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Smart city solutions: Comparative analysis of waste management models in IoT-enabled environments using multiagent simulation

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ABSTRACT

Effective waste management arises as a crucial challenge for smart city development in the current era of rapid urbanization, shifting towards sustainability and public health. Harnessing modern technologies, especially the integration of the Internet of Things (IoT) with intelligent waste bins, can revolutionize urban waste collection, optimizing efficiency and reducing costs. This paper delves into a multiagent simulation-based framework for understanding and assessing the dynamics of an IoT-enabled smart waste management system. Initiating with the intricate process of garbage generation, we shift our focus to the real-time monitoring capabilities of IoT-connected waste bins. The study further explores protocols to regulate bin status, along with timing mechanisms to trigger garbage collection rounds. Subsequently, a predictive routing system is introduced to determine the most efficient garbage collection routes. For the bins' filled level tracking, the ultrasonic sensors are commonly used that send out sound waves and track their echo return time, whereas weight sensors measure the garbage load in the bin, providing insights into waste production trends. For data transmission from bins to the central system, various communication technologies such as Wi-Fi, cellular networks, and long-distance networks are considered. Through a simulation, we contrast the innovative IoT-enabled sensor-based collection mechanism against the conventional periodic review strategy. Field experiments at the Al Rayyan locale, proximate to Doha, Qatar, facilitate the model demonstration. By leveraging region-specific data, we simulated various aspects including economic factors, environmental impact, public satisfaction, and operational efficiencies. The findings indicate that with an average daily garbage generation of 1.3 kg per individual, the sensor-driven mechanism remarkably outperforms the periodic review approach by covering fewer distances with fewer trucks, while concurrently achieving the key objectives of cost-efficiency, environmental preservation, public satisfaction, and reduced employee workload. This research contributes to the developing field of smart city technology by providing critical insights for urban planners, policymakers, and technologists attempting to build more sustainable, efficient, and livable cities.

1. Introduction

Urbanization has been progressing at an unprecedented rate in the twenty-first century, resulting in multiple challenges that demand new solutions. One of the most important of these issues is waste management, which is essential for urban sustainability and public health. Various household activities generate a diverse range of domestic waste that must be handled, stored, collected, and disposed of properly to avoid endangering the environment or public health (Yoada et al., 2014). Economic growth, industrialization, and improved living conditions have all been linked to increased solid waste creation and management issues (Poletto et al., 2016). The World Bank estimates that waste generation will rise 70 % by 2050, from 2.01 billion tons to 3.40 billion (The World Bank, 2022). Solid wastes should be managed in a methodical and planned manner; however, investigations have revealed widespread ineffective garbage management, particularly in developing countries (AlMa'adeed et al., 2012). Furthermore, the collection process is time-consuming, complicated, and expensive. Collection expenses account for around 80 % of municipal solid waste management budgets, according to the World Bank (Hoornweg & Bhada-Tata, 2012). Solid garbage collection often consumes 60 to 80 % of a community's total solid waste expenditure, depending on the size of the community

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(Sulemana et al., 2018). Any enhancement in the collection system has the potential to considerably lower overall costs and increase environmental benefits as well as public satisfaction (Singh et al., 2014; Sulemana et al., 2018).

The concept of smart cities, which use technology to improve the quality and performance of urban services, has emerged as a promising solution to these and other urban challenges (Salman & Hasar, 2023). The Internet of Things (IoT) is a network of physical objects—"-things"—embedded with sensors, software, and other technologies for connecting and exchanging data with other devices and systems via the internet. In the context of waste management, from sorting to collection, distribution, and re-use, IoT has the potential to transform the way cities manage waste, particularly through real time data collecting and processing capabilities. Since the previous decade, IoT has been increasingly significant in the waste management operations at all levels (Yerraboina et al., 2018). The IoT concept is applied to waste management in the form of a waste bin monitoring system. Smart bins appear to be a standout feature of these new IoT-enabled solutions, which are currently being adopted in numerous places worldwide. The sensors monitor the fullness levels of the bins and alert the waste collection providers when they need to be emptied, allowing personnel to manage the collection without having to personally check whether the bins are full. Ultrasonic sensors are commonly used to monitor the fill level of bins (Karthik et al., 2023). These sensors are highly effective in precisely measuring distances with great precision, making them ideal for proximity detection, object ranging, and level sensing in a variety of materials. A notable advantage is their robust performance in challenging conditions such as fog, where optical sensors are less effective. These are suitable for sensitive situations and are appreciated for their accuracy and reliability across a wide range of applications, making them essential in modern technology. Weight sensors, on the other hand, are used to determine the amount of waste in the bin. These sensors provide significant information on waste production patterns. The data recorded through the sensors is transmitted to the cloud, where the intelligent system generates route optimization, collection schedules, waste bin filling time ratios, and forecasting services, resulting in significant operational costs and time savings. To communicate data from the bins to the central control system, a variety of communication protocols, including Wi-Fi, cellular networks, and long-distance wide area networks, can be used.

This study posits that incorporating the IoT can greatly enhance the efficiency, effectiveness, and sustainability of urban areas. By analyzing existing literature and applying these insights to a multiagent based simulation model, the research aims to thoroughly explore the implementation and advantages of this integration. The investigation extends beyond just the technological factors, delving into the social, economic, and environmental impacts of integrating IoT into urban settings. As part of this research, a multiagent simulation-based modelling framework for the assessment of an IoT-enabled smart waste management is designed. The use of IoT in waste management enables real-time monitoring, enabling greater precision and timely decision-making. Smart bins with sensors, for example, can provide data on fill levels, waste types, and disposal patterns. This data can significantly improve sustainability by enhancing waste collection efficiency, lowering operational costs, and minimizing the environmental impact of waste management practices. The study began with an examination of the waste generation process, followed by autonomous monitoring of the status of the waste bins. Protocols for changing the status of the bins and initiating garbage collection trips were designed. For garbage collection, multiple trucks-based routing system was developed that predicted optimal trucks or vehicles routes. The waste collection teams collect garbage from collection points (bins) and transport it to either landfills or disposal sites. The system has been fully developed to assess the performance for both waste collection strategies: wireless sensors-based and the current periodic review. The established practice of adhering to a predetermined schedule for emptying each bin, irrespective of its actual fill status, is both costly and time-intensive within the current periodic review collection approach. The introduction of smart and intelligent bins, while enhancing efficiency and cutting costs, imposes additional demands on the waste collection system and necessitates a shift in the traditional methods of waste collection. The synthetic data of the Al Rayyan region outside Doha, Qatar, was simulated based on a waste generation scenario and various waste collection regimes. To compare the effectiveness of collection strategies, the following performance indicators were used: economic, environmental, public satisfaction, and employee time savings. In addition, the research work addresses the following questions in the sensitivity analysis by considering different waste collection scenarios as well as varying the number of bins: how many trucks were employed to collect waste from the simulated bins? What is the distance traveled by trucks or drivers during a typical day in each scenario? What is the maximum number of bins that trucks' drivers can visit in a day to empty them? and what is the estimated amount of time required by the collection team to gather waste from the assigned bins? The Multi-Agent System (MAS) based framework known as Janus (Gaud et al., 2009), was used to develop the simulation in order to deliver well-structured organization-based modeling (OBM) and agent-based modeling (ABM) concepts.

This paper is structured as follows: Section 2 contains a survey of the literature on the agent-based modeling in waste management, and the waste collection mechanisms. Following the description, the theoretical (problem domain) and behavioral (agent domain) models are discussed in Section 3. In Section 4, the experiments and results are discussed through the use of a case study. Finally, Section 5 comprises the conclusion as well as recommendations for further work.

2. Literature review

Existing research has focused on developing new strategies in waste management and optimizing waste collection truck routes to reduce operational costs, energy consumption, and transportation pollution emissions. The following sections discuss the literature review on agent-based modeling in waste management and waste collection mechanisms.

2.1. Agent-based modeling in waste management

The use of agent-based technology to simulate waste management is effective for a large area or community; nevertheless, research in waste management is still in its early stages. Hussain et al. (2022) used an agent-based modelling approach to present a waste management simulation. It contrasts a traditional periodic review method with an IoT-enabled strategy in which waste bins are outfitted with smart sensors. The simulation presented was based on waste generation and waste management modules. The simulation was validated using economic, environmental, and citizen satisfaction performance measures. In Abuga and Raghava (2021), the presented approach obtained the real-time data of each smart waste bin distributed across the city and helped to manage and keep smart cities clean. Fuzzy logic was used to strategically place smart waste bins in the smart city. The system was built using Net-Logo, a popular multi-agent modelling platform. By downscaling the strategy to the region of Norte Pioneiro, the authors focused on simulating implementation and evaluating environmental and economic gains (de Souza et al., 2021). The plan examined the dynamics of garbage generation, collection, and disposal using an agent-based model. Targets were designed for waste reduction, collection, source separation, and waste fee charging. The authors executed multiple simulations runs and analyzed the results. A model for optimizing municipal solid waste collection was described in Nguyen-Trong et al. (2017). Multiagent-based modeling and simulation were used to establish a static strategy and incorporate it into a dynamic context. To demonstrate the effectiveness of the suggested paradigm, a case study from Hagiang City, Vietnam, was provided. Municipal Solid Waste collection costs were reduced by 11.3 % after optimizing the results.

In Barth et al. (2023), authors described a study that used bin sensor modules to analyze the trade-offs between cost savings and service quality in waste management. The authors developed a digital process twin for decision support, supplementing it with a growing database. A field study of 98 sensor-equipped waste bins, analytical modeling of cost-service quality trade-offs, and the development of a digital twin decision system all contribute to the research. The authors in Suryawan and Lee (2023) developed a framework for evaluating adaptive solid waste management. It investigates the wide range of citizen preferences and their readiness to fund future adaptive waste management initiatives. The findings indicate that governments should increase the public's awareness of climate change and the infrastructure needed for adaptive waste management. Agent-based modeling was used to simulate different plastic waste generation, collecting routes, and sorting and recycling scenarios in Kerdlap et al. (2020). For plastic bottles and takeaway containers generated in Singapore's central region, this study analyzes the life cycle greenhouse gas emissions of large-scale centralized plants and distributed small-scale facilities. Plastic sorting and recycling networks and their individual components were assessed in a multi-level life cycle assessment based on simulation findings. A decision-making tool based on the multiagent simulation model of biodegradable waste management in Normandy was described in Xu et al. (2019). Several agents were designed for collection, transportation, and treatment. The model could help future waste collection management with routing, scheduling, and pricing methods based on data acquired from local businesses.

