BIN-CT: Urban Waste Collection based in Predicting the Container Fill Level

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Abstract

The fast demographic growth, together with the concentration of the population in cities and the increasing amount of daily waste, are factors that push to the limit the ability of waste assimilation by Nature. Therefore, we need technological means to make an optimal management of the waste collection process, which represents 70% of the operational cost in waste treatment. In this article, we present a free intelligent software system, based on computational learning algorithms, which plans the best routes for waste collection supported by past (historical) and future (predictions) data.

The objective of the system is the cost reduction of the waste collection service by means of the minimization in distance traveled by any truck to collect a container, hence the fuel consumption. At the same time the quality of service to the citizen is increased avoiding the annoying overflows of containers thanks to the accurate fill level predictions performed by BIN-CT. In this article we show the features of our software system, illustrating it operation with a real case study of a Spanish city. We conclude that the use of BIN-CT avoids unnecessary visits to containers, reduces the distance traveled to collect a container and therefore we obtain a reduction of total costs and harmful emissions thrown to the atmosphere.

Keywords: Waste Collection, Machine Learning, Recycling, Circular Economy, Forecasting, Routes Generation

1. Introduction

The waste generation shows globally an unstoppable growth, in contrast, the assimilation capacity of our planet is decreasing, turning the waste treatment into a complex challenge we need to face as a modern society [Al-Salem et al., 2009]. In addition, the linear structure of our economy (extract, manufacture, use and disposal) has reached its limits and the Earth is exhausted, natural resources are drained. Therefore, nowadays a more sustainable model of economy is needed, as the known as circular economy [Tukker 2015, Ghisellini et al. 2016], which consists in the transformation of our waste in raw materials again, thus a new paradigm for a more sustainable future.

The unsustainable development of most nations has created a problem due to the growing generation of waste that must be solved. In spite of the social and governmental commitment, there are hardly any technological means to make an optimal management of the waste collection process. In fact, traditionally the solid waste collection was carried out without previously analyzing the demand or the routes of the vehicles and the decisions about the routes were taken by the drivers, although the solutions were far from optimal. The solid waste collection is usually performed based in static plans, with a pre-determined number of visits per week, designed manually in most cases. This approach has severe limitations due to the number of constraints one has to consider to find an optimal solution. Moreover, waste collection planning problems are influenced by stochastic waste generation, traffic circumstances, and many constraints unmanageable by a person, so the use of an automatic tool to solve these type of problems is mandatory.

In this article we propose an intelligent software system, called BIN-CT, for the management of solid waste collection in an urban area. The system is doubly intelligent, since it integrates algorithms to predict the fill level of waste containers, plus the subsequent optimal generation of routes for collection trucks. In other words, our software system solves the two major problems that a waste collection service face: 1) what containers should be collected? and 2) in what order are they visited to minimize the cost?

In order to solve the first question we will use computational machine learning techniques to estimate the fill level of each container. Supported by historical data (past data), the system generates predictions (future data) to know when a container should be collected. This prediction could be performed long term or short term, considering seasonality, weekends, and holidays. We want to highlight that, as far as we know, the fill level prediction of all containers individually (fine grain) is a feature not implemented in any tool for waste collection management. Additionally, our software system is able to interact with an Internet of Things (IoT) system to obtain the actual filling of the containers equipped with volumetric sensors. Moreover, the sensors information will be essential in a near future to validate the historical data (obtained by trucks drivers).

The routes generation (of waste collection in our case) is a well-known combinatorial problem called Vehicle Routing Problem (VRP) [Dantzig and Ramser 1959], however the use
of historical data, predictions and the intelligent decisions about the inclusion/exclusion of containers makes it not a simple VRP. The solutions to our problem are usually constrained by many factors like the number of available trucks, the trucks capacity, the amount of waste to collect and the characteristics of the street where the container is placed (too narrow for a big truck), among others. The planning of waste collection routes has a wide number of variants and constraints which makes it unmanageable for one single person. In contrast, there is a great room for improvement using automatic algorithms to deal with this problem. The improvement means less cost services, a reduction of harmful emissions and a better service for the citizens, in quality and costs.

