

Assessment of the differential evolution method for control of multiple-sources water supply system – case study

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Abstract. This study demonstrates the use of the differential evolution method for optimizing multi-source water supply systems. The objective was to identify a water-supply scenario that minimizes the total water-supply costs in multiple sources network. The analysis assumed varying water-production costs at each source, with control implemented through the adjustment of valve settings at the network inlets. For the research, open-source tools such as EPANET, the WNTR library, and Python's `scipy.optimize` package, were utilized. The analyses were conducted on two water distribution networks. The first was a simplified network with three water sources, designed to validate the simulation environment and perform initial assessments of the optimization algorithms, whereas the second was a complex model representing a real water distribution network. Analyses were conducted for the latter assuming three, four, five, and six sources. For both networks, multiple pricing scenarios were evaluated to explore how different conditions impact the performance of the algorithm. The results show that near-optimal solutions can be achieved with significantly reduced computation times. The differences in objective function values between the brute force and differential evolution (DE) methods were no greater than 0.2%, while the computation time for DE was substantially shorter. These findings highlight DE scalability, efficiency, and potential for real-world applications, promoting cost-effective and accessible optimization in engineering practice.

Keywords: water distribution network modeling and optimization; differential evolution; WNTR; EPANET; multisource water distribution network.

1. INTRODUCTION

A water supply system is an infrastructure network designed to provide a consistent and reliable supply of water to meet the needs of residential, industrial, agricultural, and commercial users. The primary objective of a water supply system is to consistently and reliably deliver water of adequate quality and pressure to meet consumer demands. The system includes an intake to extract water, treatment facilities to ensure it meets quality standards, reservoirs to manage supply and demand fluctuations, and distribution networks. Enhancing the efficiency of water supply networks through optimization techniques presents a multifaceted approach that addresses both design and operational challenges [1]. At first, these approaches relied on methods based on deterministic principles, e.g., linear programming gradient [2]. Over the years, evolutionary algorithms (EAs) have gained popularity for tackling various optimization issues in water resource management, including engineering design and management [3]. Among these techniques, genetic algorithms (GAs) are notable for their foundation in population genetics, applying mechanisms such as mutation and gene recombination to evolve effective solutions [4]. Evolutionary algorithms are

widely used in the optimization of water distribution networks due to their flexibility and efficiency. They excel at handling nonlinear relationships, e.g., repair sequence [5]. These algorithms can be integrated with existing simulation models, providing a natural extension to traditional optimization methods and allowing for the exploration of a wide range of potential solutions [6]. The differential evolution (DE) method distinguishes itself through its simplicity, robustness, and ability to manage nonlinear, multi-modal optimization problems effectively. Unlike GA, which relies on complex mechanisms such as crossover and mutation to explore the search space, DE uses a straightforward strategy of differential mutation and recombination. This allows DE to maintain a balance between exploration and exploitation, leading to faster convergence without premature stagnation. DE was used for minimizing the cost of network construction while ensuring meeting hydraulic constraints, such as pressure and flow requirements [7]. The hybrid approach that combines the DE method to solve the optimal design problem of water distribution systems with particle swarm optimization (PSO) [8] or nonlinear programming (NLP) [9] was described in the literature. The number of problems and methods for optimization is vast, covering a wide range of applications and yielding varying results [10]. In the comparative study, the authors reported that DE variants consistently produced higher-quality solutions while requiring fewer iterations than the GA, essentially demonstrating the superior efficiency and effectiveness

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of DE in this context [11]. Despite these advantages, existing evidence is not yet sufficient to declare DE universally superior to classical evolutionary algorithms. Although DE typically converges faster than conventional GAs, it does not inherently guarantee the discovery of the global optimum. DE can prematurely settle on nonoptimal solutions and may stagnate when the search landscape contains many local minima [12]. DE appears particularly appropriate for problems whose objective functions exhibit few local minima, thereby reducing the likelihood of converging to suboptimal points.

A water supply system for large urban centers often incorporates multiple water sources and treatment plants to meet the diverse and high-volume demands of the population. These intake sources may include surface or groundwater aquifers. This multi-source and multi-plant approach enhances system resilience, allowing for redundancy in case of source contamination, infrastructure maintenance, or emergency scenarios [13]. The use of multiple water sources and treatment plants within a single water supply system presents significant challenges in management and control, both for the needs of cities and industry. Selecting which sources to utilize and determining the quantities to supply the distribution network requires careful consideration of several dynamic factors [14]. These complexities are compounded by the need to balance economic efficiency with strict water quality and reliability requirements. A key challenge in managing multisource water supply systems is the allocation of water extraction, determining the optimal volume to be pumped from each source.

These sources often differ significantly in terms of resource availability, water quality, and the associated costs of extraction, treatment, and distribution. Sustainable operation of the system requires finding optimal variables. The development of control algorithms for managing multi-source water supply systems must be guided by specific criteria that reflect the operational goals and priorities of the system. These criteria can be classified as economic and quality-based, each addressing distinct aspects of the system. Optimization methods allow for simultaneous evaluation of cost and quality, enabling decision-makers to identify trade-offs and determine the optimal allocation of water sources under varying conditions. The issues identified pose a crucial research challenge at present. Research findings using various optimization techniques are presented, including a search method that incorporates the concepts of local search [15]. The field of water distribution system optimization has seen significant advancements through the application of DE methods. Recent studies highlight various innovative approaches to tackle the complexities associated with multiple sources in water supply systems. Studies of DE for water supply systems show that applications such as decomposition and a multistage optimization approach improve both efficiency and solution quality in water distribution systems optimization [16]. In addition to the use of standard DE, modified methods such as self-adaptive differential evolution (SADE) have emerged [17].

