





## Optimal pipe-sizing design of water distribution networks using modified Rao-II algorithm

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### ABSTRACT

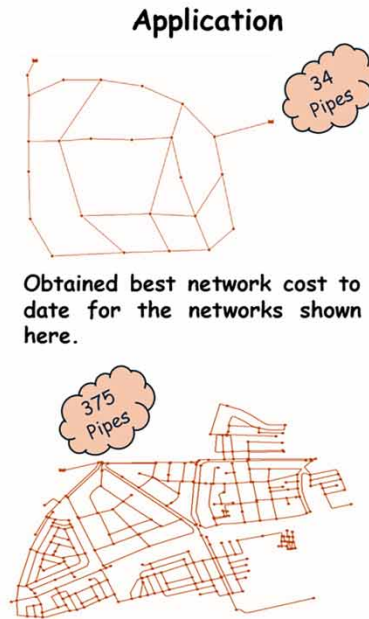
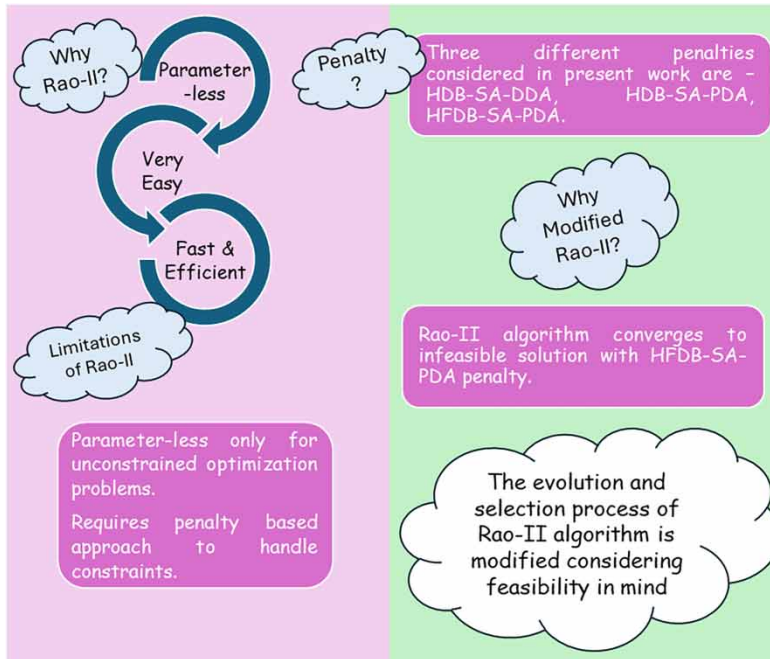
Several evolutionary algorithms (EAs) have been suggested in the last three decades for the least-cost design of water distribution networks (WDNs). EAs generally worked well to identify the global/near-global optimal solutions for small- to moderate-size networks in a reasonable time and computational effort. However, their applications to large-size networks are still challenging due to large computational effort. Recent developments in EAs are towards parameter-less techniques that avoid fine-tuning of case-specific parameters to reduce the computational effort. Further, several self-adaptive penalties and search-space reduction methodologies have been suggested to reduce the computational effort. A fast, efficient, and parameter-less Rao-II algorithm has been used earlier with penalty-based approaches for the optimal design of WDNs. In this study, the application of a Rao-II algorithm is further explored with three self-adaptive penalty approaches to compare the convergence characteristics. The Rao-II algorithm is observed to converge at an infeasible solution in cases that the applied penalty to an infeasible solution is not so substantial to make it inferior to the feasible solutions. Modifications are suggested to improve the Rao-II algorithm, named the modified Rao-II algorithm. The modified Rao-II algorithm with the self-adaptive penalty methods resulted in better solutions than those obtained earlier.

**Key words:** evolutionary algorithm, optimization, Rao-II, self-adaptive penalty, water distribution network

### HIGHLIGHTS

- Modification to Rao-II algorithm with self-adaptive penalty approaches.
- Modification in Rao-II algorithm for avoiding convergence to infeasible solutions.
- Application to benchmark networks.
- Better solutions than previously best-known solutions for both the benchmark networks.
- Application to real-life network.

GRAPHICAL ABSTRACT



ABBREVIATIONS

EA	evolutionary algorithm
WDN	water distribution network
GA	genetic algorithm
ACO	ant colony optimization
PSO	particle-swarm optimization
DDA	demand-driven analysis
PDA	pressure-driven analysis
HDB-SA-DDA	head deficit-based self-adaptive demand-driven analysis
HDB-SA-PDA	head deficit-based self-adaptive pressure-driven analysis
HFDB-SA-PDA	head and flow deficit-based self-adaptive pressure-driven analysis
DN	demand nodes
$N$	pipes
$Y$	loops
$C_T$	cost of network in monetary unit
$\Pi_j$	set of pipes connected to node $j$
$\Lambda_y$	pipes in loop $y$
$J$	number of nodes
$c(D_n)$	is unit cost of pipe $n$ having diameter $D_n$
$L_n$	length of pipe $n$
$Q$	discharge of pipe $n$
$q_j^{ref}$	required nodal demand
$q_j^{avl}$	available nodal demand
$h$	head loss in pipe $n$
$E_{pmp}$	head developed by a pump
$\Lambda_p$	pumps in loop $y$
$H_j^{avl}$	available head at node $j$
$H_j^{des}$	minimum desirable head at node $j$
$D_{min}$ and $D_{max}$	minimum and maximum diameter of available pipes, respectively
$Z$	total cost of network including penalty cost
$C_p$	penalty cost
PM or $p$	penalty coefficient

$C_{\max}$	cost of network with all pipes as largest available commercial diameter
$C_{n,j}$	cost of pipe $n$ with added penalty cost due to minimum pressure constraint at node $j$
$UC_n$	cost per unit length of pipe $n$
$Q_n$	flow in pipe $n$
$Q_{\text{node}}$	total flow into node
PWF	present worth factor
$cu_e$	unit cost of the energy in monetary units per kWh
$w$	specific weight of water ( $9,810 \text{ N/m}^3$ )
$\eta$	overall efficiency
$t_p$	total time of the pump operation in a year in hours
$X_{m,\text{best},i}$	best values for any iteration $i$ , for a variable $m$
$X_{m,\text{worst},i}$	worst values for any iteration $i$ , for a variable $m$
$X'_{m,k,i}$ and $X_{m,k,i}$	updated and old value for any variable $m$
$r_{1,m,i}$ , $r_{2,m,i}$	random numbers
$k$ and $l$	any randomly picked solution from the population set
FSS	full search space
RSS	reduced search space
DSSR	dynamic search space reduction
NFE	number of function evaluations
DNA	data not available
GA-ILP	genetic algorithm–integer linear programming
NSGA-II	non-dominated sorting genetic algorithm
MA	memetic algorithm
CFO	central force optimization
CSA	crow search algorithm
ICSA	improved crow search algorithm

## INTRODUCTION

A water distribution network (WDN) is one of the costliest components of any water supply project (Walski *et al.* 2003); therefore, the cost optimization of a WDN design is required. The simplest WDN optimization problem consists of selecting the most appropriate diameter for each pipe of the network from the set of available discrete pipe-diameters to minimize the network cost. The constraints of satisfying the pressure requirements along with the satisfaction of continuity equations at all the nodes and energy equations for all loops are imposed (Alperovits & Shamir 1977; Wu & Walski 2005; Kadu *et al.* 2008; Jain & Khare 2021; Palod *et al.* 2021; Gangwani *et al.* 2023, 2024). Researchers have suggested using various mathematical programming-based techniques to obtain the least-cost design of WDNs from the 1960s to 1990s. These techniques, called ‘deterministic search techniques’, begin the search with a solution in the search space and progress to a better solution in an iterative manner using some mathematical expressions. Such searches frequently result in a local optimal solution (Bhave 2003).

