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Design Optimization of Water Distribution Networks with Dynamic Search Space Reduction GA

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Abstract
Evolutionary algorithms (EAs) have been used extensively for the optimal design of water distribution networks (WDNs). There is evidence in the literature that search space reduction is highly effective. However, practical methods that do not introduce extra computational requirements are lacking. A dynamic search space reduction methodology is proposed to search the entire solution space without eliminating any part of the search space beforehand. The proposed methodology works on the information explored during the execution of the algorithm. Further, a self-adaptive penalty is suggested which is based on both flow and pressure deficits instead of only pressure deficit and is obtained using pressure dependent analysis. In this study, the methodology is demonstrated using a Genetic Algorithm (GA). The effectiveness of the methodology is demonstrated on the Ramnagar Network of Nagpur City, India and two benchmark problems from the literature. The proposed methodology resulted in a substantial reduction in the computational efforts and provided nine improved solutions as compared to the best solution available in the literature for one of the networks. The techniques proposed are generic and can be incorporated in other EAs.

Keywords Combined flow and pressure deficit penalty · Genetic Algorithm Optimization · Pressure dependent analysis · Water distribution network · Dynamic search space reduction (DSSR) · Self-adaptive penalty function

1 Introduction

Water distribution network (WDN) consumes 60–70% of the total outlay of a water supply project (Walski et al. 2003; Sarbu and Tokar 2018); thus, an efficient WDN design methodology is required that reduces its cost through optimization. Till the 1990s, researchers suggested the use of various mathematical programming-based techniques to obtain the least-cost design of WDNs. These techniques called "deterministic search techniques" begin the

Highlights
- A novel dynamic search space reduction methodology increases the efficiency of GA.
- New superior solutions achieved for a benchmark network.
- The proposed methodology is generic and can be used with other EAs.

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search with a solution in the search space and progress to a better solution in an iterative manner. Such searches frequently result in a local optimum solution (Bhave 2003).

In the last two to three decades, several evolutionary algorithms (EAs) have been developed that starts with several initial randomly selected solutions to optimize an objective function by exploiting the search space. These methods are inspired by the biological or other natural phenomenon and use computational methods based on them for searching the entire search space and terminates usually when sufficient search is made. It is observed that evolutionary techniques have better capacity to reach to global optimal solution and provides several near optimal solutions. These algorithms have been reviewed and compared from time to time by various researchers (Zecchin et al. 2007; Marchi et al. 2014; El-Ghandour and Elbeltagi 2018; Mala-Jetmarova et al. 2018; Moosavian and Lence 2018; Jain and Khare 2021). Moosavian and Lence (2018) compared 10 different EAs based on the final solution obtained with fixed number of functional evaluations and other properties. They observed that the covariance matrix evolution strategy (CMAES) and soccer league competition (SLC) algorithm scored well over other algorithms on the benchmark networks considered. Recent EAs applied to WDN design are hybridized grey wolf optimization (Sankaranarayanan et al. 2017), self-adaptive differential evolution (SADE) (Sirsant and Janga 2018), self-adaptive cuckoo search (SACS) (Pankaj et al. 2020), Jaya, Rao-I and Rao-II Algorithm (Palod et al. 2021), artificial intelligence algorithm (Hong and Thanh 2022) and Chaotic Sobol Sequence-based multi-objective evolutionary algorithm (MOEA) (Sirsant et al.2022).

Genetic algorithm (GA), one of the oldest EAs (Goldberg 1989), was first applied to WDNs design optimization by Murphy and Simpson (1992). Since its first application on WDN design, there have been a lot of developments in GA by various researchers to improve the efficiency and effectiveness of GA. These include improvement in the coding system and string representation schemes (Saleh and Tanyimboh 2014; Tanyimboh 2021), fitness functions, the penalty approach (Wu and Walski 2005; Kadu et al. 2008; Siew and Tanyimboh 2012; Abdy Sayyed et al. 2019), GA parameters (Czajkowska 2016), and hydraulic analyzers (Abdy Sayyed et al. 2019).

The effectiveness of EAs depends upon the fine tuning of the values of their required parameters. One of the main problems associated with the use of EAs is high computational burden (Coelho and Andrade-Campos 2012). Therefore, research on the development of new algorithms that converges rapidly and consistently is continued. Two key techniques for increasing the computational efficiency are: (1) search space reduction; and (2) a self-adaptive penalty.

The search space depends on the number of pipes in the network and the number of available pipe sizes to select from. The search space for a network of 10 pipes and 14 commercially available discrete pipe sizes will be 14^{10}. With the increase in size of the network from 10 to 20 pipes, the search space will become 14^{20}. Thus, the search space increases exponentially with the increase in number of pipes, and reduction in search space is desirable. For example, if there are 14 available sizes and 5 are selected for each of the 10 pipes to be sized, the reduced search space will be 5^{10}, which is only 0.003% of the total search space. Obviously, searching for the optimal solutions in the reduced search space would be much faster.

Vairavamoorthy and Ali (2005) considered relative importance of each pipe in a network using a pipe index vector to reduce the search space by limiting the number of candidate pipe diameters for each pipe. Initially, assuming some volume pipe flow rates and imposing minimum and maximum velocity criteria, lower and upper bounds for each pipe were determined. These bounds were tightened during the GA process by repeatedly calculating pipe index vector. Thus, calculation of pipe index vector increases the computational burden as it requires solution of linear equations several times in GA process.

