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# State of the Art Review of Ant Colony Optimization Applications in Water Resource Management

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**Abstract** Among the emerged metaheuristic optimization techniques, ant colony optimization (ACO) has received considerable attentions in water resources and environmental planning and management during last decade. Different versions of ACO have proved to be flexible and powerful in solving number of spatially and temporally complex water resources problems in discrete and continuous domains with single and/or multiple objectives. Reviewing large number of peer reviewed journal papers and few valuable conference papers, we intend to touch the characteristics of ant algorithms and critically review their state-of- the-art applications in water resources and environmental management problems, both in discrete and continuous domains. The paper seeks to promote Opportunities, advantages and disadvantages of the algorithm as applied to different areas of water resources problems both in research and practice. It also intends to identify and present the major and seminal contributions of ant algorithms and their findings in organized areas of reservoir operation and surface water management, water distribution systems, urban drainage and sewer systems, groundwater managements, environmental and watershed management. Current trends and challenges in ACO algorithms are discussed and called for increased attempts to carry out convergence analysis as an active area of interest.

**Keywords** Ant colony optimization · Review · Water resources · Water management · Algorithm · ACO

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## 1 Introduction

As the spatial and temporal complexity of the water resources management and environmental problems increases, application of metaheuristic algorithms extends dramatically. Since the introduction of ACO (Dorigo et al. 1996), Different versions and refinements to the original ant algorithm are proposed and applied to solve various problems in water resources and environmental management. Ostfeld (2011) presented a review paper on ACO for water resources systems analysis. Although his attempt is acknowledged, it does not fully address the advances made in continuous and multiple objective ACO, recent wide range applications of different versions of ACO, and the enhancements in their convergences and constraint handlings.

Reviewing large number of peer reviewed journal papers and selected conference papers with less touched subjects, we intend to describe the theory of ant algorithms and critically review their state-of- the-art applications in water resources and environmental management, both in discrete and continuous domains. The paper seeks to promote its understanding, advantages, and disadvantages when applied to different areas of water resources problems both in research and practice.

## 2 Ant Colony Optimization; an Overview

ACO is a discrete combinatorial optimization algorithm based on the collective behavior of ants in their search for food. It is argued that a colony of ants is able to find the shortest route from their nest to a food source via an indirect form of communication that involves deposition of a chemical substance, called pheromone, on the paths as they travel. Over time, shorter and more desirable paths are reinforced with greater amounts of pheromone thus becoming the dominant path for the colony.

The double bridge experiments clearly shows that ant colonies have a built-in optimization capability; whereby, an ant can find the shortest path between two points in their environment by the use of probabilistic rules based on available local information (Dorigo and Stutzle 2004).

ACO is a metaheuristic algorithm in which a colony of artificial ants cooperates in finding good solutions to various static and dynamic optimization problems both in discrete and continuous domains. It allocates the computational resources to a set of relatively simple agents (i.e., artificial ants) that communicate indirectly by pheromone trail. It is a probabilistic multi-agent algorithm which uses a probability distribution to make the transition between iterations. Although, the ant algorithms are especially effective for solving discrete combinatorial optimization problems; their successful application in continuous search space has been widely reported.

In ACO algorithms, the optimization search procedure is conducted by the number of artificial ants moving on a graph in the search space. The artificial ants are stochastic constructive agents that build solutions by moving on the construction graph. In fact, their constructive aspects distinguish ACO algorithms from other optimization algorithms. Each ant builds its own solution, or a component of it, starting from a predefined initial state. Parallel to making its own solution, each ant collects information on both the problem characteristics and its own performance. This information will be used to modify the representation of the problem, as seen by the other ants. Each ant builds a solution by moving through a finite sequence of neighbor states. Moves are selected by applying a stochastic local search policy directed by (1) ant private information and (2) publicly available pheromone trail and predefined problem-specific local information. The pheromone trail encodes a long-term memory about the entire ant search process, and is updated by the ants themselves. Differently, the heuristic value, often called heuristic information, represents a priori information about the problem instance or run-time information provided by a source different from the ants.

