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Review

Ant-Inspired Metaheuristic Algorithms for Combinatorial Optimization Problems in Water Resources Management

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Abstract: Ant-inspired metaheuristic algorithms known as ant colony optimization (ACO) offer an approach that has the ability to solve complex problems in both discrete and continuous domains. ACOs have gained significant attention in the field of water resources management, since many problems in this domain are non-linear, complex, challenging and also demand reliable solutions. The aim of this study is to critically review the applications of ACO algorithms specifically in the field of hydrology and hydrogeology, which include areas such as reservoir operations, water distribution systems, coastal aquifer management, long-term groundwater monitoring, hydraulic parameter estimation, and urban drainage and storm network design. Research articles, peer-reviewed journal papers and conference papers on ACO were critically analyzed to identify the arguments and research findings to delineate the scope for future research and to identify the drawbacks of ACO. Implementation of ACO variants is also discussed, as hybrid and modified ACO techniques prove to be more efficient over traditional ACO algorithms. These algorithms facilitate formulation of near-optimal solutions, and they also help improve cost efficiency. Although many studies are attempting to overcome the difficulties faced in the application of ACO, some parts of the mathematical analysis remain unsolved. It is also observed that despite its popularity, studies have not been successful in incorporating the uncertainty in ACOs and the problems of dimensionality, convergence and stability are yet to be resolved. Nevertheless, ACO is a potential area for further research as the studies on the applications of these techniques are few.

Keywords: ant colony optimization (ACO); combinatorial optimization problems; hydrology; hydrogeology; nature-inspired algorithm

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1. Introduction

Nature provides simplistic approaches to solve many complex and challenging problems encountered in real life. Algorithms that draw inspiration from natural systems and processes are called "Nature Inspired Algorithms" [1,2]. These algorithms help in arriving at solutions because they easily adapt to the dynamic changes in nature. They can be inspired either from biological systems or from natural systems to solve complex optimization problems [3]. Nature inspired algorithms mimic nature to solve real-life problems and are applied to obtain an optimal solution [4].

Optimization techniques have a noteworthy role to play in solving complex engineering problems. By far, many nature inspired algorithms have been able to provide convincing solutions for many optimization-related engineering problems [1,2,5–7].

It is inferred from previous studies that the capabilities of modern techniques and advanced problem-solving algorithms have not yet been utilized completely to tackle the challenges faced in the field of water resources management [8]. It is important to analyze the potential use of available evolutionary algorithms to solve complex optimization problems persisting in the domains of hydrology and hydrogeology, considering their spatial and temporal complexities. Studies related to hydrology and hydrogeology mainly comprise reservoir operations, water distribution systems, coastal aquifer management, long-term groundwater monitoring, parameter estimation, urban drainage and storm network design, etc.

Among the many nature inspired algorithms, swarm-based algorithms are the most frequently used approach for complex optimization problems. Especially in solving issues related to water resources, swarm-based optimization has been used by researchers on a wide scale. Swarm-based optimization algorithms are based on the principle of swarm intelligence, which depends on large masses of agents that work based on stochastic choices. These agents interact locally within each other and also with the environment. The strategy of a swarm system facilitates building complex simulation models that help in scheduling, optimization, routing and clustering [6–10]. Out of the many swarm-based algorithms, ant colony optimization (ACO) is one such metaheuristic approach that is widely used in the field of hydrology and hydrogeology [11].

Agarwal et al. [4] studied the applications of ACO for water resources. This study was carried out when ACO was still being explored, and hence was not able to fully address the advancements made in multiple objective and continuous domain applications of the algorithm. Although the attempt is acknowledged, since different variants of ACO and enhancements in constraint handling and convergences were not taken into consideration, it demands the need for an elaborate study. Later, another review on the applications of ACO for water resources tried to bridge the gap, however, it did not include the applications of ACO variants and hybrid ACO algorithms [8]. However, there are many algorithms which are not documented properly and implementations of them have not been reported. Thus, the researchers are not fully aware of the progress across different approaches due to rapid growth of nature inspired algorithms. Therefore, awareness of all the algorithms is very much necessary, because studies on nature inspired computing are currently skewed toward only a few algorithms. Considering these research gaps, this study presents a brief overview of the various ACO algorithms and variants that have been used for various hydrology and hydrogeology-related applications. In addition, as a cutting-edge application, hybrid ACOs in combination with other deep learning models are being used to increase the accuracy of forecasting. This study was carried out with an aim of reviewing the applications of ACO algorithms for solving various optimization-related problems in the area of water resources management. Further, this study explores the scope of application of ACOs in other domains that require large-scale global optimization. The remaining sections of this paper explain the methodology adopted, followed by behavior, variants and workflow of ACOs and their applications in the field of water resources management.

2. Methodology

This study was initiated by systematic search and identification of research articles published in renowned journals based on information available on public domains. Firefox, Google Chrome and Microsoft Edge are the browsers that were used to establish a thorough search on the internet. Further popular scientific literature search tools such as Scopus, Google Scholar, Springer Link, ScienceDirect, IEEE, Bielefeld Academic Search Engine (BASE), Clarivate Web of Science and Directory of Open Access Journals (DOAJ) were also used. The key words that were used to carry out these searches were Nature-based algorithm in hydrology and hydrogeology, applications of ACO in hydrology and hydrogeology, ACO techniques for groundwater and surface water, Groundwater and nature-based algorithms (NBA), ACO implemented on various domains, non-deterministic polynomial-time hard problems (NP-hard), hydrogeological applications of NBA, ACO for groundwater, swarm optimization for hydrogeology, hydraulic parameters using NBA, ant colony and groundwater, etc. These searches fetched about 1500 documents, which were thoroughly studied. The results included peer-reviewed journals, conference papers, technical reports, short articles, and review papers. The reports and conference publications that were available on the open-source platform were not considered for this review. Thus, the scientific and technical reports and conference abstracts were excluded. As the authenticity and originality of these documents could not be ascertained, it was decided to consider only the peer-reviewed publications in journals with an impact factor that are indexed in Web of Science. Examining these publications, it was observed that ACO approach has only been used in the field of water resources since 2001 (Figure 1). The present work reports peer-reviewed publications in the field of hydrology, hydrogeology and other related fields from 2001 until April 2023. This effort led to only 141 publications, from which 29 publications related to hydrology and water resources using ACO were finalized. Figure 1 shows the number of publications and the fields of application with respect to year. In the initial stages, ACO was extensively used for optimization of water distribution systems, and later was used for other critical applications in hydrology such as reservoir optimization, long-term groundwater monitoring, etc. After 2006, ACO was also used for optimization of parameters such as transmissivity and storage co-efficient, evapotranspiration permeability analysis, spatial evaluation of water quality, and in a few groundwater flow modelling applications. It is observed that from 2001 to April 2023, ACO has mostly been used for reservoir optimization and water distribution systems, followed by optimization problems for identifying hydrogeological parameters.

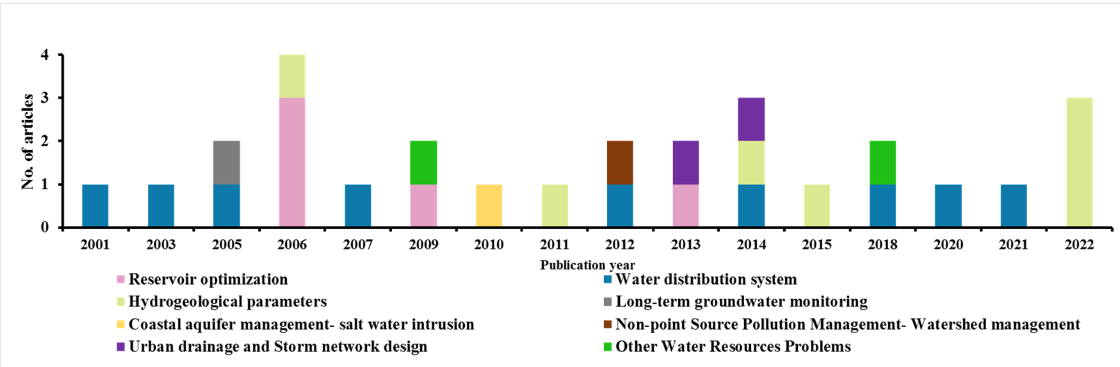

Figure 1. Quantitative analysis of publications in the field of hydrology and hydrogeology.

3. Ant Colony Optimization

3.1. Clustering Behavior of Ants

Ants possess the ability to build cemeteries by gathering dead bodies to a single place [12]. They organize the spatial disposition of larvae into clusters in such a manner that the young and small larvae occupy a position in the cluster center, while the older ones occupy a place at the periphery. This clustering behavior of ants has initiated many scientific studies, and many simple probabilistic models inspired from these behaviors have been built and tested [7]. Cooperation among ants helps them arrive at good solutions for discrete optimization problems [7,10].

