Routing Optimization Heuristics Algorithms for Urban Solid Waste Transportation Management

NIKOLAOS V. KARADIMAS, NIKOLAOS DOUKAS,
MARIA KOLOKATHI, GERASIMOULA DEFTERAIOU
Multimedia Technology Laboratory
National Technical University of Athens (NTUA)
9 Heroon Polytechneiou, Zografou Campus, 157 80 Athens
GREECE
nkaradimas@medialab.ntua.gr, nikolaos@doukas.net.gr, el00666@mail.ntua.gr,
el00661@mail.ntua.gr

Abstract: - During the last decade, metaheuristics have become increasingly popular for effectively confronting difficult combinatorial optimization problems. In the present paper, two individual meatheuristic 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). GIS are increasingly becoming a central element for coordinating, planning and managing transportation systems, and so in collaboration with combinatorial optimization techniques they can be used to improve aspects of transit planning in urban regions. Here, 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. Furthermore, the proposed interactive design of both approaches has potential application in many other environmental planning and management problems.

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

1 Introduction

Sustainable waste management is moving up to the political agenda and includes issues of reliability, escalating waste growth, cost-effectiveness and public concern over health and environmental impacts. Special emphasis, particularly in industrialized nations, is placed on concrete, comprehensive analysis of the waste management situation. To the extent possible, it is necessary to highlight the areas in which an efficient improvement is feasible and how these goals derived from the objectives and principles of the waste management act can be achieved, while making available an appropriate basis of information.

During the past 15 years, there have been numerous technological advances, new developments, 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 routing solutions [1]. It has been estimated that, of the total amount of money spent for the collection, transportation, and the disposal of solid waste, approximately 60–80% is spent on the collection phase [2]. Therefore, it can be proved extremely beneficial planning waste recovery in an environmentally friendly and economically viable way.

The routing optimization problem in waste management has been already explored with a number of algorithms. Moreover, the successful implementation of vehicle routing software has been aided by the exponential growth in computing power since 1950, the emergence of accurate and sophisticated Geographic Information Systems (GIS) technology induced multiple algorithmic solutions. 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 behavior (i.e. tour quality, running time) in many cases for the same heuristic depending on instance class.

ArcGIS 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 ArcGIS 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 field of ant algorithms studies models which are derived from the observation of real ants' behavior, and uses these models as a source of inspiration for the design of novel algorithms for solving optimization and distributed control problems. The main idea is that the self-organizing principles which allow the highly coordinated behavior of real ants can be exploited to coordinate populations of artificial agents that collaborate to solve computational problems [15]. Ants are social insects and their behavior is being focused on the colony survival rather than the survival of the individual.

Furthermore, an important insight of early research on ants' behavior was that most of the communication between the individuals and the environment is based on the use of chemicals produced by the ants. These chemicals are called pheromones. While walking from food sources and vice versa, ants deposit pheromones on the ground, forming in this way a pheromone trail. Ants can smell the pheromone and they tend to choose, probabilistically, paths marked by high pheromone concentrations [16].

It has been proved experimentally [5] that the pheromone trail-laying and -following behavior of some ants 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. The outcome is that, although in the initial phase random choices will occur, eventually all the ants will use the same path. This result can be explained as follows: Since all ants have almost the same speed, the ants choosing by chance the short route are the first to reach the nest (differential path effect). The

shorter route, therefore, receives pheromone earlier than the other one and this fact increases the probability that further ants select it.
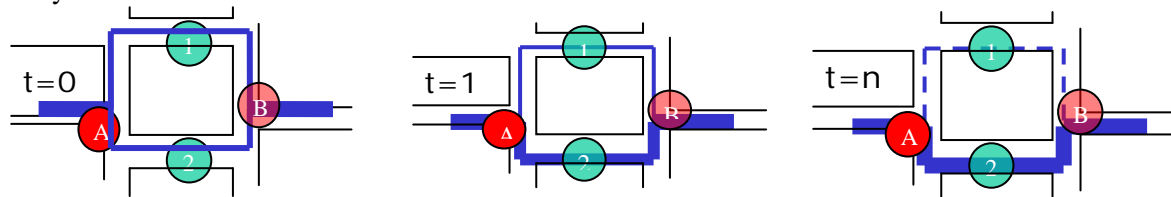

Fig. 1: The Ant Colony Optimization process.

