) → c(F)	45.72	15.34	
		2	k(F,R) → j(G) → b(G,R) → l(F) → f(F,G) → o(G,R) → g(F,R)	46.34	15.92	
		3	k(G) → l(F) → i(R) → f(R) → h(F,G) → o(F) → m(R) → e(F,G) → a(R) → g(G)	43.09	11.32	
		4	j(F,R) → c(G,R) → b(F) → l(G,R) → d(F,G) → n(G) → m(F,R)	41.54		
	(4)	1	f(F,G) → i(R) → d(F,G) → o(F) → n(R) → m(R) → b(G) → c(F) → k(R) → j(G)	44.95	14.84	
		2	a(F,G,R) → g(F,G,R) → e(F,G,R) → h(R) → l(F,G)	38.60		
		3	j(F,R) → c(G,R) → l(R) → i(F,G) → d(R) → n(F,G) → m(F) → g(G)	49.44	16.11	
		4	e(R) → a(F,G) → f(R) → h(F,G) → o(R,G) → b(F,G) → k(F,R)	42.94	12.02	
	(5)	1	h(F,G,R) → i(G) → n(F,R) → o(G) → e(G,R) → b(F,R) → k(F)	40.30		
		2	j(G,R) → c(G) → l(R) → d(R) → f(F,R) → a(F,G) → g(F,G) → m(F)	49.91	16.97	
		3	g(G) → a(G,R) → e(F,R) → n(G) → o(F,R) → h(F) → b(G) → c(F,R)	44.33	14.66	
		4	k(G,R) → j(F) → l(F,G) → i(F,R) → f(R) → d(F,G) → m(G,R)	44.64	15.12	



(a) Total cost vs No. of drivers



(b) Total routing cost vs total penalty cost (optimum case)

Fig. 5. Comparison of costs at each scenario

TSPLIB, (Reinelt, 1991). Table 6 shows the results of the VNS-ACO with the advanced GA and ACO. The advanced GA is the combination of probabilistic selection, comparison crossover, and random mutation. The results are compared in terms of the total costs. Under 20 independent runs, average results, best-found results with standard deviations (SD), and relative errors are presented here. Table 6 shows the SD values and the relative errors calculated for 25 standard problems in the TSPLIB using three different algorithms. In all cases, the average results given by the VNS-ACO are less than the corresponding average results given by the advanced GA and ACO. Moreover, as the SDs in the VNS-ACO are very small, this indicates that this method is stable and that results in each run do not differ much from the mean. We also obtained the least relative error in most cases. These errors are also very small, indicating that average solutions are nearer to the best-known

Table 6
Results for standard TSPLIB instances

Instances	Average Result			Best Found Result			Relative error & SD		
	VNS-ACO	ACO	GA	VNS-ACO	ACO	GA	VNS-ACO	ACO	GA
bayg29	1610.32	1611.01	1610.91	1610	1610	1610	0, 0.17	0, 0.76	0, 0.56
bays29	2021.14	2022.34	2022.11	2020	2020	2020	0, 0.43	0, 0.78	0, 0.72
berlin52	7547.87	7934.65	7653.42	7542	7756	7621	0, 1.56	0.05, 2.49	0.01, 2.37
dantzig42	699.21	701.73	700.02	699	700	699	0, 0.10	0, 0.68	0, 0.59
ei151	427.42	431.95	428.96	426	429	426	0, 0.98	0.01, 1.23	0.01, 1.07
ei176	539.22	557.49	542.82	538	545	541	0, 0.67	0.04, 1.93	0.01, 1.22
fri26	938.02	939.53	939.51	937	937	937	0, 0.45	0, 0.72	0, 0.69
gr17	2088.09	2092.64	2091.33	2085	2089	2087	0, 0.43	0, 1.02	0, 0.89
gr21	2712.22	2718.96	2720.24	2707	2712	2712	0, 0.86	0, 1.52	0, 1.65
gr48	5052.15	5079.23	5085.2	5046	5070	5062	0, 1.22	0.01, 2.19	0.01, 2.23
gr96	55832.29	56342.39	56349.54	55,656	55,842	55,858	0.01, 5.12	0.02, 5.71	0.02, 5.70
kroA100	21322.75	21453.86	21431.57	21,282	21,424	21,376	0, 2.89	0.01, 4.12	0.01, 4.04
kroB100	22509.29	23112.23	22979.98	22,141	22,602	22,416	0.02, 2.73	0.04, 2.91	0.04, 2.86
kroC100	21109.05	21712.56	21597.89	20,749	21,056	20,975	0.02, 2.56	0.05, 3.12	0.04, 3.06
kroD100	21642.25	22008.02	22056.22	21,294	21,767	21,643	0.02, 3.19	0.03, 4.20	0.04, 4.05
kroE100	22742.78	23652.74	23489.65	22,068	22,989	22,754	0.03, 3.16	0.07, 4.72	0.06, 4.14
kroA150	27756.87	28586.34	28423.51	26,832	27,953	27,898	0.04, 3.45	0.07, 4.89	0.06,4.63
kroB150	27231.55	27893.32	27765.43	26,130	27,187	27,112	0.04, 3.19	0.07, 3.11	0.06, 3.05
lin105	14975.67	16142.54	16093.62	14,379	15,442	15,386	0.04, 2.11	0.12, 3.06	0.12, 3.15
qa194	9372.21	9758.43	9698.62	9352	9612	9587	0, 0.26	0.04, 0.89	0.04, 0.92
rat99	1211.31	1220.86	1218.56	1211	1211	1211	0, 0.12	0.01, 0.46	0.01, 0.39
rd100	7921.41	8049.58	8043.72	7910	8002	7986	0, 0.29	0.02, 0.77	0.02, 0.69
si175	22869.28	23468.2	23343.22	21,407	22,905	22,786	0.07, 3.77	0.10, 4.62	0.09, 4.59
st70	676.02	677.72	676.94	675	675	675	0, 0.10	0, 0.55	0, 0.62
swiss42	1278.98	1287.53	1284.69	1273	1276	1275	0, 0.16	0.01,0.75	0.01, 0.59

