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Simulation and optimization of dynamic waste collection routes

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Abstract

Smart waste collection strategies have been developed to replace conventional fixed routes with dynamic systems that respond to the actual fill-level of waste bins. The variation in waste generation patterns, which is the main driver for the profit of smart systems, is exacerbated in the United Arab Emirates (UAE) due to a high expatriate ratio. This leads to significant changes in waste generation during breaks and seasonal occasions. The present study aimed to evaluate a geographic information system (GIS)-based smart collection system (SCS) compared to conventional practices in terms of time, pollution, and cost. Different scenarios were tested on a local residential district based on variable bin filling rates. The input data were obtained from a field survey on different types of households. A knowledge-based decision-making algorithm was developed to select the bins that require collection based on historical data. The simulation included a regular SCS scenario based on actual filling rates, as well as sub-scenarios to study the impact of reducing the waste generation rates. An operation cost reduction of 19% was achieved with SCS compared to the conventional scenario. Moreover, SCS outperformed the conventional system by lowering carbon-dioxide emissions by between 5 and 22% for various scenarios. The operation costs were non-linearly reduced with the incremental drops in waste generation. Furthermore, the smart system was validated using actual waste generation data of the study area, and it lowered collection trip times by 18 to 42% compared to the conventional service. The present study proposes an integrated SCS architecture, and explores critical considerations of smart systems.

Keywords

Smart waste collection, GIS-based simulation, travel time, operation cost, air pollution emissions, system architecture

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Introduction

One of the major challenges faced by developing countries is municipal solid waste management due to its direct impacts on the environment and public health. The ever-increasing waste generation, mainly due to rapid population growth and urbanization, has led to more challenging waste management processes, particularly the collection system. The conventional approach for waste collection constitutes a fleet of trucks collecting/ transferring waste from individual/communal waste bins to treatment/disposal facilities. This is a very costly process that accounts for more than 60% of total waste management expenditures due to wages, fuel consumption, maintenance, and depreciation (Kreith and Tchobanoglous, 2002). Moreover, the long-haul distances covered by collection trucks lead to ongoing environmental issues including air pollution emissions and traffic congestions. Furthermore, the temporal (seasonal) variation of waste generation rates results in lower efficiencies of the traditional collection routes, which are typically pre-defined regardless of the actual fill-level of waste bins. This results in frequently serving waste bins that are only partially full at the time of collection (Ramos et al., 2018).

Recent studies suggested new approaches to improve the waste collection process. Those methods are based on sensory data acquired from different components of the collection system, particularly waste bins and/or collection trucks. Al Mamun et al. (2016) developed an intelligent sensing algorithm for a municipal waste bin monitoring system in Malaysia. Field tests were conducted using customized waste bins equipped with multiple sensors for level, temperature, and motion. A gateway received the data sent by a ZigBee-PRO transceiver and saved it in the database. The results showed that the designed prototype could achieve an optimum collection route that reduced carbon emissions by up to 10% (Al Mamun et al., 2016). Another study

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conducted by Gutierrez et al. (2015) in Denmark was based on a sensing prototype that measures the waste level of waste bins and transmits the data over the Internet to a server for storage and processing in order to optimize collection routes. The experimentation covered a period of one month based on typical and dynamic scenarios. The waste level was measured from the top of the waste bin to the waste level by an ultrasonic ranging module. An Arduino Uno controller transmitted the received data to a Wi-Fi-based network. Route-optimization algorithms such as Shortest Path Spanning Tree and Genetic Algorithms were used to obtain the optimum collection route. Unlike traditional collection strategies, intelligent methods were found to cover the capital and maintenance costs in as low as two years (Gutierrez et al., 2015). Furthermore, Johansson (2006) equipped 3300 waste bins with sensors and wireless equipment to monitor the waste level. Four infrared light-emitting diodes (LEDs) and a tilt sensor were installed under each bin cover in order to measure the waste level every hour (Johansson, 2006). A study conducted in Italy used wireless sensors in order to monitor the status of waste bins using both proximity and weight sensors installed inside the waste bins. The measured waste level and weight were sent to a nearby coordinator, which forwarded the data to the control unit, identifying the coordinates of the bins that require collection (Catania and Ventura, 2014).

While the aforementioned studies focused on the system architecture as well as data acquisition and communication hardware, other research work has covered the route-optimization algorithms and simulations under various operating scenarios. Faccio et al. (2011) simulated a smart collection system (SCS) and found the estimated trip duration under different scenarios based on the percentage of bins attended/emptied. The study area held 100,000 capita within its borders in Northern Italy. The results of the simulation showed that in most scenarios, the traveled distance was reduced compared to the conventional scenario in which all bins were attended daily. It was observed that the difference in total traveled distance between the optimum scenario and the conventional scenario decreased from 17% to nearly 1% when the amount of collected waste increased by 5% (Faccio et al., 2011). Ramos et al. (2018) tested a simulation of a SCS under three scenarios: (1) the conventional scenario, where all bins were emptied on a daily basis; (2) a scenario where the route of the conventional scenario was fixed, but the number of emptied bins varied depending on the waste level; and (3) a scenario where the collection route was optimized according to the waste level in the bins. The results showed that the performance of the second scenario was lower than that of the conventional scenario, in terms of certain parameters such as kg waste collected per km traveled ratio and truck utilization. However, when the collection routes were optimized, the profit of the collection process increased by 150% compared to the conventional scenario (Ramos et al., 2018). Another study by Zsigraiova et al. (2013) discussed potential savings in cost, time, and emissions associated with glass waste collection systems in Barreiro, Portugal. The study was conducted using geographic information system (GIS) tools to optimize the route of the waste collection truck. The study relied on live traffic data, the actual time of unloading a waste bin, and assigning different filling rates for the bins instead of generalizing an average filling rate. The results showed that implementing the optimization can reduce the cost, total duration, fuel consumption, and emitted pollutants by 57, 62, 43, and 40%, respectively (Zsigraiova et al., 2013).