Several EAs based on different metaphors have been developed over the last three decades for the least-cost design of networks. The search in an evolutionary algorithm (EA) starts from many randomly chosen points in the search space, which move towards better solutions by mimicking the metaphor, and terminates when the search is complete. The EAs are observed to have a global search capacity to achieve global optimal and several near-optimal solutions. The main disadvantage of EAs is the high computational effort, as shown by Coelho & Andrade-Campos (2012). Mostly, the EA uses certain constants besides the population size and the number of generations to mimic the metaphor; for example, the genetic algorithm (GA) uses cross-over and mutation probabilities (Savic & Walters 1997; Wu & Simpson 2001; Deb *et al.* 2002; Kadu *et al.* 2008; Siew & Tanyimboh 2012; Abdy Sayyed *et al.* 2019); ant colony optimization (ACO) uses the rate of pheromone evaporation and the pheromone reward factor (Maier *et al.* 2003; Zecchin *et al.* 2006; Zecchin *et al.* 2007; Ostfeld & Tubaltzev 2008); and particle-swarm optimization (PSO) uses inertia weight, cognition rate, and social learning rate (Suribabu & Neelakantan 2006; Rao *et al.* 2017). These constants must be fine-tuned for case-specific problems, which increases computational efforts and is also sometimes tedious. Recent advancements are, therefore, towards the development of parameter-less EA that either adjusts required algorithm-specific constants internally or uses their fixed values.

Gajghate & Mirajkar (2021) used a parameter-less Jaya algorithm (Rao 2016) for the optimal design of irrigation pipe networks. The diameters are initially obtained using the critical path method and then this is optimized using both linear programming (LP) and the Jaya algorithm, and it was concluded that the Jaya algorithm can reach a better-optimized solution

than LP. Palod *et al.* (2020) used the same Jaya algorithm for the design of WDNs and observed that this parameter-less algorithm reduces the computational effort and is efficient. Palod *et al.* (2021) compared two parameter-less EAs – Rao-I and Rao-II (Rao 2020) – for the optimal design of WDNs and found that Rao-II is better compared with Rao-I. Jain & Khare (2021) also used the Rao-II algorithm for the design of WDNs.

The WDN optimization problem has constraints related to the satisfaction of flow continuity at nodes, energy equations for loops, and minimum pressure availability at nodes. The first two conditions are tackled in EA by involving a hydraulic solver. However, the third constraint, i.e., minimum pressure availability at nodes, is to be externally satisfied in the EA-based optimization models. Penalty approaches are mostly used to overcome this situation. The penalty is applied proportionately to the constraint violation amount using a penalty coefficient to make infeasible solutions inferior to feasible solutions. The selection of a proper penalty coefficient for the penalty function is a key to improving the efficiency of EA-based optimization models. A larger coefficient imposes a larger penalty and may quickly eliminate infeasible solutions from the population; thus, these solutions may not be given enough opportunity to improve further. Conversely, a smaller penalty may allow the infeasible solutions to remain in the population for a longer duration, thereby delaying the convergence or converging at an infeasible solution. This renders the penalty an external parameter that requires fine-tuning for proper convergence of the objective function as suggested by Abebe & Solomatine (1998) and van Dijk *et al.* (2008). On the other hand, a self-adaptive penalty does not require fine-tuning of the penalty coefficient as suggested by Kadu *et al.* (2008), Abdy Sayyed *et al.* (2019), Jain & Khare (2021), and Gangwani *et al.* (2023, 2024).

The penalty cost is thus dependent on the penalty coefficient and the amount of pressure deficit. The maximum pressure deficit among all nodes in the network is determined and multiplied by the penalty coefficient to obtain the penalty cost (Palod *et al.* 2020, 2021), or a penalty due to the pressure deficit at all nodes can be added (Abdy Sayyed *et al.* 2019) to obtain the final penalty. Kadu *et al.* (2008) recommended that for a pressure deficit node, the penalty multiplier must be proportional to the capitalized energy cost required at that node to lift the unit quantity of water through a unit head. Further, the pressure deficit can be calculated using demand-driven analysis (DDA) or pressure-driven analysis (PDA). Abdy Sayyed *et al.* (2019) showed that DDA overestimates the penalty as in this case it is assumed that the demands are fully satisfied, and pressure is determined accordingly. This leads to a larger pressure deficiency than required at the nodes. In contrast to this, PDA determines the pressure deficit according to the partial flow conditions and hence may result in lower pressure deficit values. Further, they recommend using a combined flow and pressure deficit-based penalty. Jain & Khare (2021) also showed the superiority of PDA over DDA by comparing the optimal costs obtained using the Rao-II algorithm for some benchmark problems. Recently, Gangwani *et al.* (2024) also used a combined flow and pressure deficit-based penalty in GA to obtain a better solution for a two-source network from Kadu *et al.* (2008). Although parameter-less EAs avoid the fine-tuning of a large number of problem-specific constants as required in other EAs, the penalty multiplier needs to be fine-tuned for faster convergence.

The main objective of this paper is to explore the application of Rao-II with self-adaptive penalty approaches. Three approaches are considered herein: (1) a self-adaptive penalty approach (Kadu *et al.* 2008) in which head deficit is obtained using DDA, abbreviated as head deficit-based self-adaptive demand-driven analysis (HDB-SA-DDA); (2) a self-adaptive penalty approach (Abdy Sayyed *et al.* 2019) in which head deficit is obtained using PDA, abbreviated as head deficit-based self-adaptive pressure-driven analysis (HDB-SA-PDA); and (3) a self-adaptive combined flow and head deficit penalty approach (Abdy Sayyed *et al.* 2019) in which deficit is obtained using PDA, abbreviated as head and flow deficit-based self-adaptive pressure-driven analysis (HFDB-SA-PDA). The application of the methodology is demonstrated with a two-source network from Kadu *et al.* (2008) and a Ramnagar network of Nagpur city from Gangwani *et al.* (2024).

The remainder of the paper consists of the description of the general WDN optimization problem to be solved by EA, a brief literature on constraint-handling through different types of penalties, the Rao-II algorithm and proposed modifications, application to benchmark problems, comparison of solutions, and conclusions of the study.