Kadu et al. (2008) reduced the search space by selecting candidate pipe sizes using the critical path method (Bhave 2003). The critical path method involves several steps including the need to determine the critical path beforehand. The critical paths and sub-paths are obtained based on the available hydraulic slopes on different paths only, and some hydraulic parameters like pipe discharges and temporal variation in demands are not considered that may also affect critical node and critical path. Thus, determining the critical path beforehand is challenging if not practically impossible.

Haghighi et al. (2011) reduced the search space indirectly. The GA was coupled with integer linear programming (ILP). The looped WDN was converted to a branching configuration to identify loop-forming links. The GA was used to size the loop-forming links. The rest of the pipes were sized using ILP. This hybrid approach is observed to increase the efficiency of GA; however, it required two optimization algorithms to be iteratively used in sequence.

Zheng et al. (2011) used non-linear programming (NLP) and graph theory to find near-optimal solutions that were then used to define the reduced search space. Barlow and Tanyimboh (2014) first executed the GA with full search space, and then the number of decision variables was reduced by removing those variables whose optimal values did not vary across the solutions obtained with full search space. Also, only three candidate pipe sizes were selected for the remaining decision variables. Reca et al. (2017) used quadratic programming to obtain two extreme flow-distributions along with minimum and maximum velocity criteria to limit the number of candidate pipe diameters for each pipe.

Tanyimboh and Czajkowska (2018) reduced the active search space dynamically in the optimization process by considering the most likely flow distribution based on the maximum entropy formalism (Jaynes 1957). Some of the above methodologies keep the reduced search space constant in the optimization run and can be termed as static search space reduction (SSSR) methodology. In SSSR, there are chances that the candidate sizes of some of the pipes are over-restricted and the reduced search space may not encompass a combination leading to the global optimal solution (Abdy Sayyed et al. 2019). Thus, the dynamic search space reduction (DSSR) methodologies are better than SSSR. However, they require some external criteria like the pipe index vector and maximum entropy formalism, thereby increasing the computational efforts.

A new DSSR methodology is proposed herein that obviates the need for such additional considerations. The proposed methodology keeps on updating the reduced list of candidate pipe sizes as the evolutionary search progresses. The proposed DSSR methodology is generic and can be applied to any EA. Its properties are shown herein with a Genetic Algorithm (GA).

The application of the proposed DSSR methodology using GA is demonstrated with two benchmark problems in the literature and a larger real-world network. The solutions obtained by the proposed methodology are compared with those obtained earlier using other evolutionary techniques.

2 Methodology

2.1 Optimization Model Formulation

The minimum cost design of a WDN involves solving non-linear hydraulic equations. The general optimization problem formulation for a WDN with J demand nodes, N pipes and Y loops, can be formulated as below. The objective function consists of minimization of the initial pipe cost of the network. The constraints consist of satisfying the minimum residual pressure requirements at the demand nodes and the flow governing equations. The problem can be described as follows.

$$\text{Minimize} f\left(D_1, \ldots, D_N\right) = \sum\nolimits_{n=1}^{N} c\left(D_n\right) \times L_n \tag{1}$$

Subject to constraints:

$$\sum\nolimits_{n \in \Pi_j} Q_n + q_j^{req} = 0; j = 1, \ldots, J \tag{2}$$

$$\sum\nolimits_{n \in \Lambda_y} h_n + \sum_{p \in \Lambda_y} E_p = 0; y = 1, \ldots, Y \tag{3}$$

$$H_j^{\text{avl}} \geq H_j^{\text{des}}; j = 1, \ldots, J \tag{4}$$

$$D_n \in \{D_{min}, \ldots, D_{max}\}; n = 1, \ldots, N \tag{5}$$

where, Π_j is the set of pipes connected to node j; Λ_y represents the pipes in loop y; J is the number of demand nodes; $c\ (D_n)$ is unit cost of pipe n having diameter D_n; L = length of pipe; Q = pipe discharge; q_j^{req} = nodal demand; h = head loss in pipe; E_p = energy added to water by a pump; H_j^{avl} = available head at node j, H_j^{des} = minimum desirable head at node j, *above which the demands are satisfied in full;* and D_{min} and D_{max} = minimum and maximum diameter of available pipes, respectively. Equation (1) is for the minimization of capital cost of the network, Eqs. (2) and (3) are flow continuity and energy conservation equations, respectively. Equation (4) assures that the available head is more than the minimum desirable head at each demand node, and Eq. (5) allows the selection of commercial pipe sizes only.

2.2 GA Model Formulation

The constrained optimization problem shown above is converted to an unconstrained one by using the penalty approach. Constraints defined by Eqs. (2) and (3) can be handled using EPANET 2.0 hydraulic solver (Rossman 2000). Constraint defined by Eq. (5) will be satisfied as the selection of pipe sizes will be made from the list of commercial pipe sizes only. However, Eq. (4) is not necessarily satisfied with any selected set of pipes, as the available pressure at one or more nodes may be less than the desirable values. Thus, the objective function in Eq. (1) is modified to include a penalty cost, thereby reducing the fitness of an infeasible solution.

