Ant Colony System vs ArcGIS Network Analyst: The Case of Municipal Solid Waste Collection

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Abstract: - In the present paper, two individual algorithmic solutions, the ArcGIS Network Analyst and the Ant Colony System (ACS) algorithm, are introduced, implemented and discussed for the identification of optimal routes in the case of Municipal Solid Waste (MSW) collection. Both proposed applications are based on a geo-referenced spatial database supported by a Geographic Information System (GIS). The GIS takes into account all the required parameters for the MSW collection (i.e. positions of waste bins, road network and the related traffic, truck capacities, etc) and its desktop users are able to model realistic network conditions and scenarios. In this case, the simulation consists of scenarios of visiting varied waste collection spots in the Municipality of Athens (MoA). The user, in both applications, is able to define or modify all the required dynamic factors for the creation of an initial scenario, and by modifying these particular parameters, alternative scenarios can be generated. Finally, the optimal solution is estimated by each routing optimization algorithm, followed by a comparison between these two algorithmic approaches on the newly designed collection routes.

Key-Words: - Ant Colony System, ArcGIS Network Analyst, Waste Collection, Optimization Algorithms, Routing, Simulation.

1 Introduction

The collection of municipal solid waste is one of the most difficult operational problems faced by local authorities in any city. In recent years, due to a number of cost, health, and environmental concerns, many municipalities, particularly in industrialized nations, have been forced to assess their solid waste management and examine its cost-effectiveness and environmental impacts, in terms of designing collection routes. During the past 15 years, there have been numerous technological advances, new developments and mergers and acquisitions in the waste industry. The result is that both private and municipal haulers are giving serious consideration to new technologies such as computerized vehicle solutions [1].

It has been estimated that, of the total amount of money spent for the collection, transportation, and disposal of solid waste, approximately 60–80% is spent on the collection phase [2]. Therefore, even a small improvement in the collection operation can result to a significant saving in the overall cost. The present study is mainly focused on the collection and transport of solid waste from any loading spot in the area under study.

The routing optimization problem in waste management has been already explored with a number of algorithms. Routing algorithms use a standard of measurement called a metric (i.e. path length) to determine the optimal route or path to a specified destination. Optimal routes are determined by comparing metrics, and these metrics can differ depending on the design of the routing algorithm used [3].The complexity of the problem is high due to many alternatives that have to be considered. Fortunately, many algorithms have been developed and discussed in order to find an optimized solution, leading to various different results. The reason for this diversity is that the majority of routing algorithms include the use of heuristic algorithms. Heuristic algorithms are ad hoc, trial-and-error methods which do not guarantee to find the optimal solution but are designed to find near-optimal solutions in a fraction of the time required by optimal methods.

2 Relevant Work

In the literature, many methods and algorithms have been used for optimizing routing aspects of solid waste collection networks. In this context the problem is reduced to a ‘single vehicle origin round trip routing’ which is similar to the common Traveling Salesman Problem (TSP). This is the well-known combinatorial optimization problem, in which each waste truck is required to minimize the total distance traveled in order to visit, only once, all the waste bins in its list. The Ant Colony System (ACS) algorithm is an innovative algorithm in this particular research area [4].

An ACS, a distributed algorithm inspired by the observation of real colonies of ants, has been presented [5], [6], for the solution of TSP problems [7]. Montgomery & Randall [8] have also investigated alternative ways of utilizing pheromone in an ACS for the TSP. Bianchi et al. [9] have introduced the Ant Colony Optimization (ACO) for a different version of TSP, the Probabilistic TSP (PTSP), where each customer has a given probability of requiring a visit. Furthermore, Johnson et al. [10] have evaluated implementations of a broad range of heuristics for the Asymmetric TSP (ATSP), including some of the best ones currently available observing wide varieties of behaviour (i.e. tour quality, running time) in many cases for the same heuristic depending on instance class.

