Dynamic Model Implementation for Smart Solid Waste Collection

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ABSTRACT

Source scripts and Data Availability:
The source code, data, and/or other artifacts have been made available at https://we.tl/t-lHsj7TPXWN .

1 INTRODUCTION

Nowadays the concept of smart city is spreading all over the globe thanks to the development of new technologies, such as Internet of Things (IoT) [3] for environmental monitoring and Artificial Intelligence (IA) [13] for data mining. Both public administration (PA) and private sector are trying to integrate those innovations in their infrastructures to provide for more responsive and cost effective solutions. Traffic management, transportation, power consumption, health care and crime detection are just some examples of the possible fields of application that can be widely simplified by means of automated controlled systems. Particularly, the implementation of new approaches for Municipal Solid Waste (MSW) collection has become a huge source of interest for PA due to the rapid growth rate of population and urbanization [2]. As time passes the generation rate of solid MSW is getting more unpredictable and it is becoming more and more complex to manage refusals collection (80-95% of expenditure) [4]. Unfortunately standard systems are costly and not suitable to face unexpected situations or rapid modifications. In this project we propose a novel dynamic scheduling model for MSW logistics, which exploits smart bin devices for defining the garbage trucks collection spots through fulfilment level monitoring. A simulation is conducted in order to compare the behavior of the smart bin approach with the static policy employed by many waste collection operators today (fixed routes and predetermined pick-up frequencies).

2 SMART SOLID WASTE COLLECTION SYSTEM

Several researches have been conducted by the scientific community regarding both the design of smart bins [12],[10],[9], for gathering sensors information, and trucks communication networks for MSW for logistics optimization [5],[6],[7], [8]. In this section we summarize the general features and components which need to be implemented for a functioning smart waste collection model. A smart bin can be viewed as a device composed of three main parts: sensor, power supply and micro-processor (figure 1). The first one provides the environmental data that needs to be shared, such as temperature, humidity and amount of waste. Ultrasound sensors are the most commonly applied to determine the level of fulfilment in the bin. The power supply are generally rechargeable batteries or solar panels, in order to make the device independent from external electric current source, and sustain the power consumption of the whole system by means of energy harvesting techniques. The micro-processor, which is generally an Arduino or Raspberry Pi model, is in charge of both the communication with the sensors and the Data Warehouse, storing all historic data:

- Sensor-Arduino: short range communication based on Bluetooth or RFID
- Arduino-user: long range communication based on Wi -Fi or GSM module

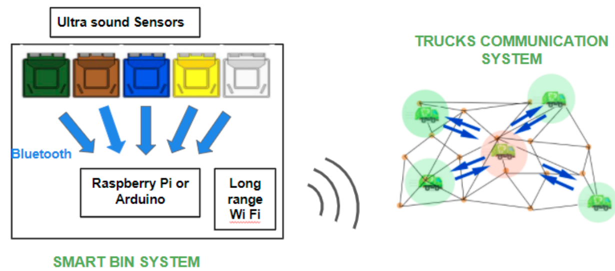

Figure 1: Smart bin components scheme

Once collected, the sensors data are analysed to optimize the vehicles route and create forecasting model to predict the level of fulfilment associated to each bin over time. This has a considerable effect on reducing the operational costs, as demonstrated by different studies that have already tried to prove the effectiveness of these innovative systems [8], [6] by means of computer simulations and empirical experimentation.