The United Arab Emirates (UAE) is considered one of the highest waste-generating countries over the world on a per capita basis (Environmental Agency – Abu Dhabi, 2016). The situation is exacerbated by the acute variation in waste generation since over 88% of the population are expatriates (Dubai Statistics Center, 2017). Hence, during short- and long-term breaks, a large proportion of expatriates travel to their home countries, and many UAE citizens travel abroad for tourism. This leads to a reduction in the efficiency of traditional rigid collection systems, and suggests that smart systems may provide potential improvements. However, there is a lack of field data and research, locally and regionally, about the efficiency of current collection systems, as well as the feasibility of smart systems. The main purpose of this study is to assess the applicability of a smart waste collection system in a typical residential area in the UAE. An extensive field survey is carried out to quantify the average filling rates (and fill-levels of waste bins) in different locations within the UAE, and to thus provide actual input data for the simulation of the SCS. The route optimization is simulated under multiple operation scenarios based on a knowledge-based decision-making algorithm, GIS mapping, and a shortest-path routing algorithm. The findings of the simulation are compared to the performance of conventional collection systems in terms of travel time, operation cost, and air pollution emissions. Moreover, the system is validated using actual daily waste generation data of the study area over the year of 2018. Additionally, this article presents a SCS adapted to the local and regional conditions. The architecture of the proposed system is outlined, and the software/hardware components are further discussed.

Methodology

Field survey

A field survey was conducted to determine the actual level of waste in the bins at different residential areas in the UAE. A total of 115 waste bins were monitored simultaneously for different types of households (high-rise buildings, mid-rise buildings, and single-family dwellings) located throughout the UAE. The objectives of the field survey were to (1) understand the typical daily variations in the fill-levels of waste bins, and (2) use the collected data of single-family dwellings for the waste bins in the simulation study area. The field survey covered essential information including (1) size of waste bin, (2) type of household, and (3) average level of waste in the bin. The measurements were taken immediately before the containers were emptied, hence reporting the maximum fill-level on a daily basis. The field survey was conducted in April 2018 – that is, when fill-levels of waste bins are expected to be regular.

Figure 1. Road network and waste bin locations at the study area.

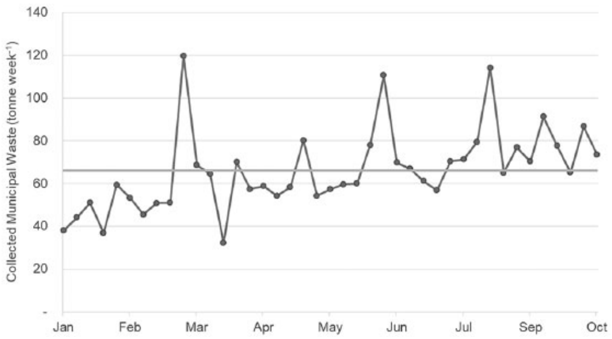

Figure 2. Weekly waste generation rates at the study area.

Study area

Um Gafa is one of the largest districts in Al Ain city, Abu Dhabi, UAE. It covers an approximate area of 4460 ha, with a population of 6772 capita in 2015 (SCAD, 2015). The district residential households consist mostly of ground, duplex, and triplex single-family dwellings. Um Gafa was selected as the study area due to: (1) its adequate size to conduct an appropriate simulation study, (2) consistent typology and land-use throughout the district, (3) being a quiet neighborhood with low traffic volumes and no atypical activities, and (4) availability of reliable data for the waste bin locations. Figure 1 shows the road network and the bins locations in the study area. The district includes a total number of 658 waste bins, each of 1.3 m^3 capacity and 172 kg empty weight. The posted speed limit in the area ranges from 60 km $hour^{-1}$ on local streets, up to 80 km $hour^{-1}$ on the main road. In addition, Um Gafa district contains a total of six roundabouts and no traffic signals due to limited traffic.

The waste bins fill-levels of Um Gafa shall follow those of single-family dwellings in the field survey. Moreover, in order to validate the proposed system over a longer assessment period, the actual daily waste generation rates were obtained for the study area. The data were recorded by the local waste collection company between January and October of the year 2018 (shown in Figure 2). Figure 2 shows the large variation in waste generation rates throughout the year. It can be observed that the generation rates did not follow general patterns, but closely corresponded to seasonal events. The maximum production was recorded during spring tourism season (mid-March), the month of Ramadan (between June and July), and back-to-school season (end of August), while the lowest waste generation occurred during the mid-year break (January) and the spring break (end of March). The waste generation rates ranged between −50% (minimum) and +180% (maximum) of the average value (66 t/$week^{-1}$). This fluctuation emphasizes the potential benefits that can be realized if a dynamic collection system is implemented.

Simulation and routing methods

The methodology followed in the present study was used in order to: (1) establish a well-coordinated GIS map of the accurate locations of waste bins in the study area; (2) develop a knowledge-based decision-making algorithm for the selection of bins; (3) utilize GIS tools to identify the optimum route between the selected bins; (4) test different operation scenarios; and (5) estimate the operation costs and air pollution emissions associated with each trip. The distance covered by the collection trucks was determined using GIS tools, while the travel time was computed based on the covered distance, maximum speed of truck, acceleration/deceleration of truck, right/left turns, road speed limit, and time for unloading waste bins.

