ANT COLONY ROUTE OPTIMIZATION FOR MUNICIPAL SERVICES

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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 account of 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 schedule of trash-collection workers and track capacities and technical characteristics are considered.

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 required dynamic factors for the creation of an initial scenario. By modifying these particular parameters, alternative scenarios can be generated leading to the several solutions.

The Optimal solution is identified by a cost function that takes into account various parameters, for instance labor and equipment costs as well as social implications.

INTRODUCTION

The last years, much effort has been made in Urban Solid Waste Collection and Transport Management. The problem can be classified as either a Traveling Salesman or a Vehicle Routing Problem. For this particular problem, several solutions and models have been proposed.(Pham and Karaboka, 2000; Ducatelle and Levine, 2001; Bianchi et al. 2002; Chen and Smith, 1996; Glover and Laguna, 1992).

The complexity of the problem is high due to many alternatives that have to be considered. The number of possible solutions is considerably high. Fortunately, many algorithms have been developed and discussed in order to find a shorter path to the optimized solution (Tarasewich and McMullen , 2002).

The most popular algorithms used today in similar cases include the Genetic Algorithm, the Simulated Annealing, the Tabu Search, the Ant Colony Optimization (ACO and others. In the present work, some of these algorithms have been tested and discussed to a certain depth.

Genetic algorithms (Pham and Karaboka, 2000; Chen and Smith, 1996; Glover et al. 1992) use biological methods such as reproduction, crossover, and mutation to quickly search for solutions to complex problems. Genetic algorithm begins with a random set of possible solutions. In each step, a fixed number of the better current solutions are saved and they are used to the next step to generate new solutions using genetic operators. Crossover and mutation are the most important genetic operations are 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 at 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 behavior 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 neighboring solutions are generated. If one of the neighboring solutions is better than the current solution, then it becomes 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

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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. 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 you try a solution, it becomes tabu in future tries.

The Ant Colony Optimization algorithm (Dorigo & 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 at the individual. Specially, 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 Traveling 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.

As it was mentioned above, the ACO algorithm is tested to the problem of collection and transport of solid waste from any loading spot in an area under study to the transshipment or the disposal sites. Of course, our research only covers how the algorithm applies to the routes included in the examined area.

Therefore, in this context, a framework (schema) for the design and implementation of a solution for solid waste collection and transport is proposed. According to this schema, the ACO algorithm, an innovative algorithm in the specific 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 sections that follow. More specifically, section 2 introduces and describes the ACO algorithm. In Section 3, the waste management problem in the selected case study area is introduced. Section 4 describes the methodology and the proposed system and how it is applied in the current situation using the ACO algorithm and at the same time outlining some of the proposed variants. Finally, Section 5, illustrates the simulation results achieved comparing them to present solutions and other algorithms. Conclusions and future developments are also discussed in this section.

ANT COLONY OPTIMIZATION ALGORITHM

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 & 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 & 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 choose the path of the nearer end of the obstacle return 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, 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 intelligenc*e [1, 4].

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 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 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.

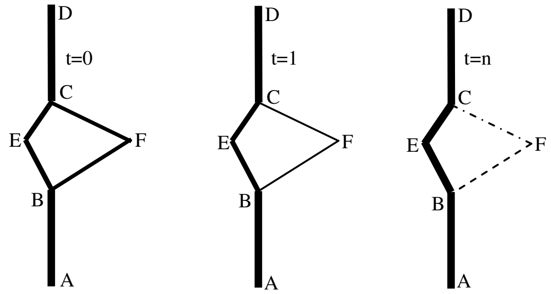

Figure 1: The ACO algorithm process

Let see 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 it 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 rest of them 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 was 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.

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.

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 route is recorded and available for further utilization.

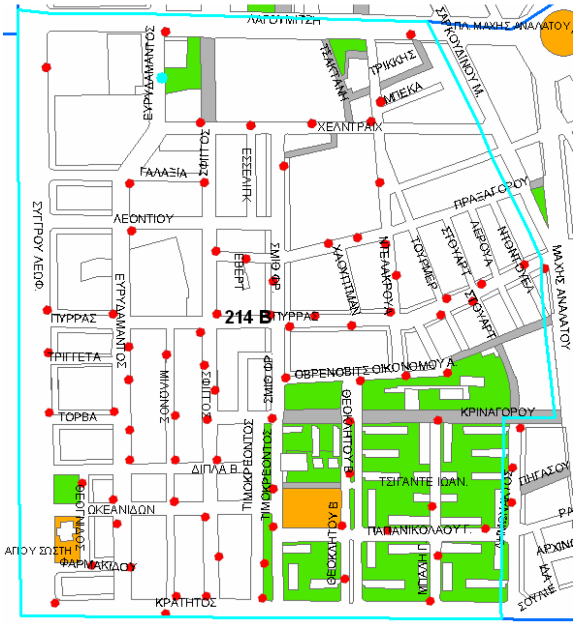

Figure 2: The suburb of Athens used in our experiments

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^{th} hour distribution of each factor.

Therefore, the problem in our case, as it 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".

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 favored. After a complete circuit is determined, "pheromone" is deposited on each of 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 favor 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 favor. 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).

Methodology

The schema, which was chosen for the solution of our problem, is the Ant cycle algorithm from (Dorigo, & 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:

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

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:

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

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

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

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:

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

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.

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

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

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

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).

CONCLUSIONS

In this paper, a new solution for the collection and a transport of the Solid Waste has been introduced. 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 in the C++ programming language environment.

The system was simulated and tested for different periods during the day, as the involved parameters are drastically changed.

Further on, the area under consideration had to be divided in a segments adequate for the execution of the ACO algorithm. In each segment, all possible collection routes are considered and the optimal one is identified.

Then, the results of the ACO algorithm were compared with the corresponding ones of those produced by the Genetic, Simulated Annealing, and Tabu Search algorithms. On the other hand, the standards of an existing empirical model used by the municipality of Athens, were used as a benchmark for the algorithmic methods.

In conclusion, a clear improvement in time and cost for waste collection and transport has been observed in the case of the ACO based algorithmic implementation. Comparing this method with Genetic Algorithms and Tabu Search, the ACO algorithm seems to function slightly better. On the other hand, Simulated Annealing showed the worst results, but still better than those produced by the empirical model.

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