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Extended Abstract

An Optimized Reservoir Operation with Stochastic Adaptive Refinement in Ant Algorithms

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Introduction

Meta heuristics algorithms are usually used for the problems that are based on the behavior of real creatures. They basically try to combine basic heuristic methods in higher level frameworks aimed at efficiently and effectively exploring a search space. This class of algorithms includes Genetic Algorithms (GA), Iterated Local Search (ILS), Simulated Annealing (SA), Tabu Search (TS), Ant Colony Optimization (ACO), etc. ACO is a meta-heuristic approach proposed by Dorigo et al. (1991). The basic algorithm of ACO is Ant System (AS). Many other algorithms have been introduced to improve the performance of the Ant system; such as Ant Colony System (ACS) [Dorigo and Bullnheimer, 1997a], Rank Ant system (AS_{rank}) [Bullnheimer et al., 1999], Max-Min Ant System (MMAS) [Stutzle and Hoos, 2000], Best-Worst Ant System [Cordon et al., 2000] and Hybrid Ant System [Gambardella and Dorigo, 2000]. ACO algorithm is used to solve many difficult combinatorial optimization problems in the filed of civil engineering (Abbaspuor, 2001; Simpson et al., 2001; Maier et al., 2003; Zecchin et al., 2003; Afshar, 2005).

In order to solve a problem with ACO algorithms, a discrete form of the search space of the problem should be used. Many of the real engineering problems such as reservoir operation problems are, however, of continuous nature and, therefore, solving them using an Ant based algorithm requires discretization of the decision variables leading to the conversion of the continuous problem to a discrete problem. The quality of such solution may, however, deteriorate when using a coarse discretization of the problem search space. On the other hand a fine discretization scheme would lead to increased computational time and facilities. An adaptive refinement mechanism is, therefore, suggested in this paper to improve the performance of Ant algorithms when solving continuous optimization problems to obtain near-optimal solutions.

Ant Colony Optimization Algorithm

ACO algorithm is based on the behavior of real ants finding the shortest path between food sources and the nest. In ACO a colony of artificial ants cooperate in finding good solutions to difficult discrete optimization problems. Application of ACO (Dorigo and Gambardella; 1997b) requires that a graph *G= (D, L, C)* is used for the definition of the underlying problem. Here $D=\{d_1,d_2,.....,d_n\}$ is the set of decision points at which some decisions are to be made, $L=\{l_{ij}\}$ is the set of options *j (j=1,2,……,J)* at each of the decision points *i (i=1,2,……,n)* and finally $C=\{c_{ij}\}$ is the set of costs associated with options ***L***. A feasible path on the graph is called a solution (φ) with a cost of $f(\varphi)$ and the minimum cost path on the graph is called the optimal solution $(\varphi°)$ with a cost of $f(\varphi°)$. The basic steps of the Ant algorithms may be defined as follows (Maniezzo and Colorni, 1996):

1. Each ant is randomly placed on one of the n decision points and the amounts of pheromone trail on all options are initialized to some proper value at the start of the computation.
2. A transition rule is used at each decision point *i* to decide which option is to be selected. The ant

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moves to the next decision point and this procedure is repeated until all decision points of the problem are covered.

3. The cost $f(\varphi)$ of the generated trail solution is calculated.
4. The pheromone is updated when step 2 and 3 are repeated for all ants.

For ACO algorithm, the heuristic value η_{ij} is analogous to providing the ants with sight and is sometimes called visibility. This value is calculated once at the start of the algorithm and is not changed during computation. Here $\eta_{ij} = (1/c_{ij})$ is used for the heuristic value representing the local cost of choosing option *j* at decision point *i*.

Ant System (AS) is the first basic algorithm of ACO algorithms. Max-Min Ant System (MMAS) developed by Stutzle and Hoos (2000) introduces some modifications with respect to AS. To overcome the problem of premature convergence whilst still allowing for exploitation, MMAS introduces dynamically evolving bounds on the pheromone trail intensities such that on all paths they are always within a specified lower bound $\tau_{\min}(t)$ and a theoretically asymptotic upper limit, $\tau_{\max}(t)$. This means $\tau_{\min}(t) \le \tau_{ij}(t) \le \tau_{\max}(t)$.

Methodology

ACO is a discrete algorithm that is used for finding good solutions to difficult optimization problems. However, many of the real engineering problems such as reservoir operation problems are continuous and solving problems with ACO algorithms requires discretization of the decision variables. Coarse discretization of the search space of the problem often leads to poor quality solutions and fine discretization of the search space increases the computational effort required. A stochastic adaptive refinement mechanism is, therefore, suggested in this paper to improve the performance of ant algorithms in order to obtain a near-optimal solution for continuous optimization problems. In this method, the continuous optimization problem is replaced with a set of discrete optimization problems. The proposed mechanism is an iterative method starting with uniform discretization of the search space. A Gaussian distribution is then used for discretization of the decision variables in subsequent iterations. At each iteration the average and standard deviation of the Gaussian distribution is computed using the optimal solution obtained in the previous iteration. In this mechanism, the spaces adjacent to the average solution play a more decisive role in defining the discrete search space of the problem. As a result, the spacing of the discretized points (decision points) found in previous iteration is less around the optimal solution compared to the other points.

Results and Discussion

The application of the proposed mechanism to solve some benchmark function optimization problem (Ackely and XOR function) and a dam reservoir operation problem (aiming water supply and the hydropower generation) is considered and the results are presented and compared with the solutions obtained by linear optimization algorithm solved in LINGO (version 8) and other methods. The results indicated the efficiency and effectiveness of the proposed method in solving difficult continuous optimization problems with low computational effort.

***Keywords*:** Ant Colony Optimization, Stochastic Adaptive Refinement, Reservoir Operation.

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