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Multi-criteria decision-making methods for optimal design of intermittent water distribution network

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ABSTRACT

Multi-objective optimization of water distribution networks (WDNs) is crucial for achieving a balance between cost, equity, and reliability. The present study conducts a comparative analysis, evaluating the effectiveness of four multi-objective optimization algorithms implemented within the EPANET framework for the optimal design of three distinct WDNs taken from the literature. The networks were optimized considering three objectives: maximizing network resilience, and uniformity coefficient (*CU*, a measure of uniformity), alongside minimizing the cost of the network. Further, multi-criteria decision-making (MCDM) analysis is carried out, encompassing various MCDM techniques and weighting methods, to explore the sensitivity of solution rankings. In Network 1, non-dominated sorting genetic algorithm 2 (NSGA-II) produced suboptimal solutions with *CU* and I_n values below 0.4, while caRamel, multi-objective particle swarm optimization based on crowding distance (MOPSO-CD), and multi-objective evolutionary algorithm with decomposition (MOEA/D) showcased increasing *CU* and I_n values towards 1, paralleled by a rise in network cost. The performance of NSGA-II in Network 3 was unsatisfactory ($CU < 0.32$), while the other algorithms demonstrated satisfactory values (>0.98) for reliability and (>0.5) for *CU*. The findings offer valuable insights into cost-effective strategies for achieving equity in water supply without substantial impact on overall network cost. The findings of the study also underscore the sensitivity of ranking outcomes in MCDM analysis to the choice of technique and weighting method.

Key words: multi-criteria decision-making, multi-objective optimization, network resilience, water distribution networks, water supply

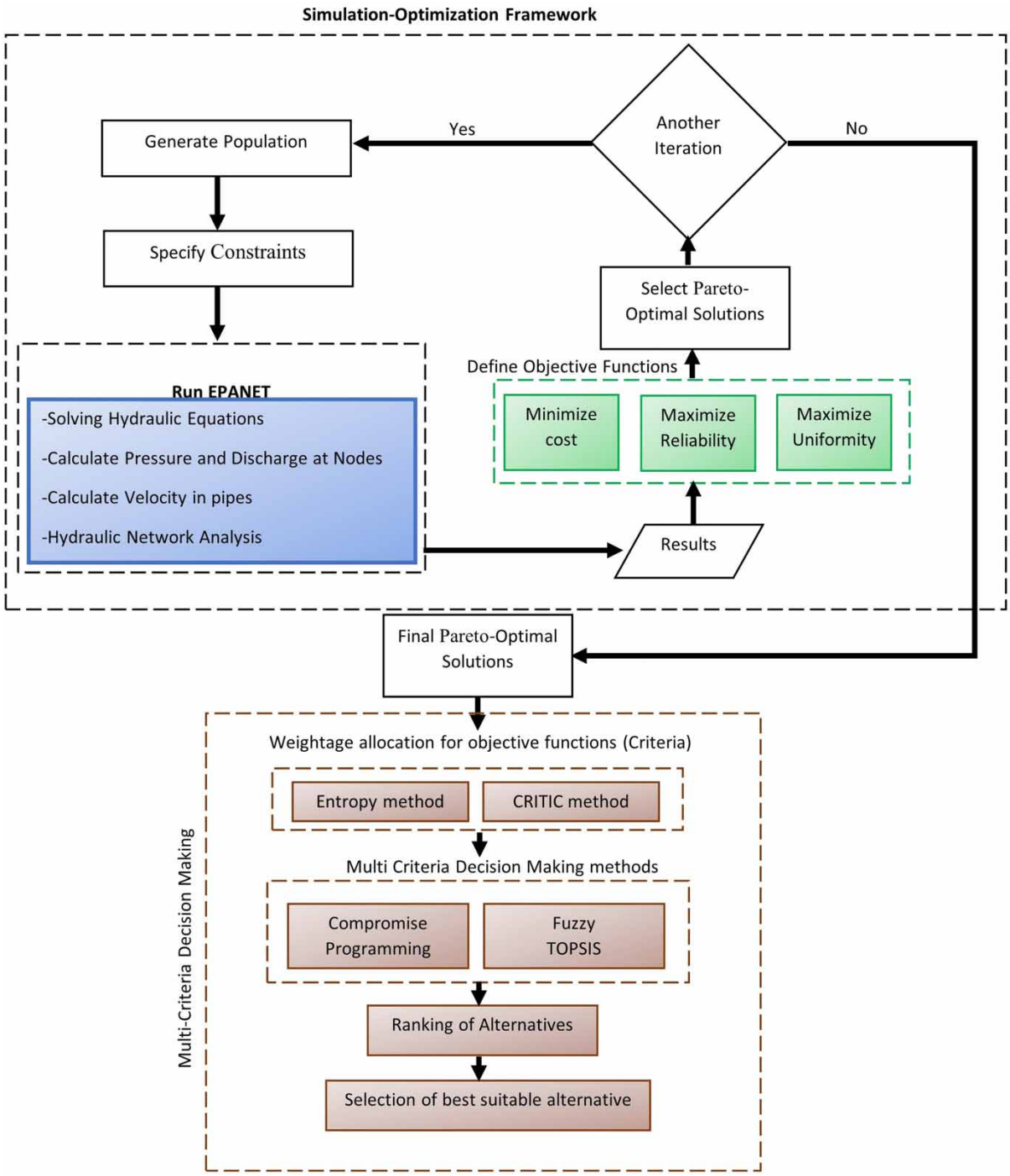
HIGHLIGHTS

- A multi-objective optimization model is developed for the design of an intermittent water supply system.
- The equity in water supply and network resilience along with the cost for the optimal design is considered.
- A comparative analysis of various multi-objective optimization algorithms for the design of WDNs is made.
- Ranking of optimal solutions is made.
- The sensitivity of the ranking by different MCDM techniques is explored.

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GRAPHICAL ABSTRACT



1. INTRODUCTION

Water distribution networks (WDNs) stand as vital infrastructure, essential for providing communities with reliable access to clean water (Cunha *et al.* 2023). In the present day, WDNs are complex and multifaceted systems, demanding substantial investments for both their establishment and ongoing maintenance (Monsef *et al.* 2019; Ghobadian & Mohammadi 2023). The complexities of water distribution networks necessitate strategic planning that takes into account the inevitability of

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uncertainties arising from unpredictable user behaviours, leading to variations in demand. In addition, aging water WDN infrastructure presents challenges including leaks, water quality issues, and reduced hydraulic capacity, prompting water authorities to initiate costly rehabilitation and replacement efforts (Farmani *et al.* 2006). Balancing capital and operational expenses in WDN optimization requires a comprehensive approach, considering multiple performance metrics and objectives to address this complex challenge.

The exploration of WDN optimization is categorized into two primary domains: single-objective and multi-objective optimization. However, the paradigm governing WDN design objectives has evolved, transitioning from the exclusive focus on economic efficiency (single objective) to a more holistic and comprehensive multi-objective approach (Zheng *et al.* 2016). The domain of multi-objective WDN design has garnered significant attention over the past two decades. Numerous investigations have focused on delineating the trade-offs inherent within the Pareto front – a set of solutions that characterize the equilibrium between cost and performance-based benefits, evaluated through various indicators (Keedwell & Khu 2003; Prasad & Tanyimboh 2009; Fu *et al.* 2013). Particularly in scenarios involving conflicting objectives, where enhancing one aspect may compromise another, the Pareto front surfaces as a pivotal concept, emphasizing the concept of multi-objective optimization (Kollat & Reed 2006).

Pioneering the transition to multi-objective optimization, Gessler (1985) introduced one of the first instances of multi-objective optimization in WDN design by employing a partial enumeration method to concurrently maximize minimum pressure and minimize network costs. Researchers subsequently introduced additional objectives such as hydraulic and mechanical reliability, water quality, operation cost, and leakage, expanding the optimization landscape (Farmani *et al.* 2003; Prasad & Park 2004). Halhal *et al.* (1997) employed a multi-objective genetic algorithm to optimize water distribution networks within budgetary constraints. Farmani *et al.* (2005) conducted an extensive comparison of multi-objective evolutionary algorithms (MOEAs) for WDN design optimization, highlighting the superiority of non-dominated sorting genetic algorithm 2 (NSGA-II) and revealing the promise of the strength Pareto evolutionary algorithm 2 (SPEA-II) on larger WDN scenarios. Through thorough evaluations, Raad *et al.* (2011) identified NSGA-II and its derivatives as top-performing contenders for WDN design optimization, shaping optimal methodologies. Exploring the behaviour of the differential evolution (DE) algorithm, Zheng *et al.* (2015) investigated performance and convergence properties, setting the stage for Moosavian & Lence (2017) to introduce multi-objective different evolution (MODE), a competitive multi-objective DE variant. Shrivatava *et al.* (2015) harnessed multi-objective particle swarm optimization (MOPSO) to investigate the influence of swarm dynamics on algorithmic behaviour for WDN design optimization. However, utilizing a Pareto front in decision-making can be challenging due to the complexity of assessing the trade-offs among multiple objectives (Tian *et al.* 2019).