In addition, we must take into account that the actual city system is under discussion. Many local authorities have been forced to examine its cost-effectiveness and environmental impact since we have a system based on static collection frequencies (one per week, twice a week, everyday...) that sometimes makes unnecessary trips to semi-empty containers. The pollution generated by these trips could be more dangerous for the environment than the benefits of the collection. This is especially critic in the case of selective collection (plastic, paper, glass,...), where the waste volume is smaller than in the organic waste case. So, when you deal with recyclable waste, the planning of optimal collection routes is even more influential. Actually, the recyclable waste collection process represents 70% of the operational cost in waste treatment (Teixeira et al., 2004). The main objective of this work is the reduction of the collection process cost and is essentially dependent on the distance traveled by the collection trucks.

In Figure 1 we show the steps followed to solve the problem we face in this article. The main phases are the following: First, we treat all the data needed to solve the problem and store it in a database. In this way the BIN-CT system is able to load the information from the database instead of using several large files. In the second phase the software system uses the historical fill level data of each container and generates the fill level predictions. In the third step, the software system decides which containers are going to be involved in the next routes. The decision is taken according to a given criterion based on the predictions and estimated fill levels. In the fourth phase the route algorithm computes optimal solutions, i.e. the complete routes that the trucks must follow to collect the containers selected in the previous step. Finally, we show the best solution in a navigable map in an web browser.

The main contributions of this article are as follows:

- We propose an intelligent system called BIN-CT for the generation of optimal waste collection routes.
- We compare three machine learning algorithms for the forecasting of filling levels of each container (fine grain) from historical data.
- We use a new real case study of a city with 217 containers to illustrate the behavior of the proposed system.
- We compare versus the work of a real company and beat experts in waste planning doing this same job.

The remainder of the article is as follows. In Section 2 we describe some works relating waste collection optimization, especially the different variants studied in the literature. Section 3 describes the waste collection problem we face in this article. Section 4 is devoted to the explanation of our proposal, the BIN-CT software system. The four modules that compose our software system are described and we outline the most important features of the system. Our experimental setup is presented in Section 5 then we describe the real-world case study, and analyze the results of two different experiments. Finally, we present our conclusions and future work in Section 6.

2. Related Work

The waste collection is a process with uncountable variants and constraints which have led to a multitude of studies in recent years due to its importance. The works in the literature could be classified, among other ways, according to the waste type that is treated: residential waste commonly known as garbage (Garvin et al., 2011), industrial waste where customers are more dispersed and the amount of waste is higher (Sahoo et al., 2005), recyclable waste (Dat et al., 2012) increasingly important for our society, where the collection frequency is lower than organic waste and hazardous waste where the probability of damage is minimized (Alagöz and Kocasoy, 2008).

In the municipal solid waste collection (Beliën et al., 2014), the authorities need global studies to quantify the waste gener-
ated in a period of time to be able to manage them. Particularly, the waste generation forecasting for Xiamen city (China) inhabitants was studied by [Xu et al., 2013]. The main difference with our approach is the granularity of the object under study. They predict the amount of waste produced in the whole city, in contrast, we generate predictions for every single container in a city.

This supposes a considerable increase of the complexity of the problem that is solved, because it is necessary to consider multiple aspects such as the location, the customs of the citizens, the population density of the area, etc. In the same research line, the impact of the intervention of local authorities on waste collection has also been studied [Cole et al., 2014], being this relevant in the medium-long term.

Regarding the location where the collection takes place, there exist multiple variants of the problem. There are communal collections where the local authority identifies a place shared by the community [Tung and Pinnoi, 2000], in most cases a local waste facility for recycling. In the other side we found the kerbside collection [Sniezek and Bodin, 2006] where the household waste is collected from individual small containers located near each house. The intermediate case studied here is the collection of containers that give service to several streets and blocks of flats [Bodin et al., 2000].

In medium/large cities the amount of containers is of hundreds or even thousands, therefore the use of advanced computational methods are required to find an optimal solution. In the past, exact methods were used to solve this problem like Branch and Bound and based on mathematical programming [Arribas et al., 2010], however the execution time tends to increase exponentially with the number of containers, then the use of metaheuristics and bioinspired methods is recommended. Despite some metaheuristics have already been explored in the literature such as Ant Colony optimization or Genetic Algorithms [Buenrostro-Delgado et al., 2015], there is still room for improvement when one deals with the waste collection problem at the fine granularity we face it in our approach, that is, analyzing each single container.