solution in the TSP literature for all instances having fewer than 60 nodes. Therefore, our developed VNS-ACO algorithm is quite effective.

5.5.2. Dispersion results of TSPLIB instances

The performance of the proposed hybrid algorithm (VNS-ACO) was also found by dispersion tests based on TSPLIB instances. Performance of the proposed hybrid algorithm was statistically tested by running it 50 times and calculating the average value, standard deviation, and percentage relative error according to the optimal solution against 25 standard test problems. The results are given in Table 7. The percentage relative error is defined as

$$Error(\%) = \frac{(average\ solution - best\ known\ solution)}{best\ known\ solution} \times 100.$$

BKS stands for the best-known solution. Table 7 shows that the proposed method generates closer results to the optimal solutions with minimal standard deviations for the problems bayg29, bays29, fri26, dantzig52, fri26, gr17, gr21, qa194, rat99, rd100, st70, swiss42, and so on. It can be seen from Table 7 that except for gr96, the best results by VNS-ACO are the same as the corresponding best results in the TSPLIB literature. Given the data shown in Table 7, most of the SD values of the standard problems are convincible. Hence, we can conclude that the proposed algorithm satisfies the statistical test.

Table 7
Dispersion results of VNS-ACO for different TSPLIB instances

Instances	BKS	VNS-ACO				
		Best	Worst	Average	SD	Error(%)
bayg29	1610	1610	1616	1610.3	0.28	0.02
bays29	2020	2020	2028	2020.2	0.72	0.01
berlin52	7542	7542	7556	7544	1.04	0.03
dantzig42	699	699	703	700.02	0.59	0.15
ei151	426	426	429	426.72	0.98	0.17
ei176	538	538	551	541.19	1.16	0.59
fri26	937	937	939	937.18	0.71	0.02
gr17	2085	2085	2095	2087.8	0.45	0.14
gr21	2707	2707	2718	2712.2	0.84	0.19
gr48	5046	5046	5078	5052.1	1.21	0.12
gr96	55,656	55,656	56,262	56,025	4.72	1.48
kroA100	21,282	21,282	21,450	21,313	2.87	0.14
kroB100	22,141	22,141	23,110	22,503	2.71	1.63
kroC100	20,749	20,749	21,709	21,101	2.54	1.7
kroD100	21,294	21,294	22,004	21,546	3.11	1.18
kroE100	22,068	22,068	23,579	22,710	3.12	2.91
kroA150	26,832	26,832	27,896	27,453	3.42	3.5
kroB150	26,130	26,130	27,454	27,043	3.05	3.49
lin105	14,379	14,379	15,987	14,899	2.07	3.62
qa194	9352	9352	9522	9370.6	0.24	0.2
rat99	1211	1211	1219	1211.8	0.11	0.06
rd100	7910	7910	8039	7920.4	0.28	0.13
si175	21,407	21,407	23,098	22,123	3.72	3.34
st70	675	675	679	676.01	0.09	0.15
swiss42	1273	1273	1285	1277.9	0.14	0.39

5.5.3. Efficiency test with analysis of variance

We did a statistical test for quantitative decisions about our proposed algorithm by comparing it with other algorithms. The analysis of variance (ANOVA) is done to show the statistical significance of our proposed algorithm with two algorithms, ACO and GA. The waste bin allocation and routing problem (WBARP) for Scenario 1 is solved by our developed VNS-ACO and compared with ACO and GA. For this purpose, we took different parametric values, such as the different numbers of bin locations and the different numbers of drivers. In this model, five different types of data sets are taken for the ANOVA test and comparative study. We have taken the result using three algorithms, VNS-ACO, ACO, and GA. We considered 100 runs from them, taking the number of successful runs for three types of algorithms (i.e., VNS-ACO, ACO, and GA), which are given below in Table 8. The ANOVA test results are given in Table 8.

