

# Analysis of IoT-Enabled Applications in Domestic Waste Management

**Seifedin Neffati**

Qatar University College of Engineering

**Adel Elomri** (✉ [aelomri@hbku.edu.qa](mailto:aelomri@hbku.edu.qa))

Hamad Bin Khalifa University <https://orcid.org/0000-0003-1605-9800>

**Tarek El Mekkawy**

Qatar University College of Engineering

**Laoucine Kerbache**

Hamad Bin Khalifa University College of Science and Engineering

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## Research

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# Abstract

This research paper addresses the application of the internet of things (IoT) to waste collection systems. It compares the traditional periodic review strategy versus an IoT-enabled strategy where we assume that the waste bins are equipped with smart sensors proving continuous monitoring of waste volume and weight per bin. A simulation model was developed for each strategy and tested using six different waste generation scenarios and different collection policies. The models were evaluated based on economic, environmental, and citizen satisfaction measures. Our results show that each collection model was best in a specific setting. For instance, the three collections per week policy performed the best for high waste scenarios whereas the IoT-enabled model with a 70% threshold was best for low waste scenarios.

To the best of our knowledge this paper is among the first attempt to model the use of smart bins in domestic waste management and to analyze its implications on three main features including economic, environmental and citizen satisfaction.

## 1 Introduction

Nowadays, the terms Internet of Things (IoT), big data, and Industry 4.0 are common in many fields. Many companies are interested in these new techniques and assessing their potential to gain a competitive advantage. The concept of the IoT was introduced by the British entrepreneur and start-up founder, Kevin Ashton, in the late nineties. He described a system in which items in the physical world would use sensors to capture data and send those data to computers. In 2009, the number of devices connected to networks exceeded the world population. At this point according to the global leader in the IT industry, CISCO, the IoT was truly born. The IoT is also known as the “Internet of Everything,” since everything from computers, machines, people, and even animals can connect and communicate with each other (Witkowski, 2016).

IoT solutions can benefit many fields, such as businesses, governments, and other organizations. For instance, businesses are using the IoT to monitor their supply chains, track customers’ spending patterns, dynamically monitor and maintain inventory levels, and plan preventive maintenance of machinery (Terra, 2019).

In the specific field of waste management, IoT started to play an important role since the last decade. Many innovative solutions and business concepts are being deployed worldwide to improve waste management processes at all levels including sorting, collecting, logistics and re-use. The use of smart bins seems to stand out of these new IoT-enabled solutions. For instance, traditional waste bins can now be equipped with sensors that record and remotely emit the physical characteristics of the bins (volume filled, waste weight, etc.) to a control room. Such smart bins are now being deployed in many cities and smart cities in the world and are being considered amongst Innovative Waste Management Solutions. Despite demonstrable proof of concept and industry experience, there is a lack of research on how such smart bins-referred to as IoT-enabled waste collection- can affect waste management. Within this context,

this paper is among the first attempts to model the use of smart bins in domestic waste management and to analyze its implications on three main features including economic, environmental and citizen satisfaction.

For instance, this paper assesses two strategies for domestic waste collection systems: a periodic review strategy and an IoT-enabled strategy. In most countries, the traditional way that municipalities collect waste is through periodic reviews. Collection trucks follow prescheduled routes and timings, regardless of the actual amount of waste in bins. On the other hand, the IoT-enabled strategy is more modern and makes better use of technology. Data are continuously collected on the amount and volume of waste generated in bins using sensing technology. The data are processed to identify bins that need to be emptied and to find an optimal route between these bins. Each route depends on the data collected, and hence, represents a dynamic side of this strategy.

These two strategies were evaluated with three performance measures. The economic performance was assessed by the total distance traveled by a collection truck. The environmental performance was evaluated based on the vehicle's total CO<sub>2</sub> emissions, and the citizen satisfaction was quantified as the percentage of overfilled bins. This research evaluates the two waste collection strategies by developing a simulation model for each strategy. The models developed allow us to study the waste collection systems over a year for different waste generation scenarios for Doha, the capital of Qatar. Finally, a comparison is conducted to determine the best model for the various scenarios.

The paper includes five sections: (1) Introduction that describes the IoT and its importance in smart waste management and presents the research objectives. (2) Literature review that presents papers published on waste collection problems. (3) Model development that describes, in details, the built model, the parameters, and the formulas used as well as the verification and validation of the model. (4) Experimental details that present the performance measures and the experimental policies and scenarios and, (5) Results and discussion to evaluate the different policies, scenarios, and conclusions.

## 2 Literature Review

Research into waste management started a few decades ago. However, there has been an increase in the number of publications since 2000 (Beliën et al., 2014). Researchers have examined solid waste management with a particular focus on vehicle routing. Nuortio et al. (2006) worked on optimizing vehicle routes and schedules for municipal solid waste collection in Eastern Finland and found that a significant reduction in waste collection costs could be obtained. Buhrkala et al. (2012) studied the routing of waste collection vehicles to find a cost-effective and optimal route for collection trucks, considering that all bins have to be emptied within a specified time window to satisfy customer demand.

Other researchers have focused on assessing the efficiency of the waste collection process. For instance, Guerrini et al. (2017) examined the effect of many key variables on the efficiency of the municipal waste collection services in the Province of Verona, Italy. The team collected data for five years between 2008

and 2012 and compared the efficiency of different municipalities. They found that properly organizing collection routes and frequencies, with a suitable allocation of trucks for a specific route, could improve the efficiency of the operations.

On the other hand, Ferreira et al. (2017) focused on assessing and benchmarking various municipal waste collection schemes. They highlighted the efficiency differences between schemes, which may help in improving waste management strategies. The study monitored three performance indicators: effective collection distance, effective collection time, and effective fuel consumption. These indicators were considered crucial for the efficiency and costs-effectiveness of waste collection for each collection scheme.

Many methods have been used to optimize waste collection. Bautista et al. (2008) found a solution for the waste collection problem in the municipality of Sant Boi de Llobregat in Barcelona using ant colony heuristics that reduced operating costs and acoustic contamination. Santos et al. (2008) designed a spatial decision support system that creates routes as a solution for multiple-vehicle routing problems. This decision support system includes a geographical information system (GIS) and heuristics, and incorporates real details such as time constraints, routing constraints, shift durations, and vehicle capacities. After designing the system, the team tested it for collecting waste in Coimbra, Portugal. They concluded that this system can be of significant help in analyzing and solving many complicated vehicle routing problems as well as providing benefits and cost reductions. The system can help in devising a more efficient waste collection scheme.

Optimizing waste collection routes has often been formulated as a traveling salesman problem (TSP). Das and Bhattacharyya (2015) focused on minimizing the length of municipal waste collection routes and proposed a heuristic solution to optimize municipal solid waste collection and transportation using the TSP. The result was a reduction of 30% in the length of the overall waste collection path. Jakubiak (2016) also tried to improve the collection of municipal waste by analyzing four routes used by the Municipal Cleaning Service in Krakow, Poland. The author focused on minimizing the distance covered by collection trucks and used a solution to the TSP to show that it was possible to shorten significantly the distance covered with an optimized routing schedule.