This study is focused on the simulation and optimization of collection routes under various operating conditions. The proposed SCS is designed to correspond to the changes in waste generation patterns. The route optimization process was performed by: (1) reducing the number of waste bins serviced in a trip based on the actual fill-levels, and (2) minimizing the distance traveled between the bins which need to be serviced. A simplified knowledge-based decision-making algorithm was developed to select the waste bins to be serviced based on the historical data of fill-levels. The flowchart of the bin-selection algorithm is presented in Figure 3. The algorithm obtains the fill-level for each bin, and adds the expected level increase of the following day. If the total level is larger than the bin capacity minus a safety margin, then the bin is selected for collection; otherwise, the algorithm decides to skip the bin from the collection route, and repeats the fill-level check for the same bin on the next day, and so on. In a field application of such an algorithm, the fill-level historical database can be updated on a daily basis based on the actual measurements from the sensor-equipped waste bins.

The geospatial processing platform used in the present study was ArcMap, and the network-based routing tool was the ArcGIS Network Analyst extension. Route optimization was carried out based on Dijkstra's algorithm, which is the simplest path-determining algorithm computed according to the expected travel times (Khan and Samadder, 2016). Dijkstra's method defines all possible routes between several points on the grid (e.g. nodes A to F in Figure 4) and allocates an expected travel time to each link in the route (e.g. time T_1 to T_8 in Figure 4). Since the traffic of Um Gafa is typically low, particularly during waste collection hours, the optimum path is defined as the path with the minimum travel time, which is the shortest path in terms of distance.

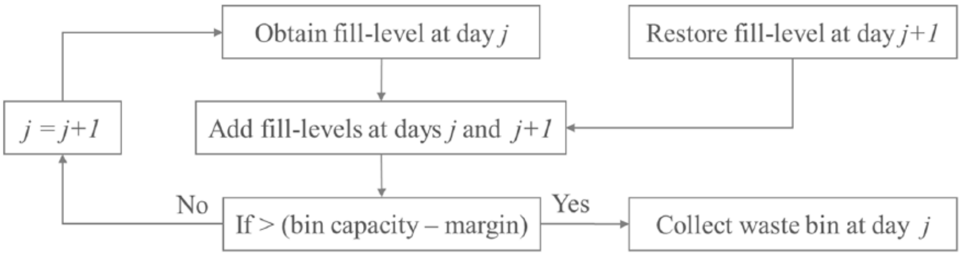

Figure 3. Flowchart of the knowledge-based decision-making algorithm.

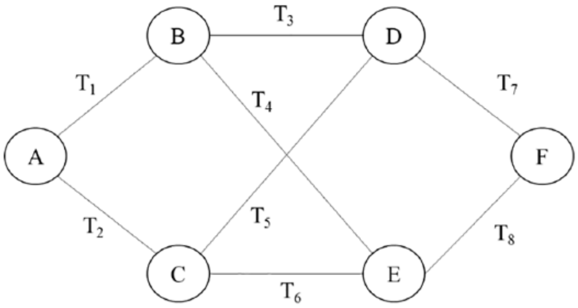

Figure 4. Demonstration of Dijkstra shortest-path algorithm.

Tested scenarios

In order to simplify the bin selection and optimization process, the 658 waste bins of Um Gafa were divided into 25 sets, each set including 25–27 random bins that share the same filling rate and collection day. Each day, different sets of bins are selected for collection via the knowledge-based decision-making algorithm, depending on whether the remaining bin capacity is sufficient to accommodate the expected waste generated in the following day. The simulation of the SCS, which collects only full or semi-full bins, was performed on a GIS-based map where the locations of bins were indicated. The operation of the SCS during two regular weeks (SCS-regular scenario) was simulated based on the actual results of waste bin fill-levels from similar districts of the field survey. SCS-regular tests a potential realistic scenario where the bins are unloaded only when the remaining capacity is insufficient for an additional day of waste generated. The SCS-regular scenario was simulated based on the field survey data, while in a real-life operation of SCS, the call for unloading a bin would be triggered by a signal from a level sensor installed in the bin.

The other set of tested scenarios were defined to mimic the variations in waste filling rates throughout the year since a real-life operation of SCS will operate under variable generation rates. During short- and long-term breaks, a large number of expatriates, who represent around 88% of the population in the UAE, travel to their home countries. Moreover, many UAE citizens travel abroad for tourism. Consequently, waste generation during breaks is reduced significantly and the filling rates of waste bins become significantly slower. In order to evaluate the reduction in the operation cost and emissions during SCS operation in breaks, the fill-levels used in SCS-regular were reduced by 10, 20, 30, and 40%, generating four scenarios: SCS-90%, SCS-80%, SCS-70%, and SCS-60%, respectively. These scenarios were simulated for two weeks to capture any carryover between consecutive weeks. The results of the operation cost and emissions obtained from the simulation of SCS, whether during regular days or breaks, were compared to the conventional scenario (S-conventional), in which the collection trucks unload all bins on a daily basis regardless of their fill-level. Furthermore, the actual data of waste generation rates in the case study area were used to validate the system performance throughout the year. Based on the results shown in Figure 2, the months of January, April, July, and October were selected for the validation of the simulated SCS on a quarterly basis. The monthly waste generation data were also used to estimate the potential annual savings due to the implementation of a SCS.