The ANOVA test compares the differences between groups and the differences within groups. The sum of the square gives the total variation both between groups and within groups. The degree of freedom is calculated between groups as the (number of samples of the individual group − 1) and is calculated within groups as the (sum of all the samples - number of the sample of individual groups). The mean of the square is the sum of the square is divided by the degree of freedom (mean of square = sum of square/degree of freedom). The F is calculated as the comparison of the mean of the square between groups and the mean of the square within groups. The given table shows the ANOVA test result for our proposed WBARP model by using our developed VNS-ACO and

Table 8
ANOVA test for different algorithms

Data set (No. of bin locations)	Number of winning runs for different algorithms					
	VNS-ACO	ACO	GA			
10	100	90	82			
15	100	87	80			
20	97	75	78			
25	95	68	72			
30	92	56	64			
ANOVA test results						
Source of Variation	Sum of squares	Degrees of freedom	Mean of squares	F	P-value	F critical
Between Groups	1555.2	2	777.6	8.986133	0.004119	3.885294
Within Groups	1038.4	12	86.53333			
Total	2593.6	14				

two other algorithms. The total sample size is five for each algorithm, and the number of algorithms is three. The critical value of F (3.88) and p is much smaller than $\alpha = 0.05$ for all the cases. As the critical value of F is much smaller than F, we should reject the null hypothesis, which gives statistical significance to the result. A significant difference is observed between the algorithms. Therefore, our algorithm works more efficiently than the other two algorithms.

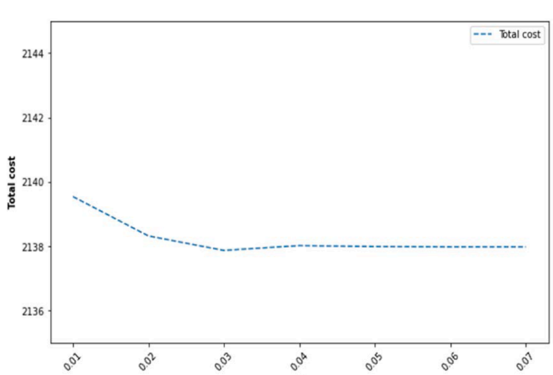
5.5.4. Parameter sensitivity

The performance of the ACO algorithm depends on a few parameters like ρ, n, and M. Fig. 6(a) shows that when ρ increases, the total cost decreases and converges from 0.03 to onwards. The size of the population (n) also affects the total cost, including the total cost decreases while n increases, and converging point is $n = 80$. Fig. 6(b) shows the relation between the total cost and population size. M represents the number of total filled bins, the neighboring bins with a depot, and the disposal center. It may vary from time to time and the total routing costs to visit these filled bins depend on the respective bin positions. If the previous data are available, then it may be used in a decision-making unit. In Table 3, we observe that the routing cost not only depends on the value of M but depends on the bin locations. According to our model, the total number of filled bins, including neighboring bins, may be changed, and the routing cost to visit these bins depends on the bin allocation, and the filling status to satisfy the vehicle capacity. A sensitivity analysis is done on TFL, and 80 % of TFL shows the best performance to minimize the total cost in our model. Fig. 7 shows the behavior of routing cost and penalty cost in different scenarios with various TFL.

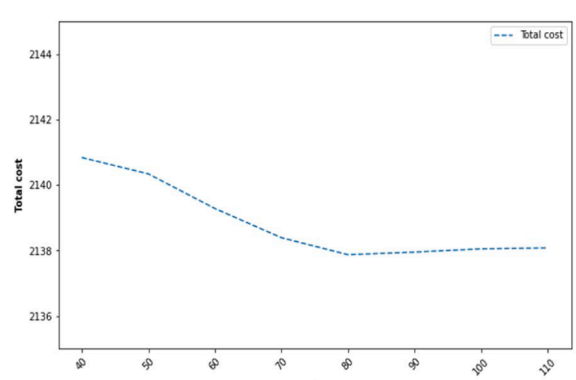
5.6. Discussion and managerial insights

In each scenario, we could find some meaningful results. In Scenario 1, the optimal number of drivers is five and the total cost is $2,137.87. In Scenario 2, the optimal number of drivers is four and the total cost is $1,920.94. In Scenario 3, the optimal number of drivers is three and the total cost is $1,868.50. Through these experiments, we conclude that the total cost of collecting waste is minimized when there are vehicles simultaneously collecting all types of waste using multiple compartments. Furthermore, we found that the more compartments a vehicle has, the fewer drivers are needed to collect waste. We did a performance test of our VNS-ACO by solving standard TSPLIB instances and comparing the results with advanced GA and ACO, thereby showing that our proposed algorithm works better than the other two algorithms. Also, we did an efficiency test of VNS-ACO using ANOVA to prove the efficiency of our model statistically.