ACO is structured into three main phases: (1) solution construction, (2) pheromone updating, and, (3) daemon action. In solution construction phase, artificial ants move through adjacent states of a problem according to a transition rule, iteratively building solutions. In the pheromone update phase the pheromone trail updates by both pheromone trail reinforcement and pheromone trail evaporation. Daemon actions is an optional step in the algorithm which involves applying additional updates from a global perspective, such as pheromone promotion, pheromone re-initiation, etc. (Jalali et al. 2007a, b). The decisions about when and how the ants should release pheromone on the "environment" depend on the characteristics of the problem and on the design of the implementation. Ants can release pheromone in an online step-by-step procedure while building the solution, or postpone it till the solution is completely built, or both.

A stochastic functional composition of the locally available pheromone and heuristic values is used to direct their search towards the most interesting regions of the search space. The stochastic component of the move choice in the decision space and the pheromone evaporation mechanism may avoid from an immature convergence on which all the ants may rapidly drift towards the same part of the search space. The balance between the exploration of new points in the state space and the exploitation of accumulated knowledge may be controlled by the level of stochasticity in the policy. Once a solution is built and the pheromone is updated, the ant will be deleted from the system (i.e., new ants are generated for the next iteration).

Although, very many versions of ACO algorithms have been emerged, their main characteristics may comply with one or combination of ant system (*AS*) (Dorigo et al. 1996), ant colony system (*ACS* or *ACO*) (Dorigo and Gambardella 1997);, elitist ant system (*ASelite*) (Dorigo et al. 1996), rank-based ant system (*ASrank*) (Bullnheimer et al. 1997); and max-min ant system (*MMAS*) (Stutzle and Hoos 2000).

## 3 Continuous Ant Colony Algorithms

Ant colony optimization was originally developed for discrete optimization problems. Its application in continuous domain started with discretization of the search space. Although, some advances in the discretization methodology, such as discrete-refining (DR) approach, to improve the performance of the original ACOs in continuous domains are reported (Jalali et al. 2007a, b), their comparative performances remain to be improved. To overcome this issue new version of ACO based algorithm has been developed.

The most recent approach to continuous problems proposed by Socha and Dorigo (2006) is the closet to the spirit of ant-based algorithms. In their proposed algorithm (ACOR), incremental construction of solutions based on probabilistic choice of solution components remains the central idea in ACOR.

As the number of available options at each construction step increases, the discrete probability distribution (in discrete ACO) approaches to a probability density function. In this case, instead of choosing a solution component from an allowable set, an ant samples the solution components from a continuous probability density function (pdf).

To define a bi-modal pdf, they proposed a Gaussian kernel pdf, $G_i$, as weighted sum of several one-dimensional Gaussian functions $g_l^i(x)$:

$$G^i(x) = \sum_{l=1}^{k} \omega_l g_l^i(x) = \sum_{l=1}^{k} \omega_l = \frac{1}{\sigma_l^i \sqrt{2\pi}} e^{-\frac{\left(x-\mu_l^i\right)^2}{2\sigma_l^{i2}}} \tag{13}$$

Here, k is the number of single pdfs, used to form the Gaussian kernel pdf at the ith construction step. As presented in Eq. 13, is parameterized with vectors of $\overrightarrow{\omega}$, $\overrightarrow{\mu}$, and $\overrightarrow{\sigma}$. In any kernel function, $\overrightarrow{\omega}$ is the vector of weights, whereas $\overrightarrow{\mu}$ and $\overrightarrow{\sigma}$ are the vectors of means and standard deviations, respectively. The size of all these vectors is equal to the number of Gaussian functions constituting the Gaussian kernel (k).

For more information the interested readers are referred to Socha and Dorigo (2006). In an extension to the original ACOR, Madadgar and Afshar (2009) proposed some improvements to make the algorithm adaptive and more efficient in locating near optimal solutions. Application of the proposed improvements for optimization of few water resources problem revealed its robustness in searching the continuous space more efficiently.

## 4 Multiple Objectives ACO

A large selection of multi-objective ACO (MOACO) algorithms are listed and discussed by Angus and Woodward (2009). They reviewed the existing ant-based multiple objective optimization algorithms and proposed taxonomy for their classification. They discussed MOACO specific design issues, such as the choice of single or multiple pheromone matrices and pheromone update and decay, with a focus on how these choices affect algorithm performance. Few of the existing algorithms use a priori preference articulation in solving their particular problems. These approaches, either implicitly or explicitly, weight their chosen problems' multiple objectives in some kind of preferential order. They argue that this approach may be superior to the alternative Pareto-based MOACO where we target a specific area of the Pareto front, or for problems with a single dominant objective.