Selecting a single parameter set from the Pareto front is pivotal for translating the trade-offs and options presented into a feasible solution for WDN design that aligns with specific objectives, constraints, and practical considerations. As an evaluation of the Pareto front involves many metrics, it can be regarded as a multi-criteria decision-making (MCDM) problem (Manikanta & Vema 2022). Several MCDM techniques are available to rank the alternatives (solutions obtained from Pareto front) with respect to the criteria (multiple objective functions). Few past studies presented MCDM analysis for choosing the best alternative from the Pareto front obtained from multi-objective optimization (Reynoso-Meza *et al.* 2017; Carpitella *et al.* 2018; Yu *et al.* 2018). However, it is important to acknowledge that the results of MCDM analysis highly depend upon the employed MCDM technique and weightage allocation method (Anil *et al.* 2021).

Amidst the array of multi-objective optimization algorithms available, a comprehensive comparative study is imperative to understand the strengths and limitations of these techniques in the context of WDN design. Such a study holds the potential to offer insights into the diverse trade-offs presented by different algorithms, paving the way for informed decisions regarding algorithm selection based on specific design objectives and problem characteristics. In this context, our study seeks to compare four different multi-objective optimization algorithms integrated within the Environmental Protection Agency Network Evaluation Tool (EPANET) framework. By applying and comparing advanced optimization techniques, our research strives to unravel the trade-offs inherent in designing WDNs capable of meeting the evolving demands of urban environments. In addition, our study explores the different MCDM techniques and weightage allocation methods for the selection of the best suitable solution obtained from the Pareto front. For this purpose, three benchmark WDNs were taken from the literature and optimized considering equity, cost, and reliability as the objectives based on pressure-driven analysis (PDA).

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2. METHODOLOGY

2.1. Optimization of WDN

2.1.1. Pressure-driven analysis

In the implementation of the PDA method, three crucial steps are involved. Firstly, a hydraulic model of the WDN is constructed using EPANET Version 2.2 to simulate hydraulic behaviour, incorporating essential data on network topology, nodal demands, boundary conditions, pipe characteristics, and nodal demands. Secondly, demands are allocated at each node with the aim of achieving precise demand estimates. This allocation relies on demographic projections, trends in historical consumption, consumer-specific information, while also accounting for highly fluctuating demand patterns and seasonal variations. Thirdly, pressure heads are simulated under various scenarios related to the network's behaviour. This process takes into consideration operational aspects such as tank levels, valve configurations, and pump operations, integrating computations to ascertain pressure levels and flow rates across the network while focusing on water conservation and energy efficiency. Lastly, the network's performance is evaluated using simulation results, where a range of key performance indicators is examined. These indicators include flow rates, network resilience, minimum and maximum pressures, uniformity coefficients, equity, and pressure deficits. These comprehensive assessments serve the purpose of identifying problematic areas within the network, such as potential water quality challenges and high and low-pressure zones. Ultimately, these steps contribute to the overall optimization and management of the WDN.

Several iterative techniques have been proposed in the literature to address the challenges of PDA (Martin-candilejo *et al.* 2020; Muranho *et al.* 2020). In the study, the source-head approach, an iterative procedure proposed by Tanyimboh & Tabesh (1997) and Tanyimboh *et al.* (2001) was employed for computing the nodal discharges (Q_j) at all nodes. Initially, a demand-driven analysis using EPANET (Rossman 2000) is performed using the demands Q_j^{req} at all nodes in the network. Subsequently, the desired head at the source that will satisfy the demand at node j (H_{sj}^{des}) and the minimum source head required (H_{sj}^{min}) were computed iteratively, and these values were then used to compute the actual nodal discharges Q_j. It is important to note that the source-head method is only applicable to single-source networks. The algorithm for H_{sj}^{des} and H_{sj}^{min} is illustrated in Figure 1.

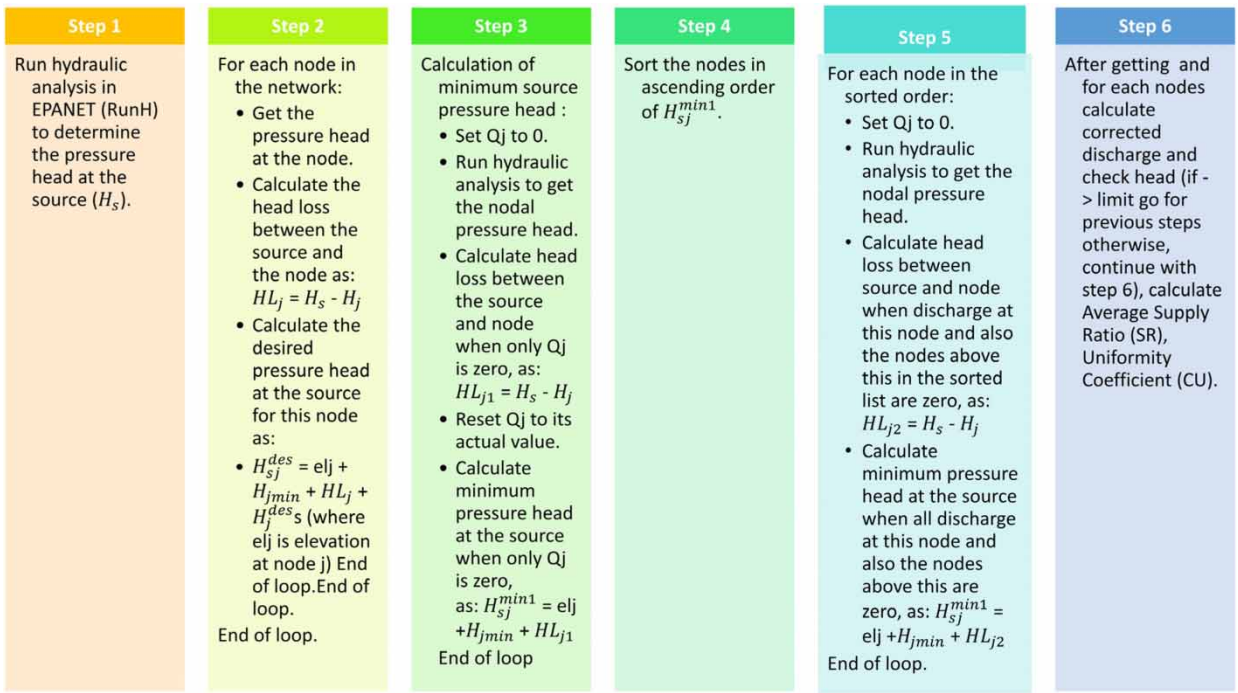


Figure 1 | Algorithm for computation of H_{sj}^{des} and H_{sj}^{min} using EPANET.

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2.1.2. Performance indicators

In addition to cost, the present study considers two performance indicators, for optimization of WDNs, namely, uniformity coefficient (*CU*) and network resilience (I_n). The former assesses supply equity during pressure-deficit conditions whereas the latter quantifies the network reliability (Todini 2000; Prasad & Park 2004; Gottipati & Nanduri 2014). The equations to compute *CU* and I_n are given in the following equations, respectively:

$$\mathrm{CU} = 1 - \left(\frac{\mathrm{DEV}}{\mathrm{SR}}\right) \tag{1}$$

$$I_n = \frac{\sum_{j=1}^{nn} C_j Q_j (H_j - H_j^l)}{\left[\sum_{k=1}^{nr} Q_k H_k + \sum_{i=1}^{np}\left(\frac{P_i}{\gamma}\right)\right] - \sum_{j=1}^{nn} Q_j H_j^l} \tag{2}$$

where SR is the average supply ratio (average ratio of actual water supply to demand) at all the nodes. DEV represents the average of the deviations between the nodal supply ratio and SR across all nodes; *nn* is the number of junction nodes; Q_j and H_j are the discharge and the head at node *j*, respectively; Q_k and H_k are the discharge and head, respectively, at reservoir node *k*; H_j^l is the minimum head required at node *j*; *nr* and *np* denote the number of reservoirs and pumps in the network, respectively; P_i represents power supplied by pump *i* and γ is the specific weight of water. The term C_j measures the uniformity of the pipes connected to node *j* and is calculated using the following equation:

$$C_j = \frac{\sum_{i=1}^{npj} D_i}{npj \times \max\{D_i\}} \tag{3}$$

where *npj* represents the number of pipes connected to the node *j* and D_i is the diameter of the pipe *i*.

The *CU* value, ranging from 0 to 1, serves as an indicator of equity in water distribution. A *CU* value of 1 signifies perfect equity in water distribution under water deficit conditions. On the other hand, I_n, also ranging from 0 to 1, measures network resilience. Maximizing network resilience improves the reliability of the WDN under failure conditions (Prasad & Park 2004).