Ombuki-Berman et al. (2007) studied the routing of waste collection vehicles. They incorporated a time window, the multiple disposal trips of real waste collection systems, and staff lunch breaks, which made the problem more challenging. The team presented a multi-objective genetic algorithm for waste collection based on benchmarked data from the real world. Farrokhi-Asl et al. (2018) solved a multi-objective sustainable waste collection problem. They formulated three objective functions that included both operational and social costs. The model was used to evaluate fuel consumption, CO<sub>2</sub> emissions, and the impact on the environment. These have been some one of the few researchers to have considered the impact of waste collection on the environment.

Furthermore, other researchers have looked at the impact of using information technology, the IoT, and sensors. Milić and Jovanović (2011) considered waste collection as a dynamic vehicle routing problem. Not all information relevant to vehicle routing is known initially, and routes can be changed as more information becomes available. The system used mobile technology to monitor the current load of a collection truck in real time. The data collected were used to identify better routes to enhance collection efficiency. This dynamic collection methodology is more flexible for routing, providing better collection solutions that can accommodate instant changes.

IoT-enabled systems have been modeled to find optimal policies. For instance, Rovetta et al. (2009) implemented a network of waste bins equipped with sensors all linked to a data management system in Pudong, China, to monitor the overall and the bin-specific amount of waste generated and to identify the types of waste material. This helped to identify potentially hazardous materials and the data collected were used to optimize truck collection routes to minimize the costs of collection.

Mes et al. (2014) developed an IoT-enabled collection policy for underground containers equipped with sensors. They proposed heuristics with various parameters that were tuned depending on the requirements using optimal learning techniques and a simulation. An important part of their work was that they divided the containers into three different groups based on the level of waste: MustGo containers, MayGo containers, and NoGo containers. As the name indicates, a MustGo container needs to be emptied as soon as possible and it should be incorporated in that day's routing plan. A MayGo container can be emptied if it is on the MustGo route plan or nearby, and it holds a sufficient amount of waste. A NoGo container is not incorporated into that day's routing plan. They tested their solution using real-world data from a company in the Netherlands and found that with optimized parameters the cost savings could be as high as 40%.

Faccio et al. (2011) introduced an innovative vehicle routing model combined with real-time traceability data to find an optimized solid waste collection system. The real-time data were collected using different technologies, such as volumetric sensors, RFID, and weighing systems. The research had three objectives: minimize the number of vehicles per fleet, minimize travel times, and minimize the total distance covered. The authors conducted an economic feasibility study, which proved that the benefits of using the optimized routing method covered the costs of implementing the technology.

Anagnostopoulos et al. (2015) introduced a new approach by defining high-priority bins in predetermined critical areas in Saint Petersburg in Russia. Such areas require time-critical waste collection and could be hospitals, tourist sites, or the town hall. The authors developed four different models to ensure the speedy collection from these high-priority bins: the dedicated truck model, the detour model, the minimum distance model, and the reassignment model. The aim was to minimize the time needed for waste collection to reduce the possible negative effects of overfilled bins on citizens. The models were compared and a summary of the cases for which each model performs best was presented.

Sharmin and Al-Amin (2016) developed a cloud-based system that uses the ant colony optimization method to find an optimal waste collection route. They used sensors to monitor the waste level in bins

and to establish a usage pattern to improve the planning of waste collection. The system is flexible and dynamic and can handle changes in waste generation patterns or road traffic. Johansson (2006) examined the effect of different scheduling and routing strategies for solid waste collection. He assessed four collection policies: (1) static scheduling and static routing, (2) dynamic scheduling and dynamic routing to full containers, (3) dynamic scheduling and dynamic routing to almost full containers, and (4) static scheduling and dynamic routing to almost full containers. The study concluded that the dynamic scheduling and routing policies have lower operating costs and shorter collection distances compared with the static policies.

Blazquez and Paredes-Belmar (2020) worked on designing a domestic waste collection system that is composed of two stages. The first stage is a location-allocation problem solved using MILP and the second is a VRP in which Large Neighborhood Search heuristics are used to determine efficient collection routes. A case study for the commune of Renca in Santiago, Chile was analyzed and the researchers compared the designed bin to bin collection system with the existing door to door collection system and found that the former performed more efficiently in terms of the total daily distance traveled and the average work shift duration.

Vu et al. (2020) modeled a waste collection system in Texas and studied the inter-relationships of its parameters. The inter-dependency between collection frequency, collection type, waste composition, and truck compartment configurations was investigated using 48 scenarios. They found that travel time and distance can be saved by increasing the waste density and its collection frequency. Moreover, the use of dual compartments trucks were proven to be beneficial in reaching a more efficient collection system.

The objectives of most of the reviewed papers were to find optimal routes to collect the domestic waste at the least possible cost. While the majority focused on optimizing the process from an economic perspective, few researches also included the impact of this process on the environment. The contribution of this paper resides in: (1) quantifying the environmental impact of the proposed waste collection policies, (2) measuring the impact on the citizen satisfaction which was overlooked in previous papers, and (3) assessing these policies based on the three performance measures: economic, environmental, and citizen satisfaction.

### **3 Model Development**

Qatar is developing at a fast pace, with many construction projects running for several years. In addition, Qatar has a high average income, which results in a large amount of domestic waste. Statistics collected by the Ministry of Development Planning and Statistics (2017) show that the total amount of solid waste generated in Qatar in 2015 was 7.7 million tons, which included domestic waste, construction waste, bulky waste, and other types of waste. Domestic waste amounted to around 1.1 million tons, representing 14% of the total amount of solid waste generated. From 2010 to 2015, the amount of domestic waste generated each day has increased by around 30%, reaching 3002 metric tons per day in 2015 with an average of 1.23 kg per capita per day. According to the World Bank, collection costs represent around 80%

of municipal solid waste management budgets (Hoornweg and Bhada-Tata, 2012). Therefore, evaluating different domestic waste collection strategies could be valuable in terms of reducing costs, benefitting the environment, and increasing citizen satisfaction.

This paper analyzes the periodic review and IoT-enabled strategies for waste management from three aspects: economic, environmental, and citizen satisfaction. A waste collection model was built for each strategy, and the two simulation models were run for a simulation time of one year under different waste generation scenarios.

## 3.1 Agents

The agent-based simulation modeling software AnyLogic was used to develop both models. Three types of agents were built: bins, a truck, and a collection facility. The bins were used to model waste generation, and the truck was used to model the waste collection. The third type of agent, the collection facility, was the initial and final destination of the collection truck in each collection cycle.

Each cycle in the models has two phases that run simultaneously. In the first phase, the waste is generated by citizens who arrive at the bins to dispose their waste. For the periodic review model, at the end of this phase, all the bins send a message to the collection facility to be emptied. In contrast, for the IoT-enabled model, only the bins reaching a threshold send messages to be emptied.

In the second phase, the waste is to be collected. Initially, the truck is stationed at the collection facility waiting for the scheduled collection period. If the periodic review strategy is being modeled, the truck will collect waste from every bin and goes back to the collection facility. If the IoT-enabled strategy is being applied, the truck will go only to those bins that needed to be emptied. Once all the relevant bins have been emptied, the vehicle will go back to the collection facility. The total amount of waste collected, the total distance traveled, and the total estimated CO<sub>2</sub> emissions are recorded for this cycle, and a new cycle will begin.

