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Achieving sustainable water distribution through penalty-free multi-objective evolutionary design optimization

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Abstract

Water distribution networks are costly long-term investments, prompting researchers to seek cost reduction and efficient design solutions using optimization techniques. In this context, the Penalty-Free Multi-Objective Evolutionary Algorithm (PFMOEA) is employed alongside pressure-dependent analysis (PDA) to optimize water distribution systems (WDSs). This integrated approach facilitates a multi-objective evolutionary search, leading to improved WDS designs. The research aimed to improve the computational efficiency of PFMOEA by using real coding, where decision variables are represented as real numbers rather than integers or binary formats. Additionally, it adjusted the allocation of feasible and infeasible solutions near the Pareto front (the boundary of optimal or least-cost solutions) during the elitism step of the optimization process. A feasible solution was regarded as the one that meets all the pressure and flow rate requirements while an infeasible solution fails to meet these requirements. These adjustments were labeled as PFMOEA-A, PFMOEA-B, and PFMOEA-C, with allocation percentages of 15% feasible and 15% infeasible solutions, 20% feasible and 10% infeasible solutions, and 30% feasible and 0% infeasible solutions, respectively. The study utilized two benchmark network problems, the two-looped and Hanoi networks, for analysis. A comparative assessment was then conducted to evaluate the performance of the real-coded PFMOEA in comparison to other approaches documented in the literature. The algorithm demonstrated competitive performance for the two benchmark networks by implementing real coding. The real-coded PFMOEA achieved the novel best-known solutions ($419,000 and $6.081 million) and a zero-pressure deficit for the two networks, requiring fewer function evaluations than the binary-coded PFMOEA. Additionally, by replacing 15% of the feasible solutions with infeasible ones that are close to the Pareto front with minimal pressure deficit violations, the computational efficiency of the PFMOEA was enhanced. This led to a 20% and 17% reduction in the number of function evaluations required to identify the optimal solutions for the Two-looped network and the Hanoi network, respectively. The findings of this study aim to contribute to a more equitable and resilient water management framework. Ultimately, the insights gained will not only support the optimization of existing water distribution networks but also inform policy decisions that prioritize sustainability and resource conservation. This holistic approach will facilitate improved water security and support the overarching goal of achieving sustainable water management against the growing challenges related to climate change and urbanization.

HIGHLIGHTS

- PFMOEA eliminates the need for penalties through the adoption of a pressure-dependent analysis within a multi-objective optimization search.
- Employing real coding in PFMOEA instead of binary coding enhances the computational efficiency of PFMOEA.
- Retaining a small percentage of infeasible solutions near the boundary of optimal solutions during

optimization also improves the computational performance of PFMOEA.

KEYWORDS

elitism, optimization, real coding, water distribution network

1 | INTRODUCTION

Water Distribution Systems (WDSs) are essential in modern society, and their value cannot be overstated. These systems serve as passive infrastructure for transporting potable water from treatment plants to consumers, satisfying residential, industrial, commercial, and firefighting requirements (WHO, 2014). Nonetheless, it is worth noting that the construction, operation, and maintenance costs associated with WDS are usually very high (Sangroula et al., 2022). According to Sangroula et al. (2022), the WDS accounts for approximately 80% of the entire cost of a water supply project. Therefore, designing a cost-effective and sustainable Water Distribution Network (WDN) is vital.

Previously, engineers relied on trial-and-error techniques to find low-cost WDS solutions (Zarei et al., 2022). However, for a few decades, engineers have been using optimization techniques to select cost-effective WDS that meet the required water demands while maintaining adequate pressure (Zarei et al., 2022). One distinctive aspect of engineering optimization is the use of multiple yet sometimes conflicting decision-making criteria alongside constraints (Deb et al., 2002; Mala-Jetmarova et al., 2018). Such problems have optimal solutions in the constraint boundary region, whereas the infeasible and feasible solutions are located on both sides of the boundary region (Siew & Tanyimboh, 2012a).

The computational complexity of optimizing WDNs is high due to the numerous physical components and operational requirements inherently associated with the systems (Sangroula et al., 2022). As a result, traditional optimization approaches such as enumeration and calculus have seen a major decline in recent decades (Savic & Walters, 1997; Tran, 2005). The more recent development of random guided search techniques known as metaheuristics enables a trade-off between computational time and quality (Mala-Jetmarova et al., 2018). These search techniques include hill climbing, Tabu search, and Evolutionary Algorithms (EAs) (Savic & Walters, 1997; Tran, 2005). Fang (2007) stated that EAs solve complex multi-objective optimization problems by mimicking biological theories. EAs are integrated into hydraulic models like EPANET, and the resulting nodal head values are assessed using pressure-related constraints (Zarei et al., 2022). Over the past decade, various techniques falling under the umbrella of EAs have been developed and employed (Mala-Jetmarova et al., 2018). One prominently used approach within the array of EAs is Genetic Algorithms (GAs), which has gained recognition and broad usage (Deb et al., 2002; Tran, 2005).

One significant drawback of GAs is their inability to directly handle constraints, particularly those related to pressure violations (Siew et al., 2014). Most WDS optimization studies use the conventional Demand Driven Analysis (DDA) method as a hydraulic solver (Kadu et al., 2008). However, DDA cannot simulate pressure-deficient conditions due to the assumption that all nodal demands are fully supplied regardless of pressure (Siew & Tanyimboh, 2012b). Therefore, many past studies (Abdy Sayyed et al., 2019; Kadu et al., 2008; Sangroula et al., 2022; Zarei et al., 2022) utilized penalty functions or special techniques to handle pressure constraint violations. In this context, infeasible solutions (those violating pressure constraints) under the cost-driven objective function incur extra penalty costs based on their current state of deficiency (Siew & Tanyimboh, 2012a). The extent of this shortfall is directly proportional to the corresponding penalty cost (Kadu et al., 2008). This implies that as the level of deficiency increases, so does the penalty cost (Kadu et al., 2008). However, the disadvantage of this approach is that additional expertise is required to calibrate the penalty parameters (Siew & Tanyimboh, 2012a). Furthermore, the method is not simple and is fine-tuned on a case basis (Mala-Jetmarova et al., 2018).

Siew and Tanyimboh (2012a) developed the Penalty-Free Multi-Objective Evolutionary Algorithm (PFMOEA) approach to optimize WDSs to address the drawback mentioned earlier. The approach creates a multi-objective evolutionary search, eliminating the requirement for ad hoc penalty functions, additional "boundary search" parameters, or specialized constraint handling procedures (Siew et al., 2014). It achieves this using pressure-dependent analysis (PDA) (Siew et al., 2014). PDA can simulate both normal and pressure-deficient networks, enabling accurate and rapid identification of feasible solutions in the solution space (Siew & Tanyimboh, 2012b).

In earlier PFMOEA research, solutions were encoded and decoded using binary representation between the solution and coding spaces (Seyoum & Tanyimboh, 2016; Siew & Tanyimboh, 2012a; Tanyimboh & Seyoum, 2020). Although binary coding is simple to use, it generates redundant codes that do not match any members of the finite discrete set to which the encoded parameter belongs (Siew, 2011; Siew et al., 2014). Thus, real coding has been suggested by Tanyimboh (2021) as an approach to increase the GA's computational efficiency as it does not generate redundant codes.

Previous studies (Seyoum et al., 2016; Siew et al., 2014, 2016) have characterized the PFMOEA as a bias-free approach that does not impose penalties on infeasible solutions. However, a closer examination reveals that this perception is not entirely accurate. The PFMOEA incorporates an elitism mechanism that involves preserving 30% of the population, consisting of the least cost-effective feasible solutions, within each generation (Siew & Tanyimboh, 2012a). Concurrently, the remaining 70% of solutions undergo selection using the crowding distance operator, which fills the remaining population slots (Siew & Tanyimboh, 2012a). Consequently, the preference for preserving feasible solutions in the PFMOEA leads the solutions to primarily approach the active constraint boundary from the feasible side (Siew & Tanyimboh, 2012a). This behavior limits the exploration of both the infeasible and feasible sides (Siew et al., 2014). However, Ray et al. (2009) observed that maintaining a small percentage of infeasible solutions close to the constraint or optimal boundary during optimization enhances the GA's convergence rate. Hence, enabling elitism to include infeasible solutions of the PFMOEA could be crucial for improving the performance of the GA (Ray et al., 2009).