The waste collection process implies lots of stakeholders like authorities, citizens, the company in charge of the collection service and the company workers. Depending on the stakeholder, the objectives to optimize are different. Some examples of optimization goals are the number of vehicles for the service [Ombuki-Berman et al., 2007], the service total cost [Arribas et al., 2010], the environmental impact [Tavares et al., 2009], the required staff for the service [Hansmann and Zimmermann, 2009], the collection routes length [Ustundag and Cevikcan, 2008], and the total time of the waste collection [Arribas et al., 2010]. Our approach considers several objectives at a time, finding solutions which minimize the number of vehicles needed, the total cost, the routes length, and the environmental impact.

3. Problem Description

The waste collection management is a global problem that affects most cities in the world. In fact, this problem falls within the initiative of Horizon 2020 and Smart City for innovation and research, promoted by the European Union: the concept of reducing energy consumption and making better use of resources has become a key to combat the rigors of the economic crisis. Specifically, one of the objectives of the Smart City initiative is to reduce the emission of greenhouse gases, use sustainable resources, and efficiently manage energy sources. Then, we deal with a problem of general interest in this article. We focus on some of the aspects discussed in Section 2. Specifically, we study recyclable waste, we use fine grain predictions for every single container, we manage hundreds of containers, and we use an evolutionary algorithm as resolution technique.

The problem consists in planning how the waste collection will take place in a determined area. The objective is defining optimal collection routes for the available trucks whose capacity cannot be exceeded. An optimal collection route is an ordered list of collection places to visit that minimizes the total distance traveled by all the trucks involved.

Since the number of containers is too much to collect them every day and it is not a cost-effective strategy, the containers must be visited at some most appropriate time (ideally when their filling level is close to 100%). In addition, routes are constrained by the trucks capacity, that may be different. Moreover, there exists constraints that affects specific containers that must be collected by a small truck (with less capacity) due to space restrictions. Route duration is determined by the travel time between containers and the time to unload them.

Generally, there are some difficulties in estimating the distances and durations of trips between containers due to traffic circumstances. Most works [Nuortio et al., 2006, Teixeira et al., 2004] only use the distance as criterion for the generation of the cost matrix and they calculate the shortest paths between pairs of waste containers using the Dijkstra algorithm [Dijkstra, 1959]. In contrast, we opted to calculate the estimated distance and duration between pairs of containers using the Google Maps Api v3. Thanks to that, we obtain a most accurate value for travel distance and duration taking into account traffic regulations and circumstances.

The quantity deposited daily in each container is unknown, it depends on multiple factors such as the number of citizens sharing a container, the seasonality, the lifestyle, etc. In other works, authors assume the quantity deposited in the containers is constant every day, however, BIN-CT treats every container as a different entity that can change daily. Since the previous fill levels of the containers are available, the software system forecasts future fill levels based on historical data. This information will help determining which containers must be collected in the next shift. Besides, the predictions generation is really complex, since we need to model the behavior of the population that deposits its waste in a specific container.

Overall, the complexity of this problem can be derived from the amount of restrictions that can be applied to the model, so that the more restrictions applied, the more the realism of the solution found and the larger its computational complexity. The constraints we take into account are very diverse. Regarding the trucks, we can restrict the capacity of each different vehicle, the number of them and the ability to collect containers in narrow
streets. The quality of service defined by the waste management company could be seen as a soft constraint. In this work the company establishes that all the containers with a filling estimation greater than 80% must be collected. As a summary, we enumerate the constraints considered in this work:

- **Containers:**
  - Variable number of containers
  - Different capacities
  - Different locations
  - Custom unloading time
  - Only specific trucks can unload a particular container

- **Vehicles:**
  - Variable number of vehicles
  - Different loading capacities
  - Ability to unload specific containers (narrow streets)
  - Custom cost based on distance traveled

All constraints imposed to the model make the problem difficult to be solved by exact methods in practice and even less by a person, thus evolutionary algorithms could be used for this purpose.