As shown in Fig. 1, the model diagram has 50 bins located randomly in Qatar. The bins have two states. There is an 'idle' state when the bin is collecting waste deposited by citizens. During each cycle, the amount of waste deposited in each bin varies from bin to bin. In the 'waiting for truck' state, the bin is waiting for the truck to collect the accumulated waste. The transition between these two states is governed by messages. For the periodic review model, the transition from idle to waiting is triggered when the second phase starts. For the IoT-enabled model, an event called 'check bin level' is scheduled at the end of the first phase. It identifies all the bins that need to be emptied because the level of waste is above the threshold and changes their state to waiting. For both models, when a bin moves to the waiting state, it sends a message to the collection facility so that it is included in the next collection plan.

When the collection truck reaches a bin and collects the waste, the amount of waste in the bin is reset back to zero and the message 'bin emptied' is sent from the collection facility to the bin to change its state back to "idle".

Another event that occurs continually is called 'overflowed bin.' It checks the amount of waste in each bin. If the bin has reached its maximum capacity before it is emptied, then it is considered to be overflowed, which translates into an unsatisfied citizen. Another event counts the number of overflowed bins to provide an average daily percentage of overflowed bins. This metric is a proxy of citizen dissatisfaction and it is used to compare the different performances of the waste collection policies.

In all, the truck has six states. Initially, when the truck is at the collection facility, it is in the 'idle' state. Depending on the collection policy (once per week, twice per week, three times per week, or every day), an event will be triggered to transition the truck to the state 'waiting for start'. In this state, the truck is waiting to receive a message from a bin to be emptied. A conditional event called 'check bin filled' checks to see if any bin needs to be emptied. If not, the truck will return to the 'idle' state, otherwise it will enter the state 'moving to bin.' If the truck receives messages from several bins needing to be emptied, it will go to the nearest bin to its current location using the nearest neighbor routing logic. 'At a bin', the truck transitions between the three states 'moving to bin,' 'at bin,' and 'emptying bin' until it has serviced all the bins that needed to be emptied. Each time, it will move to the closest bin. When all bins have been serviced, the conditional transition 'check all bins serviced' will be satisfied and the truck will enter the last state 'moving back to facility' where it will return to the collection facility.

When the truck enters the 'emptying bin' state, it will send the message 'Bin emptied' to the bin and the waste level of the bin will go back to zero. The waste collected will move from the bin to the truck, and the CO<sub>2</sub> emissions and the distance traveled will be calculated. When the truck returns to the collection facility, the amount of waste collected will be added to the cumulative total waste. The emissions and distance traveled are added to cumulative totals as well. The truck will enter the idle state and wait for a 'start routing' event to trigger another collection cycle.

## 3.2 Parameters

The waste generation was modeled using the agents for bins using two events: the 'arrival of a citizen to dispose of waste' and the 'weight of the waste'. The arrival of citizens was modeled using a Poisson distribution with different rates of occurrences. A Poisson process is used to model a series of discrete events. In a Poisson process, the average time between events ( $1/\lambda$ ) is known but the exact time when an event happens is random and the events are independent of each other (Koehrsen, 2019). A Poisson distribution is appropriate here because the time when a citizen arrives to dispose of waste is not known and an arrival does not affect any other arrival.

Every time a citizen throws waste into a bin, the amount of waste is modeled by a normal distribution. The average weight of waste deposited by an arrival is 6 kg and the standard deviation is variable as described in Sect. 4.2. These parameters were chosen based on a study by Ahmad (2016), who collected waste generation data for 84 households in Doha for three months between February 2015 and April 2015. The bins have a capacity of 660 Liters (L) and the domestic waste density used was 0.481 kg/L (Aqua Calc). Furthermore, the bins were located randomly across the city of Doha.

The truck's average speed was 15 km/hour, and its capacity was not limited to simplify the model. The empty truck weighed 15 metric tons (Smith, 2017).

### 3.3 Problem Formulation

The distances between different bins and the collection facility were directly computed by AnyLogic. The latter has an integrated GIS map that includes all the routes and regions along with their names and locations, which allowed us to determine the real distances between bins. The map was downloaded in real time from OpenStreetMap.

The carbon dioxide emissions were calculated using:

$$EM_{ij} = FE \times FC_{ij} \quad (1)$$

where  $FE$  is the fuel emission factor, which is defined as the amount of carbon emissions per liter of fuel used. It measures the truck's efficiency by converting fuel consumption into carbon emissions. The fuel emission factor is a constant set to 2.62 kg/L (Li et al., 2015).  $FC_{ij}$  is the total amount of fuel consumed between two bins constituting the arc  $ij$ . Many studies have estimated fuel consumption using distance only, but this formula also takes into account the truck weight, its load, and the speed at which it is moving. The fuel consumption (Li et al., 2015) was calculated using:

$$FC_{ij} = (\alpha_{ij}(\omega + y_{ij}) + \beta v_{ij}^2)d_{ij} \quad (2)$$

where

$\alpha_{ij}$  is an arc-specific constant related to acceleration, road gradient, and rolling resistance.

$\omega$  is the empty truck weight.

$y_{ij}$  is the load carried by the collection truck between bins  $i$  and  $j$ .

$\beta$  is a vehicle speed coefficient that depends on air density and the frontal surface area of the truck.

$d_{ij}$  is the distance covered by the truck between bins  $i$  and  $j$  in kilometers.

### 3.4 Model Testing and Validation

Building the waste collection model in AnyLogic was done through numerous steps. At each step, the model was tested to ensure that it compiled and that the results were as expected. First, we built the waste generation process and defined the behavior of the bins ('idle' and 'waiting for truck' states). The waste generated was specific for each bin, so at each point in time, each bin will have a different fill level and accordingly, will be in a different state. The visual capabilities of the software made the verification straightforward, as bins in the 'waiting for truck' state were marked with a red dot. Furthermore, the model was paused and the waste level in each bin was checked to confirm that it was different for each.

Next, we included the routing logic for the waste collection truck, which was defined by a state chart as described in Sect. 3.1. The model was run and the state chart was carefully examined. All errors and misbehaviors were identified and corrected.

Then validation purposes, the same model was tested for a week using a sample of five bins. Three collection frequencies were tested for the periodic review: once per week, twice per week, and every day. Three types of data were analyzed: the total weight of waste collected, the total distance traveled by the collection truck, and the total CO<sub>2</sub> emissions. The results were compared with manual calculations done in Microsoft Excel, and the percentage errors did not exceed 10%. Since the model includes many uncertainties, these errors were considered acceptable.

## 4 Experimental Design

### 4.1 Performance Measures

In this research, the periodic review strategy and the IoT-enabled strategy were compared using three performance measures. The economic performance is very important for municipalities as waste collection costs, as mentioned earlier in the literature review, represent 80% of the total municipal waste management budget (Hoornweg and Bhada-Tata, 2012). Many studies have shown that collection costs increase linearly with the distance traveled by collection vehicles. Therefore, in this study, the economic performance indicator, monitored in the different scenarios, was the total distance traveled. Maintenance costs and salaries were assumed to be negligible since there was only one truck used in the model.

