Allocating Refuse Bins for Selective Waste Collection, A Case Study *

Joaquín BAUTISTA [a], Jordi PEREIRA [b]

[a] *Nissan Chair, Escola Técnica Superior d'Enginyeria Industrial de Barcelona. Universitat Politècnica de Catalunya, Barcelona, SPAIN*

[b] *Departament d'Organització d'Empreses. Universitat Politècnica de Catalunya, Barcelona, SPAIN*

Abstract

One of the problems found in Municipal Waste Management is the allocation of refuse bins to different collection areas where waste (glass, paper, plastic, organic material) is left by the citizens. The relationship between the studied problem and the apportionment of seats in a parliament is tackled and it is used to develop an ant algorithm approach to solve the problem. The algorithm is then compared to an exact procedure for a real life instance found in the metropolitan area of Barcelona.

Key words: Location, Allocation, Integer Programming, Heuristics

1 Introduction

Municipal Waste Management deals with the design, management and control of systems oriented towards the return and treatment of disposable goods, as well as the recovery and recycling of containers, bottles, packages and other forms of waste.

Proper recovery of waste has gained importance in waste management due to social concerns. Municipal waste is not only a great source of recyclable goods, but it is also the nearest source of waste to citizens, more and more socially aware of their importance. Additionally, waste generation has increased during last years. For instance, the OECD has reported an increase of municipal waste generation per capita from 1990 to 2000 ranging from a 4% increase in the US to 26% in the EU. This increase, which has been continuous in recent years, generates serious problems not only during the collection phase, but also in the subsequent treatment phases.

Those facts have been reflected in government legislations. For example, in the EU, a growing body of community directives based on the framework given by directives 75/442/CEE, 91/156/CEE and 94/62/CEE obliges its members to recover and recycle many products and components (e.g. containers, glass, paper, plastic, consumer goods, automotive components, electronics, etc…), as covered in the case of Spain by the July 15, 6/1993 and April 21, 10/1998 royal decrees.

---

* This paper was not presented at any other revue. Corresponding author J. Bautista. Tel. +34934011703. Fax +34934016044
Email addresses: joaquin.bautista@upc.edu (Joaquín Bautista), jorge.pereira@upc.edu (Jordi Pereira).

Within this setting, properly collecting waste is one of the most important phases of the cycle of waste generation-transformation-elimination. The EU directives aimed at caring for the environment have created favourable conditions for the study of problems arising from municipal waste management. In the specific case of Spain, April 21, 10/1998 royal decree has conducted to the National Plan of Urban Waste, whose regulations force each city and town of more than 1000 citizens to set up an adequate selective collection system before 2006.

The scientific community has studied a great variety of problems related to urban waste management ranging from the waste generation phase [9], the evaluation of different government policies [12], the life cycle of waste [2], the behaviour of citizens towards selective collection [10] and the design of collection systems [14] between many others. The literature shows not only the broad variety of problems found but also a wide level of different perspectives regarding the specific characteristics of each region, mainly due to economic differences between countries but also due to specific characteristics and traditions.

In most industrial countries, the waste generated in urban areas is collected by municipal organizations or its collection is adjudicated to private companies. It is their responsibility to collect the waste and transport it to its final destination. In Spain, as in many other places in Europe, the usual collection system is composed of two phases. First, citizens leave their refuse at special collection areas where different types of waste (glass, paper, plastic, organic material) are stored separately in special refuse bins with dimensions ranging from 1 to 3.2 m^3. Subsequently, each type of waste is collected and moved to its final destination (a recycling plant or refuse dump). Three different problems can be identified: (1) a location problem associated to find which are the best locations for the collection areas, [5], [7]; (2) the allocation of refuse bins, [11], and; (3) the design of collection routes, [6] [15] [16].

Mansini and Speranza work, [11], is the only one the authors are aware of treating the allocation of refuse bins to different collection areas. Their work is based on the joint treatment of the allocation of refuse bins and routing decisions with the objective of minimizing the number of routes required. The present work treats the allocation problem alone. A separate treatment is proposed due to the different time span for allocation and routing decisions, and the interest of decision makers to eliminate any capacity overflow in the collection areas, or equivalently to eliminate waste deposited in the street due to shortages in capacity.

