

A Scoping Review of the Literature on Swarm Intelligence Applications in Water Scheduling

Cheslin van Wyk * , Taryn Michael and Colin Chibaya 

Faculty of Natural and Applied Sciences, Sol Plaatje University, Kimberley 8300, South Africa; taryn.michaels@spu.ac.za (T.M.); colin.chibaya@spu.ac.za (C.C.)

* Correspondence: 201701545@spu.ac.za

Abstract

Water scheduling is a complex optimization problem that requires efficient and adaptive solution approaches. Metaheuristic techniques, particularly swarm intelligence models, have increasingly been applied to address these challenges. This study presents a scoping review that maps and synthesizes the existing literature on the application of swarm intelligence in water scheduling. Guided by the PRISMA-ScR framework and the JBI Population–Concept–Context (PCC) model, relevant studies published between 2015 and 2025 were identified across multiple databases. From an initial pool of 1357 studies, only 23 met the inclusion criteria and were subjected to detailed analysis. The findings reveal a strong concentration of research on water distribution networks, coupled with limited methodological diversity across the reviewed studies. There is an absence of explicit focus on resource-constrained or arid environments contexts where water-scheduling challenges are often most acute. Geographically, the literature is heavily skewed toward Asia, with the majority of studies conducted in China ($n = 7$) and Iran ($n = 6$). In contrast, only one study originated from Africa and one from Australia despite the disproportionate severity of water scarcity challenges across the African continent. The review exposes a critical gap in the literature and underscores the need for more context-aware, hybrid swarm intelligence models that explicitly account for the socio-economic and environmental constraints of water-stressed regions.

Keywords: water scheduling; swarm intelligence; metaheuristic optimization; water distribution networks; resource-constrained environments; hybrid optimization models

1. Introduction

Metaheuristics are high-level optimization techniques that search for near-optimal solutions in complex, often non-convex solution spaces [1,2]. Unlike exact optimization methods, which frequently become computationally intractable as problem size and complexity increase, metaheuristic algorithms trade guaranteed optimality for scalability, flexibility, and robustness. These characteristics have driven their widespread adoption across diverse application domains, including computer vision [3,4], power and energy management [5], machine learning [6], and robotics [7]. In resource allocation and scheduling contexts, where efficiency, adaptability, and scalability are critical, metaheuristics consistently demonstrate advantages over traditional deterministic approaches [3–7].

Swarm intelligence algorithms are a subset of metaheuristics inspired by collective behavior in nature: ant colonies [8], bird flocks, bee swarms [9], fish schools, and predator–prey dynamics. By modeling decentralized decision-making, self-organization, and



Academic Editor: Paolo Bellavista

Received: 30 April 2026

Revised: 26 May 2026

Accepted: 12 June 2026

Published: 10 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

cooperative search, swarm intelligence algorithms enable effective exploration and exploitation of complex solution spaces. Well-established swarm intelligence methods include Particle Swarm Optimization [10], Ant Colony Optimization [8], Artificial Bee Colony [9], Grey Wolf Optimizer [11], Firefly Algorithm [12], and more recent approaches such as the Slime Mold Algorithm [13]. These algorithms have demonstrated strong performance in solving nonlinear, high-dimensional, and multi-modal optimization problems.

Water scheduling constitutes a highly complex and inherently multi-objective optimization problem, involving the simultaneous consideration of competing objectives such as operational cost, water availability, demand satisfaction, water quality, infrastructure constraints, and system reliability [14]. The increasing scale and complexity of modern water systems driven by population growth, urbanization, climate variability, and ageing infrastructure have exposed the limitations of conventional optimization techniques, which often struggle to handle large-scale, nonlinear, and multi-objective formulations efficiently. As a result, metaheuristic approaches, and swarm intelligence algorithms in particular, have emerged as promising alternatives for addressing the water-scheduling problem.

Looking at nonlinearity in hydraulic problems such as pressure flow dynamics, small changes in pump operations can produce disproportionate system-wide effects. Decisions are temporally coupled. Infrastructure can impose mixed discrete–continuous decisions. Demand for water is uncertain. These characteristics combine to produce solution landscapes that are well suited to metaheuristics. However, despite a growing body of research applying swarm intelligence techniques to water scheduling, the literature remains fragmented. Algorithm selection is frequently ad hoc, with limited justification for choosing specific techniques [15]. Evaluation metrics vary widely, from single-objective cost minimization to multi-objective Pareto-based analyses. Case studies differ significantly in scale and complexity. This heterogeneity limits cross-study comparability [16]. It hinders methodological consolidation, and obscures emerging research trends.

Existing studies are predominantly concentrated in well-resourced and data-rich environments, with limited attention given to resource-constrained or arid regions where water-scheduling challenges are most severe [17,18]. In this case, a well-resourced and data-rich environment refers to contexts where extensive, reliable, and continuously updated hydrological, operational, and environmental data are supported by advanced technological infrastructure and computational capacity, and institutional resources to enable efficient and intelligent water allocation and management. This imbalance highlights a critical gap in the literature and underscores the need for context-aware optimization approaches that explicitly account for socio-economic and environmental constraints.

To address these challenges, this study conducts a scoping review to systematically map and synthesize the literature on the application of swarm intelligence models in water scheduling. The review consolidates fragmented evidence, identifies dominant algorithms and application contexts, examines methodological trends, and highlights underexplored research areas. In doing so, it provides a structured understanding of the field and supports the development of more robust, adaptive, and context-sensitive optimization solutions.

1.1. Problem Statement

Water scheduling is a complex, multi-objective, and nonlinear optimization problem that involves balancing competing demands such as cost, availability, infrastructure constraints, and system reliability [14]. While metaheuristic approaches, particularly swarm intelligence algorithms, have been successfully applied to complex optimization problems across various domains, their adoption within the water-scheduling domain remains dispersed and insufficiently synthesized.

Existing studies differ widely in terms of algorithm selection, application focus, and evaluation contexts, making it difficult to identify dominant trends, methodological patterns, and research gaps. As a result, there is limited consolidated knowledge on which swarm intelligence models are most appropriate for specific water-scheduling contexts and under what conditions they perform best. This fragmentation hinders informed decision-making, methodological advancement, and the development of context-aware optimization strategies. To address this gap, this study conducts a scoping review to systematically map research trends, algorithmic approaches, application domains, and temporal developments in the use of swarm intelligence techniques for water scheduling, while explicitly identifying underexplored contexts.

1.2. Research Questions

This study is guided by five sequential research questions as follows:

1. What swarm intelligence models have been applied to the water-scheduling problem?
2. In which application contexts have these models been implemented?
3. What methodological trends characterize swarm intelligence-based water-scheduling studies?
4. How has research evolved over time and across geographical regions?
5. What gaps exist in the literature, particularly in resource-constrained and arid environments?

1.3. Aim

The aim of this study is to systematically map and synthesize the existing literature on the application of swarm intelligence models in water scheduling, to identify dominant algorithms, application contexts, methodological trends, and research gaps, with particular attention to underexplored environments.

1.4. Objectives

To achieve the aim and in line with the research questions, the study pursues five objectives as follows:

1. To identify and characterize the swarm intelligence algorithms applied to water-scheduling problems.
2. To map application contexts of the identified swarm intelligence algorithms, including water distribution networks, allocation planning, and reservoir management.
3. To examine methodological trends inferred in these swarm intelligence models, including hybridization strategies and evaluation frameworks.
4. To analyze temporal and geographical patterns of the studies identified in the literature.
5. To highlight gaps and underexplored areas of research, particularly in resource-constrained and arid environments.

1.5. Scope Definition

This review uses water scheduling as a catch-all for operational optimization problems in water systems. We split the term into four types: Scheduling problems are about timing: so, when to pump, when to release, when to deliver. The decision variables are time-indexed: pump on/off at each hour, reservoir release rates by day. Allocation problems are about volume: how much water each user or sector gets when there is not enough to go around. These show up as volumetric assignments across competing demands. Distribution problems are about routing: which pipes carry water, which valves open, how flows move through the network [19]. Resource management covers broader coordination, multi-year planning, inter-agency governance, strategic oversight that operates above

day-to-day operations. The boundaries between these problem types are not always clear. Water-scheduling problems are inherently multi-objective, involving cost, reliability, equity, and sustainability considerations. A reservoir release schedule is not only a scheduling problem, it is also an allocation and distribution problem. We used water scheduling as our search term because it is inclusive, then classified studies by their dominant focus.

1.6. Overview

The remainder of this review paper is divided into five sections. Section 2 presents the theoretical background on metaheuristics and swarm intelligence models. It contextualizes water scheduling as a critical optimization problem. Section 3 outlines the research methodology, including the strategy used in searching for relevant studies, inclusion and exclusion criteria, data extraction procedures, as well as data charting and analysis methods. Section 4 presents the results yield, focusing on swarm intelligence algorithm usage, application contexts, geographical distribution, and temporal trends. We discuss the results in Section 5, presenting the key findings, research gaps, and outlining the contributions and implications for future work. The need for hybrid and context-aware swarm intelligence models is highlighted in this section, along with the conclusions thereto.

2. Theoretical Background

Water scheduling requires balancing cost efficiency, water availability, demand satisfaction, infrastructure constraints, and water quality [14]. These objectives often conflict. Modern water systems have grown more complex due to urbanization, population growth, climate variability, and aging infrastructure. Classical optimization techniques struggle with large-scale, nonlinear, dynamic problems at this scale.

Swarm intelligence algorithms offer a way forward. Their population-based search explores solution spaces in parallel. Their stochastic nature helps them escape local optima. They adapt to changing system conditions [9,10]. These characteristics make swarm intelligence algorithms especially suitable for water-scheduling problems, where uncertainty, nonlinearity, and competing objectives are inherent. From a theoretical perspective, the application of swarm intelligence to water scheduling offers several key advantages. First, adaptive optimization enables algorithms to dynamically adjust their search behavior in response to evolving system states and constraints. Second, distributed computation supports scalability in large, networked water systems by decentralizing the search process. Third, inherent multi-objective handling capabilities allow swarm intelligence algorithms to balance competing criteria such as cost, efficiency, and reliability within a unified optimization framework.

Rather than presenting the mathematical formulation of a single swarm intelligence algorithm, this review adopts a general algorithmic view of swarm-intelligence-based optimization. As shown in Figure 1, most swarm intelligence algorithms follow a common optimization cycle: candidate solutions are initialized, evaluated using a fitness or objective function, updated through algorithm-specific collective interaction rules, checked against constraints, and iterated until a stopping criterion is reached. The differences between algorithms lie mainly in how candidate solutions interact and update their positions. As seen in Table 1, PSO uses velocity-position updates, ACO uses pheromone-based path reinforcement, ABC uses bee-foraging phases, GWO uses leadership hierarchy, and SMA uses adaptive foraging behavior inspired by slime mold.

