URBAN SOLID WASTE COLLECTION AND ROUTING: THE ANT COLONY STRATEGIC APPROACH

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Abstract: In the present paper the Ant Colony Optimization (ACO) Algorithm is introduced for best routing identification applied in urban solid waste collection. The proposed solid waste management system is based on a geo-referenced Spatial Database supported by a Geographic Information System (GIS). The GIS takes into account all the required parameters for solid waste collection. These parameters involve static and dynamic data, such as positions of trash-cans, road network, related traffic and population density. In addition, time schedules of trash-collection workers, track capacities and technical characteristics are considered. The ACO spatio-temporal statistical analysis model is used to estimate interrelations between dynamic factors, like network traffic changes in residential and commercial areas in a 24 hour schedule, and to produce optimized solutions. The user, in the proposed system, is able to define or modify all of the required dynamic factors for the creation of an initial scenario. By modifying these particular parameters, alternative scenarios can be generated leading to several solutions. 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.

Keywords: Ant Colony Optimization (ACO) Algorithm, Quality of Service, Solid Waste, Cost Optimization, Simulation

1. 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 manipulate the generated waste. The management of urban solid waste is intrinsically complex, because it involves various relative factors, 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 [Leao et al., 2001]. 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 [Karadimas et al., 2005b]. 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. In addition, other factors that affect 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 the particular 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: More specifically, Section 2 describes the theoretical and methodological aspects for urban solid waste management. Section 3, introduces and describes the ACO algorithm. In Section 4, the waste management problem in the selected case study area is introduced. Section 5 describes the methodology and the proposed system and how it is applied in the current situation using the ACO algorithm, outlining at the same time, some of the proposed variants. Section 6 illustrates the results of the ACO algorithm and compares them with the present empirical solution that the Municipality of Athens uses. Finally, in Section 7, conclusions and future developments are also discussed in this section.

2. RELATED WORK

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) [Hsieh and Ho, 1993], [Lund and Tchobanoglous, 1994]. 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 [Huang et al., 1995], the hypothetical solid waste management problem in Canada [Koo et al., 1991], an integrated solid waste management system in Taiwan [Chang and Wang, 1997]. To cope with non-linear optimization problems, such as deciding about efficient routing for waste transport, methods based on Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search and Ant Colony Optimization (ACO) are also proposed [Chang and Wei, 2000], [Pham and Karaboka, 2000], [Ducatelle and Levine, 2001], [Bianchi et al. 2002], [Chen and Smith, 1996], [Glover and Laguna, 1992], [Tarasewich and McMullen , 2002].

The problem could be classified as either a Traveling Salesman Problem (TSP) or a Vehicle Routing Problem (VRP) and for this particular problem, several solutions and models have been proposed. However, the complexity of the problem is high due to many alternatives that have to be considered and the number of possible solutions is considerably high, too.

As it is mentioned above, the most popular algorithms used today in similar cases include the Genetic Algorithms, the Simulated Annealing (SA), the Tabu Search and the Ant Colony Optimization (ACO) Algorithm.

Genetic Algorithms [Glover et al., 1992], [Pham and Karaboka, 2000], [Chen and Smith, 1996] use biological methods such as reproduction, crossover, and mutation to quickly search for solutions to complex problems. GA begins with a random set of possible solutions. In each step, a fixed number of the best current solutions are saved and they are used in the next step to generate new solutions using genetic operators. Crossover and mutation are the most important genetic operations used. In the crossover function parts of two random solutions are chosen and they are exchanged between two solutions. As a result two new child solutions are generated. The mutation function alters parts of a current solution generating a new one. The mutation function is included to keep from becoming trapped in a local optimum. These procedures are repeated for a predefined number of iteration until an acceptable solution is generated.