Multi-objective optimization of WDN is carried out by maximization of CU, I_n, and minimization of cost, with nodal mass balance and energy conservation equations serving as the constraints. These constraints are externally enforced by a hydraulic network solver (Prasad & Park 2004). The total cost of the pipe network is computed by summing up individual pipe costs (c_i), which are determined using diameter (D_i) and length (L_i) as expressed in the following equation:

$$C = \sum_{i=1}^{np} c_i(D_i,\ L_i) \tag{4}$$

2.2. Multi-objective optimization algorithms

2.2.1. Non-dominated sorting genetic algorithm II

NSGA-II is a fast and elitist multi-objective genetic algorithm devised by Deb *et al.* (2002). It is an extension of the original NSGA algorithm proposed by Deb in 1995. NSGA-II addresses computational complexity, non-elitism, and sharing parameter challenges of prior algorithms by employing a fast non-dominated sorting algorithm to rank individuals based on nondomination levels. A crowding distance, which represents the proximity to neighbours in the objective space, is assigned to each individual to maintain diversity, measuring its distance to its neighbouring solutions across multiple objective dimensions. NSGA-II utilizes binary tournament selection, ensuring diverse parent selection, and employs crossover and mutation operators to maintain genetic diversity. Elitism approach is one of the key features NSGA-II, as it preserves an external archive of the best individuals found so far. This archive preserves optimal solutions across generations and avoids losing track of the Pareto-optimal front. The algorithm addresses sharing parameter issues via a niche count method, ensuring an even distribution of solutions across the objective space.

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2.2.2. caRamel

The caRamel algorithm is a member of the genetic algorithm family and is built upon the fundamental idea of evolving an initial population of parameter sets through a series of generation rules (Monteil *et al.* 2020). Each generation involves evaluating these sets based on predefined objectives, with only the most promising ones being retained to form the next population. caRamel is inspired from the multi-objective evolutionary annealing simplex method (MEAS) for directional search strategies and the NSGA-II algorithm for classifying parameter vectors and ensuring precision through dominance relationships.

The algorithm employs five key rules to generate new solutions in each generation. Firstly, it utilizes interpolation and extrapolation techniques, based on Delaunay triangulation within the objective space, to estimate directions of improvement in the parameter space based on Pareto-optimal improvements in the objective space. Consequently, it incorporates independent sampling with prior parameter variance, enabling exploration of the parameter space without directional bias. Additionally, it employs sampling with respect to the correlation structure to generate parameter sets in a more multivariate manner, based on covariance information. Finally, the algorithm includes a recombination rule, which creates new parameter sets by combining partial subsets from previously evaluated parameter sets, inspired by earlier work by Baluja & Caruana (1995). These rules collectively guide the evolution of parameter sets, facilitating efficient multi-objective optimization.

2.2.3. Multi-objective particle swarm optimization based on crowding distance

In the realm of multi-objective optimization, MOPSO emerges as an evolutionary advancement of the traditional particle swarm optimization (PSO) algorithm. The MOPSO algorithm uses a particle-based population to explore the Pareto front, with each particle representing a potential solution to the optimization problem and characterized by both velocity and position vectors. The algorithm continuously updates these vectors based on the particle's personal best position and the global best position (Coello *et al.* 2004). In this study, crowding distance has been integrated into MOPSO with the goal of preserving the diversity of non-dominated solutions within the population, aiming to encourage the population to span as much of the Pareto front as possible, rather than converging to a single point. Notably, the MOPSO-CD algorithm also includes a mutation operator to maintain the diversity of non-dominated solutions in the external archive. The better performance of MOPSO is attributable to its incorporation of an external repository of non-dominated solutions from previous iterations and its innovative mutation operator, which initially encompasses the entire population and design variable range, gradually narrowing it during subsequent iterations (Raquel & Naval 2005). Additionally, it also has a robust mechanism for handling constraints in the context of solving constrained optimization problems.

2.2.4. Multi-objective evolutionary algorithm with decomposition

Multi-objective evolutionary algorithm with decomposition (MOEA/D) is a state-of-the-art algorithm in aggregation-based approaches for multi-objective optimization, known for its effectiveness in solving a wide range of multi-objective optimization problems and its extensive utilization in real-world applications (Zhang & Li 2006; Pruvost *et al.* 2020). The optimization process in MOEA/D unfolds in two main phases: the decomposition phase and the optimization phase. During the decomposition phase, the algorithm dissects the initial problem into an array of sub-problems, each characterized by a weight vector determining the significance of individual objective functions. These weight vectors cover the entire objective space, and the number of sub-problems aligns with the number of weight vectors. In the optimization phase, MOEA/D enhances each sub-problem using an evolutionary process. These sub-problems are optimized concurrently, with their results combined to form the final Pareto set. MOEA/D employs a selection mechanism to identify the best solutions from each sub-problem and a mating mechanism to generate new solutions.

All the four multi-optimization optimization algorithms were run in R environment using '*nsga2R*' (Tsou & Lee 2013), '*caRamel*' (Monteil *et al.* 2019), '*mopsocd*' (Naval 2013), and '*MOEADr*' (Campelo *et al.* 2020) packages, respectively. The parameters of the four algorithms are fixed based on several trial runs and the values of the parameters used in this study are given in Table 1.

2.3. Multi-criteria decision-making

2.3.1. Generation of payoff matrix

A payoff matrix (M) is generated, with alternatives (solution obtained from Pareto front) as rows and performance indicators (reliability, uniformity, and cost) as columns. The values within the payoff matrix may have varying ranges, and they are

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Table 1 | Parameters setting of employed multi-objective optimization algorithms

NSGA-II	MOPSO	caRamel	MOEA/D
Size of population: 200 Probability of crossover: 0.6 Probability of mutation: 0.2	Size of repository: 200 Inertia weight: (w) 0.6 Personal learning coefficient (C1): 1 Global learning coefficient (C2): 2	Size of population: 200 Crossover probability: 0.5 Mutation probability: 0.3.	Size of population: 200 Neighborhood size: 20 Mutation rate: 0.2 Crossover rate: 0.8

standardized to a common range of 0 to 1 using the linear sum normalization technique. The normalized element (N_{ij}) is computed using the following equation:

$$N_{ij} = \frac{M_{ij}}{\sum_{i=1}^{T} M_{ij}} \tag{5}$$

where M_{ij} is the value of jth performance indicator of ith solution obtained from Pareto front, and T is the total number of solutions in a Pareto front.

2.3.2. Objective weights of criteria

In this study, two objective weightage allocation methods were used: (i) entropy method and (ii) criteria importance through intercriteria correlation (CRITIC) method. The entropy method, based on the concept of information entropy, quantifies the uncertainty within the context of probability theory, with higher entropy indicating lower information quantity. The weightage for each criterion is allocated by measuring the relative entropies of criteria computed using the following equations:

$$E_j = -\frac{1}{G}\sum_{i=1}^{G} N_{ij} \log_e N_{ij} \tag{6}$$

$$d_j = 1 - E_j \tag{7}$$

$$w_j = \frac{d_j}{\sum_{j=1}^{J} d_j} \tag{8}$$

where E_j, d_j, and w_j are entropy, degree of divergence, and weight of jth indicator, respectively, J is the total number of criteria, and G is the total number of alternatives.

CRITIC method assigns weightage to the criteria by accounting the intercriteria correlations. It involves transforming the values of payoff matrix M_{ij} to the interval [0, 1] based on the ideal point concept (Manikanta *et al.* 2023). Subsequently, a symmetric matrix ($J \times J$) of correlations is constructed, where each element r_{jk} represents a linear correlation coefficient between jth column and kth column. The correlation matrix assesses how changes in one criterion correlate with others, considering both positive and negative correlations, and uses these coefficients to allocate weights. Highly positively correlated criteria receive higher weights, while negatively or weakly correlated criteria receive lower weights. The transformed value-C_{ij}, the quantity of information (Q_j), and the objective weights (w_j) of each criterion are calculated using the following equations:

$$C_{ij} = \frac{M_{ij} - M_j^{**}}{M_j^{*} - M_j^{**}} \tag{9}$$

$$Q_j = \sigma_j * \sum_{k=1}^{J} (1 - r_{jk}) \tag{10}$$

$$w_j = \frac{Q_j}{\sum_{j=1}^{J} Q_j} \tag{11}$$

where M_j^{*}, M_j^{**} denote the ideal and anti-ideal values of jth criteria, respectively, and σ_j represents the standard deviation of each column in the transformed payoff matrix C.