While the advancements in DE methods for water supply systems are significant, ensuring the adaptability and scalability of these algorithms in real-world applications remains a challenge. Water supply systems that rely on multiple sources continue

to struggle with ensuring reliable distribution while minimizing costs. Although numerous tools for network optimization have already been developed, there remains a need for further research that incorporates new optimization methods. Traditionally, most existing tools rely on genetic algorithms. This study is based on the premise that differential evolution can also serve this purpose effectively. However, one of the key issues with current approaches is their limited transparency, particularly when commercial software is involved. Existing studies in this field often fail to provide full details of the optimization tools used, frequently relying on proprietary software that may not be accessible to all researchers or utilities. In contrast, the main advantage of the proposed approach is its exclusive reliance on open-source solutions. A fully open and transparent computational environment is proposed (based on EPANET, WNTR, and Python software), enabling complete reproducibility of the results. This also allows the presented workflow to be rigorously benchmarked against alternative methods.

The main aim of this article is to demonstrate the usefulness of the differential evaluation method in supporting the management of multi-source water distribution networks. For the purposes of research, open-source software packages were used as an accessible alternative for optimizing and improving both efficiency and sustainability. This decision reflects the objective of ensuring methodological transparency and accessibility without licensing constraints. While commercial systems may offer alternative or more advanced optimization workflows, their closed-source nature prevents direct methodological inspection and broader open-science dissemination.

2. RESEARCH METHODOLOGY

2.1. Modeling water distribution systems

Computer hydraulic modeling of water networks is based on representing the operational states of water supply networks under specified boundary conditions. It enables the evaluation and comparison of various operational scenarios by simulating the behavior of individual components and the overall system. Components of a water supply network are represented in models to reflect their hydraulic and physical properties:

- Pipes/Pipelines, which are modeled to calculate water flows and pressure losses, considering factors such as pipe diameter, length, and roughness.
- Junctions/Nodes, where water demand or extraction is specified, often vary over time and therefore require representation in discrete time steps.
- Tanks/Reservoirs, which serve as boundary conditions by specifying water levels that influence flow distribution and system stability.
- Pumps, whose operational characteristics, such as lifting height and flow rates, are described using performance curves to increase pressure.
- Valves, which control flow resistance and are used to regulate pressure or limit flow within specific sections of the network.

The mathematical models for water supply networks are based on fundamental principles of mass and energy conservation.

The mass conservation principle states that the total water inflow equals the outflow minus the water extracted at nodes. The energy conservation principle relates to pressure loss between nodes, expressed through a loss coefficient dependent on flow. These principles form the basis for nonlinear equations in water distribution models, which are solved using numerical methods, e.g., through EPANET software, developed by the US EPA, which is a widely used, open-source tool for water network modeling.

2.2. Optimization problem

The economic aspect of water supply control focuses on minimizing operational costs while meeting system demands. The core principle is to prioritize water extraction from the least expensive sources, thereby reducing the reliance on more costly sources. Key factors influencing the economic criteria include:

- **Energy costs:** The cost of pumping water is a significant operational expense, determined by factors such as pump efficiency, the height of the water head, and the distance to the distribution network. Sources located closer to the water consumer or requiring less energy for pressure are generally prioritized.
- **Treatment costs:** If raw water from a particular source requires extensive treatment to meet quality standards, this adds to the operational costs. Conversely, sources with naturally high-quality water that require minimal treatment are more economical to utilize.
- **Fixed and variable costs:** Agreements with external suppliers often involve fixed charges (e.g., infrastructure or standby fees) and variable costs based on the volume of water extracted. Efficient scheduling can reduce the reliance on high-cost suppliers, thereby lowering the overall cost.

Using economic criteria, control algorithms should aim to dynamically adjust the allocation of water sources to ensure that the cheapest feasible options are prioritized while still meeting demand and maintaining operational constraints. The economic aspect of water supply control is simplified by reducing the operational costs of each source to a single, average unit cost of water. This approach allows for the evaluation of sources based on their relative cost-effectiveness while meeting system demands.

The objective of the control system is to determine pressure on the system boundary (model boundary condition). For the modeling purposes, the pressure on the system boundary is set to be the valve Z_i (value of throttling is determined – mH₂O). The cost function is to maximize the utilization of water from the most cost-effective sources and minimize reliance on the more expensive ones, while ensuring compliance with all operational and system constraints. The objective function can be formulated as follows:

$$\min \left(CT = \sum C_i Q_i \right), \quad (1)$$

where CT – total cost [PLN], C_i – cost per unit of water from the i -th source (aggregated total costs of producing, pumping, and treating groundwater) [PLN/m³], Q_i – the quantity of water extracted from the i -th source [m³], where $Q_i = f(Z_i)$.

The primary objective of a water distribution system is to ensure a reliable and continuous supply of water. The supply ability of the network is commonly assessed through the pressure maintained at individual nodes, which must remain above the required minimum threshold. Pressure values are computed using the EPANET hydraulic simulation engine and arise directly from the hydraulic characteristics and operational conditions of the water distribution system. In the context of formulating the optimization problem, nodal pressure is treated as a fundamental constraint that the optimization process must satisfy. This condition is expressed as:

$$H_i > H_{\min}, \quad (2)$$

where H_i – pressure in each node [mH₂O], H_{\min} – minimal required water pressure [mH₂O].