When the objective is to minimize the waste deposited outside refuse bins in the street, the most favourable case is the allocation of refuse bins when no constraints exist. In this unconstrained case, a simple capacity calculation should be carried to determine the required quantity of bins per fraction and collection area, but when the availability of bins is restricted or additional constraints must be handled, optimization techniques should be used to obtain good solutions based on some criteria associated to the quality of service.

The present paper is focused on the allocation of refuse bins under availability and space constraints as it is faced on many Spanish municipalities and more specifically in the metropolitan area of Barcelona. A review of the available work associated to sharing out objects based on numerical criterions lead us to the study the theory and procedures for the apportionment problem, as can be seen in section 2. The differences between the studied problems and the problem faced force us to develop a mathematical model to take into account the specifications required for this case. The resulting model and its justification are presented in section 3. Section 4 is devoted to the development of an Ant Colony System (ACS), [8], algorithm specifically tailored for the problem, to define the randomized construction procedure based on the Divisor Method (DM) for the apportionment problem and to describe a local search procedure. The algorithm presented differs from the ACS for the Travelling Salesman Problem in several points; (1) several heuristics are used during the construction procedure; (2) the elite candidate list is dynamically constructed to reflect the dynamic nature of the heuristic information in use; and (3) trail is read in a cumulative way. Section 5 compares the different approaches using a real life instance. Finally section 6 presents the conclusions of this work.

2 Apportionment and fair representation

An apportionment problem can be described as follows: a limited resource must be apportioned to different groups. Each group has a weight and the objective is to share out the resources as evenly as possible between the groups, understanding as even a proportional distribution to each group based on their weights.

The main work in this topic is due to Balinski and Young [1], where one of the applications of the apportionment problem, the distribution of seats in a parliament to different regions or political parties, is tackled. In this case, a number of seats, h, must be distributed to m different groups, each with a population p_i ($p_1,\ldots,p_m$). Ideally each group should get its quota, $q_i=h\bullet p_i/\sum_{\forall i}p_i$, but this is usually impossible because seats are indivisible and quotas tend to be fractional. The objective is then to find an apportionment ($x_1,\ldots,x_n$) such that the integer values x_i are as close as possible to their quotas.

Similar descriptions could be given based on other apportionment problems as the allocation of teaching staff to university departments, schools to city districts, computers to departments of a company, copies of a book to bookstores, servers to queuing facilities or identical machines to workers. In fact, any problem in which h objects are to be allocated in non-negatives integers based on some numerically criterion belongs to this class.

The first procedures to apportion seats to a parliament date back to the end of the 18th century, [1]. These procedures are due to two early American politicians, Alexander Hamilton and Thomas Jefferson, and were introduced to deal with the US House of Representatives apportionment. The Jefferson procedure and four others presented during the 19th century constitute the family of methods known as divisor methods (DM) which are the most usually found in political circumstances, and they will be the ones used in this paper. DMs posses an interesting property known as "house monotonic", that is, if h gets bigger, the number of objects awarded to any option do not diminish. The lack of the house monotonic property leads to the Alabama Paradox which is not recommendable as it is difficult to explain why someone can get less if more is going to be shared between the same numbers of people.

The traditional procedure to apply DMs is to search for a common divisor,λ, such that the quotients p_i/λ, rounded with a specific rule defined by each method, add up to h. The rounding rule characterizes the method. For example, in Jefferson's method x_i is calculated as the largest integer smaller or equal to p_i/λ (the quotient is truncated). An alternate procedure is developed in section 4 to use divisors as a heuristic information source for the ACS algorithm. The procedure is based on the usage of DMs to solve a Just-in-Time scheduling problem, [4].

Refuse bin allocation can also be seen as the previously described apportionment problem where h is the number of available refuse bins, the groups are the collection areas, and each area has a population equal to the citizens or the amount of waste generated by the citizens using the collection area. Unfortunately several key differences appear: (1) while the apportionment problem studies the allocation of a single resource, we are interested in allocating several resources, bins from different fractions together and common constraints prevent us to solve separated apportionment problems; (2) there exists an interaction between the fractions of waste and interactions between different collection areas depending on their composition; and (3) we are not interested in an equitable distribution but in an efficient distribution, even if both terms are very near one to the other.