3 MODEL IMPLEMENTATION

In order to evaluate the effectiveness of the proposed dynamic algorithm a solid waste collection system has been implemented, by means of *MATLAB* software, to perform the simulations. It can be divided into three main components/sections:

- City
- Trucks
- Waste Generation and Traffic Generation System

3.1 City

A urban area inhabited by 100000 people is modelled has a graph. Each node represents a waste collection spot and 5 different solid waste categories are taken into account: organic, plastic, glass, paper and residual waste. The number of bins for the model, necessary to satisfy the population, has been sized by assuming, for the sake

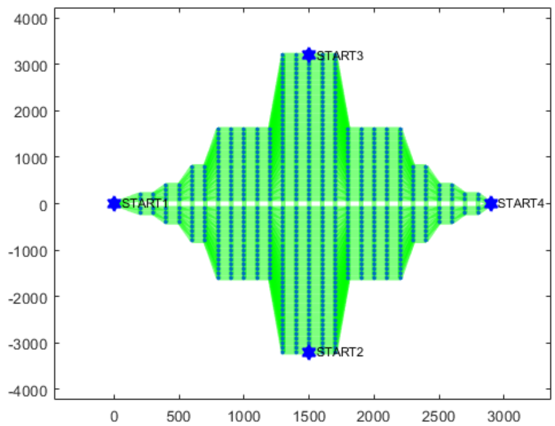

Figure 2: Graph model of the city at the beginning of the turn. A system of colors is applied to represents the amount of traffic on each nodes, expressed in minutes (green for low, yellow for medium and red for high). Star shaped nodes represent the deposits

of simplicity, that the garbage production is uniformly distributed during a year. This is done in order to have just a general idea of the amount of different solid waste produced in a week, distinguishing it by waste categories and following the general disposition proposed in the ANPA documentation [11]:

- Evaluation of the overall weekly produced solid waste $[Kg]$

$$W_{tot,week} = \frac{n10^5}{52} \tag{1}$$

- Volume produced weekly, per waste category i $[m^3]$

$$V_{tot,week}(i) = \frac{W_{tot,week} w_{\%}(i)}{\rho(i)} \tag{2}$$

- Number of bins necessary to overcame the weekly produced volume, per waste category

$$n_{bins}(i) = \frac{V_{tot,week}(i)}{V_{bin}(i)} \tag{3}$$

Where n is the annual average waste produced by one person (500 $Kg/(year*person)$), ρ is the density (Kg/m^3), V_{bin} is the bin volume capacity (m^3) and $w(i)_{\%}$ is the waste percentage rate, associated to each waste category. The overall number of nodes is defined as the maximum value throughout the number of bins 3 and the remaining ones are uniformly distributed in the graph (figure 2). In order to simplify the model of the city, we took into account of only street pick up service for the refusal collection. Otherwise it would have been necessary to consider also the volume for bins associated to residential buildings, which would have implied a further source of complexity of the graph implementation.

Each node is characterised by a numeric index for the identification, the waste percentage level from the ultrasound sensors and the GPS coordinates tags (in the model x and y coordinates). The edges, connecting the nodes by means of the city streets, are instead defined with two properties: the distance and the monitored traffic level. The model is then divided into 4 main subareas (sub-graphs), accordingly to the implemented deposit nodes. This is done in order to simplify the logistic of the trucks, which can only operate in a preassigned area of the city.

3.2 Agents

The trucks for the waste collection, are modelled as *MATLAB* structures, which move along the graph during the simulation, starting and finishing at the same node (deposit), which depends on the served subarea of the graph. They communicate between each other: the occupied positions in the model, in order to avoid collision are also provided with counters for the evaluation of the total collected waste and travelled distance. Each one of them is associated to a particular category of waste and they have been sized considering a daily turn of 6 hours.By assuming 5 minutes as the average time to empty a bin (transportation and collection), the number of trucks per kind, necessary to travel along the whole model at each turn, can be determined by dividing n_{bin} over the steps per turn (72). The resulting value is then rounded by a multiple of the number of the considered start/end nodes (in this model is equal to 4), in order to guarantee that the trucks operating at each deposit are the same.

