# An Innovative Algorithmic Approach for Urban Solid Waste Collection

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*Abstract*-In the present paper, a new framework for urban solid waste collection and transfer is proposed. It consists of a geo-referenced Spatial Database, integrated in a Geographic Information System (GIS) and includes all the parameters required for solid waste management. These parameters involve point sources (loading spots) of waste collection, road network, and related traffic data. Moreover, dynamic data for population density, commercial traffic, time schedule of labour workers, transportation facilities and their technical characteristics are considered.

In addition, an innovative methodology for the solid waste collection and transport is introduced, based on the Ant Colony Optimization (ACO) Algorithm. The objective of the proposed system is to identify the most cost-effective alternative scenario for waste collection and transport, to estimate its running cost and to simulate its application.

## I. Introduction

Urbanization is one of the most evident global changes worldwide. The rapid and constant growth in urban population led to a dramatic increase in urban solid waste production, with a crucial socio-economic and environmental impact. There are many proposed solutions for the construction of a solid waste management system which would monitor and manipule the generated waste. The management of urban solid waste is intrinsically complex, because it involves various relative problems, which are often in conflict. Moreover, given that this solution cannot be reduced to the optimization of just one parameter, a formal multi-criteria urban waste management approach is needed. Urban waste management problems contain a number of these characteristics and each is sufficient to justify a formal multi-criteria analysis.

Nowadays, there is a general agreement on the best practices for sustainable management of urban solid waste, but only isolated efforts have been made in this domain, which are adapted to the specific regulations and needs of each national or regional authority [1]. Waste management issues should be confronted in a more generalized manner, which means that new strategies should be designed in order to consider diverse and variable urban models. This leads to the necessity of developing integrated, computerized systems for obtaining optimal solutions for the management of urban solid waste. However, this work mainly focuses on the collection and transport of solid waste from any loading spot in the area under study to the transshipment or disposal sites. In addition, all other factors that affect directly the whole system will be mentioned and discussed. Of course, this research covers only the routes included in the given area.

Therefore, in this context, a framework (schema) for the design and implementation of a solution for the solid waste collection and transport is proposed. According to this schema, the ACO algorithm, an innovative algorithm in that research area, is introduced and implemented, for monitoring, simulation, testing, and cost optimization of alternative scenarios of a solid waste management system. This schema is described in the rest of the paper as follows: Section 2 describes the theoretical and methodological aspects for urban solid waste management. In Section 3, the waste management problem in the selected case study area is introduced. Section 4 introduces and describes the ACO algorithm and how it is applied in the current situation. Section 5 illustrates the results of the ACO algorithm achieved and compares them to present solutions. Conclusions and future developments are also discussed in this section.

## II. State-of-the-Art

In the literature of the past few years, much effort has been made in the domain of urban solid waste. The effort focuses either on theoretical approaches, including socio-economic and environmental analyses, concerning waste planning and management, or on methods, techniques and algorithms

developed for the automation of the process.

The theoretical approaches examined in the literature refer to issues concerning the conflict between urban residents and the municipality for the selection of sites for waste treatment, transshipment stations and disposal, the issue of waste collection and transport and its impact to human health due to noise, traffic, etc. In this context, the calculation of total cost for collection and transport, for a specific scenario, is implemented. The identification of the most cost-effective alternative scenario and its application is simulated.

In the literature, methods and algorithms have been used for optimizing sitting and routing aspects of solid waste collection networks that were deterministic models including, in many cases, Linear Programming (LP) [2],[3]. However, uncertainty frequently plays an important role in handling solid waste management problems. The random character of solid waste generation, the estimation errors in parameter values, and the vagueness in planning objectives and constraints, are possible sources of uncertainty. Fuzzy mathematical programming approaches for dealing with systematic uncertainties have been broadly used in the last few years. For example, the sitting planning of a regional hazardous waste treatment center [4], the hypothetical solid waste management problem in Canada [5], an integrated solid waste management system in Taiwan [6]. To cope with non-linear optimization problems, such as deciding about efficient routing for waste transport, methods based on Genetic Algorithms (GA) are also proposed [7].

## III. Problem Definition

A part of the Attica prefecture (the municipality of Athens) was chosen as the case study area. The municipality of Athens has empirically divided its area in about 145 solid waste collection programs. In general, a collection program, comprises a region of about 0,5 km$^2$, with a population of more than 8500 citizens and a production of about 3800 tones of solid urban waste per year, according to the latest statistics taken from the municipality. The waste buckets, in the area under study, have been placed by experts of the municipality and theoretically they are able to cover the needs of the citizens. Any garbage truck that it is responsible for the collection of solid waste for that area, must visit all waste buckets.