This study aimed to determine whether the computational efficiency of the Penalty-Free Multi-Objective Evolutionary Algorithm (PFMOEA) for optimizing water distribution system designs could be improved by using real coding (actual numbers) instead of binary coding (1 s and 0 s). Furthermore, it investigated the potential benefits of retaining some infeasible solutions that do not fully meet the problem's constraints but are close to the least-cost (Pareto optimal) boundary. This investigation focused on the application of elitism in the GA optimization process.

2 | METHODOLOGY

2.1 | Incorporating real coding in PFMOEA

The real-coded Non-dominated Sorting Genetic Algorithm II (NSGA II) (Deb et al., 2002), an algorithm designed for multi-objective optimization using real-number representations of solutions, was integrated with the EPANET model within the MATLAB environment (Figure 1). NSGA II exhibits robustness and adaptability by handling complex, multi-objective, and constraint-based optimization problems. On the other hand, MATLAB was chosen due to its user-friendly interface, making it accessible to researchers and engineers with limited programming experience (Khalifeh et al., 2020). EPANET 2.0 was used for network modeling and hydraulic simulation. The real-coded NSGA II source code was modified to incorporate key principles of PFMOEA. This modification included altering the constraint-handling mechanism to allow the algorithm to focus on optimizing multiple objectives without applying penalties for infeasible solutions. It also incorporated GA operators such as tournament selection, which was used to choose high-performance solutions and simulated binary crossover (SBX), which combined two solutions to create improved ones. Additionally, polynomial mutation (PM) was applied to introduce small random variations, promoting greater solution diversity.

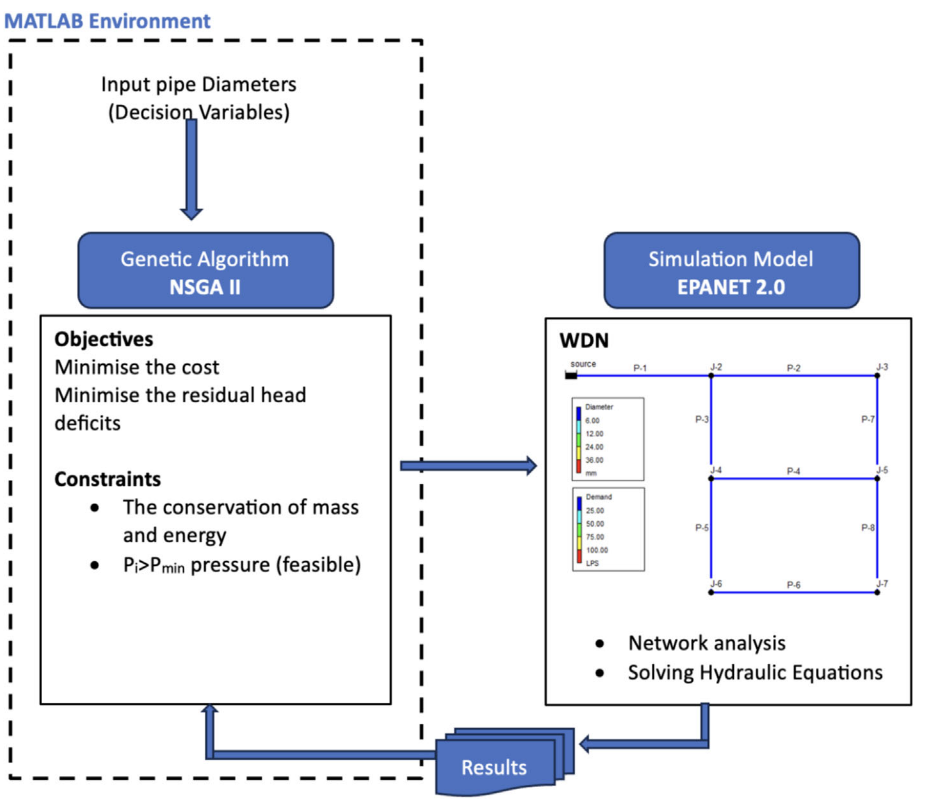

FIGURE 1 Coupling of computational tools in the study.

2.1.1 | Design optimization problem formulation

Objective function

The design optimization model aimed to achieve two main objectives: minimizing the cost of the initial construction and minimizing the pressure deficit at the critical demand node i.e., characterized by a significant shortfall in the required head. The cost minimization objective was expressed as a function, f_1 (Equation 1) and was straightforward to implement as it simply involved solving the corresponding equation. It is worth observing that the optimization design focused solely on reducing the initial construction cost. Although operational, rehabilitation, and expansion costs contribute to the total cost of the WDS (Shirajuddin et al., 2023), this study did not consider their inclusion within its scope.

The head deficit objective was defined by function, f_2 (Equation 2) and involved converting head shortfall values to positive values, while surplus heads were set to zero. Feasible solutions were identified as those with zero values of f_2, indicating that the nodal head was fully satisfied, meeting or exceeding the desired head value. Infeasible solutions, on the other hand, were associated with positive values of f_2, indicating that the nodal head did not meet the desired requirements.

$$\text{Minimize the cost} f_1 = \sum_{x=1}^{X} c(D_x)\, L_x \tag{1}$$

$$\text{Minimize the residual head deficits } f_2 = max\left(H_n^{des} - H_n, 0\right) \tag{2}$$

where $c(D_x)$ is the cost per unit length of pipe x with diameter D_x, L_x is the length of pipe x, and X is the number of pipes in a network. In Equation 2, the nodal pressure deficit at node n was obtained by subtracting the available head (H_n) from the desired head (H_n^{des}) at node n.

Constraints

The optimization objectives were subject to the following hydraulic constraints.

1. The conservation of mass and energy as indicated by Equations 3 and 4, respectively, were satisfied by integrating the EPANET 2 simulator into NSGA II. The continuity equation represents the mass conservation principle, met when a network's sum of inflows and outflows is zero (Zarei et al., 2022). In network modeling, outflows are taken at network junctions. The continuity equation is written as follows:

$$\sum_{i=1}^{n} \boldsymbol{q_i} = \mathbf{0} \tag{3}$$

where i is the node, q_i is the nodal inflows and outflow, and n is the number of pipes connected at the node.

The conservation of energy is stated using the head loss equation (Zarei et al., 2022). This occurs when the total head losses in the pipes that constitute each loop are equal to zero as expressed in Equation 4.

$$\sum_{j=1}^{m} h_j = 0 \tag{4}$$

where m is the number of pipes in the loop, and h_j is the head loss in each pipe j.

Much of the head loss in a pipeline system is caused by friction between the fluid and the walls of a pipe (Bhave & Gupta, 2006). Additionally, it is also because of fluid particles as they move relative to one another (Bhave & Gupta, 2006). Darcy-Weisbach (Equation 5), Hazen-Williams (Equation 6), and Chezy-Manning's (Equation 7) equations can be used to calculate pipe head loss (Bhave & Gupta, 2006).

$$h = \frac{8fLQ^2}{gD^5\pi^2} \tag{5}$$

$$h = \frac{\omega L Q^{1.852}}{C^{1.852} D^{4.871}} \tag{6}$$

$$h = \frac{\eta L (CQ)^2}{D^{5.33}} \tag{7}$$

where h, L, and D are the pipe's head loss, length, and diameter in meters, respectively. f is the pipe's Darcy-Weisbach friction factor, Q is the flow rate in a pipe in cubic meters per second, g is the gravitation due to gravity, C is the roughness coefficient, and η is the Chezy-Manning dimensionless conversion factor (10.29 in International System of Units).

The unit conversion factor ω is determined by the units used in Equation (6). As a result, the calculation of head loss in Equation (6) is strongly dependent on the specific value assigned to ω. By choosing a greater ω value, the head loss in the pipe increases, necessitating larger pipe sizes and increasing the network's overall cost (Palod et al., 2021). A lower ω value, on the other hand, minimizes head loss, allowing for smaller pipe diameters and thereby lowering network costs (Palod et al., 2021). As a result, it is not appropriate to directly compare the costs of different networks from different studies since researchers utilize different values of ω (Palod et al., 2021). Thus, ω refers to problem-specific parameters or scaling factors that might be used to normalize or adjust the units of measurement within the optimization problem. These factors can vary widely between different problems and do not provide a consistent basis for comparing algorithmic performance across different contexts. Siew and Tanyimboh (2012a), as well as Savic and Walters (1997), used similar ω values of 10.5088 and 10.9031. On the other hand, Cunha and Sousa (2001) solely employed a ω value of 10.5088 while Ilemobade and Stephenson (2006) used a ω value of 10.7. EPANET 2 hydraulic simulator (the one used for this research) uses a Hazen-Williams equation with ω value of 10.667 (Rossman, 2000). Thus, this study evaluated the efficiency of the optimization approach using the maximum number of function evaluations (NFEs) because it is a direct, standardized, and widely applicable measure of computational cost. Additionally, it provides a clear and objective basis for comparing the performance of different algorithms, making it the preferred metric over problem-specific parameters like the unit conversion factor (ω) (Abdy Sayyed et al., 2019; Palod et al., 2021).