A high penalty cost may eliminate the infeasible solutions too quickly from the population and prevent their further exploration subsequently. On the other hand, a very small penalty costs may make infeasible solutions seem better than some of the feasible solutions in the population and may finally produce an infeasible solution. Therefore, application of a proper penalty approach is essential. Wu and Walski (2005) compared various penalty approaches and recommended self-adaptive penalty approach in which penalty factors were improved periodically using certain rules. Kadu et al. (2008) suggested a penalty factor based on capitalized energy cost to lift the unit quantity of water by unit head. Abdy

Sayyed et al. (2019) modified the penalty by considering the deficiencies in the nodal pressures as well as nodal flows using pressure dependent analysis (PDA) to obtain more accurate values of penalties on constraint violation.

Abdy Sayyed et al. (2019) recommended pressure dependent analysis (PDA) to identify accurately: (a) the pressure-deficient nodes; and (b) the corresponding outflow and pressure deficits. The nodal outflow in PDA is modelled considering the node head-flow relationship and depends on the available pressure. There are various node-head-flow relationships that can be used (Bhave and Gupta 2006). The most widely used relationship suggested by Wagner et al. (1988) and Chandapillai (1991) was adopted here:

$$q_j^{\text{avl}} = q_j^{\text{req}}, \text{if } H_j^{\text{avl}} \geq H_j^{\text{des}} \tag{6}$$

$$q_j^{\text{avl}} = q_j^{\text{req}} \left(\frac{H_j^{\text{avl}} - H_j^{\text{min}}}{H_j^{\text{des}} - H_j^{\text{min}}} \right)^{\frac{1}{n_j}}, \text{ if } H_j^{\text{min}} < H_j^{\text{avl}} < H_j^{\text{des}} \tag{7}$$

$$q_j^{avl} = 0, if H_j^{\text{avl}} \leq H_j^{min} \tag{8}$$

where, q_j^{avl} is available flow at node j; q_j^{req} is required flow at node j; H_j^{avl} is head available at node j; H_j^{min} is minimum head required, below which there is no outflow at node j; and H_j^{des} is head desirable at node j, above which the demand is fully satisfied. The exponent n in Eq. (7) is usually taken as either 1.5 or 2 (Gupta and Bhave 1996).

Therefore, the unconstrained optimization problem can be written as

$$Minimize\ f(D_1, \dots, D_n) = \sum\nolimits_{n=1}^{N} c(D_n)L_n + \sum\nolimits_{j=1}^{DN} \delta_j \times (q_j^{req} - q_j^{avl}) \times \{max(H_j^{des} - H_j^{avl}, 0)\} \tag{9}$$

where, δj is a penalty multiplier (Kadu et al. 2008). The penalty cost in Eq. (9), i.e., the second term, represents an equivalent cost of energy required to lift the outflow deficit by the head deficit (Abdy Sayyed et al. 2019). Herein, accordingly, the penalty cost has the advantage that it is generic; it does not require prior setting or calibration.

The penalty multiplier δj *can* be calculated as detailed below, where δj is the capitalized energy cost per unit of flow and per unit of head. This is expressed as (Kadu et al. 2008)

$$\delta_j = PWF \times cu_e \times \frac{w}{1000 \times \eta} \times t_p; \text{j} = 1, \dots, \text{J} \tag{10}$$

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

The PWF can be calculated as

$$PWF = \frac{\left(1 + i_r\right)^m - 1}{i_r\left(1 + i_r\right)^m} \tag{11}$$

where, i_r = interest rate, expressed as a fraction of one; m = design life of the WDN. Considering, i_r = 0.08 (i.e., 8%); m = 30 years; cu_e = 4.5 (Rs /kWh); and η = 0.6; the penalty multiplier is obtained as δj = 7.261 × 10^6 (Kadu et al. 2008) for discharge in m^3/min and head in m.

2.3 Dynamic Search Space Reduction Methodology

The basic principle of GA is to choose an initial population of solutions that are dispersed at random in the search space. These solutions are modified iteratively to obtain better solutions with the help of GA operators, such as selection, crossover, mutation, and elitism. The iterative process is terminated when the required stopping criteria is met.

A dynamic search space reduction (DSSR) methodology is developed in which the active solution space is reduced after a predefined number of generations. Subsequently, the active search space is updated based on the frequency of selection of a particular diameter for a particular pipe in the best solutions of previous generations. For example, in the best solutions of the last 30 generations, if a 500 mm diameter is selected 20 times for a particular pipe, its frequency of selection becomes 2/3. A maximum of five candidate diameters are selected for each pipe. Select the first diameter having the highest frequency of selection in the best solutions of previous generations, then select two diameters immediately below and two diameters immediately above to that size. If there is only one or no diameter below or above the first diameter, then less than five diameters are selected for the reduced active search space. Figure 1 shows the flowchart for the DSSR GA methodology.

3 Computer Code Development

A general GA code available from IIT Kanpur GA Lab, (http://www.iitk.ac.in/kangal/) and EPANET 2.0 were integrated on the C platform Visual Studio for the optimal design of WDN using the proposed methodology. As EPANET 2.0 does not have PDA facility, the modelling approach with a series of additional artificial elements as suggested by Abdy Sayyed et al. (2015) at each demand node is used to get a solution in a single run of EPANET 2.0. This requires modification in the input file for the network and can be done using a separate C code proposed by Gupta et al. (2018). However, as EPANET 2.2, a modified version having PDA facility is now available, it can be used as an alternative. Other PDA methods are available in the literature also (Sivakumar et al. 2023).