Mamun et al. (2016) developed a novel paradigm, architecture, and intelligent sensing algorithm for a real-time solid waste bin monitoring system. In a wireless sensor network, decision algorithms sensed solid waste data. The system had three levels: smart bin, gateway, and control station. The basic idea was that smart bins would collect their status and send it to a server via an intermediary coordinator. Rahman et al. (2020) showed a waste management system based on deep learning and IoT. Murugesan et al. (2021) presented an IoT-based garbage management system for smart cities. Each bin was assigned a new ID and a little gadget to help keep track of their condition. The device sent the filling level along with a unique ID when it arrived faster. The waste collector could quickly clean the waste bins with the help of the Internet and produce better results. A multi-agent decision support system for handling oil spills and greasy wastewater is presented in Mohammadiun et al. (2024). To reduce the volume of weathered oil, response times, and costs, the system employs evolutionary optimization and operational agents. A hypothetical case study in Canada demonstrates its efficacy in resource scheduling, taking waste storage and vessel capacities into account. The application of evolutionary optimization significantly improves response efficiency, showcasing the system's potential to handle complicated marine oil spill scenarios.

2.2. Waste collection mechanisms

This section outlines the research on the truck route optimization for waste collection. The substantial uncertainty associated with the real waste bins' fill-levels is addressed in Ramos et al. (2018) using sensors to provide real-time information. In order to maximize garbage collection and minimize transportation costs, sensors must be used in conjunction with optimization algorithms that identify the most efficient collection routes. Ferrer and Alba (2019) provided a free intelligent software system named BIN for the CiTy (BIN—CT) that organized waste collection routes based on historical and forecast data. The system's goal was to reduce waste collection costs by reducing truck travel distance and, thereby, fuel usage. Hannan et al. (2020) sought to enhance garbage collection efficiency, save costs, and reduce emissions by combining fixed routing optimization and variable routing optimization in a mixed-integer linear programming model for optimization. The authors of Salehi-Amiri et al. (2022) created two models based on the vehicle routing problem concept. The first model uses modern traceability IoT-based devices to collect data in real time, while the second model considers waste separation as well as transfer to the recovery value center. The authors of Tran et al. (2023), presented a mixed-integer nonlinear programming model for improving agricultural waste collection and transportation networks. The purpose was to reduce waste burning by reusing agricultural waste for the creation of bio-organic fertilizer. The model helps rural planners to locate waste storage facilities and plan ideal routes for a vehicle fleet to carry waste from these storages to a bio-organic fertilizer producing facility. In Alsobky et al. (2023), authors aim to provide optimized collection systems that can accommodate various housing levels. Collection routes in Al-Mostakbal City, for example, are optimized by selecting the appropriate location and container order. Rahmanifar et al. (2023) presented a two-tier waste management system that employs the industry 4.0 concept to reduce operational costs and environmental impact. Both models compare real-time waste level information in bins using modern traceability IoT-based devices.

To optimize waste collection operations, Shah et al. (2018) developed a stochastic optimization model using chance-constrained programming. The optimization model's goal was to reduce total transportation costs while maximizing value recovered from waste bins. Given the varying conditions and quality of waste, the value of collected waste was modeled as an unpredictable parameter. Lu et al. (2020) described an ICT-based smart waste categorization and collection system (SWCCS) that optimizes garbage collection. An enhanced multi-objective hybrid algorithm based on whale optimization and genetic algorithms with a fast, non-dominated sorting approach was designed to implement the suggested SWCCS. This article explained how the ICT-based SWCCS works and how it may assist sanitation firms in collecting waste more efficiently and sustainably. Sarmah et al. (2019) identified waste collection routes in Bilaspur, India. The daily waste generation from many sources was measured and vehicles were routed considering different constraints: vehicle numbers, routes, and capacity. The Clark and Wright method was used to find the vehicle's optimal route. The ArcGIS network analyzer tool set was used to discover the optimal path for solid waste collection. The authors of Roy et al. (2022) developed an integrated IoT-based smart bin allocation system with a central monitoring system and a better vehicle routing algorithm for solid waste management. The authors proposed a time-based penalty concept to waste management authorities if these waste bins are not emptied within a reasonable amount of time after becoming full.

Delgado-Antequera et al. (2020) used multi-objective approaches to model and solve the waste collection problem in less computation time. Travel cost, route length balance, route time balance, and route number were used to model the waste collection problem. An iterated greedy algorithm and variable neighborhood search were used to approximate the Pareto front. Shang et al. (2022) extended a novel waste management transportation model, the capacitated location routing problem with queuing time, and designed a cross-entropy and simulated-annealing hyper-heuristic algorithm. The presented system includes a character encoding scheme, decoding procedure, and local search strategy. To solve the combinatorial optimization problem, simulated annealing and cross-entropy-based hyper-heuristic algorithms are combined. Lavigne et al. (2021) presented a routing optimization model for waste collection that allows multiple depots with homogeneous, capacitated vehicles, intermediate stops at multiple processing facilities, and multiple pick-ups per waste collection location. A hybrid metaheuristic was created by Jorge et al. (2022) to handle the smart garbage collecting problem. The metaheuristic comprised (i) a look-ahead heuristic to determine collection days and waste to collect (must-go) based on current and predicted bin fill levels; and (ii) a simulated annealing/neighborhood search method to determine profitable bins to collect and the optimal route(s) to visit the bins. In Lella et al. (2017), the authors investigated effective solid waste collecting methods. It explains how to use GIS-based network analysis to optimize waste collection and transportation. The statistics reveal that the established collecting routes reduce travel distance by 59.12 %. The report also offers potential transfer station locations, considering aspects such as accessible open area, accessibility from composting units or dustbin locations, tractor trailer transportation, and sanitation and environmental standards.

Only a few works of research, with limited scope, have employed an agent-based strategy to model the waste management process. Academics are currently unable to model a holistic framework for garbage generation and waste collection processes using IoT containers. Similarly, in the current periodic review waste collection approach, the driver must visit each bin location on a fixed schedule (i.e., daily, weekly, or biweekly) to collect the garbage. Because of smart bin innovation, the driver will only visit bins whose status is filled and will begin their trip based on the requirements. This could save the driver a significant amount of time as well as fuel and emission costs.

3. Multiagent simulation-based modelling and assessment framework

In this study, we developed a waste management model that integrates IoT-enabled bins, utilizing a multiagent simulation framework. This model simulates the entire waste management lifecycle, from its generation to final disposal, employing the OBM and ABM approaches. ABM is particularly effective in capturing the individual characteristics and behaviors of agents in the management systems. It is distributed as well as individual-centric and is suitable for complex, multiple faceted systems. Previous research by Ferber et al. (2004) and Jennings (2000) indicates that ABM is suitable for handling scenarios where the agents frequently alter their roles. In the context of waste management, agents are dynamic and focused on individual behaviors. By implementing these concepts, agents can adapt their actions in response to changing conditions without altering their inner structure.

This section outlines the scope of the waste management model and presents a system model addressing the issue at hand. It emphasizes the use of IoT-enabled waste bins distributed across various geographical locations. The system, which is housed on a cloud platform, is responsible for initiating collection trips or rounds and designing truck routes based on the status of the bins (full or overfilled). Following that, the waste management model is described, comprising numerous activities and decision-making models required for the model's functionality. Finally, using OBM and ABM approaches, the problem domain is transformed into a multiagent simulation within the agent domain section.

3.1. *Problem description and system model*

The waste collector company's location is specified by l_1 whereas the waste landfill location is indicated by l_n. For a set of bins B, $b_{1,2,3,\ldots,n} \in B$ is given. Each b_i is assigned a location l_i, where $l_{2,3\ldots,n-1} \in L$. A group of households h_m is formed from a set of households H and associated with each b_i to dispose of their daily waste. Here, m is the maximum number of households associated with each bin. Each bin is equipped with sensors that measure the density ρ (mass / volume) and can autonomously transmit the recorded data to the cloud. Collection schedules and routes for multiple waste collection trucks, as well as the time ratio of waste bins to fill up and other forecasting services, are generated by the system on the cloud. Based on the information provided by the system, the planner or manager located at l_1 will assign *drivers* to collect waste from the specified bin locations and dispose of it at allocated l_n. Trucks' *drivers* will begin the *trips* from the l_1, pick up the garbage from the specified bin locations, dispose of it at l_n, and return to the l_1 at the end of *trip*. The truck *driver* is responsible for emptying the bins whose ultimate state is *filled* and *overfilled*, determined by the value of parameter ρ. Fig. 1 depicts the waste management process system model, which has economic and environmental impacts, increases citizen satisfaction, and saves employees' time.

A few distinct activities, as depicted in Fig. 2, occur during the waste management process. These activities are carried out by various actors or agents including households, the manager or planner, and the truck drivers. Each of these activities is discussed in detail in the following subsection.