2. The optimization problems involved the selection and sizing of discrete pipe diameters from a predefined set of commercially available sizes. Thus, the aim was to determine the most suitable diameters for the pipes (Tanyimboh & Czajkowska, 2018).
3. The minimum node pressure constraints, as defined in Equation 8, were addressed in the second optimization objective that deals with head deficit conditions. Demands were aggregated and allocated at the nodes even though they occurred along the pipes.

$$\boldsymbol{H_n} \geq \boldsymbol{H_i^{req}} \tag{8}$$

where H_i^{req} is the required pressure head at the node. The required pressure head is the minimum pressure at a node above which all demands are met. H_i is determined by hydraulic simulation.

2.1.2 | Elitism criteria in PFMOEA

In this study, the PFMOEA was used to find the best solutions for complex WDS problems. The process involved two key steps: selecting and keeping the best solutions and ensuring diversity among them.

1. SELECTION AND RETENTION OF BEST SOLUTIONS

At each stage (or generation) of the algorithm, the top 30% of the solutions, considered the best and most feasible, were preserved for the next generation. These solutions were selected based on a high "crowding distance" value, which is a measure that ensures these solutions are far apart from each other, helping maintain diversity.

2. FILLING THE REMAINING POPULATION SLOTS

After preserving the top 30%, the rest of the population was filled by evaluating the remaining solutions based on their crowding distance. This ensured that not only were the best solutions kept but also that a variety of other solutions were considered to fill the rest of the population.

The main goal of this method was to keep feasible solutions that were close to the problem's boundary region, meaning they were close to the optimal solution. At the same time, it ensured that there was enough diversity in the population, which is important for exploring a wide range of possible solutions and avoiding premature convergence on suboptimal solutions.

2.1.3 | Application of the real-coded PFMOEA approach

The applicability of the real-coded PFMOEA was evaluated using two benchmark optimization problems: the Two-Loop Network, which is a water distribution system designed with two interconnected loops (Alperovits & Shamir, 1977), and the Hanoi Network (Fujiwara & Khang, 1990). While these networks do not completely represent the real-world situations of WDSs, they have been extensively examined in prior research including the previous binary-coded PFMOEA research. In this study, the effectiveness of the real-coded PFMOEA approach was assessed by considering both the optimal cost and the number of function evaluations. Additionally, a comparative analysis was conducted against other approaches with the smallest number of function evaluations in the literature.

The parameters for the crossover distribution index and mutation distribution index, which influence the offspring's distribution relative to parent solutions in simulated binary crossover (SBX) and polynomial mutation, were set to $\eta_c = 20$ and $\eta_m = 20$, respectively, based on the approach described by Deb et al. (2002). The crossover distribution index (η_c) affects the similarity between offspring and parents during the crossover, while the mutation distribution index (η_m) controls the extent of variation introduced in the offspring through mutation. For both networks, 20 runs were permitted. Each run began with a randomly generated population with a total of 200,000 function evaluations which effectively corresponds to 1,000 generations for a population size of 200. The objective was to find pipe diameters that minimized total cost while satisfying demand and pressure constraints at every node.

2.1.4 | Description of case study networks

1. Two-looped network

Alperovits and Shamir (1977) proposed the two-looped network which consists of a single reservoir and eight pipes that are 1,000 m long. A Hazen-Williams coefficient of 130 was assumed for new pipes. The minimum pressure required to satisfy the nodal demands in full was 30 m. This design optimization problem was based on a set of 14 commercially available pipe diameters, leading to a search of 1.4 X 10^9 solutions. The two-looped network's layout is

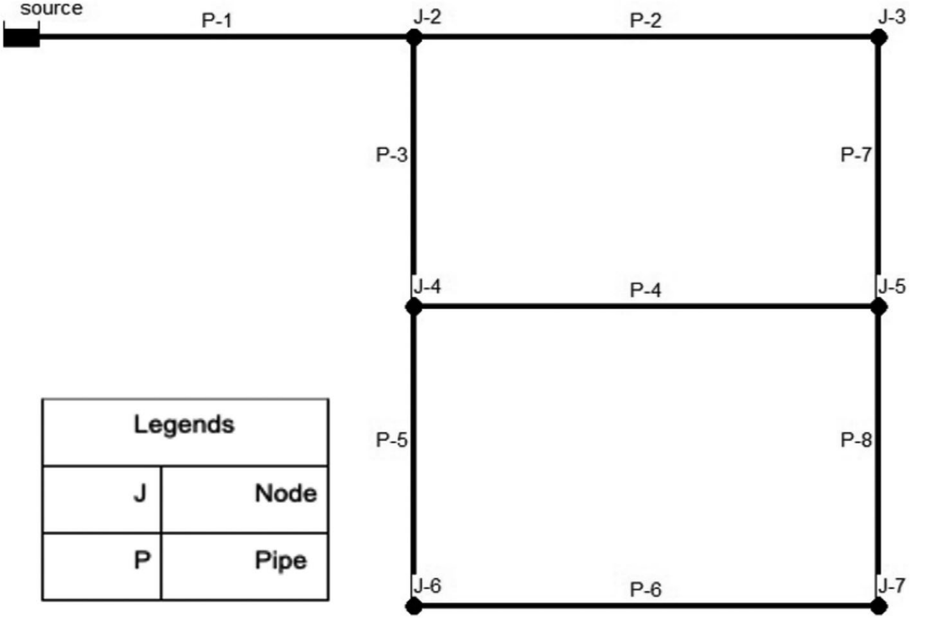

FIGURE 2 Layout of two-loop network (Alperovits & Shamir, 1977).

depicted in Figure 2, whereas other nodal and pipe data can be found in Alperovits and Shamir (1977).

2. Hanoi network

The Hanoi network (Figure 3) is composed of 34 pipes and 32 nodes, with a reservoir located at an elevation of 100 m (Fujiwara & Khang, 1990). The nodal demands required a minimum head of 30 m to ensure sufficient flow. All new pipes were assumed to have a Hazen-Williams friction coefficient of 130. The nodes were placed at ground level, at an elevation of 0.0 m. The diameters of the pipes utilized in designing the system are listed by Siew and Tanyimboh (2012a).

2.2 | Altering the elitism retention of PFMOEA

The elitism mechanism in evolutionary algorithms preserves high-quality solutions by retaining the best-performing individuals across generations without modification. In this study, the elitism strategy within the Pareto Front Multi-Objective Evolutionary Algorithm (PFMOEA) was modified by adjusting the retention percentages of both feasible and least infeasible solutions, particularly at the boundary regions as illustrated in Figure 4. This adjustment aimed to enhance solution diversity and improve convergence towards optimal solutions. Three different allocation percentages labeled as PFMOEA-A, PFMOEA-B, and PFMOEA-C were used. These allocations comprised 15% feasible and 15% infeasible solutions, 20% feasible and 10% infeasible solutions, and 30% feasible and 0% infeasible solutions, respectively. Each solution within the population underwent individual evaluation based on the optimization objectives (Equations 1

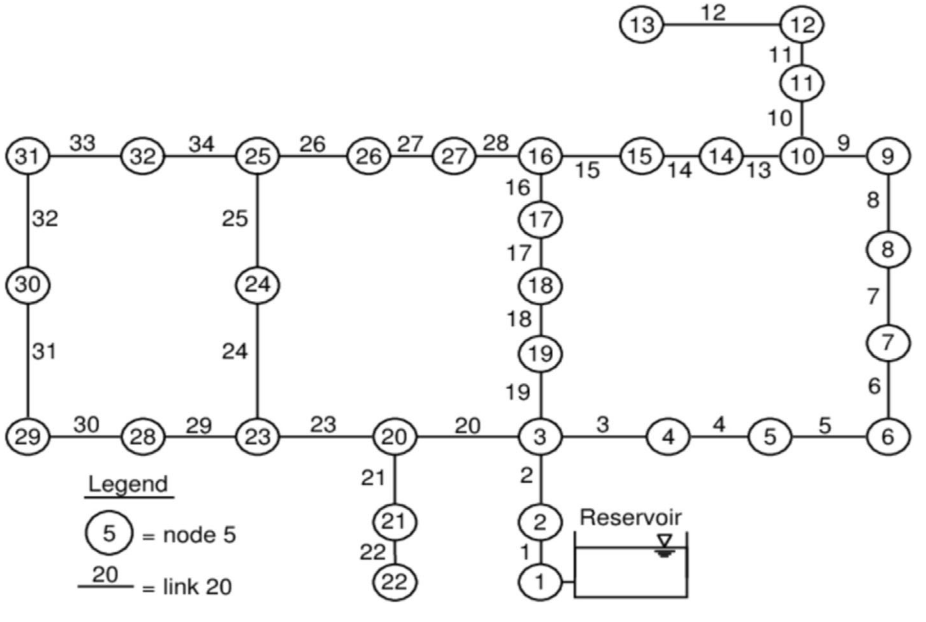

FIGURE 3 Layout of Hanoi network (Fujiwara & Khang, 1990).