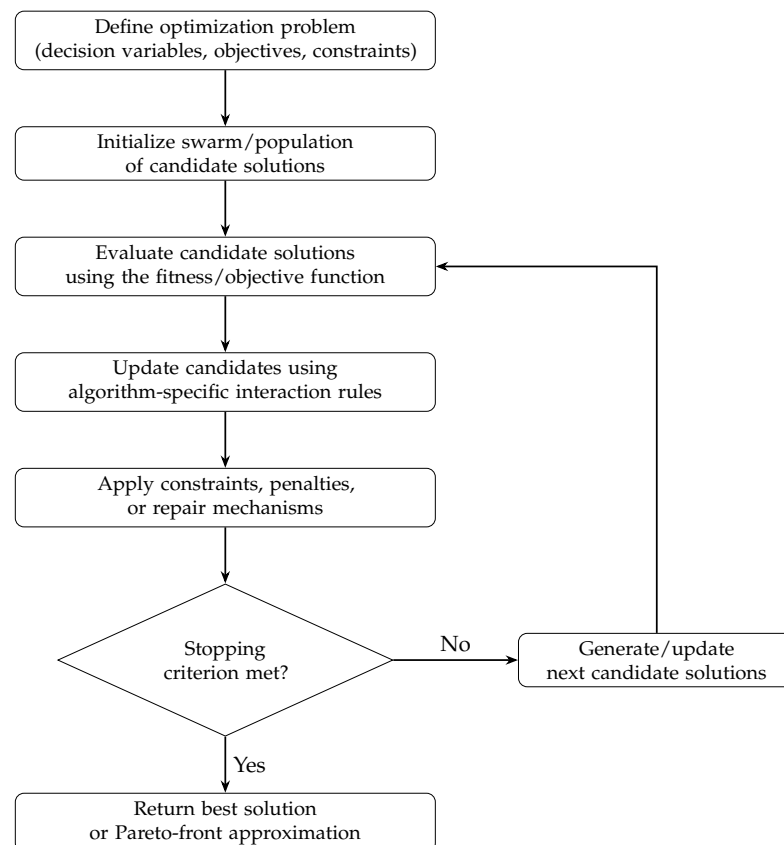


Figure 1. General workflow of swarm-intelligence-based optimization algorithms.

Table 1. General mechanisms of common swarm intelligence algorithms.

Algorithm	Natural Inspiration	Main Optimization Mechanism
PSO	Bird flocking / fish schooling	Particles update positions using personal and global best solutions.
ACO	Ant foraging	Candidate paths are reinforced through pheromone-like feedback.
ABC	Bee foraging	Employed, onlooker and scout bees explore and exploit food-source candidates.
GWO	Grey wolf hunting	Candidate solutions follow alpha, beta, and delta leadership positions.
FA	Firefly flashing behavior	Candidate solutions move toward brighter or more attractive solutions.
SMA	Slime mold foraging	Search behavior adapts through oscillation, exploration, and exploitation around food sources.

3. Materials and Methods

A scoping review methodology is adopted to systematically map and synthesize the literature on the application of swarm intelligence techniques in water scheduling. Scoping reviews are particularly well suited to emerging and heterogeneous research domains, where studies differ in methods, objectives, and application contexts [20]. The review followed the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) framework [21] and was guided by the Population–Concept–Context (PCC) model proposed by the Joanna Briggs Institute (JBI) [20,22].

This methodology was explicitly aligned with the research questions outlined in Section 1.2, which informed the search strategy, eligibility criteria, study selection process, data extraction, data charting, and data analysis procedures.

3.1. Eligibility Criteria

Study selection was guided by the Population–Concept–Context (PCC) framework. In this framework, the population refers to water-scheduling systems, including water distribution networks, reservoir operations, allocation planning, and related infrastructure. On the other hand, the concept remained application of swarm intelligence algorithms, including PSO, ACO, ABC, GWO, FA, SMA, and hybrid swarm intelligence approaches. EC algorithms are included only when they appear alongside SI algorithms as baseline or comparator. On the contrary, the contexts are all geographical regions and environmental settings, with particular attention to resource-constrained and arid environments.

To ensure relevance and quality, peer-reviewed journal articles and conference paper publications between 2015 and 2025 were considered. Studies applying swarm intelligence techniques to the water-scheduling problem were key. The selected time frame reflects a period in which classical swarm intelligence models reached maturity while hybrid approaches became increasingly prevalent.

Studies were excluded if they did not employ swarm intelligence techniques or addressed problems in unrelated domains such as non-water-scheduling problems. Purely conceptual studies without practical application were also excluded, along with studies not written in English. Some studies were also excluded for constituting grey literature, such as theses, reports, and non-peer-reviewed sources. This criterion ensured a focused and methodologically consistent collection of studies for further analysis.

3.2. Information Sources

A comprehensive search was conducted across seven electronic databases, namely: ScienceDirect, Scopus, IEEE Xplore, EBSCO, SpringerLink, MDPI, and Taylor & Francis. These databases were selected for their coverage of the engineering, computer science, and applied mathematics literature relevant to swarm intelligence and water systems research. The following query can be seen as the base that is executed across all selected databases, modified slightly to match each database's syntax.

```
SELECT * WHERE KEYWORD <--
(
  "swarm intelligence" OR "particle swarm optimization"
  OR "ant colony optimization" OR "grey wolf optimizer"
  OR "artificial bee colony"
)
AND
(
  "water scheduling" OR "water distribution network"
  OR "pump scheduling" OR "water supply network"
)
```

Table 2 shows the detailed search query of the seven databases. Here we have more details such as Search field, Queries and Filters used.

Searches were limited to search by titles, abstracts, and keywords to ensure relevance. Additional studies were identified through reference chaining. Searches were conducted between the 18 January 2026 and the 30 March 2026. Differences in indexing fields, metadata coverage, and search filters may have influenced retrieval counts. We also acknowledge the omission of databases and languages will have an impact on the results of the article count. This includes omitting well-known databases such as the Web of Science (access constraints at the time of data collection). This presents an opportunity to expand databases and the inclusion of non-English papers for future works.

Table 2. Database-specific search strategy.

Database	Search Field	Query Used	Filters
Scopus	Title, abstract, keywords	TITLE-ABS-KEY(("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization" OR "artificial bee colony" OR "grey wolf optimizer" OR "firefly algorithm" OR "slime mould algorithm" OR "slime mold algorithm") AND ("water scheduling" OR "water distribution network" OR "water distribution networks" OR "pump scheduling" OR "reservoir operation" OR "water allocation" OR "water supply network"))	2015–2025; English; journal articles and conference papers
IEEE Xplore	Metadata	((("All Metadata":"swarm intelligence") OR ("All Metadata":"particle swarm optimization") OR ("All Metadata":"ant colony optimization") OR ("All Metadata":"artificial bee colony") OR ("All Metadata":"grey wolf optimizer") OR ("All Metadata":"firefly algorithm") OR ("All Metadata":"slime mould algorithm") OR ("All Metadata":"slime mold algorithm")) AND (("All Metadata":"water scheduling") OR ("All Metadata":"water distribution network") OR ("All Metadata":"pump scheduling") OR ("All Metadata":"reservoir operation") OR ("All Metadata":"water allocation") OR ("All Metadata":"water supply network"))	2015–2025; English; journal articles and conference papers
ScienceDirect	Title, abstract, keywords	("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization" OR "artificial bee colony" OR "grey wolf optimizer" OR "firefly algorithm" OR "slime mould algorithm" OR "slime mold algorithm") AND ("water scheduling" OR "water distribution network" OR "water distribution networks" OR "pump scheduling" OR "reservoir operation" OR "water allocation" OR "water supply network") (TI("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization" OR "artificial bee colony" OR "grey wolf optimizer" OR "firefly algorithm" OR "slime mould algorithm" OR "slime mold algorithm") OR AB("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization" OR "artificial bee colony" OR "grey wolf optimizer" OR "firefly algorithm" OR "slime mould algorithm" OR "slime mold algorithm") OR SU("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization")) AND (TI("water scheduling" OR "water distribution network" OR "pump scheduling" OR "reservoir operation" OR "water allocation") OR AB("water scheduling" OR "water distribution network" OR "pump scheduling" OR "reservoir operation" OR "water allocation") OR SU("water scheduling" OR "water distribution network" OR "water allocation"))	2015–2025; research articles and conference papers
EBSCO	Title, abstract, subject terms	("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization" OR "artificial bee colony" OR "grey wolf optimizer" OR "firefly algorithm" OR "slime mould algorithm" OR "slime mold algorithm") OR SU("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization")) AND (TI("water scheduling" OR "water distribution network" OR "pump scheduling" OR "reservoir operation" OR "water allocation") OR AB("water scheduling" OR "water distribution network" OR "pump scheduling" OR "reservoir operation" OR "water allocation") OR SU("water scheduling" OR "water distribution network" OR "water allocation"))	2015–2025; English; peer-reviewed
Taylor & Francis	Title, abstract, keywords	("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization" OR "artificial bee colony" OR "grey wolf optimizer" OR "firefly algorithm" OR "slime mould algorithm" OR "slime mold algorithm") AND ("water scheduling" OR "water distribution network" OR "water distribution networks" OR "pump scheduling" OR "reservoir operation" OR "water allocation" OR "water supply network")	2015–2025; English; articles
SpringerLink	Article search	("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization" OR "artificial bee colony" OR "grey wolf optimizer" OR "firefly algorithm" OR "slime mould algorithm" OR "slime mold algorithm") AND ("water scheduling" OR "water distribution network" OR "water distribution networks" OR "pump scheduling" OR "reservoir operation" OR "water allocation" OR "water supply network")	2015–2025; English; articles; conference paper; open access
MDPI	Article search	("swarm intelligence" OR "particle swarm optimization" OR "ant colony optimization" OR "artificial bee colony" OR "grey wolf optimizer" OR "firefly algorithm" OR "slime mould algorithm" OR "slime mold algorithm") AND ("water scheduling" OR "water distribution network" OR "water distribution networks" OR "pump scheduling" OR "reservoir operation" OR "water allocation" OR "water supply network")	2015–2025; English; articles

3.3. Study Selection

The study selection process comprised three stages. During the study identification stage, a total of 1357 records were retrieved across the seven databases. Immediately, 130 duplicate studies were reviewed and removed, leaving 1227 unique records. The next stage involved screening studies by titles and abstracts against the inclusion and exclusion criteria. In this case, studies were dropped if they did not apply swarm intelligence approaches, addressing water-related scheduling or allocation problems. Articles that were not peer-reviewed were also excluded. A total of 1093 studies did not meet the inclusion criteria. This left 134 studies before full-text assessment. This high study exclusion rate reflects the specificity of the intersection between swarm intelligence and water scheduling, as many studies applied swarm intelligence to unrelated domains such as energy, logistics, and robotics [23,24]. In the final screening stage, full-text analysis was administered. This resulted in the exclusion of 112 more studies, to remain with 22 relevant studies. One additional study was identified through citation chaining, yielding a final sample of 23 studies for further analysis.

