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Hybrid algorithm to enhance water pump stations efficiency and water distribution networks optimization

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Abstract

Designing water distribution networks is a difficult task with many search parameters and restrictions. Evolutionary algorithms have been widely used in this manner to minimize costs while satisfying pressure limits. A new hybrid evolutionary framework with four unique phases is proposed in this research. Reinforcement learning, an efficient artificial technique, was used in the first phase to improve the performance of pump stations. CMA-ES, a strong adaptive meta-heuristic for continuous optimization, was used in the second phase. An upward-greedy search phase to eliminate pressure violations comes next. Lastly, to minimize large pipes, a downward greedy search phase is employed. The hybrid method was applied multiple WDSs case studies in order to evaluate its efficacy. The findings show that on the majority of benchmarks, the new framework performs better than the previously used heuristics in terms of both optimization speed and network cost.

Keywords: Water distribution network, reinforcement learning, CMA-ES, upward greedy algorithm, downward greedy algorithm

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خوارزمية هجينة لتعزيز كفاءة محطات ضخ المياه وتحسين شبكات توزيع المياه

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الخلاصة

تصميم شبكات توزيع المياه يُعدّ مهمة معقدة تتطلب التعامل مع العديد من المعايير والقيود البحثية. وقد تم استخدام الخوارزميات التطورية على نطاق واسع في هذا المجال بهدف تقليل التكاليف مع ضمان استيفاء الحدود المسموح بها للضغط. يقدم هذا البحث إطارًا تطوريًا هجينًا جديدًا يتألف من أربع مراحل متميزة. في المرحلة الأولى، تم استخدام التعلم المعزز، وهو تقنية ذكاء اصطناعي فعالة، لتحسين أداء محطات الضخ. أما في المرحلة الثانية، فقد تم تطبيق خوارزميةCMA-ES ، وهي طريقة استدلالية قوية وقابلة للتكيف للتحسين المستمر. تلي ذلك مرحلة البحث التصاعدي الجشع بهدف تصحيح انتهاكات الضغط. وأخيرًا، تم اعتماد مرحلة البحث التنازلي الجشع لتقليل أحجام الأنابيب الكبيرة. تم تطبيق المنهجية الهجينة على عدة دراسات حالة لشبكات توزيع المياه لتقييم كفاءتها. وقد أظهرت النتائج أن الإطار الجديد يتفوق على الخوارزميات المستخدمة سابقًا من حيث سرعة التحسين وتكلفة الشبكة في معظم معايير التقييم.

الكلمات المفتاحية: شبكة توزيع المياه، التعلم المعزز، خوارزمية CMA-ES، خوارزمية البحث الجشع التصاعدي، خوارزمية البحث الجشع التنازلي.

1. Introduction

Amid the convergence of increasing population figures, changing climate patterns, rapid urban growth, and rising environmental deterioration, the world stage is witnessing the rise of complex water concerns. Countries, particularly those with advanced water infrastructure, must reevaluate their management techniques and infrastructure capabilities to handle the anticipated increase in water demands. Conventional methods of managing water resources typically focus on cost and quantity. However, to achieve the best and long-lasting distribution of water, it is essential to adopt a holistic strategy that considers all parties involved and recognizes the interdependence of essential resources. This comprehensive approach must include the expenses related to energy and food production, as well as the environmental effects, in acknowledgment of the complex network of resource interconnections. In addition, factors such as increasing population, changing climatic patterns, expanding metropolitan areas, and growing energy demands emphasize the necessity for complex decision-making frameworks. Therefore, it is crucial to carefully analyze the compromises involved in water management in order to promote sustainable resource conservation in the face of the increasing water shortage, both now and in the future (KULAT, 2017).

The current worldwide scenario is characterized by the interconnected influences of population growth and economic development, which have greatly increased the need for sufficient, uncontaminated, and secure water supplies. The increasing demand for water presents a difficult challenge to current policies, strategies, frameworks, and initiatives for managing water resources and developing infrastructure on a global scale. This dilemma is particularly severe in regions that are dealing with water scarcity worsened by causes like climate change (V. A. Tzanakakis, 2020).

The Middle East and North African (MENA) region is known for its dry or semi-arid environments, resulting in substantial water scarcity. The shortage, which is especially widespread in the Middle East, has a vital role in determining regional stability and is an essential factor in promoting economic growth and prosperity (Al-Ansari N. A., 2013).

