Route Planning using Wireless Sensor Network for Garbage Collection in COVID-19 Pandemic

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Abstract—**Garbage collection is a responsibility faced by all cities and, if not properly carried out, can generate greater costs or sanitary problems. Considering the sanitary situation due to the COVID-19 pandemic, it is necessary to take sanitary safety measures to prevent its spread. The challenge of the present work is to provide an efficient and effective solution that guarantees a garbage collection that optimizes the use of resources and prioritizes the attention to garbage containers located in or near contagion risk zones. To this end, this research proposes the integration of a basic garbage monitoring system, consisting of a wireless sensor network, and a route planning system that implements the decomposition of the Vehicle Routing problem into the subproblems of clustering and sequencing of containers using the K-Means and Ant Colony algorithms. For the monitoring of garbage, a significant reduction in the measurement error of waste level in the containers was achieved compared to other authors. About route planning, adequate error ranges were obtained in the calculation of the optimal values of distance traveled and travel time indicators with respect to an exhaustive enumeration of routes.**

Keywords*—*K-Means; ant colony optimization; route planning; vehicle routing problem; garbage collection; wireless sensor network

I. Introduction

Garbage collection is one of the most complex tasks of urban governments. Often, this task requires that collection vehicles travel along a specific route and manually check all the garbage containers along that route to empty them if necessary. The selection of routes followed by the vehicles is usually done at the discretion of the drivers which causes inefficient use of resources [1]. In general, there is no permanent monitoring of the containers to alert them about their possible overflow to avoid potential sanitation problems. In Peru, on average more than seven million tons of garbage are generated annually, of which about 50% comes from the capital city [2]. In addition, the city of Lima is ranked seventh with the highest traffic congestion worldwide [3]. Since March 2020, Peru has been in a state of health emergency due to the COVID-19 pandemic whose infection and mortality rates, as of January 2022, were 11.64% with respect to the number of tests and 7.22% with respect to the level of infected people in the whole country, respectively. Metropolitan Lima has a case fatality rate of 6.89% with respect to the number of people infected by coronavirus nationwide [4]. Waste collection costs in Peru are close to one billion soles annually, in addition to the work of thousands of operators, and the employment of hundreds of fleets of vehicles [5]. It is important to have an efficient waste collection service capable of dealing with the current health situation. Otherwise, the inefficient use of resources by the municipalities will continue, as well as the increase in the contagion and mortality rate due to the spread of the pandemic. This article presents a solution to the problem of optimizing the garbage collection, considering not only the associated costs but also the impact on public health; it will focus on minimizing collection costs, but at the same time guaranteeing timely attention to the containers by not allowing them to overflow. In this way, by saving collection costs, more resources can be allocated to other municipal processes, meanwhile contributing to the containment of the pandemic and additionally having a positive impact on the environment. It will be assumed that the containers belong to the municipality and it is possible to insert wireless sensors in the containers. This solution includes two systems, the first is a basic monitoring system composed of a network of wireless sensors to detect the volume and level of decomposition of garbage in the containers, with which it will be possible to alert about the imminent overflow of the containers. This monitoring system feeds into a route planning system that uses a heuristic approach to determine the optimal routes for the collection trucks, i.e. the most economical routes. In this solution, preferential attention will be given to containers located in contagion risk zones[1] as follows: for the contents of a container to be emptied, its contents must exceed a certain threshold; for containers located in an contagion risk zone or close to one, this threshold is lower. In section two, related work is reviewed. In section three, the solution methodology is explained. The results and discussion are presented in sections four and five, respectively. In the last sections, conclusions are formulated and future work is proposed.

II. Related Work

A. Waste Monitoring Sensors

An efficient garbage collection process requires knowing the current status of the garbage containers, which can be achieved through the use of different sensors and image processing methods, for which it is necessary to take into account the measurement range, accuracy, sensitivity, consistency, energy consumption, ease, and cost of the device [8]. Several solutions for this process use different sensors such as infrared [9] or ultrasound (HC-SR04) to determine the amount of stored waste, load cells to calculate the weight of the container [10], humidity sensors (DHT11), temperature sensors (LM35) for detecting the presence of fire [11], gas sensors (QS-01) for air quality monitoring [12], and tilt sensors (Itead) to detect possible container overturning. Among these reviewed works,

[1] A contagion risk zone refers to an area facing a health emergency and having a high rate of population density and/or mobility over time [6], [7].