3.3 Waste and Traffic Generation

Both the functions for the evaluation of solid waste and traffic have been modelled as stochastic processes. For what concerns the generation of the different categories of waste inside the bins, we considered three possible scenarios taking as reference values the minimum and maximum daily produced solid waste by one citizen, provided by the *ANPA* documentation [11]. The gaussian distributions are defined in such a way, the 99.7% of the possible waste outcomes are contained within certain upper and lower bounds 3 :

- Low production :

$$\begin{cases} \mu(i) = \frac{w_{mean}(i)+w_{min}(i)}{2} \\ \sigma(i) = \frac{\mu(i)-w_{min}(i)}{3} \end{cases} \tag{4}$$

- Medium level :

$$\begin{cases} \mu(i) = w_{mean(i)} \\ \sigma(i) = \frac{\mu(i)-w_{min}(i)}{6} \end{cases} \tag{5}$$

- High level :

$$\begin{cases} \mu(i) = \frac{w_{mean}(i)+w_{max}(i)}{2} \\ \sigma(i) = \frac{w_{max}(i)-\mu(i)}{3} \end{cases} \tag{6}$$

Similarly, the traffic level is simulated considering it as a random process taking into consideration three possible scenarios: low,

Table 1: References and number of bin per kind

Param	O	PA	PL	G	R
ρ $[Kg/m^3]$	450	230	200	200	80
V_{bin} $[m^3]$	2.4	3	3.2	3.2	3.2
$w_{\%}$	30	15	24	11	20
n_{bins}	268	210	361	166	752

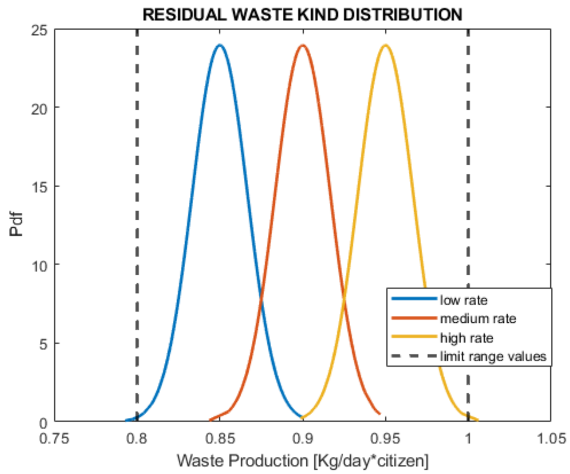

Figure 3: Distribution of residual solid waste for the considered 3 different waste generation scenarios.

medium and high level. It is modelled as spreading from some intersection of the model roads (nodes), which depends on the selected case.The intensity t_{tr} is defined as a model penalty, quantified as wasted time (minutes), and it implements itself at each simulation step accordingly to the following expression:

$$\begin{cases} t_{tr}(t) = t_{tr}(t-1) + \Delta t_{tr} \\ \Delta t_{tr} = T_{step} B(0,1) N(0,1) \end{cases} \tag{7}$$

Where T_{step} is the maximum admissible increment per turn and depends on the traffic scenario, $B(0,1)$ is a binomial probability distribution value (1 or 0) and $N(0,1)$ is a normal standardized gaussian variable. In the first half of the turn the simulation traffic intensity can either increase or remain stable, while in the second half it can decrease or remain constant. An upper bound constraint of 10 minutes is imposed to the model streets traffic in order to simplify the evaluation of the simulations, by considering a more compact range of possibilities for the model evolution.

4 WASTE COLLECTION ALGORITHMS

4.1 Dynamic model

The proposed decision algorithm for the waste collection is based on the evaluation of each truck surrounding (in a range of 1 Km) for establishing which of the considered bins is the best candidate to visit, in terms of travelled distance,space d_{bin} (m) and wasted time $t_{tr,bin}$ (min) between the position of the truck and the smart bin, and the refusal percentage in the bin w_p. A loss function has been implemented in order to determine the most suitable move to pursuit:

$$f_{MIN} = (\frac{d_{bin}}{500} + t_{bin,tr})(1 + (\frac{w_{p,ref}}{w_p})^{\alpha}) \tag{8}$$

where 500 is the conversion factor from m to min assuming the average speed of a truck during its turn is 30 km/h and α and $w_{p,ref}$ are parameters to weight the distance and the solid waste percentage over the decision to make.