An illustrative instance can be observed in Iraq, where the consequences of drought caused by climate change are significant, worsening the already present problems of water scarcity. Due to its high susceptibility to water scarcity, Iraq is currently at a crucial point where the combination of population expansion, economic activities, and environmental pressures are causing an increased demand for water resources. In Iraq, the drinking, agriculture, and industrial sectors are the main stakeholders that depend heavily on the supply of water. As a result, they are ready to experience the full impact of the negative consequences of climate change on water supplies. Iraq is currently facing the predicament of reduced water flow in the Euphrates River as a result of the construction of dams by Syria and Turkey along the Euphrates and Tigris Rivers. The decrease in flow is a substantial challenge for Iraq's water resources (Al-Ansari N. , 2011). The construction of these dams in Iraq has resulted in a decrease in both the quantity and quality of its water, posing a significant challenge for the country (Ammar Hatem Kamel, 2013). This information raised additional concerns about future water allocations and their worrying implications for national security and policies.

2. Previous studies

Few studies have concentrated on employing hybrid approaches, such as reinforcement learning, even if earlier research has improved utilizing evolutionary algorithms. The goal of this study is to create a more effective model that offers better solutions for water networks by fusing the CMA-ES algorithm with clever search strategies.

1. Optimal Cost Design of the Water Distribution Network for Jableh City Using Genetic Algorithm and Harmony Search Algorithm.

In this study, the drinking water network in the city of Jableh was designed using the harmonic search algorithm (Harmony Search) and the genetic algorithm (Genetic Algorithm). The goal of the study was to come up with the best possible design that would save expenses while yet meeting hydraulic criteria (2020 ,د. هناء سلمان).

2. Optimal Solution for Drinking Water Distribution Systems Using Genetic Algorithms.

In order to develop economical and effective designs, this study uses the Darwin Designer technique to apply genetic algorithms to determine the best solution for drinking water distribution networks (2012 ,خليفة).

3. Evolutionary Machine Learning: Machine Learning Models Optimized and Trained Using Genetic Algorithms.

Genetic algorithms have been extensively employed to optimize machine learning models (Albu-Salih, 2023). Moreover, their applications have extended to various engineering domains, including water distribution network design.

4. Hybrid Genetic Algorithm for Optimal Design of Water Distribution Networks.

In order to achieve optimal water distribution network design with an emphasis on cost reduction and efficiency, this study proposes a hybrid framework that incorporates genetic algorithms and other methods (Edward Keedwell, 2005).

5. Genetic Algorithm for Optimization of Water Distribution Systems.

Focuses on enhancing water distribution network design through the application of genetic algorithms. While making sure that hydraulic requirements, like water pressure in pipes, are satisfied, this study uses genetic algorithms to save costs and achieve the optimal water distribution within a given network (Khanna, 1999).

3. Methodology

3.1 Reinforcement learning

The term "reinforcement learning" is commonly used by researchers in artificial intelligence and engineering to refer to a particular approach to learning tasks and the algorithms developed for them. Reinforcement learning is based on the principle of reinforcement, which involves the idea that activities leading to favorable outcomes or progress in the current state are more likely to be repeated. This concept forms the basis for the most straightforward approaches in reinforcement learning. This concept embodies the fundamental principles of reinforcement learning, highlighting the process of enhancing or fortifying activities based on their outcomes, resembling how living organisms, including humans, acquire knowledge from past events and adjust their behaviors accordingly. Reinforcement learning is a framework that allows computers to learn and make decisions independently. This is achieved by having the machines interact with their environment and learn from the results of their actions in an iterative manner (Barto, 1997).