Network Analyst is still relatively new software, so there is not much published material concerning its application on solid waste management Only few researchers during the last years have reported the use of the GIS Network Analyst extension in order to solve solid waste collection problems. Karagiannidis et al [11] introduce a design and a pilot application of a GIS for the optimization of waste collection in the Municipalities of Panorama and Sikies in the Thessaloniki, Greece. Moreover, Moussiopoulos et al [12] via GEOLORE [13] program have estimated the waste quantity produced and optimized the route of a waste collection vehicle within a densely populated area. Miller [14] compares the ArcMap Network Analyst extension with other software packages on their ability to create routes usable by the Solid Waste Department in a timely, efficient manner for the city of Richardson in Texas.

3 Ant Colony Optimization Algorithm

3.1 Real Ants

The basic idea of Ant Colony Optimization (ACO) algorithm was inspired through the observation of swarm colonies and specifically ants [15]. Ants are social insects and their behaviour is focused on the colony survival rather than the survival of the individual. Specifically, Ant Systems simulates the way ants’ forage, to find optimum solutions in computational problems. 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. [16]. Ants can smell pheromone and when choosing their way, they tend to choose, in probability, paths with high pheromone density.

It has been proved experimentally [5] that the pheromone trail affects the detection of shortest paths. For example, a set of ants builds a path to some source of food. An obstacle is then placed in their way, creating two new routes to their destination. So they have to choose between the first and the second route. Initially the pheromone trail is the same for both alternative routes, so half of them will choose the first route and the rest the second one. If the ants that chose the second route return in shorter time than the others, this means that the pheromone trail deposited on the second route evaporates less than that on the first route.

Since all ants have almost the same speed, the ants which choose the shortest path return before the ants that chose the other path (differential path effect). The amount of pheromone deposits on the shortest path increases more rapidly and so, more ants prefer the shortest path. Finally, with 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.

3.2 Artificial Ants (ACO)

Now in artificial life, ACO uses artificial ants, called agents, to find optimal solutions to difficult combinatorial optimization problems [17]. The behavior 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 features of the problem 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.

The Ant Colony System (ACS) incorporates a candidate list that is a static data structure of length which contains, for a given loading spot i, the preferred loading spots to be visited. An ant in ACS first uses the candidate list with the state transition rule to choose the loading spot to move to. This rule provides a direct way to balance between the exploration of new states and the exploitation of a priori and accumulated knowledge. If none of the nodes in the candidate list can be visited the ant chooses the nearest available node using a local optimization heuristic (hybridization) based on an edge exchange strategy.

4 Network Analyst

ArcGIS Network Analyst (ArcGIS NA) is a powerful extension of ArcGIS desktop 9.1 that provides network-based spatial analysis including routing, travel directions, closest facility, and service area analysis. ArcGIS NA enables users to dynamically model realistic network conditions, including turn restrictions, speed limits, height restrictions, and traffic conditions at different times of the day.

The algorithm used by the ArcGIS NA route solver attempts to find a route through the set of stops with minimum cost (a combination of travel times and time window violations). It first computes an asymmetric origin-destination cost matrix holding the travel times between the stops using the Dijkstra algorithm [18] and then applies an insertion algorithm to construct an initial solution. At each step, the insertion algorithm inserts the least-cost unvisited stop into the current partial solution. The initial solution is then improved upon by a Tabu-Search process, where an existing solution is augmented by performing two-opt and three-opt moves [19].

ArcGIS NA software determines the best route by using an algorithm which finds the shortest path, developed by Edgar Dijkstra [18]. Dijkstra's algorithm is the simplest path finding algorithm, even though these days a lot of other algorithms have been developed. Dijkstra's algorithm reduces the amount of computational time and power needed to find the optimal path. The algorithm strikes a balance by calculating a path which is close to the optimal path that is computationally manageable [20].

The algorithm breaks the network into nodes (where lines join, start or end) and the paths between such nodes are represented by lines. In addition, each line has an associated cost representing the cost (length) of each line in order to reach a node. There are many possible paths between the origin and destination, but the path calculated depends on which nodes are visited and in which order. The idea is that, each time the node to be visited next is selected after a sequence of comparative iterations, during which, each candidate-node is compared with others in terms of cost [21].