4.1.1 $w_{p,ref}$. Defines which percentage is sufficiently high to consider a bin as a plausible target. It have to take into account of the level of fulfillment of the other bins present in the sub graph. For this reason, after a certain period of time (30 min), the reference waste level is updated accordingly to each category of trash and subgroup of trucks operating in the same area(figure 4). Since we are considering a distributed system, and so the amount of solid waste in the whole number bins is unknown, $w_{p,ref}$ is defined accordingly to the actual information the moving trucks happen to gain for a particular instant of time. Each truck shares the waste level in the surrounding bins with a leader truck. Once the whole picture is gathered together, the mean value is determined and the reference value is sent back to the others to use it as $w_{p,ref}$ for the cost function. Furthermore the trucks communicate between each other at each time step their position in order to avoid traffic congestion during the turn (figure 5).

4.1.2 α. It defines how much the waste percentage weights over the travelled distance term in the bin evaluation. At first, it is assigned equal to 3 such that the decision is biased to maximize the overall collected amount of garbage. After a while, when the trucks are almost finished with the turn (90%), α is changed to 1 and the cost function is slightly modified:

$$f_{MIN} = (\frac{d_{dep}}{500} + t_{tr,dep})(1 + (\frac{w_{p,ref}}{w_p})^{\alpha}) \tag{9}$$

where d_{dep} and $tr_{tr,dep}$ are the distance and traffic time between the considered target bin and the deposit to which the truck is supposed to move back.

One advantage of this approach is that it permits to have a wide understanding of the model refusals distribution, without the need of monitoring all the smart bins present in the system. Plus, the "pick-up dilemma" can be treated dynamically, as the behavior evolves over time. On the other hand it results in a lack of knowledge whenever the trucks are close together and the gained information overlap, and so its capability in evaluating the actual percentage of waste is highly associated to the configuration of the moving agents and their relative position in the graph.

Table 2: Daily waste generation per kind

Daily Waste Production	O	PA	PL	G	R
w_{min} $[Kg/cit * day]$	0.25	0.15	0.36	0.15	0.8
w_{mean} $[Kg/cit * day]$	0.29	0.18	0.375	0.19	0.9
w_{max} $[Kg/cit * day]$	0.33	0.21	0.39	0.23	1

4.2 Standard model

Standard waste collection can be simplified as a logistic optimization problem in which the objective is to reach the maximum number of available collection spots while minimizing the overall time-distance between each over. This is conventionally known as the Traveller Salesman Problem (TSP), which is an algorithmic problem tasked with finding the shortest route between a set of points and locations that must be visited. The trucks are the moving agents,

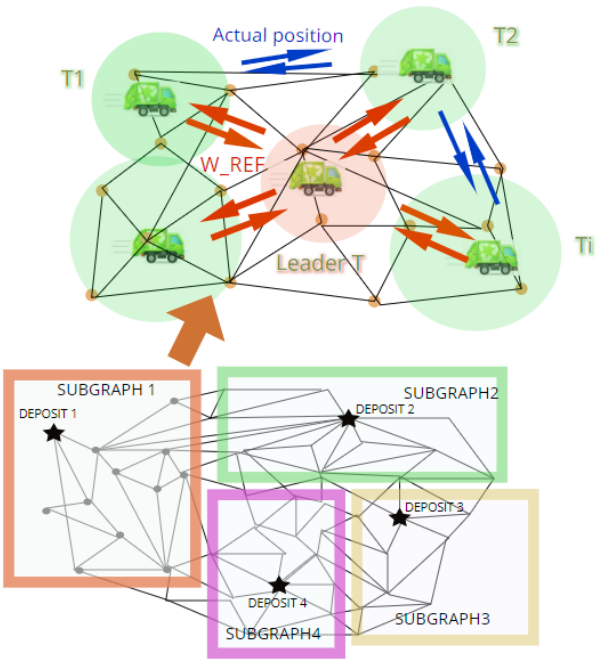

Figure 4: Vehicles moving in the sub-graph communicates between each other their position and exchange information regarding the surroundings to compute the reference waste value