## OPTIMIZATION MODEL FORMULATION

A general optimization problem for a WDN with  $J$  demand nodes,  $N$  pipes, and  $Y$  loops for the minimization of the network cost by satisfying various constraints can be described as follows:

$$\text{Minimize } C_T = f(D_1, \dots, D_N) = \sum_{n=1}^N c(D_n) \times L_n \quad (1)$$

Subject to constraints:

$$\sum_{n \in \Pi_j} Q_n + q_j^{\text{req}} = 0; j = 1, \dots, J \quad (2)$$

$$\sum_{n \in \Lambda_y} h_n + \sum_{\text{pmp} \in \Lambda_p} E_{\text{pmp}} = 0; y = 1, \dots, Y \quad (3)$$

$$H_j^{\text{avl}} \geq H_j^{\text{des}}; j = 1, \dots, J \quad (4)$$

$$D_n \in \{D_{\text{min}} \dots D_{\text{max}}\}; n = 1, \dots, N \quad (5)$$

where  $C_T$  = cost of network in Rs.;  $\Pi_j$  is the set of pipes connected to node  $j$ ;  $\Lambda_y$  represents the pipes in loop  $y$ ;  $j$  is the number of nodes;  $c(D_n)$  is unit cost of pipe  $n$  having diameter  $D_n$ ;  $L_n$  = length of pipe  $n$  in m;  $Q_n$  = discharge of pipe  $n$  in  $\text{m}^3/\text{sec}$ ;  $q_j^{\text{req}}$  = nodal demand in  $\text{m}^3/\text{sec}$ ;  $h_n$  = head loss in pipe  $n$  in m;  $E_{\text{pmp}}$  = head developed by a pump in m;  $\Lambda_p$  represents the pumps in loop  $y$ ;  $H_j^{\text{avl}}$  = available head at node  $j$  in m;  $H_j^{\text{des}}$  = upper and lower bounds for minimum desirable head at node  $j$  in m; and  $D_{\text{min}}$  and  $D_{\text{max}}$  = minimum and maximum diameter of available pipes in m, respectively. Equations (2) and (3) are general flow continuity and loop head-loss equations, respectively. Equation (4) ensures that the available head is more than the minimum desirable head at each demand node, and Equation (5) allows the selection of discrete pipe sizes only.

## CONSTRAINTS HANDLING IN EA

Constraints defined by Equations (2) and (3) can be handled using EPANET 2.0 hydraulic solver (Rossman 2000). Constraints defined by Equation (5) will be satisfied in the optimization model as the selection of pipe sizes will be made from the list of commercially available sizes only. However, Equation (4) cannot necessarily be satisfied with any selected set of pipes, as the available pressure at one or more nodes may be less than the desirable value, causing pressure deficiency at that node. Thus, the objective function in Equation (1) is modified to include penalty cost as shown in Equation (6):

$$\text{Minimize } Z = C_T + C_P \quad (6)$$

where  $Z$  is the addition of network cost and penalty cost and  $C_P$  is the penalty cost.

Martínez-Bahena *et al.* (2018) used the death-penalty approach in GA in which infeasible solutions are discarded. While applying the GA operators to the initial population, a tournament selection method was used in which only feasible solutions were selected. Further, after the cross-over and mutation, a feasibility check was applied, and infeasible solutions were discarded. Only feasible solutions were added to the new population until the population size was obtained.

Abebe & Solomatine (1998), Mohan & Jinesh Babu (2010), and Palod *et al.* (2021) considered the maximum deficiency in meeting the pressure requirement at any node of the network to calculate the penalty cost. Abebe & Solomatine (1998) used GA formulation, Mohan & Jinesh Babu (2010) used honey-bee mating optimization, and Palod *et al.* (2021) used Rao-I and Rao-II algorithms. The penalty cost is given in Equation (7):

$$C_P = \text{PM} \times \max\{\max(H_j^{\text{des}} - H_j^{\text{avl}}, 0)\}; j = 1, \dots, J \quad (7)$$

where PM is a penalty coefficient,  $H_j^{\text{avl}}$  is the head available at node  $j$ , and  $H_j^{\text{des}}$  is the head desirable at node  $j$ , above which the demand is fully satisfied. The max operator inside the parenthesis is provided to consider 0 in the case of no deficiency, and the max operator outside indicates the maximum at any demand node. Abebe & Solomatine (1998) considered PM as a function of maximum possible cost, i.e.,  $\text{PM} = p \cdot C_{\text{max}}$ , where  $C_{\text{max}}$  can be calculated based on the largest available commercial pipe. The penalty coefficients, PM or  $p$ , are case-specific and require fine-tuning for every problem.



Jinesh Babu & Vijayalakshmi (2013) added the deficiency in pressure at different nodes to calculate the penalty cost as shown in Equation (8) in the PSO-GA-based hybrid model:

$$C_p = \sum_j^{\text{DN}} \text{PM} \cdot \{\max(H_j^{\text{des}} - H_j^{\text{avl}}, 0)\}; \quad j = 1, \dots, J \quad (8)$$

where the addition of deficiency at all the nodes will reduce the value of PM as compared with that in Equation (7); however, it requires fine-tuning.

Sangroula *et al.* (2022) suggested applying a penalty at all the nodes. Two different penalty coefficients, PM1 for nodes with pressure above the required pressure and PM2 for nodes with deficiency in pressure, are used to calculate the penalty cost. The values of PM1 and PM2 are case-specific and were obtained by trial and error as 0.02 and 1.9.

Montesinos *et al.* (1999) considered a penalty based on the number of nodes having constraint violations instead of degree of constraint violation. The severity of failure is better indicated by the degree of constraint violation. In fact, DDA overpredicts the number of nodes with pressure deficiency as compared with PDA (Abdy Sayyed *et al.* 2019). Deb & Agrawal (1999) suggested a niched penalty based on the comparison in tournament selection in which two feasible solutions are compared based on the cost, the two infeasible solutions are compared based on their constraint violation, and the feasible solution is considered better than infeasible solution in the tournament.

Wu & Walski (2005) compared the then-available penalty approaches and suggested the use of a self-adaptive approach in which the penalty coefficient is to be evolved and adapted during optimization. Djebedjian *et al.* (2006) suggested a self-adaptive penalty approach in which the cost of any infeasible solution is obtained based on the pipe cost, the number of nodes, and the pressure deficiency at nodes, and the penalty cost is given in Equation (9):

$$C_p = \frac{C_T}{\text{DN}} \cdot \sum_j^{\text{DN}} \max\{(H_j^{\text{des}} - H_j^{\text{avl}}, 0)\} \quad (9)$$

Van Dijk *et al.* (2008) suggested a weighted penalty approach in which penalty cost is added to the pipes connected at pressure-deficient nodes in proportion to the flow carried by them to meet the demand of the node. The cost of pipe that results in a node not meeting the pressure requirements is calculated using Equations (10) and (11):

$$C_{n,j} = \text{UC}_n^{1+b} \cdot L_n \quad (10)$$

$$b = \text{PM} \cdot \left[ \frac{H_j^{\text{des}} + (H_j^{\text{des}} - H_j^{\text{avl}})}{H_j^{\text{des}}} \right] \frac{Q_n}{Q_{\text{node}}} \quad (11)$$

where  $C_{n,j}$  = cost of pipe  $n$  in monetary units with added penalty cost due to minimum pressure constraint at node  $j$ ;  $\text{UC}_n$  = cost per unit length of pipe  $n$ ;  $b$  = penalty coefficient (=5, if  $H_j^{\text{avl}} < 0$ , and =0, if  $H_j^{\text{avl}} > H_j^{\text{des}}$ ); PM = user-specified penalty factor;  $Q_n$  = flow in pipe  $n$  in  $\text{m}^3/\text{sec}$ ; and  $Q_{\text{node}}$  = total flow into node in  $\text{m}^3/\text{sec}$ . The penalty cost component  $b$  increases the unit cost of pipe. The higher the value of the user-specified penalty factor (suggested as between 0.5 and 10), the higher the penalty cost will be. The penalty factor needs to be fine-tuned to get a good design solution.

