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An Analysis of Applications to Nonstandard Problems in ACO

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Abstract: Ant colony optimization (ACO) takes inspiration from the foraging behaviour of some ant species. These ants deposit pheromone on the ground in order to mark some favourable path that should be followed by other members of the colony. Ant colony optimization exploits a similar mechanism for solving optimization problems. This protocol is highly adaptive, efficient, scalable and reduces the overhead for routing. Ant Algorithms are used to find the shortest route in Mobile Ad Hoc Networks. ACO has been widely applied to solving various combinatorial optimization problems such as Traveling Salesman Problem (TSP), Job-shop Scheduling Problem (JSP), Vehicle Routing Problem (VRP), Quadratic Assignment Problem (QAP), etc. The behaviour of ACO algorithms and the ACO model are analysed for certain types of permutation problems. It is shown analytically that the decisions of an ant are influenced in an intriguing way by the use of the pheromone information and the properties of the pheromone matrix. This paper provides a brief outline of some significant applications of ACO algorithms. In this paper we are considering the applications to problems with nonstandard features and we have also discussed the use of ACO in TSP. ACO is taken as one of the high performance computing methods for TSP. Metaheuristic algorithm is an efficient method to obtain near-optimal solutions of NP-hard problems.

Keywords: metaheuristic; stochastic; swarm; overhead and mobile ad hoc network.

I. INTRODUCTION

Ant colony optimization (ACO) [1][2][3] is a metaheuristic for solving hard combinatorial optimization problems inspired by the indirect communication of real ants. The basic idea of the ant colony optimization metaheuristic is taken from the food searching behavior of real ants. When ants are on the way to search for food, they start from their nest and walk toward the food. When an ant reaches an intersection, it has to decide which branch to take next. While walking, ants deposit pheromone, which marks the route taken. The concentration of pheromone on a certain path is an indication of its usage. With time the concentration of pheromone decreases due to diffusion effects. This property is important because it is integrating dynamic into the path searching process (figure 1). At the intersection, the first ants randomly select the next branch. Since the below route is shorter than the upper one, the ants which take this path will reach the food place first. On their way back to the nest, the ants again have to select a path. After a short time the pheromone concentration on the shorter path will be higher than on the longer path, because the ants using the shorter path will increase the pheromone concentration faster. The shortest path will thus be identified and eventually all ants will only use this one. This behaviour of the ants can be used to find the shortest path in networks.

In ACO algorithms, (artificial) ants construct candidate solutions to the problem being tackled, making decisions that are stochastically biased by numerical information based on (artificial) pheromone trails and available heuristic information. The pheromone trails are updated during algorithm execution to bias the ants search toward promising decisions previously found. Despite being one of the youngest metaheuristics, the number of applications of ACO [1][2][3] algorithms is very large. In principle, ACO can be applied to any combinatorial optimization problem for which some iterative solution construction mechanism can be conceived. Most applications of ACO [1][3] deal with Nonstandard problems, that is, to handle problems with multiple objectives, stochastic data, and dynamically changing problem information. There are extensions of the ACO metaheuristic for dealing with problems with continuous decision variables, as well. This paper provides a concise overview of several noteworthy applications of ACO [1] [3] algorithms. This overview is necessarily incomplete because the number of currently available ACO applications goes into the hundreds.

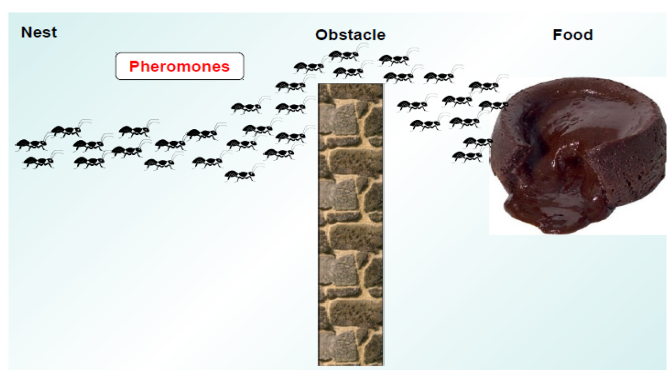

Figure 1. Food searching behaviour of real Ants.