several issues are reported that impact on the quality of the information, such as the angle of measurement and the position of the sensors inside the container, this issue can be solved by using high cost devices to reduce the percentage error in the measurement; therefore, a horizontal measurement is proposed to reduce the percentage error in the measurement through the use of low cost sensors, the mentioned served as motivation to seek to address these challenges evidenced in the research of other authors. Container status information needs to be sent and stored in a database for further analysis and monitoring. There are multiple data transmission techniques, e.g. the use of the Ethernet SPI module via network cable [13], as well as low-power communication technologies such as LoRa, which provides a long transmission range over long distances [14], and ZigBee, which improves data transfer speed [12]. However, these solutions generate a bottleneck by centralizing the sending of information. Another solution is a GSM transmission sensor, which allows data to be sent via SMS to a telephone number [9]. Finally, the NodeMCU device with a built-in Wi-Fi module allows each node of the sensor network to operate independently in data transmission [15]. Container status information can be used in the design of collection truck routes.

B. Route Optimization

The determination of adequate garbage collection routes is crucial for efficient service. This is a combinatorial optimization problem known as the Vehicle Routing Problem (VRP); it is an extension of the classical traveling salesman problem, where multiple vehicles travel through a network, starting from and returning to an origin. Its objective is to find optimal routes for multiple vehicles visiting a set of locations [16]. The VRP is a difficult problem to solve exactly, but it can also be solved with approximate methods [17]. The exact method guarantees the computation of an optimal solution but can be computationally inefficient with large numbers of nodes to visit, while the approximate method can provide a good quality solution in a reasonable time, independent of the number of nodes [18]. Route planning can be approached with the mathematical programming method whose objective is to maximize or minimize an outcome by choosing the values of real or integer decision variables [1]. For example, [19] developed a mixed-integer linear programming model that integrates a continuous perspective, using formulas to provide asymptotic estimates of routing costs, with a discrete perspective, through an iterative stochastic approximation procedure. To solve capacitated vehicle routing problems, when vehicles do not necessarily return to the starting point at the end of their trip, a model was proposed through the use of LINGO and the Branch and Bound technique to obtain the optimal routing [20]. Regarding approximate methods, [21] propose an approach based on NSGA-III, a multi-objective evolutionary algorithm taking into consideration indicators such as distance, travel time, and the number of traffic lights, to find multiple solutions to different levels of traffic congestion. Likewise, [22] seeks to address the problems related to the adequate provision of garbage collection services, through the use of a heuristic model based on the Pagerank web ranking algorithm, which is complemented by the application of constructive heuristics to the entire system. Meanwhile [23] apply the Ant Colony Algorithm (ACO) adapted to a set of routes to search for those that consume the least amount of energy, in addition to a Pareto solution that is deployed to find the optimized route in terms of energy and distance. On the other hand, [24] proposes a hybrid metaheuristic algorithm called GACO that adopts the path construction procedure of the ACO algorithm and incorporates the crossover and mutation operations used in the genetic algorithm to improve the local and global search for the solution. Some authors employ the strategy of decomposing the routing problem into two subproblems, the grouping of nodes into clusters or groups and the sequencing of nodes in each cluster. For example, [16] uses the Modified Capacity K-Means algorithms to group the new garbage cans concerning their distance and demand, and Variable Neighborhood Search to reorder the collection sequence of the garbage cans. In his work [25] uses the K-Means algorithm to group the garbage cans to form small clusters and the ACO algorithm to calculate the sequencing of the garbage cans in each cluster.

1) Clustering Problem: K-Means Algorithm: The clustering problem consists of gathering objects into groups or clusters according to some measure of similarity so that objects must be homogeneous within a group and heterogeneous in other groups [26]. Clustering techniques are used in various disciplines such as software engineering, statistics, data mining, image analysis, machine learning, web clustering engines, and text mining [27]. Among these techniques is the K-Means algorithm, which is widely used as an unsupervised learning technique [28]. This technique starts with the random selection of several centroids, where the centroid is defined as a point equidistant from the objects that belong to that group, each object is assigned to the nearest centroid, then the centroid in each group is recalculated as well as the distances of the objects to the new centroids, and new centroids are assigned again until the function F, called inertia, shown in the following expression, stabilizes [27], [29].

$$F = \sum_{k=1}^{K} \sum_{i \in C_k} \|x_i - m_k\|^2 \tag{1}$$

Notation:

- K: Number of groups.
- C_k: Partitioning of group k (set of objects that compose it).
- x_i: Object data i for partition C_k.
- m_k: Centroid of group k.

One method to compute the number of groups to be formed is the Elbow method, which evaluates the inertia shown in expression (1) so that, if you add another group, the inertia does not improve significantly [30]. Researcher in [31] argue that the choice of the number of groups will be determined at the point of highest curvature after multiple iterations.