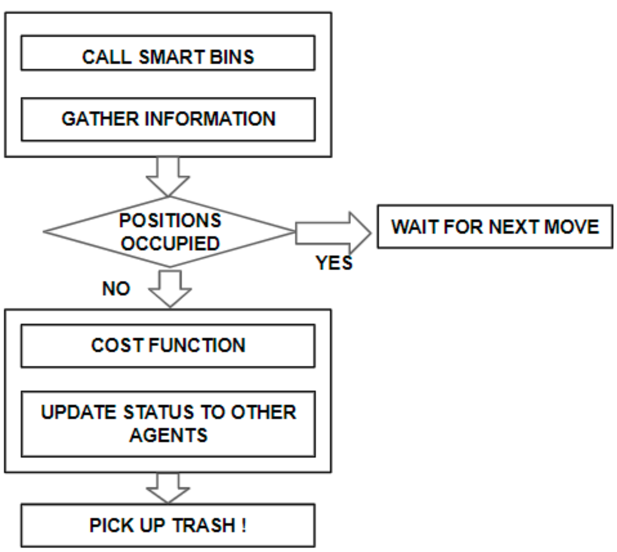

Figure 5: Algorithm scheme applied by each agents to define the best location to visit while considering the other trucks

which need to start and end their refusal collection path to the same position (deposit node), and so we would refer to the problem as a multi-agent TSP. The main issue with its resolution is that is a Non Polynomial problem, since the definition of an optimal global solution would require a computational cost $O(n!)$. It is still possible to find a more computationally suitable solution by adopting heuristic approaches reducing the complexity from factorial to exponential. In this case the definition of the trucks paths have been done by applying a genetic algorithm, which searches for the solution which minimize a predefined cost function (travelled distance) from an initial guest configuration, using an open-source *MATLAB* package [1]. This approach is applied distinguishing between subareas (sub graphs) of the city model and waste categories, so to have predetermined pick-up routes for each truck.

5 MODELS COMPARISON

The comparison between the two approaches, dynamic and standard, is accomplished by defining a simulation of one week composed of 7 working days, with a 6 hours. The week schedule for the waste collection is summarized in table **??**.

Table 3: Week schedule

MON	TH	WEN	TU	F	SAT	SUN
R	O	R	O	R	O	R
G	PA	PL	R	PA	G	PL

Several environments are set up to evaluate the model behavior under different operative conditions. Combining the previously mentioned levels of waste and traffic, a total of 9 conditions have been considered, each one of which is repeated 10 times. The evaluation parameters applied for the comparison are the following ones:

- Total Collected Waste C_{tot}: is the total amount of solid waste mass collected by the vehicles in a week.
- Total spent time T_{tot}: is the time spent by the vehicles during the week and it takes into account of the time to move from one pick up location to the next one, the average time to empty the bin and the one wasted in traffic.
- $\Phi_{tot} = \frac{C_{tot}}{T_{tot}}$

The results in figure 6 suggest that the two model have similar performances in terms of quantity of collected waste C_{tot}. The dynamic models is characterized by a higher variability due to the decision making process attributed to the cost function, while the other one remains steady for all the 10 repetitions since the truck route is predefined. For what concerns the time spent T_{tot} it can be noticed that the dynamic case assumes much lower values (figure 7), meaning that the algorithm does seem to be able to avoid busy roads and minimize the travelled distance between pick up stops. Both those aspects can be appreciated by looking at figure 8, where is evident the upper hand capabilities of the dynamic solutions regardless of the environmental condition. However some considerations must be done about the limits presented by the simulation of a week schedule. Some assumptions and simplifications have been done, such as the function for waste and traffic generation, which can be refined to represent more closely real life conditions. Unexpected situations should be taken into account, such as malfunctioning of