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2.3.3. Fuzzy technique for order preference by similarity to ideal solution

Fuzzy technique for order preference by similarity to ideal solution (FTOPSIS), by integrating MCDM and fuzzy set theory, has an added advantage due to its ability to handle imprecise and uncertain information in the decision-making process. In this study, the triangular membership function is employed for the three performance indicators (reliability, uniformity, and cost). The membership function of normalized payoff matrix N_{ij} along with their ideal (N_j^*) and anti-ideal (N_j^{**}) values are defined as $\tilde{N}_{ij}(x_{ij}, y_{ij}, z_{ij})$, $\tilde{N}_j^*(x_j^*, y_j^*, z_j^*)$, and $\tilde{N}_j^{**}(x_j^{**}, y_j^{**}, z_j^{**})$, respectively; with x, y, and z denoting the lower, middle, and upper values of the triangular membership function with a symmetric spread both sides, computed as $\min\{(1 - \max(N_j), \ \min(N_j)\}$. DS_i^+ and DS_i^- measure the proximity of an alternative from the fuzzy positive ideal solution (1,1, minimum cost) and fuzzy negative ideal solution (0,0, maximum cost) for reliability, uniformity, and cost, respectively. Subsequently, for each alternative, relative closeness (CR_i) is computed using Equations (12)–(14) and the higher the CR_i, the closer to the ideal solution:

$$\mathrm{DS}_i^+ = \sum_{j=1}^{J} w_j \times d(\tilde{N}_{ij}, \ \tilde{N}_j^*) = \sum_{j=1}^{J} w_j \times \sqrt{\frac{(x_{ij} - x_j^*)^2 + (y_{ij} - y_j^*)^2 + (z_{ij} - z_j^*)^2}{3}} \tag{12}$$

$$\mathrm{DS}_i^- = \sum_{j=1}^{J} w_j \times d(\tilde{N}_{ij}, \ \tilde{N}_j^{**}) = \sum_{j=1}^{J} w_j \times \sqrt{\frac{(x_{ij} - x_j^{**})^2 + (y_{ij} - y_j^{**})^2 + (z_{ij} - z_j^{**})^2}{3}} \tag{13}$$

$$\mathrm{CR}_i = \frac{\mathrm{DS}_i^-}{(\mathrm{DS}_i^- + \mathrm{DS}_i^+)} \tag{14}$$

2.3.4. Compromise programming

Compromise programming (CP) is a widely used MCDM technique that aims to find a solution that compromises between conflicting criteria by aggregating multiple criteria into a distance metric (L_p) as expressed in Equation (15). Subsequently, the alternative with minimal distance from the ideal solution is identified as the best suitable alternative:

$$L_p(i) = \left[\sum_{j=1}^{J} w_j |N_j^* - N_j(i)|^p\right]^{\frac{1}{p}} \tag{15}$$

where w_j represents the weightage of jth indicator and p is the parameter (1 for linear and 2 for Euclidean distance).

The overall methodology of the present study is illustrated in a flow chart presented in Figure 2.

2.4. Multidimensional Pareto analysis

The Pareto analysis method, often known as Brute Force Dominance Check, involves systematically comparing each solution in a dataset with every other solution to establish dominance relationships based on multiple objectives (Demir *et al.* 2019). The algorithm operates by iterating through all solution pairs, checking for dominance relationships according to the Pareto principle, which underpins multi-objective Pareto analysis. The code includes key steps such as constructing a dominance matrix, where each element (i, j) signifies whether solution i dominates solution j, identifying Pareto-optimal solutions based on the dominance matrix analysis, and subsequently extracting the Pareto front solutions from the original dataset.

3. STUDY NETWORKS

The multi-objective optimization model discussed in the previous sections is applied to three networks. The networks considered in the present study are taken from the literature (Kansal *et al.* 1995; Prasad & Park 2004). It is assumed that all the pipes are made of cast iron. The list of commercially available pipe diameters and their costs are given in Table 2. The details of the three networks used in the study and the corresponding results are presented in the following sections.

The layouts of the study networks are shown in Figure 3. Network-1 considered in the study shown in Figure 3 is a simple network consisting of eight pipes with two loops fed by gravity from a constant head reservoir (Prasad & Park 2004). This

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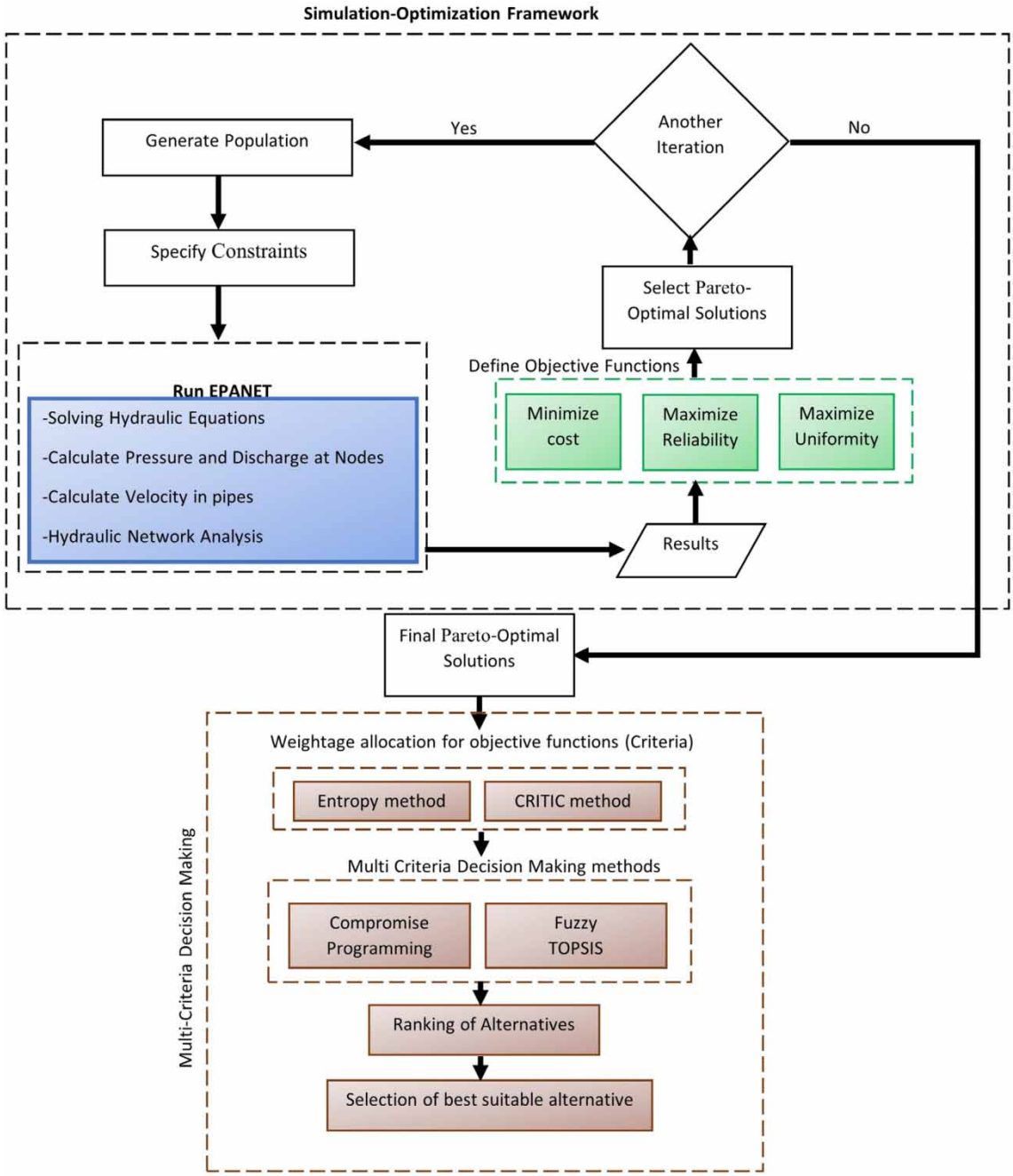


Figure 2 | Flowchart of multi-objective optimization for water distribution networks using EPANET with NSGA-II, caRamel, MOPSO-CD, and MOEA/D along with selection of the best suitable solution from the Pareto Front using MCDM techniques.

network consists of eight links, six demand nodes, and one source node. The minimum head required at all demand nodes is taken as 30 m. Hazen–William's equation is used as the head loss equation and the roughness coefficient for all the pipes is taken as 100.

Network-2, sourced from Kansal *et al.* (1995), features 17 demand nodes and 21 links. Network-3 consists of nine demand nodes and 12 links (Rossman 2000). The node elevation and demands for all three networks are shown in Figure 4. Additionally, all pipes in these networks assume a Hazen–Williams roughness coefficient of 100, and the minimum head required at all demand nodes across these networks is 30 m. The details of links for these networks are tabulated in Table 3.

