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A Study on Energy Efficient Routing in Smart Water Distribution Network Using the ACO Algorithm

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Abstract

This study explores energy-efficient routing methods in smart water distribution networks using the Ant Colony Optimization (ACO) algorithm. With the growing need for optimal water resource management in smart cities, the use of metaheuristic algorithms for improving energy efficiency has gained significance. In this research, an ACO-based routing model is proposed to minimize energy consumption in water distribution systems. Through various simulations, the performance of this approach is evaluated in comparison to traditional methods. The results indicate that the proposed approach reduces energy consumption, enhances network reliability, and optimizes water distribution routes.

Keywords: Water distribution network, Smart city, Ant colony optimization, Energy efficiency, Water resource management.

1 | Introduction

The Water Distribution Network (WDN) is one of the main smart utilities considered in every smart city. Water conservation on any given day can be achieved using Internet of Things (IoT) technology to make the conventional citywide WDN smart. This will simplify recognizing trends in water consumption, quality, and leaks in real-time. The most important considerations in designing and operating a WDN are: 1) recognizing the city's dynamic demand requirements while taking into account its ongoing expansion [1], 2) providing customers with sufficient quantity of water to suit their consumption requirements [2], and 3) identifying anomalous water network situations, such as leaks, pipe breaks, valve, meter, etc., and prioritizing their scheduling, and, keeping an eye on the water quality that is supplied to customers and supporting treatment cycles in the case of contaminated water [3]. The development of smart water is urgently needed. Networks that adapt to demands keep an eye on crucial variables like altitude, pressure, flow rate, and water quality measurements, and they identify line leaks [4]. Additionally, this needs the information to flow from every

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part of the water system to a central observation point where it can be used to evaluate the information and send out warnings to interested authorities for prompt action.

An IoT-driven architecture was created, experiments were conducted, and a water test bed was established with an emphasis on creating smart water meters and billing systems for residential customers, remotely operated automatic distribution valves, and systems for water quality monitoring carried out by using analytics on the network data that was gathered [5]. The use of metaheuristic algorithms expands significantly as the temporal and spatial complexity of environmental issues and water resources management rises. Since ACO was first introduced [6], different versions and refinements of the original ant algorithm have been proposed and applied to solve various water resource problems and environmental management problems. Ants' collective behavior in their quest for food is the basis for the discrete combinatorial optimization method known as ACO. An indirect method of communication involving deposition is thought to allow an ant colony to determine the quickest path from its nest to a food supply of a chemical compound known as a pheromone on the pathways during their journey [7]. With time, shorter and more pheromones are used to promote more preferred pathways, making them the colony's dominant route. Ant Colony Optimization (ACO) was initially developed for discrete optimization problems. Its application in the continuous domain started with the discretization of the search space. Although some advances in the discretization methodology, such as the Discrete-Refining (DR) approach, have been reported to improve the performance of the original ACOs in continuous domains, their comparative performances remain to be improved [8]. A new version of the ACO-based algorithm has been developed to overcome this issue. The main benefit of ACO algorithms in reservoir operation, as with any search-based algorithms, is their ability to be readily connected to any comprehensive and detailed system simulation model. To determine rule curve parameters and/or the best times for record releases, various ACO versions have been used [9]. Although the costly processing requirements of ACO algorithms may restrict their applicability for implicit and/or explicit stochastic optimization applied to numerous reservoir systems unless operational strategies can be adjusted, these methods are quite robust in solving highly nonlinear, non-convex problems [10]. Despite its popularity, mathematical analysis of the algorithm lags. Its popularity is partly attributed to its potential to solve nonlinear, non-convex, and multi-modal in discrete and continuous domains for which deterministic search techniques incur difficulty or fail [11].

2 | Literature Review

A smart city can be defined as a municipality in which an investment in human and social capital is performed by encouraging the use of Information and Communication Technology (ICT) as an enabler of sustainable economic growth, improving the quality of life for its citizens and the efficiency of its operations, and consequently, allowing better management of energy and natural resources [12]. This innovative approach not only leverages technology but also prioritizes the well-being of its residents. Thus, the idea of a smart city extends beyond just technological advancements; it also focuses on fostering socio-economic development [13], allowing a city to assess its current status and identify areas needing improvement to fulfill the criteria for becoming a smart city [14]. Water management has emerged as a paramount concern among the critical areas for development. With pressing demands for the sustainable use of scarce water resources and water distribution systems, water management for smart cities emphasizing financial and environmental sustainability is becoming more valued across the water sector [15].