The GA code downloaded from IIT Kanpur GA lab is a general code which works on both the constrained and the unconstrained optimization problems. The GA operators used are selection, crossover, mutation and elitism. Implementations can be done using both binary and real coding and user is asked to specify the type of coding. In this study, real coding is used. In case of real coding, it uses restricted tournament selection operator, simulated binary crossover, and polynomial mutation. The inputs to the program are: population size; number of generations; crossover and mutation probabilities and the objective function in mathematical form defined using the decision variables. Further, a seed number is given that helps in regenerating the same initial population. The above GA code was modified to integrate the PDA, self-adaptive penalty and the DSSR methodology. The code is written to perform a predefined number of runs and provides the best solution from these runs.The information about the RSS for each pipe at the end of the run is passed on to next run to reduce the computational efforts.

4 Application of Methodology

Different benchmark networks of varying sizes and complexities were solved using the proposed methodology. Results of a two-source network (Kadu et al. 2008) and the GoYang Network of Kim et al. (1994) are presented herein, along with the real-world

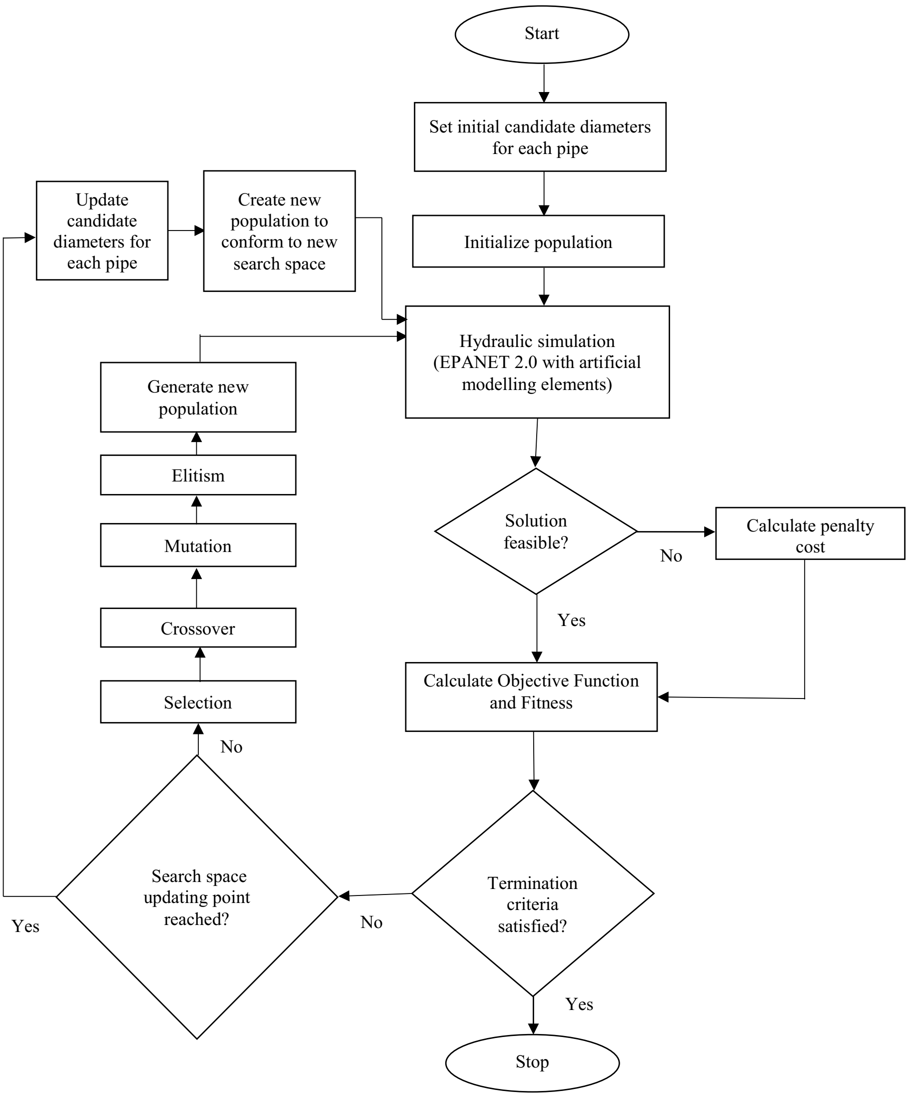

Fig. 1 Flow chart of DSSR Genetic Algorithm

network of Ramnagar Zone in Nagpur City, India. The computation environment was as follows Dell 10th GEN, 8 GB RAM, Intel(R) Core (TM) i7-10510U, CPU @ 2.30 GHz.

The GA search depends on the values of GA parameters like crossover probability, mutation probability, population size and number of generations. The DSSR GA code needs adjustment of these parameters for each example depending upon the size and complexity of the problem. The optimum range for cross over probability was 0.7 to 0.95, and for the mutation probability the range was in between 0.001 to 0.1. The program was executed initially to adjust these GA parameters by selecting them randomly in the range as above with different population sizes and number of generations, by keeping the seed number same. The adjustment process was terminated when the consistent results were obtained.