2) Sequencing Problem: Ant Colony Optimization: Metaheuristics are defined as an iterative process that guides heuristics to explore and exploit the search space, are not specific to a particular problem, and can be applied to a wide variety of optimization problems [18]. Among these techniques is the Ant Colony Method (ACO), which is a development paradigm used to solve optimization problems, inspired by the behavior of the ant colony [17], [32]: to reach the food source, ants

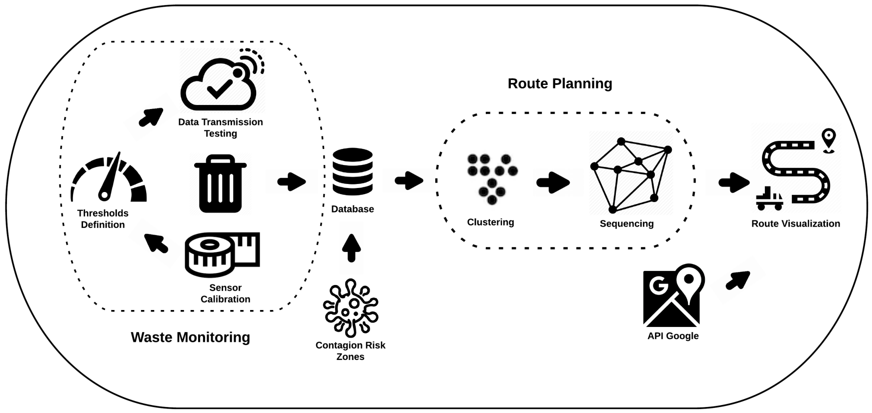

Fig. 1. Solution Diagram.

are guided by pheromone information, which is a substance that ants leave on the path as they pass through it, with ants preferring to follow the paths with the highest amount of pheromones. Artificial ants start at nodes chosen according to some initialization rule. Each ant incrementally builds a path by applying a state transition rule [33]. For this path to be visited by more ants, the local pheromone update rule is applied each time an ant crosses an arc in which, a pheromone level is calculated based on the total number of nodes and the visibility to the nearest node which are affected by a decay parameter will be added. Finally, when the ants complete their path, the global pheromone update rule is applied, this change is only performed on the best of the constructed paths. Since the Routing Problem can be solved with exact methods or with approximate methods, many authors have compared both types of methods in terms of computational efficiency. In [34], an exact solution method using the LINGO software and the Clark & Wright metaheuristic algorithm were compared, registering a processing time of 611 hours and 0.14 seconds respectively, which shows the higher computational efficiency of the latter. In the same way, [35] performed a comparison between the results obtained by applying exact methods using the LINGO program and the Simulated Annealing algorithm where vehicles must reach a customer before their competitors. For large instances, the former was not able to obtain an optimal solution in a reasonable time, while the latter achieved a quality result in an acceptable processing time. On the other hand, in [33], to minimize resources and provide efficient management of the garbage collection process focused on a vehicle routing problem with stochastic demand, a solution based on ant colony optimization was implemented and compared with the simulated annealing algorithm under different values of vehicle capacity. The results indicated that the former showed better performance for all ranges and sizes of the problem, and even has an additional advantage over the latter and the genetic algorithm because it can adapt the model to parameter changes in real-time. In this literature review, no published papers have been found that report solutions to the garbage collection problem that combine the advantages of sensors to monitor the containers and the effectiveness of existing methods that solve the vehicle routing problem. In this paper, a solution with such characteristics is proposed and will be described in the next section.

III. METHODOLOGY

As explained in the previous section, this work proposes the implementation of a network of sensors that record and transfer the information from the containers through wireless links to a digital repository. This network would consist of low cost and ease of use ultrasound sensors for waste monitoring to measure the level of waste, as well as gas sensors to identify those containers with a higher level of biodegradable waste; for data transmission, the NodeMCU device was selected to work with each container independently to avoid bottlenecks, which ensures greater availability of the monitoring system. For route planning, the use of approximate methods was chosen, through a decomposition scheme and making use of the K-means algorithm and the Ant Colony algorithm to obtain adequate solutions in an acceptable processing time. Fig. 1 shows the outline of the solution to the problem of the garbage collection consisting of two components, Waste Monitoring, and Route Planning. Therefore, the framework is composed of two stages, the first one corresponds to the implementation of the smart container, that is, the container provided with ultrasound and gas sensors that allow monitoring of the volume and CO_2 concentration of the waste inside. This implementation involves sensor calibration, the definition of thresholds, and data transmission tests. The information obtained by the wireless sensor network, the location of the waste bins, and contagion risk zone will be stored in a database for later use. In the second stage, the Route Planner is implemented using a heuristic approach that decomposes the vehicle routing problem into the subproblems of container clustering and container sequencing. For clustering, the Elbow method and the K-Means algorithm will be used to obtain the appropriate number of container clusters and their distribution, respectively. On the other hand, sequencing will be implemented using the Ant Colony algorithm. Finally, the routes will be visualized on a map using Google Maps API Directions application.