3.2. *Problem domain – waste management process*

3.2.1. *Waste disposal and filling bins*

At any moment during the day, the inhabitants from the group of households h_m can dispose of their daily waste g_j in the bin b_i assigned to them. In this model, we assumed that approximately 50 % of the inhabitants disposed of their daily waste in the evening [between 17:00 and 20:00 h], 25 % in the morning [between 6:00 and 9:00 h], and the remaining 25 % at other times. To handle the weekly events, a random sample of households that could dispose of numerous garbage bags of the same size, or a larger bag, in a single day was selected. Additionally,

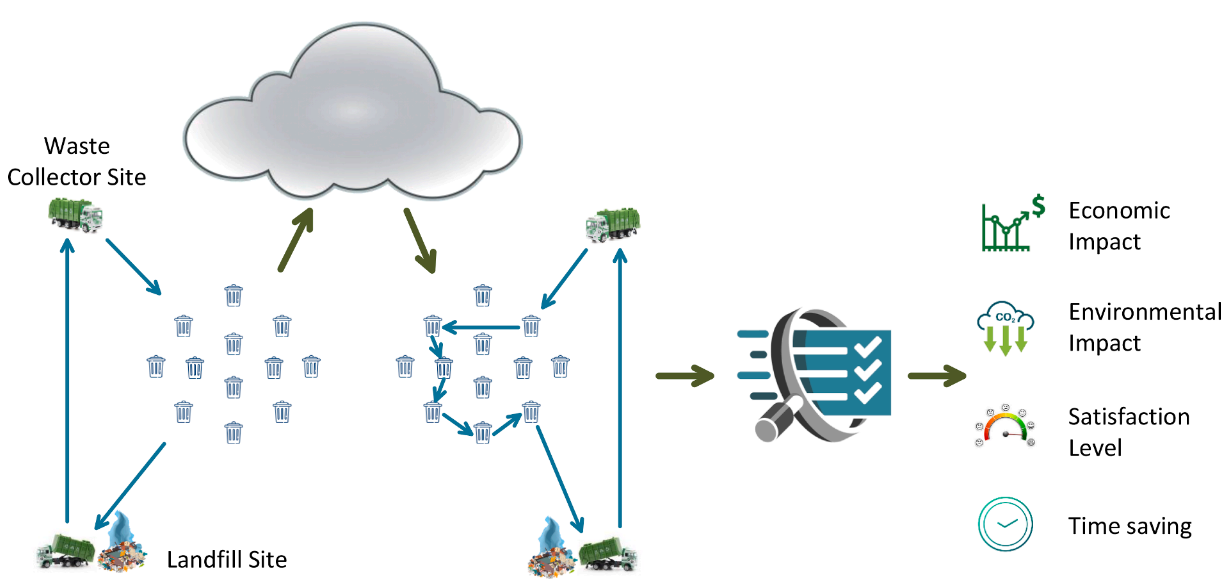

Fig. 1. The waste management process is represented as a system model.

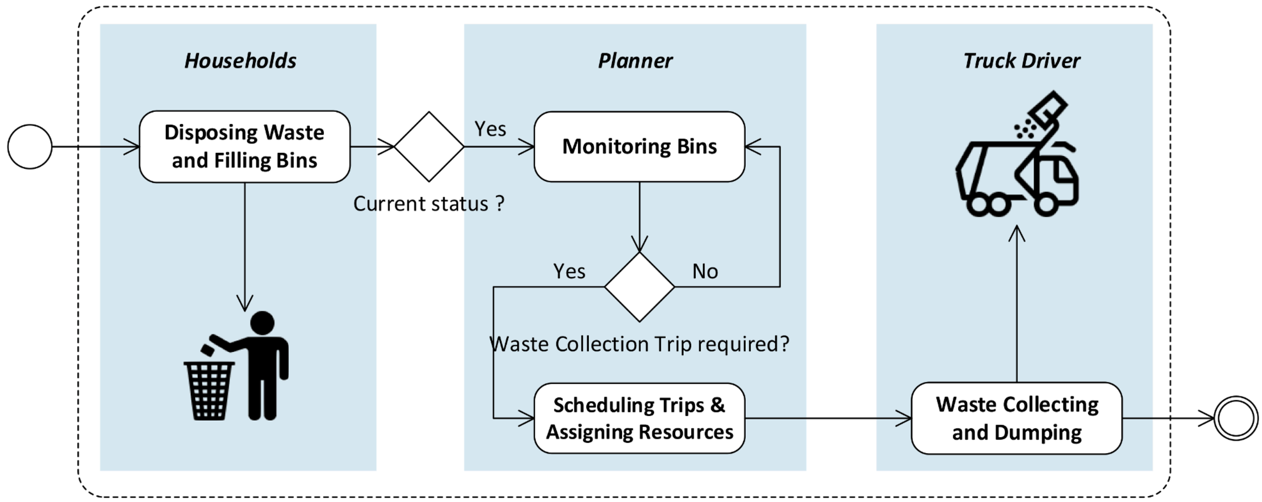

Fig. 2. The activities carried out by the households, as well as the planner and driver, in the waste management process.

because most people leave their homes on weekends (for outings), the garbage disposal ratio may be lower on weekends. However, the extent to which this occurs varies from region to region; for this model, we assumed that only 10 % of households did not produce their daily amount of garbage on the weekend.

As mentioned previously, the bins are enabled by sensors that can determine the bin's current status. Every b_i has a maximum weight and volume capacity (w_b^{max} and v_b^{max}, respectively). In this model, the maximum weight and volume capacity is modeled by the volumetric mass density ρ. The maximum density for a bin is denoted by $\rho_b^{max} = \frac{w_b^{max}}{v_b^{max}}$ (Table 1 shows symbol meanings). The current status of the bin is determined by the amount of waste disposed of by the households in b_i. Every household disposed of their g_j on a daily basis. The weight w_{g_j}, and volume v_{g_j} are properties of g_j, and the types of waste significantly impact the values of these attributes. In this study, we assumed that each household's garbage g_j included a mixture of different garbage categories, since g_j comprises a household's garbage and a household can have multiple family members. The volumetric mass density ρ of the waste varies from region to region and across waste types; as a result, the weight and volume of the bag are largely reliant on the density of the garbage. It should be noted that the seasonal variation in waste generation was not investigated in this study. The average waste disposed of per capita in the specific region was considered as the minimum density (on average) of g_j (i.e., 1.3Kg/m^3 for only one family member). As multiple households are associated with one bin, the number of households can fall between minimum and maximum ranges, e.g. 1 and 5. In this model, the average density ρ_{g_j} for a g_j is calculated by Eq. (1).

Table 1
Symbols used and their definitions.

Symbols	Meanings and definitions
B	Set of bins $b_{1,2,3,\ldots,n} \in B$
h_m	The inhabitants from the group of households
g_j	Waste disposed by a household j
b_i	The waste bin associated to h_m
w_b^{max} and v_b^{max}	Maximum weight and maximum volume capacity of b_i
ρ_b^{max}	Maximum density capacity of b_i
ρ_{g_j}	The average density of g_j
$\rho_{b_i}^{curr}$	The current status of b_i, The density of garbage collection demand at a certain location.
$truck_k^{mCapacity}$	Maximum density capacity of a truck k.
$l_{2,3,\ldots,n-1}$	Each b_i is assigned a location l_i
l_1	Waste collector company's – the origin location
l_n	The landfill location

$$\rho_{g_j} = \triangle \frac{w_{g_j}}{v_{g_j}} \tag{1}$$

The current status of the bin is determined by adding the density of all the waste bags in the bin. Eq. (2) specifies the status of the bin in terms of ρ.

$$\rho_{b_i}^{curr} = \sum_{j=1}^{m} \left(\rho_{g_j}\right) \tag{2}$$

The sensors broadcast the $\rho_{b_i}^{curr}$ information with its current location to the cloud to monitor and analyze the bin's present status. The transmitted information is monitored on the cloud and is visible to the planner or manager, allowing them to make decisions based on the data received. This is also regarded as a density waste collection demand at the particular location.

3.2.2. Monitoring bins and planning waste collection trips

In this study, ***the current status of each bin*** was accessible to the waste collection planner based on the information transmitted by the sensors. The system automatically declared the status of the bins as *filled* or *overfilled*: (1) when $\rho_{b_i}^{curr}$ parameter exceeds the threshold value (i.e., 80 %) of $\rho_{b_i}^{max}$, the bin status is considered as *filled*, and (2) when $\rho_{b_i}^{curr}$ parameter exceeds $\rho_{b_i}^{max}$, the status is deemed *overfilled*. Eq. (3) depicts the conditions:

$$b_i^{filled} = \left(\rho_{b_i}^{curr} \geq threshold \times \rho_{b_i}^{max}\right) \wedge \left(\rho_{b_i}^{curr} \leq \rho_{b_i}^{max}\right)$$

$$b_i^{overfilled} = \left(\rho_{b_i}^{curr} > \rho_{b_i}^{max}\right) \tag{3}$$

Individual dissatisfaction may develop if overfilled bins are not emptied in a timely manner. The planner can explicitly specify the threshold value, i.e., 0.7 or 0.8, depending on the situation. The other two states of the bin can be *partially filled* and *empty*.

Initiating a garbage collection trip is considered as a challenging task since it varies with situation and region. Normally, the waste collection trip is carried out on a daily basis, after every two or three days, or on a weekly basis. In this study, to collect *garbage* from filled or overfilled bins, multiple cases were tried and analyzed; these have been presented in the Experiments and Results section. In addition to the regular-basis case, a waste collection trip can be made when there are enough filled or overfilled bins (i.e., 50 % of the total bins). Another strategy could be dependent on waste density: when the waste density in the bins (both filled and overfilled) to be collected reaches the available trucks' maximum capacities as shown in Eq. (4), then the trips can be triggered automatically:

$$t_i^{initiating} = \sum_{i=1}^{n}\left(\rho\ {}^{curr}_{b_{i,filled\ \vee\ overfilled}}\right) \geq \sum_{k=1}^{m}\left(truck\ {}^{mCapacity}_{k}\right) \quad (4)$$

The minimum number of trucks (m is this case) required to collect waste from all of the bins that must be emptied.

The density of waste has a considerable impact on the efficiency of waste collection routes and schedules. High-density locations frequently generate more waste, necessitating more frequent collection and sometimes larger or more vehicles to avoid overflow and environmental problems. This increased activity may result in greater emissions and operational costs. Lower density, on the other hand, may result in unused resources. Efficient waste management systems that take advantage of data analysis, IoT devices, and route optimization software are critical for adjusting to these variations and maintaining cost-effective and environmentally friendly operations.