Kadu *et al.* (2008) suggested calculating the PM in Equation (8) based on the capitalized energy cost per unit of flow and per unit of head ( $p$ ). The value of  $p$  was expressed as given in Equation (12):

$$p = \text{PWF} \times \text{cu}_e \times \frac{w}{1,000 \times \eta} \times t_p; \quad (12)$$

where PWF is the present worth factor;  $\text{cu}_e$  = unit cost of the energy in monetary units per kWh;  $w$  = specific weight of water ( $9,810 \text{ N/m}^3$ );  $\eta$  = overall efficiency; and  $t_p$  = total time of the pump operation in a year in hours.

The PWF can be calculated based on the interest rate as shown in Equation (13):

$$\text{PWF} = \frac{(1 + i_r)^m - 1}{i_r(1 + i_r)^m} \quad (13)$$

where  $i_r$  = interest rate, expressed as a fraction of 1 and  $m$  = design life of the WDN. Considering  $i_r = 0.08$  (i.e., 8%),  $m = 30$  years,  $\text{cu}_e = \text{Rs. } 4.5$  (Rs/kWh), and  $\eta = 0.6$ , the penalty multiplier was obtained as  $p = 7.261 \times 10^6$  (Kadu *et al.* 2008) for discharge in  $\text{m}^3/\text{min}$  and head in m. Equation (8) can be modified for the HDB-SA-DDA and HDB-SA-PDA approaches as given in Equation (14):

$$C_p = \sum_{j=1}^{\text{DN}} p \cdot q_j^{\text{req}} \cdot \{\max(H_j^{\text{des}} - H_j^{\text{avl}}, 0)\} \quad (14)$$

Abdy Sayyed *et al.* (2019) recommended PDA to identify accurately (a) the pressure-deficient nodes and (b) the corresponding outflow and pressure deficits. They suggested and compared GA solutions obtained using Equation (14) with those obtained by using two different penalty approaches based on PDA. In the HFDB-SA-PDA, the pressure deficit in Equation (14) is obtained using PDA, and it is modified as shown in Equation (15):

$$C_p = \sum_{j=1}^{\text{DN}} p \cdot (q_j^{\text{req}} - q_j^{\text{avl}}) \cdot \{\max(H_j^{\text{des}} - H_j^{\text{avl}}, 0)\} \quad (15)$$

where  $q_j^{\text{req}}$  is required flow at node  $j$ .

The penalty cost has the advantage that it is generic; it does not require prior setting or calibration. Jain & Khare (2021) compared solutions using the Rao-II algorithm by considering penalty costs using Equation (14), in which head deficit was calculated using DDA and PDA. However, while using PDA,  $q_j^{\text{req}}$  was replaced by  $q_j^{\text{avl}}$  in Equation (14). They recommended calculating penalties based on PDA. Abdy Sayyed *et al.* (2019) observed that the HFDB-SA-PDA approach (Equation (15)) provided faster and better results in GA compared with HDB-SA-PDA. Gangwani *et al.* (2023, 2024) also used Equation (15) in the GA approach with dynamic search-space reduction methodology. As EPANET 2.0 is used, PDA can be carried out using the most widely used relationship suggested by Wagner *et al.* (1988) (Equations (16)–(18)) or any other head flow relationship. However, the EPANET 2.2 version is also available with PDA facility, which can be used directly. As per Wagner *et al.* (1988),

$$q_j^{\text{avl}} = q_j^{\text{req}}, \text{ if } H_j^{\text{avl}} \geq H_j^{\text{des}} \quad (16)$$

$$q_j^{\text{avl}} = q_j^{\text{req}} \left( \frac{H_j^{\text{avl}} - H_j^{\text{min}}}{H_j^{\text{des}} - H_j^{\text{min}}} \right)^{1/n_j}, \text{ if } H_j^{\text{min}} < H_j^{\text{avl}} < H_j^{\text{des}} \quad (17)$$

$$q_j^{\text{avl}} = 0, \text{ if } H_j^{\text{avl}} \leq H_j^{\text{min}} \quad (18)$$

where  $q_j^{\text{avl}}$  is available flow at node  $j$  and  $H_j^{\text{min}}$  is minimum head required, below which there is no outflow at node  $j$ . The exponent  $n$  in Equation (17) is usually adopted as either 1.5 or 2; however, it varies with the requirement of pressure head at demand nodes (Gupta & Bhawe 1996; Sivakumar *et al.* 2023).

## PARAMETER-LESS RAO-II ALGORITHM

Rao (2020) developed a metaphor-less optimization technique known as Rao-II. No algorithm-specific parameters are required for the convergence of the objective function in Rao-II. Parameters such as population size and number of iterations are only required for this algorithm. However, the algorithm is completely free from parameters only for unconstrained problems. A penalty factor is involved to prevent the algorithm converging to infeasible solutions in the case of constrained optimization problems. The penalty may depend on various factors. Thus, for an algorithm to be called entirely parameter-less, the penalty involved in the optimization should also be parameter-less or self-adaptive. Rao-II begins just like any meta-heuristic technique, i.e., by generating a random initial population. It works by finding the best and worst solution

from the entire population. The solutions for the next iteration are updated using Equation (19). The solutions with minimum and maximum objective function values are selected as best and worst, respectively. The total cost for any solution is the summation of network cost and penalty (due to constraint violation):

$$X'_{m,k,i} = X_{m,k,i} + r_{1,m,i}(X_{m,best,i} - X_{m,worst,i}) + r_{2,m,i}(|X_{m,k,i} \text{ or } X_{m,l,i}| - |X_{m,l,i} \text{ or } X_{m,k,i}|) \quad (19)$$

In Equation (19), the best and worst values for any iteration  $i$ , for a variable  $j$ , are represented by  $X_{m,best,i}$  and  $X_{m,worst,i}$ , respectively.  $X'_{m,k,i}$  and  $X_{m,k,i}$  represent the updated and old values for any variable  $m$ ;  $r_{1,m,i}$  and  $r_{2,m,i}$  are random numbers distributed uniformly, and the range of  $r_{1,m,i}$  and  $r_{2,m,i}$  is  $(0,1)$ ;  $l$  is any randomly picked solution from the population set, and  $X_{m,l,i}$  represents its value for variable  $m$  at the  $i$ th iteration. Solutions  $k$  and  $l$  are compared based on the total cost. Suppose solution  $l$  is better than  $k$  (total cost of solution  $l <$  total cost of solution  $k$ ). In that case, information must be exchanged from  $l$  to  $k$ , and hence, the term  $X_{m,k,i}$  or  $X_{m,l,i}$  is simplified to  $X_{m,l,i}$  and the term  $X_{m,l,i}$  or  $X_{m,k,i}$  is simplified to  $X_{m,k,i}$ . This delineates the transfer of information from a superior solution to an inferior solution. In contrast to this, if the total cost of solution  $k <$  solution  $l$ , the term  $X_{m,k,i}$  or  $X_{m,l,i}$  is simplified to  $X_{m,k,i}$  and the term  $X_{m,l,i}$  or  $X_{m,k,i}$  is simplified to  $X_{m,l,i}$ . Once the updated values of all solutions in the population are determined, a completely fresh population set is created. The updated values are compared with the previous values of the solution, and a better-performing solution (solution with minimum total cost) is directed to the next iteration. This process of updating and comparing the solutions is continued until the termination criterion is reached, which is generally a fixed number of iterations or when, over a larger number of iterations, no improvement is observed in the fitness value of the solutions. For the present case, the former serves as the termination criterion.