The existing MOACO algorithms which seek the Pareto fronts either use single pheromone matrix or benefit from multiple pheromone matrix. More detail information and taxonomy of the existing MOACO algorithms are available at Angus and Woodward (2009).

## 5 Application of ACO Algorithms in Water Resource Management (WRM)

A graph is required for a successful application of the ACO algorithms to combination optimization problems. Consider G=(D, L, C), in which D={di} is the set of decision points at which some decisions are to be made, L={lij} is defined as the set of the options j=1,2, …, NC, at each decision point i=1, 2, …, NT and C={cij} is the set costs associated with L={lij}. An acceptable solution based on the graph is called an answer and the path associated with minimum cost is called the optimum solution.

This review paper intends to present an exhaustive survey of the applications of ant based algorithms in water resources and environmental engineering problems. Application and algorithmic innovations are explored within the major areas of (1) reservoir operation and surface water management, (2) water distribution systems, (3) drainage and wastewater engineering, (4) groundwater systems including remediation, monitoring, and management, (5) Environmental and Watershed Management Problems, and (6) other applications.

### 5.1 Reservoir Operation and Surface Water Management

Like all search based algorithms, the significant advantage of ACO algorithms in reservoir operation is its capability to be directly linked with any full scale and detailed system simulation models. Different versions of ACO have been applied to derive rule curve parameters (Kangrang and Lokham 2013) and/or the optimal periods-of-record releases (Jalal et al. 2007a). ACO algorithms are rather robust to solve highly nonlinear, nonconvex problems, however; the expensive computational requirements may limit their suitability for implicit and/or explicit stochastic optimization applied to multiple reservoir systems unless operating policies can be parameterized.

Although less cited, the first application of the basic ACO algorithm in reservoir operation for hydroelectric generation scheduling was addressed by Huang (2001) for a 24-h period. Later, Jalali et al. (2006a) employed ACO algorithm to determine the optimal period-of-record releases in finite horizon reservoir operation problems. In subsequent papers, Jalali et al. (2006a, b) presented improved versions of classical ACO algorithm for single and multiple reservoir operation. They introduced pheromone promotion, explorer ants, pheromone re-initiation and a partial path replacement to improve performance of the standard ACO algorithm. In a simultaneous attempt, Kumar and Reddy (2006) derived operating policies for a multi-purpose reservoir system by ACO algorithm.

In order to minimize the possibility of losing the global optimum domain in continuous problems, Jalali et al. (2007a, b) used multiple colonies to generate non-homogeneous and more or less random meshes in the entire search space for discretization of the state variables. Benefiting from the solution building feature of the ACO algorithms, Moeini and Afshar (2009) explicitly satisfied the constraints in a reservoir operation problem. By providing a tabu list for each ant at each decision point, they forced the ants to select their solutions from the list of available feasible solutions. Partially constrained and fully constrained version of the proposed method were formulated and used to derive the optimal periods-of-record releases in a hydropower reservoir operation. The constrained ACO algorithm was extended in a more recent contribution to optimal operation of multiple reservoir system (Moeini and Afshar 2013a).

Not very many applications of ant algorithms have been reported that efficiently benefits from the concept of heuristic function in the formulation. In fact, direct exploitation of the heuristic information has often been overlooked due to formulation difficulties. Only few articles have explicitly or implicitly employed the heuristic information in definition of decision points and search space (Afshar and Moeini 2008; Moeini and Afshar 2009, 2011; Guo and Wang 2010).

Introducing the Non-dominated Archiving Ant Colony Optimization (NA-ACO) as a multiple objective version of ACO algorithm, Afshar et al. (2009a, b) employed the concept of multi-colony ant and incorporated a new information-exchange policy between the colonies. They formulate and apply the NA-ACO for developing the set of optimum non-dominated solutions for a reservoir with conflicting objectives.