Collection schedules and determining routes for multiple waste collection trucks are considered difficult tasks because they vary depending on constraints i.e. number of trucks, trucks' maximum capacity, drivers' availability and so on. ***The optimized routes*** are extracted using graph theory concepts. A directed graph $G = (V, E)$ consisting of n vertices (locations) is created. The first node is the waste collector's location, and the final node is the landfill location. All the locations between waste collector and landfill are the bins' locations. A function $c : E \rightarrow R)$ associates a travel distance to each edge. The problem defined with *directed graph* is an asymmetric travel salesman problem, which means that the distance of onward journey from a location to another may be different from the distance of return journey. The truck driver will visit each location exactly once and minimize the total distance (i.e., the length of the waste collection trip). In the wireless sensors-based waste collection approach, only locations with bin status as *filled* or *overfilled* are visited, whereas in the periodic review, all the bin locations must be visited to collect the waste.

In this model, to achieve the Multiple Vehicle Routing (MVR), the Travel Salesman Problem (TSP) is extended to create the wireless sensors-based waste collection mechanism to collect waste from the (filled or overfilled) bins and dump the collected waste at the landfill location. The TSP is a classic optimization problem that seeks the shortest possible route that visits a set of given locations exactly once before returning to the starting location. The problem becomes more complex when multiple trucks are involved, because each truck has a limited capacity and must visit only a subset of the cities. This is referred to as the Multiple TSP (MTSP).

For the wireless sensors-based waste collection strategy, first, all the locations (including those of waste collector company, bins, and landfill) are labeled with the numbers $l_1, \ldots, l_n$. Note that the l_1 location is the location of the waste collector company, from where the trip will start, and l_n is the landfill location where the collected waste will be dumped. $l_2, \ldots, l_{n-1}$ are the bin locations. The waste collection trip always starts from l_1, and l_n (landfill location) will be visited at the end before return to l_1.

Given (i) a set of L locations ranging from l_1 to l_n, (ii) a set of vehicles $k = \{1, \ldots, m\}$ with varying capacity, (ii) a distance matrix $d[l_i, l_j]$ contains distances between l_i and l_j. The variable $x_{l_i l_j, k}$ determines whether vehicle k uses the edge between locations l_i and l_j. The cost of travelling between l_i and l_j is given by parameter $c_{l_i l_j}$. The goal is to develop a set of m routes that visits all locations exactly once while reducing the distance travelled by all waste collection trucks and not exceeding the capacity of each vehicle. objective function for MTSP can be expressed as an integer linear programming (ILP) as described in Eq. (5):

$$\min \sum_{k=1}^{m} \sum_{i=1}^{n} \sum_{j=1}^{n} c_{l_i l_j} x_{l_i l_j, k} \quad (5)$$

Subject to (6), (7), (8), (9), and (10).

In (6), $x_{lilj,k}$ represent a binary variable that equals 1 if location l_j is visited by vehicle k after location l_i, and 0 otherwise.

$$x_{lilj,k} = \begin{cases} 1\, if\ l_j\ visited\ by\ vehicle\ k after\ l_i \\ 0\, otherwise \end{cases} \quad (6)$$

The edge between l_i and l_j with a cost greater than 0 will be considered, as demonstrated by (7).

$$c_{lilj} > 0, \quad l_i \neq l_j \quad (7)$$

Each location l_i is only visited by one vehicle; a vehicle from $k = \{1, \ldots, m\}$ can enter and leave a location precisely once, as shown by (8).

$$\sum_{k=1}^{m} \sum_{i=1, l_i \neq l_j}^{n} x_{l_i l_j, k} = \sum_{k=1}^{m} \sum_{j=1, l_j \neq l_i}^{n} x_{l_i l_j, k} = 1 \quad (8)$$

The number of vehicles (i) leaving the planner's location l_1 (to collect waste), (ii) visiting the dumping location l_n (for waste disposal) and (iii) entering back to l_1 from l_n must be equal, as shown by (9). m is the number of vehicles used for collecting waste.

$$\sum_{k=1}^{m} \sum_{i=2}^{n-1} x_{l_1 l_i, k} = \sum_{k=1}^{m} \sum_{i=2}^{n-1} x_{l_i l_n, k} = \sum_{k=1}^{m} x_{l_n l_1, k} = m \quad (9)$$

Each truck has a maximum density capacity of loading $truck^{mCapacity}$. The $\rho\ {}^{curr}_{b_{i,filled\ \vee\ overfilled}}$ is the density demand at the specific location where the bin is installed. For wireless sensors-based collection strategy, the bins are considered either filled or overfilled. For periodic review collection strategy, bins are considered to be of any status. The Eq. (10) ensures that no route exceeds the vehicle capacity.

$$\sum_{k=1}^{m} \sum_{i=1}^{n} \rho\ {}^{curr}_{b_{i,filled\ \vee\ overfilled}} \leq truck\ {}^{mCapacity}_{k} \quad (10)$$

Solving this ILP will result in best routes for each vehicle that reduce overall distance travelled while meeting capacity limitations. The system will recommend optimized schedules and routes between the locations that each capacitated truck must visit after determining the waste collection trips for multiple trucks. The planner agent will assign resources to waste collection trips, such as drivers and trucks, and the planner agent will assign recommended routes to the drivers, who will then follow the specified routes to empty the assigned bins (both full and overfilled) and dispose of the waste at the designated disposal site.

3.2.3. Waste collection and dumping

The number of vehicles or trucks used, as well as their maximum loading capacity, are considered important factors in waste collection. Since the drivers and waste collection teams are required to work for eight-to-ten hours per day, they can collect waste from a large number of bins. Each truck driver will begin the trip at the origin location l_1 and then visit all of the assigned bins in order to empty them and dispose the loaded waste at the dumping location l_n. The driver will load the waste on the truck by emptying the bins and then move on to the next assigned bin and repeat the process until they reach the last fully loaded bin. After visiting each bin, the driver will follow the route to the landfill location, where the driver will unload the waste and then return to the origin or planner's location. If only one truck is available and the waste volume in the (filled or overfilled) bins exceeds the truck's maximum capacity, the driver will collect waste in multiple rounds. Each round involves waste collection from the designated bins and disposal at the landfill. After unloading the truck at the landfill in the last round, the driver will return to the planner's location and may complete their day's work.

Whenever drivers adopt the periodic review method to complete a waste collection trip, they will iterate to each assigned bin in accordance with the established timetable, resulting in an increase in both time and travel expenses.

3.3. Agent domain: multiagent-based simulation modelling

The agent domain is devoted to the development of a multiagent-based simulation that serves as a solution for the model described in Section 3.2. Agents are people whose personal features and social connections have been discretely implanted. A group is an organizational unit in which all members must follow predefined definitions and protocols. Groups are used to refer to an entire set of roles and to define shared norms for those roles. The environment for the agents is established, which contains non-agent materials and provides the necessary environmental circumstances. The environment comprises the bins and their locations as well as the planner's location and the dumping site. Moreover, the environment includes the road network of the study area.

The multiagent-based waste management simulation involves three major types of agents: household, planner, and driver agent. The simulation begins by launching each agent with the dataset that it has been assigned. The behavior of each agent is described using a finite state machine (FSM). The following sections provide in-depth descriptions of these agent types.

3.3.1. Household agent

Household agent is the most common form of agent in the simulation. The number of household agents associated with the bins can vary, but they must all be of the same agent type. Each household agent handles waste generation and disposal of their assigned bin. The operations executed by each household agent in the waste management simulation are depicted in Fig. 3(a). In this simulation, the bins are represented by organizational concepts, which are used to model them. The WasteDisposalOrganization.class is responsible for grouping the household agents and creating separate groups for each bin. Each household agent, within the associated group, plays the role of wasteDisposingRole.class to dispose the garbage. The household agent operates in two states: idling and disposing.

Idling: The household agent will remain idle while in this state, and it is presumed that the persons in the household are responsible for waste generation.

Disposing: In the *disposing* state, the household agent will dispose of its daily waste and transit back to the *idling* state. This means, when the garbage bag is ready, the household agent will change its state and transit to the *disposing* state, where it will dispose of the garbage bag in the corresponding bin.

All garbage-bag-related parameters are set in accordance with the details described in Section 3.2.1. During garbage bag disposal, bin-related information is updated.

For waste management, the "WasteManagementOrganization.class" organization is used for grouping the planner agent and the driver agent. The planner agent, within the associated group, plays the role of facilitatingRole.class to monitor bins, plan trip and assign resources to the planned trip. The driver agent plays the role of executingTripRole.class to execute the trip by emptying the bins and dumping waste at the landfill. The behavior of the respective agents is modeled using the FSM in their respective roles.

3.3.2. Planner agent

The planner agent is responsible (1) for monitoring the current status of the bins and initiating waste collection trips and, (2) for determining the most efficient route for waste collection and disposal. The mechanism for determining the best waste collection route for each vehicle is described in Section 3.2.2. This agent employs the *monitoring* and *planning* states (Fig. 3(b)), which are described as follows:

Monitoring: In this state, the planner agent keeps track of all of the bins based on the values explicitly assigned by the planner agent. All of the groups that represent the bins are visible to the planner at all times. The automated script is also employed in this state to show and alter different states of the bins in order to handle the bins. Consequently, the planner agent can decide whether or not to initiate a waste collection trip. When sufficient bins with filled and overfilled statuses are found, or based on explicit parameters, the planner agent will initiate the waste collection trip and change its state to *planning*.

Planning: In the planning state, the planner agent assigns all resources to the waste collection trips, including vehicles and drivers. The proposed ideal route is also assigned to each driver, along with the sequence of locations to visit for waste collection (emptying the bins) and disposal. When this agent has assigned all of the resources and initiated the trip, they will transit back to the monitoring state and continue monitoring bins for the next trip.