The Simulated Annealing was inspired from the behaviour of solids in temperature [Pham and Karaboka, 2000]. A solid is heated to a high temperature and then slowly cooled, until the desired properties of the solid are obtained. When the Simulated Annealing begins, an initial solution is generated as the first solution. Then the "temperature" is symmetrically reduced and neighbouring solutions are generated. If one of the neighbouring solutions is better than the current solution, then it replaces the current one. If not, these solutions remain as candidate solutions and one of them can become the final one, if it satisfies some predefined criteria. The acceptance of inferior solutions allows the search, of many different locations, so the probability of falling in a local optimal solution decreases dramatically. This procedure is repeated, until some stopping criteria are met.

Tabu (or taboo) search as described by [Glover, 1986] is a meta-heuristic algorithm. The basic gist of tabu search is to iteratively try to find solutions to the problem, but to keep a short list of previously found solutions and to avoid 're-finding' those solutions in subsequent iterations [Battini and Tecchiolli, 1994]. Basically, if the program tries a solution, it becomes tabu in future tries.

The Ant Colony Optimization (ACO) algorithm [Dorigo and Maniezzo, 1996], was inspired through the observation of swarm colonies and specifically ants. Ants are social insects and their behaviour is focused to the colony survival rather the survival of the individual. Specifically, the way ants find their food is noteworthy. Although ants are almost blind, they build chemical trails, using a chemical substance called pheromone. The trails are used by ants to find the way to the food or back to their colony. The ACO simulates this specific ants' characteristic, to find optimum solutions in computational problems, such as the Travelling Salesman Problem. As this context is mainly focused on the ACO algorithm and its testing to the solid waste collection problem, the ACO is analytically described in the next section.

3. THE ACO ALGORITHM

3.1 Real Ants

The basic idea of ACO algorithms was inspired through the observation of swarm colonies and specifically ants [Beckers et al., 1989]. Insects like ants are social. That means that 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. Most species of ants are blind. However, while each ant is walking, it deposits on the ground a chemical substance called pheromone [Dorigo and Caro, 1999]. Ants can smell pheromone and when choosing their way, they tend to choose, in probability, paths with high pheromone density. The ants using the pheromone trail have the ability to find their way back to the food source. The pheromone evaporates over time. It has been shown experimentally [Dorigo and Maniezzo, 1996] that the pheromone trail following behaviour can affect the detection of shortest paths. For example, a set of ants built a path to some food. An obstacle with two ends was then placed in their way, such that one end of the obstacle was more distant than the other. In the beginning, equal numbers of ants spread around the two ends of the obstacle. Since all ants have almost the same speed, the ants which chose the path of the nearer end of the obstacle returned before the ants that chose the path of the farther end (differential path effect). The amount of pheromone deposits by the ants on the shortest path increases more rapidly than the farther one and so, more ants prefer the shortest path. Finally, in time, the pheromone of the longest path evaporates and the path disappears. This cooperative work of the colony determines the insects' intelligent behaviour and has captured the attention of many scientists and the branch of artificial intelligence called *swarm intelligence* [Leao et al., 2001], [Huang et al., 1995].

3.2 Artificial Ants (ACO)

Now in artificial life, the Ant Colony Optimization (ACO) uses artificial ants, called agents, to find good solutions to difficult combinatorial optimization problems [Bonabeau, Press]. The behaviour of artificial ants is based on the traits of real ants, plus additional capabilities that make them more effective, such as a memory of past actions. 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.

Compendiously, 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.

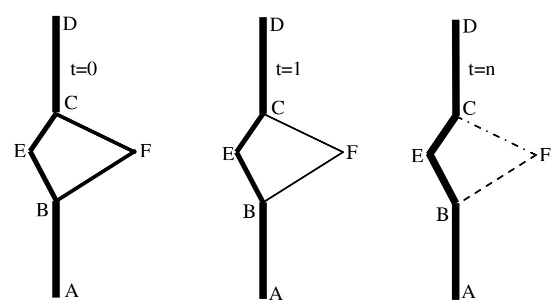

Figure 1: The ACO algorithm process

Let us present an example of artificial ants' movement. We suppose that at time t=0, a number of ants are moving from point A (colony) to D (food) as depicted in Figure 1. When ants arrive to point B they have to choose between BEC and BFC route. Initially the pheromone trail is the same for two alternative routes, so half of them will choose the first route and the rest the second one.