A. Waste Monitoring

To obtain quality data, it is necessary to calibrate the sensors. To do this, the values obtained by the devices must be sampled, then the least-squares method is applied to obtain the linear relationship between the values provided by the sensors and the real values, obtaining the coefficients to calculate the waste and CO2 levels. Thresholds must be defined to identify the containers to be collected. In the works reviewed, the so-called vertical measurement is used in which a waste level sensor is used; in this work, the horizontal measurement of the waste level will be carried out by inserting four waste level sensors which will be placed horizontally inside the container and, depending on the dimensions of the container, the low, medium and high thresholds will be defined. For the contents of a container to be emptied, it must exceed the high threshold, but if the container is in an contagion risk zone or sufficiently close to an area at risk, it will be sufficient for it to exceed the medium threshold. On the other hand, for the gas sensor, taking into account the CO2 concentration standards in the air, a value between 250 and 400 particles per million (ppm) represents adequate air quality. Values between 400 and 1000 ppm define a reduction in air quality being able to perceive unpleasant odors and possible discomfort. And a value higher than 1000 ppm represents a critical state capable of generating serious problems in air quality and serious diseases in the locations where it is perceived [36]. Therefore, the threshold for CO2 concentration is 1000 ppm, i.e., any container exceeding this threshold will be emptied. Finally, to send data, a series of tests must be performed to confirm the transmission of information from the NodeMCU device to a database through a wireless connection to the Internet, to effectively analyze and monitor the status of the garbage containers.

B. Route Planning

1) Clustering: Previously, based on the data obtained by the Waste Monitoring system, the containers that will be identified will be emptied; a container will be attended only if its content exceeds at least one of the established thresholds. Subsequently, the K-Means algorithm will be applied to group these containers to be served in K clusters, based on the distances between them. The algorithm is as follows:

1) Randomly select K centroids
2) Repeat while there are new centroid assignments
    a) Repeat for each node
        i) Find the nearest centroid
        ii) Assign the node to the cluster of that centroid
    End repeat
    b) Repeat for each cluster $k \leftarrow 1$ to K
        i) New centroid $\leftarrow$ "Average of the elements assigned to the cluster"
    End repeat
End repeat

2) Sequencing: After grouping the containers, the routes or sequences of attention of the containers in each of the groups or clusters will be defined using the Ant Colony metaheuristic. The corresponding algorithm to build a route for each cluster is shown below [37].

1) Initialize parameters and pheromone level in each arc
2) Repeat while the iteration limit is not exceeded
    a) Repeat until each ant has built a solution
        i) Repeat for each ant k
            A) Choose the next node by applying the state transition rule
            B) Apply local pheromone update rule
        End repeat
    End repeat
    b) Update the best solution
    c) Apply global pheromone update rule
End repeat

In this algorithm, during the construction of a route, the ant k currently positioned at node i, moves to a node n according to the following state transition rule: A random variable q between 0 and 1 is evaluated, and if $q > q_0$ then it is chosen to the next node n, through a biased scan of the arcs, based on expression (2), otherwise, a probabilistic random proportional rule is applied that uses the best weight, product of the pheromone level and the visibility in the arc, to move to a next node n, provided that it belongs to N_ik, described in expression (3) [28].

$$p_{in}^k = \frac{(\tau_{in})^\alpha * (\eta_{in})^\beta}{\sum_{l \in N_i^k} (\tau_{il})^\alpha * (\eta_{il})^\beta} \tag{2}$$

$$n = \arg\max_{j \in N_i^k} \left\{ (\tau_{ij}) * (\eta_{ij})^\beta \right\} \tag{3}$$

Notation:

- τ_{in}, represents the level of pheromones in the arc (i, n).
- η_{in}, represents visibility (inverse of distance/cost) in the arc (i, n).
- N_i^k, represents the list of previously unvisited nodes that the ant k, positioned at node i, can access.