The second performance indicator is the environmental impact of the collection process. In particular, the focus is on the carbon dioxide emitted by the collection truck, which was estimated using Equations (1) and (2). These equations use not only the distance traveled but also the load carried by the vehicle and its speed.

The third performance indicator—the citizen satisfaction level—which was not considered so far in the literature, is a contribution of our study. Citizen satisfaction depends on the policies adopted by the municipalities for collecting waste. This indicator was estimated by recording the percentage of overfilled bins. Citizens passing by an overfilled bin and those who want to dispose waste will be certainly displeased by the bin state but also by the smell and the aesthetics of the public spot. Thus, the performance of the model is better when this indicator shows low numbers of overfilled bins.

### 4.2 Experimental Policies and Scenarios

The periodic review model was tested with four different collection frequencies: once per week, twice per week, three times per week, and every day. The IoT-enabled model was tested with three different thresholds for how full a bin was: 70%, 80%, and 90%. These are referred to as 'Policies'.

Two levels in the variability of the weight of waste deposited by each arrival of a citizen were tested. Low variability scenarios (LV) were modeled using a normal distribution with a mean of 6 kg and a standard

deviation of 2 kg. These scenarios simulate a homogeneous neighborhood in which citizens have similar waste generation patterns. The high variability (HV) scenarios had the same distribution but with a higher standard deviation of 4 kg to model a heterogeneous neighborhood where citizens come from different backgrounds and lifestyles and have different waste generation patterns.

Three different arrival rates were tested: a high arrival rate (HA: Poisson distribution with  $1/\lambda = 45$  min), a low arrival rate (LA: Poisson distribution with  $1/\lambda = 60$  min), and a variable arrival rate (VA: uniform at 45–120 min). These were used because at different times of the year, waste is generated in different patterns. During the summer, for example, the amount of waste is usually lower than the average since many expatriates leave the country on annual leave. On the other hand, during special events, such as a big sports event, a considerable flow of incoming tourists into the country will increase the waste generation rate.

The six scenarios were simulated for a year with 30 replications. The replications were necessary due to the stochastic nature of the model.

## 5 Analysis Of Results

### 5.1 Evaluation of the Periodic Review Model

The total weight of waste collected, the total distance traveled, the CO<sub>2</sub> emissions, and the percentage of overfilled bins were plotted and analyzed for the four policies and six scenarios.

The total weight was almost the same for each scenario in all policies. Nevertheless, the higher the arrival rate, the more waste was collected, which is logical as the amount of waste generated is directly related to the number of arrivals. The VA rate yielded the lowest amount of waste, with an average of 1910 tons per year compared to an average of 3489 tons per year for the HA rate. This is because the VA in the model lead to fewer citizens disposing of waste.

Increasing the variability of the waste disposed from a standard deviation of 2 kg to 4 kg with a mean of 6 kg had a negligible impact. The effect of increasing the variability on the total distance, total CO<sub>2</sub> emissions, and the percentage of overfilled bins was negligible. Therefore, we limit the analysis of the periodic review model to only the scenarios with a low variability.

We note that the total distance traveled was significantly affected by the collection interval. It increased as the number of collections in a week increased. The distance did not change with the arrival rate or the variability, since the distance traveled is independent of the amount of waste generated. The truck was scheduled to pass by all the bins and therefore the total distance traveled was the same in all scenarios.

Figure 2 (a) shows that the CO<sub>2</sub> emissions increased with an increase in the frequency of collection. This is the direct result of the significant increase in the distance traveled. The percentage increase between

one collection per week and daily collection is significantly high for each scenario, amounting to an average of 65%.

On the other hand, for all scenarios, when the frequency of collection was increased, the percentage of overfilled bins was reduced. It was zero for daily collections, as shown in Fig. 2 (b). The lower the arrival rate, the lower the number of overfilled bins. Since the VA rate leads to the lowest amount of waste, it is obvious that it had the lowest percentage of overfilled bins.

## 5.2 Evaluation of the IoT-enabled model

The total amount of waste collected under this model was similar to that for the periodic review model.

Figure 3 shows that, for almost all scenarios, the total distance decreases as the threshold increases. This is because the truck only visits bins at or over the threshold. Therefore, for a higher threshold, the truck visits fewer bins, leading to a lower total distance.

For the scenario with a LA-LV and the scenario with a LA-HV, the total distance decreased by 7% and 9%, respectively, when comparing a 70% threshold with a 90% threshold. The highest percentage decrease was for the VA rate scenarios, with an almost 10% decrease in distance traveled when comparing a 70% threshold with a 90% threshold. This is because, as previously noticed, the VA rate generates the least amount of waste, and the lower the amount of waste, the higher is the impact of changing the threshold.

The total distance decreased for the HA rate scenarios as well, but the drop was minor, from 42,547 km down to 42,108 km for the HA-LV scenario. Changing the threshold with a HA rate does not affect much the number of bins that need to be serviced. In other words, after a bin has been emptied by the truck, it reaches the threshold faster on subsequent days, and so it is included in routing schedules more often. The effect of changing the threshold could be better observed if it is accompanied with increasing the size of the bins.

The total CO<sub>2</sub> emissions are directly related to the distance traveled and the amount of waste. The shorter the distance traveled, the less carbon dioxide is emitted. Figure 4 shows that, in general, increasing the threshold reduces the CO<sub>2</sub> emissions. The lowest CO<sub>2</sub> emissions are for the VA rate scenarios, as they generate the lowest amount of waste. The decrease of emissions in the HA scenarios on increasing the threshold is not significant, due to the limited decrease in the distance and the high amount of waste.

Figure 5 shows that there was no significant change in the percentage of overfilled bins as the threshold changed for the HA rate scenarios. On average, almost half of the bins became overfilled and changing the threshold did not improve the situation. In contrast, changing the threshold had an impact on the percentage of overfilled bins for the LA rate and VA rate scenarios. The lower the threshold, the better the results. This is because when the threshold was increased, the probability of a bin becoming overfilled was higher. The best results were with the 70% threshold for the LA-LV scenario, which had a percentage of overfilled bins close to zero.

## 5.3 Comparison of the Two Models

Comparing the two models will give more insightful observations on their advantages and disadvantages. The total waste generated is not included in this comparison, as it is independent of the collection method used and the focus is on the performance of each method.

Furthermore, note that from analyzing each model separately, it was concluded that the variability does not have a significant impact on the output of the periodic review model or the IoT-enabled model. Thus, only scenarios with low variability will be analyzed. The conclusions attained from analyzing these scenarios will be assumed to be valid for the high variability scenarios as well.

### 5.3.1 High Arrival Rate

Figure 6 illustrates that the highest travel distance was for the daily collections policy. Thus, it was the worst performing policy in terms of this measure. The three IoT-enabled policies were comparable to each other and to the three collections per week policy. The lowest distance was for the one collection per week policy. Similar results were observed for total CO<sub>2</sub> emissions.

On the other hand, although it had the lowest distance traveled and lowest emissions, the one collection per week policy had the highest percentage of overfilled bins, more than 80%. The daily collections policy was best with zero overfilled bins. The second-best results were for the three collections per week policy with around 30% overfilled bins. The IoT-enabled model yielded similar results with all policies, which were slightly worse than the three collections per week policy, with an average of 50% overfilled bins.