3.3.3. Driver agent

Once the planner agent assigns a specific trip with the optimal route and truck, the driver agent will begin their trip from the planner's location and visit each bin to collect waste and empty the bins. The driver agent will then drive to the dumping site to dump the collected garbage and return to the planner's location at the end. The idling, emptying, and dumping states (Fig. 3(b)) are used to model the behavior of this agent.

Idling: The truck driver agent remains idle in this state until they receive the signal from the planner agent to begin their waste collection trip. Once they receive the signal to begin the journey, they will depart

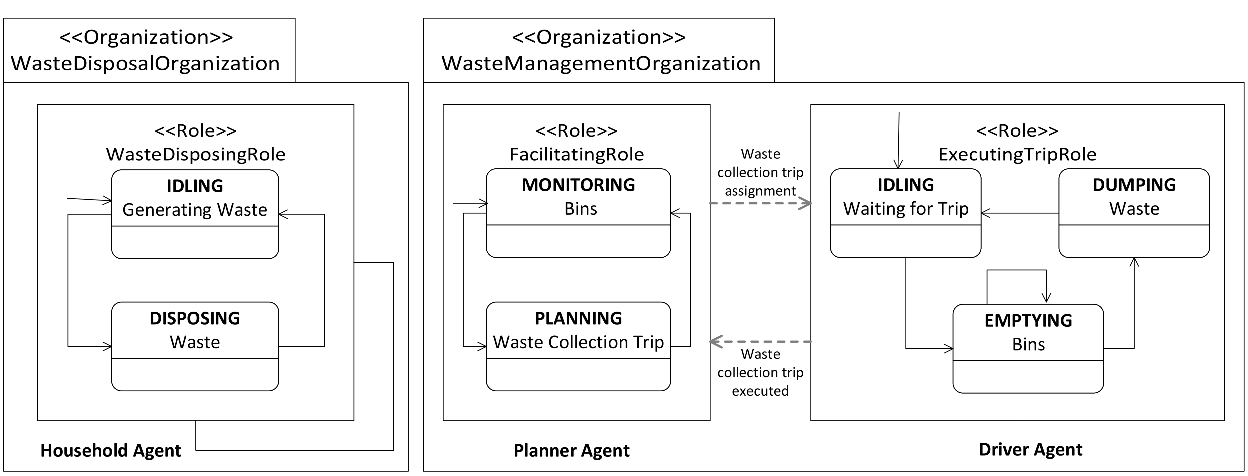

Fig. 3. (a) The household agent playing the waste disposing role in the waste disposal organization. (b) The planner agent playing facilitating role and the driver agent is playing executing-trip role in the waste management organization. Both planner and driver agents coordinate for the execution of the waste collection trips successfully.

from the planner's location and change their state to the emptying state.

Emptying: In this state, the driver collects garbage from the bin locations by emptying them and remains in this state until all waste has been collected from all bin locations. The driver follows the route that was provided by the planner agent and empties the bins in the prescribed order. After collecting waste from each bin, the driver moves to the dumping state.

Dumping: In this state, the driver agent unloads the truck and dumps the waste at the designated disposal site. After unloading the vehicle, the driver enters the idling state and remains there until the next trip is scheduled.

All the above-described agents are executed autonomously and constantly throughout the simulation period.

4. Case study, experiments and results

The partial dataset of Al Rayyan, located just outside the Doha (Qatar region) is used as a case study. Fig. 4 showcases the study area, in which the study area is distinctly highlighted. The Qatari government has identified waste management as a major environmental issue (Symms & Singh Kler, 2021). Population growth, development measures undertaken for the FIFA World Cup 2022, and overall industrial growth have all contributed to increased waste generation in Qatar. In addition, Qatar has a high average income, which results in generation of a large amount of domestic waste. According to Symms and Singh Kler (2021), Qatar generates almost 2.5 million tons of municipal solid waste annually, or about 2.5 kilogram per capita. Municipalities with a large population and industrial concentration (e.g. Doha, Al Rayyan, and Umm Salal) contribute to a higher waste generation Symms and Singh Kler (2021). In Qatar, municipalities are responsible for solid waste collection, both directly, through their own logistics, and indirectly, through private sector contract. The collection and transportation of waste is handled by a massive fleet of trucks that pick-up waste from thousands of locations scattered across the country. This collected solid domestic waste is then disposed of in landfills, with only a small percentage of the total waste being recycled. It is worth noting that Qatar has three landfill sites dedicated to waste disposal. Only one landfill site (named as Umm Al-Afai) is designated for bulky and domestic waste disposal, while the other two are designated for construction waste and sewage water.

The experiments focused on periodic review and wireless sensors-based garbage collection strategies to demonstrate the anticipated outcomes of the multiagent simulation. For the experiments, in alignment with Qatar's practice of designating a single landfill site for bulky and domestic waste, we assumed that Al Rayyan has one waste collection facility and one landfill site located in the Umm Al-Afai area specifically for domestic waste disposal. Different numbers (ranges between 200 and 500 bins) of bin locations (spread over the northern area of the Al Rayyan) are used for various investigations. The size of each bin was considered to be 1 m^3, and the maximum capacity to be 312 kg per cubic meter. The value is based on Palanivel and Sulaima's (2014) study on the Oman region where the waste was generated at an average density of 311.73 kg per cubic meter per day. The authors collected samples from the landfill during two distinct seasons—summer and winter. A comparable study (Katiyar et al., 2013) conducted in Bhopal, India, discovered a nearly same density of 314.9 Kg/m^3.

In the waste generation process, the number of agents assigned to each household was determined based on the current practice in Al Rayyan. It was found that both types of residences (individual and numerous) are associated with bins. A villa can be based on both single-family and multi-family homes. As a result, the household agents were chosen at random between the minimum and maximum values: The number of chosen households were associated to a bin. According to the Planning and Statistics Authority, the average number of people living in a household in Qatar is 5.5 (Ministry of Development Planning and Statistics [MDPS], 2014). The average household size in the Al Rayyan, Qatar region, is 5.7, according to the Qatar Open Data Portal (2015). According to Symms and Singh Kler (2021), a person generates 2.5 kg of garbage per day; in the proposed model, we simulated 1.3 kg per capita on average for the domestic waste. The average daily waste generated by a household was calculated at random from the range of values between minimum and maximum. The travel times and distances were extracted using trucks as a mode of transportation from OSM (OpenStreetMap)

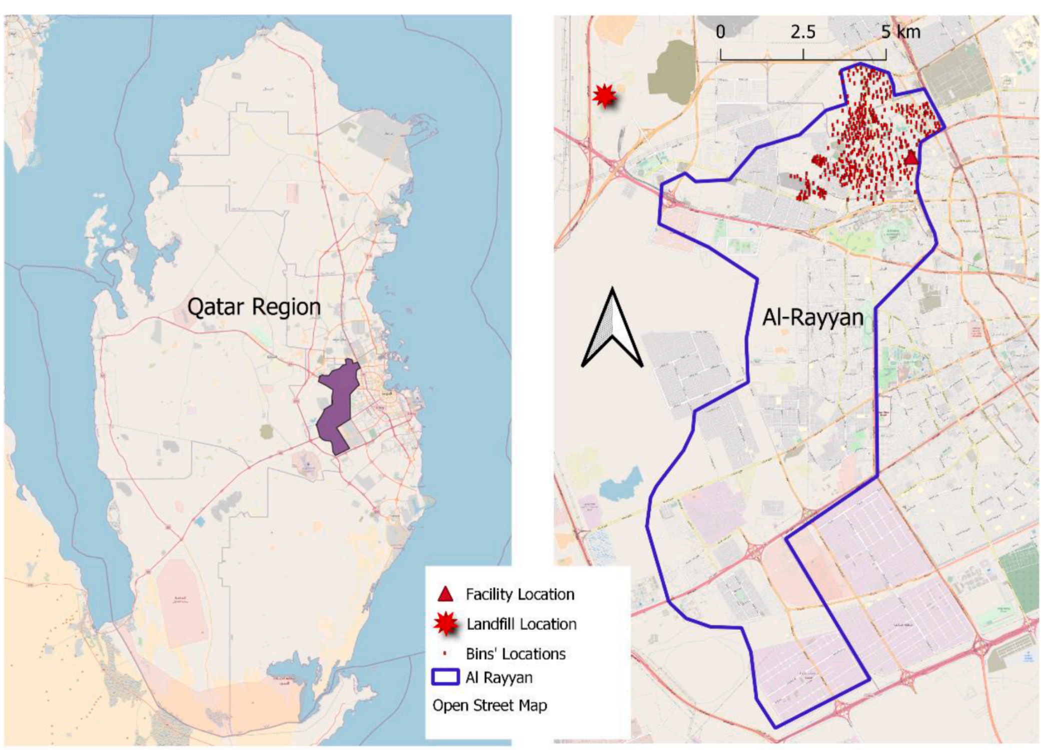

Fig. 4. Distribution of bins in the Al Rayyan region.

datasets with the GraphHopper (Karich, 2014) API and server. Finally, a one-year simulation duration was established based on the parameter values described in Table 2.

4.1. Waste generation

Waste was generated by randomly selecting around 900 household agents from the study area, which were associated with 300 bins. The number of household members (average 5.7 per family) and number of families (average 3 per bin) was chosen at random. Fig. 5(a) displays the daily waste generation during the simulated period. The results revealed that the simulation created 6.67 tons of garbage on average, and the pattern was found to be linear throughout the simulation period. Fig. 5 (b) shows the cumulative occurrence (actual and linear frequency) distribution of the generating waste. The number of observations that lie above or below a specific waste generation for a year using a specific number of households in a data set is used to calculate the cumulative frequency for waste generation. Fig. 5(c) depicts the daily garbage generated by bins, family, and per capita over the simulated period of one year. The blue curve indicates per bin waste, the orange curve per household, and the grey curve per capita. The figure shows that households dispose of 22.5 kg of waste per bin on average. Similarly, on average 7.5 kg of garbage is thrown off per family, and approximately 1.31 kg is disposed of per person. The simulation produced the same quantity of waste as expected: A person in Qatar produces 1.3 kg of domestic waste per day on average, and we simulated the same density of waste per capita. Fig. 5(d) depicts the total garbage created in a year for each waste collection plan and scenario: (1) daily, after 2 days, after 3 days, and weekly for the periodic review approach, and (2) 0.6, 0.7, 0.8, and 0.9 bin filling threshold for the sensors-based waste collection strategy. The data demonstrate that households generate the same amount of waste for each collection strategy, which is around 2450 tons in a year.