Sustainability is an imperative to be studied around the world. Cities are the stage upon which social, economic, and environmental issues interact with each other, and they provide a good proving ground in which to try out solutions to the challenges of waste management. Given this, smart cities and their technological advances are being increasingly studied and discussed. In keeping with this trend, our research proposed a smart and innovative solution that integrates waste level detection and communication technology solutions. Our proposed waste collection method addresses a new approach through IoT-based technologies that consider the collection of waste from filled bins and their neighboring bins. In this study, we also proposed a time-dependent penalty for overfilled bins (above 100 percent capacity) in order to directly benefit the social, economic, and environmental aspects of large cities. The proposed smart bin was designed, prototyped, evaluated, demonstrated,

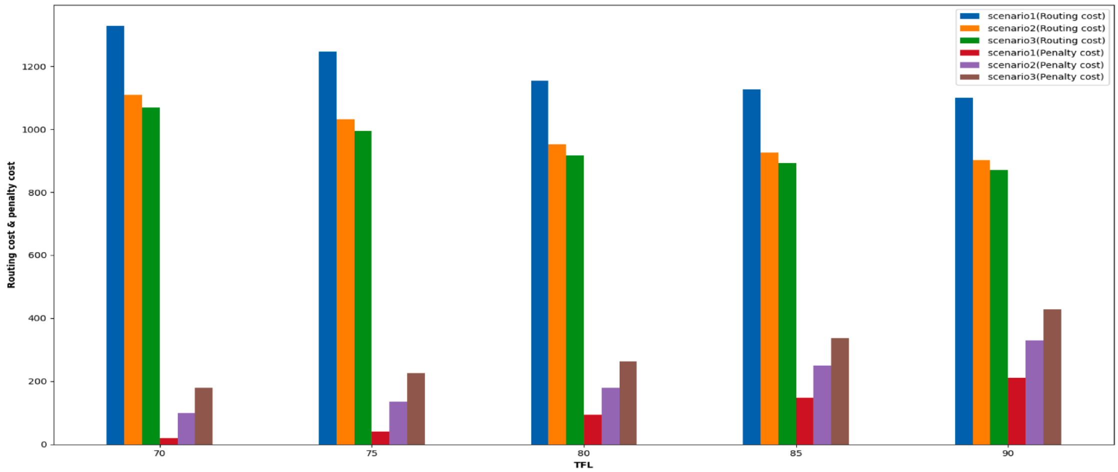


(a) ρ vs total cost

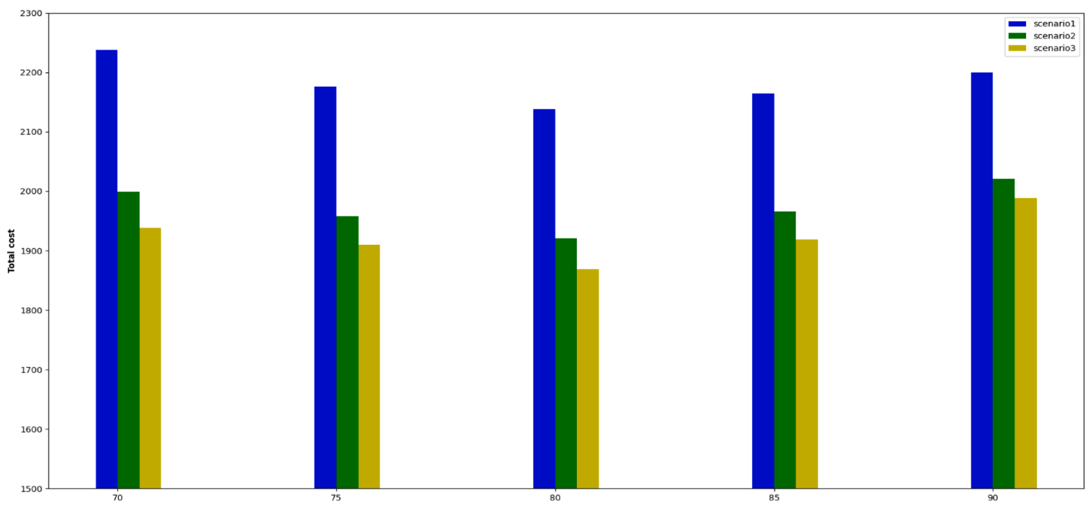


(b) n vs total cost

Fig. 6. Sensitivity analysis of ρ vs total cost and n vs total cost



(a) TFL vs different costs (Optimum cases)



(b) TFL vs total costs (Optimum cases)

Fig. 7. Sensitivity analysis of TFL vs different costs

and validated and is ready for real deployment. Furthermore, this approach, with its focus on efficiency and recycling, offers meaningful steps for sustainability. As we are living in an era also known as "the fourth Industrial Revolution," our approach in this study could provide a blueprint for smart cities with clean environments. In Korea, some smart waste management measures have already been implemented. For food waste, the Korean government introduced food waste bins with RFID tags. These bins send real-time fill level information to central monitoring systems, and after the data is received, a food waste collecting vehicle starts its journey to the full bins. In the past decade, the Korean government has proved the effectiveness of food waste management not only with RFID tags but also with penalty concepts. (This penalty concept is different from the penalty concept in our paper in that it involves an imposed penalty whenever people throw garbage into waste bins intended for food only.) Based on this empirical research carried out in Korea, our model could pave the way for smart waste management globally.