Section II describes briefly ACO Routing Algorithm; Section III illustrates the Applications to problems with Non-Standard features. Finally this paper is concluded in Section IV.

II. ACO ROUTING ALGORITHM

The routing algorithm is very similar constructed as many other routing approaches and consists of three phases.

A. Route Discovery Phase

In the route discovery phase new routes are created. The creation of new routes requires the use of a forward ant (FANT) and a backward ant (BANT). A FANT is an agent which establishes the pheromone track to the source node. In contrast, a BANT establishes the pheromone track to the destination node. The FANT is a small packet with a unique sequence number. Nodes are able to distinguish duplicate packets on the basis of the sequence number and the source address of the FANT[1][3].

A forward ant is broadcasted by the sender and will be relayed by the neighbours of the sender (figure 2). A node receiving a FANT for the first time creates a record in its routing table. A record in the routing table is a triple and consists of (destination address, next hop, pheromone value). The node interprets the source address of the FANT as destination address, the address of the previous node as the next hop, and computes the pheromone value depending on the number of hops the FANT needed to reach the node. Then the node relays the FANT to its neighbours. Duplicate FANTs are identified through the unique sequence number and destroyed by the nodes.

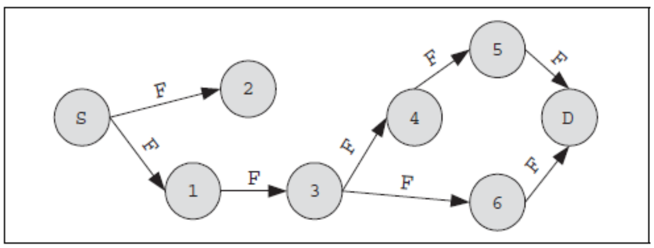

Figure 2. Relay using FANT.

When the FANT reaches the destination node, it is processed in a special way [1][3]. The destination node extracts the information of the FANT and destroys it. Subsequently, it creates a BANT and sends it to the source node (figure 3).

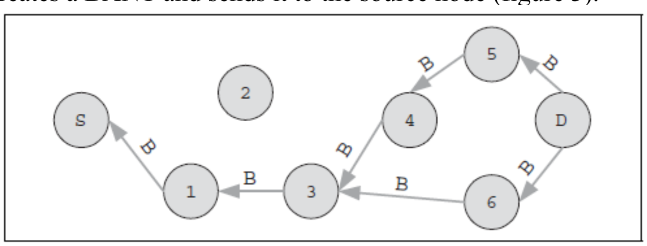

Figure 3. Relay using FANT.

The BANT has the same task as the FANT, i.e. establishing a track to this node. When the sender receives the BANT from the destination node, the path is established and data packets can be sent. Figures 2 and 3 schematically depict the route discovery phase. In the depicted case, node 3 has two ways for the path, via node 4 and over node 6. In our case, the forward ant creates only one pheromone track toward the source node, but the backward ant creates two pheromone tracks toward the destination node. So multi-path routing is also supported by ARA [1].

B. Route Maintenance Phase:

The second phase of the routing algorithm is called route maintenance, which is responsible for the improvement of the routes during the communication. ARA [1][2][3] does not need any special packets for route maintenance. Once the FANT and BANT have established the pheromone tracks for the source and destination nodes, subsequent data packets are used to maintain the path.

Similar to the nature, established paths do not keep their initial pheromone values forever. When a node v_i relays a data packet toward the destination v_D to a neighbour node v_j, it increases the pheromone value of the entry (v_D, v_j, □) by Δ□, i.e., the path to the destination is strengthened by the data packets. In contrast, the next hop vj increases the pheromone value of the entry (v_S, v_i, □) by Δ□, i.e. the path to the source node is also strengthened. ARA prevents loops by a very simple method, which is also used during the route discovery phase. Nodes can recognize duplicate receptions of data packets, based on the source address and the sequence number. If a node receives a duplicate packet, it sets the DUPLICATE ERROR flag and sends the packet back to the previous node. The previous node deactivates the link to this node, so that data packets cannot be send to this direction any more.