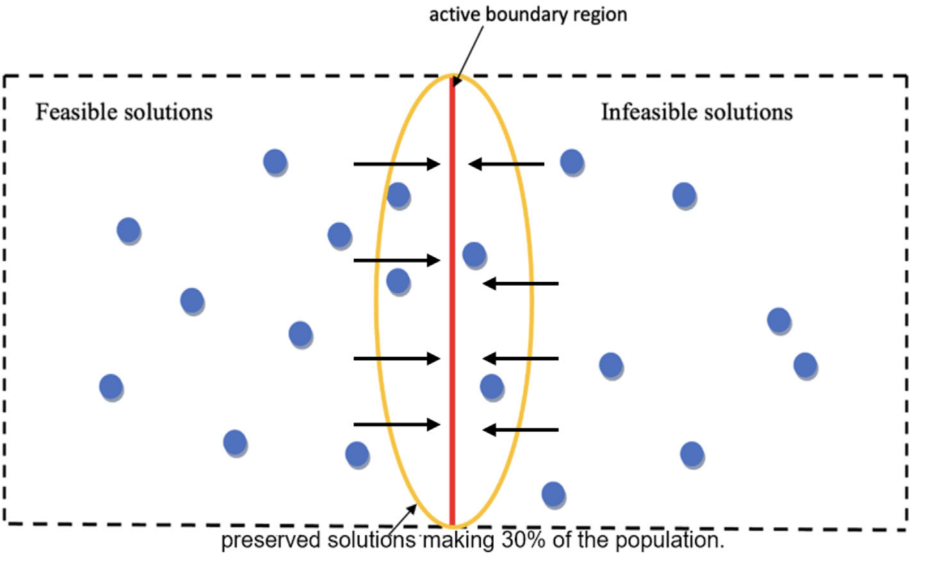

FIGURE 4 Schematic diagram of the altered elitism criteria in PFMOEA.

and 2). Solutions violating the pressure constraint were identified as infeasible, while feasible solutions were those exhibiting zero-deficit pressure.

The elitism retention process in PFMOEA for optimizing water distribution networks was carried out as follows:

1. An initial population (P_t) of network configurations was randomly generated, comprising N possible design layouts.
2. Each of these configurations were evaluated and ranked based on two key criteria: total system cost and pressure head shortfall (deficit).
3. The GA optimization steps of selection, crossover, and mutation were applied to the population (P_t) to produce a new set of network designs (Q_t) with the same size (N).
4. After the first round, where both the initial and offspring configurations were generated, the next iteration was processed as follows:

- Combinations of the original network designs (P_t) and the newly generated ones (Q_t) created a second set (R_t) with 2 N configurations.
- The R_t set was ranked using a non-dominated sorting method (Deb et al., 2002), where solutions were grouped into layers (F1, F2, etc.) based on their performance across the two objectives.
- The next generation of network designs (P_{t+1}) was created by selecting N configurations from the sorted R_t set, which would be used in the next round of the algorithm. This was applied for PFMOEA-C, while some adjustments as described in the next paragraph were made for PFMOEA-A and PFMOEA-B.
- Selection, crossover, and mutation were then applied to this new generation (P_{t+1}) to generate a new offspring population (Q_{t+1}) for the next cycle.

5. This iterative process (step1 to 4) continued until the optimization attained the termination criterion.

For PFMOEA-A, the process in steps 1 through 3 remained the same, but step 4 was modified. Specifically, 15% of the most cost-effective feasible network designs were retained, based on their ranking by cost. Additionally, 15% of the infeasible designs with the lowest head pressure deficits were also reserved. This iterative refinement continued until the optimization met its termination criteria. A similar approach was used for PFMOEA-B, but with different percentages of retention in step 4.

3 | RESULTS AND DISCUSSION

3.1 | Effectiveness of real coding in PFMOEA

1. Two-looped network optimization

The real-coded PFMOEA approach implemented on the Two-looped network in this study identified an optimum solution of $419,000 and a pressure deficit of zero within 2,000 function evaluations. This represents a fraction of 1.35×10^{-4}% of the total solution space (i.e., $14^8 \approx 1.48 \times 10^9$). Additionally, the average CPU time required to perform a single optimization run comprising 200,000 function evaluations was approximately 48 hrs. The pressure heads and deficits for the optimal solution with a consistent 30 m minimum head requirement across all network nodes. The actual pressures obtained at the nodes surpass the minimum pressure heads specified for each node. Furthermore, there is no shortfall in pressure as evidenced by a zero-pressure deficit at all nodes. Thirty percent of the most cost-effective feasible designs were retained in the analyses, while the remaining 70% were selected based on a crowding distance operator.

Figure 5 illustrates the Pareto optimal front obtained for the two-looped network with a parameter value of $\omega = 10.667$, based on 20 randomly initialized runs. The Pareto front of cost against head deficit shows a range of solutions that achieve different levels of cost and head deficit, highlighting the trade-off between these two objectives. Moreover, in Figure 5 it is evident that several hydraulically feasible designs exist in close proximity to the least expensive feasible solution, valued at $419,000. This indicates that the non-domination sorting process guarantees the survival of only the most economically feasible design at the boundary of feasibility (Siew et al., 2014).

Previously binary-coded PFMOEA approach by Siew and Tanyimboh (2012a) identified the optimal solution of $419,000 and $420,000 within 2,200 and 2,600 function evaluations, respectively. The optimal solution was obtained in a single run out of 10 conducted runs. Similarly, the real-coded PFMOEA in the present study achieved the same optimal solution ($419,000) within lesser (2,000) functional evaluations. The optimal value was achieved three times out of 20 runs which were conducted as seen in Figure 6.

Figure 7 shows a graph of function evaluation against the run number displaying fluctuations in both the binary-coded and real-coded PFMOEA. It was observed that the real-coded PFMOEA fluctuated on a lower side than the binary-coded PFMOEA curve. In addition, the average number of function evaluations of 3,797 which was obtained for the real-coded PFMOEA was smaller than the average of 5,290 obtained by the binary-coded PFMOEA. This