3.4. Data Extraction

A standardized data extraction form was developed to ensure consistency and completeness. The following information was extracted from the 23 studies; bibliographic details (authors, year, country of origin), the swarm intelligence algorithms used (PSO, ACO, ABC, GWO, FA, SMA, or hybrid models), application domain (distribution networks, reservoir scheduling), problem characteristics (objectives, constraints, scale), and methodological details (hybridization strategies, parameter settings). Finally, the key findings and limitations of each study were documented. This structured approach facilitated systematic comparison and synthesis across studies.

3.5. Data Synthesis

Data were analyzed using a descriptive-analytical approach to identify patterns in algorithm usage, application domains, temporal trends, and geographical distribution. The synthesis emphasized identification of research gaps, particularly around water scheduling in underrepresented contexts such as resource-constrained and arid environments. Findings were presented using tables, figures, and graphs to clearly map trends and literature distributions across patterns.

3.6. Data Charting

A structured data charting template was used to organize extracted information in alignment with PRISMA-ScR guidelines. The key variables included publication year, geographic region, study objectives, application domain, swarm intelligence algorithms used, and contextual characteristics such as urban, rural, arid, and resource-constrained settings. Visualizations were mainly generated using Python-based tools, including Matplotlib, Seaborn, Plotnine, and VOSviewer, to illustrate trends in algorithm prevalence, application domains, and geographic distribution.

3.7. Data Analysis

Descriptive statistical analysis was employed to quantify patterns. Temporal evolution and geographic distribution were analyzed to identify dominant research clusters. In addition, thematic analysis was conducted on study objectives, methodologies, and findings to identify recurring patterns, methodological strengths, and underexplored areas. This combined analytical approach provided both quantitative and qualitative insights into the state of the field.

3.8. Technical Profiling

In addition to the descriptive data charting, we mapped how the included studies reported computational and optimization characteristics. This assessment was not used as a formal methodological quality appraisal; rather, it was used to support the scoping purpose of identifying how SI and related metaheuristic methods are formulated, implemented, evaluated, and reported within the water-scheduling literature. For each included study, the following were extracted when available: algorithm type, algorithm family, problem type, constraints considered, objective function, convergence reporting, and reproducibility indicators. Therefore, findings are interpreted to surface reporting patterns and methodological gaps rather than to rank algorithms. Where studies report head-to-head comparisons, we report their results without endorsing the comparison methodology.

4. Results

4.1. The PRISMA Flowchart

The study selection process, illustrated in Figure 2, followed the PRISMA-ScR framework. Database searches yielded 1357 records across ScienceDirect (n = 511), Scopus (n = 384), IEEE Xplore (n = 19), EBSCO (n = 91), Taylor & Francis (n = 115), SpringerLink (n = 115), and MDPI (122). After removing 130 duplicates, 1227 records remained. Title, abstract, and keyword screening resulted in the removal of 1093 records. The remaining 134 records were assessed in full-text screening and a further 112 were removed. Reasons included: paywall articles, non-English articles, articles not containing swarm intelligence as the main algorithm or baseline algorithm, and finally, articles that had mismatched domains. A single article was added through citation chaining, resulting in a final record count of 23.

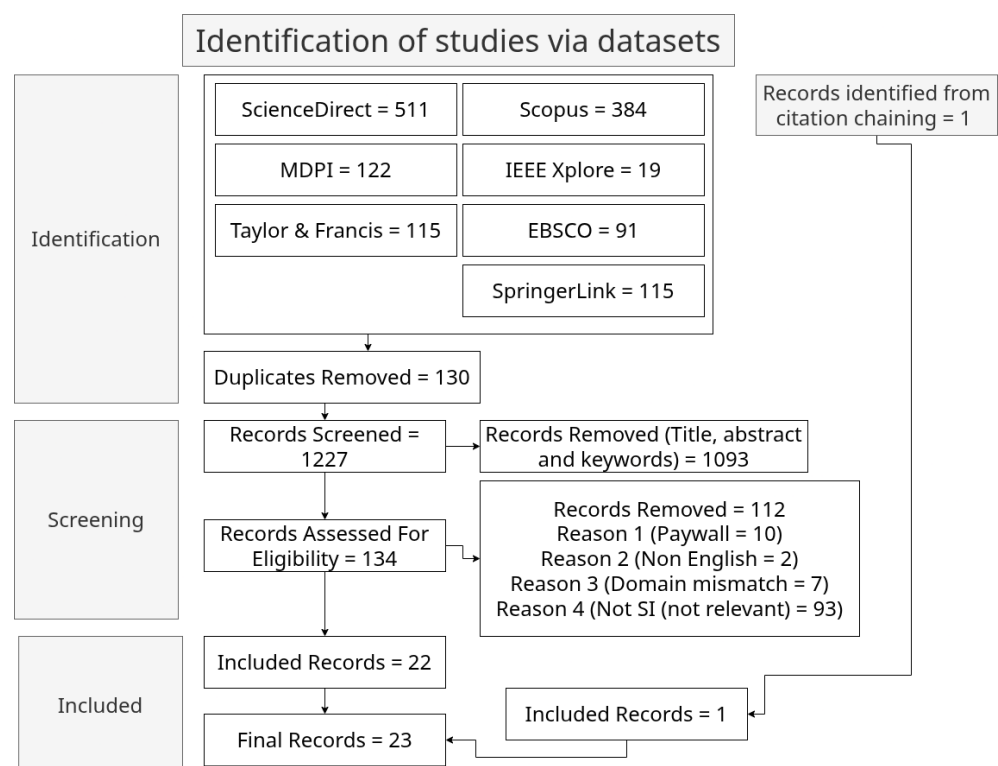


Figure 2. Prisma flowchart.

4.2. Distribution by Place of Publication

Figure 3 shows the distribution of the 23 included studies by country of origin. China contributed 7 studies, Iran 6. By continent: Asia 14, Europe 4, Americas 3, Africa 1, Australia

1. The sample is small ($n = 23$) and not statistically representative, but the geographic imbalance is clear. Africa and Australia are severely underrepresented despite facing acute water scarcity [17,18]. This disparity underscores a critical gap in the literature and highlights the need for increased research attention in resource-constrained and water-stressed regions [17,18].

While the trend is observed, it is important to acknowledge limitations in the search strategy. Restricting the review to English-language publications and use of a limited set of databases may have excluded relevant studies published in other languages. Expanding both linguistic and database coverage in future reviews may yield a more globally representative dataset.

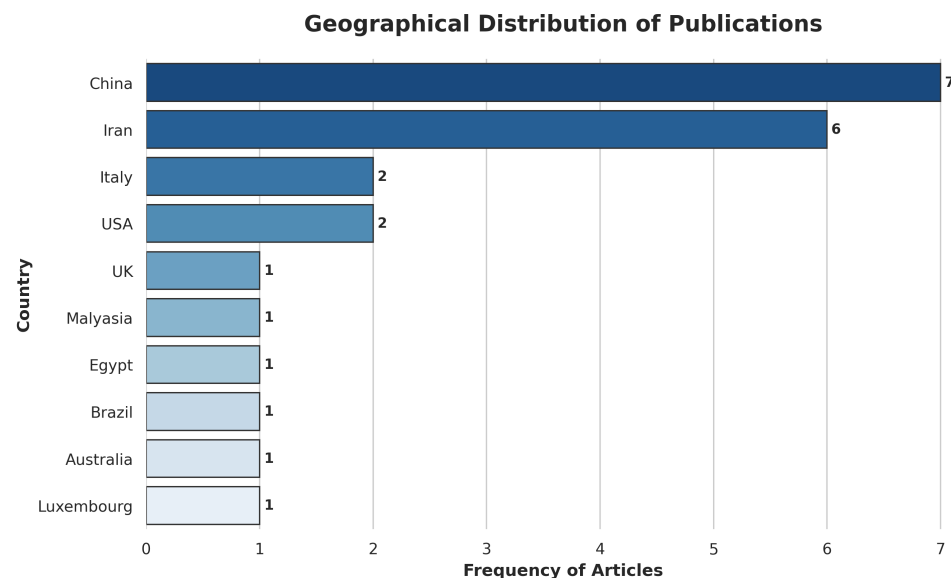


Figure 3. Frequency of articles by country.

4.3. Distribution by Year of Publication

Figure 4 illustrates the publication frequency between 2015 and 2025. A slight increase was observed in 2019 with four publications. The results of the PRISMA-ScR represent too small a dataset ($n = 23$); it is not possible to identify a growth trend or statistically significant pattern in publication frequency.

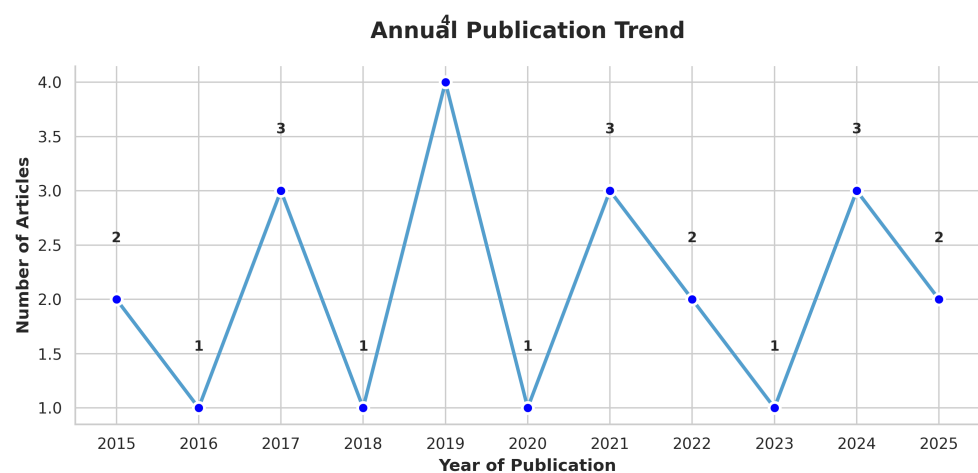


Figure 4. Frequency of articles by year.

4.4. Distribution by Processing Technique

The dominance of hybrid models suggests that single-algorithm approaches may be insufficient for capturing the full complexity of water-scheduling problems. However, it also raises an important methodological question on whether these hybridizations are systematically designed or primarily driven by ad hoc experimentation and benchmark optimization (see Figure 5 and Table 3).