If arrival rates are high, three collections per week is a good strategy, as it is the best model economically and environmentally and has a low citizen dissatisfaction level.

### 5.3.2 Low Arrival Rate

Figure 7 summarizes the performance of the models for a LA rate. The total distances traveled, and the CO<sub>2</sub> emissions are similar to those for the HA rate scenarios. The IoT-enabled model, for all thresholds, had around 16% less emissions compared to the three collections per week policy.

In terms of overfilled bins, the daily collections policy was still the best, with zero overfilled bins. The IoT-enabled model performed better, with only 2%, 4%, and 22% of bins overfilled on average per year for the 70%, 80%, and 90% thresholds, respectively.

Thus, for the LA rate scenarios, the IoT-enabled model is the most promising, when all measures are considered simultaneously, particularly with a 70% threshold.

### 5.3.3 Variable Arrival Rate

The results of the VA rate scenarios presented in Fig. 8 show that the best option is either the three collections per week policy or the 70% IoT-enabled policy. The policies had similar total distances (35,432

km and 35,838 km). The three collections per week policy has a lower percentage of overfilled bins, nearly 0% compared to 14% for the IoT-enabled model. However, the 70% IoT-enabled policy has 16% lower total CO<sub>2</sub> emissions. Thus, for this scenario, the optimal policy will depend on the priorities fixed by the municipality. If the latter prioritizes citizen satisfaction, the three collections per week policy will be the best option. Otherwise, if the priority is to minimize the environmental impact of waste collection, the IoT-enabled model with a 70% threshold is the best strategy.

## 6 Conclusions

This study was the first to incorporate the three performance measures—economic, environmental, and citizen satisfaction—to compare the traditional waste collection process, as commonly implemented by municipalities, and the IoT-enabled model, which exploits sensing technology and the IoT. Important conclusions can be drawn from the results, which may help municipalities in devising waste collection strategies that are greener and less expensive with higher citizen satisfaction:

If the amount of waste generated is high, a traditional waste collection strategy with three collections per week will yield better results than an IoT-enabled strategy.

If the amount of waste generated is low, switching to an IoT-enabled strategy may improve the economic, environmental, and citizen satisfaction aspects of the waste management process.

If the amount of waste generated is highly variable, the decision to switch from a periodic review strategy to an IoT-enabled strategy will depend on the government's priorities. A 70% IoT-enabled strategy may have a positive environmental impact, as vehicle emissions are lower, although citizen satisfaction is higher with three collections per week. The variability does not have a significant impact on the total amount of waste collected over a year.

This research is a good initial assessment of the impact of different waste collection strategies. It could be used as a baseline for future work that investigates these crucial aspects of waste management in the State of Qatar. The results could be refined by collecting real historical data on waste generation patterns. Using the actual number of bins in the streets, their exact location, and their actual capacity may also help in getting more accurate results. Furthermore, citizen satisfaction was quantified based solely on the percentage of overfilled bins. This could be enhanced, for example, by incorporating a metric that measures the intensity of the smell from a bin or the hazards related to the public health and the environment.

The models in this study had one truck with unlimited capacity. It serviced only Doha, the capital city of Qatar. Future work can extend the models to incorporate other cities with a fleet of trucks with limited capacities. Qatar could be divided into zones, with a fleet of trucks allocated to each. Investigating different strategies for allocating trucks and the impact of the different waste collection policies on the entire state may provide useful insights.

Another extension would be to compare different truck routing methods, such as nearest neighbor routing and TSP, and even a hybrid approach that includes both methods. The model could evaluate which routing method is currently better for a specific zone. The waste collection model would then include all the sectors along with their respective fleet of trucks and routing logic.

## Declarations

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.

Authors have contributed equally to this research work.

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## Figures

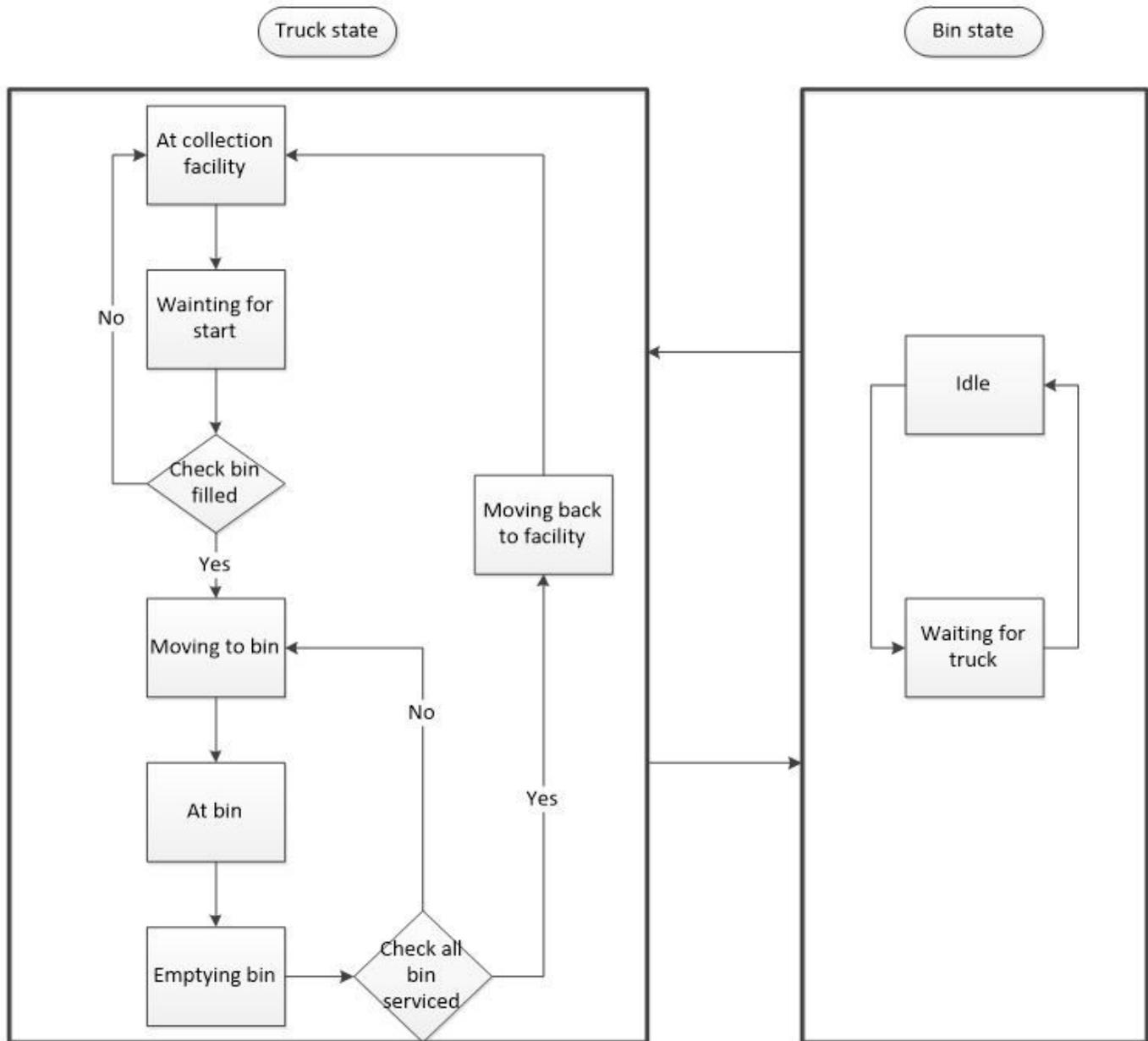
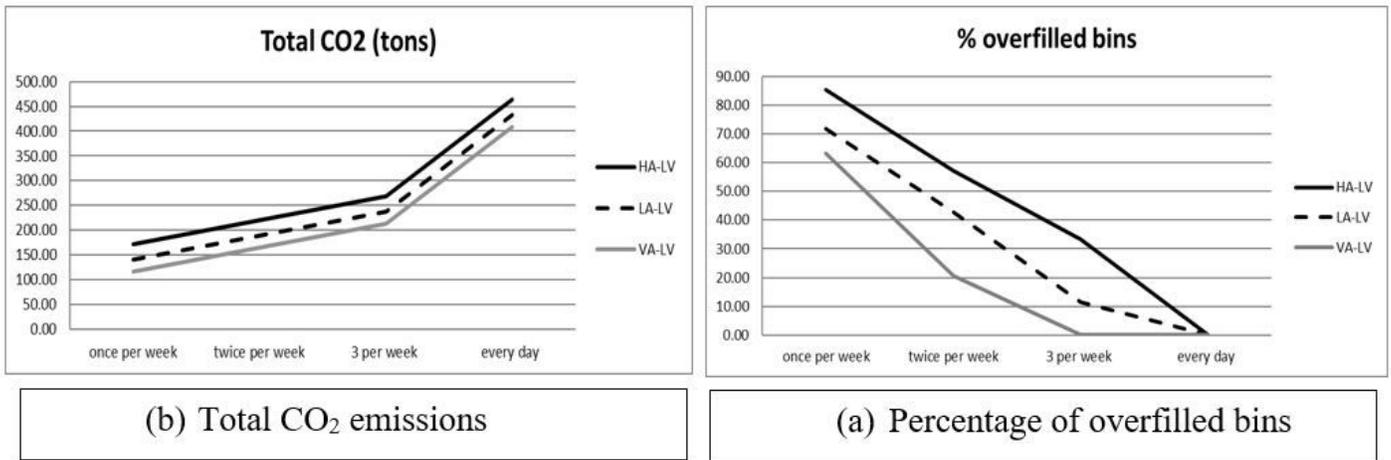