Thus, pheromone starts to accumulate faster on the shorter route, which will eventually be used by all the ants due to the autocatalytic process described previously. Finally, during the time the pheromone of the longest path evaporates and the path disappears. This cooperative work of the colony has determined the insects' intelligent behavior and has captured the attention of many scientists and the branch of artificial intelligence called swarm intelligence.

3.2 Artificial Ants (ACO)

In ACO, a number of artificial ants build solutions to an optimization problem and exchange information on the quality of these solutions via a communication scheme that is reminiscent of the one adopted by real ants [17]. The behavior of artificial ants is based on the traits of real ants, plus additional abilities that make them more effective, such as a limited form of memory in which they can store the partial paths they have followed so far, as well as the cost of the links they have traversed. 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 process the problem.

Compendiously, ACO algorithms are based on the following idea:

- Each path followed by an ant on a graph is associated with a candidate solution for a given problem. Ants perform stochastic walks in the graph, consisting of a series of stochastic steps until the termination criterion is reached.
- 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. Moreover, artificial pheromone evaporation is often used to avoid

premature convergence on a suboptimal solution (stagnation).

- When an ant has to choose between two or more paths, the path(s) with a higher amount of pheromone has a greater probability of being chosen by the ant. What is relevant to realize is that a stochastic choice is made based on the probability distribution. The possibility of an ant choosing a path with low probability is often decisive because it enables the discovery of new solutions. The stochastic state transition rule is responsible for defining the relevance of different local variables, like the emphasis on pheromone values or other local heuristics.

Fig. 1 illustrates an example of the artificial ants' movement. At time t=0, a number of ants are moving from loading spot A to B as depicted in the above figure. When ants arrive at point A, they have to choose between the 1st and the 2nd 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. 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 concentration in 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.

Dorigo and Gambardella [6] also proposed the Ant Colony System (ACS), which is an improvement to the AS. Since ACS is the base of our implemented algorithm, we focus the attention on ACS rather than the other versions of ACO algorithms. As Maniezzo et al. [18] point out the ACS differs from AS, because of the following

three main aspects:

1. *Pheromone:* In ACS once all ants have computed their tour, only the best solution computed since the beginning of the computation is used to globally update the pheromone. The global updating rule of ACS enables the algorithm to run faster in comparison to AS, since it avoids long convergence titrating the search around the best tour. In ACS, ants visit edges and change their pheromone level by applying a local updating rule, while building a solution (i.e., a tour) of the ATSP. The effect of this rule is to make the desirability of edges change dynamically: every time an ant uses an edge this becomes slightly less desirable (since it loses some of its pheromone).

2. *State Transition Rule:* ACS algorithm uses a new state transition rule called pseudo-random-proportional. This rule provides a direct way to balance between exploration of new states and exploitation of a priori and accumulated knowledge.

3. *Hybridization and performance improvement:* ACS incorporates a candidate list (cl) that is a static data structure of length cl which contains, for a given loading spot i, the cl 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. 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

Geographic Information Systems (GIS) is a field with an exponential growth that has a pervasive reach into everyday life. Basically, GIS provides a mean to convert data from tables with topological information into maps. Subsequent GIS tools are capable of not only solving a wide range of spatially related problems, but also performing simulations to help expert users organize their work in many areas, including public administration, transportation networks and environmental applications. ArcGIS Network Analyst (ArcGIS NA) is a powerful tool 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's algorithm [19]. Dijkstra's algorithm is the simplest path finding algorithm since it 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 being 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].