6. Conclusions

This study represents a vehicle routing problem for smart waste management. The above system is configured with IoT-based smart bins. All bins' monitoring processes are controlled through CMS. Additionally, we implemented an innovative approach—a time-dependent penalty cost to the waste management authorities if smart bins are not emptied in time after becoming full. Furthermore, we introduced another concept. When filled bins are cleaned at certain times, their neighboring bins will also be cleaned if adequate space is available in the vehicle to hold the waste. We considered multiple waste types and after conducting different scenarios we propose that, especially in Korea, using vehicles with multiple compartments results in minimized total waste collection costs. This article includes both bin allocation and routing problems considering the optimal number of drivers in each scenario. We suggest an intelligent hybrid VNS-ACO, and this algorithm outperforms classical algorithms. We conducted an empirical study that established a new waste-collection method. We considered common disposal centers for all types of waste for the sake of simple calculation. However, in Korea, each waste type is disposed of at different disposal centers. To be specific, food waste is almost 100 percent recyclable unless it is mixed with other types of waste materials. Also in Korea, once general waste is collected, it is sent to incinerators for disposal, and the incineration process generates electricity, which is beneficial to industry and residents. Recyclable waste is treated for different repurposing uses, such as reconstituted paper, plastic, and metal. Considering different types of disposal centers could also be a direction in which to extend our model in future studies. The best waste management system has two wings. One is efficient waste collection and savings in transportation costs. The other is maximizing utilities for reusing waste. Our proposed model WBARP has a few restriction on maximizing utilities for reusing waste. While we consider various types of waste, disposal center is the same for all types of waste. For future research, we may differentiate each disposal center for each type of waste. Proper waste management is necessary to build a pollution-free smart city. The best way to represent WBARP is using time window to visit all types of bins in a regular interval. In the future, special types of bins could be considered, such as medical waste bins, chemical waste bins, and industrial waste bins, to broaden our WBARP model.

CRediT authorship contribution statement

Arindam Roy: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Funding acquisition. **Apurba Manna:** Methodology, Software. **Jungmin Kim:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Validation. **Ilkyeong Moon:** Validation, Supervision, Writing - review & editing.

Declaration of Competing Interest

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

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Appendix

Notations:

B_1	Set of food waste bins (type-1), $B_1 = \{b_{11}, b_{12}, \cdots, b_{1u}$: u is a positive integer$\}$.
B_2	Set of general waste bins (type-2), $B_2 = \{b_{21}, b_{22}, \cdots, b_{2u}$: u is a positive integer$\}$.
B_3	Set of recyclable waste bins (type-3), $B_3 = \{b_{31}, b_{32}, \cdots, b_{3u}$: u is a positive integer$\}$.
B	Set of all waste bins, $B = (B_1 \cup B_2 \cup B_3)$.
$B^{'}$	$(B_2 \cup B_3)$
V_1	Set of vehicles carrying food waste only.
V_2	Set of vehicles carrying general waste only.
V_3	Set of vehicles carrying recyclable waste only.
V_4	Set of vehicles carrying general and recyclable waste together in different compartments.
V_5	Set of vehicles carrying all waste together in different compartments.
V	$V = \bigcup_{i=1}^{5} V_i$
D_r	The number of drivers available, $D_r \leq \lvert V \rvert$.
d_0	Depot.
D	Set of disposal center, $D = \{d_1, d_2, ..., d_m : m$ is a positive integer$\}$.
B_{1f}	Set of all filled food waste bins; filled level $\geq$ TFL,$B_{1f} \subseteq B_1$.
B_{2f}	Set of all filled general waste bins; filled level $\geq$ TFL,$B_{2f} \subseteq B_2$.
B_{3f}	Set of all filled recyclable waste bins; filled level $\geq$ TFL,$B_{3f} \subseteq B_3$.
$N[b_{ki}]$	Neighbor of $b_{ki}\{b_{kx} : b_{kx} \in B_k$ if $b_{ki} \in B_{kf}$ where $B_{kf} \subseteq B_k; \forall k = 1, 2, 3$, and $d(b_{kx}, b_{ki}) \leqslant K^{'}, K^{'}$ is a fixed positive number, d denotes the euclidean distance; where fill level of $b_{kx} <$ TFL $\}\bigcup b_{ki}, \forall\ i, x = 1, 2, 3, \cdots, u$.
B_{1f}^{+}	$(\{d_0\}\bigcup B_{1f}\bigcup D)$; consider $G_{1f}^{+} = (B_{1f}^{+}, E_{1f}^{+})$ to be the undirected graph where B_{1f}^{+} is the vertex set and $E_{1f}^{+} = \{(i,j) : i,j \in B_{1f}^{+}, i \neq j\}$ is the edge set.
B_{2f}^{+}	$(\{d_0\}\bigcup B_{2f}\bigcup D)$; consider $G_{2f}^{+} = (B_{2f}^{+}, E_{2f}^{+})$ to be the undirected graph where B_{2f}^{+} is the vertex set and $E_{2f}^{+} = \{(i,j) : i,j \in B_{2f}^{+}, i \neq j\}$ is the edge set.
B_{3f}^{+}	$(\{d_0\}\bigcup B_{3f}\bigcup D)$; consider $G_{3f}^{+} = (B_{3f}^{+}, E_{3f}^{+})$ to be the undirected graph where B_{3f}^{+} is the vertex set and $E_{3f}^{+} = \{(i,j) : i,j \in B_{3f}^{+}, i \neq j\}$ is the edge set.
$B_f^{'}$	$(B_{2f}\bigcup B_{3f})$.
$B_f^{'+}$	$(\{d_0\}\bigcup B_f^{'}\bigcup D)$; consider $G_f^{'+} = (B_f^{'+}, E_f^{'+})$ to be the undirected graph where $B_f^{'+}$ is the vertex set and $E_f^{'+} = \{(i,j) : i,j \in B_f^{+}, i \neq j\}$ is the edge set.
B_f	Set of all filled waste bins; fill level $\geq$ TFL,$B_f(= B_{1f}\bigcup B_{2f}\bigcup B_{3f}) \subseteq B$.
B_p	Set of all penalty bins; fill level ≥ 100 %,$B_p \subseteq B_f$.
B^{+}	$(\{d_0\}\bigcup B\bigcup D)$; consider $G^{+} = (B^{+}, E^{+})$ to be the undirected graph where B^{+} is the vertex set and $E^{+} = \{(i,j) : i,j \in B^{+}, i \neq j\}$ is the edge set.
B_f^{+}	$(\{d_0\}\bigcup B_f\bigcup D)$; consider $G_f^{+} = (B_f^{+}, E_f^{+})$ to be the undirected graph where B_f^{+} is the vertex set and $E_f^{+} = \{(i,j) : i,j \in B_f^{+}, i \neq j\}$ is the edge set.
$N^{+}[b_{ki}]$	$(\{d_0\}\bigcup N[b_{ki}]\bigcup D)$; consider $G_{N[b_{ki}]}^{+} = (N^{+}[b_{ki}], E_{N[b_{ki}]}^{+})$ to be the undirected graph where $N^{+}[b_{ki}]$ is the vertex set and $E_{N[b_{ki}]}^{+} = \{(i,j) : i,j \in N^{+}[b_{ki}], i \neq j\}$ is the edge set, $k =$ 1,2,3.
r_k	Traveling cost of the vehicle h per unit distance; $h \in V_k$, $k =$ 1,2,…,5.
C_{kb}	Unit bin allocation cost of type k bin, $k =$ 1,2,3.
d_{ij}	Distance between node i and node j $(i \neq j)$ in the undirected graph,$d_{ij} = d_{ji}\ \forall i,j$.
$\beta_0 =$ 1	if $B_{1f} \neq \phi$ else$\beta_0 = 0$.
$\beta_1 =$ 1	if $N[b_{ki}] \neq \phi$ else$\beta_1 = 0, \ \forall\ b_{ki} \in B_{kf}, k = 1, 2, 3\ \&i = 1, 2, .., u$.
$\beta_2 =$ 1	if $B_f^{'} \neq \phi$ else$\beta_2 = 0$.
	if $B_p \neq \phi$ else$\beta_3 = 0$.

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(*continued*)

$\beta_3 =$ 1	
$\beta_4 =$ 1	if $B_f \neq \phi$ else$\beta_4 = 0$.
$\beta_5 =$ 1	if $B_{2f} \neq \phi$ else$\beta_5 = 0$.
$\beta_6 =$ 1	if $B_{3f} \neq \phi$ else$\beta_6 = 0$.
$P_{ki}(t)$	Penalty cost of waste bin b_{ki} at time t (in hours),$b_{ki} \in B_p$.
lb_{ki}	Amount of waste at bin i of type k (b_{ki}), $k = 1,2,3$, $i = 1,2,\ldots,u$
L_k	Maximum load capacity of the vehicle h; $h \in V_k, k = 1,2,..,5$.
l_{ijh}	Load of the vehicle h; when visited between node i to node j ($i \neq j$) in the undirected graph using a vehicle h; $h \in V_k, k = 1,2,..,5$.
q	Average vehicle speed in kilometers per hour.
SR_{t1}	Set-up time on a bin location before cleaning waste bin.
SR_{t2}	Cleaning time of each type of waste bin.
S_l	Wages of each driver per day.
B_{ac}	Bin allocation cost.
T	Time horizon.