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Table 2 | Commercially available standard pipe diameters and their respective costs

S. No	Pipe diameter (in mm)	Total cost of pipe (in Rs per meter)
1	100	560
2	150	900
3	200	1,303
4	250	1,757
5	300	2,267
6	350	2,848
7	400	3,485
8	450	4,220
9	500	4,820
10	550	5,795
11	600	6,794
12	650	7,352
13	700	8,050
14	750	9,280
15	800	10,692

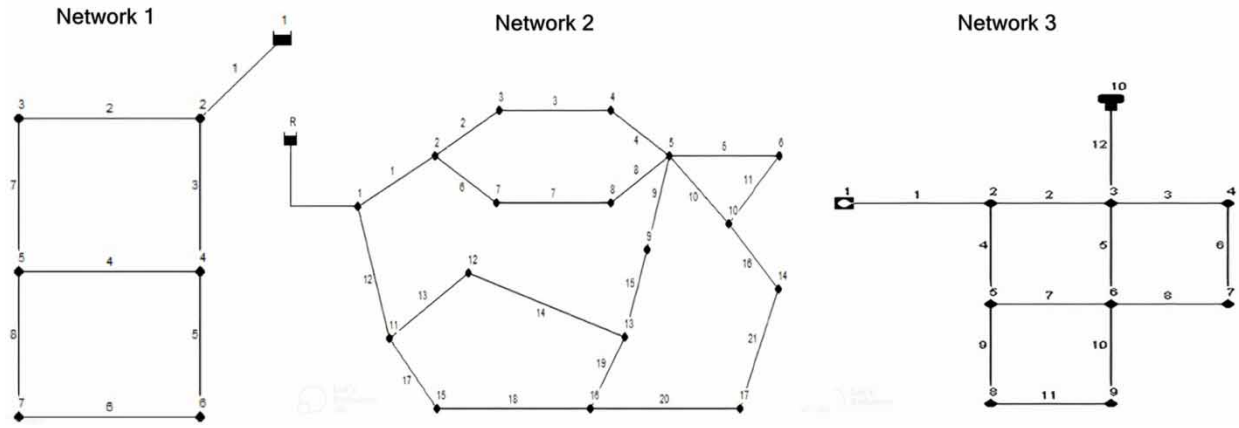


Figure 3 | Layouts of three study networks.

4. RESULTS AND DISCUSSIONS

In the present study, a comparative performance analysis is conducted for four different multi-objective optimization algorithms: NSGA-II, caRamel, MOPSO-CD, and MOEA/D, aiming to optimize the design of water distribution networks. In intermittent water supply systems, equity and reliability are closely interconnected and crucial for customer satisfaction. Hence, our optimization framework employs PDA to simultaneously maximize uniformity coefficient (*CU*) and network reliability (represented by network resilience, I_n), while minimizing the network cost. To enhance reliability, we integrate excess energy availability into the resilience index, especially to prevent service failures resulting from changes in flow patterns. By combining equity and reliability, our assessment strives for equitable service delivery while recognizing that ensuring higher reliability might require introducing new pressure heads into the system.

4.1. Trade-offs between the objective functions

The Pareto fronts were generated by applying four multi-objective optimization algorithms to the three networks described earlier. Figure 5 shows the trade-off between (i) *CU* and cost of the network, (ii) I_n and cost of the network, and (iii) I_n and *CU* of Network 1. Similarly, the trade-offs for Networks 2 and 3 are plotted in Figures 6 and 7, respectively.

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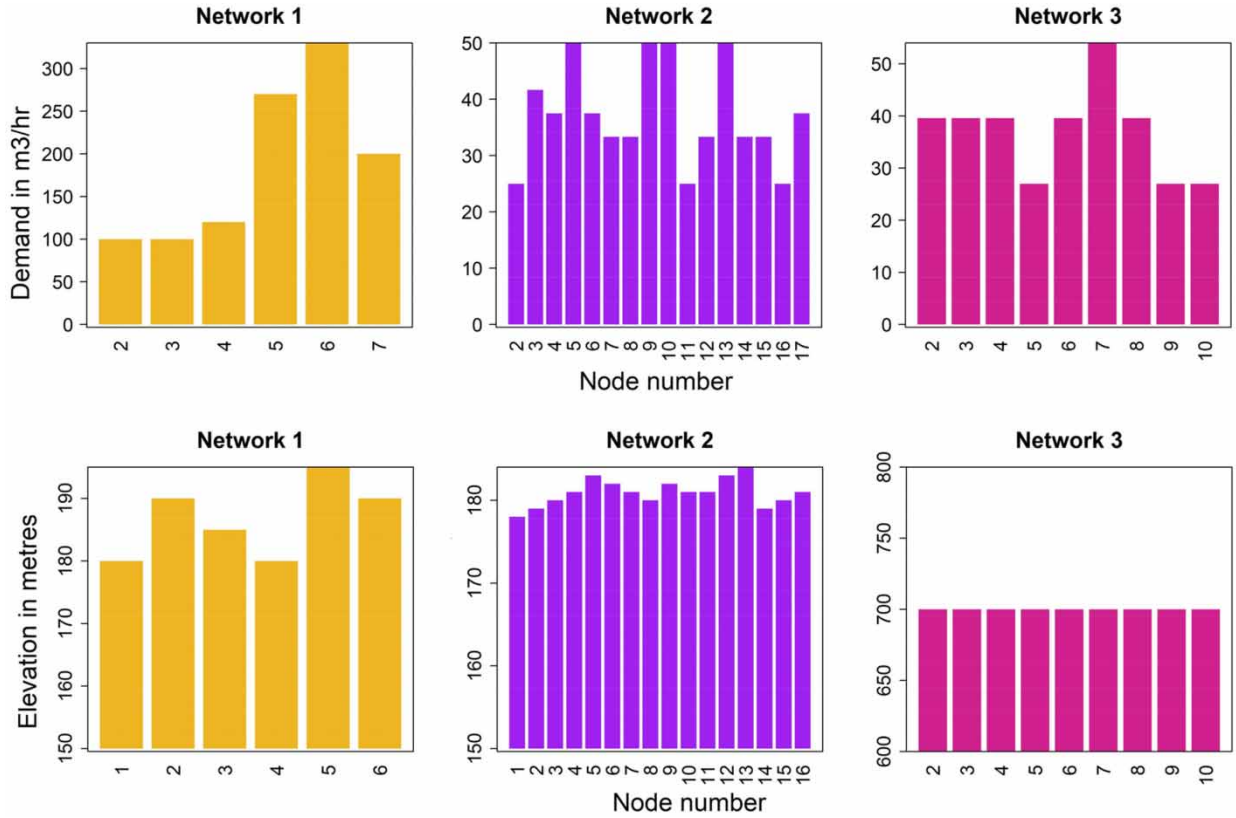


Figure 4 | Node data of three study networks.

Examining Figure 5 for Network 1 reveals that NSGA-II-generated solutions exhibit suboptimal performance, with *CU* and reliability values below 0.4. In contrast, for caRamel, MOPSO-CD, and MOEA/D, a clear trend emerges: as *CU* and I_n values approach 1, there is a corresponding increase in the network's cost. Beyond a threshold where both I_n and *CU* exceed 0.8, there is a pronounced exponential rise in the network's cost, aligning with existing literature (Prasad & Park 2004; Wang *et al.* 2015). Additionally, it is worth noting that reliability values consistently surpass 0.98 whenever *CU* values exceed 0.8.

For Network 2 (Figure 6), Pareto-optimal solutions from NSGA-II exhibit comparatively better performance than Network 1, with reliability values exceeding 0.93 and *CU* values surpassing 0.72. In the case of the other three algorithms, reliability values are greater than 0.95, and *CU* values are above 0.8. Remarkably, for all reliability and *CU* values, the cost remains constant for solutions obtained from MOPSO-CD and MOEA/D. However, a decline in reliability values is noted at higher *CU* values.

In the case of Network 3, NSGA-II performs unsatisfactorily in terms of *CU*, with values less than 0.32. However, the other three algorithms demonstrate satisfactory performance with higher reliability (>0.98) and *CU* (>0.5) values. Similar to Network 2, the relationship between cost and reliability, as well as cost and *CU*, lacks a clear pattern, and a decrease in reliability values is observed at higher *CU* values.

Regarding Network 1, it is evident that achieving high equity in water supply (*CU* close to 1) comes at a substantial cost, marked by a sharp increase. This aligns with the findings of Gottipati & Nanduri (2014), highlighting the significant impact of the source location and network layout on *CU*. While the present study maintains a fixed network layout and source location, there is potential for enhancing supply equity without a significant cost increase by optimizing the network layout during design (Gottipati & Nanduri 2014). Notably, for Networks 2 and 3, optimization using MOPSO-CD and MOEA/D does not lead to a significant cost increase, indicating more cost-efficient ways to achieve equity in water supply in these network configurations.

In summary, the graphical representations offer valuable insights into the trade-offs between cost, uniformity, and network resilience, guiding decision-makers in network optimization. These results highlight the crucial role of tank structure and

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Table 3 | Link data for three study networks

Network 1				Network 2				Network 3			
Link ID	Start node	End node	Length (m)	Link ID	Start node	End node	Length (m)	Link ID	Start node	End node	Length (m)
1	1	2	1,000	1	1	2	1,400	1	1	2	300
2	2	3	1,000	2	2	3	1,700	2	2	3	1,600
3	2	4	1,000	3	3	4	1,000	3	3	4	1,600
4	4	5	1,000	4	4	5	900	7	5	6	1,600
5	4	6	1,000	5	5	6	1,350	8	6	7	1,600
6	6	7	1,000	6	2	7	900	11	8	9	1,600
7	3	5	1,000	7	7	8	1,100	12	11	6	60
8	5	7	1,000	8	8	5	1,400	4	2	5	1,600
	9	5	9	900	5	3	6	1,600			
	10	5	10	1,000	6	4	7	1,600			
	11	6	10	1,200	9	5	8	1,600			
	12	1	11	1,100	10	6	9	1,600			
	13	11	12	800							
	14	12	13	1,400							
	15	13	9	800							
	16	10	14	1,100							
	17	11	15	1,200							
	18	15	16	800							
	19	16	13	900							
	20	16	17	1,400							
	21	17	14	1,200							

placement in improving water supply equity within a network, underscoring their significance in network design. Performance indicators like the uniformity coefficient and resilience index contribute to designing WDNs while considering costs.