4.1 Two-Source Network (Kadu et al. 2008)

A two-reservoir network from Kadu et al. (2008) with 34 pipes, 24 nodes, and 9 loops is shown in Fig. 2(a). Nodes 1 and 2 are the source nodes having reservoir water levels of 100 m and 95 m, respectively. A set of 14 commercial pipe diameters was used in this design problem. Pipe data, node data, available pipe sizes, and their respective unit costs can be found in Kadu et al. (2008).

Kadu et al. (2008) used the Hazen-Williams pipe friction head loss formula

$$h_l = \frac{\omega L Q^{\alpha}}{C_{HW}^{\alpha} D^{\beta}} \tag{12}$$

where, h_l = head loss; ω, α, and β are constants; and C_{HW} = Hazen-Williams pipe roughness coefficient. Kadu et al. (2008) considered values of ω, α, and β as 2.234×10^{12}, 1.85 and 4.87 for the discharge in m^3/min, and diameter in mm in the hydraulic analysis software they developed. Later, other researchers used EPANET for hydraulic simulation with the default values of these constants as set in EPANET. The default values in current version of EPANET 2.0 (Build 2.00.12.01) for ω, α, and β are 10.667, 1.852 and 4.871 for the discharge in m^3/s, and diameter in m.

The GA results for the network with the FSS were obtained after fine tuning of the parameters by varying the seed number. The following GA parameters provided the best solution: population size = 320, number of generations = 1000, crossover probability = 0.72, and mutation probability = 0.003.

The network cost obtained was Rs. 125,209,860 in 157,760 function evaluations, and the time required for that run was 254.81 s. This solution is cheaper than the first *feasible* best-known solution reported in the literature of Rs.125,460,980, obtained by Siew et al. (2014) in 436,000 function evaluations. It is also less expensive than the current best-known solution in the literature (Rs. 125,434,170 in 19,700 function evaluations (Palod et al. 2021) as shown in Table 1.

Further, the GA results for the network were obtained by the proposed DSSR methodology also. The search space was modified after every 50 generations using the proposed methodology. The best result was obtained with the following GA parameters: population size = 300, number of generations = 400, crossover probability = 0.72, and mutation probability = 0.003. The optimal cost was Rs.125,019,790 in 1,125,300 function evaluations, and the time required was 261.488 s. This solution is cheaper than the solution obtained with FSS. The second-best solution has a cost of Rs. 125,076,190 in 267,000 function evaluations. The third-best solution has a cost of Rs.125,254,880 obtained in 397,800 function evaluations. In total, eight solutions that are superior to the previous best solution were achieved as detailed in Tables S1 and S2. These solutions have not been reported in the literature to date.

Thus, based on the best solutions achieved herein, it can be stated that overall the combined flow and pressure deficit penalty approach performed better than the penalty-free approach (Siew et al. 2014) in terms of the cost of the final solution and the required number of function evaluations with both FSS and DSSR. While the number of function evaluations for Rao II (Palod et al. 2021) is smaller (Table 1), the solution is more expensive than the nine new solutions achieved in total.