After several conversations with waste managers and politicians in charge of waste management, they faced the following objectives, and restrictions: (O1) They paid attention to minimize the quantity of waste found outside refuse bins; (O2) they tried to maximize the waste collected using special bins for recyclable fractions; (R1) they had a limited number of refuse bins and, more importantly, recyclable waste bins; and (R2) they wanted to keep the number of refuse bins per collection area within some limits related to physical and aesthetical considerations. Section 3 shows a model based on the previous observations where efficiency is understood as the optimization of objectives (O1) and (O2).

3 A model for apportionment of refuse bins

An instance (M,N,π) of the apportionment problem under study consists of three elements. M = {1,…,*j*,…,*m*} is the set of collection points where citizens leave their waste. Every collection area has an associated population $P_j>0$, number of inhabitants of the city whose nearer collection area is *j*, and a space limitation, $A_j>0$, in terms of maximum number of refuse bins in area *j*. N = {1,…,*i*,…,*n*} is the number of different fractions to collect separately. Every fraction has a number of refuse bins, C_i, available and a number of kilograms generated per period and citizen, v_i. Fraction 1 is associated to general refuse, a mixed fraction with no special recovery. π stands for the percentage of population participating in selective collection. Any population not participating in selective collection leaves their whole waste in general refuse bins.

From the combination of v_i and π, we obtain the kilograms of refuse per fraction and citizen reaching a collection area, v_i', calculated as in (1) and (2). We must differentiate the general fraction, *i*=1, from other fractions, *i*≠1, as the general fraction receives not only their general fraction but also the refuse which has not been properly separated by the citizens in their houses.

$$v_1' = v_1 + \sum_{i=2}^{n} (1-\pi)\cdot v_i \tag{1}$$

$$v_i' = \pi \cdot v_i \qquad (\forall i \neq 1 \wedge \forall i \in N) \tag{2}$$

The goal is to assign the refuse bins, such that objectives (O1) and (O2) are optimized. Let us note that the apportionment problem seen in section 2, is a special case of the present formulation where *n*=1, v_1=1 and the objective function is a measure of closeness between the assigned bins to each collection area and their population.

To describe the mathematical model in use, we shall employ x_{ij} as non negative integer decision variable, denoting the number of refuse bins of fraction *i* assigned to collection area *j*. An auxiliary binary variable y_{ij} will be required denoting the presence (1) or absence (0) of a refuse bin of fraction *i* assigned to collection area *j*.

From observation, we assume that population will only participate in the selective collection of a fraction if his collection area has a refuse bin for this kind of waste, no population would incur in additional distance trips to reach their second, or third, nearest collection area to search for an appropriate bin. In the nearest collection area do not contain a specific refuse bin, the waste will end up in one of the general refuse bins and the citizen will not continue separating the specific fraction in their house. Let Z_{ij} be the total quantity of waste from fraction *i* deposited in the collection area *j*, and Z_{ij}^+ as the total quantity of waste surpassing the capacity, CAP_i, of bins from fraction *i* in the collection area *j* (note that formula (5) can be easily linearized).

$$z_{1j} = v_1' \cdot P_j + \sum_{i=2}^{n} \left(1 - y_{1j}\right)\cdot v_i' \cdot P_j \qquad \left(\forall j \in M\right) \tag{3}$$

$$z_{ij} = y_{1j} \cdot v_i' \cdot P_j \qquad \left(\forall i \in N \wedge i \neq 1, \forall j \in M\right) \tag{4}$$

$$z_{ij}^+ = \max\left\{0; z_{ij} - CAP_i \cdot x_{ij}\right\} \qquad \left(\forall i \in N, \forall j \in M\right) \tag{5}$$

The sum of refuse surpassing the capacity of the allotted bins corresponds to (O1) as defined above and the sum of refuse collected in refuse bins for fractions different to general waste, fraction 1, correspond to (O2). Our objective will be to simultaneously optimize both factors. Given the previous notation we can proceed with a mathematical programming formulation.