4.2. Multidimensional Pareto analysis

Multidimensional Pareto analysis was carried out using brute-force dominance check algorithm and the outcomes are visualized in Figure 8 as a three-dimensional plot. The blue dots on the plot represent solutions that excel in at least one objective without being surpassed by any other solution. These are classified as Pareto-optimal, illustrating trade-offs between objectives, such as reliability versus cost. Among these Pareto-optimal solutions, the red dots represent a subset chosen through the brute-force dominance check algorithm, offering specific combinations of cost, reliability, and uniformity that align with our decision criteria.

In summary, the plot provides a clear visualization of the complex trade-offs among cost, reliability, and CU. Solutions located in the lower left corner are cost-effective but may compromise on reliability and uniformity. Conversely, solutions in the upper right corner prioritize reliability and equity but tend to incur higher costs. The red dots highlight the selected solutions that achieve a desirable balance among these objectives through the brute-force Pareto analysis. Analysing the spatial arrangement of these points within the three-dimensional space offers valuable insights into the complex interplay of these factors, facilitating informed decision-making for optimizing network design.

4.3. Multi-criteria decision-making

Two MCDM techniques, namely CP and Fuzzy TOPSIS (FTOPSIS), were employed to evaluate the Pareto-optimal solutions derived from four multi-objective optimization algorithms. The MCDM techniques incorporated two weight allocation approaches: the entropy method and CRITIC method. To summarize, the solutions obtained from the Pareto fronts were ranked using four methods: CP-entropy, CP-CRITIC, FTOPSIS-entropy, and FTOPSIS-CRITIC. Figure 9 illustrates the

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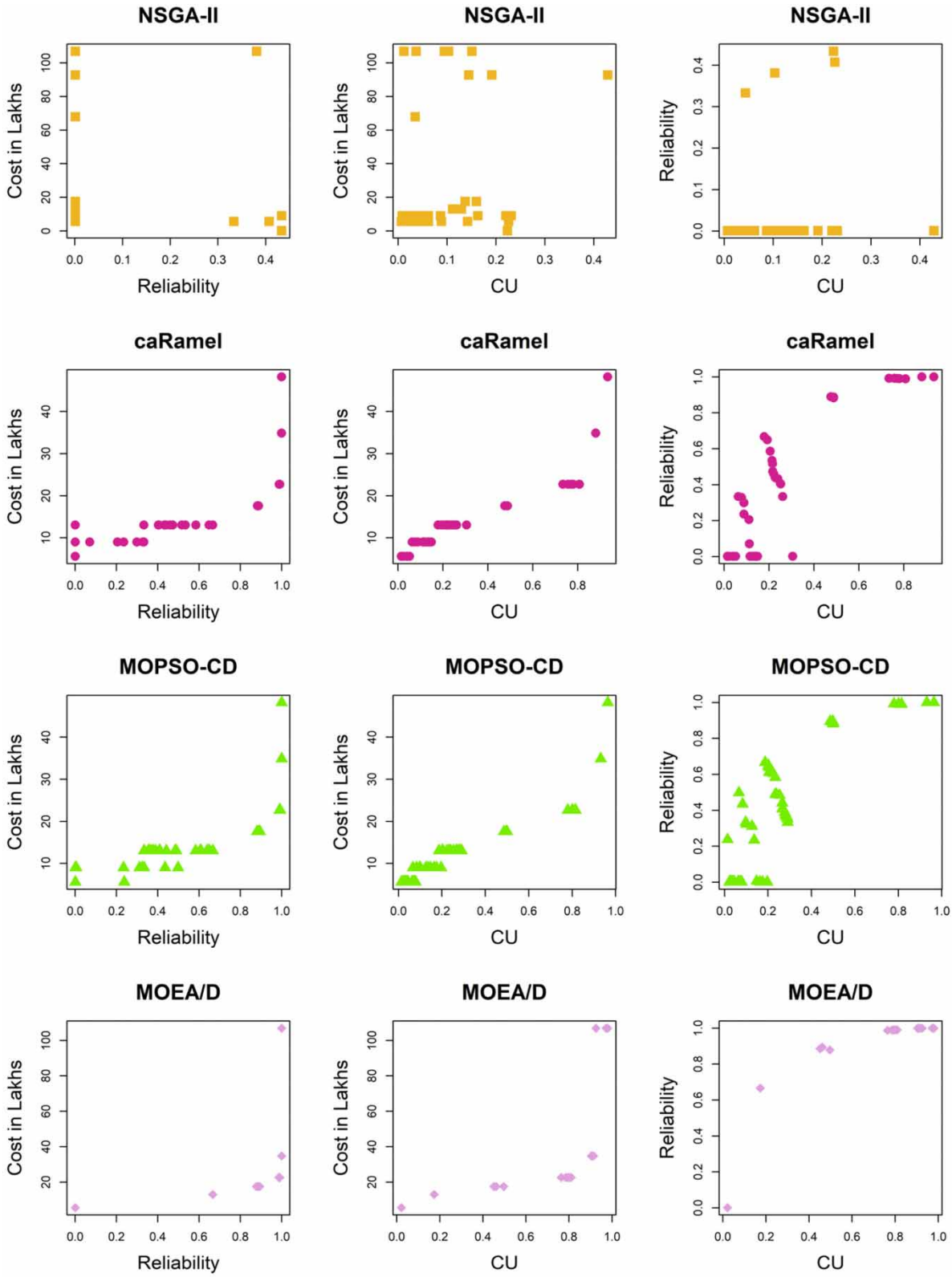


Figure 5 | Trade-offs between (i) CU and cost of the network, (ii) I_n and cost of the network, and (iii) I_n and CU for Network 1, obtained from Pareto fronts of NSGA-II, caRamel, MOPSO-CD, and MOEA/D.

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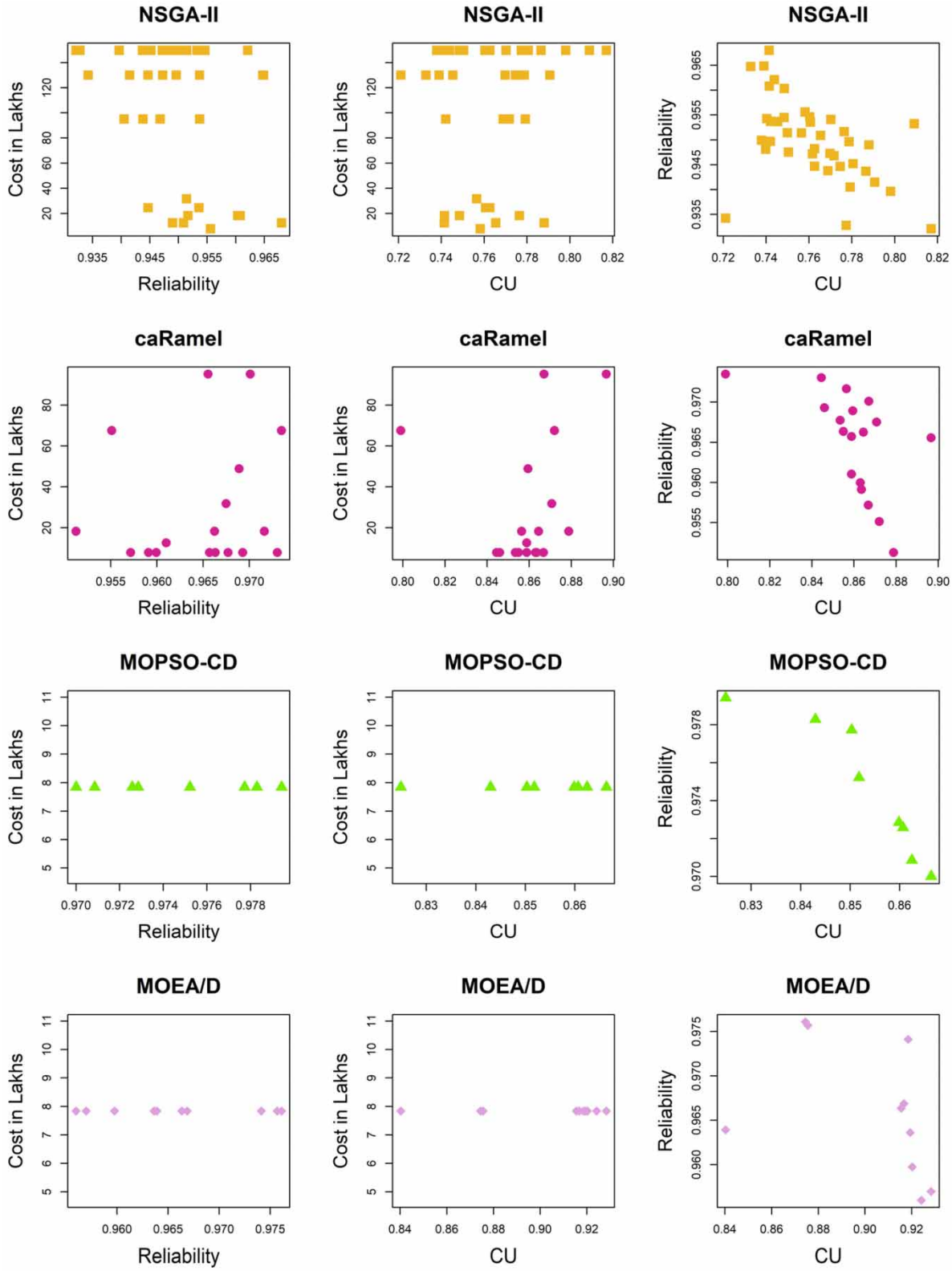


Figure 6 | Trade-offs between (i) CU and cost of the network, (ii) I_n and cost of the network, and (iii) I_n and CU for Network 1, obtained from Pareto fronts of NSGA-II, caRamel, MOPSO-CD, and MOEA/D.