Smart water management systems can improve many existing urban networks characterized by degraded infrastructure, irregular supply, and low customer satisfaction or substantial deviations of the proportional bills from real consumption [16]. Implementing such systems, which are carried out through data collection, analysis, and control technologies, helps public service companies build a complete database for identifying the areas where water losses or illegal connections occur. This, in turn, contributes to leakage detection and correction, water quality assurance, improved consumer experience, and operational optimization, amongst other key benefits [17]. Implementing a smart water management system usually involves deploying multiple sensor and actuator nodes throughout the water distribution system. Sensor nodes play a vital role in collecting water flow data from various parts of the distribution network, enabling water usage tracking and system fault identification [18]. Data collection is performed manually, supplemented by IoT technologies for data communication and data analytics for processing. The process includes monitoring water levels in the tanks and sending the readings to a server via Arduino or Raspberry Pi, with results visualized through a web interface like Ubidots [19]. The integration of ICT has thus addressed the challenges urban water networks face by facilitating continuous water distribution system monitoring [20].

It has been estimated that approximately 80% of the total cost of a water supply project is invested in its water distribution system [13]. Therefore, designing a cost-effective and reliable WDN is essential. The optimization of a WDN involves the design of a reliable, efficient, and cost-effective distribution network that meets the necessary water demand while maintaining adequate pressure heads. This optimization is crucial for conserving water resources and reducing energy requirements and maintenance costs. WDN optimization can be categorized into several types: design, operation, calibration, level-of-service, monitoring system, and network testing [14]. Recognizing the importance of operational costs, many researchers have focused on pump scheduling to reduce energy costs by taking advantage of off-peak electricity and reservoir storage in water distribution systems. In parallel with applying Genetic Algorithms (GAs) and other search-based algorithms, some researchers have also focused on using various concepts based on Swarm Intelligence (SI) to optimize pumping stations in WDNs [15].

SI is a field inspired by the social behaviors of insects and animals, such as ants, bees, and fireflies, to develop algorithms for solving complex optimization problems. One such algorithm, ACO has achieved good effect in addressing problems such as the Traveling Salesman Problem (TSP), Quadratic Assignment Problem (QAP), Job-Shop Scheduling Problem (JSSP), and many more. The algorithm was primarily intended to solve combinatorial optimization problems, among which NP-hard problems (such as those mentioned previously) were the most challenging. Since no polynomial-time algorithms are known for such problems, heuristic techniques such as ACO are often used for generating high-quality solutions in reasonable computation times [21]. An improvement to current network-routing analysis methods is suggested by implementing intelligent path-traversing algorithms, particularly artificial agent technologies, one of which is the ACO algorithm. This metaheuristic mimics the collective behavior of real-life ant colonies. This algorithm is characterized by a collective knowledge-processing system that relies on information acquired by individual ants as they explore potential paths during the 'trail laying' phase; the colony then memorizes the processed information in the 'trail following' phase, searching for path solutions to a destination. Over time, this process converges on an optimal solution to the path traversal problem, akin to techniques used in pipe routing and network optimization [22].

As the spatial and temporal complexity of resource management and environmental issues increases, the use of metaheuristic algorithms has expanded dramatically. Among its various applications, the ACO algorithm has garnered considerable attention in water resources and environmental planning and management over the last decade. Since its introduction, different versions and refinements to the original algorithm have been proposed and applied to address various challenges in these fields [23]. The algorithm was first used for hydroelectric generation scheduling by Huang [24] and later optimized for reservoir operation by Jalali et al. [25], incorporating enhancements such as pheromone promotion and explorer ants. Kumar and Reddy [26] also utilized ACO to derive operating policies in a multi-purpose reservoir system [23]. In the earliest application of ACO in WDN optimization, the algorithm was employed for the optimal design of a small network comprising fourteen pipes, two reservoirs, and three loops, focusing on demonstrating the application of ACO in WDN design and investigating the sensitivity of the method to changes in tunable parameters [27].