Emissions and operation cost calculations

In order to assess the feasibility of SCS, its performance in terms of operating costs and emissions was compared to that of the conventional system. The trip details for each scenario were inserted to SIDRA TRIP software to estimate the air pollution emissions, which include carbon dioxide (CO_2), carbon monoxide (CO), and hydrocarbons (HC). The vehicle type was set to heavy vehicle, driver type was set as a slow driver, maximum vehicle speed was set to 60 km hour^{-1}, and input distances were based on the GIS simulations of the tested scenarios. The cost of the trip was calculated based on fuel consumption and labor costs, as shown in equation (1):

$$C = C_t \times D + N_w \times C_w \times T_c \tag{1}$$

where C is the total operation cost of the optimized route (US$), C_t is the transportation cost per distance (US$ km^{-1}), D is the driving distance of route (km), N_w is the number of workers per loading team, C_w is the labor cost per working man hour (US$ worker^{-1} hour^{-1}), and T_c is the total duration of the collection trip (hour). It should be noted that this is a high-level operating cost computation in which some aspects were not considered – for example, maintenance and depreciation of collection vehicles. The total duration of the trip (T_c) can be divided into travel time and bin unloading time, as shown in equation (2):

$$T_c = \left(N_b \times T_b\right) + T_r \tag{2}$$

where N_b is the number of bins to be collected, T_b is the time needed for unloading each bin (hour), and T_r is the driving time of the route (hour). The time from the garage to the study area, and from the study area to the disposal site, was not taken into consideration, being almost identical between different scenarios. The driving time of the route (T_r) can be calculated using the modified equations of motion (equations (3) to (6)) depending on the distance between consecutive bins (d_b) as follows:

If $d_b > d_a + d_d$

$$d_a = \frac{v_s^2}{2a_a} \tag{3}$$

$$d_d = \frac{v_s^2}{2a_d} \tag{4}$$

$$T_r = \frac{v_s}{a_a} + \frac{v_s}{a_d} + \frac{(d_b - d_a - d_d)}{v_s} \tag{5}$$

If $d_b \leqslant d_a + d_d$

$$T_r = \sqrt{2d_b(\frac{1}{a_a} + \frac{1}{a_d})} \tag{6}$$

where d_b is the distance between two consecutive bins (km), d_a is the distance needed to reach the speed limit (km), d_d is the distance needed to stop (km), v_s is the road speed limit (km hour^{-1}), a_a is the acceleration rate of the truck (km hour^{-2}), and a_d is the deceleration rate of the truck (km hour^{-2}). The assumptions used to calculate the travel time and cost were selected based on the local operation and market conditions. The cost of the fuel consumption of waste collection trucks was assumed as US\$1.84 km^{-1}. Each truck is typically operated by three workers (a driver and two operators) at an average wage of US\$4.1 hour^{-1}. According to the local waste management operator, the time needed for unloading each bin is 36 seconds, and the vehicles travel at a maximum speed of 60 km hour^{-1} and acceleration/deceleration rates of 1 m s^{-2}. A time penalty was added for right and left turns of 15 and 25 seconds, respectively.

Results and discussion

The discussion covers the findings of the field survey, followed by the simulation results of the tested scenarios, as well as the validation of the proposed system. The architecture and main components of a proposed SCS, in which the route-optimization algorithm can be incorporated, are presented. We conclude with critical considerations about the applicability of a SCS.

Field survey

A field survey of 115 waste bins was conducted to determine the actual filling rates for various types of households in the UAE. High- and mid-rise buildings typically had waste collection depots at their basements. Those depots either constitute a single large container (hauled directly to the disposal facility, and replaced with an empty one), or multiple standard waste bins (at the time of collection, only the full and semi-full bins are placed outside to be emptied by the trucks). In the case of single-family dwellings, multiple households were typically served with standard waste bins, which are usually placed on the curbside. It was found that bins in high-rise buildings have an average daily fill-level of 84%, followed by mid-rise buildings (48%), and the minimum fill-levels were observed in single-family dwellings (46%). Therefore, an average waste bin in a mid-rise building or single-family dwelling requires unloading every two days, compared to daily in the case of high-rise buildings. Figure 5 shows the average fill-level of waste bins during the week in various types of households. It should be noted that the working days in the UAE are either six days (Saturday to Thursday) or five days (Sunday to Thursday) – that is, Friday only, or Friday and Saturday are off, respectively. The variation of waste level was found to be minimal during the week in high-rise buildings, but more noticeable in mid-rise buildings and single-family dwellings. This can be attributed to the high population served in high-rise buildings, which diminishes any potential variations. It was shown that the fill-level of waste bins was highest during weekends (Friday and Saturday), likely due to the longer time during which waste generators stay at home. The difference in fill-levels between different types of households and the daily variation within the same type show that the waste collection process should be dynamic and responsive to the changes in waste generation patterns.

Routing simulation

The analysis results were obtained from the simulation of trips traveled by the waste collection trucks under different scenarios. The assessment of various scenarios was critical to understand the significance of the SCS when operated under different fill-level conditions. Table 1 shows the percentage of collected bins in the daily trips of the examined SCS scenarios. Overall, the percentage of collected bins in the smart scenarios ranged between 21 and 82% of the total number of bins, compared to 100% in conventional collection. It can be observed that in the SCS-90% scenario, the minimum percentage of collected bins was 45%, while it was 41% in SCS-regular. This indicates that reducing the filling rates does not necessarily decrease the number of collected bins in all daily trips. Moreover, it is noticed that the number of collected bins did not change when the fill-levels dropped from 90 to 80% (maximum) and from 80 to 70% (minimum); this means that the knowledge-based bin-selection algorithm decided that the remaining bin capacities in the lower fill-level scenarios were not large enough to accommodate an additional day of the expected waste generation.