4.2. Comparison between periodic review and sensors-based collection models

A total of 300 bins (about 900 households) were simulated to compare the periodic review and sensor-oriented collection procedures. The periodic review waste collection approach was simulated on a daily, after-two-days, after-three-days, and weekly basis. The wireless sensors-based garbage collection strategy was tested by using different bin filling threshold values of 0.6, 0.7, 0.8, and 0.9. Both strategies were examined based on the following performance measures: economic, environmental, citizens' satisfaction, and employees' time savings. The assessment of the system relies on an in-depth analysis of various essential data points linked to each performance metric. The economic issues are critical, as the cost-effectiveness of operations, budget allocation, and financial sustainability must all be considered. Environmental consequences include assessing the systems' carbon footprint, recycling efficiency, and long-term ecological viability. Citizen satisfaction levels reveal the public's perceptions of service quality, responsiveness, and overall effectiveness. Finally, efficient time management is critical in analyzing operational productivity, garbage collection punctuality, and adaptability to unexpected problems. Each of these indicators helps to provide a comprehensive picture of the strengths and weaknesses of waste management systems, leading to improvements and innovations in this critical public service sector. These measures are essential for assessing performance and outcomes; however, these come with intrinsic limitations and are based on certain assumptions. This understanding is required for conducting a comprehensive and accurate evaluation of any initiative. The subsequent section offers an in-depth explanation of each performance metric.

Table 2
Simulation parameters and their values.

No. of facilitating or planner's locations	1 (Waff Facilities & Waste Management)
No. of landfills	1 (Umm Al-Afai)
No. of same-sized bins (1 m^3)	Varies with experiment: 200 to 500 bins
Maximum bin capacity (density)	Average: 312 kg per cubic meter
No. of planners (planning agents)	1
No. of trucks and trucks drivers	Multiple capacitated trucks and multiple drivers
Households/families associated with each bin	Average: 3
People affiliated with a household	Average: 5.7
Minimum garbage bag capacity (density)	1.3 per capita
Waste collection scenario in the periodic review approach	daily, after 2 days, after 3 days, and weekly
Sensors-based waste collection scenario	bins' filling threshold values: 0.6, 0.7, 0.8, and 0.9
Simulated period	1 year

4.2.1. Performance measures

Economic performance is crucial for municipalities as waste collection costs amount to 80 % of the total municipal waste management budget (Hoornweg & Bhada-Tata, 2012). Many studies including (Singh et al., 2014; Sulemana et al., 2018) have demonstrated that the cost of waste collection increases linearly with the distance traveled by trucks. Consequently, the cost related to the total distance traveled was used to assess the economic performance indicator. Maintenance costs and employees' salaries were assumed to be negligible, and the cost related to the distance travelled to collect waste is considered as shown by Eq. (11).

$$Cost_{overall} = \sum_{i=1}^{n} d_i \times u_{cost} \tag{11}$$

$Cost_{overall}$ computes the total cost using n trucks (here n is the number of trucks used to collect waste), d_i is the distance travelled by a truck and u_{cost} is the cost per unit distance (e.g. per Km or per mile). Therefore, the cost is related to fleet size and also the distance travelled by each used truck.

Cost measurements often assume stable economic conditions and prices. Variations in material costs, labor wages, and other operational expenses, on the other hand, can impact the accuracy of these calculations. Furthermore, indirect costs, such as those associated with environmental damage or health consequences, are frequently overlooked.

The **environmental performance** indicator is used to measure the environmental impact of the collection process. In particular, it focuses on CO_2 emitted by the collection truck, and the total CO_2 emissions are directly related to the distance traveled. In this research, the overall CO_2 emission ($CE_{overall}$) for all trucks' trips was calculated using Eq. (12).

$$CE_{overall} = \sum_{i=1}^{n} (FC \times d_i) \times ER + (L \times C) \tag{12}$$

FC is the fuel consumption ratio per 100 km, d_i is distance traveled by truck i, and ER is the fuel emission factor, which is defined as the amount of carbon emissions per liter. Also, L is the number of locations visited by i, and C is the CO_2 emission at a stop or location. According to Solutions (2020), a large vehicle carrying a weight of more than 23 tons consumes 38 liters of diesel to travel 100 km; moreover, a truck carrying less than 16 tons uses 25 liters (diesel) to travel 100 km. Further, according to Fleetnews (2021), a vehicle emits 2.62 kg of CO_2 per 1 liter diesel.

The accuracy of emission measures can be modified by a variety of factors, including fuel type, vehicle efficiency, and route choices. Inaccuracies in determining the real environmental impact can result from assumptions regarding these factors.

The policies set by municipalities for waste collection significantly impact **citizen's happiness**. This indicator was calculated by keeping track of the average number of overfilled bins per trip. Citizens passing

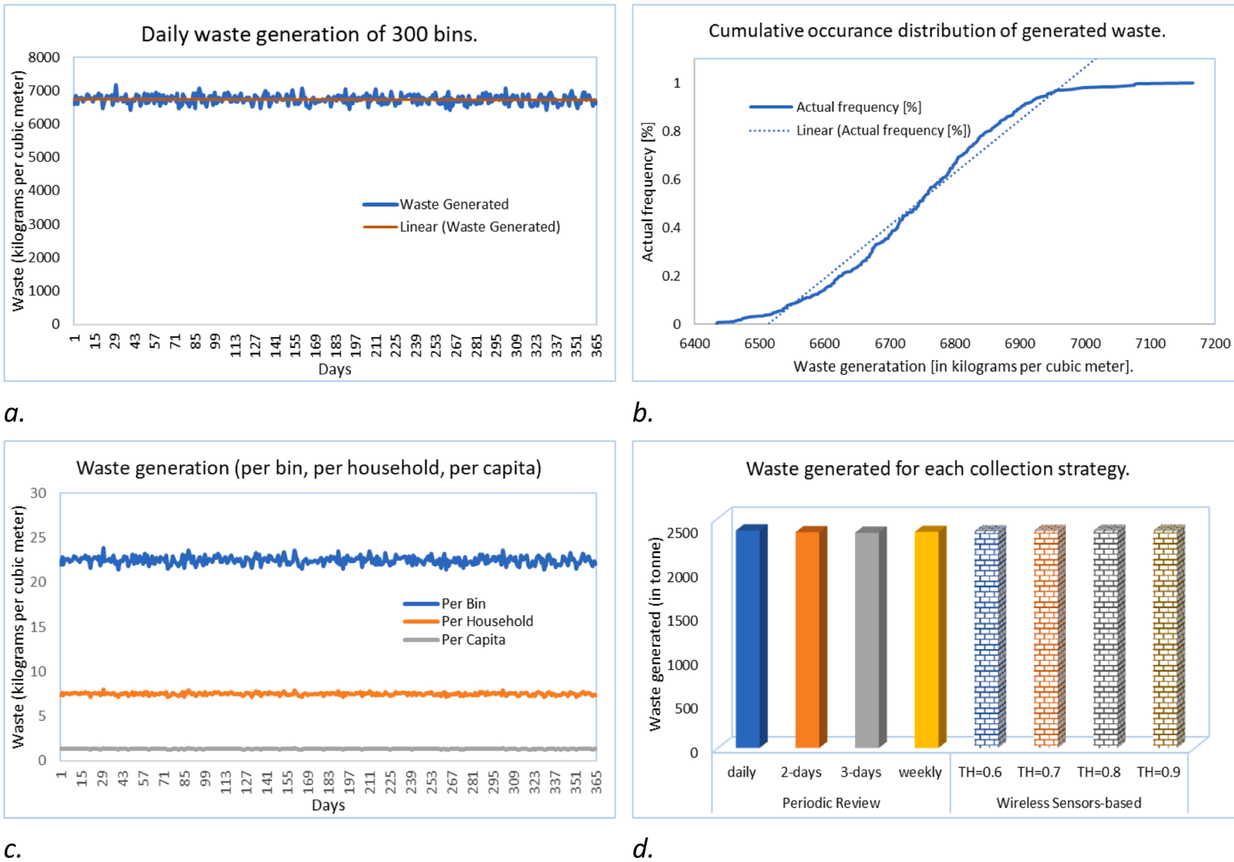

Fig. 5. (a) The daily waste generation throughout the simulation period, (b) the cumulative occurrence distribution of the waste generation, (c) the per bin (blue curve), per household (orange curve), and per capita (grey curve) waste generation, and (d) the yearly waste generation by households under various waste collection strategies.

by an overfilled bin and those looking to dispose of waste will be irritated not only by the state of the bin but also by the smell and aesthetics of the public space. Thus, when this indicator indicates a low number of overfilled bins, the model's performance improves. The Eq. (13) computes the quantity of overfilled bins, denoted as $B_{b_{of}}$, that a truck driver empties from the assigned bins. The $f(b_i)$ returns 1 if the bin is overfilled otherwise, it will return 0.

$$B_{b_{of}} = \sum_{i=1}^{n} f(b_i) \ : \ \begin{cases} 1 \ if \ b_{i,density} > b_{i,\ capacity} \\ \quad 0 \ otherwise \end{cases} \tag{13}$$

Measuring social impact requires assumptions about a community's beliefs and objectives. These measures are sensitive to interpretation and may not capture the entire spectrum of effects on various social groups. Furthermore, long-term societal consequences are frequently difficult to define and forecast.