Figure 1. The area of the municipality of Athens used in the experimental measurements

So far it is obvious that the urban solid waste collection and transport is a complex problem with many limitations. Minimization of cost means minimization of collection time but not necessarily, minimal route. There are two crucial sets of factors:

- The limited waste capacity of each garbage truck and waste bucket,

- The numerous factors that can affect the garbage truck movement from one loading spot to another.

Each garbage truck is able to collect a specific quantity of solid waste. So, the collected area should be fragmented to sub areas, which produce a quantity of solid waste, equal to or less than the capacity of each truck (max_quantity). The second point is that, the time of truck movement is affected by many factors, such as the road width, the traffic, the number of turns etc. All these parameters are included in the transportation cost calculation model. Historical data provide us with the ability to extract the 24th hour distribution of each factor.

## IV. Ant Colony Optimization (ACO) Algorithm

The basic idea of ACO algorithms was inspired through the observation of ant colonies. Ants live in colonies and their behaviour is directed more to the survival of the colony as a whole rather than to that of a single individual component of the colony [8], [9]. While each ant is walking, it deposits a chemical substance on the ground called pheromone [10], which helps ants to find their way back to the food source (or to the nest). Ants can smell pheromone and, when choosing their way, they tend to choose, in probability, paths marked by strong pheromone concentrations. The pheromone evaporates over time to allow search exploration. It has been shown experimentally [11] that the pheromone trail following behaviour can lead to the emergence of shortest paths.

The Ant Colony Optimization (ACO) algorithm uses artificial ants, to find good solutions to difficult optimization problems. Each ant of the "colony" builds a solution to the problem under consideration, and uses information collected on the problem characteristics and its own performance to change how other ants see the problem. The ACO algorithms are based on the following ideas:

- Each path followed by an ant is associated with a candidate solution for a given problem.
- When an ant follows a path, the amount of pheromone deposited on that path is proportional to the quality of the corresponding candidate solution for the target problem.
- When an ant has to choose between two or more paths, the path(s) with a larger amount of pheromone have a greater probability of being chosen by the ant.
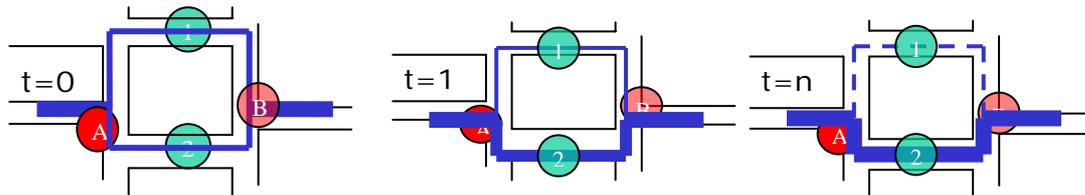


Figure 2. The Ant Colony Optimization process

Figure 2 illustrates an example of artificial ants' movement. We suppose, that at time t=0, a number of ants are moving from waste bucket A to B as depicted in the above figure. When ants arrive to point A they have to choose between the 1st and the 2nd route. Initially the pheromone trail is the same for the two alternative routes, so half of them will choose the first route and the rest the second one. The ants which chose the 2nd will return in shorter time than the others. This means, that the pheromone trail deposited on the 2nd route evaporates less than in the 1st route.

At time t=1, ants start again their route. When they arrive in point A, the pheromone trail 2 will be stronger than in the 1st route, so more ants will choose the second route. After several cycles (t=n) the 1st pheromone trail, completely evaporates and all ants choose the 2nd trail which is the shortest path.

## V. The Proposed System & Results

The Ant Colony Optimization algorithm implementation requires a three dimensional approach to face the solid waste collection and transport problem. These three dimensions are the following:

1. In the beginning, the area under study is fragmented into a series of sub-areas which produce a quantity of solid waste, equal to or less than a fixed quantity. This is necessary due to the capacity limits for the carrier trucks. For each sub area, the local optimal truck route is identified at each specific time slot.
2. Then, the optimized solution is calculated for a 24 hour distribution. There is a 24 hour periodicity in parameters that influence traffic flow related factors, and
3. Finally, a new fragmentation is applied until a total optimal solution is found.