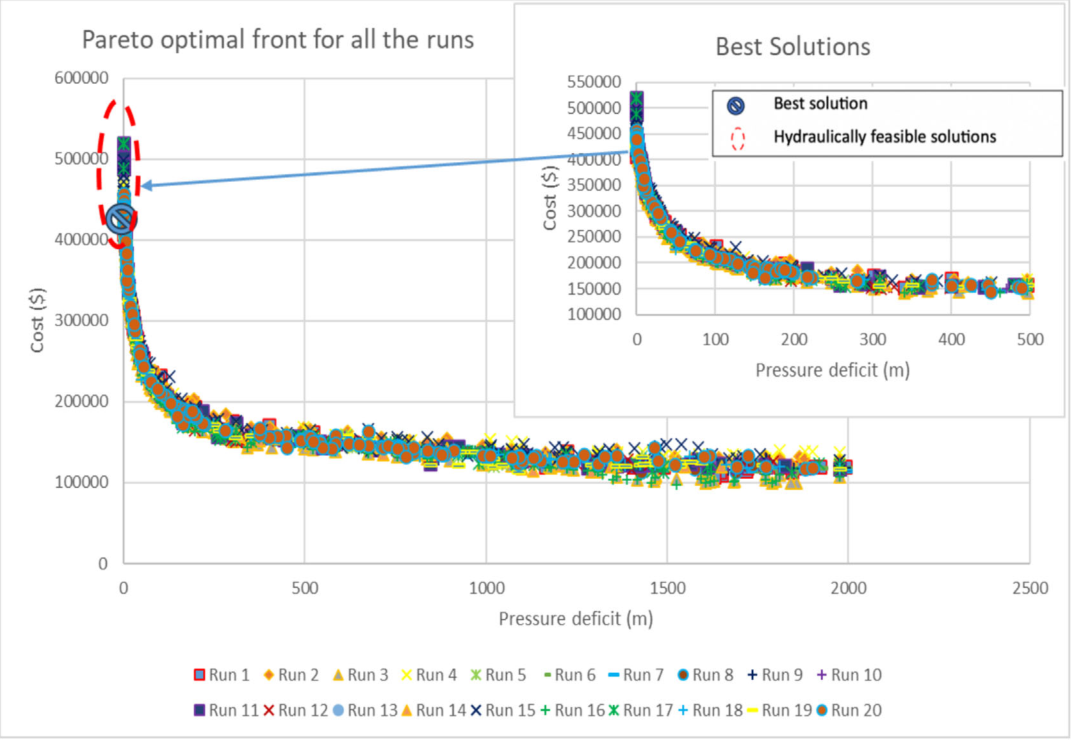

FIGURE 5 Pareto fronts for the two-loop network.

represents a 28.21% reduction in the number of function evaluations and indicates that the real-coded PFMOEA outperformed the binary-coded PFMOEA in computational efficiency. Therefore, the real-coded PFMOEA may be a more effective and efficient optimization approach than the binary-coded PFMOEA.

The application of real-coded PFMOEA in water resource management significantly improves the optimization process, enabling managers to respond proactively to emerging challenges. By streamlining complex calculations and reducing computational demands, this approach equips resource managers with the tools needed for timely and effective decision-making. As a result, water distribution systems become not only more efficient but also more resilient to fluctuations in supply and demand.

Table 1 presents a comparison of optimal costs and the number of function evaluations for the Two-looped network from various studies. To facilitate easy comparison, the pipe diameters in the table have been provided in SI units. Particularly, the real-coded PFMOEA surpassed other studies by achieving an optimal cost of $419,000 with just 2,000 function evaluations. This contrasts with the respective function evaluations of 7,467 (Wu et al., 2001), 25,000 (Cunha & Sousa, 1999), and 9,500 (Sirisant & Janga, 2018). However, these results were not compared based on computation time due to its heavy dependence on the specific computer configuration used (Palod et al., 2021).

2. Hanoi network optimization

The real-coded PFMOEA identified the least cost feasible solution of $6.081 million, and a pressure deficit of zero using $\omega = 10.667$. This was achieved four times out of 20 runs in which

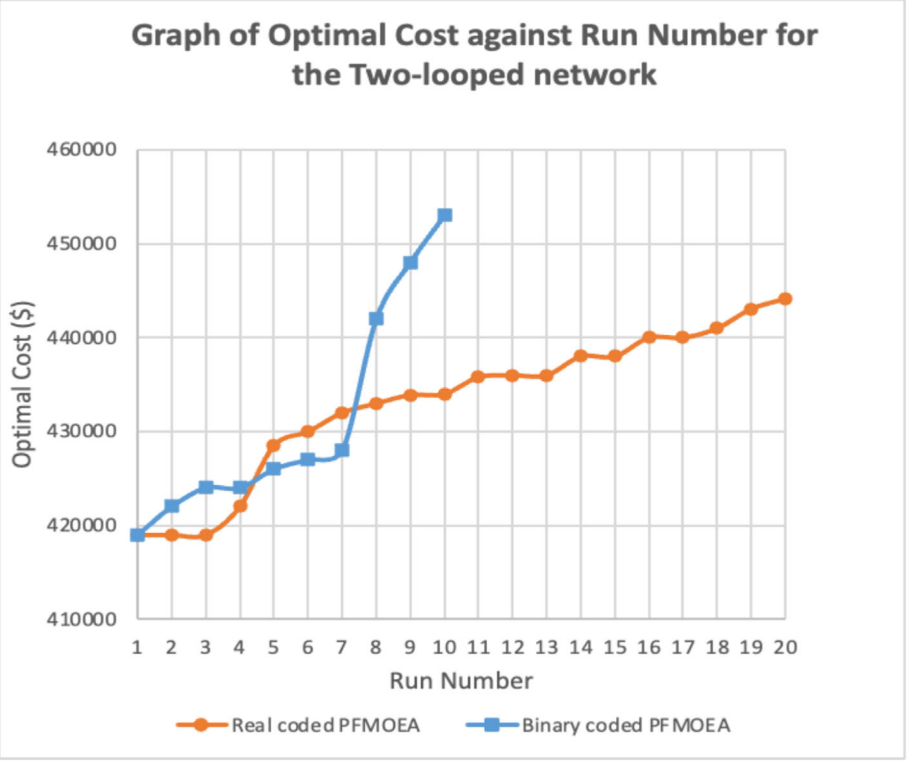

FIGURE 6 Comparison of the optimal cost against the run number for the binary-coded and real-coded PFMOEA using the two-looped network.

the best run took 48,000 function evaluations. The solution, therefore, corresponds to $1.67\times10^{-20}\%$ of the entire search space ($6^{34} \approx 2.865 \times 10^{26}$). In all those runs the minimum required pressure of 30 m was met for all nodes for the least cost feasible solution. Moreover, it took approximately 24 hours on average for a single optimization run comprising of 200,000 function evaluations to be completed.

Figure 8 depicts the pareto-optimal fronts from the 20 runs of the real-coded PFMOEA approach. It is evident that the PFMOEA consistently performs well, as all the fronts presented in the figure exhibit a remarkable level of similarity.

The Hanoi optimization problem which was solved using the real-coded PFMOEA in the present study, slightly outperformed the binary-coded PFMOEA (Siew & Tanyimboh, 2012a) based on the number of function evaluations needed to reach the optimum solution. In contrast to Siew and Tanyimboh (2012a) who attained the least cost design of $6.056 million in 51,000 function evaluations, the present research achieved the optimal solution of $6.081 million with 48,000 function evaluations. This was attained four times out of 20 runs while the binary-coded PFMOEA obtained the optimal solution eleven times out of 60 runs (Figure 9). Additionally, the average costs for the 20 runs of real-coded PFMOEA were found to be $6.17 million. Conversely, the 60 runs of binary-coded PFMOEA had an average cost of $6.16 million (Siew & Tanyimboh, 2012a). The two approaches are therefore reasonably close in effectiveness based on the ability to achieve the global optimum.

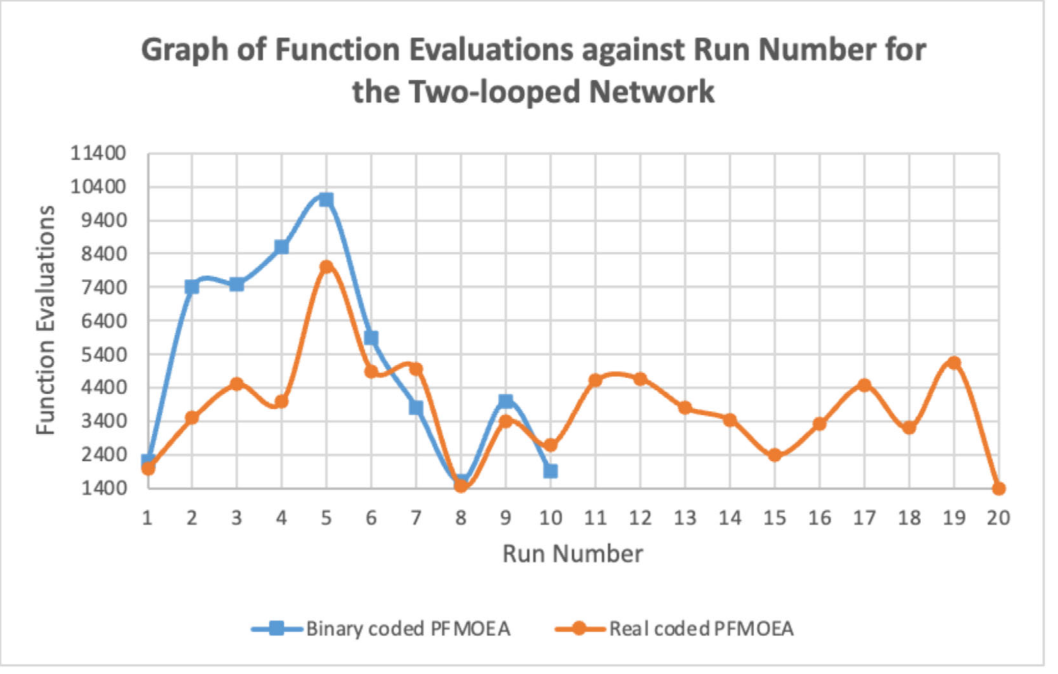

FIGURE 7 Comparison of the function evaluation against the run number for the binary-coded and real-coded PFMOEA using the two-looped network.