## MODIFIED RAO-II ALGORITHM

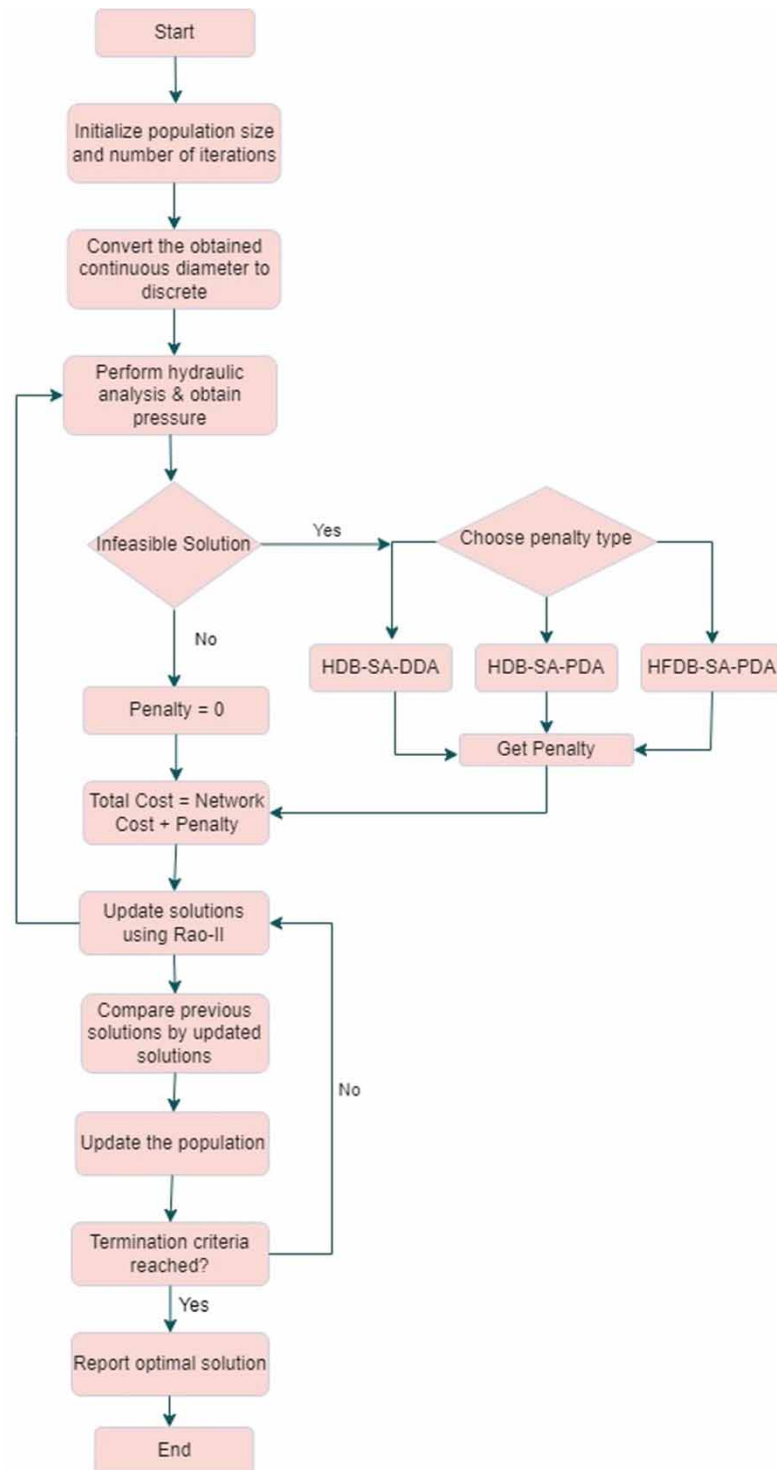
The Rao-II algorithm is a two-step methodology that identifies the best and worst solution from the entire population. Further, it evolves the solution to move towards the best solution and away from the worst solution. In the second step, a comparison is made between the old and updated, i.e., the evolved solution. The better-performing solution is sent to the next iteration. It is essential to remember that for the optimal design of WDN, performance in the Rao-II algorithm solely depends on the total cost (total cost = network cost + penalty). While applying the self-adaptive penalty, care must be taken to keep the infeasible solutions near the feasible–infeasible front more active by applying just enough penalty (Wu & Walski 2005). It was observed that the penalty cost may be significantly less if the constraint violation is very low. Therefore, some solutions, though infeasible, may have lesser total cost than feasible solutions. This leads to the selection of an infeasible solution over a feasible solution. Once an infeasible best is identified, the entire population starts moving towards this infeasible best and ultimately becomes infeasible. Such situations can be avoided by selecting a higher penalty coefficient or varying the penalty coefficient as iteration progresses. Herein, a different approach is suggested to overcome the aforementioned drawback. Two modifications are suggested for the Rao-II algorithm.

1. The entire population is segregated into two groups: the feasible (penalty = 0) and infeasible group (penalty  $\neq$  0). It is suggested that the minimum cost solution be selected as the best solution from the group of feasible solutions. This approach ensures that the best solution consistently results in a feasible solution. It is important to note that the entire population may be initially infeasible with larger penalty values. This may be due to the random generation of solutions. In such a case, a minimum total cost solution from the group of infeasible cost solutions is selected. Penalty decreases and feasible solutions appear with the progress of the algorithm.
2. The Rao-II algorithm compares the updated solution with the original one based on the total cost value only to pass it on to the next iteration. Hence, an infeasible solution with a lower total cost is selected over a feasible solution with a higher total cost during the comparison process. To rectify this, the following changes are made:
  - a. Between two infeasible solutions, the least total cost solution is selected and sent to the next iteration.
  - b. Between an infeasible (penalty  $\neq$  0) and feasible solution (penalty = 0), a feasible solution is selected and sent to the next iteration.
  - c. Between two feasible solutions, the least total cost solution is selected and sent to the next iteration.

This step guarantees the alignment of feasible solutions with the advancement of the algorithm.

The flowchart of the modified Rao-II algorithm with self-adaptive penalty approaches is shown in Figure 1.