The first application of the early formulation of continuous ant algorithm in reservoir operation may be attributed to the work of Afshar (2006a). They proposed an elitist strategy for continuous ACO algorithm in which a single Gaussian probability density function (pdf) was used to move from discrete probability distribution to a continuous one. The original ACOR proposed by Socha and Dorigo (2006) for continuous domain has successfully been used in reservoir operation (Dariane and Moradi 2009; Madadgar and Afshar 2009). The original algorithm was modified by including adaptation operator and explorer ants as a mutation operator to improve its performance (Madadgar and Afshar 2009). The improved algorithm was then employed to solve a nonlinear and non-convex multiple period hydro-power reservoir operation problem. In application to a 240- period problem, it outperformed the original ACOR, both in identifying the best solution and the average performance over large number of independent runs. It was also illustrated that the improved algorithm is remarkably less sensitive to the initial values of the tunable parameters.

Application of hybrid ACO to reservoir operation is in the early stages of development. Wang and Pan (2008) introduced the hybrid chaos optimization and ACO for optimization of reservoir operation. They argued that the hybrid algorithm can effectively increase the computing efficiency, is easy to improve the stagnation and could not fall into the local optima. In a most recent work, Afshar et al. (2015) introduced a hybrid ACO-LP formulation for reservoir design under reliability constraints. They successfully applied the model to solve the reliability based model for a 480-period problem.

### 5.2 Water Distribution System

Water distribution networks (WDNs) are known as non-linear, constrained and multi-modal problems The very first use of ACO in WDN optimization may be attributed to Simpson et al. (2001) and Maier et al. (2001, 2003). They applied ACO algorithm for optimum design of a small network with 14 pipes, two reservoirs, and three loops. Their focus was to illustrate ACO's application in design of WDN and investigate the performance sensitivity of the ACO method to changes in the tunable parameters. In a more comprehensive work, Maier et al. (2003) presented a generalized approach for the optimal design of WDNs. At each decision point, the available choices for each ant were addressed by the available pipe diameters and/or pipe rehabilitation options. Pheromone intensities and heuristic values were directly linked with each of the available choices. To provide the ants with virtual visions, the heuristic values were taken as the inverse of the cost of each choice. Pheromone intensities were updated using the priority of choices that resulted in smaller total network costs. To handle the constraints, the pheromone intensities associated with choices that resulted in infeasible solution were decreased by penalizing the solution. They argued that ACO algorithms are true attractive alternative to GAs for the optimal design of WDNs, as they outperformed GAs for the two case studies considered.

Introducing a new transition rule, Afshar (2005a) claimed that the proposed transition rule would overcome the stagnation problem and found to be less sensitive to the sensitivity indexes.

In a series of papers, Zecchin and his colleagues applied different versions of ACO algorithms andtested their performances in design of water distribution systems with various topologies (Zecchin et al. 2003; 2005; 2006; Zecchin et al. 2007a, b a–b). The performance of MMAS was compared to that of AS for two commonly used WDS case studies, namely the New York Tunnels Problem and the Hanoi Problem (Zecchin et al. 2006). In their study the MMAS outperformed AS and performed better than any other heuristic driven from nature (HDN) in the literature for both case studies. They argued that consistent high performance of the MMAS, compared to AS, illustrates that the additional mechanisms incorporated in MMAS to manage the relationships between exploitation and exploration are effective in improving the performance of ACO algorithms. Although, driven from a case study with little mathematical support, this desirable robustness characteristic of the MMAS may be attributed to its unique combination of anti-convergence mechanisms with its elitist pheromone updating rule (Zecchin et al. 2006). Based on four case studies, the results for MMAS and ASrank were extremely promising, however a wider experimentation believed to be required to support their utility for real world WDS design problems (Zecchin et al. 2007a, b). Ostfeld and Tubaltzev (2008) linked an ant colony scheme with EPANET for the minimization of the systems design and operation costs. Although they argued that their proposed methodology produced better results than those of Zecchin et al. (2005), it is difficult to generalize their findings.