In addition, Table 1 summarizes the travel time and air pollution results of each scenario over a two-week analysis period. The results show that switching to a SCS-regular directly decreases the required collection time by 29.4%. It was found that the time needed to unload the total waste bins biweekly

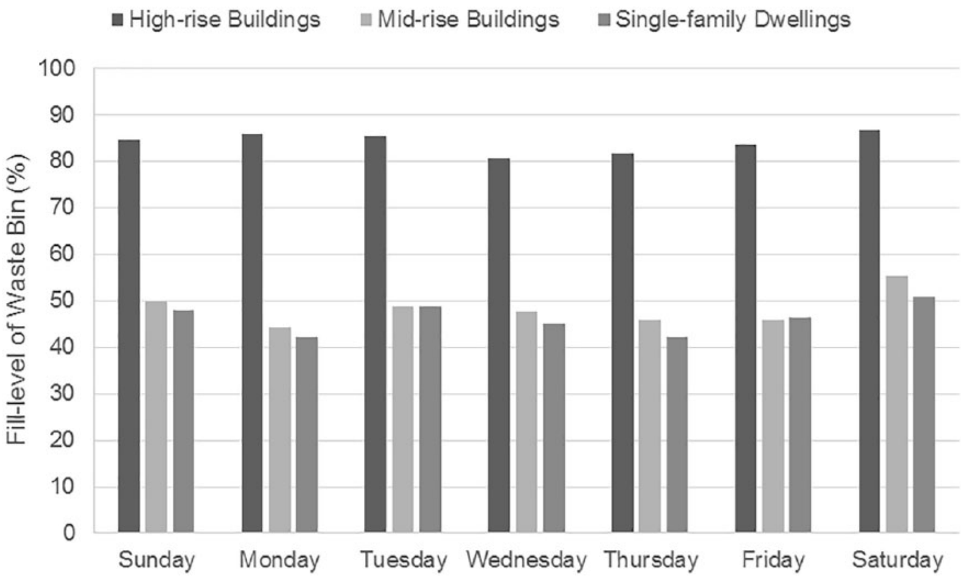

Figure 5. Average fill-level of waste bins in different types of households throughout the UAE.

Table 1. Performance parameters of the tested collection scenarios over a two-week period.

Scenario	Daily collected bins (%)		Travel time (hour)			Air pollution emissions (kg)		
	Minimum	Maximum	Driving	Unloading	Total	CO_2	CO	HC
S-conventional	100	100	70.5	92.1	162.6	1236.2	43.4	0.56
SCS-regular	41	82	57.3	57.5	114.9	1176.0	43.4	0.42
SCS-90%	45	74	54.9	53.5	108.3	1150.8	42.0	0.42
SCS-80%	25	74	49.8	44.0	93.8	1078.0	39.2	0.42
SCS-70%	25	57	48.2	36.2	84.5	1030.4	37.8	0.42
SCS-60%	21	41	41.3	28.4	69.6	966.0	36.4	0.28

could be reduced from 162.6 hours in S-conventional to 69.6 hours in SCS-60%. The incremental 10% drops in waste filling rates (from 90 to 60%) resulted in 33.4, 42.3, 48.1, and 57.2% reductions in travel time, respectively, compared to the conventional scenario. This nonlinearity and variability in travel time reductions can be attributed to the randomness of the locations of bins to be emptied in each scenario as determined by the bin-selection and route-optimization algorithms. The total travel time of the tested scenarios constituted 43.4 to 59.3% driving time and 40.7 to 56.6% unloading time. The drops in bin unloading times were constantly larger than those in the driving times, which highlight a more significant impact of the bin-selection algorithm versus the GIS route-optimization algorithm.

Compared to the conventional collection, scenarios SCS-regular, SCS-90%, SCS-80%, SCS-70%, and SCS-60% reduced CO_2 emissions by 4.9, 6.9, 12.8, 16.6, and 21.9%, respectively. On the other hand, CO emissions were not reduced in the regular SCS scenario; however, they dropped by 3.2, 9.7, 12.9, and 16.1% in SCS-90% to SCS-60%, respectively. As shown in Table 1, the reduction in the air pollution emissions was found to be nonlinearly proportional to the collection trip duration due to variations in the number of unloaded bins and optimized routes (including travel distances and right/left turns). The drops in CO_2, CO, and HC emissions present another crucial benefit of the SCS, as it reduces the environmental footprint of the waste collection process.

The operation cost in the present study covered only the fuel consumption and labor expenses. Figure 6 shows that there was a drop in operation costs of 18.9% between S-conventional and SCS-regular, which indicates that the current operating expenses of the conventional collection system are significantly larger than needed. Compared to normal operation (S-conventional), the scenarios SCS-90% to SCS-60% reduced the operating costs by 21.4, 28.3, 32.9, and 39.0%, respectively. Figure 6 also shows that the drop in operation costs corresponding to the reductions in filling rates was not linear. The maximum reduction in operation costs occurred when the filling rates dropped from 70 to 60% (9.1%), while a drop of 40% in the filling rates (from 100 to 60%) resulted in only a 24.8% drop in operation costs.