$$\min \sum_{j=1}^{m} \sum_{i=1}^{n} z_{ij}^+ \tag{6}$$

$$\max \sum_{i=2}^{n} \sum_{j=1}^{m} \left(z_{ij} - z_{ij}^+\right) \tag{7}$$

Subject to:

$$x_{ij} \le M \cdot y_{ij} \qquad i \in N, j \in M \tag{8}$$

$$\sum_{j=1}^{m} x_{ij} \le C_i \qquad i \in N \tag{9}$$

$$\sum_{i=1}^{n} x_{ij} \le A_j \qquad j \in M \tag{10}$$

$$x_{1j} \ge 1 \qquad j \in M \tag{11}$$

Objective (6) represents the objective of minimizing the refuse outside bins and objective (7) represent the volume of recyclable goods properly collected. Constraint (8) associates the existence of one or more refuse bins of a specific fraction in a collection area y_{ij} to the variables of the problem x_{ij}, being M a positive number near to infinite. Constraint (9) and (10) limit the number of refuse bins available for each fraction and each collection area respectively, and constraint (11) associates at least a refuse bin of the general fraction to each collection area. Additionally to those constraints, the formulas (3), (4) and (5) should be included in the formulation.

A first look lead to treat the problem using a multi objective optimization approach, but corresponding to the interests indicated by practitioners, this problem is nearer to a hierarchical decision problem where objective (6) is more important than (7) in all cases. The reason is that objective (6) represents a serious problem for the municipality as citizens can judge the quality of the service provided by the quantity of waste found in the streets outside the refuse bins, whereas objective (7), associated to the quantity of recyclable waste collected is harder to appreciate by citizens, even if enforced by law. This fact leads us to first propose a hierarchical solution approach, using objective (7) as a value to break ties.

An alternative formulation could lead to treat objective (O2) as a constraint, following an interpretation of the legislation imposing a minimum ratio of waste recovery and recycling. The model is based on the appreciation of most practitioners that recycling is more an objective to achieve rather than a constraint to fulfil.

4 An Ant Colony System to solve the problem

Ant Colony Optimization is a metaheuristic in which a colony of artificial ants cooperates in finding good solutions to optimization problems. A population of artificial ants repeatedly constructs solutions to a problem using a joint population memory as well as heuristic information derived from a constructive procedure priority rule. After a solution is built, the memory is updated with a bias towards the best solutions found. Gradually the memory will positively influence the solutions built by the ants evolving to the global optimum. Various frameworks have been given for the metaheuristic, [8], with applications covering a broad range of areas like routing, assignment, scheduling or covering problems, between others.

This work is based on the Ant Colony System (ACS) approach. We proceed to illustrate the differences between the original algorithm and the procedure implemented to solve the apportionment problem under study.

4.1 Construction Phase

As in the original ACS we apply a biased priority based procedure to obtain a feasible solution. Starting with a void solution, let x_{ij}=0 for $\forall i$, $\forall j$, at each step of the constructive procedure the algorithm assigns a refuse bin from a fraction to a collection area using the so-called pseudorandom proportional rule. The procedure finds a final solution when all refuse bins have been assigned. The differences between this construction procedure and the original Ant Colony System (ACS-TSP) proposal are:

(1) Our algorithm always starts from the same starting point instead of starting from different initial cities as in the ACS-TSP. This modification is needed as only one viable starting point exists and modifies the frequency of trail updating as only one solution is generated per iteration of the ACS procedure.

(2) We must select not only the collection area but the fraction of the refuse bin. Two different proposals have been investigated. The first one randomly selects the fraction before using the pseudorandom proportional rule to select the collection area. Each fraction is selected with probability equal to the ratio between the remaining bins of this fraction with respect to the total remaining bins to allocate. The second one follows an ordering of fractions. Each refuse bin of the majority fraction, the general fraction, are assigned before proceeding to the next majority fraction. This selection rule is based on the relative importance of fractions to the quality of the final solution, being the general fraction the most important one in the primary objective function. After short experiments the second proposal was selected due to the observed computational superiority.

(3) The pheromone information is associated to the number of refuse bins, k, of each fraction, j, to each collection area, i, τ_{ijk}, as the desirability of selecting a refuse bin is related to the desirability of the following refuse bins of the same fraction and collection area, this information is used in a cumulative way as in [13]. Pheromone is initialized by setting τ_{ijk}=0.5 for each $i \in N$, $j \in M$, $k \in \max_{\forall i}\{C_i\}$.

(4) The heuristic information is dynamically calculated. As it is hard to associate a direct cost or benefit in the objective functions to the selection of a single refuse bin, we are forced to use a guide as the heuristic information. The divisor method, sketched in section 2, can distribute evenly the refuse bins between collection areas obtaining a fair distribution of bins between citizens. This solution can be seen as a "rule of thumbs" to allocate refuse bins between collection areas.