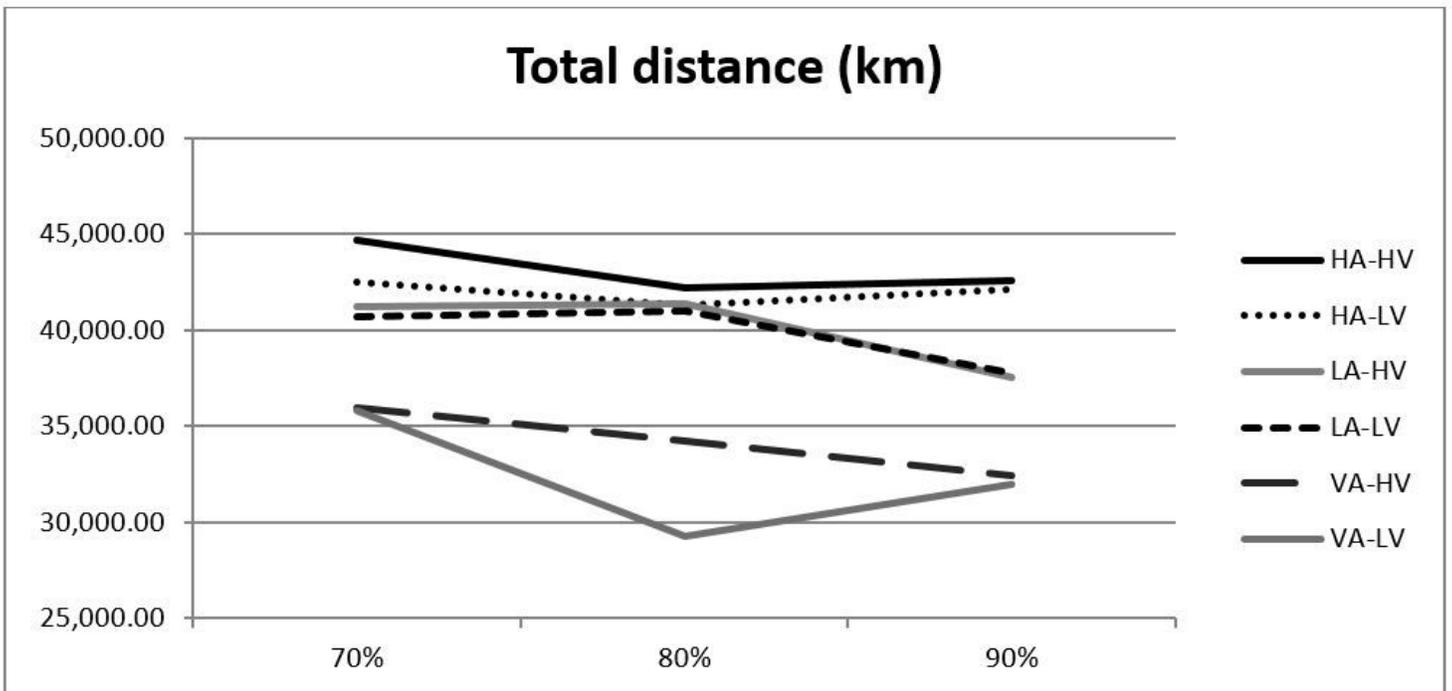
Figure 1

Model flow diagram



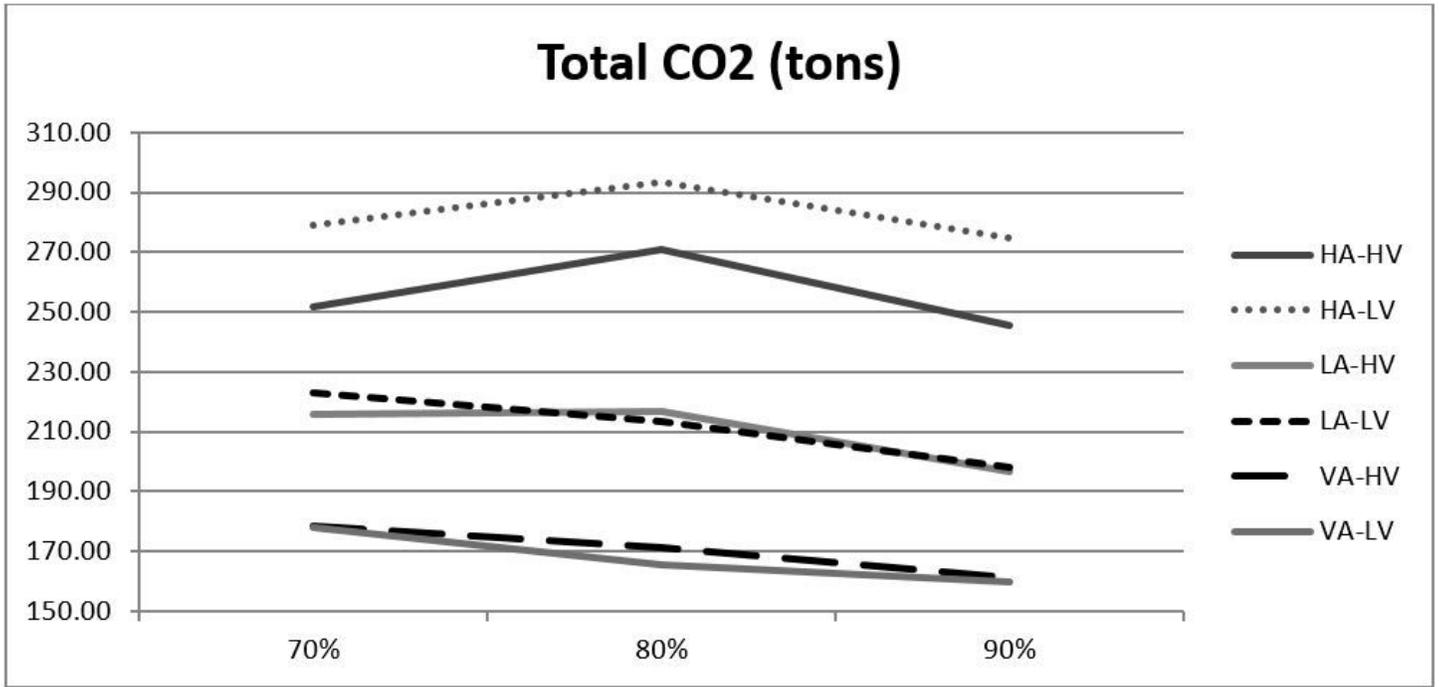
**Figure 2**

Performance of the periodic review model for