4. Our Proposal: BIN-CT Predictive System

The BIN-CT predictive system was designed for improving municipal waste collection planning. To deal with the complexity of the global problem, we face it in four sequential phases. In the first phase the travel distances and durations for all pairs of containers are computed to give more realism to the solution. Then, in the second phase, the fill levels are estimated and the containers which are not going to be part of the routes for the next service are discarded. In the third phase the routes are generated, minimizing the total cost, and in the last phase we show the best solution in a web browser. Therefore, we divided the tool in four different modules which can be observed in Figure 2.

In this section we detail the main features of our software, as well as the solution quality it achieves when solving an instance of the solid waste collection problem described in this work. The BIN-CT predictive system is composed by four software modules: Data Management module, Intelligent Decision module, Routes Generation module and Visualization module.

4.1. Data Management Module

All information for the execution of the software program that comes from the waste management company, which performs the collection, can be loaded from a database. The use of a database is desirable due to the amount of information needed to solve the problem. The main entities used in our system are shown in Figure 3.

The main entity is Containers, where we store the identification of the container, information about the location such as coordinates and addresses, the maximum capacity of the container, how long it takes to collect the container, the type of the waste (glass, paper,...), the type of the truck it needs be to collected (e.g. small truck for downtown narrow streets) and whether it has a sensor or not to measure the fill level.

The container is related to the historical filling data entity where we store the filling data of each container. It is also related to the Costs entity where we store the distance and estimated duration of the trip between containers. This information is extracted with the Google Maps Api v3 and is used to solve the underlying VRP. The generation of the duration and distance matrix is essential to generate a realistic solution.

The table Forecasts stores the predictions generated by machine learning algorithms that are used to estimate which containers will be collected in the next service. To perform a service, the company has vehicles that have different sizes and loading capacities we must consider as constraints. A smaller truck has less loading capacity, thus it usually collect less containers.

Finally, once the execution of the route optimization algorithm is finished, we store the best solution in the database for visualization purposes. A solution of the whole problem is an ordered list of containers that must be visited by each vehicle. This information is stored in the entities Solution and Tasks.

4.2. Intelligent Decisions Module

The fundamental characteristic of our software is the ability to predict the daily waste contribution for each of the containers that are part of the analyzed set. We have carried out an individualized mathematical modeling of each container using Weka’s machine learning library (Frank et al., 2016). Particularly we use time series analysis, which is the process of using statistical techniques to model and explain a time-dependent series of data points. Then, time series forecasting is the process of using a model to generate predictions (forecasts) for future events based on known past events, like the fill level of each container. The time series forecasting algorithms allow the tool to generate filling predictions for containers not monitored with sensors.

In this module we have also defined the inclusion/exclusion criteria used to make decisions about the containers that will be collected in the generated routes. The inclusion/exclusion criteria can be defined according to container capacity, forecast made, and real reading of the sensors if possible. In addition, given a set of containers and a criterion, we have the possibility of forcing the inclusion of some containers with higher priority in the generated routes, and some may be excluded due to the defined criteria and constraints.

4.3. Routes Generation Module

This module has, as its main functionality, the generation of optimal routes for the waste collection. Given a set of containers, we use an evolutionary algorithm EA(1+1) based on the principle of ruin and recreation (Schrimpf et al., 2000) that allows us to generate efficient collection routes, taking into account the distance and the driving time between them.
In general, all containers usually have the same capacity, but as time progresses, city managers buy new containers with a potential new different capacity. Our software considers containers of different sizes and, therefore, different capacity. The capacity of each one is managed individually, and this allows us to estimate the total load that the vehicle will collect, since we cannot exceed this limit. In addition, vehicle fleets are not only made up of identical vehicles, but vehicle fleets are heterogeneous, so vehicles are also considered individually. For example, we can assign a larger number of containers to vehicles with higher capacity.

Sometimes there are special cases where the compatibility between container and vehicle has to be taken into account. This case happens when a container has to be picked up by a small vehicle. Our software allows us to take this restriction into account in order to generate valid routes. In addition, this feature can also influence the collection time per container, which is the time it takes to the driver to collect the container once it is in front of it. This input time is assigned depending on the location or characteristics of the container to be collected. This characteristic has a beneficial effect on the fact that the total estimated collection time is more realistic.