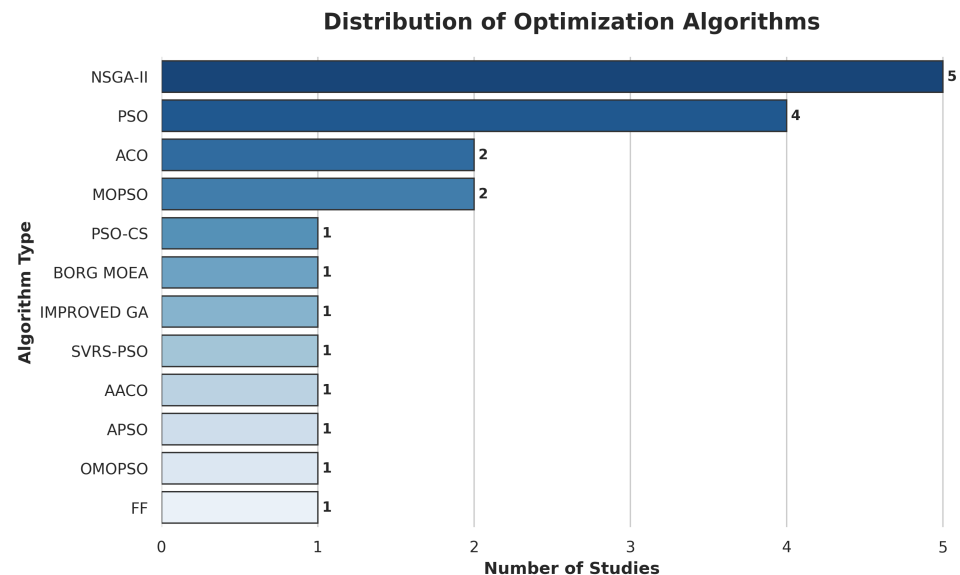


Figure 5. Number of identified techniques used.

Technical performance reporting was inconsistent. Most studies reported solution-quality metrics (cost minimization, Pareto-front coverage). Nine reported convergence curves [25–33]. NSGA-II studies typically showed Pareto-front approximations as evidence of performance. But Pareto fronts can appear early in optimization without demonstrating actual convergence. Few studies reported hypervolume stability, generational distance, or other convergence indicators. This inconsistency is itself a gap.

Table 3. Algorithm mapping.

Algorithm	Hybrid	Objective Type	Application Domains	n
NSGA-II	0/5	Multi-objective (Pareto-front)	Water distribution network, Water supply system, Multi-reservoir system, Water resource system	5
PSO	Mixed	Multi-objective (mixed)	Water distribution network, Water pump stations, Agricultural water supply, Water resource system	10
ACO	Mixed	Single-objective (flow)	Water pump stations, Water distribution network	3
Other	Mixed	Mixed	Various	1

Table 3 reveals three dominant algorithmic clusters: NSGA-II ($n = 5$), PSO, and its variants ($n = 10$) (the PSO row aggregates all PSO-based variants shown disaggregated in Figure 5), and ACO ($n = 3$), with the remaining five studies applying algorithms that appear only once. The following analysis examines each cluster in depth, profiling representative studies.

NSGA-II cluster consists of five studies. Although NSGA-II is technically an EC method rather than SI, it appears in this review because it serves as the dominant multi-objective baseline against which swarm methods are compared, and because water scheduling is inherently multi-objective in ways that classical SI algorithms struggle to handle natively.

Abdolazimi and colleagues developed a multi-objective mixed-integer nonlinear programming (MINLP) model for pipe material selection in water distribution systems, applied to a real case study of the Isfahan water network in Iran. The model balances three competing objectives: maximizing buried pipe mean time to failure (reliability), minimizing total cost (including pipe purchase, installation, maintenance, replacement, and worker cancer treatment costs), and minimizing environmental impact (soil, air, water quality damage from various pipe materials). The problem involves 48 pipe locations, 6 candidate materials, and a 10-year planning horizon. The authors solved the model using three approaches: the Weighted Sum Method (WSM) implemented in GAMS 24.1.3 with CPLEX as an exact baseline, NSGA-II programmed in MATLAB R2015b, and MOPSO also in MATLAB. Critically, both NSGA-II and MOPSO parameters were tuned using the Taguchi method. The study compared all three methods across 15 numerical examples of varying problem sizes ($I = 10$ to $I = 60$). Results revealed that NSGA-II was not the recommended method, MOPSO outperformed NSGA-II on three of four key metrics: Average cost (Z_2): MOPSO USD 47.3M vs. NSGA-II USD 48.1M (1.54% better); Average environmental impact (Z_3): MOPSO 578.94 MU vs. NSGA-II 591.90 MU (2.19% better); Average CPU time: MOPSO 171.5 s vs. NSGA-II 200.95 s (14.64% faster); and Average reliability (Z_1): MOPSO 57.71% vs. NSGA-II 54.48% (MOPSO marginally better, but with high variance, NSGA-II reached 65.66%). Applied to the real Isfahan case study using the selected MOPSO method, the final solution achieved reliability of 64.32%, cost of USD 86,404,779, environmental impact of 646.76 MU, and CPU time of 130.52 s. This is one of the few studies in our sample with both a real validated case study and a clear best-method recommendation supported by quantitative evidence. Despite this, no standard deviations or confidence intervals were reported across runs, and no convergence evidence was provided. The 130.52 s runtime on a real 48-location case study demonstrates practical scalability. The expert questionnaire process (28 pairwise comparisons) for weighting water health factors brings domain expertise into the optimization formulation in a structured way.

Makaremi and colleagues addressed pump scheduling as a multi-objective optimization problem using a self-adaptive NSGA-II algorithm coupled with the EPANET hydraulic simulator. The study formulated two competing objectives: minimizing pumping energy cost (consisting of consumption charge based on time-of-day tariffs, and demand charge based on peak power consumption) and minimizing the total number of pump switches (a surrogate for maintenance costs, reflecting mechanical wear). Each pump-scheduling program was encoded as a binary string where each bit represents on/off status per hour. Case Study I involved 3 pumps over 24 h = 72 binary decision variables. Case Study II (Bagh-malek potable water supply network in Iran) involved 6 pumps over 24 h = 144 binary decision variables. The authors used the Blend Crossover method (BLX- α) with binary tournament selection. For Case Study I: population size 100, mutation ratio 0.05. For Case Study II: population size 150, mutation ratio 0.04. Parameters were tuned through preliminary sensitivity analysis. Each scenario was run 10 independent times to verify reproducibility. The algorithm converged in approximately 50,000 evaluations for Case I and 75,000 for Case II. The paper's methodological contribution is a modified tournament selection criterion that handles constraints adaptively without penalty functions. Three constraint categories are modeled: hydraulic compatibility (mass conservation, energy conservation, Hazen–Williams head losses all handled inside EPANET), system performance (minimum pressure ≥ 15 m at all demand nodes), and infrastructure capacity (pump curve limits, tank level bounds, end-of-period tank storage recovery). All 10 runs of NSGA-II converged to the same Pareto front in both case studies, demonstrating algorithmic stability. The headline finding from Case Study II: the number of pump switches can be reduced by 69% (from 13 switches to 4) while energy cost increases by at most 10% (from USD 390.9 to USD 431.1 per month). The authors compared their results to previous single-objective

approaches on the same Case Study I benchmark: hybrid GA required 6000 evaluations per single Pareto point, ACO required similar effort, while NSGA-II found the entire Pareto front equivalent to 1389 evaluations per pump-switch alternative. Despite strong reproducibility (10 runs, same Pareto front), the study reports only final Pareto fronts. No source code is released, though EPANET use and full parameter specification enable reasonable reproduction. The authors acknowledge the study is limited to fixed-speed pumps and propose variable-speed pump scheduling as future work.

Ben Ammar et al. addressed pump scheduling as a multi-objective optimization problem using NSGA-II with a pseudo-weights decision-making approach. The study formulated three competing objectives: minimization of daily pumping energy cost (F_{pc}), minimization of total daily pump switches (F_{sw} , representing mechanical wear), and minimization of daily tank volume variation ($F\Delta v$). Decision variables using two alternative schemes: an explicit scheme with 24 binary pump on/off commands per day (48 genes for two pumps, 480 genes for twenty), and an implicit scheme with paired threshold volumes triggering pump switches (4 genes for two pumps, 40 genes for twenty). The authors implemented NSGA-II using the pymoo Python library. Algorithm parameters were: population size 100, generations 1000 (small case)/200 (scalable case), crossover rate 0.9, binary tournament selection, polynomial mutation with rate 1/chromosome length. The pseudo-weight decision-making method, translates Pareto front candidates into normalized weight vectors representing each solution's relative position across the three objectives, allowing the decision-maker to specify a target weight vector and select the closest matching solution. Four target strategies were compared: balanced, cost-saving, switch-saving, and volumes-cyclicity. The authors publicly released their entire testbed as a GitHub repository (<https://github.com/>), reported all algorithm hyperparameters and hydraulic simulation parameters, specified the pymoo framework version, and even validated the small case study on a Raspberry Pi. No convergence is reported. The authors themselves acknowledge this in their conclusions: "Further research is necessary to compare different metaheuristics on different and large scenarios." While the hydraulic constraints are more realistic than Abdolazimi et al., the model still lacks pressure constraints and pipe head losses. The authors acknowledge this limitation and propose future integration. The most novel contribution of this study is the systematic comparison of explicit versus implicit pump-scheduling encoding.

Hojjati and colleagues compared NSGA-II against MOPSO for two reservoir operations in Iran. They followed a similar methodology pattern as the above articles, and reported that NSGA-II achieved 22% higher revenue and 3% higher flood storage. No convergence metrics or multiple runs were reported. Zarei and colleagues applied the same NSGA-II versus MOPSO head-to-head comparison to two benchmark water distribution networks (the Alperovits–Shamir two-looped network and the Lansey network), using EPANET 2 for hydraulic simulation and MATLAB 2010 for algorithm implementation. These two studies follow a similar methodological pattern. Zarei's study reported finding is a sharp reduction in iterations required to reach the optimal solution. Across the NSGA-II cluster, several patterns emerge. First, NSGA-II is rarely justified on water-specific grounds. Only Makaremi [33] reported multi-run reproducibility evidence, while Abdolazimi, Ben Ammar, Hojjati, and Zarei [34–37] present single-run or limited-run results despite NSGA-II's stochastic nature.

PSO cluster is the largest in the review with 10 studies, split between standalone PSO ($n = 4$) applications, as seen in Figure 5 and PSO hybrids ($n = 6$). This split shows that researchers acknowledge PSO's limitations for certain optimization problems and reach for hybridization if needed.

Mehdi and Asghar developed a PSO-based methodology for optimizing the location and setting of Pressure-Reducing Valves in WDN's, with the single objective of maximizing

a fuzzy Network Pressure Reliability Index (NPRI). It used a deterministic stochastic pipeline rather than a single joint optimization. A custom Valve Selection Index (VSI) ranks pipes by flow-weighted pressure differential to pre-filter candidate valve locations. PSO is then used twice in sequence, first to calibrate Hazen–Williams roughness coefficients on the selected pipes against the NPRI, then to set PRV openings hourly over a 24 h horizon. EPANET 2.0 provides the hydraulic simulator and the formulation uses both demand-driven simulation for nodal outflows and head-driven simulation for pressure-dependent leakage modeled via an orifice equation with pressure exponent $\beta = 1.18$. The method is applied to the Jowitt–Xu benchmark (37 pipes, 26 nodes) and to the Ahar WDN in East Azerbaijan, Iran (192 pipes, 169 nodes, 5 tanks, 3 pumping stations), with reported gains on Ahar of 24.8% in average NPRI and 15% in average leakage rate relative to the no-PRV baseline. No PSO parameters are reported.