3 | Proposed Work

Optimizing water distribution in smart cities is crucial for efficient resource management and energy conservation. The fact that traditional routing methods often overlook energy consumption, leading to unnecessary costs and environmental impacts, has led to the development of smart WDNs. This study aims to enhance energy efficiency in these networks by employing the ACO algorithm. The proposed method will focus on finding optimal routing paths for water distribution that minimize energy usage while maintaining service quality [28]. To develop a routing algorithm tailored to the specific characteristics of smart WDNs based on the ACO approach. To evaluate the energy efficiency of the proposed routing strategy compared to traditional methods. To assess the performance of the ACO algorithm under different network configurations and demand scenarios. To investigate the scalability of the ACO algorithm for large-scale WDNs.

3.1 | Proposed Methodology

3.1.1 | Study area selection and data collection

Location: selection of a representative urban area (smart city) with a smart water distribution system in place.

Data requirements:

I. Network topology (pipe lengths L, diameters D, and material).

II. Demand patterns (residential, commercial, industrial, etc.).

III. Energy consumption data for pumps, treatment plants, and other equipment.

IV. Sensor data from the smart water distribution system.

Modeling: create a detailed hydraulic model of the selected WDN based on the collected data using software such as EPANET or Water GEMS. This model will simulate the flow dynamics and energy consumption involved in the network.

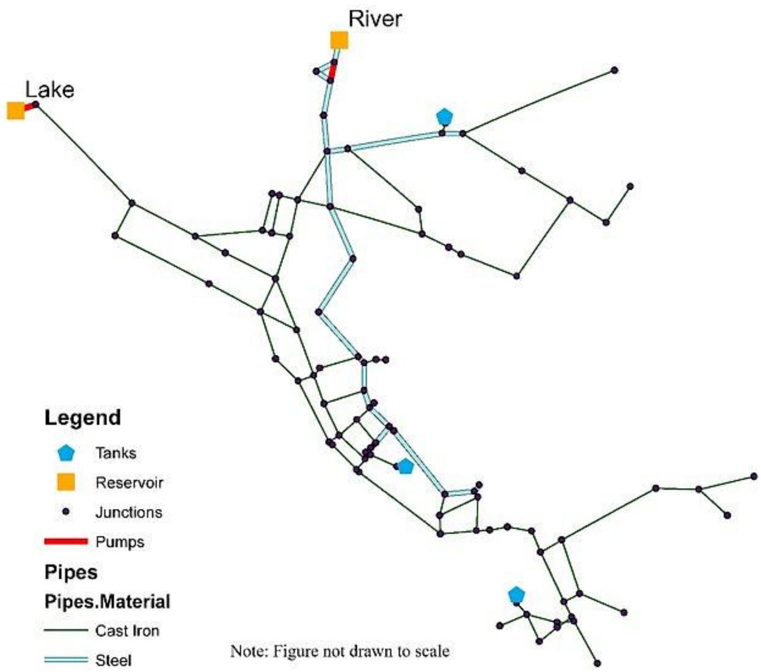

Fig. 1. A sample WDN designed using EPANET.

3.2 | Problem Formulation

The smart WDN is modeled as a graph G = (V, E), where V denotes the set of nodes representing water sources, treatment plants, storage tanks, pumps, and consumer locations, and E denotes the set of edges representing the pipes connecting these nodes [29]. The objective will be to find the optimal route for water to flow from the sources to the consumers while minimizing energy consumption. Let cij be the cost of transporting water from node i to node j, and dij be the distance between nodes i and j. The following objective function can represent the energy consumption of the network:

$$\min \sum_{i\epsilon V} \sum_{j\epsilon V} CijXij. \tag{1}$$

Xij is a binary variable indicating whether water flows from node i to node j.

3.3 | ACO-Based Algorithm Design

The ACO algorithm simulates the behavior of ants searching for food, with pheromone trails representing the energy consumption involved in each possible route. The algorithm will iteratively update these pheromone trails based on the quality of the solutions found [30].