In every sub area a colony of artificial ants is created which, at first travels randomly complete circuits that contain every waste bucket of the given set. During the first step, the local travel to closer waste buckets is favoured. After a complete circuit is determined, "pheromone" is deposited on each link. The colony is then released to travel circuits again, but this time the ants favour links with higher concentrations of pheromone in addition to links that are shorter. The pheromone evaporates at a constant rate, and links that are not part of good overall circuits eventually fall out of favour.

This procedure is repeated for every sub area in a 24 hour distribution. The summary of optimal solutions for each sub area, calculates the final solution. The same scenario is followed in the third layer too, where the sub areas are re-fragmented. New sub areas are calculated based on previous ones, excluding old and adding new waste buckets.

As mentioned above, the minimization of cost corresponds to the minimization of collection time and not necessarily to the minimum route. However, the distance minimization of route was used initially in the evaluation phase. In that phase, one hundred iterations were applied and figure 3 illustrates their respective solutions. These experimental results were compared with the empirical model, used in the municipality of Athens.
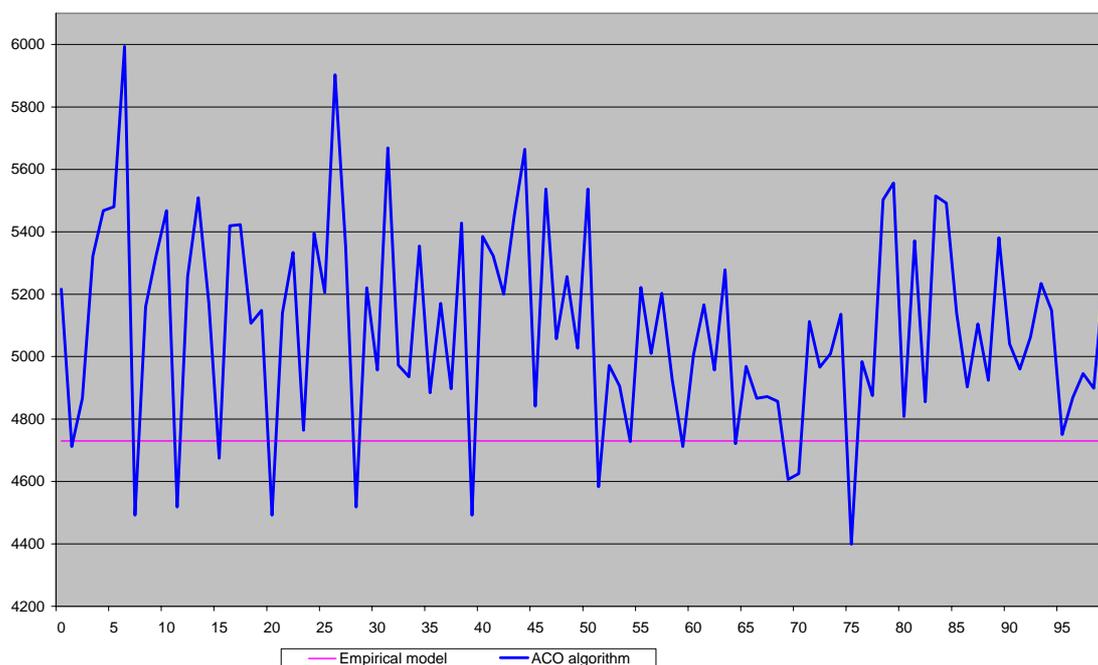

Figure 3: Experimental results (distance based)

Although the average route distance from the experimental results is longer than the distance of the empirical route (5095m and 4730m respectively), the minimum route length which was extracted from the ACO algorithm is better as the table 1 describes. This means that ACO calculates at least one solution better than the current one. The distance route improvement from the empirical model is about 6.7 %. The total amount of optimum solutions which are better than the empirical model is 14.

| Empirical model (meters) | Average route length (meters) | Optimized route length (meters) | Percentage of improvement | Amount of better routes |
|---|---|---|---|---|
| 4730 | 5095 | 4399 | 6.7% | 14 |

Table 1: Analysis of experimental results (distance based)

Furthermore, a first approach of cost minimization based on time produced very satisfactory results. Specifically, the movement cost function between any loading spot i and j included factors which affect the movement speed, such as the number of turns and road width. The movement cost function which used is the following:

$$c_{ij} = t_{turn} * n_{turn} + \frac{d_1}{u_1} + \frac{d_2}{u_2} + \frac{d_3}{u_3} + ... + \frac{d_k}{u_k}$$

Where $t_{turn}$ the average time is required for each turn, $n_{turn}$ the amount of turns during the movement between the loading spots i and j, $d_{ij} = d_1 + d_2 + d_3 + ... d_n$ the total distance and $u_1, u_2, u_3 .... u_n$, the average waste truck speed in the distances $d_1, d_2, d_3 ... d_n$.