In practice, this condition is influenced by multiple factors, including pipe friction losses, flow rates, and the performance of pumps and valves. The calculation of H_i at each node is derived in the model from the application of energy conservation principles across the network, incorporating terms for head loss and elevation head.

The cost function was evaluated for a single time step (daily average). In practical applications, however, this type of analysis can be extended to any time horizon by applying an appropriate demand pattern.

2.3. Differential evolution method

Differential evolution is a heuristic optimization method that iteratively refines a population of candidate solutions based on mutation, crossover, and selection operations. It is well-suited for nonlinear, nondifferentiable, and multi-modal optimization problems, such as those met in water distribution networks. DE achieves its effectiveness in addressing complex optimization problems through the following steps (Fig. 1) [18]:

- **Population initialization:** The process starts with an initial group of candidate solutions, known as the population. Candidates represent different possibilities across the search space and act as the starting point for algorithm exploration.
- **Mutation:** The algorithm introduces variation by combining elements from randomly selected candidates in the population. This generates a new solution, called the mutant vector, which is crucial for maintaining diversity and exploring unexplored areas of the search space.
- **Crossover:** The mutant vector is then blended with the current solution, referred to as the target vector. This step produces the trial vector, a new candidate that mixes useful characteristics from both, striking a balance between keeping strong traits and introducing beneficial changes.
- **Selection:** Here, the algorithm compares the trial vector with the target vector to determine which performs better according to the objective function. The trial vector replaces the target vector in the population if it shows improvement, thereby ensuring that only the most promising candidates move forward.
- **Termination criteria:** The algorithm stops once certain conditions are met, for example, finishing a fixed number

of iterations or reaching a satisfactory solution. These criteria help to balance between exhaustive exploration and computational efficiency.

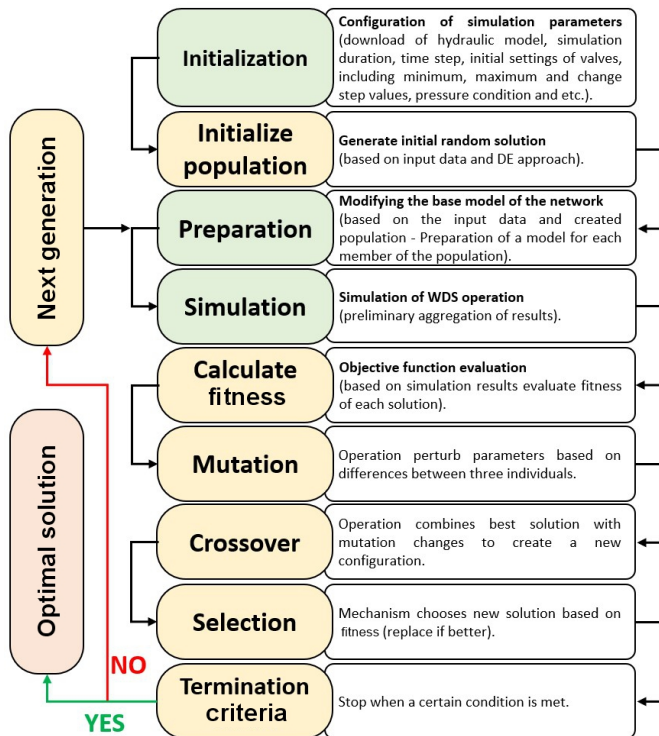


Fig. 1. The algorithmic workflow of the differential evolution

Iterative nature of DE is essential to its capacity to tackle intricate optimization issues. The algorithm continuously enhances the population of potential solutions by iterative mutation, crossover, and selection. Every iteration advances the work of earlier iterations while striking a balance between using promising regions of the solution space and investigating novel options. Over time, this iterative procedure improves the caliber of solutions and makes it possible for DE to successfully adjust to the difficulties presented by the issue, guaranteeing stable and dependable optimization performance.

For the purpose of research, distribution network models were developed using EPANET. For numerical calculations, the Python programming language was utilized in conjunction with the Water Network Tool for Resilience (WNTR), a library designed to extend EPANET's functionalities. WNTR facilitates dynamic simulation of network hydraulics, resilience analysis, and integration with optimization algorithms. Its modular design and Python compatibility make it highly suitable for conducting detailed and customized studies on water distribution networks.

To address the optimization problem, two algorithms were implemented to minimize the objective function, which aimed to balance operational costs and system constraints. The first method was the brute force approach, where all possible valve settings were systematically evaluated to identify the optimal solution. While brute force guarantees finding the global optimum, it is computationally expensive and impractical for large-scale networks due to the exponential growth of the search space. Re-

sults serve as a valuable baseline for verifying the accuracy of results from nondeterministic optimization algorithms.

The second approach employed the differential evolution (DE) algorithm, implemented via the `scipy.optimize.differential_evolution`. The algorithm was configured using the following control parameters:

- Strategy ("best1bin") uses the current best solution plus the scaled difference of two random population members to generate a new candidate, then applies binomial crossover. It converges quickly but may get trapped in local minima.
- Maxiter ("1000") means the maximum number of generations over which the entire population has evolved.
- Popsiz ("15") is a multiplier for setting the total population size.
- Tol ("0.05") is stopping tolerance, which prevents unnecessary computational cost at the expense of fine-tuning in the final stage. Increasing the number of iterations or decreasing the tolerance reduces this gap but significantly increases computation time.
- Mutation ("0.5-1") is differential weight F . Specifying an interval makes the algorithm draw F uniformly from 0.5 to 1.0 in each generation. This adaptive choice improves robustness and reduces the risk of premature convergence.