C. Route Failure Handling:

The third and last phase of ARA handles routing failures, which are caused especially through node mobility and thus very common in mobile ad-hoc networks. ARA [1] recognizes a route failure through a missing acknowledgement. If a node gets a ROUTE ERROR message for a certain link, it first deactivates this link by setting the pheromone value to 0. Then the node searches for an alternative link in its routing table. If there exists a second link it sends the packet via this path. Otherwise the node informs its neighbours, hoping that they can relay the packet. Either the packet can be transported to the destination node or the backtracking continues to the source node. If the packet does not reach the destination, the source has to initiate a new route discovery phase.

III. APPLICATIONS TO PROBLEMS WITH NONSTANDARD FEATURES

A. Multiobjective Optimization:

In many real-world problems, candidate solutions are evaluated according to multiple, often conflicting objectives. Sometimes the importance of each objective can be exactly weighted, and hence objectives can be combined into a single scalar value by using, for example, a weighted sum. This is the approach used by Doerner et al. [29] for a biobjective transportation problem. In other cases, objectives can be ordered by their relative importance in a lexicographical manner. Gambardella et al. [4] proposed a two-colony ACS algorithm for the vehicle routing problem with time windows, where the first colony improves the primary objective and the second colony tries to improve the secondary objective while not worsening the primary one [48].

When there is no a priori knowledge about the relative importance of objectives, the goal usually becomes to approximate the set of Pareto-optimal solutions—a solution is Pareto optimal if no other solution is better or equal for all objectives and strictly better in at least one objective. Iredi et al. [5] were among the first to discuss various alternatives for extending ACO to multiobjective problems in terms of Pareto-optimality. They also tested a few of the proposed variants on a biobjective scheduling problem. Another early work is the application of ACO to multiobjective portfolio problems by Doerner et al. [6,7].

Later studies have proposed and tested various combinations of alternative ACO algorithms for multiobjective variants of the QAP [8,9], the knapsack problem [10], activity crashing [11], and the biobjective orienteering problem [12]. Garc´ıa-Mart´ınez et al. [13] reviewed existing multiobjective ACO algorithms and carried out an experimental evaluation of several ACO variants using the bicriteria TSP as a case study. Angus and Woodward [30] give another detailed overview of available multiobjective ACO algorithms.

B. Stochastic Optimization Problems:

In stochastic optimization problems, data are not known exactly before generating a solution. Rather, because of uncertainty, noise, approximation, or other factors, what is available is stochastic information on the objective function value(s), on the decision variable values, or on the constraint boundaries. The first application of ACO algorithms to stochastic problems was to the probabilistic TSP (PTSP). In the PTSP, each city has associated a probability of requiring a visit, and the goal is to find an a priori tour of minimal expected length over all cities. Bianchi et al. [16] and Bianchi and Gambardella [17] proposed an adaptation of ACS for the PTSP. Very recently, this algorithm was improved by Balaprakash et al. [18], resulting in a state-of-the-art algorithm for the PTSP. Other applications of ACO to stochastic problems include vehicle routing problems with uncertain demands [19], and the selection of optimal screening policies for diabetic retinopathy [20]. The latter approach builds on the S-ACO algorithm proposed earlier by Gutjahr [32].

Table I. Applications of ACO Algorithms to Nonstandard Problems.