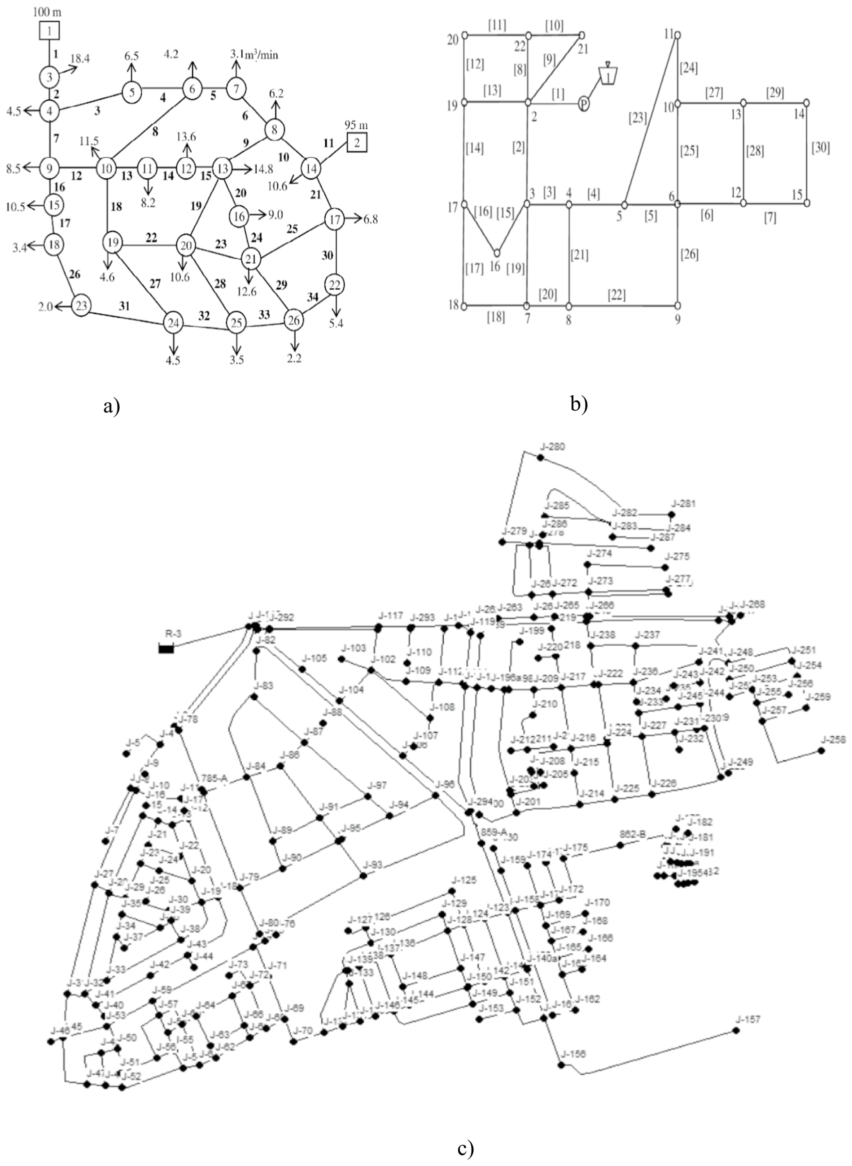

Fig. 2 Layout of Water Distribution Networks: **a** Kadu's Network; **b** Goyang Network; **c** Ramnagar Network

The progress of the feasible solutions in the FSS and DSSR is shown in Fig. 3(a) and (b) respectively. Figure 3(b), (d) and (f) show only the run with the best solution. Also, the pipe diameters and available nodal heads achieved are shown in supplementary material in Figs. S1(a) and S2(a), respectively. The variation of penalty cost is shown in Fig. S3, and details of GA progress runs for FSS and DSSR are shown in Figs. S4 and S5,respectively. As expected, the average penalty cost reduced very fast in the initial

Table 1 Comparison of solutions for Kadu's Two-source Network

Authors	Method used	Optimal Cost (Rs.)	Total Number of Function Evaluations	Residual Heads at nodes in EPANET 2.0 (m)	
				Maximum	Minimum
A. Full Search Space (FSS)					
Kadu et al. (2008)	GA with FSS and head deficit-based penalty	131,678,935[a]	120,000	13.96	0.14
Haghighi et al. (2011)	GA and Integer Linear Programming	131,312,815[b]	4,440	13.97	-0.01
Siew et al. (2014)	Penalty-free Multi-objective Evolutionary Algorithm (PF-MOEA) with FSS	125,460,980[a]	436,000	13.29	0.24
Barlow and Tanyimboh (2014)	GA-based Memetic Algorithm	124,690,000[b]	142,000	13.97	-0.39
Jabbary et al. (2016)	Central Force Optimization (CFOnet)	126,535,915	259,476	13.29	0
Kadu et al. as revised by Abdy Sayyed et al.	GA with FSS and head deficit-based penalty	128,381,245	7,600	13.28	0.06
Palod et al. (2021)	Rao I Algorithm	126,825,885	24,950	13.98	0.07
Palod et al. (2021)	Rao II Algorithm	125,434,170	19,700	13.98	0.04
Tanyimboh (2021)	GA considering redundant binary codes effects	127,368,355[a]	339,000	13.26	0.24
Present Work	GA with adaptive penalty	125,209,860	157,760	13.28	0.16
B. Reduced Search Space (RSS)					
Kadu et al. (2008)	GA with RSS and head deficit-based penalty	126,368,865[a,b]	25,200	13.99	-1.39
Siew et al. (2014)	PF-MOEA with RSS	125,826,425[a]	82,400	13.29	0.23
Abdy Sayyed et al. (2019)	GA with RSS and combined head and flow deficit-based penalty	126,365,955	7,000	13.32	0.03
Abdy Sayyed et al. (2019)	GA with revised RSS and combined head and flow deficit-based penalty	125,754,310	7,600	13.29	0.06
Present Work	GA with adaptive penalty and DSSR	125,019,790	1,125,300	13.28	0.15

[a] $(\alpha, \beta, \omega) = (1.85, 4.87, 10.68)$

[b] Infeasible solution with current EPANET parameters $(\alpha, \beta, \omega) = (1.852, 4.871, 10.667)$

few generations and remained relatively stable for the rest of the generations. Also, closer examination of the penalty costs seems to provide evidence of renewed further exploration whenever the reduced search space was updated.