5 Case Study

In this research work, a small part of Attica's prefecture (a suburb of Athens) was chosen as the case study area. The municipality of Athens is empirically divided into about 122 solid waste collecting programs, where each one includes approximately 100 waste bins. Any waste truck that is responsible for the collection of the solid waste in that given area must visit all the bins in order to complete its collection program.

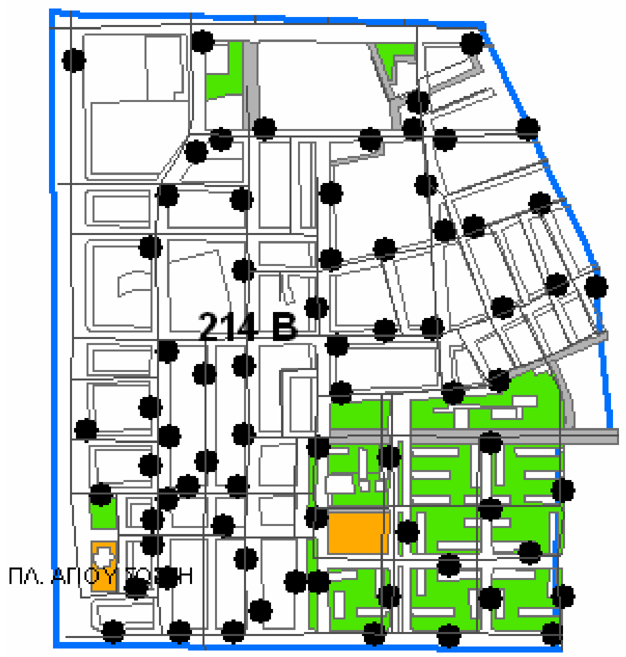

Fig. 1: The waste bins in the area under study.

The examined area (Fig. 1) is about 0.45 km^2, with a population of more than 9,000 citizens and a production of about 4,000 tones of urban waste per year. The data concerning the area under examination was obtained from the pertinent agency of the MoA. The data includes maps of the examined area, the building blocks as well as the locations of the existing waste bins.

The waste bins locations, as they are illustrated in Figure 1, were initially derived from a pilot program that the MoA was using for the allocation of their trucks.

ArcGIS NA and ACO are two alternative algorithmic solutions that were chosen in order to optimize the empirical method used so far by the MoA.

6 Results

6.1 ACS Algorithm

ACS algorithm reduces the problem to a 'single vehicle origin round trip routing' which is similar to the common TSP Problem. This is the well-known combinatorial optimization problem, in which each waste truck is required to minimize the total distance travelled in order to visit, only once, all the waste bins in its list. It is worth mentioning that the vast majority of routing algorithms have difficulty in finding a solution to this kind of problem due to the various constraints that should be taken into consideration. Therefore, the ACS was applied many times to our problem with a wide range of parameter settings in order to find solutions of high quality.

The objective function of the ACS algorithm is the tour length of the waste truck. Therefore, the objective of the ACS program is to minimize the total tour length of the vehicle through the loading spots. It should be noted that the acceptable solutions yielded by the ACS are considered to be those whose tour length is less than 1,000,000. This value is used in the algorithm implementation in order to illustrate the distance between two loading spots, which are not connected and as a result the particular movement is not allowed.

The parameters of the ACS algorithm, which have to be adjusted in order to find the optimum solution, are the following:

- $\boldsymbol{a}$ is the relative weight of pheromone trail,
- $\boldsymbol{\beta}$ is the relative weight of visibility,
- ***NC*** is the number of cycles,
- $\boldsymbol{\rho}$ is the pheromone trail persistence ($1-\rho$ represents the evaporation of the trail)
- $\boldsymbol{m}$ is the total number of ants at each iteration (in our experiments it is set equal to the number of loading spots), and
- $\boldsymbol{q_0}$ is the relative importance of exploitation versus exploration.