Problem Type	Problem Name	References
Multi-objective	Scheduling Portfolio Selection Quadratic Assignment Knapsack Traveling Salesman Activity Crashing Orienteering	Iredi et al. [5] Doerner et al. [6,7] L´opez-Ib´a˜ nez et al. [8,9] Alaya et al. [10] Garc´ıa-Mart´ınez et al. [11] Doerner et al. [12] Schilde et al. [13]
Continuous	Neural Networks Test Problems	Socha and Blum [14] Socha and Dorigo [15]
Stochastic	Probabilistic TSP Vehicle Routing Screening Policies	Bianchi et al. [16] Bianchi and Gambardella [17] Balaprakash et al. [18] Bianchi et al. [19] Brailsford et al. [20]
Dynamic	Network Routing Dynamic TSP Vehicle routing	Di Caro and Dorigo [21] Di Caro et al. [22] Guntsch and Middendorf [23,24] Eyckelhof and Snoek [25] Sammound et al. [26] Montemanni et al. [27] Donati et al. [28]

C. Dynamic Optimization Problems:

Dynamic optimization problems are those whose characteristics change while being solved. ACO algorithms have been applied to such versions of classical NP-hard problems. Notable examples are applications to dynamic versions of the TSP, where the distances between cities may change or where cities may appear or disappear [23–26]. More recently, Montemanni et al. [27] and Donati et al. [28] discuss applications of ACS to dynamic vehicle routing problems, reporting good results on both artificial and real world instances of the problem. Other notable examples of dynamic problems are routing problems in communication networks, which are discussed in the following section [48].

D. Communication Network Problems:

Some system properties in telecommunication networks, such as the availability of links or the cost of traversing links, are time-varying. The application of ACO algorithms to routing problems in such networks is among the main success stories in ACO. One of the first applications by Schoonderwoerd et al. [32] concerned routing in circuit-switched networks, such as classical telephone networks. The proposed algorithm, called ABC, was demonstrated on a simulated version of the British Telecom network. A very successful application of ACO to dynamic network routing is the AntNet algorithm, proposed by Di Caro and Dorigo [21,33].

AntNet was applied to routing in packet-switched networks, such as the Internet. Experimental studies compared AntNet with many state-of-the-art algorithms on a large set of benchmark problems under a variety of traffic conditions [21]. AntNet proved to be very robust against varying traffic conditions and parameter settings, and it always outperformed competing approaches.

Several other routing algorithms based on ACO have been proposed for a variety of wired network scenarios [34,35]. More recent applications of these strategies deal with the challenging class of mobile ad hoc networks (MANETs). Because of the specific characteristics of MANETs (very high dynamics and link asymmetry), the straight forward application of the ACO algorithms developed for wired networks has proven unsuccessful [36]. Nonetheless, an extension of AntNet that is competitive with state-of-the-art routing algorithms for MANETs has been proposed by Ducatelle et al. [37]. For recent, in-depth reviews of applications of ACO to dynamic network routing problems, we refer to Refs 38 and 39.

E. Continuous Optimization Problems:

Continuous optimization problems arise in a large number of engineering applications. Their main difference from combinatorial problems, which were the exclusive application field of ACO in the early research efforts, is that decision variables in such problems have a continuous, real-valued domain. Recently, various proposals have been made on how to handle continuous decision variables within the ACO framework [40–42]. In the continuous ACO algorithm proposed by Socha and Dorigo [15], probability density functions, explicitly represented by Gaussian kernel functions, correspond to the pheromone models. Extensions of this approach also exist for mixed-variable—continuous and discrete—problems [43]. A notable application of ACO algorithms for continuous optimization is the training of feed-forward neural networks [14]. Interestingly, there exist also successful applications of ACO to continuous problems that discretize the real-valued domain of the variables. An example is the PLANTS algorithm for the protein–ligand docking problem, which combines a discrete ACO algorithm with a local search that works on the continuous domain of the variables.

F. Industrial Applications:

While most research is done on academic applications, commercial companies have started to use ACO algorithms for real-world applications. The company AntOptima (www.antoptima.com) develops and markets ACO-based solution methods for tackling industrial vehicle routing problems. Features common to real-world applications are time-varying data, multiple objectives, or the availability of stochastic information about events or data. Moreover, engineering problems often do not have a mathematical formulation in the traditional sense. Rather, algorithms have to rely on an external simulator to evaluate the quality and feasibility of candidate solutions. Examples of applications of ACO relying on simulation are the design [44] and operation [45] of water distribution networks. Other interesting real-world applications are those of Gravel, Price and Gagn´e, who applied ACO to an industrial scheduling problem in an aluminum casting center, and those of Bautista and Pereira [46,47], who successfully applied ACO to solve an assembly line balancing problem for a bike line assembly.