Figure 10 shows that the real-coded PFMOEA applied to the Hanoi network, converged in fewer function evaluations in many more runs than the binary-coded PFMOEA. On average, the real-coded PFMOEA obtained 82,281 function evaluations. This represents a 34.38% decrease from the average of 125,398 achieved for the binary-coded PFMOEA. These results are comparable to those of the Two-looped network optimization problem. This indicates that the real-coded PFMOEA has superior computational efficiency over the binary-coded PFMOEA.

Table 2 presents the optimal diameters, optimal costs, and their corresponding maximum function evaluations for various approaches including the real-coded PFMOEA. This study's optimal cost of \$6.081 million at $\omega = 10.667$ is consistent with the findings of Suribabu (2010). However, it differs from the results of other researchers (Cunha & Sousa, 1999; Geem, 2006; Kadu et al., 2008; Siew & Tanyimboh, 2012a; Vairavamoorthy & Ali, 2000; Wu & Walski, 2005) who obtained their optimum cost at a higher function evaluation as indicated in Table 2.

The variations in optimal costs in Table 2 can be attributed to the different ω values employed in the head-loss equation (Equation 6) and the reduction in the search space. Kadu et al. (2008) utilized a search space reduction technique, where only a subset of candidate pipe diameters from the six commercial pipe sizes were considered. As a result, the GA search was performed on a reduced search space of 2.351×10^{19} which accounts for approximately 8.2×10^{-6}% of the entire solution space (i.e., $6^{34} = 2.865 \times 10^{26}$). In contrast to Kadu et al. (2008), this current research explored the entire solution space.

TABLE 1 Solutions for the two-looped network.

Pipe number	Diameter of pipes (mm)							
	ω = 10.508				ω = 10.9031		ω = 10.667	
	Savic and Walters (1997)	Cunha and Sousa (1999)	Wu et al. (2001)	Siew and Tanyimboh (2012a)	Savic and Walters (1997)	Siew and Tanyimboh (2012a)	Sirisant and Janga (2018)	Present work
1	457.2	457.2	457.2	457.2	508	508	457.2	457.2
2	254	254	254	254	254	254	254	254
3	406.4	406.4	406.4	406.4	406.4	406.4	406.4	406.4
4	101.6	101.6	101.6	101.6	25.4	25.4	101.6	101.6
5	406.4	406.4	406.4	406.4	355.6	355.6	406.4	406.4
6	254	254	254	254	254	254	254	254
7	254	254	254	254	254	254	254	254
8	25.4	25.4	25.4	25.4	25.4	25.4	25.4	25.4
Optimization method	GA	SA	GA	Binary- coded PFMOEA	GA	Binary-coded PFMOEA	SADE	Real-coded PFMOEA
Total cost ($)	419,000	419,000	419,000	419,000	420,000	420,000	419,000	419,000
Maximum function evaluation	250,000	25,000	7,467	2,200	250,000	2,600	9,500	2,000

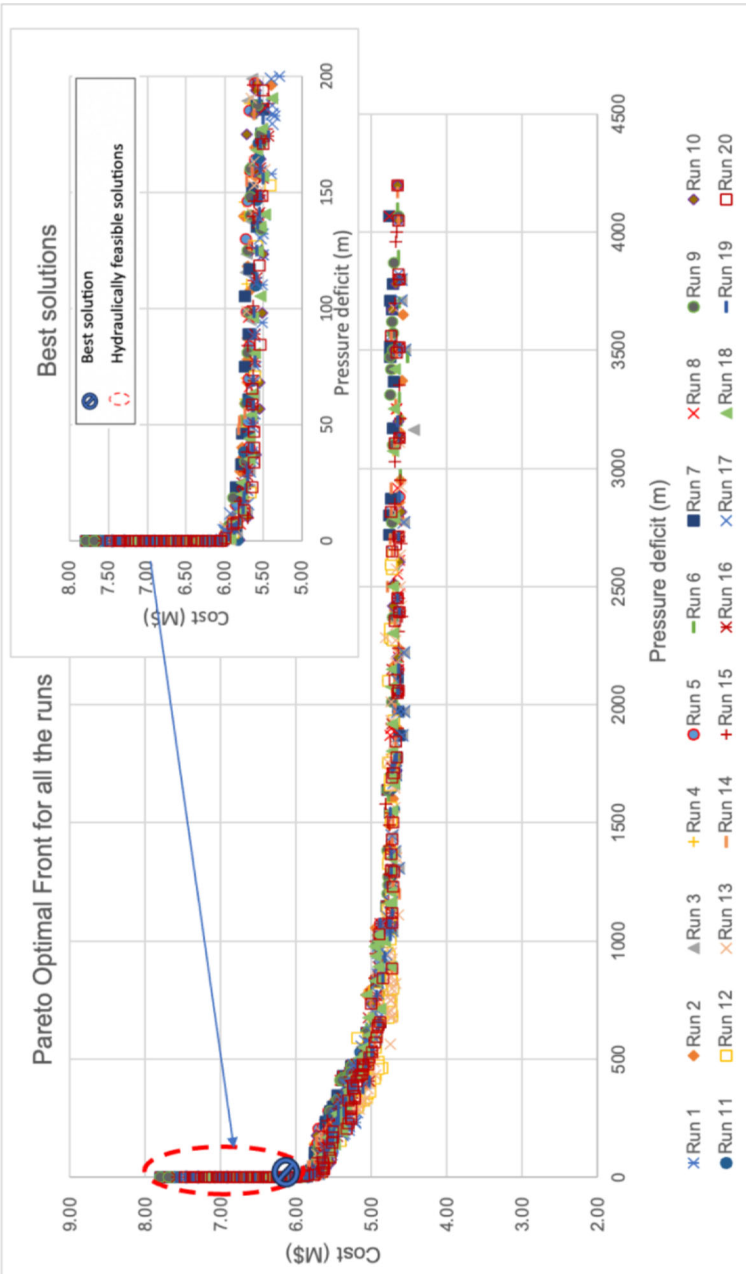

FIGURE 8 Pareto-optimal fronts of the 20 real-coded PFMOEA runs for the Hanoi network.

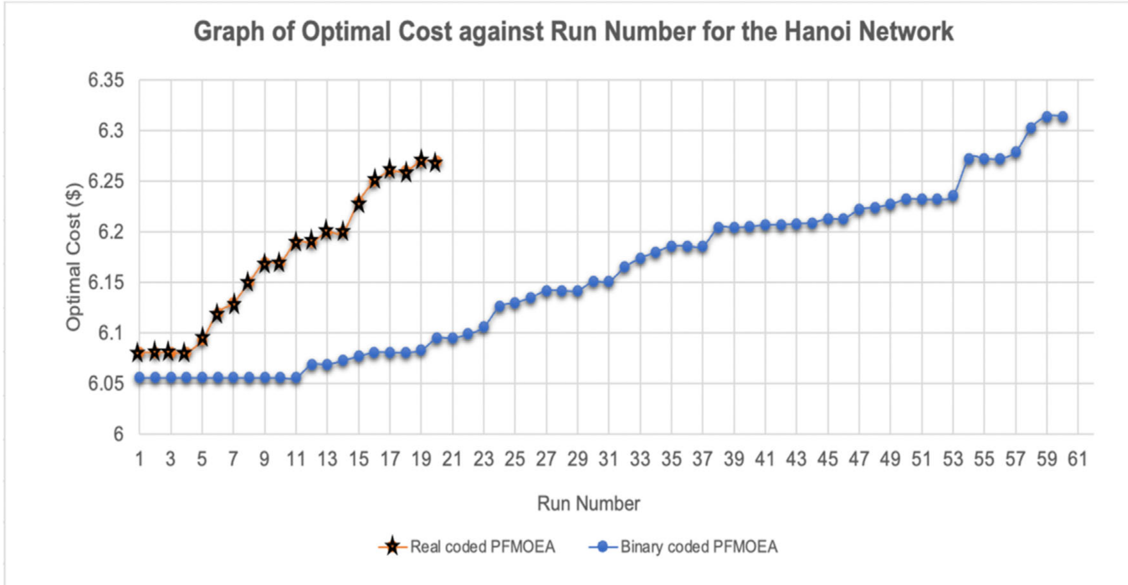

FIGURE 9 Comparison of the optimal cost against the run number for the binary-coded and real-coded PFMOEA using Hanoi network.