The performance of the smart system highly depends on the number of collected bins per trip. However, the randomness of the locations of those bins plays a major role in changing the required time and cost of the trip. Figure 7 shows the duration range of the simulated trips from the tested scenarios. A collection trip in the conventional scenario would always take 11.6 hours, while the trip duration would range from 5.0 to 8.2 hours when only full or semi-full bins are collected (SCS-regular).

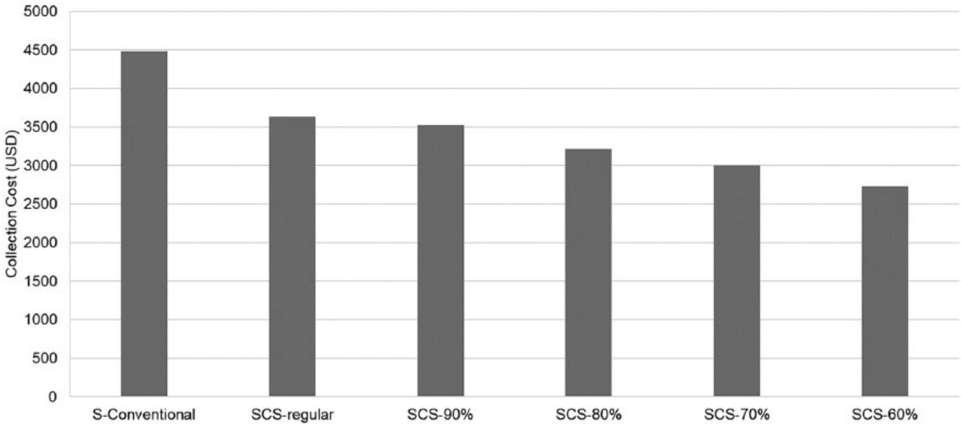

Figure 6. Operation costs of the tested collection scenarios over a two-week period.

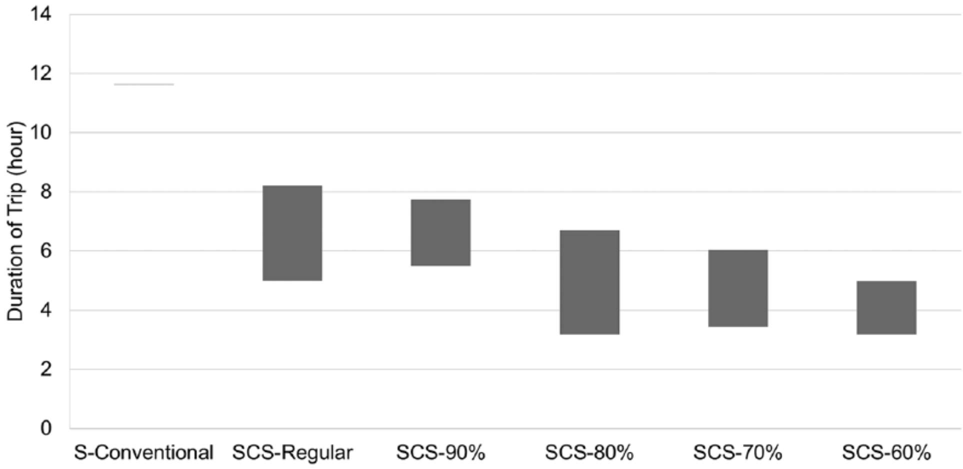

Figure 7. Duration of trips for different collection scenarios.

The reductions in operating costs corresponding to the incremental drops in waste filling rates were due to the lower number of bins collected in each trip, which decreased the trip duration and fuel consumption. Figure 8 shows the range of operation costs for the simulated trips from the tested scenarios. Similar to the trip duration, this figure indicates that reducing more than 20% of the original filling-levels did not reduce the trip cost significantly because the difference in the travelled distances was minimal, regardless of the number of collected bins. The maximum trip cost was found in the conventional scenario (US$320), while the collection trip cost in the smart system ranged from a minimum of US$143 in SCS-70% to a maximum of US$271 in SCS-90%.

System validation

The proposed system was validated using the actual waste generation rates in Um Gafa district. The simulation was carried out quarterly in the months of January, April, July, and October 2018. As shown in Table 2, the total savings in the collection trip duration compared to the conventional scenario ranged between 18.2 and 42.3%. Moreover, the operation cost reductions were computed between 14.8 and 31.2%. It can be observed that although the duration of the waste collection trip in April was lower than that in January, the corresponding operation cost was actually larger. This emphasizes the effect the number of unloaded bins, different collection routes, and travel distance have on the estimated operation cost.

Based on the waste generation data plotted in Figure 2 and the operation costs presented in Table 2, the annual estimated savings for the study area could roughly reach US$25,929 year^{-1} – that is, 22.5% savings relative to the conventional scenario. This was computed by assuming that each of the selected months in Table 2 represents a quarter of the year. With a total built area of about 1160 ha within the study area, the annual savings can be translated to around US$22.35 per hectare of land served. Since the SCS can potentially reduce the environmental footprint of the waste collection process while saving about 22.5% of the operation cost, it can be concluded that SCS can be considered a sustainable alternative to conventional collection systems.