IV. RESULTS

The San Borja district of the city of Lima was selected as a test case for the experimentation since it had 74 underground containers, which are suitable for inserting the monitoring sensors since they are not exposed to the environment or the public [38]. However, due to the impossibility of experimenting with real containers, due to the health situation of the pandemic, a dataset (waste level) of 32 containers, generated by an Australian government project and applied to Wyndham City Council, was used [39]. Therefore, 32 of the 74 containers in the district of San Borja were randomly selected and assigned the data from the dataset. As for the contagion risk zones the "Peru en tus Manos" application was used to determine the exact locations with confirmed cases of COVID-19. Using the Google Maps API Distance Matrix application, the distances between the containers and between the areas at risk of infection and the containers were obtained.

A. Smart Container

1) Waste Level Sensor: First, an algorithm was developed to calculate the distance between the objects and the ultrasonic sensor, a cylindrical test container, 34 cm high and 20 cm in diameter, was experimented with, and a sample of 84 values measured both real and by the sensor was taken, as shown in Fig. 2 the relationship between these values is approximately a linear function $(y = a * x + b)$. Subsequently, the least-squares

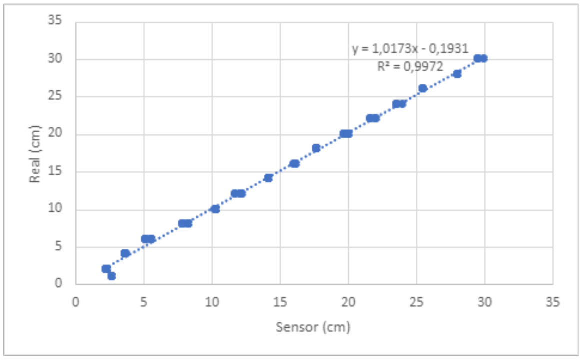

Fig. 2. Relationship Between Sensor Measurement and Real Measurement.

method was applied to obtain the values of the coefficients a and b of this function. Table I shows the results of the application of the developed algorithm and the Ultrasonic 1 [40] and Ultrasonic 2 [41]. In Table I it can be seen that the percentage error of the algorithm developed is 0.1%, while the library errors are 0.14% y 0.13% respectively, which shows that the algorithm developed provides a better approximation to the real distance. For experimental purposes, four ultrasonic sensors, a gas sensor, a NodeMCU device, and a portable battery were incorporated into the test container to monitor the level and decomposition of waste. The distribution of the ultrasound sensors was set horizontally about the dimensions of the garbage bin, i.e., for the low level at 3 cm from the base, for the medium level two sensors were placed at 1/3 and 3/5 of the height of the garbage can, finally, for the high level at 5 cm below the height of the garbage can alert the collection action before the garbage can overflow. As shown in the left container in Fig. 3, the sensors are distributed on the sides of the container according to the defined thresholds. Likewise, the present solution called horizontal measurement

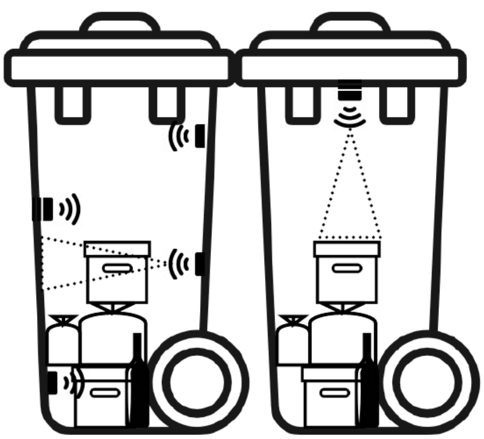

Fig. 3. Horizontal and Vertical Measurement of Container Contents.

was compared with the classic vertical measurement proposed by other authors [42]. In the right container in Fig. 3, a sensor located in the lid of the container can be seen to perform the vertical measurement. The results are shown in Table II, where the real measurement indicates the different levels of waste inside the container, symbolized by L, M, and H (low, medium, and high) respectively; the real location refers to the position in which the waste is distributed, which can be in the center, to one side or uniformly, symbolized by C, L, and U, respectively. Finally, the horizontal and vertical measurements are the waste levels obtained by the sensors for the respective methods. According to Table II, the horizontal measurement reduces the number of erroneous results by 23%; the errors in the vertical measurement are generated because the value H or M can be obtained instead of M or L respectively since the waste is not necessarily uniformly distributed within the garbage bin. For example, in Fig. 3, the horizontal measurement would give the value B (low level of waste), while the vertical measurement would give M, when in fact it is L. It can be stated that with horizontal measurement better results are achieved than with vertical measurement. Moreover, adequate results are achieved by using low-cost sensors.