After calculating the cost matrix between the stops, ArcGIS NA 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. This kind of greedy algorithms, even though they construct feasible solutions within reasonable computing time, they don't always produce the best solution. Therefore, the initial solution is then improved upon by a Tabu-Search heuristic process, where an existing solution is augmented by performing two-opt and three-opt moves [22]. The most common way to improve an initial route generated by greedy algorithms are the two-optimal (2-opt) and three-optimal (3-opt) local searches. The 2-opt algorithm, in order to find a better solution from the current one basically removes two edges from the route and then reconnects the two paths created. The 3-opt algorithm works in a similar way but does so by removing three edges. Given a feasible route, these improvement heuristic algorithms repeatedly apply the aforementioned operations to every sub-route, replacing current paths with better ones, until a route is calculated for which no operation yields an improvement (a locally optimal tour). Tabu-Search is a metaheuristic which guides the other heuristic processes to explore the solution space beyond local

optimality and allows non-improving moves to be performed in a limited fashion.

5 Case Study

In this research work, a small part of Attica's prefecture (a suburb of Athens) has been 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.

The examined area (Fig. 2) is approximately 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 selection of settlements was based on computerized geographical analysis of existing municipal datasets, literature review and a mapping study. The data includes maps of the examined area, the building blocks as well as the locations of the existing loading spots (waste bins).
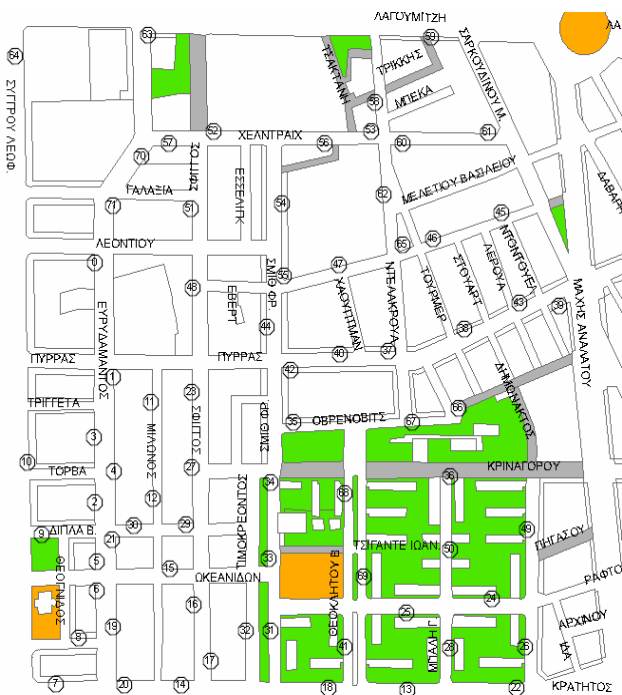

Fig. 2: The loading spots in the area under study.

The loading spots, as they are illustrated in Figure 2, were initially derived from a pilot program that the MoA was using for the allocation of their trucks. The location of these loading spots was defined by the MoA to serve the needs of the present waste collection system. The management of urban solid waste is an intrinsically complex procedure involving various relative factors, which are often in conflict; here a different placement of the loading spots would have probably assisted the proposed model better.

This research utilizes two powerful alternative algorithmic solutions, ArcGIS NA and ACS, 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 can be simulated as a TSP instance. The TSP is a well-known representative example of combinatorial optimization, in which each waste truck is required to minimize the total distance traveled in order to visit, only once, all the loading spots 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, to test the adequacy of this algorithmic approach, a number of computational experiments have been carried out, with a wide range of parameter settings so as to find solutions of high quality.

The objective function of the ACS algorithm is the tour length of the waste truck. Hence, 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 this ACS implementation to illustrate when the path between two loading spots is infeasible.