Proposed system architecture

The GIS-based route-optimization algorithm discussed earlier can be incorporated within an integrated smart waste collection solution, as shown in Figure 9. The proposed system combines multiple hardware and software components, including smart waste bins, a control unit (with route-optimization and artificial

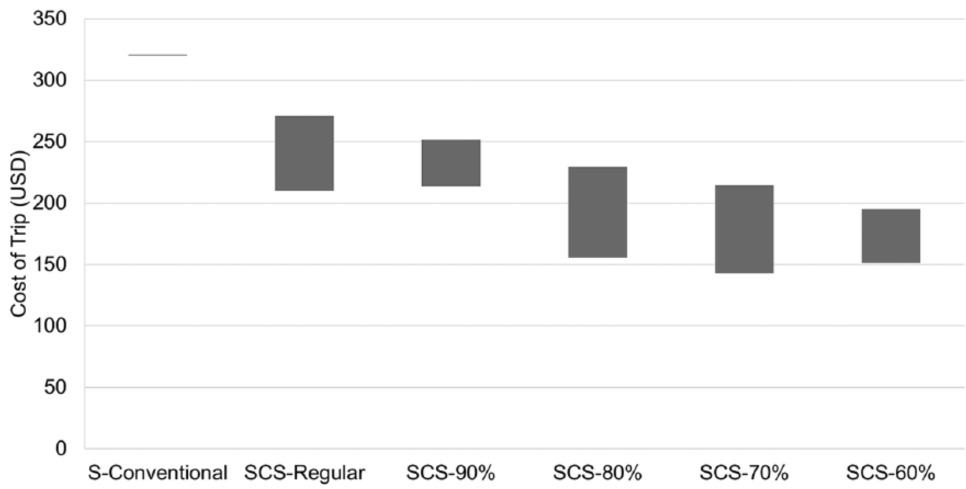

Figure 8. Cost of trips for different collection scenarios.

Table 2. Time and cost validation results of the proposed system over a one-week period.

Scenario	Trip duration (hour)	Time savings (%)	Trip cost (US$)	Cost savings (%)
Conventional	11.62		320.0	
January 2018	6.74	42.0	220.3	31.2
April 2018	6.70	42.3	244.2	23.7
July 2018	8.81	24.2	254.8	20.4
October 2018	9.51	18.2	272.6	14.8

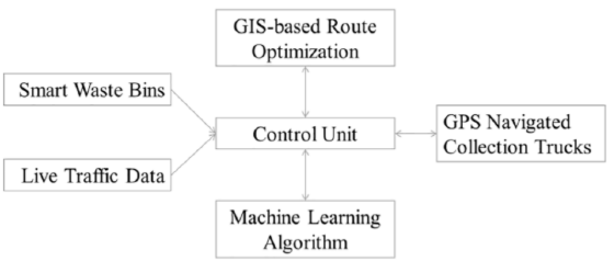

Figure 9. Architecture of the proposed smart waste collection system.

intelligence (AI) algorithms), and Global Positioning System (GPS) navigation devices in collection trucks. While most of those components are typical in SCS, except for the AI machine-learning module, the overall system is customized to fit the local operating conditions. The system utilizes real-time sensory data obtained from waste bins, along with live traffic data, in the decision-making process. The optimized collection routes are wirelessly transmitted to the GPS-navigated collection trucks. The route-optimization algorithm is continuously tuned based on the system performance feedback by means of AI machine-learning. The following sections describe the main components and processes of the proposed system.

Smart bins. There are various kinds of sensors that can indicate the fullness of the waste bins – for example, weight and level sensors. While weight sensors (load cells) are more robust, they can be misleading as waste materials typically have different densities; thus, the computed volume can be significantly over- or under-estimated. On the other hand, level sensors indicate the height of waste in the bin by means of ultrasonic, capacitance, and/or optical measures. The proposed smart bins will typically have multiple-level sensors installed at different locations inside the bin in order to accurately determine the fullness of the bins. Sensors can be installed on the inner side of the bin cover, or installed on the side wall of the bin. The measured level of waste in the bin is then wirelessly transmitted to the control unit with the coordinates of the bin to be included in the next collection trip. It should be noted that, due to the relatively high energy consumption of GPS modules, it is more feasible to send a unique ID of each bin, along with its measured waste level, and the control unit shall have a database with IDs and corresponding coordinates.

The materials used for sensors and their housings must be able to withstand the physically and biochemically harsh environment within the waste bin. Moreover, the materials and technologies must be selected and/or customized such that the system remains functional under high ambient temperatures (55°C) and humidity levels (100%) in the UAE. Since power consumption is a key issue in the feasibility of the system, the microcontrollers in the smart bins should be designed to remain in sleep mode for most of the day until they are triggered by a timer to measure and transmit a reading. There are various sources of energy that can be utilized to power the sensors and transmitters effectively. Solar panels can provide sufficient energy to power the system independently; however, their performance may decline due to the accumulation of dust, or they may be damaged due to the continuous loading/unloading of the bin (Fayeez et al., 2015). Alternatively, zinc or lithium single-cell batteries present a more economical and robust energy source.

Wireless communications. Wireless communication networks contribute significantly to the proposed system, transmitting data from the sensors to the control unit on one side, and from the control unit to the collection trucks on the other side (Figure 9). The most suitable communication protocol to sustain the operation of the proposed system is a low-power, wide-area network type that allows long-range communications at a considerably low bit rate among sensors (Mainwaring et al., 2002). LoRaWAN is one of the recommended wireless data communication specifications to run the system. LoRaWAN uses license-free, sub-gigahertz radio frequency bands like 868 MHz (Europe) and 915 MHz (North America), thus enabling very-long-range transmissions (more than 10 km in rural areas) at low power consumption. While several IoT smart city applications implement Zigbee communication protocol, LoRa outperforms Zigbee in this case as it covers a wider distance and requires less power consumption. In densely populated areas where obstacles may cause signal fading and/or interruption, another efficient communication scenario is needed. One option is to install omni-directional antennas on the roof tops of tall buildings in order to transmit/receive data between sensors and the control unit. These antennas need to be connected to transceiver circuits that are, in turn, connected to control unit(s). This option can handle high traffic loads and a large number of bins, and does not require any radio frequency planning as one can benefit from the existing infrastructure of Internet service providers.