The behavior of ants to create an optimal trail can be elucidated in four steps (Figure 2): (i) Initially, the environment is clean and the probability of ants choosing any route is the same. (ii) Ants choose different paths, some a shorter path and some longer ones. As they move, pheromones are deposited along their path. (iii) When the cycle repeats and ants continuously travel along that path, the shorter path will have a stronger pheromone trail sooner and faster. To decide the next move, ants use probability function weighted according to the number of pheromones deposited on the trail. Hence, more ants opt for the shorter trail. (iv) After some time, the initially dropped pheromones evaporate, and the shorter trail becomes dominant since more pheromone is collected in this path. Hence, it appears as if an intelligent species chose the best path, however the fact is that it evolved from the small, simple changes made by individuals.

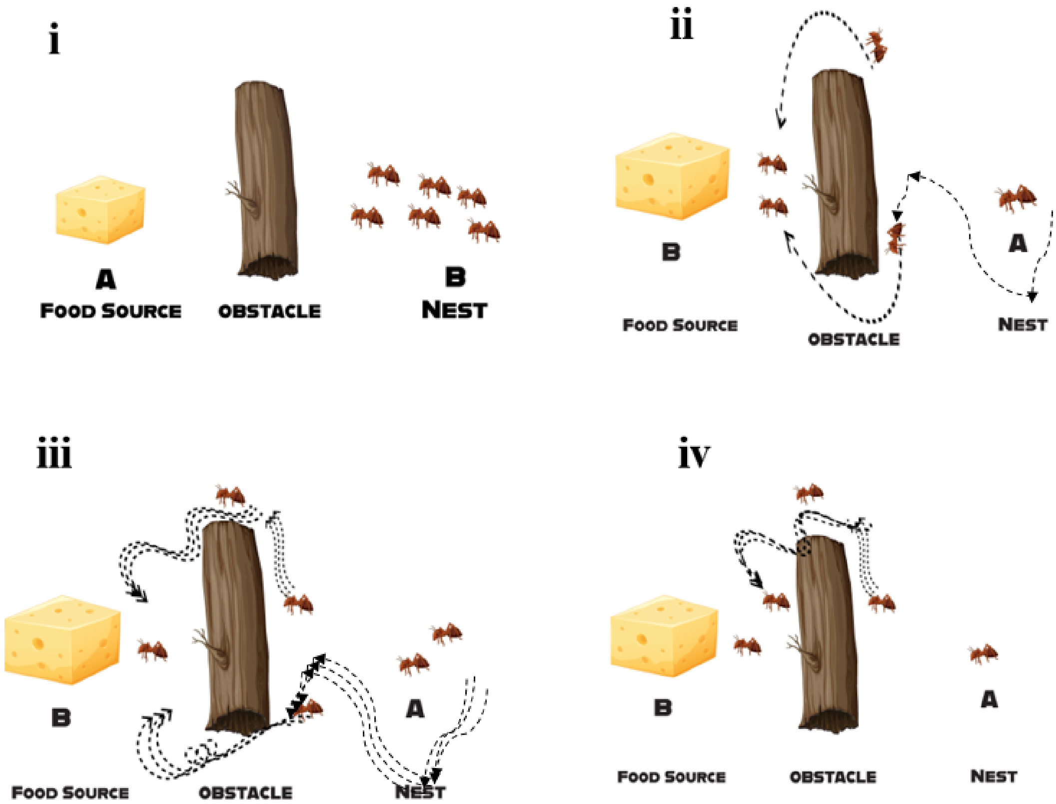

Figure 2. Basic ant colony behavior that facilitates optimization. Step (**i**) represents equal probability of ants choosing any route. Step (**ii**) shows ants choosing different paths. Step (**iii**) indicates that the shorter path has a stronger pheromone trail and reaches the food source faster. Step (**iv**) illustrates ants following the shorter path with stronger pheromone depositions.

3.2. Variants of ACO

The initial system that was inspired from the ant behavior is known as ant systems (AS) [12–14], after which max–min ant system was introduced. Since AS had an early convergence issue and many times was not able to trace the shortest path, it led to the development of other versions of ACO [11–14]. Meanwhile, MMAS is a hybrid algorithm that was developed for solving asymmetric travelling salesman problems (TSP). It is reported that MMAS follows a greedier search system than AS, and is one of the finest performing algorithms for quadratic assignment problem (QAP) and traveling salesman problems (TSP) [13,14]. To improve the suitability of the algorithm and computer efficiency, especially for dynamic topology optimization problems, the ACO algorithms were modified based on a new definition of pheromone and a new collaboration mechanism between ants, thus they were termed a modified ant colony optimization (MACO) algorithm [13–15].

Depending on the nature of the optimization problem and the objective function, different variants of ACO were used and are discussed in detail in Table 1. Some of the ACO variants used for solving optimization related problems are continuous ACO, constrained ACO (CACO), elitist ACO, partially constrained ACO (PCACO), fully constrained ACO (FCACO), ant colony system (ACS), ant system (AS), max–min ant system (MMAS), elitist rank system (AS_{rank}), AS_{ibest}, elitist ant system (EAS), arc based ACO (ABACOA), ant colony clustering algorithm (ACCA), ant colony-coupled-differential evolution (ACDE), discrete ant colony optimization (DACO), elitist continuous ant colony optimization (ECACO), fuzzy-CO and hybrid ACO algorithm.

Table 1. Variants of ACO, logic, their advantages and disadvantages.

Method & Logic	Advantages	Disadvantages
1. Ant system [10] Inspired by the foraging behavior of real ant colonies	Capturing indirect communication among the individuals of a colony of ants	–No concrete proof of how many ants would be required for convergence –Stopping criteria not mentioned –Optimal value for the stagnation behavior is not clearly specified –Getting stuck in local optima –How to decide varying the values for the various parameters
2. Ant density model [15,16] Leaves a defined trail of Q for unit length in its path		Requires extensive data on ant populations
3. Ant cycle model [16] Adaptation of the ant quantity model, which basically performs the process of reinforcement in accordance with the distance travelled		Limited scalability
4. Ant quantity model [16] Deposits a pheromone quantity of Q on the entire path.		Shorter paths will automatically have more pheromone deposits on them hence higher desirability
5. Ant colony system [11,17] –Fine-tuned version of ant system –The probability rule used to find the path to move in next area is different from AS	–Suitable for parallelization –The length of route covered is given priority	Convergence speed and solution accuracy when dealing with a large amount of data is not defined
6. ACS–3 opt local search [18] Additional local search heuristics to improve the exploitation capability of the algorithm	–Overcomes the problem of getting stuck in local optima –Provides state transition rule, a global update rule and a local pheromone update rule	–Increased computational complexity –Risk of getting trapped in local optima
7. Max–min ant system [19] Exploits the best solution found during the iteration	Limits the ant when it is about to choose an arc to travel by eliminating that arc if it does not fall between the interval	Getting stuck in local optima aggravates the problem of premature stagnation
8. Elitist ant system [20] –Preserves fittest individual of a system to save genetic information –Additional reinforcement to the parts belonging to the best path found since the beginning of the solution procedure	Risk of beginning with poor initial solution is less	–Local search becomes more important than global search –Effect of emphasizing short paths reduces when destination comes closer, especially when ants travel on good but sub-optimal paths
9. AS_{ibest} (asymmetric best-worst ant system) [21] Asymmetry in the pheromone updates, where ants differentiate between the best and worst solutions found so far, and update pheromones accordingly.	Faster convergence and improved solution quality compared to the basic AS algorithm	–Potential for over-optimization –Limited applicability –Asymmetry may cause trade-offs between exploitation and exploration

10. Elitist ant rank system AS$_{rank}$ [22] Elitism and rank used to update trail weights considering the best ants' rank-based system ranks the resultant paths according to their distance travelled and provides them with a rank value.	–Danger of over-emphasized pheromone trails using sub-optimal paths can be avoided –Emphasizing good paths and good ants equally, hence well balanced –The results of this approach provide a balanced exploration and exploitation of the search space	–Getting stuck in local optima –Potential premature convergence –Lack of diversity in solution exploration
11. Hybrid ant system [23] Combines ant system with other optimization techniques to leverage their strengths	–Enhanced performance by combining the strengths of different optimization techniques –Increased versatility –Robustness to local optima –Synergy of multiple algorithms	–Higher computational cost –Increased complexity –Difficulty in parameter tuning –Increased risk of overfitting
12. Fast ant system [24] Uses re-initialization of pheromones and does not consider pheromone evaporation	–Uses re-initialization of pheromones to avoid stagnation –Enhanced exploitation–exploration balance	Only one ant is used, not the population. Hence, becomes a biased approach
13. Cooperative genetic ant system [25] Combines both the genetic algorithm and ant system	–Better chance of achieving global solution –The global best will be chosen and then pheromone is updated –More solution space is explored using GA which yields global optimum	–Iterations give good results only for particular parameter values –Increased complexity
14. Improved ant system [26] Dynamically adjusts the pheromone density values to avoid local optima	–Pheromone density value set dynamically avoids the local optima –Efficient search –Reduced error accumulation	–Heavy computational burden with multiple algorithms –Minimal reduction of errors compared with previous algorithm
15. (Hybrid) model induced max–min ant system [27] Adjusted transition probabilities are developed by replacing static biased weighting factors with dynamic ones.	Optimal arcs will be identified at each step of tour construction using dual information derived from solving associated assignment problem (AP) and the search will be discarded from future consideration	–Requires additional computational overhead –Influenced by the bias problem-specific model
16. Cunning ant system [28] Introduces additional "cunning" behavior in ants to improve their search efficiency	–Improved convergence speed –Robustness to local optima	–Complexity in tuning parameters –Potential for bias or overfitting
17. Population based ACO [29] Involves multiple ant colonies or populations working concurrently on the same problem	–Enhanced exploration and exploitation –Improved convergence speed	–Potential for interference among colonies –Increased computational overhead