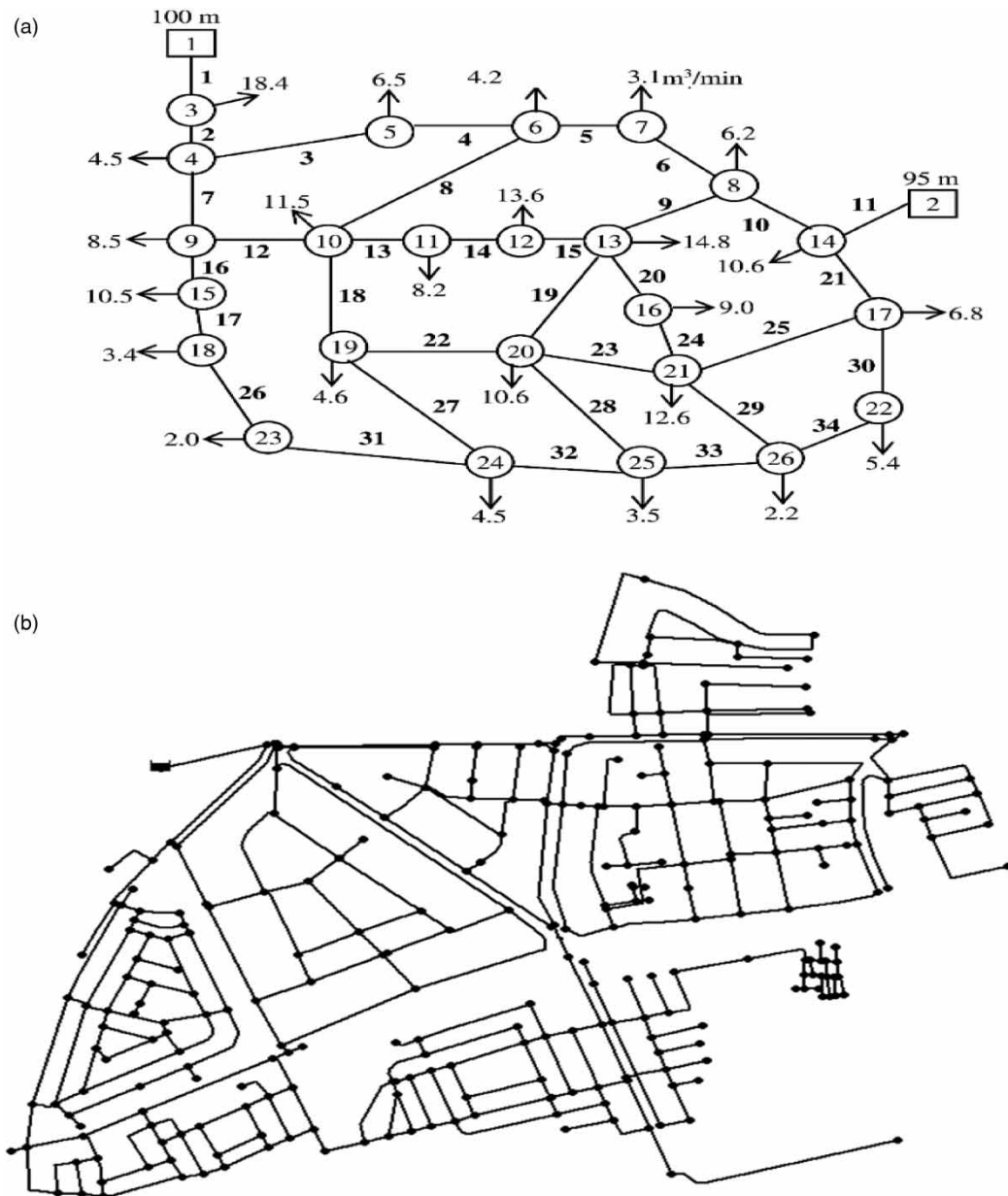


**Figure 1** | Rao-II/modified Rao-II algorithm with self-adaptive penalty approaches.

## APPLICATION OF METHODOLOGY

### Kadu – a two-source network

The Kadu network (Kadu *et al.* 2008), as shown in Figure 2(a), consists of 34 pipes, 24 nodes, and two reservoirs, all arranged in nine loops. The lowest supply level in reservoirs 1 and 2 are 100 and 95 m, respectively. The design diameters for the



**Figure 2** | Layout of water distribution networks: (a) Kadu network and (b) Ramnagar network.

network must be selected from 14 commercially available diameters, as shown in Table S1 (Supplementary Material), which leads to a total search space of 1,434. The network has different minimum pressure head requirements for different nodes. This information is given in Table S2, along with other network details and the diameters obtained by the original Rao-II by Palod *et al.* (2021).

The platform used for the coding of the Rao-II algorithm for optimization of WDN is Python, and it is integrated with EPANET 2.0 with the help of a toolkit for hydraulic simulation. As EPANET 2.0 does not have a PDA facility, a separate C code proposed by Gupta *et al.* (2018) is used to modify the input file to be used in PDA. The capacity of the computer used for running the code is Intel(R) Core (TM) i7-10510 U, 8 GB RAM, CPU @ 2.30 GHz.

Initially, the Rao-II algorithm was used with different penalty approaches. The three approaches HDB-SA-DDA, HDB-SA-PDA, and HFDB-SA-PDA as given in Equations (14) and (15) were applied for the optimal design of the Kadu network. Initially, a few runs were performed to fix the population size and the number of generations. A population size of 75 and

1,000 iterations as the termination criteria were fixed to compare the convergence characteristics. Fifteen trial runs were performed, and the best obtained in one of the 15 trials was considered. With Rao-II, HDB-SA-DDA and HDB-SA-PDA converged to feasible solutions; however, HFDB-SA-PDA converged to a non-feasible solution. The head deficit was noted at six nodes in the best solution. The head deficit was 0.18 m at node 6, 0.19 m at node 12, 0.28 m at node 16, 0.21 m at node 18, 0.79 m at node 23, and 0.49 m at node 26. The cost of the network was Rs. 123,499,991 and the penalty cost was Rs. 956,552. The total cost was Rs. 124,456,543. Moreover, none of the solutions from the final population was found feasible. This indicated the necessity of modifying the Rao-II algorithm as all the solutions were observed to move towards the infeasible solution. Considering this possibility in other penalty-based approaches, the modified Rao-II algorithm was applied. However, for the Kadu network, modified Rao-II is used with HFDB-SA-PDA, and it resulted in improved convergence.

Pipe diameters obtained in the best solution with three different penalties are shown in [Table 1](#).

The best cost solutions, along with other details as reported by other researchers and obtained herein, are given in [Table 2](#) for comparison. The following can be observed from [Table 2](#).

1. Different EAs (GA, memetic algorithm (MA), central force optimization (CFO), crow search algorithm (CSA), Jaya, Rao-II) and their variants have been applied to design this network in the last 15 years, starting from 2008 up to 2023.
2. Both penalty-free and penalty-based approaches have been applied. The penalty-free approach avoided fine-tuning of the penalty coefficient ([Haghighi et al. 2011](#); [Barlow & Tanyimboh 2014](#); [Siew et al. 2014](#)) by mostly converting the constraints as additional objectives and making it a multi-objective problem. This increases the computational efforts.
3. Computational time and efforts are reduced through self-adaptive penalty calculations using DDA and PDA ([Kadu et al. 2008](#); [Abdy Sayyed et al. 2019](#); [Gangwani et al. 2023, 2024](#)), which avoids fine-tuning of the penalty coefficient. The PDA-based head deficit calculations for penalty applications are observed to be better as compared with DDA-based calculations by [Abdy Sayyed et al. \(2019\)](#) and [Gangwani et al. \(2023, 2024\)](#). Herein, modified Rao-II with DDA-based self-adaptive penalty outperformed compared with the constant penalty approach ([Palod et al. 2021](#)) and with self-adaptive PDA-based approaches.
4. Many researchers ([Kadu et al. 2008](#); [Siew et al. 2014](#); [Abdy Sayyed et al. 2019](#); [Gangwani et al. 2024](#)) have used search-space reduction in EAs or hybrid methods to reduce the computational effort.
5. As EAs do not provide the same results in different runs, a number of trials of fine-tuned models are made, the best cost solution from different trials is considered, and the number of function evaluations (NFE) required in the best run is reported. Herein, 15 trials are considered, and the minimum cost solution from these trials is reported.
6. There are only five occasions when the researcher provides a better solution than the present best one. [Siew et al. \(2014\)](#) was the first to provide better solutions with full search space (FSS) and reduced search space (RSS) compared with that provided by [Kadu et al. \(2008\)](#). [Abdy Sayyed et al. \(2019\)](#) provided a better solution with RSS as compared with that of [Siew et al.'s \(2014\)](#) RSS solution. [Palod et al. \(2021\)](#) provided a better solution with FSS as compared with that of [Siew et al.'s \(2014\)](#) FSS solution. [Gangwani et al. \(2023\)](#) provided a better solution with FSS than [Palod et al.'s \(2021\)](#) FSS solution. [Gangwani et al. \(2024\)](#) provided a better solution with RSS than [Abdy Sayyed et al.'s \(2019\)](#) RSS solution. Herein, a better solution with FSS in 15 trials is obtained twice costing Rs. 125,019,790 in 33,525 NFE compared with [Gangwani et al.'s \(2023\)](#) FSS solution of Rs. 125,209,860 obtained in 157,760 NFEs, and [Gangwani et al. \(2024\)](#) obtained the same cost in 1,125,300 NFEs with the dynamic search-space reduction (DSSR) model.
7. [Table 3](#) shows the statistical analysis for three different penalties for 15 trial runs. Regarding the optimal solution, HDB-SA-DDA outperforms other penalties for maximum and minimum costs. The mean cost obtained for all three penalties for the Kadu network is almost the same. [Figure 3\(a\)](#) shows the convergence curve obtained for the Kadu network.
8. The program was executed for 100 trials also with the same parameters. It is interesting to note that with the number of trials increased to 100, a better feasible solution of Rs. 124,963,610 emerged. This solution is not obtained earlier by any other algorithm and is cheaper by 0.045% than the earlier best-known solution. This is obtained in the 73rd trial at the 562nd iteration with HDB-SA-DDA and in the eighth trial at the 557th iteration with HDB-SA-PDA penalties, leading to total NFEs of 42,150, and 41,775 respectively. However, execution of the program for a higher number of trials,