Control unit. The control unit receives three types of data to be incorporated into the route-optimization algorithm: (1) wirelessly transmitted waste levels indicating the fullness of bins; (2) live traffic data through a JavaScript API or traffic layer on GIS; and (3) performance indicators such as actual travel time of the collection trips. The unit stores historical data of the system metrics, which are continuously updated and used in the decision-making process. In order to optimize the performance of the system, an AI machine-learning algorithm can be developed to adjust the parameters of the optimization algorithm based on the inputs and outputs of actual trips. In the proposed system, the AI algorithm would construct regression models based on the incoming data from waste bins and live traffic, together with individual/total travel times in every collection trip. Additionally, AI algorithms can be utilized to estimate future waste generation rates, thus predicting if the waste bin can be delayed for an additional day.

Navigation system. GPS is an integrated system that combines the locations, navigation, and timing of a specific trip. Taking into consideration the expected low skill level of the drivers, the GPS navigation system must have a user-friendly interface that low-skilled workers would be able to follow and operate. The actual time and route of the collection trips are transmitted back to the control unit, and fed to the machine-learning algorithm.

Additional considerations

Smart waste collection systems were repeatedly found to outperform the conventional methods as they aim to optimize the rigid irresponsive collection routes. In addition to having an optimized route, using trucks with different capacities to collect corresponding amounts of waste can minimize fuel consumption as lower-capacity trucks tend to consume less fuel. However, unlike conventional collection systems, the performance of smart systems is affected by certain limitations, as follows:

- A SCS may not be applicable all year long for commingled waste, which is mostly organic in the UAE. The reason behind this is that storing organic waste for multiple days in bins under the extremely high temperature and humidity levels in the UAE, particularly during the long summer months, could have serious environmental and health risks. This includes producing harmful gases, offensive odors, and breeding of flies and/or other disease vectors. On the other hand, a SCS seems to be advantageous for recycling bins, which receive source-separated non-organic materials and, thus, can be safely stored for multiple days regardless of meteorological conditions.
- The waste bins are typically designed with a capacity margin ranging from 66 to 100% based on a six-day collection service (Rahman and Al-Muyeed, 2017). Hence, if properly designed, the waste bins would frequently be at least one-third empty and could be delayed for service without affecting the overall performance. Therefore, it is evident that the benefits of a SCS are maximized if the existing system was originally designed adequately. If the waste bins are under-designed, and, hence, continuously overloaded, a smart system would not seem to be as beneficial under regular operation scenarios.
- The maintenance and replacement costs of sensors, controllers, and transmitters must be taken into consideration in the overall assessment of a SCS since those items are not incurred in current systems. Moreover, as the traditional system is simple and quite easy to operate, upgrading to a more complex system with multiple hardware and software components will require more skilled and costly operators. Therefore, a detailed cost–benefit analysis would be essential to verify if the benefits outweigh the capital and operation and maintenance costs.
- Prior to full-scale application, the implementation of a fully functional pilot SCS project is essential in order to test the integration and performance of the system under real local operating conditions, and also to assess the actual economic and environmental benefits compared to current methods.

Conclusion

The present study tested the feasibility of implementing a smart waste collection system based on a GIS model for a residential study area in the UAE. The study simulated different scenarios based on filling rates obtained from a field survey conducted on different types of households (high-rise buildings, mid-rise buildings, and single-family dwellings) throughout the UAE. It was found that average waste bins in high-rise buildings have the highest fill-levels (84%), followed by mid-rise buildings (48%), and single-family dwellings (46%). The results of the field survey were used to simulate a smart route optimization against the conventional practices in Um Gafa district. The simulation was divided into sub-scenarios based on the filling rates of waste bins (SCS-regular, SCS-90%, SCS-80%, SCS-70%, and SCS-60%). The developed smart system was composed of a knowledge-based decision-making algorithm for bin selection, as well as a GIS-based shortest-path algorithm for route optimization. An operation cost reduction of 19% was achieved with the optimized route compared to the conventional scenario. The operation costs were non-linearly reduced with the incremented drops in waste generation rates. A drop of 40% in the filling rate of waste bins resulted in only a 25% drop in operation costs compared to the regular scenario. Moreover, SCS outperformed the conventional scenario by having lower air pollution emissions, as SCS-regular, SCS-90%, SCS-80%, SCS-70%, and SCS-60% reduced CO_2 emissions by an average of 4.9, 6.9, 12.8, 16.6, and 21.9%, respectively. The simulation was validated using the actual waste generation rates of the study area, and the reduction of the trip cost ranged between 14.8 and 31.2% compared to the conventional scenario. Based on the high-level operation cost analysis, and under the local operation and market conditions, a SCS can potentially achieve annual savings of US$22.4 per hectare.Therefore, the study concludes that implementing the SCS is a potentially feasible and sustainable alternative to conventional methods. It should be noted that the outcomes of the present study can be carefully generalized to other countries with seasonal tourism or high expatriate ratios, such as Gulf Cooperation Council countries.

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