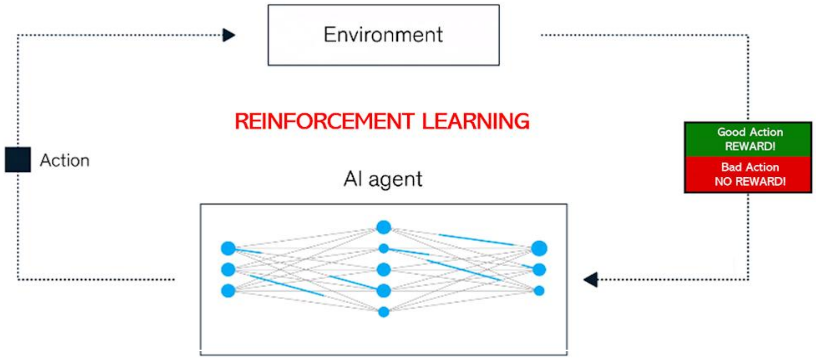

Figure (1): Reinforcement learning

One of the uses of Reinforcement Learning is in the water sector, where Reinforcement Learning (RL), specifically Deep Reinforcement Learning (DRL), has great potential in tackling urgent water distribution issues like Water Scarcity. Due to water scarcity impacting billions of people worldwide and an expected 40% increase in demand by 2030, conventional water conservation methods are proving unsustainable and jeopardizing clean water supply. Deep Reinforcement Learning (DRL) is a promising approach that utilizes advanced neural networks to address complicated challenges in the real world. It can learn from past experiences and is particularly effective in optimizing water management in urban water systems. As the study in this field grows, DRL algorithms integrated with computational techniques provide opportunities to overcome obstacles and enhance outcomes, indicating a possible revolution in water distribution networks (Ahmed Negm, 2024).

3.2 Artificial Neural Networks (ANNs) and Their Mechanism

Computational models known as artificial neural networks (ANN) are modeled after the composition and operation of biological neural networks seen in the human brain. They are extensively employed in many different applications, such as forecasting, data classification, pattern detection, and decision-making. ANN is capable of intelligent prediction, complicated pattern recognition, and data learning.

Artificial Neural Networks (ANN) function by simulating the information processing capabilities of the human brain. They are made up of interconnected layers of neurons that use activation functions and weighted connections to change incoming data. Data enters the network through the "input layer" at the start of the operation. After that, it moves via "hidden layers", where neurons use "activation functions" (like Sigmoid or ReLU) to make mathematical modifications. The "output layer" is where the final output is created. The network uses "backpropagation" to modify its weights during training, reducing mistakes via methods like Gradient Descent. An essential part of artificial intelligence, ANN is utilized extensively in image identification, financial forecasting, and medical diagnostics.

3.3 Artificial Neural Network Structure

Multiple layers of interconnected nodes, or neurons, make up an ANN. Each layer processes incoming data in a different way. In an ANN, the main layers are:

1. Input Layer: External sources provide raw data to this layer. A feature of the input data is represented by each neuron in the input layer.

2. Hidden Layers: These layers employ activation functions and carry out weighted calculations to process the input data. The capacity of the model to learn intricate patterns is determined by the quantity of hidden layers and neurons.
3. Output Layer: Using the data that has been analyzed, this layer generates the final classification or prediction.

ANN's Operational Mechanism is weighted connections between linked neurons allow ANNs to transmit signals (Abraham, 2005).

3.3.1 Enhancing Pumping Stations and Water Distribution Networks Using ANN

Because they optimize operations, lower energy usage, and guarantee effective water delivery, artificial neural networks, or ANNs, are essential for enhancing the performance of pumping stations and water distribution networks.

1. Enhancing the Efficiency of Pumping Stations:

In order to identify trends and inefficiencies, ANNs examine operational data in real time, including pump efficiency, flow rates, pressure levels, and energy use. By forecasting ideal operating circumstances, the network modifies pump schedules and speeds to save energy consumption and preserve sufficient water pressure. Predictive maintenance techniques that lower downtime and repair costs are made possible by ANNs' ability to recognize possible failures or performance degradation using past data.

Artificial neural networks, or ANNs, are crucial for improving the efficiency of pumping stations and water distribution networks because they maximize operations, reduce energy consumption, and ensure efficient water delivery.

2. Improving Water Distribution Networks:

In order to reduce leaks and pressure losses, ANNs help optimize the network's water pressure and flow distribution. Better resource allocation is made possible by ANNs' ability to predict seasonal variations in water demand by combining environmental factors and satellite data.

Real-time control systems are supported by ANN models, which dynamically modify pumping stations and valves to effectively meet changing water demands.

These uses of ANN-based optimization guarantee intelligent, sustainable, and reasonably priced water management solutions for contemporary water distribution systems.