The performance of the ACS algorithm depends on the current tuning of several parameters specified as follows:

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

The probability distribution of a move depends on the combination of the parameters a and β. α is the attractiveness of the move as computed by some heuristic indicating the a posteriori desirability of that move, while β represents an a priori indication of the desirability of that move.

If 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 β is set close to zero, only pheromone amplification is at work and so this method will probably lead to the rapid emergence of stagnation – a situation in which all ants repeatedly construct the same solutions which, in general, are strongly sub-optimal, making any further exploration in the search process impossible. Thus, an appropriate trade-off has to be set between heuristic value and trail intensity.

During the construction of a new solution the state transition rule is the phase where each ant decides which is the next state to move to. In ACS a new state transition called pseudo-random-proportional is being introduced. To obtain good results, an ant should prefer actions that it has tried in the past and proved to be effective in producing desirable solutions (*exploitation*); but to discover them, it has to try actions not previously selected (*exploration*). The ACS pseudo-random-proportional state transition rule provides a direct way to balance between exploration of new states and exploitation of a priori and accumulated knowledge. With the pseudo-random rule a chosen state is the best with probability q_0 (*exploitation*) while a random state is chosen with probability $1- q_0$ (*exploration*).

The ACS algorithm was executed for more than 27,700 times for different combinations of parameter settings. During these iterations it was noticed that for very small values of parameter a the system became deterministic without memory and was finally unable to generate a proper solution, since 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 sufficient sub-optimal results compared to the performance 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: NC=2,000, a=1, β=2, ρ=0.1,

q_0=0.5. This result is the best in all calculated cases. The ACS algorithm was executed for 2,010 times with the above parameter settings and Figure 3 depicts the deviation of obtained solutions from the provably optimal solution for these settings.
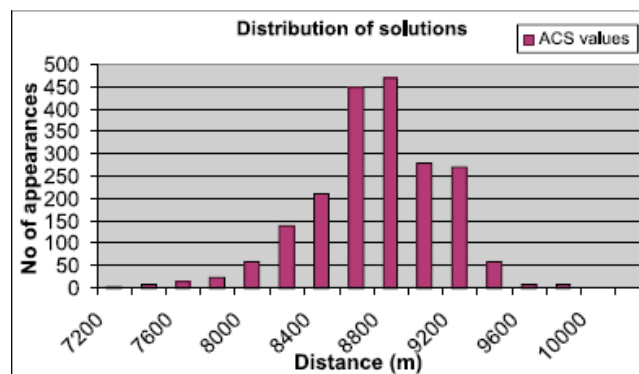

Fig. 3: Distributions of solutions for the parameter setting: $NC = 2,000$, $a = 1$, $\beta = 2$, $\rho = 0.1$, $q_0 = 0.5$.

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, with all the aforementioned combinations of parameter settings.

6.2 ArcGIS NA Algorithm

Modeling the area under study as a Geographic Information System (GIS) instance is extremely beneficial in terms of managing and analyzing geo-referenced and attribute data together. Attribute data refers to any type of descriptive or statistical data linked to geographical features while geo-referenced data is associated with geographic co-ordinates. Data in a GIS is stored as map layers and output is usually in the form of maps or data tables. The ability to integrate spatial and attribute data enables a GIS to visually represent landscape features, to associate these features with a host of descriptive and spatial information and to use this information together in analysis to generate new information. For example, in this case-study, a view environment module is fully integrated with the GIS and has standard GIS display capabilities; the generated map can display all roads and produce an attribute list with information like length, name, type of the road

etc. Technically, GIS software packages may be fundamentally different from one another, any GIS, however, will contain a series of operations which allow it to perform three primary functions: present the current data, find new patterns in current data, and calculate new information.

At the same time, spatial analysis is benefiting from geo-computational tools which can handle more diverse data and can better exploit very large spatial datasets than traditional spatial analytical techniques. ArcGIS NA is a user-friendly, sophisticated 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. To cope with the problem's complexities and complete the solution within a reasonable time, ESRI developed and implemented a series of algorithms based on heuristic strategies; an Origin-Destination matrix containing the costs between pairs of loading spots provides the primary data for the sequencing and route-improvement heuristic procedures.