18. Beam ACO [30] Uses limited number of top-ranked ants, also known as the "beam width," for pheromone update and solution construction.	–Faster convergence –Reduced memory usage –Better exploitation –Enhanced solution quality	–Sensitivity to beam width parameter –Limited solution diversity –Reduced exploration
19. Hyper cube ACO [31] Uses hypercubes to represent the search space and facilitate exploration.	–Enhanced exploration as ants can search space concurrently –Robust to changes in problem characteristics	–Additional layer of complexity to the algorithm –Requires careful tuning of hypercube-related parameters
20. Continuous ACO [32] Specifically designed for solving continuous optimization problems	–Can handle a wide range of continuous optimization problems –Robust to noise and can tolerate small perturbations in the objective function or constraints –Capable of performing global search in the continuous search space	–May face challenges in fine-tuning and exploiting solutions to achieve high-quality solutions –May have slower convergence speed compared to gradient-based optimization algorithms
21. Constrained ACO [33] Specifically designed to solve optimization problems with constraints, where the feasible solution space is restricted.	–Capable of handling optimization problems with constraints, making it suitable for solving real-world problems –Versatile –Robust to constraints violations during the search process	–Computationally expensive, especially for complex optimization problems –Needs to strike a balance between exploration and exploitation –May face challenges in finding high-quality solutions that satisfy all the constraints
22. Elitist ACO [34] Incorporates an elitist strategy to improve the exploitation of the best solutions found	Elitist ACO reinforces the global best solution during each iteration, thereby enabling faster convergence towards the optimal solution	–May converge prematurely to a suboptimal solution, especially if the elite solutions are not updated or diversified effectively
23. Partially constrained ACO [35] Designed to handle optimization problems where some constraints are present but not strictly enforced	–Allows for flexibility in handling constraints by not strictly enforcing them –Can explore solutions that violate constraints	–Does not strictly enforce constraints, which can result in solutions that violate constraints –Uses a penalty-based approach to handle constraints, where violations are penalized –May lead to a trade-off between convergence speed and solution quality
24. Fully constrained ACO [35] Optimization process takes into consideration the constraints of the problem and generates solutions that strictly adhere to all the constraints	–Guaranteed constraint satisfaction –Convergence to feasible solutions	–Strictly adheres to constraints, which may limit the exploration of the search space –Sensitivity to constraint changes
25. Arc based ACO [36] Uses arcs, or directed edges, as the building blocks for constructing solutions	–Ants only need to select arcs instead of vertices or components, hence reduced solution space –Improved solution quality	–Less flexible compared to vertex-based ACO –More complex to implement and configure

26. Ant colony clustering [37] Objective is to group a set of data points into clusters based on some similarity or distance measure	–Flexible algorithm that can be adapted to various types of clustering problems –Good scalability	–Converge to suboptimal clustering solutions if the search process becomes trapped in local optima
27. Ant colony coupled differential evolution [38] Combines the principles of ant colony optimization (ACO) and differential evolution (DE) to solve optimization problems	–Benefits from the global search capability of both ACO and DE –Converges to high-quality solutions efficiently due to the use of both exploitation (DE) and exploration (ACO) mechanisms	–Computational complexity –Algorithm complexity
28. Elitist continuous ACO [8] Designed for continuous optimization problems where the decision variables are continuous instead of discrete	–Good global search capability –Can converge to high-quality solutions efficiently	–Requires careful parameter tuning to achieve optimal performance –Limited exploitation capability
29. Fuzzy-ACO [39] Incorporates fuzzy logic into the ACO algorithm.	–Robustness to uncertainty –Good exploitation–exploration balance	–Requires careful parameter tuning –Computationally expensive
30. Hybrid ACO [40] Combines ACO with other optimization techniques to create a hybrid approach	–Combines the strengths of different optimization techniques to provide enhanced optimization performance	–Increased complexity –Computationally expensive
31. Quantum ACO [41] Combines ACO with quantum computing principles, specifically utilizing quantum bits (qubits) and quantum gates to encode and manipulate information during the optimization process	–Quantum parallelism –Quantum entanglement –Overcomes energy barriers and access search spaces that are inaccessible using quantum tunneling	–High computational overhead –Limited quantum computing resources
32. Induced max–min ACO [27] Uses additional heuristics and rules to update pheromone trails	–Uses "induced perturbation" technique to introduce additional randomness in the search process, which enhances exploration of the solution space –Improved convergence speed	–There is no guarantee that it will always find the global optimal solution –Induced perturbation technique adds additional computational overhead to the algorithm

Apart from these, there are other variants of ACO like quantum ACO and cooperative genetic ant system approach, etc., that are used in other fields but not yet in hydrology and hydrogeology [42]. ACO variants that are being used for hydrological and hydrogeological applications are shown in Figure 3.

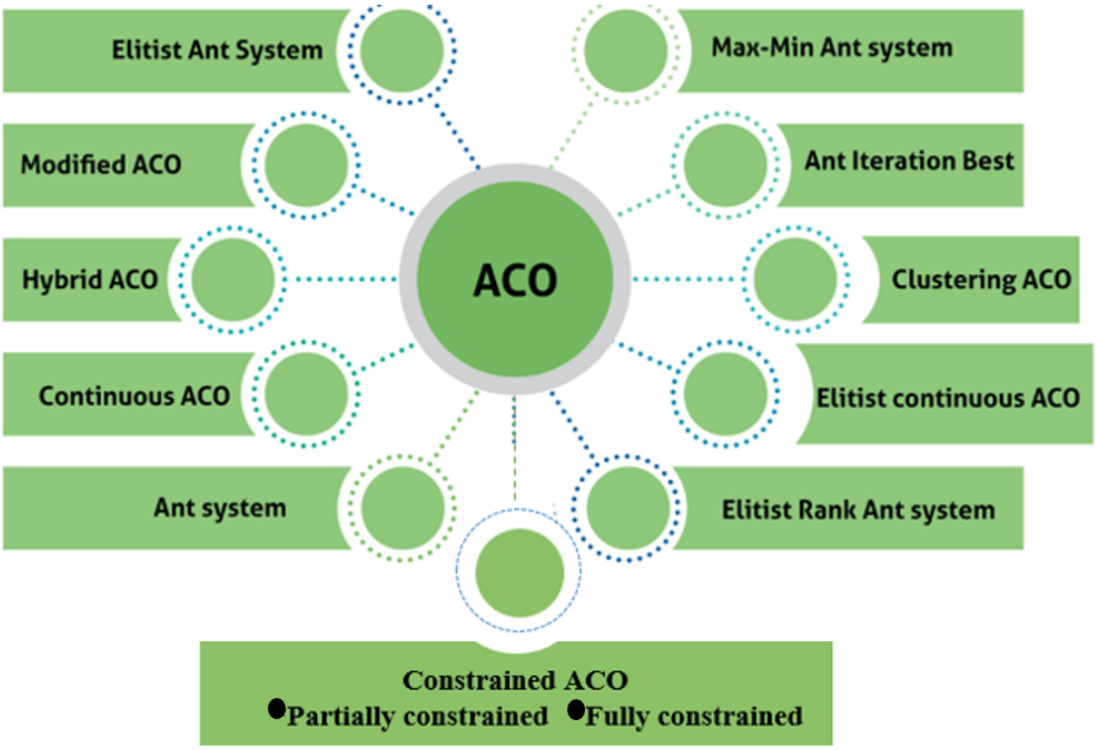

Figure 3. Variants of ACO used in hydrology and hydrogeology.

3.3. Workflow

ACO is a population-based metaheuristic method that functions according to an ant's ability to find the best and the closest path from the nest to a food source [10]. The pheromone-based trail-following nature of ants is the motivation for the development of ACOs. Ants as a single unit can perform only a limited set of functions, while a colony of ants can enslave other ant species, build superhighways of food and information, wage war against others, and build bridges [6,7,10,11]. This influence of pheromones is mathematically modeled as a weighted random function and the weight is calculated using the existing pheromones in the trail. Studies have reported that ACO outperforms many other evolutionary algorithms such as genetic algorithms (GA) [7,10,11]. ACO algorithms can be used for discrete and continuous domains that have single and multiple objectives and have proven to be a metaheuristic approach that can find high-quality solutions to NP-hard, significant combinatorial optimization problems within a reasonable time [4]. They are also flexible and powerful tools in solving many spatially and temporally multifaceted water resources related problems.