3.4 Hybrid algorithm

The proposed hybrid algorithm depends mainly on the CMA-ES. The three main processes of CMA-ES are recombination, mutation, and selection. While the operator of selection is used for selection, recombination and mutation are used for search space exploration and the creation of genetic variants. Taking advantage of and arriving at the best answer. In CMA-ES, a multivariate Gaussian distribution is used, and the mutation operator is important. A comprehensive elucidation of several selection operators is exposed in (SCHWEFEL, 2002). As a deep local search that is equipped with a self-adaptive method for selecting an appropriate vector of mutation step sizes (σ) rather than having only one global mutation step size, CMA-ES can, in fact, be a good candidate for investigation and exploitation. This is due to the fact that tackling high-dimensional problems with a single step size is inefficient. Acceptable convergence speeds and diversity are produced by applying a multivariate Gaussian distribution with the appropriate σ and mean sizes (Nikolaus Hansen S. K., 2004).

Based on the variations in the mean values of two sequential generations, the covariance matrix is calculated. In that instance, it anticipates that there will be enough data in the present population to estimate the correlations favorably. In order to expand the multivariate Gaussian distribution in the proper direction toward the global optimum, the rotation matrix will be derived from the covariance matrix after it has been calculated. In order to obtain an orthogonal basis for the matrix, it can be achieved by performing an eigen-decomposition of the covariance matrix (Nikolaus Hansen A. A., 2014). The initial stage involves applying a CMA-ES, which plays a crucial function. The CMAES is a self-adaptive stochastic approach whose performance can be competitive when the fitness functions are nonlinear or non-convex. Covariance matrix adaptation that is restricted into a multivariate normal distribution cooperates well with the CMA-ES. The covariance matrix adaptation serves as a means of approximating the inverse Hessian matrix, similarly to a quasi-Newton approach applied to the covariance matrix.

The main purpose of the second portion of the suggested hybrid architecture is to engage in two distinct direct search strategies for altering the CMA-ES outcomes, notwithstanding the discrete pipe sizes of the networks. When compared to other EAs, CMA-ES can identify extremely inexpensive network design configurations; nevertheless, these inexpensive suggested layouts are impractical due to nodal pressure head restrictions. Thus, an Upward Greedy Search technique contributes to the CMA-ES in order to compensate for the issue. By increasing the discrete size of pipe diameters based on a greedy selection of those solutions with the largest reduction in the sum of pressure violations for the least amount of money, the Upward Greedy Search increases the amount of the CMA-ES achieved solutions that are not feasible and pushes the infeasible layouts toward the feasible area. Notwithstanding all of Upward Greedy Search's advantages, occasionally it's suggested fixes need to be improved due to avaricious selection behaviors that disregard the circumstances of the past or the future. In order to lower the additional cost of some of the produced solutions, a third phase is proposed. This section consists of an additional Greedy Search concept. A downward greedy search is the concept behind the third part of the hybrid framework. The Downward Greedy Search's primary goal is to smooth the pipe cost in relation to the limitations by gradually reducing each pipe's diameter. Stated differently, the Downward Greedy Search algorithm seeks enhancements that result in the lowest number of pressure violations while achieving the greatest possible pipe cost reduction.

3.5 Model Inputs

Important inputs for effective decision-making in water distribution networks will be incorporated into the model. These inputs include network pressure levels, pumping station performance, and daily water consumption data. The Ministry of Water Resources' records, which provide comprehensive details of water use trends and pumping station operations, are among the reliable sources from which data for these inputs are collected. The model's ability to optimize water distribution in real time will also be enhanced by incorporating satellite data, such as those from Landsat7 or Landsat8, which will provide temporal and spatial insights into environmental conditions and water availability.

4. Results and Discussions

The first phase of our system is the reinforcement learning algorithm for the pump stations where it decreases power usage and water waste, we tested the system figure (2) by running a simulation with simulation time of 7 days. The water demand during the simulation can be seen in figure (3), and figure (4) shows the performance differences between a schedule system for the water station and the reinforcement learning model where we can see that the model performs better than scheduling because it can adapt to the changes in water demand.