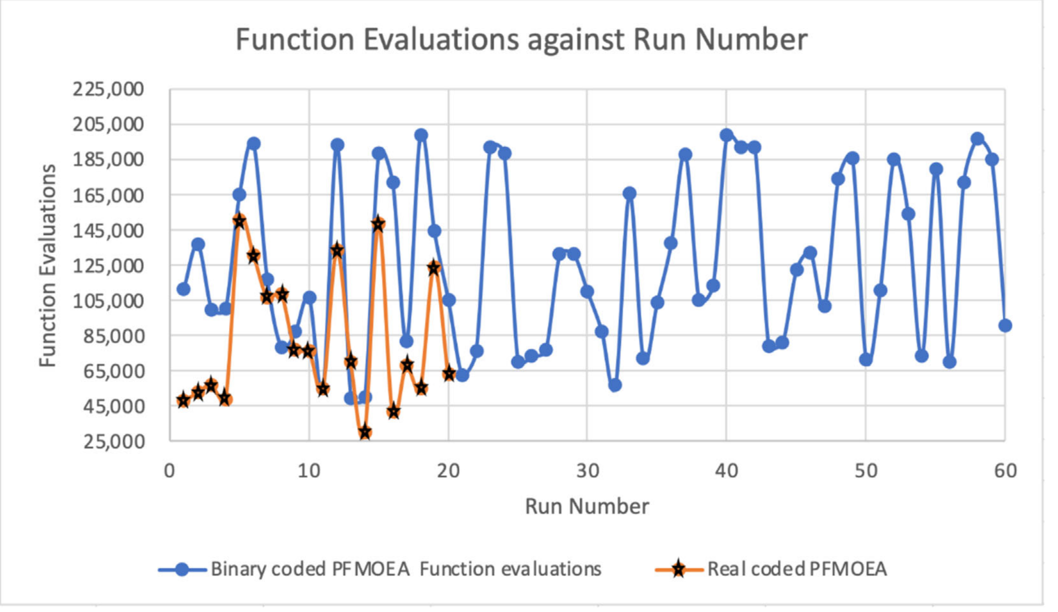

FIGURE 10 Comparison of the function evaluation against the run number for the binary-coded and real-coded PFMOEA.

3.2 | Effect of including infeasible solutions near the constraint boundary in elitism

The progress in achieving the optimal solution for the two-looped network across function evaluations for different retention percentages in real-coded PFMOEA is presented in Figure 11. The Figure shows that in the early stages of the evolutionary process, PFMOEA-A, PFMOEA-B, and PFMOEA-C exhibited rapid improvements in minimizing the network cost. Remarkably, the progress made by PFMOEA-A with a 15% allocation on both sides of the boundary region surpassed the progress of the other percentage allocations. Additional runs not reported here also revealed the same. During the optimization process, the progress lines for PFMOEA-A, PFMOEA-B, and PFMOEA-C continued to advance, resulting in the attainment of the optimal solution at 1,600, 1,680, and 2,000 function evaluations, respectively. The results of the computational effort required by PFMOEA-A were 20% lower than that of PFMOEA-C. Notably, none of the allocations encountered a plateau before reaching the optimal solution ($419,000) which indicates efficient optimization.

Furthermore, the findings indicate that the 15% feasible and 15% infeasible percentage allocation of PFMOEA-A is superior to the other two. This allocation imposes greater pressure on the search to stay in proximity to the boundary, where both good feasible solutions and the least costly infeasible solutions are situated. By preserving infeasible solutions near the boundary region, it becomes easier to transform them into feasible and optimal solutions (Ray et al., 2009). This strategy improves diversity among population members while satisfying constraints (Ray et al., 2009).

The results presented in Figure 12 are for the three percentage retentions in elitism for the Hanoi WDS. The figure demonstrates a similarity to the findings for the two-looped network. PFMOEA-A, PFMOEA-B, and PFMOEA-C attained the optimal solution ($M 6.081) with

TABLE 2 Historic and current solution for the Hanoi network.

Diameter of pipes (mm)										
ω	10.508	10.508	10.508	10.509	10.508	10.508	10.903	10.9031	10.667	10.667
Pipe number	Cunha and Sousa (1999)	Vairavamoorthy and Ali (2000)	Wu and Walski (2005)	Geem (2006)	Kadu et al. (2008)	Siew and Tanyimboh (2012a)	Kadu et al. (2008)	Siew and Tanyimboh (2012a)	Suribabu (2010)	Present study
1–8	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016
9	1,016	1,016	1,016	1,016	1,016	1,016	762	1,016	1,016	1,016
10	762	762	762	762	762	762	762	762	762	762
11	609.6	609.6	609.6	609.6	609.6	609.6	762	609.6	609.6	609.6
12	609.6	609.6	609.6	609.6	609.6	609.6	609.6	609.6	609.7	609.6
13	508	508	508	508	508	508	304.8	304.8	508	508
14	406.4	406.4	406.4	406.4	406.4	406.4	304.8	304.8	406.4	406.4
15	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8
16	304.8	304.8	304.8	304.8	304.8	304.8	406.4	304.8	304.8	304.8
17	406.4	406.4	406.4	406.4	406.4	406.4	508	508	406.4	406.4
18	508	508	508	508	508	508	609.6	609.6	609.6	508
19	508	508	508	508	508	508	609.6	609.6	508	508
20	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016
21	508	508	508	508	508	508	508	508	508	508
22	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8
23	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016
24–25	762	762	762	762	762	762	762	762	762	762
26	508	508	508	508	508	508	508	609.6	762	508
27–28	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8
29	406.4	406.4	406.4	406.4	406.4	406.4	406.4	406.4	406.4	406.4
30	304.8	304.8	304.8	304.8	304.8	304.8	304.8	406.4	304.8	304.8

TABLE 2 (Continued)

Diameter of pipes (mm)										
ω	10.508	10.508	10.508	10.509	10.508	10.508	10.903	10.9031	10.667	10.667
Pipe number	Cunha and Sousa (1999)	Vairavamoorthy and Ali (2000)	Wu and Walski (2005)	Geem (2006)	Kadu et al. (2008)	Siew and Tanyimboh (2012a)	Kadu et al. (2008)	Siew and Tanyimboh (2012a)	Suribabu (2010)	Present study
31	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8	304.8
32	406.4	406.4	406.4	406.4	406.4	406.4	406.4	406.4	406.4	406.4
33	406.4	406.4	406.4	406.4	406.4	406.4	508	406.4	406.4	406.4
34	609.6	609.6	609.6	609.6	609.6	609.6	609.6	609.6	609.6	609.6
Optimization method	SA	GA	GA	HS	GA	Binary-coded PFMOEA	GA	Binary-coded PFMOEA	Differential evolution	Real-coded PFMOEA
Total cost ($M)	6.056	6.056	6.056	6.056	6.056	6.056	6.19	6.182	6.081	6.081
Maximum function evaluation	53,000	160,000	150,000	200,000	18,000	51,000	18,000	100,000	48,724	48,000