4.3.1. Algorithm

The evolutionary algorithm EA(1+1) used to solve the routing problem is based on the ruin-and-recreate principle. It is a large neighborhood search that combines elements of simulated annealing and threshold-accepting algorithms. This approach is suited for complex problems that have many constraints (Schrimpf et al., 2000, Misevicius, 2003). It is an all-purpose meta-heuristic that can be used to solve a number of classical VRP types and basic search strategies can be easily varied to small and large moves according to the complexity. 
of the problem. The pseudocode of the algorithm is shown in Algorithm 1.

Algorithm 1 Pseudocode of the algorithm.

Inputs: Set of containers (location, fill level, predictions), set of vehicles, distance matrix, duration matrix, deposit location

Output: Set of ordered lists of containers

1: bestSolution ← randomSolution()
2: while evals < totalEvals do
3: initialSolution ← randomSolution()
4: removedTasks ← ruin(initialSolution)
5: newSolution ← reCreation(removedTask)
6: evaluate(newSolution)
7: if (newSolution<bestSolution) then
8: bestSolution←newSolution
9: end if
10: end while
11: return bestSolution

The algorithm starts with a random initial solution. It divides parts of the solution leading to a set of tasks (collecting a container) that are not going to be assigned to a vehicle and a partial solution containing all other tasks. This process is called ruin the solution because we extract some tasks from the solution. Based on the partial solution the algorithm re-introduces the tasks extracted leading to a new solution. Hence, this is the recreation process. If the new solution has more quality than the best-so-far solution, it is accepted as the new best solution. These steps are repeated until the algorithm reaches a number of iterations.

4.4. Visualization Module

The solutions are shown in an HTML navigable map. The software generates solutions for one or more days, and these can be viewed in a web browser. In Figure 4 we show the interface of the web application, which can also be viewed online at http://mallba3.lcc.uma.es/bincy/. The main part shows a solution obtained for two vehicles: one red route and another black route, for two different trucks. In addition, we can observe the containers marked in red, which will be those whose prediction indicates a percentage of filling higher than 80%.

The solutions can be accessed from any mobile device and the user interface adapts itself to the platform on the fly. This feature is especially desirable when the trucks’ drivers have any doubts regarding the route they should follow.

5. Experiments

In this work we carry out two different experiments. First, we focus on the predictions, which is the most innovative part of our system and which will allow us to achieve the greatest savings in the operation of our waste collection service. This first experiment consists in the comparison of three different algorithms to generate predictions.

The second experiment is the generation of routes for a working day, starting from the real state that the containers had, so that, they have different filling states. These fill levels are complemented with the predictions for the next day. We compare our solution with the real solution provided by company’s human experts for that exact day (what really happened that day). In this way we try to show that our approach is realistic, and therefore our solutions are too. As quality measures we analyze the distance, duration, and amount of waste collected using the generated routes. As performance measure we report the time required to run the algorithm. We performed 30 independent runs in order to provide a fair value for the runtime. Finally, the experiments were run in a machine with Intel Core i7-3770 processor at 3.40 GHz and 16 GB memory.

5.1. Case of Study

In this article we illustrate the behavior of BIN-CT with a real case study of an Andalusian city (Spain), where we highlight the benefits of our approach, being effective and realistic at the same time. Our case study considers 217 paper containers from the metropolitan area of a city. The choice of an instance of recycling waste is more attractive than an organic waste collection to show the quality of our approach because most paper containers do not need to be collected everyday like the organic waste, so they have a high variability in collection frequency. The problem instance parameters used in the case of study are shown in Table 1.

| Parameter               | Value |
|-------------------------|-------|
| Regular containers      | 208 units |
| Small truck containers  | 9 units  |
| Total containers        | 217 units |
| Container capacity      | 75 kg   |
| Trucks                  | 2 units  |
| Unload container        | 3.5 min |
| Small truck capacity    | 1700 kg |
| Big truck capacity      | 2000 kg |
| Historical data         | 11 months |

5.2. Experiment 1: Comparison of Time Series Algorithms

This experiment is devoted to perform a comparison between three time series algorithms used for forecasting the fill level for all containers. The algorithms used in this comparison are the following: Linear Regression [Su et al., 2012], Gaussian processes [MacKay, 1998] and Support Vector Machine for regression (SMMReg) [Rivas-Perea, 2013]. In the following we briefly describe the techniques in which the algorithms are based on:

- Linear regression works by estimating coefficients for a line that best fits the training data. It is a good idea to evaluate linear regression on a problem as a baseline, before moving onto more complex algorithms.
- Gaussian process is a collection of random variables, any finite number of which have a joint Gaussian distribution. A Gaussian process is completely specified by a mean function and a positive definite covariance function.
• SMOreg works by finding a line of best fit that minimizes the error of a cost function. This is done using an optimization process that only considers those data instances in the training dataset that are closest to the line with the minimum cost.