Constraint handling in all ant based algorithms is a major and challenging issue. Penalized objective function seems to be the most attractive and generalized approach for tackling this problem. Determination of the most desirable penalty coefficient in modeling WDNs has remained as an ongoing argument (Afshar 2007a; Afshar 2008; Afshar et al. 2009a, b). Afshar (2008) and Afshar et al. (2009a, b) proposed and applied a penalty adapting-based ACO algorithm for optimum design of WDNs. Their proposed approach iteratively adapts the value of the penalty parameter assuming an arbitrary value at the beginning of the search. In a comparative study, Gil et al. (2011) presented and evaluated the performances of a new ACO implementation tailored to solve the single-objective constrained nonlinear water distribution network (WDN) for optimum investment. He concluded that, for the two benchmark networks, the ACO solutions outperformed those of GA and scatter search.

Realizing the importance of operational cost, relatively large number of researchers has focused on pump scheduling as a means of reducing energy costs by taking advantage of off-peak electricity and reservoir storage in a water distribution system. Parallel to application of GA and other search-based algorithms, few researchers focused on application of various structures of ACO for optimum operation of pumping stations in WDNs (Ibanez et al. 2008). Ibanez et al. (2008) used a new constraint handling approach in which constraint violations were ordered according to their importance and solutions were ranked based on this criterion. The approach reduced the search space which led to reduction in the number of functional evaluations. More comprehensive and detail analysis and formulations are provided in Ibanez et al. (2008).

The search space of the pump scheduling problem grows exponentially with the number of control elements such as pumps leading to increased number of function evaluations required to adequately explore the search space. More important, in an operational scheduling problem, calculation of the objective function value and performance indices requires integration of an extended period hydraulic simulation model with an optimizer. Hybrid methods are sometimes practiced to reduce the computational time.

Highlighting the computational burdens and benefits of using variable-speed pump (VSP) in water distribution systems, Hashemi et al. (2014) combined the ant system iteration best algorithm (ASib) with EPANET2.0. They claimed that the proposed heuristic approaches considerably improved the quality of solutions and enhanced the navigation of the optimization process.

Successful applications of different versions of ACO algorithms with varying structures for layout and size optimization of tree-like and looped pipe networks has been reported (Afshar 2005b, 2006b, 2008; Afshar and Marino 2006). It was argued that treating the network nodes as decision points in an incremental solution building approach, where ants are restricted to choose from the available links provided by a tree-growing algorithm, will lead to a very small search space. It was also emphasized that the approach may fully exploit the sequential nature of the ant algorithm in building solutions, which is believed to be one of the main advantages of ant algorithms compared to other general heuristics (Afshar 2008). It has been argued that the simultaneous layout and size optimization of networks is needed if an optimal or near optimal solution is desired (Afshar and Marino 2006; Afshar 2008).

This section is closed by citing successful applications of ACO algorithms to joint layout and size optimization of pipe networks (Afshar 2006c), to water transfer pipeline design (Abbasi et al. 2005); mixed variable domain in pipeline design (Afshar et al. 2012); forced water main design (Madadgar and Afshar 2011) and pipeline routing problem (Christodoulou and Ellinas 2010). Much more interesting problem in design of forced main water pipeline system under transient condition was tackled by Abbasi et al. (2010). They coupled a numerical presentation of the system's hydraulics with the ant colony optimization algorithm to form a simulation-optimization interaction loop that cycled between the steady-state and transient flow modules.

### 5.3 Urban Drainage and Sewer System

Although, use of the evolutionary computation in optimum sewer design is fairly old, application of ACO in this area is of recent origin. When coupled with full scale and appropriate hydraulic simulator in a simulation-optimization framework, it highly reduces the need for simplification of system representation and holistically considers inter-network effects such as surcharge and backwater.

An adaptive refinement procedure was proposed by Afshar (2006a) to restore the computational efficiency of the ACO algorithm as applied to sewer network design. It was discussed how the level of discretization of the continuous search space may lead to undesirable final solutions and/or enlarge the scale of the problem and computational cost. In a subsequent paper (Afshar 2007b), two partially constrained ACO algorithms were formulated and successfully applied to storm water network design. The method provides a tabu list for each ant at each decision point to satisfy some of the constraints in the solution building process.

Simplifying the original structure of the ACOR introduced by Socha and Dorigo (2006) and further elaborated its application in WRM problems by Madadgar and Afshar (2009), two alternative, namely constrained and unconstrained, approaches were presented for implementation of the algorithm to storm sewer network design (Afshar 2010). It was claimed that the algorithms effectively located the near optimal solutions and were efficient in terms of the convergence characteristics.