The ants which chose the BEC will return in shorter time than the rest of them. That means, that the pheromone trail deposited on BEC route evaporates less than BFC route. At time t=1, ants start again their route to the food. When they arrive in point B, the pheromone trail in BEC will be stronger than in BFC route, so more ants will choose the first route. After several cycles the pheromone trail in BFC, completely evaporates and all ants choose the BEF trail which is the shortest path.

4. CASE STUDY

In this context, a suburb of Athens was chosen as the case study area. The municipality of Athens has empirically divided its area in about 145 solid waste collecting programs. Figure 2 illustrates one of these collecting programs.

This area of Athens 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 by the municipality of Athens.

Figure 2 also illustrates the approximately 100 loading spots. Any garbage truck that is responsible for the collection of the solid waste in that given area must visit all in order to complete its collection program.

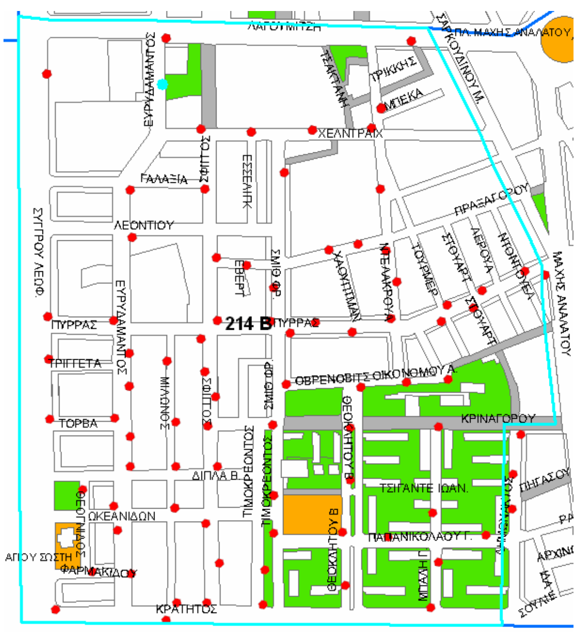

Figure 2: The suburb of Athens used in our experiments

The definition of these loading spots is beyond the scope of the present paper, but their placement is empirically able to cover the needs of the citizens. Additionally, any difficulties that the truck might face, while following a given route, or any other information that could be useful to future considerations during the design and implementation of alternative routes is recorded and available for further utilization.

According to the above, the urban solid waste collection and transport is a complex problem with many limitations. Minimization of cost means minimization of collection time and not necessarily choosing the minimal route. There is a crucial set of factors, such as the route traffic, the width of the roads that a specific route contains the number of turns, the parked cars that in many cases block the smooth traffic flow, etc.

On the other hand, each garbage truck is able to collect a specific quantity of solid waste due to its limited waste capacity. So, the collected area, considering all parameters for that part of the problem, should be fragmented to sub programs which produced quantity of solid waste, equal to or less than the capacity of each truck (max_quantity). All these parameters are included in the transportation cost calculation model. Historical data provide us with the ability to extract the 24 hour distribution of each factor.

Therefore, the problem in our case, as mentioned above, it can be classified as a Traveling Salesman Problem (TSP): “ Given a set of **n** loading spots and the transport cost between any loading spots, the TSP can be stated as the problem of finding a minimal cost closed tour that visits each loading spot once”.

5. PROPOSED SOLUTION

In the proposed solution the ACO algorithm is tested in the solid waste collection and transport problem. Any garbage truck must travel among a set of loading spots, passing from each bin only once. A colony of artificial ants is created and at first it randomly travels complete circuits that contain every loading spot of the given set. During the first step, local travel to the closer loading spots is favoured. After a complete circuit is determined, “pheromone” is deposited on each link. The amount of pheromone is inversely proportional to the length of the circuit; shorter distances receive more pheromone. The colony is then released to travel circuits again, but this time ants favour links with higher concentrations of pheromone in addition to the links that are shorter. The pheromone evaporates at a constant rate, and links that are not part of efficient overall circuits eventually fall out of favour. The ant approach to this problem also provides the advantage of backup routes. Since the ants are continuously exploring different paths, alternative routes already exist if the link between two loading spots becomes unusable (for example, if weather conditions or road construction constitute impossible the movement between two loading spots).