In this experiment we use the fill level of all 217 containers in 11 months. The data is obtained by the truck driver when the container is unloaded. If the container is not visited, then there is no datum for that specific day. Thus, the system must deduce what happened on the days when we do not have data.

In order to alleviate this issue, we have performed a pre-processing of the data that has allowed us to obtain the estimated daily load increase of the containers. From the processed data, we have generated the daily predictions for the following month using the three forecasting algorithms.

The results indicate that the learning algorithm based on Gaussian processes is the best algorithm in the comparison, obtaining only an average of 3.83% mean absolute error in the filling predictions of the next month. Regarding the other techniques, the algorithm based on linear regression has an average of 7.41% mean absolute error and the SMOreg algorithm has 9.52%. After performing the Kruskal-Wallis statistical test (with Bonferroni correction to compare more than two samples) with 95% confidence, we can state that there are significant differences between the results of the algorithm based on Gaussian processes with the other two algorithms of the comparison.

As the main conclusion of the first experiment, we can infer that the estimation provided by the best algorithm is more than acceptable, with less than 4% mean absolute error. Note that a container is scheduled for the next collection service when the filling estimation is greater than 80%, so the error is negligible so as to influence the decision to collect a container. After analyzing these results, we decided to use the algorithm based on Gaussian processes for the second experiment.

5.3. Experiment 2: The Daily Use of the System

In the second experiment we want to illustrate the general behavior of the system considering all the parameters specified in Table 1. In this experiment we generate routes for the first working day of the twelfth month starting from the real state of the containers and then we compare our solution with the real solution implemented that day. Once our system makes the predictions for the next day, we obtain the estimated fill level for all containers. Next, BIN-CT chooses the subset of containers that fulfills the following inclusion/exclusion criteria. Those containers with a fill level higher than 50% are considered optional, while those with a filling greater than 80% are marked as mandatory for their collection. The application of this criterion to the set of 217 containers results in a subset of 77 containers to be picked up by two vehicles (the smallest is able to pick up the nine containers that cannot be collected by the big truck).

In Table 2 we show the containers collected, the duration and distance of the routes, and the load of the trucks for the experts solution and the solution provided by BIN-CT. In addition, we show the totals of the measures for both vehicles and the average per container. After the execution of the route generation algorithm, we obtain two different routes: the biggest truck should pick up 41 containers and the smallest truck should visit 33 containers. Therefore, our solution is able to schedule most of the containers with only 3 containers not scheduled for the next service due to trucks capacity constraints.

The system provides very accurate information on the duration of the routes, the duration of the four routes can be seen in the forth column in Table 2. On the one hand, the route of the small truck has an estimated duration of 3 hours, 39 minutes and 51 seconds for collecting a total of 33 containers. On the other hand, the route of the big truck will last 3 hours, 52 minutes and
40 seconds for collecting a total of 41 containers. However, if we take a look on the distance, the small truck’s route is 32.4 km compared with only 25.2 km of the other route. Therefore, it seems that the constraint of picking up those 9 containers, which cannot be collected by the big truck, is a disadvantage for the small truck’s route. Regarding the trucks load, the amount of waste collected is proportional to their size.

Let us compare the experts solution with our solution. First of all, we analyze how many containers, which are also in the experts solution, were selected by BIN-CT. The result is that 66% of the experts solution’s containers are also collected in the solution provided by BIN-CT. This means that using static plans, sometimes they collect containers that are below 50% according to our estimations. Actually, around 20% of the containers (12 units) of the studied day had less than 50% fill level. Our system is then unique in detecting them and saving costs in the planning.