In this phase, the ant colony optimization algorithm was applied to the area under study and a set of one hundred optimum solutions was extracted, as represented in figure 4. The experimental results confirm an additional improvement of the optimum route, in the range of 10.3%. Table 2 illustrates the results of the ACO system.
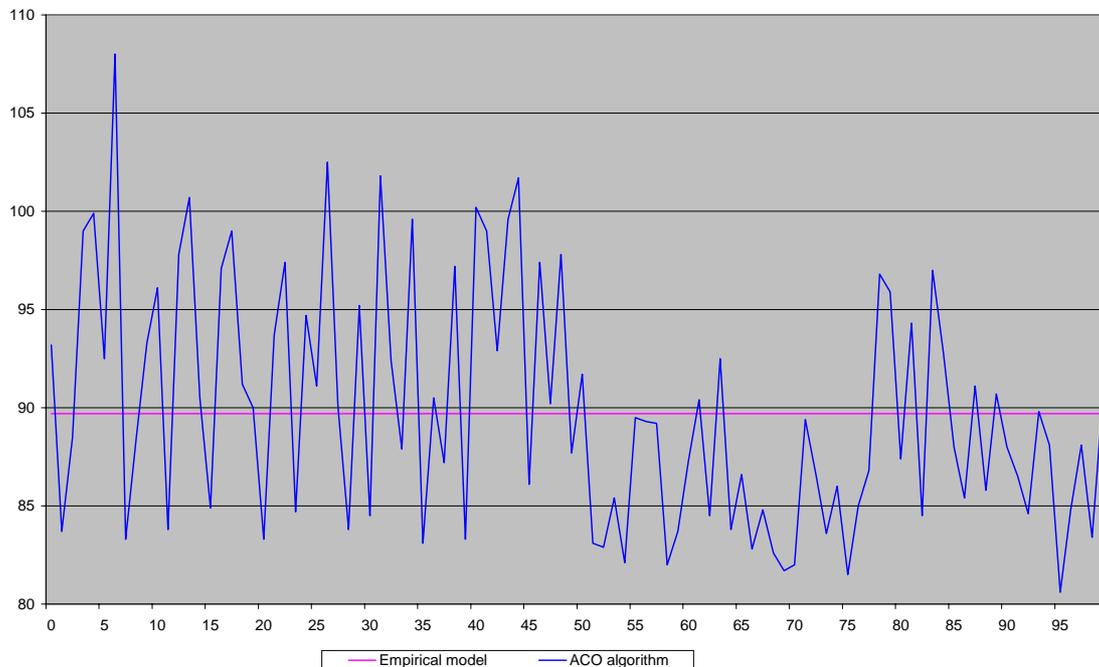


Figure 4: Experimental results (time based)

In this phase, the average route time of experimental results is quite close to the route time of the empirical model (89,7 and 89,9 respectively), while the time duration of the optimum route is 10,3% shorter than the time duration of the empirical model. The total amount of optimum solutions, which are better than the empirical model, is 54.

| Empirical model (minutes) | Average route time (minutes) | Optimized route time (minutes) | Percentage of improvement | Amount of better routes |
|---|---|---|---|---|
| 89.7 | 89.9 | 80.6 | 10,3% | 54 |

Table 2: Analysis of experimental results (time based)

The first experiments have shown that an algorithmic approach of this every-day problem - the collection of the urban solid waste - can greatly minimize the total cost in time and money. However, as it was reported above, the particular problem is much more complex than presented in current work. The proposed methodology was applied in a region of the municipality of Athens which contains a quantity of solid waste equal to the capacity of the waste truck is used in this particular area. Therefore, the problem can be reduced in a classic TSP problem.

The next step towards the total confrontation of the problem, will aim in optimizing the fragmentation of the areas and then in optimizing the time for collection and transport in every region. Another approach would be to reduce the problem as a Vehicle Routing Problem (VRP) problem.

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