The role of the parameters, $\boldsymbol{a}$ and $\boldsymbol{\beta}$, is the following: if $\boldsymbol{a}$ is set close to zero, then the closest loading spots have higher chances of being selected. This corresponds to a classical stochastic greedy algorithm (with multiple starting points since ants are initially randomly distributed on the loading spots).

If on the contrary $\boldsymbol{\beta}$ is set close to zero, only pheromone amplification is at work and then this method will lead to the rapid emergence of stagnation – a situation in which all ants make the same tour that, in general, is strongly sub-optimal. Therefore, an appropriate trade-off has to be set between heuristic value and trail intensity.

The ACS algorithm was executed for more than 27,700 times for different combinations of parameter settings. Through these executions it was noticed that for very small values of parameter $\boldsymbol{a}$ the system became deterministic without memory and was finally unable to find a proper solution, because it was not capable of converging at an optimal route. The efficiency of the ACS was proved, since from a total set of 27,700 runs, the algorithm was unable to produce solutions for only 120 runs, because these solutions seem to be impasse situations. It should be noted that 26,550 executions of ACS produced better results than the result of the empirical method used by the MoA (tour length = 9,850 m). The ACS algorithm managed to find the best tour length which was equal to 7,328m for the following parameter settings: $\boldsymbol{NC}$=2,000, $\boldsymbol{a}$=1, $\boldsymbol{\beta}$=2, $\boldsymbol{\rho}$=0.1, $\boldsymbol{q_0}$=0.5. This result is the best in all the calculated cases. The ACS algorithm was executed for 2,010 times with the above parameter settings and Fig. 2 depicts the distribution of solutions for these settings.

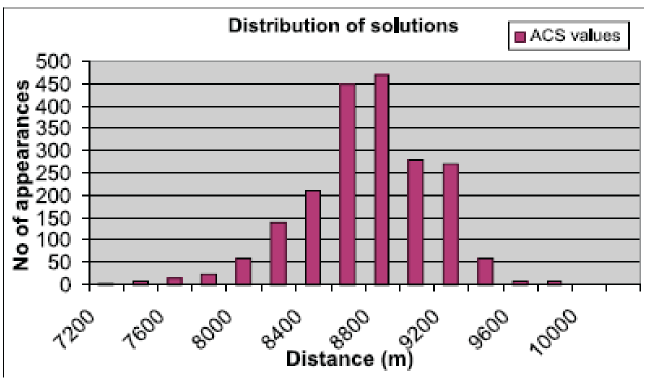

Fig. 2: Distributions of solutions for the parameter setting: $\boldsymbol{NC}$ = 2,000, $\boldsymbol{a}$ = 1, $\boldsymbol{\beta}$ = 2, $\boldsymbol{\rho}$ = 0.1, $\boldsymbol{q_0}$ = 0.5.

The experimental results confirm an improvement of the optimum route by about 25.6%, in comparison with the empirical method of MoA, and an improvement of the average route by about 10.45%. This improvement reduces the collection and transportation costs of the trucks considerably, as might be expected. However, it should be noted that the ACS algorithm is time-consuming in terms of CPU time. Each execution of the ACS algorithm takes approximately 15–20 min, a fact which resulted in running the algorithm for several months, efficiency with all the aforementioned combinations of parameter settings.

6.2 ArcGIS NA Algorithm

On the other hand, ArcGIS NA is a user-friendly extension of ArcGIS, which provides efficient routing solutions in a simple and straightforward manner. ArcGIS NA gives the user the ability to produce a map and directions for the quickest route among several locations. Furthermore, in ArcGIS NA, the routes can be calculated either by user variables such as the distance of each segment or the drive time for each segment [22]:

1. ***Distance criteria:*** The route is generated taking only into consideration the location of the loading spots. The volume of traffic in the roads is not considered in this case.
2. ***Time criteria:*** The total travel time in each road segment should be considered as the: Total travel time in the route = runtime of the vehicle + collection of loading spots. The runtime of the vehicle is calculated by considering the length of the road and the speed of the vehicle in each road. The time of the waste large items collection would be the total time consumed by the vehicle to collect these objects from all the loading spots In the second criteria, the length, width and the volume of traffic are taken into account in each road segment.