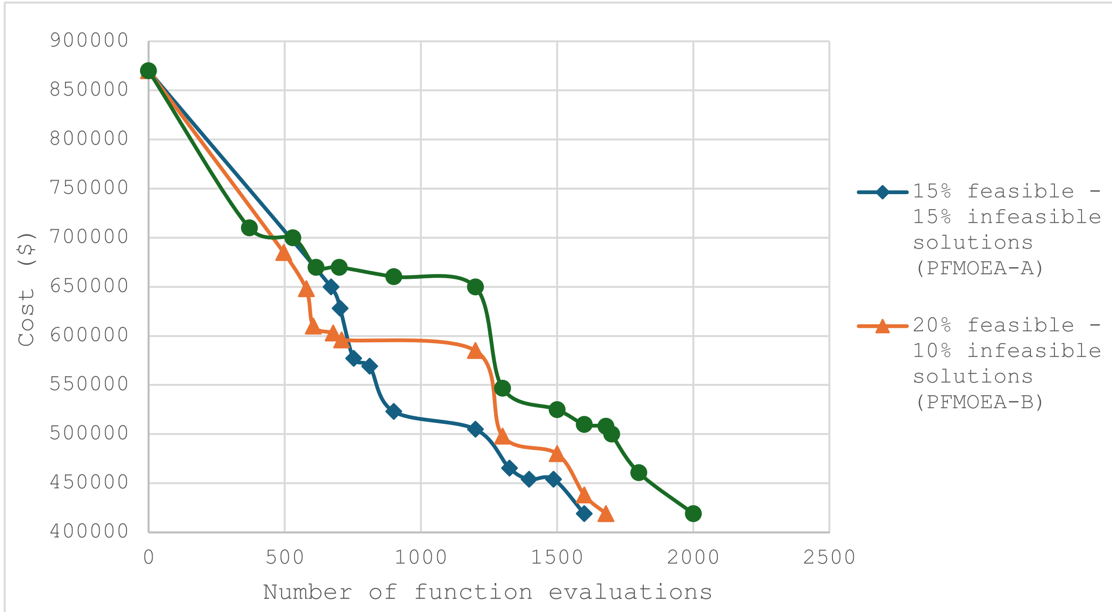

FIGURE 11 Progress of the real-coded PFMOEA optimization with varied percentages of retention in the boundary region for the two-looped network.

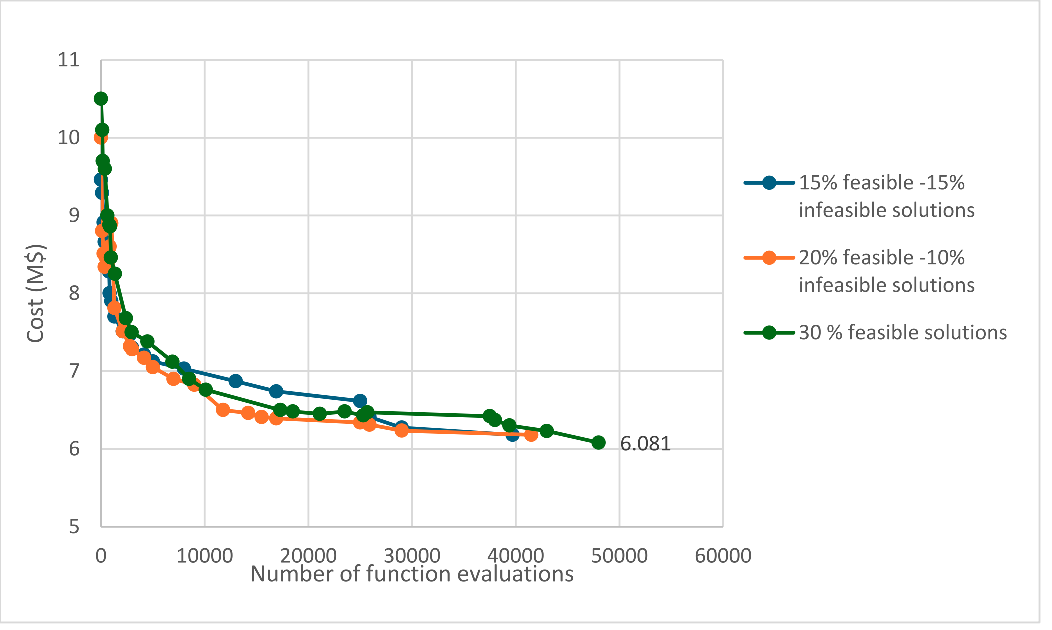

FIGURE 12 Progress of the real-coded PFMOEA optimization with varied percentage allocations on the constraint boundary region for the Hanoi network (ω = 10.667).

39,700, 41,500, and 48,000 function evaluations, respectively. This confirms that the 15% feasible and 15% infeasible percentage allocation employed by PFMOEA-A outperformed PFMOEA-B (20% feasible-10% infeasible solutions) and PFMOEA-C (30% feasible solutions).

The inclusion of infeasible solutions near the constraint boundary in the elitism process presents important implications for water policy and practice. By strategically incorporating solutions that slightly violate constraints but are close to optimal, decision-makers can explore a broader range of potential designs that may lead to more efficient and robust water distribution systems. This approach enables water managers and stakeholders to identify solutions that balance performance and feasibility, particularly in complex real-world networks where strict adherence to constraints may limit innovation.

4 | CONCLUSIONS

This study aimed to find out if the Penalty-Free Multi-Objective Evolutionary Algorithm (PFMOEA) for Water Distribution Systems (WDS) could be improved by incorporating real coding representation and including infeasible solutions in the elitism step of optimization. Previous PFMOEA research utilized binary representation to encode and decode solutions. Although binary coding is simple to use, it tends to generate redundant codes that do not match any members of the finite discrete set to which the encoded parameter belongs. Hence, the need to find out if using real coding could improve PFMOEA performance. The study applied two benchmark networks; the two-looped and the Hanoi networks that have been applied in previous studies using binary-coded PFMOEA and other optimization methods.

The real-coded PFMOEA succeeded in identifying the least cost-feasible solution of $419,000 and $6.081 million for the two-looped and Hanoi networks, respectively, with fewer function evaluations than the binary-coded PFMOEA. For the Two-looped network, there was a decrease of 28.21% in the number of function evaluations while for the Hanoi network, the reduction amounted to 34.38%. As a result, the real-coded PFMOEA outperformed the binary-coded PFOMEA in computational efficiency as it converged to the optimal solutions faster. This might be attributed to a more effective exploration of the solution space, as real coding does not generate redundant genes, unlike binary coding.

In the elitism step of previous PFMOEA studies, 30% of the least-cost feasible solutions were retained in each generation with no inclusion of any infeasible solutions. Therefore, the second objective of this research was to find out if replacing various percentages of both feasible and infeasible solutions close to the active constraint boundary could improve the PFMOEA performance. The allocation of 15% feasible and 15% infeasible solutions achieved the most efficient solution for both networks. For the Two-looped network, this allocation required 1,600 function evaluations to achieve the optimal solution while allocating 20% feasible and 10% infeasible solutions required 1,680 function evaluations. Allocating 30% feasible and 0% infeasible solutions required 2000 function evaluations. For the Hanoi network, the allocation comprising 15% feasible and 15% infeasible solutions required 39,700 function evaluations to obtain the best solution while allocating 20% feasible and 10% infeasible solutions required 41,500 function evaluations. Allocating 30% feasible and 0% infeasible solutions needed 48,000 function evaluations. Thus, including infeasible solutions close to the least-cost boundary significantly enhanced the computational efficiency of the PFMOEA. This led to a 20% and 17% reduction in the number of function evaluations required to identify the optimal solutions for the Two-looped network and the Hanoi network, respectively.

5 | RECOMMENDATIONS AND IMPLICATIONS TO WATER POLICY

The results of this study have significant implications for water policy and practice, particularly in optimizing water distribution systems for sustainability. Policy and decision-makers should consider integrating advanced optimization algorithms, such as the real-coded PFMOEA, into water distribution planning to enhance system performance while minimizing computational requirements. Stakeholders, including water utilities and municipalities, can leverage these tools to achieve cost-effective solutions that minimize deficits and energy consumption. On the other hand, policymakers should, therefore, promote flexible regulatory frameworks that allow for the testing and adoption of near-feasible solutions to improve the efficiency and resilience of water distribution system analysis. Strategy planners must also recognize the value of computational methods that incorporate infeasible solutions to enhance decision-making processes, ensuring that water distribution optimization is both innovative and adaptable to changing conditions and demands.

In the future, there is also a need to use a wider range of WDNs with diverse configurations and characteristics. This broader analysis would assess the generalizability and applicability of the findings of the current study and could enhance the applicability of real-coded PFMOEA to real-world WDN problems. Furthermore, exploring a spectrum of retention percentages in the elitism step of the PFMOEA optimization would be appropriate as the default of 30% as a total retention percentage is subjective and a broader range of the proportion of feasible and infeasible solutions could be explored. The selection of infeasible solutions for retention in this study was based on head deficit only and other approaches for this selection could be investigated in future studies.

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CONFLICT OF INTEREST STATEMENT

There is no conflict of interest.

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