the low variability scenarios



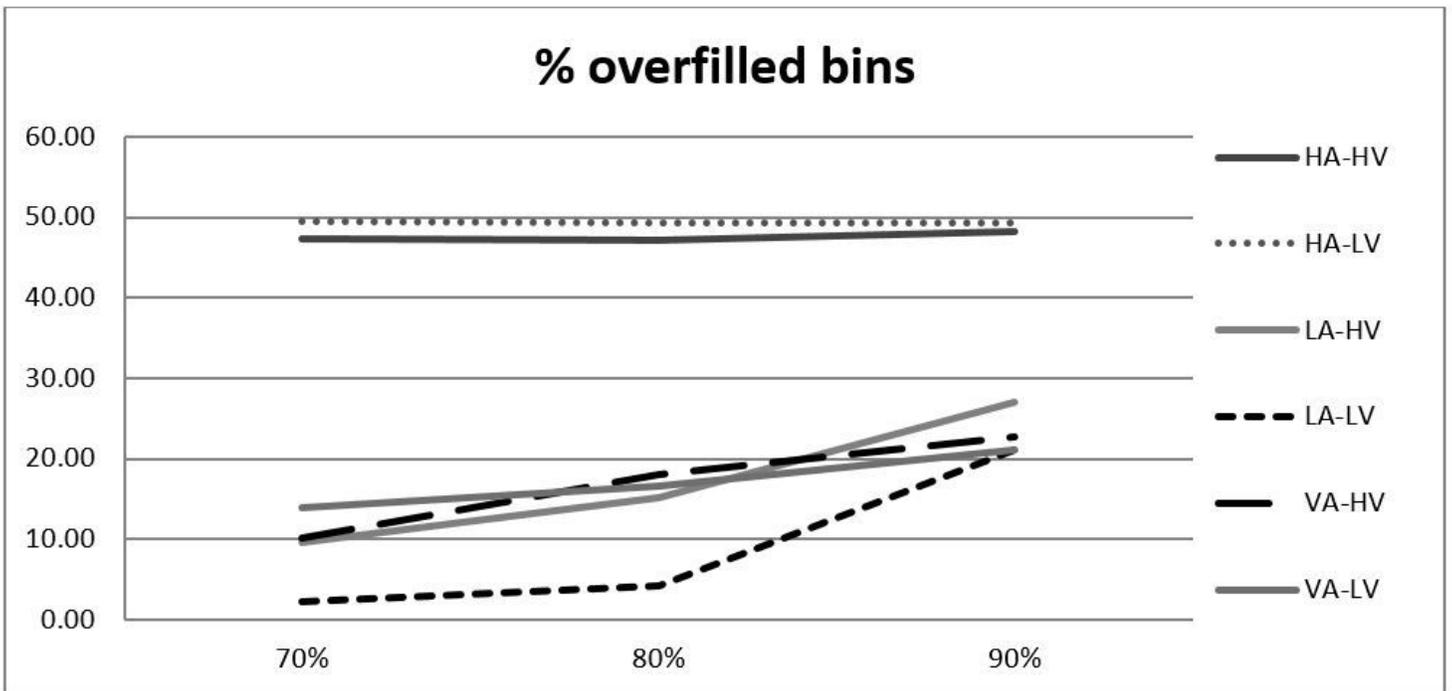
**Figure 3**

Total distance traveled by the truck for the IoT-enabled model for the six scenarios