**Table 1** | Diameters obtained for the Kadu network using three different penalties

Pipe no.	Diameters in mm				Node no.	Required head	Available head (m)			
	HDB-SA-DDA	HDB-SA-PDA	HFDB-SA-PDA	HDB-SA-DDA <sup>a</sup>			HDB-SA-DDA	HDB-SA-PDA	HFDB-SA-PDA	HDB-SA-DDA <sup>a</sup>
1	900	1,000	900	900	1	100	100.0	100.0	100.0	100.0
2	900	900	900	900	2	95	95.00	95.00	95.00	95.00
3	350	350	350	400	3	85	98.28	98.96	98.28	98.27
4	300	300	300	250	4	85	95.04	95.65	95.04	95.00
5	150	150	150	150	5	85	87.33	87.50	87.42	90.71
6	250	200	250	200	6	85	85.35	85.19	85.50	85.00
7	800	800	800	800	7	82	85.21	82.49	85.49	82.02
8	150	150	150	150	8	82	87.81	88.54	88.22	87.96
9	450	450	450	450	9	85	91.13	91.70	91.13	91.09
10	500	500	500	500	10	85	88.31	88.70	88.32	88.27
11	750	800	800	750	11	85	86.44	86.83	86.45	86.40
12	700	700	700	700	12	85	85.15	85.55	85.16	85.12
13	500	500	500	500	13	82	82.38	83.10	82.58	82.48
14	500	500	500	500	14	82	92.95	93.53	93.50	92.96
15	150	150	150	150	15	85	88.01	87.04	88.02	87.97
16	500	450	500	500	16	82	82.17	82.84	82.16	82.22
17	350	350	350	350	17	82	89.56	90.19	91.10	89.58
18	400	400	400	400	18	85	85.45	85.20	85.46	85.42
19	150	150	150	150	19	82	86.11	85.82	86.11	86.08
20	150	150	150	150	20	82	82.33	83.09	82.07	82.38
21	700	700	750	700	21	82	86.35	87.00	84.31	86.38
22	150	150	150	150	22	80	85.09	80.45	81.26	85.12
23	450	450	500	450	23	82	83.01	82.19	83.01	82.98
24	350	350	400	350	24	80	80.17	83.65	80.15	80.15
25	700	700	600	700	25	80	80.52	81.57	80.50	80.56
26	250	200	250	250	26	80	80.22	80.06	80.66	80.25
27	250	350	250	250						
28	300	300	300	300						
29	200	200	250	200						
30	300	250	250	300						
31	150	150	150	150						
32	150	150	150	150						
33	150	150	150	150						
34	150	150	150	150						
<b>Cost (Rs. 106)</b>	<b>125.02</b>	<b>125.44</b>	<b>125.24</b>	<b>124.96</b>						
<b>Iterations</b>	<b>447</b>	<b>488</b>	<b>931</b>	<b>562</b>						

<sup>a</sup>Best result from 100 trial runs.

especially for large WDN, is not recommended, as it may or may not result in a better solution. Therefore, certain termination criteria are to be set initially and may be used to assess the performance of any EA rather than running it multiple times.

**Table 2** | Comparison of results for the Kadu network

Author	Algorithm	Penalty description	Search-space reduction approach	No. of trials	Minimum NFE	Optimal cost in million Rs.	Residual heads at nodes in EPANET 2.0	
							Max	Min
Kadu <i>et al.</i> (2008)	GA	HDB-SA-DDA	FSS	10	120,000	131.68	13.96	0.14
		HDB-SA-DDA	RSS	10	25,200	126.37 <sup>a</sup>	13.99	-1.39
Haghighi <i>et al.</i> (2011)	GA-ILP	Penalty-free	FSS	DNA	4,440	131.31 <sup>a</sup>	13.97	-0.01
Siew <i>et al.</i> (2014)	NSGA-II	Penalty-free	FSS	100	436,000	125.46	13.29	0.24
		Penalty-free	RSS	30	82,400	125.83	13.29	0.23
Barlow & Tanyimboh (2014)	GA-based MA	Penalty-free	FSS	100	142,000	124.69 <sup>a</sup>	13.97	-0.39
Jabbary <i>et al.</i> (2016)	CFO	HDB-CP-DDA	FSS	DNA	259,476	126.53	13.29	0
Abdy Sayyed <i>et al.</i> (2019)	GA	HDB-SA-PDA	RSS	DNA	8,300	128.38	13.28	0.06
		HFDB-SA-PDA	RSS	DNA	7,600	125.75	13.29	0.06
Fallah <i>et al.</i> (2019)	CSA	HDB-CP-DDA	FSS	30	81,250	128.26 <sup>a</sup>	13.14	-0.22
	ICSA	HDB-CP-DDA	FSS	30	65,000	125.49 <sup>a</sup>	13.95	-0.24
Palod <i>et al.</i> (2020)	Jaya	HDB-CP-DDA	FSS	30	39,680	126.05	DNA	DNA
Tanyimboh (2021)	NSGA	Penalty-free	FSS	10	339,000	127.36	13.26	0.24
Palod <i>et al.</i> (2021)	Rao-II	HDB-CP-DDA	FSS	30	19,700	125.43	13.98	0.07
Gangwani <i>et al.</i> (2023)	GA	HFDB-SA-PDA	FSS	10	157,760	125.21	13.28	0.16
Gangwani <i>et al.</i> (2024)		HFDB-SA-PDA	DSSR	10	1,125,300	125.02	13.28	0.15
Present work	Modified Rao-II	HDB-SA-DDA	FSS	15	33,525	125.02	13.28	0.15
		HDB-SA-PDA	FSS	15	36,600	125.44	13.96	0.06
		HFDB-SA-PDA	FSS	15	69,825	125.24	13.28	0.07