IV. ACO IN TRAVELING SALESMAN PROBLEM

ACO has been widely applied to solving various combinatorial optimization problems such as Traveling Salesman Problem (TSP), Job-shop Scheduling Problem (JSP), Vehicle Routing Problem (VRP), Quadratic Assignment Problem (QAP), etc. Although ACO has a powerful capacity to find out solutions to combinational optimization problems, it has the problems of stagnation and premature convergence and the convergence speed of ACO is very slow. Those problems will be more obvious when the problem size increases. Therefore, several extensions and improvements versions of the original ACO algorithm were introduced over the years. Various adaptations: dynamic control of solution construction, emergence of local search, a strategy is to partition artificial ants into two groups: scout ants and common ants and new pheromone updating strategies [49], using candidate lists strategies are studied to improve the quality of the final solution and lead to speedup of the algorithm. All these studies have contributed to the improvement of the ACO to some extents, but they have little obvious effect on increasing the convergence speed and obtaining the global optimal solution.

Traveling salesman problem (TSP) [49] is one of the well-known and extensively studied problems in discrete or combinational optimization and asks for the shortest roundtrip of minimal total cost visiting each given city (node) exactly once. TSP is an NP-hard problem and it is so easy to describe and so difficult to solve. Ant System was first introduced and applied to TSP by Marco Dorigo. Initially, each ant is randomly put on a city. During the construction of a feasible solution, ants select the following city to be visited through a probabilistic decision rule. Graph theory defines the problem as finding the Hamiltonian cycle with the least weight for a given complete weighted graph. It is widespread in engineering applications and some industrial problems such as machine scheduling, cellular manufacturing and frequency assignment problems can be formulated as a TSP. A complete weighted graph G= (N, E) can be used to represent a TSP, where N is the set of n cities and E is the set of edges (paths) fully connecting all cities. Each edge $(i,j)\in E$ is assigned a cost d_{ij}, which is the distance between cities i and j. d_{ij} can be defined in the Euclidean space and is given as follows:

$$d_{ij} = \sqrt{((xi - x j)^2 + (yi - y j)^2)}$$

In TSP, the main modifications introduced by ACO are the following. First, to avoid search stagnation and ACO is more effective if ants are initially placed on different cities. Second, information entropy is introduced which is adjust the algorithm's parameters. Additionally, the best performing ACO algorithms for the TSP [49] improve the solutions generated by the ants using local search algorithms.

V. CONCLUSION

Nowadays, ACO is a well-established metaheuristic applied to a wide range of optimization problems and with hundreds of successful implementations. By analyzing the many available ACO implementations, one can identify ingredients necessary for the successful application of ACO. Firstly, an effective mechanism for iteratively constructing solutions must be available. Ideally, this construction mechanism exploits problem-specific knowledge by using appropriate heuristic information. Secondly, the best performing ACO algorithms have specialized features that allow to carefully controlling the balance between the exploration of new solutions and the intensification of the search around the best solutions. Thirdly, the usage of local search algorithms for improving the solutions constructed by the ants is very successful in practice. Finally, the integration of other techniques such as constraint programming, tree search techniques, or multilevel frameworks often yields a further improvement in performance or increases the robustness of the algorithms. ACO has been widely applied to solving various combinatorial optimization problems such as Traveling Salesman Problem (TSP), Job-shop Scheduling Problem (JSP), Vehicle Routing Problem (VRP), Quadratic Assignment Problem (QAP), etc. This paper provides a brief outline of some significant applications of ACO algorithms. In this paper we are considering the applications to problems with nonstandard features and we have also discussed the use of ACO in TSP. This overview is necessarily incomplete because the number of currently available ACO applications goes into the hundreds.

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