The results obtained by the proposed methodology and those reported by other researchers for FSS and DSSR are provided in Table 1 for comparison. Siew et al. (2014) observed that the solutions reported by Kadu et al. (2008) and Haghighi et al. (2011) have negative value of residual pressure head considering the original values of constants used by Kadu et al. (2008). Herein, the feasibility of all the reported solutions has been checked using EPANET 2.0 (Build 2.00.12.01) as most of the researchers used EPANET as hydraulic simulator. The detailed simulation results are given in the supplementary material in Tables S1 and S2. From the analysis using EPANET 2.0, it is observed that the solutions reported by Kadu et al. (2008) for RSS and that by Haghighi et al. (2011) have negative value of residual pressure head and cannot be considered as feasible solutions. Abdy Sayyed et al. (2019) revised the solution using the penalty

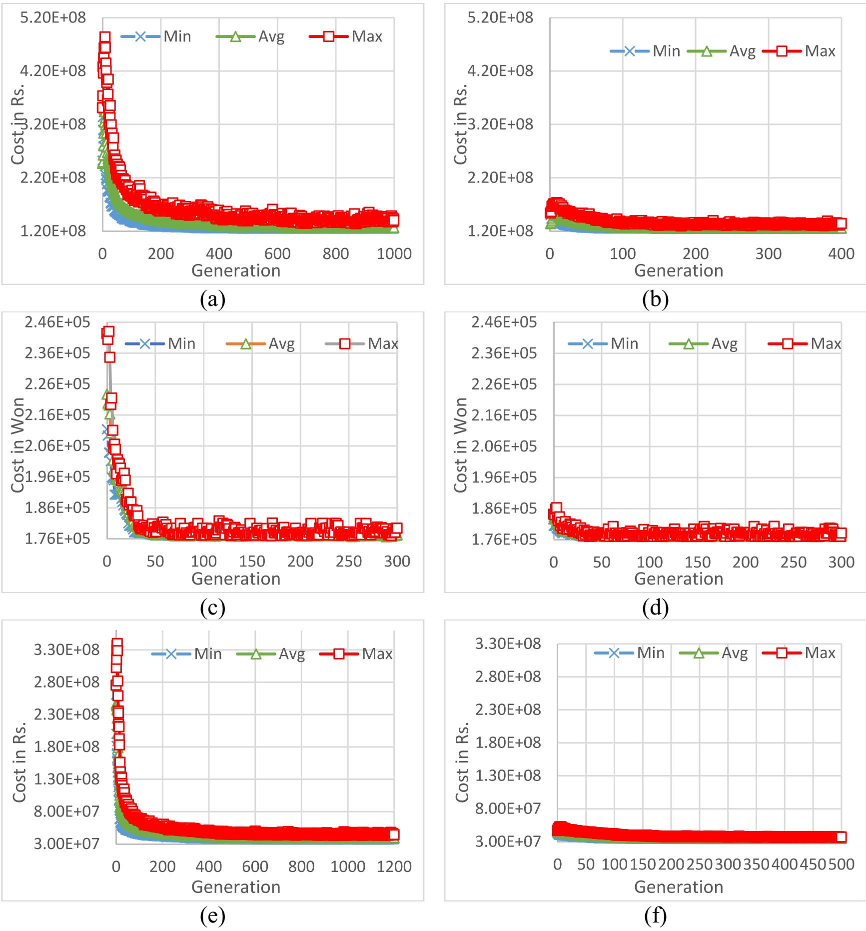

Fig. 3 Progress of the costs of the feasible solutions: **a** FSS for Kadu's Network; **b** DSSR for Kadu's Network; **c** FSS for Goyang Network; **d** DSSR for Goyang Network; **e** FSS for Ramnagar Network; **f** DSSR for Ramnagar Network

method suggested by Kadu et al. (2008) and EPANET 2.0 for hydraulic simulation. The revised solution is feasible and has a cost of Rs. 128,381,245 as given in Table 1.

Thus, in over 15 years since Kadu et al. introduced the network in 2008 and to the best of our knowledge this is only the third occasion where new feasible best-known solutions have been reported. It is observed, also, that Barlow and Tanyimboh (2014) obtained a solution in which EPANET 2.0 was used as hydraulic solver with pipe friction head loss parameters ω, α, and β as 10.6668, 1.852 and 4.871, respectively, for the discharge in m^3/s, and diameter in m). This solution is also given in Table 1 and has a cost of Rs. 124,693,590 obtained in 142,000 function evaluations. With the above default values, residual pressure at all the nodes were found above the minimum required values, with a minimum of 0.04 m at node 12, by Barlow and Tanyimboh (2014). However, when the simulation is carried out with the current EPANET 2.0 (Build 2.00.12.01), this solution showed deficiency in pressure at node 24 by 0.39 m.

4.2 GoYang Network

The GoYang Network was first presented by Kim et al. (1994). It includes 30 pipes, 22 demand nodes, and a constant head pump of 4.52 kW linking to reservoir with a head of 71 m, as shown in Fig. 2(b). The Hazen-Williams roughness coefficient for each new pipe is 100. The minimum required pressure head above the ground elevation at each node is 15 m. A set of 14 commercial pipe diameters was used in this design problem. The node and pipe data are available in Geem (2006).

The GA results for the network were obtained by the proposed FSS and DSSR methodology. The best result was obtained with the following GA parameters in both cases: population size = 10, number of generations = 300, crossover probability = 0.79, and mutation probability = 0.089. The optimal cost obtained is 177,010,355 won, obtained in 630 function evaluations and the time required was 3.75 s with full search space and in 3340 function evaluations in 18.23 s with dynamic search space reduction. The progress of the feasible solutions in FSS and DSSR is shown in Fig. 3(c) and (d) respectively. Also, the pipe diameters and nodal heads achieved are shown in Figs. S1(b) and S2(b) respectively.