Chong and colleagues developed a hybrid simulation optimization framework for adapting the operating rule curve of the Klang Gate Dam (KGD) in Malaysia under temperature-driven demand scenarios, comparing four pipeline combinations (SVRS-FA, SVRS-PSO, MLPS-FA, MLPS-PSO) over a 228-month historical record between 2001 and 2019. The single objective formulation minimizes the sum of squared release demand deviations over a 12-month operating cycle, subject to monthly mass balance, storage bounds, and release bounds. PSO uses population 500, max iterations 5000, $w = 0.8$, $c1 = c2 = 1.494$. FA uses population 100, max generations 1000, $\alpha = 0.2$, $\beta_0 = 0.2$, $\gamma = 1.0$. The reported finding is that PSO dominates FA on every reservoir performance index across all scenarios. The MLPS-PSO model achieves the highest periodic reliability (0.6491) and resilience (0.6750) under the minimum temperature scenario, while SVRS-PSO achieves the lowest vulnerability (0.0237) and shortage index (0.0047) in the same scenario.

Sharafkhane and colleagues developed AquaCrop plug-in-PSO, a hybrid simulation optimization framework coupling the Food and Agriculture Organization's AquaCrop crop water productivity model with particle swarm optimization. The single objective formulation maximizes crop water productivity. The PSO is implemented with population 200, cognitive and social parameters $c1 = c2 = 2$, and an inertia weight reported as $\omega = 10$ (an unusually high value, an order of magnitude above typical PSO inertia weights of 0.4–0.9, that the authors do not justify or sensitivity test). The framework's central methodological move is the static versus dynamic contrast. The same AquaCrop PSO algorithm is run twice on the same field, once using only 50-year-old historical weather data ("static") and once using rolling 7-day weather forecasts blended with historical data for the remaining season ("dynamic"). The dynamic approach achieved the highest WPc among all five irrigation methods tested under full irrigation (3.12 kg m⁻³ vs. 2.70 for soil-moisture-based, 2.42 for static, 2.09 for fixed, 1.80 for ET-based), with a 127 mm water saving over static and a 264 mm saving (33% reduction) over the fixed irrigation practice of local growers. Under deficit irrigation (90% and 70%), the dynamic approach again recorded the highest WPc (3.00 and 2.21 kg m⁻³, respectively), outperforming both ET-based and soil-moisture-based methods. No multi-run statistics, standard deviations, or convergence diagnostics are reported. The framework is not compared against any alternative metaheuristic algorithm.

Across the PSO cluster, the remaining articles shows similar methodology. PSO is consistently a means rather than a contribution, the algorithm functions as infrastructure behind a novel formulation, hybrid pipeline, or domain-specific application rather than as the research target itself. Reporting on the optimization step tracks the contribution type, not the algorithm [38]. The application diversity is far broader than in NSGA-II.

The ACO cluster, whilst being a small cluster, is a finding in itself. Sang developed a cost-effective pump-scheduling algorithm for mine drainage systems based on ACO, applied to the Jinchiling Gold Mine in Shandong, China. The problem in the study is formulated

as a discrete optimization problem, minimizing total daily pump costs under time-of-use electricity tariffs. The decision space is represented as a multistage directed weighted graph where each stage corresponds to a 20 min period and each vertex represents the number of running pumps (0 to 5); ACO ants traverse the graph to find the lowest-cost feasible schedule. Sump water inflow is predicted using double exponential smoothing with smoothing factor $\omega = 0.7$, with reported mean relative prediction errors of 0.039%, 0.066%, and 0.091% for one-, two-, and three-step-ahead forecasts. The reported finding is a 34.09% average cost reduction over 30 days of real operational data compared to the manual baseline schedule, achieved by shifting pump operation from peak hours (17.67 to 2.65 machine hours) to valley hours (54.62 to 98.55 machine hours). The methodological limitations are significant: no multi-run statistics, no convergence diagnostics, no comparison against alternative metaheuristics.

Nguyen and colleagues developed a generic simulation optimization framework combining ant colony optimization with the process-based Root Zone Water Quality Model in Greeley Colorado. The objective was to maximize three-year net return. The methodological contribution is dynamic decision variable option adjustment, which reduces the effective search space by checking the annual water availability constraint at each decision point and removing infeasible options as the ACO ant constructs its solution. Twenty-one experiments tested water availability levels from 100% to 22% of irrigation system capacity, with each experiment repeated 30 times from random starting points (a total run time of approximately 60 h per replicate on a high-performance computing cluster). The reported findings: only 41% of maximum irrigation capacity was needed to achieve the optimal net return of USD 7760.7. It showed ACO-DDVO outperformed the Microsoft Excel based Colorado Irrigation Scheduler benchmark by 1.80% in net return while using 0.20% more water and 16.67% less fertilizer (Experiment 4), or alternatively by 1.52% in net return with 9.57% less water and 16.67% less fertilizer. The methodological strengths are substantial: formal ACO parameter sensitivity analysis, 30 independent runs per experiment to address stochasticity; it has the same limitation as Sang with no comparison against alternative metaheuristics.

The DDVO mechanism originated in [30], which applied the same ACO+DDVO framework to annual crop and water allocation using crop-water production functions rather than a process-based simulator; the 2017 paper extends the framework to within-season irrigation and fertilizer scheduling.

The two ACO studies in this review form a contrast pair (noting that [30] extends [39]) that exposes both the algorithm's natural fit and its scaling limits. ACO originated as a combinatorial optimization method for discrete graph-search problems, and Sang's mine drainage application sits comfortably in that territory. The contrast suggests that ACO's appearance in this review's literature reflects two distinct usage patterns: ACO as a natural-fit solver for genuinely combinatorial water-scheduling problems, and ACO as a candidate metaheuristic stretched onto continuous allocation. ACO appearing only twice shows that the algorithm can still be chosen when researchers have specific use cases.

Across the three clusters, a consistent pattern emerges: the methodological rigor of the optimization step is determined less by which algorithm a study uses than by how the algorithm sits in the study's contribution chain. Where the metaheuristic is itself the methodological centrepiece, multi-run statistics, parameter sensitivity analysis, and convergence diagnostics are present. Where the metaheuristic is incidental infrastructure behind a novel formulation, hybrid pipeline, or domain application, the optimization step is typically reported as a parameter list without sensitivity, multi-run statistics, or alternative algorithm comparison. This pattern cuts across NSGA-II, PSO, and ACO clusters and operates independently of algorithm family. The implication for this review is that the algorithm family taxonomy used to organize these 23 studies, while reflecting how the field commonly categorizes itself, captures less of the methodological variation than

a contribution-type taxonomy would. A consequence for readers seeking comparative evidence on algorithm effectiveness in water scheduling is that head-to-head algorithm comparisons within this literature (NSGA-II vs. MOPSO in Hojjati and Abdolazimi, PSO vs. firefly in Chong et al.) are conducted with single runs, unmatched parameter tuning, and aggregate scalar metrics rather than distributional indicators, which limits what scoping review readers can infer about relative algorithm performance even when individual studies report substantial percentage gains. The remaining five studies appear only once and are too heterogeneous to support cluster-level synthesis.

4.5. Technical Profiling

Table 4 shows a quick technical profile where this is expanded to a more detailed study-level technical profile in Appendix A. The appendix reports the algorithm family, algorithm type, application domain, constraints, objective-function focus, convergence reporting, and reproducibility indicators for each included study.

Table 4. Summary of technical reporting across included studies,

Technical Category	Main Observation	Implication
Algorithm family	Studies included swarm intelligence, evolutionary computation, and hybrid metaheuristic approaches.	Clearer classification is required between SI, EC, and hybrid methods.
Objective functions	Most studies focused on cost, energy, pressure, reliability, or multi-objective Pareto trade-offs.	Objective formulation is heterogeneous across studies.
Constraints	Common constraints included pressure, demand, storage, pump limits, water availability, and hydraulic equations.	Constraint reporting varies by application domain.
Convergence reporting	Only some studies reported convergence curves, stopping criteria, hypervolume, or generational distance.	Convergence evidence is inconsistent.
Reproducibility	Software, datasets, code, and parameter settings were not consistently reported.	Reproducibility remains a key reporting gap.

4.6. Distribution by Application Focus

Application domains were characterized to highlight practical relevance. Water distribution networks were the most common focus, appearing in six studies. Other domains include pump scheduling, reservoir operation, irrigation scheduling, water resource management, and broader water resource systems (see Figure 6).

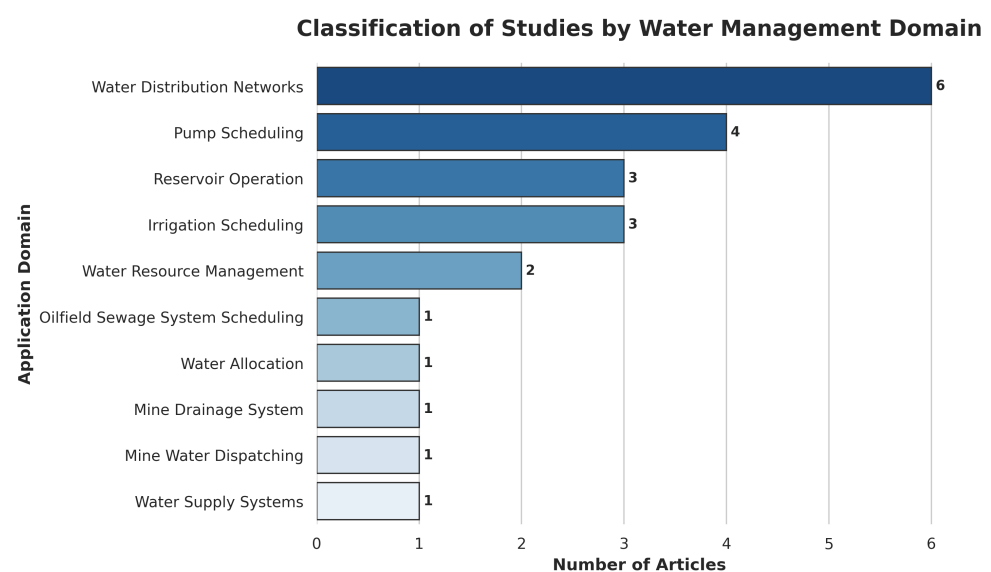


Figure 6. Frequency of application focus,

4.7. Keyword Co-Occurrence

Figure 7 illustrates the thematic evolution of the reviewed literature. Early-stage research is characterized by broad themes such as general optimization and water resource management, with MATLAB commonly used as the computational platform for modeling hydraulic systems.