The classical divisor method (DM), as found in the application of D'Hondt Law during electoral nights, calculates an index I_{ij} for each party, i, and seat, j, as in (12), based on the quota q and the divisor in use d, for example d=1 if the applied divisor corresponds to D'Hondt Law or Jefferson divisor in US. Usual values for d are 0, Adams divisor, 0.5, Webster divisor and 1, Jefferson divisor. After the calculation, the greatest s divisors are chosen and each party gets a number of seats equal to the number of selected divisors, where s is the number of seats to apportion.

$$I_{ij} = \frac{q_i}{j + d} \tag{12}$$

Our implementation is dynamic and calculates an index I_{ij} for each collection area i, and fraction j, and recalculates the divisor each time a refuse bin is allocated. The procedure corresponds to algorithm 1, using and index obtained as in (13).

$$I_{ij} = \frac{p_i}{x_{ij} + d} \tag{13}$$

Algorithm 1. Divisor Methods

Input: divisor in use d, population vector per collection area P ($1 \le i \le m$), refuse bins to allocate S and fraction j, $\varepsilon = 10^{-9}$

Output: Number of refuse bins per collection area X_i

0. Initialization: x_{ij}=0, set $I_{ij}=p_i/(d+\varepsilon)$
1. for each S
   a. Sort P in decreasing order of I_{ij}
   b. Choose the collection area i with greatest I_{ij}
   c. Let $x_{ij} \leftarrow x_{ij} + 1$, $I_{ij}=p_i/(d+\varepsilon+x_{ij})$
2. end for

Algorithm 1 is then modified to use a pseudorandom proportional rule. Instead of selecting in step 1.b the collection area with greatest index, the decision is based on two sources of information: heuristic information based on the divisors plus a memory based source of information represented by pheromone left by previous solutions. To add an additional level of exploration to the search, a different value of divisor, d, is randomly chosen at every construction phase. The values of d are obtained from a uniform distribution between 0 and 1.

When a collection area is to be chosen, step 1.b from algorithm 1, we use the following logic instead. With probability q_0 an exploitation decision is adopted as represented in (14) where the candidate with maximum likelihood is chosen, otherwise an exploration step is conducted where each collection area is chosen with probability p_i as in (15).

$$\underset{i \in N}{\arg\max} \left\{ \tau_i^{\alpha} \cdot \eta_i^{\beta} \right\} \tag{14}$$

$$p_i = \frac{\tau_i^{\alpha} \cdot \eta_i^{\beta}}{\sum_{x \in N} \left(\tau_x^{\alpha} \cdot \eta_x^{\beta} \right)} \tag{15}$$

The heuristic source, denoted as η_i, is the desirability of establishing an additional refuse bin of the fraction currently being allocated in the collection area i and it is equal to I_{ij} for fraction j in the current step of the algorithm 1. The trail information, τ_i, corresponds to the pheromone τ_{ijk} where k equals to the number of order of a new bin of fraction i in collection area j.

4.2 Local Search

A local improvement is applied to the solutions offered by the building procedure that transforms one feasible solution into others.

The proposed improvement procedure is based on movements. A movement (j,k_1,k_2) consists in transferring a refuse bin j from collection area k_1 to collection area k_2, and it is considered a feasible movement if receiving collection area still fulfils the space limitation constraints, that is the sum of refuse bins in the receiving collecting area is less or equal to the space limitation of the collection area.

To reduce computing times we restrict the candidate list of receiving areas to: (1) those collection areas where the refuse bins allotted do not cover the total refuse assigned to the area and (2) those collection areas lacking of refuse bins for recyclable fractions.

4.3 Pheromone Update

As in the original ACS-TSP, pheromone update is done by a local update and a global update phase.