The crossover operation is determined by the selected strategy. For "best1bin", the selected solution applies binomial crossover with a default probability of $CR = 0.7$. This value aligns with standard recommendations in the DE literature, and preliminary sensitivity tests in this study showed stable convergence without noticeable gains from further tuning [19].

To improve methodological transparency and facilitate reproducibility, Algorithm 1 provides a structured pseudocode representation of the complete optimization workflow. It summarizes how EPANET/WNTR hydraulic simulations are integrated with the differential evolution algorithm, including constraint handling and cost evaluation.

Both approaches were evaluated for their effectiveness in solving the optimization problem under the configurations and constraints of the same network. To explore the problem of supplying a water distribution network from multiple sources, the cases and scenarios described below were analyzed. All simulations were performed on a Lenovo V14 machine with a processor: i7-1355U, SSD: 500GB, RAM: 64GB, Windows 11 Pro.

Algorithm 1. Differential evolution-based optimization of a multisource water supply system

Input: EPANET input file (.inp), costs of water C_i for each source I , minimum required pressure H_{min} , bounds for valve settings $Z_i \in [Z_{min}, Z_{max}]$, DE parameters: strategy, popsize, maxiter, $F \in [0.5, 1.0]$, $CR = 0.7$, tol, penalty coefficient α .

Output: Z^* – optimal valve settings, CT^* – minimum total water supply cost

1: Load the EPANET network model into Python and WNTR

2: Define objective function $f(Z)$:

3: Apply valve settings Z (PBV pressure losses) to the model

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4: Run hydraulic simulation using WNTR
 5: Extract pressures H_i and source inflows Q_i
 6: Compute total cost: $CT = \sum (C_i * Q_i)$
 7: If any pressure constraint is violated ($H_i < H_{min}$):
 8: $\Delta H = \max(H_{min} - H_i)$
 9: $CT = CT + \alpha * \Delta H$ # penalty
 10: Return CT
 11: Initialize DE population:
 12: Create $NP = \text{popsize} * D$ candidate vectors inside bounds
 13: For iter = 1 to maxiter:
 14: For each candidate Z_k in the population:
 15: Select three distinct individuals, Z_a, Z_b, Z_c # Mutation step
 16: Draw F uniformly from $[0.5, 1.0]$
 17: $V = Z_a + F * (Z_b - Z_c)$
 18: For each dimension $j = 1 \dots D$: # Crossover (binomial)
 19: If $\text{rand}() \leq CR$ or $j = j_rand$: $U_j = V_j$
 20: Else: $U_j = Z_{k,j}$
 21: Clip U to $[Z_{min}, Z_{max}]$ # Boundary handling
 22: If $f(U) \leq f(Z_k)$: Replace Z_k with U # Selection
 23: If $|\text{best_f}(\text{iter}) - \text{best_f}(\text{iter}-1)| \leq \text{tol}$: Break
 24: Return best individual Z^* and $CT^* = f(Z^*)$

3. CASE STUDY

3.1. Simplified water distribution network model

The first model was deliberately simplified to perform a preliminary evaluation of the simulation environment and to conduct an early assessment of the algorithms. The first model is a simplified water distribution system, designed specifically for testing algorithms. The diagram of the model is presented in Fig. 2. This model consists of 12 nodes and 14 pipes. Water is supplied to the system from three sources: A, B, and C. At source A, constant pressure is assumed. The pressures at sources B and C are adjustable. For regulating pressure, a pressure breaker valve (PBV), as implemented in EPANET, is utilized. These valves enable flow regulation by introducing variable pressure losses to simulated variable pressure in outlet of water pumping station.

The main assumption is that the network is supplied with three independent water sources. Source A is the water supplier

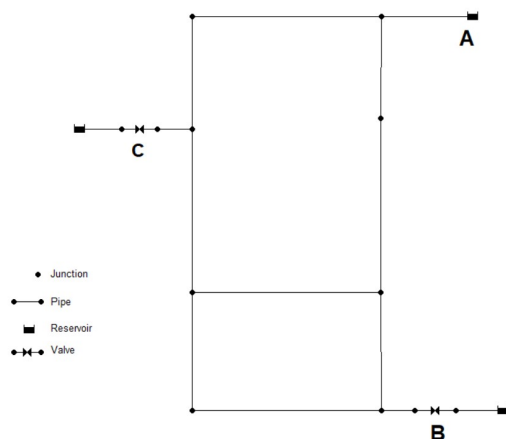


Fig. 2. Exemplary simplified water supply network with 2 rings, 14 pipelines, 8 nodes, and 3 sources

source, maintained at a constant pressure of 20 meters. No control adjustments are applied to this source during the simulation. The unit cost of water from Source A is assumed to be 0.4 PLN/m³. Sources B and C are external sources from which the supplier purchases water. The unit cost of water from these sources is significantly higher, at 3.00 PLN/m³. These sources are controllable via the valve settings, with adjustments made in discrete steps for methods: BF 0.05 and DE 0.01. Total costs are calculated by multiplying the flow through each valve by the respective water unit cost. The results of optimisation with brute force methods and differential evolution for the simplified model are presented in Table 1.