Abbreviations:

Abbr	Meaning
IoT	Internet of things.
CMS	Central monitoring system.
VNS	Variable neighborhood search.
ACO	Ant colony optimization.
VNS-ACO	Variable neighborhood search with ant colony optimization.
TSP	Traveling salesman problem.
TSPLIB	Traveling salesman problem library.
GA	Genetic algorithm.
MSW	Municipal solid waste.
SC	Soft computing.
WBARP	Waste bin allocation and routing problem.
ANOVA	Analysis of variance.
TFL	Threshold fill level.
US	Ultrasonic sensor.
CPU	Central processing unit.
GSM	Global system for mobile communication.
GPS	Global positioning system.
RFID	Radio-frequency identification.
VRP	Vehicle routing problem.
BSA	Backtracking search algorithm.
CVRP	Capacitated vehicle routing problem.
SD	Standard deviation.

References

Angelelli, E., & Speranza, M. G. (2002a). The periodic vehicle routing problem with intermediate facilities. *European Journal of Operational Research, 137*(2), 233–247. https://doi.org/10.1016/S0377-2217(01)00206-5

Angelelli, E., & Speranza, M. G. (2002b). The application of a vehicle routing model to a waste-collection problem: Two case studies. *Journal of the Operational Research Society, 53*(9), 944–952. https://doi.org/10.1057/palgrave.jors.2601402

Alves, C., Brás, P., Valério De Carvalho, J. M., & Pinto, T. (2012). A variable neighborhood search algorithm for the leather nesting problem. *Mathematical Problems in Engineering, 2012*. https://doi.org/10.1155/2012/254346

Akhtar, M., Hannan, M. A., Begum, R. A., Basri, H., & Scavino, E. (2017). Backtracking search algorithm in CVRP models for efficient solid waste collection and route optimization. *Waste Management, 61*, 117–128. https://doi.org/10.1016/j.wasman.2017.01.022

Beltrami, E. J., & Bodin, L. D. (1974). Networks and vehicle routing for municipal waste collection. *Networks, 4*(1), 65–94. https://doi.org/10.1002/net.3230040106

Benjamin, A. M., & Beasley, J. E. (2010). Metaheuristics for the waste collection vehicle routing problem with time windows, driver rest period and multiple disposal facilities. *Computers & Operations Research, 37*(12), 2270–2280. https://doi.org/10.1016/j.cor.2010.03.019

Armas, J. D., Lalla-Ruiz, E., Expósito-Izquierdo, C., Landa-Silva, D., & Melián-Batista, B. (2015). A hybrid GRASP-VNS for ship routing and scheduling problem with discretized time windows. *Engineering Applications of Artificial Intelligence, 45*, 350–360. https://doi.org/10.1016/j.engappai.2015.07.013

Delgado-Antequera, L., Caballero, R., Sánchez-Oro, J., Colmenar, J. M., & Martí, R. (2020). Iterated greedy with variable neighborhood search for a multi-objective waste collection problem. *Expert Systems with Applications, 145*. https://doi.org/10.1016/j.eswa.2019.113101

Hauge, K., Larsen, J., & Lusby, R. M. (2014). A hybrid column generation approach for an industrial waste collection routing problem. *Computers & Industrial Engineering, 71*, 10–20. https://doi.org/10.1016/j.cie.2014.02.005

Hemmelmayr, V. C., Doerner, K. F., Hartl, R. F., & Vigo, D. (2014). Models and algorithms for the integrated planning of bin allocation and vehicle routing in solid waste management. *Transportation Science, 48*(1), 103–120. https://doi.org/10.1287/trsc.2013.0459

Huang, S. H., & Lin, P. C. (2015). Vehicle routing-scheduling for municipal waste collection system under the "Keep Trash off the Ground" policy. *Omega, 55*, 24–37. https://doi.org/10.1016/j.omega.2015.02.004

Karadimas, N. V., Papatzelou, K., & Loumos, V. G. (2007). Optimal solid waste collection routes identified by the ant colony system algorithm. *Waste Management and Research, 25*(2), 139–147. https://doi.org/10.1177/0734242X07071312

Kyriakakis, N. A., Marinaki, M., & Marinakis, Y. (2021). A hybrid ant colony optimization-variable neighborhood descent approach for the cumulative capacitated vehicle routing problem. *Computers & Operations Research, 134*, Article 105397. https://doi.org/10.1016/j.cor.2021.105397