5.1 Methodology

The schema, which was chosen for the solution of our problem, is the Ant cycle algorithm from [Dorigo and Maniezzo, 1996], [Dorigo and Caro, 1999], where each ant is a simple agent with the following characteristics:

- Initially an ant is placed in every loading spot. The number of ants is equal to the number of loading spots.
- Every ant chooses the bin to go to with a probability that is a function of the movement cost between two loading spots and of the amount of trail pheromone.
- Movements to already visited loading spots are disallowed until a tour is completed.
- When a tour is completed, ants update pheromone on each edge (i, j) they visited.

As mentioned above, the optimization quantity is the collecting time and not necessarily the distance of the route. Thus, the truck movement cost between loading spot i and j, is a function of all separate costs for each factor which affects the track route:

$$d_{ij} = \alpha \cdot da_{ij} + \beta \cdot db_{ij} + \gamma \cdot dc_{ij} + ... \qquad (1)$$

Let tij(t) be the *intensity of trail* on edge (i,j) at time t. Each ant at time t chooses the next loading spot, where it will be at time t+1. Therefore, if we call an *iteration* of the ACO algorithm the n moves carried out by the n ants in the interval (t, t+1), then for every n iterations of the algorithm (which we call a cycle) each ant has completed a tour. At this point the trail intensity is updated according to the following formula:

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij} \qquad (2)$$

Where ρ is a coefficient such that (1 - ρ) represents the *evaporation* of trail between time t and t+n,

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \qquad (3)$$

Where $\Delta\tau_{ij}$ k is the quantity per unit of length of trail substance (pheromone in real ants) laid on edge (i,j) by the k-th ant between time t and t+n; it is given by:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k} & \text{if k ant uses edge (i, j) in its tour} \\ 0 & \text{Otherwise} \end{cases} \qquad (4)$$

where Q is a constant and L_k is the tour length of the k-th ant.

The coefficient ρ must be set to a value <1 to avoid unlimited accumulation of trail (see note1). In our experiments, we set the intensity of trail at time 0, tij(0), to a small positive constant *c*.

In order to satisfy the constraint that an ant visits all the n different loading spots, we associate with each ant a data structure called the *hlist*, that saves loading spots already visited up to time t and forbids the ant to visit them again before n iterations (a tour) have been completed. When a tour is completed, the *hlist* is used to compute the ant's current solution (i.e., the movement cost of the path followed by the ant). The *hlist* is then emptied and the ant is free to choose again. The total number of cycles is called *NC*.

$$\eta_{ij} = 1 / d_{ij} \qquad (5)$$

We call *visibility* hij the quantity 1/dij. This quantity is not modified during the run of the AS, as opposed to the trail which instead changes according to the previous formula (5). We define the transition probability from loading spot i to loading spot j for the k-th ant as

$$p_{ij}^{k} = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} \qquad (6)$$

where allowed$_k$ = {N - *hlist*} and where a and b are parameters that control the relative importance of trail versus visibility. Therefore the transition probability is a trade-off between visibility (which states that close loading spots should be chosen with high probability, thus implementing a greedy constructive heuristic) and trail intensity at time t (which states that if there is a lot of traffic on edge (i,j) then this edge is highly desirable, thus implementing the autocatalytic process).

6. RESULTS

In this paper, an original solution for the collection and transport of Solid Waste has been presented. There is no simple solution to this kind of problems due to interactions between conflicting requirements. Therefore, an innovative approach for Solid Waste Management, based on the ACO algorithm, has been applied. This algorithm has been implemented into a C++ programming language environment.

In the beginning, the total area 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 limited capacity of the trucks.

In every sub area, a colony of artificial ants is created, which at first, travels randomly complete circuits that contain every waste bin of the given set. During the first step, the trip to the closest waste bin 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 effective overall circuits eventually fall out of favour. After a number of cycles an optimal route is calculated.