Table 1

Simulation results on the simplified model

		Brute force (BF)	Differential evolution (DE)
Valve settings [mH ₂ O]	A	–	–
	B	28.20	28.53
	C	29.55	29.27
Source inflow [CMH]	A	109.32	109.26
	B	34.54	32.76
	C	0.14	1.98
Water cost [PLN]	A	43.73	43.70
	B	103.62	98.28
	C	0.42	5.94
Total water cost [PLN]		147.77	147.92
Execution time (D, hh:mm:ss)		0, 06:08:32	0, 00:00:11

The results are described with a set of attributes for each defined water source within the network:

- **Source valve settings** [m H₂O] – indicating the pressure drop added for each water source.
- **Inflow from source** [CMH] – representing the volumetric flow rate from each source.
- **Water cost in source** [PLN] – specifying the associated cost of water supply from each source.

Results provide a comprehensive overview of the operational performance of the water network under the defined pricing scenarios, facilitating the evaluation of valve settings and cost distribution among multiple water sources. Figure 3 presents the visualization of the cost function in variations of B and C valve settings.

Each point on above figure denotes a combination of B and C valve positions analyzed during the brute force step, with the associated cost function values determining the performance of each solution. The surface shows how the cost of total water supply changes with selected valve setting values. The visible curvature indicates that the cost function is smooth but nonlinear, with a well-defined global minimum corresponding to the economically optimal distribution of flows between sources. The lowest region of the surface marks the optimal settings, where water from the cheapest source is maximized while still main-

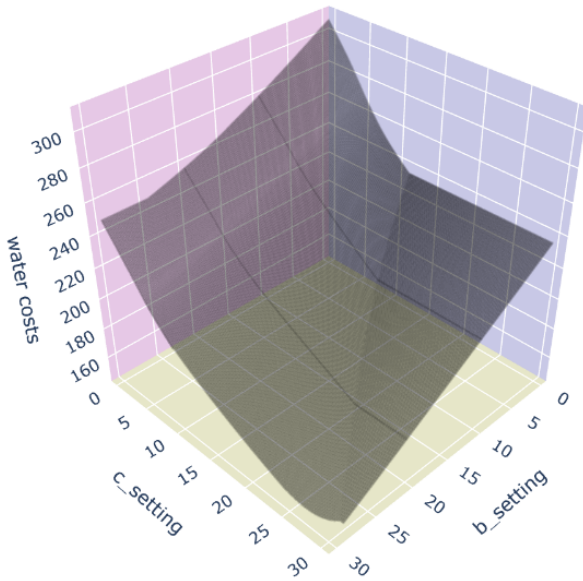


Fig. 3. Visualization of solutions of valve settings for sources B and C obtained using the brute force method as a function of total cost

taining hydraulic constraints. The graph highlights the global minimum, which represents the most cost-effective solution satisfying the network constraints, including water demand and minimum pressure requirements. These values are detailed in Table 1. To evaluate the sensitivity of the optimization methods, additional simulations were conducted under various scenarios with altered water prices (Table 2).

Table 2

Price of water in the source [PLN/m³]

Source	CASE 1	CASE 2	CASE 3	CASE 4
A	0.40	0.40	0.40	3.00
B	3.00	3.00	1.50	2.00
C	3.00	1.50	3.00	2.00

These cases allowed for the assessment of how price variations impact the allocation of water and the performance of optimization methods. The results obtained for this additional scenario demonstrate the differences between the BF and DE methods in terms of cost optimization. In Case 2, the difference in the total cost between the BF and DE methods was 0.66 PLN, corresponding to a percentage difference of 0.5669%. For Case 3, the cost difference decreased to 0.19 PLN, with a percentage difference of 0.1992%. Lastly, in Case 4, the cost difference was 0.49 PLN, representing a percentage difference of 0.1459%. By performing calculations for all possible valve settings, it was possible to identify the exact value of this extremum and compare it to differential evolution. These findings confirm that the DE method achieves results remarkably close to those obtained by the exhaustive BF approach while significantly reducing computational time. This is particularly evident from the small magnitude of the percentage differences across all scenarios.

3.2. Medium-sized water distribution network model

Secondly, a more advanced model used to represent a real-world water distribution network is a medium-sized water distribution system. Due to confidentiality restrictions, a model of the real water distribution network cannot be used for publication purposes. Therefore, a publicly available model, closely resembling the real network (so-called “benchmark model”), was used. From a practical perspective, the developed algorithm is expected to operate seamlessly when applied to other real systems. For this study, the modified Wolf-Cordera Ranch model [20], a benchmark model, was adapted for the purpose of research. This model represents a distribution network for the city, covering an area of 160 hectares, with an estimated average daily water demand of 14 000 m³/day. It includes 1981 pipes and 1782 nodes; the terrain was assumed to be flat. A schematic overview of the network is presented in Fig. 4.