ACOs have been applied to many NP-hard combinatorial optimization problems such as QAP, the TSP, etc. A basic workflow of an ACO is depicted in Figure 4. In order to perform this task, the process is divided into steps and a pseudocode is developed with rules and constraints [10,11] (Figure 5).

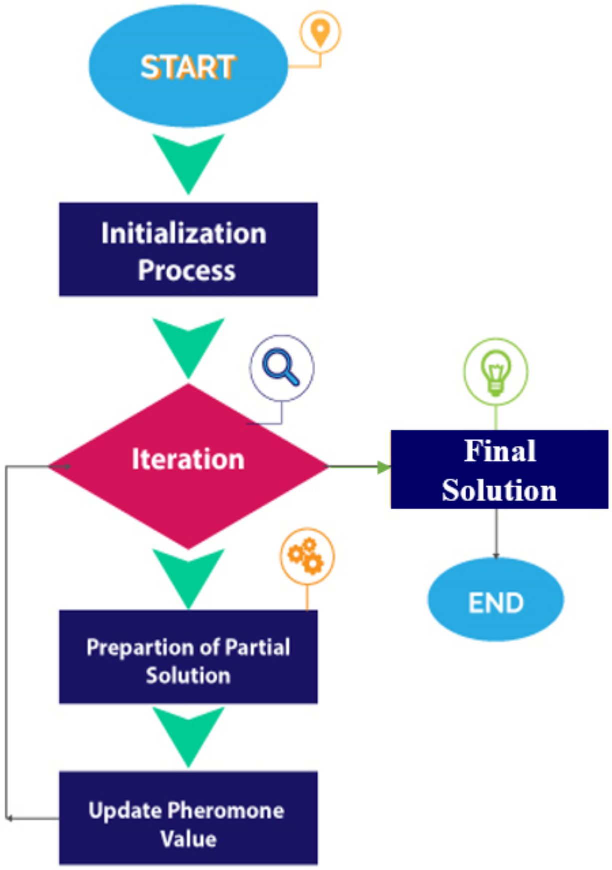

Figure 4. Workflow of ACO.

```
Begin;
    Initialize pheromone trail and parameters;
            Generate population of solutions (ant);
            For each ant calculate fitness;
            For each ant determine best position;
            Determine best global ant;
    Check if termination=True;
End;
```

Figure 5. Pseudocode for ACO algorithm.

4. Applications of ACOs

Applications of ACO with respect to hydrology and hydrogeology include irrigation water allocation, urban drainage network design, groundwater long-term monitoring, reservoir optimization, watershed management, coastal aquifer management, hydraulic parameters stimulation and water distribution systems (Figure 6).

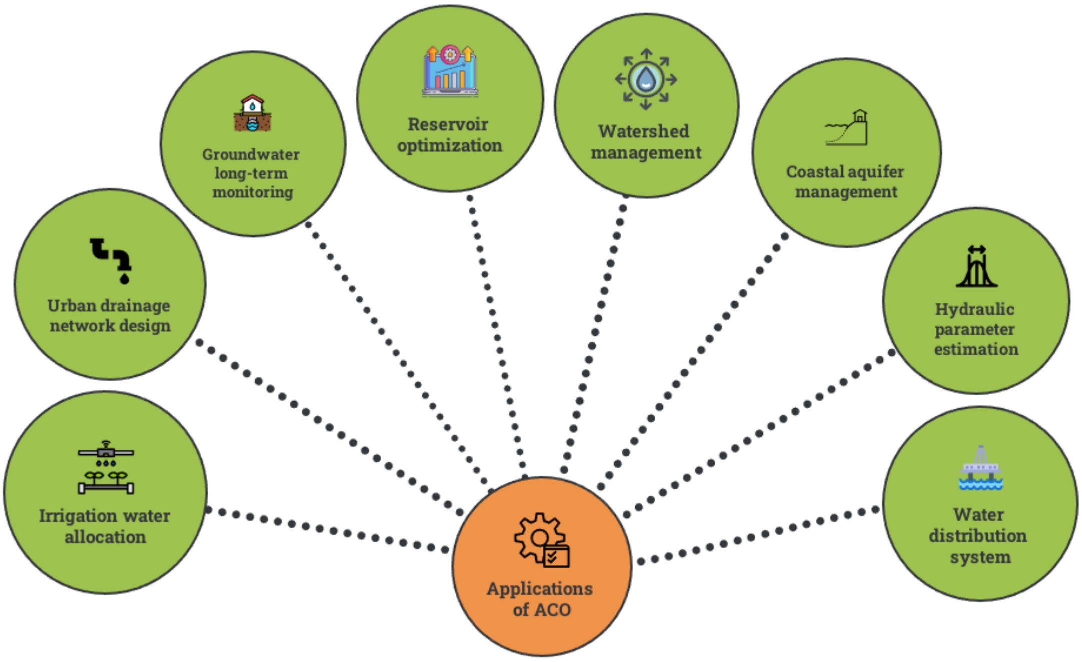

Figure 6. Applications of ACO in hydrology and hydrogeology.

4.1. Reservoir Optimization

Reservoir optimization is important to attain the paramount possible performance of a reservoir system [43,44]. It helps in arriving at decisions pertaining to storage over a period of time and release from reservoirs, taking into consideration the variations in inflows and demands. There are many studies that compare the applications of the traditional ACO algorithm to GAs in solving reservoir operations problems (Table 2). ACO was applied for optimizing operations of Hirakud Reservoir, which is a multi-purpose reservoir system situated in Orissa, India, and identifies that ACO outperforms genetic algorithms in arriving at global-optimum solution for long-time horizon reservoir operation [45]. An improved ACO algorithm helped in refining the estimates of the optimal releases of the Dez Reservoir, as compared to the GAs, while the improvised ACO algorithm needs fine tuning of the parameters to arrive at expected results [46]. Moeini et al. [46] proposed a modified ant colony algorithm to determine optimal reservoir operation for continuous domains (ACO_R). This algorithm was applied to the Dez Reservoir in southern Iran, and the performance has been compared to GAs. The main disadvantage of ACO algorithm is the enormous computer runtime, so an efficient methodology to decrease the runtime has been developed in this study. The same CACO algorithm for multi-reservoir parameter optimization has been used by [46]. Three different formulations of ACO, such as partially constrained ACO algorithm, max–min ant system, and fully constrained ACO algorithm were used to solve fourteen reservoir operation problems, and these techniques are compared to the conventional ACO algorithm. It was inferred that the new modified ACO techniques have an upper hand when compared to the traditional ACO algorithm to solve large-scale multi-reservoir operation problems [47] and can be used for solving complex water resource problems. CACO algorithm was used to determine a set of control parameters to identify the optimal operation of the Dez Reservoir. It is stated that CACO gave a good performance for global minimization of continuous test functions. A normalized squared deviation of the releases from the desired demands was assigned as the fitness function. In this study, CACO algorithm was compared with the solution obtained by DACO models and nonlinear programming (NLP) models. The CACO model is superior to the NLP and DACO models as they provide an alternative to the tedious trial and error-based approach by adopting an elitist strategy [48]. It is inferred that the previously experienced difficulty in substantiating the computational efforts required to execute an ant colony-based optimization problem has been resolved by some researchers; however, the techniques to overcome difficulties faced while parameter tuning are yet to be addressed seriously by researchers.

Table 2. ACO for reservoir operations.

Year	ACO Variant	Application	Name of the Reservoir	Reference
2006	Improved ACO	Single purpose	Dez Reservoir, Iran	[43]
2006	ACO	Multi-purpose	Hirakud Reservoir, India	[45]
2008	ACO for continuous domains	Single purpose	Dez Reservoir, Iran	[44]
2013	CACOA, UCACO, PCACO, FCACO, max–min ant system	Multi-purpose	Theoretical study	[46]
2018	CACO & DACO	Single purpose	Dez Reservoir, Iran	[47]

4.2. Water Distribution Systems

Several studies have been dedicated to the improvement of techniques to optimize the capital costs allied to water distribution system (WDS) infrastructure (Table 3). Although traditional linear and nonlinear techniques have been used to solve many WDS optimization issues, for a constrained minimization problem, variants of ACO have been fruitful in managing the trade-off between various conflicting attributes [48]. A significant aspect of WDS network design is to find the optimum network layout that satisfies power consumption, pressure, and also minimizes cost while meeting a performance criterion. In their research, Simpson et al. [49] have studied with 14 pipes and have tried to optimize the WDS using different combinations of parameters. Global optimum solutions were achieved, and the sensitivity of the ACO algorithm performance has been analyzed using the optimal range for six parameters. The drawback of this technique is that experience is required to decide which parameter needs to be selected, but an alternate method that helps in deciding which parameter needs to be selected is lacking. [50]. Two benchmark WDS optimization problems were considered and budgeting for the two were studied. The findings of this study revealed that ACO algorithms can be considered as an alternative to GAs for finding near global optimal solutions and also computational efficiency [50]. The cost solutions mentioned in previous literature are not practically possible since they seem to be violating the minimum pressure constraints while studying using EPANET [51]. The ACO parameters were explained better by developing parametric guidelines for the application of ACO to WDS optimization using an ACO variant known as $AS_{i\text{-best}}$, since it uses an iteration-best pheromone updating scheme [50]. It is observed that $AS_{i\text{-best}}$ provides the best efficiency and solution quality for the New York Tunnels problem but is only partially satisfactory for the Hanoi problem [51]. On the other hand, in order to understand the searching behavior of ants, their behavior was characterized into three categories: i) searching behavior for feasible and infeasible regions, ii) effective search for arriving at optimal or near-optimal regions of the search space, and iii) the algorithm exploration extent as it converges to solutions. Variants of ACOs were tested under these conditions, including how internal operators affect each algorithm's searching behavior [52].