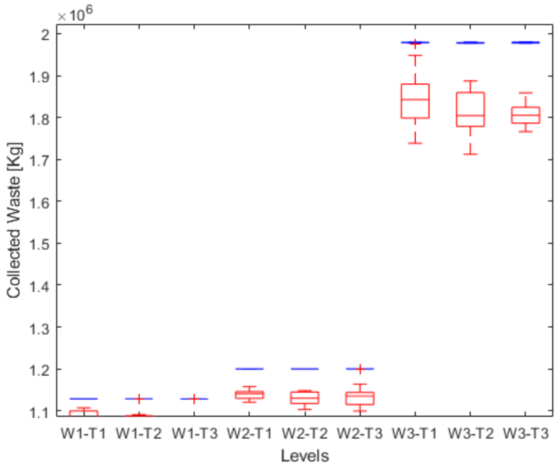

Figure 6: Box plot representing C_{tot} for the considered 9 environmental conditions. The blue boxes are associated to the dynamic model results while the blue ones are for the standard model.

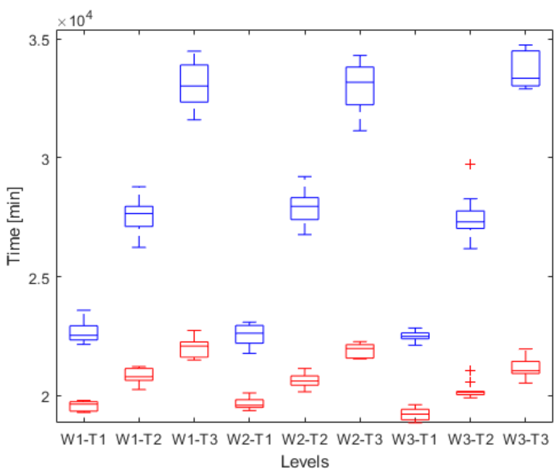

Figure 7: Box plot representing T_{tot} for the considered 9 environmental conditions. The blue boxes are associated to the dynamic model results while the blue ones are for the standard model.

sensors and truck unavailability due to failure, and implement policies to overcome those issues. Another important aspect to consider is that the time spent by the vehicles for displacements is different from the one assumed as t_{step} for the purpose of computation. The first one has been treated as a penalty value for the comparison of the two models, while the second one is the measure with respect to which the simulation duration (number of iterations per turn) has been defined. Furthermore the use of TSP solution algorithm to define the trucks path by means of distance minimization, is just an approximated approach to represent the standard model. MSW management does take into account of other variables to define

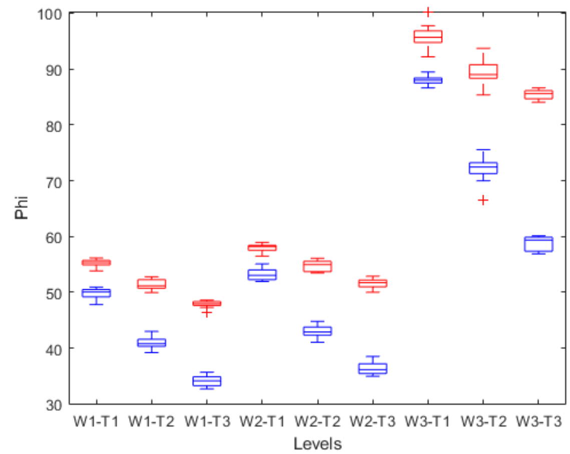

Figure 8: Box plot representing Φ_{tot} for the considered 9 environmental conditions. The blue boxes are associated to the dynamic model results while the blue ones are for the standard model.

the collection schedule: traffic, noise, population density and many others. The definition of the vehicle paths requires all those aspects to be considered as constraints of the route optimization problem.

6 CONCLUSION

The simulations provide interesting results and show the potentiality of the application of smart bins for logistics of MSW, reducing operational cost,fuel emissions and labour time. Further studies should be done to implement a more refined version of the simulation in this project, considering real data to represent the environmental conditions and more complex interactions between the vehicles to verify the robustness of the proposed waste management algorithm.

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