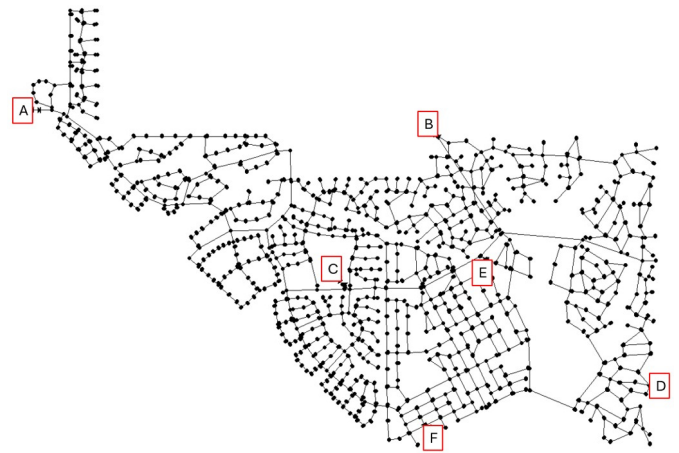


Fig. 4. Overview of model Network6 – a complex water supply network with 6 sources (A, B, C, D, E)

In the first phase of research, a model named Network3 supplied by three water sources (A, B, C) was applied. Source A was modeled as operating at its maximum capacity (with a fully open valve), while the control variables are the valve settings that regulate the water inflow from the other sources, B and C. This approach reflects realistic conditions where a primary water source operates continuously, and secondary sources are optimized to minimize total operational costs while satisfying system constraints.

This model was analyzed under four distinct scenarios, each differing in the cost of water supplied by the respective sources. The variability of water prices allows for a comprehensive assessment of the impact of different economic conditions on the optimization algorithm performance. Table 3 presents the pricing schemes for the investigated cases.

For Cases 1 and 2, optimization was performed using both BF and DE methods to compare their effectiveness in optimization results. In Case 1, the cost difference between BF and DE was minimal at 0.26 PLN with a percentage discrepancy of 0.0031%, indicating near-identical results. For Case 2, the cost difference increased to 5.83 PLN, but the percentage difference remained

Table 3
Price of water in the source [PLN/m³]

Source	CASE 1	CASE 2	CASE 3	CASE 4
A	0.40	0.40	0.40	3.00
B	3.00	3.00	1.50	0.40
C	3.00	1.50	3.00	0.40

small at 0.1193%, confirming the reliability of the DE method despite higher complexity. Details are presented in Table 4.

Table 4
Simulation results for Network3 for Case 1 and Case 2

Method		CASE 1		CASE 2	
		BF	DE	BF	DE
Valve settings [mH ₂ O]	A	–	–	–	–
	B	0.05	0.03	17.20	17.15
	C	17.95	17.94	0.00	0.04
Source inflow [CMH]	A	523.41	523.31	405.90	406.08
	B	2103.04	2103.45	335.81	339.83
	C	593.70	593.39	2478.43	2474.23
Water cost [PLN]	A	209.36	209.32	162.36	162.43
	B	6309.12	6310.35	1007.43	1019.49
	C	1781.10	1780.17	3717.65	3711.35
Total water cost [PLN]		8299.58	8299.84	4887.44	4893.27
Execution time (D, hh:mm:ss)		5, 09:31:08	0, 00:06:29	5, 12:06:24	0, 00:04:05

The visualization of all solutions obtained for Case 1 is presented in the corresponding graphs: Fig. 5 presents results for the brute force method, while Fig. 6 presents results for the dif-

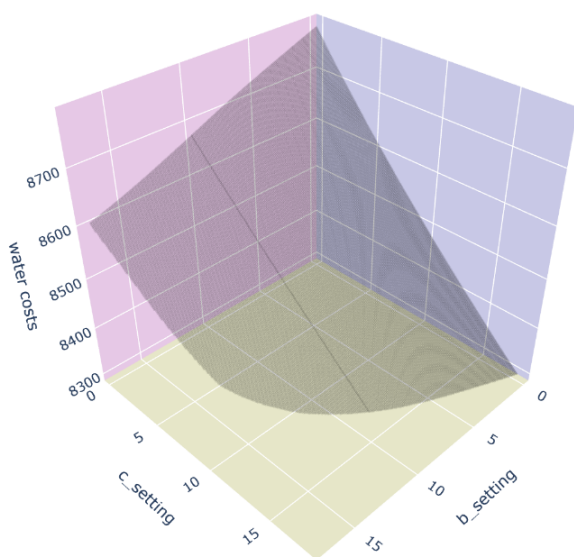


Fig. 5. Visualization of solutions of valve settings for sources B and C obtained using the brute force method as a function of total cost

ferential evolution method. In Fig. 5, compared to the simplified system, the surface is smoother, and the minimum is located in a shallow basin, indicating that multiple nearby settings achieve nearly identical cost. This behavior explains the small numerical differences between the results of brute force and differential evolution and indicates that the optimization problem becomes less sensitive to fine adjustments of valve throttling as system size and hydraulic redundancy increase. Each polyline in Fig. 6 represents one candidate solution evolving over the optimization process. The algorithm initially explores a wide region of the feasible domain and gradually converges toward the vicinity of the global minimum identified via brute force. The dense clustering of points near the optimal settings demonstrates stable convergence behavior and confirms that DE efficiently focuses on the most cost-effective region of the decision space.