Levis, J. W., Barlaz, M. A., DeCarolis, J. F., & Ranjithan, S. R. (2013). A generalized multistage optimization modeling framework for life cycle assessment-based integrated solid waste management. *Environmental Modelling & Software, 50*, 51–65. https://doi.org/10.1016/j.envsoft.2013.08.007

Mladenović, N., & Hansen, P. (1997). Variable neighborhood search. *Computers & Operations Research, 24*(11), 1097–1100. https://doi.org/10.1016/S0305-0548(97)00031-2

Marques, P., Manfroi, D., Deitos, E., Cegoni, J., Castilhos, R., Rochol, J., & Kunst, R. (2019). An IoT-based smart cities infrastructure architecture applied to a waste management scenario. *Ad Hoc Networks, 87*, 200–208. https://doi.org/10.1016/j.adhoc.2018.12.009

Molina, J. C., Eguia, I., & Racero, J. (2019). Reducing pollutant emissions in a waste collection vehicle routing problem using a variable neighborhood tabu search algorithm: A case study. *TOP*. https://doi.org/10.1007/s11750-019-00505-5

Nidhya, R., Kumar, M., Ravi, R. V., & Deepak, V. (2020). Enhanced route selection (ERS) algorithm for IoT enabled smart waste management system. *Environmental Technology & Innovation, 20*. https://doi.org/10.1016/j.eti.2020.101116

Nuortio, T., Kytöjoki, J., Niska, H., & Bräysy, O. (2006). Improved route planning and scheduling of waste collection and transport. *Expert Systems with Applications, 30*(2), 223–232. https://doi.org/10.1016/j.eswa.2005.07.009

Pardini, K., Rodrigues, J. J. P. C., Diallo, O., Das, A. K., de Albuquerque, V. H. C., & Kozlov, S. A. (2020). A smart waste management solution geared towards citizens. *Sensors (Switzerland), 20*(8). https://doi.org/10.3390/s20082380

Rabbani, M., Sadati, S. A., & Farrokhi-Asl, H. (2020). Incorporating location routing model and decision making techniques in industrial waste management: Application in the automotive industry. *Computers & Industrial Engineering, 148*. https://doi.org/10.1016/j.cie.2020.106692

Ramson, S. R. J., & Moni, D. J. (2017). Wireless sensor networks based smart bin. *Computers and Electrical Engineering, 64*, 337–353. https://doi.org/10.1016/j.compeleceng.2016.11.030

Reinelt, G. (1991). TSPLIB. A traveling salesman problem library. *ORSA Journal on Computing, 3*(4), 376–384. https://doi.org/10.1287/ijoc.3.4.376

Rathore, P., & Sarmah, S. P. (2021). Modeling and identification of suitable motivational mechanism in the collection system of municipal solid waste supply chain. *Waste Management, 129*, 76–84. https://doi.org/10.1016/j.wasman.2021.05.011

Sarbijan, M. S., & Behnamian, J. (2022). Multi-fleet feeder vehicle routing problem using hybrid metaheuristic. *Computers & Operations Research, 141*, Article 105696. https://doi.org/10.1016/j.cor.2022.105696

Sinha, T., Kumar, K. M., & Saisharan, P. (2015). Smart Dustbin. *International Journal of Industrial Electronics and Electrical Engineering, 3*(5), 101–104.

Vicentini, F., Giusti, A., Rovetta, A., Fan, X., He, Q., Zhu, M., & Liu, B. (2009). Sensorized waste collection container for content estimation and collection optimization. *Waste Management, 29*(5), 1467–1472. https://doi.org/10.1016/j.wasman.2008.10.017

Wang, S., Huang, G. H., & Yang, B. T. (2012). An interval-valued fuzzy-stochastic programming approach and its application to municipal solid waste management. *Environmental Modelling & Software, 29*(1), 24–36. https://doi.org/10.1016/j.envsoft.2011.10.007

Wassan, N., Wassan, N., Nagy, G., & Salhi, S. (2017). The Multiple Trip Vehicle Routing Problem with Backhauls: Formulation and a Two-Level Variable Neighbourhood Search. *Computers & Operations Research, 78*, 454–467. https://doi.org/10.1016/j.cor.2015.12.017

Schrader-King, K., & Liu, A. (2018). Global Waste to Grow by 70 Percent by 2050 Unless Urgent Action is Taken: World Bank Report. https://www.worldbank.org/en/news/press-release/2018/09/20/global-waste-to-grow-by-70-percent-by-2050-unless-urgent-action-is-taken-world-bank-report..

Zeb, A., Ali, Q., Saleem, M. Q., Awan, K. M., Alowayr, A. S., Uddin, J., & Bashir, F. (2019). A Proposed IoT-Enabled Smart Waste Bin Management System and Efficient Route Selection. *Journal of Computer Networks and Communications, 2019*. https://doi.org/10.1155/2019/7043674