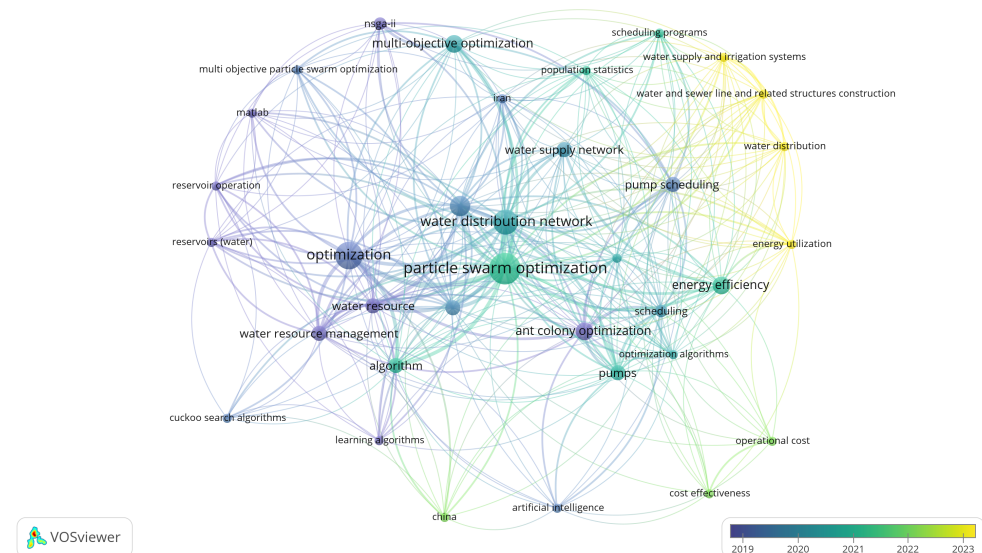


Figure 7. Keyword co-occurrence.

The intermediate phase reflects increased adoption of swarm intelligence techniques, particularly PSO and ACO, with Iran emerging as a key contributor during this period. This stage marks a transition from general optimization toward algorithm-focused research.

More recent developments indicate a shift toward application-driven research, with emphasis on energy efficiency, pump operation, and system-level optimization. This evolution suggests that the focus of water scheduling has expanded beyond hydraulic reliability to include operational efficiency and sustainability considerations. China's increased presence in this cluster reflects its growing contribution to the field.

Overall, the keyword analysis highlights a progression from general optimization frameworks to specialized, application-oriented research, signaling a gradual maturation of the field, albeit one that remains uneven and geographically concentrated.

5. Discussion and Conclusions

A clear emergence of evolutionary computation (EC) showed throughout the results (with NSGA-II). Although EC and SI are both metaheuristic algorithms, they are distinct. EC algorithms based on mutation, Darwinian selection, and evolution [40]. Articles containing EC algorithms were included if they included SI baseline algorithms in their articles as well. SI algorithms such as the PSO required multi-objective modifications (MOPSO) to handle the Pareto fronts; this may explain why SI algorithms mostly showed up as hybridized models rather than standalone models, a stark contrast to the EC models (NSGA-II).

5.1. Conclusions

This scoping review mapped SI and related metaheuristic applications in water scheduling across 23 studies published between 2015 and 2025 through the PRISMA-ScR framework and JBI Population–Concept–Context methodology. The review identified three dominant algorithmic clusters (NSGA-II, PSO, ACO), profiled representative studies

in technical depth, and surfaced patterns invisible to frequency-based analysis alone. The literature exhibits a reproducibility gap that limits its cumulative knowledge value.

These findings have practical implications. For water utility decision-makers in resource-constrained regions, the available literature offers limited transferable guidance, as research concentrates on well-resourced contexts with reliable data and established infrastructure. For researchers, the most valuable contribution to this field is not another algorithm comparison on synthetic benchmarks, but methodological consolidation.

The sample size of 23 studies, while appropriate for a scoping review, limits statistical generalizability. The technical profiling framework introduced here charts reporting practices descriptively rather than evaluating algorithmic performance, consistent with scoping review methodology. Future systematic reviews with meta-analytical synthesis will require the benchmarking infrastructure that this review identifies as currently absent.

Within these limits, the review provides a structured map of swarm intelligence applications in water scheduling, identifies methodological patterns that frequency-based analysis cannot surface, and establishes a baseline against which future research can be positioned. The intersection of swarm intelligence and water scheduling remains sparsely populated and methodologically heterogeneous.

5.2. Key Observations

Four observations are outstanding in this study as follows:

1. The geographic distribution of studies is highly skewed. The majority of studies originate from Asia and Europe, while Africa is represented by only one study despite facing some of the most severe water scarcity challenges globally [17,18].
2. The application contexts are biased toward well-resourced or idealized environments. Few studies explicitly address the constraints typical of arid or resource-limited regions, such as data scarcity, infrastructure unreliability, or socio-economic limitations. This misalignment between research focus and real-world need represents a significant gap in the literature.
3. The dominance of hybrid and multi-objective approaches reflects the inherent complexity of water-scheduling problems. However, the design of these hybrid models is often insufficiently justified, raising concerns about reproducibility and methodological rigor.
4. The literature exhibits a reproducibility gap: only 9 of 23 studies report convergence curves, none report hypervolume or generational distance, and fewer than 30% provide reproducibility indicators (code, full parameterization, shared datasets). Head-to-head algorithm comparisons rely on single runs and aggregate scalar metrics rather than distributional indicators.

These observations should be interpreted cautiously. With a final sample of 23 studies, the review is not intended to provide statistically generalizable conclusions. Rather, consistent with the purpose of scoping reviews [20], it offers a structured mapping of the field, identifying dominant patterns, gaps, and emerging directions. Within this scope, the study demonstrates that the intersection of swarm intelligence and water scheduling remains sparsely populated and methodologically heterogeneous, reinforcing the need for further systematic investigation.

5.3. Contributions

This study highlights two primary contributions.

1. The systematic mapping of the field provides a structured synthesis of swarm intelligence applications in water scheduling, including algorithm usage, application domains, methodological trends, and geographic distribution. This contributes

to consolidating a fragmented body of knowledge and establishes a baseline for future research.

2. The study highlights significant underrepresentation of resource-constrained and arid regions, particularly in Africa, despite their acute water challenges [17,18]. It also exposes methodological gaps, including inconsistent evaluation practices and limited attention to context-aware model design.

Together, these contributions position the study as both a diagnostic overview of the current state of the field and a foundation for targeted research development.

5.4. Future Directions

Six likely directions for future research emerge as follows:

1. Future work should prioritize the development of swarm intelligence models tailored to resource-constrained and arid environments. This includes incorporating real-world constraints such as limited data availability, infrastructure variability, and socio-economic factors into optimization frameworks.
2. There is a need for robust optimization frameworks capable of operating under data scarcity and environmental variability. Designing swarm intelligence algorithms that explicitly account for uncertainty will enhance their practical applicability.
3. The field would benefit from consistent benchmarking practices, including standard datasets, performance metrics, and reporting protocols, to enable meaningful comparison across studies.
4. Existing studies predominantly focus on operational metrics such as cost and pressure optimization. Future research should expand objective functions to include equity, accessibility, and sustainability, particularly access to water as a fundamental outcome.
5. Broadening future reviews to include non-English publications and additional regional databases will provide a more globally representative understanding of the field.
6. Advancing swarm intelligence from standalone optimization tools to integrated decision-support frameworks will enhance their relevance for policy-makers and practitioners, particularly in community-center water management contexts.

Author Contributions: Each author contributed as follows: Conceptualization: C.v.W. (80%), C.C. (20%); methodology: C.v.W. (80%), C.C. (20%); validation: C.v.W. (80%), C.C. (20%); formal analysis: C.v.W. (80%), C.C. (20%); investigation: C.v.W. (100%); data curation: C.v.W. (100%); writing—original draft preparation: C.v.W. (100%); writing—review and editing: C.v.W. (80%), C.C. (20%); visualization: C.v.W. (100%); supervision: C.C. (80%); T.M. (20%); funding acquisition: C.v.W. (50%), C.C. (50%). All authors have read and agreed to the published version of the manuscript.

Funding: This research was conducted as part of the activities of the Center for Artificial Intelligence Research, which receives funding from the Center for Scientific and Innovation Research (CSIR) under grant number CSIR/BEI/HNP/CAIR/2020/10.

Data Availability Statement: The original contributions presented in this study are included in the article; further inquiries or requests can be directed to the corresponding authors.

Acknowledgments: We acknowledge both the moral and technical support given by Sol Plaatje University—Department of Computer Science and Information Technology. We would also like to extend our gratitude to the National Research Foundation regarding funding support. Lastly, we also thank Taryn Michael and Colin Chibaya for their supervision and guidance.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PCC	Population, Concepts, and Context
JB	Joanna Briggs Institute
PRISMA-ScR	Preferred Reporting Items for Systematic reviews and Meta-Analyses Extension for Scoping Reviews
SI	Swarm Intelligence
EC	Evolutionary Computation
PSO	Particle Swarm Optimization
ACO	Ant Colony Optimization
SMA	Slime Mold Algorithm
ABC	Artificial Bee Colony
GWO	Grey Wolf Optimizer
FF	Firefly Algorithm
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
MATLAB	Matrix Laboratory
NLP	Natural Language Processing
EPANET	Environmental Protection Agency Network

Appendix A. Technical Algorithmic Profile of Included Studies

Table A1. Technical algorithmic profile of included studies

Study	Algorithm Family	Algorithm Type	Application Domain	Constraints Considered	Objective/Fitness-Function Focus	Conv.	Reproducibility Indicators
[34]	Hybrid SI–EC	MOPSO, NSGA-II	Water distribution system	Pipe age, pipe material, maintenance or replacement need	Multi-objective optimization using CPU time and objective-function values	No	Dataset/case: Iran; software: GAMS 24.1.3 and MATLAB; code not reported
[25]	Evolutionary computation	Borg MOEA	Reservoir operation	Annual reservoir drawdown, release constraints, storage constraints	Multi-objective optimization using hypervolume and generational distance	Yes	Dataset/case: Iran; software: C++; code not reported
[35]	Evolutionary computation	NSGA-II	Water distribution networks	Daily water availability, lower-tank volume, upper-tank volume	Minimization of daily pumping cost, tank-volume variation, and pump switches	No	Software: EpanetSimulator and WNTRSimulator; dataset/code not reported
[26]	Hybrid SI	PSO-CS	Oilfield sewage system scheduling	Supply and demand, water quantity, effluent concentration, injection-station pressure	Minimization of total water-delivery cost and improvement of water-resource utilization	Yes	Dataset/case: China; benchmarked against PSO, WOA, SA, COA, and HO; software/platform: CEC2022
[41]	Hybrid SI	SVRS-PSO, FF	Reservoir operations	Storage continuity, storage capacity, release constraints	Minimization of water deficit	No	Dataset/case: Malaysia; benchmark methods reported; software/code not reported

Table A1. Cont.