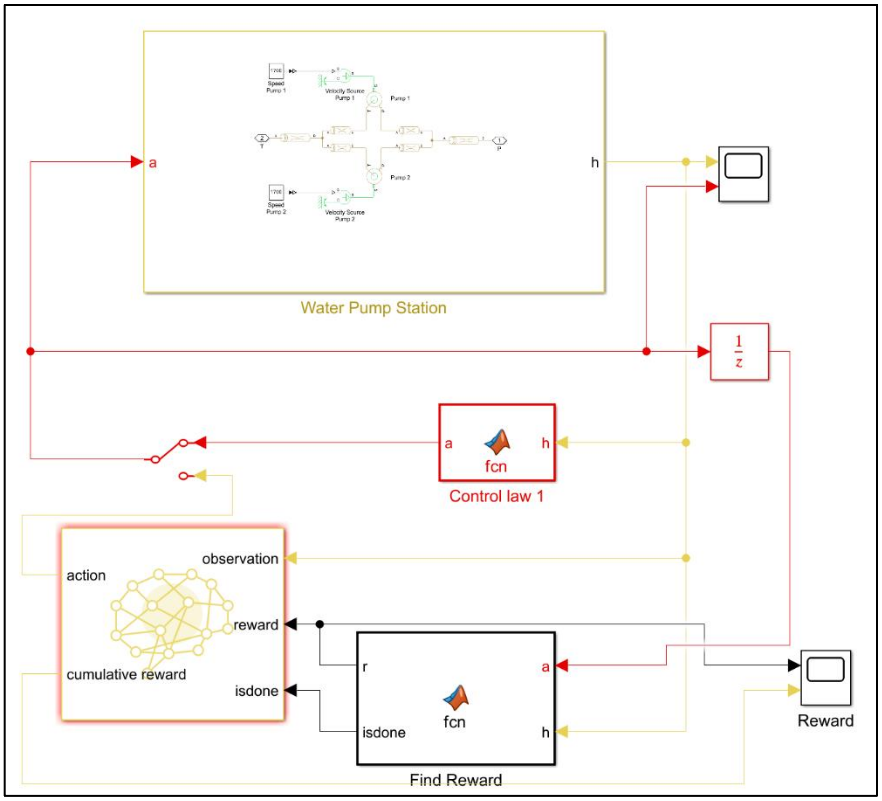

Figure (2): the reinforcement learning algorithm for the pump stations

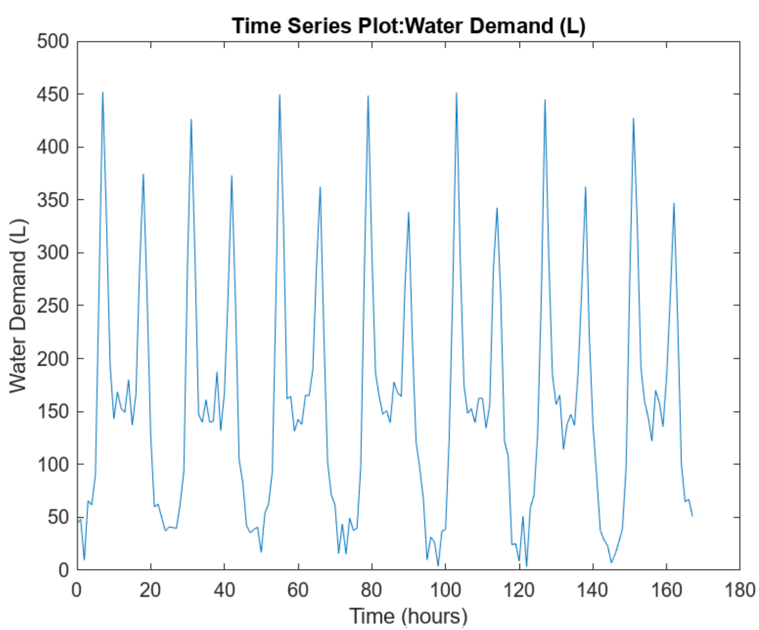

Figure (3): the results of the simulation

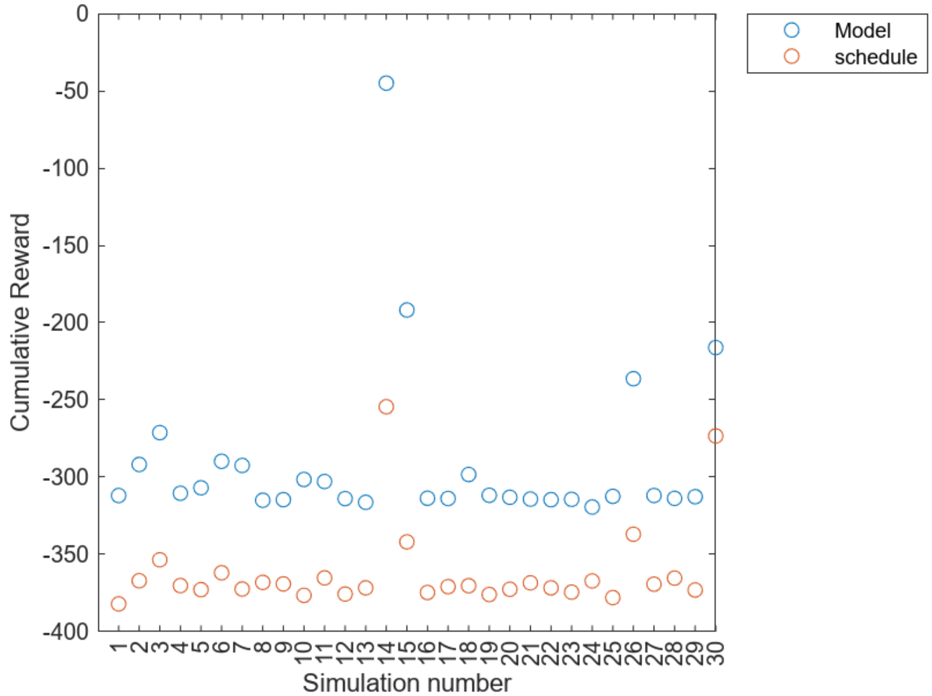

Figure (4): the results of the simulation

As for the second phase two well-known case studies of water distribution networks—the Balerma Network (BN) (Juan Reca, 2006) and the New York Tunnels (50NYTP) (Feifei Zheng, 2011) —have been used to assess the efficacy of the suggested hybrid structure. Table (1) displays the case studies' specifics.

Table (1): Studies specifics.

Network	Variables	Options	Nodes	Space size
NYTP50	1050	16	1000	2.12×10^{1264}
BN	454	10	447	10^{454}

4.1 Case Study One: 50NYTP

One tank connects fifty individualized NYTP in terms of hydraulical equations that make up the NYTP50 (Feifei Zheng, 2011). With the same design options as the original NYTP, this issue can serve as a large-scale optimization benchmark with a decision variable number of 50 × 21. The most well-known design cost comes to $1932 million. Table (2) illustrates that, using our suggested algorithm of ten independent runs with a uniform random scenario for initializing the choice variables and a population size of 500, the best and average founded design costs are $2021(M) and $2030(M). These somewhat near-optimal designs outperform the 50NYTP designs from (Feifei Zheng, 2011) by a significant margin. Comparing the suggested hybrid method to earlier optimization techniques and the decision variable length, it can appropriately explore a large search space in a small number of repetitions.

Table (2): proposed method vs older method on the NYTP50

algorithm	No. of runs	Best sol.($ M)	Avg Cost ($ M)	Max no. of evaluations
GA[12]	100	2238	2321	40.0×10^6
Proposed method	20	2021	2030	1.0×10^6

4.2 Case Study Two: BN

The Balerma Network (BN), an irrigation WDS founded in the Spanish region of Almeria, is the subject of the second case study (Juan Reca, 2006). Four reservoirs, 454 pipes, eight loops, and 443 demand nodes make up its parts. Ten PVC commercial pipes in diameters ranging from 125 to 600 mm are available. Consequently, the search space is 10454, classed as a large-scale optimization issue, and is significantly larger than the preceding three case examples in this work. A minimum of 20 m of nodal pressure is needed. Additional information and pipe costs are provided in the reference (Juan Reca, 2006). Zheng et al. have shown that the BN's present optimal configuration is located at 1.923 million. The DE and nonlinear programming are combined to create this functional design (NLP-DE). The average performance of the suggested hybrid framework is unquestionably superior to all earlier approaches in terms of quality, efficiency, and convergence rate, as shown by the findings from Table 3. At 1.894 million, the proposed solution is less expensive.