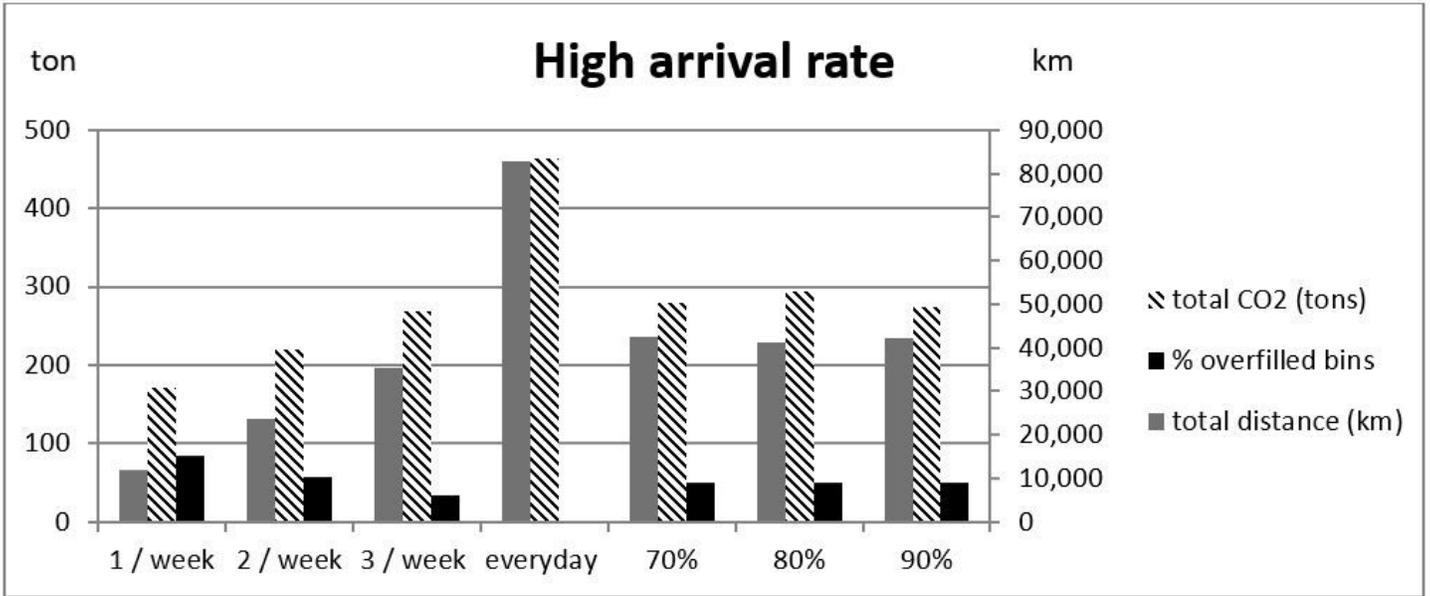
**Figure 4**

Total CO2 emissions for the IoT-enabled model for the six scenarios



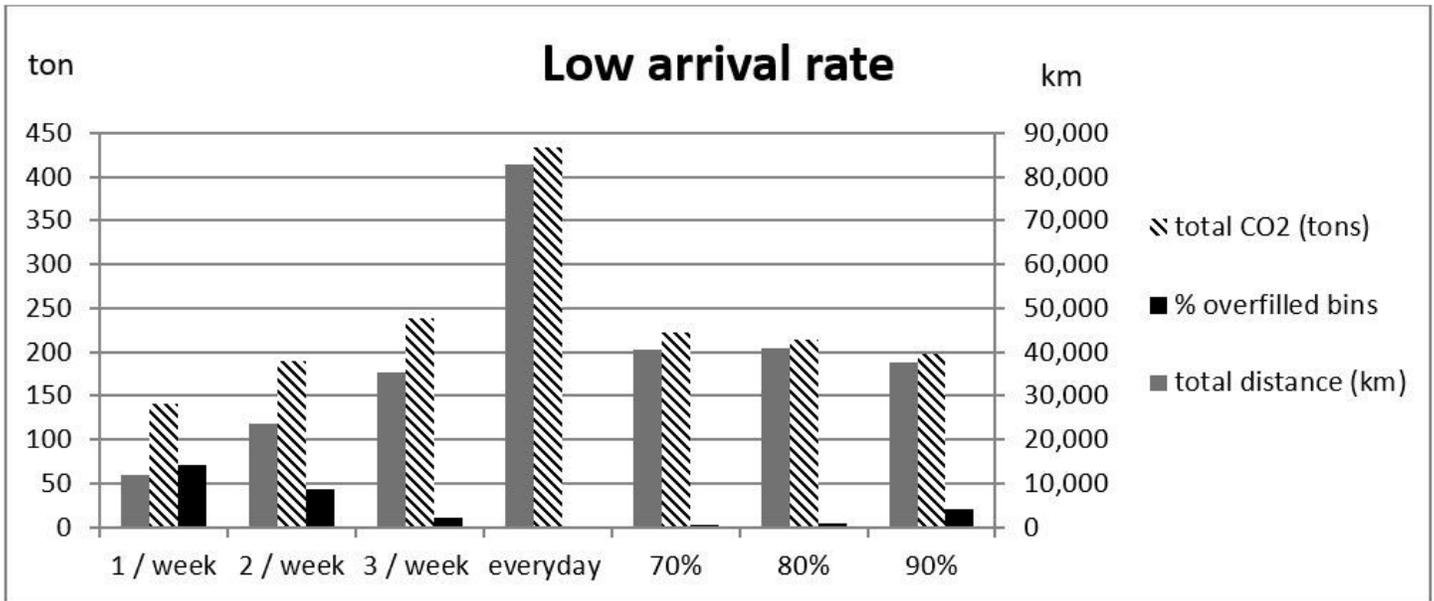
**Figure 5**

Percentage of overfilled bins for the IoT-enabled model for the six scenarios



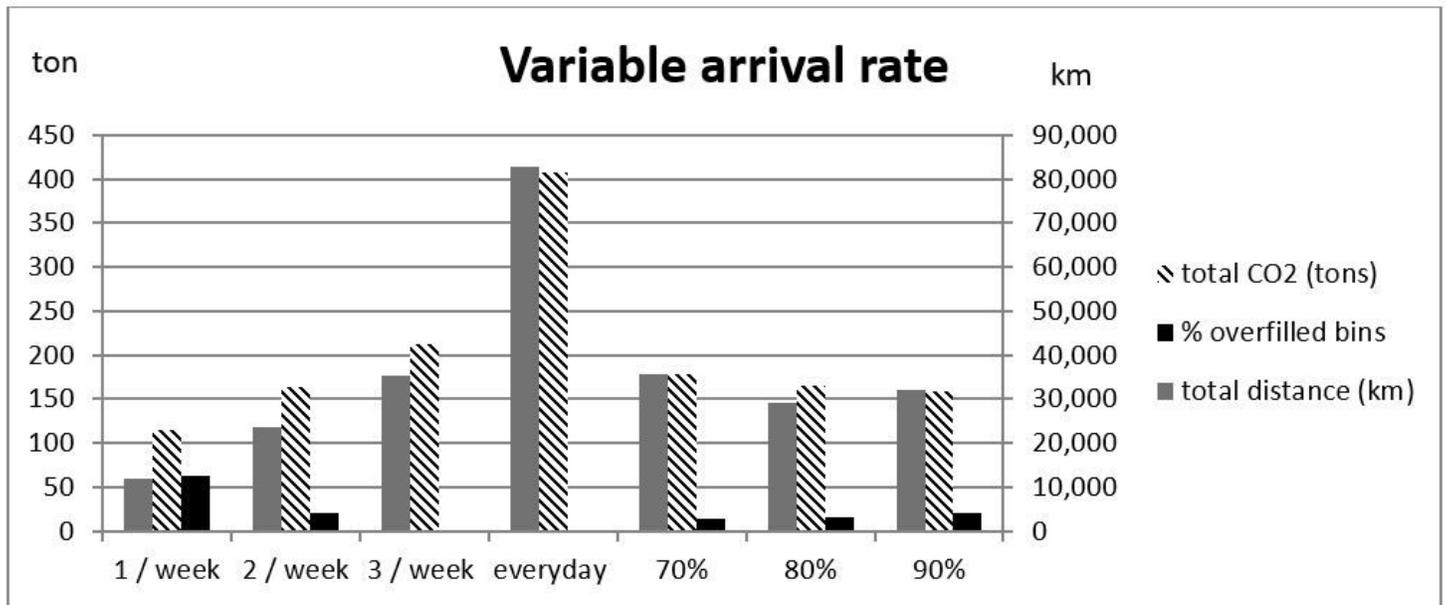
**Figure 6**

Performance for a high arrival rate



**Figure 7**

Performance for a low arrival rate



**Figure 8**

Performance for a variable arrival rate

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