2) CO2 Level Sensor: A preheating stage was performed for 24 hours to establish the appropriate environmental conditions and eliminate excess impurities or humidity in the sensor [43]. Next, the sensor output resistance (R_s) was measured over five minutes to obtain an average equivalent of 13480.265, which will be the final value of R_s. Then, the CO2 gas values specified in the sensor datasheet were used, obtaining an exponential function $(y = a * x^b)$, shown in Figure 4, where $x = R_s/R_o$, where R_o is the initial resistance. Subsequently, the least-squares method was applied, obtaining the values of the coefficients a and b, so that $y = 114.308 * (R_s/21285.605)^{-2.829}$. Table III shows the

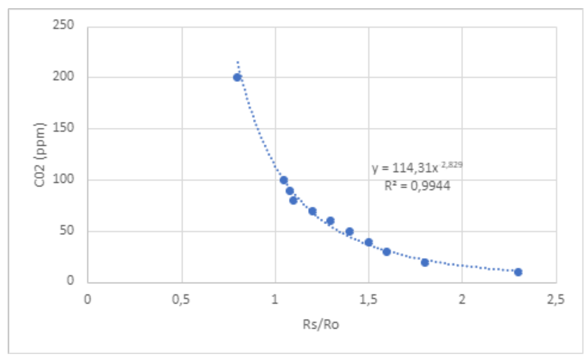

Fig. 4. CO2 Gas Measurement Curve.

average values obtained with the algorithm developed and with the MQ135 Library [44] for three scenarios: Scenario 1 refers to a container with organic waste, in Scenario 2 a container with non-organic waste was used and in Scenario 3 an empty container was used. While in scenarios 1 and 2 the variations of the results are 10.76% and 12.98% respectively, in scenario 3 a significant difference of 35.14% is observed. However, the average concentration of CO2 in free air is between 250 and 400 ppm [36], so when comparing the results in this scenario, it can be verified that the algorithm yields adequate values that are in this range.

B. Route Planning

1) Clustering: With respect to the sample of 32 containers indicated above, only 12 exceeded the corresponding thresholds to be served. The Elbow method was used to determine the appropriate number of clusters to use in the clustering. Fig. 5 shows the plot of the inertia function concerning the

TABLE I. RESULTS OF THE ELABORATED ALGORITHM AND LIBRARIES FOR THE ULTRASOUND SENSOR

Test Number	1	2	3	4	5	6	7	8	9	10	11	12
Real Values (cm)	20	18	16	14	12	10	8	6	4	2	1	0
Elaborated Algorithm (cm)	20	18	16	14	12	10	8	5	4	2	2	1
Ultrasonic Library 1 (cm)	19	17	16	14	12	10	7	5	4	2	2	51
Ultrasonic Library 2 (cm)	20	18	16	14	12	10	8	5	4	2	2	357

TABLE II. HORIZONTAL AND VERTICAL MEASUREMENT RESULTS

Test Number	1	2	3	4	5	6	7	8	9	10	11	12	13
Real Measurement	L	L	L	L	L	M	M	M	M	M	M	H	H
Real Location	U	C	U	C	L	U	C	L	U	C	L	U	C
Horizontal Measurement	L	L	L	L	M	L	L	M	M	M	H	H	H
Vertical Measurement	L	M	M	H	M	M	H	M	M	H	H	H	H

TABLE III. RESULTS OF THE ELABORATED ALGORITHM AND THE LIBRARY FOR THE GAS SENSOR

Scenario	1	2	3
Elaborated Algorithm (ppm)	9578.98	613.41	318.83
MQ135 Library (ppm)	8648.64	533.81	491.59
Variation (%)	10.76	12.98	35.14

number of clusters where a sharp change in slope, similar to that of an arm and its elbow, is observed between two and three clusters, given that in the following numbers of clusters no substantial improvement in inertia is observed. Therefore, the 12 trash containers will be gathered in two clusters (which also coincides with the Municipal Tax Ordinance of San Borja [45]). Using the K-means algorithm, a group of the 12 garbage

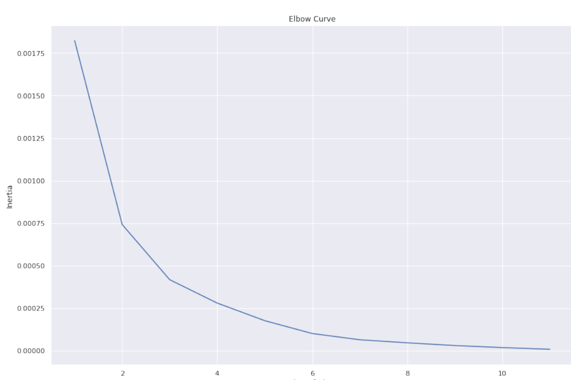

Fig. 5. Elbow Curve.

cans into two clusters of 6 garbage cans each was obtained as shown in Fig. 6. In each cluster, one more node appears which is the centroid, which is not an element of the cluster but is calculated as the average of the cluster elements.