A comparison between the performances of five ant colony algorithms was conducted to study the efficiency in optimization for WDS [52]. The algorithms are EAS, ACS, MMAS, and Elitist-AS_{rank}. It was observed that MMAS and AS_{rank} outperform all the other ant colony optimization techniques available, particularly in minimizing the design costs of WDS. The drawback is that the study has been carried out only for systems that are mentioned in the literature, but no real time applications have been carried out yet to check the validity of the results. While looking at the application of ACOs for various WDS applications, there are a lot of convincing results and satisfactory observations, but most of them have been conducted based on literature data, and real-time applications are not available. Further, studies involving the sensitivity of ACOAs to the parameters are few, and scenarios where ACOAs should be used in preference to GAs are not very convincing. To overcome this, a real water distribution network of El-Mostakbal City, Egypt, to determine the least-cost design was applied and determined that ACO is suitable only for simple networks, while PSO is the best for complex designs and they converge to the best solution [53]. In a parallel study for two typical canal irrigation systems in China, ACO algorithms yielded reduced leakage loss of delivered water from 7.29% to 5.40%, and 8.97% to 7.46% [54,55]. In order to optimize scheduled water delivery under water shortage conditions from an irrigation canal in Iran, applications of ACO were compared with Fuzzy SARSA learning model (FSL) [56]. The FSL method outperformed ACO method under three emergency operations and also led to less maximum absolute error (MAE) and integral of absolute magnitude of error (IAE) in comparison to the ACO method.

Table 3. ACO for WDS.

Year	ACO Variant	Application	Reference
2001	ACO	Parameter selection	[49]
2003	ACO	Optimal design	[50]
2005	ACO, $AS_{i\text{-}best}$	Optimal design	[51]
2012	ACO	Metric analysis for ACO search behavior	[52]
2014	Elitist AS, AS, ERAS, MMAS	Minimize design cost	[53]
2017	EA, GA, PSO, ACO, MA	Design and rehabilitation	[54]
2018	ACO	Planning of water delivery schedules	[55]
2020	Fuzzy SARSA learning and ACO	Water delivery scheduling under water shortage conditions	[56]

4.3. Hydrogeological Parameter Estimation

Studying movement of water, drinking water quality, transmissivity, storage coefficient and water level are of some important hydrogeological parameters that are instrumental in setting up environmental policies (Figure 7 and Table 4). A hybrid ACO algorithm to identify the storage coefficient and transmissivity for a two-dimensional, unsteady state groundwater flow model has been used [57]. Hybrid ACO algorithms are more advantageous in applications of gradient-based optimization methods [57]. This is mainly because ACO algorithms are global search algorithms and possess the ability to identify a parameter set in a stable manner. As an added advantage, this study has successfully formulated an optimization problem for parameter identification in an inverse problem [58].

ACO algorithms have the ability to search for a globally optimal solution. Hence, for estimating optimum permeability ACO has been used in Mansuri Bangestan Reservoir located in Ahwaz, Iran [58]. A hybrid ACO algorithm along with back propagation algorithm (ACA-BP) was used to fasten the evolution of neural networks and improve its forecasting precision. The available geophysical well log data was made use of, and it is proposed that ACA-BP yields better results than using the BP algorithm alone. However, while using this methodology, it is reported that identification of optimal neural network topology is strenuous, and the validity of these results when compared to the already proven GAs do not have any valid proof [58].

Since drinking water quality is an important parameter, [59] reported an evaluation method for spatial evaluation of drinking water quality by using GIS and ant colony clustering algorithm. This method integrates ACCA along with geographical information system (GIS). Strategies such as probability conversion functions, average similitude degree, and mixed distance function were used to improvise an ACCA algorithm. Various water quality grades were developed using ACCA in the GIS environment. The results derived from ACCA were compared with competitive Hopfield neural network (CHNN). The spatial water quality grades obtained from ACCA possess the upper hand when compared to CHNN [59]. Since spatial water quality assessment is an important parameter, it is very important that we make maximum use of this intelligent methodology. This methodology takes into consideration over 35 parameters, and hence it can be considered a valid procedure for evaluating water quality.

A methodology to assess the movement of water in the unsaturated media has been studied, where the ACO algorithm has been used extensively since it is a metaheuristic approach [60]. As metaheuristic approaches require parameters to be differentiable or continuous, ABACOA is preferred, especially because they have not used gradient or Hessian matrix from classic optimization. A modified ACO algorithm estimates Mualem-van Genuchten unsaturated hydraulic soil parameters for vadose zone using a sequential fitting. Inferring from the above studies it can be concluded that there is a future scope for estimation of parameters in inverse problems for groundwater hydrology. ACOR is coupled with ANFIS (ANFIS-ACOR) and used to study spatial salinity distribution. ACO is being widely coupled with machine learning algorithms to predict soil salinity in different environmental conditions and prediction of groundwater salinity [61]. Electrical resistivity imaging is used to reconstruct a conductivity model of subsurface water-bearing bodies. A priori constrained improved ACO algorithm for 3-D resistivity inversion was observed to be good at controlling search direction and improving inversion efficiency [62]. The efficacy of ACOs has been positively harnessed in combination with Fuzzy logic as well as the recently developing machine learning models such as neural networks, support vector regression, etc. in optimizing parameters in water quality simulation model, simulating of discharge, and evapotranspiration. ACOs, when compared to other optimizing algorithms, offered increased accuracy and better performance [63–66].

Table 4. ACO for hydraulic and hydrogeological parameters.

Year	ACO Variant	Application	Reference
2006	Hybrid ACO	Transmissivity and storage co-efficient for unsteady groundwater flow	[57]
2012	ACO-BP	Permeability analysis	[58]
2014	ACCO	Spatial evaluation of water quality	[59]
2016	Modified ACO	Flow modelling	[60]
2021	ACOR	Water quality management	[61]
2022	Improved ACO	Earth resistivity	[62]

2022	ACO	Groundwater salinity	[63]
2022	ACO	River water level forecasting	[64]
2023	ACO	Evapotranspiration	[65]
2023	ACO	Discharge	[66]

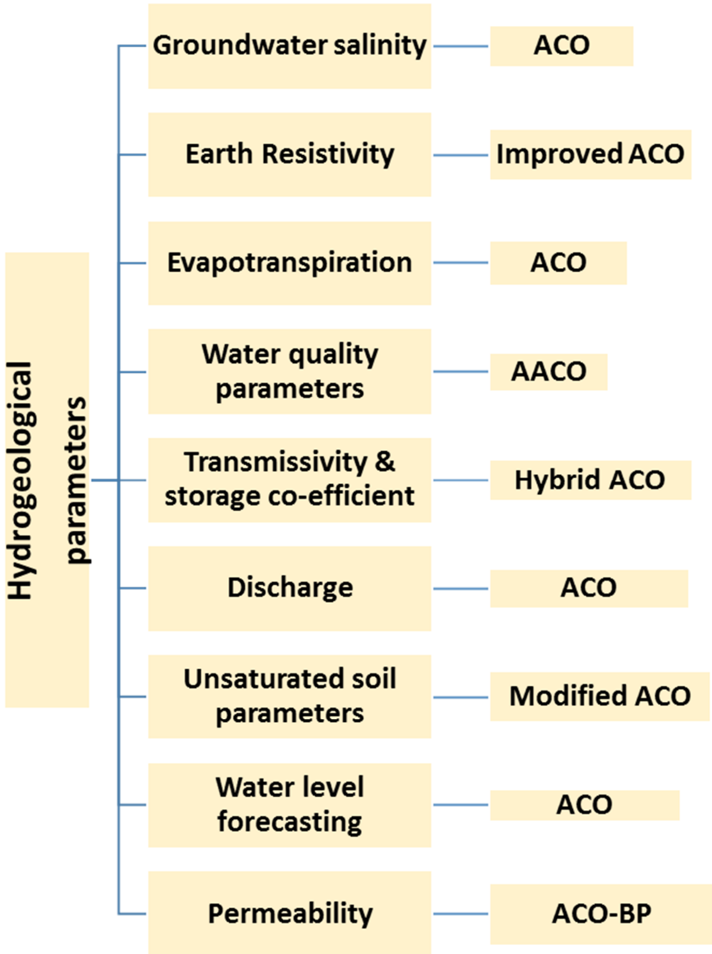

Figure 7. Variants of ACO for hydrogeological parameter optimization.