The routes provided by BIN-CT are able to pick up more containers, in less time per container, traveling less kilometers and taking more advantage of the load capacity of the trucks. We must highlight the difference in distance traveled: we would save 20% of the distance traveled in comparison with the real solution even when our routes last 19 minutes and 55 seconds more than the real ones. If we used the average distance to collect a container and multiply by the 62 containers of the real solution, then the estimated distance traveled would be 48,333 meters, which means we would have routes 33.2% shorter than the routes used by the company. The algorithm run with the default parameters and a stop criterion of 10,000 iterations. The median runtime was 27,350 milliseconds that is less than half a minute, so the algorithm is quite fast. Moreover, if we increase the iteration budget, potentially we would obtain even better results.

After specialized staff from the company, which gave us the data for the case of study, validated the solutions generated by BIN-CT, we can conclude that our system generates realistic solution and reproduce with enough reliability what happens in reality. Besides, the use of the fill predictions discarded 140 containers not included as nodes to visit in the generation of routes process. Actually, all containers (except one) which were not included in our routes but included in the real ones, were discarded based on the forecasting and not because of trucks capacity constraints. This fact means that with high probability we have saved unnecessary visits to semi-empty containers that are part of a predefined static route for the analyzed day. Therefore using BIN-CT implies a reduction in both the cost of the routes and the harmful emissions thrown by the trucks.

6. Conclusions and Future Work

BIN-CT is an intelligent predictive software system designed to use the knowledge and technology that is part of the state-of-the-art in urban sustainability research. We are convinced that our intelligent system will help to improve the quality of life of the city where it is implemented, due to the reduction of costs and the efficient treatment of the waste generated, which will constitute a way to achieve the sustainability in a city.

Our aim is to reduce the costs of the waste collection service, while increasing the quality of service to the citizen. Our software suggests the collection of containers above 80 % and thus avoids the annoying overflows of containers. In the case of study that we have analyzed in this article, we prove that the solutions generated are realistic, and at the same time they are more efficient because it avoids visits to semi-empty containers and the generated routes are 33.2% shorter than the used by the company. Moreover, after the comparison of three different algorithms, we used the best which generates predictions with only 3.83% mean absolute error. This fact indicates that the forecasting performed is fairly reliable for the calculations we need to make in our system.

BIN-CT has a direct application for waste management companies, both in Spanish cities and anywhere in the world. This non-commercial software system, based on computational learning algorithms, does not require a large investment in infrastructure, which is why it is very interesting for companies. There is also an interesting scientific part (use of time series, predictions, efficient algorithms, ...) that companies may be interested in, which could make the leap in quality and distinction that seeks in a market as competitive as the current one.

As future work, we can highlight the possible integration of an indeterminate number of sensors, in a larger cyber-physical system, to measure the amount of waste in the containers. The way the system is built allows an easy sensors integration. The use of sensors makes it possible to change a route in real time by adding or removing containers. Fortunately, this valuable feature could save more unnecessary visits to containers, meanwhile is also able to avoid possible overflows of containers.

| Solution  | Truck  | Containers | Duration (s) | Distance (m) | Collected (kg) |
|-----------|--------|------------|--------------|--------------|----------------|
| **Experts** |        |            |              |              |                |
| Small     | 31     | 12,044.00  | 34,554.00    | 1,665.00     |                |
| Big       | 31     | 13,912.00  | 37,799.00    | 1,838.00     |                |
| Total     | 62     | 25,956.00  | 72,353.00    | 3,503.00     |                |
| Average   | -      | 418.64     | 1,166.98     | 56.50        |                |
| **BIN-CT** |        |            |              |              |                |
| Small     | 33     | 13,191.00  | 32,407.00    | 1,689.00     |                |
| Big       | 41     | 13,960.00  | 25,281.00    | 1,984.00     |                |
| Total     | 74     | 27,151.00  | 57,688.00    | 3,673.00     |                |
| Average   | -      | 366.90     | 779.57       | 49.63        |                |
Regarding the algorithms for the generation of predictions, we have studied in this work some techniques for time series prediction based on regression. However, nowadays the recurring neural network technique has emerged again as a good method for the generation of time series predictions [LeCun et al., 2015; Cameron et al., 2018]. We plan to improve the fill level predictions by using an algorithm based on recurring neural networks.

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