Table (3): The findings of the average performance of the suggested hybrid framework.

Algorithm	Number of runs	Best solution ($M)	Success rate(%)	Average Cost ($M)	Avg evaluations	Max no of evaluations
HS [12]	NA	2.018	0.0%	NA	10.00×10^6	10.0×10^6
GAs [13]	10	2.061	0.0%	NA	NA	2.00×10^6
CS [14]	10	2.036	0.0%	2.079	4.50×10^6	5.0×10^6
HD-DDS-2 [15]	10	1.956	0.0%	NA	30.00×10^6	10.0×10^6
DE3 [16]	10	1.982	0.0%	1.986	9.21×10^6	10.0×10^6
SADE [17]	10	1.983	0.0%	1.995	1.20×10^6	1.3×10^6
CSHS [14]	10	1.988	0.0%	2.031	3.00×10^6	5.0×10^6
DE [17]	10	1.998	0.0%	2.031	2.30×10^6	2.4×10^6
GENOME [11]	10	2.302	0.0%	2.334	10.00×10^6	10.0×10^6
NLP-DE2 [16]	10	1.923	10.0%	1.927	1.428×10^6	2.0×10^6
HD-DDS-1 [15]	1	1.941	0.0%	NA	30.00×10^6	30.0×10^6
NLP-DE1 [16]	10	1.956	0.0%	1.957	4.12×10^3	1.0×10^6
GHEST[18]	10	2.002	0.0%	2.055	0.25×10^6	10.0×10^6
Proposed	10	1.894	0.0%	1.900	0.84×10^6	2×10^6

Table (3)'s results show that, aside from the exceptional BN designs discovered by the CMA-ES (Continuous), average discrete best-founded BN designs outperform the current techniques. Sixty percent of the computational cost is saved. This feature shows how well the CMAES-GSU and CMAES-GSU -GSD approaches can be used, and it also shows that the suggested optimization framework can find decent quality solutions with much increased computational effectiveness when dealing with large-scale WDS. It is observed that Table (3) shows that the suggested hybrid framework is unable to defeat the NLP-DE2.

It is evident that, as compared to all previous approaches with smaller computational budgets, the suggested hybrid method achievements are positioned within overall lower cost BN architectures. Meanwhile, when the best solution cost (near-optimum) is $1.961 million and the average evaluation number is just 0.56 × 106, the discrete CMA-ES is ranked greatest in terms of convergence speed. It is true that the discrete CMA-ES's suggested solutions are not of the highest quality, but they can converge to semi-optimal solutions 18, 8, 18, and 16 times quicker than the HS, CS, GENOME, and DE3, in that order.

5. Conclusions

This study presents a novel hybrid evolutionary framework for networks of water delivery. The proposed structure is divided into four separate phases, each of which adds to the process's overall efficacy and efficiency. The first phase's application of reinforcement learning shows how it can improve pump station performance and cut down on water waste and power consumption. This novel method shows promise in resolving pressing water distribution problems like water scarcity, especially when paired with deep reinforcement learning. Subsequently, the CMA-ES algorithm is integrated, which successfully explores the search space and produces near-optimal solutions, further improving the optimization process. Because of its adaptive characteristics, CMA-ES can effectively handle challenging, high-dimensional optimization issues, which makes it an important part of the system. Later stages of the framework's implementation of upward and downward greedy search algorithms help to improve the CMA-ES solutions, especially when it comes to minimizing pipe sizes and handling pressure violations. The suggested ideas' cost-effectiveness and viability are enhanced by these extra search techniques. The hybrid framework's superiority over conventional heuristics and optimization techniques in terms of optimization speed and network cost is demonstrated by the examination of the framework through several case studies. The obtained results demonstrate the suggested framework's capability to address practical issues in water distribution network design, particularly in areas with limited infrastructure and water availability.

Essentially, this study establishes the foundation for creating novel approaches to tackle the intricate dynamics of managing water resources, emphasizing the promotion of sustainability, effectiveness, and fair allocation of water resources. The suggested hybrid framework presents a viable way to address the various demands of communities and industry in the present and the future while also optimizing water distribution networks by utilizing developments in artificial intelligence and evolutionary algorithms

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