4.4. Other Applications

ACO and its variants are also used for other applications in water resources management. A brief description of those applications are described in this section (refer Table 5).

Table 5. ACO for other applications in water resources.

Year	ACO variant	Application	Reference
2006	ACO-LTM	Groundwater long-term monitoring	[67]
2009	ACDE	Water resource problems	[68]
2010	ECACO	Seawater intrusion management	[69]
2012	ACO + SWAT	Non-point source pollution management	[70]
2016	ABACO-TGA	Urban drainage network design	[71]
2018	ACO	Water management in irrigation areas	[72]

4.4.1. Long-Term Groundwater Monitoring

ACO has been incorporated to develop a methodology that optimizes long-term monitoring (LTM) of groundwater to help monitor human health risk at post-closure sites where contaminants are still present and to study the performance of groundwater remediation [67]. A set of redundant sampling locations was identified by the ACO-LTM algorithm, and global optimal or near-optimal solutions were determined. This algorithm has been applied to a small network comprising 30 wells; however, it needs to be applied to large-scale field sites, and it requires temporal optimization of a long-term monitoring network.

4.4.2. ACDE-Water Resources Problems

ACO coupled with differential evolution for solving a few real-time water resources problems such as water pumping system formulation, parameter estimation of water quality model, etc. was studied. To overcome the slow convergence rate and large computational time required for optimization of objective function, differential evolution was coupled with ACO to develop a modified algorithm known as ACDE [62]. ACDE was validated for two real-life problems, and also for a test bed of seven benchmark problems. As aimed, the computational effort was reduced, and the global optimal solution was attained without compromising the quality of the solution. ACDE algorithm also outperformed other algorithms in solving a few real-life problems [68].

4.4.3. Coastal Aquifer Management–Salt Water Intrusion

ECACO algorithm was used for optimal control variable management of a coastal aquifer to control saltwater intrusion. ECACO was used for maximizing the total water-pumping rate as well as simultaneously controlling the drawdown limits and protecting the wells from saltwater intrusion. In addition, a numerical simulation approach was combined with an ECACO algorithm to study potential applicability of the model for optimal management of a coastal aquifer [69]. Although this study gave reasonable results, there was more scope for integrating the proposed methodology approach, with already commercially available simulation tools. This study was carried out for a complex aquifer; however, only preliminary studies were conducted. With saltwater intrusion being an alarming issue of the hour, the maximum potential of variants of ACOs are yet to be utilized by researchers.

4.4.4. Non-Point Source Pollution Management–Watershed Management

ACO algorithm was applied on a breakthrough watershed management methodology. The ultimate aim of this study was to practice cost allocation among landowners in a watershed and control the total sediment yield in the watershed. The problem of non-point source pollution management in watershed scale reached a feasible solution as ACO algorithm helped in decision making without any additional computational burden. ACO coupled with a SWAT model helped in selecting optimum decision vectors [70]. Hence, they can help landowners to optimally control the sediment release from basins in pre and post development conditions and reach payoffs.

4.4.5. Urban Drainage and Storm Network Design

Sewer networks play crucial roles in human protection and environmental health management. Hence, it is very important to solve sewer network design optimization problems. ACO and its variants were coupled with an appropriate hydraulic simulator in a simulation-optimization framework, taking into consideration inter-network effects such as surcharge and backwater, and reduced simplification of system representation. ACO algorithms were also successfully used to optimize the management of stormwater retention tanks. Studies suggest that heuristic approaches solve large-scale sewer network design optimization problems better when compared to other methods. ACO algorithms augmented with tree growing algorithms (TGA) resulted in efficient estimation of network design and they are known as ABACOA [71]. Verdaguer et al. [71] have used both constrained and unconstrained versions of ABACOA algorithms to determine the nodal cover depths of sewer pipes, by considering the pipe slope. This is mainly because of the incremental solution building capability of the ACO algorithms. Constrained ABACOA-TGA produced better results with the same computational effort [71]. This technique appears to always be feasible for arriving at a minimum slope constraint. Further research and development are necessary in this area of water distribution system by considering design efficiency, multiple objectives, integrated design, risks and uncertainties, and constraint performance-based design. Applications of ACO algorithms in the area of urban drainage and stormwater network design has still not gained popularity and importance.

4.4.6. Optimal Crop and Irrigation Water Allocation

An improved ACO formulation for the allocation of crops and water to different irrigation areas enables dynamic decision variable option adjustment and utilizes domain knowledge to bias the search towards selecting crops that give maximum net returns and water allocations that result in the largest net return for the selected crop, given a fixed total volume of water [72]. The use of visibility factors optimized the ability to identify better solutions at all stages of the search, especially at smaller events of function evaluations. Hence, using ACO to identify near-optimal solutions for detailed irrigation scheduling for individual crops is better than the computationally costly, mechanistic crop growth models.

5. Conclusions

ACO algorithms have gained immense attention of the researchers in recent years since they are nature-based approaches providing solutions to multi-dimensional and multi-modal problems. Many researchers have used ACO in the field of manufacturing and production, robotics, bioinformatics, telecommunication, water resources management, etc. ACOs have gained attention of the water resource managers as they are one of the most suitable optimization algorithms for non-deterministic polynomial hard problems and most of the optimization problems are complex and have multiple parameters for optimization. Due to its self-evolved simplicity and natural distribution, ACO is prevalent in solving multi-objective optimization problems in hydrology and hydrogeology. ACOs have mostly been applied for hydrological applications such as optimizing reservoir operations and water distribution and stormwater network design. However, the hydrogeological applications are limited only to parameter estimations. ACO algorithms have claimed to arrive at better results as compared to GAs. It is inferred that ACO techniques consume significant computational time, and that ACO algorithms have not been able to overcome the problem of dimensionality at a desired level of satisfaction. On the other hand, the literature also presents a debate on the stability and convergence of these algorithms. In addition, since real-time systems are susceptible to uncertainty, the deterministic models seem to be oversimplified versions of real-life systems. Hence, incorporating real-life uncertainty in a natural way is needed. Nevertheless, ACOs are giving reasonable solutions for complex hydrology and hydrogeological applications and have potential for further research.