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 [23]:

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 on each road. The time of the waste collection would be the total time consumed by the vehicle to collect 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 dead-ends) and also, the fact that the truck should follow true-shape route (i.e. it mustn't pass over the squares). Figure 4 illustrates the route as it was derived by the ArcGIS NA application.
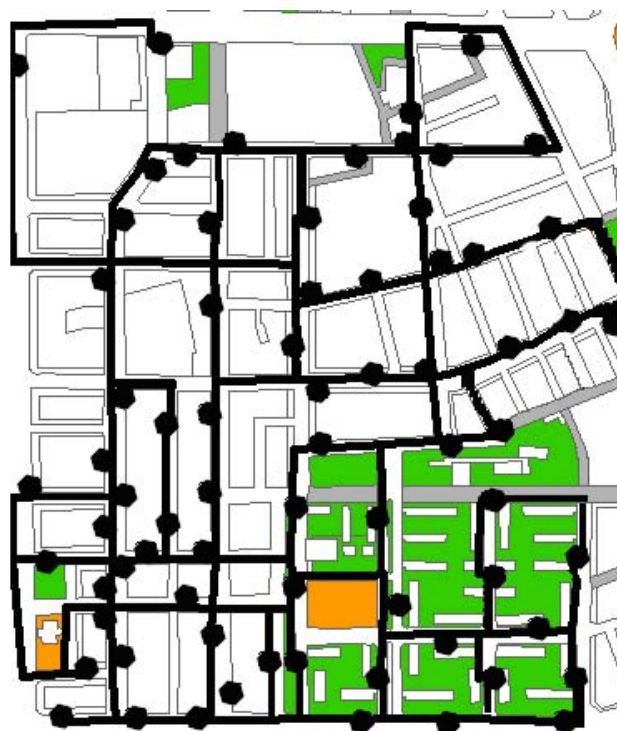

Fig. 4: The optimum route calculated by ArcGIS NA

7 Conclusions and Discussion

This work focuses on the collection and transport of solid waste from specific loading spots in the area under study, the problem is modelled as a TSP instance. Recent results in complexity theory indicate that a lot of network optimization problems such as TSP are inherently difficult to solve. In fact, it is unlikely that polynomial algorithms can be obtained for exact solution to these problems. Considering this, heuristic algorithms have become increasingly important. In this paper, an efficient and accurate heuristic algorithm for efficient solution of TSP, ACS algorithm, and a hybrid heuristic approach via ArcGIS NA are presented and evaluated.

These 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 experiments have revealed that applying any of the two suggested heuristic methods, for the solution of this every day problem, the tour length and eventually the total cost in time and money can be greatly minimized.

Table 1 summarizes the chief computational test results of the heuristics that has been used. More specifically, ACS achieved to calculate the most efficient route, closely followed by ArcGIS NA. However, both algorithms have outperformed the empirical method used so far by the MoA. Computational time of each algorithmic solution wasn't included in the table, instead some qualitative remarks on this regard are following up.

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%

The objective of this research is to provide an adequately fast heuristic algorithm which yields solutions within 10% of the optimal solution. Although ACS calculated the shortest route, the running time and the number of iteration cycles until an optimal solution was found is a considerable drawback. In the first cycles, the ACS algorithm produced routes which were far from the optimum solution, while ArcGIS NA proved not only capable to reproduce a satisfying number of scenarios, able to be easily adapted to new conditions, but also its computational time far surpasses that of ACS. An explanation of why ACS is extremely time-consuming compared to ArcGIS NA is following.