2) Sequencing: 5000 iterations of the Ant Colony algorithm was run to find the best sequence of containers to serve, by optimizing each of the following two indicators: distance traveled and travel time separately, and for each of the two groups. Table IV shows the values obtained for each indicator in each group: the minimum travel distance to empty all the containers in group 1, starting from the Lurin depot and finally returning to the same depot is 101.122 kilometers, which requires the collection vehicle to be used for a time of 2.11 hours with a fuel cost of 61.4821 soles, calculated as the

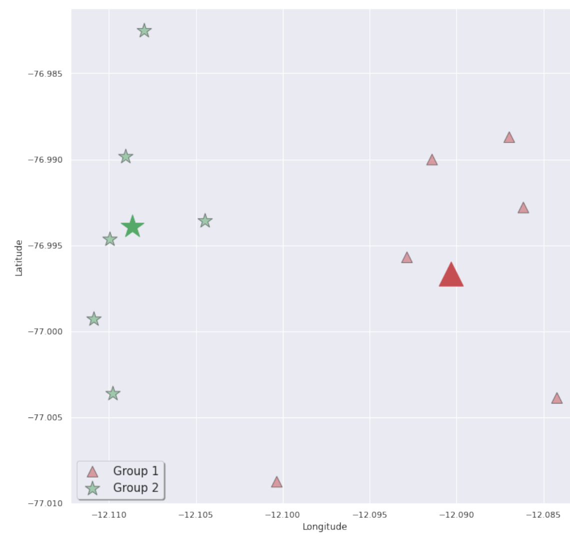

Fig. 6. Container Clustering.

product of the travel time and the unit cost of fuel. Likewise for group 2 with its corresponding indicators. Fig. 7 shows the

TABLE IV. ROUTE PLANNING INDICATORS

Indicator	Group 1	Group 2
Distance traveled (km)	101.122	97.015
Fuel cost (S/.)	61.482	58.985
Travel time (Hs)	2.11	2.12

sequence in which the containers of group 1 are visited by the collection truck that starts its route in the garbage depot located in the district of Lurin, being container A and F the first and the last to be emptied. To visualize this route, various tools provided by Google Maps, such as API Directions, markers, etc. were used.

V. DISCUSSION

To evaluate the results obtained by the proposed solution, we proceeded to the exhaustive enumeration (EE) of the routes for each of the two groups of 6 containers each that were obtained in the clustering phase, which allowed us to calculate the corresponding optimal values of the 2 indicators distance traveled and travel time, shown in Table V. Two additional scenarios were evaluated, scenario 2 with two groups of 8

TABLE V. OPTIMIZATION BY ACO AND EE FOR EACH GROUP AND EACH SCENARIO

Indicator	**Distance traveled (km)**						**Travel time (Hs)**					
Scenario	**1**		**2**		**3**		**1**		**2**		**3**	
Group	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
EE Optimal Value	100.807	96.830	97.971	98.608	98.440	97.831	2.03	1.99	2.12	1.87	1.93	2.11
ACO Optimal Value	101.122	97.015	98.361	98.608	99.097	97.831	2.11	2.12	2.18	1.87	1.99	2.11
Error (%)	0.31	0.19	0.40	0	0.67	0	3.84	6.70	2.43	0	2.43	0

TABLE VI. OPTIMIZATION BY ACO AND EE FOR ALL CONTAINERS AND EACH SCENARIO

Indicator	**Total distance traveled (km)**			**Total vehicle usage time (Hs)**			**Total travel time (Hs)**		
Scenario	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
EE Optimal Value	197.637	196.579	196.271	4.02	3.99	4.03	2.03	2.12	2.11
ACO Optimal Value	198.137	196.969	196.928	4.23	4.04	4.10	2.12	2.18	2.11
Error (%)	0.253	0.198	0.335	5.25	1.29	1.70	4.38	2.43	0