The user, in the proposed system, is able to define or modify all required dynamic factors, like network traffic changes (closed roads due to natural or technical causes, for example, fallen trees, car accidents, etc) in residential and commercial areas in a 24 hour schedule, for the creation of an initial scenario. By modifying these particular parameters, alternative scenarios can be generated leading to several solutions. Finally, the optimal solution is identified by a function that refers to various parameters, like the shortest distance, road network as well as social and environmental implications. The calculated waste collection route is then displayed on the screen and a file consisted of the directions to drive through the specified route is created. Here, some essential restrictions were taken into account, such as the streets' directions, no U-Turns rules (with the exception of the dead-ends) and also, the fact that the truck should follow true-shape route (i.e. it mustn't pass over the squares). Fig. 3 illustrates the route as it was pointed out by the ArcGIS NA application.

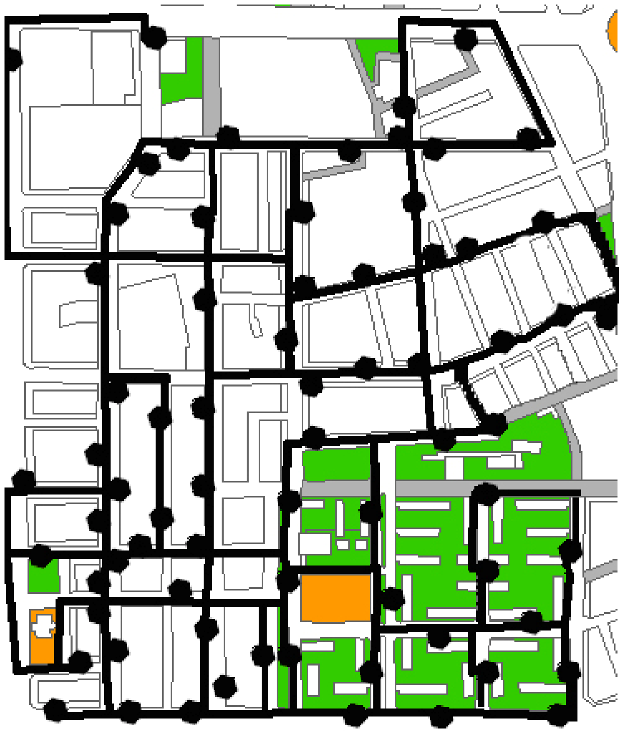

Fig. 3: The optimum route calculated by ArcGIS NA

7 Conclusions and Discussion

Computation of shortest paths is a famous area of research in Computer Science. Although there is a great number of ways to calculate shortest paths, there is no simple solution due to interactions between conflicting requirements.

This work focuses on the collection and transport of solid waste from waste bins in the area under study. The ACS algorithm and the ArcGIS NA, two innovative algorithmic approaches in this particular research area, are 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 applying the ACS and the ArcGIS NA for the solution of this every day problem – the collection of MSW – the tour length and eventually the total cost in time and money can be greatly minimized. However, as it was reported above, the particular problem is much more complicated than presented in the current work.

More specifically, ACS achieved to calculate the most efficient route, closely followed by ArcGIS

NA. However, both of these algorithms produce better results than the result of the empirical method used by the MoA (Table 1).

Table 1: Comparison between ACS algorithm, ArcGIS NA and the Empirical Model used by the MoA.

	Optimum Route (meter)	**Improvement from Optimum Route (%)**
Empirical Model	9,850m	
ACS	7,328m	25.6%
ArcGIS NA	7,491m	23.9%

Nevertheless, the time and the number of iteration cycles is a considerable drawback, since in the first cycles, the ACS algorithm produced routes which were far from the optimum solution, while ArcGIS NA is not only capable to reproduce a satisfying number of scenarios, but also it has the ability to be easily adapted to new conditions.

The proposed methodology was applied in a region of the MoA, 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 into a classic TSP problem.

Although the case study covers an area of about 0.45 km^2, 8,500 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.

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