Study	Algorithm Family	Algorithm Type	Application Domain	Constraints Considered	Objective/Fitness-Function Focus	Conv.	Reproducibility Indicators
[27]	Hybrid SI-EC	Improved GA, AACO, APSO	Water pump station scheduling	Flow demand, speed limits, maximum/minimum flow, parallel pumps, model summarization	Optimal pump-group scheduling and energy-use minimization	Yes	Dataset/case: China; software: MATLAB and Python; benchmarked against GA, ACO, and APSO
[28]	Hybrid SI-EC	OMOPSO, NSGA-II	Water distribution systems	Continuity equations, energy-balance equations, pressure-head constraints	Multi-objective optimization evaluated using convergence and hypervolume metrics	Yes	Software: MATLAB; benchmarked against MMOPSO and PSO; dataset/code not reported
[36]	Hybrid SI-EC	NSGA-II, MOPSO	Water resources systems	Reservoir water balance, release restrictions, minimum downstream environmental flow	Maximization of hydroelectric energy production and flood-storage volume	No	Dataset/case: Iran; software: MATLAB; code not reported
[42]	Swarm intelligence	PSO	Pump optimization and pressure management	Standard pressure requirements, tank-level constraints	Minimization of operational cost, pump energy consumption, and water loss	No	Software: EPANET toolkit for MATLAB; dataset/code not reported
[43]	Reinforcement learning / comparator study	Multi-agent DDPG	Pump and valve scheduling in water distribution networks	Pressure requirements and final tank-level bounds	Minimization of energy cost and water-loss cost	No	Software: Python and MEALPY; benchmarked against GA, PSO, and DE; code not reported

Table A1. Cont.

Study	Algorithm Family	Algorithm Type	Application Domain	Constraints Considered	Objective/Fitness-Function Focus	Conv.	Reproducibility Indicators
[44]	Swarm intelligence	BDA	Pump scheduling in water supply systems	Continuity law, energy conservation law, tank minimum/maximum capacity	Reduction of total energy cost	NR	Dataset/case: Iran; software: MATLAB; benchmarked against GA, EA, ABC, FF, PSO, ACO, and BDA
[38]	Swarm intelligence	PSO	Large-scale water distribution network	Not explicitly reported	Maximization of NPRI index using roughness coefficients of selected pipes	No	Dataset/case: Iran; software: MATLAB; code not reported
[29]	Nature-inspired metaheuristic	Cuckoo Search	Multi-reservoir system	Power output, continuity equation, water level, outflow	Multi-objective reservoir operation with convergence-performance evaluation	Yes	Dataset/case: China; benchmarked against GA and PSO; software/code not reported
[30]	Swarm intelligence	ACO-DDVO	Crop and water allocation	Area allocation and water-allocation constraints	Reduction of computational effort for optimal crop and water allocation	Yes	Benchmarked against ACO-SDVO and LP; dataset/software/code not reported
[39]	Swarm intelligence	ACO	Irrigation scheduling	Annual water allocation	Maximization of net return	No	Dataset/case: USA; software/code not reported
[31]	Swarm intelligence	SMP SO	Irrigation scheduling	Pipeline capacity	Minimization of energy costs in rotational irrigation management	Yes	Dataset/case: Italy; software: Python; code not reported

Table A1. Cont.

Study	Algorithm Family	Algorithm Type	Application Domain	Constraints Considered	Objective/Fitness-Function Focus	Conv.	Reproducibility Indicators
[45]	Swarm intelligence	ACO	Mine drainage system	Solution-size bounds, cost-type classification, pressure-head limits	Reduction of mine operation cost	No	Dataset/case: China; software/code not reported
[46]	Hybrid simulation-SI	AquaCrop-PSO	Irrigation scheduling	Reported as unconstrained	Maximization of crop water productivity	No	Dataset/case: Iran; software/code not reported
[32]	Hybrid metaheuristic	GA, SA, PSO	Water-pumping systems	Pump activation limits, cavitation-risk limits, reservoir overflow limits	Minimization of pump energy consumption	Yes	Benchmarking/ software/code not reported
[47]	Swarm intelligence	PSO	Mine water dispatching	Water quality and quantity at each water point	Maximization of recycling rate	No	Dataset/case: China; software/code not reported
[33]	Evolutionary computation	Self-adaptive NSGA-II	Water supply systems	Mass conservation, energy conservation, pipe head loss, hydraulic compatibility equations	Minimization of energy and maintenance costs	Yes	Benchmarked against GA, ACO, and SPEA2; dataset/software/code not reported
[48]	Swarm intelligence	PSO	Pumping-unit scheduling	Target water-quality requirements and allowable water-level variation	Minimization of operational cost	No	Dataset/case: China; software/code not reported
[37]	Hybrid SI-EC	NSGA-II, MOPSO	Water distribution network	Velocity bounds, commercial pipe diameter set, continuity equation, energy conservation, allowable pressure range (penalty-based)	Multi-objective minimization of network cost and total pressure deficit; modified cost function with pressure-violation penalty	Partial	EPANET 2, MATLAB 2010; benchmark networks (two-looped, Lansey); no code release, no multi-run statistics, no hypervolume

References

1. Chang, J.H.; Kumar, M.; Selvaraj, S.; Samuel, M.S.; Ethiraj, S.; Senthilkumar, A.; Dong, C.D.; Shkir, M. Green Energy Breakthroughs: Harnessing Nano-Catalysts and Enzymatic Catalysts for Bioenergy Generation. *Ind. Crop. Prod.* **2024**, *215*, 118527. <https://doi.org/10.1016/j.indcrop.2024.118527>.
2. Park, J.; Cho, J.; Jung, K.Y. Nature-Inspired Metaheuristic Optimization Algorithms for FDTD Dispersion Modeling. *AEU-Int. J. Electron. Commun.* **2024**, *187*, 155564. <https://doi.org/10.1016/j.aeue.2024.155564>.
3. Chou, J.S.; Liu, C.Y.; Shih, H.Y.; Lin, Z.T. Automated Annotation of Steel Corrosion in UAV-captured Images from beneath Bridge Decks Using Metaheuristic-Optimized Computer Vision. *Structures* **2025**, *75*, 108696. <https://doi.org/10.1016/j.istruc.2025.108696>.
4. Nguyen, H.; Hoang, N.D. Computer Vision-Based Classification of Concrete Spall Severity Using Metaheuristic-Optimized Extreme Gradient Boosting Machine and Deep Convolutional Neural Network. *Autom. Constr.* **2022**, *140*, 104371. <https://doi.org/10.1016/j.autcon.2022.104371>.
5. Khafaga, D.S.; El-kenawy, E.S.M.; Khodadadi, N.; Alhussan, A.A.; Eid, M.M. Enhancing Footstep Power Generation Prediction through Metaheuristic Optimization and Feature Selection Using Puma Optimization. *Energy Rep.* **2025**, *14*, 2864–2892. <https://doi.org/10.1016/j.egy.2025.09.017>.
6. Ahsan, M.S.; Islam, S.; Shatabda, S. A Systematic Review of Metaheuristics-Based and Machine Learning-Driven Intrusion Detection Systems in IoT. *Swarm Evol. Comput.* **2025**, *96*, 101984. <https://doi.org/10.1016/j.swevo.2025.101984>.
7. My, T.; Hoa, T.; Ngoc, T. Optimized Metaheuristic Strategies for Addressing the Multi-Picker Robot Routing Problem in 3D Warehouse Operations. *CMC* **2025**, *84*, 5063–5076. <https://doi.org/10.32604/cmc.2025.064610>.
8. Gan, R.; Guo, Q.; Chang, H.; Yi, Y. Improved Ant Colony Optimization Algorithm for the Traveling Salesman Problems. *J. Syst. Eng. Electron.* **2010**, *21*, 329–333. <https://doi.org/10.3969/j.issn.1004-4132.2010.02.025>.
9. Bo, X.; Bo, A. Application of Portfolio Optimization Based on Multi-Strategy Improved Artificial Bee Colony Algorithm. In Proceedings of the 2024 IEEE 2nd International Conference on Electrical, Automation and Computer Engineering (ICEACE), Changchun, China, 29–31 December 2024; pp. 916–921. <https://doi.org/10.1109/ICEACE63551.2024.10898408>.
10. Ye, A. Study of the Vehicle Routing Problem with Time Windows Based on Improved Particle Swarm Optimization Algorithm. In Proceedings of the 2011 International Conference on Computer Science and Service System (CSSS), Nanjing, China, 27–29 June 2011; pp. 4053–4057. <https://doi.org/10.1109/CSSS.2011.5974924>.
11. Ge, F.; Li, K.; Xu, W.; Wang, Y. Path Planning of UAV for Oilfield Inspection Based on Improved Grey Wolf Optimization Algorithm. In Proceedings of the 2019 Chinese Control And Decision Conference (CCDC), Nanchang, China, 3–5 June 2019; pp. 3666–3671. <https://doi.org/10.1109/CCDC.2019.8833455>.
12. Islam, N.N.; Hannan, M.A.; Shareef, H.; Mohamed, A. SVC Damping Controller Design Based on Firefly Optimization Algorithm in Multi Machine Power System. In Proceedings of the 2013 IEEE Conference on Clean Energy and Technology (CEAT), Langkawi, Malaysia, 18–20 November 2013; pp. 66–70. <https://doi.org/10.1109/CEAT.2013.6775601>.
13. Izci, D. An Enhanced Slime Mould Algorithm for Function Optimization. In Proceedings of the 2021 3rd International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), Ankara, Turkey, 11–13 June 2021; pp. 1–5. <https://doi.org/10.1109/HORA52670.2021.9461325>.
14. Yao, J.; Xue, H.; Pu, Y.; Chu, Q.; Wang, G.; Mu, L. *Scheduling Algorithm of Urban Raw Water Supply Based on Swarm Intelligence Optimization*; Institute of Electrical and Electronics Engineers Inc.: Hefei, China, 2022; pp. 1212–1216. <https://doi.org/10.1109/CCDC55256.2022.10033731>.
15. Maier, H.R.; Kapelan, Z.; Kasprzyk, J.; Kollat, J.; Matott, L.S.; Cunha, M.C.; Dandy, G.C.; Gibbs, M.S.; Keedwell, E.; Marchi, A.; et al. Evolutionary Algorithms and Other Metaheuristics in Water Resources: Current Status, Research Challenges and Future Directions. *Environ. Model. Softw.* **2014**, *62*, 271–299. <https://doi.org/10.1016/j.envsoft.2014.09.013>.
16. Reed, P.M.; Hadka, D.; Herman, J.D.; Kasprzyk, J.R.; Kollat, J.B. Evolutionary Multiobjective Optimization in Water Resources: The Past, Present, and Future. *Adv. Water Resour.* **2013**, *51*, 438–456. <https://doi.org/10.1016/j.advwatres.2012.01.005>.
17. Hadipour, A.; Ahmadi, S.H.; Sepaskhah, A.R. Consequences of Water and Land Scarcity and Unhealthy Diets on the Productive Capacity of the Middle East and North Africa. *Environ. Sustain. Indic.* **2025**, *25*, 100594. <https://doi.org/10.1016/j.indic.2025.100594>.
18. Konstadinos, M.; Pantazis, G.; Dimitra, L.C.; Christos, M.; Stefanos, N.A.; Giovanna, S.; Mantent, K.J.; Joseph, A.D.; Adombilla, R. Assessing Sustainable Water Management in a Resource-Scarce Environment (Ghana, West Africa) via the Analytic Hierarchy Process. *Agric. Water Manag.* **2025**, *313*, 109497. <https://doi.org/10.1016/j.agwat.2025.109497>.
19. Becker, B.P.J.; Jagtenberg, C.J.; Horváth, K.; Mitchell, A.; Rodríguez-Sarasty, J.A. Optimization Methods in Water System Operation. *WIREs Water* **2024**, *11*, e1756. <https://doi.org/10.1002/wat2.1756>.
20. Peters, M.D.J.; Godfrey, C.M.; Khalil, H.; McInerney, P.; Parker, D.; Soares, C.B. Guidance for Conducting Systematic Scoping Reviews. *Int. J.-Evid.-Based Healthc.* **2015**, *13*, 141–146. <https://doi.org/10.1097/XEB.000000000000050>.