An obvious difference between the two heuristic methods is that ArcGIS NA route solver technique can be described as hybridization in terms of combining ideas of two different methods in one approach. Such proceedings -like associating a local optimizer with the metaheuristics- are common practice for hard combinatorial optimization problems and have been successfully applied to many problems, giving birth to the so-called hybrid methods. This is an interesting marriage since local optimizers often suffer from the initialization

problem where the application of local search to randomly generated initial solutions has been proved to be a poor choice since the local search procedure spends most of its time improving the initial low-quality solution [24]. Therefore, it becomes interesting to find good metaheuristic-local optimizer couplings where the metaheuristic will generate initial solutions that will lead to very good local optima by the local optimizer. The most well known improvement heuristic -already used by NA-for the TSP is the 2-opt algorithm where two edges currently in the solution are exchanged for two other edges (still keeping a tour). If the resulting tour is better then it becomes the current solution. The same improvement can be achieved for solutions constructed by artificial ants.

The first type of hybridization concerning ant colony optimization algorithms consists of the incorporation of local search procedures, like 2-opt heuristic. In particular, in the most classical hybridization, the local search procedure is applied to some (or all) solutions constructed by the ants. The local optimum returned is then used for the pheromone update. This approach is generally accepted to improve the performance of ACO. It is widely used in the literature, to the extent that often it is not even considered an hybridization. The second typical way for coupling ACO and local search consists in having the two approaches working in parallel and sharing information. Among the others, Chen and Ting [25] propose to use ant colony system and simulated annealing in parallel. The two approaches share the best solution found, which is used both for the pheromone update, and as starting solution of the search.

In conclusion, 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.

References:
[1] Nuortioa T., Kytöjokib J., Niskaa H. and Bräysy O., Improved Route Planning and Scheduling of Waste Collection and Transport, 2005, http://www.sciencedirect.com/science?...3520c6c9ea5&ie=/sdarticle.pdf (Accessed on February 10, 2007).
[2] Municipality of Athens, Estimation, Evaluation and Planning Of Actions for Municipal Solid Waste Services During Olympic Games 2004. Municipality of Athens, Athens, Greece, 2003.

[3] Parker M., Planning Land Information Technology Research Project: Efficient Recycling Collection Routing in Pictou County, 2001. http://www.cogs.ns.ca/planning/projects/plt200 14/images/research.pdf (Accessed on February 10, 2007).

[4] Karadimas, N.V., Papatzelou, K. and Loumos, V., Optimal Solid Waste Collection Routes by the Ant Colony System Algorithm. *International Journal of Waste Management & Research*, Vol. 25, 2007, pp. 139-147.

[5] Dorigo M., and Maniezzo V., The Ant System: Optimization by a Colony of Cooperating Agents. *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 26, No. 1, 1996, pp. 1-13.

[6] Dorigo, M. and Gambardella, L.M., Ant Colony System: A Cooperative Learning Approach to the Travelling Salesman Problem. *IEEE Transactions on Evolutionary Computation*, Vol. 1, 1997.

[7] Karadimas, N.V., Kouzas, G., Anagnostopoulos, I. and Loumos, V., Urban Solid Waste Collection and Routing: the Ant Colony Strategic Approach. *International Journal of Simulation: Systems, Science & Technology*, Vol. 6, 2005, pp. 45–53.

[8] Montgomery J. and Randall M. Alternative Pheromone Applications for Ant Colony Optimisation, *Technical Report TR02-07*. Bond University, Robina, Australia, 2002.

[9] Bianchi, L., Gambardella, L.M. and Dorigo, M. An Ant Colony Optimization Approach to the Probabilistic Travelling Salesman Problem. In: Proceedings of PPSN-VII, Seventh International Conference on *Parallel Problem Solving from Nature*, Lecture Notes in Computer Science. Springer Verlag, Berlin, Germany, 2002.

[10] Johnson, D.S., Gutin, G., McGeoch, L.A., Yeo, A., Zhang, W. and Zverovitch, A., The Travelling Salesman Problem and its Variations, *Chapter: Experimental Analysis of Heuristics for the ATSP*, pp. 445–487, Kluwer Academic Publishers, Dordrecht, The Netherlands, 2002.