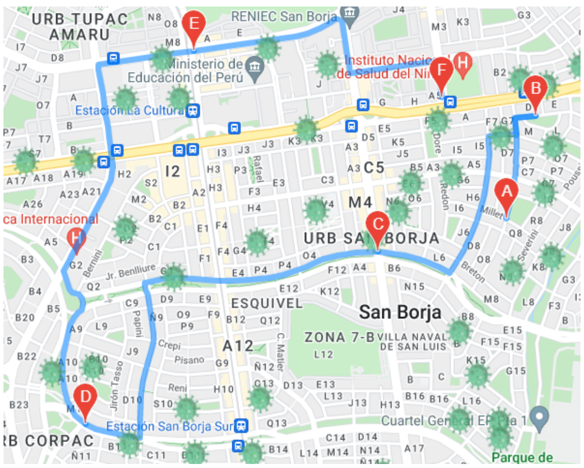

Fig. 7. Route for Group 1.

and 4 containers, and scenario 3 with two groups of 7 and 5 containers respectively. In scenario 1, 0.31% and 0.19% error was obtained in the results obtained by the ant colony algorithm (ACO) with respect to the exhaustive enumeration (EE) results about the distance traveled indicator for group 1 and 2, respectively, while for the travel time indicator, errors of 3.84% and 6.70% were obtained for group 1 and 2. Lower percentages error were observed in scenarios 2 and 3 for the distance traveled indicator. These results are evidence of the quality of the solutions computed by the ACO metaheuristic and are reported in a multitude of papers, some of which were referred to in section 2. Although acceptable results have been obtained for each of the two groups, it is necessary to evaluate the integrated solution that covered all 12 containers, analyzing the indicators of total distance traveled, total vehicle use time, and total travel time (time taken for the garbage collection process); the three indicators are referred to the set of all containers and in the same three scenarios defined in the previous analysis. The indicators are shown in Table VI as well as the percentages error. A fourth indicator would be the fuel cost indicator, however; as it is directly related to the distance indicator, it will have the same percentage error. In scenario 1 we noticed that the optimal ACO value of the total travel distance (and fuel costs), has an error of 0.253% with respect to the EE Optimal Value, while for the indicators of time of use of the collection vehicles and total travel time the errors were 5.25% and 4.38%, respectively. Improvements in the percentages error can be seen in the other scenarios.

VI. CONCLUSION

Taking into account the limitations of the experimentation due to the sanitary situation, and the quality of the results obtained, it can be affirmed that the objective of presenting a solution that optimizes the resources used in the collection of solid waste, keeping in mind the impact on public health, has been adequately fulfilled. On the one hand, the use of wireless sensors allows efficient monitoring of waste and contamination levels inside a container, since it is no longer necessary to check the garbage bins in situ to know the state they are in. Better quality data was obtained with the algorithms developed than with the standard libraries, as a lower percentage error was achieved in the measurement of waste and contamination levels. Likewise, evidence was found that through the horizontal measurement, the number of erroneous results generated by the vertical measurement is reduced, since not only the maximum level is considering when the waste is not uniformly distributed within the containers. In summary, by using low-cost devices, adequate results have been obtained. On the other hand, the low percentage error obtained with the model based on the K-Means algorithm and the Ant Colony metaheuristic evidences the quality of the results concerning parameters such as container location, location of contagion risk zones, fuel cost, thresholds for waste level and contamination inside the container, etc. The implementation of Route Planning using a heuristic approach guarantees its scalability by providing adequate results using a reasonable execution time. Moreover, by integrating the basic Waste Monitoring system with the Route Planning system, a continuous flow of information has been established to ensure traceability of results. This integration allows for agile planning of garbage collection since route planning is based on online information. Finally, the integrated system can be transformed into an online system, i.e., while the garbage collection is in progress, a container not scheduled to be collected might exceed one of the alert thresholds. In this case, the remaining containers to be collected would be rescheduled.

VII. FUTURE WORK

Future work includes the incorporation of special sensors in the smart container to monitor the humidity and temperature inside the containers since the speed of sound and the concentration of carbon dioxide (CO2) are sensitive to these variables. To preserve the energy and mobility of the smart container, it recommends using an independent long-life battery (LIPO), as well as a library that is characterized by setting the ESP8266 microcontroller in sleep mode to reduce the battery consumption and guarantee a long lifetime for the smart container. The proposed solution can be transformed into an online system through real-time route planning so that if any container not scheduled to be collected reaches a monitoring threshold during the route of the collection trucks, it will be integrated into the most convenient collection route. This will provide more timely attention. The proposed route planning model is essentially a Vehicle Routing model (VRP). This model could be made more realistic by taking into account other parameters that affect actual waste collection problems, e.g. number of vehicles, vehicle capacity, time windows, etc. Its application to larger cases is recommended due to the scalability of the Route Planning model.

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