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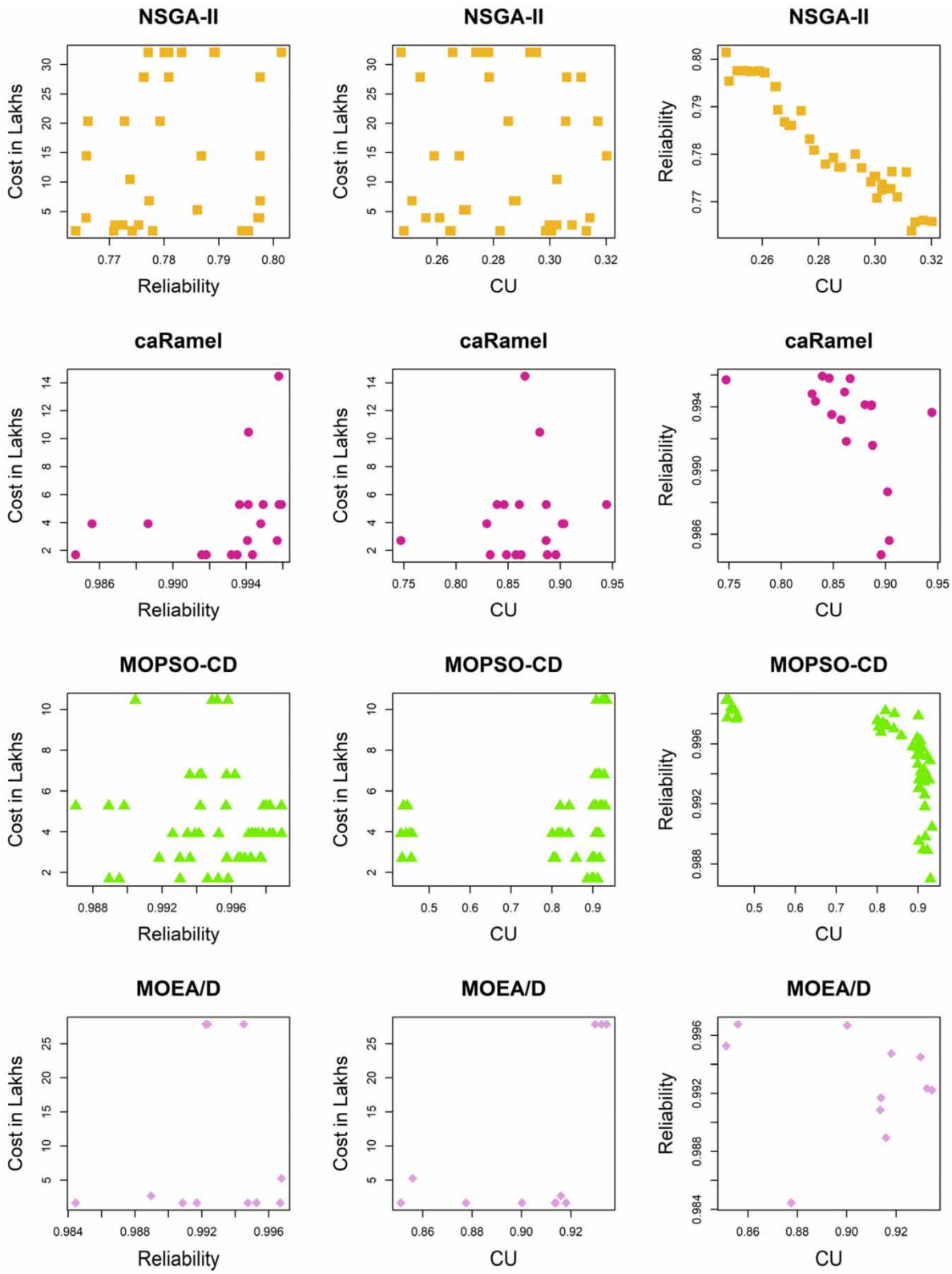


Figure 7 | Trade-offs between (i) CU and cost of the network, (ii) I_n and cost of the network, and (iii) I_n and CU for Network 1, obtained from Pareto fronts of NSGA-II, caRamel, MOPSO-CD, and MOEA/D.

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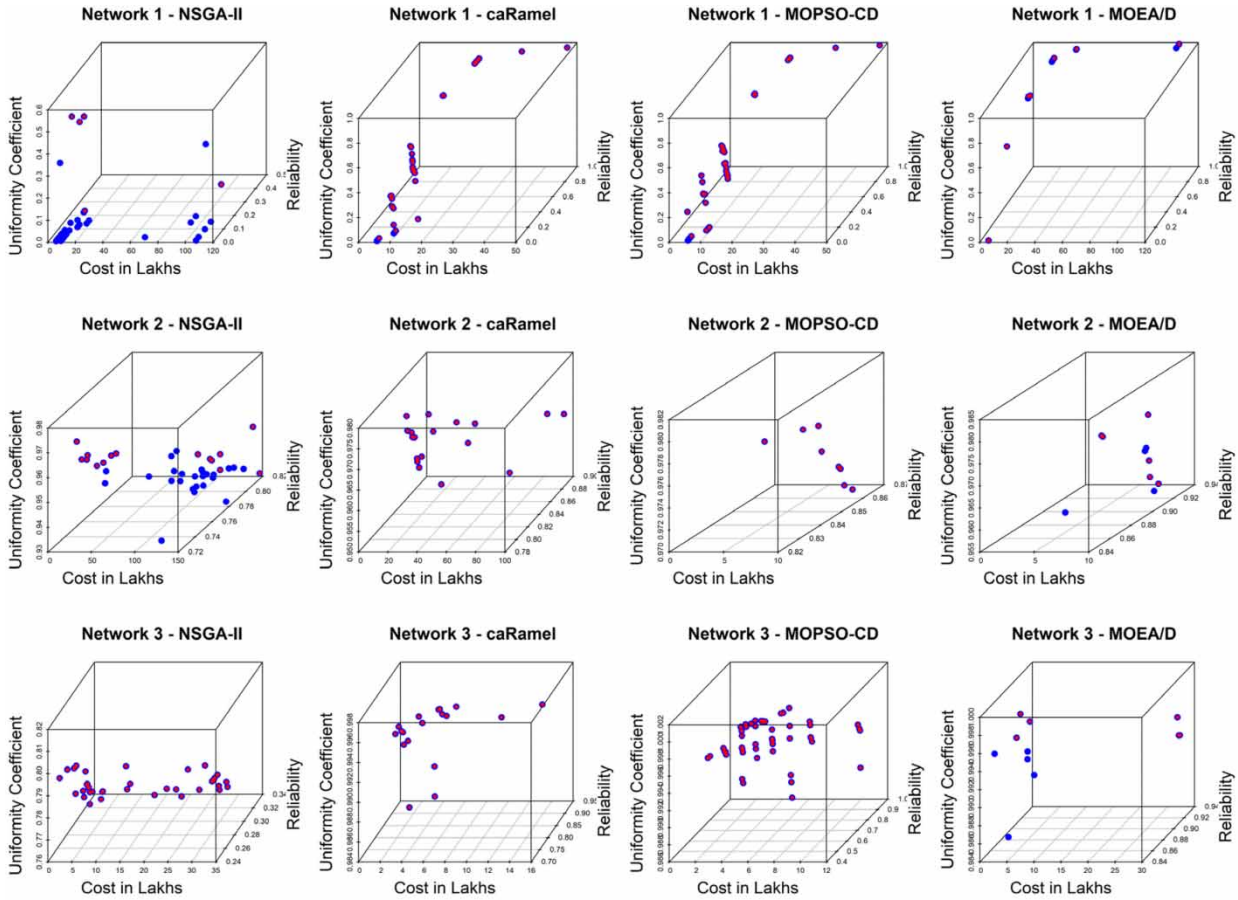


Figure 8 | Three-dimensional Pareto analysis of cost, reliability, and uniformity coefficient (CU) in water distribution network design: blue dots represent non-dominated solutions, while red dots indicate the final selected solutions using the brute-force dominance check algorithm.

boxplots of Lp metric values obtained from CP, providing a comparative analysis of solutions obtained from four different algorithms across all three networks. Lower Lp metric values indicate solutions that are closer to the ideal solution, signifying higher optimization performance.