The sewer network design optimization problem may be viewed as two sub-problems addressed as optimal layout determination and optimal sizing of its components. Moeini and Afshar (2012, 2013b) coupled ACO algorithm with a Tree Growing Algorithm (TGA) to simultaneously solve the sewer network layout and size optimization problems. The method assumes an existing base layout with all possible links, from which TGA constructs feasible tree like layouts for ACO to optimally determine the pipe diameters. It was argued that the proposed method is capable to optimally solve the problem of layout and size determination of sewer networks. Further, future developments in sewer optimization may consider improvements in design efficiency, integrated design, multiple objectives, constraint performance based design, and risks and uncertainties in their approaches.

### 5.4 Groundwater Managements

Groundwater management problems are often very complex because they are highly nonlinear in nature with discrete and/or discontinuous decision domain and computationally expensive numerical simulation model. Groundwater optimization problems may include groundwater aquifer management, monitoring network design, aquifer parameters estimation, pollution source identification and groundwater remediation. Although, seems to be quite suitable for all classes of groundwater management, ACO algorithms have not been extensively used in groundwater management problems. Authors believe that the large number of required function evaluations and significant computational requirement of the numerical simulation model may impose sever constraints both on practical and research works. Although these limitations stay valid for all variety of search-based algorithms, overwhelming application of GA in groundwater management problems have been reported. Nonetheless, application of ACO algorithms in groundwater management has been receiving growing attention. One of the earliest applications of ACO in water resources uses an inverse modeling procedure to estimate the unsaturated soil hydraulic parameters (Abbaspour et al. 2001). Using ACO, in a series of papers, Li and his colleagues have tackled different aspects of groundwater long term monitoring plans (Hilton et al. 2005; Li and Hilton 2005; Li and Hilton 2007).

When compared to the results of complete enumeration, the solutions of ACO based long term groundwater monitoring (ACO-LTM) were globally optimal for the cases with 21 to 27 remaining wells. They argued that the results from the proposed ACO-LTM algorithm provide a proof-of-concept for the application of the general ACO analogy to address the optimum locations of groundwater LTM sampling stations.

Hybrid ACO with simulated annealing was used to provide an adaptive algorithm for estimating the transmissivity and storage coefficient for a two-dimensional, unsteady groundwater flow model. The inverse problem of parameter identification was formulated as an optimization model based on information from the observed and calculated water heads. It was claimed that the ill-posedness of the inverse problem was overcome by employing computational intelligence (Li et al. 2006a, b, 2008; He and Liu 2009). In a most recent work, Ataie-Ashtiani and Ketabchi (2011) employed an improved Elitist Continuous Ant Colony Optimization (ECACO) algorithm for optimal control variables setting of coastal aquifer management problem. The comparison of the results with those available in the literature for steady state problems was promising in application of the algorithm in such a complicated and numerically complex management problem.

### 5.5 Environmental and Watershed Management

The most recent and interesting application of ACO in watershed management was reported by Emami Skardi et al. (2013). They combined the Soil Water Assessment Tool (SWAT) watershed simulation model with an Ant Colony Optimization (ACO) module and the cooperative game theory approach for deriving the optimum strategy for watershed management. Fair reallocation of the maximum cost saving to the participating players was investigated using Nash Bargaining Theory. In a subsequent work, Emami Skardi et al. (2015) coupled a multi-objective non-dominated archived ant colony optimization (NA-ACO) algorithm as an optimization tool with WAT as the simulation module for optimum management of Total Suspended Solids loading to downstream water bodies. To increase the computational efficiency of the watershed simulation model, the SWAT model was replaced by a surrogate ANN model to form a hybrid (NA-ACO)-SWAT-ANN model to develop the set of optimum non-dominated solutions for configuration and design of detention ponds in basin scale.

Dealing with instream quality management issues, Mostafavi and Afshar (2010a, b) proposed two single and multiple pollutant waste load allocation models to minimize the total treatment cost and overall violation index using the previously addressed multiple objective ACO (NA-ACO) model. They identified the trade-off relationship between the wastewater treatment cost and the overall violation from a predefined standard level in the river system. To resolve the conflicts in a waste load allocation problem through a quality trading scheme, Sharifi et al. (2010) presented a multiple objective ACO-based negotiation algorithm. In their approach, the waste dischargers are allowed to negotiate with each other using Ant Colony Optimization (ACO) to decide on their level of discharge while severely meeting the environmental standards at the checkpoints.