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References

1. Agarwal, P.; Mehta, S. Nature-Inspired Algorithms: State-of-Art, Problems and Prospects. Available online: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.678.3042&rep=rep1&type=pdf (accessed on 1 February 2023).
2. Vassiliadis, V.; Dounias, G. Nature–Inspired Intelligence: A Review of Selected Methods and Applications. *Int. J. Artif. Intell. Tools* **2009**, *18*, 487–516. Available online: https://www.worldscientific.com/doi/pdf/10.1142/S021821300900024X (accessed on 9 January 2023).
3. Fister, I.; Yang, X.S.; Brest, J.; Fister, D. A brief review of nature-inspired algorithms for optimization. *Elektrotech. Vestnik Electrotech. Rev.* **2013**, *80*, 116–122.
4. Ostfeld, A. *Ant Colony Optimization for Water Resources Systems Analysis—Review and Challenges*; InTech: Rijeka, Croatia, 2011. Available online: https://www.intechopen.com/books/ant-colony-optimization-methods-and-applications/ant-colony-optimization-for-water-resources-systems-analysis-review-and-challenges (accessed on 2 April 2021).
5. Soto, R.; Crawford, B.; Olivares, R.; Taramasco, C.; Figueroa, I.; Gómez, Á.; Castro, C.; Paredes, F. Adaptive Black Hole Algorithm for Solving the Set Covering Problem. *Math. Probl. Eng.* **2018**, *2018*, 2183214. https://doi.org/10.1155/2018/2183214.
6. Dorigo, M.; Stützle, T. *Ant Colony Optimization, Book by Morco Dorigo and Thomas Stützle*; MIT Press Direct: Cambridge, MA, USA, 2004. Available online: https://web2.qatar.cmu.edu/~gdicaro/15382/additional/aco-book.pdf (accessed on 15 August 2022).
7. Colorni, A.; Dorigo, M.; Maniezzo, V. Distributed optimization by ant colonies. In *European Conference of Artificial Life*; SciSpace: Bangalore, India, 1991; pp. 134–142.
8. Afshar, A.; Massoumi, A.; Afshar, A.; Mariño, A. State of the Art Review of Ant Colony Optimization Applications in Water Resource Management. *Water Resour. Manag.* **2015**, *29*, 3891–3904.
9. Bonabeau, E.; Corne, D.; Poli, R. Swarm intelligence: The state of the art special issue of natural computing. *Nat. Comput.* **2010**, *9*, 655–657. Available online: https://www.researchgate.net/publication/220132796_Swarm_intelligence_The_state_of_the_art_special_issue_of_natural_computing (accessed on 25 September 2021).
10. Dorigo, M.; Maniezzo, V.; Colorni, A. Ant System: Optimization by a colony of cooperating agents. *IEEE Trans. Syst. Man Cybern. Part B* **1996**, *26*, 29–41. Available online: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=4129846 (accessed on 1 June 2019).
11. Dorigo, M.; Gambardella, L.M. Ant colony system: A cooperative learning approach to the traveling salesman problem. *IEEE Trans. Evol. Comput.* **1997**, *1*, 53–66.
12. Franks, F.R.; Dornhaus, A.; Best, C.S.; Jones, E.L. Decision making by small and large house-hunting ant colonies: One size fits all. *Anim. Behav.* **2006**, *72*, 611–616. https://doi.org/10.1016/j.anbehav.2005.11.019.
13. Kube, C.R.; Bonabeau, E. Cooperative Transport by Ants and Robots. *Robot. Auton. Syst.* **1999**, *30*, 85–101. Available online: https://www.researchgate.net/publication/222658235_Cooperative_Transport_By_Ants_and_Robots (accessed on 16 November 2021).
14. Dorigo, M.; Di Caro, G.; Gambardella, L.M. Ant algorithms for discrete optimization. *Artif. Life* **1999**, *5*, 137–172.
15. SeonYoo, K. A modified ant colony optimization algorithm for dynamic topology optimization. *Comput. Struct.* **2013**, *123*, 68–78. https://doi.org/10.1016/j.compstruc.2013.04.012.
16. Prakasam, A.; Savarimuthu, N. Metaheuristic algorithms and probabilistic behaviour: A comprehensive analysis of Ant Colony Optimization and its variants. *Artif. Intell. Rev.* **2016**, *45*, 97–130. https://doi.org/10.1007/s10462-015-9441-y.
17. Dorigo, M.; Gambardella, L.M. Ant colonies for the travelling salesman problem. *Biosystems* **1997**, *43*, 73–81. https://doi.org/10.1016/S0303-2647(97)01708-5.
18. Mahi, M.; Baykan, Ö.K.; Kodaz, H. A new hybrid method based on Particle Swarm Optimization, Ant Colony Optimization and 3-Opt algorithms for Traveling Salesman Problem. *Appl. Soft Comput.* **2015**, *30*, 484–490. https://doi.org/10.1016/j.asoc.2015.01.068.
19. Stützle, T.; Hoos, H.H. MAX–MIN Ant System. *Future Gener. Comput. Syst.* **2000**, *16*, 889–914. https://doi.org/10.1016/S0167-739X(00)00043-1.
20. Shtovba, S.D. Ant Algorithms: Theory and Applications. *Progr. Comput. Softw.* **2005**, *31*, 167–178. https://doi.org/10.1007/s11086-005-0029-1.
21. Yan, Z.; Hao, W.; Yonghua, Z.; Yun, C. BEST-WORST Ant System. In Proceedings of the 3rd International Conference on Advanced Computer Control, Harbin, China, 18–20 January 2011. https://doi.org/10.1109/ICACC.2011.6016438.
22. Bernd, B.; Richard, H.; Christine, S. A New Rank Based Version of the Ant System—A Computational Study. *Cent. Eur. J. Oper. Res.* **1999**, *7*, 25–38.
23. McKendall, A.R.; Shang, J. Hybrid ant systems for the dynamic facility layout problem. *Comput. Oper. Res.* **2006**, *33*, 790–803. https://doi.org/10.1016/j.cor.2004.08.008.
24. Taillard, E.D.; Gambardella, L.M. *Adaptive Memories for the Quadratic Assignment Problem*; Technical Report, IDSIA-87-97; IDSIA: Lugano, Switzerland, 1997.
25. Abbattista, F.; Abbattista, N.; Caponetti, L. An evolutionary and cooperative agents model for optimization. In Proceedings of the 1995 IEEE International Conference on Evolutionary Computation, Perth, WA, Australia, 29 November–1 December 1995; Volume 2; pp. 668–671. https://doi.org/10.1109/ICEC.1995.487464.

26. Pintea, C.M.; Dumitrescu, D. Improving ant systems using a local updating rule. In Proceedings of the Seventh International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC'05), Timisoara, Romania, 25–29 September 2005; p. 4. https://doi.org/10.1109/SYNASC.2005.38.
27. Bai, J.; Yang, G.-K.; Chen, Y.-W.; Hu, L.-S.; Pan, C.-C. A model induced max-min ant colony optimization for asymmetric traveling salesman problem. *Appl. Soft Comput.* **2013**, *13*, 1365–1375. https://doi.org/10.1016/j.asoc.2012.04.008.
28. Tsutsui, S. cAS: Ant Colony Optimization with Cunning Ants Parallel Problem Solving from Nature. In Proceedings of the PPSN IX, 9th International Conference, Reykjavik, Iceland, 9–13 September 2006; Volume 4193; ISBN 978-3-540-38990-3.
29. Guntsch, M.; Middendorf, M. A Population Based Approach for ACO. In *Applications of Evolutionary Computing. EvoWorkshops 2002*; Lecture Notes in Computer Science; Cagnoni, S., Gottlieb, J., Hart, E., Middendorf, M., Raidl, G.R., Eds.; Springer: Berlin/Heidelberg, Germany, 2002; Volume 2279. https://doi.org/10.1007/3-540-46004-7_8.
30. Blum, C. Beam-ACO—Hybridizing ant colony optimization with beam search: An application to open shop scheduling. *Comput. Oper. Res.* **2005**, *32*, 1565–1591. https://doi.org/10.1016/j.cor.2003.11.018.
31. Blum, C.; Dorigo, M. The hyper-cube framework for ant colony optimization. *IEEE Trans. Syst. Man Cybern. Part B* **2004**, *34*, 1161–1172. https://doi.org/10.1109/TSMCB.2003.821450.
32. Omran, M.G.H.; Al-Sharhan, S. Improved continuous Ant Colony Optimization algorithms for real-world engineering optimization problems. *Eng. Appl. Artif. Intell.* **2019**, *85*, 818–829. https://doi.org/10.1016/j.engappai.2019.08.009.15.
33. Meyer, B.; Ernst, A. Integrating ACO and Constraint Propagation. In *Ant Colony Optimization and Swarm Intelligence. ANTS 2004*; Lecture Notes in Computer Science; Dorigo, M., Birattari, M., Blum, C., Gambardella, L.M., Mondada, F., Stützle, T. Eds.; Springer: Berlin/Heidelberg, Germany, 2004; Volume 3172. https://doi.org/10.1007/978-3-540-28646-2_15.
34. Aristidis, V. An Ant Colony Optimization (ACO) algorithm solution to Economic Load Dispatch (ELD) problem. *WSEAS Trans. Syst.* **2006**, *5*, 1763–1771.
35. Thiruvady, D.; Singh, G.; Ernst, A.T.; Meyer, B. Constraint-based ACO for a shared resource constrained scheduling problem. *Int. J. Prod. Econ.* **2013**, *141*, 230–242. https://doi.org/10.1016/j.ijpe.2012.06.012.
36. Yaghini, M.; Foroughi, A. ACO-Based Neighborhoods for Fixed-charge Capacitated Multi-commodity Network Design Problem. *Int. J. Transp. Eng.* **2014**, *1*, 311–334. https://doi.org/10.22119/ijte.2014.6301.
37. Shelokar, P.S.; Jayaraman, V.K.; Kulkarni, B.D. An ant colony approach for clustering. *Anal. Chim. Acta* **2004**, *509*, 187–195. https://doi.org/10.1016/j.aca.2003.12.032.
38. dos Santos Coelho, L.; de Andrade Bernert, D.L. A modified ant colony optimization algorithm based on differential evolution for chaotic synchronization. *Expert Syst. Appl.* **2010**, *37*, 4198–4203. https://doi.org/10.1016/j.eswa.2009.11.002.
39. Di Caprio, D.; Ebrahimnejad, A.; Alrezaamiri, H.; Santos-Arteaga, F.J. A novel ant colony algorithm for solving shortest path problems with fuzzy arc weights. *Alexandria Eng. J.* **2022**, *61*, 3403–3415. https://doi.org/10.1016/j.aej.2021.08.058.
40. Jiang, H.; Zhang, J.; Xuan, J.; Ren, Z.; Hu, Y. A Hybrid ACO algorithm for the Next Release Problem. In Proceedings of the The 2nd International Conference on Software Engineering and Data Mining, Chengdu, China, 23–25 June 2010; pp. 166–171.
41. Ghosh, M.; Dey, N.; Mitra, D.; Chakrabarti, A. A novel quantum algorithm for ant colony optimisation. *IET Quant. Comm.* **2022**, *3*, 13–29. https://doi.org/10.1049/qtc2.12023.
42. Sakthipriya, N.; Kalaipriyan, T. Variants of Ant Colony Optimization—A State of an Art. *Indian J. Sci. Technol.* **2015**, *8*, 1–15. https://dx.doi.org/10.17485/ijst/2015/v8i31/87296.
43. Jalali, M.R.; Afshar, A.; Marino, M.A. Improved Ant Colony Optimization Algorithm for Reservoir Operation. *Sci. Iran* **2006**, *13*, 295–302.
44. Kumar, D.N.; Reddy, M.J. Ant Colony Optimization for Multi-Purpose Reservoir Operation. *Water Resour. Manag.* **2006**, *20*, 879–898. https://doi.org/10.1007/s11269-005-9012-0.
45. Dariane, A.B.; Moradi, A.M. Reservoir Operating by Ant Colony Optimization for Continuous Domains (ACOR) Case Study: Dez Reservoir. *Int. J. Math. Phys. Eng. Sci.* **2009**, *3*, 2.
46. Moeini, R.; Afshar, M.H. Extension of the constrained ant colony optimization algorithms for the optimal operation of multi-reservoir systems. *J. Hydroinf.* **2013**, *15*, 155–173. https://doi.org/10.2166/hydro.2012.081.
47. Mohammad, A.; Ketabchi, H.; Rasa, E. Elitist Continuous Ant Colony Optimization Algorithm: Application to Reservoir Operation Problems. *Int. J.* **2006**, *4*, 274–285.
48. Sarbu, I.; Popa-Albu, S. Optimization of urban water distribution networks using heuristic methods: An overview. *Water Int.* **2022**, *48*, 120–148.
49. Simpson, A.R.; Maier, H.R.; Foong, W.K. Selection of parameters for ant colony optimization applied to the optimal design of water distribution systems. In Proceedings of the International Congress on Modelling and Simulation, Canberra, Australia, 10–13 December 2001; Australian National University: Perth, WA, Australia, 2001; pp. 1931–1936.
50. Maier, H.R.; Simpson, A.R.; Zecchin, A.C.; Foong, W.K.; Phang, K.Y.; Seaha, H.Y.; Tan, C.L. Ant colony optimization for design of water distribution systems. *J. Water Resour. Plan. Manag.* **2003**, *129*, 200–208. https://doi.org/10.1061/(ASCE)0733-9496(2003)129:3(200).
51. Zecchin, A.C.; Simpson, A.R.; Maier, H.R.; Nixon, J.B. Parametric study for an ant algorithm applied to water distribution system optimization. *IEEE Trans. Evol. Comput.* **2005**, *9*, 175–191. https://doi.org/10.1109/TEVC.2005.844168 https://aip.scitation.org/doi/abs/10.1063/1.4886855.