The comparison in Figure 9 reveals that NSGA-II exhibits relatively poorer performance compared to the other three optimization algorithms, as indicated by its higher median Lp metric values. Across all three networks, solutions derived

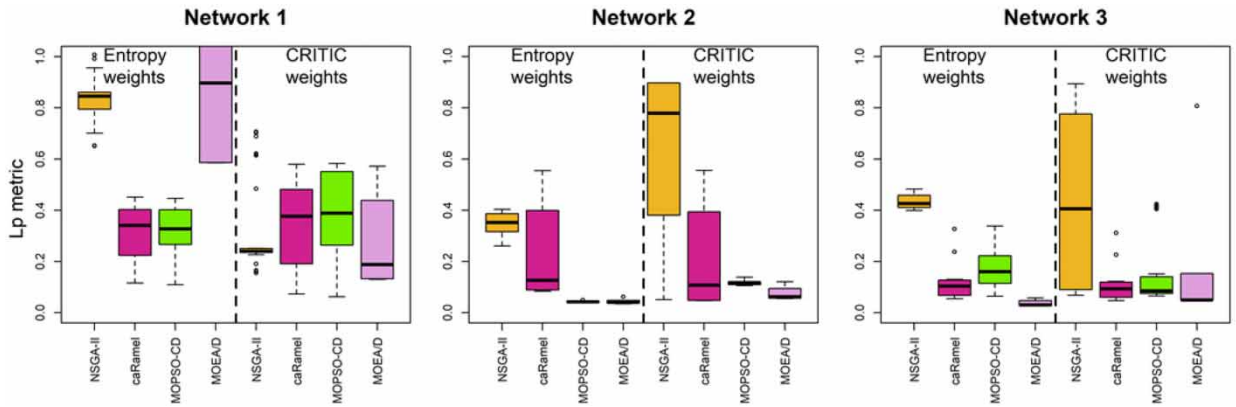


Figure 9 | Boxplots of Lp metric values obtained from compromise programming to compare four different algorithms across three networks. Note that the lower the Lp metric value, the closer to the ideal solution.

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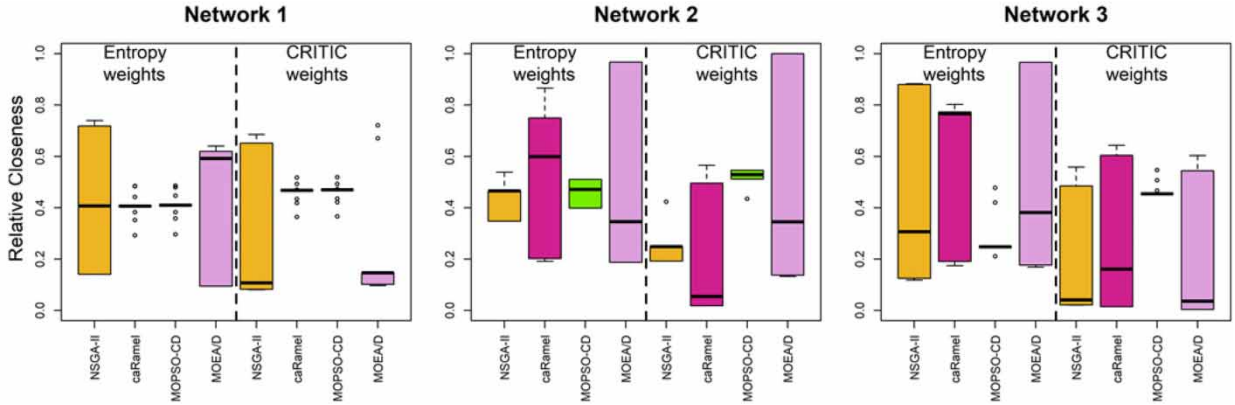


Figure 10 | Boxplots of relative closeness values obtained from Fuzzy TOPSIS to compare four different algorithms across three networks. Note that the higher the relative closeness value, the closer to the ideal solution.

from MOEA/D consistently demonstrate lower median Lp metric values, except in the case of CP-entropy method for Network 1. Further, MOPSO-CD demonstrates second-best performance after MOEA/D across all networks. Notably, there is observable variation in the spread and median of the boxplots between entropy weights and CRITIC weights, underscoring the influence of weight allocation methods on the results. Further, it can be noticed that the boxplots plotted for CP-CRITIC methods exhibit a higher interquartile range, indicating higher uncertainty.

Boxplots of relative closeness obtained from FTOPSIS were plotted in Figure 10 to compare the solutions obtained from four different algorithms across all three networks. Higher relative closeness values indicate closer proximity to the ideal solution, indicating superior optimization performance. From the figure, it can be noticed that both NSGA-II and MOEA/D exhibit a wider range of spread in relative closeness values compared to other methods, indicating higher variability in their performance across different solutions. Unlike CP-based methods, there is no clear better-performing model in FTOPSIS. The performance of caRamel and MOPSO-CD was better in Network 1 for both weighting methods. In Network 1, both weighting methods favour caRamel and MOPSO-CD. In Networks 2 and 3, in terms of median relative closeness, caRamel performs well with entropy weights, while MOPSO-CD excels with CRITIC weights.

Further analysis was carried out to identify the top five performing solutions to understand the ranking pattern obtained from the four methods. In CP-based methods, a consistent ranking pattern was observed across both weighting methods. In CP-entropy and CP-CRITIC methods, MOPSO-CD held the top five positions in Network 1, while MOEA/D occupied the top five positions in Networks 2 and 3. However, the ranking pattern differed between weighting methods in Networks 1 and 2. In Network 1, although NSGA-II and MOEA/D both held the first five ranks in both weighting methods, the ranking pattern was different. In Network 2, NSGA-II and caRamel occupied the first five ranks with entropy weights, while NSGA-II alone held the first five ranks with CRITIC weights. In Network 3, NSGA-II and caRamel occupied the first five ranks in both weighting methods with a similar ranking pattern.

The consistent ranking pattern in CP under both weighting schemes suggests that CP may be less sensitive to variations in criteria weights compared to Fuzzy TOPSIS. This could be due to CP's approach of minimizing deviations without explicitly considering the relative importance of criteria. On the other hand, in FTOPSIS, the use of fuzzy set theory introduces additional complexity and uncertainty handling, causing rankings to be more sensitive to changes in weight allocation methods (Anil *et al.* 2021).

5. CONCLUSIONS

The present study on the comparative analysis of multi-objective optimization algorithms and MCDM methods holds paramount importance in the field of WDN design by providing comprehensive insights into the complex trade-offs between cost, uniformity, and network resilience. By leveraging advanced optimization algorithms and MCDM techniques, the research offers a robust framework for decision-makers to strike an optimal balance among these crucial factors (Vijayakumar *et al.* 2022; Chadee *et al.* 2023). The following conclusions were drawn from the study:

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- Multi-objective optimization algorithms (NSGA-II, caRamel, MOPSO-CD, MOEA/D) exhibited varying performance across different networks, underscoring the importance of tailoring approaches to network characteristics.
- Analysing Network 1, NSGA-II exhibited suboptimal solutions with CU and Reliability values below 0.4, while caRamel, MOPSO-CD, and MOEA/D demonstrated an increasing trend in network cost as CU and I_n approached 1. A notable exponential rise in cost occurred when both I_n and CU exceeded 0.8.
- Network 2 revealed improved performance by NSGA-II, with reliability values > 0.93 and CU values > 0.72, while MOPSO-CD and MOEA/D maintained constant costs for various reliability and CU values.
- In Network 3, NSGA-II exhibited unsatisfactory CU values (<0.32), while the other algorithms showed satisfactory performance with higher reliability (>0.98) and CU (>0.5) values.
- The Pareto fronts generated by multi-objective optimization algorithms offered valuable insights into the trade-offs between cost, reliability, and uniformity within the networks. Multidimensional Pareto analysis, employing brute-force dominance check, provided a clear visualization of the intricate trade-offs among cost, reliability, and uniformity.
- The present study carried out a comprehensive analysis, incorporating advanced multi-objective optimization algorithms and MCDM techniques (CP and FTOPSIS) along with weight allocation methods (entropy and CRITIC) for ranking Pareto-optimal solutions, providing a robust framework for decision-makers. It offers critical insights for optimizing network design and aids in selecting optimal network configurations.
- Consistent ranking patterns in CP revealed MOPSO-CD as the top performer in Network 1 for CP-entropy and MOEA/D as the best algorithm in Networks 2 and 3 for both CP-entropy and CP-CRITIC methods.
- The study underscores the sensitivity of ranking outcomes in MCDM analysis to the choice of MCDM technique and weighting method, emphasizing the need for careful consideration in the decision-making process.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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