The local update phase is applied simultaneously to the constructive phase. Each time a refuse bin is assigned, trail associated to the fraction, collection area, number of bins is reduced as indicated by formula (16).

$$\tau_{ijk} \leftarrow (1-\rho)\tau_{ijk} \tag{16}$$

During the global update, the best so far solution adds pheromone as indicated by the equation (17).

$$\tau_{ijk} \leftarrow \tau_{ijk} + \rho \cdot \frac{f_6^b - 10^{-2} \cdot f_7^b}{f_6 - 10^{-2} \cdot f_7} \tag{17}$$

Where f_6, f_7, f_6^b and f_7^b stand for the value of the current solution for equation (6), the value of the current solution for equation (7), and the values of the best known solution for equations (6) and (7) respectively. Formula (17) tries to leave more pheromone for better solutions, those with smaller values of f_6 and bigger values of f_7. As the importance of objective O1, equation 6, is greater than objective O2, equation 7, the importance is scaled down by a constant factor 10^{-2}.

5 Computational Experience

The proposed algorithm was implemented in ANSI C and compiled using GCC 3.4.2. Experimental results were obtained on an Intel Pentium 4 (3Ghz.) with 512 Mb. of Memory running Windows XP. The MILP package CPLEX 9.0 was used to solve MILP instances.

A real life instance provided by the municipality of Sant Boi del Llobregat was used for testing purposes. Sant Boi del Llobregat is a city of 78000 inhabitants located in the metropolitan area of Barcelona. The system in use by the municipality in 2004, which is used in these tests, contains 426 collection areas, with assigned population ranging between 1 and 1726 inhabitants with a mean value of 183 and standard deviation of 186, that is, the distribution of population is highly variable.

Four different fractions are collected separately. The number of bins per fraction is: 1095 bins for the general refuse fraction, 142 bins for the paper and cardboard fraction, 154 bins for the glass fraction and 75 bins for the plastic fraction. Three different scenarios are proposed, based on the level of participation in selective collection by the inhabitants, represented by three different values of parameter π. The first scenario represents the current situation, as presented by the municipality, where π=0.3. The second scenario is based on the desires of the municipality to increase the participation in selective collection, π=0.5, and finally we give a hypothetical case where every inhabitant is active in selective collection, π=1.

Table 1 collects the results. The algorithms tested are: (1) the ANT algorithm described in section 4 with the standard parameters found in most works in the literature, [8], α=1, β=1, ρ=0.1 and q_0=0.15; (2) Three different Divisors with and without local search (LS), Adams, d=0, Webster, d=0.5, and Jefferson, d=1, (3) The results provided by MILP and (4) The evaluation of the solution in use by the municipality using the objective function stated in formula (6) and (7). Two values are reported per algorithm and level of participation. The first one corresponds to the total quantity of refuse over the capacity provided by the refuse bins assigned, represented in m^3. The second one corresponds to the total quantity of recyclable waste collected in the desired bins. For the first value, a lower number is preferred, while for the second value a higher number is desired. Numbers in bold are the best found. All algorithms are deterministic except the ANT algorithm. For the ant algorithm we provide mean values for ten different runs.

Table 1
Results of each procedure for a real life instance with different levels of participation, π, are provided. For each algorithm and level of participation two values, waste surpassing allotted capacity and recyclable waste collected, are provided. The mean running time in seconds for each algorithm are also given.

Procedure	π=0.3	π=0.5	π=1.0	Mean Time (s)
ANT	(521.2; 179.2)	(423.3; 279.7)	(345.5;**412.1**)	5
Adams	(626.7; 138.6)	(538.2; 227.2)	(507.5; 382.6)	0
Webster	(579.7; 123.9)	(504.8; 205.7)	(511.8; 360.4)	0
Jefferson	(595.6; 104.7)	(549.8; 174.5)	(537.2; 329.2)	0
Adams+LS	(561.7; 138.6)	(474.3; 227.2)	(388.1; 382.6)	0
Webster+LS	(576.4; 123.9)	(494.7; 205.7)	(390.3; 360.4)	0
Jefferson+LS	(595.6; 104.7)	(525.8; 174.5)	(396.2; 329.2)	0
MILP	(**519.1**; **181.2**)	(**417.2**; **283.9**)	(**294.6**; 409.1)	7
Real Case	(931.4; 95.2)	(884.4; 154.9)	(815.8; 270.1)	-

An analysis of table 1 shows the potential of application of any of the described applications to the real problem. As already noted in [3] where a Decision Support System was developed for the same problem, as requested by the Sant Boi Municipality, even the use of simple procedures, like the divisor methods highly improve the quality of the solutions. Other improvements are possible if more elaborate algorithms are used, like the ANT algorithm or the MILP formulation.