The results obtained by proposed methodology and those reported by other researchers for FSS and RSS are provided in Table 2 for comparison. It can be observed that the solution obtained by Jain and Khare (2021) and Palod et al. (2021) obtained using FSS are the same but have more function evaluations as compared to that obtained using proposed method. The advantage of search space reduction is not particularly seen in this network as 23 out of 28 pipes are of minimum size of 80 mm as can be observed from Fig. S1(b). Detailed results are given in supplementary material in Tables S3 and S4.

4.3 Ramnagar Network

The methodology was also applied to a real-world water distribution network in the Ramnagar zone, located in Nagpur City, Maharashtra, India. The network consists of 375 pipes, 292 junctions, and a Ground Service Reservoir with a constant head of 327.205 m. The layout of the network is shown in Fig. 2(c). The minimum pressure that is allowable at the demand nodes is 8 m. A set of 16 commercial pipe diameters was used in this design problem; the costs of the available diameters are presented in Table S5 of the supplementary materials.

Table 2 Comparison of solutions for GoYang Network

Authors	Method used	Optimal Cost (Won)	Total Number of Function Evaluations	Residual Heads at nodes in EPANET 2.0 (m)	
				Maximum	Minimum
Kim et al. (1994)	Method not mentioned	179,428,600	-	31.18	15.61
Kim et al. (1994)	Non-Linear Programming	179,142,700	-	31.15	15.61
Geem (2006)	Harmony Search	177,135,800	10,000	26.32	15.06
Jain and Khare (2021)	DDA-Rao II	177,010,355	1,400	28.93	15.33
Jain and Khare (2021)	PDA-Rao II	177,010,355	890	28.93	15.33
Palod et al. (2021)	Rao I Algorithm	177,010,355	1,120	28.93	15.33
Palod et al. (2021)	Rao II Algorithm	177,010,355	800	28.93	15.33
Present Work	GA with adaptive penalty	177,010,355	630	28.93	15.33
Present Work	GA with adaptive penalty and DSSR	177,010,355	3,340	28.93	15.33

The best GA solution for the network with FSS was obtained with the following GA parameters: population size = 800, number of generations = 1200, crossover probability = 0.78, and mutation probability = 0.004. The network cost obtained is Rs 37,837,223.72, obtained in 881,600 function evaluations, and the time required for that run was 6,377.917 s (106.30 min).

The GA results for the network were obtained by the proposed DSSR methodology also. The search space was modified after every 50 generations. The best result was obtained with the following GA parameters: population size = 500, number of generations = 500, crossover probability = 0.8, and mutation probability = 0.02.

The optimal cost obtained was Rs 34,289,227.43 in 382,500 function evaluations, and the time required was 2240.46 s (37.34 min). The progress of the feasible solutions in FSS and DSSR is shown in Fig. 3(e) and (f) respectively. Also, the available pipe diameters and nodal heads achieved are shown in Figs. S1(c) and S2(c) respectively. The details are given in supplementary material (Tables S6 and S7.)

The results as obtained by proposed methodology for FSS and DSSR are provided in Table 3. The network cost, total number of function evaluations, time required, the maximum and minimum values of residual pressures at demand nodes are given in columns 2 to 6, respectively. The advantage of DSSR methodology can be seen very clearly with this network. The best FSS cost was Rs. 37.837 million obtained with 881,600 function evaluations in 106.30 min of run time. DSSR provided 9.38% cheaper solution in 382,500 function evaluations in 37.34 min of run time.

5 Summary and Conclusions

SSR was suggested by different researchers using some algorithms based on the pipe index vector, critical path method, flow entropy, graph theory and NLP techniques to improve the efficiency of EAs. If the reduced search space is set beforehand, this may eliminate the global optimum solution. An effective DSSR approach that does not require prior initialization or configuration of the reduced solution space is proposed. The reduced search space accelerates the search around the active constraint limits after workable solutions have been found in the initial stage, which places a priority on exploration. The approach is universal, self-adaptive and clubbed herein with self-adaptive penalty approach, based on the deficiency in meeting the demand and pressure at the demand nodes using PDA. The application of DSSR is demonstrated with GA here. However, it can be applied to other EAs also. In terms of cost, CPU time, and function evaluations, the results produced by the DSSR algorithm were better than those from the entire solution space. Additionally,

Table 3 Comparison of Solutions for Ramnagar Network

Method used	Optimal Cost (Rs.)	Total Number of Function Evaluations	Time Required (Minutes)	Residual Heads at nodes in EPANET 2.0 (m)	
				Maximum	Minimum
GA with adaptive penalty	37,837,223.72	881,600	106.30	18.72	8.03
GA with adaptive penalty and DSSR	34,289,227.43	382,500	37.34	15.92	8.07

convergence was consistently quick for both FSS and DSSR. The method proves to be an important contribution in solving large networks. Finally, with no additional esoteric features, the algorithm is effective, computationally efficient, practical, and the utility of the artificial modelling elements approach to PDA is thus demonstrated also. The advantages of DSSR over both FSS and SSR methodologies are seen with the solution of Kadu's network. The smaller solution space yielded eight new best-known solutions that were not achieved in the FSS.

The application of DSSR to a real-life Ramnagar network showed both reduction in time and number of function evaluations. With DSSR, a 9.38% cheaper solution was obtained in 56.61% fewer functional evolutions and 64.87% less time as compared to FSS.

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Declarations

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