The system confirmation has been accomplished in two main phases. In the first phase, the values of crucial parameters, (such as *a, b* and *Number of Cycles*) were defined. In the second phase, the experimental results of the algorithm are compared with the empirical model which is presently in use.

6.1 Evaluation Phase

The distance minimization of the route was used in the evaluation phase. In this phase, the Number of Cycles (*NC*) parameter was defined. Figure 3 depicts a typical execution of the algorithm and the length of the optimum tour for each cycle.

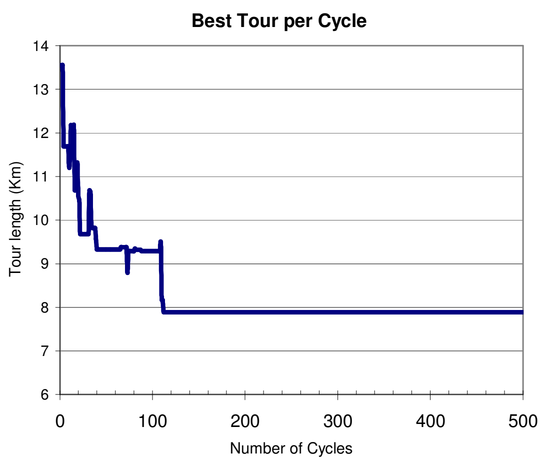

Figure 3: Evolution of best tour length in a typical run.

As figure 3 shows, the algorithm finds "bad" routes in the first cycles. However, the solution is rapidly refined in a range of 100-140 cycles. Subsequently, the variability of solution decreases and is finally stabilized in an optimum value for the rest of the algorithm run. Practically, the algorithm is converged at the final optimum solution in approximately 300 cycles. The value of the Number of Cycles (NC) parameter is very significant because a small value drives the algorithm to inaccurate results, as mentioned above, whereas a sizeable value increases the complexity of algorithm and thus the run time. The value of *NC* parameter was finally set equal to 500.

a\b	**2**	**3**	**4**	**5**
0.5	No solution	No solution	Bad	Bad
1	Good	Excellent	Excellent	Good
2	Stagnation	Stagnation	Stagnation	Stagnation

Table 1: The system behaviour for different pairs (a,b)

The second step of the evaluation phase was the definition of *a* and *b* parameters. The algorithm was tested for different pairs (*a, b*). For small values of the *a* parameter, the system becomes deterministic without memory and is finally unable to find a proper solution because is not capable to converge at an optimal route. On the other hand, for very large values for the pair (*a, b)*, the system appears to be stagnated. This means that the first solution which is produced by the algorithm will become the final solution, as well.

Therefore, the best system performance is accomplished for a=1 and b = {3, 4} as table 1 illustrates. Finally, in the evaluation phase the pair of values (1, 4) is chosen for the (*a, b*).

6.2 Measurements

In that phase, the algorithm was executed for two thousand (2000) runs and their respective solutions are illustrated in table 2. From a total set of 2000 runs, the algorithm was unable to produce solutions for 516 runs, because these solutions seem to be in an impasse situation.

Num of runs	Not accepted	Accepted		
		Better	Worse	**Total**
2000	516	1431	53	1484

Table 2: The analysis of experimental results

Therefore, these 516 solutions are not accepted. The majority of the accepted solutions are better than the value of the empirical model. The impasse situation of the algorithm emerges perforce due to the large number of restrictions in the transportation between the waste bins in the area under study. Specifically, the placement of the waste bins in the area, allows the truck to move from one bin to a restricted number of neighbouring bins. This means that designing a route can many times be driven to a dead end route, probably because all the neighbouring bins have been used and the truck is not allowed to visit the same bin for a second time.

However, the experimental results confirm an improvement of the optimum route, in the range of 24%. Table 3 illustrates the comparison between the results of the ACO system and the empirical model.