[11] Karagiannidis A., Perkoulidis G., Erkut E. and Tjandra S., Optimization of Urban Solid Waste Collection through GIS Use: A Part Implementation for the Municipalities of Panorama and Sikies. *21st European Conference for ESRI Users*, 2006.

[12] Moussiopoulos N., Karagiannidis A., Xirogiannopoulou A., Theodoseli M.,

Perkoulidis G., Antonopoulos J., Malamakis A., Trenstiou E., Vlachocostas Ch., Pardali S., Tjandra S., McCartney D., Leonard J., Haight D., Using GIS to Assess the Local Problem of Waste Management in an Urban Area, 2006, http://aix.meng.auth.gr/geolore/model/local/loc al%20problem.pdf (Accessed on February 10, 2007)

[13] GEOLORE, Development of a Geographical Information System for the Organization and Implementation of an Integrated Waste Management at a Local and/or Regional Level, 2003, http://aix.meng.auth.gr/geolore (Accessed on February 10, 2007).

[14] Miller Ch., Brush and Bulky Item Collection Routing Program Comparisons, 2005. http://charlotte.utdallas.edu/mgis/prj_wrkshp/2 005/Miller/BABIC_Website_Files/index.html (Accessed on February 10, 2007).

[15] Beckers R., Goss S., Deneubourg J.L. and Pasteels J.M., Colony size, communication and ant foraging strategy, *Psyche (Cambridge)*, Vol. 96, No. 3-4, 1989, pp. 239-256.

[16] Dorigo M. and Caro G.D., The Ant Colony Optimization Meta-heuristic, in D. Corne, M. Dorigo, and F. Glover, (eds): *New Ideas in Optimization*, London, McGraw-Hill, 1999, pp. 11-32.

[17] Bonabeau, E., Dorigo, M. & Theraulaz, G. *Swarm Intelligence: From Natural to Artificial Systems*. Oxford University Press, 1999.

[18] Maniezzo, V., Gambardella, L. M. & Luigi, F., Ant Colony Optimization. In: Onwubolu, Godfrey C. & Babu B.V. (eds.): *New Optimization Techniques in Engineering,* Springer – Verlag, Berlin, Heidelberg, Vol. 141, 2004, pp. 101-117.

[19] Dijkstra, E.W., A note on two problems in connexion with graphs. *Numerische Mathematik*, Vol. 1, 1959, pp. 269-271.

[20] Olivera F., Map Analysis with Networks. http://ceprofs.tamu.edu/folivera/GIS-CE/Spring2002/Presentations/NetworksIntro.p pt 2002 (Accessed on February 10, 2007).

[21] Stewart L.A., The Application of Route Network Analysis to Commercial Forestry Transportation, 2004.http://gis.esri.com/library/userconf/proc05 /papers/pap1309.pdf (Accessed on February 10, 2007).

[22] Rice M., ArcGIS Desktop - Extension - Network Analyst forum, 2006. http://forums.esri.com/Thread.asp?c=93&f=19 44&t=187632&mc=21#msgid565389 (Accessed on February 10, 2007).

[23] Lakshumi A.P.Poun, Ramiya A.M. and Ssthya R., Optimal Route Analysis For Solid Waste Disposal Using Geographical Information System,2006.http://www.gisdevelopment.net/proceedings/mapindia/2006/student%20oral/mi06stu_113.htm. (Accessed on February 10, 2007).

[24] Aarts E. H. and J. K. Lenstra, 1997, Introduction, in *Local Search in Combinatorial Optimization*, Aarts E. H. and J. K. Lenstra (Eds.). Chichester: John Wiley & Sons, 1–17.

[25] Chen C. and Ting C. A hybrid Ant Colony System for vehicle routing problem with time windows. *Journal of the Eastern Asia Society for Transportation Studies*, 6:2822–2836, 2005.