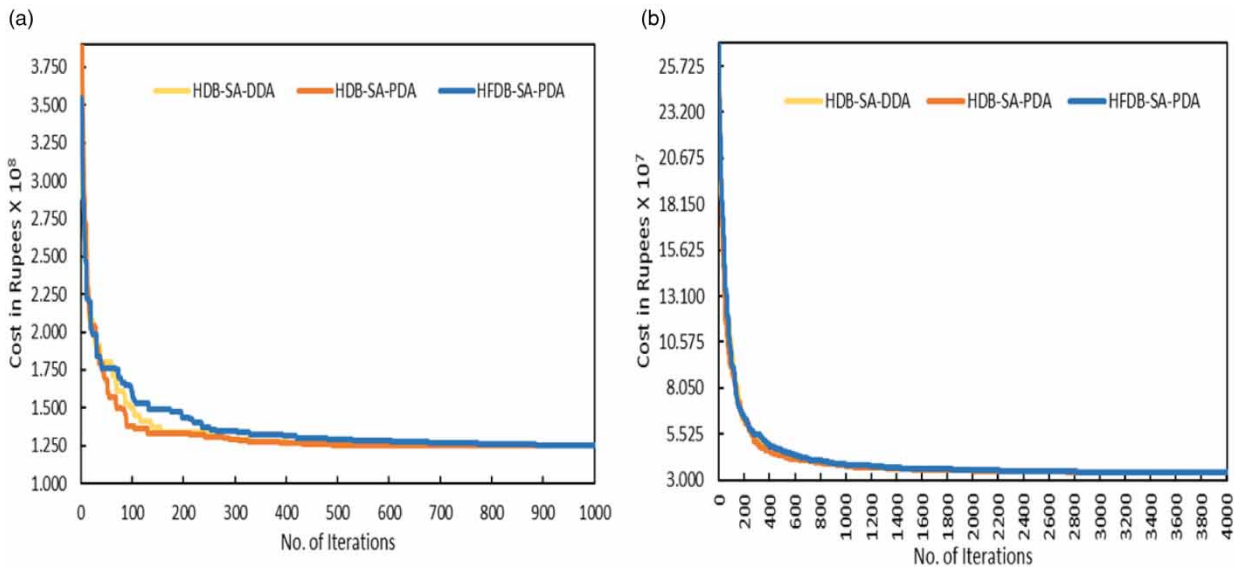
<sup>a</sup>Infeasible solution with current EPANET parameters ( $\alpha, \beta, \omega$ ) = (1.852, 4.871, 10.667).

DNA, data not available; HDB, head deficit based; HFDB, head flow deficit based; CP, constant penalty; GA-ILP, genetic algorithm-integer linear programming; NSGA-II, non-dominated sorting genetic algorithm; MA, memetic algorithm; CFO, central force optimization; CSA, crow search algorithm; ICSA, improved crow search algorithm.

**Table 3** | Minimum, maximum, and mean cost of the Kadu network obtained for 15 trial runs

Type of penalty	Minimum cost (Rs. 10 <sup>6</sup> )	Maximum cost (Rs. 10 <sup>6</sup> )	Mean cost (Rs. 10 <sup>6</sup> )	Computational time (seconds per run)
HDB-SA-DDA	125.02	127.97	126.44	117
HDB-SA-PDA	125.44	128.98	126.29	95
HFDB-SA-PDA	125.24	128.75	126.43	116





**Figure 3** | Convergence curve for (a) the Kadu network and (b) the Ramnagar network.

9. When a similar exercise is performed using HFDB-SA-PDA, the modified Rao-II algorithm converges to Rs. 125,019,790 in the eighth trial at the 544th iteration.

**Ramnagar network**

The Ramnagar network shown in Figure 2(b) was first used by Gangwani *et al.* (2024) to illustrate their design methodology. The network consists of 375 pipes, 292 junctions, and a ground service reservoir with a lowest supply level of 327.205 m. The design diameters for the network must be selected from 16 commercially available diameters, as shown in Table S3, which leads to a total search space of 16,375. The pipe and node details of the network are shown in Tables S4 and S5, respectively. The penalty multiplier, *p*, for the Ramnagar network is calculated as 145,220 using Equations (12) and (13), based on the prevailing unit energy charges of Rs. 5.4/kWh.

Five trial-runs were performed with a population size of 500 and 4,000 iterations as the termination criteria to obtain the convergence curve of the modified Rao-II algorithm. Pipe diameters obtained from three different penalties are shown in Table S6. A comparison of results as obtained by GA (Gangwani *et al.* 2024) and modified Rao-II for the Ramnagar network is shown in Table 4. GA, using the HFDB-SA-PDA penalty approach, provided the optimal cost of the network as Rs.

**Table 4** | Comparison of results for the Ramnagar network

Author	Algorithm	Search space	Penalty description	No. of trials	Minimum NFE	Optimal cost (Rs. 10 <sup>7</sup> )	Residual heads at nodes in EPANET 2.0		Computational time (seconds per run)
							Max	Min	
Gangwani <i>et al.</i> (2024)	GA	FSS	HFDB-SA-PDA	10	881,600	3.783	18.72	8.03	6,378
		DSSR	HFDB-SA-PDA	10	382,500	3.428	15.92	8.07	2,240
Present work	Modified Rao-II	FSS	HDB-SA-DDA	5	1,615,000	3.424	8.01	15.78	12,856
		FSS	HDB-SA-PDA	5	1,499,500	3.443	8.00	14.78	12,792
		FSS	HFDB-SA-PDA	5	1,591,500	3.417	8.01	16.66	13,392

37,837,223 and Rs. 34,289,227 with FSS and DSSR, respectively. The modified Rao-II algorithm with FSS resulted in better solutions than that obtained by GA using FSS and DSSR for the HDB-SA-DDA and HFDB-SA-PDA penalty approaches as shown in Table 4. The minimum cost solution is obtained as Rs. 34,166,161 by modified Rao-II with HFDB-SA-PDA. Modified Rao-II with HDB-SA-PDA obtained a 8.98% cheaper solution than GA with FSS. When compared with GA-DSSR, modified Rao-II obtained a solution with only 0.438% higher cost. However, it cannot be overlooked that only five trial runs are performed in the present work, and hence, there might be a possibility to obtain a cheaper solution than reported here if a greater number of trial runs are performed. The NFEs required by modified Rao-II are on the higher side when compared with GA. Figure 3(b) shows the convergence curve obtained for the Ramnagar network.

Thus, it can be stated that penalty approaches play an important factor in determining the efficiency of an EA in terms of both network cost and computational time. The network cost could be further reduced by increasing the number of iterations or trials, subsequently increasing the computational time. However, for a large-size network, incorporating search-space reduction methodology could be more beneficial to obtain the optimal solution with reasonable computational efforts.

## CONCLUSIONS

The self-adaptive penalty approaches as suggested by many researchers for constraint handling do not require fine-tuning of penalty coefficients. Three different self-adaptive penalty approaches used earlier by researchers are proposed herein to improve the performance of the parameter-less Rao-II algorithm. The Rao-II algorithm is improved herein to avoid convergence to the infeasible solutions. The modified Rao-II algorithm prioritizes the feasible solutions over infeasible solutions during both the evolution and the selection process. The modified Rao-II algorithm was then tested on a real-life network consisting of 375 pipes. For this network, the modified Rao-II algorithm was observed to be a better performer when compared with GA. Further, when the number of trials is increased to 100 for the Kadu network, the Rao-II algorithm obtained the minimum cost solution of Rs. 124,963,610, which does not feature in the literature so far. The modified Rao-II algorithm also converges to a lesser optimal cost than given in the literature. This highlights the potential that the modified Rao-II algorithm holds in obtaining the optimal solution. The modified Rao-II algorithm can be further improved by amalgamating it with search-space reduction techniques.

## 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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