Empirical Model (meter)	Average route (meter)	Optimized route (meter)	Improvement (%)	Better Solutions (%)
9850	8725	7483	24%	96%

Table 3: The comparison between the accepted solution and the empirical model

Furthermore, a statistical analysis was applied to the sample set of accepted runs for the proposed algorithm. Figure 4 illustrates the distribution of the 1484 accepted solutions in proportion to the distance. The dark grey bar illustrates the value of the empirical model that the Municipality presently uses. As it is clearly illustrated, the majority of the solutions are better than the empirical model that is currently used.

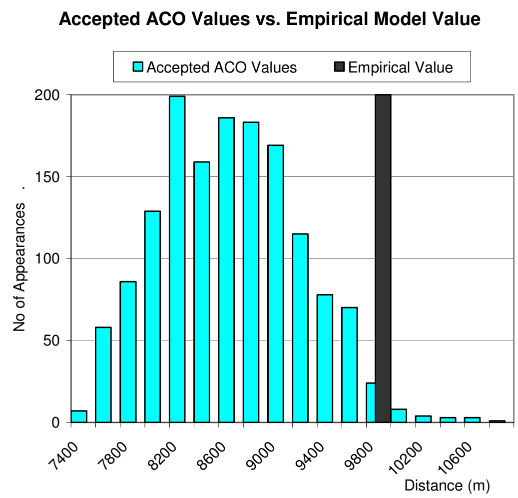

Figure 4: The distribution of solutions per distance

A short analysis of the experimental sample set proves that the distribution follows the Gumbel (maximum) distribution, also known as Largest Extreme Value, with the location parameter μ equal to 8448 and the scale parameter β equal to 508.5. Figure 5 depicts the probability density function of the Gumbel distribution with the parameters mentioned above.

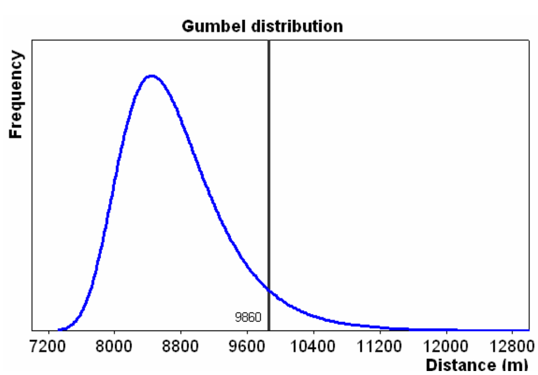

Figure 5: The Probability Density Function of Gumbel distribution

The Gumbel distribution was chosen due to the appearance of largest extreme values. Applying other distributions over the experimental sample set, such as Gaussian or Weibull, was not suitable because there was a vast deviation. The Anderson-Darling Test was used for the distribution evaluation. Moreover, the statistical analysis of the Probability Density Function of the Gumbel distribution showed a 93% probability that a sample is better than the empirical value, which is close to our experimental result of 96%.

7. CONCLUSIONS

This work focuses on the collection and transport of solid waste from any waste bin in the area under study. Other factors that affect the whole system were mentioned and discussed in some depth. However, this research covers only the routes included in the given area.

Therefore, the ACO algorithm, an innovative algorithmic approach in this particular research area, is introduced and implemented, for monitoring, simulation, testing, and cost optimization of alternative scenarios for a solid waste management system.

The first experiments have shown that the ACO algorithm for 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 the 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 used in this particular area. Therefore, the problem was transformed in a classic TSP problem.

Although the case study covers an area of about 0,45km^2, 8500 citizens and over 100 building blocks, to ensure the reliability of the derived results, a future prospect of this work is that the proposed model should be tested in an even more extended area.

The next step towards the total confrontation of the problem, will aim in optimizing the fragmentation of the total area of the Municipality of Athens and then in optimizing the time for collection and transport in every region. That approach would solve the existing problem as a Vehicle Routing Problem (VRP) problem. This means that the total area should be automatically fragmented in sub-regions according to the capacity of each truck that will be assigned in that particular region.

8. ACKNOWLEDGMENTS

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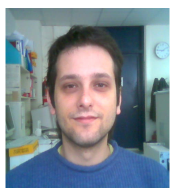

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