Realizing the ever increasing attention on sensor location and consequence management on intentionally polluted water distribution network, Ehsani and Afshar (2010) applied NA-ACO for multi-objective optimization of a sensor location problem. It was illustrated that the proposed method may form a competitive approach in deriving the Pareto solutions for early detection of contaminant in a water distribution system. Recently, Afshar and Marino (2012) presented an ACO-based multiple objective frameworks for optimally locating the water quality sensors. Although, the optimization model was formulated in terms of integer programming, the solution to the mathematical problem was efficiently approximated by means of a multi-objective multi-colony ant algorithm. Its robustness in analyzing the effects of different scenarios and number of potential monitoring stations was illustrated by eliminating the need of employing an off-line routine for coverage matrix identification and its application to a real world large network

Employing ACO algorithm, Charvalho et al. (2008) and Souto et al. (2004, 2006) reconstructed the chlorophyll profile from radiance experimental measurements in the ocean water for several depths by solving the inverse problem. Vertical profiles of the absorption and scattering coefficients are estimated from the Chlorophyll profile by means of bio-optical models and the inverse problem was formulated as an optimization problem and iteratively solved by an ACS using the radiative transfer equation as direct model. For the first time the ACO algorithm was successfully used for identification of optimal scheduling of environmental flow management alternatives (EFMAs) (Szemis et al. 2012; 2010). It was claimed that, unlike other currently popular algorithms, the ACO algorithm was able to account for all aspects of the problem and efficiently provided the trade-offs between the competing needs of species under a range of operating conditions and valuable insight for managers. In a multi-objective approach, Szemis et al. (2013) employed a multi-objective ACO approach for scheduling environmental flow management alternatives in a river- wetland-floodplain system. The formulation maximized ecological benefits while minimizing water allocations within the infrastructure constraints of the system for developing the optimal trade-off between the conflicting objectives.

## 5.6 Other Applications

Other than those listed and cited in the above sections, some diverse applications of different versions of ACO algorithms has also been reported (Afshar and Daraeikhah 2008). Marino and Morales (1999) tested a multi-objective Ant-Q algorithm for design of water distribution network. In a PhD dissertation, Reddy (2006) developed and applied versions of swarm intelligence and evolutionary computational schemes for optimization of water resources systems in single and multi-objective environments. Although not statistically sound, performance of versions of single and multi-objective GA were compared with those of ACO in various hydraulics and water resources management problems (Olarte and Obregon 2004; Cui et al. 2009; Mortazavian et al. 2009; Nourian et al. 2009; Rezapour et al. 2012). Versions of hybrid ACO for different operations and applications have been developed and applied to solve number of water resources management problems (Bowden et al. 2002; Musrrat and Millie 2009; Wang and Guo 2010).

## 6 Current Trends in ACO

While both the performance of ACO algorithms and our theoretical understanding of their working have significantly increased, there are several areas in which only preliminary steps have been taken and much more research are to be done. Extension of ACO algorithms to more complex optimization problems such as (1) dynamic problems, (2) stochastic problems, and (3) multiple objective problems is known to be the first area. Other active research directions in ACO include the effective parallelization of ACO algorithms and understanding and characterization of the behavior of ACO algorithms and their convergences while solving a novel problem (Dorigo and Stutzle 2004).

Despite the rapid development and application of ACO algorithms, their mathematical analysis remains partly unsolved. This difficulty is largely due to the fact that the interaction of various components in all metaheuristic algorithms, including ACO, is highly nonlinear, complex, and stochastic. Although, various studies have attempted to carry out convergence analysis, it remains an active and challenging topic. On the other hand, however, we have not proved or cannot mathematically prove their convergence but, we still can compare the performance of various algorithms. This has indeed formed a majority of current research in developing and applying ACO algorithms in the research community of optimization

Despite its popularity, mathematical analysis of the algorithm lacks behind. Its popularity is partly attributed to its potential in solving nonlinear, nonconvex, multimodal, in both discrete and continuous domains for which deterministic search techniques incur difficulty or fail completely.

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