21. Tricco, A.C.; Lillie, E.; Zarin, W.; O'Brien, K.K.; Colquhoun, H.; Levac, D.; Moher, D.; Peters, M.D.; Horsley, T.; Weeks, L.; et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann. Intern. Med.* **2018**, *169*, 467–473. <https://doi.org/10.7326/M18-0850>.
22. Munn, Z.; Barker, T.H.; Moola, S.; Tufanaru, C.; Stern, C.; McArthur, A.; Stephenson, M.; Aromataris, E. Methodological Quality of Case Series Studies: An Introduction to the JBI Critical Appraisal Tool. *JBI Evid. Synth.* **2020**, *18*, 2127. <https://doi.org/10.11124/JBISRIR-D-19-00099>.
23. Akbari, R.; Rezaei Ochbelagh, D.; Gharib, A.; Maiorino, J.; D'Auria, F. Small Modular Reactor Full Scope Core Optimization Using Cuckoo Optimization Algorithm. *Prog. Nucl. Energy* **2020**, *122*, 103271. <https://doi.org/10.1016/j.pnucene.2020.103271>.
24. Sohail, N.; Khan, A.; Memon, A. *Swarm Robots on a Mission: Optimizing Inspections with Fuzzy Logic and Particle Swarm Optimization*; Institute of Electrical and Electronics Engineers Inc.: Bhurban, Murree, Pakistan, 2023; pp. 19–25. <https://doi.org/10.1109/IBCAST59916.2023.10712943>.
25. Al-Jawad, J.Y.; Tanyimboh, T.T. Reservoir Operation Using a Robust Evolutionary Optimization Algorithm. *J. Environ. Manag.* **2017**, *197*, 275–286. <https://doi.org/10.1016/j.jenvman.2017.03.081>.
26. Chen, S.; Zhou, S.; Li, Y.; Jiang, M.; Guan, B.; Xi, J. Optimization Method for Digital Scheduling of Oilfield Sewage System. *Water* **2024**, *16*, 2623. <https://doi.org/10.3390/w16182623>.
27. de O. Turci, L.; Wang, J.; Brahmia, I. Adaptive and Improved Multi-population Based Nature-inspired Optimization Algorithms for Water Pump Station Scheduling. *Water Resour. Manag.* **2020**, *34*, 2869–2885. <https://doi.org/10.1007/s11269-020-02588-3>.
28. Torkomany, M.; Hassan, H.; Shoukry, A.; Abdelrazek, A.; Elkholy, M. An Enhanced Multi-Objective Particle Swarm Optimization in Water Distribution Systems Design. *Water* **2021**, *13*, 1334. <https://doi.org/10.3390/w13101334>.
29. Ming, B.; Chang, J.X.; Huang, Q.; Wang, Y.M.; Huang, S.Z. Optimal Operation of Multi-Reservoir System Based-On Cuckoo Search Algorithm. *Water Resour. Manag.* **2015**, *29*, 5671–5687. <https://doi.org/10.1007/s11269-015-1140-6>.
30. Nguyen, D.C.H.; Maier, H.R.; Dandy, G.C.; Ascough, J.C. Framework for Computationally Efficient Optimal Crop and Water Allocation Using Ant Colony Optimization. *Environ. Model. Softw.* **2016**, *76*, 37–53. <https://doi.org/10.1016/j.envsoft.2015.11.003>.
31. Peretti, F.; Menapace, A.; Zanfei, A.; Righetti, M. Optimal Irrigation Scheduling for Sustainable Agriculture: Minimising Energy Costs in Rotational Management. *Agric. Water Manag.* **2025**, *322*, 109986. <https://doi.org/10.1016/j.agwat.2025.109986>.
32. Torregrossa, D.; Capitanescu, F. Optimization Models to Save Energy and Enlarge the Operational Life of Water Pumping Systems. *J. Clean. Prod.* **2019**, *213*, 89–98. <https://doi.org/10.1016/j.jclepro.2018.12.124>.
33. Makaremi, Y.; Haghighi, A.; Ghafouri, H.R. Optimization of Pump Scheduling Program in Water Supply Systems Using a Self-Adaptive NSGA-II; a Review of Theory to Real Application. *Water Resour. Manag.* **2017**, *31*, 1283–1304. <https://doi.org/10.1007/s11269-017-1577-x>.
34. Abdolazimi, O.; Esfandarani, M.S.; Kashani, H.M.; Aghashahi, N. Maximizing Failure Occurrence in Water Distribution Systems: A Multi-Objective Approach Considering Reliability, Economic, and Environmental Aspects. *Expert Syst. Appl.* **2025**, *264*, 125910. <https://doi.org/10.1016/j.eswa.2024.125910>.
35. Ammar, S.; Cimino, M.; Foglia, P.; Galatolo, F.; Nouiri, I. Multi-Objective Optimization of Water Distribution Networks via NSGA-II and Pseudo-Weights. In *Proceedings of the 2021 IEEE 19th International Conference on Embedded and Ubiquitous Computing (EUC)*; EUC, Wan, S., Cheng, X., Wu, C., Eds.; Institute of Electrical and Electronics Engineers Inc.: Shenyang, China, 2021; pp. 181–186. <https://doi.org/10.1109/EUC53437.2021.00034>.
36. Hojjati, A.; Monadi, M.; Faridhosseini, A.; Mohammadi, M. Application and Comparison of NSGA-II and MOPSO in Multi-Objective Optimization of Water Resources Systems. *J. Hydrol. Hydromech.* **2018**, *66*, 323–329. <https://doi.org/10.2478/johh-2018-0006>.
37. Zarei, N.; Azari, A.; Heidari, M.M. Improvement of the Performance of NSGA-II and MOPSO Algorithms in Multi-Objective Optimization of Urban Water Distribution Networks Based on Modification of Decision Space. *Appl. Water Sci.* **2022**, *12*, 133. <https://doi.org/10.1007/s13201-022-01610-w>.
38. Mehdi, D.; Asghar, A. Pressure Management of Large-Scale Water Distribution Network Using Optimal Location and Valve Setting. *Water Resour. Manag.* **2019**, *33*, 4701–4713. <https://doi.org/10.1007/s11269-019-02381-x>.
39. Nguyen, D.C.H.; Ascough, J.C.; Maier, H.R.; Dandy, G.C.; Andales, A.A. Optimization of Irrigation Scheduling Using Ant Colony Algorithms and an Advanced Cropping System Model. *Environ. Model. Softw.* **2017**, *97*, 32–45. <https://doi.org/10.1016/j.envsoft.2017.07.002>.
40. Yanes Luis, S.; Gutiérrez-Reina, D.; Toral Marín, S.; Stateczny, A. A Dimensional Comparison between Evolutionary Algorithm and Deep Reinforcement Learning Methodologies for Autonomous Surface Vehicles with Water Quality Sensors. *Sensors* **2021**, *21*, 2862. <https://doi.org/10.3390/s21082862>.
41. Chong, J.Y.; Hooi, G.L.; Goh, Q.Y.; Lai, V.; Huang, Y.F.; Koo, C.H.; El-Shafie, A.; Ahmed, A.N. Adapting reservoir operations for optimal water management under varying climate and demand scenarios using metaheuristic algorithms. *Ain Shams Eng. J.* **2024**, *15*, 102835. <https://doi.org/10.1016/j.asej.2024.102835>.

42. Brentan, B.M.; Luvizotto, E.; Montalvo, I.; Izquierdo, J.; Pérez-García, R. Near Real Time Pump Optimization and Pressure Management. *Procedia Eng.* **2017**, *186*, 666–675. <https://doi.org/10.1016/j.proeng.2017.06.248>.
43. Hu, S.; Gao, J.; Zhong, D. Multi-agent reinforcement learning framework for real-time scheduling of pump and valve in water distribution networks. *Water Supply* **2023**, *23*, 2833–2846. <https://doi.org/10.2166/ws.2023.163>.
44. Jafari-Asl, J.; Azizyan, G.; Hashemi Monfared, S.A.H.; Rashki, M.; Andrade-Campos, A.G. An enhanced binary dragonfly algorithm based on a V-shaped transfer function for optimization of pump scheduling program in water supply systems (case study of Iran). *Eng. Fail. Anal.* **2021**, *123*, 105323. <https://doi.org/10.1016/j.engfailanal.2021.105323>.
45. Sang, J. A Cost-effective Pump Scheduling Method for Mine Drainage System Based on Ant Colony Optimization. *J. Eur. Syst. Autom.* **2019**, *52*, 123–128. <https://doi.org/10.18280/jesa.520202>.
46. Sharafkhane, M.G.; Ziaei, A.N.; Naghedifar, S.M.; Akbari, A.; Verdi, A. AquaCrop Plug-in-PSO: A novel irrigation scheduling optimization framework for maize to maximize crop water productivity using in-season weather forecast and crop yield estimation. *Agric. Water Manag.* **2024**, *306*, 109153. <https://doi.org/10.1016/j.agwat.2024.109153>.
47. Zhang, Z.; Bo, L.; Liu, Y.; Zhu, D.; Yue, Y. Research on Optimal Scheduling Problem of Mine Water Based on Swarm Intelligence. In Proceedings of the 2021 2nd International Conference on Electronics, Communications and Information Technology (CECIT), Sanya, China, 27–29 December 2021; pp. 1025–1030. <https://doi.org/10.1109/CECIT53797.2021.00182>.
48. Dong, W.; Yang, Q. Data-Driven Solution for Optimal Pumping Units Scheduling of Smart Water Conservancy. *IEEE Internet Things J.* **2020**, *7*, 1919–1926. <https://doi.org/10.1109/JIOT.2019.2963250>.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.