Another performance metric is employees' **time saving**, which is also a significant consideration when scheduling garbage collection excursions. The planner agent plans the trip when the drivers and other employees are available to execute the trip. When staff and drivers spend less time collecting waste, they have more time for other activities and can perform more allocated duties in less time. Ultimately, municipalities can save money as a result of this. The Eq. (14) calculates the overall travel time T_{trip} of a trip performed by a truck driver including the waiting time at each location for collecting and dumping waste at bins and dumping locations.

$$T_{trip} = \left(\sum_{i=1}^{n} \frac{d_{l_{i-1},l_i}}{v} + t_{wait,l_i} \right) + \frac{d_{l_n,l_0}}{v} \tag{14}$$

The distance travelled between bins' locations l_{i-1} and l_i is represented by d_{l_{i-1},l_i} and v denotes the average speed of the driver. Note that the l_0 is the origin location from where the truck driver starts trip and l_n is the waste dumping location where the truck driver dumps the collected waste. The parameter t_{wait,l_i} represents the waiting time at each location. Finally, the truck driver ends his trip at the origin location. Time-saving indicators often assume a direct relationship between efficiency gains and time savings. However, external factors like road congestion, regulatory compliance, and unexpected delays can all have an impact on time-saving indicator. Furthermore, the perceived value of time saved can fluctuate between stakeholders.

4.2.2. Periodic review and sensors-based collection models

The comparisons in Fig. 6 are between the business-as-usual (the periodic review) and the wireless sensors-based collection models. As previously stated, that in the periodic review collection strategy, the truck driver must visit all bin locations to collect waste however in the wireless sensors-based waste collection strategy, only the bins with *filled* or *overfilled* status are visited. In the periodic review, the number of trips varies during the year depending on the collection scenarios (daily, after-2-days, after-3-days, and weekly) and also on the use of different capacitated trucks. Waste collection trips can be triggered daily in the wireless sensor-based collection strategy, and the per-trip distance varies based on filled or overfilled bin locations simulated using different collection scenarios with bin filling threshold values: 0.6, 0.7, 0.8, and 0.9. The experiments were conducted with identical input values, as given in Table 2, and by altering different collection scenarios.

Fig. 6(a) shows the average per-trip distance (in kilometers) traveled by the truck driver based on various collection scenarios under the periodic review and wireless sensors-based strategies. The figure shows that average distances of 156, 197, 244, and 366 km per daily trips are

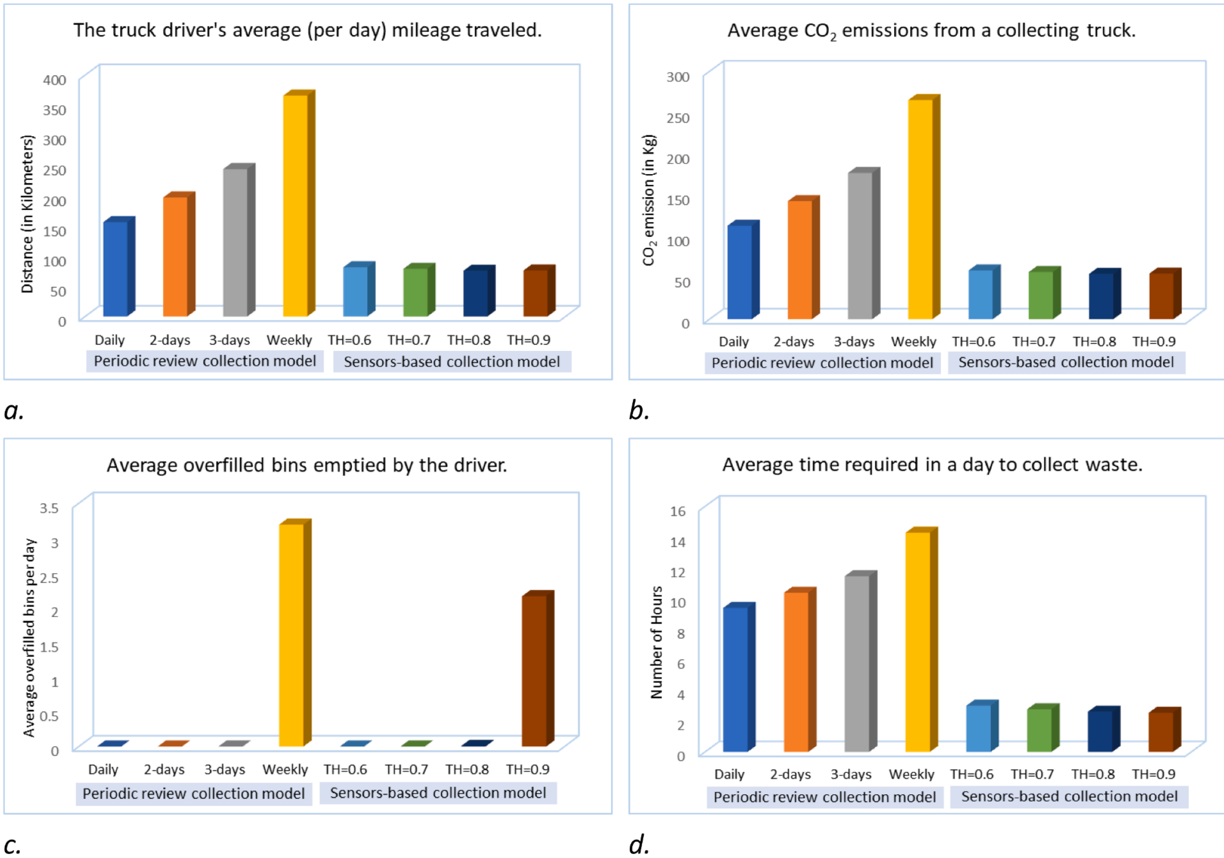

Fig. 6. Simulation results for different waste collection scenarios, i.e., daily, after every two days, after every three days, and weekly, under the periodic review waste collection strategy and with different bin filling threshold scenarios, i.e., 0.6, 0.7, 0.8, and 0.9, under the wireless sensors-based waste collection strategy—in terms of (a) travel distance, (b) CO2 emission, (c) number of emptied overfilled bins, and (d) waste collection time.

traveled by the truck driver under daily, after-two-days, after-three-days, and weekly scenarios, respectively. However, the trucks travel under different scenarios with threshold values of 0.6, 0.7, 0.8, and 0.9 of the wireless sensors-based strategy in 81, 78, 75, and 76 km per day. With a higher bin filling threshold, the truck driver travelled fewer kilometers, while a lower threshold led to more bins being emptied and more distance travelled. Fig. 6(b) depicts the CO_2 emissions (in ton) under each scenario. Although the weekly collection scenario generates the highest amount of CO_2 emissions per-day-trips, since the higher number of trucks used and each truck is driven for a longer distance during the day. It releases less CO_2 overall (in a year) since only 52 trips are conducted in a year. A slight change in CO_2 emissions was observed under different scenarios of the wireless sensors-based model. It was found that with an increase in the threshold value, less CO_2 is emitted, since a smaller number of bins locations are visited. Fig. 6(c) shows the number of overfilled bins emptied by the truck driver per trip. In the periodic review, the weekly scenario leads to the highest number of overfilled bins—more than 3.2 (on average) per day. In the wireless sensors-based strategy, the overfilled bins are represented only by the bin filling threshold of 0.9 scenario. The average number of overfilled bins emptied per trip was close to 2.16. The lower the threshold value, the better were the results. Fig. 6(d) represents the travel times taken by the truck driver to collect the waste. The result shows that the weekly collection strategy leads to a greater amount of time spent in a day (14.28 h); this is because the scenario requires a higher number of trucks in a day to collect the waste. The driver spends less time around 2.55 h under the threshold value of 0.9, since a small number of bins are emptied as compared to the other threshold scenarios. With the threshold value of 0.6, a higher number of hours (around 3) are spent for the waste collection and the collection time is reduced by increasing the threshold value.

The same amount of domestic waste was gathered and dumped on average using each waste collection scenario.

4.3. *Sensitivity analysis*

The periodic-review and wireless sensors-based collection scenarios were simulated by varying number of bins (200, 300, 400, and 500). Fig. 7(a) depicts the average distance traveled by trucks to collect waste. The x-axis shows different scenarios related to different collection strategies. Different curves represent different number of bins: blue curve for the 200 bins, orange curve for the 300 bin, grey curve for the 400 bins, and yellow curve for the 500 bins. The results demonstrated that the periodic review collection strategy scenarios covered more average mileage on collection day than the sensor-based collection scenarios. The milage covered during periodic-review waste collection scenarios varies depending on the large amount of waste which requires multiple trucks to be used for waste collection. The number of bins visited is constant across scenarios in the periodic-review waste collection strategy, but the mileage covered changes due to differences in the number of trucks used. In sensor-based collecting scenarios, the milage covered is greater when the threshold value is lower, and it decreases as the threshold value increases. This occurs because when the threshold value is lower, more bins are visited than when the threshold value is greater. Overall, the pattern of each curve remains consistent regardless of the number of simulated bins. Simulating a greater number of bins led to a larger amount of waste being collected, which required the use of an increased number of trucks. Fig. 7(b) illustrates the number of trucks employed for waste collection in each collection scenario, for various numbers of bins. The findings revealed that, on average, more vehicles