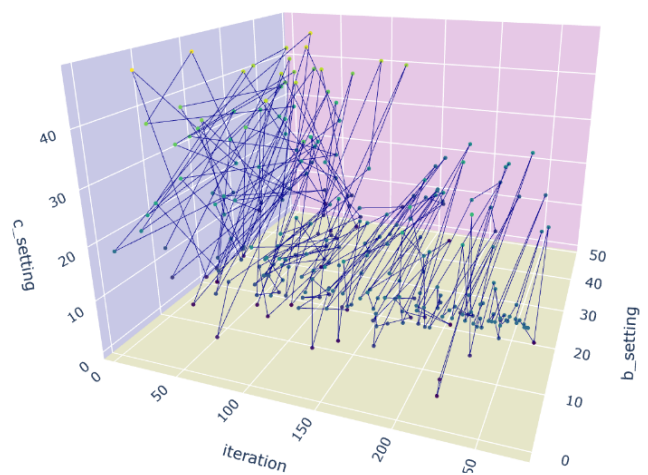


Fig. 6. Visualization of solutions of valve settings for sources B and C obtained using the differential evolution method as a function of total cost

Overall, the DE method achieved results remarkably close to the exact solution from BF, with reduced computational effort. Compared to the BF method, the DE algorithm significantly reduces computational effort and runtime while maintaining a high probability of converging to a near-optimal solution. Due to the significantly long computation time for the BF method, which amounted to 5 days, and the confirmed convergence of results with the DE method, further analyses were conducted exclusively using the DE algorithm. Table 5 presents the results for Case 3 and Case 4, presenting the optimal valve settings and corresponding cost values obtained using the DE algorithm. The DE method proved to be computationally efficient while maintaining solution accuracy.

Additional simulations were conducted for expanded water distribution networks to evaluate the performance of optimization methods under increasingly more complex scenarios. The big water supply network system was extended by incrementally adding new water sources while maintaining the same network structure of nodes. Unchanged distribution infrastructure allowed for systematic comparisons of cost optimization strategies. The number of water sources started at 4 (model

Table 5

Simulation results for Network3 for Case 3 and Case 4

		CASE 3	CASE 4
Valve settings [mH ₂ O]	A	–	–
	B	0.02	0.56
	C	17.78	1.22
Source inflow [CMH]	A	521.89	354.72
	B	2097.48	1314.44
	C	600.77	1550.99
Water cost [PLN]	A	208.76	1064.16
	B	3146.22	525.78
	C	1802.31	620.40
Total water cost [PLN]		5157.29	2210.33
Execution time (D, hh:mm:ss)		0, 00:05:16	0, 00:04:12

name Network4) and was increased by one for each subsequent model, up to a total of six sources (model name Network6). For each of the networks, simulations were performed by adopting varying water prices, and four distinct pricing cases were prepared for analysis, allowing for a detailed study of the system performance under varying economic conditions. The locations of the water sources can be characterized by distinct configurations for cases:

- **Case 1:** All sources maintain identical costs.
- **Case 2:** Peripheral sources (B, D) are more expensive, while central sources (C, E, F) are cheaper.

- **Case 3:** Peripheral sources are cheaper, while central sources are more expensive.
- **Case 4:** Source A is the most expensive, while the remaining sources are cheaper, representing an inverse configuration to Case 1.

Price details for the investigated network scenarios are presented in Fig. 7.

Sources in given network				CASE 1	CASE 2	CASE 3	CASE 4	Water price in network sources [PLN/m ³]			
Network6	Network5	Network4	Network3					Network3	Network4	Network5	Network6
A	A	A	A	0.40	0.40	0.40	3.00	3			
B	B	B	B	3.00	3.00	1.50	0.40	ABC			
C	C	C	C	3.00	1.50	3.00	0.40	ABCD			
D	D	D		3.00	3.00	1.50	0.40	ABCD			
E	E			3.00	1.50	3.00	0.40	ABCDEF			
F				3.00	1.50	3.00	0.40	ABCDEF			

Fig. 7. Price of water in the sources in different cases within network scenarios

By altering the cost structure of the water sources, the impact of price variations on valve settings and total operational costs could be evaluated for each network configuration. This approach enabled a thorough evaluation of cost variations and valve settings under different spatial and economic conditions for multiple water supply configurations. Table 6 includes simulation outcomes for these scenarios. The results emphasized the computational efficiency of DE compared to BF, particularly in larger networks with complex configurations.

Table 6

Simulations results for Network4, Network5, Network6 for four cases

		CASE 1			CASE 2			CASE 3			CASE 4		
Source		Network4	Network5	Network6	Network4	Network5	Network6	Network4	Network5	Network6	Network4	Network5	Network6
Valve settings [mH ₂ O]	A	–	–	–	–	–	–	–	–	–	–	–	–
	B	5.04	9.93	2.69	–	46.48	48.52	5.22	5.31	4.21	0.28	0.74	0.17
	C	37.42	42.54	33.69	17.12	2.72	6.81	29.08	49.68	28.09	0.08	0.95	0.26
	D	1.36	12.40	25.27	0.01	47.63	46.20	0.54	0.18	5.16	0.53	15.41	2.04
	E	N/A	16.08	23.45	N/A	0.02	0.21	N/A	47.11	33.90	N/A	1.53	29.47
	F	N/A	N/A	28.90	N/A	N/A	1.89	N/A	N/A	31.74	N/A	N/A	2.70
Inflow [CMH]	A	597.28	596.97	596.94	405.72	421.66	440.70	597.16	597.82	596.02	331.30	345.22	325.90
	B	2135.38	1856.70	2290.98	339.93	0.00	0.00	2127.94	2124.58	2171.48	1155.16	1179.86	1120.70
	C	0.00	0.00	0.00	2474.49	2209.73	1689.92	0.00	0.00	0.00	1454.38	1436.89	1309.73
	D	487.49	378.78	188.55	0.00	0.00	0.00	494.60	497.74	452.63	279.31	15.06	228.99
	E	N/A	387.70	33.99	N/A	588.75	581.17	N/A	N/A	0.00	N/A	243.10	0.00
	F	N/A	N/A	109.67	N/A	N/A	508.35	N/A	N/A	0.00	N/A	N/A	234.82
Total water cost [PLN]		8107.522	8108.328	8108.35	4893.8	14366.38	4345.44	4172.67	4172.61	4174.57	2149.44	2185.62	2135.40
Execution time (D, hh:mm:ss)		0, 00:03:59	0, 00:05:07	0, 00:04:26	0, 00:04:35	0, 00:06:11	0, 00:06:02	0, 00:05:01	0, 00:05:31	0, 00:06:12	0, 00:03:12	0, 00:04:11	0, 00:05:48