52. Zecchin, A.C.; Simpson, A.R.; Maier, H.R. Improved understanding of the searching behavior of ant colony optimization algorithms applied to the water distribution design problem. *Water Resour. Res.* **2012**, *48*, 1–16. https://doi.org/10.1029/2011WR011652.
53. Zecchin, A.C.; Maier, H.R.; Simpson, A.R. Ant Colony Optimization Applied to Water Distribution System Design: Comparative Study of Five Algorithms. *J. Water Resour. Plan. Manag.* **2007**, *133*, 87–92. https://doi.org/10.1061/(asce)0733-9496(2007)133:1(87).
54. El-Ghandour, H.A.; Elbeltagi, M.E. Comparison of Five Evolutionary Algorithms for Optimization of Water Distribution Networks. *J. Comput. Civil Eng.* **2018**, *32*. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000717. Available online: https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29CP.1943-5487.0000717 (accessed on 1 February 2023).
55. Liu, Y.; Yang, T.; Zhao, R.-H.; Li, Y.-B.; Zhao, W.-J.; Ma, X.-Y. Irrigation Canal System Delivery Scheduling Based on a Particle Swarm Optimization Algorithm. *Water* **2018**, *10*, 1281. https://doi.org/10.3390/w10091281.
56. Omidzade, F.; Ghodousi, H.; Shahverdi, K. Comparing Fuzzy SARSA Learning and Ant Colony Optimization Algorithms in Water Delivery Scheduling under *Water Short. Cond.* **2020**, *146*. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001496. Available online: https://ascelibrary.org/doi/10.1061/%28ASCE%29IR.1943-4774.0001496 (accessed on 1 February 2023).
57. Li, S.; Liu, Y.; Yu, H. Parameter Estimation Approach in Groundwater Hydrology Using Hybrid Ant Colony System. In *Computational Intelligence and Bioinformatics*; Springer: Berlin/Heidelberg, Germany, 2006; pp. 182–191. https://doi.org/10.1007/11816102_20.
58. Irani, R.; Nasimi, R. An evolving neural network using an ant colony algorithm for a permeability estimation of the reservoir. *Pet. Sci. Technol.* **2011**, *30*, 375–384. https://doi.org/10.1080/10916466.2010.483442.
59. Hou, J.W.; Mi, W.B.; Li, L.T. Spatial quality evaluation for drinking water based on GIS and ant colony clustering algorithm. J. *Cent. South Univ.* **2014**, *21*, 1051–1057. https://doi.org/10.1007/s11771-014-2036-y.
60. Dobre, G.; Drobot, R. Estimating soil hydraulic parameters using a metaheuristic algorithm. *Model. Civil Eng.* **2011**, 102–111.
61. Ghorbani, M.K.; Afshar, A.; Hamidifar, H. River water quality management using a fuzzy optimization model and the NSFWQI Index. *Water SA* **2021**, *47*, 45–53. https://doi.org/10.17159/wsa/2021.v47.i1.9444.
62. Guo, Q.; Wang, H.; Bai, J.; Liu, B.; Wu, H.; Wu, Z.; He, Z. A Priori Constrained ACO Method Applied to Three-Dimensional Imaging of Subsurface Electrical Resistivity. *Geotech. Geol. Eng.* **2023**, *41*, 15–25. https://doi.org/10.1007/s10706-022-02258-8.
63. Jamei, M.; Karbasi, M.; Malik, A.; Abualigah, L.; Islam, A.R.M.T.; Yaseen, Z.M. Computational assessment of groundwater salinity distribution within coastal multi-aquifers of Bangladesh. *Sci. Rep.* **2022**, *12*, 11165. https://doi.org/10.1038/s41598-022-15104-x.
64. Ahmed, A.A.M.; Deo, R.C.; Ghahramani, A.; Feng, Q.; Raj, N.; Yin, Z.; Yang, L. New double decomposition deep learning methods for river water level forecasting. *Sci. Total Environ.* **2022**, *831*, 154722. https://doi.org/10.1016/j.scitotenv.2022.154722.
65. Ghorbani, M.K.; Afshar, A.; Hamidifar, H.; Reddy, M.J. Proceedings of the Institution of Civil Engineers. *Water Manag.* **2022**, *175*, 190–205.
66. Eslamitabar, V.; Ahmadi, F.; Sharafati, A.; Rezaverdinejad, V. Bivariate simulation of river flow using hybrid intelligent models in sub-basins of Lake Urmia, Iran. *Acta Geophys.* **2023**, *71*, 873–892. https://doi.org/10.1007/s11600-022-00933-1.
67. Li, Y.; Chan Hilton, A.B. Reducing Spatial Sampling in Long-Term Groundwater Monitoring Networks Using Ant Colony Optimization. *Int. J. Comput. Intell. Res.* **2010**, *1*, 19–28. https://doi.org/10.5019/ijcir.2005.1.2.
68. Ali, M.; Pant, M.; Abraham, A. A Hybrid Ant Colony Differential Evolution and its application to water resources problems. In Proceeding of the 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC), Coimbatore, India, 9–11 December 2009; pp. 1133–1138. https://doi.org/10.1109/NABIC.2009.5393816.
69. Ataie-Ashtiani, B.; Ketabchi, H. Elitist Continuous Ant Colony Optimization Algorithm for Optimal Management of Coastal Aquifers. *Water Resour. Manag.* **2010**, *25*, 165–190. https://doi.org/10.1007/s11269-010-9693-x.
70. Skardi, M.J.E.; Afshar, A.; Solis, S.S. Simulation-optimization model for non-point source pollution management in watersheds: Application of cooperative game theory. *KSCE J. Civ. Eng.* **2013**, *17*, 1232–1240. https://doi.org/10.1007/s12205-013-0077-7.
71. Verdaguer, M.; Clara, N.; Gutiérrez, O.; Poch, M. Application of Ant-Colony-Optimization algorithm for improved management of first flush effects in urban wastewater systems. *Sci. Total Environ.* **2014**, *485–486*, 143-152. https://doi.org/10.1016/j.scitotenv.2014.02.140.
72. Nguyen, D.C.H.; Dandy, G.C.; Maier, H.R.; Ascough, J.C., II. Improved Ant Colony Optimization for Optimal Crop and Irrigation Water Allocation by Incorporating Domain Knowledge. *J. Water Resour. Plan. Manag.* **2016**, *142*. Available online: https://ascelibrary.org/doi/10.1061/%28ASCE%29WR.1943-5452.0000662 (accessed on 1 February 2023).