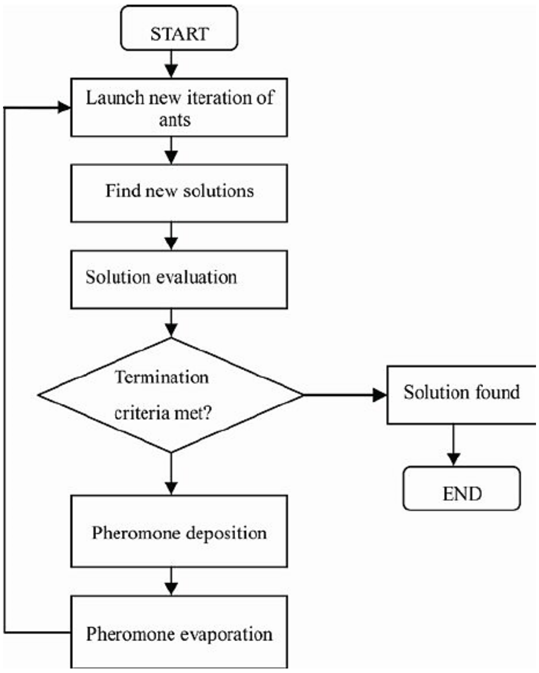

Fig. 2. Flowchart depicting the structure of the ACO algorithm.

Step 1. Initialization.

The following table summarizes the key parameters that can be adjusted for the ACO algorithm used in the study.

Table 1. Summary of parameter settings for the ACO algorithm.

Parameter	Description
Number of ants, N	Total number of ants used in the simulation of the network (i.e., the number of agents exploring the solution space)
Pheromone evaporation rate, ϱ	The rate at which pheromone evaporates/ decays
Influence of pheromone, α	Weighting factor for pheromone in decision-making
Influence of heuristic factors, β	The weighting factor for heuristic information
Maximum iterations, T	Maximum number of iterations for the ACO algorithm
Initial pheromone level, τ_0	Initial pheromone level on all paths helps in starting the search process
Heuristic information, η	Information related to path quality (inverse of path length)
Local search enablement	Indicates if local search is applied for optimization
Convergence criteria	Criteria for stopping the algorithm

The values of the influence factors α and β can be tuned depending on specific application needs to emphasize either pheromone trails or heuristic information.

Moreover, τij is initialized on all paths as the pheromone trail from node i to node j.

Step 2. Heuristic information.

Heuristic information related to pipe lengths and energy consumption is incorporated as follows:

$$\eta_{ij} = \frac{1}{L_{ij}},$$

where Lij is the length of the pipe between nodes i and j.

Step 3. Ant movement.

Each constructs a routing path based on the following probability equation:

$$P_{IJ} = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{k\epsilon J} \tau_{ik}^{\alpha} \cdot \eta_{ik}^{\beta}},$$

where J denotes the set of candidate nodes for the next move.

Step 4. Pheromone update.

After all ants complete their paths, pheromone levels are updated. The following formula can represent the update rule for the pheromone trails:

$$\tau ij \leftarrow (1 - \rho)\tau ij + \Delta\tau ij,$$

where Δτij is the pheromone increment at node i and node j, calculated based on the quality of the solution (energy consumption).

Step 5. Iteration.

The process is repeated for a predefined number of iterations T or until convergence criteria are met (e.g., minimal change in solution quality).

3.4 | Simulation and Analysis

I. Scenario testing: Various network configurations and demand scenarios are simulated to evaluate the robustness of the ACO algorithm. These simulations will determine the energy consumption of the optimized routes and compare them with the baseline routes [24].

II. Metrics for comparison

- *Total energy consumption, E (summation of the energy consumed by each pump).*
- *Service reliability is expressed by pressure and flow rate consistency.*
- *Computational efficiency is expressed by the time T takes to reach an optimal solution.*

3.5 | Validation

ACO-based routing solutions are compared with traditional optimization methods (e.g., Dijkstra's algorithm) using real-world data to demonstrate their effectiveness.

4 | Expected Outcomes

I. Energy savings: The proposed algorithm is expected to reduce energy consumption in the smart WDN by optimizing the routing of water [25].

II. Improvement in network performance: The optimal routing paths will improve the network's overall performance by reducing congestion and increasing the reliability of water supply [26].

III. Comparison with other methods: The proposed algorithm will be compared with other optimization techniques to demonstrate its effectiveness [31].

5 | Conclusion

This study aims to provide an approach to improving energy efficiency in intelligent WDNs using the ACO algorithm [32]. The findings will contribute to sustainable urban water management practices and offer a framework for future research.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

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