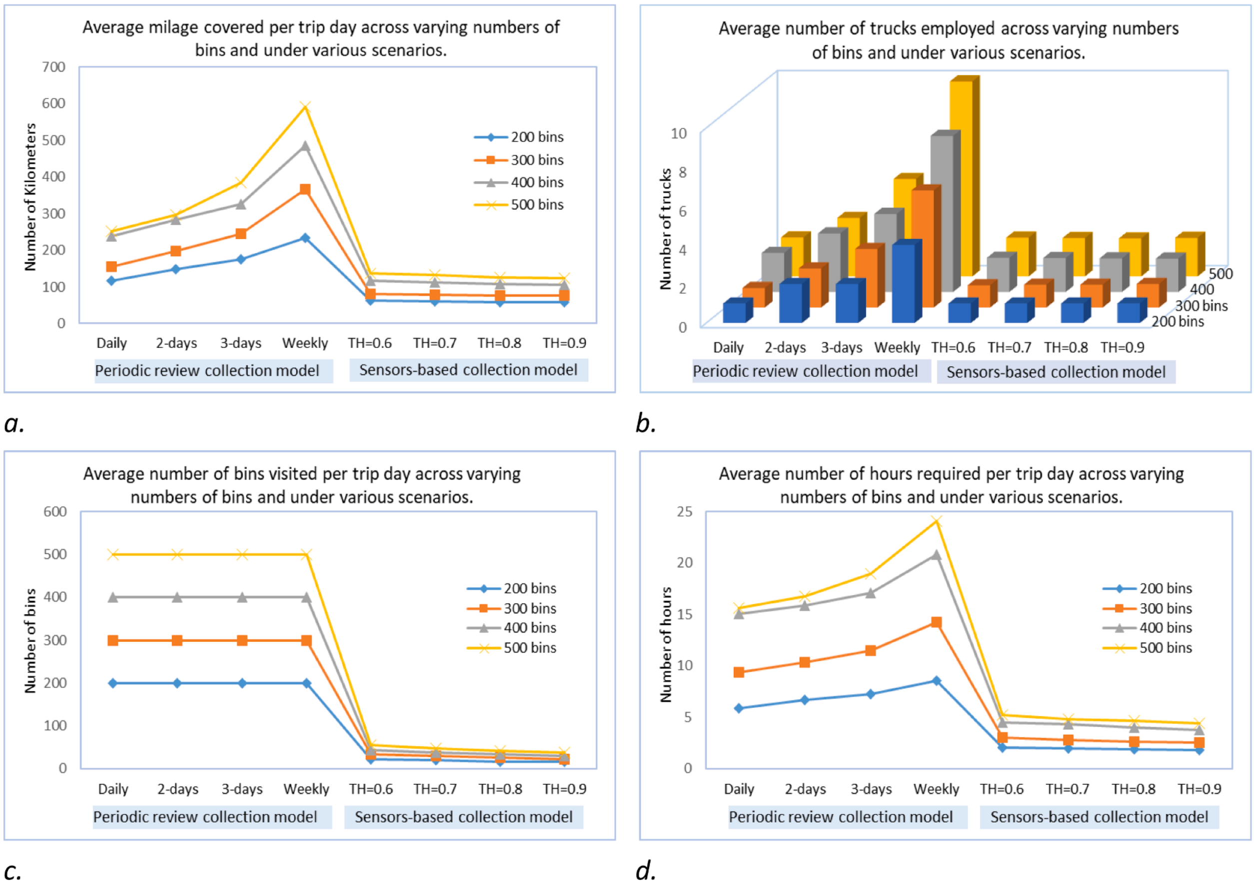

Fig. 7. By simulating varying bins (200, 300, 400, and 500), the average (a) number of kilometers traveled every trip day, (b) number of trucks used, (c) number of bins visited, and (d) number of hours to collect waste.

are needed in periodic-review waste collection scenarios because large amount of waste is collected, and a greater number of bins are visited than in sensor-based scenarios. As the number of bins grows, a greater amount of waste will be accumulated, necessitating a larger number of trucks for waste collection in every collection scenario.

Fig. 7(c) displays the average number of bins visited per trip day for different numbers of bins and also on various collection scenarios. The results revealed that the number of bins visited in the periodic-review waste collection scenarios remained the same for the simulated bins, whereas the number of bins visited in the sensor-based scenarios differs according to their threshold values. In sensor-based collecting scenarios, increasing the threshold values reduces the number of bins visited, and the pattern remained the same for each curve. The average number of hours spent by a garbage collection team collecting waste from the allotted bins is depicted in Fig. 7(d). The results demonstrate that the number of hours required to collect waste in the periodic-review scenarios is more than in the sensor-based collection scenarios. As a result, periodic-review scenarios demanded more resources than sensor-based scenarios. The sensor-based scenarios take only a few hours (between 2 and 5) to gather waste from the simulated bins (between 200 and 500), but the periodic-review scenarios take 5 to 24 h. As a result, in the periodic-review garbage collection scenarios, multiple waste collection teams will be required. The more bins there are, the longer it will take to collect waste therefore multiple waste collection teams are required.

4.4. Results discussion

When the two strategies were compared, it was found that by adopting the periodic review approach (in every scenario), the mileage covered much longer compared to when the wireless sensors-based strategy was used. The trucks covered a greater distance in wireless sensors-based collection with the lower threshold values (i.e., 0.6) than with the higher threshold value (i.e., 0.9). As a result, when the truck traveled a shorter distance to collect the waste, the garbage collection expenses were reduced. The truck emitted more CO_2 when utilizing the periodic review method (in the daily and after 2 days scenario) than when using the wireless sensors-based strategy. In the wireless sensors-based method, scenarios having higher bin filling threshold values may reduce CO_2 emissions. In terms of public satisfaction, in the first three scenarios for each strategy, overfilled bins were not emptied. However, for the fourth scenario, which was the weekly waste collection for the periodic review and the bin filling threshold scenario of 0.9 for the wireless sensors-based strategy. The periodic review technique discovered more overfilled bins (3.2 per day) than the wireless sensors-based strategy (2.16 per day). Overall, employees following the wireless sensors-based strategy needed less time to collect and dispose of the waste than those following the periodic review strategy in regard to the employees' time-saving performance metric. The time required to collect waste increased with various scenarios i.e., after 2 days, after 3 days, and weekly, since the capacitated truck was used to collect the waste by using multiple trucks in a day. When following the wireless sensors-based strategy, the driver took less time when the threshold value was higher since there were fewer bins to be emptied. As a consequence, the wireless sensors-based waste collection strategy was considered more robust than the periodic review approach.

The findings obtained from considering multiple capacitated trucks and simulating a different number of bins during the sensitivity analysis for each collecting scenario. The results showed that the periodic review collection scenarios covered greater average mileage on collection day than sensor-based collection scenarios. In sensor-based collection scenarios, the distance covered decreases as the threshold value increases. This happens because when the threshold value is lower, more bins are visited than when they are higher. Similarly, on average, more vehicles will be needed in periodic-review waste collection scenarios because more waste is collected, and a greater number of bins are visited than in sensor-based scenarios. The number of bins visited in the periodic-review waste collection scenarios remained same for the simulated bins, whereas the number of bins visited in the sensor-based scenarios differs according to their threshold values; increasing the threshold values reduces the number of bins visited. The periodic-review scenarios demanded more resources than sensor-based scenarios for collecting waste on time in a day. The sensor-based scenarios take only a few hours to gather waste from the simulated bins. However, in the periodic-review scenarios, a higher amount of time is required. As a result, in the periodic-review garbage collection scenarios, multiple waste collection teams and trucks will be used.

This study has contributed to the existing literature by outlining a comprehensive agent-based architecture that encompasses a wide range of aspects, including the garbage collection method. The computation speed of the simulation model for wireless sensor-based scenarios is observed, and the model takes only a few seconds (between 1 and 2) to run for a day by simulating 200 bins. We discovered that the model took linear time to execute as the number of bins increased. The findings could be improved by gathering real-world historical data on waste generation patterns. Using the exact quantity of bins present on the streets as well as their actual capacity may also aid in obtaining more accurate findings. Investigating the various tactics used for distributing trucks as well as the impact of various waste collection rules on the entire state may yield helpful information.

5. Conclusions and future works

This research encompasses a comprehensive assessment of IoT integration in urban environments, focusing on its role in enhancing efficiency, effectiveness, and sustainability. It delves into the benefits of real-time monitoring in waste management, highlighting its contribution to improved decision-making and operational efficiency. A key aspect of the study is the development of a predictive model aimed at optimizing waste collection routes. Additionally, the introduction of a multiagent simulation framework facilitates a detailed analysis of the advantages IoT brings to urban settings. The study offers a streamlined comparison between innovative IoT sensor-based systems and traditional methods of waste collection, with a particular emphasis on evaluating the economic, environmental, and livability outcomes of each approach. Using a subset of data from Qatar's northern Al Rayyan region, our experiments validated the waste production module's ability to effectively simulate and anticipate waste generation across various scenarios, comparing periodic review and wireless sensor collection strategies. Significantly, the findings reveal that the periodic review method resulted in longer waste collection travel distances, which increased expenses, increased CO_2 emissions, and required more time from workers. In contrast, the wireless sensor-based solution was more efficient and effective, resulting in cheaper collection costs, lower emissions, and faster completion times for drivers. This study focuses not just on waste collection efficiency, but also on broader environmental monitoring. The implications of these advancements are substantial, as they not only improve urban sanitation and public health but also contribute to smart city sustainability.

This study paves the path for more adaptable, responsive, and sustainable urban ecosystems, with waste management playing an important part in preserving the balance between urbanization and environmental conservation. It lays a foundation for future studies focusing on waste management's critical aspects within Qatar. To improve accuracy, forthcoming studies should incorporate the real quantity and capacity of bins on the streets. Expanding the study's scope to include multiple municipalities simultaneously, such as a nationwide analysis in Qatar or statewide studies in large countries, might provide more comprehensive insights. Furthermore, additional enhancements to the model and simulation components, such as performance and usability, are recommended. Looking ahead, integrating advanced technologies such as Artificial Intelligence to optimize collecting routes and blockchain for increased data security represents a natural progression in this rapidly evolving field. These innovations align with the dynamic advancements in the technical landscape, holding the potential for substantial enhancements in the efficiency and reliability of IoT-enabled waste management systems.

CRediT authorship contribution statement

Dr. Iftikhar Hussain: Writing – original draft, Validation, Software, Formal analysis, Conceptualization. **Dr. Adel Elomri:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing – review & editing. **Dr. Laoucine Kerbache:** Writing – review & editing, Validation, Supervision. **Dr. Abdelfatteh El Omri:** Writing – review & editing, Resources.

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.

Data availability

Data will be made available on request.

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