4. DISCUSSION

It was shown that the differential evolution method is effective for solving optimization problems in multi-source water distribution networks. Examples were used to compare effectiveness brute force methods with differential evolution. The differences in objective function values were no greater than 0.2%, while the computation time for DE was significantly shorter. For instance, in a simple case, BF method required over six hours, whereas the DE method completed the calculations in 11 seconds.

The brute force approach produced slightly lower total costs, which can be attributed to its brute force procedure, while DE, being a stochastic method, may stop before reaching the exact global minimum. This effect is reinforced by the stopping tolerance used in the experiments ($\text{tol} = 0.05$), which limits unnecessary computations but reduces the degree of final fine-tuning. Lowering the tolerance narrows the difference between the two methods, although at the expense of substantially longer computation times. Overall, the results reflect the expected trade-off between accuracy and efficiency and confirm the practical advantages of DE in this class of optimization tasks.

The method was tested across various network operation configurations to reflect real-world water distribution scenarios. In a more complex model, four cases were analyzed. In the first case, all additional water sources were assumed to have the same cost (in this case, network configuration and hydraulic parameters determining water distribution). The analysis showed that under this configuration, source B emerged as the dominant source, indicating its greatest hydraulic capacity within the network.

In scenarios where central sources were assumed to be more expensive, the system automatically minimized the volume of water drawn from these sources and prioritized peripheral sources. Conversely, when peripheral sources were assumed to be more expensive, the system adjusted operations to maximize the use of central sources. The analysis revealed that the optimization method could dynamically adjust system settings in response to changing costs for different sources, such as those influenced by fluctuating energy prices.

Additionally, it is worth noting the robustness of the differential evolution method in the context of the studied problem. Although the algorithm was applied with standard parameter settings, the results across multiple networks and pricing scenarios indicate that solution quality was not extremely sensitive to moderate variations in population size, mutation range, or crossover configuration. These parameters typically affect the balance between exploration and convergence speed, yet in all analyzed cases, DE consistently produced solutions remarkably close to the BF optimum. The discretization of valve settings may also influence the search landscape, but the continuous representation used in DE, combined with appropriate bounds, ensured stable behavior without premature convergence. A more systematic sensitivity analysis could be considered in future work, but the current results suggest that the chosen DE configuration is sufficiently robust for practical applications.

The results also lead to practical implications for energy efficiency and operational resilience. The brute force approach, requiring computation times of several hours, cannot be applied

to ongoing system control and therefore offers limited practical value in dynamic operating conditions. The ability of differential evolution to deliver cost-effective settings within seconds strengthens its usefulness for supporting energy-aware and adaptive management of multi-source water distribution networks. The substantially shorter computation time obtained with the DE method means that the optimization results can be used in near-real-time system operation. This enables the system to respond to changes in energy prices or demand patterns by adjusting source allocation accordingly.

5. CONCLUSIONS

Differential evolution consistently produced solutions remarkably close to the brute force optimum while reducing computation time from hours to seconds. The study confirmed that open-source integration of EPANET, WNTR, and optimization of the differential evolution algorithm provides a robust and cost-effective tool for optimizing water supply systems. Open-source solutions contribute to reducing design costs and popularizing optimization methods in engineering practice. The application of the presented methodology proved effective in addressing scientific problems of water distribution network optimization. The authors will provide the script and model files upon request.

In this study, the focus was primarily on cost optimization; however, in practice, the problem may be considerably more complex and may require the simultaneous consideration of water quality parameters such as water age, mixing, or the concentration of potential contaminants. The optimization methods used, such as DE, are open to changes in the objective function, and therefore, further research should also include criteria related to water safety and quality to provide a realistic and comprehensive assessment of system performance. Such systems could be supported by monitoring and operations tools, including, real-time data collection (sensors systems provide continuous updates on water quality and resource availability), computer hydraulic models (to simulate network behavior, helping to predict the impact of different control strategies on cost and quality), decision-support systems to integrate optimization algorithms with user-friendly interfaces, enabling operators to test and implement control strategies effectively. Future work will focus on applying these solutions to real-world water supply systems and practical engineering scenarios and additionally extend the comparison to selected commercial tools.

Finally, it should be noted that the full potential would be revealed if the presented methodology was applied to real-world water distribution systems, where operational decisions are strongly influenced by technical constraints, demand variability, and dynamically changing energy prices. Integrating elements such as actual demand patterns, pump and supply limitations would enable a more realistic verification of the method in the context of daily utility operations. Furthermore, combining the optimization framework with developing a digital-twin platform and sensor-based monitoring infrastructure would allow for the actual execution and automation of the optimization process and application in real-time control systems.

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