The results show that the preferred method of solution for the problem is a direct MILP approach, as it can solve to optimality a large real size instance. Even so, the Ant Algorithm performs remarkably well and it is likely to be a preferred option for further research in this area. Our assumption is based on the quality of the offered solutions and the existence of additional concerns that the model described in section 3 fails to cover.

Firstly, the mathematical model offers only one optimal solution. The Ant Algorithm is capable of providing several near optimal solutions, allowing decision-makers to implement a final solution taking into account additional information which is relatively difficult to formalize in a mathematical model. Mathematical Programming techniques could overcome this drawback but at an expense of a higher computational time.

Secondly, the mathematical model is only applicable to linear models. A slight extension to consider is the removal of the assumption that population will only participate in the selective collection of a fraction if his collection area has a refuse bin for this kind of waste. A small portion of the population will willingly travel some additional meters to participate in selective waste collection. Changes to the mathematical model will lead to quadratic models where exact algorithms are less efficient, while changes to the Ant Algorithm are small.

Finally, the mathematical model lacks of the aforementioned house-monotonic property of the solutions. As in the previous case, few changes are required for the ANT algorithm or the divisor methods with local search to implement this property without any lack of efficiency.

6 Conclusions

In this work, we have presented a new mathematical model and an Ant Algorithm for the problem of allocating refuse bins to different collection areas in a Selective Urban Waste Management problem found in the real life. To the best of our knowledge, this is the first time that this problem is tackled in the literature in the form presented in this work. The results obtained show the potentiality of the aforementioned methods to solve real life instances.

7 Aknowledgements

The present work has been partially funded by the BEC2003-03809 and DPI2004-03475 from the Spanish Government. We are also grateful for the support of the Nissan Chair UPC and Spanish Industrial Operations Nissan.

8 References

[1] M.L. Balinski, Young H.P. Fair Representation Meeting the Ideal of One Man, One Vote, Brookings Institution Press 2nd edition, 2001
[2] J.R. Barton, Dalley, D., Patel, V.S. Life cycle assessment for Waste Management. Waste Management 16:35-50, 1996.
[3] J. Bautista. Proyecto integral de gestión de residuos urbanos en el municipio de Sant Boi de Llobregat. CPDA. Barcelona, 2001
[4] J. Bautista, Companys R., Corominas, A. Solving the generalized apportionment problem through the optimization of discrepancy functions. European Journal of Operational Research, 131:676.684, 2001
[5] J. Bautista, Pereira J., Modeling the problem of locating collection areas for urban waste management. An application to the metropolitan area of Barcelona. OMEGA, 34:617-629, 2006.
[6] J. Bautista, Pereira J., Fernández E., Solving an Urban Waste Collection Problem using ant heuristics within a decision support system, Computers and Operations Research, to appear.
[7] N-B. Chang, Wang, S.F. A fuzzy goal programming approach for the optimal planning of metropolitan solid waste management systems, European Journal of Operational Research, 99:303-321, 1997.
[8] M. Dorigo, Stützle T. Ant Colony Optimization, MIT Press, 2004.
[9] R. Gamba, Oskamp, S. Factors influencing community residents' participation in commingled curbside recycling programs. Environment and Behaviour 26:587-612, 1994.

[10] C. Garces, Lafuente A., Pedraja M., Rivera P. Urban Waste Recycling Behavior: Antecedents of Participation in a Selective Collection Program. Environmental Management, 30:378-390, 2002.

[11] R. Mansini, Speranza, M.G. A linear Programming model for the separate refuse collection service, Computers and Operations Research, 25:659-673, 1998.

[12] T. Masui, Policy evaluations under environmental constraints using a computable general equilibrium model. European Journal of Operacional Research, 166:843-855, 2005.

[13] D. Merkle, Middedork M., Schmek H, Ant Colony Optimization for Resource Constrained Project Scheduling, GECCO-2000, 2000.

[14] C. Revelle, Research Challenges in environmental management, European Journal of Operational Research, 121:218-231, 2000.

[15] J.Teixeira, Pais Antunes A., Pinho de Sousa J. Recyclable waste collection planning – a case study, European Journal of Operational Research, 158:543-554, 2004.

[16] D.V. Tung, Pinnoi A. Vehicle routing-scheduling for waste collection in Hanoi, European Journal of Operational Research 125:449-468, 2000.